A maturity model for valuable maintenance data management

Abstract

The increasing data provide new opportunities for data-based maintenance management. However, decision makers are struggling to harvest optimally value from their data. This paper presents a maturity model to support analysing maintenance data management processes from the value perspective. Maturity models related to data management and business intelligence have been presented before, but they have not addressed the specific features of maintenance, and have not analysed what makes data valuable. The model presented in this paper categorizes value of data into six dimensions, and defines five maturity levels to assess them. A real-life industrial case example is presented to demonstrate the use of the model. The model takes into account that the most advanced data management solutions do not always represent the optimal target level for every situation. For instance many small and medium enterprises would struggle creating enough additional value from big data to make the required investment profitable.

Keywords

Maturity model; Maintenance; Value; Data; Information; Strategy; Decision support; Case study

1 Introduction

Following the recent technological development (related to e.g. sensors, cloud computing, and big data), the role of data in maintenance decision making is ever increasing. Information management is recognized as an important part of asset management (BS ISO 55000, 2014). However, in practice the adoption of new data-driven technologies and maintenance service concepts has been limited. Most organizations have for more data than they can analyse and use, but still they do not have all the data actually required in their maintenance decision making (Levitan and Redman, 1998; Raguseo, 2018; Tiwari et al., 2018; Thirathon et al., 2017). In particular, small and medium –sized enterprises (SMEs) have very limited resources and need to evaluate carefully how to get the best value out of their maintenance data management process.

This paper examines the requirements of successful data exploitation in industrial maintenance, and presents a maturity model to support companies in developing their preparedness in making the most of the data available to them in their maintenance decision making. Wendler (2012) conducted a systematic review of maturity models, and concluded that while the majority of the existing models focus on software engineering, there is also a variety of other application domains including, for example, information management, process management, and business intelligence. Maturity models related to e.g. maintenance (see Chemweno et al., 2015; Hauge and Mercier, 2003; Macchi and Fumagalli, 2013), business intelligence (see Carvalho et al., 2019; Rajterič, 2010), and Industry 4.0 (see Comuzzi and Patel, 2016; Schumacher et al., 2016) exist, but the topics have been addressed in an isolated manner. In addition, the previous models tend to assume that more data (with advanced data analytics) is always better. This is in line with Proença and Borbinha (2016), who state that one of the common limitations to the existing maturity models is their tendency to ignore potential alternative paths to increase maturity.

In this paper maintenance data and data analytics are studied from the value perspective. In addition, data management strategies not based on big data are considered. The objective of the paper is to design a maturity model for supporting companies in valuable data-based maintenance decision making. An empirical case example is presented to demonstrate the use of the model. The next section discusses the selected research design. In section 3 the maturity model is built based on a literature review. Section 4 present the industrial case example, and the paper finished with conclusions in section 5.

2 Research design

In this paper a maturity model for valuable maintenance data management is designed and provisionally tested with an empirical case example. According to Wendler (2012), maturity models are used to describe the development stages of e.g. processes, functions, or human beings, thus providing a way to measure and improve their quality. Maturity models originated in software engineering, but they have been applied in a variety of fields. This section is written based on the process for developing maturity models presented by De Bruin et al. (2005).

2.1 Determining a scope

The first phase in creating a maturity model is to determine a scope. The decisions to be made at this stage include defining the model as domain specific or general, and identifying the stakeholders to be involved in the development of the model. A maturity model can be descriptive (assessing the current state with no input for improving maturity), prescriptive (enables building a domain-specific roadmap for the future), or comparative (benchmarks maturity across regions or industries) (De Bruin et al., 2005). The research need and the way data creates value in maintenance is domain specific, and the practitioners are in need of tools to support the maturity improvements in the future. Thus the model presented in this paper is a prescriptive model specific to the maintenance domain. The development stakeholders of the model include academia and the industrial case company, a tier-one automotive parts supplier in the UK.

2.2 Determining an architecture

The model architecture should be built on user needs. The decisions to be made include e.g. defining the intended use (internal or external), the users (management, staff, customers, etc.) of the model, and defining the drivers of organizations to apply the model (De Bruin et al., 2005). Kohlegger et al. (2009) have analysed the design parameters of a sample of maturity models. In their sample, most models were intended for organizations' internal assessments. In the maturity model development presented in this paper, the user needs are related to the internal data processing challenges faced by the maintenance manager of the case company. The maintenance manager identified several problems in the maintenance data management process (for example wrong data, poor quality, slow process) and the organization joined in a research project to study how the data could be better exploited to increase the business value of their maintenance function. Developing this maturity model is one part of this research project.

2.3 Defining the content

The next phase regards to defining the criteria and metrics to assess the maturity of the selected object. The two basic components of maturity models are *maturity levels* and the measured *dimensions*. The *maturity levels* simplify the development stages of the object into a set of sequential, progressive levels (Wendler, 2012). Often the maturity levels are defined based on a five-point Likert scale (De Bruin et al., 2005). Wendler (2012) distinguishes maturity models with a defined evolution path approach (the target is to reach a final maturity level which has been well defined) from those with a potential performance perspective (each maturity level has a different value creation potential and the optimal level depends on the situation).

The *dimensions* are criteria used to measure the maturity and development of the object. Maturity models can be one-dimensional, providing a simple way of assessing maturity but not giving much insight on how to improve, or multi-dimensional, if the maturity of a number of specific dimensions is assessed (De Bruin et al., 2005; Wendler, 2012). The dimensions should ideally be comprehensive and mutually exclusive. If the domain is mature, the components can be identified through a literature review (De Bruin et al., 2005). In a study by Kohlegger et al. (2009), most models were based on literature reviews.

Our multi-dimensional model is built on five-point scale maturity levels with the potential performance perspective. This is an important part of the design of the model, as we suggest that the ideal maturity of maintenance data management is case dependent. A literature review was conducted to identify the dimensions for assessing the value of maintenance data management processes on different levels of maturity.

2.4 Model testing

According to De Bruin et al. (2005), the validity, reliability and generalisability of the model should be tested through e.g. focus groups, surveys, or application in case organizations. Wendler (2012) see testing by e.g. proof of concept or empirical applications as part of the design science approach. In the study of Kohlegger et al. (2009), part of the studied maturity models was supported by assessment models with data from interviews, questionnaires, or documented data from the partner organizations. In this study a real-life industrial case example is used to show how the developed maturity model can support organizations in understanding their current state and developing plans for the future. The assessment data was collected through an interview of the maintenance manager of the case company, as well as from the company's selected production plant's maintenance and breakdown times from 1st January to 22nd June 2018.

2.5 Deployment and maintenance

The last phases of maturity model development include model deployment and maintenance. The stakeholders taking part in the model development are usually the first adopters, but until also independent organizations have deployed the model its generalisability can be questioned. As for the maintenance of the model, the model needs to be updated as the domain knowledge develops. Prescriptive models should also be supported by longitudinal studies to analyse the success of the interventions to improve maturity (De Bruin et al., 2005). As important as this phase is, it is left out of this paper due to practical reasons. Longitudinal case studies, more extensive deployment, and model updates are important topics for future research.

3 Requirements and maturity levels of valuable maintenance data exploitation

This section presents a literature review to define the value dimensions and difference maturity levels in valuable maintenance data management. Data analytics is not a new topic regarding the existing maturity models. According to Carvalho et al. (2019), although a number of analytics and business intelligence –related maturity models already exist, new ones are continuously needed due to the constant pressure to evolve faced by organizations. Intelligence can be defined as exploiting valuable data to support decision making, while not drifting towards information overload (López-Robles et al., 2019). Intelligence as a research field is growing, and the key terminology is developing with terms such as “business intelligence” and “competitive intelligence” gaining more attention. Brooks et al. (2015) state that most of the existing business intelligence maturity models are generic and do not focus on any particular business domain. This limits the models’ application to the requirements and features of specific industries and their decision-making needs. Božič and Dimovski (2019) state that an organization’s absorptive capacity plays a key role in transforming the business intelligence information into valuable knowledge. They understand absorptive capacity as a domain- and company-specific ability to recognize the value of information and turn it into business. Therefore, domain-specific maturity models are required.

Kaner and Karni (2004) have summarized literature on business process and knowledge management –related maturity models. Typical factors considered in these models include e.g. awareness of maturity, process type, process operation (ranging from ad-hoc to optimizing), process integration (ranging from independent to synergetic), process enactors (ranging from individuals to organizations), performance metrics and measurement, knowledge representation, and knowledge management. In their own decision-making capability maturity model, Kaner and Karni (2004) define four attributes (formality, foundation, assessment, and feedback) on different maturity levels of decision making. Another example is the business intelligence maturity model by Hewlett-Packard (HP, 2007), where information management, strategy and program management, and business enablement come together to form the basis of successful business intelligence. It is interesting how they have defined various maturity levels of information, for instance they connect the term “information” with monitoring, whereas “insight” includes a certain level of intelligence. Shi and Wang (2018) present maturity levels for the integration of business transactional data and big data. The three levels are called “Defender” (a conservative approach aiming for continuous incremental improvements), “Analyzer” (a balance between continuous improvement and disruptive innovations), and “Prospector” (focus on experimenting to find revolutionary innovations). An organization can have various maturity levels in their different business functions. Chuah (2010) presents enterprise business intelligence management as a function of data warehousing, data quality, and knowledge processes.

Comuzzi and Patel (2016) have presented a big data maturity model, built on five dimensions: 1) strategic alignment, 2) data, 3) organization, 4) governance, and 5) information technology. Arunachalam et al. (2018) discuss big data analytics capabilities and highlight the role of data generation capability, data integration and management capability, advanced analytics capability, data visualization capability, data-driven culture, cloud computing capability, and absorptive capacity. The monetary value of e.g. faster availability of better information is challenging to evaluate. Rajterič (2010) suggests using maturity models to assess the return on investment of business intelligence.

Parra et al. (2019) have presented a maturity model for assessing the information-driven decision-making processes of organizations. The original model is called the Circumplex Hierarchical Representation of the Organization Maturity Assessment (CHROMA), whereas a Simplified Holistic Approach to DMP Evaluation of the CHROMA model (SHADE-CHROMA) is intended especially for information-driven SMEs. Both models measure five dimensions: data availability, data quality, data analysis and insights, information use, and decision making. While models like CHROMA contribute to the maturity of data-based decision making, they do not assess the value (the benefits with relation to the costs) of the process.

Another topic interesting for the purposes of this paper is digitalization and Industry 4.0. Existing maturity models for digital transformation capabilities have been discussed by Bansmann et al. (2019). They highlight the importance of a holistic view, where aspects like leadership, human resources, corporate culture, and collaboration are taken into account in addition to the technical skills and tools. Mettler and Pinto (2018) have studied digital maturity as a learned ability of an organization relative to its environment and time. In their research on the digital maturity of hospitals, they found out that a large share of the existing research simply connects digital maturity with the ability to transition from paper-based systems to electronic ones. However, in addition to the existence of technological solutions also aspects like data integration, quality, and governance have been emphasized.

Schumacher et al. (2016) defined a maturity model for adopting Industry 4.0. Similarly to the view of Bansmann et al. (2019), they adopted a holistic view with 9 specific dimensions included into the model: strategy, leadership, customers, products, operations, culture, people, governance, and technology. Industry 4.0 readiness has also been analysed by Castelo-Branco et al. (2019). They concluded that the two main dimensions of Industry 4.0 readiness are 1) the existence of digital Industry 4.0 infrastructure, and 2) big data analytic capabilities. Both are needed in order to create value through digitalization. This supports our paper's view on that big data does not always create big value.

Regarding maintenance, quality (and maturity) is usually understood as the systematic prevention of asset faults and failures (Oliveira et al., 2012). However, this view is closely linked to advanced maintenance strategies with focus on predictive maintenance, and not all organizations are, nor should they be, pursuing a highly sophisticated maintenance management process. BS ISO 55001 (2014) recommends organizations to determine their asset information requirements in terms of attribute and quality requirements, as well as defining the processes to collect and analyze the identified information.

Maturity models have also been applied to maintenance. Macchi and Fumagalli (2013) developed a generic maturity model for maintenance, with maturity levels: 1) Initial, 2) Managed, 3) Defined, 4) Quantitatively managed, and 5) Optimizing. Another generic maintenance maturity model was presented by Chemweno et al. (2015). Hauge and Mercier (2003) presented a reliability-centred maintenance maturity model, where the maturity levels range from Initial (ad-hoc maintenance processes dependent on individual effort and skills) to Continuous improvement (an integrated, innovation and technology –driven enterprise system with quantitative and qualitative feedback loops).

Despite the several existing maturity models on business intelligence, digitalization or maintenance, there are no domain-specific maturity models on maintenance data management. The existing models also tend to assume that bigger data, advanced analytics, and sophisticated technological solutions lead to better end results by default. However the level and success of data exploitation should not be assessed based just on the amount of data and advanced technological solutions, but based on the value of the collected and processed information. According to the view of Bucherer and Uckelmann (2011), the value of information services is built on having the right information, in the right amount, quality, format, time, place, and for an appropriate price or costs. The maturity model presented in this paper is based on this view. The dimensions of information value are discussed in the following subsections, after which the maturity model is presented as a summary of the section.

3.1 Right information

The first prerequisite for information to be valuable is to collect the right information. Asset management information has been defined as *"meaningful data relating to assets and asset management"* (PAS 55-1, 2008, p. 2). BS ISO 55002 (2018) states that the asset management information requirements of an organization depend on *"…the criticality and value of the information to enable decision making, relative to the cost and complexity of collecting, processing, managing and sustaining the information"*. Typical information valuable for asset management purposes includes e.g. asset identification and description, asset use and criticality, performance data, specific risks and requirements, commercial and contractual information, as well as financial information.

As reminded by Koronios and Lin (2007), modern organizations are often drowning in data without always being able to find valuable information. This is why PAS 55-1 (2008) recommends promptly removing obsolete asset management information from the data management process. But what does obsolete information mean? In statistical data analyses, sample size is of course important to ensure the statistical power of the analyses and to avoid type II errors (Yeh et al., 2012). According to PD ISO / IEC TR 38505-2 (2018), the advances in data management technologies have made extracting value from big data an economically feasible option for an ever increasing share of organizations. However, whether or not to pursue this value depends on the data strategy, and the data risk appetite of the company. Big data offers potential value, but it also requires a lot of resources.

In general, evidence-based decision making utilizes four types of analyses (Cech et al., 2018):

1) Descriptive (aims at analyzing what has happened and what is happening),
2) Diagnostic (aims at analyzing why specific events have occurred),
3) Predictive (aims at analyzing what will happen in the future), and
4) Prescriptive (aims at analyzing what kind of interventions should be done to achieve a specific outcome in the future).

These four types are well in line with the different maintenance approaches: corrective maintenance focuses on restoring asset functionality after failure, predetermined maintenance tries to prevent failures, whereas condition-based maintenance monitors the actual condition of the asset to define the optimal maintenance action (BS EN 13306, 2017). It is generally acknowledged that while condition-based maintenance results in the least amount of asset failures, it is also costly and requires a lot of data, skills and resources and for this reason is not the optimal maintenance type for all situations. Similarly it can be said that conducting prescriptive analyses would result in the best understanding of the studied phenomena, but the data and resources required are significant and not always exceeded by the additional value in decision making.

Small and medium sized enterprises (SMEs) are an example of a group of companies that should carefully consider whether it is beneficial for them to adopt big data in their decision making. The digitalization and Industry 4.0 –related challenges faced by industrial SMEs are discussed by Hobscheidt et al. (2019). They conclude that even though the potential impact of the digital transformation for their business is widely acknowledged, in general SMEs are struggling to identify the technical solutions most suitable for their needs and that quite often the solutions applied by large, digitally advanced companies are not even applicable to SMEs. For instance Sharpe et al. (2019) refer to a study in 2016 where 56% of the studied manufacturing companies in the UK had little or no understanding at all of the technological solutions related to Industry 4.0. Mittal et al. (2018) discuss the typical features of SMEs (e.g. scarce resources, low technology maturity, limited software umbrellas, not much research and development, specialized products, and many outsourced functions) and their impact on the organizations' ability to adopt smart manufacturing. Most of the existing studies assume that the evolutionary path of SMEs is similar to that of larger companies, and in most maturity models level 1 already assumes that the company is aware of and has access to resources such as ICT systems and interconnected assets. In practice many SMEs would first have to tackle fundamental issues like personnel training, change of mind-set, and infrastructure development.

For organizations that choose to extract value from big data, Grossman (2018) has presented an Analytic Processes Maturity Model (APMM) which evaluates the maturity of six processes: 1) building analytic models, 2) deploying analytic models, 3) managing and operating analytic infrastructure, 4) protecting analytic assets through appropriate policies and procedures, 5) operating an analytic governance structure, and 6) identifying analytic opportunities, making decisions, and allocating resources based upon an analytic strategy. The maturity levels of APMM range from (1) building reports and (2) models to (3) repeatable analytics, (4) enterprise analytics, and finally (5) strategy-driven analytics. However, models like APMM do not consider the situations where big data is not the preferred option. An interesting maturity model, in the area of Lean and Green, has been presented by Reis et al. (2018). In the model, the maturity levels of leanness progress from being unaware of the waste to using isolated and standardized indicators and objectives to finally carrying out proactive improvements. The lean maturity model presented by Jørgensen et al. (2007) is built on somewhat similar maturity levels, however they have added the perspective of the inter-organizational manufacturing value chain to the highest level of maturity. A logic similar to these two models can also be applied in striving for the right information in maintenance data management, because unnecessary information can be seen as waste and in that sense the data management process should be lean. The maintenance data management process should be developed to ensure it produces the right information to the decision makers.

There are some challenges in measuring how lean specific processes are. Nesensohn et al. (2014) discuss some of these issues in maturity models which measure leanness. *First of all*, in practice full maturity cannot be reached but it is necessary to set an ideal target to support the development of the organization. *Secondly*, leanness is often measured through the use of various lean tools and methods, even though this does not reveal if the organization actually is lean or not. For example Liu et al. (2017) state that the application of lean tools is a highly subjective and case dependent process, which fails to accurately reflect the state of lean maturity in the organization. Jørgensen et al. (2007) point out that most lean implementation models focus on measuring the horizontal progression of lean in the organization (application of lean tools in different organizational areas), whereas the vertical progression (the depth and performance achieved through applying the lean tools) has been measured considerably less. *Thirdly*, maturity models tend to assume that the target state, and the optimal path to reach it, is the same for every organization. However, according to Anvari et al. (2011) the optimal lean tools to be implemented are highly dependent on e.g. the production type (mass production vs. customization) and the industry of the company in question.

3.2 Right level of detail

For data to be valuable it has to be reliable and accurate enough. If the decision makers cannot rely on the quality of the data, they often end up not using the data and making decisions based on their judgment (Koronios and Lin, 2007). BS ISO 8000-8 (2015) differentiates syntactic, semantic, and pragmatic quality of data. The first two categories are related to meeting the requirements set by the metadata and the represented phenomenon, whereas pragmatic quality refers to the suitability and value of the data for a specific purpose. Closely linked to the pragmatic dimension, literature often defines data quality as *fitness for use*, defined as a combination of attributes such as accuracy, consistency, completeness, and timeliness (Ardagna et al., 2018) as well as some more subjective criteria such as the reputation of data sources (Sampaio et al., 2015). Measuring the fitness for use is highly subjective, as the quality sufficient for one use might not be enough in other decision-making situations (Baskarada et al., 2006). For traditional databases, various algorithms for assessing and improving certain technical attributes of quality of data exist (Song et al., 2017). However the variety, volume and unfamiliarity of big data pose new kind of challenges, and traditional data cleaning processes are not applicable (Ardagna et al., 2018; Sampaio et al., 2015).

Another view has been presented by Ryu et al. (2006), who differentiate the depth of data quality (including the attributes discussed above) from the width of data quality (integrated data quality with regard to structural integration and consistency, including data standardization and architecture management). They present a data quality management maturity model where the two lower levels include the management of just the depth of data quality, and the two higher levels also include the width of data quality on the enterprise level, contributing to dimensions such as reusability and discrepancies. To support integrated enterprise data quality, BS ISO 8000-61 (2016) recommends defining processes for managing data quality, and improving the processes by systematically identifying and removing the root causes of poor quality data. Data quality should not be the responsibility of just the end users of the data. Also data administrators and senior management have to be involved in terms of embedding quality management processes across the organization and ensuring the availability of the required resources (BS ISO 8000-61, 2016).

Maintenance and asset management are often not considered part of the organization's core business, which causes the processes to be poorly defined and the data to be of poor quality. Despite the recurring problems in information quality, information cleansing is rarely included in the existing asset management information systems (Baskarada et al., 2006; Madhikermi et al., 2016). In their study Madhikermi et al. (2016) present a maintenance reporting quality assessment dashboard, including criteria customized to the maintenance context such as believability (reflected by e.g. the length of the maintenance work description), completeness (asset location, description, targeted and actual start and finish dates, and defect location code reported), and timeliness (measured by the delay of reporting). According to PAS 55-2 (2008), asset management information is needed for e.g. asset management strategy optimization, asset life-cycle cost assessments, evaluating the remaining economic life of assets and asset systems, as well as assessing the operational and financial effects of asset failures, planned improvements and maintenance actions. Often the required level of detail in asset management data is the lowest level of discrete maintainable units, although more detailed data might be useful in identifying failure modes and failure root causes (PAS 55-2, 2008).

Information quality management has been the topic of several maturity models. In Table 1 the maturity levels of three of these models are summarized. The models presented by Caballero et al. (2008) and BS ISO 8000-62 (2018) are quite similar, and the maturity of information quality management processes progresses from non-existent to sporadic, repeatable, measurable, and finally predictive or continuously evolving. The model introduced by Neff et al. (2014) is somewhat different, as it assesses the maturity of maintenance service systems in heavy equipment manufacturing companies. Data quality assurance was included as one dimension of the model. It is interesting that according to Neff et al. (2014), the progressiveness of the maintenance services is linked to the maturity of the data quality management in the organization. Thus, referring to the categorization of evidence-based analyses, ranging from descriptive to prescriptive, presented in the previous subsection, in general the more advanced analyses require not just more data but also higher data quality, compared to the more simple decision-making needs.

Table 1. Examples of information quality management maturity levels.

Maturity model	**Information quality management maturity model (Caballero et al., 2008)**	**Data quality management process maturity model (BS ISO 8000-62, 2018)**	**Data quality assurance maturity in a maintenance service system (Neff et al., 2014)**
Level 0	-	*Immature* Data quality management processes not used, no evidence of the quality of the data.	-
Level 1	*Initial* No information quality management goals.	*Basic* Data security is managed but other data quality management processes are not used. The requirements for the data used by operational processes are managed.	*Rudimentary spare parts service* No data quality assurance.
Level 2	*Defined* A repeatable information management process is in place.	*Managed* In addition to level 1, data specifications, work instructions, data quality monitoring and control are used. The quality of the data can be demonstrated.	*Reactive maintenance service* Sporadic quality checks.
Level 3	*Integrated* The information management process is aligned with organizational information quality policies.	*Established* In addition to level 2, the organization has e.g. a data quality strategy and policies, and manages the data architecture. There are repeatable data quality management processes.	*Predictive maintenance service* Quality assurance is integrated horizontally, for example between product and service business segments.
Level 4	*Quantitatively managed* Plans to define measures for the information quality management process are made.	*Predictable* In addition to level 3, the data quality issues are reviewed, data quality and data quality management processes are measured and evaluated, and data quality is included in human resource management.	*Performance contracting service* Quality assurance is integrated vertically, for example between analytical and operative systems.
Level 5	*Optimized* The information quality management process is continuously measured and improved.	*Innovating* In addition to level 4, root cause analysis for data quality issues, preventive data quality management process improvements, and data cleansing are in place. Data quality management is aligned with organizational goals.	*Managing the customer's operations* Data quality assurance integrated included in continuous improvement.

3.3 Right condition

The next dimension of information value to consider is the condition, and the format, of the data. Compared to the value dimensions discussed above, the optimal format has been considerable less discussed in existing literature. For example BS ISO 55002 (2018) simply states that the optimal structure and format of data should be considered as part of organizational information requirements. However, no further guidelines, processes, or maturity levels are given. Similarly, PAS 55-2 (2008) says that asset information systems can be anything between paper based and sophisticated software, and that organizations must decide what is best for their specific needs.

Kans (2009) studied the evolution of maintenance information systems. She refers to a survey conducted by Alsyouf (2004), where 22% of the studied industrial companies in Sweden had a manual maintenance management system in place, and 35% used a combination of manual and computerized systems. Kans (2009) sees the evolution of advanced maintenance strategies enabled by the increased support of IT systems. Thus the computerized and more advanced maintenance information systems should become more and more common when the advanced maintenance approaches are adopted in industry. Of course the state of this kind of development also depends on the studied area. For instance, a survey to industry in Brazil revealed that 55% of the surveyed companies still rely on solely corrective maintenance, and 85% use spreadsheets in their maintenance management (Oliveira et al., 2012).

Overall, it is quite common that asset management information is entered manually into e.g. an electronic spreadsheet at some phase of the information management process. The manual work increases the risk of errors, is slow, and is challenging to audit (Baskarada et al., 2006). However, it is quite clear that not all maintenance decision-making situations would benefit from sophisticated and elaborate software. If only a small amount of data is needed, and there is no requirement to provide the data to the decision maker in real time, a simple manual information process might be of better value. It is important to notice that the best data format for an organization should be evaluated, and not selected just because “that it how it has always been done”.

3.4 Right time

The timeliness of data has been discussed recently due to the emergence of real-time data –based information systems. Timeliness can contribute to the value of data depending on the situation. Data can be either static (which is not updated), or dynamic. Dynamic data can be further classified as either seldom-update data or frequent-update data (Sampaio et al., 2015). Regarding static data, timeliness can be irrelevant in many decision-making situations. However, for dynamic data the importance of timeliness is likely higher.

PAS 55-1 (2008) recommends periodic reviews and version control to increase the timeliness of the asset management data. The standard also suggests identifying archival information, which is stored for mostly passive use. Data timeliness can be measured through e.g. currency (how fast the user gets the data) and volatility (how long the data stays valid) (Sampaio et al., 2015). Some maintenance decision-making situations require real-time or close to real-time data, but in many cases the requirements for timeliness are considerably lower and improving the timeliness of the data would only cause additional costs without creating added value.

Yeh et al. (2012) discuss the lifecycle of manufacturing data collection processes, and present an interesting perspective of dividing the lifecycle into three parts: early, mature, and oversized. Data collection processes in the early stage have produced small data with only limited statistical power. Mature processes result in sufficient and robust information, while processes in the oversized stage produce data with decreased representability because the studied system has had too much time to change. This is a good example of the interconnectedness between the value dimensions studied in this paper: not only does the oversized data collection process produce waste in terms of too much data, but it also causes the timeliness of the data to decrease, finally affecting the quality of the data.

3.5 Right place

The next value dimension is related to getting the information in the right place (e.g. to the right person, system, or organization). It is typical for asset management that the information environment is fragmented into a variety of applications. This often creates a need to transform, rewrite, or otherwise manually handle the data to pass it from application to another (Baskarada et al., 2006). Another aspect of getting the information to the right place is that of allocating responsibilities in the organization for the various tasks related to creating, collecting, storing, securing, analysing, exploiting, and deleting the data (PAS 55-1, 2008). The importance of data security should not be undermined. Digitalization has caused new requirements for cybersecurity to emerge (see e.g. Thaduri et al., 2019).

Due to (especially big) data management requiring lots of skills and resources, it is becoming more and more common for organizations to buy parts of the data management process as services from outside service providers. In this case it is important to ensure that all the subsystems included in the data management process are compatible and allow cross system analysis (PAS 55-2, 2008). The maturity model for maintenance service systems discussed earlier in this paper (Neff et al., 2014) presents maturity levels for mobile support for the service personnel as well as for integration of the service and product data. The maturity levels can be described as follows:

- Level 1 (Rudimentary spare parts): Mobile support not needed. Data collected based on need, no integration.
- Level 2 (Reactive maintenance service): Access to asset and customer data. Manual data collection, with basic integration.
- Level 3 (Predictive maintenance service): Access to history data such as service history and best practices. Partially automated data collection and partial integration through e.g. intranet.
- Level 4 (Performance contracting service): Access to transaction data such as billing and service execution. Fully automated data collection, integration between all major data.
- Level 5 (Managing the customer’s operations): Fully integrated mobile devices. Fully automated and optimized data collection, global real-time integration.

Also BS ISO 55002 (2018) highlights the importance of data integration (with e.g. the quality and finance systems, safety and risk management, and human resource function of the organization) for asset management.

3.6 A maturity model for maintenance data exploitation

Based on the five dimensions of information value discussed above, a maturity model for valuable maintenance data exploitation is presented in table 2. The costs or price of the data has been added to the background, because the performance in the other five value dimensions has to be balanced with the costs of the required resources. The maturity levels range from 1) unawareness, 2) awareness (focusing on descriptive analyses), 3) identifying the problems (focusing on diagnostic analyses), 4) controlled (focusing on predictive analyses), to 5) continuously optimized (focusing on prescriptive analyses).

The model takes into account that some organizations pursue to exploit big data analytics and advanced data management systems, whereas others benefit from simple data management processes and small data, if the maintenance decision-making needs of the organization do not require more advanced solutions. The maturity levels are defined based on value, not based on the use of technological solutions. Adopting simple, e.g. manual maintenance data management and analysis can also lead to surprising development paths: Usually organizations make their way towards the mature state one maturity level at a time. With this model it is possible for e.g. an SME to start from unawareness (level 1) and very quickly develop to level 4 (controlled) if they only require simple improvements into their data management processes.

Table 2. The maturity model for valuable maintenance data management

Definitions of maturity levels		1 - Unawareness	2 – Awareness (descriptive)	3 – Identifying the problems (diagnostic)	4 – Controlled (predictive)	5 – Continuously optimized (prescriptive)
FOR AN APPROPRIATE PRICE	**RIGHT INFORMATION** *a) the data required by the maintenance and analytical strategies is available, b) obsolete data is removed or not collected at all, c) the costs of the data are balanced against its value*	The organization is unaware of which data they need in their maintenance.	The organization is able to tell that their data collection is not in balance with the value extracted from the data.	The organization is able to identify missing valuable data and obsolete data causing additional costs.	The organization is able to analyze the costs and benefits of the data they are using, and adapting their data collection accordingly.	The organization is able to predict which data will be valuable for them in the future, and continuously identifies novel ways of creating more value of the data they have.
	RIGHT LEVEL OF DETAIL *a) data quality defined as fitness for use, b) data collected at suitable levels*	The organization is unaware if the data is of high quality and on a suitable level for their decision making needs.	The organization can identify issues in data quality and level of detail that decrease the value of their maintenance decision making.	The organization can measure the quality of the data and determine suitable levels to collect data.	The organization is able to solve problems with data quality and level of detail that might decrease the value of their maintenance decisions.	Data quality and level of detail are continuously analyzed and embedded in electronic and manual processes.
	RIGHT CONDITION *a) suitable data systems, b) information exchange and integration*	The organization is unaware if their data system is compatible with their maintenance and analytical strategies.	The organization is aware of compatibility issues between their data system and their maintenance and analytical strategies.	The organization is able to identify specific features of their data system which are causing decrease of value in their maintenance decision making.	The organization is able to monitor and control the compatibility of their data system in relation to their maintenance and analytical strategies.	The organization is able to make long-term decisions about their data system, taking into account compatibility with maintenance and analytical strategies, and information integration in the value chain.
	RIGHT TIME *a) currency and volatility of dynamic data, b) version control,*	The organization does not analyse the timeliness of their data.	The organization is aware that their decision makers sometimes need to wait for data, and that	The organization knows what static and dynamic data they need, and can measure the currency and	The organization has tools and processes to improve the timeliness of the data and is able to analyse if it is	Ensuring the timeliness of the data is embedded in the everyday processes.

	c) identification of archival information		sometimes the data is outdated.	volatility of the data.	necessary.	
	RIGHT PLACE *a) roles and responsibilities,* *b) system compatibility,* *c) mobile solutions,* *d) data integration and sharing,* *e) also in the value chain especially when something outsourced*	The organization is unaware if their data is in the right place or not.	The organization is aware that the value of their data management is decreased by the data not always being in the right place.	The organization is able to pinpoint root causes for their data not being in the right place.	The organization is able to identify and solve the possible problems in getting the data to the right place.	The organization is continuously improving their processes and systems to predict problems in getting the data to the right place in the future.

4 Industrial case example

The case example addresses a company which manufactures various parts for the automotive industry. The analysis focuses on a three-shift production plant operating in the UK. The company participated in a research project (from 2017 to 2019) the objective of which was to find methods to maximize the business value of maintenance through lean data management. The developed maturity model is used here to demonstrate how the research conducted during the project increased the awareness and the maturity of the case company's maintenance data management process.

4.1 Original state of maturity

At the start of the research project, the state of maintenance data management in the case company was assessed. Table 3 shows a summary of the original maturity. The maintenance manager of the case company felt like he could not use the data collected in the process to improve maintenance. The data collection process had not been updated in 25 years, and it was very production-led. The data mostly consisted of maintenance and breakdown times, and key information such as failure causes were missing. The data could not be used to prevent failures, so the maintenance engineers used 70% of their time reacting to asset breakdowns. Thus the "Right information" –dimension was considered to be at level 2 (Awareness).

Considering the "Right level of detail" –dimension, the level of detail was not really considered by the case company as there were more pressing issues to be handled. The data was collected with paper forms, and the maintenance manager was aware that there were quality problems related to e.g. the legibility of the engineers' handwriting, and incorrect reports. However, there were no metrics or processes to assess the extent or impact of the poor quality data. Thus the maturity of this dimension was placed at level 1 (Unawareness).

The case company used a manual data collection process, where data from the paper forms was inserted into electronic spreadsheets once a day. The maintenance manager was aware that part of the data recorded on the paper forms was lost in the process of turning it electronic, as the data coding in the spreadsheets did not accommodate all the details collected. The maturity of the "Right condition" –dimension was at level 2 (Awareness).

The timeliness of the collected data was not addressed at all in the case company, mostly because the data was used for historical trend analyses etc. but not for preventive maintenance actions. The "Right time" –dimension was considered to be at maturity level 1 (Unawareness).

Finally, the roles, responsibilities, and transfer of data were not given much thought in the case company. This is also mostly due to the limited use of the collected data; having the data at the right place is not crucial if the data is rarely actually used in decision making. The maturity level of the "Right place" –dimension was seen to be 1 (Unawareness).

Table 3. The original maturity of maintenance data management in the case company.

Maturity levels		1 Unawareness	2 Awareness (descriptive)	3 Identifying the problems (diagnostic)	4 Controlled (predictive)	5 Continuously optimized (prescriptive)
For an appropriate price	**Right information**		x			
	Right level of detail	x				
	Right condition		x			
	Right time	x				
	Right place	x				

4.2 Tool and method development to increase the value

During the research project, the profitability of the case company modernizing their maintenance data management process by adopting a Computerized Maintenance Management System (CMMS) was evaluated. The analysis (reference to be added after the review process) concluded that based on the various dimensions of value of data (which are also discussed in this paper), the CMMS investment would not be profitable with the case company's current reactive maintenance policy. The additional and more structured data would not create much added value but would cause more costs due to the actual software investment and the increased data collection and processing. However, if the case company would use the improved data management to increase the role of preventive maintenance and decrease asset downtime, the investment could be profitable.

An analytical Wasted Value of Data –model was created to assess the value of data –based profitability of maintenance investments (reference to be added after the review process). The model quantifies the waste created by unnecessary data, unnecessary data transfer, unnecessary data processing, underutilized data management resources, incorrect data and analyses, and waiting for data. An analysis on the impact of the CMMS adoption on three selected pilot production lines of the case company showed that whilst the investment would increase the annual costs of data processing by over £10,000, the additional value due to a decrease in production downtime (£65,000, requires successful preventive maintenance), an increase in data quality (£8,500), and a decrease in unnecessary data transfer (£1,900) would make the investment profitable.

The CMMS investment decision was also analyzed based on a conceptual framework on the factors influencing the adoption of big data and lean data –based innovations in industrial maintenance (reference to be added after the review process). The analysis concluded that big data analytics would not create much additional value to the case company, so lean data is the preferred option. The main factors influencing the investment decision were identified as i) relative advantage and value of the CMMS in the context of corrective vs. preventive maintenance, ii) management support (the centralized decision making in the case company creates risks for IT system investments), iii) the low complexity tolerance driven by penalties issued by the company's main customer in case of severe production issues, iv), costs, and v) the training and competence required to exploit the CMMS (reliable preventive maintenance is required to make the investment profitable).

4.3 Current state of maturity

The case company is currently conducting more detailed analyses to reach a decision on whether or not to invest in a CMMS. Not many tangible changes have been made to the maintenance data management process during the research project, but the awareness and understanding of the company have matured a lot. Table 4 shows a summary of the current maturity of the maintenance data management process. It should be noted that level 5 (Continuously optimized) is not an optimal target for the company, as their maintenance decision making would not benefit from big data or very sophisticated technologies in data analytics.

Table 4. The current maturity of maintenance data management in the case company.

Maturity levels		**1 Unawareness**	**2 Awareness (descriptive)**	**3 Identifying the problems (diagnostic)**	**4 Controlled (predictive)**	**5 Continuously optimized (prescriptive)**
For an appropriate price	**Right information**				x	
	Right level of detail		x			
	Right condition			x		
	Right time		x			
	Right place			x		

The created analyses, the Wasted Value of Data –model, and the conceptual framework on data-based innovation adoption provide the case company tools to assess the different dimensions of value of data. The company is now aware of the issues related to poor quality data (the "Right level of detail" –dimension) and the timeliness of the data (the "Right time" –dimension), however the tools do not include explicit metrics for measuring these dimensions. Thus the maturity level of these two dimensions can be seen to be 2 (Awareness).

Regarding the "Right condition" and "Right place" –dimensions, the conducted research provided methods and examples on how to quantify the value potential related to specific causes of waste in the data management process. For example, a method for assessing the value of not having to insert the data manually into the spreadsheets was presented. The maturity of these two dimensions is considered to be at level 3 (Identifying the problems).

Finally, the "Right information" –dimension is seen to have matured to level 4 (Controlled). The conducted research produced several analyses on how the data currently collected cannot be exploited to support preventive maintenance policies. The importance of being able to make reliable data-based preventive maintenance schedules on the profitability of investing in the data management system was identified and included in sensitivity analyses. If the case company decided not to invest in a CMMS and continue with the reactive maintenance policy, there would not be much potential for improvement considering additional information. However, if the company would decide to increase the role of preventive maintenance and support this transition with additional data and an improved data management system, the maturity of this dimension could (at least temporarily) move back down to e.g. level 3.

5 Conclusions

This paper presented the design of a maturity model for supporting organizations in valuable data-based maintenance decision making. It remains unclear what the maturity of data management or business intelligence mean in the domain-specific context of industrial maintenance. In addition, most existing maturity models assume that the optimal target for each organization is the level with advanced technologies and big data. Depending on the skills and resources of the organization and the uses of the collected data, this is not always the case. The maturity model presented in this paper provides organizations a method to analyse the current state and development potential of their maintenance data management processes from the perspective of additional value.

The main limitations of the study are related to the validation process of the maturity model. A preliminary testing was conducted and reported due to a number of practical limitations. To study the impact of the intervention on the performance of the case company in more detail, further research is needed. The model would also have to be validated with a more extensive group of organizations to properly assess its validity, reliability and generalisability. Future research could tackle this e.g. through a survey to industrial organizations producing in-house and outsourced maintenance services.

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To be added.

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