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Abstract

Purpose – Big data and related technologies are expected to drastically change the way industrial maintenance in managed. However, at the moment many companies are collecting large amounts of data without knowing how to systematically exploit it. It is therefore important to find new ways of evaluating and quantifying the value of data. This paper addresses the value of data –based profitability of maintenance investments.

Design/methodology/approach – An analytical Wasted Value of Data –model is presented to quantify how the value of data can be increased through eliminating waste. The use of the model is demonstrated with a case example of a maintenance investment appraisal of an automotive parts manufacturer.

Findings – The presented model contributes to the gap between the academic research and the solutions implemented in practice in the area of value optimization. The big data hype has led organizations into gathering data without systematic exploitation plans, but it is crucial to evaluate if the benefits of the investment will exceed the additional costs.

Originality/value – The model is designed and developed on the principle of eliminating waste to increase value, which has not been previously extensively discussed in the context of data management.

Article classification – Research paper

Keywords: Maintenance cost management; Value creation; Maintenance process

1. Introduction

Industrial maintenance is expected to be revolutionized by the recent manufacturing-related technological developments. The emergence of concepts such as Industry 4.0, cyber-physical systems, and big data has boosted the need to exploit data in maintenance decision making (Kamble *et al.*, 2018). This includes using various supportive technologies for example in non-destructive degradation assessment, prognostics, remote maintenance, and task visualization (Roy *et al.*, 2016). As a result of this technological development, the information technology landscapes connected to the asset lifecycles are complex, heterogeneous, and often include various systems and stakeholders (El Kadiri *et al.*, 2016). The complexity together with the big data hype has resulted in a situation where many companies are examining the need to collect big data without a specific purpose or a systematic data exploitation plan, which often leads to the maintenance decision makers feeling overwhelmed and unable to exploit the data (Günther *et al.*, 2017).

Chen *et al*. (2015) describe big data as 'a hammer looking for nails' because it can provide solutions to an undefined range of decision-making situations. It can be argued that achieving widespread value from big data often requires the use of extensive resources. Konecranes, a global provider of industrial lifting equipment and solutions, is an example of an organization that are excelling in embedding big data into their maintenance business. They have connected over 19,000 assets world-wide with their remote monitoring center, providing them sensor-based real time usage data to support their customers with, for example, remote maintenance, maintenance planning, prognostics, automatic warehouse management, and analytics services. In the future they are striving for an increase in digital operations in their equipment and service business with increased use of artificial intelligence, machine-learning, economies of scale through an ever larger fleet of intelligent assets, and eventually autonomous assets (Konecranes, 2018). However, many organizations do not have the resources and competence to extensively experiment with big data and the related technologies. This is emphasized by the low technology maturity of the manufacturing and maintenance industries reported by Diez-Olivan *et al*. (2019) and Kans (2013). Günther *et al*. (2017) state that a majority of the existing literature on big data has focused on its benefits without sufficient critical discussion, and that it is easy for decision makers in industry to forget that the value from big data needs to surpass the resources required to collect, analyze, and exploit the data. To support maintenance decision making, it is important to evaluate and quantify the value of data.

The objective of this paper is to develop a method to assess the value of data –based profitability of maintenance investments. This objective is pursued through analytical modelling. A Wasted Value of Data –model (WVD-model) is developed on the concept of increasing value through eliminating waste, which is an integral part of lean maintenance data management. The use of the model is presented through a case example of a maintenance investment idea developed within an industrial manufacturing company. Kleinberg *et al*. (1998) describe the value optimization problems often addressed in microeconomics and mathematical programming to be so complex and unknown that there is a wide gap between the academic research and the solutions implemented in practice: the managerial contribution of the research-based models is often limited to providing heuristic guidelines, whereas company decision makers rely on their subjective and limited knowledge of the problem. The research approach adopted in this paper will decrease this gap in the context of maintenance decision making support in terms of contributing to the existing theories of lean management, maintenance processes, and data management, while ensuring the model is easy to use and adaptable to provide possibilities for practical implementation in industry.

2. Value of data-based maintenance investments

2.1 Data-based maintenance investments

In this paper maintenance investments mean organizations investing their resources in developing certain aspect(s) of their maintenance functions. It is therefore different from investing in new assets or machines, which is also closely related to maintenance. The existing literature has not explicitly defined maintenance investments, nor presented taxonomies. Alsyouf (2009) stated that maintenance investments can be directed at people, training, or technology. This is somewhat congruent with the ISO 55001 standard (2014), which lists that asset management systems are built upon resources, competence, awareness, communication, information requirements, and documented information. According to Tam and Price (2008), organizations should maximize the return on their maintenance investments by the optimization of three specific decision dimensions: output dimension (achieving objectives related to production, service delivery, and compliance), risk dimension (achieving objectives related to unexpected faults and failures), and resources dimension (achieving objectives related to cost-efficient supply of supporting resources). It can be stated that maintenance investments aim at objectives related to one or more of these dimensions. All three dimensions should be taken into account in investment decision making, although the importance of individual dimensions is system dependent.

Data is an integral part of an increasing share of maintenance investments, as the amount of data available to support maintenance decision making is ever increasing (Baglee *et al*., 2015; Candell *et al*., 2009). Data is used to build maintenance decision-support models and predictions, and to construct history databases to ensure the reliability of the adopted decision logics (Takata *et al*., 1999). The optimal amount of data to be collected to support maintenance decision making varies depending on the size, business, asset and process complexity, and competence of the organization (BS ISO 55001, 2014). To optimize maintenance investment decisions, it would be important to be able to assess the value of data in various maintenance-related decision making contexts. The existing academic discussion on defining and quantifying the value of data is fragmented. Examples exist in the contexts of financial investment decisions (Kadan & Manela, 2018), biology and ecology (e.g. disease control, threatened species management) as well as economics through the value of information –theory (Alfonso *et al*., 2016; Bennett *et al*., 2018). Bucherer and Uckelmann (2011) state that the value of information services consists of having the right information, in the right amount, quality, format, time, place, and for an appropriate price. This view approaches information as a factor of production, which has been discussed in various development stages of modern information technology (see e.g. Dewan & Min, 1997; Imran *et al*., 2018). However there is limited research to support presenting Bucherer and Uckelmann's statement in a quantifiable format to provide managerial guidance for the companies' decision makers.

2.2 The value of lean maintenance data

The increased amount of data provides new possibilities for data-based decision making in maintenance, but it also brings forward challenges. The decision makers can feel overwhelmed by the vast data, and the process of gathering, analyzing and exploiting data is managed sub-optimally (Kinnunen *et al*., 2016). To make the waste caused by data overload transparent, a lean data approach can be suggested. Lean, within the context of manufacturing, is a management approach built on maximizing value through eliminating waste (Gupta *et al*., 2016), which has been widely discussed in the context of managing the material flows of manufacturing systems. Lean management has also been adapted to service processes (Andersson *et al*., 2015; Jylhä & Junnila, 2013), and software projects (Staats *et al*., 2011), but the discussion on lean data management are somewhat limited at best (see e.g. Bevilacqua *et al*., 2015; Hicks, 2007; Keltanen, 2013; Obeysekare *et al*., 2016).

Summarizing the existing body of knowledge on waste in lean production (Andersson *et al*., 2015), lean maintenance (Huang *et al*., 2012; Mostafa *et al*., 2015), and lean information management (Hicks, 2007; Verhagen *et al*., 2015), previous research has presented eight types of waste in maintenance data management processes:

1) Unnecessary data in decision making,
2) Unnecessary data in other parts of the data management process,
3) Unnecessary transfer of data,
4) Unnecessary processing of data,
5) Underutilized data management resources,
6) Incorrect data,
7) Incorrect analysis, and
8) Waiting for data and decision making (Marttonen-Arola & Baglee, 2019).

Erkoyuncu *et al*., (2017) note that the majority of maintenance models are focused on specific cases and tend to optimize direct maintenance efforts with expected savings, without taking the resources used in collecting data and developing new methods into account. In this paper we argue that to evaluate data-based maintenance investments and optimize the output, risk, and resource dimensions, it is necessary to quantify the costs and benefits of the data management process. The next section presents the WVD-model to analyze the investments based on the information wastes listed above.

3. Wasted Value of Data -model for evaluating maintenance investments

3.1 Calculating the annual net value

To assess the profitability of data-based maintenance investments, we begin by evaluating the annual value generated by the investment, based on the various waste types listed above:

$$V = \sum_{y=1}^{5} V_y + (1-\alpha) * V_6 \tag{1},$$

where V is the additional annual value generated by the investment, excluding the actual investment costs,

V_1 is the value of the investment generated by decrease of unnecessary data in decision making,

V_2 is the value of the investment generated by decrease of unnecessary data in other parts of the data management process,

V_3 is the value of the investment generated by decrease of unnecessary transfer of data,

V_4 is the value of the investment generated by decrease of unnecessary processing of data,

V_5 is the value of the investment generated by decrease of underutilised data management resources,

α is an uncertainty coefficient generated by incorrect data and/or analyses, and

V_6 is the value of the investment generated by decrease of waiting for data.

It should be noted that the maintenance investment could generate an increase in a number of the waste types. An example of this would be adopting an advanced data system which records data unnecessary to the maintenance decision makers, causing V_1 and V_2 to become negative and decrease the annual net value. In the next paragraphs the components of value in equation (1) are discussed in further detail. First of all, the value generated by decrease of unnecessary data in decision making can be defined as

$$V_1 = (t_{1a} - t_{1b}) * c_1 \tag{2},$$

where t_{1a} is the time used in the decision making process before the investment,

t_{1b} is the time used in the decision making process after the investment, and

c_1 is the cost of the time of the decision maker.

Similarly, the value generated by decrease of unnecessary data in other parts of the process, unnecessary data transfer, and unnecessary data processing can be defined as in equations (3) to (5).

$$V_2 = (t_{2a} - t_{2b}) * c_2 \tag{3},$$

where t_{2a} is the time used in the data management process before the investment,

t_{2b} is the time used in the data management process after the investment, and

c_2 is the cost of the time of the personnel managing the data.

$$V_3 = (t_{3a} - t_{3b}) * c_3 \qquad (4),$$

where t_{3a} is the time used in transferring the data before the investment,

t_{3b} is the time used in transferring the data after the investment, and

c_3 is the cost of the time of the person transferring the data.

$$V_4 = (t_{4a} - t_{4b}) * c_4 \qquad (5),$$

where t_{4a} is the time used in processing the data before the investment,

t_{4b} is the time used in processing the data after the investment, and

c_4 is the cost of the time of the person processing the data.

In addition to the data, the resources required for data-based maintenance include various maintenance systems and personnel. The capacity and potential underutilisation of resources is easy to overlook in investment decision making but it can have a significant impact on the profitability of the investment. According to Wienker *et al*. (2016), only 6%-15% of the users of Computerized Maintenance Management Systems (CMMS) exploit the systems at their full capacity. Many organizations purchase features and applications that they rarely or never use. Regarding the personnel, as a result of the increased data and technology many maintenance organisations are in need of new kind of skill related to e.g. data analytics (Diez-Olivan *et al*., 2019). If an organisation decides to recruit new personnel based on their maintenance investment they should be aware of the share of costs to be allocated to the maintenance function. Allocating employees' time to different tasks and evaluating system underutilisation rates is likely to be based on subjective and inaccurate estimates. However the value generated by the decrease in underutilisation of data management resources could be significant to the investment decision and should be evaluated as a share of the costs of maintenance systems and personnel:

$$V_5 = (F_a * x_a) - (F_b * x_b) \qquad (6),$$

where F_a is the annual cost of the data management resources before the investment,

x_a is the share of time the resources are unused before the investment,

F_b is the annual cost of the data management resources after the investment, and

x_b is the share of time the resources are unused after the investment.

The value generated by decrease in waiting for data and decision making is possibly the most significant component of the total value. However it also includes uncertainty, and is challenging to evaluate accurately. In this paper this value component is addressed as

$$V_6 = A - B \quad (7),$$

where A is the annual cost of the actual maintenance work and the value of production lost due to asset breakdowns before the investment, and

B is the same annual cost after the investment.

The maintenance costs in A and B include direct labour costs, direct materials, spare parts, tools, equipment, purchased services, administration and management, training, energy and utilities, other overheads, and the value of the production lost due to asset unavailability (see e.g. El-Haram & Horner, 2002; Salonen & Deleryd, 2011). The value of lost production caused by asset breakdowns is rarely included in the total maintenance costs in the existing standards (see BS EN 15341, 2007) because it is often a significant amount (multiple times bigger than the maintenance costs) (see e.g. Knapp & Mahajan, 1998; Sinkkonen *et al*., 2013; Wu & Clements-Croome, 2005) and is considered a significant issue that should not be allocated only to the maintenance function. However, the value of lost production has to be taken into account in maintenance investment decisions so in the WVD-model it is addressed as a part of the maintenance costs. Despite their importance the value of lost production and other indirect maintenance costs tend to be time-consuming to evaluate accurately, which is why they are often approximated based on average asset productivities, contribution margins, and downtimes (see Edwards *et al*., 2000).

The three common maintenance actions, ignoring run-to-fail, are referred to as corrective, predetermined, and condition based. Corrective maintenance aims to restore asset functionality after a failure, predetermined maintenance seeks to prevent failures based on time- or use-based maintenance, and condition-based maintenance relies on monitoring the actual condition of the asset to decide on the optimal maintenance actions (BS EN 13306, 2017). It is generally acknowledged that compared to corrective maintenance, adopting predetermined and condition-based maintenance strategies requires more resources although this can result in increased performance in terms of reduced probability of breakdowns, improved asset condition, less deficiencies in quality, and equipment life extension (Swanson, 2001). Optimal maintenance seeks to minimize the total costs, including the actual maintenance costs and the value of lost production (Wang & Wang, 2015; Weinstein *et al*., 2009). Thus compared to planned maintenance, corrective maintenance is seen to be more costly in the end (Gulati, 2009).

In equation (1) V_6 is influenced by the uncertainty coefficient α. This coefficient takes into account the quality of both the maintenance data and analyses used to support decision making:

$$\alpha = P(\beta_2 \cup \gamma_2) - P(\beta_1 \cup \gamma_1) = P(\beta_2) + P(\gamma_2) - P(\beta_2 \cap \gamma_2) - P(\beta_1) - P(\gamma_1) + P(\beta_1 \cap \gamma_1) \quad (8),$$

where $P(\beta_1)$ is the probability of the maintenance data being incorrect before the investment,

$P(\beta_2)$ is the probability of the maintenance data being incorrect after the investment,

$P(\gamma_1)$ is the probability of conducting the data analyses incorrectly before the investment, and

$P(\gamma_2)$ is the probability of conducting the data analyses incorrectly after the investment.

Thus the probabilities of the data and the analyses being incorrect need to be estimated, and the probability of both incorrect data and analyses would need to be identified. In practice these probabilities could either be estimated based on the views of industrial experts, or be evaluated based on a quality analysis of a sample of the data in question.

3.2 Evaluating the profitability of the investment

As with any investment, the profitability assessment requires studying the actual investment costs in relation to the decreased waste (which impacts the annual operating and maintenance costs) addressed above. Depending on the objective and scope of the maintenance investment, the investment costs may include the costs of software, hardware, labour, training, consulting, etc. (see e.g. O'Donoghue & Prendergast, 2004). There is a number of established methods to evaluate the profitability and feasibility of an investment, including for example the payback period (see e.g. Yard, 2000), net present value (Liljeblom & Vaihekoski, 2004), and internal rate of return (Juhász, 2011). In this paper the investments are evaluated based on the net present value, calculated from the annual value V as:

$$NPV = \sum_{T=1}^{t} \frac{V}{(1+i)^T} - I \quad (9),$$

where NPV is the net present value of the investment,

i is the discount rate,

t is an estimate of the life cycle of the investment or the analysis period, and

I is the total initial investment.

Out of the investment appraisal methods, NPV was selected because it has been extensively adopted in practice, presents the results in monetary terms, and takes the time value of money into account. However, it is important to state that this method is based on variables such as i and t, both of which are prone to uncertainty and more or less subjective assumptions (see Juhász, 2011). To overcome this issue, sensitivity analyses is often used to study the impact of uncertainty on the profitability of investments.

4. Case example

4.1 Introduction to the case

The case focuses on a company which manufactures a range of parts for the automotive industry. The analysis is based upon a three-shift production plant operating in the UK. Currently the company uses manual forms to collect data on their maintenance, and inserts the data into electronic spreadsheets once a day. The maintenance managers feel that they cannot use the data for improving their maintenance processes, because it is mostly focused on maintenance and breakdown times, and important information such as the data on failure causes are missing. Accordingly, the maintenance engineers at the production plant are currently using 70% of their time on breakdowns and repairs, as opposed to only 2.9% on preventive maintenance tasks.

The maintenance managers are thinking about investing in the data management of the maintenance process to implement a CMMS and to develop their maintenance policies towards predetermined, instead of corrective, maintenance. Referring to the three literature-based decision dimensions of maintenance investments (see Tam & Price, 2008) as presented above in section 2.1, the main objectives of the company are to increase production (output dimension), decrease unplanned breakdowns (risk dimension), and improve data-based decision making (resources dimension). There are 15 production lines in the plant, of which the company is particularly interested in three that are causing a large share of the breakdowns of the plant and are important in terms of plant productivity: Floor Carpet 3 (FC3), Foam Line 1 (FL1), and Foam Line 2 (FL2). In this case example, the value of additional data and CMMS in the maintenance management of the selected production lines is analysed. The data used for the analysis includes the selected production plant's maintenance and breakdown times from 1 January to 22 June 2018. In addition the maintenance manager of the plant was interviewed to gain insight on the maintenance and data management processes.

4.2 Annual costs and benefits of the case investment

In the case example, V_1 and V_2 (the value generated by decrease in unnecessary data) are assumed to be insignificant and are thus omitted. The case company is currently manually collecting data which could be of value if they adopt a predetermined and/or condition-based maintenance strategies instead of the corrective maintenance they are currently running.

Regarding the unnecessary transfer of data, investing in the CMMS would remove the need to manually insert the collected data into electronic spreadsheets. Currently a production planner uses 1h per production shift to transfer the data into the spreadsheets. With regard to the breakdowns in the production plant during the research period, 7.8% occurred at FC3, 25.1% at FL1 and 21.0% at FL2. Thus 53.9% of the breakdowns in the plant can be reached through the three selected production lines. Allocated based on the number of breakdowns per each production line during the research period, the annual time saved from transferring the data into spreadsheets would be 20.3h for FC3, 65.2h for FL1, and 54.5h for FL2. Based on public sources, the employee cost of the production planner's time is estimated to be 13.3£/h. Thus:

$$V_3 = (20.3h + 65.2h + 54.5h) * 13.3£/h = 1{,}862£ \quad (10).$$

Data processing includes several tasks embedded in the decision making process. A summary of these tasks before and after the investment is given in Table 1. Currently the case company collects data before each shift handover: a maintenance report sheet from each maintenance engineer who finishes their shift, maintenance shift handover details from each shift, and a production data summary from each shift. To reach the data needed for supporting maintenance decision making, after the investment the company would collect data on each maintenance event. This data would replace the data currently included in the maintenance report sheets and the maintenance shift handover details. It has been assumed that the number of maintenance events would remain unchanged (a part of the breakdowns would be replaced by preventive maintenance events), that documenting the production data would be 50% faster with a CMMS compared to the current manual process, and that the maintenance managers of the case plant would use an additional 1h per each shift to analyse the new data created by the investment. Currently the data is not systematically analysed and exploited because key information is missing.

Table 1. The impact of the investment on the processing of data.

[*Place Table 1 here*]

It can be concluded that V_4 equals -10,413£ (6,221£ - 16,634£), as implementing the CMMS and a predetermined maintenance strategy would produce more data to be processed.

If the case company were able to pilot the CMMS on only the three selected production lines, the software would be somewhat underutilized, at least before implementing it on a wider scale. Thus the whole cost of the software would at first be allocated to the three pilot lines. V_5, caused by underutilization of data management resources, could thus be assessed based on the costs of the selected CMMS software. However in this case study no specific CMMS software has been selected by the company, and the costs related to the software and its installation are not known in detail. Thus V_5 is omitted at this point, and the software costs are discussed later as part of the investment costs.

In this case example the value of decreased waiting in the data management process, V_6, is related to the availability of additional data as a result of the investment. With the correct data (failure root causes, reliabilities, repair times, performance and cost rates, etc.) the case company will be able to conduct predetermined maintenance, instead of the failure-based corrective maintenance they are currently running. Predetermined maintenance would prevent a share of the breakdowns (Meller & Kim, 1996), which would increase the annual production time and sales (assuming that there is a demand for the increased production). Table 2 shows how the value of this increased production after the investment has been assessed.

In practice predetermined maintenance schedules are often based on equipment suppliers' recommendations or experience-based assumptions of the maintenance personnel (Vilarinho *et al*., 2017). However, to increase the impact of the maintenance programme, the schedule should be defined based on a Failure Modes and Effects Analysis (FMEA), taking the specific failures and their root causes into account. Chen (2013) discussed that introducing a FMEA-based predetermined maintenance schedule decreased breakdowns by 25%. Komonen (2002) documented a prevention rate of 34% in three-shift production plants of various industries in Finland during 1996-1997. Ruifeng and Subramaniam (2012) studied Kanban controlled assembly lines and reported a 50% reduction in the probability of interruption after introducing predetermined maintenance. Muchiri *et al*. (2014) highlighted that the performance of a predetermined maintenance policy (compared to a corrective one) is higher when the reliability of the equipment is poor. Consequently, when the equipment is reliable, implementing a preventive maintenance programme can create problems and increase costs without resulting in an increase in value. The share of breakdown-induced downtime of the production time is 7.73% for FC3, 19.95% for FL1, and 17.96% for FL2. Based on the notions presented above, a prevention rate of 30% (for FC3 with a higher reliability), and 40% (for FL1 and FL2 with a larger share of breakdowns) has been assumed.

The assumptions described on prevention rates for each production line are likely to have a strong impact on the profitability of the investment. There is a lot of existing research on modelling the optimal predetermined maintenance intervals for various systems. Most of these models are case specific and assume that the decision maker knows the system's failure distribution in detail (Cavalier & Knapp, 1996). Common ways to present the failure probability functions are e.g. Weibull distributions for age-related failures (Nguyen & Chou, 2018; Sarker & Faiz, 2016), and exponential functions for constant failure rates (Peters & Madlener, 2017). In this paper we pursue a more general model to support the decision makers in evaluating the profitability of an investment which would, later on, include the FMEA to study the failure distributions of the system(s) in question.

It has been assumed that the direct maintenance costs (direct labour and materials) would not change after adopting the predetermined maintenance programme. The average value of an additional hour of production has been estimated based on the publicly available financial information of the case company from 2018 (annual sales, the share of variable costs, and the tax rate). Each production line in the plant has been assumed to be equal in terms of value of production per hour, because the case company considers the prices and profit margins of individual products to be sensitive data.

Table 2. The impact of the investment on the lost production.

[*Place Table 2 here*]

To calculate the uncertainty coefficient α, estimates are needed on the probabilities of poor quality data and analyses before and after the investment. According to Tayi and Ballou (1998), data quality goes hand in hand with fitness for use and thus is a relative and subjective concept. Measures of data quality include e.g. accuracy, completeness, consistency, timeliness, interpretability, and accessibility. However these qualities are often difficult for the data users to evaluate objectively, and thus the users often end up trusting that the data is of high quality even though the matter has not been properly addressed (Cappiello *et al*., 2004). To present an evaluation of the data quality, in this case example the case data was reviewed for visible analysis errors (#REF! error codes in the spreadsheet) in the production line downtime summary data. Based on the findings, the current probability of incorrect analysis is estimated to be 0.27%. This is assumed to reduce to 0.00% after the investment. Regarding the probability of incorrect data, the authors did not have a reliable way of assessing the quality of the actual case data since there is no way to check if the manually collected data is accurate. Instead, a general observation on the quality of data is used: according to a recent global survey, organisations with manual and excel-based data management processes reported that 41% of their data could be inaccurate, whereas organizations that used more sophisticated data management tools reported an average of 27% or less (Experian Data Quality, 2015). Inserting these figures into equation (8), and assuming that the occurrence of poor quality data and poor quality analyses are independent events, α is estimated to be -0.13. Thus the investment increases the quality of data and analyses, which will be taken into account when calculating the total value of the investment.

Through inserting the figures presented above into equation (1), an estimate of the annual added value of the investment is:

$$V = 1{,}862£ - 10{,}413£ + (1 + 0.13) * 65{,}428£ = 65{,}383£ \quad (11).$$

4.3 Profitability of the case investment

The case company have yet to identify specific CMMS software or specific additional data items to be collected. This creates uncertainty regarding the investment costs. Therefore, rather than calculating the *NPV* based on the costs, the authors opted to calculate a break-even level of the investment costs based on a predefined *NPV*. The logic is similar to that of target costing (see e.g. Monden & Hamada, 1991), the objective of which is traditionally to establish a target cost for a product in its planning or design stage, based on predetermined target levels of sales price and profit margin.

From equation (9) we get:

$$I = \sum_{T=1}^{t} \frac{V}{(1+i)^T} - NPV \quad (12).$$

To calculate the break-even level of investment costs, *NPV* is set to 0. There is no universal solution to choosing the discount rate *i*. For instance Harrison (2010) recommends including the selected rate into a sensitivity analysis to decrease the uncertainty. One of the commonly used methods in choosing the discount rate is to calculate the Weighted Average Cost of Capital (WACC) of the company (see Keane, 1975). Following this method and using the publicly available consolidated financial statement of the case company, the discount rate has been calculated as:

$$i = \frac{i_D * D + i_E * E}{D + E} \quad (13),$$

where i_D is the average interest rate of debt,

D is the amount of debt,

i_E is the return on equity, and

E is the amount of shareholder equity.

For the case company the WACC-based discount rate is:

$$i = \frac{i_D * D + i_E * E}{D + E} = \frac{4.6\% * 2{,}584M€ + 19.5\% * 4{,}071M€}{2{,}584M€ + 4{,}071M€} = 13.7\% \quad (14).$$

The investment lifecycle t is an estimate of how long the data management system (including the CMMS and the data exploitation processes in maintenance) is expected to outperform other alternatives. According to Richmond *et al.* (2006) the software lifecycle is affected by a number of variables including project scope, level of customization, and fit with technology standards. In this case example the investment lifecycle is set to 3 years to represent the dynamic pace of ICT-related investments.

Based on equation (12), the break-even level of the investment costs is:

$$I = \frac{65{,}383\ £}{(1+0.137)^1} + \frac{65{,}383\ £}{(1+0.137)^2} + \frac{65{,}383\ £}{(1+0.137)^3} - 0\ £ = 152{,}563\ £ \quad (15).$$

According to Labib (2004), commercial CMMS solutions with features for data collection and analysis typically cost in excess of £10,000, whereas features for real-time data analysis increase the price to at least 30,000£. Real-time analysis is usually related to condition-based maintenance, and at this point would not be required by the case company. Thus based on the analysis presented above, investing in the CMMS and additional maintenance data seems very profitable to the case company. Even significant changes in parameters such as the assumed failure prevention rates, α (the uncertainty coefficient describing the quality of data and analyses), i (the discount rate used to describe the WACC of the company), or t (the assumed lifecycle of the investment) would not turn the investment unprofitable.

5. Conclusion

This paper presented the analytical WVD-model to quantify the value of data in maintenance investments. The model is designed and developed on the principle of eliminating waste to increase value, which has not been previously extensively discussed in the context of data management. The big data hype has led many organizations into gathering data without systematic exploitation plans. However in terms of the output, risk, and resource dimensions (see Tam & Price, 2008) of data-based investments it is crucial to evaluate if the benefits created by the investment will exceed the additional costs. This has previously been discussed by Pape (2016), who applied his model in human resources.

The managerial use of the WVD-model has been demonstrated through an empirical case example. However applying the model in practical decision making situations still involves some aspects which have not been extensively studied in the literature. For example, in the WVD-model the impact of data and analysis quality is measured through a simple uncertainty coefficient α. Further research should be directed at studying how the quality affects the value of data and analyses in maintenance decision making, how the quality should be measured, and what is the current state-of-practice in industry. Another limitation of the presented WVD-model is related to the maintenance types adopted by the applying organizations. In the case example presented in this paper, corrective and predetermined maintenance were considered. It would be considerably more complex to quantify the value of data in a context where condition-based maintenance is applied. Thus further research should study how the specific features of condition-based maintenance (e.g. large real-time datasets, integration of various data, and human-machine interaction) impact the value modelling process.

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Table 1. The impact of the investment on the processing of data.

Data processing task	Documenting the work before shift handover	Documenting maintenance event data	Data analysis and exploitation	TOTAL
Time and cost required by the current process (annually)	465 h 6,221 £ *(15 min per maintenance report sheet, 20 min per maintenance shift handover, and 20 min per production data summary)*	*(Maintenance event data not currently recorded)*	*(Currently not properly analysed and exploited)*	**465 h** **6,221 £**
Time and cost required after the investment (annually)	70 h 946 £ *(10 min per production data summary)*	681 h 8,989 £ *(5 min per maintenance event)*	420 h 6,699 £ *(1 h per shift)*	**1,171 h** **16,634 £**

Table 2. The impact of the investment on the lost production.

Production line	Share of breakdowns of the production time	Assumed prevention rate	Increase in production time per year	Value of the increased production per year
FC3	7.73%	30%	145 h	8,696 £
FL1	19.95%	40%	498 h	29,865 £
FL2	17.96%	40%	448 h	26,867 £
In total	-	-	1,091 h	65,428 £