An Approach to Identifying Waste in Data Management Processes

David Baglee and Salla Marttonen-Arola

***Abstract*—Computing power and the data it generates to support decision making in industry is growing exponentially. This unprecedented growth in data will result from ubiquitous sensors, using the Internet of Things to monitor and measure a number of productivity performance indicators. The move to data-rich technological systems for gathering and exploiting the 'right' data will provide organizations with the necessary tools and techniques to ensure a competitive advantage. However, to ensure the data is valuable, organizations employ analytic strategies to develop their data management processes. This paper introduces a lean-based approach to identify waste in data management processes. An industrial case example is used to illustrate the approach.**

***Index Terms*—Data collection, Decision making, Food manufacturing, Maintenance management, Profitability**

I. Introduction

THE role of data in industrial decision making is crucial and still growing. In practice different strategies can be employed by organizations to identify which data are required in order to provide reliable decision support. An analytic strategy has previously been defined as:

"…the long term decisions an organization makes about how it uses its data to take actions that satisfy its organizational vision and mission…" [1, *p. 46*].

When choosing the optimal analytic strategy it needs to be taken into account that often large amounts of data need to be analyzed quickly and effectively. New intelligent data mining tools and techniques are often required to support data analysis and to produce valuable information for manufacturing organizations. Extracting, organizing and analyzing such [illegible] collected but not understood, never used and finally discarded. There is a lack of systematic tools and methods to support the development of data management processes. There is evidence that most organizations have far more data than they possibly use; yet, at the same time, they do not have the data they would really need [2] [3] [4] [5].

There are also associated problems of poor data quality which leads to undesired data discarded by the organizations. Companies across industries have struggled and sometimes failed outright as a result of poor data management: they often lack the ability and tools to identify reliable and valuable data and [6].

The data management process includes a technical layer as well as a business layer [7], both of which are required to ensure that high quality data is used optimally to support decision making in the organization. There is still a lack of understanding both in industry and academia considering the value of data [8] [9]. In order to ensure data integrity it is important to systematically evaluate all sources of data and to optimize the use of the data based upon a set of predefined performance criteria. In this paper the principles of lean management have been adopted to contribute to this need.

The adoption of lean techniques allows organizations to identify areas of waste in any resource (equipment, people and data alike) and to illuminate the unnecessary or wasteful tasks and processes. The objective of this paper is to introduce a lean-based approach to identify waste in data management processes. This supports lean data management through making the development needs in the process more transparent as well as acknowledging the value and profitability impact of data. The aim is to align the needs of the organization with a set of common principles and practices which allow for systematic checking of data to prevent waste in the data management process. This would require a plan to 'cleanse' the data at creation to ensure that the correct data is used and the unnecessary data is discarded.

The structure of the paper is as follows. In section two the [illegible] xt, and data are briefly discussed. Section three presents a summary of previous literature on different aspects of lean maintenance data management. Section four showcases the lean-based approach to data management through analysing the waste in the current maintenance data management process of a case company, and suggesting an alternative process. The paper finishes with discussion and conclusions in sections five and six.

II. Research Design

The research uses an industrial case example to validate a lean maintenance data management framework which was first introduced in [10]. The case company operates in the food

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manufacturing industry in the UK, and the selected case focuses on the maintenance data management processes in the company. Maintenance has been defined by the BS EN 13306 standard [11, *p. 5*] as a "combination of all technical, administrative and managerial actions during the life cycle of an item intended to retain it in, or restore it to, a state in which it can perform the required function". The most common way of categorizing different types of maintenance is to distinguish corrective and preventive maintenance, the latter of which can be further divided into predetermined and condition-based maintenance. The definitions for these three types of maintenance are as follows [11, *pp. 12-13*]:

- Corrective maintenance – "maintenance carried out after fault recognition and intended to put an item into a state in which it can perform a required function",
- Predetermined maintenance – "preventive maintenance carried out in accordance with established intervals of time or number of units of use but without previous condition investigation",
- Condition based maintenance – "preventive maintenance which include a combination of condition monitoring and/or inspection and/or testing, analysis and the ensuing maintenance actions".

The maintenance tasks selected for this case study belong to the category of corrective maintenance and include: 1) changing retort probes when they get damaged, 2) installing and removing a specific conveyor belt used in producing cannelloni, and 3) cleaning the printer heads in videojets after the print quality has deteriorated too much to pass the quality check. All three tasks are part of maintenance in the assembly department of the case company, and they were selected because they take up a lot of the maintenance engineers' time. The case company was interested in studying whether transferring these tasks to the asset operators would be valuable and help to free the maintenance engineers to conduct more complex maintenance tasks.

The data used in the research includes maintenance work requests documented in the case company from July 2017 until mid-January 2018, as well as an interview of two of their maintenance managers in January 2018. The semi-structured interview included questions about the production and maintenance related objectives of the facility, the organization, performance measurement and development of maintenance, as well as the data exploitation paths in the three selected maintenance tasks.

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 equal 12% of all the maintenance work requests from the assembly department, and 5.3% of all the maintenance work requests in the case company. The studied maintenance tasks are simple, and 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.

III. LEAN MAINTENANCE DATA MANAGEMENT

The data exploited in maintenance management generally falls under three categories: data related to the equipment, data related to maintenance actions, and supportive data on the business context [10]. The recent technological developments have provided maintenance managers extensive amounts of data, however in practice companies seem to be struggling with exploiting their maintenance data. In a survey conducted by PricewaterhouseCoopers and Kantar Emnid in 2017 to 200 executives of German industrial companies, 39% of the respondents said they use connected sensors to gather data, and 64% expected to use them by 2022. On the other hand, 28% of the respondents use predictive maintenance technologies, while 66% expected to have them in use by 2022 [12].

It should be noted that several levels of predictive maintenance can be identified based on what kind of data is analyzed and with which methods [13]:

1) The most basic level includes visual inspections and relies on the experience of the inspector,
2) On the second level the inspector's expertise is supported by periodic instrument inspections,
3) The third level uses continuous real-time condition monitoring and pre-defined action limits, and
4) The fourth level combines continuous real-time condition monitoring with dynamic action limits based on predictive techniques.

In a survey conducted by Kantar TNS to 280 people responsible for maintenance and operations in their organizations in the Netherlands, Germany and Belgium in 2017, two thirds of the companies had not reached level three and only 11% of the respondents were on level four. When asked to identify the critical success factors for implementing the fourth level of predictive maintenance, the respondents of the survey saw availability of data and budget as the most important factors. [13]

In [10] a literature-based framework for lean maintenance data management was introduced to increase the value and resource efficiency of data management processes. According to [14], lean management comprises of the following five principles:

1) Specification of customer value,
2) Identification of the value stream,
3) Flow between the remaining value-added steps,
4) Letting customers pull the product, and
5) Continuous improvement

In addition to these principles, the elimination of waste is an important aspect of lean management [15]. The framework presented in [10] defined the customer, product, value, and waste in lean (maintenance) data management processes as shown in Table I.

TABLE I
THE BASIC CONCEPTS OF LEAN MAINTENANCE DATA MANAGEMENT

CUSTOMER	PRODUCT	VALUE
Maintenance decision makers	Valuable information for maintenance decision making	- Right information, - In the right level of detail, - In the right condition, - At the right time, - At the right place, - At an appropriate price.

WASTE
1. Unnecessary data in the decision making situations,
2. Unnecessary data in other phases of the data management process,
3. Unnecessary transfer of data,
4. Unnecessary processing of data,
5. Waiting for data,
6. Incorrect analysis,
7. Incorrect information for decision support,
8. Under-utilisation of maintenance data management resources.

Gupta et al. [16] mention two alternative methods to apply lean techniques: rapid improvement events, and a full implementation. To achieve maximum benefit from lean the full implementation is recommended, but it takes at least three years and thus most organizations prefer rapid improvement events instead. That is also what the case company of this study wishes to do to improve specific aspects of their data management processes.

IV. CASE STUDY

In this section the results of the case study are addressed, starting with the current data management process in the case company, followed by the identification of waste in the process, and finally suggestions for a new improved process.

A. *The Current Data Management Process*

The current data management process of the case company is depicted in Fig. 1.

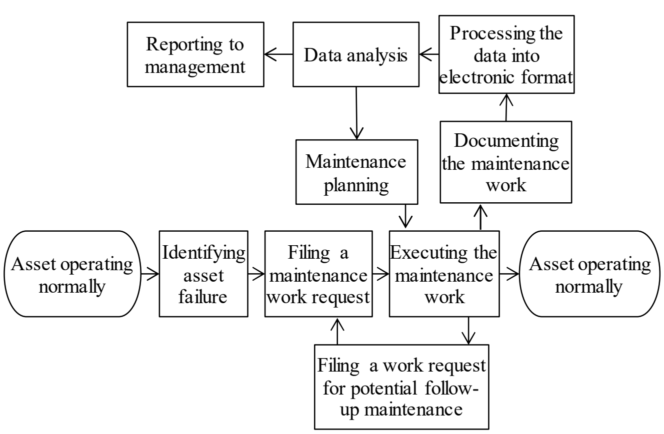

Fig. 1. The current corrective maintenance data management process in the case company.

The corrective maintenance process is triggered by an asset failure, after which the asset operators file a maintenance work request with a specific manual form. The maintenance engineer(s) then execute the requested maintenance task to restore the asset into normal operating condition, and document any possible needs for follow-up maintenance work. The maintenance engineers document the details of the conducted maintenance task into the work request forms, which are then manually transferred to the maintenance management team. The maintenance managers take time once a week to insert the data gathered with the manual work request forms into electronic spreadsheets.

Every week a report is constructed based on the spreadsheet data and presented to the company management to describe the performance of the maintenance department. In addition, the maintenance management team regularly uses the spreadsheets to identify bottlenecks and development needs in their maintenance processes.

B. *The Identified Waste*

When the data management process described above was studied from the perspective of lean management, four main sources of waste were identified (see Fig. 2). Each of these four wastes is discussed below.

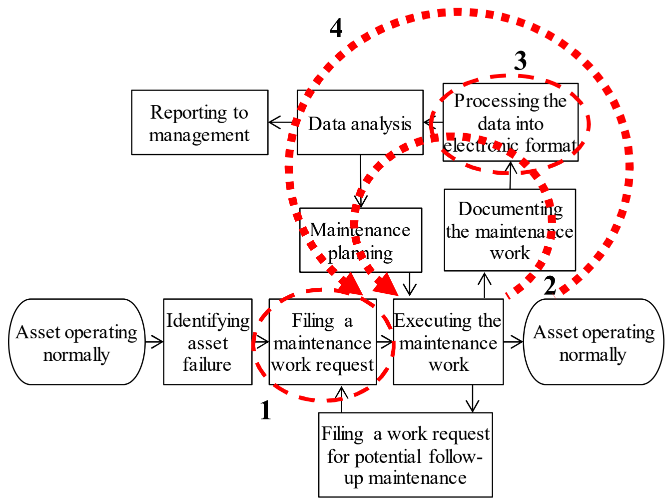

Fig. 2. The four identified sources of waste in the data management process.

1) *Unnecessary Transfer of Data*

The first source of waste is unnecessary transfer of data as the maintenance work requests are created to let the maintenance engineers know their help is needed at the assembly lines. As the studied maintenance tasks are straightforward and simple to execute, the case company is interested in assessing whether the asset operators could perform the tasks to help free the maintenance engineers' time for more complex maintenance situations. If the responsibility for executing the tasks was transferred to the asset operators, maintenance work requests would not be needed at this phase of the process. The studied maintenance tasks are production critical, meaning that in case of failure the production line has to be stopped until the task(s) have been executed. The asset downtime starting from creating the work request and ending when the actual maintenance work starts could thus be saved by transferring the execution phase to the asset operators. Table II shows the time that could be saved for each of the three studied maintenance tasks.

TABLE II
THE TIME WASTED DUE TO UNNECESSARY TRANSFER OF DATA

TASK	TIME WASTED IN EACH TASK	NO. OF TASKS PER YEAR	TIME WASTED PER YEAR
Retort probe change	25.85 min	460	198 hours
Cannelloni belt change	0.23 min	156	0.6 hours
Videojet head cleaning	15.33 min	184	10 hours
IN TOTAL	-	800	209 hours

The annual decrease in downtime could thus be 209 hours. The average downtime per year for the whole plant is about 1927 hours (37 hours per week during the research period). Eliminating the unnecessary transfer of data could decrease the annual downtime of the production plan by

$$209\ hours/1927\ hours = 10.8\% \quad (1).$$

2) Incorrect and Unnecessary Data

In total, 12% of the studied maintenance work request forms had visible quality problems that made them unreliable regarding data analysis. The most common quality problems included having several maintenance tasks bundled in the same work request, the filed maintenance start time being later than the reported finish of the task, and having multiple work requests on the same asset failure. In addition to the quality problems, the manual forms used to gather the maintenance data contain some data items that are unnecessary regarding the three specific maintenance tasks studied in the case; the impact of asset failure, the nature of the conducted work, and the asset breakdown type are all constant for each individual three task, so using time to document them separately for each work request is not necessary.

Documenting the incorrect and unnecessary data first into the manual forms and later on into the electronic spreadsheets causes both the maintenance engineers and the maintenance managers to waste their time. Table III shows the time that could be saved through eliminating this waste.

TABLE III
THE TIME WASTED DUE TO INCORRECT AND UNNECESSARY DATA

SOURCE OF WASTE	TIME WASTED PER FORM	NO. OF FORMS PER YEAR	TIME WASTED PER YEAR
Incorrect data into the manual forms	5 min	106	8.8 hours
Incorrect data into the spreadsheets	5 min	106	8.8 hours
Unnecessary data into the manual forms	0.5 min	794	6.6 hours
Unnecessary data into the spreadsheets	0.33 min	794	4.4 hours
IN TOTAL	-	-	28.7 hours

The maintenance engineers are thus wasting 15.4 hours (8.8 + 6.6) per year, and the maintenance managers 13.2 hours (8.8 + 4.4) per year. Considering that the total amount of time used by the engineers to execute the maintenance work of the studied three tasks is 312 hours per year (174 hours during the research period), eliminating this waste caused by incorrect and unnecessary data could increase by

$$15.4\ hours/312\ hours = 4.9\% \quad (2).$$

The maintenance managers currently use about 74 hours per year (41 hours during the research period) to transfer the manual data into spreadsheets. Eliminating the incorrect and unnecessary data could decrease this time by

$$13.2\ hours/74\ hours = 17.8\% \quad (3).$$

In addition to the wasted time discussed above, it should be noted that in the later phases of the data management process the costs of incorrect data are related to making incorrect decisions. The value of this is difficult to quantify but it could be significant.

3) Unnecessary Processing of Data

The maintenance engineers go through the manuals forms when they document their work. However, the maintenance management team goes through each form again when inserting the data into the electronic spreadsheets. This can be seen as unnecessary processing of the data. Inserting the data from one work request form into the spreadsheet file takes on average 5 minutes, and the double processing of the data in the three selected maintenance tasks wastes

$$5\ min \times 900\ requests/year = 75\ hours/year \quad (4).$$

This is a massive amount of time, considering that the three simple maintenance tasks only represent a small part of the whole maintenance process in the case company. If the unnecessary processing of data was eliminated from all maintenance tasks of the plant, the case company could save the time of their maintenance management team by

$$5\ min \times 16649\ requests/year = 1387\ hours/year \quad (5).$$

4) Waiting for Data

The manual data gathering and processing makes the current data management process quite slow. It can take a long time for the data to make their way from maintenance execution to data analysis. At the moment this is not a very significant problem for the case company, as the data is currently mostly used in monitoring the performance of their corrective maintenance processes on a weekly or even monthly basis. However, in the near future the company is planning to increase the role of preventive maintenance in their processes, which will create a need for a faster data management process so that the maintenance data can be used to prevent asset failures before they occur.

C. The Suggested Data Management Process

To eliminate the four main sources of waste identified in the current maintenance data management process of the case company, the process visualized in Fig. 3 is suggested.

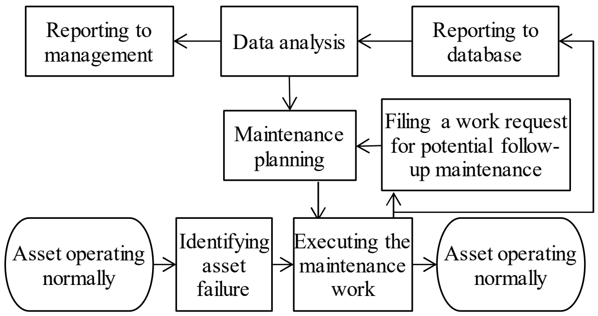

Fig. 3. The suggested data management process to eliminate the identified waste.

Compared to the current data management process and analytic strategy of the case company, the following changes are suggested:

1) Transferring the responsibility of executing the studied three simple maintenance tasks from the maintenance engineers to the asset operators. This eliminates the waste of unnecessary data transfer.
2) Implementing a computerized maintenance data management system to eliminate the unnecessary processing of data, unnecessary data, and to speed to whole data management process up.
3) Taking action to increase the quality of data. In practice the most important aspect to consider here is the training of the maintenance engineers and the asset operators to ensure that everybody understands what data is needed, in which format, and why.

V. Discussion

Before implementing the changes suggested above, the case company needs to once more assess the overall profitability and key enablers of the suggested actions. For instance, before deciding to transfer the execution of the studied maintenance tasks from maintenance engineers to asset operators it needs to be taken into account that the maintenance tasks can take a bit longer if being performed by the operators. Training the operators to 1) perform the maintenance, 2) reliably identify the need for these specific maintenance tasks, and 3) identify the need for potential follow-up maintenance takes time and will cause costs. It should also be considered that freeing more time for the maintenance engineers is valuable only if they have something more valuable to do.

Similarly, the overall costs and benefits of implementing the computerized data management system must be properly assessed before making the final decision. The development towards exploiting big data and predictive data analytics must be done one step at a time so that the culture has time to adapt to the new processes and technology. At the moment the case company is struggling with producing high-quality data for their manual forms, and ensuring data quality should be prioritized over developing a faster process which would still produce poor-quality data.

VI. Conclusions

This paper demonstrated how a lean-based approach can be adapted to data management processes to identify waste. The method was validated in a maintenance related industrial case example in collaboration with a food manufacturing company.

The paper contributes to the previous theoretical discussion on data management through linking it with the principles of lean management. The presented approach takes lean to the level of studying data management processes, whereas the majority of existing lean-related research has studied manufacturing processes and their material flows. From a managerial point of view, there is a lack of systematic approaches to improve data management in organizations. The method introduced in this study enables making the waste transparent in data management processes. The approach helps integrating data with value and business performance of organizations. This is important when developing industrial data management applications, because company managers often require "proof" of increasing value before committing to novel data-based applications.

The analysis presented in this paper partly quantified the waste identified in the studied data management process. However there is still a lack of systematic methods to quantify the value of data. This should be covered in further research of the topic to support the data-related decision making in organizations.

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