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Data-driven machine criticality assessment – maintenance decision support for increased productivity

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ABSTRACT

Data-driven decision support for maintenance management is necessary for modern digitalized production systems. The data-driven approach enables analyzing the dynamic production system in real-time. Common problems within maintenance management are that maintenance decisions are experience-driven, narrow-focussed and static. Specifically, machine criticality assessment is a tool that is used in manufacturing companies to plan and prioritize maintenance activities. The maintenance problems are well exemplified by this tool in industrial practice. The tool is not trustworthy, seldom updated and focuses on individual machines. Therefore, this paper aims at the development and validation of a framework for a data-driven machine criticality assessment tool. The tool supports prioritization and planning of maintenance decisions with a clear goal of increasing productivity. Four empirical cases were studied by employing a multiple case study methodology. The framework provides guidelines for maintenance decision-making by combining the Manufacturing Execution System (MES) and Computerized Maintenance Management System (CMMS) data with a systems perspective. The results show that by employing data-driven decision support within the maintenance organization, it can truly enable modern digitalized production systems to achieve higher levels of productivity.

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Productivity; criticality assessment; bottleneck; maintenance prioritization; data-driven decision-making

1. Introduction

The fourth industrial revolution, triggered by the German initiative Industrie 4.0 (Kagermann, Wahlster, and Helbig 2013), is fuelled by digital technologies in manufacturing. This revolution has increased the expectations of manufacturing companies to become highly productive, to have high resource efficiency, and to increase automation (Monostori et al. 2016). However, in order for the highly automated production systems to produce autonomously, managing machine breakdown becomes very important. In other words, increases in productivity are sought after at all times. Hence, planning and control of production and maintenance of industrial machines are the backbone of manufacturing companies for achieving higher productivity and to remain globally competitive. Particularly, industrial maintenance practices have been reported to be well behind maintenance research, and maintenance organization needs to comply quickly with the rapid advancements of digitalized manufacturing (Bokrantz et al. 2017). In order to close the gap between practice and research, probable future scenarios for maintenance organizations in manufacturing companies were predicted as follows: to manage large volumes of data, perform data analytics, make fact-based decisions, and provide education and training, among others (Bokrantz et al. 2020).

The above-mentioned problems are exemplified through the lack of effective maintenance decision support tool systems in manufacturing companies. Also, the existing Computerized Maintenance Management Systems (CMMS) are argued to no longer meet the needs of dynamic maintenance operations (Ni and Jin 2012). Specifically, managing maintenance for multiple machines in a system i.e. approaching this problem from a systems perspective, is an important problem for the future (Roy et al. 2016). Traditionally, the maintenance organization is considered to be the provider of technical availability of individual machines rather than improving plant-level performance, such as productivity. A wealth of single-machine maintenance problem literature is a reflection of this narrow approach. Contrarily, a system perspective for solving maintenance problems needs addressing (Helu and Weiss 2016). For example, within Reliability Centred Maintenance (RCM), Failure Mode and Effect Analysis (FMEA) is a tool which supports maintenance planning decisions by assessing failure modes of a specific machine (Pintelon and Parodi-Herz 2008). But it cannot provide decisions on identifying which machines in the production system are critical to the production system as a whole.

Machine criticality assessment is a tool which assesses the criticality of machines in order to support prioritized maintenance allocation decisions (Márquez et al. 2009; Antosz and Ratnayake 2016; Bengtsson 2011; Marquez et al. 2016). Many existing machine criticality assessment tools provide support only for a specific long term decision, especially,

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maintenance strategy selection for an individual machine (Márquez et al. 2009), whereas they have the potential to support much wider maintenance management prioritization decisions including a variety of short- and long term decisions. Additionally, the existing assessment tools are highly qualitative in nature (Pelaez and Bowles 1994; Singh, Singh, and Kumar 2015) and qualitative approaches have shown to be non-factual (Gopalakrishnan and Skoogh 2018). With the development of computer technology and large amounts of data collected by the Manufacturing Execution System (MES), industries have reached a stage where data-based decisions can be made (Subramaniyan et al. 2016). Therefore, in order to provide maintenance prioritization decision support not only on a strategic level but also on an operational level, a data-driven machine criticality assessment is needed. This assessment tool will aid decision-making for the maintenance engineers and planners by making the problem recognition easier (Santana 1995).

As a result, this study aims to develop and validate a data-driven machine criticality assessment framework. The criticality assessment primarily focuses on the maintenance prioritization decisions for long- and short-term mitigation through integrating productivity as an objective for the assessment. Specific goals of this study are:

- *Goal 1:* To develop a data-driven machine criticality assessment framework through integrating productivity as a goal
- *Goal 2:* To validate the criticality assessment framework through a simulation experiment and evaluation through a qualitative study

The decoupling of maintenance theory and practice can be put down to a lack of solving real-world maintenance problems, i.e. lack of empirical research studies (Fraser, Hvolby, and Tseng 2015). Hence, an empirical multiple case study approach was followed in this study. The paper is structured as follows. It starts with a literature review where the existing theory on data-driven decision support and the principles of machine criticality assessment are presented. Based on the literature review, an approach for data-driven criticality assessment tool is proposed. This is followed by a description of the research methodology of the multiple case study. Subsequently, the results of the study are presented. This is then followed by of the development and validation of the framework. Lastly, the results are discussed based on their implications to industry and research before concluding.

2. Literature review

Recently, many research articles have been published in the field of digitalized manufacturing and data-driven decision support. However, there is a lack of literature focussing on the maintenance decision support tool for digitalized manufacturing. Maintenance research is largely reduced to predictive maintenance and prescriptive analytics (Karim et al. 2016; Van Horenbeek and Pintelon 2013). Decision support systems for maintenance planning other than predictive and prescriptive are also needed to enable manufacturing companies to effectively manage the maintenance of complex systems. A literature review on the need for maintenance decision support tools and the principles of machine criticality assessment is provided in this section.

2.1. Decision support in maintenance management

Maintenance decision-making is a complex task. Maintenance operations have a direct influence on the performance of the production system (Li and Ni 2009). A maintenance decision depends on several information sources, such as machine health condition and degradation, the maintenance plan and schedule, maintenance costs, and system configuration (Ni and Jin 2012). Many industrial practices have revealed the unstructured way in which maintenance decision-making is done through ad-hoc planning, production operator influences, and through the experience of the maintenance technicians (Gopalakrishnan et al. 2019; Guo, Jin, and Hu 2013). As a result, machines in manufacturing companies have returned poor Overall Equipment Effectiveness (OEE) figures, about 50% on average (Ingemansson 2004; Ljungberg 1998). Traditionally, maintenance organizations have been focussing on improving the availability (one of the OEE components) of the machines, but the operational efficiency (another of the OEE components) was shown to have a greater impact on the poor OEE figures than the availability of machines (Ylipää et al. 2017).

The operational efficiency of the machines is calculated using the utilization losses and speed losses of the machines during production (Nakajima 1988). These loss categories are traditionally not considered to be maintenance problems. However, these losses also contribute towards reduced productivity of the entire systems. Particularly, utilization losses in machines are created by blockage and starvation of machines, i.e. idling losses. Machine downtimes are one of the contributors to causing the rippling effects in the production system creating idling losses in the machines (Andersson and Danielsson 2013). These idling losses are the unused productivity improvement potentials that have not been tapped properly by maintenance organizations. Maintenance organizations, on the other hand, have been focussing on single machine problems, specifically, improving the availability and reliability of individual machines. Individual machine focus cannot boost their opportunity for productivity increase and cannot increase their responsiveness to production system changes (Ni and Jin 2012). Even though they are important, a systems perspective is needed to prioritize the machines for availability and reliability improvement.

Due to the lack of decision support tools with a systems perspective, maintenance organizations do not focus on productivity improvement. The normally used Key Performance Indicators (KPI) of maintenance, namely, Mean Time Between Failure (MTBF) and Mean Time To Repair (MTTR), which are individual machine KPIs indicates lack of productivity focus. These KPIs need to be combined with system-level KPIs to support maintenance prioritization decisions (Ni and Jin 2012). Historically, the relationship between maintenance and production has been characterized by conflict (Rishel and Christy 1996). However, system-level decision support tools can bring them together to have joint maintenance and production plans in order to maintain high productivity and production system performance (Wong, Chan, and Chung 2013).

2.2. Data-driven maintenance decisions

Maintenance organization needs to make decisions are on strategic, tactical, and operational levels (Pintelon and Parodi-Herz 2008). This study is mainly focussed on operational level, but it has the potential to be a decision support tool for strategic and tactical levels as well. The operational phase of the maintenance management includes maintenance planning and maintenance scheduling of preventive (PM) and reactive maintenance (RM) activities. Planning PM for machines on a systems-level includes identifying the type of PM activities that a machine needs and scheduling them with no or minimum stoppage of the production flow. A stoppage in the slowest machine will result in permanent production system losses, demonstrating that stoppage of the slowest machines is the least desirable among all machines (Liu et al. 2012). The slowest machine which impedes the throughput of the entire system is called a bottleneck machine (Goldratt and Cox 1992). By identifying the bottleneck the critical downtime of each machine in a system can be identified. The critical downtime is defined as the maximum time a machine can be down without making the bottleneck idle (Gu, Jin, and Ni 2015; Gu et al. 2013). The critical downtime can enable achieving a Maintenance Opportunity Window (MOW) by incorporating real-time information about production and machine failure conditions (Ni and Jin 2012; Wakiru et al. 2020). MOW offers a window of opportunity for the creation of a PM plan that will not affect productivity. Regarding RM planning and scheduling, bottleneck-based prioritisation have shown to increase the throughput of the system (Wedel, Noessler, and Metternich 2016; Langer et al. 2010; Li et al. 2009). Specific to this study, the active period of machines is used to detect bottlenecks.

The active period method of bottleneck detection was proposed by Roser, Nakano, and Tanaka (2001) and was tested in a discrete event simulation environment. Their method assumes that the machine with the longest average period is considered to be the bottleneck, as this machine is least likely to be interrupted by other machines, and in turn is most likely to dictate the overall system throughput. The main idea of this method is that a machine can be classified into two states during a production run: active and inactive. A machine is said to be in its active state when the machine is producing a product, when under setup, reactive maintenance, preventive maintenance, etc. On the other hand, a machine is said to be in its inactive state when the machine is blocked from production, starved for products, idle, etc. An example of active and inactive states of the machine during a production run is shown in Figure 1. The active duration of a machine can be calculated across a production run by aggregating the different active states of the machine. From this active duration, when computed for all machines across production, the potential group of bottleneck machines for that production run can be discovered.

Even though Roser, Nakano, and Tanaka (2001) developed and tested this method on a discrete event simulation environment, this method needs to be adapted to the real-time data which is collected from the shop floor to detect the bottlenecks. Subramaniyan et al. (2018) proposed a manufacturing execution system (MES) based data-driven algorithm which converts the real-time data of the machines into active states and statistically detects the group of bottlenecks. More information on the details of the algorithm are available in Subramaniyan et al. (2018). Furthermore, the algorithm can also give diagnostic insights into the bottlenecks in terms of different components of active states. This will help to understand the nature of bottlenecks in the production system. For example, the bottleneck could be a cycle time bottleneck, downtime bottleneck or setup time bottleneck (Chiang, Kuo, and Meerkov 1998). Understanding the nature of the bottleneck will help in framing specific strategies to manage the bottlenecks and reduce its effect on the desired throughput.

The central aspect of this type of decision support tool is the need for real-time production system data. A study has shown that on an average, 100 data rows are collected per hour per machine by the MES, implying that 500,000 data rows are collected per year per machine (Subramaniyan et al. 2016). Therefore, manufacturing companies can collect a large amount of data and use advanced data analytics to make fact-based decisions (O'Donovan et al. 2015). However,

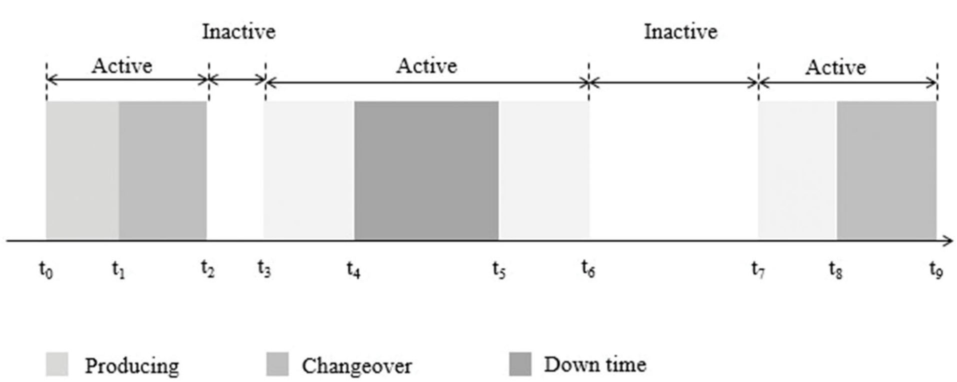

Figure 1. Representation of active states of a machine during a production run (adapted from Roser et al. (2001)).

Table 1. Literature on machine criticality assessment.

Author and Year	Purpose of assessment	Data requirement
Moss and Woodhouse 1999	To improve productivity. Criticality analysis is used for prioritizing maintenance, workshop loading, tools and spare parts planning.	Usage of qualitative data for setting criticality. For example: day-to-day priorities are set by workforce
Moore and Starr 2006	Prioritizing condition-based maintenance jobs using a strategy called cost-based criticality (CBC)	CBC weighs each incident flagged by condition monitoring alarms with up-to-date cost information and risk factors
Márquez et al. 2009	Prioritize assets and to align maintenance actions to business targets	Qualitative data for criticality assessment
Bengtsson 2011	Objective classification of machines for prioritized maintenance efforts and improvement activities	The classifications were performed in teams consisting of representatives from maintenance- and production engineering as well as production managers and operators
Ratnayake, Stadnicka, and Antosz 2013	Prioritization of machinery for minimizing the economic burden due to higher maintenance cost, loss of production, potential damage to health, safety and environment	Type of data used includes specific documentation, procedures, criteria and expert knowledge
Stadnicka, Antosz, and Chandima Ratnayake 2014	Machine classification for mitigating health, safety and environmental challenges	The data corresponding to machine failures, product quality deterioration, machine up-down time, cost of failures and elimination
Singh, Singh, and Kumar 2015	Prioritization of maintenance to increase productivity	Qualitative data for criticality assessment
Marquez et al. 2016	Asset priority for maintenance management program	Engineering data (for asset functional loss) and operational data (for current frequency of functional loss
Antosz and Ratnayake 2016	Scheduling preventive maintenance activities for machinery	Data in relation to machine failures, product quality deterioration, machine up- downtime

data quality is important to ensure that data-driven decisions are reliable and effective. Extensive research is being conducted to ensure data quality, as good data can dramatically increase the size and scope of improvements in companies (Batini et al. 2009). Additionally, competence in maintenance personnel is needed to execute the data analytics. Education and training for maintenance personnel are identified as activities critical for managing future competence requirements and maintain competitiveness (Bokrantz et al. 2017).

2.3. Principles of machine criticality assessment

Machine criticality assessment is a maintenance decision support tool that enables maintenance prioritization decisions for the critical machines (Antosz and Ratnayake 2016). Literature regarding machine criticality assessment is scarce. The available literature was analyzed to identify the purpose of assessment and data requirements. The summary of the literature analysis is tabulated in Table 1.

Based on the analysis of the aforementioned literature, the main aspects to consider in a criticality assessment are, (i) a clear purpose, (ii) data requirements, (iii) the method for assessment, and (iv) a list of maintenance actions that can be supported. Much of the work presented above on machine criticality assessment is with the purpose of maintenance prioritization. The main sentiment is that many of them aim at improving maintenance to contribute towards productivity or cost or maintenance optimization. However, the method of assessment varies between them. Much of the literature provides a qualitative approach for criticality assessment. Subsequently, several machines end up being classified as high critical machines (Bengtsson 2011). Additionally, many of them provide a static approach for setting machine criticality. Even in the literature which proposes the use of data for assessing criticality, mostly maintenance data, such as failure data, failure frequency (i.e. data from CMMS) is used. Data requirements such as machine data from MES is rare. This implies that existing assessment methods do not take a system view into consideration. Industrial practices have also shown that maintenance prioritization is not based on machine criticality (Gopalakrishnan and Skoogh 2018). In addition to the above mentioned main aspects to consider, Gopalakrishnan and Skoogh (2018) have proposed the following to address develop data-driven machine criticality assessment:

- A system perspective – to shift the focus from individual machine focus to problems on a systems perspective
- A dynamic approach – criticality of machines changes with time and, to counter the dynamic nature of production systems, continuous monitoring is needed. The improvement opportunities lie in the variations in real-time production
- A data-driven approach – even though the qualitative approach can provide valuable information, real-time analysis of large sets of machine data (MES data) need to be analyzed in real-time to enable the decision to be relevant and correct to the needs of the machine

And lastly:

- A productivity focus – Many maintenance organizations do not consider productivity as a maintenance goal, but it has the potential to contribute to productivity increase

3. Proposed generic approach machine criticality assessment

In this section, a generic approach for a data-driven criticality assessment tool is proposed by synthesizing the literature presented in Chapter 2. The structure of this framework is proposed based on the inspiration from the empirical formula proposed in Stadnicka, Antosz, and Chandima Ratnayake (2014). It essentially consists of three continuous steps. (1) Data availability & quality assessment from MES and CMMS systems, (2) analysis of the acquired data using advanced data analytics, and (3) the decision making support for the maintenance personnel. This is shown in Figure 2. In each step, we further define the goals and conditions that need to be fulfilled. These goals and conditions are however fixed based on the individual maintenance planning requirements of the plant. Additionally, determining the time-frame for the analysis to update the tool is scalable based on data availability as well as data relevance.

The proposed approach from literature is further developed into a framework for a data-driven criticality assessment tool by demonstrating it in a real-world production system. With the help of real-time data and industrial use cases, a multiple case study methodology is employed to develop the details of the framework and a simulation experiment is used to validate the results achieved.

4. Methodology

Since there is an apparent lack of empirical research in the maintenance field and the large discontinuity between maintenance theory and maintenance practice (Fraser, Hvolby, and Tseng 2015), an empirical study was performed to develop and validate data-driven machine criticality assessment. The empirical study was performed by choosing an embedded multiple case study research approach (Yin 2013). By using a multiple case study approach the phenomenon of machine criticality assessment can be studied in its natural setting and meaningful theory can be generated (Voss, Tsikriktsis, and Frohlich 2002). Additionally, the multiple case study methodology was inspired by similar research which developed an empirical formula for machine classification for prioritization of maintenance tasks (Stadnicka, Antosz, and Chandima Ratnayake 2014). The empirical formula was developed by studying three machine classifications from separate industrial cases and a generic formula was derived. However, in this study, a different and more rigorous approach was adopted by studying not only the machine classification but also the maintenance practices and machine states for the development of a machine criticality assessment. In addition, the developed assessment framework was validated within each case sites using a simulation experiment and qualitative study. The research design is presented in Figure 3. The detailed explanation of the research conducted in the study is presented further below.

4.1. Case description

Four industrial cases were chosen from three multi-national automotive manufacturing companies. The cases were selected from different production sites, which had different ways of working with maintenance to increase the generalizability of results (Eisenhardt 1989). The criteria for choosing the cases include:

i. cases should use machine criticality assessment for their maintenance planning purposes, where the decision support tool was ensured to be either a criticality classification tool or a maintenance priority classification tool,
ii. the cases should have automated production lines and the company's willingness to improve maintenance practices,
iii. different parts (automotive components) being produced in each case, and
iv. geographically located at different places.

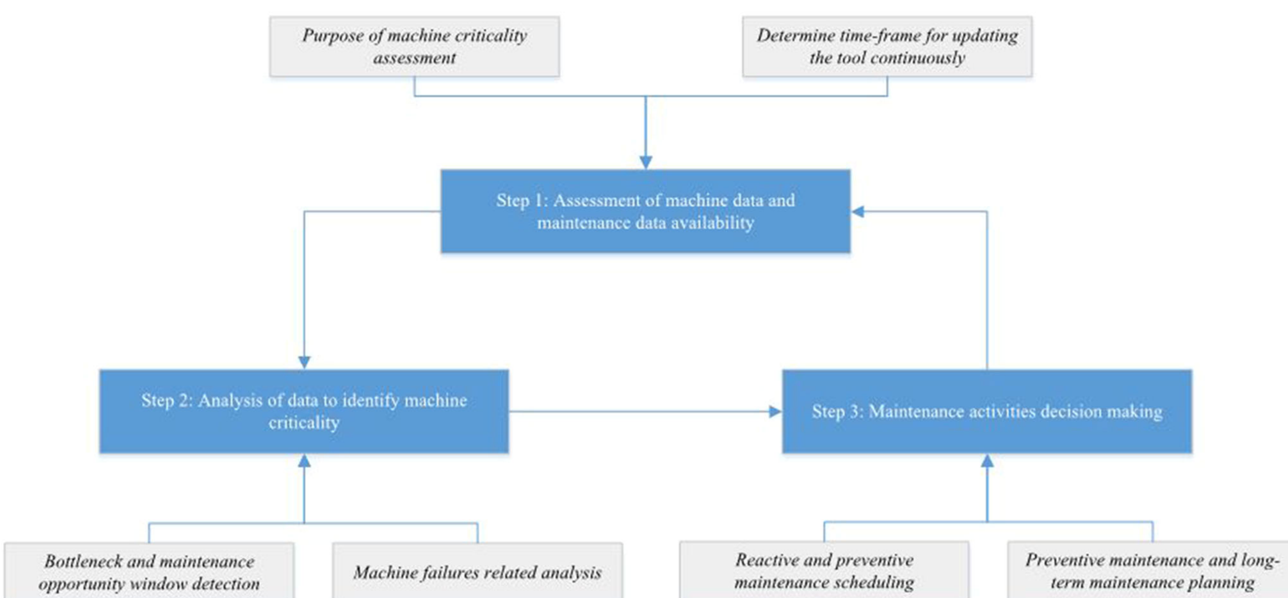

Figure 2. The proposed data-driven criticality assessment tool framework based on literature.

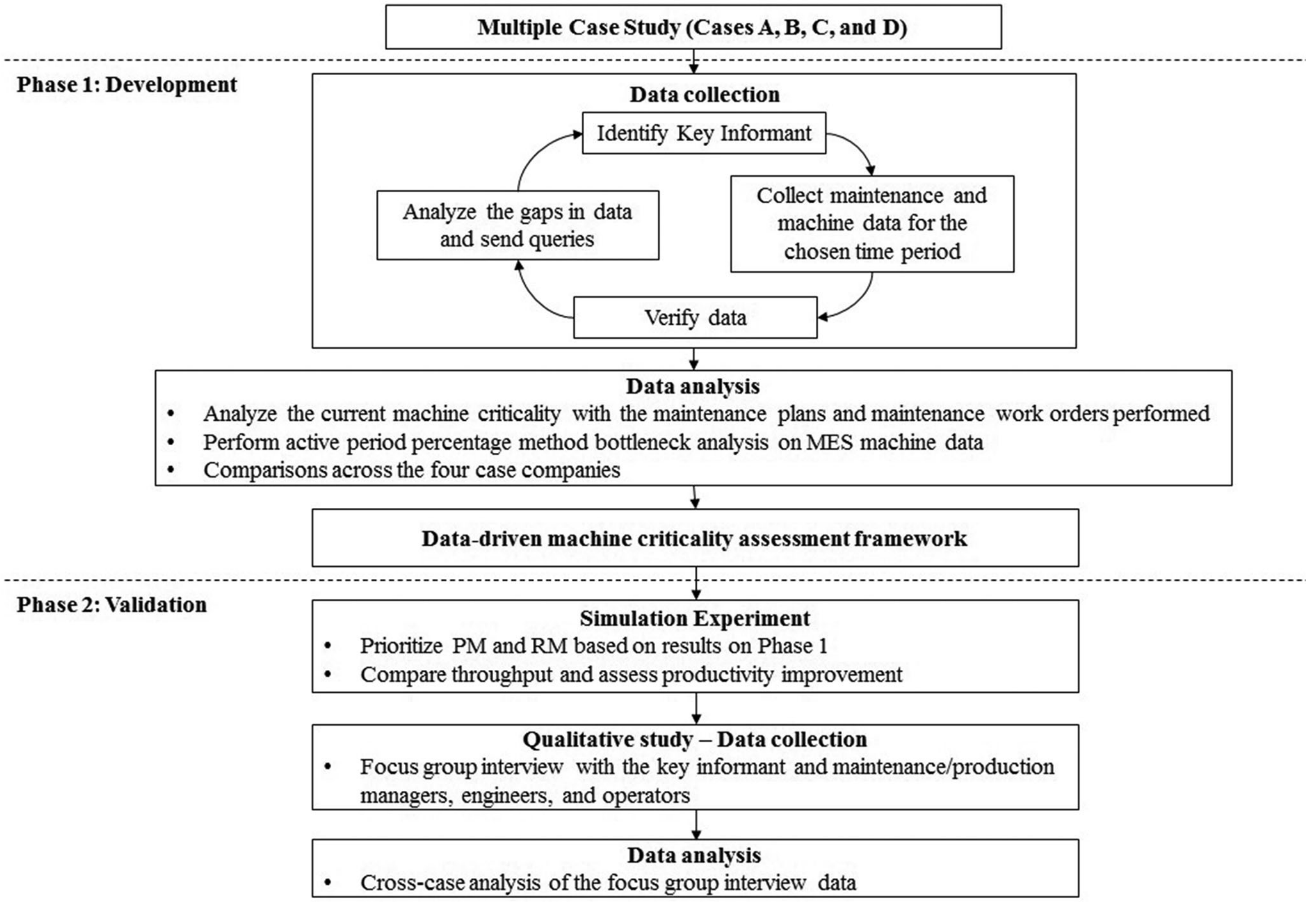

Figure 3. Research design of the development and validation phases.

Case A was selected from a large off-road vehicle automotive company. The chosen production cell consisted of a production cell that had five machining pieces of equipment that were serially connected. Conveyor paths were used to transport the parts between each machine, i.e. they acted as buffers. All of the machines performed different operations and the production cell produced six different variants of the product. This case company had poor data availability in terms of MES machine data as they do not have automated data collection from the machines. But it did have maintenance data, i.e. PM schedules, PM types, and failure data. This case company had a long history of having machine criticality classification and during the time of study, they were moving to a newly created classification. However, it did not affect the study as the timespan chosen for study lies completely during the old classification period.

Case B was selected from a large car manufacturer. The chosen production line consisted of a fully automated serial production line that had five stations performing different tasks. A total of 22 robots were spread across the five stations, two in station 1, three in station 2, one in station 3, ten in station 4, and lastly, six in station 5. The company had maintenance data on individual robots but collected automated MES data on station level. Each station represents the flow of products, as an individual robot stops the entire station is halted. Therefore, the analysis was performed on the maintenance and MES data on the station level. Additionally, unlike the other cases which used criticality classification as a tool, this case company used a maintenance priority classification tool.

Case C was selected from a large automotive company. The case companies A and C belong to the same group of companies, but they function as separate entities and were geographically separated. The chosen production line consisted of 12 machines in total. Six pairs of machines were similar, and the machine pairs were connected in parallel. However, the six machine pairs were serially connected with buffers in between. The company used the cost deployment model (CD) for classifying its critical machines (Yamashina and Kubo 2002). The CD model was used to calculate the cost of lost production for each machine, which subsequently was used for creating criticality classification. The case company had MES and maintenance data for all their machines.

Case D was also selected from a large automotive company. The chosen production line consisted of a production line that had 14 machines serially connected with buffers in between. The company had a maintenance priority classification as well as criticality classification for all their machines. Additionally, this case company had MES and maintenance data for all their machines. However, there was an upgrade in their maintenance management system during the timespan chosen for the study. Hence, the data from two maintenance management systems were integrated to derive the total amount of data. The MES data was collected entirely from a single MES system.

4.2. Phase 1: development

The studies were performed simultaneously in the four chosen case sites. The research was conducted in two phases, i.e. the development phase and validation phase. Apart from the multiple case study approach, a separate data collection, implementation, and data analysis were conducted for each phase as guided by empirical research methods in operations management (Flynn et al. 1990).

4.2.1. Data collection

As the first step, a key respondent on each case site was identified. A key respondent is one who can be relied on to answer questions regarding the cases (Voss, Tsikriktsis, and Frohlich 2002). This does not mean that the person is the only respondent. The key respondent was identified in order to set up the case study, facilitate data collection, and set up the qualitative study (in Phase 2). The identified key informant was a maintenance manager or engineer within the respective case companies. Secondly, the data collection included gathering maintenance data from CMMS systems and machine data from MES systems for the chosen timespan. The timespan of MES and CMMS data for analysis was decided with the help of the key respondent. The timespan was initially chosen to be two years for all cases, however, due to security and data availability, the timespan varied from case to case. Table 2 provides a summary of the collected data including the chosen timespan and number of machines in the chosen cases. CMMS data included failure data, PM data (PM plans and schedules), and criticality/prioritization classifications. MES data included timestamps of the different states that machines were under during the chosen timespan. This data was not always obtained in a single cycle with the key informant. Due to communication difficulties in terms of asking for and comprehending the right data and data quality, the data was obtained and verified and analyzed for gaps. Subsequently, queries were raised with the key informant to obtain the necessary data. On an average two cycles were followed in all the cases in order to get the desired data from case companies.

Specifically, in Case A, where there was no automated data collection in their MES system, machine time stamps data were not collected. Instead, equivalent data in terms of average cycle times of each of the different variants produced in the machines was collected.

4.2.2. Data analysis

The data analysis was performed within each case and also between cases. Firstly, within each individual case analysis, the maintenance data was analyzed to identify the amount of time spent on preventive maintenance and total machine downtimes. Secondly, the machine data was analyzed to identify the throughput bottleneck machines. The bottleneck analysis was conducted by the method described in Subramaniyan et al. (2018). During these two analysis steps, the criticality/prioritization classification of the corresponding cases was used to compare the critical machines with the actual machine statistics. Lastly, the maintenance data analysis and the machine analysis were compared against each other. The cross-case analysis was performed separately to identify the similarities and differences between the cases.

Table 2. Summary of the data collected.

Industrial cases	Number of machines	Timespan of data	CMMS data	MES data
Case A	5	7 months	Yes	No
Case B	5	4 months	Yes	Yes
Case C	12	4 months	Yes	Yes
Case D	14	2 years	Yes	Yes

The results from Phase 1 and the principles of machine criticality assessment (see Section 2.2) were used as inputs to develop the data-driven machine criticality assessment framework. The results of Phase 1 show the productivity improvement opportunities, whereas the assessment principles obtained from the theory derived provided the areas of focus in the proposed framework.

4.3. Phase 2: validation

The developed framework is validated in Phase 2 of the study. The validation is performed by using a simulation experiment and a qualitative study.

4.3.1. Simulation experiment

A simulation experiment was conducted on each of the four cases. A discrete event simulation model was created with the help of the data collected in Phase 1. Additionally, through the key informant, the production layout and buffer data were also obtained for model building. The simulation experiment was conducted by following the steps described by Banks, Carson, and Nelson (1996). The model was verified and validated as suggested by Rabe, Spieckermann, and Wenzel (2008). Specifically, raw data and prepared data were desk checked and face validated; the conceptual model was reviewed; and the results were compared with other models and validated internally. The simulation model was run on two maintenance plans. The first one was on a first-come-first-served basis for repairs and scheduled production shut down for preventive maintenance operations to replicate industrial practices. In the second, the developed framework of a data-driven decision support tool was applied for prioritizing repairs and performing preventive maintenance operations during the identified maintenance opportunity windows. Throughput, i.e. production rate, was used as the performance indicator to assess the effectiveness of the data-driven framework within current industrial practices. The simulation models were replicated 50 times including a full shift for warm-ups. The statistics from the warm-ups were not included and the final results were gathered from the steady-state analysis. All the simulation results have been gathered with a 95% confidence interval calculated using Welch's *t*-test.

Table 3. List of participants for the focus group interview study.

Industrial Cases	Number of participants	Profession of the participants
Case A	3	1 – Production manager, 1 – Maintenance management specialist, and 1 – Maintenance engineer
Case B	4	3 – Maintenance engineers, 1 – Maintenance manager
Case C	3	1 – Maintenance engineer, 1 – Production engineer, 1 – Production manager, and 1 – Operator
Case D	2	1 – Maintenance manager, 1 – Data analyst

4.3.2. Qualitative study

This part of the study was conducted as part of validating the developed framework and was thus performed within each case site. It aimed at evaluating the data-driven decision support tool together with the results obtained in Phase 1 and the simulation results. The qualitative study was designed in the form of focus group interviews, as the aim was to explore the practitioners' views on the results obtained in Phase 1 and the framework development (Creswell 2013). It was expected that some of the results could be surprising for the participants and hence choosing a focus group type interview provided the discussion platform amongst the participants. The participants for the interview were chosen based on their relevance to the production line of each case. Personnel who were managers, engineers, or operators working within maintenance and/or production organizations were typically chosen. Particularly in Case D, a data analyst who worked with the chosen production line was also chosen. The criteria for selection included knowledge of their current machine criticality assessment, whether they were maintenance-related decision-makers, and their production system domain knowledge, especially for the chosen timespan (in Phase 1). The detailed list of participants and their professions are presented in Table 3. The key informant was also one of the participants in the focus group interviews. The selection of participants ensured that the data gathered were highly contextual and deep insights were obtained.

A focus group interview was conducted at each of the case sites individually. With the help of the key informant, the participants were given prior information regarding the objective of the interview. Firstly, the results of the study's Phase 1 and the simulation results were presented in a PowerPoint format to the participants. Subsequently, the focus group interviews were performed with the help of semi-structured and open-ended questions. The questions were focussing on existing criticality/prioritization classifications, its usage as a decision support tool, the usage of data for planning maintenance and the productivity potentials. Towards the end of the focus group interview, participants were allowed to have an open discussion about the presented results. After a 20 minutes presentation of results of Phase 1 and simulation experiment, the focus group interview took about 45 to 60 minutes on average. The focus group interview data of each of the cases were transcribed and coded using NVIVO analysis software. A total of 79 first order codes were generated during the analysis. Using them second order themes emerged.

5. Case study results

The results of the multiple case study are presented separately through the development (Phase 1) and validation (Phase 2) phases. In this section the Phase 1 results are presented, which includes individual and cross case analysis results.

5.1. Industrial Case A

The analysis of the CMMS data is presented in Figure 4. The criticality level of each of the machines is shown next to the machine names in the figure. The criticality classification used in this case had classes AAA, AA, A, B, and C. The machines were differentiated in these classes as it represents the levels of criticality, AAA class is highest criticality class and C is the lowest criticality class. Observe that machine M4 was not classified, hence Not Applicable (N/A). As seen from the figure, the amount of planned maintenance (PM activities) is very similar between machines M1, M2, and M3 but marginally higher in M4 and lower in M5. It was disclosed that as the analysis period was seven months there seem to be variations in PM activities, but across one year (PM cycle) all machines would have the same amount of PM. It was also disclosed that PM activities are performed during scheduled production stops, where the entire line is stopped to perform PM activities on all machines. However, the total downtime shown in the figure occurred during the production run. The figure shows that the machines had varying failure rates and repair times. It can also be observed that the criticality classes provided had little to do with the PM activities as well as the machine's total downtime. Additionally, most of the machines were classified as AA (high critical), with one having AAA.

Case A did not have automated data collection of machine states from their machines. Hence, machine level analysis for bottlenecks was not performed. However, using the product variants data, cycle time data, and the maintenance data from CMMS, a static active period percentage was calculated to identify bottlenecks. The results are presented in Table 4. M1 has the highest active period, so it is the primary bottleneck of the machine with the given data. However, comparing the active periods with other machines, M3's active period is as high as M1. Hence, the grey shaded machines indicate the probable bottlenecks. A diagnostic analysis was not performed for Case A, as that will give results identical to Figure 3. On comparing the total downtime of the probable bottleneck machines, M1 has considerably fewer downtime stops than M3. Hence, M1 is actually a cycle time bottleneck.

The maintenance organization in Case A focussed on reducing the criticality of the machines and total number of machine failures. However, the results suggest that the same PM was planned for all machines irrespective of the machine criticality and the maintenance decisions were not based on the criticality classification.

5.2. Industrial Case B

The analysis of maintenance data from CMMS of Case B is presented in Figure 5. In Case B a prioritization classification was used to classify the machines. In this particular chosen production line all the machines had the highest priority in the prioritization classification. Hence, it is not mentioned in the figure. Similar to Case A, the PM activities varied but it was disclosed that all machines will have the same amount of PM across one year and PM activities are performed during scheduled production stop. The total downtime of the machines also varied drastically across them. However, machines M4 and M5 spent more time on PM but had less total downtime.

The MES data was used to perform bottleneck analysis. From Table 5, it can be seen that the M2 has the highest active period percentage compared to all other machines in the production system. Therefore, M2 is the primary bottleneck in the production system. However, when comparing other machines' active period percentages with respect to M2, M4 is also a potential bottleneck in the production system as the t value is between −1.96 and 1.96. Therefore, there is an uncertainty in estimating the true bottlenecks in the production system. Hence, M2 and M4 can be classified as a potential group of bottleneck machines in the production system. On the other hand, diagnostic analysis on the potential group of bottleneck machines reveals that M2 and M4 are cycle time type bottlenecks as their producing states duration is much higher than other states duration. Also, it can be seen from Table 5 that M2 has a higher percentage of error.

In addition, the error percent from the MES data and total downtime percent of the CMMS data were compared. It was observed that the MES data showed machines stopped longer than the CMMS data on all the machines. The maintenance organization in Case B did not use their prioritization classification for maintenance decisions as well as prioritized maintenance activities.

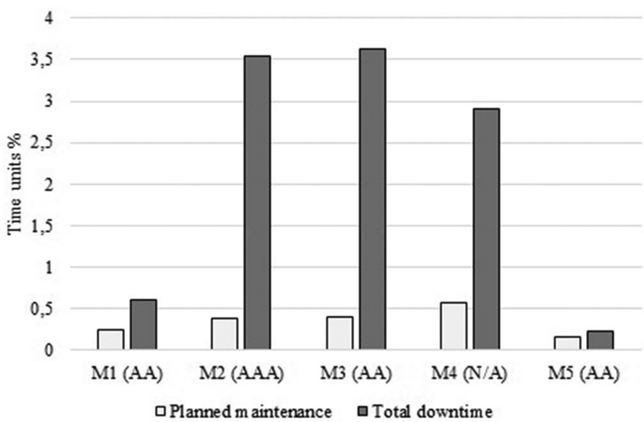

Figure 4. Analysis of CMMS data – Case A.

Table 4. Bottleneck analysis from CMMS data – Case A.

		Active states as a % of active time		
Machines	Active period %	Working %	Planned maintenance %	Total downtime %
M1	53.3	52.5	0.2	0.6
M2	43.7	39.8	0.4	3.5
M3	52.8	48.8	0.4	3.6
M4	41.1	37.6	0.6	2.9
M5	11.3	10.9	0.2	0.2

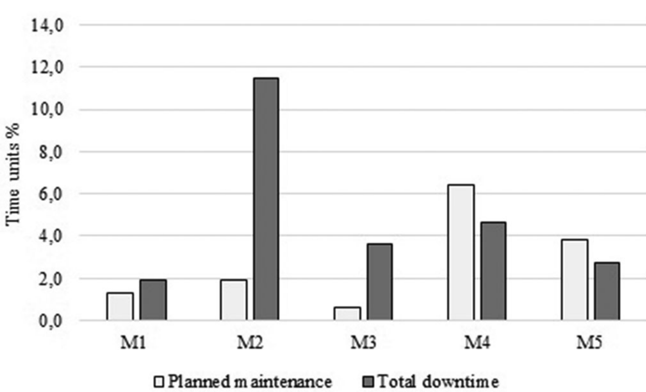

Figure 5. Analysis of CMMS data – Case B.

5.3. Industrial Case C

From Figure 6 the analysis of maintenance data from CMMS and corresponding machine criticality classes can be observed. The criticality classification used in this case had classes AA, A, B, and C. Not all machines were classified as high critical, as M1 and M2 are AA classified and M3 and M4 are A classified with the rest of the machines B classified. Similar to the previous two cases, the PM activities varied but it was disclosed that all machines will have the same amount of PM across one year and PM activities are performed during a scheduled production stop. The total downtime of the machines also varies drastically across each other. It can also be observed from the figure that several machines spend more time on PM stops than having machine downtime.

Table 5. Bottleneck analysis results by data-driven algorithm – Case B.

	Descriptive statistics			Diagnostics statistics		
				Active states as a % of active time		
Machine	Active period (%)	Standard error	*T*-test value	Producing %	Error %	Others %
M1	52.47	0.84	11.19			
M2	66.41	1.1		72.4	26.5	1.1
M3	42.76	0.82	20.92			
M4	64.19	0.99	−0.73	87.1	11.3	1.5
M5	60.04	1.12	3.24			

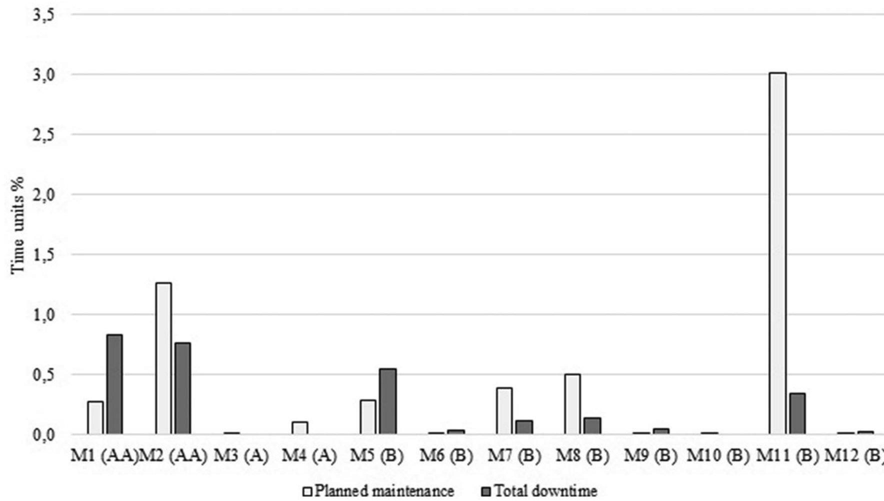

Figure 6. Analysis of CMMS data – Case C.

Table 6. Bottleneck analysis results by data-driven algorithm – Case C.

				Diagnostics statistics			
	Descriptive statistics			Active states as a% of active time			
Machine	Active period (%)	Standard error	*T*-test value	Producing %	Part changing %	Error %	Others %
M1	93.3	1.22	−1.62	94.8	2.9	1.1	1.2
M2	94.31	0.57		94.8	3.1	0.5	1.6
M3	92.21	1.1	−0.43	94.8	3.6	0.8	0.9
M4	93.04	0.69	−0.93	94.5	3.1	0.5	2
M5	86.11	1.87	5.14				
M6	86.77	1.13	4.99				
M7	82.08	0.85	9.89				
M8	81.35	0.86	10.62				
M9	86.38	1.13	5.37				
M10	85.09	1.53	6.39				
M11	85.82	1.25	5.85				
M12	88.77	1.22	2.92				

Similar to Case B, the analysis of MES data was performed and is presented in Table 6. It summarizes the descriptive results for all the machines in the production system and diagnostic results for the bottlenecks from the data-driven algorithm. From Table 1, the machine M2 is the primary bottleneck as M2 has the highest active period percentage among other machines. The more detailed statistical analysis reveals that M1, M3, and M4 can also be potential bottleneck machines when compared to M2 in the production as their t value with respect to the bottleneck machine is within −1.96 and 1.96 at 95% confidence level. Therefore, M1, M2, M3 and M4 are the group of potential bottleneck machines in the production system. Diagnostic results on potential bottlenecks reveal that M1, M2, M3 and M4 are mostly cycle time type bottlenecks and they have less downtime.

Subsequently, the MES and CMMS data on the total stop time of machines were compared. Both the data sources showed very similar total machine stop time on all the machines. It has to be noted that all machines in the system had very few failures and repair times, which were evident in both data sources. The maintenance organization in Case C also did not use their criticality classification for PM planning of RM prioritization. However, criticality based long-term maintenance decisions were made, such as planning autonomous maintenance or planning professional maintenance packages for critical machines.

5.4. Industrial Case D

The analysis of maintenance data from CMMS of Case D is presented in Figure 7. In this case, there was a criticality classification that existed in the company. However, it was disclosed that the classification tool was old and not used for any maintenance related activities. Hence, it was omitted from the analysis. Similar to the previous three cases, the PM activities varied but it was disclosed that all machines will have the same amount of PM across one year and PM activities are performed during scheduled production stops where the entire production line was stopped. The total downtime of the machines also varied drastically across them. Similar to Case C, many machines have spent more time on planned maintenance stops than machine downtime.

The bottleneck analysis from MES is presented in Table 7. It can be seen from the table, machine M6 is the primary bottleneck machine as it has the highest active period percentage compared to other machines in the production system. However, there is no significant statistical difference between mean active period percentages of M9 with respect

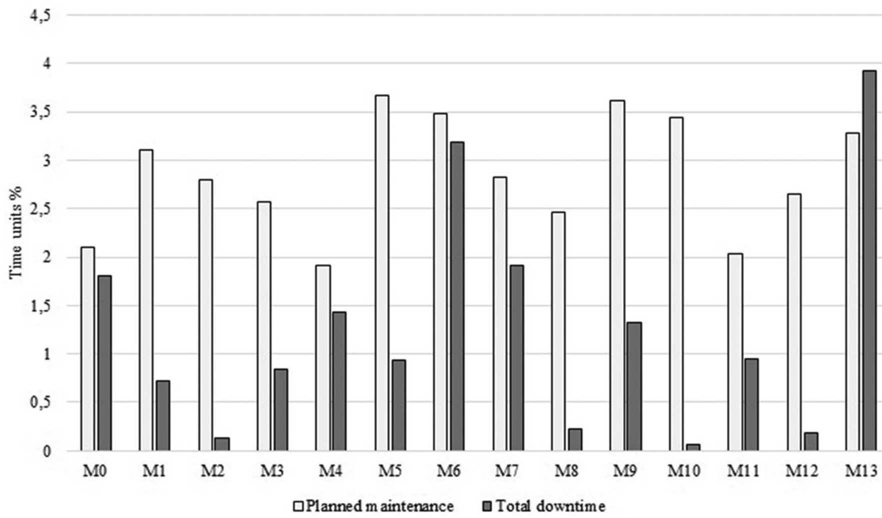

Figure 7. Analysis of CMMS data – Case D.

Table 7. Bottleneck analysis results by data-driven algorithm – Case D.

Descriptive statistics				Diagnostics statistics	
				Active states as a% of active time	
Machine	Active Period %	Standard error	T-test value	Producing %	Error %
M1	74.38	0.65	7.44		
M2	72.66	0.64	9.6		
M3	75.36	0.55	6.91		
M4	72.75	0.57	10.24		
M5	69.88	0.65	13.02		
M6	80.41	0.49	–	88.41	11.59
M7	78.22	0.54	3.01		
M8	75.03	0.68	6.44		
M9	80.28	0.46	0.2	89.79	10.21
M10	76.69	0.49	5.39		
M11	73.24	0.6	9.29		
M12	65.28	0.71	17.57		
M13	61	0.49	28.15		

to M6. Therefore, M9 and M6 can be called a group of potential bottlenecks in the production system. Detailed diagnostic analysis of the bottleneck machines group indicates that M6 and M9 are predominantly producing state bottlenecks as the producing values are much higher compared to down state of the machine.

The MES and CMMS data were compared on the total stop time of machines. Similar to Case B, it showed longer machine stop time in MES data than CMMS data for the machines. The maintenance organization in Case D made maintenance decisions without using any criticality assessment tools. They used a centralized call centre system, where machine breakdowns were logged as complaints and maintenance personnel were assigned based on a first-come-first-served basis.

5.5. Cross-case analysis

Based on the analysis of CMMS and MES data, the results of the individual cases were compared. The comparison is tabulated in Table 8.

The cross-case analysis shows a larger proportion of similarities than differences between the four cases. Preventive maintenance planning and scheduling are done in a similar way, e.g. standard PM packages for all machines irrespective of the machine's actual performance, forcing the production stop of entire lines to perform PM activities, and lack use of the classification tool for planning. Therefore, it is likely that improper maintenance activities are carried out. Additionally, repair work orders are prioritized by maintenance personnel on a shop floor level, usually based on experience. This also could potentially lead to non-bottlenecks being prioritized which can reduce the productivity. Further, the data that maintenance organizations use, i.e. CMMS data, appears to provide lower machine downtime than MES data. Therefore, there is a likelihood that wrong decisions can be made even when maintenance organization use data for decision-making.

6. Data-driven machine criticality assessment

Based on the Phase I results achieved from the four cases several design factors can be identified. The existing criticality/prioritization classification used in the case sites were not entirely used for designing the framework because none of them are used in the respective cases for maintenance decisions. The proposed framework is presented in two parts, namely, data analysis part and decision-making part respectively. On generalization of the results, the data availability and the analysis of data were identified as the main factors in the data analysis part. On the decision making part, choosing the right maintenance decision, time-frame for decision-making and type of maintenance effort used were the main factors. Using these factors and combining the principles of criticality assessment, i.e. theoretical input (see Section 2.3), a generic criticality assessment framework was proposed.

The criticality assessment process begins with identifying a clear purpose for the criticality assessment, i.e. to support maintenance decisions for productivity increase. It provides guidelines for working with machine criticality assessment with the intent of using it for maintenance activities on tactical and operational levels. The framework is presented in Figure 8, which contains the two parts. First, the data analysis part provides the guidelines on the methods for assessment and data requirements for criticality assessment. Second, the decision-making part provides the guidelines for the list of maintenance actions that can be supported from the assessment.

Firstly, the data analysis part starts with assessing the data availability in the company and determining the data timespan. The type of decision-making determines the frequency of updates. For example, a repair work order prioritization needs to be prioritized on short-term basis, whereas a maintenance

Table 8. Cross-case analysis of the CMMS and MES data analysis.

Similarities
- Same PM activities across all machines during one cycle. A calendar-based scheduling.
- Hardly any connection between the criticality classification and maintenance planning, including PM and RM.
- Repair activities are random or prioritized on shop floor through experience
- Many cases showed that during setting of criticality levels multiple machines end by being high classified.
- The total downtime of the bottleneck machines were high.
- The downtime data of the CMMS data and the machine stop time of MES data did not match. MES data showed more machine stop time.
- Mostly the maintenance data collection was not automated. Maintenance work orders were manually entered in CMMS systems.
- Maintenance data contains description on the type of failures, root cause (if available), whereas MES data are only time stamps of machine states.

Differences
- The active periods of machines across the cases were different. Case A, B and D had much lower active periods for their machines than Case C.
- Case C had much less total downtime across machines compared to other cases.
- The MES data format across the cases were different.

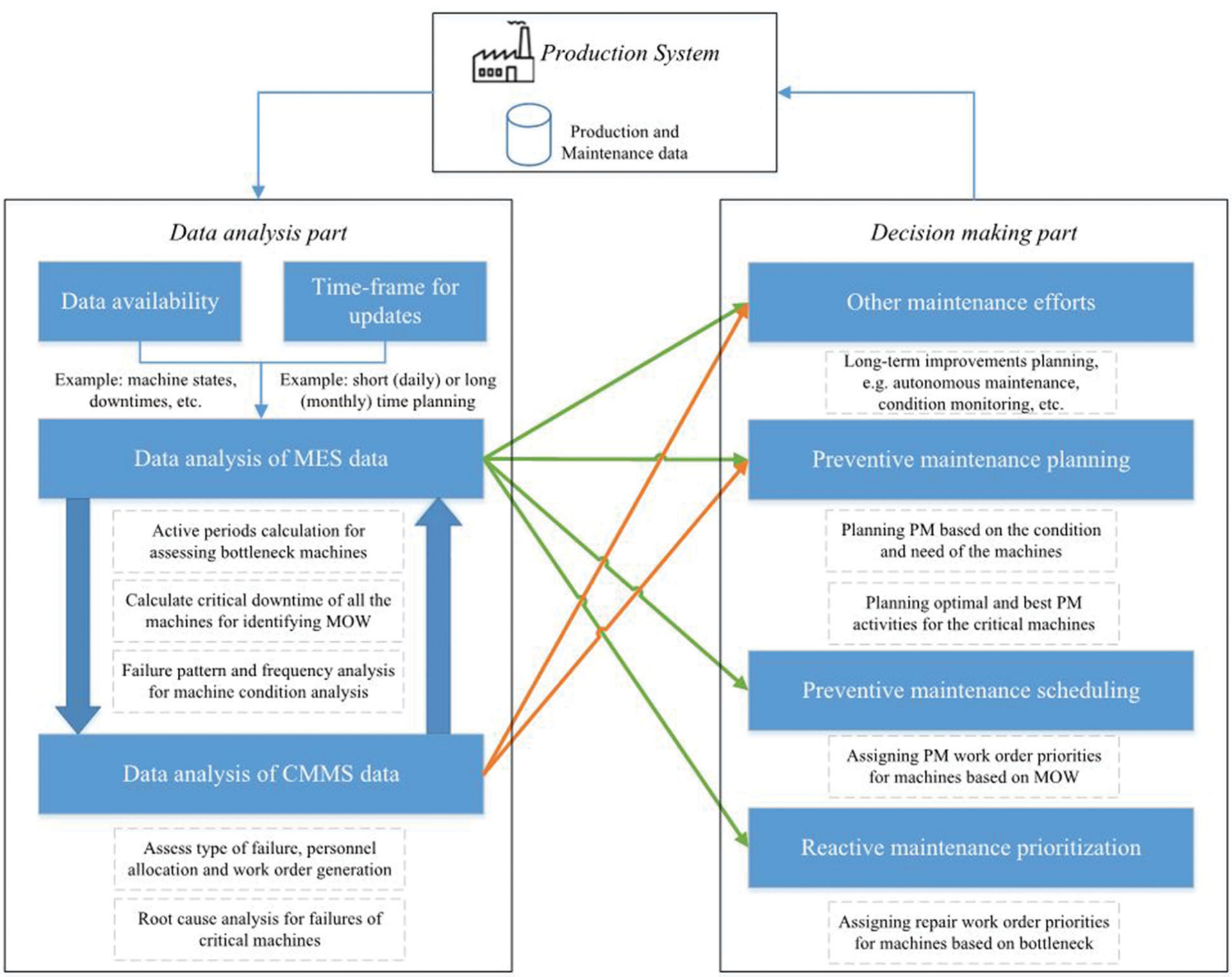

Figure 8. Data-driven machine criticality assessment framework.

plan requires long-term updates. As seen from the empirical cases, companies tend to have CMMS and MES data (except Case A). Both data are required for further analysis. An important addition from traditional assessment methods is the use of MES data for assessment. The nature of MES data, i.e. machine level data, ensures the assessment of criticality on a systems-level. The data are used to assess the bottleneck of the system, the maintenance opportunity window, and the failure pattern and frequency. It was observed from the case results that maintenance data tends to show fewer machine stops than MES data, however they are still relevant to assessing criticality as it can give details of the type of failures, maintenance efforts needed, work order generation and root causes. With the help of this analytical part, the criticality assessment will provide not only a list of critical machines but also the reason for criticality (i.e. why a machine is critical), the critical downtime for which machines can be stopped without affecting production (MOW), and maintenance prioritization list (based on bottleneck detection).

Secondly, the decision-making part provides the list of maintenance decisions that can be made using the assessment from a systems perspective. The findings showed that the maintenance organizations do not trust their classifications enough to base maintenance decisions on it. However, through the new information that the criticality assessment has provided, maintenance decisions can be made with increased certainty of making the right decisions. When there are multiple machine failures, reactive maintenance decisions needs be prioritized based on the bottleneck machines. Scheduling PM activities by forced production system shut down leads to productivity losses. Therefore, PM activities need to be planned during MOWs. Further, instead of static PM plans for the machines, a tailor-made PM plan needs to be prepared based on the needs of the machine. These are the type of decisions that the proposed criticality assessment can support. Lastly, other types of maintenance efforts can also be prioritized with the help of the criticality assessment, for example, choosing the right critical machine to invest in to develop autonomous maintenance or plan condition monitoring. The entire decision support process is cyclical as the production system needs to be monitored continuously and machine criticalities need to be assessed. This leads back to the data analysis part of the framework. The most important part of the framework is of course the human decision-maker, because the maintenance managers and engineers need to make the decision and the criticality assessment provides them with the decision support.

7. Case study validation

The developed data-driven machine criticality assessment was subsequently validated in Phase 2. The validation was also performed within each of the case sites individually. The validation results are presented below.

7.1. Simulation results

Simulation experiments were performed within each of the empirical cases in order to validate the developed framework. Four separate models were developed for each case. The data for model development was the same MES data that were used in Phase 1. Naturally, the timespan considered for the experiments also corresponded to the data collected for Phase 1. However, additional information such as production layout and product flow was collected form the key respondents of each case. Due to the nature of the experiment, i.e. experimenting with maintenance plans mean cycle time, PM schedules, MTBF and MTTR were the only variables considered. Other variables such as demand rate, scrap rate, product variants and set-up times were not used in modelling. Single maintenance personnel was assumed in all cases to perform the maintenance tasks. PM activities were modelled as recurring planned stops.

The simulation experiments were performed using two maintenance execution plans. Firstly, the current state maintenance plan execution was performed by PM execution during forced production stops and RM execution by the first-come-first-served basis of repair occurrences. Secondly, the future state maintenance plan execution was performed by adopting the proposed framework of the article i.e. PMs executed during MOWs and RM execution based on bottleneck prioritization. The experiment was performed using 50 replications for each maintenance plan. Additionally, a warm-up period of eight hours for achieving steady-state was considered. The results are presented in Figure 9. The results are presented at a 95% confidence interval. The preventive maintenance planning and other maintenance efforts from the framework were not part of the validation process as there was not enough data available to simulate them. Also, quantifying the effects of a new way of PM planning requires a separate study in itself. Since Case A did not have MES data, it is to be noted that Case A's model was built using mean cycle times and failure times provided by Case A's key respondent.

From the figure, it can be observed that in each case the system throughput increased when the data-driven decision support tool was applied compared to first-come-first-served based maintenance plans. The percentage throughput increments are substantial when maintenance decisions are data-driven. Case A and B had production lines that are tightly coupled, i.e. few buffers between machines. In those cases, repair prioritizations had less effect as when one machine

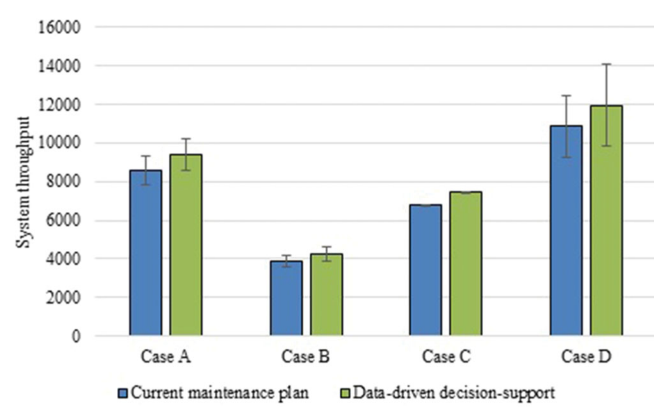

Figure 9. Results of the simulation experiment for all cases.

stops, the entire production line stops shortly after. However, even in cases with few buffers throughput increment was achieved, when PM activities are performed during production hours (i.e. during MOWs) instead of forced PM stops.

7.2. Focus group interview results

Subsequent to the simulation study, a focus group interview study was conducted within each case as part of the validation process. Specifically, the results of the focus group interviews were used to evaluate the results achieved in Phase 1 and 2. The interviewees were first presented the results from Phase 1, i.e. the data-driven criticality assessment framework, and the simulation results. Subsequently, the interviews were conducted. The interviews were conducted in each case site and the answers were related to their own plants. But the data analysis was performed as a cross-case analysis to achieve generalization. On cross-case analysis of the interview data, four major themes emerged. The results are presented in Figure 10.

Out of the four main themes that came out of the analysis of the interview, two were observed in Phase 1 results, they were the problems with maintenance planning on PM and RM. Apart from the data quality problems observed previously, additional important issues were observed: non-reporting of work orders (incomplete data), problem with manual reporting (lack of automated data collection), and improper data reporting. These results explain the poor quality of maintenance data from CMMS. Particularly, when the disparity of the data was presented, the participants gave a surprised reaction. In the evaluation of the data-driven tool, the quality of MES data were questioned. Some machine stops in MES data were uncategorized in that they were not maintenance related. Therefore, this calls for improving the data quality when it is put to use. On an ending note, the proposed data-driven tool was largely treated with positive

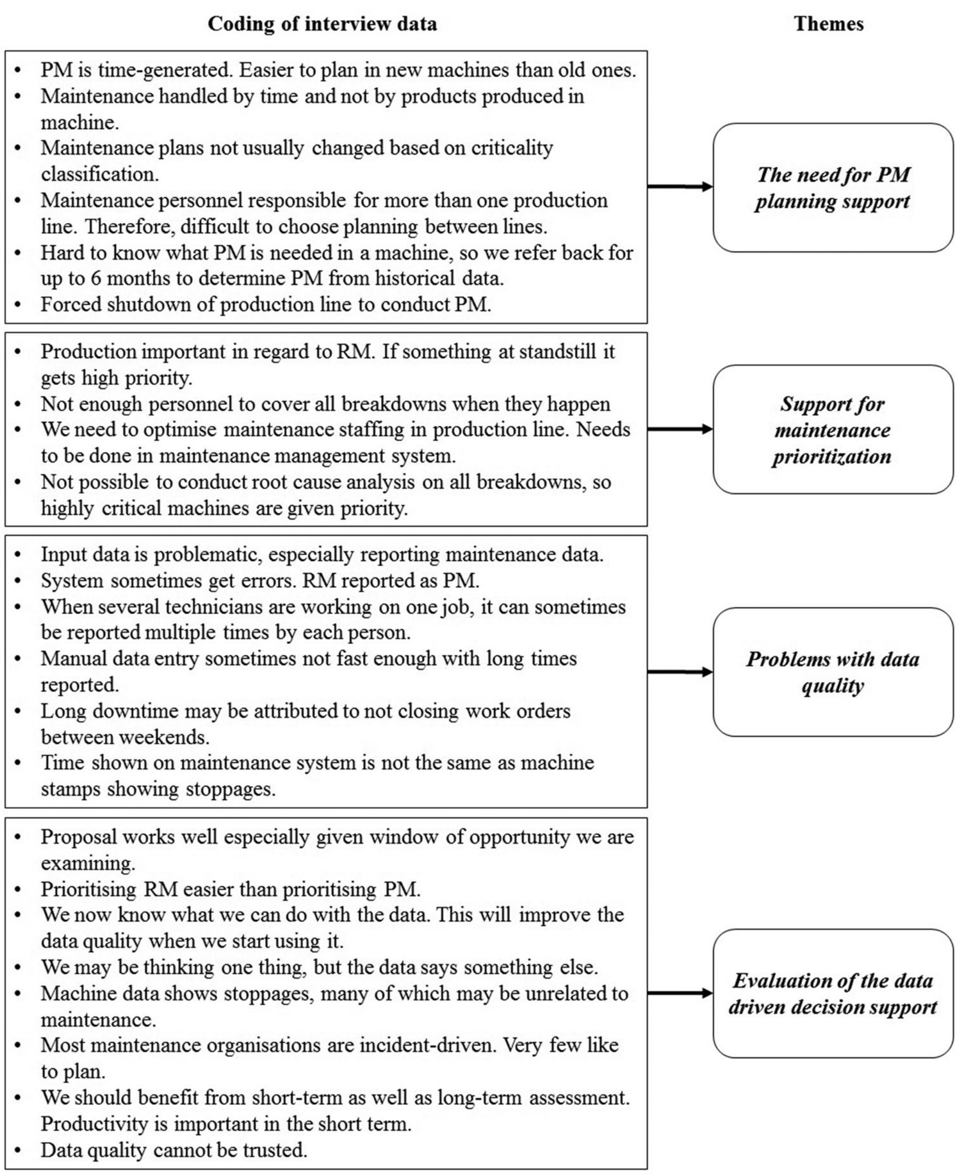

Figure 10. Analysis of the interview data and main themes.

response. Particularly, the relation between maintenance and productivity was highlighted.

8. Discussion

This multiple case study aimed at developing and validating a generalized data-driven decision support tool for supporting maintenance decisions for discrete manufacturing. A data-driven machine criticality assessment was proposed based on the literature. This was implemented in four industrial case studies. The existing maintenance plans, criticality assessment tools and actual performance of the machines were analyzed (Phase 1) to develop a generic framework for data-driven maintenance decision support tool in discrete manufacturing. Within the case studies, the framework was validated by simulation and further the results were evaluated by focus group interviews (Phase 2). The development and validation of the decision support tool resulted in a data-driven machine criticality assessment that provides guidelines for using existing data in manufacturing companies to analyze and make fact-based maintenance decisions with the goal of increasing system productivity. The contribution of this study is the systems perspective to assessing machine criticality with high relevance to both industry and academia.

8.1. Maintenance planning – current practices and gap

Phase 1 of the study provided insights into the problems in current maintenance management practices. These problems, such as single-machine focussed, lack of fact-based decisions, unutilized machine capacity, and lack of focus for maintenance from a systems perspective represent the opposite of future maintenance management literature is arguing to achieve (Helu and Weiss 2016; Roy et al. 2016). The results showed that in existing practices maintenance performance does not contribute to increasing production system efficiency. On the contrary, analysis in Phase 1 shows that current practices are using valuable production time to perform maintenance, thereby inducing idling losses and production inefficiency. Interestingly, no connection was observed between the planned maintenance of machines to its downtime from the analysis. Furthermore, the machine downtimes were not used as an input for PM planning. Instead, PMs were based on pre-planned calendar-based schedules. Machine failures, on the other hand, were dealt with instinctive or shop-floor level prioritization by using the experience of maintenance technicians. Even though all of the chosen cases had a criticality/prioritization classification, none of the cases showed the tool's usage for maintenance planning. Neither did the classification tools identify the right critical machines (throughput focussed) on comparing it to MES data analysis. Mainly, the tools often ended up classifying most of the machines as high critical, which equates to all machines as being (equally) critical, but this is seldom true. Therefore, it is clearly shown that existing criticality assessment tools in companies are outdated, and a more effective maintenance decision support system is needed (Ni and Jin 2012).

As seen from the results, maintenance organizations tend to use CMMS data for analysis related to maintenance decisions, but not the MES data. The study showed that maintenance data from CMMS often returned low and poor machine downtime data when compared to MES data. This is because of poor recording (manual recording in the cases) of data by the CMMS systems. The MES data, on the other hand, represented the state of the machines in the production system much better. During the interviews, the disparity prompted a surprise from the participants. Additionally, MES data provides possibilities for systems-level decision-making analysis, whereas maintenance data are usually machine specific (e.g. MTBF, MTTR). Hence, the developed framework proposes the use of MES data for systems-level decision-making analysis. However, the CMMS data can still provide quality insights on the type of failure, maintenance efforts needed, work order generation, and root causes of the machine failures. Naturally, data availability becomes a problem in the manufacturing environment. The data availability on the machines and maintenance plans was not a criterion in this study, as one of the intentions was to understand how maintenance can be planned in situations where data availability was low.

8.2. Data-driven decision support tool

Generally, in machine criticality assessment literature, the assessment method tends to be subjective and have low data requirements (mainly CMMS data) from machines (Bengtsson 2011; Stadnicka, Antosz, and Chandima Ratnayake 2014; Márquez et al. 2009). The criticality/prioritization classifications used in the case sites reflected this but were also not used enough in current maintenance planning practices. Hence, they were not entirely used in the development of the proposed framework. Even though the data requirements are higher than the previously described methods, one of the benefits of the proposed approach is that it uses easily obtainable real-time production line data as captured by the MES. Additionally, MES data captures systems-level dynamics, especially idling losses. The timestamps of the machines show a lot more information about a machine than what the mean values of MTBF and MTTR can provide. Automated data collection of the MES data can also provide a continuous update which enables real-time criticality assessment. Even though the results showed that the MES data format varied from case to case, it was possible to achieve a generic framework within discrete manufacturing industries. Hence the framework has the potential to be developed into a plug-in to existing maintenance and production management systems in the future.

Criticality assessment tools aim at improving production systems by supporting decisions for maintenance prioritization (Stadnicka, Antosz, and Chandima Ratnayake 2014). The proposed framework supports specific maintenance plans for supporting production systems without affecting its flow. The critical downtime of machines (Gu, Jin, and Ni 2015) and bottleneck detection algorithm (Subramaniyan et al. 2018) approaches included in the framework enables decision-making on PM scheduling as well as RM prioritization without affecting the throughput. Both the abovementioned approaches create maintenance workspace on the idling losses of the machines (starved and blocked machine states). Idling losses are a type of machine loss where the machine cannot be used for production because of the ripple effects caused in the system (Andersson and Danielsson 2013). By making use of this hidden maintenance improvement potential, maintenance management can sharpen its focus to solve maintenance problems from a systems perspective (Roy et al. 2016).

The results of the validation (Phase 2) showed that substantial productivity increases can be achieved by applying the framework for maintenance decision-making. An important finding is that when RM was prioritized with few buffers in between, the potential to increase throughput reduced. This is because when one machine fails, it caused the entire production system to stop. In such situations, the frequency of failure of the bottleneck machine becomes important, as maintenance efforts need to be focussed on reducing the failure frequency to reduce systems-level downtime. The criticality assessment can provide information for effective decision-making. The integration of MES and CMMS data can provide valuable information not only on the condition of a machine but also its relevance to the other machines in the system. This type of information that the criticality assessment provides is needed to design preventive maintenance packages tailored for individual machines. Also, long-term improvement activities can also be prioritized.

The proposed decision support framework can enhance the decision-making quality of maintenance engineers and managers to run an effective production system (Santana 1995). Production system effectiveness also depends on the cross-functional collaboration with production organizations. Nonetheless, maintenance and production organizations are characterized by conflict (Rishel and Christy 1996). Maintenance is often seen as a support function, ensuring machine availability for the production organization. The results of this study challenge this notion as maintenance operations were shown to contribute towards increasing productivity. With a common goal of productivity increase, maintenance and production organization can truly achieve synergy, and joint planning is possible.

Probable future scenarios for the future for maintenance organizations are to manage large volumes of data, perform data analytics, make fact-based decisions, and provide education and training, among others (Bokrantz et al. 2017). The framework aligns with these probable projections to ensure that maintenance decision-making can be made on a systems-level in a way that is dynamic, fact-based and focussed on productivity (Gopalakrishnan and Skoogh 2018). Through following the principles given, the empirical research conducted in this study increases the relevance of the current problems studied and the solutions help towards narrowing the gap between maintenance theory and maintenance practice (Fraser, Hvolby, and Tseng 2015).

8.3. Limitations of the developed framework

One of the main drawbacks of applying this framework was also identified in the findings of the study. The quality of data is a central problem the manufacturing industry is facing. The findings of the focus group interviews showed that even though participants accepted the value of a data-driven approach for planning maintenance, scepticism was observed regarding the quality of the data that the company produced. Signs of poor data quality were evident during the data collection process in Phase 1, where a single cycle of data collection was insufficient from the data systems. Firstly, because data are not used currently for making maintenance decisions, a lack of understanding of the data requirements was evident in the data collection process. Secondly, ensuring data quality is an important future research area as good data can dramatically increase the size and scope of improvements in companies (Batini et al. 2009). However, improving data quality is a continuous process and companies should start using data-driven decision-making in order to push for higher data quality. Further research is also needed to increase the reliability and accuracy of the results achieved through data analytics (Subramaniyan et al. 2018). Another limitation is that the framework cannot be applied when the company lacks MES data as seen from Case A. Despite this, a static approach was presented for bottleneck analysis and MOW analysis by using mean cycle time, MTTR, and MTBF data of machines. A continuously updating criticality assessment will be difficult to achieve in such situations. However, with digitalization getting full attention in manufacturing industries, automated data collection is anticipated as well as the technological advancements that can enable them.

Another implementation issue of the framework is the competence of the maintenance personnel to execute the data analysis part (see Figure 8). The stakeholders of the decision-making part of the framework are the maintenance managers and engineers who plan and execute the maintenance decisions. However, current personnel in maintenance organization are not well equipped with data analytics expertise to perform the tasks of the analysis part. Continuous training and education are needed for the maintenance personnel to keep up with technological developments (Bokrantz et al. 2017).

8.4. Implications for industrial practitioners

The results of the study provide valuable implications for practitioners in the industry. The empirical study was performed focussing on industry problems, hence, the results achieved are highly relevant for industrial applications.

- The gaps identified in Phase 1 of the study, i.e. same PM for all machines, ad-hoc RM prioritization, poor recording of data in CMMS, and lack of criticality-based maintenance allocation, provide insights to the problems and improvement potentials in maintenance management.

- The application of the framework enables fact-based decision-making for maintenance planning.
- The proposed framework provides productivity improvement potential without any major needs for investments. Investments in data quality and competence building are needed, but not on the level of changing the production system.
- Cross-functional work between maintenance and production is needed to achieve data-driven decision-making. Data sharing and working towards common KPIs are important goals for cross-functional work.
- Lastly, the willingness for organizational change is an important step towards achieving data-driven decision-making. As such, a complete effort from management is needed to actively work towards productivity and fact-based decision-making is needed.

8.5. Academic contributions

In this study, the authors have made important contributions to the machine criticality assessment literature. The central approach when it comes to machine criticality assessment is qualitative and approached in a static manner (Gopalakrishnan and Skoogh 2018). The central problems discussed in this paper are coming directly from industrial practice. Industrial practice clearly showcases the lack of systems perspective and production losses while not using data for maintenance decision making (Gopalakrishnan and Skoogh 2018). On one hand, data-driven techniques have proven to be the popular approach when it comes to maintenance decision making. Whereas on the other hand, productivity focus within maintenance planning is not well established. By taking advantage of the well-established data-driven bottleneck detection method, a data-driven approach was chosen with a clear productivity focus. The dynamic pattern of the production system ensures the system is constantly changing. Therefore by adopting this data-driven approach, real-time data can be used for criticality analysis which can lead towards real-time decision support. The framework presented in this paper has three distinct advantages over other criticality assessment methods: (1) real-time decision-making capability, (2) productivity as the main focus, this can ensure strong collaboration with production planning, and (3) decision making opportunity not only on a strategic level but also on operational levels are feasible. A strong decision support system for maintenance organization can be achieved, which can solve future maintenance problems when the outcomes of this paper are rigorously pursued (Ni and Jin 2012; Roy et al. 2016).

8.6. Future research

The multiple case study approach and empirical research employed in this study come with limitations that directly impact the direction of future research. Firstly, expanding the scope of the proposed framework to other types of production layouts other than discrete manufacturing is needed. Both continuous and discrete manufacturing face maintenance issues and need to approach maintenance planning based on criticality (Stadnicka, Antosz, and Chandima Ratnayake 2014). Secondly, there is a further need to extend the results to small- and medium scale companies, which are greatly different from large multi-national companies in terms of maintenance approaches and practices. Moreover, the sample size of four cases in this study followed the trend from the previous study, which used three cases for obtaining generic machine classification (Stadnicka, Antosz, and Chandima Ratnayake 2014). Thirdly, the results have shown clearly that research is needed in how to ensure data quality. Especially, data analytics and fact-based decision-making are identified as future scenarios for maintenance (Bokrantz et al. 2017). Lastly, expanding the scope of the study to include joint production and maintenance planning and control would be beneficial, as joint efforts are needed to ensure productivity increases. Hence, the transformation of maintenance organizations to include productivity as an objective is a desirable future change.

9. Conclusion

A data-driven machine criticality assessment tool framework was developed and validated in this study. The framework provides a guideline for data collection, data analytics, and a list of maintenance decisions that can be supported. The main aim of the data-driven decision support tool is to enable maintenance organizations to focus on maintenance problems with a systems perspective and increase the productivity of the system. The proposed framework also shifts the criticality assessment from a traditional subjective approach to a data-driven decision-making approach. The development and validation were conducted through four empirical case studies focussing on real-world maintenance problems. Through cross-case analysis, a generalized framework for discrete manufacturing was developed. Therefore, the developed decision support framework is highly relevant for industrial applications and research communities. The results of the study comply with the future projections within the existing literature regarding maintenance in digitalized manufacturing. In addition, the paper also identifies problem areas that need addressing before the framework can be employed in an industrial setting. This is exemplified in the themes that emerged from the focus group interview study. The emergent themes were the need for a data-driven decision support tool for preventive and reactive maintenance planning, the need to address data quality problems, and the benefits of the proposed framework. Overall, the results of the study show that effective maintenance management has a large potential to improve productivity and the framework provides a powerful decision support tool to exploit those opportunities.

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Disclosure statement

No potential conflict of interest was reported by the author(s).

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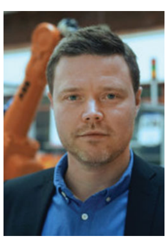

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References

Andersson, J., and M. Danielsson. 2013. "Analysis of System Losses." Master Thesis., Chalmers University of Technology, Gothenburg, Sweden.

Antosz, K., and R. M. C. Ratnayake. 2016. "Machinery Classification and Prioritization: Empirical Models and AHP Based Approach for Effective Preventive Maintenance." *IEEE International Conference on Industrial Engineering and Engineering Management (IEEM), Bali*, 1380–1386.

Banks, J., J. S. Carson, and B. L. Nelson. 1996. *Discrete-Event System Simulation*. Upper Saddle River, NJ: Prentice-Hall.

Batini, C., C. Cappiello, C. Francalanci, and A. Maurino. 2009. "Methodologies for Data Quality Assessment and Improvement." *ACM Computing Surveys* 41 (3): 1–52. doi:10.1145/1541880.1541883.

Bengtsson, M. 2011. Classification of Machine Equipment." International Conference on Maintenance Performance Measurement & Management, Luleå.

Bokrantz, J., A. Skoogh, C. Berlin, and J. Stahre. 2017. "Maintenance in Digitalised Manufacturing: Delphi-Based Scenarios for 2030." *International Journal of Production Economics* 191: 154–169. doi:10.1016/j.ijpe.2017.06.010.

Bokrantz, J., A. Skoogh, C. Berlin, T. Wuest, and J. Stahre. 2020. "Smart Maintenance: An Empirically Grounded Conceptualization." *International Journal of Production Economics* 223: 107534. doi:10.1016/j.ijpe.2019.107534.

Chiang, S.-Y., C.-T. Kuo, and S. M. Meerkov. 1998. "Bottlenecks in Markovian Production Lines: A Systems Approach." *IEEE Transactions on Robotics and Automation* 14 (2): 352–359. doi:10.1109/70.681256.

Creswell, J. W. 2013. *Research Design: Qualitative, Quantitative, and Mixed Methods Approaches*. Thousand Oaks, CA: Sage Publications.

Eisenhardt, K. M. 1989. "Building Theories from Case Study Research." *The Academy of Management Review* 14 (4): 532–550. doi:10.2307/258557.

Flynn, B. B., S. Sakakibara, R. G. Schroeder, K. A. Bates, and E. J. Flynn. 1990. "Empirical Research Methods in Operations Management." *Journal of Operations Management* 9 (2): 250–284. doi:10.1016/0272-6963(90)90098-X.

Fraser, K., H.-H. Hvolby, and T.-L. Tseng. 2015. "Maintenance Management Models: A Study of the Published Literature to Identify Empirical Evidence." *International Journal of Quality and Reliability Management* 32 (6): 635–664. doi:10.1108/IJQRM-11-2013-0185.

Goldratt, E. M., and J. Cox. 1992. *The Goal: A Process on Ongoing Improvement*. Croton-on-Hudson, NY: North River Press.

Gopalakrishnan, M., and A. Skoogh. 2018. "Machine Criticality Based Maintenance Prioritization: Identifying Productivity Improvement Potential." *International Journal of Productivity and Performance Management* 67 (4): 654–672. doi:10.1108/IJPPM-07-2017-0168.

Gopalakrishnan, M., A. Skoogh, A. Salonen, and M. Asp. 2019. "Machine Criticality Assessment for Productivity Improvement." *International Journal of Productivity and Performance Management* 68 (5): 858–878. doi:10.1108/IJPPM-03-2018-0091.

Gu, X., X. Jin, and J. Ni. 2015. "Prediction of Passive Maintenance Opportunity Windows on Bottleneck Machines in Complex Manufacturing Systems." *Journal of Manufacturing Science and Engineering* 137 (3): 31017–310179. doi:10.1115/1.4029906.

Gu, X., S. Lee, X. Liang, M. Garcellano, M. Diederichs, and J. Ni. 2013. "Hidden Maintenance Opportunities in Discrete and Complex Production Lines." *Expert Systems with Applications* 40 (11): 4353–4361. doi:10.1016/j.eswa.2013.01.016.

Guo, W., J. Jin, (Judy), and S. J. Hu. 2013. "Allocation of Maintenance Resources in Mixed Model Assembly Systems." *Journal of Manufacturing Systems* 32 (3): 473–479. doi:10.1016/j.jmsy.2012.12.006.

Helu, M., and B. Weiss. 2016. "The Current State of Sensing, Health Management, and Control for Small-to-Medium-Sized Manufacturers." Proceedings of the ASME 2016 International Manufacturing Science and Engineering Conference, Blacksburg, VA.

Ingemansson, A. 2004. "On Reduction of Production Disturbances in Manufacturing Systems Based on Discrete-Event Simulation." PhD Thesis. Lund University, Lund, Sweden.

Kagermann, H., W. Wahlster, and J. Helbig. 2013. "*Securing the Future of German Manufacturing Industry. Recommendations for Implementing the Strategic Initiative INDUSTRIE, 4.0.*" Germany: Federal Ministry of Education and Research.

Karim, R., J. Westerberg, D. Galar, and U. Kumar. 2016. "Maintenance Analytics – The New Know in Maintenance." *IFAC-PapersOnLine* 49 (28): 214–219. doi:10.1016/j.ifacol.2016.11.037.

Langer, R., J. Li, S. Biller, Q. Chang, N. Huang, and G. Xiao. 2010. "Simulation Study of a Bottleneck-Based Dispatching Policy for a Maintenance Workforce." *International Journal of Production Research* 48 (6): 1745–1763. doi:10.1080/00207540802555769.

Li, L., Q. Chang, J. Ni, and S. Biller. 2009. "Real Time Production Improvement through Bottleneck Control." *International Journal of Production Research* 47 (21): 6145–6158. doi:10.1080/00207540802244240.

Li, L., and J. Ni. 2009. "Short-Term Decision Support System for Maintenance Task Prioritization." *International Journal of Production Economics* 121 (1): 195–202. doi:10.1016/j.ijpe.2009.05.006.

Liu, J., Q. Chang, G. Xiao, and S. Biller. 2012. "The Costs of Downtime Incidents in Serial Multistage Manufacturing Systems." *Journal of Manufacturing Science and Engineering* 134 (2): 021016. doi:10.1115/1.4005789.

Ljungberg, Õ. 1998. "Measurement of Overall Equipment Effectiveness as a Basis for TPM Activities." *International Journal of Operations and Production Management* 18 (5): 495–507. doi:10.1108/01443579810206334.

Márquez, C. A., P. M. Leon, J. F. G. Fernandez, P. C. Marquez, and L. M. Campos. 2009. "The Maintenance Management Framework: A Practical View to Maintenance Management." *Journal of Quality in Maintenance Engineering* 15 (2): 167–178.

Marquez, A. C., P. M. Leon, A. S. Rosique, and J. F. G. Fernandez. 2016. "Criticality Analysis for Maintenance Purposes: A Study for Complex in-Service Engineering Assets." *Quality and Reliability Engineering International* 32 (2): 519–533.

Monostori, L., B. Kadar, T. Bauernhansl, S. Kondoh, S. Kumara, G. Reinhart, O. Sauer, G. Schuh, W. Sihn, and K. Ueda. 2016. "Cyber-Physical Systems in Manufacturing." *CIRP Annals - Annals* 65 (2): 621–641. doi:10.1016/j.cirp.2016.06.005.

Moore, W. J., and A. G. Starr. 2006. "An Intelligent Maintenance System for Continuous Cost-Based Prioritisation of Maintenance Activities." *Computers in Industry* 57 (6): 595–606. doi:10.1016/j.compind.2006.02.008.

Moss, T. R., and J. Woodhouse. 1999. "Criticality Analysis Revisited." *Quality and Reliability Engineering International* 15 (2): 117–121. doi:10.1002/(SICI)1099-1638(199903/04)15:2<117::AID-QRE238>3.0.CO;2-I.

Nakajima, S. 1988. *Introduction to TPM*. Cambridge, MA: Productivity Press.

Ni, J., and X. Jin. 2012. "Decision Support Systems for Effective Maintenance Operations." *CIRP Annals – Annals* 61 (1): 411–414. doi:10.1016/j.cirp.2012.03.065.

O'Donovan, P., K. Leahy, K. Bruton, and D. T. J. Sullivan. 2015. "Big Data in Manufacturing: A Systematic Mapping Study." *Journal of Big Data* 2 (1): 20. doi:10.1186/s40537-015-0028-x.

Pelaez, C. E., and J. B. Bowles. 1994. "Using fuzzy Logic for System Criticality Analysis." Proceedings of Annual Reliability and Maintainability Symposium (RAMS), Anaheim, CA, 449–455. doi:10.1109/RAMS.1994.291150.

Pintelon, L., and A. Parodi-Herz. 2008. "Maintenance: An Evolutionary Perspective." In *Complex System Maintenance Handbook,* 21–48. London: Springer.

Rabe, M., S. Spieckermann, and S. Wenzel. 2008. "A new procedure model for verification and validation in production and logistics simulation." In Proceedings to the 40th Winter Simulation Conference, Piscataway, NJ, 1717–1726.

Ratnayake, R. M. C., D. Stadnicka, and K. Antosz. 2013. "Deriving an Empirical Model for Machinery Prioritization: Mechanical Systems Maintenance." *IEEE International Conference on Industrial Engineering and Engineering Management, Bangkok*, 1442–1447.

Rishel, T. D., and D. P. Christy. 1996. "Incorporating Maintenance Activities into Production Planning; Integration at the Master Schedule Versus Material Requirements Level." *International Journal of Production Research* 34 (2): 421–446. doi:10.1080/00207549608904912.

Roser, C., M. Nakano, and M. Tanaka. 2001. "A Practical Bottleneck Detection Method." Proceedings of the 2001 Winter Simulation Conference, Piscataway, New Jersey, 949–953. doi:10.1109/WSC.2001.977398.

Roy, R., R. Stark, K. Tracht, S. Takata, and M. Mori. 2016. "Continuous Maintenance and the Future – Foundations and Technological Challenges." *CIRP Annals – Annals* 65 (2): 667–688. doi:10.1016/j.cirp.2016.06.006.

Santana, M. 1995. "Managerial Learning: A Neglected Dimension in Decision Support Systems." Proceedings of the 28th Annual Hawaii International Conference on System Sciences, Kihei, Maui, Hawaii, 82–91.

Singh, S.,. H. Singh, and R. Kumar. 2015. "Criticality Analysis of Equipments under Maintenance Policy by Using Multi Criteria Decision Making." *International Journal of Applied Engineering Research* 10 (54): 108–112.

Stadnicka, D., K. Antosz, and R. M. Chandima Ratnayake. 2014. "Development of an Empirical Formula for Machine Classification: Prioritization of Maintenance Tasks." *Safety Science* 63: 34–41. doi:10.1016/j.ssci.2013.10.020.

Subramaniyan, M., A. Skoogh, M. Gopalakrishnan, H. Salomonsson, A. Hanna, and D. Lämkull. 2016. "An Algorithm for Data-Driven Shifting Bottleneck Detection." *Cogent Engineering* 3 (1): 1–19. doi:10.1080/23311916.2016.1239516.

Subramaniyan, M., A. Skoogh, H. Salomonsson, P. Bangalore, M. Gopalakrishnan, and A. Sheikh Muhammad. 2018. "Data-Driven Algorithm for Throughput Bottleneck Analysis of Production Systems." *Production and Manufacturing Research* 6 (1): 225–246. doi:10.1080/21693277.2018.1496491.

Van Horenbeek, A., and L. Pintelon. 2013. "A Dynamic Predictive Maintenance Policy for Complex Multi-Component Systems." *Reliability Engineering and System Safety* 120: 39–50. doi:10.1016/j.ress.2013.02.029.

Voss, C., N. Tsikriktsis, and M. Frohlich. 2002. "Case Research in Operations Management." *International Journal of Operations and Production Management* 22 (2): 195–219. doi:10.1108/01443570210414329.

Wakiru, J. M., L. Pintelon, P. Muchiri, and P. Chemweno. 2020. "Integrated Maintenance Policies for Performance Improvement of a Multi-Unit Repairable, One Product Manufacturing System." *Production Planning and Control* : 1–21.

Wedel, M., P. Noessler, and J. Metternich. 2016. "Development of Bottleneck Detection Methods Allowing for an Effective Fault Repair Prioritization in Machining Lines of the Automobile Industry." *Production Engineering* 10 (3): 329–336.

Wong, C. S., F. T. S. Chan, and S. H. Chung. 2013. "A Joint Production Scheduling Approach considering Multiple Resources and Preventive Maintenance Tasks." *International Journal of Production Research* 51 (3): 883–896. doi:10.1080/00207543.2012.677070.

Yamashina, H., and T. Kubo. 2002. "Manufacturing Cost Deployment." *International Journal of Production Research* 40 (16): 4077–4091. doi:10.1080/00207540210157178.

Yin, R. K. 2013. *Case Study Research: Design and Methods*. 5th ed. Thousand Oaks, CA: Sage Publications.

Ylipää, T., A. Skoogh, J. Bokrantz, and M. Gopalakrishnan. 2017. "Identification of Maintenance Improvement Potential Using OEE Assessment." *International Journal of Productivity and Performance Management* 66 (1): 126–143. doi:10.1108/IJPPM-01-2016-0028.