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It's about time: Managing implementation dynamics of condition-based maintenance

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PROEFSCHRIFT

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Without data, you're just another person with an opinion.

Sir Kenneth Robinson

Summary

Condition-Based Maintenance (CBM) is an approach to preventive maintenance that aims to predict future malfunction of an asset by monitoring several conditions, so maintenance can be executed at “the right time”. CBM relies on Condition Monitoring (CM) technologies – such as vibration monitoring, oil analysis, and thermography technologies – with which the condition of the asset can be assessed. Although most CM technologies have been around for some time, recent advancements in connectivity, data storage and data processing have increased the potential performance of condition monitoring both in terms of efficiency and accuracy, making CBM one of the expected key value drivers of Industry 4.0. At the same time, recent surveys have identified that many organizations still struggle with successfully adopting and applying advanced CM technologies.

This is the starting point and central puzzle of this dissertation: *if it is possible technically, interesting economically, and desired by organizations, why is the uptake of CBM still so low?* What is keeping organizations from using CBM?

In this dissertation, we combine three loosely coupled studies. These studies do not attempt to solve the puzzle collectively, nor are they designed to be mutually exclusive. Instead, we searched for specific research questions within this field that are relevant for practitioners and are interesting scientifically. This resulted in three studies, each focussing on a different process, adopting a different level of analysis and applying different theories: the implementation of CBM, the diffusion of CM technologies, and the CBM maturation of asset owners.

In Chapter 2, we analyse the introduction process of CBM based on a new CM technology over a 4-year time period. The purpose of this chapter is twofold: to provide the readers of the dissertation insight into the challenges and considerations present during the introduction of CBM and CM technologies (with an extensive empirical description) and to elaborate on organizational learning theory. In Chapter 3, we analyse the intra-firm diffusion process of twelve CM technologies (six at Oilco and six at Steelco) and argue that this process depends upon technical, economic and institutional considerations. The results of this study are used to elaborate on diffusion theory and generate a middle-range theory of intra-firm diffusion. In Chapter 4, we adopt a design science approach to develop a CBM Maturity Model and Assessment for asset owners. The main purpose of the maturity model is to enable asset owners and their maintenance managers to visualize their desired end state, assess their as-is situation and derive opportunities for

improvement. Maturity models are helpful tools in addressing such ill-structured issues. Lastly, in Chapter 5, we elevate the findings of each individual study to a higher level, elaborating on the connections and overarching lessons between the studies, and highlight the main theoretical contributions of this dissertation.

Throughout our studies, we have identified several pieces of the puzzle. First, the introduction of CBM and advanced CM technologies can be complex, especially if integration of the technology is costly or introduces risks, and if it is unknown how well the CM technology can detect upcoming failures. It takes time to identify the technology's potential performance with targeted experiments, to integrate the technology into the existing hardware and processes, and to further improve the quality of analyses via processes of learning-by-doing. Second, the diffusion of advanced CM technologies within the firm can be troublesome, especially if the CM technology is complex, expensive and conflicts with existing institutional logics. Moreover, the more the assets and decision-makers are fragmentized across different factories, the smaller the strength and reach of diffusion mechanisms. Within each factory, it takes time to institutionalize the technology's usage, to increase the technology's legitimacy, to increase the technology champion's influence, to gain additional resources for adoption, and to institutionalize further adoption of the technology. Third, the transition asset owners need to make to fully utilize CBM on a larger scale is versatile and elaborate. For example, factories have to identify what assets are suitable for CBM, the IT-infrastructure has to become easily accessible for CM technologies, maintenance engineers have to get well-connected to internal and external CM service providers, decision-makers have to identify how the CM information can best be incorporated into decisions, and the culture has to become CBM-oriented. Again, these processes take time.

If we assume that most advanced CM technologies are recently developed, time also becomes a piece of the puzzle. Since it takes time to introduce a CM technology and to diffuse it within the firm, high levels of diffusion cannot be expected for new CM technologies. Rather, we expect to see an evolution in the usage of CBM, in which CM technologies will gradually become more potent and less costly, in which asset owners experiment with and diffuse an increasing number of CM technologies, and in which condition information is utilized in an increasing number of asset management decisions. Yet, the speed of this evolution can be sped up with the right efforts from management, technology champions and other innovators. The current technological possibilities exceed the current usage of advanced CM technologies, so we believe it's about time asset owners start capturing the full potential of condition-based maintenance.

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Chapter 1: Introduction

1. Introduction

For many capital goods – such as trains, aircrafts, and industrial plants –, the costs of maintenance represent a large fraction of the Total Cost of Ownership (Van Dongen, 2011). In the Netherlands, the Maintenance, Repair and Overhaul (MRO) sector is responsible for about 4% of the gross domestic product, and around 4% of the Dutch working population is active in this sector (NVDO, 2018). The purpose of maintenance is to preserve the availability, productivity and safety of assets, while limiting the resources needed for this (Garg & Deshmukh, 2006). This function is growing in importance, as a large part of the public and industrial infrastructure in the Netherlands is reaching its designed technical lifetime, relying on lifetime extending maintenance to delay investments (WCM, 2015). In addition, societal expectations of the maintenance function are increasing because of the predicted revolution towards digital manufacturing – coined the 4th industrial revolution, Industry 4.0, Smart industry, etc. –, expecting higher levels of availability, productivity, and safety, against lower costs (Bokrantz, Skoogh, Berlin & Stahre, 2017; McKinsey, 2015).

One promising approach to boost maintenance productivity is Condition-Based Maintenance (CBM); a proactive maintenance strategy that aims at predicting future malfunctions by monitoring several conditions (e.g., temperature, vibrations), so the maintenance can be executed at ‘just the right time’ (Jardine, Lin & Banjevic, 2006). For the sake of simplicity, we adopt a high-level taxonomy of maintenance strategies and distinguish condition-based maintenance from two other maintenance strategies: corrective maintenance and periodic maintenance (Tiddens, 2018). Corrective maintenance, or run-to-failure, is a reactive maintenance strategy, in which an asset is replaced or repaired after a failure has occurred and been identified (Moubray, 1997). Periodic maintenance is – like CBM – a proactive maintenance strategy, in which a predetermined interval is set at which the asset will be overhauled or replaced (Alaswad & Xiang, 2017). This interval can be based on calendar time (every so many months) or usage (every so many production hours, every so many activities), but the decision to maintain is made regardless of the actual condition of the asset. In line with ISO (13372:2012), Olde Keizer (2016) and Tiddens (2018), we consider predictive maintenance as a form of condition-based maintenance in this thesis, as both maintenance strategies rely on an assessment of the asset’s condition.

The assessment of an asset’s current (and future) condition can be performed with human senses or with the aid of Condition Monitoring (CM) equipment (Tinga &

Loendersloot, 2014). An incredibly wide range of CM techniques has been developed over the past 60 years (for reviews, see Moubray, 1997; Davies, 2012), including portable and on-line monitoring techniques (e.g., thermography, ultrasound, vibration), laboratory analyses (e.g., ferrography, chromatography, spectroscopy), and in-line analyzers (e.g., corrosivity, composition of liquids and gases). Also, many customizable techniques exist, such as statistical process control, physics-based models and data-driven models, that can be used to create a tailored monitoring application for an asset (Tiddens, 2018). As a consequence, for most assets, multiple CM techniques can be used to assess its condition. For example, degradation of a compressor can be identified by monitoring the energy-to-output ratio (tailored model), by monitoring the vibrations with an on-line system, and by periodic inspections of an experienced operator, who gets triggered by deviations in the noise produced. These CM techniques are complementary and together determine the quality of the maintenance decision.

In this dissertation, we define condition monitoring as the process of assessing an asset's current and/or future condition, which can be done by acquiring and processing data (ISO 13372:12). By definition, condition monitoring is a prerequisite for being able to perform condition-based maintenance. We make the distinction between condition-based maintenance (CBM) and condition monitoring (CM) however, for three reasons. First, with CBM, the maintenance decision can be based on one or multiple CM techniques, so they are not equal in number of applications. Second, implementing a(n additional) CM technique does not imply a switch in maintenance strategy (either because the asset was already maintained condition-based or the asset still won't be maintained condition-based), so they have different implementation processes. In fact, multiple practitioners have described the implementation of CBM as a two-step or dual implementation process. Third, condition information can also be used for other maintenance and asset management decisions, such as modification decisions, production decisions, and purchasing decisions, so they differ in value generated (ISO 55000:2014).

The general rationale behind CBM is depicted in Figure 1.1, which shows the P-F curve of an asset (Moubray, 1997). Within this curve two states are prevalent: (1) a functional failure (F), entailing the inability of the equipment to meet a specified performance standard, and (2) a potential failure (P), entailing an identifiable condition that indicates that a functional failure is imminent (early signal).

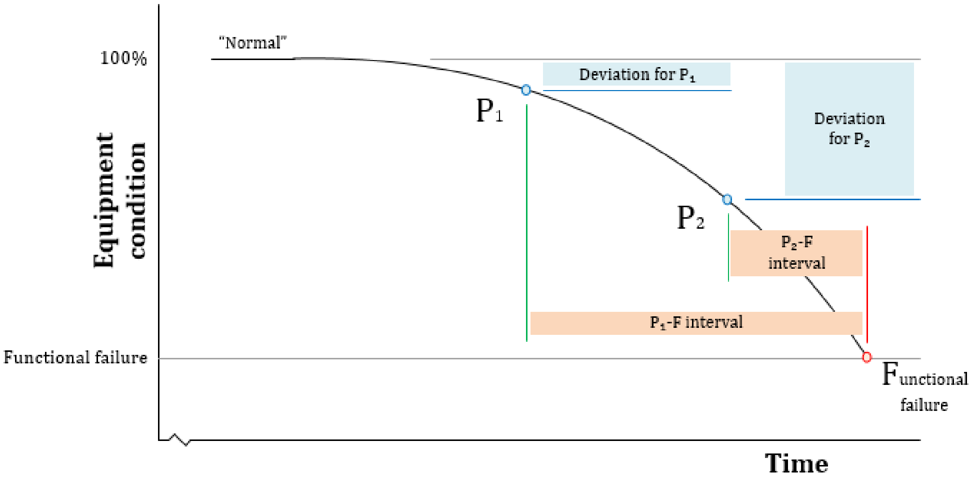

Figure 1.1: P-F curve of an asset, adapted from Moubray (1997)[1]

CBM has been possible technologically for quite some time. In fact, condition-based maintenance – based on periodic visual inspections and basic measurements – was recommended already in 1961 for production facilities in the Netherlands (Hoogovens, 1961). In 1997 Moubray indicated that condition monitoring is technically feasible for about 20% of failure modes, and worth doing in less than half of these cases (Moubray, 1997). Recently however, advancements in connectivity, data storage and data processing have increased the potential performance of condition monitoring, both in terms of efficiency and accuracy (Bokrantz et al., 2017), vastly expanding the potential scope of CM applications (see for example, Alaswad & Xiang, 2017; Goyal & Pabla, 2015; Lee, Wu, Zhao, Ghaffari, Liao & Siegel, 2014; Sikorska, Hodkiewicz & Ma, 2011; Peng, Dong & Zuo, 2010). At the same time, the ease of purchasing monitoring equipment and services (Attewell, 1992) has been increasing, as remote monitoring techniques have engaged OEMs to

[1] In Figure 1.1, three things are important to understand. First, the earlier one detects the asset's degradation (which requires more sensitive monitoring equipment), the more time is available to take proactive actions, such as scheduling and preparing maintenance or adjusting production to minimize further degradation. Second, in reality the degradation process of many failure modes is less 'smooth' than the function depicted here, thus the actual timing of the functional failure might be earlier or (much) later than predicted (Moubray, 1997). Third, most assets have multiple failure modes, thus accurately predicting the moment of breakdown of a complex asset requires predictions about each (non-redundant) component (Moubray, 1997). The higher the number of components and failure modes, the harder it is to predict the timing of failure of the asset as a whole.

move towards servitization (Grubic, 2014; McKinsey, 2017) and many specialized CM service providers have started up recently (Venture Radar, 2020).

From an economical point of view, many model-based (e.g., Olde Keizer, 2016; Alaswad & Xiang, 2017) and empirical studies (e.g., Semiotic Labs, NVDO & WCM, 2018; PwC & Mainnovation, 2018) have shown that condition-based maintenance can be a cost-effective maintenance strategy for assets that fail frequently and entail high costs when failing unexpectedly. In addition to cost reduction, condition monitoring can help to increase the productivity of assets (by improving the availability and identifying efficiency losses), extend the useful life of assets (by repairing degradation in an early stage and postponing periodic replacements), and reduce safety hazards (by preventing the failure from occurring or reducing its consequences; Neale & Woodley, 1975; Zaki & Neely, 2014). The benefits differ per application, yet studies from different sectors show similar cost savings (including 'lost production' as a cost): 10-50% in the process industry (Olde Keizer, 2016), 30-40% in the aerospace industry (Kent & Murphy, 2000) and 30-40% in the utility sector (Jardine & Tsang, 2013). In general, real-time condition information can support a wide variety of asset management decisions (The IAM, 2015), optimizing the performance of the installed asset base, while limiting the risks and costs.

Despite the above, in many sectors the extent of adoption of CBM is still limited (Grubic, Redding, Baines & Julien, 2011; PwC & Mainnovation, 2018). In recent surveys in Northwest Europe up to 60% of organizations (out of 268) indicated they have concrete plans or intentions to use predictive maintenance in the near future, while only 11% are already employing predictive maintenance practices (PwC & Mainnovation, 2018). An extensive survey among 1,837 UK-based manufacturers showed similar results, indicating less than 10% of organizations were applying diagnostic and prognostic techniques (Grubic et al., 2011). Moreover, from the organizations that did apply these techniques, more than half experienced a gap between potential and realized benefits.

This is the starting point and central puzzle of this dissertation: *if it is possible technically, interesting economically, and desired by organizations, why is the uptake of CBM still so low?* What is keeping organizations from using CBM?

We expect that limited usage cannot be explained by technical and economic factors alone. Diffusion theory has shown that adoption rates are primarily affected by an innovation's relative advantage (the degree to which it is perceived being better than the idea it supersedes), compatibility (the degree to which it is perceived to be consistent with existing values, past experiences and needs), and complexity (the degree to which it is perceived as relatively easy to understand and use; Rogers, 1995; Tornatzky & Klein, 1982). Innovation research has shown that implementing new technologies successfully requires translating and reinventing the technology to the organizational context (Rice & Rogers 1980), adjusting work processes and structures to the technology (Van de Ven, Polley, Garud & Venkataraman, 2008), and institutionalizing the technology’s usage (Venkatesh & Bala, 2008; Volberda, Commandeur, Bosch & Heijblom, 2013). Understanding innovation processes and their outcomes – such as the technology’s usage – therefore requires studying the technology and adopting organization collectively and over time (Van de Ven et al., 2008).

Unfortunately, studies on the implementation and management of CBM is scarce (Veldman et al., 2011; Bousdekis, Magoutas, Apostolou & Mentzas, 2015). In contrast, there is an abundance of scientific literature about CM technologies (for reviews, see Moubray, 1997; Carden & Fanning, 2004; Ragavathiapan, Lahiri, Saravanan, Philip & Jayakumar, 2013), modelling maintenance policies (for reviews, see Alaswad & Xiang, 2017; Olde Keizer, 2016; Jardine & Tsang, 2013), and developing tailored diagnostic and prognostic models (for reviews, see Tinga, 2010; Ahmadzadeh & Lundberg, 2014). Practitioners’ experiences, accumulated in books, and international guidelines provide some guidance (e.g., Nicholas, 2016; ISO 17359:2011), but lack theoretical foundations and systematic empirical evidence.

Recently, some empirical studies have emphasized the role of organizational aspects in the implementation and execution of CBM. For example, Tiddens (2018) identified multiple organizational barriers to the adoption of CBM, such as insufficient financial resources, a lack of trust in the monitoring technique, limited fit to the skills and abilities of personnel, and poor correspondence with existing procedures. Veldman et al. (2011) identified that few organizations have a structured, systematic approach to CBM. In many cases, employees have received limited training, have not developed procedures, and base prognoses and maintenance decisions primarily on gut feeling. In addition, Tiddens, Braaksma and Tinga (2015) observed that organizations face difficulties in selecting the right CM technique for their application and find it difficult to determine what data is useful for condition monitoring purposes, resulting in a long and costly implementation process. These scholars call for further investigation of the actual use of CBM in various industrial settings, to better understand the challenges involved in using CBM and to derive practical guidelines for maintenance management (Bokrantz et al., 2017).

In this dissertation, we combine three loosely coupled studies. These studies are conceived from the central puzzle of the dissertation: why is the use of CBM still so low? However, the studies do not attempt to solve this puzzle collectively, nor are they designed to be mutually exclusive. Instead, we searched for specific research questions within this field that are relevant for practitioners and are interesting scientifically (Ketokivi & Choi, 2014). This resulted in three loosely coupled studies, each focussing on a different process, taking a different level of analysis and applying different theories: the implementation of CBM, the diffusion of CM technologies, and the CBM maturation of asset owners.

The research questions are:

> *Chapter 2*: How are performance considerations used to manage the introduction process of CBM, if the CM technology's performance is uncertain and ambiguous?
> *Chapter 3*: How are CM technologies diffused within firms and how do technical-economic and institutional factors influence this process?
> *Chapter 4:* What is CBM maturity for an asset owner, and what are logical stages in the path to maturity?

Central in these studies is the concept of time. We aim to understand why it is taking organizations multiple years to properly implement CBM, to roll out a well-performing CM technology, and to transform from a reactive maintenance organization to one that is driven by CBM. If the current usage of CBM is unsatisfactory, how fast can increments be expected? And what can management do to increase the pace at which the organization starts capturing the potential of condition-based maintenance?

2. Structure of the dissertation

The main body of this dissertation consists of four chapters. First, in (the last section of) the introduction, we test the assumption that there is a gap between the actual and desired usage of CBM at our case companies. Via three ways – exploring maintenance concepts, maintenance activities performed and CM technologies adopted – we aim to identify whether the current level of applications is indeed too low, resulting in suboptimal performance of the maintenance function. This exploration teaches us that both case companies are already employing a wide variety of CM technologies and perform quite some maintenance condition-based, but a large part of the potential value of CBM still remains uncaptured. In particular, value is to be gained from implementing more advanced CM technologies (Chapter 2, increasing diagnostic and prognostic capabilities), rolling out successful CM technologies (Chapter 3, replacing visual inspections as the primary determinant for CBM decisions), and using condition information in more asset management decisions (Chapter 4).

In Chapter 2, we analyse the introduction process of CBM based on a new CM technology over a 4-year time period. The purpose of this chapter is twofold. First, we provide an extensive empirical description to give the readers of the dissertation more insights into the challenges and considerations present during the introduction of CBM and CM technologies. Second, we aim to elaborate on organizational learning theory in general (Argote & Miron-Spekter, 2011), and on Van de Ven et al.’s (2008) adaptive learning model in particular, by further investigating the recursive relationship between technology integration and technology performance (Fisher & Aguinis, 2017). This case teaches us about the effects of performance ambiguity and uncertainty on the technology integration process, establishes technology integration as a key determinant of performance, and provides several lessons for practitioners managing the implementation process of CBM practices and CM technologies.

In Chapter 3, we analyse the intra-firm diffusion process of twelve CM technologies (six at Oilco and six at Steelco) and argue that this process depends upon technical, economic and institutional considerations. Our findings indicate that most CM technologies diffuse slowly, rather than fast, especially when the technology is complex, expensive and meets resistance from entrenched institutional logics. In these cases, usage of the technology is institutionalized first to increase and stabilize the technology’s performance and, in time, make the technology legitimate. However, diffusion (only) really takes off when the adoption decision itself is institutionalized within the organization – when adoption has become compulsory, expected, or taken-for-granted. The results of this study are used to elaborate on diffusion theory and generate a middle-range theory of intra-firm diffusion (Craighead, Ketchen Jr & Cheng, 2016).

In Chapter 4, we adopt a design science approach to develop a CBM Maturity Model and Assessment for asset owners. At the highest stage, stage 5, an asset owner makes optimal usage of CBM[2]. That is, the asset owner applies the optimal combination of CM technologies (that are currently available) to all assets that could benefit from CBM and optimally uses the information provided by these CM technologies. The main purpose of the maturity model is to enable asset owners and their maintenance managers to visualize their desired end state, assess their as-is situation and derive opportunities for improvement. Maturity models are helpful tools in addressing such ill-structured issues (Simon, 1977). In addition, since the maturity model integrates the findings from our prior studies, the literature on CBM, and the knowledge of practitioners into a comprehensive overview of core elements of CBM employment, it helps in highlighting elements of CBM that require further research.

In Chapter 5, we elevate the findings of each individual study to a higher level, elaborating on the connections and overarching lessons between the studies, and highlight the main theoretical contributions of this dissertation. We close the dissertation with three avenues for further research that are especially important to strengthen the usage of CBM.

3. Research context

This dissertation is part of the larger research program CAMPI – Coordinated Advanced Maintenance and Logistics planning for the Process Industries –, a collaborative effort of the University of Groningen, Tilburg University, Eindhoven University of Technology, World Class Maintenance, Dinalog, and eight companies from the process industry. The overall objective of the CAMPI program was to study the advantages and disadvantages of pooling data and coordinating condition-based maintenance activities from a centralized control tower. Although the centralized control tower never came in existence, many diagnostic and prognostic technologies have been developed at the companies involved, based on data from multiple sources. We conducted our research primarily in cooperation with two of the eight companies – BP Refinery Rotterdam and Tata Steel in IJmuiden.

The process industry is characterized by large multinational asset owners with an extensive, diverse and stable asset base, and high financial and safety risks connected with breakdown (Smit, 2011; Veldman et al., 2011). Since plants can remain operational for over 100 years (with occasional updates) and are capital-intensive, the maintenance function is very important in this industry (Roy, Stark, Tracht, Takata & Mori, 2016; Moubray, 1997). In fact, in the process industry worldwide, typically between 2-5% of the asset replacement value is invested in maintenance of

[2] In Chapter 4, we explain the meaning of the word ‘optimal’.

these assets every year (Gulati & Smith, 2012). Maintenance tasks are typically performed by local or centralized teams of maintenance technicians, clustered in disciplines (electrical, static, machinery, etc.), or outsourced to maintenance service providers. Condition monitoring is organized similarly: measurements and analyses can be automated, performed by local or centralized teams of CM specialists, clustered in disciplines (vibration monitoring group, ultrasound group, etc.), or outsourced to CM service providers (Veldman et al., 2011). While many options exist for the organization of condition monitoring, the subsequent maintenance decisions are typically made by local maintenance technicians and engineers.

The description above also characterizes our main case companies: a refinery (BP Refinery Rotterdam, from here on out specified as “Oilco”) and a steel manufacturer (Tata Steel in IJmuiden, from here on out specified as “Steelco”). Their basic features are described in Table 1.1.

Table 1.1: Description of case companies

Characteristics	Oilco	Steelco
Type	refinery	steel manufacturer
Plants (at the site)	3	10
Employees (in thousands)	0.7	9
Annual production (yearly)	150M barrels oil	7M tonnes of steel
Age	>50	>90
Part of larger corporation	yes	yes

The process industry provides a good setting to study the use of CBM. High capital investments, high opportunity costs of downtime and high safety requirements put pressure on the maintenance function and causes a need for advanced maintenance technology and practice (Arts, Knapp & Mann, 1998; Tan & Kramer, 1997; Neale & Woodley, 1975). The empirical study of Veldman et al. (2011) and our initial observations, however, reinforced the idea that as yet very few asset owners in the process industry are optimally employing the range of CM technologies available.

4. Exploration of central assumption

Before we started our studies, we performed an exploration of the central assumption of this dissertation: there is a gap between the actual and desired usage of CBM at our case companies. That is, the current number of CBM applications is *too low*, resulting in a suboptimal performance of the maintenance function and the plant as a whole. This exploration had three purposes: to test whether or not the assumption was correct, to gain a better understanding of the field, and to identify opportunities for valuable research. In this exploration, we attempted to quantify the assumption in three ways: by assessing the maintenance concepts (the input), the executed maintenance activities (the output), and the usage of Condition Monitoring (CM) technologies (the process).

4.1 Maintenance concepts

The maintenance strategy for most equipment is documented in a maintenance concept. Hence, these can be used – in theory – to assess what percentage of equipment is *intended to be* maintained correctively, periodically or condition-based. In practice however, we encountered that most maintenance concepts consist of a large number of maintenance activities – some periodic, some condition-based – to deal with different components and different failure modes of the equipment. This made it very hard to classify an equipment as being maintained mainly correctively, periodically or condition-based (even for the maintenance engineers), and to identify whether or not this was suboptimal. Therefore, no conclusion is drawn from the first analysis.

4.2 Maintenance activities

For managerial and administrative purposes, all executed maintenance activities are administered in a Computerized Maintenance Management System (CMMS) through work orders and notifications. The advantages of this approach are – in theory – that it can give an accurate account of the number of corrective, periodic and condition-based activities that *have been performed* in a given year, which can be benchmarked with similar plants to identify what distribution of maintenance activities results in the highest maintenance- and plant performance (World Steel Association, 2013). Table 1.2 presents the maintenance activities of Oilco and Steelco in 2014, both in number of activities and in maintenance costs, although one should be careful with comparing the two sites. According to the maintenance managers, 2014 was a representative year at both sites (i.e., no financial crisis, no abnormal maintenance budget restrictions, no major maintenance stops).

Table 1.2: Percentage of maintenance activities and costs in 2014[1]

	Oilco		Steelco	
	activities[2]	**costs[23]**	**activities[2]**	**costs[23]**
Corrective	55%[5]	73%[5]	23%	29%
Periodic	18%[6]	8%[6]	29%	37%
Condition-based	27%	20%	48%	
inspections[4]	27%	18%	37%	10%
maintenance[4]	0%[7]	2%[7]	11%	24%
Total	6,500	11	115,000	190

[1] only includes the work orders and notifications that were active in 2014 (calendar year)
[2] 'modifications' (one-time adjustments or larger maintenance projects) are excluded from the analysis
[3] costs incorporate material- and contractor expenses, no downtime (opportunity) costs; approximate costs provided, in million euros
[4] the CBM activities can be subdivided into inspection- and maintenance activities
[5] this percentage is likely to be overestimated; it contains CBM activities
[6] a large portion of the periodic maintenance at Oilco is performed during major maintenance stops, once every 4-6 years; 2014 didn't contain such a maintenance stop
[7] this percentage is likely to be underestimated

Main inaccuracies and approximations:
- not all maintenance activities are recorded separately; for administrative efficiency quite some activities are bundled into a work order per maintenance stop or a year order per contractor
-the maintenance activities have been assigned to the categories by an automated protocol, based on characteristics of the work orders and notifications and text analysis of the activity's short description
- all data are manually entered into the CMMS and depend upon individual judgment; consequently, different maintenance groups and -engineers might assign different characteristics to a similar activity

Based on Table 1.2 one could argue that Steelco uses CBM to a much larger extent than Oilco. However, given the observed practices of Oilco and Steelco, this difference is expected to be caused primarily by a different design and usage of the CMMS, rather than a difference in actual practices. Since the design of the CMMS at Steelco specifically includes a "CBM" category and Oilco's CMMS does not (CMMS procedure Oilco, 2009), many of the 'CBM: maintenance' activities at Oilco have been grouped under the 'corrective' activities category[3]. By grouping the characteristics of the work orders and notifications and analysing the activity's

[3] At Oilco, PM01 is typically used for all emerging work, which corresponds with the corrective activities category. The difference between corrective emerging work and preventive emerging work (i.e., CBM) is the subtle judgment whether or not an equipment has already failed functionally. In most instances this difference could not be retrieved from the activity's description, nor from the work order and notification characteristics.

description, an attempt has been made to identify the CBM activities, but this could not accurately correct for the deficit.

Two main conclusions can be drawn from this analysis. First, benchmarking is not easy, especially not between plants that differ in terms of size, production characteristics, age of equipment or CMMS design. Moreover, throughout the research we encountered that people have different perceptions and definitions of CBM, resulting in a lack of uniformity in the CMMS data, even within organizations. Second, and more important, the data at Steelco shows that CBM is already *quite extensively used*: 48% of all maintenance activities and 34% of the maintenance costs can be attributed to CBM and around 1/6th of all maintenance is executed condition-based. However, whether or not this level is (sub)optimal cannot be determined with the current data set alone; such an analysis requires additional performance measures, like ‘availability’, ‘unscheduled downtime’ and ‘production turnover’, as well as insight into the performance of CBM applications.

4.3 CM technologies

The CBM process consists of two phases: (1) monitoring the state of the equipment – with a CM technology – and (2) scheduling and executing the maintenance before functional failure. By evaluating the CM technologies one can acquire insight into what information is used to make the maintenance decision. Therefore, I have identified and characterized most of the CM technologies Oilco and Steelco currently apply to monitor their equipment[4]. This was done through 38 interviews with 21 condition monitoring specialists from different disciplines and departments, exploring how the CM technology is used, on what equipment, by whom, how often and with what performance[5]. The main results of this inquiry can be found in Table 1.3.

[4] Although the list of CM technologies is comprehensive, I do not expect this list to be complete. The main condition monitoring specialists have been identified with snowball sampling, but these are not the only ones performing condition monitoring; for example, maintenance engineers at Steelco are free to outsource monitoring activities to (specialized) contractors.

[5] Since the performance of a CM technology might differ greatly between applications, most condition monitoring specialists found it challenging – if not impossible – to assign a value to common performance measures, such as the Probability of Detection and False Call Rate. Therefore, performance is not included in Table 1.2.

Table 1.3: Characteristics of applied CM technologies: snapshot in 2015

	Oilco	Steelco
Number of unique CM technologies	49	64
Discipline	49	64
rotating equipment	9	10
static equipment	24	36
electrical equipment	12	17
analyzers & instrumentation	4	1
Monitoring	49	64
off-line	84%	88%
on-line	16%	12%
Used mainly for[1]	49	64
structural monitoring (periodic)	53%	55%
further investigation (on request)	47%	45%
Frequency of data collection[2]	49	64
continuous (high-frequent)	10%	6%
weekly - monthly	14%	8%
yearly	29%	41%
on request	47%	45%
Diffusion[3]	*40*	*59*
0-20%	70%	68%
21-50%	5%	10%
51-80%	10%	12%
81-100%	15%	10%
Used since	*48*	*64*
<1990	52%	58%
1990-2000	8%	17%
2001-2010	31%	16%
>2010	8%	9%

[1] if used both periodically and on request (might differ per application), counted as structural monitoring
[2] might differ per application, average taken
[3] diffusion is the percentage of equipment on which the CM technology is currently applied, given the set of equipment it can be applied to (100%). Note that some CM technologies can only be applied to a specific type of equipment, while others encompass a whole range of equipment.

A couple of findings stand out from the analysis. First of all, the majority of CM technologies are off-line and have been around for a long time, such as visual inspections, NDE technologies (e.g., ultrasound, vibration, electromagnetism, radiographic, thermography; Moubray, 1997) and functional tests. The first on-line CM technology, an on-line vibration monitoring system, has been introduced in 1995. Since 2005 however, the usage of on-line CM technologies has taken off, with multiple on-line vibration monitoring, ultrasound and instrumentation monitoring systems being installed, all of which have a high data collection frequency (continuous-weekly). Their application is still limited though, as the diffusion of these CM technologies ranges between 1% (rounded up) and 13% (see the 3rd subscript of Table 1.3 for the definition of diffusion). The same goes for the advanced NDE technologies that have been introduced after 2000, for which the diffusion level ranges between 1% and 10%. Only visual- and functional inspections, as well as several CM technologies with a small application base, have reached diffusion levels over 50%.

Secondly, despite the fact that over half of the CM technologies are used for structural monitoring (as well), in most instances the frequency of data collection and analysis is once every (couple of) year(s). This has three main implications: (1) there is little condition data available, (2) the equipment's condition is only assessed (and thus known) periodically, and (3) the collected data is mainly used for diagnoses (i.e., assessing the current state), rather than prognoses (i.e., predicting the timing of failure). This limits both the potential benefits of CBM, as the organization's response time is shorter for diagnoses, as well as the possibilities to develop data-driven prognostic models (Heng, Zhang, Tan & Mathew, 2009). In fact, at the time of this exploratory study, zero purely data-driven prognostic models were observed at Oilco and Steelco.

So, both Oilco and Steelco perform many inspections (Table 1.2) and are currently applying a large number and variety of CM technologies (Table 1.3). Nonetheless, condition monitoring specialists indicate that most inspections are primarily – if not completely – based on visual inspections. This is in line with the findings that most NDE technologies are used upon request or with a (very) low frequency and that almost all CM technologies have a low level of diffusion. This leads to the conclusion that, although quite some maintenance is performed condition-based, the CBM practices of both Oilco and Steelco can be much more sophisticated.

4.4 Concluding

Identifying what extent of CBM usage is optimal for an asset owner is not an easy task. Whether CBM is preferred over corrective and periodic maintenance depends upon characteristics of the equipment, the CM technologies available and the organization in which the CBM application is embedded. The optimal level of CBM can therefore differ per site and over time.

However, based on the three analyses however we can conclude that most of the condition-based maintenance decisions are based on visual inspections. To improve the quality of maintenance decisions, *better insight* in the current and future state of the equipment is required. This insight can be gained through purchasing new, advanced CM technologies, through increasing the monitoring frequency, or through more widely applying the available set of CM technologies. In the second chapter, we dive into the introduction process of a new, advanced CM technology and aim to understand how asset owners can increase the value derived from such technologies. In the third chapter, we study the process of intra-firm diffusion (Battisti, 2008) and aim to understand how asset owners can roll out their successful CM technologies.

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Chapter 2: Implementation process of CBM: the recursive relation between technology integration and performance

1. Introduction

A central problem in managing the innovation journey is determining whether and how to continue a developmental effort in the absence of concrete performance information (Van de Ven, Polley, Garud & Venkataraman, 2008). This is also a common problem for asset owners who are introducing a new Condition Monitoring (CM) technology with the aim of implementing Condition-Based Maintenance (CBM). The value organizations derive from CBM is a function of the CM technology's performance and the extent to which the CM technology is used for maintenance decision-making. If implementation and operation of CBM is costly, rational organizations are motivated to either (a) not invest at all (or abandon as soon as possible), or (b) rapidly improve the performance of the newly developed or purchased CM technology and integrate it into maintenance decision-making as soon as possible. Which of the two options is optimal depends on the value that can be derived and the costs of implementation and operation. But here's the rub: especially for CM technologies that are novel or customizable (i.e., users can adapt the underlying technological features; Orlikowski, 1996) and have not yet been applied to a certain type of equipment, it is uncertain what levels of future performance can be achieved, and thus, what value can be derived. How are asset owners managing the introduction process of CBM then?

Technology integration is the process of managing the acquisition and incorporation of technology (Karlsson, Taylor & Taylor, 2010), starting with the decision to acquire a given technology and concluding when the technology is fully utilized by the adopting organization (Stock & Tatikonda, 2000; Edmondson, Bohmer & Pisano, 2001). The concept of technology integration is related to the notion of IT assimilation, which refers to the extent to which IT has been infused into specific business activities (Armstrong & Sambamurthy, 1999). In both concepts, the extent of integration and assimilation affects the value that can be derived from the technology (Karlsson et al., 2010). The more the technology is integrated with the organization and its existing technology base, the better the capabilities of the technology can be utilized to enhance business performance (Armstrong & Sambamurthy, 1999). At the same time, integration can be disruptive (if it conflicts with existing routines) and costly (if the technology's performance is inadequate), making it important to manage the integration process of new technologies well (Karlsson et al., 2010; Edmondson et al., 2001).

For many innovations, performance considerations play an important role during the innovation's introduction process. For example, performance feedback guides the process of learning-by-doing (Argote & Miron-Spektor, 2011), the allocation of resources across goals (DeShon, Kozlowski, Schmidt, Milner & Wiechmann, 2004), and can trigger external resource controllers to increase or decrease the resources available (Van de Ven et al., 2008; Cooper, 1990). At the individual level, the perceived usefulness of an information technology has been identified as the main predictor of technology adoption and usage (Venkatesh & Bala, 2008). However, most of these studies presume that performance is observable and interpreted similarly by the people involved. On the contrary, Van de Ven et al. (2008) indicate that – during an innovation's developmental process – goals are often vague, can shift over time, and are hard to measure. Via repeated interviews they found that criteria of innovation success and failure changed over time and were different for resource controllers and innovation managers. Therefore, they call for additional research in real-world organizational settings to elaborate on the dynamic relationship between perceived innovation outcomes and innovation decisions. Also the organizational change literature has requested to shed more light on the dynamics between change processes and organizational outcomes (Pettigrew, Woodman & Cameron, 2001).

In this research, we answer these calls by exploring the question: *how are performance considerations used to manage the introduction process of CBM, if the CM technology's performance is uncertain and ambiguous?* The purpose of this research is twofold. First, we aim to elaborate on organizational learning theory in general (Argote & Miron-Spekter, 2011), and on Van de Ven et al.'s (2008) adaptive learning model in particular, by further investigating the recursive relationship between technology performance and technology integration (Fisher & Aguinis, 2017). Second, we give an extensive empirical description to provide the readers of this dissertation insight into the challenges and considerations present during the introduction process of CBM practices and novel CM technologies.

We investigate the introduction process of CBM based on a novel Condition Monitoring (CM) technology at a large asset owner in the process industry over a 4-year time period. We apply a longitudinal, single-case design to thoroughly follow the dynamic relationship between technology performance and technology integration over time. In addition, this design allows us to delve into the ambiguous natures of technology integration and performance (Van de Ven et al., 2008). By tracking multiple dimensions of integration and performance over time, we can investigate how different aspects of performance affect the technology's introduction process, and vice versa (Fisher & Aguinis, 2017).

The rest of this chapter is structured as follows. First, we define technology integration and reflect on the known roles of performance during innovation introduction. Second, in the Methods section we describe the case setting, the operationalization of variables and the process of collecting and analysing the performance and change data. Third, in the Findings section we trace the performance of three performance indicators and explore the relationship between technology integration and performance. Finally, in the Discussion section we reflect on the findings, provide recommendations for further research and derive managerial implications.

2. Literature review

2.1 Technology integration

The concept of technology integration has been mainly used to describe and study processes in which new technology is integrated into products, for example when new software is integrated into mechanical products (Karlsson et al., 2010; Stock & Tatikonda, 2000), and into processes, such as production processes (Iansiti, 1995; Stock & Tatikonda, 2004) and surgery processes (Edmondson et al., 2001). In this research we are interested in the latter. From a more general perspective, to integrate means to blend into a functioning or unified whole. If we adopt the notion that systems – such as organizations, groups and production facilities – have a deeper structure (Gersick, 1991) of interrelated components, we can define technology integration as the process in which a new technology is blending into a system's deeper structure. A higher extent of technology integration implies that the technology is integrated more strongly and with more components of the adopting system's deeper structure.

The process of technology integration is not the same for each technology and each organization. For example, Stock and Tatikonda (2000) show that the nature of the technology, such as its novelty, complexity and tacitness, affects the ease with which a technology is transferred and integrated. Whether or not an adopting organization possesses the required knowledge to integrate the technology – and has a high absorptive capacity (Cohen & Levinthal, 1990) – also affects the integration process. Van de Ven et al. (2008) describe the innovation processes of innovations with substantial technical and organizational uncertainty as a journey, characterized by iterative processes, setbacks, fluid participation, and investor involvement. Similar technology integration processes have been observed with technologies that require customization, reinvention, or translation (Orlikowski, 1996; Rice & Rogers, 1980).

Customizable technologies – tools that enable users to adapt its underlying technological features – have been shown to follow a more emergent, situated change process (Orlikowski, 1996). These technologies rely on reinvention and customization for effective use, thus ongoing learning and subsequent technological and organization changes are encouraged (Rice & Rogers, 1980; Leonard-Barton, 1988; Orlikowski, 1996). Typically, the performance of these technologies improves over time – starting out low in each application – and takes some time to reach maximum performance (Iansiti, 1995; Edmondson et al., 2001). Because adaptations have to be enacted in situ and are not known beforehand, it is hard to predict the technology's future performance (Orlikowski, 1996).

2.2 Role of performance

The organizational learning and organizational change literatures have identified multiple functions of performance during the innovation process. First, performance opportunities and – especially – performance shortfalls are common triggers of innovation processes, providing motivation to change (Weick & Quinn, 1999). Second, performance feedback guides processes of learning-by-doing and resource distribution decisions, reinforcing successful activities and lessening unsuccessful ones (DeShon et al., 2004). Third, performance outcomes are used by resource controllers as input for continuation and intervention decisions (Cooper, 1990; Van de Ven et al., 2008). Here we elaborate on these functions and reflect on the effect of uncertainty and ambiguity on the strength of these functions. With respect to performance, uncertainty implies that the people involved have imperfect information about the actual state of performance (e.g., because performance is hard to assess objectively, can only be observed partially or is subject to stochasticity), ambiguity implies that the people involved have different perceptions of the concept of performance (e.g., because 'performance' has multiple dimensions and the people involved value different aspects of performance).

The punctuated equilibrium perspective of change elicits that growing misalignment between a system's deep structure and its environment, caused by internal and external events, can create the need for revolutionary change (Gersick, 1991) and reduce inertial pressures on the system (Weick & Quinn, 1999). Similarly, Van de Ven et al. (2008) observed that many innovative ideas are not acted upon until some form of shock occurs. Shocks can occur in many different forms and serve to concentrate attention, elicit resources and consolidate support around an idea to solve the crisis or capitalize on the opportunity (Van de Ven et al., 2008). Only when a shock is of sufficient magnitude, will it be successful in initiating change. Thus, if a performance shortfall or opportunity would act as a shock, it has to be clear – not uncertain – and perceived similarly – not ambiguous – by the people involved. If it is uncertain or ambiguous, it is unlikely that the shock has sufficient magnitude to concentrate attention, elicit resources, and consolidate support.

In processes of learning-by-doing, performance is used as an anchor to guide future behaviour (Argote & Miron-Spektor, 2011). In particular, experiencing increased or decreased performance (as opposed to unchanged performance) is likely to alter behaviour (Crossan, Lane & White, 1999). Similar dynamics have been observed at the group-level, where performance feedback affects the allocation of resources across goals (DeShon et al., 2004). The better a group performs a certain task, the more likely they are to continue dedicating resources towards that task. People learn to like what they do well (March & Simon, 1958). Performance however has to be observable if it is to guide behaviour. Moreover, if performance outcomes are strongly affected by external influences, connections between actions and outcomes are likely to be misspecified (Levitt & March, 1988). For complex and relatively infrequent organizational tasks, it has been identified that experience can even have a negative effect on performance outcomes (Zollo, 2009). In these situations, superstitious learning leads to overconfidence in one’s own competencies and incorrect judgments (Levitt & March, 1988). Thus, when performance is subject to external influences – uncertain – and outcomes are ambiguous, superstitious learning is more likely to occur (Zollo, 2009).

In a staged innovation introduction process, the innovation’s performance is commonly evaluated by management and other resource controllers at specific times during stages. For example, the performance of innovations following a stage-gate process is evaluated at the end of each stage and determines whether or not the innovation can continue to the next stage of development (Cooper, 1990). Also, intermediate milestones and midpoints – halfway between start-up and deadline – have been found to trigger evaluations of performance and corresponding interventions (Gersick, 1991). Van de Ven et al. (2008) indicate that negative outcomes often trigger interventions from external resource controllers, which may subsequently lead to changes in the course of action pursued by the innovation team. When significant failures are perceived by investors, they are likely to intervene, for example by reducing the resources available or by posing an alternative course of action. Positive outcomes on the other hand increases the investors’ willingness to delegate control to the change agents, as their confidence in the course of action is increased (Van de Ven et al., 2008). The authors note that performance indicators that are subject to high variability are more likely to encounter an instance of negative performance over time. Moreover, they indicate that uncertainties about the innovation's performance stimulate resource controllers to intervene. Thus, innovations with high performance uncertainty are more likely to receive an intervention (Van de Ven et al., 2008; Sommer & Loch, 2004).

Van de Ven et al.'s (2008) adaptive learning model, presented in Figure 2.1, summarizes this knowledge on how an innovation's performance affects the innovation process. The inner loop represents the process of learning-by-doing and the bottom loop represents the interventions by resource controllers. The upper loop reflects that actions may create new goals or that performance criteria may shift to justify action, often resulting in continuation of the current course of action. This loop incorporates March's (1972) question "how something as conspicuous as the fluidity and ambiguity of objectives can plausibly be ignored in a theory that is offered as a guide to organizational behaviour?" Lastly, environmental effects occur independently of the learning process and can result in shifts in outcome criteria, affect assessments of outcomes, and trigger interventions by resource controllers.

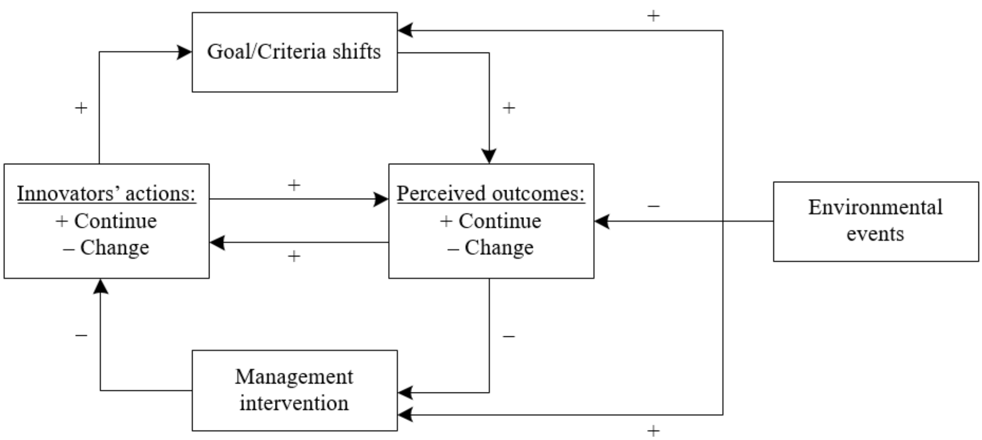

Figure 2.1: Adaptive learning model to guide the innovation journey (Van de Ven et al., 2008)

The general uptake from these studies is that positive performance reinforces actions and negative performance increases the likelihood of alternative actions. Yet, the function of performance is limited if the performance is uncertain, ambiguous, or both. Instead, performance uncertainty and ambiguity can lead to superstitious learning and interventions by resource controllers, lowering future performance. How should managers then use performance considerations to manage the technology integration process? Knowledge on this issue is limited still (Pettigrew et al., 2001), even though Van de Ven et al.’s (2008) empirical studies vastly increased our understanding of the fluidity and ambiguity of objectives in new product development innovation processes. We extend their studies by further exploring how uncertain and ambiguous performance assessments are used in another type of innovation process – the implementation of new practices and technologies –, by investigating the recursive relationship between technology integration and technology performance.

3. Methodology

To explore the dynamic relationship between technology integration and the technology’s performance, we conduct a longitudinal single-case study. Following Van de Ven et al. (2008), the study combines quantitative data from databases, reports and management systems – to track performance and events over time – with qualitative data from interviews and internal documents – to understand why events were initiated and their effects. The period of observation is 4 years, from December 2013 to November 2017.

3.1 Case setting

The study has been conducted at Steelco, a large steel manufacturer in the Netherlands. The technology of interest is a novel Condition Monitoring (CM) technology – Shock Pulse Method (SPM) – that is applied to three converters. Converters are core equipment in the steelmaking process; in a converter, pig iron is made into steel by blowing oxygen through a lance over the molten pig iron. In the two years prior to the study, three of the bearings of the converters had failed unexpectedly (in separate instances), causing high maintenance costs and multiple days of production loss. This urged management to replace the converters and to vastly improve the converters’ monitoring practices.

Monitoring the bearings of converters is challenging however. Conventional vibration monitoring technologies require the rotating equipment to rotate continuously, but converters don’t rotate, they tilt. A team was assembled at Steelco to identify CM technologies that are capable of identifying bearing faults at an early state, providing at least several months to prepare maintenance activities. One CM technology seemed most promising – SPM – and was selected for a pilot test at one of the converters in December 2013. This technology monitors the bearings multiple times a day, collecting a data sample during the tilt of the converter, and uses advanced algorithms to transform the data into analysable formats and trigger alarms. In addition to this automated measurement, a semi-automated measurement was developed specifically for the converters. Approximately once a month, the operator makes the converter rotate five consecutive rounds, during which a longer vibration measurement is executed. Together, the two measurements can be used for determining the lubrication condition, diagnosing and locating bearing damage, and trending.

The application was new to all parties involved. The CM technology was new to Steelco, and the supplier of the CM technology had not applied the CM technology to converters before. Therefore, the parties involved – the supplier of the CM technology and Steelco's maintenance engineer, vibration monitoring specialist, and project manager – engaged in a collaborative learning process. After the pilot phase, the CM technology was applied to the other converters in April 2014 and September 2014 respectively. In 2015 and 2016, the CM technology was further applied to important rotating equipment in other factories, including a wheel excavator, a blast furnace top, and a loading crane. At the end of the study, in December 2017, 8 equipment were monitored structurally with the shock pulse technology. Because different actors are involved in these applications (different maintenance organizations, different monitoring specialists), we limit the scope of our study to the 3 converters.

3.2 Operationalization of CM technology integration and CBM performance

The CBM process consists of three steps: data acquisition, data processing, and maintenance decision-making (Jardine et al., 2006). Therefore, following the recommendations of Pettigrew et al. (2001), we operationalize performance with three outcomes, indicating the performance of each step: data quality, analysis quality, and maintenance costs.

With respect to the CM technology integration process, we observed three different domains of integration. First, hardware integration implies that the technology is integrated in the organization's existing technology, for example by connecting the monitoring system to the existing IT-infrastructure, initiating the transfer of data to existing databases, and automating measurements. Process integration implies that the technology is embedded in the organization's processes, for example by incorporating measurement and analysis activities in procedures and routines, and agreeing upon roles and responsibilities. Outcome integration is specific to CM technologies, implying that the outcome of the CM technology – the condition assessment – is integrated in (maintenance) decision-making procedures. Outcome integration is separated from process integration because this is an essential step in the integration process; only if the outcome is integrated, can value be derived from the CM technology.

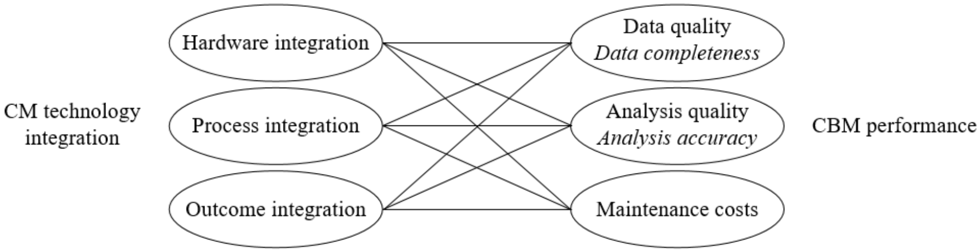

Figure 2.2: Operationalization of CM technology integration and CBM performance (incl. recursive relations studied)

The lines in this figure represent recursive relations. For example, we are interested both in the effect of hardware integration on data quality, and on the effect of data quality on the decisions for further hardware integration. Each of these relationships has been studied. Figure 2.7 shows which relationships have been found in the study.

Within the information science literature, data quality is typically defined as the degree to which data is “fit for use” by data consumers (Strong, Lee & Wang, 1997). In the seminal work of Wang and Strong (1996), and in the stream of research following this study, many dimensions of data quality have been identified, such as objectivity, currency, interpretability, accessibility, consistency, etc. (Laranjeiro, Soydemir & Bernardino, 2015). Some of the main and most frequent dimensions are: relevance, the extent to which data are applicable to that task of the data user (Wang & Strong, 1996); accuracy, the extent to which data values are in conformance with the actual or true values (Wang & Strong, 1996), and; completeness, the degree to which an entity has values for all expected attributes and related entity instances (Laranjeiro et al., 2015). In the context of this study, each of these attributes directly and positively affects the achievable quality of condition monitoring. The relevance and accuracy of the data are static however, as they are predetermined by the supplier’s hardware. Therefore, we operationalize data quality here in terms of its *completeness*: at each moment in time, when the data is complete, all expected attributes and related entity instances are available, such that condition monitoring can be performed optimally. The completeness is expressed as a percentage, comparing the current completeness to the amount of data required to be complete.

Condition monitoring can be done via detection, diagnostic or prognostic analyses (Tinga & Loendersloot, 2014). Detection aims to detect anomalies in a system, diagnoses intend to identify and quantify the damage that has occurred, while prognostics tries to predict the future state of the system and time of failure (Tiddens, Braaksma & Tinga, 2015). For each type of analysis, performance metrics have been developed (Saxena, Sankararaman & Goebel, 2014). The most common are the statistical measures of the performance of a binary classification test, such as sensitivity, specificity, and accuracy (different from 'data accuracy'). Since both false positives and false negatives can result in additional maintenance costs, we adopt *analysis accuracy* (i.e., the proportion of actual positives and actual negatives that are identified as such; Benjamini & Hochberg, 1995) as the main performance indicator. Here, we operationalize the accuracy in a given period as the proportion of correct analyses (i.e., true positive or true negative). The accuracy of analyses is expressed as a percentage.

The core purpose of CBM is to reduce the costs of maintenance and to increase the asset's performance. From these two variables, the cost of maintenance is most directly related to the decisions based on the CM technology. The asset's performance is affected more strongly by other decisions, such as production decisions and the decision to renew the converters. We adopt the *maintenance costs* as our primary outcome variable. The costs of maintenance include the costs for implementing and utilizing the focal CM technology, for utilizing other CM technologies, and for performing maintenance activities (Gulati & Smith, 2012). Note that the costs of maintenance do not include costs of downtime. For our analysis, we separate the costs of monitoring and the costs of maintenance. Since the CM technology is scaled up to multiple converters during the observation period, costs are averaged per bearing and per year. To conceal the actual maintenance costs, costs are indexed (cumulative costs in the first year = 100). This way it is still possible to compare consecutive years and identify the size and timing of increases and decreases in costs.

3.3 Data collection and analysis

The data completeness of both the automated and semi-automated measurement is derived from the CM system's database, in which the exact date and time of each measurement is stored. The analysis quality is determined from the analysis reports from the monitoring specialist(s). Each report contains an analysis and a recommendation. Classification of each analysis (true positive/true negative/false positive/limited analysis) is done based on the next report(s) and maintenance data: since bearing damage can only progress over time (materials used are not self-regenerating), consecutive reports should indicate the same type of bearing damage until maintenance is performed. The maintenance costs are extracted from the Computerized Maintenance Management System (CMMS), in which all maintenance activities and their respective costs are administered.

The timing and content of events have been collected via internal documents and interviews. Especially internal memos and the timeline in the converter specialist’s extensive report about the converters, were very helpful in identifying the timing of events. Interviews were used to complement the missing timings, to gather more information about the content of the events, to understand how the events affected performance, and to identify the rationale behind technology integration decisions. Why were technology integration decisions made, and why where they made at that moment in time? An overview of the interviews is presented in Table 2.1. Each interview lasted between 0.5 and 2 hours.

Table 2.1: Interviews

Roles	Number of interviews
Project manager	8
Monitoring specialist	7
Maintenance engineer	6
Information manager	1

The data analysis has been conducted in four steps. First, an overall storyline was constructed with the main technological and organizational events. Second, the records of performance were converted into graphs and tables and verified with the project team. Third, the performance was connected to the events; can the pattern of performance be explained from the events and how did technology integration events affect performance? Fourth, the interviews and internal documents were analysed to construct an explanation of why each technology integration decision was made and why it was made at that moment in time. These explanations have been verified with the project team in additional interviews, until no new information was generated in the interviews. To check for errors and misinterpretation, the people involved read through and commented on the draft version of the Findings. All comments were discussed personally and corrected afterwards.

To analyse the data, all events were codified (in the fourth step) to their nature (“technological” or “organizational”), whether and how they facilitated technology integration (“hardware”, “process”, or “outcome”), and what triggered the event (“management”, “shock”, “experience”, “performance”, “window of opportunity”, “cascade”, or “exogenous change”).

The codes for the triggers of events have been derived primarily from literature. The first codes were derived from the dominant change perspectives (By, 2005): “management” (planned change), “shock” (punctuated equilibrium), and “experience” (emergent change). The code “performance” was added to mark the events that were initiated based on performance considerations, the core of this study. If management decided to initiate a planned change based on performance arguments, the code “performance” was selected instead of “management”. The code “window of opportunity” was added to be able to compare our findings to the study of Tyre and Orlikowski (1994), indicating events for which the timing was driven mainly by a temporary reduction of inertia – installing a CM system when the converter is in a maintenance stop, for example. Not all events could be codified with this set of codes however, so two complementary codes have been added: “cascade” and “exogenous”. Events were tagged as a cascade of changes if they were the direct and logical consequence of a recent event (Hannan, Pólos & Carroll, 2002; Siggelkow, 2001), such as the assignment of a functional owner (organizational change) directly after the CM technology was installed (technological change). Events were tagged as exogenous if they were outside the control of the people involved with the CM technology (Dutton & Thomas, 1984), like the replacement of the converters and the installation of a frequency drive.

4. Findings

In this section the findings of the case are elaborated. First, we highlight the timeline of main events, to get an overview of the case. Then, for each performance measure (data completeness, analysis accuracy, and maintenance costs), we aim to understand how and why the performance changed over time and why efforts of technology integration were initiated at particular moments in time. Then, the findings from the three performance measures are aggregated to analyse the relationship between technology integration and performance more directly.

4.1 Main events

An overview of the main events is presented in Figure 2.3.

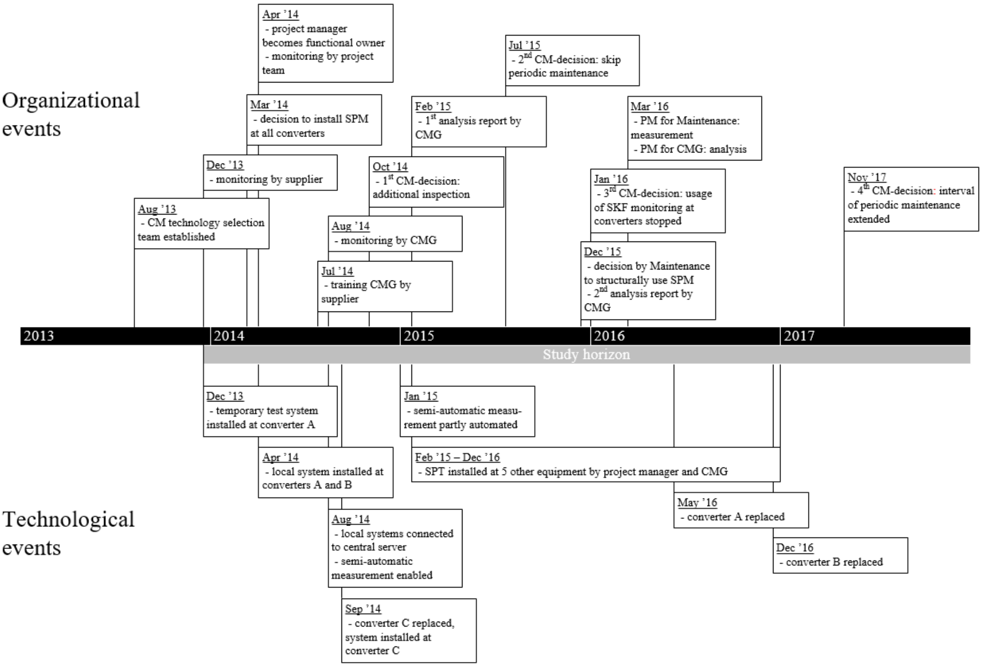

Figure 2.3: Timeline of main events

SPM = Shock Pulse Method

CMG = Condition Monitoring Group

The main technological events include the installation of the CM technology, the introduction and automation of an additional measurement method, the centralization of the server, and the replacement of the converters. The replacements of the converters were scheduled across three years to deal with financial and manpower capacity constraints and minimize production loss. The first CM system – an easy to install test system – was installed as soon as the project team and maintenance head had decided to start a proof of concept with this CM technology. The second CM system was installed during a maintenance stop of the converter, the third CM system was installed during the construction of the new converter. During this time, the server was centralized, such that the centrally located monitoring specialists could access the data from their own computers. Lastly, since the monitoring specialists were not satisfied with the analysis possibilities of the automated measurement, an additional measurement method – semi-automated measurement – was created. The semi-automated measurement consists of 2 steps. First, the operator needs to 'manually' rotate the converter in a steady pace for five consecutive rounds. Then, the SPM system needs to start and stop measuring. Initially, the SPM system was controlled 'manually' by the project manager. At the beginning of 2015, the system was programmed to recognize that the converter is making five rotations and to measure two out of five rotations. Thus, the main technological changes took place during the first 14 months.

The main organizational events were the decisions to install the CM system and continue with the CM system, the changes in monitoring organization – who is monitoring, who is managing the technology – and the changes in maintenance practices, based on the analyses with the CM technology. Both the decision to install the CM system and the decision to start structurally using the CM system were primarily made by the maintenance head, informed by the project team, as he was the budget owner[6]. Not everyone was convinced at the time that the changes were ideal, but since the factory had experienced multiple bearing failures in the past years, ‘doing nothing’ was not an option:

“*During the supplier’s presentation I said ‘I’m not convinced yet, but I’d like to give this technology a try.’ […] But I wasn’t satisfied with the test system. Not at all. The settings were bad, I wanted an additional measurement, […] But then the maintenance head decided ‘let’s do it’. […] Normally with a proof of concept, you first check whether you’re satisfied with the performance, and then you decide to continue. Apparently, this took too long, so it was just forced through.*” – Monitoring specialist

Unfortunately, the first decision (partly) based on the CM technology (to inspect the bearing for damage in October 2014) was perceived as a false alarm by some. Afterwards, it took another 14 months before it was decided to structurally use this CM technology, instead of the previously used CM technology. Then things started to happen fast: processes were specified, financial arrangements were made, and both were documented in the CMMS. From that moment on the semi-automated measurements were performed more consistently, the analyses were performed more consistently, and the maintenance engineers received a report after each measurement, which could be used for maintenance decision-making. By the end of our observation period, 48 months after technology introduction, the maintenance organization and rotating engineer had gained sufficient trust in the CM technology to extend the periodic maintenance interval of the bearings from 3 to 10 years, thus losing the warranty of the supplier, but vastly reducing the costs of maintenance.

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[6] The purchase and installation of the CM system was partly paid from a central innovation budget and partly from the factory’s maintenance budget. The analyses by the monitoring specialist were paid from the factory’s maintenance budget only.

4.2 Data completeness

The data completeness of both types of measurements is presented in Figure 2.4.

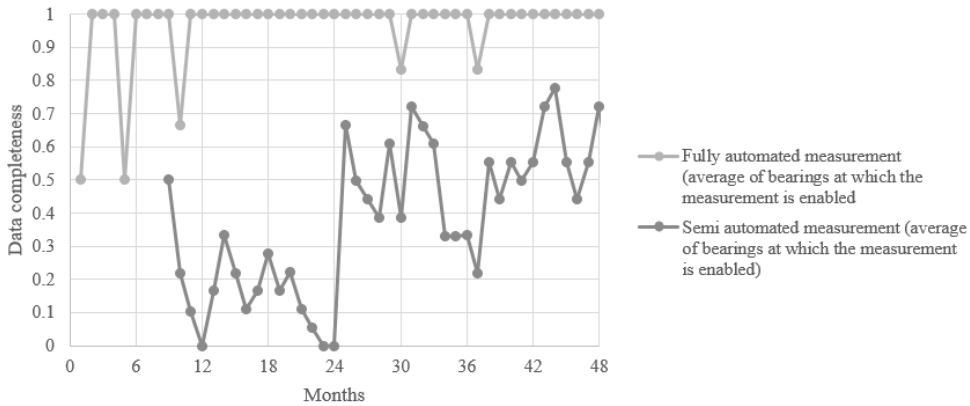

Figure 2.4: Data completeness of both type of measurements

Fully automated measurement: Con A enabled in month 1, Con B in month 5, Con C in month 10

Semi-automated measurement: Con A and B enabled in month 9, Con C in month 10

The data from the fully automated measurement – used for trend analyses – is perceived to be complete when the data has been collected non-stop during the previous two months. Ever since installing the CM system(s), the data has been collected automatically with each tilting of the converter. With each new CM system, the supplier of the technology and the project team together initialized the measurement automation, which has worked without fail throughout the observed period. The drops in data completeness are caused by installing new CM systems (months 1, 5 and 10: no prior data), the replacement of the test system with a local system (month 5: prior data lost), and the replacement of converters A and B (months 30 and 37: prior data has become irrelevant). Even when the CM system switched to new databases (months 9 and 40), no data was lost, as back-ups could be copied to the new database.

The data from the semi-automated measurement – used for diagnostic analyses of the current condition – is perceived to be complete directly after the data has been collected. The monitoring specialist indicated he requires at least one measurement every three months, to keep track of the speed of degradation and be able to compare the current measurement to the previous one. Therefore, the data completeness linearly declines over the time period of three months, reaching 0% after three months if no new measurement is taken.

In Figure 2.4, we observe a clear difference in the data completeness of two time periods: the time before month 25 (months 9 to 24) and the time after month 25 (months 25 to 48). Initially, there was a strong focus on ‘get it working technically’. During the ‘Proof of Concept’ phase, the project team wanted to identify whether they could make it work and whether or not it was better than other CM technologies. With the semi-automated measurement, the execution of a measurement is dependent upon Production. Multiple production teams however had expressed their concerns with the technology to the maintenance head via internal memos:

“*Hereby I’d like to indicate that my years of experience are telling me that the CM system is not measuring reliably. Because the sensors are placed at the wrong places, they are measuring different forces than the vibration monitoring technologies from our CMG. Therefore, we should abolish the CM system and go back to the old situation. The system is complex, I don’t understand it and I don’t want to bother my men with the problems of this system. It’s a waste of time to explore this system further*.” – Production team leader

Therefore, during the first months, measurements were only executed if project team members were present at Production to supervise the operator(s). Unfortunately, few of the project members had (or made) the time to structurally perform the measurements with operators[7]; the project manager was occupied with introducing this and similar CM technologies to other factories and the monitoring specialists were overflowing in periodic monitoring work. Partly automating the measurement (month 14: the CM system was programmed to automatically start and stop measuring once the operator starts the five rotations) was not sufficient to convince Production to structurally perform the measurements.

In total 7 measurements have been conducted during these 16 months. Still, during these 7 measurements, the project manager and maintenance engineer guided the operators on how to perform the measurements. With the old converters, this required quite some skill, as the converters needed to rotate at a constant speed (which is hard when the mass is not evenly distributed, the tipping point is similar to a rollercoaster’s tipping point; the new converters have a frequency drive that

[7] This activity takes quite some time from the project manager and monitoring specialist: both are not located in the factory, thus have to travel to the factory and back. More importantly, measurements could only be executed at specific times during production (right after a batch is finished), which occurs several times a day. To not miss the timing, they had to be present early. If the measurement didn’t go right the first time, they had to wait for the next window.

stabilizes the rotational speed). Although measurements were performed infrequently, the operators had started to develop the required skills in this period.

In January 2016 (month 26) the maintenance organization officially decided to embrace the CM technology, a few weeks after a new maintenance head was installed:

“*We didn’t get approval from management to switch to the new CM technology. The old maintenance head said ‘I want to be sure that we won’t get issues with the bearings.’ So, he didn’t want to stop our old measurements from the CMG. […] The moment he left, we switched. […] The old maintenance head was more proficient with vibration monitoring himself, he knows how difficult it is to measure the bearings of a converter and wasn’t convinced yet of the new CM technology. […] The new maintenance head agreed with us, based on our explanation he believed this was a good option.*” – Maintenance engineer

Directly afterwards, the maintenance engineer started embedding the technology’s usage. A process was informally agreed upon with Production and the monitoring specialist (month 26: the maintenance engineer gives a call to Production, the operators schedule and conduct the measurement and give a call when the measurement is conducted, the maintenance engineer then sends an e-mail to the monitoring specialist and requests an analysis), the measurement activities were administered in the CMMS (month 28: making the maintenance engineer responsible for conducting the monthly measurement) and the financial process was automated in the CMMS (month 28: automatically generating a payment for the monitoring specialist’s analysis). Because the decision was made at the factory’s top management level, the operators were also instructed by their management to support in conducting the measurements. Finally, in February 2017 (month 39) the project manager arranged a terminal server for the maintenance engineer, so he could check whether the measurement was conducted correctly from his computer. From that moment onwards, the maintenance engineer checked the measurement and directly requested a new one, if needed – a small update to the established routines.

The main events affecting the data quality are presented in Table 2.2. The timing indicates the month in which the event occurred, the nature marks whether the event was organizational or technological, the trigger describes the dominant trigger of the event, and the integration indicates the type of technology integration.

Table 2.2: Overview of main events affecting the data completeness

Event	Timing	Nature	Trigger	Integration
Automated measurement enabled at Con A	1	technological	window of opportunity	hardware
Decision by maintenance head to continue with SPM	5	organizational	performance	-
Test system replaced at Con A	5	technological	cascade	hardware
Automated measurement enabled at Con B	5	technological	window of opportunity	hardware
Project manager becomes functional owner	5	organizational	cascade	process
Semi-automated measurement enabled at Con A and B	9	technological	experience	hardware
Semi-automated measurement conducted by project team	between 9-25	organizational	cascade	process
Con C replaced	10	technological	exogenous	-
Automated measurement enabled at Con C	10	technological	window of opportunity	hardware
Semi-automated measurement enabled at Con C	10	technological	window of opportunity	hardware
Semi-automated measurement partly automated	14	technological	experience	hardware
Decision by maintenance head to start monitoring structurally	26	organizational	performance	-
Informal agreements about data collection process	26	organizational	cascade	process
Semi-automated measurement conducted by operators	from 26	organizational	cascade	process
Semi-automated measurement administered in CMMS	28	technological	cascade	process
Database back-ups arranged	28	technological	experience	hardware
Con A replaced	30	technological	exogenous	-
Con B replaced	37	technological	exogenous	-
Enabled remote check for maintenance engineer	39	technological	experience	hardware
Procedure updated: maintenance engineer checks quality	39	organizational	cascade	process
Switch to new databases	40	technological	exogenous	hardware

It should be noted that the data completeness in the current situation cannot exceed 84%; with the hardware installed, it is not possible to monitor both bearings of the same converter simultaneously, and the maintenance organization and monitoring specialist agreed upon measuring each converter only once a month. Therefore, the bearings are measured in turns, where each bearing is measured every other month. Although the CM technology's supplier has enabled the option to measure both bearings simultaneously in newer versions of the system, the maintenance organization is not convinced of the added value, thus has decided not to purchase the new system.

In addition, in the interviews multiple instances were mentioned in which the manual steps of the semi-automated measurement procedure led to errors. These were uncovered over time (learning-by-doing). For example, initially the project manager had to determine, prior to each measurement, which bearing will be measured. This worked, until the project manager went on an extended holiday, during which the same bearing was measured three times in a row.

4.3 Analysis accuracy

No CM analysis is perfect right from the start:

"*Especially not with one-of-a-kind installations. With a dime a dozen installations, bulk installations, it's possible to quickly generate a lot of data and have a very steep* *learning curve. But here we have three converters. […] It takes time to start recognizing the patterns of degradation.*" – Project manager

Figure 2.5 shows the accuracy of the analyses reported. Each report, developed by the monitoring specialist, contained an analysis and a recommendation. These analyses have been labelled as 'true negative' (analysis: no fault in bearing, actual: no fault in bearing), 'true positive' (analysis: fault in bearing, actual: fault in bearing); 'false positive' (analysis: fault in bearing, actual: no fault in bearing) and 'limited analysis' (hard to draw conclusions, no maintenance recommendation provided). The analyses were limited for example when there was too much external disturbance during the measurement, when the rotation speed was fluctuating, and when basic information was missing (e.g., no bearing characteristics or rotational speed available). In the first two years, some analyses have been performed, but only one of these has been documented in an official report. Therefore, the accuracy has been calculated for the last two years only.

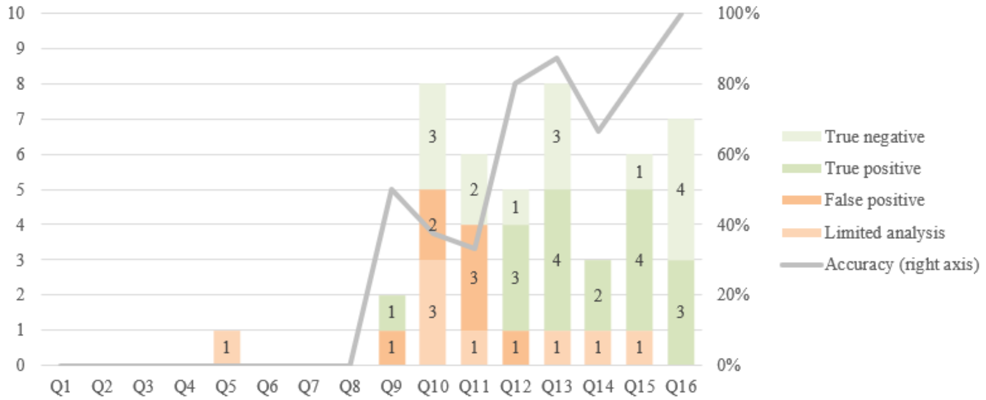

Figure 2.5: Accuracy of analyses

To understand the pattern of performance, we have to delve into both the technological and organizational events. In the first 9 months, before the semi-automated measurement was enabled, only the trend from the continuous measurement could be analysed.

"*The trend only provides so much information. All you see is a trend. Does it go up? Yes, it goes up. Now what? From this point on it's just guessing. How will the trend develop further? What is causing the increase? […] I cannot analyse a trend. So, I'm not going to base any conclusions on a trend alone.*" – Monitoring specialist

In August 2014 (month 9, Q3), the first semi-automated measurement was conducted at converter B. When this measurement was analysed (month 10, Q4), the monitoring specialist identified strong vibrations, indicating possible bearing damage. This was also indicated by a series of prior measurements with a more basic CM technology (portable vibration monitoring). Based on these analyses, the maintenance organization decided to conduct a thorough and costly internal inspection of the bearing in October (month 11, Q3). Unfortunately, or luckily, no bearing damage was found during the inspection. Instead, the increase in vibrations was identified to be caused by an external disturbance (solidified steel at the side of the converter was scraping against the converter when tilting). Some of the people involved did perceive this first analysis as a costly false alarm however.

Nonetheless, the project team continued. In the process of partly automating the measurement, multiple test runs were conducted. In the analysis of these runs (month 15, Q5), the project team learned that the measurement itself had to be slightly adjusted – the current resolution was insufficient for good analyses. Thus, the learning process went on, but it progressed slowly: in the remainder of 2015, only four additional measurements have been performed and the monitoring specialist was requested only once to conduct an analysis (month 20). During the year, the project manager and maintenance organization did compare the continuous measurement with the results from lubrication analyses (an alternative CM technology, conducted every thirteen weeks, that shows whether components of the bearing are crumbling), to verify the quality of the algorithms behind the trend.

Learning really took off from December 2015 (month 25, Q9). Because the monitoring specialists were not convinced yet of the SPM technology, they had purchased an additional, advanced CM technology that allows a much more thorough diagnosis of the converter bearings. This CM technology requires 40 minutes of production downtime however, so the maintenance organization and monitoring specialist decided this measurement could be conducted once every six months at each converter (thus six times per year for three converters). In December 2015 (month 25, Q9) and January 2016 (month 26, Q9) the project team used this new CM technology to judge the quality of the semi-automated measurement at two converters, both at an old converter and at a new converter. Convinced by these tests, the project manager and maintenance engineer recommended the maintenance head to start structurally using the semi-automated measurement.

After the maintenance organization had made the decision to continue, the maintenance engineer and monitoring specialist started formalizing the analysis process. Within two months, operational routines were agreed on verbally and actions and financial agreements were anchored in the CMMS. In addition, the monitoring specialist developed a standard format to report the results from the analysis, making it easier for the maintenance organization to use the results in their maintenance decision-making. Also, the required information about the bearings and rotation speed was provided, reducing the number of 'limited analyses'.

These changes created the context in which the improvement of analysis accuracy could really start: the monitoring specialists were consistently performing analyses, and they frequently received feedback about the quality of their analysis. The main source of feedback came from two other CM technologies – the advanced CM technology and the lubrication samples – that verified periodically whether the trend and the semi-automated measurement analyses were correct. In addition, the monitoring specialists have regularly requested an external visual inspection (17 times in the last 21 months), mainly to check for external disturbances (e.g., solidified steel). As a result, within two years' time the quality of the analyses increased greatly: the quality of the measurements improved and, more importantly, the number of false positives (false alarms) went down.

"*The analysis of the semi-automated measurement consists of a time signal and a spectrum analysis, standard vibration analyses. […] We (vibration monitoring specialists) already had a lot of experience (with these types of analyses). Yet, here we really had to learn what is bad, and what is not. In the past, whenever we saw a vibration, panic quickly arose. Now we can much better estimate: how urgently do we have to deal with this deviation?*" – Monitoring specialist

It should be noted that the monitoring specialist has been requesting for two additions to the semi-automated measurements since early 2016 – a phase measurement[8] and a simultaneous measurement[9] – to enhance the diagnostic capabilities of the analysis. The phase measurement requires a software update from the CM technology's supplier, which is not available yet. The simultaneous measurement on the other hand requires a hardware update: installing new sensors. These sensors are available

[8] The phase measurement connects the position of the converter during its rotations to the vibration data and aids in identifying the location of a fault in the bearing.
[9] The simultaneous measurement – measuring both bearings of the converter simultaneously – allows comparisons between the vibration data and aids in identifying whether vibrations are caused by an internal fault in a bearing or an external disturbance.

Table 2.3: Overview of main events affecting the analysis accuracy

Event	Timing	Nature	Trigger	Integration
Alarm levels set on automated measurement at Con A	1	technological	cascade	hardware
Analysis by supplier	between 1-4	organizational	cascade	process
Alarm levels set on automated measurement at Con B	5	technological	cascade	hardware
Local analysis by project team	between 5-8	organizational	cascade	process
Training of monitoring specialist by SPM	8	organizational	window of opportunity	process
CM systems connected to central database	9	technological	performance	hardware
Additional analyses enabled by semi-automated measurement	9	technological	cascade	hardware
Fingerprint semi-automated measurement of Con B	9	technological	window of opportunity	-
Analysis conducted by project team	between 9-25	organizational	cascade	process
Frequency drive at Con C	10	technological	exogenous	-
Alarm levels set on automated measurement at Con C	10	technological	cascade	hardware
Feedback on analysis: thorough internal inspection	11	organizational	cascade	-
Semi-automated measurement adjusted	15	technological	experience	hardware
Fingerprint semi-automated measurement of Con C	17	technological	window of opportunity	-
Verification of semi-automated measurement with advanced CM	25	organizational	experience	-
Feedback on analysis: advanced vibration monitoring	from 25	organizational	experience	process
Informal agreements about analysis process	26	organizational	cascade	process
Analysis conducted by monitoring specialists	from 26	organizational	cascade	process
Standard report developed by monitoring specialist	26	organizational	cascade	process
Analysis of semi-automated measurement administered in CMMS	28	organizational	cascade	process
Financial payment arranged via CMMS	28	organizational	cascade	process
Feedback on analysis: external visual inspection	from 28	organizational	experience	process
Frequency drive at Con A	30	technological	exogenous	-
Fingerprint semi-automated measurement of Con A	31	organizational	window of opportunity	-
Frequency drive at Con B	37	technological	exogenous	-

at the CM technology supplier, but the maintenance organization has to purchase them, and their urgency to improve this CM technology has diminished over time.

"*We see that they (the maintenance organization) think it's okay this way. For years they didn't have any real damage to the bearings. The external disturbances are detected. So, the willingness to improve the system fades away. I have made my requests for further automation of the measurement and additional phase and simultaneous measurements ages ago, but little is coming of it. We should have kept going while the urgency was still high.*" – Monitoring specialist (2019)

4.4 Maintenance costs

Lastly, the costs of maintenance are expressed in Table 2.4. Here we show the average inspection and maintenance costs per converter per year in an indexed form (cumulative costs in the first year set at 100). The years in which a converter has been replaced are marked in italic. The costs for the replacement of the converter (bearings) have been excluded from Table 2.4, as they are paid from a different budget (project budget) and overshadow the much smaller differences in inspection and maintenance costs. By presenting the costs in this format, it is possible to draw comparisons between the inspection and maintenance costs of consecutive years, identifying the timing of cost changes, and between the inspection and maintenance costs of old and new converters (main alternative explanation).

On average, we see that the costs of maintenance are reduced for the new converters.

"*With the new converters we have a new situation in which everything is heavily engineered, with high load carrying capacity and multiple preventive measures. This does not break down easily.*" – Maintenance engineer

In addition, it should be noted that the maintenance costs for Con B in 2015 and Con C in 2016 consist almost entirely of periodic maintenance costs for the bearing seals and straps (maintenance activities that are unaffected by the usage of the CM technology). To understand the other changes in costs, we have to dig into the maintenance decisions that have been taken based on the analyses with the CM technology.

Table 2.4: Maintenance costs of converter bearings (excl. cost of replacement of converters)

		Year			
Converter		**2014**	**2015**	**2016**	**2017**
A	Inspection	4.8	2.9	*1.0*	0.7
	Maintenance	0.7	0.0	*0.5*	0.0
B	Inspection	25.5	3.5	*2.5*	0.2
	Maintenance	60.1	6.9	*0.8*	0.0
C	Inspection	*5.4*	3.5	2.0	0.4
	Maintenance	*3.5*	0.8	5.9	0.3
Total per year		100.0	17.6	12.6	1.6

The first maintenance decision was taken in October 2014 (month 11), the decision to thoroughly inspect the bearing of converter B. As Table 2.4 confirms, this was a costly endeavour. The inspection, which lasted a week, entailed disassembling, transporting, inspecting, and reassembling the bearing. In Table 2.4 only the costs which have been administered directly under "inspection costs" are presented as inspection costs, but one could argue that (at least part of) the costs for assembly and transport should be assigned to the inspection as well. This decision was based on the analysis of the first semi-automated measurement, as well as multiple analyses of the 3-weekly measurement with basic vibration monitoring technology, but more was at stake here: the bearing was replaced preventively 6 months earlier (April 2014, month 5) with a new type of bearing.

"*We are the first ones in the world to apply this type of bearing. When we saw that the values increased over the past six months, we were wondering whether the bearing was functioning correctly. That's why we decided to use these seven days (there was a window of seven days between the maintenance stops of the other two converters) to fully inspect the bearing and solve it right away. […] What you really don't want, is for the scope to increase at the end of the week. Delay is not an option. […] Right at the start of the inspection we observed the lump of solidified steel, but we completed the entire inspection.*" – Maintenance engineer

The second maintenance decision was taken in July 2015 (month 20), the decision to skip a considerable 3-yearly maintenance activity of the other bearing of converter B (approximate indexed cost: 54). This decision was based primarily on the analysis with the new, advanced CM technology (advanced portable vibration monitoring), but the analysis of the semi-automatic measurement, the trend of the continuous measurement and the lubrication samples also indicated that the bearing's condition was good. Moreover, the risk of skipping this periodic maintenance activity was perceived to be limited: the bearing was recently renewed (May 2012), the average lifespan of that type of bearing was 10 years, and the converter was going to be replaced 9 months later.

In January 2016 (month 26), the decision was taken to stop the 3-weekly basic vibration measurement (approximate yearly indexed cost: 12) and rely completely on the combination of the continuous measurement, monthly semi-automated measurement, quarterly lubrication sample and biannual advanced measurement. The timing of this decision is no coincidence. In the two months prior to this decision, the project manager and maintenance engineer created three documents drafting and substantiating a new monitoring program, including financial calculations. One month before the decision, the project team validated the quality of the measurements with the advanced vibration measurement, establishing (within the project team) sufficient trust in the analytical capabilities of the CM technology. Armed with this information, the project team convinced the newly installed maintenance head to start structurally using the SPM technology and stop the basic measurement – a simultaneous decision.

The final maintenance decision was taken in November 2017 (month 48), the decision to increase the interval of the bearing's periodic maintenance from three years to ten years (approximate indexed cost per activity: 80; approximate indexed total saving per year for three converters: 56). This decision is made by the maintenance organization, based on the recommendation of the organization's converter specialist. In a 50-page document, he described and substantiated the optimal maintenance program for the converters, deviating from the manufacturer's recommended maintenance program (and thereby losing the warranty on the bearings).

"*On the basis of this document it is adjusted. The maintenance plan from the bearings' supplier describes different intervals, but we follow our converter specialist. […] We have difficulties changing maintenance plans based on results. […] I notice that it still takes a lot of time to think it through together, write the proposals and get approval. […] You have to substantiate it. The converter bearings are a sensitive topic of course. […] But, if we don't experience any problems for a long period, I believe we should dare to change it. It takes courage. […] If you make a wrong adjustment, you'll introduce new risks. […] This way (by demanding a good substantiation), we help each other to think it through properly and only implement actual improvements.*" – Maintenance engineer

Why did it take an additional two years to make this last, most valuable decision? First, it is also the riskiest decision. Not only due to the loss of warranty, but also because an unexpected breakdown incurs high opportunity costs for lost production, costs that easily overshadow the costs for these periodic maintenance activities. Secondly, the converter specialist was not fond of the CM technology, since he deemed it unnecessary (with the new design of the bearings, the likelihood of a breakdown had been reduced greatly) and risky (false alarms can create unnecessary maintenance activities and each maintenance activity has the potential to introduce faults). Only after the project manager and monitoring specialist had convinced him (sufficiently) of the technology's usefulness and had shown him that the quality of analyses (with the monitoring program as a whole) had improved, he was willing to incorporate the CM technology in the maintenance program and rely on the monitoring program to extend the bearings' maintenance interval. Lastly, the decision-making process itself took time and faced resistance, especially because multiple organizational units were involved in the process and the remembrance of the consequences of bearing failure was still fresh.

Table 2.5: Overview of main events affecting the maintenance costs

Event	Timing	Nature	Trigger	Integration
Decision by maintenance organization to inspect bearing	11	organizational	window of opportunity	outcome
Decision by maintenance organization to skip a periodic maintenance activity	20	organizational	window of opportunity	outcome
Decision by maintenance organization to stop basic vibration measurement	26	organizational	performance	outcome
Decision by maintenance organization to increase interval of periodic maintenance	48	organizational	performance	outcome

4.5 Technology integration and performance

Finally, we aggregate the findings of each performance aspect and assess the recursive relationship between technology integration and performance more directly. Figure 2.6 shows the distribution of events throughout the observed period, Table 2.6 presents an overview of the events, technology integration levels, and performance aspects. In Figure 2.6, four periods can be observed with a high number of events: month 1 (installation of test system, monitoring by supplier), month 5 (decision to continue with proof of concept, installation of two monitoring systems, assignment of functional ownership), months 9 to 11 (connection to central database, initialization of semi-automated measurement, installation of third monitoring system) and months 26 to 28 (decision to continue usage, informal agreements about procedures, administration in CMMS, development of standard report).

These periods coincide with the main steps in technology integration. In Table 2.6, we identify five levels, or configurations, of technology integration: (1) a test system, in which the monitoring is provided by the supplier (hardware and process integration), (2) a local system, in which the monitoring is performed locally by the project team (hardware and process integration), (3) a centralized system, in which the monitoring is performed from a distance by the monitoring specialist (mainly hardware and process integration), (4) an embedded system, in which measurements and analyses are performed consistently and the analyses are used for maintenance decision-making (process and outcome integration), and (5) a fully integrated system, in which the maintenance organization relies mainly on this CM technology to schedule maintenance activities (outcome integration). At the final level of technology integration, the maximum value is derived from the technology.

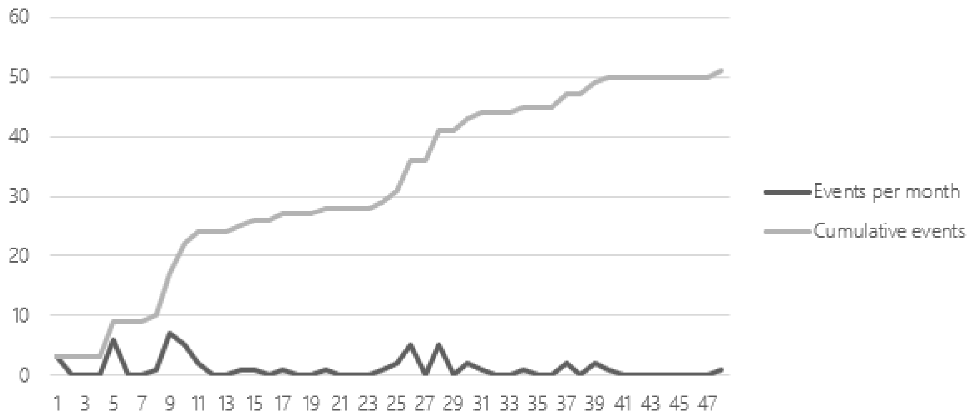

Figure 2.6: Distribution of events

In studying the effect of technology integration on performance, we observe different effects for each performance aspect considered. The data completeness of the automated measurement is mainly improved by automation – installation and initialization of the CM technology – after which the data is collected automatically (hardware integration). From the moment a CM system is installed, the data completeness increases rapidly. The data completeness of the semi-automated measurement on the contrary is mainly improved by institutionalizing the measurements: assigning roles and responsibilities, agreeing on a procedure, and administering the measurement actions in the CMMS (process integration). Based on Figure 2.4 and Table 2.6, one could argue that the performance increased twice to a new, relatively stable performance level: at month 9 (project team became responsible for conducting the measurements) and at month 26 (maintenance engineer and operators became responsible for conducting the measurements).

For the analysis quality, it took two years before it started improving. First, the conditions needed to be established – consistent measurements, consistent analyses, and frequent feedback – in which the quality of the analyses could be improved in a process of learning-by-doing. These conditions were established in months 26 to 28, when the measurement and analyses processes were integrated. The actual learning (and performance increment) however took place in the period thereafter, months 28 to 48, a stable period with few events. During this period, small changes were made based on experience, such as additional visual inspections, removal of solidified steel, and more conservative maintenance recommendations. Larger changes, such as the replacement of converters A and B, were detrimental to performance, as they required relearning patterns of degradation. Thus, for the quality of analyses, the performance mainly improved via learning-by-doing in a period of stability, after the technology had been integrated sufficiently.

Finally, the costs of maintenance increase or decrease with specific decisions being made – conducting a thorough inspection, skipping a maintenance activity, stopping the usage of an alternative CM technology and extending a periodic maintenance interval. Integrating the technology into the maintenance decision-making process is beneficial if and only if the performance of the analysis is high enough for each of the maintenance decisions to have a positive expected gain. Therefore, perceptions of the technology's current performance – the *current analysis quality* in particular – played an important role in the decision to use the outcomes from the CM technology – the analyses – for specific maintenance decisions. Yet, the technology's current performance was not the only performance aspect that affected integration

Table 2.6: Overview of events and performance

Month	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
Events per month	3	0	0	0	6	0	0	1	7	5	2	0	0	1	1	0	1	0	0	1	0	0	0	1
Technology integration	test				local				central analysis, testing semi-automated measurement															
hardware	test system				local system				connected to central database, semi-automated measurement enabled															
process	supplier				local analysis				central analysis															
outcome	not used										used as back-up													
Performance																								
Uncertainty																								
Data completeness: automated	lowering					low																		
Data completeness: semi-automated	n/a								lowering															
Analysis accuracy	high										lowering													
Current performance																								
Data completeness: automated	0.5	1.0	1.0	1.0	0.5	1.0	1.0	1.0	1.0	0.7	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
Data completeness: semi-automated	-	-	-	-	-	-	-	-	0.5	0.2	0.1	0.0	0.2	0.3	0.2	0.1	0.2	0.3	0.2	0.2	0.1	0.1	0.0	0.0
Analysis accuracy	unk			unk			unk			unk			0%			unk			unk			unk		
Maintenance costs (cumulative)	100												17.6											
Events: Categorized																								
Type of event																								
Organizational					2			1			2									1				
Technological	2				3				5	5				1	1		1							
Trigger of event																								
Management																								
Shock																								
Experience									2					1	1									
Window of opportunity	1				1			1	1	2	1						1			1				
Cascade	2				4				3	1	1													
Performance					1				1															
Exogenous change										2														1
Technology integration																								
hardware	2				3				4	3				1	1									
process	1				2			1	2															
outcome											1									1				
Performance aspect affected by event																								
Data quality	1				4				2	3				1										
Analysis quality	1				1			1	3	2	1				1		1							
Maintenance costs											1									1				

Month	25	26	27	28	29	30	31	32	33	34	35	36	37	38	39	40	41	42	43	44	45	46	47	48
Events per month	2	5	0	5	0	2	1	0	0	1	0	0	2	0	2	1	0	0	0	0	0	0	0	1
Technology integration		embedded, consistent measurement & analysis																						fully integrated
hardware																								
process		operational organization																						
outcome		used as main information source																						fully used
Performance																								
Uncertainty																								
Data completeness: automated																								
Data completeness: semi-automated		low																						
Analysis accuracy		low																						
Current performance																								
Data completeness: automated	1.0	1.0	1.0	1.0	1.0	0.8	1.0	1.0	1.0	1.0	1.0	1.0	0.8	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
Data completeness: semi-automated	0.7	0.5	0.4	0.4	0.6	0.4	0.7	0.7	0.6	0.3	0.3	0.3	0.2	0.6	0.4	0.6	0.5	0.6	0.7	0.8	0.6	0.4	0.6	0.7
Analysis accuracy	50%			37.5%			33.3%			80%			87.5%			66.7%			83.3%			100%		
Maintenance costs (cumulative)	12.6												1.6											
Events: Categorized																								
Type of event																								
Organizational	1	5		3			1			1					1									1
Technological				2		2							2		1	1								
Trigger of event																								
Management																								
Shock																								
Experience	2			1											1									
Window of opportunity							1																	
Cascade		3		3											1									
Performance		2																						1
Exogenous change				1		2				1			2			1								
Technology integration																								
hardware				1											1	1								
process	1	3		4						1					1									
outcome		1																						1
Performance aspect affected by event																								
Data quality		2		2		1							1		2	1								
Analysis quality	1	2		3		1	1			1			1											
Maintenance costs		1																						1

Dotted lines: showing whether the performance-based decisions were stand-alone or led to additional events (cascaded changes) decisions. In fact, initially the project team was interested primarily in the technology's *potential* performance:

"*In the beginning it was just testing. […] We knew the performance wasn't good yet. But since the converters are really complex to monitor, we had to find out whether it would be possible at all with this technology. Can we get good data? Can we perform good analyses? […] Together with the lubrication specialist, we compared the data to the lubrication samples. This showed us that the values were actually lower for less polluted samples. […] Later on, we compared it to the (advanced vibration) measurement, with the same results, raising our trust in the capabilities of the system.*" – Project manager

In the interviews we identified three aspects of performance that were considered especially relevant for integration decisions: data quality potential, analysis quality potential, and current analysis quality. Due to the newness of the technology and application, there was a high uncertainty about the performance that could be realized with the technology. Over time, this uncertainty was reduced via technology integration, generating experience with the technology, and deliberate additional activities, such as testing the system with the supplier, performing a thorough inspection and comparing the results to analyses from other, established CM technologies (for which the performance was known). The complete interaction between the technology's perceived current and potential performance and its integration process is shown in Figure 2.7.

The *data quality potential* – whether it is possible to generate useful and complete data – was reduced in the first couple of months during the test with the supplier. By installing a test system and checking frequently whether the data is collected correctly, the supplier and project team generated confidence that the automated data collection functioned well. This provided sufficient impetus for the maintenance head and project manager to purchase a local system (month 5). Some months later, when the semi-automated was introduced, the question "can we get good data?" became relevant again. By performing multiple test runs, automating part of the semi-automated measurement, and making additional adjustments to the measurement, it became clear to the project team that it was possible to conduct the measurement properly.

The *analysis quality potential* – whether it is possible to analyse the data correctly and foresee machine failure – was reduced mainly in the months 11 to 25. Initially

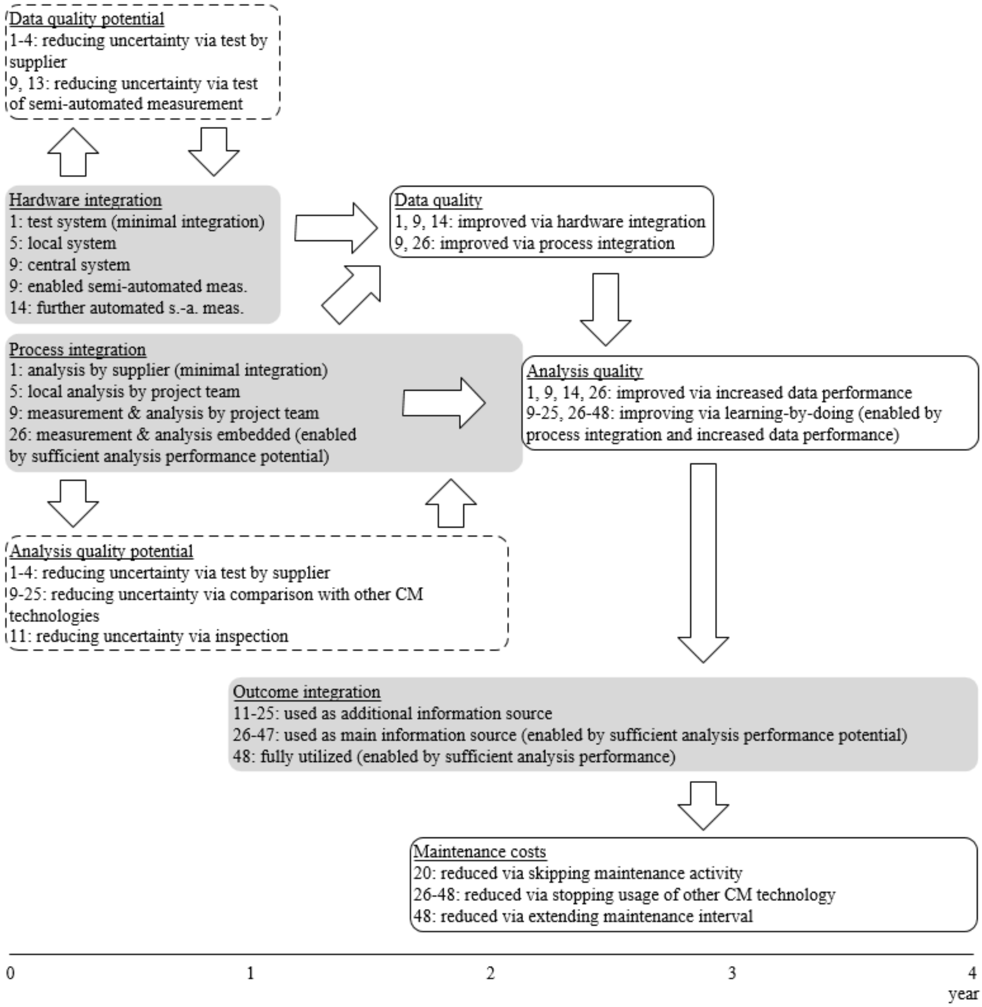

Figure 2.7: Observed interaction between technology integration (grey) and performance (white)

the uncertainty was perceived to be very high, especially by the monitoring specialist, since he was unsure about the data collection method[10], didn't get access to the algorithms transforming the data into a health status, and was unfamiliar with SPM's value for health status. The semi-automated measurement on the other hand enabled standard vibration analyses (spectrum analysis, time signal analysis), which

[10] In the vibration education program, they emphasize that vibration analysis requires longer time samples, capturing multiple rotations of a bearing. The automated data collection method of SPM takes a very small sample, but multiple times a day, of a fraction of the bearing's rotation (1 round takes ±30 seconds, a sample consists of 0.2 seconds).

the monitoring specialist was very proficient with. Yet, since the application (converter bearings) was new, the measurement was shorter than recommended by vibration monitoring standards[11], and a high level of analysis performance was desired (due to the criticality and history of the converters), the project team desired a trial period to find out how good the analyses could be performed. In the months 11 to 25, they verified analyses with a thorough visual inspection (month 11), comparisons with lubrication analyses (every three months) and a comparison with another, newly purchased advanced vibration monitoring system (month 25). Together, these verifications had reduced the uncertainty of the potential analysis performance to a sufficiently low level, allowing the decision to further integrate the technology.

So, in studying the effect of the technology's performance on the technology integration process, we observe that some – important – decisions only occur after the technology's performance is perceived as satisfactory, or the perceived uncertainty about the technology's performance has been reduced to a sufficiently low level. As can be seen in Table 2.6, from the 51 events, 5 have been triggered primarily by performance considerations. These performance-based decisions however were important decisions: the decision to continue the proof of concept, the decision to make the data accessible for the central monitoring specialist, the decision to start structurally using the CM technology, the decision to stop an alternative CM technology and the decision to extend the periodic maintenance interval. The first three of these changes enabled further improvement of the technology's performance, the last two enabled realizing the value from the CM technology.

Two additional observations are noteworthy. First, an order can be observed in the technology integration decisions. The first decisions, to continue the proof of concept and set up a central database, require an investment for the hardware, but carry little additional risk. The decisions to start structurally using the CM technology and stop the usage of the alternative CM technology contain more risk, as they might increase the probability of missing an upcoming breakdown of the bearings – if the analysis quality is insufficient. Yet, the last decision contains most risk: extending the maintenance interval from 3 to 10 years and losing the supplier's warranty might increase the probability and the cost of an unexpected breakdown. Thus, an order

[11] Typically, 10 rotations are recommended of the slowest rotating part. Here, due to the perceived risk of rotating a converter, the maintenance organization agreed on 5 rotations.

can be observed that is based on risk. The better the performance of the technology, the more risk can be mitigated, making further integration attractive.

"*Think big, start small. […] We started isolated. In a test environment you can learn working with the system, you can easily remove the system (if the performance is unsatisfactory), you have minimal impact on the environment. […] The quality of the system, the trust in the system, it all needed to grow. […] Not just for the production teams, also for me, for the monitoring specialist, for the maintenance engineer. For each of us the belief in the system had to grow. […] In the past, without this measurement, you would have been a tough guy to postpone a maintenance activity. But now everybody trusts the system.*" – Project manager

Second, at any moment in time, people have different perceptions of the technology's performance, so whether or not further integration is carried out depends mainly on the decision maker's perception of performance. For example, the decision to continue the proof of concept and install the CM system on all three converters was made by the maintenance head, but was resisted at that time by the monitoring specialist. The decision to start using the CM technology structurally was made by the new maintenance head, not by the old maintenance head, while the data and analysis performance were unchanged. And the decision to extend the maintenance interval was made by the converter specialist, only after the project manager and monitoring specialist had convinced him of the performance of the CM technology. Thus, the decision makers' perception of the technology's performance can be an important determinant of the technology integration efforts.

5. Discussion

So, how did the organization manage the introduction process of CBM, and how were performance considerations used to decide upon CM technology integration? We observed a stepwise process, starting small, in which the technology gradually became more integrated in the organization's hardware, processes and decision-making. Integration decisions were based on different aspects of performance and made by different people. Windows of opportunity were used to reduce the costs of technology integration (hardware integration took place during maintenance stops and renovation projects) and organizational changes were clustered with technological changes. Experience, as well as various tests, helped in reducing the uncertainty about the technology's potential performance, and positive feedback encouraged the organization to integrate the technology further.

In this case, ambiguity of the technology’s performance enabled earlier integration and prevented technology abandonment. While the analysis’ potency remained uncertain, information about the quality of the data – which arrived in the first months – provided sufficient trust in the technology to purchase three systems. Performance ambiguity also helps in explaining why the technology – which had low performance throughout the first two years – wasn’t abandoned after the first incorrect analysis (month 11), even though multiple production teams had specifically asked for abandonment. The decision makers made a distinction between the technology’s current performance and the technology’s potential performance, and their decision to abandon – or not – was based primarily on the latter. As long as the technology’s potential performance was unknown, the decision makers opted against abandonment.

On the other hand, uncertainty about the technology’s performance was the main factor delaying technology integration activities. If the technology’s performance was less uncertain, decisions to integrate the technology further would have been taken earlier, according to the interviewees. For example, the decision to start using the technology structurally was taken after the technology’s potential performance was perceived as satisfactory, the decision to rely on the technology for scheduling maintenance activities was made after sufficient trust in the technology’s current performance was established.

Figure 2.8 presents the synthesis of the main relationships between technology integration and performance, abstracting away from individual performance aspects. Each decision to integrate the technology – whether it’s hardware integration, process integration, or outcome integration – has a desired level of performance or certainty, related to the costs and risks involved with the integration decision. The uncertainty of the potential performance is reduced over time with experience, but can also be reduced with specific investments and activities, such as performing test runs to identify whether the data can be collected properly and comparing analyses with the results of other CM technologies. The current performance of the technology can increase directly from technology integration (e.g., hardware integration enabled the automated collection of data, hardware and process integration accomplished semi-automated measurements), but also indirectly; the extent of technology integration affects the nature and frequency of experiences, enabling building proficiency via processes of learning-by-doing. It is also possible to increase the technology’s performance via other investments and activities, such as employee training and purchasing new hardware. However, correspondent with the satisficing principle (Winter, 2000), we observed that these investments lessened over time, as the maintenance organization became satisfied with the current level of performance.

Thus, we observe a strong dynamic relationship between the extent of technology integration and the technology's performance. Two of the performance-based decisions – to continue the test with local systems and to start structurally using the technology – were vital in further increasing the technology's performance. These decisions freed up additional resources to purchase CM systems and periodic analyses, and led to institutionalizing the technology's usage. In fact, without these decisions, the technology's performance would not have increased as fast (or at all). Thus, the actual performance of the technology affects the perceived performance of the technology, which affects the resources invested in the technology and the extent of technology integration, which, in turn, affects the actual performance of the technology. This reinforcing feedback loop either spirals to an equilibrium of acceptable performance, adequate resources invested and a stable technology integration level or never takes off, if the desired performance levels are not achieved or achievable.

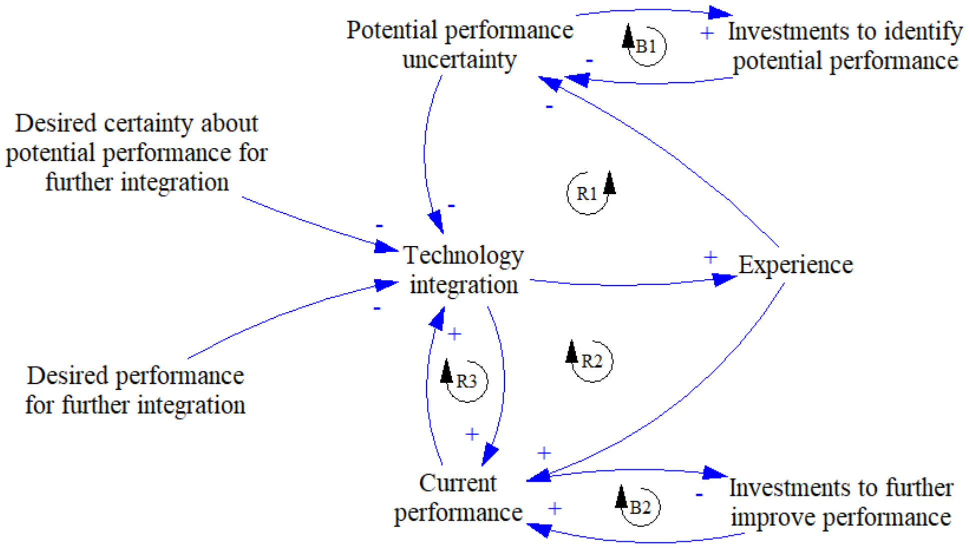

Figure 2.8: Dynamic relationship of technology integration and performance

B1: Learning-by-experimentation (uncertainty reduction)
R1: Learning-by-doing (uncertainty reduction)
R2: Learning-by-doing (performance improvement)
R3: Further technology integration (performance improvement)
B2: Satisficing principle

Organizational learning theory, as well as Van de Ven et al.'s (2008) adaptive learning model, assumes an ongoing cycle in which task experience is converted into knowledge, that in turn changes the organization's context and affects future task experiences (Argote & Miron-Spekter, 2011). In our case however, a very limited amount of learning-by-doing occurred in the first two years, as the measurements and analyses were not embedded yet. Learning-by-doing requires repetition and performance feedback, such that routines can be developed and improved over time (Levitt & March, 1988). Did the project team learn nothing then in the first two years? On the contrary, in the first two years the project team learned that the data could be collected accurately and completely (data quality potential), and that these data could be used to conduct proper analyses (analysis quality potential). They didn't learn this through repetition, but via specific tests and experiments. This type of learning has been described as learning-before-doing (Pisano, 1996) and learning-by-experimentation (Bohn & Lapré, 2011), which entails a deliberate and targeted effort to solve a problem or generate new knowledge.

In this case, *learning-by-experimentation* holds the key to solving the initial stalemate: the organization is willing to invest in the technology if its performance potential is sufficient, but the 'only way' to identify whether the performance potential is sufficient is by investing in the technology. Apparently, there are two other ways. One way is for management to enforce integration of the CM technology, based on a belief in the CM technology's potential performance, but note that nobody was convinced yet initially: the operators were not convinced yet, the monitoring specialist was not convinced yet, and the maintenance head was not convinced yet. Another way is for the project team to first reduce the technology's potential performance uncertainty via targeted experiments, after which the organization can make a better-informed decision. Thus, to summarize Figure 2.8, technology integration has facilitated learning-by-doing, and – in the absence of repetitive actions – learning-by-experimentation has facilitated further technology integration.

The insights from our study contribute to the literature in two ways. First, our findings indicate that the adaptive learning model of Van de Ven et al. (2008: p.69) can also be used to understand the implementation of new practices and technologies, another type of innovation process. With the implementation of new practices and technologies, technology integration decisions act as gates to determine whether or not the implementation process will be continued, separating different phases (Cooper, 1990). This type of innovation also encounters ambiguous organizational settings in which goals are vague and can shift over time, outcomes are difficult to assess, and new courses of actions emerge during the innovation process. In our case, the core of the model – the innovators' behavioural process of trial-and-error (learning-by-doing) – did explain some of the performance increments, but most of the improvement was created by technology integration. Moreover, we observed that when the outcomes of interest are hard to assess (uncertain), innovators search for information about other, related outcomes via targeted experiments (learning-by-experimentation, or learning-before-doing) to determine the course of action. We also observed that innovators persisted on a course of action, even while the first analysis was perceived as incorrect (negative perceived outcome), because they had – at that moment in time – sufficient belief in the technology's future potential (analysis quality potential). One last note: the adaptive learning model emphasizes that negative outcomes will trigger interventions from external resource controllers, while positive outcomes lead to smooth, "uneventful" continuation of the innovation process. In our study, main events were initiated by the maintenance head – an external resource controller – upon observation of positive outcomes, reinforcing his perceived usefulness of the technology and creating the willingness to make additional resources available. Thus, for the implementation of new practices and technologies, positive outcomes can also strongly affect the course of action being pursued by the innovation team.

Second, several researchers have emphasized that the initial episode of adaptation is especially important (e.g., Pettigrew et al., 2001; Tyre & Orlikowski, 1994), which is reflected in the literature on path dependency (Mahoney, 2000). Our findings, in line with Amis, Slack and Hinings (2004), show that innovations can also have a gradual introduction, with important decisions being taken at later moments in time. In our case, due to the complexity of the monitoring application and the newness of the technology, it made sense to start experimenting with the technology in a proof of concept, delaying the full-fledged integration of the technology. In such an innovation process, multiple decisive moments exist – and may be desirable – that determine how the technology will be used by the organization over the longer term. According to decision science, when valuable information about a technology's performance arrives over time, it can be economically optimal to delay important decisions (Rhys, Song & Jindrichovska, 2002).

Our study is a single case study, so we will be modest in making general claims about the introduction process of new technologies. Especially since we've seen that the relationship between technology integration and performance can vary for different performance aspects, and it is known that technologies have idiosyncratic performance criteria, dependent upon the technology, the organizational context, the people involved, and even time (Van de Ven et al., 2008). We do expect however that similar performance dynamics will be found with the introduction of other CM technologies, or information technologies with uncertain and ambiguous performance in general. The processes that integrating the technology and investing resources aid in increasing the technology’s performance, and that a better performance makes it more likely the technology will be integrated further and additional resources will be invested, seem universal.

If technologies can be found with similar relevant performance aspects, such as the same CM technology at different asset owners or similar CM technologies at the same asset owner, the relationships between technology integration and performance can be tested quantitatively. As many organizations are currently experimenting with new CM technologies, we believe additional research towards the optimal introduction process – including the optimal pace and sequence of integration – is useful. In addition, more research might be conducted towards the way the nature of the technology shapes the (optimal) change process. In particular, Orlikowski (1996) distinguishes between technologies that are more rigid and fixed-function technologies that are more open-ended and customizable. Typically, changes for the latter group are less costly and are even encouraged – customization is required for effective use. Since it is hard to predict, up front, what adaptations are required to implement such a technology effectively, these technologies benefit more from emergent change (Orlikowski, 1996). With CM technologies, both types exist; many ultrasound and vibration monitoring systems, for example, have been well-developed by now and can be purchased off the shelf from different suppliers. Other CM technologies, such as statistical process control and data-driven models, have to be developed in situ. Thus, we recommend future research towards the introduction process of CM technologies to incorporate both rigid and customizable technologies.

Maintenance managers can derive three lessons from this study. First, if the integration of a CM technology is costly (in financial or human resources) and risky, it can be wise to perform small and targeted experiments to reduce the uncertainty of the CM technology’s potential performance. Ultimately, the CM technology’s potential performance determines whether or not CBM is desired. Second, when introducing CM technologies that depend upon learning-by-doing to increase their performance, start with creating the conditions in which learning can occur as soon as possible. Learning based on experience takes time. Involve the people who will (after technology integration) perform the measurements and analyses and make the maintenance decisions, and perform measurements and analyses whenever feedback can be obtained (e.g., from inspections during a maintenance stop, other CM analyses). Third, instead of relying on subjective assessments of the CM technology's performance, management can best objectively assess – calculate – from what level of performance (e.g., analysis accuracy) it is cost-efficient to use the CM technology for maintenance decision-making. By making the assessment objective, it is more likely the technology will not be used too early (resulting in unnecessary inspections and maintenance and reduced trust) and not too late (resulting in a longer payback period), increasing the value derived from the technology. If the CM technology can be used for multiple maintenance decisions, each decision might have its own level of risk and corresponding level of required performance.

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Chapter 3: Where the revolution gets stuck: Barriers to intra-firm diffusion of CM technologies

1. Introduction

It is proclaimed that we are witnessing the fourth industrial revolution (Schwab, 2017), in which a range of new digital technologies will dramatically increase the efficiency of many industries. However, casual observations suggest that the uptake of digital technologies in industry is far from universal. This is also true for Condition Monitoring (CM) technologies. Condition monitoring is the process of assessing an asset’s current and/or future condition (ISO 17337:12), which can be used for performing Condition-Based Maintenance (CBM; Jardine, Lin & Banjevic, 2006). An asset’s condition can be monitored with human senses, or with one (or multiple) CM technologies. Whereas the idea of CBM has been around since the late 1940s (Shin & Jun, 2015), recent technological developments have made real-time condition monitoring much more feasible and affordable, dramatically expanding the potential scope of CBM applications. Various studies have established that preventive maintenance based on CM can result in a substantial reduction of the downtime and total maintenance costs of a piece of equipment, compared to other maintenance strategies (Veldman, Wortmann & Klingenberg, 2011). Still, the actual use of CM technologies in industry remains limited (PwC & Mainnovation, 2018; Van de Kerkhof, Akkermans & Noorderhaven, 2016).

It seems the “digital revolution” gets stuck in a tortuous implementation process within companies. The extent of an innovation’s adoption, or its diffusion level, is defined as the number of members of a social system that have adopted the innovation (Rogers, 1995). However, initial adoption of an innovation by a firm often is just the beginning of another process: diffusion of the innovation within the organization. The overall level of diffusion of CM technologies thus is a function of the overall inter-firm diffusion level and each firm’s intra-firm diffusion level (Mansfield, 1963). Taking both inter-firm and intra-firm diffusion into consideration helps to understand why adoption of CM technologies may seem to go both fast and slow. When looking at inter-firm diffusion, many sources indicate that we are in the middle of a digital revolution, as digital technologies play a rapidly expanding role across many industry sectors (Wohlers & Caffrey, 2015). In Germany for example, over 40% of organizations in manufacturing and process industries have adopted digital manufacturing technologies (Jonker & Kooiman, 2015). However, at the same time we see that very few organizations are extensive users of digital manufacturing technologies (Jonker & Kooiman, 2015; McKinsey, 2015), even for digital manufacturing technologies that have already been in existence for several decades (Battisti, 2008). While the inter-firm diffusion level has steadily risen over the years for these technologies, the total level of diffusion is still low (Battisti, 2008; McKinsey, 2015).

This observation of fast inter-firm diffusion followed by slow intra-firm diffusion confronts us with a conundrum. Once a firm has decided to adopt a certain technology, why should it be slow in rolling it out to all potential applications? After all, firms are assumed to be efficient in internal knowledge dissemination, as they are “social communities that specialize in the creation and internal transfer of knowledge” (Kogut & Zander, 1993: 627). Yet for many innovations, firms face a long journey from their first adoption to complete internal diffusion (Battisti, 2008).

A large body of research has identified, both theoretically and empirically, the main drivers of innovation adoption by firms, as well as the mechanisms by which an innovation diffuses through a population of firms (for an overview, see Rogers, 1995). In contrast, only a handful of studies have focused on the intra-firm diffusion process (e.g., Shibeika & Harty, 2016; Fuentelsaz, Gómez & Palomas, 2016). The scholars that did, question whether the theoretical logic from diffusion theory can be directly applied to the intra-firm diffusion process. In-depth case studies of intra-firm diffusion have established that after the initial adoption of an innovation, subsequent adoption decisions are made by different actors in the firm (Fichman, 2000), with different adoption motivations and through different decision-making processes (Shibeika & Harty, 2016), and through different diffusion mechanisms (Fuentelsaz et al., 2016).

To date, models of intra-firm diffusion have particularly focused on technical and economic aspects of intra-firm diffusion (for an overview, see Battisti, 2008). While these categories of factors are important, we put forward that for understanding the process of intra-firm diffusion of an innovation the nature of firms as organizations exhibiting institutionalized behaviors needs to be taken into account. Practices in a firm do not only follow the logic of rationality, efficiency and effectiveness (do the practices contribute maximally to the realization of the goals of the firm?), but also the institutional logic predominating in the firm (does the new practice comply with internal regulations, is it accepted as being good and appropriate, and is it understood and socially accepted?). The institutional view emphasizes that behavior within firms is, at least to a certain extent, institutionalized, i.e., it is “more-or-less taken-for-granted repetitive social behavior that is underpinned by normative systems and cognitive understandings that give meaning to social exchange and thus enable self-reproducing social order" (Greenwood, Oliver, Sahlin & Suddaby, 2008: 4-5).

Intra-firm diffusion of a new practice from this perspective is a process that is likely to defy elements of the institutional logic reigning in a firm. The outcome of this process, i.e., the speed and extent of intra-firm diffusion, is more likely to be more successful if the practice is more attractive from a technical-economic point of view. But ultimately this remains uncertain as technical-economic expediency may conflict with institutional demands (Oliver, 1991). In this research, we explore the question: *how are CM technologies diffused within firms and how do technical-economic and institutional factors influence this process?* We perform a longitudinal multiple case study of the internal diffusion of twelve digital maintenance technologies by two asset owners in the process industry. The aim of this exercise is to elaborate on diffusion theory (Ketokivi & Choi, 2014) and to generate a middle-range theory of intra-firm diffusion (Craigheid, Ketchen Jr & Cheng, 2016). Additionally, we aim to derive insights that can aid firms in managing their uptake of CM technologies.

The remainder of this chapter is composed as follows. Below, we will first discuss diffusion theory and argue why processes of intra-firm diffusion do not follow the same logic, thus require a separate theory. Then we review the knowledge on intra-firm diffusion and bring in insights from the literature on institutionalized behaviors in organizations, and surmise how these can influence intra-firm diffusion processes. Subsequently we describe the empirical context of our study, and our methods of data collection and analysis. We then present our findings, after which we discuss how these lead us to a middle-range theory of intra-firm diffusion of new technologies. Conclusions follow.

2. Literature review

2.1 Diffusion theory

Diffusion is a process by which over time more members of a social system adopt an innovation. Understanding how such a process unfolds requires insight into the adoption decision of each potential adopter – what motivates this potential adopter – and insight into the diffusion mechanisms – how do the drivers of each potential adopter's motivation change over time (Compagni, Mele & Ravasi, 2015)? The standard diffusion process is shaped like an S-curve, with slow diffusion initially, speeding up over time via one or multiple diffusion mechanisms, and stabilizing towards the end, when almost all members have adopted the innovation (Rogers, 1995). This process is presented in Figure 3.1.

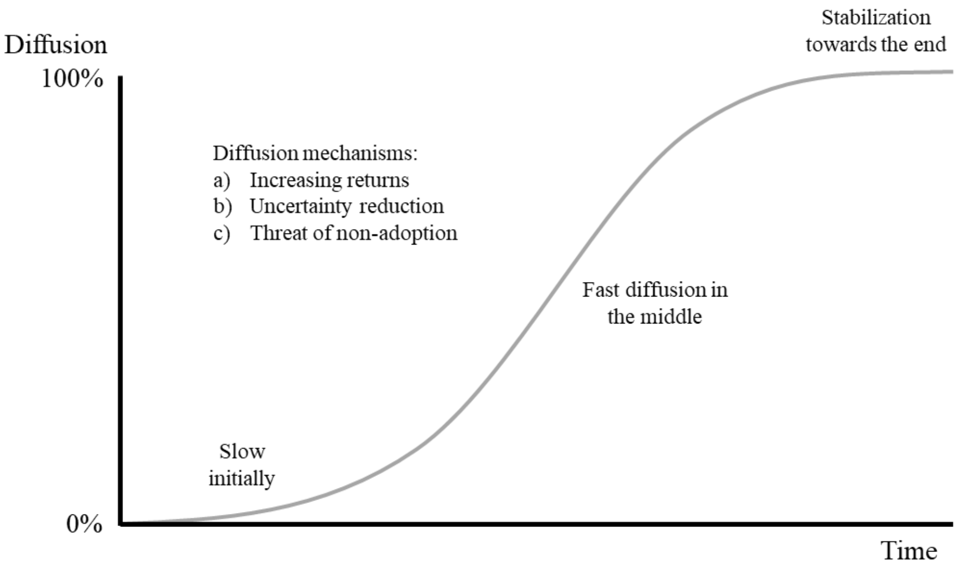

Figure 3.1: Standard image of diffusion (S-curve) (Rogers, 1995)

Diffusion theory has established the perceived attributes of innovations as the main determinant of an individual decision maker's adoption decision (Rogers, 1995). Three attributes of innovations have been found to have a strong effect on adoption (Tornatzky & Klein, 1982): (1) relative advantage, the degree to which an innovation is perceived being better than the idea it supersedes, (2) compatibility, the degree to which an innovation is perceived to be consistent with the existing values, past experiences and needs of potential adopters, and (3) complexity, the degree to which an innovation is perceived as relatively difficult to understand and use (negative effect). Based on these findings, diffusion studies typically assume that potential adopters will adopt an innovation the moment the perceived gains of adoption exceed the adopter's adoption threshold (Abrahamson & Rosenkopf, 1997). Since the perceived compatibility and complexity of the innovation differ per individual and per firm (as well as characteristics like risk averseness, desired return on investments, etc.), potential adopters have varying predispositions towards adopting the innovation, reflected in different adoption threshold levels.

Diffusion theory has also established multiple core mechanisms that can induce potential adopters to embrace an innovation, either by increasing the expected gain of adoption or by lowering the adopters' adoption threshold (Rogers, 1995). The primary mechanisms are increasing returns, uncertainty reduction, and threats of non-adoption. These mechanisms have in common that the expected gain of adoption increases over time, such that it surpasses the adoption threshold levels of additional potential adopters each time period.

The *increasing returns* mechanism suggests that as the number of adopters increases, so does the profitability of adoption (Abrahamsom & Rosenkopf, 1997). The most common example here is network externalities, in which the usefulness of an innovation increases as more people have adopted the innovation, such as a communication standard (Farell & Saloner, 1985). In the case of complex technologies, returns of adoption increase with the number of adopters when further improvements are made to the technology itself (Rosenberg, 1972), the technology is produced at a lower price (e.g., economies of scale, Rosenberg, 1972), technical know-how is developed (Attewell, 1992), complementary technologies are invented (Rosenberg, 1972) and the supporting infrastructure to employ the technology is constructed (Fichman, 2000).

However, for many innovations potential adopters cannot assess the innovation’s value directly. They might have to depend upon various sources of information, for instance from their suppliers (Van den Oever & Martin, 2016) or proximate adopters, for estimates of the value of the innovation, *reducing the uncertainty* of the return of adoption (Abrahamson & Rosenkopf, 1997). In fact, many diffusion studies assume that those who have adopted share, willingly or unwillingly, information with potential adopters, as well as information about their experiences with and the actual value of the innovation (Greve, 2011). This information flows for example through interpersonal networks, conference presentations and media articles (Compagni et al., 2015).

Other theories of diffusion focus not on the gains of adoption, but on the *threats of non-adoption*. These theories describe increasing competitive- or institutional pressures on potential adopters, progressively strengthening their incentives to adopt the innovation (Abrahamson & Rosenkopf, 1997). When competitors innovate and thereby acquire greater operational capabilities, offer a better service or reduce their costs, potential adopters experience growing competitive pressure to adopt as well, risking a loss of market share and profitability (Fuentelsaz et al., 2016). Similarly, when an innovation is widely diffused and has become taken for granted by constituents, stakeholders and other influential organisations, institutional pressures provide a strong incentive to adopt as well (Fuentelsaz et al., 2016).

2.2 Intra-firm diffusion

Intra-firm diffusion is the process by which over time more members *within the firm* adopt an innovation, and thereby drives the extensiveness with which an innovation is adopted by the firm (Mansfield, 1963). Intra-firm diffusion takes place between the firm's first adoption of an innovation and the moment the innovation is 'fully deployed' (Fuentelsaz, Gómez & Palomas, 2016). The process of intra-firm diffusion is especially relevant for large firms (Stoneman, 1981) and technologies with a large number of potential applications within the firm (Fuentelsaz et al., 2016), such as CM technologies.

If an innovation turns out to be valuable, one would expect a rapid process of intra-firm diffusion. Information is shared more easily and freely within organizations than between competitors (Kogut & Zander, 1993), profit-maximizing firms are incentivized to derive maximum value from investments (sooner, rather than later), adoption decision-making can be centralized (Shibeika & Harty, 2016), and firms can build proficiency with the innovation itself, becoming less dependent upon market-side factors (Attewell, 1992). However, empirical studies have observed that, for a wide array of technologies, few firms reach the state of full deployment (100% diffusion), and that, for most of these technologies, the rate of intra-firm diffusion is low (Battisti, 2008). This has been observed for multiple manufacturing technologies (Battisti, 2008; Cool, Dierickx & Szulanski, 1997), such as microprocessors, computerized machines and flexible production systems, but also for technologies such as diesel locomotives (Mansfield, 1963), optical scanners (Levin, Levin & Meisel, 1992), automated teller machines (Fuentelsaz, Gómez & polo, 2003) and building information modelling (Shibeika & Harty, 2016).

Intra-firm diffusion shares common features with diffusion between individuals and diffusion between firms (Mansfield, 1963), but has several distinguishing characteristics as well. The main difference is that intra-firm diffusion decisions typically are not independent of one another, as influential actors (e.g., managers) may influence – or even take – multiple adoption decisions (simultaneously) (Shibeika & Harty, 2016; Garud, Tuertscher & Van de Ven, 2013). Also, the resources required for adoption are typically not independent; often firms have dedicated innovation budgets, from which multiple adoptions are funded (Mansfield, 1963). Hence, the nature of the adoption decision is different, as well as the process of decision-making (Shibeika & Harty, 2016). Moreover, several scholars have identified that the main mechanisms of diffusion theory work differently for intra-firm diffusion (Fuentelsaz et al., 2016). For example, while firms initially have to rely on sources of information from proximate adopters for estimating the value of an innovation, in the post-adoption intra-firm diffusion process the firm has the opportunity to learn about the value of the technology through its continued use (Attewell, 1992). As a result, external sources of information become less relevant; subsequent adoption decisions can be made on the basis of experience and performance feedback (Simon & Lieberman, 2010). Therefore, we argue that intra-firm diffusion calls for a separate process theory.

So, what do we know already about the motivation for intra-firm adoption decisions? Models of intra-firm diffusion have focussed primarily on technical-economic factors and have established the costs of adoption, as well as the relative productivity of the new with respect to the old technology, as the main predictors of adoption (Battisti, 2008). Moreover, these models indicate that firm characteristics, such as size, liquidity, old technology, use of complementary technologies, and R&D, are important. A large survey on innovation has identified that economic considerations, such as the cost of innovation, the availability of finance and the cost of finance, are important innovation-inhibiting factors, in addition to the impact of external regulation and a lack of qualified personnel (Stockdale, 2002). Recent empirical studies have added competitive pressures (Fuentelsaz et al., 2016), innovation champions (Shibeika & Harty, 2016), and organizational structure (Shibeika & Harty, 2016).

To date, most of the studies on intra-firm diffusion have thus focused on the innovation's relative advantage, adopting a technical-economic perspective. Yet, the perceived compatibility – the degree to which an innovation is perceived to be consistent with the potential adopters' existing values, past experiences and needs – has received limited attention. In the inter-firm diffusion literature, institutions at the level of the society or organizational field have been shown to have a strong effect on the rate of diffusion (Lynn, Reddy & Aram, 1996). Adopting a new practice is not only subjected to rational deliberations of a technical-economic nature, but also to a logic of appropriateness: "what does a person such as I, or an organization such as this, do in a situation such as this?" (Sahlin & Wedlin, 2008). A recent stream of institutional theory has demonstrated that institutions also materialize at the organizational level, in the form of institutional logic (Scott, 2008). Within firms, many practices are institutionalized over time, becoming constellations of meaningful activities and acquiring a rule-like status (Thornton, Ocasio & Lounsbury, 2012; Simard & Rice, 2007). If a technology's compatibility with the dominant institutional logic is low, adoption is unlikely (Simard & Rice, 2007). On the other hand, if a technology's compatibility is high – or becomes high, as continued use of the technology results drives *institutionalization of the technology* –, institutions can be a strong driver of adoption (Thornton et al., 2012). In section 2.3, we further explore the concept and elements of institutional logic.

First, what is known about the main mechanisms of intra-firm diffusion? Models of intra-firm diffusion have incorporated three endogenous mechanisms – increasing returns, increasing resources, and reduced adoption costs – in addition to several external effects, such as supply side changes to the technology (Mansfield, 1963), market effects (Battisti, 2008), and competitive pressures (Fuentelsaz et al., 2016). *Increasing returns* can be realized from identifying additional ways of generating profit with the technology (Mansfield, 1963), reducing operational costs of the technology via economies of scale (Rosenberg, 1972), and improving the technology's performance by developing the skills of the people who work with the technology (Attewell, 1992). All models of intra-firm diffusion restrict the number of adoptions per time period, due to the limited availability of resources. Mansfield (1963) however assumes that if the uncertainty of the return on adoption is decreased, firms are willing to invest more, effectively *increasing the resources* available. Yet, even if the resources per time period are stable, the rate of intra-firm diffusion can increase if the *costs of adoption decrease*, for example because the supporting infrastructure is in place already (Fichman, 2000) or because personnel has received training already (Attewell, 1992).

2.3 Institutional logic

Thornton et al. (2012) define an institutional logic as the socially constructed, historical patterns of cultural symbols and material practices, including assumptions, values and beliefs, by which individuals and organizations provide meaning to their daily activity, organize time and space, and reproduce their lives and experiences. While actors may reproduce behaviours consistent with existing institutional logics, they also have the capacity to innovate and thus transform institutional logics (Thornton et al., 2012). Following Scott (2008), we distinguish between three types of institutions: regulatory, normative and cognitive institutions.

Regulatory institutions are the "rules of the game" that are sanctioned by powerful actors (Scott, 2008). These may be external (e.g., regulators, courts of justice) or internal to the firm (e.g., rules set by higher management). Both types of regulative institutions can be important, external rules because they may impede the use of a new technology, at least in certain implementations, and internal rules because they may be predicated on the use of older, accepted technologies and need to be changed for the innovation to be further diffused. But regulative institutions can also promote innovation, for example by demanding performance levels that cannot be attained by existing practices (Blind, 2012).

Normative institutions refer to values and norms. Values are “conceptions of the preferred or the desirable”, and norms “specify how things should be done” (Scott, 2008: 54-55). Normative institutions lack the more formal sanctions linked to transgression of regulative institutions, but that does not mean they cannot influence diffusion decisions. Specifically, normative institutions may be linked to commonly held ideas of how a certain practice should be performed (Thornton et al., 2012), and this may either impede or promote diffusion of a new technology.

Cognitive institutions (also called “cultural-cognitive institutions”, Scott, 2008: 56), finally, are the “shared conceptions that constitute the nature of social reality and the frames through which meaning is made” (Scott, 2008: 57). This is about what is taken-for-granted, within the firm and/or its environment, and any innovation will have to surmount the obstacle of being different from often subconscious expectations. However, at higher levels of diffusion the effect may become opposite, if new practices are adopted because of their growing taken-for-grantedness (Aguilera & Cuervo-Cazurra, 2004).

It should be noted that institutions – in particular normative and cultural-cognitive institutions – are closely related to organizational routines. Routines are habitual or mechanical performances of an established procedure and have become a central concept of organizational theory (Argote & Greve, 2007). Routines are viewed as knowledge repositories (storing the results of organizational learning) and as a stabilizing factor in firm behaviours, allowing firms to maintain high levels of performance (Argote & Miron-Spekter, 2011). Some scholars even perceive routines as one of the outcomes of the process of institutionalization (Crossan, Lane & White, 1999). Similar to institutions, path dependence of routines can lead to difficulties in adapting to invasions by new routine sets, required by the adoption of new technologies (Argote & Greve, 2007). In this study however, we adopted the institutional logic perspective, because former diffusion theory studies have shown that institutions in general, and regulative institutions in particular, can have strong effects on diffusion rates (Kennedy & Fiss, 2009). The institutional logic perspective therefore provides a broader angle to investigate the process of intra-firm diffusion.

Although institutions have the tendency to be reproduced over time, they are not static. In particular, two behaviours of institutions are especially relevant for understanding intra-firm diffusion processes: institutions can grow (or decline) in strength over time – the process of *institutionalization* – and can spread to other entities – the *diffusion of institutions* (Thornton et al., 2012). According to Scott (2008), institutionalization occurs via three mechanisms, which might interact and reinforce each other: increasing returns (further developments in the same direction are rewarded, while the costs of switching to an alternative increase over time), increasing commitments (to norms, values, structures, procedures, etc.), and increasing objectification (into documents, tools, best practices, routines, etc.). Institutions can also diffuse across time and space through coercive mechanisms (mainly for regulative institutions, enforced by higher powers), normative mechanisms (mainly for normative institutions, spread through network ties and commitments), and mimetic mechanisms (mainly for cultural cognitive institutions, copied from actors who are regarded as similar).

In summary, processes of intra-firm diffusion do not follow the exact same logic as diffusion processes between firms and individuals, mainly due to differences in the nature of the adoption decision and the diffusion mechanisms present. For many firms however, the amount of value that will be derived from adopting a new technology is mainly dependent upon the speed and extensiveness of adoption. Hence, understanding how intra-firm diffusion processes unfold, and what managers can do to influence them, is important. The first studies of intra-firm diffusion have identified that adoption decisions within the firm are influenced by considerations of technical feasibility and economic desirability (Battisti, 2008). Drawing from the institutional logic perspective, we add another consideration: the extent to which adoption of the innovation is seen by organization members to be a legitimate and appropriate thing to do (Greenwood et al., 2008). Both technical-economic factors and institutions can be subject to exogenous as well as endogenous forces of change, and these will influence the unfolding diffusion process. Important endogenous mechanisms that stimulate intra-firm diffusion are increasing returns, increasing resources, reducing adoption costs, and institutionalization of the technology. Yet, in order to develop a middle-range theory of intra-firm diffusion, more detailed insight is needed into the motivation of potential adopters, the mechanisms that drive diffusion, and how they change and interact over time.

3. Methods

3.1 Empirical context

Condition Monitoring (CM) technologies are technologies used to monitor the condition of an equipment (Moubray, 1997), primarily in order to execute the maintenance of equipment preventively (Jardine, Lin & Banjevic, 2006). For a long time, most inspections have been performed with human senses (sight, sound, touch and smell), but the downside of relying on human senses is that they are relatively imprecise, subjective and can only detect larger defects (i.e., at a late stage of degradation; Moubray, 1997). Therefore, a wide range of digital CM technologies have been developed over the years, such as vibration monitoring, ultrasound, electromagnetic and thermographic technologies (Davies, 2012). In addition, recently several digital CM technologies have been established that rely mainly on data from other sources (e.g., process data, product data) and use data-processing techniques (e.g., statistics, machine learning) to draw inferences about the equipment's condition (Bousdekis, Magoutas, Apostolou & Mentzas, 2015). The output of all digital CM technologies is (processed) data, which in turn can be used for detection of faults, diagnoses of the equipment's current state or prognoses about its future state (Davies, 2012). Hence, the CM technologies are part of a (partially automated) service, usually consisting of data acquisition, data processing, diagnosis, prognosis, recommendations and maintenance decision steps (Bousdekis et al., 2015; Jardine et al., 2006).

We conducted our empirical study at two asset owners in the process industry: a refinery (Oilco) and a steel manufacturer (Steelco). The process industry is typically characterized by large and multinational asset owners, a broad, diverse and stable asset base and high financial and safety risks connected with breakdown (Veldman, Klingenberg & Wortmann, 2011). This also applies to both case companies, whose basic features are described in Table 1.1.

The usage of digital CM technologies at large asset owners in the process industry provides an ideal context to study intra-firm diffusion processes for multiple reasons. First, asset owners are expected to pursue intra-firm diffusion, as they have large and diverse asset bases that offer numerous potential applications for most CM technologies (Davies, 2012), as the total gains are dependent upon the number of applications and as the gains in operational uptime and safety generally outweigh the implementation costs per application (Moubray, 1997; Grubic, 2014). Second, from a methodological perspective, the context allows for observation of the full population of adopters and the full diffusion process within an asset owner (Fuentelsaz et al., 2016). In addition, since asset owners are employing a variety of digital CM technologies with differing maturities (Veldman et al., 2011), multiple diffusion paths and phases can be observed simultaneously within the same organizational context, enabling a comparative study. Third, from a theoretical perspective, CM technologies are 'complex technologies' (Attewell, 1992) with uncertain and ambiguous gains (Moubray, 1997) that entail both a product and process innovation (Garud, Tuertscher & Van de Ven, 2013; Aboelmaged, 2015), thus allow for the observation and integration of findings from multiple streams of diffusion research.

3.2 Data collection

The main purpose of this research is theory generation (Ketokivi & Choi, 2014). To this end, we conduct a longitudinal multiple case study, incorporating multiple digital CM technologies and asset owners.

Understanding diffusion, a context-specific and time-sensitive phenomenon, requires longitudinal observations (Shibeika & Harty, 2016). Longitudinal case research allows for observing sequential relationships of events (Voss, Tsikriktsis & Frohlich, 2002), linking content, context and processes over time (Pettigrew, 1990) and observing variations in the (impact of) factors. In addition, multiple-case studies offer the researcher a deeper understanding of processes, causality and dynamics than do single-case studies (Eisenhardt, 1989). Moreover, multiple-case studies enhance the external validity of findings, reduce researcher bias and support the development of more robust theory (Eisenhardt & Graebner, 2007; Barratt, Choi & Li, 2011). Therefore, this combination of in-depth longitudinal studies and comparison between cases facilitates theory elaboration (Eisenhardt & Graebner, 2007; Yin, 2013) and generation of middle-range theories (Craighead et al., 2016).

The study incorporates 12 cases of digital CM technology diffusion processes, evenly distributed over 2 asset owners. We conducted our empirical study between 2014 and 2017, collecting between 2 and 26 years of data per case (1992-2017). The research proceeded through 3 stages: (1) mapping and selecting the CM technologies, (2) mapping the diffusion paths, and (3) exploring the intra-firm diffusion mechanisms.

In the first stage, the cases were selected following a purposive sampling strategy (Miles, Huberman & Saldaña, 2014). At both asset owners, the research team mapped – together with local CM specialists – all CM technologies that were currently being applied. During these meetings, the CM specialists were asked to evaluate several properties of each CM technology, such as the year of first adoption, the current performance, the current diffusion level and the current diffusion rate. This inquiry resulted in a total of 77 unique CM technologies (49 at Oilco, 64 at Steelco). Based on this overview a subset of 12 unique digital CM technologies were selected together with the managers involved. The cases were selected primarily upon their current diffusion level (maximizing the variation in diffusion) and the initial technical-economic and institutional conditions (including a combination of cases with initial T-E drive and I drive (quadrant I), T-E drive and I resistance (quadrant II), T-E resistance and I resistance (quadrant III), and T-E resistance and I drive (quadrant IV)). Additionally, the cases were selected as such that the sample would include different dates of first adoption and that the sample as a whole would be representative for the array of digital CM technologies that are employed by Oilco and Steelco. The main features of the cases are presented in Table 3.1 and Table 3.3.

Table 3.1: Sample characteristics

				Initial conditions		
Case	**Organization**	**Technology**	**Population**	**T-E**	**I**	**Quadrant**
A	Oilco	instrumentation monitor	instruments	resistance	resistance	III
B	Oilco	portable thermography	electrical equipment	drive	drive	I
C	Oilco	on-line ultrasound monitor	piping	drive	drive	I
D	Oilco	portable vibration monitor	rotating equipment	drive	resistance	II
E	Oilco	catalyst model	hydrofiners	drive	drive	I
F	Oilco	quality control system	emission monitors	resistance	drive	IV
G	Steelco	roller model	rollers	drive	resistance	II
H	Steelco	statistical process control	instrumented equipment	drive	resistance	II
I	Steelco	alarm monitor	entire units	resistance	resistance	III
J	Steelco	on-line vibration monitor	slowly rotating equipment	resistance	drive	IV
K	Steelco	on-line vibration monitor	fast rotating equipment	drive	drive	I
L	Steelco	portable ultrasound monitor	blast stoves	resistance	drive	IV

In the second stage, the diffusion path was identified in focussed group meetings with CM specialists and other relevant informants, such as maintenance engineers, integrity officers and project managers (1-4 people per meeting). Central in these meetings were the questions: (a) for what number of equipment can the CM technology be applied at this site (population size), (b) in what year, where and by whom has the CM technology first been applied, and (c) for each consecutive year, for what number of equipment was the CM technology applied (absolute intra-firm diffusion level)? In most instances, archival data were available to verify the population size and absolute intra-firm diffusion level for one or multiple years, minimizing the retrospective bias (Langley, 1999). When these data were unavailable, the group made a collective estimation, with discussion continuing until consensus was reached.

In the third stage, interviews were the main source of data. All interviews lasted between thirty minutes and one and a half hour and have been transcribed and validated afterwards by the interviewees for completeness and correctness. Table 3.2 provides an overview of the interviews and group sessions per case.

Table 3.2: Interviews

		Interviews/group sessions[a]			
Case	**Interviewees**	**Stage 1**	**Stage 2**	**Stage 3**	**Total**
A	5	1	1	5	7
B	4	2	2	2	6
C	3	2	1	9	12
D	8	2	1	11	14
E	7	1	1	14	16
F	3	2	1	6	9
G	3	1	1	6	8
H	4	1	1	7	9
I	3	1	1	5	7
J	4	1	1	10	12
K	4	2	1	9	12
L	7	2	1	11	14
Total	55	18	13	95	126

[a] Stage 1: mapping the CM technologies
Stage 2: mapping the diffusion paths
Stage 3: exploring the intra-firm diffusion mechanisms

We supplemented the interviews with field observations and field notes. The field notes were validated afterwards with the people involved, similar to the interview transcriptions. Additionally, secondary data was used to verify the interview statements and research notes, using internal documentation (e.g., meeting notes, e-mails, internal guidelines, project documentation, condition monitoring reports, industry standards) and internal databases (e.g., project data, maintenance data, financial data) when available.

3.3 Data analysis

Analysis of the data took place in three steps. In the first step, the diffusion levels were visualized in absolute and relative numbers to get an understanding of the diffusion trajectories and diffusion speed. We categorized the diffusion speed of each technology as slow, medium or fast, based on the year of first application and the current relative diffusion level (i.e., average relative diffusion per year). Technologies with an average diffusion rate over 10% were characterized as ‘fast’; they require less than 10 years to complete diffusion. Technologies with an average diffusion rate between 1% and 10% were characterized as ‘medium’ (between 10-100 years to complete diffusion) and technologies with an average diffusion rate lower than 1% were characterized as slow (more than 100 years to complete diffusion). Technologies that are (almost completely) abandoned are characterized as 'abandoned'.

In the second step, we wrote a 'storyline', a synopsis, for every case, aiming to understand the diffusion path in each case. What enabled diffusion? Why didn't diffusion go faster? This within-case analysis helped us to identify the driving forces in each case, how and why mechanisms changed over time and how mechanisms interacted with each other. Due to space limitations, we present four of these storylines in the Findings section, one from each quadrant.

In the third step, we coded the interviews, field notes and internal documentation for a cross-case analysis. In order to identify all diffusion mechanisms present in the cases, we used open codes, staying close to the content of the quotes. When the diffusion mechanisms were identified, we assessed whether or not each mechanisms was present in a case or not and whether or not the mechanism had a large impact on diffusion in that case. This was done on the basis of the quotes. If the mechanism was actually referred to in one or multiple quotes, it was expected to be present. Only if it was explicitly mentioned that in some moment(s) in time this mechanism was important for diffusion, the mechanism was marked as having a large impact.

Finally, we displayed the cases per quadrant and per diffusion speed category to recognize patterns that give insight in whether a technology's starting conditions affect what diffusion mechanisms are present and what (combination of) diffusion mechanisms result in high diffusion speeds.

4. Findings

4.1 Intra-firm diffusion levels

The absolute and relative intra-firm diffusion levels of all cases are presented in Figure 3.2 and Figure 3.3 respectively. The cases from Oilco are shown with solid lines, the cases from Steelco with dotted lines.

In Figures 3.2 and 3.3 we observe quite some differences in extensiveness of first adoption. This is mainly explained by the extent to which the implementation and application of technologies can be clustered. A portable inspection instrument for example can be applied to a variety of equipment, while an on-line monitoring system is typically installed at one equipment at a time.

It should be noted that many diffusion paths are characterised by alternating periods of stability and diffusion. For most of the cases and for the majority of observed time, the diffusion rate is zero (63 instances) or positive (56 instances). Only in 4 instances

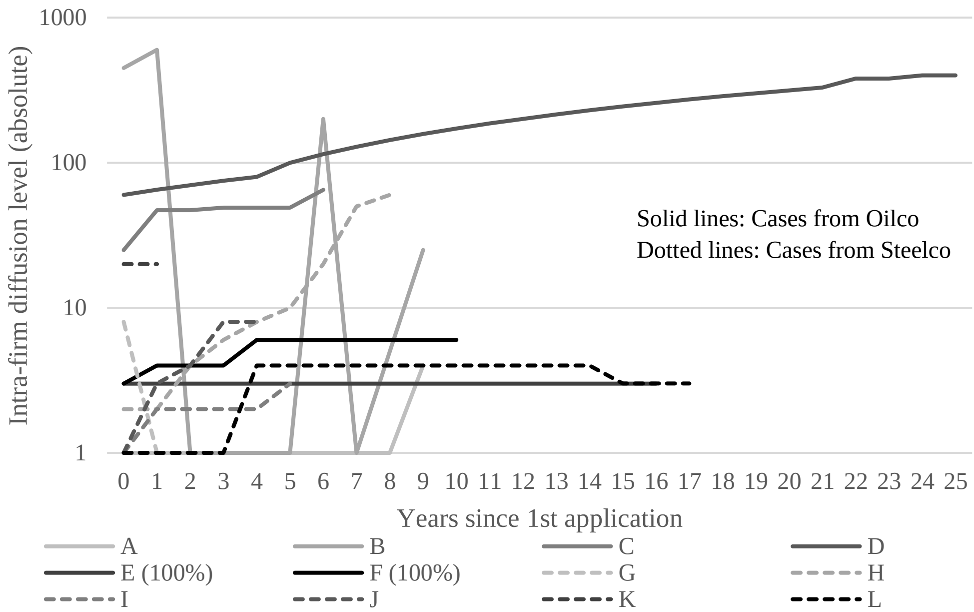

Figure 3.2: Diffusion Processes of 12 Technologies (absolute # of applications)

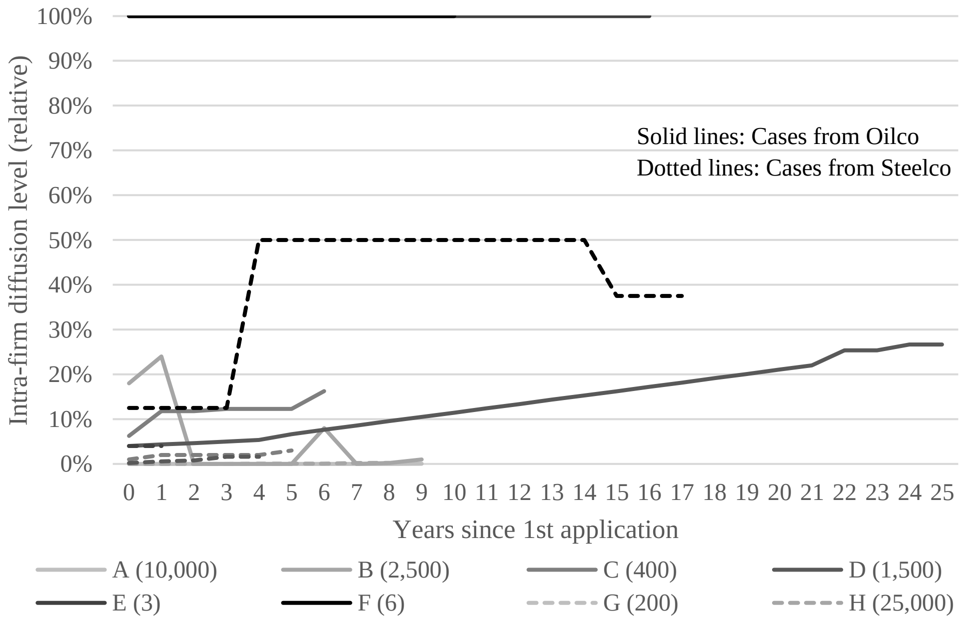

Figure 3.3: Diffusion Processes of 12 Technologies (relative % of the population)

the net diffusion rate was negative, in cases B, G and L. In fact, the technologies in cases B and G have been (almost completely) abandoned at the end of the observation period.

The current diffusion levels, both in absolute and relative terms, and the derived speed of diffusion have been summarized in Table 3.3 for each technology.

Table 3.3: Presentation of cases

Quadrant	Case	Year of 1st application	Year of complete diffusion	Population size	Current diffusion level: Absolute	Current diffusion level: Relative	Average diffusion speed[a]
I	B	2008	n.a.	2,500	25	1%	Abandoned (Fast initially)
	C	2011	n.a.	400	65	16%	Medium
	E	2001	2001	3	3	100%	Fast
	K	2016	n.a.	500	20	4%	Medium
II	D	1992	n.a.	1,500	400	27%	Medium
	G	2016	n.a.	200	0	0%	Abandoned (Medium initially)
	H	2009	n.a.	25,000	60	0%	Slow
III	A	2008	n.a.	3,800	4	0%	Slow
	I	2012	n.a.	100	3	3%	Slow
IV	F	2006	2006	6	6	100%	Fast
	J	2013	n.a.	500	8	2%	Slow
	L	2000	n.a.	8	3	38%	Medium

[a] Abandoned: majority of applications have been abandoned (98% in case B, 100% in case G);
Slow: on average between 0-1% (relative) new applications per year (>100 years to complete diffusion);
Medium: on average between 1-10% (relative) new applications per year (>10 years to complete diffusion);
Fast: on average more than 10% (relative) new applications per year (<10 years to complete diffusion).

Table 3.3 shows that, on average, the technologies starting off in quadrant I (T-E drive and I drive) have the highest diffusion speed, yet starting in quadrant I does not guarantee a fast and complete diffusion. In contrast, the technologies starting off in quadrant III (T-E resistance and I resistance) have the lowest diffusion speed on average. Quadrant II (T-E drive and I resistance) contains a mixture of medium and slow diffusions and quadrant IV (T-E resistance and I drive) contains fast, medium and slow diffusions.

4.2 Case storylines

Here we present the storylines of 4 out of 12 cases, one from each quadrant, to understand what drove and impeded diffusion in each case. These storylines give an image of how and why diffusion mechanisms change over time and how mechanisms interact with each other.

Quadrant I: Case E – catalyst model, Oilco. In 2001, Oilco adopted a physics-based model that predicts the remaining lifetime of the catalyst in gas oil hydrotreaters. This model had been developed by Oilco's centralized technology center for all refineries to optimize production planning and the exchange timing of the catalyst. During the implementation project at Oilco, the model was directly applied to (all) 3 gas oil hydrotreaters, reaching complete diffusion directly upon technology introduction.

Although the technology was expected to greatly improve production and maintenance processes (based on prior experiences from other refineries), the main driver for adoption was a change in regulation. From 2000 onwards, European regulation demanded stricter product specifications (less sulphur allowed), requiring better functioning of the catalyst. Almost directly afterwards, the implementation project was initiated by Oilco's management and the centralized technology centre. It was evident to the people involved that the catalyst functioning had to be monitored thereafter.

Quadrant II: Case H – statistical process control, Steelco. In 2007, one of Steelco's hot rolling mill process engineers investigated and started mastering Statistical Process Control (SPC), which can be applied to a wide variety of processes and equipment. In most cases, the data processing procedures and alarm thresholds have to be determined and managed by local process and maintenance engineer(s), after which local operators and maintenance technicians are trained in acting on the alarms. Since the first real application of SPC in 2008, SPC has slowly been applied to a number of equipment within the hot rolling mill, but not yet to equipment in one of the other 9 plants.

In 2016, 8 years after the first application, the hot rolling mill's management incorporated SPC into their strategic plans and made additional resources available: two extra people were assigned part-time to implement the technology (up until this point the process engineer was the only person developing, operating and managing all applications). Since then, the three of them have developed a standard implementation procedure, decided upon the required interface, and trained operators and maintenance teams to start using the applications. When the interface is implemented, the number of applications is expected to increase quickly to around 1,000 in a couple of years – all within the hot rolling mill.

However, to reach high(er) levels of diffusion, the technology has to be adopted within the other plants as well. For this, an implementation structure is needed in which (many) teams of local process and maintenance engineers develop and implement specific applications. At the beginning of 2017, around 30-40% of these engineers were aware of the technology. This number is expected to increase in the near future, as well as the number of SPC applications in other plants, as several customers of Steelco (from the automotive industry) recently imposed a quality management system certification (TS 19649). Therefore, a centralized program to implement the quality management system across plants has been initiated. SPC is part of this quality management system.

Quadrant III: Case A – instrumentation monitor, Oilco. In 2008 the first new asset management system was installed at one of Oilco’s units, making it possible to remotely configure and generate status information of the 763 instruments and analysers that were connected to the system from a central computer. If configured completely (including data filters and alarm thresholds), each instrument is monitored automatically and – when an alarm arises – can be diagnosed remotely. Over the years, during large maintenance stops of the units, the old asset management systems of that unit were replaced with new asset management systems, increasing the number of instruments and analysers that are configured in the asset management systems to 3,800 in 2017. Out of these 3,800, only 4 are monitored remotely via this software.

The main challenges in this case are organizational: full diffusion of the technology requires a new way of working, new responsibilities and new skills for a large group of people within the site, but neither the implementation nor the operational process have been institutionalized yet. Since developing an application requires domain knowledge about the instrument/analyser and the conditions of the process in which it is functioning, each application has to be developed by a team of local process and maintenance engineers. Until 2016 however, Oilco’s IT specialist, the person who implemented the asset management systems and configured the instruments, was the only person who attempted to develop new applications, when he had some spare time.

In 2016, the first maintenance engineers got involved. They were involved with the configuration of the instruments and analysers at the newest plant, after which they became interested in the possibilities of remote monitoring and diagnoses with the asset management system. Two years later, they started experimenting with different data filters and alarm thresholds.

Quadrant IV: Case J – on-line vibration monitor, Steelco. In the last month of 2012, an unexpected breakdown of one of Steelco's converters resulted in major production loss. Afterwards, the plant's management assembled a team of vibration monitoring specialists to select and implement a vibration monitoring technology that was capable of monitoring this type of equipment, slowly rotating equipment. Costs of the system were irrelevant at that time, according to management, as they were outweighed by the costs of production losses.

At the time of first adoption, the technology had not been applied before (anywhere) on this type of equipment (it was new to the supplier as well). Therefore, some changes had to be made to the technology after adoption and the people involved needed to learn how to work with the technology. These performance increments were not merely relevant for the current applications, but also increased the expected performance of new applications. Right now, the technology is expected to be optimal and cost-effective for around 100 of the 500 important rotating equipment at Steelco.

In 2014, after positive experiences with the converters, a centralized program was initiated to test the potential of the technology in a so-called 'proof of concept'. A dedicated project manager was assigned, who obtained a central innovation budget from which part of the adoption costs could be paid (around 30%). During the program, the project manager deliberately applied the technology to different equipment and at multiple plants. As a result, diffusion required convincing different maintenance managers, acquiring financial resources from different budgets (owned by each maintenance manager) and establishing collaborations with different people (per application), making the diffusion quite slow (at least initially). The procedures and specifications of the roles that have been developed during the program however can be applied to most, if not all, plants, making future implementations less complex.

Interviewees indicate that in the upcoming years the diffusion speed is expected to increase vastly. The performance with the technology has increased for multiple types of equipment, the innovation program has expanded and has been incorporated into the site's strategy, and more maintenance managers have become enthusiastic about the technology's capabilities. Consequently, vibration monitoring has been incorporated in multiple plants' strategy as well, making sufficient resources available locally for new adoptions. Whether or not the diffusion will really take off now is mainly dependent upon the increase in capacity of the vibration monitoring group, according to the program manager. They are hiring new vibration specialists at the moment, but it is not certain whether this increase in capacity can keep up with the demand.

4.3 Intra-firm diffusion mechanisms

In the cases multiple technical, economic and institutional mechanisms have been observed that drove intra-firm diffusion. These mechanisms are presented in Table 3.4, including illustrative quotes.

In many of the cases we noted that most of the mechanisms do not work in isolation; rather, many interactions exist between the mechanisms. In the technical-economic domain for example, increments in technical performance of the technology leads to an increased cost-effectiveness. Increments in technical fit result in reduced adoption costs, which further increases the cost-effectiveness.

In the institutional domain, institutionalization of usage – specifying roles and responsibilities, training users, developing procedures, etc. – tends to increase the legitimacy of the technology (if the technology’s performance is satisfactory), as the people involved gain experience with the technology, the performance of the technology becomes apparent and the technology becomes ‘proven’ over time. Institutionalization of usage also provides the basis for technology champion(s) to become trusted, increasing their influence on adoption decision makers and management over time.

Institutionalization of adoption – incorporating diffusion of the technology in the plant’s strategy, setting ramp-up targets, initiating a diffusion program, making it common practice to adopt the technology, etc. – has been triggered by different events, such as (changes in) regulation, perceived successes with the technology and requests from technology champion(s). Yet, in almost all cases in which adoption of the technology became institutionalized, the technology was perceived as legitimate and the technology champion(s) had become trusted partners (with the exception of case E, here institutionalization of adoption was dictated by higher management).

However, there are also multiple interactions between the technical-economic and institutional domains. For example, the performance of the technologies did not improve before usage of that technology became institutionalized: only when people are structurally using the technology, do they get more proficient with the technology and start making improvements to the technology. The performance of the technology in turn affected the technology’s legitimacy and the reputation of the

Table 3.4: Intra-firm diffusion mechanisms: Selected quotes

Category	2nd order codes	Selected quotes on 1st order codes
Technical mechanisms	Increase in technology's performance	*Improvements to the technology* "I've been working for some time to improve the model together with the developers from Oilco's central technology department. [...] We've done several exercises to test different feed properties, to see what is best for the model." (Case E, Optimization engineer) "We have now developed the dashboard. [...] With this dashboard, the operators and process engineers can perform many more analyses on the data by themselves." (Case H, Project manager) *Learning curve of technology users* "I've been trained for example, together with a former colleague. Together we've given instructions to specific people from Maintenance. [...] The analysis works the same for most equipment, although you have to adjust the settings for most locations. We've learned how to do this during the training." (Case B, Teamlead electrical events) "We've built experience in the past, that's very useful now. Some areas of the blast stoves become warmer than others. In the past we've learned these are the places the stress corrosion cracking starts. [...] For the new blast stove these are the places we start monitoring." (Case L, Inspector) *Institutionalization of technology usage* "Every month, when I analyse (the equipment), I make a sheet with multiple easy-to-interpret graphs. I send this to the people involved with the equipment. [...] I think communication is the most important link between all parties. As far as I know, this is going quite well. We have a good process and good formats to communicate within the organisation." (Case E, Optimization engineer) "In the beginning we have developed one matrix for all blast stoves. Depending on the length and depth of the cracks we have agreed upon a letter encoding and a corresponding action. When it is A, we perform this action. When it is B, that action. [...] Since we agreed upon the matrix, we have always followed the inspector's maintenance advice." (Case L, Maintenance head)
	Increase in technological fit	*(Complementary) technology in place* "I think it (the model) is quite transferable. [...] The more the roll and process looks like the ones for which I've developed the model, the more we can copy." (Case G, Technology developer) "Once a factory has been connected to the central condition monitoring network, it's easy to connect new applications to it." (Case J, Condition monitoring specialist)
	Increase in implementation & operational capacity	*Obtaining additional FTE* "We hire someone (extra) for the measurements now, I don't have to walk the measurement rounds myself anymore." (Case D, Vibration monitoring specialist) "What Rob (new project manager) is filling in now, is what I've been missing the past 4 years: time to deliver it to the factory. Technically everything is working perfectly, but you also need to

		support the people in the factory such that they will start to work with it.” (Case H, Process engineer)
Economic mechanisms	Increase in cost-effectiveness	*Increased performance of technology* “Eventually we'll arrive at the point at which we can make the next step, then it will be good. And then we'll start earning money. Truth be told, at the moment this is still costing us money.” (Case A, Instrumentation engineer) “The performance of the technology is reasonable, not more. [...] 50% at the max (of the potential performance), maybe 40% even. [...] Using the technology is not efficient yet. This is going to improve a lot in the upcoming years.” (Case K, Condition monitoring specialist)
	Reduction in adoption costs	*(Complementary) technology can be reused* “We have purchased the camera, including training and instructions, [...] The analysis is the same for most equipment, [...] The camera can be used for all switchboards, […] it is brand and type independent.” (Case B, Teamlead Electrical Events) “The software is already there, so I only have to install and configure it. This costs me in total about 4 hours. [...] The database is on a server here, [...] this was built for the first installation. [...] For other factories, I only need to make a dedicated connection to their database. Technically you can do this fairly quickly” (Case I, Software developer)
	Increase in adoption & operational budget	*Obtaining additional adoption budget* “I had hoped to install 180 sensors from my remaining budget (dedicated to installation of the technology) during the last maintenance stop. Only a small part of the initial budget was remaining. [...] We agreed with the project team to install as many sensors as possible from this budget, which turned out to be 45.” (Case C, Corrosion engineer) “The pilots are partially paid by AMD, partly by the factories. [...] I've arranged that the budget is part of AMD's annual plan [...], a subsidy pot. [...] The factories also have to incorporate it in their annual plans. [...] The factories that have done this can progress in the upcoming year, the ones that didn't cannot.” (Case J, Condition monitoring specialist)
Regulative mechanisms	Regulative institutionalization of adoption	*Internal regulation of adoption* “In 2006 the regulation was made stricter. The government made it obligatory to monitor and guarantee the quality of emission monitoring systems. [...] Over time the quality requirements have become stricter.” (Case F, Environmental engineer) “The customer is imposing it on us. [...] We have to adhere to the Automotive Core Tools, otherwise we're not allowed to sell to the automotive industry. [...] SPC is one of the ways with which we can prove the process was in control at the time the product was made.” (Case H, Project manager)
Normative mechanisms	Increase in normative fit	*Normative institutionalization of technology’s usage* “People are well aware we're not doing this for fun. It's compliance. Everybody realizes this is necessary. [...] (Although the technology was installed,) It took some time to get there, [...] that usage (of the

		technology) became priority.” (Case F, Teamlead Analyzers & Instrumentation)
		“I expect it to be quicker this time. Within one-and-a-half-year people will be structurally working with it. [...] The procedures are in place now. Roles have been specified. People are familiar with it. [...] Therefore I think that a large part of the last 5 years will be omitted.” (Case I, Software developer)
	Normative institutionalization of adoption	*Normative institutionalization of technology adoption*
		“The development of the maintenance concept of the new plant [...] was easy. We have a standard program for vibration monitoring, so we just extend the maintenance order and that's it.” (Case D, Maintenance manager)
		“Because I saw the success of the technology at the first applications, I got the idea for a Proof of Concept to increase the awareness of the technology at the site. [...] Now the Proof of Concept has developed into a full program, in which we try to monitor the 500 most critical equipment by 2023.” (Case J, Condition monitoring specialist)
Cultural-cognitive mechanisms	Increase in legitimacy of technology	*Technology gains legitimacy*
		“People have become much more aware of the technology since the incident at the heat exchanger in 2015 [...] (and) several instances in which we used the technology to make the right maintenance decision. [...] We notice that people get enthusiastic about the technology nowadays. That they start seeing it as a solution to their problems. [...] So I have been getting more requests to install the technology lately.” (Case C, Corrosion engineer)
		“At this moment, almost all of the nine 'Managers techniek' are enthusiastic about the possibilities of vibration monitoring. These managers are the key decision makers in the adoption of more expensive systems, such as the vibration monitoring systems. [...] The system is paid for from their budget.” (Case J, Innovation manager)
	Increase in influence of technology champion(s)	*Influence of technology champion(s) on adoption decision makers and management increases*
		“We always take his advice very serious. Whenever he measures a deviation, it's a fact. [...] Because he has been here for 10 years, and was hired specifically for this function, you build a level of trust. In what he does. Because he performs the analyses consequently, because of the way he reports, because of the content of his reports. It's just good.” (Case D, Maintenance manager)
		“This is exactly the reason I went to AMD (central department). I was at the Warmband (one of the factories) and realized: I cannot reach other factories. Whenever I went to the Staalfabriek (another factory) to recommend them to adopt a technology, they said 'who are you?' Now I'm more of a facilitator. I bring people together from different departments that weren't talking to each other before.” (Case J, Condition monitoring specialist)
		Technology champion(s) promote the technology more
		“Eventually, only 45 were installed during the last maintenance stop (out of the 180 she planned). It was a very difficult process. [...] I spent much more time on it than I was supposed to. [...] If I hadn't

	done that, only halve of those 45 would have been installed." (Case C, Corrosion engineer) "The vibration monitoring group had lost their vigour; they had similar ideas in the past, but couldn't convince the factories. [...] Because we have picked this up centrally and have shown the factories that it works, the doors have opened up for the vibration monitoring group as well. Now they are actively promoting these technologies again." (Case K, Condition monitoring specialist)

technology champion(s). Moreover, resources for adoption and operation of the technology did not get expanded before adoption of the technology became institutionalized: only when there was sufficient momentum in the organization and it was in line with their unit's strategy and targets, did management make additional resources available.

Note that the timing of these mechanisms differs. Increments in the technical fit and reduction in adoption costs find place directly after purchase and installation of the (complementary) technology. Institutionalization of usage and increments in the technology's performance also start from the moment the technology is implemented, but take several months to years to arrive at their full potential. The legitimacy of the technology and influence of the technology champion(s) start increasing when the people involved build experience with the technology and the technology's performance becomes apparent. Finally, institutionalization of adoption and the addition of resources for adoption and operation take place after the technology has become legitimate and managers feel the need to further diffuse the technology. Hence, especially for new technologies for which the performance was uncertain, it took multiple years before the technology became legitimate and adoption became institutionalized.

4.3.1 Intra-firm diffusion mechanisms per quadrant

Table 3.5 provides an overview of what intra-firm diffusion mechanisms have been observed in each case. Not all intra-firm diffusion mechanisms have been observed in all cases. The distinction is made in Table 3.5 between merely observing a diffusion mechanism and observing that the mechanism was essential for progressing diffusion.

In Table 3.5 it can be observed that the starting conditions of the technology – whether there is technical-economic and institutional drive or resistance – do not affect what mechanisms are observed, but do affect which mechanisms have an impact on diffusion. For the technologies with an initially high institutional resistance (quadrants II and III), increments in the legitimacy of the technology, the

Table 3.5: Observed intra-firm diffusion mechanisms per quadrant[a]

			I				II			III		IV		
Category	**2nd order codes**	**1st order codes**	**B**	**C**	**E**	**K**	**D**	**G**	**H**	**A**	**I**	**F**	**J**	**L**
Technical mechanisms	Increase in technology's performance	Improvements to the technology		◦	◦		●		●	◦	◦	◦	◦	◦
		Learning curve of technology users	◦	◦	◦	◦	●		◦	◦	◦	◦	●	●
		Institutionalization of technology usage	◦	◦	◦	◦	●		◦	◦	◦	◦	●	●
	Increase in technological fit	(Complementary) technology in place	◦	◦	◦	◦	◦	◦	◦	◦	◦	◦	◦	◦
	Increase in implementation & operational capacity	Obtaining additional FTE	●			◦	◦		●				●	
Economic mechanisms	Increase in cost-effectiveness	Increased performance of technology	◦	◦	◦	◦	●		◦	◦	◦	◦	●	◦
	Reduction in adoption costs	(Complementary) technology can be reused	●	◦		◦	●	●	●	◦	◦	◦	◦	◦
	Increase in adoption & operational budgets	Obtaining additional adoption budget		●		●						●	●	
		Obtaining additional operational budget	◦	◦		◦	●						◦	●
Regulative mechanisms	Regulative institutionalization of adoption	Internal regulation of adoption			●				◦			●		●
Normative mechanisms	Increase in normative fit	Normative institutionalization of technology usage	◦	◦	◦	◦	●		◦		◦	◦	◦	◦
	Normative institutionalization of adoption	Normative institutionalization of technology adoption	●	◦	●	●	●		●		◦	◦	●	●
Cultural-cognitive mechanisms	Increase in legitimacy of technology	Technology gains legitimacy	◦	●	◦	◦	●		●		◦	◦	●	◦
	Increase in influence of technology champion(s)	Influence of technology champion(s) increases		◦		◦	●		◦	◦			●	●
		Technology champion(s) promote the technology more	●	●		◦	●	●	●	●	●		●	●

[a] ◦ observed, minor impact on diffusion;
● observed, large impact on diffusion;
Quadrant I: T-E drive & I drive; II: T-E drive & I resistance; III: T-E resistance & I resistance; IV: T-E resistance & I drive.
In grey: the areas that start with 'resistance'.

influence of the technology champion(s) and institutionalization of adoption positively affect the diffusion speed (Case G was abandoned after 2 years). For the technologies with an initially high technical-economic resistance (quadrants III and IV), increments in the technology's performance and cost-effectiveness make the technology viable for a larger subset of the population (Case F was diffused completely upon adoption). Thus, the technical-economic and institutional starting conditions of the technology affect what mechanisms are imperative for further diffusion of the technology.

Note that the technologies that start in quadrant III have many of the diffusion mechanisms present, but few actually impact diffusion. In these cases, the technology champion(s) are promoting the technology, but substantial organizational changes are required before diffusion of the technology can really take off. This requires management intervention, which is not expected to take place before the technologies have become legitimate. Until that time, the technology champion(s) keep on tinkering.

4.3.2 Intra-firm diffusion mechanisms and diffusion speed

In Table 2.7 the same diffusion mechanisms are presented, categorized here against the diffusion speed. Since cases B and G have been abandoned primarily due to external and unrelated events (change in equipment, change in regulation, external job opportunity), they are categorized here according to their average diffusion speed.

In contrast, all of the cases with a slow diffusion speed have strong (mainly organizational) barriers to overcome. In cases A, H and I, diffusion is mainly driven by local, decentralized technology champion(s), who do not have access to – nor are they responsible for – the majority of the population. Hence, these cases require (extensive) organizational changes to be able to reach the entire population, which have not occurred to date (adoption of H’s technology has only been institutionalized locally).

It should be noted that the diffusion speed in cases H and J has increased in the last observed years, after the first successes with the technology were perceived by management and, consequently, adoption of the technology has started to become institutionalized (from 2016 and 2015 onwards respectively). If the observation period had been longer, case J would most likely move to the Medium speed category, case H possibly as well.

The technologies with a medium diffusion speed each had or have to deal with one or multiple barriers, which differ from case to case. In cases D and K, the performance of the technology needed to increase before the technology became cost-effective for a large(r) part of the population. In cases C, D, K and L, additional resources were required to speed up adoption. In case G, the technology champion(s) had access to a small subset of the population only. The cases with a relatively high diffusion level (cases C, D and L) were successful in creating a well-performing technology, that gained legitimacy throughout the population and, as a result, delivered the technology champion(s) more (adoption) decision power (cases D and L) and led to the institutionalization of the adoption of the technology (cases D and L).

Table 3.6: Observed intra-firm diffusion mechanisms and diffusion speed[a]

Category	2nd order codes	1st order codes	Slow				Medium[b]					Fast[b]		
			A	H	I	J	C	D	*G*	K	L	*B*	E	F
Technical mechanisms	Increase in technology's performance	Improvements to the technology	◦	●	◦	◦	◦	●			◦		◦	◦
		Learning curve of technology users	◦	◦	◦	●	◦	●		◦	●	◦	◦	◦
		Institutionalization of technology usage	◦	◦	◦	●	◦	●		◦	●	◦	◦	◦
	Increase in technological fit	(Complementary) technology in place	◦	◦	◦	◦	◦	◦	◦	◦	◦	◦	◦	◦
	Increase in implementation & operational capacity	Obtaining additional FTE		●		●		◦		◦		●		
Economic mechanisms	Increase in cost-effectiveness	Increased performance of technology	◦	◦	◦	●	◦	●		◦	◦	◦	◦	◦
	Reduction in adoption costs	(Complementary) technology can be reused	◦	●	◦	◦	◦	●	●	◦	◦	●		◦
	Increase in adoption & operational budgets	Obtaining additional adoption budget				●	●			●				●
		Obtaining additional operational budget				◦	◦	●		◦	●	◦		
Regulative mechanisms	Regulative institutionalization of adoption	Internal regulation of adoption		◦							●		●	●
Normative mechanisms	Increase in normative fit	Normative institutionalization of technology usage		◦	◦	◦	◦	●		◦	◦	◦	◦	◦
	Normative institutionalization of adoption	Normative institutionalization of technology adoption		●	◦	●	◦	●		●	●	●	●	◦
Cultural-cognitive mechanisms	Increase in legitimacy of technology	Technology gains legitimacy		●	◦	●	●	●		◦	◦	◦	◦	◦
	Increase in influence of technology champion(s)	Influence of technology champion(s) increases	◦	◦		●	◦	●		◦	●			
		Technology champion(s) promote the technology more	●	●	●	●	●	●	●	◦	●	●		

[a] ◦ observed, minor impact on diffusion; ● observed, large impact on diffusion.
[b] The applications in the cases in Italic (B and G) have been largely abandoned. Initially however their diffusion speed started off as Medium and Fast respectively. Therefore, they are presented within those categories.
Slow: on average between 0-1% (relative) new applications per year (>100 years to complete diffusion);
Medium: on average between 1-10% (relative) new applications per year (>10 years to complete diffusion);
Fast: on average more than 10% (relative) new applications per year (<10 years to complete diffusion).

From an intra-firm diffusion mechanism perspective, we observe that normative institutionalization of adoption (7 out of 12) and an increased influence of technology champions (9 out of 12) were important mechanisms in the highest number of cases. Increments in the technology's performance and reductions in the cost of adoption were observed in almost all cases, but had a strong effect on diffusion in only a couple of them. Lastly, 8 out of 12 cases had to face constraints regarding resources (FTE or budget) for adoption or operation. In 5 cases, increments in resources for adoption enabled higher rates of intra-firm diffusion, and in 7 cases, increments in operational resources allowed for higher levels of diffusion.

In conclusion, we find that the speed of intra-firm diffusion in our cases is dependent upon the activation of specific diffusion mechanisms. Which diffusion mechanisms need to be activated depends upon the specific technical-economic and institutional conditions of the technology. Generally however, regulation of adoption (regulative institutionalization of adoption) clearly is the most potent diffusion mechanism. Normative institutionalization of adoption comes second, especially for technologies that are complex, expensive, and require organizational changes for diffusion, for example because the population of equipment is dispersed. Increments in the actual performance of the technology and reductions in the adoption costs were part of the main drivers for diffusion in, respectively, (only) 3 and 4 out of 12 cases. More important is the extent (a) to which the technology champion(s) actively pursue diffusion, especially when their influence on adoption decision makers and management increases over time, and (b) the increments in legitimacy of the technology, creating additional demand and reducing resistance for adoption.

5. Discussion

The overall uptake of innovations depends on processes of inter-firm diffusion as well as intra-firm diffusion. While most of the literature concentrates on the first process, we study the second process in this chapter, focusing on condition monitoring (CM) technologies. We argue that intra-firm diffusion crucially depends on processes influenced by technical and economic considerations, as well as regulative, normative and cognitive institutions inside and outside of the firm. Understanding the factors that affect these intra-firm diffusion processes better may help us understand why the increase of use of many digital technologies, like CM, is slower than what one would expect (PwC & Mainnovation, 2018; Van de Kerkhof et al., 2016).

5.1 Elaboration on diffusion theory

Diffusion theory can be applied to the intra-firm diffusion process of CM technologies, but to a limited extent. In line with diffusion theory (Rogers, 1995), the technology’s relative advantage, compatibility with the existing technical infrastructure and prevailing institutional logic, and complexity, have been observed as important determinants of adoption decisions. Moreover, we have also observed that the strength of diffusion mechanisms depends upon characteristics of the adopting system. When a technically well-functioning and cost-effective technology is first adopted within an environment of high institutional resistance (quadrant II), becoming legitimate, increasing the technology champion’s influence and institutionalizing adoption are essential mechanisms to overcome the institutional resistance. In contrast, when management wants to implement a technology that is not (yet) cost-effective for a large subset of the population (quadrant IV), increments in the technical fit, improvements to the technology's performance and reductions in the technology's cost can extend the subset of the population for which the technology is cost-effective.

However, the well-established assumption that diffusion processes follow a S-shape trajectory – continuous, progressive diffusion until complete diffusion – was not detected in our cases (see Figures 3.2 and 3.3). Instead, we observed no diffusion in over half of the years (zero additional adoptions), many technologies that will most likely never reach complete diffusion (10 out of 12), and in some cases even complete abandonments of the technology. Similar findings have been reported in other empirical studies of intra-firm diffusion processes (Battisti, 2008), questioning the appropriateness of the S-shaped curve assumption for this process.

In addition, the core mechanisms of diffusion research – increasing returns, uncertainty reduction and threats of non-adoption (Abrahamson & Rosenkopf, 1997) – played a minor role in our cases. We did observe increasing returns, as the technical fit increased, the cost of adoption decreased, the technology's performance increased and the technology's cost-effectiveness increased, but only in 4 cases this had a strong impact on the diffusion process. Uncertainty reduction was also observed, as the performance of the technology became apparent over time, but this reduction in uncertainty can only explain a small window of the diffusion process. Once the technology's performance is known, it is shared openly with employees within the organization, reducing most of the uncertainty within the population at that moment in time.

Instead, institutionalization of adoption and increased influence of technology champions were the most common and strongest mechanisms of diffusion across the cases, especially for the technologies that were complex, expensive, and required organizational changes for diffusion. When the technology was incorporated into a plant's or team's strategy, when a dedicated program was established and/or when ramp-up targets were set, diffusion really took off. Also the increase of resources, for adoption and operation, enabled faster diffusion and higher levels of diffusion. These mechanisms might be unique to the intra-firm diffusion process; inter-firm and interpersonal diffusion processes are to a much lesser extent bound by the same institutional logics – they do not necessarily share the same strategy, programs, and resources.

Lastly, diffusion theory distinguishes between three types of innovation decisions: optional decisions, collective decisions, and decisions enforced by authority (Rogers, 1995). Decisions that are made by individuals, as opposed to firms, and by smaller groups, as opposed to larger collectives, typically have a higher rate of adoption. With intra-firm diffusion processes, we have also observed these three types of adoption decisions. Yet, each of these types assumes that the individual or collective is responsible for making a single adoption decision. In many of our cases, individuals and collectives made multiple, clustered adoption decisions. Similar observations have been made in other empirical studies of intra-firm diffusion (Shibeika & Harty, 2016; Fuentelsaz et al., 2016). Thus, it appears that intra-firm diffusion processes face other adoption decision processes and are subject to other diffusion mechanisms than inter-firm and interpersonal diffusion processes. Therefore, we argue that a middle-range theory of intra-firm diffusion is desired.

5.2 Middle-range theory of intra-firm diffusion

A middle-range theory of intra-firm diffusion should allow its user to understand how and why context-specific processes of intra-firm diffusion occur (Craighead et al. 2016). In the development of a middle-range theory of intra-firm diffusion of CM technologies, we draw from the grand, more general diffusion theory (Rogers, 1995), and stay close to the empirical context, conceptualizing variables as they are used. That way, a middle-range theory provides theoretically grounded insights that can be readily applied to other intra-firm diffusion processes of CM technologies (Craighead et al., 2016). In line with diffusion theory, a middle-range theory of intra-firm diffusion of specific technologies should at least include insight into adoption decisions – how are they made, what is the motivation – and insight into the mechanisms of diffusion – why is the technology adopted by additional potential adopters over time? But first, we drop the assumptions that diffusion takes place progressively and continuously, following an S-shaped curve, until complete diffusion is achieved.

In our cases, intra-firm adoption decisions were based on technical, economic and institutional considerations. Whether or not a technology is truly helping engineers in their condition monitoring and maintenance efforts, whether it is cost-effective and can be realized with the resources available, and whether adoption is perceived as the right thing to do, were common arguments. This is in line with the main attributes of innovations – perceived relative advantage, compatibility and complexity – in diffusion theory.

An important characteristic of intra-firm adoption decisions is that they are generally not mutually independent. Adoption decisions can be taken by a single individual or a collective (in line with diffusion theory), but we observed that consecutive adoption decisions are often taken by the same individual or collective, and that adoption decisions can be clustered. In one instance for example, a small group of decision-makers decided to apply the technology to 25 new equipment during the upcoming maintenance stop. Another important and related characteristic of intra-firm adoption decisions is that the decision-makers' resources are not independent. Instead, potential adopters often rely on the same (limited supply of) resources, creating a need to prioritize adoption decisions. If we cannot implement the technology to all potential equipment in the upcoming year, due to limited resources, which ones should we start with?

Yet, a static view on the intra-firm diffusion process fails to appreciate that the underlying factors (drivers as well as impeding factors) change over time (Wunderlich, Größler, Zimmerman & Vennix, 2014). Such changes may be exogenous as well as endogenous to the diffusion process itself. Examples of exogenous change are the development (outside of the firm) of new technology, decreasing costs of equipment needed for new practices, or a change in regulations. Exogenous changes in factors are (by definition) not linked to the intra-firm diffusion process, but may very well be influenced by the degree of inter-firm diffusion of a practice. As a new practice becomes more widely spread, the underlying technologies may gradually be improved, vendors realize economies of scale which drive down prices, and regulators are more likely to sanction the use of the practice (see, e.g., Compagni et al., 2015; Fuentelsaz et al., 2016).

However, changes in factors may also be endogenous to the intra-firm diffusion process. Use of a new technology for example will increase a company's know how over time, enhancing the performance of the CM technology in new applications. Furthermore, setup costs of new adoptions can decrease with each new adoption, internal regulative institutions can become more conducive, adoption targets can be set, and the technology can become taken-for-granted, all increasing the likelihood of adoption. In our cases, the main endogenous mechanisms for diffusion were the institutionalization of adoption, the increased influence of (internal) technology champions and legitimacy of the technology, the increase in resources for adoption and operation, the reduction in adoption costs, and the improvements to the technology's performance.

It should be noted that these diffusion mechanisms can interact. In fact, our cases suggest that adaptation of institutions often trails behind improvement of the technical and economic performance of an innovation. For instance, in case D (portable vibration monitor) increased technological performance over time made the technology more common sense, hence increased the adaptation of cognitive institutions. Likewise, in case H (statistical process control - SPC) one process engineer had been tinkering with SPC for 8 years, after which the factory's management incorporated it in their strategic plans and made additional resources available, speeding up the diffusion process. Although it seems most likely that technical and economic advantages of an innovation, with a delay, lead to change in institutions, the effect can also be the other way around. In fact, in most cases improvements to the technology were made after usage of the technology had become institutionalized. In case F (quality control system) for example, regulators enforced adoption of the technology. Over time however, as the requirements from external regulators and auditors expanded, the maintenance team started working more actively with the system, gaining experience and making several technical improvements to the system. In section 5.1 of the dissertation, we further explore the dynamics of the intra-firm diffusion mechanisms.

Here, we focus on explaining the observed diffusion trajectories, or lack thereof. As the strength of any theory is determined by its explanatory power, a middle-range theory of intra-firm diffusion should be able to explain why we have observed so little diffusion (in the majority of years no diffusion took place), even though in almost all cases multiple diffusion mechanisms were active. We believe three principles aid in understanding the speed of intra-firm diffusion of CM technologies.

First, some CM technologies are better suited for fast diffusion than others. Characteristics of the CM technology and the adopting context affect the speed of diffusion: the extent to which adoptions can be clustered (technical), the performance of the CM technology (technical), the cost-effectiveness and adoption cost of the technology (economical), and the extent to which the technology matches with existing institutions (institutional).

Second, at the level of the population (all potential application within the firm), certain barriers or ceilings exist. In line with the equilibrium perspective (Battisti, 2008), we have observed that diffusion ceases if such a barrier is reached. For example, when a CM technology is the optimal CM technology for only a subset of the population (technical), it is unlikely to be applied to the whole population.

Similarly, when operational capacity is restricted (technical/economical), the technology is cost-effective (economical) and perceived as legitimate (institutional) for a subset of the population, the technology is unlikely to be applied to the whole population.

These factors and barriers can change over time with the help of diffusion mechanisms. If the technology's performance increases, the cost-effectiveness of the technology increases (factor), as well as the subset of the population for which this technology is the optimal CM technology (barrier). However, in many cases we have observed that the diffusion mechanisms *function locally* only. If the technology requires an extensive IT-infrastructure, then installing that infrastructure reduces the costs of subsequent adoptions. In multiple cases however, each factory required their own IT-infrastructure – installing the IT in one factory does not lower the costs of adoption in another factory. In a similar fashion, we have observed that increments in the influence of technology champions and legitimacy of the technology, as well as institutionalization of adoption, function mostly locally. As soon as a factory has one or multiple successful applications of the technology, diffusion takes off in that factory. But not in the other factories. So, third, the strength and reach of diffusion mechanisms depends upon the structure of the population, in particular to which extent the assets and decision-makers are fragmentized across different factories (or organizational units; see also Abrahamson & Rosenkopf, 1997, for an analysis of how the structure of a network affects diffusion processes).

5.3 Generalizability of middle-range theory

What is the scope of the present middle-range theory of intra-firm diffusion? Are the findings generalizable to other technologies, and industries? If the structure of the population, the nature of the adoption decisions, and the essence of the technology are similar, we expect they can. In our study, the assets are dispersed over multiple factories. Adoption decisions can be made locally by the factory's maintenance engineers, centrally by CM specialists, or by a combination of both. Consecutive adoption decisions are often made by the same people, and adoption decisions can be clustered. Adoption implies starting to use the CM technology to monitor the condition of an asset, and CM technologies consist of hardware components (sensors, databases, etc.), software components (algorithms, interfaces, etc.), and practices (measurement procedures, analysis methods, etc.).

Studies towards technology acceptance and usage of information technologies within firms have identified similar factors with diffusion theory, such as perceived usefulness and perceived ease of use (Venkatesh & Davis, 2000; King & He, 2006).

Since CM technologies are not perfect (predicting upcoming failures is hard) and are used for (maintenance) decision-making, trust in the technology is important. Yet, also performance and legitimacy of technology are generally accepted as drivers for adoption (Fichter & Clausen, 2016). As long as the technology is sufficiently complex, costly, and divisible (Fuentelsaz et al., 2016) – and thus requires a process of intra-firm diffusion – we expect that the same adoption considerations and diffusion mechanisms will be found.

Smit (2011) distinguishes between several types of technical assets – concentrated assets (e.g., in factories), network assets (e.g., roads, railways: covering large areas), distributed assets (e.g., printers, computers: distributed across geographical areas), and mobile assets (e.g., trains, ships) – each having their own types of maintenance organizations. We expect that the factors and diffusion mechanisms found are especially relevant for large asset owners with concentrated assets, such as other firms in the process industry, but also for large manufacturers and energy producers. If assets and maintenance organizations become more dispersed, additional challenges might arise, such as high travel costs for portable measurements (cost-effectiveness), separate budgets (resources), differences in regulation (regulative institutions), and differences in norms and cultures (normative and cultural-cognitive institutions). So, the weight of adoption considerations and strength of diffusion mechanisms are likely to be different. Yet, also for these asset owners, the same principles are expected to apply: some technologies diffuse faster than others, restrictions exist at the population level, and diffusion mechanisms function mostly locally.

6. Conclusions

Our study suggests that a middle-range theory of intra-firm diffusion of technological innovations should contain technical, economic and institutional factors and take the dynamic interplay between these factors into account. When a technology is complex, expensive and conflicts with existing institutional logics, a slow diffusion process can be expected. In the domain of technologies that we have studied, Condition Monitoring, this is where the digital revolution got stuck. Institutionalization of usage is needed to increase and stabilize the technology's performance and, over time, make the technology gain legitimacy. Institutionalization of adoption is needed to overcome organizational barriers, provide sufficient resources for adoption and operation and truly speed up diffusion. Both processes take time. Since many digital technologies are complex, expensive and require new institutional logics, we expect an evolution of digital technologies, no revolution.

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Chapter 4: CBM Maturity Model (CBM^3) for asset owners

"*Every initiative uses resources. Therefore, I want to start with the initiatives which have the highest impact. Currently, they're asking me to provide manpower to develop an asset health monitor here. That's possible, but it reduces the likelihood of success of my other initiatives. Furthermore, before we have the basics established, the asset health monitor will have less impact.*" – Maintenance manager

1. Introduction

Recent advancements in connectivity, data storage and data processing have increased the potential performance of condition monitoring (Bokrantz, Skoogh, Berlin & Stahre, 2017), both in terms of efficiency and accuracy, making predictive maintenance one of the key value drivers of Industry 4.0 (McKinsey, 2015). In recent surveys in northwest Europe up to 60% of organizations indicated they have concrete plans or intentions to use predictive maintenance in the near future (PwC & Mainnovation, 2018). In those same surveys, only 11% of organizations indicated they are already employing predictive maintenance practices. In reality, many organizations are struggling with adopting advanced CM technologies (PwC & Mainnovation, 2018) and, when adopted, with fully diffusing these technologies throughout the organisation (Van de Kerkhof, Akkermans & Noorderhaven, 2016, 2019). Unfortunately, there is a lack of relevant, actionable guidance for industrial maintenance organizations to meet their maintenance ambitions (Bokrantz et al., 2017), as well as a lack of understanding of what optimal usage of CBM entails for maintenance organizations (Tiddens, 2018).

Maturity models are helpful tools for addressing these issues (Wendler, 2012). Based on the assumption of predictable patterns, maturity models represent theories about how organizational capabilities evolve in a stage-by-stage manner along an anticipated, desired, or logical maturation path (Pöppelbuß & Röglinger, 2011). In general, the term 'maturity' refers to a state of being complete, perfect, or ready (Schumacher et al., 2016). The main purpose of maturity models is to help an organization or entity reach a more sophisticated maturity level (Mittal, Khan, Romero & Wuest, 2018), by enabling the organization to assess the as-is situation, by illustrating the desired 'final' stage of maturity and by providing guidance on how to improve (Wendler, 2012). A maturity model can be a helpful tool in structuring and solving ill-structured problems, such as how to design an organization (Simon, 1977).

Although the maturity concept emerged out of quality management (Shewhart, 1931), the first instruments with maturity stages building on each other were developed by Crosby (1979: quality management process maturity grid) and Nolan (1979: maturation of data processing). The development of maturity models really took off since the Software Engineering Institute introduced the Capability Maturity Model (Paulk, Curtis, Chrissis & Weber, 1993). Since then, the maturity concept has been widely applied across many domains, such as software development (e.g., Haase, 1996; Subramanian, Jiang & Klein, 2007), project management (e.g., Kerzner, 2002; Hilson, 2003; Pennypacker & Grant, 2003), knowledge management (e.g., Hsieh, Lin & Lin, 2009; Khatibian, Hasan & Abedi, 2010), and many more (see Wendler, 2012 for an overview). Recently some maturity models have also been developed in fields that are related to CBM, such as digitalized manufacturing (e.g., Mittal et al., 2018), big data (e.g., Comuzzi & Patel, 2016), asset management (The IAM, 2016), and reliability-centred maintenance (Hauge & Mercier, 2003). Yet, an actual CBM maturity model is still missing.

In this chapter we aim to develop a descriptive maturity model (Pöppelbuß & Röglinger, 2011) for the deployment of Condition-Based Maintenance by (the maintenance organizations of) asset owners, and answer the question(s): *what is CBM maturity for an asset owner, and what are logical stages in the path to maturity?* The main purpose of this descriptive maturity model is to enable asset owners and their maintenance managers to assess their current capabilities. The outcomes of these assessments can then be used to create improvement plans and prioritize projects and investments. To achieve these objectives, the CBM Maturity Model is translated into a CBM Maturity Assessment instrument and procedure, such that asset owners and maintenance managers are enabled to perform the assessments by themselves.

This chapter is structured as follows. First, we present the mapping study of related maturity models, identifying building blocks that can be used for a CBM maturity model. In the Methods section we elaborate on the methodology, describing in detail how the maturity model and assessment method have been constructed and tested. In the Results section we exhibit the design of the maturity model and assessment method and the results from the evaluations. Lastly, in the Discussion section we discuss the contributions of our study, both to the literature on maturity models and to practice.

2. Mapping study

Within the fields of asset management, maintenance, condition-based maintenance and predictive maintenance multiple maturity models and readiness assessments have been developed. The main related maturity models are presented in Table 4.1.

Table 4.1: Mapping study, main related maturity models (Steelco)

Maturity model name	Author(s)/ Organization(s)	Field	Maturity levels	Dimensions
Growthmodel CBM & Big Data[1]	BOM (2014)	CBM	1. Pure product manufacturer; 2. Value added manufacturer; 3. Full service provider; 4. Integrated solutions provider	Maintenance proposition; CBM stage; Data; Big data IT-infra; Organisation; Processes; People & culture[1]
Predictive Maintenance capability matrix	PwC & Main-novation (2018)	Predictive maintenance	1. Visual inspections; 2. Instrument inspections; 3. Real time condition monitoring; 4. PdM 4.0	Processes; Content; Performance measurement; IT; Organisation
Maturity model Inspection[1]	Steelco (2017)	Condition monitoring	1. Regressive; 2. Reactive; 3. Planned; 4. Proactive; 5. World Class[1]	Strategy; Risk; Maintenance concepts; Planning & scheduling; Execution; Registration; Follow-up; Analysis; Improvement[1]
Stages in business development to World Class Maintenance	International Iron and Steel Institute (2008)	Maintenance	1. Regressive; 2. Reactive; 3. Planned; 4. Proactive; 5. World Class	Culture; Performance; Corrective work; Scheduled work; Failure reduction; Maintenance concepts; KPIs
Maintenance maturity assessment	Macchi and Fumagalli (2013)	Maintenance	1. Initial; 2. Managed; 3. Defined; 4. Quantitatively managed; 5. Optimizing	Managerial capability; Organisational capability; Technological capability
RCM maturity model	Hauge and Mercier (2003)	Maintenance	1. Initial; 2. Repeatable; 3. Defined; 4. Self sustaining; 5. Continuous improvement	Analysis; Analysis documentation; Metrics; Mentoring & Facilitation; Training; Living process
Asset Management Maturity Scale	The Institute of Asset Manage-ment (2016)	Asset management	1. Learning; 2. Applying; 3. Embedding; 4. Integrating; 5. Optimising	AM strategy & planning; AM decision-making; Lifecycle delivery activities; Asset knowledge enablers; Organisation & people enablers; Risk & review
Infrastructure Management Maturity Matrix	Volker et al. (2011)	Asset management	1. Ad hoc; 2. Repeatable; 3. Standard; 4. Managed; 5. Optimal	Information management; Internal coordination; External coordination; Market approach; Risk management; Processes & roles; Culture & leadership
Industry 4.0 Maturity Model	Mittal et al. (2018)	Industry 4.0	0. Incomplete; 1. Performed; 2. Managed; 3. Established; 4. Predictable; 5. Optimizing	Leadership; Process; System & automation; Performance
Big Data Maturity Model	Comuzzi and Patel (2016)	Big data	0. No awareness; 1. Initial; 2. Repeatable; 3. Defined; 4. Managed; 5. Optimized	Strategic alignment; Data; Organisation; Governance; Information technology

[1] translated from Dutch

Three maturity models have been found that describe CBM practices: the Growthmodel CBM & Big data (BOM, 2014), the Predictive Maintenance capability matrix (PwC & Mainnovation, 2017), and the Maturity model Inspection (Steelco, 2017). The BOM model (2014) takes the perspective of the OEM, not the asset owner, and identifies how CBM and big data can be used in the OEM's service propositions. PwC & Mainnovation (2017) focus in their model on predictive maintenance, concisely describing several key capabilities that are required to exploit the potential of predictive maintenance. Their model has been developed for high-level surveying purposes, not for extensive assessments. In contrast, Steelco's (2017) maturity model of inspection practices is very detailed, providing a good basis for assessments. This model however limits its scope to visual inspections, not including other CM technologies, which have different technological and organizational requirements. Thus, a complete maturity model for the CBM practices of asset owners is still missing. These models do however provide a good starting point.

Because condition-based maintenance is part of maintenance and asset management, prevalent maintenance and asset management maturity models have been incorporated in the mapping study as well. These models typically follow a flow from a firefighting organization to a planned and continuously improving organization. Their dimensions incorporate technological, organizational and cultural elements, as they emphasize the interplay between technology and people. The same holds for condition-based maintenance, wherein people are responsible for conducting measurements and analyses, making decisions, and performing maintenance activities – all with the help of technology.

We also have explored the large body of Industry 4.0 and big data maturity models, since predictive maintenance is often mentioned as one of the core capabilities of Industry 4.0 (McKinsey, 2015) and big data technologies are advancing the CM technology frontier (Bokrantz et al., 2017). Two of the more complete and transparent maturity models have been developed by Mittal et al. (2018), helping SMEs in their journey towards Industry 4.0, and Comuzzi and Patel (2016), supporting organisations in the realisation of value created by big data. Comparing these models (and other models in these fields) to Steelco's inspection model for example, shows that big data technologies put different demands on the organization and the people operating and managing these technologies. These models have multiple new dimensions, such as data governance, cyber security strategy, and the ability to analyse big data. Considering that optimal usage of CBM is likely to also include the usage of big data technologies, these demands should be taken into account in the CBM Maturity Model.

Thus, none of the maturity models so far has extensively described the deployment of Condition-Based Maintenance by asset owners. The maturity models developed however do provide useful building blocks for a CBM maturity model. Maintenance and Asset management maturity models typically have 5 levels of maturity, moving from a reactive to a proactive and optimized organisation. Relevant dimensions include both technological aspects – such as data and IT – and organizational aspects – such as strategy, organisation, processes, people and culture. Further development of a CBM maturity model for asset owners requires incorporating different CM technologies, including big data technologies, and tailoring the dimensions to the asset owner context.

3. Methods

We have adopted the design science paradigm (Hevner, March, Park & Ram, 2004) for developing and evaluating the maturity model, the assessment instrument and the assessment procedure. Typically, design science research seeks to create innovative artefacts that are useful for coping with human and organizational challenges by following an iterative process of development and testing (Hevner et al., 2004). Our methodology, as depicted in Figure 4.1, is based on the procedure of Becker, Knackstedt and Pöppelbuß (2009), who have translated the design science principles into a dedicated procedure for the development of maturity models. Following the recommendations of Wendler (2012), we have applied a combination of multiple methods in different research states to evaluate the maturity model's completeness, validity, usefulness and ease of use. Specifically, the study has been performed in three consecutive phases: (1) scoping, (2) development and testing of the maturity model, and (3) development and testing of the assessment instrument and assessment procedure.

The maturity model and assessment method have been developed in cooperation with two large asset owners in the Dutch process industry: Steelco and Oilco. Most focus group sessions, as well as the practical setting evaluation, were held with domain experts from these organizations. To safeguard the external validity of the developed maturity model, additional interviews and focus group sessions were held with domain experts from other asset owners and knowledge institutes in the Netherlands.

3.1 Scope

The idea for the development of a CBM maturity model came from our key contact person at Steelco. It was his desire to translate the lessons learned in our research program into a maturity model that could be used to improve the CBM practices at Steelco's plants. Seeing practice impact in new ways, we followed a leading pathway (Simsek, Bansal, Shaw, Heugens & Smith, 2018), working in cooperation with this practitioner to establish the research design, as well as the first version of the maturity model, the assessment instrument and the assessment procedure.

Nonetheless, we first evaluated the practical and theoretical need for the development of a new maturity model. The theoretical need was assessed by identifying calls for research and guidelines (Bokrantz et al., 2017; Tiddens, 2018) and by reviewing existing maturity models – no maturity model existed yet for the usage of CBM by asset owners (see section 2). The practical need was assessed by consulting managers and domain experts from the organizations involved in our research program, asking whether or not and how a maturity model would aid them in improving their CBM practices. The results from both endeavours confirmed the need for a CBM maturity model.

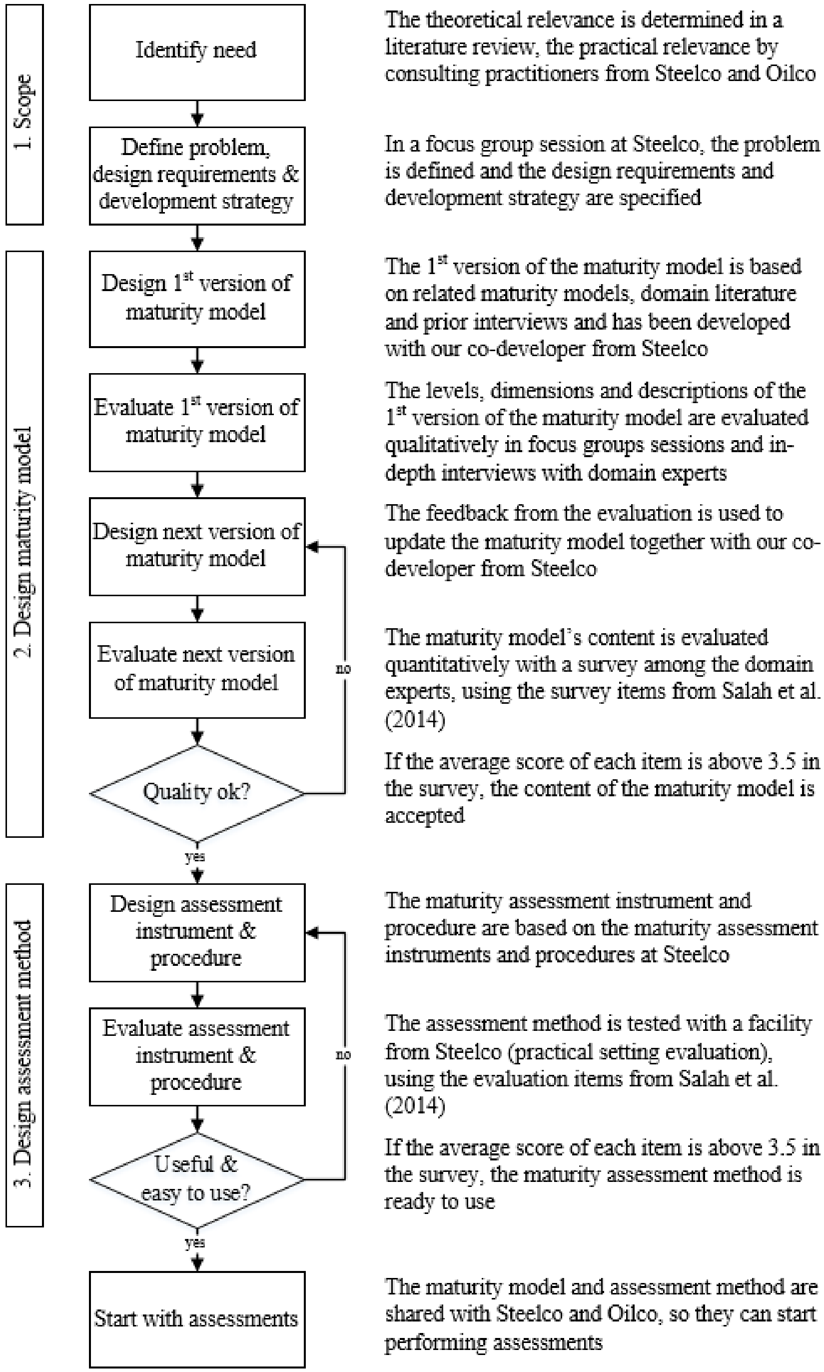

Figure 4.1: Applied design science procedure, adapted from Becker et al. (2009)

Then a focus group session was held with domain experts (including asset management maturity model experts) and future users from Steelco to define the problem, the design requirements, and the development strategy. The design specifications are displayed in Table 4.2.

Table 4.2: Design specifications

	Specifications
Maturity model	
Application domain	Condition-Based Maintenance (CBM)
Entity under investigation	process industry facility/production line
Maturity levels	matching Steelco's asset management maturity levels
Dimensions of maturity	multi-dimensional, based on literature and results in research program
Perspective of evolution	potential performance perspective (Wendler, 2012)
Differentiation from related maturity models	similar to Steelco's asset management maturity models
Assessment instrument	
Purpose of use	descriptive: performing a gap-analysis that provides input for an improvement plan
Target group	facilities' practitioners: maintenance managers, maintenance engineers, production managers, etc.
Performance scale	maturity levels
Design	similar to Steelco's asset management maturity assessments
Assessment procedure	
Procedure model	facilitated (self-)assessment
Advice on the assessment of criteria	by facilitator

3.2 Development of maturity model

The maturity model has been developed in four consecutive steps. First, we have reviewed the structure and content of existing and accessible maturity models – from scientific journals, conference proceedings, and knowledge institutes, as well as Steelco's prior developed maturity models – to identify what structure best fits the application of CBM by asset owners and to ensure a structural fit with Steelco's asset management maturity models. This mapping study is described in section 2. Based on the mapping study, interviews with domain experts that had been held before within the research program, and additional domain literature, the first version of the CBM Maturity Model has been constructed. The few gaps that remained were closed by performing additional interviews with domain experts. An overview of the interviews is presented in Table 4.3, the design of the maturity model in sections 4.1 and 4.1.1.

Table 4.3: Interviews

		Interviews during this study		
	Prior interviews	**Design MM**	**Evaluate MM**	**Design AI & AP**
Steelco	159		2	3
Oilco	154		3	1
Other	32	3	2	1

After the first version of the maturity model was developed, 10 focus group sessions were scheduled with domain experts from asset owners and maintenance providers in the process industry, a knowledge institute and a maintenance organization from a different industry (external validation). The participants for the sessions were selected as such that, as a whole, their knowledge covered all maintenance disciplines (rotating, static, electric, instrumentation) and all CM technologies (visual inspections, off-line NDE, on-line NDE, physics-based models and advanced analytics), and the key stakeholders within the organisation were represented (maintenance, operations, projects, IT). In total 58 people were invited to the focus group sessions, from which 39 could make it on the scheduled dates. An overview of the focus group sessions is presented in Table 4.4.

During these sessions, participants were asked to evaluate the maturity levels (would you add/remove levels, would you adjust the description of levels? If yes, why and what/how?), the categories (would you add/remove/adjust categories? If yes, why and what/how?), and the description of each category-level combination (would you adjust the description? If yes, why and how?), based on the evaluation template of Salah et al. (2014). The design of the feedback form is shown in Appendix A. All sessions were recorded and transcribed.

Table 4.4: Domain expert evaluation: focus group sessions

	Focus groups	**Total participants**	**Length of each focus group**
Steelco	3	17	1-2 hours
Oilco	7	18	1-2.5 hours
Other	2	4	1.5-2 hours

After the sessions the written feedback was aggregated per maturity level, category and description. The main researcher used this feedback to adapt the content of the maturity model and develop the 2nd version. This version was extensively discussed in two sessions with Steelco's key contact person, until agreement was reached about each description in the maturity model.

As the final step, a survey was used to evaluate the maturity model's relevance (the elements are relevant to CBM maturity), comprehensiveness (all elements are included), accuracy (elements are correctly assigned to maturity levels) and mutual exclusiveness (elements are clearly distinct). The survey was sent to all the 39 participants of the focus group sessions, as well as the 19 persons who couldn't make it, from whom 16 replied. The setup of the survey is based on the evaluation format of Salah et al. (2014) and can be found in Appendix B. The results of the evaluation are discussed in section 4.1.2.

3.3 Development of assessment method

The assessment method consists of an assessment instrument and an assessment procedure that describes how the instrument should be used. The design specifications for both were determined in the focus group session with future users at Steelco (see Table 4.2). As Steelco's central asset management department had over 10 years of experience with developing maturity models and performing maturity assessments, we could build on their instruments and procedures for designing the first version of the CBM Maturity Assessment. The design of the assessment instrument and procedure is discussed in section 4.2.1 and 4.2.2 respectively.

After development, an assessment was performed at one facility at Steelco to test the usefulness and ease of use of the assessment instrument and procedure in a practical setting evaluation (Salah et al., 2014). Three facilities were approached to perform the assessment evaluation – one at Oilco and two at Steelco – but for two the timing was off. The assessment evaluation was performed with 5 people from the facility: the maintenance manager, three maintenance engineers and an operator. The session lasted 2 hours, in which we followed the prescribed procedure. At the end of the session, the participants received a survey to evaluate the usefulness and ease of use of the assessment instrument and procedure (based on the evaluation format of Salah et al., 2014, see Appendix C), followed by a discussion (what changes would you recommend? Why? How can we make the assessment more useful?). The results of the evaluation are discussed in section 4.2.3.

3.4 Criticism of maturity research

In our research design we have attempted to deal with the most common criticism of maturity model research: lacking empirical foundation, limited external validity, and dissatisfactory documentation of the design process (Pöppelbuß & Röglinger, 2011). Specifically, the content of the maturity model is empirically founded on extensive field research and backed up with the experiences of the domain experts in the focus group sessions. Secondly, we have developed and validated the model with domain experts outside the process industry, to enhance the external validity of the model. Lastly, in the Methodology section and appendices we have devoted additional space to transparently document the design and evaluation processes.

One other criticism, the simplification of reality (Pöppelbuß & Röglinger, 2011), was not attempted to be overcome. On the contrary, the purpose of the maturity model is to analyse the current capabilities of an asset owner. A simplification of reality – abstracting away from technological details – helps the participants to understand the principles of CBM maturity and increases the external validity and usefulness. As will be discussed in section 4.1, the optimal mix of CM technologies is likely to differ per asset owner and over time. Identifying what CM technologies are currently optimal for an asset owner is therefore part of the assessment procedure, not of the maturity model itself.

4. Results

In this section the design of the CBM Maturity Model and CBM Maturity Assessment are elaborated, as well as the results from the domain expert evaluation and practical setting evaluation.

4.1 CBM Maturity Model

We define CBM maturity as a state in which an asset owner makes optimal usage of CBM. In particular, when an asset owner has reached CBM maturity, the asset owner applies the optimal combination of CM technologies (that are currently available) to all assets that could benefit from CBM and optimally uses the information provided by these CM technologies.

According to the domain experts, maturity assessments can best be performed at the 'facility' level. For most sites the entire production process is too large to be managed by a single production and maintenance department, thus the organization is divided into smaller teams, each responsible for a subset of the asset base. A facility is the organizational unit that is responsible for managing their subset of the asset base, such as a production line or cracker unit. Typically, each facility has its own production teams, maintenance team(s), engineers and management.

It should be noted that the exact features of the optimal state of an asset owner (and facility) are likely to differ per asset owner and can change over time. First, the applicability and usefulness of CBM depends upon the characteristics of the assets (e.g., degradation mechanisms) and the production process (e.g., consequences of breakdown). Secondly, new CM technologies and the capabilities of existing CM technologies are still being developed. To stay mature, the organization thus needs to keep track of changes in their asset base and innovations in CM technologies, and adapt their CM technology portfolio accordingly.

In addition, in the maturity model we use the word ‘optimal’ in the descriptions of the mature stage, for lack of a better word. During multiple feedback sessions, we received the comment that optimal is vague and impossible to attain. Yet, during those same feedback sessions, the participants were able to visualize together what would be optimal for their facility. The image pictured was different in each session (as explained above) and was probably incorrect in all sessions. Yet, each of the pictures sketched was a clear improvement compared to their current situation. The word ‘optimal’ thus provided a sense of direction and was useful in the discussion.

4.1.1 CBM Maturity Model Design

In our interviews and in line with CBM (Steelco, 2017), maintenance (International Iron and Steel Institute, 2008) and asset management maturity models (The IAM, 2016), we identify five logical states of using CBM.

In the first state, CBM is not used, for example because assets are not maintained. In the second state, CBM is used reactively. None of the assets are monitored structurally, but when an operator or a maintenance technician encounters an anomaly with an asset, an external CM service provider is asked to properly investigate the asset in order to better prepare maintenance activities. In the third state, CBM is used structurally and planned, mainly to improve the efficiency of maintenance. In this state, the asset owner has built some internal capabilities with easy-to-learn and easy-to-use CM technologies (Nicholas, 2016) and uses CBM to reduce corrective and periodic maintenance activities.

In the fourth state, CBM is used proactively to increase the reliability and productivity of (mainly important) assets (Van Dongen, 2011; Moubray, 1997). Here the asset owner has decided to invest more heavily in CBM and has started experimenting with multiple hard-to-learn and specific CM technologies, for example within a dedicated Condition Monitoring Program. Better equipped CM specialists have become important partners in reliability improvement initiatives, as insight into the assets’ condition can aid in identifying why assets have failed. In this state, the higher costs for CBM are justified by even higher gains from reliability and asset productivity improvements.

In the fifth state, CBM is used optimally, or World Class, to increase the value realised from the asset base (The IAM, 2016). Here the asset owner has ramped up all successful CM technologies, while maintaining the exploration for new CM technologies. The asset owner has embraced asset management (as described in ISO 55.000) and information about the assets’ condition has become an essential component of many asset management decision processes, including optimization of production, inventory management, project prioritization, and designing new assets. Because processes become more stable and predictable now, the asset owner starts actively reducing buffers, such as redundancy and stocks. To facilitate this, CM teams have gained a central position in the organization and have become well-connected to knowledge institutes, equipment and CM technology manufacturers and specialist CM service providers.

Then, we distil twelve categories of elements that are required to perform CBM successfully and that differ between maturity levels. These categories have been derived from the maturity models in Table 4.1, the CBM literature, and our prior studies towards the implementation of CBM practices and the diffusion of CM technologies, and updated with the feedback from the focus group sessions. The categories discussed here are the categories in the second version of the CBM maturity model, in section 4.1.2 we discuss the changes that have been made between the first and second version of the maturity model.

In the technological realm, four categories are relevant. First, the category *CM technologies* describes what CM technologies are used by the organization and how they are used, starting off with ad hoc and infrequent inspections and moving towards high-frequent and automated measurements (Nicholas, 2016). Second, the category *Assets* describes to what assets CBM is applied, starting with the assets that are easy to monitor, but incorporating more and more assets for which the highest value of monitoring can be attained towards higher maturity levels (Moubray, 1997). The third category, *Data*, describes the data used to perform the CM analyses and make the decisions thereafter, including for example master data, financial data, failure data, production data, and environmental data (Tiddens, 2018; Tsang, Yeung, Jardine & Leung, 2006). The fourth and last technological category, *IT-infrastructure*, describes the characteristics of the IT-infrastructure, starting with stand-alone systems for each CM technology, but moving towards a standardized IT-infrastructure that enables smooth ramping up of successful CM technologies (Wang, 2016).

In the organizational realm, we have identified six main categories. The category *Strategy and goals* describes the strategy of the asset owner (or facility) and the main KPIs for the facility, moving from minimizing maintenance costs to improving reliability, production and the value realised from assets (The IAM, 2015). The category *Decisions* describes what decisions and actions are (also) based on information about the assets' condition, starting with maintenance decisions only, but moving gradually towards other asset management decisions as well (The IAM, 2015). The category *Structure* describes how the monitoring is organized, first relying mostly on external CM service providers, but moving towards a structure in which centralized and decentralized CM teams work in close cooperation with specialist external CM service providers (Nicholas, 2016). The category *Budget and capacity* describes what budgets and capacities are reserved for condition monitoring, CBM, experimenting with new CM technologies and maintaining adopted CM technologies. This category moves from no or very limited budget and capacity to structural and dedicated budget and capacity for each of these purposes (Van de Kerkhof et al., 2019). The category *Processes and documentation* describes the processes and documentation that are used for the CBM practices, gradually defining processes and documentation for monitoring and decision-making, for experimenting with and implementing new CM technologies, and for evaluating and managing the CM technology portfolio. Important documentation includes standard CM reports, maintenance concepts, CM concepts (how an asset type is monitored), a list of critical assets, and an overview of what CM technologies are applied to each asset. The final organizational category, *Governance*, describes how the CBM practices are governed, including defined procedures, specified acceptance criteria, certification of CM specialists, formal agreements about data rights and responsibilities, and obligations for project managers to consider CM technologies in their projects (Comuzzi & Patel, 2016).

Finally, we have classified two categories that focus on the characteristics of the people involved in the CBM practices. We have observed that people are essential in successfully realizing CBM implementation and diffusion, therefore we have separated these categories from the organizational categories. First, the *Knowledge*, *skills and abilities* of those people is one of the key determinants of the success of a CBM practice. Specifically, domain knowledge about the asset and its (production) context – what is 'normal', how can it fail, what influences degradation, how does degradation influence production – and proficiency with CM technologies are determining the quality of analyses and decisions. Second, the *Culture* of the organization has to match the CBM practices for the practice to be sustainable (The IAM, 2015). Typically, organizations progress from a firefighting culture towards a bureaucratic culture, after which the organization can transition to a reliability and asset management culture.

In addition, multiple maintenance managers indicated during the domain expert evaluation that the rationale was lacking in the first version of the CBM Maturity Model: "why should our facility aim pursuing a higher maturity level?" Therefore, we added one category to the maturity model: *Value*. This category describes the primary gains that can be realised at each maturity level, going from better and more efficient maintenance to increased productivity and return on assets. The design for the CBM Maturity Model is shown in Table 4.5, the final CBM Maturity Model in Appendix D.

Table 4.5: Design of CBM Maturity Model

	1. No CBM	**2. Reactive CBM**	**3. Planned CBM**	**4. Proactive CBM**	**5. World class CBM**
Description	[…]	[…]	[…]	[…]	[…]
Value	[…]	[…]	[…]	[…]	[…]
Technology					
CM technologies	[…]	[…]	[…]	[…]	[…]
Assets	[…]	[…]	[…]	[…]	[…]
Data	[…]	[…]	[…]	[…]	[…]
IT-infrastructure	[…]	[…]	[…]	[…]	[…]
Organization					
Strategy & goals	[…]	[…]	[…]	[…]	[…]
Decisions	[…]	[…]	[…]	[…]	[…]
Structure	[…]	[…]	[…]	[…]	[…]
Budget & capacity	[…]	[…]	[…]	[…]	[…]
Processes & documentation	[…]	[…]	[…]	[…]	[…]
People					
Knowledge, skills & abilities	[…]	[…]	[…]	[…]	[…]
Culture	[…]	[…]	[…]	[…]	[…]

4.1.2 Evaluation of CBM Maturity Model

The ten focus group sessions provided useful feedback about the structure and content of the CBM Maturity Model. The main feedback, and how this is incorporated in the second version of the maturity model, is shown in Table 4.6. In line with Zou, Chen and Chan (2009), a clear distinction has been made between states (maturity levels) and transitions (progression between maturity levels), only including the state descriptions in the maturity model. In addition, many small changes have been made, such as adding or removing elements in descriptions, rephrasing elements, and relocating elements to different maturity levels. As a result, the second version of the maturity model is more tailored to CBM, has more clearly distinct maturity levels, is more compact, and is written in full sentences, making it easier to understand.

The second version of the CBM Maturity Model was evaluated with a survey among the people that were invited to the focus group sessions. From the 58 people invited, 16 responded to the survey. The results of the survey are presented in Table 4.7. Each item is evaluated on a five-point Likert scale (from “1-strongly disagree” to “5-strongly agree”). The results show that the maturity levels are sufficient and understandable. The domains are relevant, comprehensive, and mutually exclusive. In the comment field no new domains were proposed. Most descriptions are perceived to be relevant, but the accuracy and comprehensives of – mainly – the technological aspects can be improved.

The descriptions of the categories Value, CM technologies and Data scored the lowest, mainly due to a low accuracy and comprehensiveness. All three have been described relatively abstract, because the optimal combination of CM technologies (and the combination of CM technologies applied at each level of maturity) is likely to differ between facilities. In turn, both the data used and the value generated are dependent upon the CM technologies applied and the facility’s context, thus are likely to differ between facilities as well. The descriptions of the categories Strategy & goals, Processes & documentation, Knowledge, skills & abilities, and Culture scored the highest, mainly because of their high relevance. These categories describe organizational aspects, which are more similar between facilities and can be described in more detail.

More importantly, all scores are above the desired score of 3.5. The second version of the CBM Maturity Model can therefore be used to develop the CBM Maturity Assessment.

Table 4.6: Main feedback in focus groups

Topic	Feedback	Change in second version
Maturity levels	there should be a level at which CBM is not used	changed level 1 from "Regressive" to "No CBM"
	titles of level 3 and 4 are unclear	changed the title of level 3 from "Operations in control" to "Planned CBM" and level 4 from "Performance in control" to "Proactive CBM"
Domains	add a short description of each domain itself	short description of domains added
	why should our facility go to level 4 or 5?	added the domain "Value" to describe the rationale for moving to a higher maturity level
	title of the domain "CM info" does not represent its content	changed the title to "Decisions"
	capacity is just as important as budget	incorporated capacity into the domain "Budgets", not titled "Budget & capacity"
	documentation is used as part of processes, so they are connected	bundled the domains "Processes" and "Documentation" into "Processes & documentation"
Descriptions	make sure each level describes a stable state of the organization, not a transition period	added transition phases between the levels, moved some of the descriptions to these transition phases (these are not included in the model, but aid in the assessment procedure)
	use sentences, no bullet points	rewrote the descriptions into sentences
	make the descriptions of CM technologies more robust: the available CM technologies differ per context and over time	changed the categorization of CM technologies from a technological classification to a classification based on their ease of adoption and ease of use
	refrain from using the word "optimal", clearly describe what the domains are like	rewrote the descriptions of level 5

Table 4.7: Results of domain expert evaluation: survey

	Sufficiency	Understan-dability	Accuracy	Relevance	Comprehen-siveness	Mutual exclusion	Average
Model design							
Maturity levels	4.3 (0.46)	4.0 (0.86)					4.2 (0.71)
Domains				4.3 (0.46)	4.1 (0.24)	4.1 (0.60)	4.2 (0.47)
Descriptions							
Value			3.6 (0.88)	4.3 (0.46)	3.6 (0.78)	3.8 (0.75)	3.8 (0.79)
CM technologies			3.6 (0.93)	4.1 (0.66)	3.6 (0.70)	3.7 (0.98)	3.8 (0.85)
Assets			4.1 (0.24)	4.0 (0.24)	3.8 (0.66)	3.9 (0.48)	3.9 (0.56)
Data			3.9 (0.86)	3.9 (0.75)	3.8 (0.83)	3.7 (0.85)	3.8 (0.83)
IT-infrastructure			3.7 (0.87)	4.0 (0.63)	3.9 (0.68)	4.0 (0.37)	3.9 (0.68)
Strategy & goals			4.0 (0.73)	4.1 (0.50)	3.9 (0.77)	4.0 (0.73)	4.1 (0.67)
Decisions			4.0 (0.50)	4.2 (0.39)	3.9 (0.66)	4.1 (0.57)	4.0 (0.55)
Structure			3.9 (0.77)	4.0 (0.73)	3.9 (0.57)	3.9 (0.77)	4.0 (0.72)
Budget & capacity			3.9 (0.72)	3.9 (0.85)	3.9 (0.57)	4.1 (0.50)	3.9 (0.71)
Processes & documentation			4.1 (0.50)	4.3 (0.44)	4.0 (0.52)	3.9 (0.59)	4.1 (0.53)
Governance			4.1 (0.57)	4.1 (0.57)	4.0 (0.52)	3.9 (0.50)	4.0 (0.55)
Knowledge, skills & abilities			4.0 (0.63)	4.3 (0.44)	4.1 (0.44)	4.0 (0.52)	4.1 (0.53)
Culture			4.1 (0.62)	4.3 (0.59)	4.1 (0.44)	4.0 (0.53)	4.1 (0.56)

Numbers represent mean and (standard deviation). Number of respondents: 16.

4.2 CBM Maturity Assessment

The assessment instrument and procedure are designed as such that they can be integrated in Steelco's asset management assessment program. This program focuses on facilitated assessments and self-assessments to aid facilities in improving their asset management practices. Specifically, the assessments help in understanding how well a facility performs certain asset management practices, in identifying gaps, in creating improvement plans, and in transferring knowledge between facilities.

4.2.1 CBM Maturity Assessment Instrument

The design of the first version of the assessment instrument is displayed in Figure 4.2. For each of the twelve categories, the assessment group assigns the best fitting maturity level (score and description). When selecting a score, the group has to present evidence that supports their choice, such as data or references to documentation, interviews or observations. If the maturity level's description doesn't perfectly match their current situation, they can outline the differences in the comments. The scores are automatically converted into a snake diagram, making it easy to see what categories are at a lower-than-desired maturity level.

Figure 4.2: Screenshot of the CBM Maturity Assessment Instrument

4.2.2 CBM Maturity Assessment Procedure

The first version of the assessment procedure consists of six steps. First, the facilitator and the facility's initiator (often a management position) agree on a plan for carrying out the assessment, including the date, who is going to participate, and whether or not a preparatory session is required. If so, secondly, a brief CBM awareness session is held for the assessment's participants two weeks prior to the assessment. The CBM Maturity Model is shared with the participants about one week prior to the assessment. This gets the participants thinking about the topic and their maturity already, and it speeds up the introduction during the assessment session.

The third step is the assessment itself, guided by the facilitator. The ambition is to get a common shared view on the maturity of each element in the assessment. If the group does not reach a consensus or the score is in between two scores, the lowest score is to be selected. In these cases, the comments box is used to explain the score. It was noted by the practitioners that low scores are at least as valuable as high scores, since these provide opportunities for improvement. These scores were supported by comments as well, so that it was easier to define the steps to improve the maturity in the next step.

In the fourth step, the facility’s management translates the assessment results into an improvement plan. At this stage it is sufficient to have a prioritised list of improvement areas, rather than a detailed plan. If needed, the facilitator can support in this step, but the facility’s management should take responsibility for drafting and executing the improvement plan. Then, in the fifth step, the facilitator and facility’s management decide upon a realistic timescale for re-assessing, dependent on the planned improvement process.

Lastly, after each assessment process, the facilitator reviews the assessment process and communicates learning points to the people who were involved in conducting the assessment and to the people who will be involved in setting up and facilitating future assessment sessions.

4.2.3 Evaluation of CBM Maturity Assessment

The practical setting evaluation provided useful feedback. In the practical setting evaluation, the first and third step of the CBM Maturity Assessment Procedure have been performed. The results from the survey are presented in Table 4.8, the qualitative feedback at the end of the session in Table 4.9. As can be seen in Table 4.8, not all items are evaluated above 3.5, thus the current performance of the CBM Maturity Assessment is insufficient.

The main feedback was that, with this procedure, the assessment was not very useful. During the assessment the facilitator acquired a good perception of the facility’s maturity, but the participants not (yet). This had multiple causes. First, the participants had disparate views about CBM, resulting in repeated discussions about what should and should not be included at different maturity levels. Secondly, the facilitator was new to the facility, thus needed some time during the assessment to be informed of the asset context. Thirdly, during the assessment it was not straightforward to identify concrete improvement opportunities, both because no desired maturity level was determined yet and multiple descriptions were perceived as abstract and high-level.

Table 4.8: Results of practical setting evaluation: survey

Evaluation items	Score
Understandability	
The maturity levels are understandable	3.8 (0.4)
The elements are understandable	3.8 (0.4)
The assessment guidelines are understandable	4.2 (0.4)
The documentation is understandable	4.2 (0.4)
Ease of use	
The scoring scheme is easy to use	3.0 (0.6)
The assessment guidelines are easy to use	4.0 (0.0)
The documentation is easy to use	3.8 (0.4)
Usefulness	
The maturity model is useful for conducting assessments	3.2 (0.7)
The maturity model is practical for use in our industry	3.2 (0.4)

Numbers represent mean and (standard deviation). Number of respondents: 5.

Therefore, in following assessments, a good preparation is needed. The facilitator first needs to get a basic understanding of the facility's assets, their current challenges and initiatives in a meeting with the assessment initiator (extension of step 1). Then, a brief CBM awareness session should be held, aligning the assessment participants' view on CBM beforehand (step 2). These sessions can also be used to determine a desired maturity level for the facility. This way, the perceived usefulness of the assessment is expected to increase.

Moreover, participants indicated that the assessment is not easy to perform by themselves. Although the maturity levels, the assessment guidelines, and the assessment document are understandable, they found it difficult to determine a score for each category. More often than not they found themselves between levels, engaging in discussions about what is and what is not part of a level. The guideline "when in doubt, select the lowest level" helped, but this group would not have been able to (properly) conduct a self-assessment by themselves.

There are two options for solving this. One, by conducting every assessment with an independent facilitator who understands the CBM Maturity Model, clarifies descriptions with examples, and challenges the participants to get a shared and correct view of the situation. This imbues the risk that the quality of the assessment is as good as the facilitator. Two, by changing the format of the assessment. In the current format the group has to select the ‘best-matching scenario’ from five described levels. An alternative format for a self-assessment is to distil the elements from these five levels into separate statements and score each element individually. The underlying assumption here is that it’s easier for a group to agree on a single element than on scenarios with clusters of elements.

Table 4.9: Main feedback in practical setting evaluation

Topic	Feedback	Proposed changes in second version
Understandability	make sure participants have the same perception of CBM at the start of the assessment	have a preparatory session with the participants to introduce CBM and the CBM maturity model
	including all CM technologies results in high-level statements	create two versions of the assessment: one with a facility perspective, one with a CM technology perspective (outside scope)
Ease of use	the scoring scheme is hard: we’re often in between maturity levels	change the form of the assessment instrument: separate descriptions into multiple statements
	many of the descriptions needed explanation	a facilitator provides explanation and examples of the statements when needed
Usefulness	quite some time was spent on explaining the asset context to the assessors during the session	have a preparatory session with the asset management team to discuss the asset context
	determine a target/desired maturity level for the facility before the assessment	have a preparatory session with the asset management team and/or participants to determine the desired maturity level
	descriptions are at a high level, making it hard to identify specific improvement opportunities	create two versions of the assessment & use the comments section to note the improvement opportunities mentioned in the discussion
	facility level is a good level of analysis	write the elements more clearly from a facility’s perspective

Finally, the participants found it particularly challenging to abstract away from specific CM technologies. Indeed, the technological and organizational requirements for an established and basic CM technology, such as thermography, are different from a novel and complex CM technology, such as physics-based models and data-driven models (Tiddens, 2018). The current CBM Maturity Assessment assumes that a combination of these technologies are present at higher levels of maturity, but doesn’t specify what technologies specifically. A solution might be to remove the categories CM technologies and Assets from this assessment, and assess them in an alternative way, for example during the preparatory awareness session (step 2). Knowing in detail what CM technologies are currently being applied to what assets, makes it easier to assess the organizational requirements during the CBM Maturity

Assessment (step 3). Another solution might be to create two versions of the assessment: one with a facility perspective, focussing primarily on the organizational requirements of using CBM (assuming a combination of CM technologies), and one with a CM technology perspective, focussing on the requirements for successfully using each CM technology specifically.

Concluding, a new version of the CBM Maturity Assessment is needed. The next steps include incorporating the feedback provided into a second version of the CBM Maturity Assessment instrument(s) and procedure and testing the updated CBM Maturity Assessment with at least one facility, preferably more.

5. Discussion

This chapter established a CBM Maturity Model for asset owners and laid the foundation for a CBM Maturity Assessment method. In the development process we followed a leading pathway (Simsek et al., 2018), working in close cooperation with practitioners from Steelco and Oilco, and a design science procedure tailored to the development of maturity models (Becker et al., 2009). The structure of the first version of the CBM Maturity Model was based on related maturity models from the fields of maintenance, asset management and Industry 4.0, the content was based primarily on domain literature and interviews held prior in the research program. The feedback from the domain experts in the focus group sessions was then incorporated in the second version of the CBM Maturity Model. Based on the CBM Maturity Model and Steelco's assessment methods, the first version of the CBM Maturity Assessment instrument and procedure have been developed.

This chapter contributes to the literature in three ways. First, this research answers the call for actionable guidance for industrial maintenance organizations to meet their maintenance ambitions (Bokrantz et al., 2017), as well as the call for a better understanding of what optimal deployment of CBM entails for (maintenance) organizations (Tiddens, 2018). At the highest level of CBM maturity, the asset owner has maximized the value derived from CM technologies and CBM applications, by applying the optimal combination of CM technologies to each asset and optimally using the information provided by these CM technologies. The CBM Maturity Model delineates both the technological and organizational requirements for this state, improving our holistic understanding of what optimal deployment of CBM entails. Actionable guidance to arrive at this state is provided by the CBM Maturity Assessment.

Secondly, our findings emphasize the organizational innovation aspect of CBM (Hollen, Van den Bosch & Volberda, 2013) and provide guidance for future research towards CBM. In the CBM Maturity Model, only four out of twelve categories are technological in nature; eight out of twelve involve organizational aspects. In particular, the categories Strategy & goals, Structure, and Governance are important to explore further. Subgroups within organizations are known to have conflicting goals (Cyert & March, 1963), so how can these goals best be reconciled to maximize the value derived from CBM? With regards to the structure, is it best to perform all condition monitoring in-house, is it best to rely only on specialized CM service providers or is a combination of both optimal? To date it is unknown what the consequences are of these options, both in the short and the long term, and under what conditions each option is optimal. Similarly, many options exist to govern the quality of monitoring and CBM, such as contracts, certificates, standards, and procedures. Important questions to be answered in this field are: what is the optimal contract for outsourcing condition monitoring activities, what are the implications of making CM technology mandatory in projects, and how can the condition data best be governed? In addition, if the CBM Maturity Assessment is structurally used in the future, it can guide practice-oriented research by highlighting the areas asset owners have most difficulties with.

Thirdly, we have adapted the design science procedure of Becker et al. (2009) to better accommodate for the main methodological criticisms of maturity research (Pöppelbuß & Röglinger, 2011). Specifically, we have extended the iterative maturity model development phase, added a similar process for developing an associated assessment method, and combined multiple methods for evaluating the qualities of the maturity model and assessment (Wendler, 2012; Salah et al., 2014). Using both qualitative and quantitative forms of domain expert evaluation and practical setting evaluation (Salah et al., 2014) increases the empirical foundation of the maturity model and its external validity. Combining the development of a maturity model with an assessment instrument enhances its usefulness (Wendler, 2012). Thus, scholars aiming to develop a new maturity model can build upon this method to do so.

The results from this research also contribute to practice. In general, the CBM Maturity Model and CBM Maturity Assessment can help asset owners to reach a more sophisticated CBM maturity level. The CBM Maturity Model can aid management to determine a realistic end state ("for our facility, it is optimal to go to maturity level 4") and create a tailored and detailed vision of what this optimal state looks like for the facility (what CM technologies are used, what assets are monitored, etc.). Subsequently, the CBM Maturity Assessment can be used to gauge the facility's current capabilities, providing input for an improvement plan to achieve the desired end state.

The CBM Maturity Model and CBM Maturity Assessment have been designed primarily with large asset owners in the process industry, so to what extent is it applicable elsewhere? We expect that the CBM Maturity Model remains valid for other large asset owners in the process industry, as the structure of their facilities and maintenance organizations is quite similar: facilities typically have their own production teams, maintenance team(s), engineers and management. SMEs on the other hand are known to have less financial resources, a low usage of advanced manufacturing technologies, little R&D activities, and less specialized employees (Mittal et al., 2018). It is unsure whether small(er) asset owners with less financial resources have the same organizational features when optimally using CBM. For example, small asset owners are less likely to build an extensive in-house CM team, since this is relatively more expensive. The same question can be asked for asset owners in other industries, such as the energy industry, the manufacturing industry, the transportation industry, and the infrastructure sector. Some of the asset owners have similar characteristics to the process industry's asset owners – stationary assets, clustered at a single location, organized in facilities, workforce with high domain knowledge, etc. – but many have not. For example, with rolling, sailing or flying stock, the maintenance location can depend upon the location of asset breakdown, affecting the number of people that have to be trained with CM technologies. With wind turbines, the asset owner is typically not the most knowledgeable about the asset's failure mechanisms, (s)he is mainly exploiting the wind farm. Thus, it is recommended to test whether the CBM Maturity Model can be applied to these contexts.

The main limitation of this research is specifying and evaluating maturity level 5. This maturity level, the final maturity level, portraits an imaginary scenario of the future. None of the facilities at Steelco or Oilco have reached maturity level 5 yet, and none of the domain experts we involved has observed maturity level 5 in practice. For some of the categories, such as CM technologies, Assets, Decisions, and Culture, domain literature provides clear descriptions of the 'optimal state'. For others, the optimal state had to be derived by extrapolating the requirements: applying the optimal combination of CM technologies to all relevant assets and optimally use the condition information, can best be done with this type of organizational structure, processes, governance, etc. Therefore, it is sensible to not only validate the CBM Maturity Model at other asset owners (smaller, different industry), but also in time, when more asset owners have improved their usage of CBM.

Another limitation is the evaluation of the CBM Maturity Assessment. Ideally, the development process continues in an iterative way, testing the CBM Maturity Assessment (also) at other asset owners, and incorporating the lessons learned after each test. When the scores on Salah et al.'s (2014) survey are satisfactory and new assessments provide no new feedback (saturation), the CBM Maturity Assessment can be finalized.

6. Conclusion

The CBM Maturity Model provides scholars with more insight into the multi-faceted nature of CBM and the areas of CBM that require further research. Maturity model developers can build upon the design science methodology employed, which is tailored to the development of maturity models and assessment instruments and deals with most critiques of maturity model research. Managers from asset owners can use the CBM Maturity Model and Assessment to visualize their desired end state, assess their as-is situation and derive opportunities for improvement.

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Appendix

A. Feedback form: focus groups

Datum	
Naam	
Organisatie	
Functie	

			Maturiteitsniveau					
			1	2	3	4	5	Vraag 1
Domein			Achteruitgang	Reactief	Gepland	Proactief	World class	Vraag 2
Technologie	CM technologieën	A	1A	2A	3A	4A	5A	
	Assets	B	1B	2B	3B	4B	5B	
	CM info	C	1C	2C	3C	4C	5C	
	Data	D	1D	2D	3D	4D	5D	
	IT-infrastructuur	E	1E	2E	3E	4E	5E	
Organisatie	Strategie, doelstellingen & KPIs	F	1F	2F	3F	4F	5F	Vraag 4
	Structuur, rollen & verantwoordelijkheden	G	1G	2G	3G	4G	5G	
	Budgettering	H	1H	2H	3H	4H	5H	
	Processen	I	1I	2I	3I	4I	5I	
	Governance & documentatie	J	1J	2J	3J	4J	5J	
Mensen	Kennis & vaardigheden	K	1K	2K	3K	4K	5K	
	Cultuur	L	1L	2L	3L	4L	5L	
	Vraag 3							

Vraag 1. Zou je maturiteitsniveaus toevoegen? Zo ja, hoe veel en waarom?	
Vraag 2. Zou je de beschrijving van maturiteitsniveaus veranderen? Zo ja, welke, hoe en waarom?	
Vraag 3. Zou je domeinen toevoegen/weglaten/ aanpassen? Zo ja, welke, hoe en waarom?	

Vraag 4. Zou je de beschrijving veranderen? Zo ja, hoe en waarom?

A. CM technologieën

1A. Er vindt geen monitoring plaats	

2A. Menselijke observaties (ad hoc) & Basis NDO (ad hoc)	
3A. Structurele en gedefinieerde inspecties met menselijke observaties en basis NDO	
4A. Enkele geavanceerde CM technologieën worden structureel toegepast	
5A. Alle relevante CM technologieën worden gebruikt, optimale combinatie per asset	

B. Assets

1B. Geen	
2B. Assets die vanwege andere redenen geobserveerd worden	
3B. + op een groot deel van de makkelijk te inspecteren assets en alle assets die verplicht zijn om te inspecteren	
4B. + op enkele kritische assets (alle geavanceerde CM technologieën), kritische units (advanced analytics) en grote groepen identieke assets (advanced analytics)	
5B. Op alle relevante assets	

C. etc.

B. Survey: domain expert evaluation of maturity model content

Table 4.10: Survey for domain expert evaluation of maturity model content

	Scale
Maturity levels	
The maturity levels are sufficient to represent all CBM maturation stages (Sufficiency)	strongly disagree (1) - strongly agree (5)
There is no overlap detected between descriptions of maturity levels (Accuracy)	strongly disagree (1) - strongly agree (5)
The maturity levels are understandable (Understandability)	strongly disagree (1) - strongly agree (5)
Domains	
The domains are relevant to CBM (Relevance)	strongly disagree (1) - strongly agree (5)
The domains cover all aspects impacting/involved in CBM (Comprehensiveness)	strongly disagree (1) - strongly agree (5)
The domains are clearly distinct (Mutual Exclusion)	strongly disagree (1) - strongly agree (5)
Descriptions	
The elements described are correctly assignted to their respective maturity level (Accuracy)	strongly disagree (1) - strongly agree (5)
The elements described are relevant to CBM (Relevance)	strongly disagree (1) - strongly agree (5)
The elements described cover all aspects impacting/involved in CBM (Comprehensiveness)	strongly disagree (1) - strongly agree (5)
The elements described are clearly distinct (Mutual Exclusion)	strongly disagree (1) - strongly agree (5)

C. Survey: practical setting evaluation of maturity assessment

Table 4.11: Survey for practical setting evaluation of maturity assessment method

	Scale
Understandability	
The maturity levels are understandable	strongly disagree (1) - strongly agree (5)
The assessment guidelines are understandable	strongly disagree (1) - strongly agree (5)
The documentation is understandable	strongly disagree (1) - strongly agree (5)
Ease of use	
The scoring scheme is easy to use	strongly disagree (1) - strongly agree (5)
The assessment guidelines are easy to use	strongly disagree (1) - strongly agree (5)
The documentation is easy to use	strongly disagree (1) - strongly agree (5)
Usefulness and practicality	
The maturity model is useful for conducting assessments	strongly disagree (1) - strongly agree (5)
The maturity model is practical for use in our industry	strongly disagree (1) - strongly agree (5)
Open questions	
Would you suggest any updates or improvements related to the scoring scheme? If so, please explain what and why.	open
Would you suggest any updates or improvement related to the assessment guidelines? If so, please explain what and why.	open
Would you like to elaborate on any of your answers?	open
Could the model be made more useful? How?	open
Could the model be made more practical? How?	open

D. CBM Maturity Model for asset owners in the process industry

CBM Maturity Model

Voor asset owners in de procesindustrie

versie 2.3 (25-03-2020)

		1 Geen CBM	2 Reactief CBM	3 Gepland CBM	4 Proactief CBM	5 World Class CBM
	Omschrijving	*CBM wordt niet gebruikt*	*CBM wordt ad hoc gebruikt om te anticiperen op storingen*	*CBM wordt structureel en planmatig gebruikt om de efficiëntie van onderhoud te verhogen*	*CBM wordt proactief gebruikt om de betrouwbaarheid en productiviteit van assets te verhogen (reliability perspectief)*	*CBM wordt optimaal gebruikt om de behaalde waarde uit assets te verhogen (asset management perspectief)*
	Waarde	Geen waarde	Lagere onderhoudskosten door het voorkomen van storingen	Lagere onderhoudskosten door minder correctief onderhoud en beter voorbereid onderhoud	Hogere omzet uit productie door hogere OEE en klanttevredenheid en lagere onderhoudskosten door hogere betrouwbaarheid	Hogere ROA en lagere TCO door het verminderen van buffers en het optimaliseren van het gebruik van de assets
Technologie	CM technologieën	Er worden geen CM technieken gebruikt	Makkelijk-te-gebruiken CM technieken worden enkel gebruikt als nader onderzoek	Makkelijk-te-leren en makkelijk-te-gebruiken CM technieken worden structureel gebruikt (proven technologies)	Er wordt structureel onderzocht wat de optimale (combinatie) van CM technieken per asset zijn. Hierbij wordt ook geëxperimenteerd met enkele moeilijk-te-ontwikkelen en moeilijk-te-leren CM technieken	Alle succesvolle CM technieken zijn opgeschaald en worden structureel gebruikt. Er wordt blijvend geëxperimenteerd met nieuwe CM technieken
	Assets	CBM wordt op geen van de assets toegepast	Enkel de assets die vanwege andere redenen geobserveerd worden, maken kans op een verzoek tot nader onderzoek en CBM	CBM wordt structureel toegepast op de assets waarvoor het onderhoud efficiënter uitgevoerd kan worden	CBM wordt ook structureel toegepast op de assets waarvoor de betrouwbaarheid en/of productiviteit verhoogd kan worden	CBM wordt ook structureel toegepast op de assets waarvoor de ROA verhoogd en/of TCO verlaagd kan worden
	Data	Er worden geen analyses uitgevoerd, dus er worden geen data gebruikt	Voor het uitvoeren van de onderhoudsanalyses worden master data en instrument data gebruikt (huidige meting)	Voor het uitvoeren van de onderhoudsanalyses worden ook financiële onderhoudsdata en inspectie- en instrument data uit het verleden gebruikt	Voor het uitvoeren van de reliability- en risico management analyses en het ontwikkelen van CM technieken worden ook procesdata, productdata, omgevingsdata en faaldata gebruikt	Voor het uitvoeren van de productie-, inkoop-, projecten- en ontwerpanalyses worden ook voorraaddata en voorspellingen/toekomstige data van productieplanning, omgevingscondities en marktcondities gebruikt
	IT-infrastructuur	Er wordt niet gemonitord, dus er is geen IT-infrastructuur benodigd	Monitoring gebeurt met draagbare CM systemen	De IT-infrastructuur maakt het ook mogelijk om de CM data op te slaan en de huidige meting te vergelijken met historische data	De IT-infrastructuur maakt het ook mogelijk om procesdata, productdata, omgevingsdata en faaldata te koppelen, zowel voor het ontwikkelen van nieuwe CM toepassingen en voor het structureel gebruiken hiervan	De IT-infrastructuur is gestandaardiseerd, zodat het makkelijk is nieuwe CM toepassingen hierop aan te sluiten. De CM systemen zijn gekoppeld aan productieplannings-, inkoop en procesaansturingssystemen
Organisatie	Strategie & doelstellingen	De organisatie heeft (al dan niet bewust) geen strategie, doelstellingen en KPIs op het gebied van CBM	De organisatie wil het onderhoud verbeteren, maar heeft hier nog geen concrete strategie, doelstellingen en KPIs voor	De organisatie heeft de strategie om onderhoud efficiënter uit te voeren. Onderhoudskosten is de belangrijkste KPI	De organisatie heeft de strategie om de betrouwbaarheid en productiviteit van de assets te verhogen en heeft een CM programma opgestart. De OEE, MTBF en onderhoudskosten/geproduceerd product zijn de belangrijkste KPIs	De organisatie heeft de strategie om de waarde uit de assets te optimaliseren en commiteert zich aan een CM portfolio. ROA, TCO en LCC zijn de belangrijkste KPIs
	Beslissingen	Er is geen informatie over de conditie van assets, dus hier worden ook geen beslissingen op genomen	De bevindingen uit het nader onderzoek worden alleen gebruikt voor het plannen van het onderhoudsmoment	De periodieke informatie over de conditie van assets wordt gebruikt voor (meer) onderhoudsbeslissingen	De hoogfrequente en gedetailleerde informatie over de conditie van assets wordt ook gebruikt voor reliability- en risico management beslissingen	De brede, hoogfrequente en gedetailleerde informatie over de huidige en toekomstige conditie van assets wordt ook gebruikt in een breed scala aan asset management beslissingen, inclusief beslissingen omtrent productie, projecten, inkoop en ontwerp van (nieuwe) assets
	Structuur	Er is geen structuur ingericht voor CBM	Nader onderzoek gebeurt door lokale onderhoudsteams en externe CM dienstverleners	Structurele monitoring gebeurt door een combinatie van lokale CM teams, centrale CM teams en externe specialistische CM dienstverleners. De CM teams werken nauw samen met maintenance engineers	Er is een centraal ingericht CM programma, dat nauw samenwerkt met de interne CM teams en externe specialistische CM dienstverleners. De CM teams werken nauw samen met reliability engineers en process engineers	Het CM portfolio wordt centraal gemanaged. De CM teams worden intensief betrokken bij een reeks aan asset management beslissingen en zijn geïntegreerd in een netwerk van kennisinstituten, fabrikanten van assets en CM technologieën, specialistische CM dienstverleners en data scientists
	Budgettering & capaciteit	Er is geen budget & capaciteit beschikbaar gesteld voor CBM	Er is vooraf geen budget & capaciteit gereserveerd voor CBM, maar er wordt wel budget & capaciteit beschikbaar gesteld wanneer nodig	Er zijn jaarlijkse budgetten & capaciteiten beschikbaar gesteld voor het uitvoeren van CM, het uitvoeren van CBM en het beheren van CM technologieën	Er is een apart CM programma budget & capaciteit beschikbaar gesteld voor het ontwikkelen en aanschaffen van nieuwe CM technologieën. De jaarlijkse budgetten & capaciteiten voor het uitvoeren van CM, het uitvoeren van CBM en het beheren van CM technologieën zijn uitgebreid	Er blijft budget & capaciteit beschikbaar voor het ontwikkelen en aanschaffen van nieuwe CM technologieën. De jaarlijkse budgetten & capaciteiten voor het uitvoeren van CM, het uitvoeren van CBM en het beheren van CM technologieën zijn verder uitgebreid
	Processen & documentatie	Er wordt geen CBM uitgevoerd, dus er hoeven ook geen processen en documentatie ingericht te worden	Er is geen gedefinieerd proces voor nader onderzoek en werk uit inspectie. De documentatie beperkt zich tot de communicatie van de huidige analyse	Er zijn gedefinieerde processen voor het uitvoeren van CBM, die geïntegreerd zijn in de standaard onderhoudswerkprocessen, en het beheren van CM technologieën. Belangrijke documentatie omvat (standaard) inspectielijsten en CM rapportages	Er zijn ook gedefinieerde processen voor het ontwikkelen en implementeren van nieuwe CM toepassingen, het uitvoeren van reliability analyses en modificaties en het evalueren van onderhouds-concepten. Belangrijke documentatie omvat een lijst met kritische assets, FMEAs en onderhoudsconcepten van die assets en CM concepten uit de pilots	Er zijn ook gedefinieerde processen voor het continu verbeteren van het CM portfolio en het gebruiken van informatie over de conditie van assets in beslissingsprocessen omtrent productie, inkoop, projecten en ontwerp van (nieuwe) assets. Belangrijke documentatie omvat een actueel overzicht van de CM technieken die bij elk asset gebruikt worden, een actuele lijst met kandidaten voor CBM en een CM concept per type asset
	Governance	Er is geen governance benodigd voor CBM	Technisch specialisten worden betrokken bij de beoordeling van het nader onderzoek	De CM momenten zijn vastgelegd in een onderhoudsmanagementsysteem, CM procedures zijn gedefinieerd, CM specialisten zijn gecertificeerd en de inspectierapporten worden goedgekeurd door gecertificeerde inspecteurs	Design for reliability en design for maintenance zijn een verplicht onderdeel van projecten, er zijn heldere afspraken met interne en externe partijen over het eigenaarschap en gebruik van data en waar mogelijk wordt gebruik gemaakt van technologische en organisatorische standaarden	Design for monitoring is een verplicht onderdeel van projecten, de organisatie is asset management gecertificeerd en er wordt zo veel mogelijk gebruik gemaakt van technologische en organisatorische standaarden
Mensen	Kennis & vaardigheden	Er zijn geen kennis & vaardigheden benodigd voor CBM	De onderhoudsteams hebben domeinkennis van de assets en zijn in staat om te bepalen of iets 'normaal' is	De onderhoudsteams zijn ook bekend met de basisprincipes van CM technieken, de CM teams beheersen makkelijk-te-leren en makkelijk-te-gebruiken CM technieken	De onderhoudsteams zijn ook bekend met de faalmechanismen van de assets en in staat om FMEAs en RCAs uit te voeren, de CM teams beheersen ook enkele moeilijk-te-leren CM technieken en zijn in staat om nieuwe CM toepassingen te ontwikkelen	De betrokken teams zijn ook bekend met de dragradatiemechanismen van de assets, de effecten van degradatie op productie en de laatste innovaties op CM technologie gebied. Daarmee zijn zij gezamenlijk in staat om het productieproces te optimaliseren en buffers te verminderen
	Cultuur	Er is geen onderhoudscultuur, onderhoud wordt niet als belangrijk gezien	Er is een brandweercultuur, de personen die onverwachte en urgente problemen oplossen worden gezien als helden van de dag. Ook is er een eilandencultuur, de organisatie bestaat uit veel losse teams, zoals onderhoudsteams, productieteams, projectteams, etc., die elk in eerste instantie hun eigen doelen nastreven	Er is een bureaucratische cultuur, binnen de (onderhouds)organisatie heerst sterk de behoefte om procesmatig en planmatig te werken	Er is een reliability cultuur, het verhogen van de reliability wordt vanuit verschillende teams omarmd om de productie te verbeteren, de onderhoudskosten te verminderen en de veiligheid te verhogen. Ook is er een pionierende cultuur, de personen betrokken bij het CM programma houden van het ontwikkelen van en experimenteren met nieuwe technologieën	Er is een asset management cultuur, iedereen in de organisatie voelt zich gedeeld eigenaar van de assets en wil vanuit zijn positie bijdragen aan het optimaal gebruiken ervan, zowel op korte als lange termijn. Ook is er een analytische cultuur, waarin men besluiten wil nemen op basis van actuele en accurate informatie, "meten is weten"

Voor vragen over het CBM Maturity Model of het uitvoeren van een CBM Maturity Assessment, kun u contact opnemen met:

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Afkortingen
CBM: Condition-Based Maintenance
CM: Condition Monitoring
OEE: Overall Equipment Effectiveness
ROA: Return On Assets
TCO: Total Cost of Ownership
LCC: Life Cycle Costs

Figure 4.3: Picture of the CBM Maturity Model

Chapter 5: Discussion

Six years ago, we set out on a journey to identify what is keeping organizations from using CBM. If it is possible technically, interesting economically, and desired by organizations, why is the uptake of CBM still so low?

We identified that the asset owners observed already conducted quite a large portion of their maintenance condition-based. Yet, most of these maintenance decisions were based on visual inspections. The CBM practices of both asset owners could therefore mainly be improved by performing condition assessments with *more advanced CM technologies*. Using more advanced CM technologies improves the accuracy and prediction horizon of analyses (Saxena, Sankararaman & Goebel, 2014) and thus enables better maintenance decision-making. So, the real puzzle is: if it is possible technically, interesting economically, and desired by organizations, why is the uptake of CBM – based on advanced CM technologies – still so low?

Throughout our studies, we have identified several pieces of the puzzle. First, the introduction of CBM and advanced CM technologies can be complex, especially if integration of the technology is costly or introduces risks, and if it is unknown how well the CM technology can detect upcoming failures. It takes time to identify the technology's potential performance with targeted experiments, to integrate the technology into the existing hardware and processes, and to further improve the quality of analyses via processes of learning-by-doing. Second, the diffusion of advanced CM technologies within the firm can be troublesome, especially if the CM technology is complex, expensive and conflicts with existing institutional logics. Moreover, the more the assets and decision-makers are fragmentized across different factories, the smaller the strength and reach of diffusion mechanisms. Within each factory, it takes time to institutionalize the technology's usage, to increase the technology's legitimacy, to increase the technology champion's influence, to gain additional resources for adoption, and to institutionalize further adoption of the technology. Third, the transition asset owners need to make to fully utilize CBM on a larger scale is versatile and elaborate. For example, factories have to identify what assets are suitable for CBM, the IT-infrastructure has to become easily accessible for CM technologies, maintenance engineers have to get well-connected to internal and external CM service providers, decision-makers have to identify how the CM information can best be incorporated into decisions, and the culture has to become CBM-oriented. Again, these processes take time.

If we assume that most advanced CM technologies are recently developed, time also becomes a piece of the puzzle. Since it takes time to introduce a CM technology and to diffuse it within the firm, high levels of diffusion cannot be expected for new CM technologies. Rather, we expect to see an evolution in the usage of CBM, in which technological and market advancements expand the potential scope of CBM applications, and asset owners progressively adopt and diffuse valuable CM technologies. In this evolution, management has an important role to play: when adoption of advanced CM technologies becomes compulsory, expected or taken-for-granted, is supported with an implementation structure and backed up with sufficient resources, usage of the CM technology can take off.

1. Connecting the chapters

If we take a step back, we observe overlap in and connections between the processes described in Chapters 2 and 3, which are then both incorporated in Chapter 4. Appropriately embedding new applications (Chapter 2) is an important step in the overall diffusion process of CM technologies (Chapter 3). In Figure 5.1, we have aggregated the main intra-firm diffusion and performance enhancing mechanisms.

To explore the relationships in Figure 5.1, let's consider an on-line CM technology that is installed at a single asset in a plant. As soon as the CM technology is purchased and installed, the technical fit of similar and co-located assets increases (R1). Parts of the IT-infrastructure can be reused (e.g., cables, databases), new applications can be incorporated within the same software, and the CM specialists have already received their training. As a result, the adoption costs of subsequent applications decrease, increasing the cost-effectiveness of these applications simultaneously (R2). This allows for additional applications within the same adoption budget, and can make new applications economically interesting. Both effects are direct; as soon as the technology is installed, the technical fit increases and further adoption costs decrease.

With each new application, the technology needs to be integrated by the adopting organization (Chapter 2), institutionalizing its usage (Chapter 3). Ingraining the technology into the organization's practices reduces the likelihood of abandonment (R4) and, importantly, allows the technology's performance to increase. By integrating and consistently using the technology, people become proficient and encounter opportunities to further improve the technology (R5). Because the performance is better now, the likelihood of abandonment is further reduced (R6). As we've seen in Chapter 3, increased performance in turn also positively affects

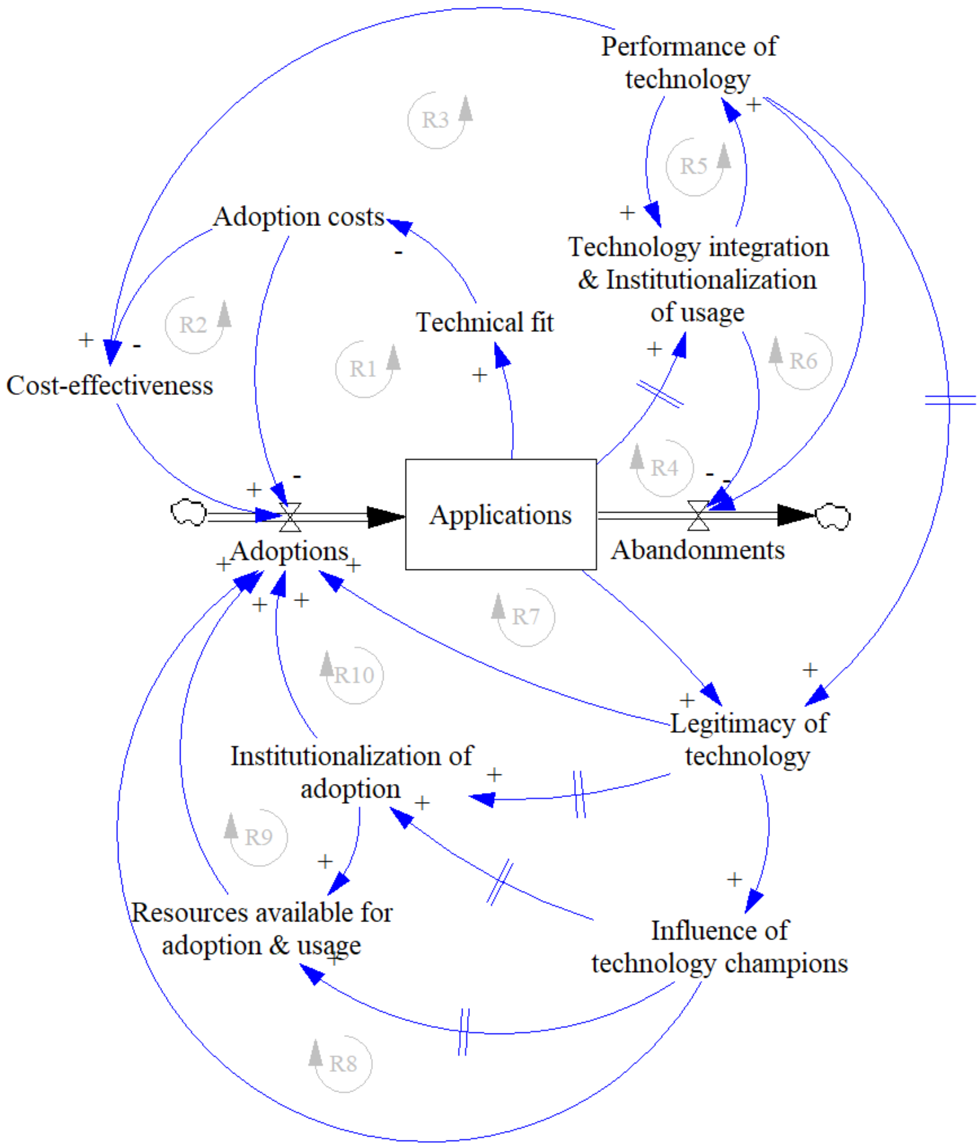

Figure 5.1: Synthesis of main relations from Chapters 2 and 3

Pluses indicate a positive relationship, similar to a positive correlation; that is, if A increases, B increases as well. Minuses indicate a negative relationship; if A increases, B decreases. Two perpendicular lines at the middle of an arrow indicate that the effect is delayed; the underlying process takes time.

In total 10 reinforcing feedback loops can be identified here, corresponding to the mechanisms identified in Chapters 2 and 3: 1. Increased technological fit; 2. Increased cost-effectiveness; 3. Increased technology performance (cost-effectiveness); 4. Institutionalization of usage (abandonments); 5. Further technology integration; 6. Increased technology performance (abandonments); 7. Increased legitimacy of technology; 8. Increased influence of technology champions; 9. Increased resources for adoption and operation, and; 10. Institutionalization of adoption.

further integration of the technology, increasing the value derived from the technology (R3). The length of this integration and institutionalization process can differ substantially between technologies and contexts, depending mainly upon the technological and organizational fit with the adopting context. For example, if a CM specialist decides to apply a new portable CM technology to an asset (s)he was already monitoring, integration and institutionalization requires little effort. If the CM technology on the other hand requires different people to perform new activities, new roles, routines, and governance have to be established – which takes considerably more time.

When the technology’s performance increases, positive experiences and success stories will raise the technology’s legitimacy. As soon a technology becomes a ‘proven technology’, resistance for adoption is reduced[12]. In fact, at both asset owners we’ve observed many instances in which stories of a successful CM technology triggered maintenance engineers and technicians to contact the CM specialist, consulting whether their problem could be solved with this technology as well. Legitimacy of the technology thus forms a pull factor for the technology (R7). In addition, when technologies become more legitimate, the people championing the technology also gain influence (R8). Armed with success stories, it becomes easier for them to convince management to free up additional resources and persuade adoption decision-makers. Thus, also the technology push becomes stronger.

Yet, for many technologies diffusion only took off (or will take off) when additional resources are made available (R9) and adoption itself is institutionalized – when it becomes compulsory, expected or taken-for granted to adopt the technology (R10). For example, at both asset owners we’ve observed that external regulation can be a strong driver of adoption. The establishment of a larger program, aimed at ramping-up the use of one or multiple CM technologies, also enabled fast diffusion, even in instances in which adoption decision-makers were local and dispersed. Taken-for-granted was most observed with “Dr. Bibber”, a vibration monitoring specialist. Whenever a new asset is constructed, the project manager and maintenance engineers turn to him, asking him to design a condition monitoring plan. No business case is needed, no formal procedures are needed, all people involved simply trust his judgment.

[12] Inspector to external CM technology provider: “*We’re not a playground for new technologies. Please come back when your technology is reliable and proven.*”

Thus, the technology's performance plays an important role in the diffusion process, and having more applications of the same technology helps in the learning process and increases the need for appropriate integration. These processes are interrelated, and both are essential in realizing the potential value of CBM.

The CBM Maturity Model (Chapter 4) incorporates these integration and diffusion processes as well.Hardware and process integration, as defined in Chapter 2, take place at every level of maturity; with each new application, the organization's structure might need to be adjusted, resources need to be dedicated, processes and documentation need to be determined, and knowledge, skills and abilities need to be developed. Outcome integration becomes more pronounced at levels 4 and 5, when condition information is also used for reliability, risk management, inventory management, production and project management decisions. Diffusion of easy-to-learn and easy-to-use CM technologies takes place at level 3, but the diffusion processes studied in Chapter 3 become especially important when aiming for level 5 – World Class CBM. At level 4 the optimal combination of CM technologies is being determined for different types of assets, including more advanced CM technologies. At level 5 these optimal combinations are ramped up and fully utilized. Successful diffusion is thus a requirement to arrive at level 5.

2. Theoretical contributions

In this dissertation, we have made several contributions to the literature. These have been discussed in detail in the Discussion sections of each individual chapter, so here we highlight the main contributions from each chapter and of the dissertation overall.

In Chapter 2, we have elaborated on organizational learning theory and Van de Ven, Polley, Garud and Venkataraman's (2008) adaptive learning model, by further exploring how uncertain and ambiguous performance assessments are used in the implementation of new practices and technologies. These theories assume that organizational learning takes place via an ongoing cycle in which task experience is converted into knowledge, that in turn changes the organization's context and affects future task experiences (Argote & Miron-Spekter, 2011). In our case however, a very limited amount of learning-by-doing occurred in the first two years, as the measurements and analyses were not embedded yet. Instead, the project team engaged in learning-by-experimentation (Bohn & Lapré, 2011) to reduce the uncertainty about the technology's potential performance. Based on the insights from deliberate and specific tests, the innovators and management decided upon further technology integration, creating the conditions in which learning-by-doing could take place. So, our study contributes to organizational learning theory by exhibiting the recursive relationship between technology integration and technology performance, by showing that the adaptive learning model can also be applied to the implementation process of practices and technologies, and by providing insight into how innovation decisions are made when the innovation’s performance is uncertain and ambiguous.

In Chapter 3, we have elaborated on diffusion theory and have created the basis for a middle-range theory of intra-firm diffusion. Our multiple-case study shows that diffusion theory can be applied to the intra-firm diffusion process of CM technologies, but only to a limited extent. Intra-firm diffusion processes do not follow the exact same logic as diffusion processes between firms and individuals, mainly due to differences in the nature of the adoption decision (i.e., they are not independent: one decision-maker can make multiple adoption decisions, and resources are shared for adoptions) and the strength of diffusion mechanisms (i.e., uncertainty reduction and threats of non-adoption play a minor role). Yet, in line with diffusion theory, a middle-range theory of intra-firm diffusion of CM technologies should include insight into adoption decisions – how are they made, what is the motivation – and insight into the mechanisms of diffusion – why is the technology adopted by additional potential adopters over time?

Our study showed that intra-firm adoption decisions are based on technical, economic and institutional considerations, and that adoption decisions are often clustered, taken by the same decision-makers, and reliant upon a shared pool of resources. In our cases, the main endogenous mechanisms for diffusion are the institutionalization of adoption, the increased influence of (internal) technology champions and legitimacy of the technology, the increase in resources for adoption and operation, the reduction in adoption costs, and the improvements to the technology’s performance. The strength and reach of these diffusion mechanisms however depends vastly upon the structure of the population, in particular to which extent the assets and decision-makers are fragmentized over different factories.

The main theoretical contribution in Chapter 4 is the overview of technical and – especially – organizational aspects that are relevant for successful deployment of CBM by asset owners. By identifying which of the required elements are understudied (Strategy & goals, Structure, and Governance), we have provided multiple directions for further research here. Of course, the main contribution of this chapter is practical, although multiple scholars have requested for actionable guidance for maintenance organizations as well (Bokrantz, Skoogh, Berlin & Stahre, 2017; Tiddens, 2018).

Overall, our studies have identified that a large part of the potential value of CBM is not captured yet. The challenge is not to perform more maintenance condition-based per se, but to gain better insight in the current and future state of the equipment. This insight can be gained through purchasing new, advanced CM technologies, through increasing the monitoring frequency, or through more widely applying the available set of CM technologies. Our studies have also identified that it is not easy to capture the full potential of CBM – especially not to capture it fast. Proper implementation takes time, diffusion takes time, and building a CBM organization takes time. However, with the insights generated into how diffusion and implementation processes of CM technologies and CBM occur over time, how these mechanisms are interrelated, and why the strength and reach of these mechanisms is limited by organizational fragmentation, we hope to incite further research.

3. Future research

The Discussion sections of the previous chapters have indicated multiple avenues for further research, primarily focussing on new scientific contributions. Here we would like to elaborate on three areas that we believe are especially important to strengthen the usage of CBM.

First, multiple roads lead to Rome. But not every road is equally efficient. In Chapter 3, we've observed multiple strategies – or trajectories – that led to the diffusion of technology. Whether a higher power enforces adoption, whether a lone wolf keeps muddling through (Lindblom, 1959), or whether management creates an implementation structure, each led to the diffusion of CM. Yet the speed of diffusion, as well as the costs of technology implementation and management, differ for each strategy employed. For the integration process of CM technologies and a plant's journey towards CBM maturity, multiple strategies can be envisioned as well. Identifying under which conditions what diffusion, implementation or maturity strategy is optimal can greatly help managers. Lindquist and Mauriel (1989), for example, compared two common strategies for adopting and implementing a management innovation in public schools: a 'depth' strategy, in which the innovation is implemented and debugged first in a test site, and a 'breadth' strategy, in which the innovation is implemented simultaneously across all organizational units. They found – in contrast to conventional wisdom – that the school district that applied the breadth strategy was more successful in institutionalizing more components of the innovation. Three explanations were provided for the success of this strategy. First, top management stayed in control of the innovation. Second, implementing a subset of the innovation resulted in less resistance than aiming to implement the innovation fully. Third, positive evidence generated in the test site was not sufficient to convince all schools to adopt the innovation. Similar studies, comparing two or more strategies in case studies or in a survey-study, might be very helpful in the field of CBM as well.

Second, condition monitoring is not perfect. Neither from the start, nor over time. Most new condition monitoring applications require learning – by machines, by humans, or both –, while over time the performance of condition monitoring is subject to changes in the asset itself (e.g., modifications), to changes in the asset’s operational context (e.g., changes to the operating process or the product specifications), and to changes in the people involved. How then can decision-makers best use the information provided by the CM technology? And what can they do to minimize the fluctuations in performance? One solution could be for decision-makers to calculate the required analysis quality (e.g., sensitivity and specificity) for each type of decision and agree that the decision will only be based on the CM technology if the technology’s sensitivity and specificity are above prespecified levels. But measuring these features can be hard, and costly. We recommend further research to identify how CM technologies can best be integrated in decision-making procedures.

Third, successful employment of CBM requires multiple organizational functions, including *operational functions* – such as measurement, analysis and decision-making (Jardine, Lin & Banjevic, 2006) – and *portfolio functions* – such as experimentation with new CM technologies, implementation of CM technologies and management of hardware, data, and organizational aspects. For each of these functions, two questions are particularly relevant: who is responsible for the function and who is paying for the function? Multiple options exist. Measurement, for example, can be conducted locally by maintenance technicians, centrally by a team of CM specialists, purchased from a CM service provider (i.e., a dedicated CM service provider or an OEM), or automated. Implementation can be paid for by local maintenance teams, a central asset management department, or the project team. What design is optimal then? Several organizational theories, such as transaction cost economics (Coase, 1937; Williamson, 1989) and agency theory (Ross, 1973; Eisenhardt, 1989), make claims about when an activity can best be performed in-house or be purchased from the market. Extending their line of thought, we can assume that the optimal design of the functions depends upon characteristics of the technology (e.g., on-line or portable), as well as characteristics of the adopting organization. Smaller asset owners might not have the same absorptive capacity

(Cohen & Levinthal, 1990) as larger asset owners, as they have fewer financial resources and specialized employees, nor do they have the scale to keep a full team of CM specialists occupied. The type of assets – mobile, network, distributed or concentrated (Smit, 2011) – affect the organization of the maintenance function and, consequently, might also affect the preferred design of the CBM function(s). If we can identify under which conditions designs are optimal and convert these into actionable guidelines, we can help the organizations that are struggling with adopting advanced CM technologies (Bokrantz et al., 2017; PwC & Mainnovation, 2018).

4. Conclusion

Maintenance is important. For many types of industrial assets, maintenance costs represent a large fraction of the total cost of ownership (Van Dongen, 2011). Even more so in countries in which a large part of the industrial infrastructure is reaching its designed technical lifetime, such as the Netherlands (WCM, 2015). Fortunately, digital developments open up new possibilities for condition-based maintenance (Bokrantz et al., 2017; McKinsey, 2015). Many of these developments are driven by suppliers and knowledge institutes. In this dissertation we have explored how – and how fast – asset owners internalize these advanced CM technologies and CBM practices.

While there are multiple ways of organizing the implementation and diffusion of CBM, success consistently depends upon a combination of technical, economic, and organizational factors. When a technology is complex, expensive and conflicts with existing institutional logics, a slow integration and diffusion process can be expected. Technology integration and institutionalization of usage are needed to increase and stabilize the technology's performance and, over time, make the technology gain legitimacy. Institutionalization of adoption is needed to overcome organizational barriers, provide sufficient resources for adoption and operation and truly speed up diffusion. These processes take time. Especially, because the strength and reach of these diffusion mechanisms depend on the structure of the population, in particular to which extent the assets and decision-makers are fragmentized over different factories.

So, even if it is possible technically, interesting economically, and desired by (some in) the organization, the uptake of many advanced CM technologies and CBM practices is slow. Throughout our studies we have encountered multiple good reasons and explanations for a slow implementation process. For example, the performance of many new CM technologies is uncertain, resources for adoption and operation are limited and are competing with other initiatives, and CBM is not perceived yet as a preferred maintenance strategy. Therefore, we expect to see an evolution. An evolution in which CM technologies will gradually become more potent and less costly, in which asset owners experiment with and diffuse an increasing number of CM technologies, and in which condition information is utilized in an increasing number of asset management decisions. Yet, the speed of this evolution can be sped up with the right efforts from management, technology champions and other innovators. The current technological possibilities exceed the current usage of advanced CM technologies, so we believe it's about time asset owners start capturing the full potential of condition-based maintenance.

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Gratitude

If you have made it to the end of this dissertation by reading each chapter, I hope you have gained some valuable insights. If you have made it here by skimming, of course I recommend you to read the dissertation first. There are quite some good insights in there!

Jokes aside, this is the end of the dissertation. The end of a journey. A journey I took off because I was curious towards the world of science, liked the idea of exploring a topic with multiple organizations, and was up to the challenge. As usual, I started optimistic and unprepared. Rather quickly however, I learned that the journey was going to be a lot longer and tougher than I expected up front. Doing longitudinal, qualitative research requires a passive role from the researcher, observing but not influencing, and follows a time-consuming iterative process: asking a question, reading through interview transcripts trying to find an answer to the question, realizing that new interviews are needed, doing the interviews, transcribing the interviews, analysing the interviews, reporting the results to my professors, hearing that the answer is not scientifically interesting enough, so maybe we should ask a slightly different question? Every so many months people have asked me whether I was fed up with my PhD already and, to be honest, sometimes the answer was "yes".

Yet, much more often, I was glad that I engaged in this journey. Over the years I have seen and learned a lot. I have observed technological and organizational innovation first-hand, I have been welcomed by many organizations, and I have learned how to persist and remain productive. In addition, I'm truly happy with the end result. I do think we have succeeded in performing practically relevant and scientifically interesting research, creating insights that can aid maintenance managers and ignite further research. I'm also very much enjoying the jobs I have now, all of which are a direct result from my PhD. Teaching, encouraging organizations in their innovation efforts, and performing some simulations every now and then, sounds like a perfectly crafted work week to me.

So, I am grateful. To quite a lot of people actually. This is also one of the benefits of doing qualitative research: while you do most of the walking by yourself, you meet a lot of interesting people and views along the way. Therefore, I'd like to spend the remainder of my dissertation expressing my gratitude to the people that I met along the way, who provided me direction, walked beside me and provided me with food to continue the journey.

First, Niels and Henk, thank you for the scientific guidance. The two of you form an excellent team. Niels, thank you for carefully reading my pieces, for challenging me repeatedly to take a more distant, theoretical perspective, and for introducing me to many theories. Thanks to you, I have developed a better sense of what theory is (and what is not, yet), what good scientific writing is, and what a conundrum is. I hope to further pursue the development of theory in the years to come. Henk, thank you for motivating me in times when I needed it most, for teaching me many things, and for the opportunities you have created. Thanks to you, I was able to perform my research at BP and Tata Steel, I have become a project leader and an entrepreneur, and I can write proper introductions now (A. The topic, B. What is known, C. What is not known yet, D. What are we going to do about it). I have to admit, quite often my heart skipped a beat when you said "wait, too much detail, let's go back to the main question". But quality comes first, time and budget second.

Members of the committee, thank you for your valuable feedback during and after the predefense as well. In particular I'd like to express my gratitude to Simme Douwe, for the extensive and detailed feedback during our additional sessions, Akhil, for the recommendations on how to best publish the work, and Leo, for indicating the relevance of the findings for other industries. The second version of the manuscript is written for a broader audience, has a better structure, and has clearer theoretical contributions.

Vijay and Nico, thank you for the practical guidance. I know I have tested your patience at several occasions, but the fact that both of you kept supporting me, meant a lot to me. It took me about four years to draw some proper conclusions from our longitudinal studies, slightly later than I wrote down in my first (, second, and third) project plan. Vijay, thank you for introducing me to the world of maintenance and reliability, for challenging the usefulness of CBM, and for listening to my struggles during our coffee breaks. Nico, thank you for sharing your experiences about the dynamics of organizations ("opa vertelt"), for your aid and guidance in the development of the maturity model, and for enabling and encouraging me to share the findings.

Throughout my research, I have been in touch with more than 170 people from BP and Tata Steel, having more than 400 recorded conversations and interviews. First, each and every one of you, thank you for participating in the research. In the upcoming weeks, I will share the results and main lessons in an easy-to-read format. If you have any questions about the results, about Condition Based Maintenance, or

about research in general, feel free to contact me (r.m.vdkerkhof@tilburguniversity.edu). I’ll happily make some time to aid you in return.

Of course, some people I visited more frequently. Ronald, Nick, and Frank, thank you for sharing your experiences with the implementation process of a novel CM technology. I think you have done an excellent job in making this a successful application. Think big, start small. Henk, Chris, Annemarie, Klaas, Dennis, Anne, Tom, Peter, Rob, Ronald, Ronald en Frank, thank you for sharing your experiences with the ramp-up process of a CM technology. While some CM technologies have ramped up faster than others, I see potential in all of the technologies and in the people championing it. Although current economic times are challenging, I hope all of you, and BP and Tata Steel, will be well.

Doing research is nice. Doing research together is nicer. Over the past 6 years, I think I enjoyed doing research the most when I could work together with students. Marlon, Chanella, Pieter and Jos, thank you for studying multiple cases. Your work has been included in Chapter 3. Of course, I’m thankful that you conducted and transcribed multiple interviews, but I’m especially grateful of our discussions about the study design. Very few ideas are perfect right away, so having multiple critical and upright students questioning your ideas helped me in improving them. Dave and Alonso, thank you for solving particular problems. Your work has been included in Chapter 4. More importantly, your work has bridged the gap between science and practice. While I was occupied with doing research, you have translated the insights from this research into practical tools that can be used by organizations.

Colleagues, thank you for keeping me motivated and optimistic. Your remarks that “Good work needs time” made me feel relieved, that “Life after PhD is so much better” made me feel hopeful, and that “Feng is almost finished, are you as well?” made me feel energized. A special shout-out goes to the PhDs. I think we are blessed with a cohesive group of good people. If you want to complain about your PhD, there’s always someone available. If you want to talk about anything but your PhD, there’s always someone available. And if you want to celebrate that a job is done, there are even more people available. Having Sinterklaas together, eating hotpot and BBQs together, canoeing together, drinking whisky together, going to conferences together, and so on, are the warmest memories of my PhD.

One of the risks of a PhD is that most of the work can be done anywhere, anytime. In the evenings, during the weekends, during holidays. Family and friends, thank you all for keeping my agenda occupied in the evenings and the weekends, so I could

avert this risk. I believe that if one has a good balance in life, one can also be more productive. Weekend trips, tennis events, (walking) dinners, sports, parties, good talks, and so on, provided me with this balance. So, thank you for distracting me and making life colourful!

Before closing this dissertation, there are three more groups of people I want to thank in particular. First, my paranymphs. Feng, my older brother, congratulations on finishing your PhD in record speed. I very much enjoyed our time together as roommates and am still very much enjoying our time together as business partners. You’re a good man, a great cook, and the best Chinese dancer I’ve seen so far. I hope the future holds many more BBQs and ganbeis for us! Coco, my source of wisdom, thank you for enhancing my self-awareness, for showing me how to do business, and for the laughter after a long day of study/work. You’re one of the people who have had a very positive and (hopefully) lasting impact on my life. You’re a strong woman, a decent cook, and the person with the coolest phone cover I will probably ever see. When life gives you lemons, make lemonade. Lars, please take good care of her.

Parents, Harold and Tabita, thank you for your unconditional love and support. You have always been there for me, have always been interested in what I was working on (or at least pretended to be), and have shared the joy of completion. Your statement “use your capabilities” has turned into one of my core principles in life. Knowing that you are proud at what I’m doing has definitely helped me continuing the journey. Bert and Corine, thank you as well for your support throughout the process and the retreats in the Sunny South.

Sabine, the love of my life, at our wedding I’ll make a more romantic speech. Here I especially want to thank you for challenging me, for cheering me up when I was down, for providing me with charity when I was broke, for taking me on writing holidays, and for encouraging me to go see friends in the evenings. Life is good with you. With a PhD, having a partner that understands the process you are going through is valuable. Although we have been walking on different journeys, we were walking side by side.

So, this is it. The completion of my dissertation. I started this journey without knowing whether I was suited to be a researcher or not. Now, by the end of this journey, I still think I am not a typical researcher (if there is something as a ‘typical researcher’). Yet, time has taught me that there are multiple ways of doing research. Personally, I like to explore, I like to teach, and I like to help others. These features might very well be combined with practically relevant research. Maybe even with developing a proper grounded theory. So, I’m open for further exploration. If you encounter an interesting question – a conundrum – that you want to explore together, feel free to contact me!

Appendix

A. Definitions of main concepts

Table A1: Definitions of main concepts

Concept	Definition
Asset Management	Coordinated activity of an organization to realize value from assets. Realization of value will normally involve a balancing of costs, risks, opportunities and performance benefits (ISO 55000:2014).
Condition-Based Maintenance (CBM)	A proactive maintenance strategy that aims at predicting future malfunctions by monitoring several conditions (e.g., temperature, vibrations), so the maintenance can be executed at 'just the right time' (Jardine, Lin & Banjevic, 2006).
CBM maturity	A state in which an asset owner makes optimal usage of CBM. In particular, when an asset owner has reached CBM maturity, the asset owner applies the optimal combination of CM technologies that are currently available to all assets that could benefit from CBM and optimally uses the information provided by these CM technologies.
Condition Monitoring (CM)	The process of assessing an asset's current and/or future condition, which can be done by acquiring and processing data (ISO 13372:12). Monitoring the condition of an asset can be done with one or multiple CM techniques.
CM equipment	The set of hardware and software that is used to monitor the condition of an asset, such as a portable vibration monitoring system (to perform the measurement) with a complementary software package (to analyse the data).
CM technique	A method to monitor the condition of an asset, such as human senses, vibration monitoring, oil analysis, and physics-based models (Moubray, 1997; Tinga & Loendersloot, 2014). With the exception of human senses, all CM techniques rely on CM equipment.
CM technology	The practical application of knowledge on how to monitor the condition of an asset; the sum of equipment, techniques, skills, and processes used in Condition Monitoring.
Cultural-cognitive institutions	The shared conceptions that constitute the nature of social reality and the frames through which meaning is made (Scott, 2008).

Data performance potential	How good the data can be; whether it is possible to generate useful and complete data.
Hardware integration	A type of technology integration in which the technology is integrated in the organization's existing technology, for example by connecting the monitoring system to the existing IT-infrastructure, initiating the transfer of data to existing databases, and automating measurements.
Institutional logic	The socially constructed, historical patterns of cultural symbols and material practices, including assumptions, values and beliefs, by which individuals and organizations provide meaning to their daily activity, organize time and space, and reproduce their lives and experiences (Thornton, Ocasio & Lounsbury, 2012).
Intra-firm diffusion	Intra-firm diffusion is the process by which over time more members within the firm adopt an innovation, and thereby drives the extensiveness with which an innovation is adopted by the firm (Mansfield, 1963).
Maturity model	A model that describes how organizational capabilities evolve in a stage-by-stage manner along an anticipated, desired, or logical maturation path (Pöppelbuß & Röglinger, 2011).
Normative institutions	Values (conceptions of the preferred or the desirable) and norms (specify how things should be done) (Scott, 2008).
Outcome integration	A type of technology integration in which the outcome of the CM technology – the condition assessment – is integrated in (maintenance) decision-making procedures.
Process integration	A type of technology integration in which the technology is embedded in the organization's processes, for example by incorporating measurement and analysis activities in procedures and routines, and agreeing upon roles and responsibilities.
Regulative institutions	The "rules of the game" that are sanctioned by powerful actors (Scott, 2008).
Technology integration	The process of managing the acquisition and incorporation of technology (Karlsson, Taylor & Taylor, 2010), starting with the decision to acquire a given technology and concluding when the technology is fully utilized by the adopting organization (Stock & Tatikonda, 2000; Edmondson, Bohmer & Pisano, 2001).

B. List of abbreviations

Table A2: List of abbreviations

Abbreviation	Word or phrase
AO	Asset Owner
CBM	Condition-Based Maintenance
CM	Condition Monitoring
CMG	Condition Monitoring Group (Chapter 2)
CMMS	Computerized Maintenance Management System
CM technology	Condition Monitoring technology
I drive/resistance	Institutional drive/resistance (Chapter 3)
IT	Information Technology
KPI	Key Performance Indicator
MRO	Maintenance, Repair and Overhaul
NDE	Non-Destructive Evaluation
OEM	Original Equipment Manufacturer
R&D	Research and Development
SMEs	Small and Medium-sized Enterprises
SPC	Statistical Process Control
SPM	Shock Pulse Method (Chapter 2)
T-E drive/resistance	Technical-Economic drive/resistance (Chapter 3)

C. List of figures

Table A3: List of figures

D. List of tables

Table A4: List of tables

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The essays collected in this PhD thesis revolve around a central puzzle: *if it is possible technically, interesting economically, and desired by organizations, why is the uptake of Condition-Based Maintenance still so low?* The first essay zooms in on the introduction process of CBM based on a new Condition Monitoring technology, shedding light on the decisions that have to be taken in the introduction process and why these are not easily (nor quickly) taken. The second essay addresses the intra-firm diffusion process of twelve CM technologies and identifies the technical, economic and institutional factors that explain the (low) speed of ramping up the technologies' usage. The third essay builds upon the findings of the first two and develops a CBM Maturity Model that helps asset owners to visualize their desired end state and analyse the transition that is required to get there.

If we assume that most advanced CM technologies are recently developed, time also becomes a piece of the puzzle. Since it takes time to introduce a CM technology and to diffuse it within the firm, high levels of diffusion cannot be expected for new CM technologies. Rather, we expect to see an evolution in the usage of CBM. An evolution in which CM technologies will gradually become more potent and less costly, in which asset owners experiment with and diffuse an increasing number of CM technologies, and in which condition information is utilized in an increasing number of asset management decisions. Yet, the speed of this evolution can be sped up with the right efforts from management, technology champions and other innovators.

Roland van de Kerkhof (1991) received his Bachelor degree in Industrial Engineering (2011) and Master degree in Operations Management & Logistics (2013) at Eindhoven University of Technology. After that, he started as a PhD candidate at the department of Information & Supply Chain Management at TiSEM, Tilburg University. He currently is a teacher at Tilburg University, project leader at World Class Maintenance and the Logistics Community Brabant, and the chairman of a system dynamic modelling cooperation.

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