University of Sunderland

Identifying current challenges of data-based maintenance management: a case study

S. Marttonen-Arola[1], D. Baglee[1]
[1] Faculty of Engineering and Advanced Manufacturing, University of Sunderland, UK

ABSTRACT

Exabytes of data from various sources are available for maintenance decision makers. The yearly increase in data is exponential due to technological developments such as the rapid increase in the amount of interconnected systems and assets, which utilize smart sensors, cloud-based computing and eMaintenance. All of these are supported by the rapid developments in the Internet. The data provide vast possibilities for smart, autonomous assets and predictive maintenance. However, in practice, there are technical, managerial, and organizational challenges, which impede the maintenance decision makers from exploiting the information retrieved from the data analyses. The existing literature has discussed the data required in different maintenance decision making situations extensively, although there is a limited number of academic publications which explore general-level frameworks or tools to support the management of maintenance data. This paper builds upon a review of the current literature on the value of maintenance data management. The data needed to support a number of different maintenance management situations are discussed, and an approach to analyze and increase the value and resource efficiency of the maintenance data management process is suggested. The paper presents a case study example conducted in collaboration with a UK manufacturing industry. The objective of the paper is to map the current state of maintenance data exploitation paths. This makes the different value-based development needs in the data management process visible. The results of this paper will contribute to future empirical research including modelling and optimizing the use of data in maintenance decision making through adopting lean management principles. The majority of previous lean management research has focused on the optimal management of production processes and the maintenance processes. In this research, the principles of lean management will be taken to the level of optimizing the maintenance data management process.

Keywords: Maintenance data; Decision making; Case study; Value; Industrial asset management.

Corresponding author: Salla Marttonen-Arola (salla.marttonen-arola@sunderland.ac.uk)

1. INTRODUCTION

The recent technological developments regarding for instance eMaintenance, sensors, and the Internet of Things have exponentially increased the amount of data available to maintenance decision makers [1-2], providing vast possibilities for novel approaches in smart, predictive maintenance [3-4]. However, in practice many companies are struggling with the process of gathering, integrating, analyzing, and exploiting their maintenance data [5], and so far they have not been able to harvest the value of the data. There is no universally agreed definition for maintenance data. In this paper it is defined to include asset data (technical, operational, financial, environmental, and performance of the assets), data on the planned and implemented maintenance actions, and supportive data (on e.g. strategy, processes, risks, and contracts) [6-10]. The optimal amount of maintenance data to be gathered and analyzed depends on the size of the company, the type of business, the complexity of processes, the competence of people, and the complexity of assets [11].

The value of data is an ambiguous term, and systematical approaches to assessing or even defining it are still scarce both in industry and in academia. The objective of this paper is to introduce a value-based approach to studying maintenance data management processes. The current state of maintenance data exploitation paths are then mapped through a case study. The paper contributes to the understanding of the value of data in maintenance management, and helps to build the foundation for further research including value-based modelling of maintenance data and methods for lean maintenance data management.

In section two of the paper, the research design and methods are discussed. Section three addresses previous literature on maintenance data and its value. Section four presents the results and observations from the case study, and the paper finishes with conclusions in section five.

2. RESEARCH DESIGN

In this research a literature-based approach to evaluating the value of maintenance data is created and evaluated using a case study example. The selected case company operates in the food and drink industry in the UK. The company is interested in increasing the value of their maintenance through better exploitation of their maintenance data. However currently, the state of maintenance data management in the company is limited; they are operating with manual data collection, the maintenance engineers are still learning how and why they should document their work, and data is mostly used to monitor corrective maintenance tasks which constitute a majority of the company's maintenance. The case company studied which maintenance tasks take up the most of their maintenance engineers' time, and based on the results they wanted to analyze the data management processes of three specific maintenance tasks in more detail:

1) Changing a retort probe when it has been damaged,
2) Installing or removing a specific conveyor belt used when making cannelloni, and
3) Cleaning the printer head of videojets after the quality of the print has been deemed suboptimal.

To analyse the data management processes in the selected maintenance tasks, the case company's maintenance work requests from July 2017 until mid-January 2018 were studied. Two maintenance managers from the company were also interviewed to gain understanding on the current processes and practices in the company. The maintenance work requests from the studied period included 284 retort probe changes, 92 cannelloni belt installations/removals, and 117 videojet head cleanings. In total, these 493 work requests equaled 12% of all the maintenance work requests from the assembly department during the studied period, and 5.3% of all the maintenance work requests in the case company during the period. All three studied maintenance tasks are simple and quite straightforward to conduct: the time used in completing them equals only 5% of the time used in completing all the work requests from the assembly department, and 1.8% of the time used to complete all the work requests in the case company.

3. LITERATURE REVIEW

The recent technological developments have taken maintenance decision making towards real-time decisions. The time available for analyzing the data to support maintenance decisions is decreasing, and so is the time required for data collection [5]. Sun et al. [12] have recognized four different time scales in asset management decisions:

1) Strategic decisions ranging from one to five years (e.g. developing strategic asset management plans),
2) Technical decisions ranging from a month to a year (e.g. creating preventive maintenance plans for major assets),
3) Implementation decisions ranging from days to a month (e.g. scheduling maintenance actions), and
4) Reactive decisions ranging from minutes to a day (e.g. selecting maintenance actions in case of unexpected asset failure).

To form a more comprehensive view of the data needed to support maintenance decisions, the authors reviewed the literature on various decision-making situations in maintenance management. In figure 1 below, various decisions are presented according to the categorization of the four different time scales in decision making. In the empirical part of this paper, the focus is on reactive decisions related to designing and implementing corrective maintenance actions. The main elements of a corrective maintenance plan can be seen as detecting failures, and deciding on whether to repair or replace the asset, immediately or later. To optimize these decisions maintenance managers would need data related to e.g. asset condition and life cycle, costs, safety and production. [13-16]

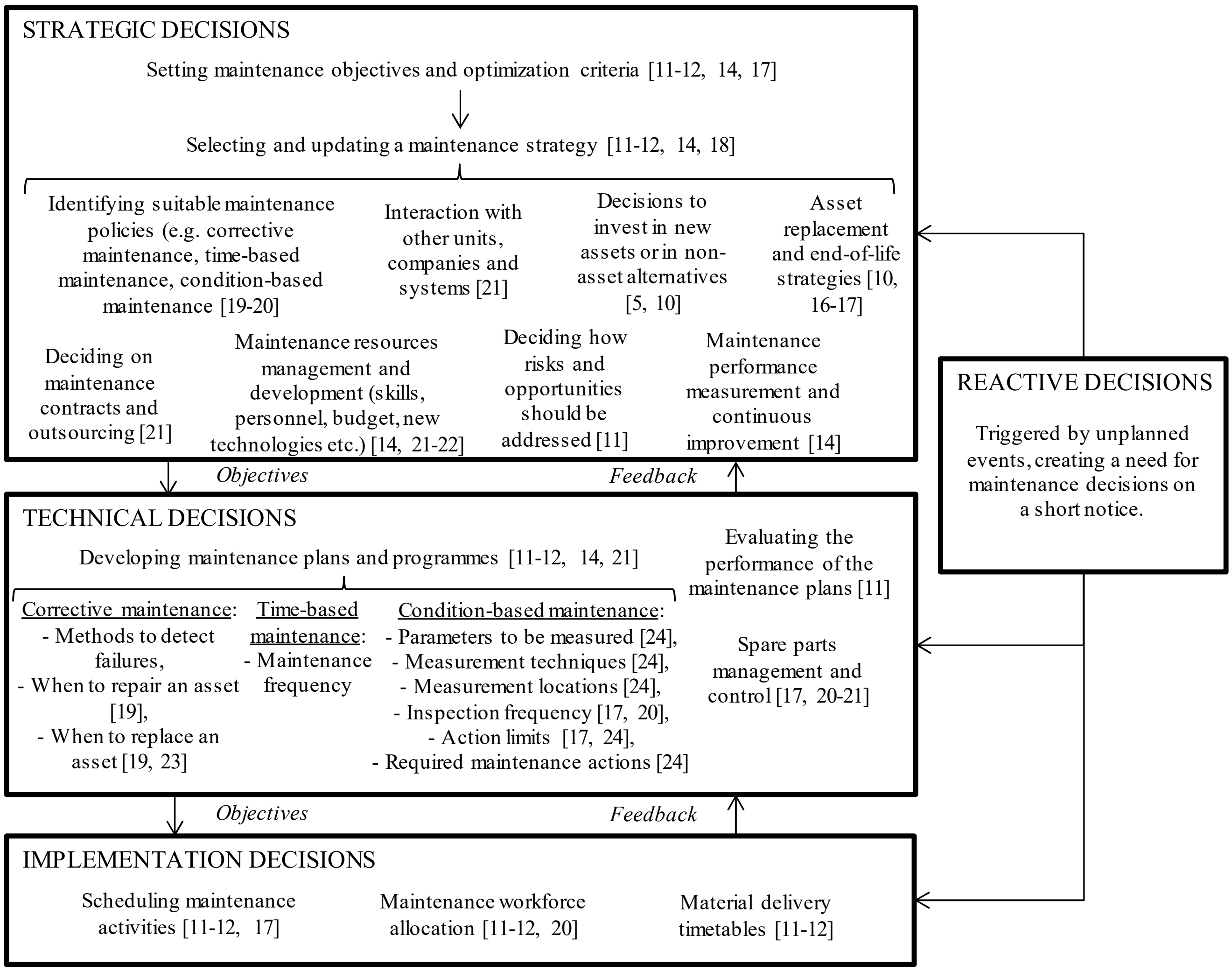

Figure 1. Classification of maintenance decision making situations.

When collecting and analyzing maintenance data it should be noted that, the objective is to create more value for the maintenance decision makers. The value of data or information still has not received much attention in scientific literature, and practical applications on the topic are mostly missing. The value of asset management data in fleet contexts has previously been discussed by e.g. [25], who consider data management to be an investment to be paid off by the benefits achieved through improved decision-making. The costs of data management can be categorized into hardware, software, and work hour based costs. The benefits, on the other hand, include saving in maintenance costs, savings in quality costs, as well as other savings and benefits. [25]

To define what constitutes value in this study, the view on value proposition in information services presented in [26] is adopted. According to this view, the value of information depends on not only the information items provided, but also on the amount, quality, format, time, place, and price or cost of the information as follows:

Value of information = Right information, in the right level of detail, in the right condition, at the right time, at the right place, and for an appropriate price [26].

The optimal extent of maintenance data to be gathered and analyzed to support decision making is highly case specific. Data collection and analysis must not be too complex or strenuous, however collecting data only on the level of e.g. large systems might invalidate the whole process if the data do not provide root causes for failures and thus do not enable improvements of maintenance plans [27]. Thus the optimal data depend on the maturity of the organization in question. Data can be collected from both internal and external sources. When considering which data to collect, [8] suggests all organizations to at least record the details of their corrective maintenance actions. The standards recommend coding data using mutually exclusive codes, and using additional free text to provide further details [8].

It is necessary to acknowledge the potential problems in data quality to evaluate and manage the impact on maintenance decisions. According to the categorization presented by [28], data uncertainty can be caused by:

1) Input data (e.g. material properties, sampling rates),
2) Measurements (e.g. sensor noise),
3) Operating environment (e.g. high variability in conditions), and
4) Modelling errors (e.g. lack of understanding about the process to be modelled).

In practice, there are often a large number of quality problems in maintenance data. According to the categorization of levels of data completeness in asset record databases presented by [29]:

- Approximately 10-20% of the records can be considered “perfect data” which do not require extrapolation or expert judgement before exploitation,
- 35-40% of the records are “imperfect data”, requiring additional efforts to ensure the quality,
- 25% of the records are “verbal/inspection data”, which require e.g. expert judgement for verification, and
- 10-15% of the records are “soft data” relying on human perceptions and/or memory, which require a lot of time to summarize and can be considered inconsistent quality-wise.

The concept of value of data offers an approach to analyzing data management processes and identifying their current value-destroying features. The case study in the next section presents an example of mapping the current maintenance data flows in an industrial context through analyzing the various dimensions of value of data.

4. CASE STUDY

4.1. The current maintenance process

Figure 2 depicts the current maintenance data management process in the case company. The corrective maintenance process is triggered by an asset failure, after which the asset operators use a specific manual form to file a maintenance work request. All the three studied maintenance tasks are production critical (the failures cause the production line to stop), so the maintenance engineer(s) react to the work requests as quickly as possible, executing the requested maintenance task and restoring the asset into normal operating condition. The engineers report any possible needs for follow-up maintenance work, and they use the manual forms to document the details of the conducted maintenance work. The forms are then manually transferred to the maintenance management team. The maintenance managers insert the data gathered with the manual work request forms into electronic spreadsheets once a week. Every week the maintenance managers use the spreadsheet to construct a report to describe the performance of the maintenance department to the company management. In addition to performance reporting, the maintenance management team regularly uses the spreadsheet data to identify bottlenecks and development needs in their maintenance processes.

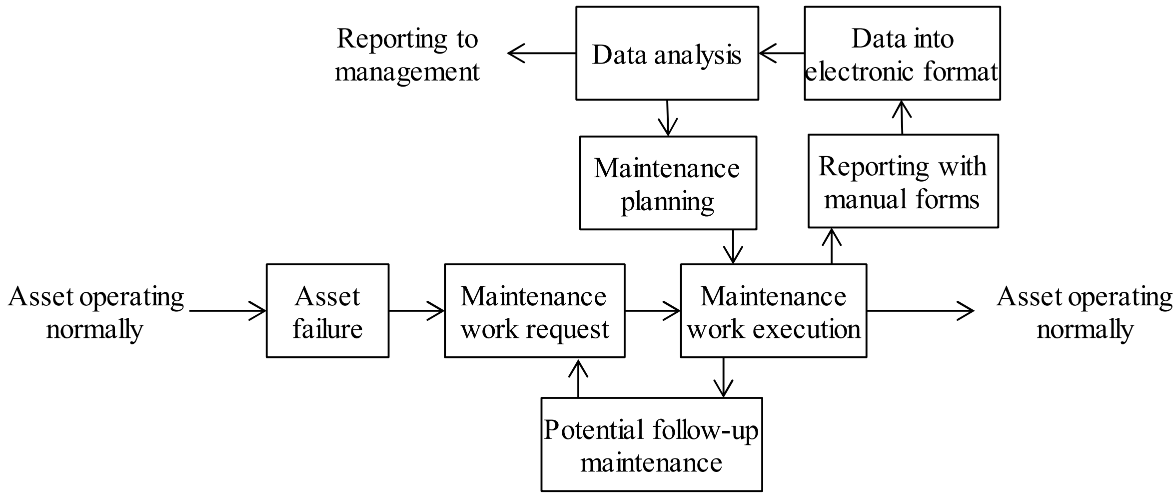

Figure 2. The current corrective maintenance data management process in the case company.

4.2. Identifying value-destroying challenges in the process

The six dimensions of value of information presented in section two have been used as the basis of the analysis addressed here. Table 1 below summarizes the identified value-destroying challenges in the current maintenance data management process of the case company. Eight challenges were identified, out of which three were deemed more significant (at the moment): poor quality data, manual data, and unnecessary data processing.

The poor quality of maintenance data is a significant challenge because it can void the entire data management process if maintenance decisions are based on incorrect data. In the future, the case company will contribute to this challenge by promoting instructions and awareness on how and why maintenance data is collected. The condition the data is processed in (documented in manual work request forms) also causes quality problems and makes data analysis slower. The case company has considered implementing technological solutions to support transferring the manual data into electronic format, or adopting a computer-based maintenance management system to make the whole data management process electronic and to increase the quality of data. However, so far the managers of the company have averted from investing in software and/or hardware before the basic process and motives of maintenance data management have been adopted and accepted by the personnel. This decision could be costly, as mentioned in table 1 the amount of time currently used in unnecessary data processing is significant and must be a cause for lots of wasted personnel costs. It would be important for the case company to conduct a quantitative investment appraisal on comparing the costs of the current process, including working hours, with the costs of implementing a computerized system.

Table 1. Identified value-destroying challenges in the current maintenance data management process of the case company.

DIMENSION OF VALUE	IDENTIFIED CHALLENGE	IMPACT ON MAINTENANCE
Right information	***1) Missing information:*** Details of the used spare parts are not documented consistently. For retort probe changes, only 11% of the work request forms documented the used spare parts at all, and most of them were missing details such as part numbers or specific location.	The costs of spare parts cannot be allocated properly, the performance of spare part management cannot be evaluated, and proactive spare part management cannot be supported by data analysis.
	2) Unnecessary information: The engineers use time documenting some information items which are constant for each of the three tasks (e.g. impact and nature of work).	The unnecessary data get carried through the process and cause both the maintenance engineers and maintenance managers to use additional time in processing it.
Right level of detail	***3) Poor quality data:*** 12% of the studied work requests had visible quality problems that made them unreliable regarding data analysis (e.g. several tasks bundled in the same work request, several work requests created on the same task, or maintenance start time later than the reported finish).	The maintenance engineers and managers use their time in inserting the poor quality data into the manual forms and spreadsheets. In addition, the incorrect data might lead to incorrect conclusions in maintenance decision making.
	4) Confusion over key terminology: There are no explicit instructions on how to document the data and what kind of terminology should be used, so the engineers use a number of different terms when writing about the same issues/assets/tasks.	The reliability of the data can be questioned because the maintenance management team has to interpret the data before inserting it into the spreadsheet. Data analysis takes more manual work.
Right condition	***5) Manual data****:* The manual forms are strenuous to fill and to interpret. The poor legibility of the forms causes additional work for the maintenance managers.	Sometimes the maintenance management team struggles to read the hand-written forms, which slows the data processing and again reduces the reliability of the data.
At the right time	***6) Slow process:*** The manual forms cause severe delays to the data management process. It can occasionally take weeks before the data of a maintenance task is inserted into the spreadsheet.	The data is not timely enough to support any kind of proactive maintenance decision making. Currently this is not a very significant problem since the data is mostly used to monitor corrective maintenance on a weekly or monthly basis, but in the future it should be taken into account.
At the right place	***7) Poor traceability:*** The traceability of the manual forms is not good and occasionally they get lost in the process.	The data management process is slower, and using data to support proactive decision making in maintenance is not possible.
For an appropriate price	***8) Unnecessary data processing****:* The arduous process causes additional work, for instance the maintenance managers examine the forms again when inserting the data into the spreadsheet.	If inserting the data from one form takes on average 5 minutes, there is 62 hours/year of unnecessary work related to the three studied maintenance tasks, and 1165 hours/year considering all work requests.

5. CONCLUSIONS

This paper has suggested an approach to analysing and increasing the value of the maintenance data management process. An industrial case study example has been presented to demonstrate how the current state and main challenges of the data management process can be mapped. The paper contributes to theory through showing how the data management process can be analysed and improved by adapting the concept of value of information, which has been presented in previous literature. Industry and academia agree on the importance of data in maintenance management, but in practice many organizations are struggling with developing their data management processes. The main managerial contribution of this paper is related to focusing on value-centred thinking, which enables achieving business feasibility in data management. It is critical to remember that data do not create value unless exploited in decision making. It is easy to forget this and implement various technological solutions to create more and more data without stopping to think whether it is actually needed.

Due to the limited extent of this paper, developing the data management process systematically to maximise the value, as well as measuring the value of information quantitatively were not included. These topics will be included in the later phases of the research project. The value-based analysis presented in this paper will be integrated into a method of adopting lean principles in the maintenance data management process to maximise the value while minimizing the waste. The majority of existing lean management research has focused on optimizing production processes, with a few exceptions of studying the maintenance process. In this research project the principles of lean management will be adapted to the data management process in maintenance. Further research will also include creating a value-based cost model for measuring and improving maintenance data management to better communicate the value of information to company managers.

ACKNOWLEDGEMENTS

This project has received funding from the European Union's Horizon 2020 research and innovation programme under the Marie Skłodowska-Curie grant agreement No 751622.

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