Machine criticality based maintenance prioritization: Identifying productivity improvement potential

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Machine criticality based maintenance prioritization

Identifying productivity improvement potential

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Abstract

Purpose – The purpose of this paper is to identify the productivity improvement potentials from maintenance planning practices in manufacturing companies. In particular, the paper aims at understanding the connection between machine criticality assessment and maintenance prioritization in industrial practice, as well as providing the improvement potentials.

Design/methodology/approach – An explanatory mixed method research design was used in this study. Data from literature analysis, a web-based questionnaire survey, and semi-structured interviews were gathered and triangulated. Additionally, simulation experimentation was used to evaluate the productivity potential.

Findings – The connection between machine criticality and maintenance prioritization is assessed in an industrial set-up. The empirical findings show that maintenance prioritization is not based on machine criticality, as criticality assessment is non-factual, static, and lacks system view. It is with respect to these finding that the ways to increase system productivity and future directions are charted.

Originality/value – In addition to the empirical results showing productivity improvement potentials, the paper emphasizes on the need for a systems view for solving maintenance problems, i.e. solving maintenance problems for the whole factory. This contribution is equally important for both industry and academics, as the maintenance organization needs to solve this problem with the help of the right decision support.

Keywords Decision support systems, Productivity, Maintenance, Machine criticality, Maintenance prioritization

Paper type Research paper

1. Introduction

Fluctuating market demands and the need for high volume and mixed products have made production systems highly dynamic and complex. Digitalization is viewed as being the linchpin for future production within manufacturing industries. Maintenance of machines, in particular, needs to adapt fast to comply with the rapid advances of digital manufacturing (Bokrantz *et al.*, 2017). Historically, maintenance concepts such as total productive maintenance and reliability centered maintenance (RCM) have been developed to maximize equipment effectiveness and equipment reliability, respectively (Pintelon and Parodi-herz, 2008). Bridging the gap between traditional maintenance and shareholders' value was provided by value driven maintenance, which brings these concepts together to establish best maintenance practices (Haarman and Delahay, 2004). Additionally, the integration of Lean and Six Sigma concepts, known as Lean Six Sigma, aims at improving operational efficiency and cost savings for companies in competitive global markets

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(Raja Sreedharan *et al.*, 2018; Albliwi *et al.*, 2015). Irrespective of these concepts in practice, safety and environment are traditionally the prime critical factors when it comes to maintenance of machines in production systems (Pintelon and Parodi-herz, 2008). However, machine downtime in production systems leads to production inefficiency not only in that particular machine, but also other machines in terms of starvation and blockage (Skoogh *et al.*, 2011). Currently, attention has been given to single machine maintenance problems (Li, Ambani and Ni, 2009; Helu and Weiss, 2016). For example, maintenance organization focuses primarily on increasing the technical availability of individual machines. An overwhelming majority of maintenance research has also focused on machine-level problems, and there seems to be a research gap in plant/system level studies (Jin *et al.*, 2016). More importantly, the question "How do we maintain more than one product (machine) in a system?" has been identified as one of the two research questions essential to the future within Industry 4.0 (Roy *et al.*, 2016). Therefore, maintenance problems in complex production systems cannot be considered only for individual machines rather focus needs to be on all machines in the system as a whole. Previously, the authors have argued for the need of a systems view for maintenance planning based on low overall equipment effectiveness figures (52.5 percent) (Ylipää *et al.*, 2017).

Maintenance costs are already a substantial part of the total production costs (Löfsten, 1999; Bevilacqua and Braglia, 2000). Hence, wasting the maintenance resources on non-value adding maintenance operations will incur more costs, reduce production efficiency, and can also lead to ecological losses. In order to solve this, priority for maintenance resources should be allotted to the most critical machines in the system. Maintenance operations prioritization is an important task for keeping the production systems effective (Levitt, 1997). However, decision support for identifying critical machines is scarce. There have been few studies on assessing machine criticality for maintenance purposes. Some machine criticality studies point to maintenance strategy selection (Bengtsson, 2011; Stadnicka *et al.*, 2014; Márquez *et al.*, 2009). Whereas, production constraint studies such as bottleneck studies state that a bottleneck machine impedes the throughput of the entire system (Chiang *et al.*, 1999) and maintenance operation prioritization improves throughput (Li, Chang Ni and Biller, 2009). However, it is unclear how the manufacturing companies work with machine criticality as regards their strategy and operational maintenance execution.

Ni and Jin (2012) state that current computerized maintenance management system cannot adhere to the dynamic maintenance needs and that new decision support tools are needed for effective maintenance operations. A decision support tool enhances decision-making capability through easier identification of the core problem (Santana, 1995). Therefore, maintenance prioritization can be an important decision support tool for planning maintenance operations (Li and Ni, 2009; Li, Ambani and Ni, 2009) when prioritization is set for the most critical machines. Improper maintenance practices are the main reasons for inefficient production systems.

As a result, the purpose of this paper is to identify the productivity potentials through current-state maintenance planning practices of manufacturing companies. In particular, the paper aims to understand the connection between machine criticality and maintenance prioritization in industrial practice as well as identify the productivity improvement potentials. An empirical research approach is chosen, as practical-focused research within maintenance is rare (Fraser *et al.*, 2015). To attain the aims of the paper, two research questions have been framed for a mixed-method approach (Onwuegbuzie and Leech, 2006). They are:

RQ1. What is the connection between machine criticality assessment and maintenance prioritization practices within manufacturing companies?

RQ2. How can maintenance operations enable productivity improvement?

This paper includes multiple data sources from literature analysis, a web-based questionnaire survey across multiple small and large manufacturing companies and in-depth semi-structured interviews across large multi-national automobile manufactures. Additionally, simulation experimentation is used to evaluate the productivity potentials and validate the results. The primary results of this paper show the importance of having a system's view on maintenance to improve system productivity and the need for data-driven decision support for maintenance prioritization.

2. Related work

The related work on machine criticality assessment and maintenance prioritization is presented in this section. With a particular focus on methods and factors used for both machine classification and maintenance prioritization.

2.1 Machine classification

Criticality in production systems has been studied since at least the late 1980s. The earliest articles on criticality suggested identifying critical machines for the improvement of system performance (Banerjee and Flynn, 1987). However, an article by the same author contained a detailed analysis of different ways machines in job shops can be critical. This was used to choose the right preventive maintenance policy for machines in the production system (Flynn, 1989). A critical machine is a machine that causes the highest impact for the intended purpose, for example, affecting the quality of a production schedule (Petrovic *et al.*, 2008) or affecting throughput and system value (Ni and Jin, 2012). Therefore, the maintenance needs to be focused on the critical machines (Baglee and Knowles, 2010). One of the modern ways of analyzing criticality is based on RCM. Particularly, using FMEA methods to identify criticality (Roy and Ghosh, 2010; Bevilacqua *et al.*, 2009). As an improvement of FMEA, a criticality classification was inducted into the FMEA analysis named failure mode effect and criticality analysis (FMECA). FMECA is used for validating maintenance expert systems (De Carlo *et al.*, 2013). Further, an environment aspect is included in an FMECA analysis (Costantino *et al.*, 2013). However, FMEA methods are not always used for machine criticality analysis. It can be intended for risk analysis using failure mode of equipment, where the failure mode that affects the equipment the most is critical (Yang *et al.*, 2010; Bertolini and Bevilacqua, 2006). Also, maintenance criticality analysis, which is similar to that of FMECA, is used to design maintenance policy (Silvestri *et al.*, 2014), whereas a quantitative and collaborative criticality analysis approach in a pharmaceutical plant uses this for preventive maintenance priorities (de León Hijes and Cartagena, 2006).

The FMEA methods are sometimes even used for not only identifying critical machines but also classify machines based on criticality (Ramli and Arffin, 2012). Criticality classification is a common way to group the different machines in a production system for a focused maintenance effort (Bengtsson, 2011). Criticality classifications are named differently, such as ABC/ABCD classification, where A-classified machines are the highest critical and C or D classified machines are the least critical (Deshpande and Modak, 2002; Ramli and Arffin, 2012). Another scale uses "very high, high, normal, low, very low" criticality levels (de León Hijes and Cartagena, 2006). One of the most common ways in which this criticality classification (ABC-type) is performed is through using multiple factors, for example (Márquez *et al.*, 2009). An innovative criticality analysis for an oil refinery includes multiple factors such as safety, quality, plant availability, environment, and maintenance costs (Bevilacqua *et al.*, 2012). Another example includes availability, reliability, and utilization for criticality analysis in process industries (Ahmed *et al.*, 2014). Assessing criticality through multiple factors can enable finding the critical machine from many different perspectives. Of which, cost is an important aspect in production systems. A new measure, criticality analysis, i.e. cost effective importance measure (CEIM) for components, includes economic aspects with criticality (Gupta *et al.*, 2013). Whereas, a cost-based criticality identifies critical machines using economies of multiple factors and is used for prioritizing maintenance work orders (Moore and Starr, 2006). Bottleneck machines are also termed critical in some articles, such as bottleneck criticality for scheduling problems (Mönch and Zimmermann, 2007), bottleneck criticality for buffering (Hadas *et al.*, 2009), and shifting bottleneck criticalities to minimize lateness in a job shop (Holtsclaw and Uzsoy, 1996).

2.2 Maintenance prioritization

Prioritization of maintenance operations can be an effective decision support tool for maintenance engineers (Ni and Jin, 2012). Many studies have noted the effects of scheduling and planning maintenance activities by setting priorities. Maintenance optimization can be done on a single machine. An integrated approach for maintenance selection, quality control, and production scheduling is presented in Tambe and Kulkarni (2016). However, optimization of multiple machines in a system is also needed. Dynamic programming models can be used to develop effective maintenance plans, where the models are used to minimize cost and maximize the system reliability (Moghaddam and Usher, 2011). Reliability is the main focus in maintenance organization and priorities are set with the aim of improving reliability (Garg *et al.*, 2010). Reliability priorities are based on failure modes and their risks. Particularly, an FMEA analysis is used for prioritizing in a petrochemical plant (Torabi *et al.*, 2006), a FMECA analysis is used in automotive assembly (Ramli and Arffin, 2012), pharmaceutical industry (Costantino *et al.*, 2013) and food company (Selim *et al.*, 2015) and a risk priority number is used in the food industry (Bertolini and Bevilacqua, 2006). In addition, availability is another factor that can be improved upon by prioritizing maintenance (Goyal *et al.*, 2009).

Prioritization of maintenance is a crucial task in production systems. Different prioritization such as a CEIM based on cost of breakdowns (Gupta *et al.*, 2013), risk analysis based maintenance decision making to reduce costs (Backlund and Hannu, 2002), and a linear programming model to cost-effectively allocate maintenance labor crews to prioritized work orders (Taylor, 1996) are used for different production system improvements. Particularly, productivity improvement is shown to improve through prioritizing maintenance work orders of bottleneck machines (Lu *et al.*, 2011; Li, Chang Ni and Biller, 2009b). In addition to this, priorities based on shifting bottlenecks have shown to improve the throughput even further (Li, Chang Ni and Biller, 2009b; Wedel *et al.*, 2016). Other than bottlenecks, priorities to improve productivity include priority based on idle machines based on past performances (Tang and Zhou, 2001) and system value based (Yang *et al.*, 2007). However, priorities for maintenance are not always set for a single purpose. Multiple criteria can include machine utilization (cumulative and current), failure rate, last repair, Preventive Maintenance (PM) delay (Gopalakrishnan *et al.*, 1997); time, investments on maintenance, and budget (Tam and Price, 2008); and production flow, time, maintenance cost, and failures (Silvestri *et al.*, 2014). Improving the production system based on multiple criteria priorities may include risk reduction and cost minimization (Roy and Ghosh, 2010) and increase return on investment (Tam and Price, 2008) among other aspects. Additionally, a multi criteria subjective approach was used to prioritize PM using collaborative efforts across various teams (Zanazzi *et al.*, 2014). Despite this, current industrial practices are highly subjective and are based on the experience and knowledge of maintenance coordinators (Guo *et al.*, 2013).

3. Methodology

The aim of the paper is to obtain a deeper understanding of machine criticality assessment and maintenance prioritization demands, using both a quantitative and a qualitative approach.

Therefore, an explanatory sequential mixed-method design (Figure 1) was chosen to collect and analyze quantitative and qualitative data (Creswell, 2013). As a result, first, a quantitative data collection and data analysis were performed. The quantitative data include literature analysis and a web-based questionnaire survey. The results of this quantitative data informed the type explanation needed in the qualitative phase. In order to deeper understand the machine criticality and maintenance prioritization practices; the qualitative data were collected in the form of face-to-face semi-structured interviews. Hence, in the second phase, the qualitative data was collected to complement and explain the observed phenomenon in quantitative data. Additionally, an empirical use case from a manufacturing company in one of the participating companies was chosen to perform a simulation experiment to evaluate the productivity potentials of machine criticality based maintenance prioritization.

3.1 Data collection

Literature analysis: One of the aims of the paper, i.e. to study machine criticality and maintenance prioritization practices, in theory, was carried out in the form of a literature analysis. A systematic categorization of the published literature is carried out through analysis and review (Creswell, 2013). The analysis follows a quantitative analysis of the selected articles as well as a review of same. The analysis is presented in the results section (chapter 4) and the review in a related work section (chapter 2). Particularly, the trends and directions and overlap between these two areas are analyzed. Using two separate searches for articles on Scopus literature database for the two research fields, two separate sets of literature articles were obtained. The search criteria were set within "Production OR Manufacturing" for both searches followed by machine criticality and maintenance prioritization. As the first step of selection, the titles and abstracts were analyzed for relevance. All the relevant articles in the second step were analyzed through the whole article. Initially, a total of 33 articles were collected for the criticality in production system research area, and 35 in the maintenance prioritization research area. However, after reviewing the articles, a total of 23 criticality-related articles and 28 maintenance prioritization-related articles were selected for the analysis. Please note that there were some articles which featured in both research fields. The analysis begins by establishing three areas for each of the research fields. Subsequently, sub-areas for the first two areas were created. The last area was used to cross map between the two topics. The articles for each of the research fields were mapped within these areas and sub-areas. There were no repetitions of articles within the areas. It is to be noted that there is substantial literature on spare parts classification. However, spare part classification research has been delimited in this study as it deals with classifying criticality of spare part inventories and not that of the criticalities of machines in the system.

Survey. The web-based questionnaire survey was conducted within Swedish industry following the steps presented in Forza (2002). A descriptive survey approach was followed (Onwuegbuzie and Leech, 2006). The invitation to the questionnaire was sent to selected respondents via e-mail, an open invitation was listed publicly on the website of Sustainability and Maintenance Global Center (SMGC), which is a non-governmental government organization with over 50 participating companies and the invitation was also printed in

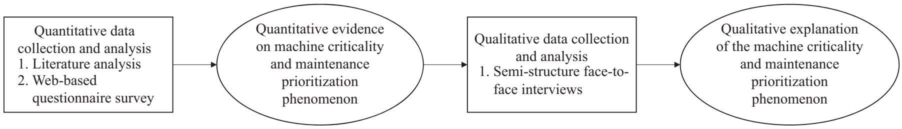

Figure 1. Explanatory sequential mixed-method approach for answering the research questions

the e-mail newsletter of SMGC. The primary targets of the survey were maintenance or production experts in manufacturing companies were obtained through a non-probabilistic judgment sample (Forza, 2002). Out of the 82 selected respondents, 62 answers were registered; a response rate of 75 percent. 22 additional responses were gathered via the open invitations. Of the total 84 responses gathered, non-experts were excluded and only the high management level responses at a plant-level were chosen for analysis. As a result, a total of 76 responses were selected from 71 different companies. The companies providing more than one response were verified for separation in geography and operating under different management. In addition, the majority of the respondents were from maintenance departments. The companies include both small and medium enterprises and large multi-national corporations representing different types of production, including manufacturing, energy, nuclear, food, and paper. The questionnaire covered topics of criticality, bottlenecks, and maintenance prioritization, in addition to production disturbances, tools and methods.

Interview. In addition to the survey data, qualitative data are collected in the form of interviews to explain the results attained from the quantitative data. Hence, four semi-structured face-to-face interviews as described by Tong *et al.* (2007) were conducted. Interviews were conducted within two of Sweden's largest manufacturing companies as part of the research project "StreaMod." Three managers and a strategist from maintenance departments were selected for the interviews. These four represent work at high strategic levels within multi-national corporations. Hence, they answer to the specific context of high level decision making in criticality identification and maintenance prioritization required in this paper. The interviewee template was created with the aim of gathering data on criticality and maintenance prioritization and to complement the survey data source. Before the interviews were conducted, interviewees were given information regarding the topics covered. The interview questions started with criticality in production systems and then on into maintenance prioritization. Semi-structured interviews were conducted with prompts and probes to increase clarity of answers.

Simulation. The simulation studies were conducted to test and evaluate machine criticality based maintenance prioritization to improve the production efficiency. A discrete event simulation methodology is applied to compare the maintenance prioritization approach to a first-come-first-served approach. The simulation study was carried out through the traditional steps of Banks *et al.* (1996) and verification and validation suggested by Rabe *et al.* (2008). The machine criticalities are identified through the active period percentage based bottleneck identification method suggested by Roser *et al.* (2003). The industrial use case is a serial production line consisting of 11 machines decoupled with buffers with three maintenance operators carrying out the repairs. One of the maintenance technician repairs machine one and two. The first two machines are delimited from priority setting as the first machine is designed to be a non-bottleneck and the other is a group of parallel operations. The other technician (T1) repairs machine three to six, and the last technician (T2) repair the remaining machines.

3.2 Data analysis and interpretation

The quantitative and qualitative data sources are analyzed separately in the explanatory mixed-method approach (Creswell, 2013). In the first phase, the quantitative data are analyzed and presented, followed by the analysis and presentation of qualitative data in the second phase. As a third phase, the data interpretation is performed, in which the qualitative data on machine criticality and maintenance prioritization explain and expand the phenomenon observed in the quantitative phase. This data triangulation not only explains the phenomenon observed but also indicates the gaps in maintenance planning practices. These are the productivity improvement potentials, which were evaluated using a simulation experimentation of an empirical use case.

4. Results

The results section presents the results gathered from the different data sources to fulfill the aim of evaluating and testing the decision support tool of maintenance work order prioritization. First, the literature analysis is presented, where the connection between machine criticality articles and maintenance prioritization is evaluated. Second, the mapping of current industrial practices is identified from survey data. This is followed by interview data to explain the phenomenon observed in the quantitative data. Thereafter, the evaluation of the productivity potential is carried out in a simulation environment to check its usefulness and validity.

4.1 Literature analysis

In the literature analysis, selected articles from the two research fields were analyzed for the chosen areas and sub-areas. First, machine criticality is analyzed followed by the maintenance prioritization. The results are presented below.

Machine criticality. The articles on machine criticality are intended for a variety of purposes. The results of the analysis are tabulated in Table I. The three areas chosen for analysis within criticality are the measure of criticality, the method to identify criticality, and use of criticality analysis for maintenance prioritization. First, criticality is identified by the measure with which the production system is analyzed. Hence, the different measures are analyzed and the emergent measures are listed as sub-areas based on the highest number of articles using them. From the table, it can be seen that using multiple factors for identifying criticality is the most common method used whereas, throughput and risks comes next. It has to be noted that if an article uses multiple factors which might include throughput and risk then it is counted as in multiple factors. Second, the method of identifying criticality was analyzed. It can be seen from the table that using criticality classification, bottleneck analysis, and FMEA/FMECA analyzes are the most common methods. Note that if an article discusses criticality classification and also uses the bottleneck or FMEA/FMECA method within the classification then it is counted under the criticality classification. Lastly, a total of 12 articles used the machine criticality assessment for the purpose of prioritizing maintenance.

Maintenance prioritization. Similar to section 3.1, articles on maintenance prioritization were analyzed for three different areas, namely the basis of priorities, purpose of priority and connection to machine criticality. The results of the analysis are presented in Table II. Each of the areas is further divided into sub-areas based on the emergent measures. First, multiple factors for choosing maintenance priorities have emerged, with the most number of articles using them, followed by bottleneck and risk-based priorities whereas throughput and risks come next. It should be noted that if an article uses multiple factors, which might

Total number of literature sources selected for analysis		23
Areas	Sub-areas	Total
1. Measure of criticality	1.1. Multiple Factors	12
	1.2. Throughput	4
	1.3. Risk	3
	1.4. Others	4
2. Method to identify criticality	2.1. Criticality classification	5
	2.2. Bottleneck	4
	2.3. FMEA/FMECA	4
	2.4. Others	10
3. Criticality used for maintenance prioritization		12

Table I.
Literature analysis of machine criticality

include bottleneck and risk, this is counted in the multiple factors. Second, the purpose of priority was analyzed. As seen in Table II, improving productivity and cost factors have emerged as the most common reasons for prioritizing maintenance, followed by safety. Third, as regard analyzing maintenance priorities for machine criticality, 12 articles clearly show a direct connection between the two.

4.2 Survey

The data obtained from the survey among the various companies include the level at which companies work with establishing machine criticality, the basis of establishing machine criticality, and the level of maintenance work order prioritization. Firs, establishing criticality levels in companies are presented in Figure 2. It can be observed that 35 percent of the companies establish criticality levels from a relatively high degree to a very high degree. However, 34 percent of the companies work with criticality to a relatively low degree, and 21 percent do not do work with machine criticality.

Second, the basis of establishing the criticality is presented in Table III. It can be seen from the table that the most common basis for establishing criticality is through an ABC classification. However, it is not clear how the ABC classifications were set, and the criteria

Total number of literature sources selected for analysis		28
Areas	Sub-areas	Total
1. Priorities are based on	1.1. Multiple factors	7
	1.2. Bottleneck	5
	1.3. Risk	5
	1.4. Others	11
2. Purpose of priority	2.1. Improve productivity	8
	2.2. Cost	7
	2.3. Safety	3
	2.4. Others	10
3. Priorities based on machine criticality		12

Table II. Literature analysis of maintenance prioritization

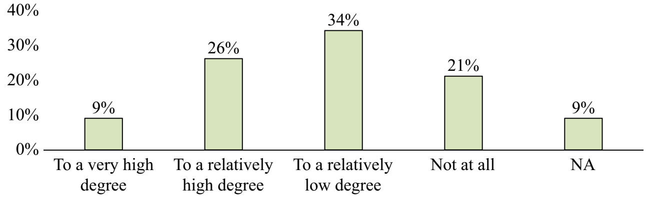

Figure 2. Establishing criticality

Primary basis for criticality levels	*n*	%
ABC classification	23	30
Operator influence	8	11
Bottleneck analysis	7	9
Cost-based priority	5	7
Time of purchase	4	5
Other basis	9	12
Do not know/"N/A"/Missing answer	20	26

Table III. Basis of establishing criticality included in that classification are not specified. Additionally, other factors such as bottlenecks, costs, and time for purchase were considered to be the basis for establishing criticality. Most importantly, the influence of operator was the second best option to establish machine criticality. Note that respondents were allowed to choose only one option.

Lastly, the level of maintenance work order prioritization in the companies is presented in Figure 3. From the figure, it can be observed that 67 percent of the companies prioritize maintenance work orders from a relatively high degree to a very high degree. However, only 20 percent work with a relatively low degree and 5 percent do not prioritize maintenance. It has to be noted that the data do not show how the priorities for the maintenance work orders were set.

4.3 Interviews

The four semi-structured interviews focused on obtaining deeper knowledge about these industrial practices concerning machine criticality based maintenance prioritization.

Machine criticality. The interview data gathered were from four different companies. These were multi-national manufacturing organizations, and all worked with the classification of machines based on criticality. One of these (interviewee 1) even indicated that they use equipment priority numbers during installation; whereas the other interviewees indicated that criticality classification is part of a technical specification of machines. Despite the differences, all interviewees indicated an ABC-type criticality classification for their machines in the production system. Interviewee 1 said they used 1-5 numbered equipment priority codes and the other three used exactly an ABC classification. However, methods used to classify the machines differed. Interviewee 1 said their equipment priority routines were set based on the production set-up, e.g. single or parallel machines. Interviewee 4 also indicated similar thinking but used alphabetic identification, e.g. A is a single line machine, B is a parallel machine, and C is a spare machine. Interviewee 2 said they use risk analysis based on fault frequency, mean time between failures (MTBF) to classify the machines. Interviewee 3 said they use a qualitative approach for classifying machines this being a tree-structure of questions that were answered to set criticality. The questions were based on such criteria as redundancy, safety, productivity, environment, etc.

Despite being familiar with criticality classifications, interviewees were not sure about the identity of the critical machine of the production system. The question generated different answers from each interviewee. Interviewee 1 defined a robot in a particular line as critical since it was the bottleneck. However, interviewee 1 said that the main criticality measure from a maintenance perspective was availability of machines. Interviewee 2 said that people being in the vicinity of machines were critical. However, when redirecting this question specifically towards the machines, the answer was bottleneck machine. Interviewee 3 answered from an overall perspective that whatever affects the delivery to the customers is critical and pointed out the assembly line. Consequently, all machines in that assembly line were classified as A-classified machines. Lastly, interviewee 4 answered

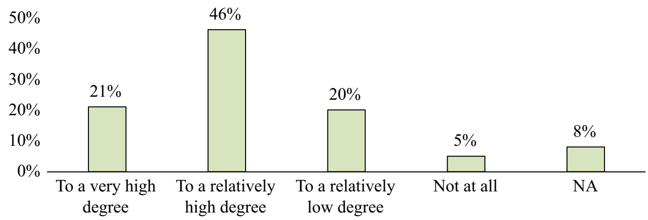

Figure 3.
Maintenance work order prioritization

that their production layout was unfortunate and that it was hard to understand the flow and analyze the losses, and that this was critical.

Maintenance prioritization. All the four interviewees agreed that they prioritize their maintenance work orders. Interviewee 1 referred to the same equipment priority routines (as used in criticality classification) and went on to explain that this was created through cross-functional meetings across departments. Whereas, interviewee 2 said that factory meetings and priorities are fixed and based on "what is crucial for us right now" and interviewee 4 said that the logistics department set plant or line priorities. On further questioning concerning reactive types of maintenance (RM) work orders, the answers from all four interviewees showed RM work orders were prioritized based on situation dependence. An excerpt from interviewee 1: "for reactive maintenance work orders, it is up to each maintenance technician to prioritize," sums up this practice very well. Interviewee 1 agreed that technicians who set priorities do in fact have knowledge about previously set priorities. However, for preventive types of maintenance (PM) work orders, interviewee 1 said they give equipment priority, whereas the other 3 interviewees typically said that "we have special windows within (planned) production (time) where we stop the production".

Interview data suggest that the criticality classification was not used directly for prioritization purposes. Despite the fact that criticality levels were printed on each work order, priorities were primarily set according to the experience of the maintenance technician who sets the priority. This situation was summarized in the words of interviewee 3, who said "if we use the criticality classification for prioritizing? Hmm, I don't know… The people who are running around have pretty good awareness of the equipment, and they know what's critical and (what is) not. So that's pretty much how we control and plan." However, criticality classification was used for managing the equipment and attempting to make it less critical, which was summed up in the words of interviewee 3: "We find a way to attack our already critical equipment, (by) making them less critical and that is most important."

4.4 Simulation experimentation

To test the impact of maintenance prioritization decision support on the efficiency of the production systems, simulation experiments were carried out where the maintenance work orders were prioritized for throughput-critical machines. The impact was tested on the throughput in two aspects. First, prioritizing maintenance for bottleneck machines and second, maintenance prioritization for different machine failure patterns.

The results of the first aspect include static bottleneck based prioritization of reactive maintenance work orders. The bottleneck is determined by active period percentages (utilization percent + downtime percent) (Roser *et al.*, 2003). Therefore, the machine having the highest active period percentage is the primary bottleneck of the system, and that machine claims priority 1 for maintenance execution. This use case featured two maintenance technicians, and therefore priorities were allotted to the machines handled by the technicians. Figure 4 shows the results obtained by the simulation models. It can be observed that prioritizing work orders (priority model) achieve a throughput increase of about 5.1 percent in comparison to a first-come-first-served (base model) basis of executing maintenance work orders. The results obtained were statistically significant, returning 95 percent confidence intervals with non-overlapping confidence intervals between the results of priority model and base model. As an additional result, the three maintenance technicians were found to work as a team across all machines. In such a scenario, throughput increases by about 11.2 percent (see Figure 4) in comparison to a first-come-first-served basis of executing the maintenance work orders.

In the next step, a sensitivity analysis was performed by varying the failure rate of the all the machines. The failure rates were increased and decreased by a factor of two in respect of

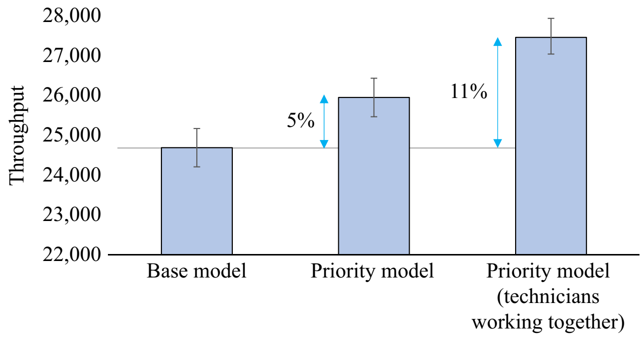

Figure 4. Throughput comparison

the actual failure rate. Corresponding to the varying failure rates, the changes in the workload of the technicians were also analyzed. The throughput improvement for each of the scenario is overlaid with the workload of the technicians. The results of this experiment are presented in Figure 5. In the figure, original represents the real-time failure rates of machines and the bar chart corresponding to it is 5.1 percent obtained previously (Figure 4). The bar charts to the right of original are increasing in failure rates and to the left are reducing in failure rates. From the figure, it can be observed that the utilization of technicians increases exponentially. However, the throughput improvement does not correspond to the increase in workloads of the technicians. Throughput improvement increases in the middle but reduces at extremely high failure rates. On the other edge, with extremely low failure rate, improvement is almost negligible.

5. Data interpretation

In this section, the individual findings from each data set are triangulated to achieve the aim of understanding the connection between machine criticality and maintenance prioritization and identifying the improvement potentials. First, the quantitative analysis of results is reported, followed by reporting qualitative results analysis. Lastly, qualitative results were used to interpret (explain) the quantitative results.

First, the results obtained in the quantitative part of the study include literature analysis and survey data. From both the data sources, maintenance prioritization is obvious. Particularly, the survey data show that, despite not setting criticality levels, most companies

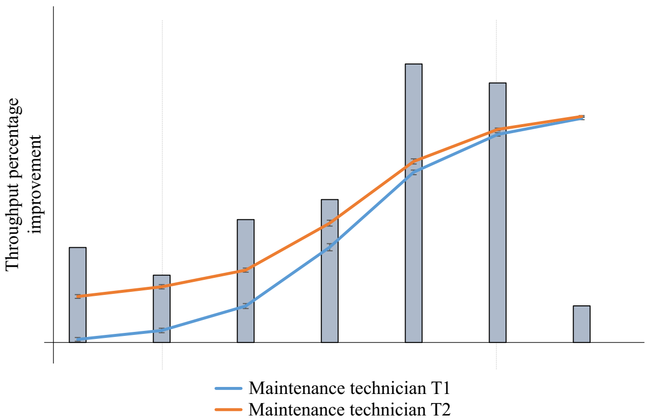

Figure 5. Comparison of throughput improvement potential with technician's workload

employ some sort of maintenance prioritization. A majority of the companies did not set criticality levels, which raises the question of the effectiveness of the maintenance prioritization practiced. Similarly, even in literature analysis, the articles on prioritization were not discussing criticality. However, it can be argued that prioritization is based on specific problems that can be construed as machine criticality. It is only natural to assume that if a machine is critical it needs prioritized focus compared to others in a system. Nonetheless, from the literature analysis, it was observed that not all articles on machine criticality concerned prioritization of maintenance efforts.

Additionally, survey data show that a classification model is used for assessing criticality (particularly an ABC-type classification). Such a classification means the machines are grouped into different classes, as well as the use of multiple criteria, for example (Márquez *et al.*, 2009; Bengtsson, 2011). On top of this, operator influence was marked as another important way for deciding criticality levels. Even though operator experience is highly valuable for the companies, decisions such as establishing criticality levels invoke questions of credibility in terms of fact-based decision making. The classification model and multi criteria way of working with machine criticality, indicated a rather static approach towards assessing machine criticality and non-factual decision making.

Second, the qualitative data were gathered in the form of interviews. All the four companies chosen for interviews used an ABC-type classification for setting the machine criticality levels and also practiced maintenance prioritization. Usually, different factors such as safety, environment, quality, maintainability, reliability, etc. are used to classify machines on different levels of criticality (A-classified machines are high critical and C classified are the least critical). However, irrespective of the type of criticality of a machine, in all high critical machines (A-classified) maintenance is planned to improve technical availability and reliability but showed a lack of adequate usage in the criticality classifications of the same. Despite having a classification in practice, the interviewees themselves were unsure what their critical machines were. This shows the lack of trust they have in their classification. Irrespective of problems with criticality, maintenance prioritization was performed through overall machine priorities, which were set by companies using department level meetings (cross-functional). This situation raises questions as to the effort and usage of classification. Unfortunately, even these priorities were not followed properly, but priority setting was carried out according to situation dependence. Usually, the maintenance technician who makes out the work orders decides on the priorities.

Lastly, qualitative results are used to explain the phenomenon observed in the quantitative aspect. From quantitative analysis, multiple criteria for assessing criticality and the majority of companies failing to set criticality levels were observed. Although all four companies in the qualitative study used a criticality classification, the use of multiple factors was plainly evident. The main reason being maintenance is responsible for environment, safety, quality, and delivery of products produced in machines. Hence, these factors were considered for assessing machine criticality. One of the issues with multiple criteria while planning maintenance is that the main criterion influencing the criticality of a machine is unclear. Operator influence was observed to be generally agreed upon as the way to set criticality levels. This is explained in the interviews in the form of situation dependence for maintenance prioritization. The production system is complex and criticality classification is untrustworthy, static, and non-factual. Hence, the maintenance technician's experience and knowledge decides the priorities rather than data-driven conclusions. The survey showed that a majority of the companies prioritized maintenance operations. The interview study showed that maintenance prioritization is needed and all companies are practicing it at some level. The priority is to solve what is critical at any given time and ensure production is not hindered.

6. Overall discussion

This paper shows the connection between machine criticality and maintenance prioritization and the productivity potentials within. This empirical study followed an explanatory mixed-method research approach followed by a simulation experiment to evaluate and validate the productivity potential.

Results have shown that maintenance prioritization is not based on machine criticality in manufacturing companies. Particularly, maintenance is prioritized situation-dependent by the maintenance technician. Even though some literature argues for criticality based prioritization (Moore and Starr, 2006; Stadnicka *et al.*, 2014), the lack of strong machine criticality assessment in companies has emerged as the main reason for ineffective maintenance prioritization. A typical example of identifying criticality is through multiple factors, as suggested by Márquez *et al.* (2009). From the achieved results, it can be said that such a machine criticality assessment is static, non-factual, and lacks system view. However, it is previously established that maintenance prioritization is a decision support tool for maintenance planning (Ni and Jin, 2012). Studies have shown productivity improvement from maintenance prioritization (Lu *et al.*, 2011; Wedel *et al.*, 2016). Therefore, the need for a strong machine criticality assessment to aid maintenance prioritization is evident.

Therefore, the productivity improvement potential lies in the maintenance planning effectiveness, i.e. machine criticality based maintenance prioritization. The simulation experiment of an empirical use case was used to evaluate the improvement potential. Throughput-critical machines were prioritized for executing reactive maintenance and yielded a 5 percent increase in throughput compared to a first-come-first-serve basis of scheduling maintenance without changing any other way of working or new investments in the system. The other important outcome showed that maintenance prioritization might always be relevant in manufacturing companies. In other words, manufacturing companies would like to establish this situation to achieve better utilization of production system resources and also reduce costs. This was shown through the same industrial use case but in varying failure rates of machines. Low utilization (overstaffing) and high utilization (understaffing) of maintenance technicians are situations that companies might not want to be in, and that is only when maintenance priorities do not affect the production system positively.

The results achieved points to the need for a holistic approach in maintenance planning in companies to make efficient production systems, i.e. a system view (Ylipää *et al.*, 2017; Roy *et al.*, 2016). Additionally, the results are invaluable to the research community also as there are not enough research in solving the systems level problems in maintenance operations (Helu and Weiss, 2016). In addition to direct machine downtime, a major part of the productivity losses are related to starved and blockage machine states (Skoogh *et al.*, 2011). Criticality-based maintenance prioritization can solve it as shown by the simulation results. Obviously, maintenance will reduce the downtime of the machines that are failed, but prioritization ensures that downtime of critical machines to be reduced first. This has ensured that improving the constraint of the system improves the entire system (Chiang *et al.*, 1999). The main take away here is that a system approach was taken for maintenance planning. Therefore, the results obtained point to the need of machine criticality assessment decision support for maintenance prioritization to be effective. Considering the growth in availability of real-time production data, such a decision support can be developed using the already existing machine data for identifying machine criticality. This decision support will enhance decision-making capabilities of the maintenance engineers (Santana, 1995), and enable the production system to be robust and effective.

6.1 Industrial contributions

The results of this study are important for maintenance managers in the manufacturing companies. Maintenance operations need to be planned effectively in order to achieve higher efficiency and reduce costs (Moghaddam and Usher, 2011; Ni and Jin, 2012). This article particularly highlights the gaps in maintenance planning that hinders achieving higher production efficiency. A practical contribution for the maintenance managers is to constantly seek for fact-based decision making in prioritizing maintenance decisions. Results from the simulation experiment showed that smartly working with the current industrial situation can lead to throughput increase. Hence, a complete effort from the industry into machine criticality based maintenance prioritization leads towards the effective planning of reactive and preventive maintenance. With the rapid growth in technology and data quality, increased efforts into production data analytics are expected to enable highly productive digitalized production system.

6.2 Methodological discussion

The explanatory research design helped in explaining the phenomenon in the industry of machine criticality assessment and maintenance prioritization. As per the design, the quantitative study was completed first and then followed by the qualitative. The qualitative study helped in explaining the phenomenon observed in quantitative part (Creswell, 2013). In the survey data a non-random sampling was used, thus sampling of the responses limits the generalizability of the results, but the selection of only the expert view makes the data relevant. The companies chosen for interview study were also part of the quantitative survey study companies, which made the obtained explanatory results highly reliable. The simulation experimentation use case was also chosen from one of the companies that participated in both qualitative and quantitative aspects of the study. Additionally, the combination of multiple data sources of literature analysis, survey, interviews, and simulation experimentation increases the reliability and credibility of the achieved results. Importantly, the results achieved are of high import and relevance to the manufacturing companies, as it is empirical research, which is limited in the field of maintenance management (Fraser *et al.*, 2015).

7. Challenges for the future

Maintenance organization in digitalized manufacturing will face complex challenges in the future. The results of this study have highlighted some of the important challenges; assessing machine criticality in particular, is a concern. Maintenance prioritization has been identified as an important decision support tool for effective maintenance operations (Ni and Jin, 2012), but prioritizing the right machine needs to be constantly identified. The general problem with maintenance organization is working with a single machine problem, i.e. lack of a systems view (Ylipää *et al.*, 2017; Roy *et al.*, 2016). The two main problems in respect to machine criticality that need addressing are the lack of fact-based decision making and static assessment methods. As Guo *et al.* (2013) explain decisions are often made based on the experience and knowledge of maintenance technicians. However, quick decision making and continuous control of production system has gained in importance in the execution phase (Li, Chang Ni and Biller, 2009b). Therefore, a robust machine criticality assessment with a systems view is required for manufacturing companies to effectively plan maintenance operations. Only such a decision support can deliver the expectations set for the digitalized manufacturing of the future (Bokrantz *et al.*, 2017). Decision support can be developed through existing manufacturing execution system (MES) data. Therefore, maintenance prioritization decision support research needs to address the following:

- Systems view – to focus on the improvement of the entire system, rather than individual machines.
- Dynamic – to counter the dynamic nature of production systems continuous decision support is needed. The fluctuations in real-time should be captured and mitigated immediately.

- Data-driven – in order to enable fact-based decision making, large sets of machine data (MES data) need to be analyzed in real-time. Additionally, using data analytics, predictive and prescriptive maintenance is possible to achieve.

Particularly, the authors' next step towards achieving maintenance decision support will be through studying in detail the industrial practices regarding machine criticality assessment. This will help in understanding the importance of different factors for criticality as well as the ways of using them for maintenance planning. Such a solid study on machine criticality assessment is missing in literature. This will be necessary in order to develop a framework for decision support on machine criticality.

8. Conclusions

This paper presents an empirical study, contributing to the connection between machine criticality and maintenance prioritization in industrial practice and providing productivity improvement potentials. The problems in maintenance planning, particularly the ripple effects of machine downtimes on production efficiency are addressed. The paper showed that companies do not prioritize maintenance based on machine criticality. The main reason was that there is a lack of strong machine criticality assessments in companies. The current criticality classifications in companies are static, qualitative, and lacks a systems view. An interesting finding was that maintenance are prioritized non-factually, i.e. operator influenced. However, maintenance prioritization based on machine criticality leads to increased production efficiency. This productivity improvement potential was evaluated in a simulation experiment, which showed an increase in throughput when maintenance is prioritized for throughput-critical machines, without added efforts. The bottom line is that the current maintenance planning practices are already ineffective for today's production and certainly, for digitalized manufacturing (Industry 4.0), where the production system will be even more autonomous. In order to solve, the authors argue that a data-driven and dynamic approach with a system view is needed for assessing machine criticality. Such a decision support can enable the practice of maintenance prioritization leading towards increased system productivity. Such a decision support could be developed based on existing MES data.

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