Machine criticality assessment for productivity improvement: Smart maintenance decision support

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Smart maintenance decision support

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Abstract

Purpose – The purpose of this paper is to increase productivity through smart maintenance planning by including productivity as one of the objectives of the maintenance organization. Therefore, the goals of the paper are to investigate existing machine criticality assessment and identify components of the criticality assessment tool to increase productivity.

Design/methodology/approach – An embedded multiple case study research design was adopted in this paper. Six different cases were chosen from six different production sites operated by three multi-national manufacturing companies. Data collection was carried out in the form of interviews, focus groups and archival records. More than one source of data was collected in each of the cases. The cases included different production layouts such as machining, assembly and foundry, which ensured data variety.

Findings – The main finding of the paper is a deeper understanding of how manufacturing companies assess machine criticality and plan maintenance activities. The empirical findings showed that there is a lack of trust regarding existing criticality assessment tools. As a result, necessary changes within the maintenance organizations in order to increase productivity were identified. These are technological advancements, i.e. a dynamic and data-driven approach and organizational changes, i.e. approaching with a systems perspective when performing maintenance prioritization.

Originality/value – Machine criticality assessment studies are rare, especially empirical research. The originality of this paper lies in the empirical research conducted on smart maintenance planning for productivity improvement. In addition, identifying the components for machine criticality assessment is equally important for research and industries to efficient planning of maintenance activities.

Keywords Productivity, Bottleneck

Paper type Research paper

1. Introduction

The modern manufacturing sector is extremely competitive, particularly given increased demands for quality, variety and shorter lead times. This competition has fueled the fourth revolution in the manufacturing industry, especially through initiatives such as Industry 4.0

and Smart Manufacturing (Thoben *et al.*, 2017). The initiatives are characterized by cyber-physical systems, where physical and engineering systems are connected through the Internet of Things (IoT), i.e. digitalized manufacturing (Hermann *et al.*, 2016). Digitalized manufacturing has placed extremely high expectations on manufacturing systems to deliver substantial increases in productivity, automation and resource efficiency (Monostori *et al.*, 2016). As a result, these places increased requirements for plant-level reliability and availability. In order to realize these expectations, maintenance organization needs to keep pace with the rapid advances in digitalized manufacturing. Dominant themes have been identified that could have great influence on the internal environment of maintenance organizations in the future: fact-based maintenance planning and maintenance planning with a systems perspective are two of them (Bokrantz *et al.*, 2017). Hence, traditional maintenance must transform into smart maintenance, which is intelligent and ready for these challenges (Acatech, 2015). However, traditional industrial maintenance practices are well behind the theory, which is reflected in the poor performance of machines. For example, overall equipment effectiveness (OEE) figures average 50–60 percent in manufacturing companies (Ljungberg, 1998; Ylipää *et al.*, 2017), whereas world-class OEE is expected to by 85 percent. Traditionally, maintenance aims at maximizing only the availability component of OEE, thereby increasing machine-level productivity. This situation is prevalent in maintenance research as well, where single-machine problems have been the primary focus of improvements for maintenance organizations (Helu and Weiss, 2016; Li *et al.*, 2009). However important this may be, the effects of single-machine failures on the system as a whole, i.e. ripple effects, are also a major concern. Ripple effects cause blocked and starved machine states on other machines (idling losses), thereby compromising system-level productivity and causing energy losses (Skoogh *et al.*, 2011). The effect is compounded further when multiple machine failures occur. The variability caused by the idling losses needs to be mitigated through achieving a swift and even production flow, which can increase productivity without reducing flexibility in production (Schmenner and Swink, 1998). Therefore, simultaneously maintaining more than one machine in a system (maintenance prioritization) is an important research problem that needs to be addressed (Roy *et al.*, 2016).

The prioritization of maintenance operations is an important task for achieving production system efficiency (Levitt, 1997; Ni and Jin, 2012). However, there is a lack of robust decision support tools for identifying critical machines for prioritizing maintenance. A previous study showed that although manufacturing companies prioritize maintenance operations, they do so without properly setting machine criticalities (Gopalakrishnan and Skoogh, 2018). Additionally, the maintenance decisions at the shop-floor level were operator-influenced or based on experiences of maintenance technicians. This phenomenon was also explained in Guo *et al.* (2013), which states that maintenance work-order prioritizations are often made based on the experience and knowledge of maintenance technicians. This clearly indicates the problem of not adhering to fact-based decision making in companies for making maintenance decisions. Therefore, the computerized maintenance management systems (CMMS), which should support maintenance decisions, are unused. Ni and Jin (2012) say that existing CMMS are outdated and do not adhere to the dynamic needs of maintenance operations.

Maintenance activities can be broadly categorized as either preventive maintenance (PM) or reactive maintenance (RM), both of which require planning and support. Machine criticality assessment is a tool that supports maintenance decision making (Bengtsson, 2011; Stadnicka *et al.*, 2014), which includes support for both PM and RM activities. The roots of criticality assessment can be found in the reliability centered maintenance (RCM) approach, where failure mode and effects analysis (FMEA) is used to assess failure modes in machine components (Moubray, 1997). This type of tool has been expanded to operate

at machine level as FMECA (where C = criticality) (Bertolini and Bevilacqua, 2006). Manufacturing companies generally employ some form of machine criticality analysis, whether that be FMECA, ABC classification (Márquez *et al.*, 2009; Bengtsson, 2011), risk analysis (Moss and Woodhouse, 1999), fuzzy-based analysis (Ratnayake and Antosz, 2017; Pelaez and Bowles, 1994), etc.

Despite the various methods available for assessing machine criticality, it was previously found that it is hardly used in practice for maintenance prioritization (Gopalakrishnan and Skoogh, 2018). This begs the questions: how can maintenance be prioritized effectively? And if manufacturing companies have criticality assessment tools at their disposal, why do not they use them? Therefore, there is a considerable need to find out how manufacturing companies work with their machine criticality assessment and identify the necessary steps to enable maintenance organization to focus on increasing productivity. Especially, the main objectives for using criticality assessment, the factors considered for criticality assessment and the type of data used for assessment will provide profound knowledge on the assessment tool. This knowledge will help toward developing decision support tools for achieving smart maintenance planning.

The purpose of this study is to increase productivity through smart maintenance planning, with the aim of including productivity as an objective for the maintenance organization. As a result, the study aimed at mapping the objectives, uses, methods and data requirements for existing machine criticality assessment and identifying the components of machine criticality assessment to support maintenance decisions that increase productivity. This paper particularly focuses on the discrete manufacturing industry. The results will provide a greater understanding of the existing gaps in criticality assessment and can identify potential productivity improvement opportunities.

Machine criticality assessment studies are rare, especially empirical research. As greater practical focus is needed in maintenance research, an empirical study was chosen (Fraser *et al.* 2015). The rest of the paper contains the literature review, methodology, results, discussion and conclusion. Additionally, the topics that were chosen for analysis in the study emerged from the literature on machine criticality, as explained in Section 2.

2. Related literature
In this section, the literature related to machine criticality assessment and its relationship with maintenance planning are presented. Based on the goals of the paper, the literature is presented under the headings Objectives of machine criticality assessment, Factors and methods, Data requirements and Maintenance planning. The design of the interviews and focus groups in each of the cases in the multiple case studies was determined by the outcome of the literature analysis. Finally, the codes for analysis were determined based on the synthesis of literature under each heading.

2.1 Objectives of machine criticality assessment
The overall objective of any machine criticality assessment tool is to support maintenance operations decisions. However, the specific objectives of an individual tool are dependent on the intended usage. Márquez *et al.* (2015) describe the maintenance management process in two parts: strategic and operational. The strategic part deals with determining objectives and priorities when choosing maintenance strategies, whereas the operational part deals with the implementation of the strategy, for example, maintenance planning, control, supervision and continuous improvement. Additionally, Márquez *et al.* (2015) and Moss and Woodhouse (1999) describe two types of criticality assessments: those performed during the operational phase and those performed during the asset design phase. For assessments carried out during the operational phase, the objective is to identify critical areas in the production system in order to meet machine availability targets (Márquez *et al.*, 2015).

Generally, maintenance prioritization is the primary objective when assessing machine criticality (Bengtsson, 2011; Márquez *et al.*, 2009). However, priorities can also be assigned with regard to reliability (Roy and Ghosh, 2010; Bevilacqua *et al.*, 2009), PM (de León Hijes and Cartagena, 2006), RM (Li and Ni, 2009; Wedel *et al.*, 2016) and costs (Moore and Starr, 2006). Additionally, the productivity as an objective (Moss and Woodhouse, 1999; Stadnicka *et al.*, 2014; Ni and Jin, 2012) and production scheduling quality (Petrovic *et al.*, 2008) are also presented in the literature. Even though productivity is considered as an objective, it is only considered implicitly. Productivity is sought after on individual machines by maximizing its availability, for example Moss and Woodhouse (1999). Another major industrial application area in which criticality assessment tools are used is spare part inventory planning (Stoll *et al.*, 2015; Sun, 2013). The objective of the criticality assessment tool determines its usage and focus in maintenance improvement. Based on the aim of the study and the criticality objectives mentioned above, the topics of the purpose of assessing criticality, productivity focus, PM and RM use and spare part planning are chosen for analysis.

2.2 Factors and methods
Generally, much of the literature on machine criticality suggests multiple factors for assessment (Bengtsson, 2011; Ratnayake *et al.*, 2014; Stadnicka *et al.*, 2014). Two common factors for maintenance organizations to focus are safety and environment (Pintelon and Parodi-Herz, 2008). Certainly, other factors have been used for assessing machine criticality for maintenance purposes. Therefore, it is important to know which factors have been included in assessing criticality. When FMEA is used to assess failure modes, particularly attention is paid to the probability and consequence of failure (Moss and Woodhouse, 1999), whereas when an ABC-type criticality classification is used, factors such as redundancy, utilization, quality, age and cost are assessed (Bengtsson, 2011; Ratnayake *et al.*, 2014). FMECA methods consider additional factors such as environmental aspects when assessing criticality (Costantino *et al.*, 2013). Moving on to methodology, FMEA uses the multiplication of factors to calculate a risk priority number (RPN) for maintenance planning (Moss and Woodhouse, 1999; Pelaez and Bowles, 1994). ABC-type criticality assessments use some form of a scoring system, where the total criticality score for each machine is calculated on a scale of A, B or C in order to determine the levels of criticality (Ratnayake *et al.*, 2014; Stadnicka *et al.*, 2014).

In additionally to the machine criticality assessment literature, there are several other methods for maintenance decision making. Maintenance decision making is often viewed as an optimization problem for planning and scheduling work orders. A large amount of literature has been published in this area for finding optimal maintenance solutions (Ding and Kamaruddin, 2014). Some of the main maintenance optimization models include multi-criteria decision making (MCDM), analytic hierarchy process, fuzzy logic and simulation (Garg and Deshmukh, 2006). Similar to criticality assessment, maintenance optimization process also includes objectives, factors and methods, analytical approach for analysis and function description (maintenance planning and scheduling activity) (Ding and Kamaruddin, 2014). One of the main criticism toward optimization models is that they are unable to fully cover the gap between research and industrial practice, as industrial environment is highly complex, and the fluctuations with factors and variables are not fully documented and analyzed (Ding and Kamaruddin, 2014). Because of the lack of extensive usage in the industry for decision making, optimization models are not considered further in this paper. Also, the central aim of the paper is about machine criticality assessment and not the optimization of the maintenance policies. Therefore, the factors and methods used to determine the ease of analysis and utility of machine criticality are considered for analysis. Hence, the topics factors for assessing criticality and methods for assessing criticality are chosen as for analysis within factors and methods of assessing criticality.

2.3 Data requirement

The next step after analyzing objectives, factors and methods for assessing criticality is to understand the data required to perform the assessment. Moss and Woodhouse (1999) state that human psychology is important as statistical considerations when implementing machine criticality assessments, meaning that all relevant members of the workforce should be included in setting priorities. The model provided by Pelaez and Bowles (1994) combines qualitative and quantitative factors to determine "riskiness." Failure data are a specific requirement in many criticality assessment methods (Stadnicka et al., 2014; Bengtsson, 2011), as these are main data that directly correspond to maintenance. In other situations, purely qualitative data such as group discussion (cross-functional) with the relevant participants are used for assessment (Bengtsson, 2011; Márquez et al., 2015). Cost-based criticality (CBC) uses different cost calculations for assessing criticality, for example, CBC (Moore and Starr, 2006) and cost deployment (CD) (Yamashina and Kubo, 2002) to assign costs for machine downtime and loss of production from which criticality is then assessed. A model developed by Antosz and Ratnayake (2016) uses real production data such as machine failures, product quality deterioration and machine availability/downtime for criticality assessment. Additionally, Gopalakrishnan and Skoogh (2018) demonstrate "operator influence" as a factor in deciding criticality levels. Machine data from manufacturing execution system are not commonly used for criticality analysis. It is therefore important to consider the usability of the criticality assessment tool and the frequency of updates. Hence, the topics of data usage and usability and updates are chosen for analysis.

2.4 Maintenance planning

Machine criticality assessment is not the only tool that supports maintenance planning. Garg and Deshmukh (2006) provide a detailed account of the various maintenance management models that are used for maintenance planning and scheduling activities. However, if machine criticality is insufficient, then achieving optimum maintenance planning is unlikely as it shows where to prioritize maintenance efforts (Stadnicka et al., 2014). To support the need for criticality assessment, Ni and Jin (2012) claim that maintenance prioritization is an effective decision support tool for maintenance engineers. There are several examples demonstrating the importance of setting priorities for maintenance staff in the execution of maintenance planning and scheduling activities (Garg et al., 2010; Wedel et al., 2016; Li et al., 2009). The above-mentioned literature seeks productivity improvement on a system level. To have productivity as objective calls for cross-functional collaboration within the company. Bengtsson (2011) and Zanazzi et al. (2014) also emphasize the importance of synergy between production and cross-functionality across the organizations. The cross-functional approach can be achieved by having a system perspective for solving maintenance problems, which will lead to improve the system productivity (Ylipää et al., 2017). Therefore, ownership synergy and production synergy are the topics chosen on the maintenance planning level for the analysis in this study. In addition to this, problems in machine criticality were also chosen as an additional topic for analysis in order to identify the perceived problems with criticality assessment.

3. Methodology

The aim of the paper requires that the study to be conducted in the natural setting (empirical) through observing actual practice and capturing the complexity of criticality assessment, which is why case research methodology was chosen (Voss et al., 2002). This approach provides a deepened knowledge of machine criticality practices in manufacturing companies. An embedded multiple case study approach was adopted for a more detailed level of inquiry (Yin, 2013). A multiple case study was chosen to increase the

generalizability of the theory-building process (Flynn *et al.*, 1990). Six cases were studied from three multi-national automobile manufacturers. The design of the study was tested in a pilot case with an industrial partner, where the data collection and analysis procedure were tested. The research design is illustrated schematically in Figure 1.

3.1 Case selection
The case selection is an important process that needs to be in order with the purpose of the study. A total of six case studies were chosen from six different production sites across three multi-national manufacturing companies located in Sweden. All the selected cases were from discrete manufacturing companies but the cases were ensured that they were varied from each other. Six empirical data sets (ED1–ED6) were collected in each of the six manufacturing sites separately, and this forms the basis for building theory within machine criticality and maintenance prioritization. The criteria for choosing the cases include: the case company should use or have machine criticality assessment tool, willingness to improve maintenance practices, different products being produced and type of production set-ups and geographically separated from each other and employed different work procedures, i.e. no two cases were from the same manufacturing site. The cases were distributed among the three companies: four data sets (referred as ED1–ED4) were collected from four chosen manufacturing sites in case company A, while one manufacturing site was selected for each of case companies B and C (referred as ED5 and ED6, respectively).

3.2 Empirical data collection
Data collection was carried out through interviews, focus groups and archival records. However, data were predominantly collected in each of the cases through interviews and focus groups. A total of eight interviews and five focus groups were conducted across all cases. See Table I for the distribution of data collection in each case. The interviews and focus groups were developed from the theory of machine criticality assessment. The interview and focus group questionnaires were revised with the help of both industrial partners and senior researchers from the university. Archival records include documents on the criticality assessment tools at the various sites, which were gathered from the CMMS system of the company.
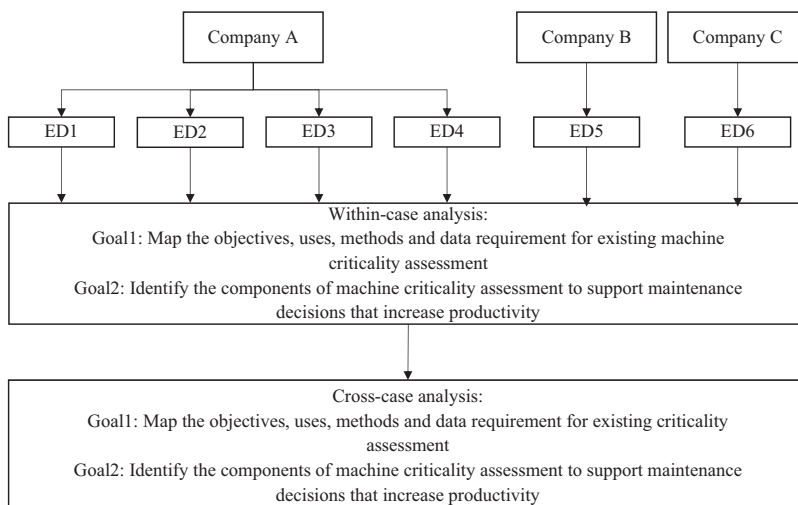
Figure 1.
Multiple case
study design

All the interviews and focus groups were performed face to face, except in ED1 (case company A). Data were collected from a single telephone interview because the production site is located outside of Sweden. However, in the other case sites (ED2–ED6) at least two interviews or focus groups were conducted. The empirical data collected focused on machine criticality assessment and maintenance prioritization practices. The face-to-face interviews lasted between 45 and 60 min, whereas the focus group interviews lasted about 120 min on average. All the interviews and focus groups were audio recorded with the consent of the participants and further transcribed for data analysis.

3.3 Data analysis

The six sets of empirical data were triangulated leading toward a strong theory-building process (Creswell, 2013). As the first step, a within-case analysis was conducted. The within-case analysis was conducted with guidance from theory, which allowed analysis to focus on the significant parts of the study (Yin, 2013). First, theory on machine criticality assessment objective (Section 2.1) was used to code the empirical data for the purpose, PM and RM use, productivity focus and spare part planning. Second, the theory on factors and methods of the criticality assessment (Section 2.2) was used to code the empirical data to identify the factors and methods involved. Third, the theory on data requirement for assessment (Section 2.3) was used to code the data on understanding the quantitative and/ or qualitative nature and usability of the criticality assessment. Finally, additional coding was performed using theory on maintenance planning (Section 2.4) for connecting the assessment tool with maintenance decision-making practices. These form the predefined topics for within-case analysis.

The predefined topics from theory were used to code the six data sets. The coding process was performed with the help of NVIVO qualitative data analysis software. The transcripts of the interviews and focus groups, which form the six data sets, were coded in the software. The software enables maintaining of the links between the predefined topics and the first-order codes from the data. A total of 284 first-order codes were coded from the six empirical data sets. These codes were used to present as results in each ED.

In addition to the within-case analysis, a cross-case analysis was also performed. With the cross-case analysis, the aim was to identify the similarities and differences between the cases (Yin, 2013). The cross-case analysis further increases the generalizability of the results achieved.

3.4 Generalizability

One of the common misunderstandings about case study research is that generalization cannot be achieved (Flyvbjerg, 2006). Even though generalizability is possible from a single case study, the use of multiple case study design in this paper increases generalizability to a large extent in comparison to a single case study (Yin, 2013). The empirical data sets were first analyzed individually within each case, thereby allowing the emergence of a unique pattern in each. A cross-case analysis was then

Data	Interviews	Focus groups	Archival records	Type of production layout
ED1	1		Yes	Assembly
ED2	3		Yes	Machining
ED3		3	Yes	Assembly, foundry and machining
ED4		2	Yes	Assembly and machining
ED5	2			Machining
ED6	2			Machining

Table I.
Cases and
data sources

conducted to assist in seeking generalization (Voss *et al.*, 2002). Additionally, in each of the cases, the data were gathered from more than one data source, with each data source including different types of production set-ups. Triangulation through the use of different methods and data sources also increases the generalizability and validity of the research (Voss *et al.*, 2002; McCutcheon and Meredith, 1993).

4. Results
The multiple case study was conducted in the form of interviews and focus groups at each of the case sites, along with archival records from some sites where available. The first six sections consist of the within-case results of the EDs, and the last section contains the cross-case analysis results.

4.1 Within-case analysis – ED1
The results of the first case (ED1) are presented in Table II. ED1 data are gathered from a single interview with the maintenance manager of an assembly line. It can be observed that the machine criticality classification is being used in this assembly line for maintenance planning purposes. A clear productivity focus is also observed in the classification by working closely with production organizations. However, a central problem in ED1 was that more machines were classified as high critical machines.

4.2 Within-case analysis – ED2
The second case (ED2) consisted of three interviews, and the chosen production line had a machining layout. The results of the analysis are presented in Table III. It can be observed that there was no clear answer regarding the productivity objectives of machine criticality. Analysis of ED2 also showed that the use of the classification tool was limited and the usage of data for the analysis was limited. Additionally, several machines ended up being classified as highly critical. The reasoning was highlighted by the lack of knowledge regarding the type of criticality each machine was classified under.

Objectives	
Purpose of assessing criticality	Critical from customers' point of view (i.e. production)
Productivity focus	Clear connection with production. Working with production organization
PM and RM use	Used to prioritize PM and deferred work orders, plus RM
Spare parts planning	Separate classification for spare parts planning
Factors and methods	
Factors for assessing criticality	Safety and environment, quality, back-up solution, production, MTBF, MTTR and repair costs were the factors
Methods for assessing criticality	Levels of criticality are AA, A, B, C. A decision tree is used to make decisions for above factors
Data requirement	
Data usage	MTBF and MTTR were used
Usability and updates	Very useful and updated annually
Maintenance planning	
Ownership and production synergy	Maintenance owns the classification and there is good consensus with production
Problems in criticality assessment	Over half the machines are classified AA; data quality becomes an issue

Table II.
Results – ED1

Objective	
Purpose of assessing criticality	Developing autonomous maintenance for critical machines, prioritizing condition-based maintenance, long-term spare parts planning, mapping repair crew competences for the factory
Productivity focus	Productivity not linked to criticality assessment
PM and RM use	Used to plan PM. RM is prioritized but not based on the classification. Critical areas are set for prioritization usually set during morning meetings. However, RM work is prioritized over other types of maintenance
Spare parts planning	Used for long-term spare parts planning
Factors and methods	
Factors for assessing criticality	Safety, environment, redundancy, utilization, quality and age were the factors
Methods for assessing criticality	AA, A, B, C classification were used as the levels. A flowchart with a scale ranging from 1 to 9 is used to evaluate quality, safety, delivery and human factors. Scale rating based on probability and consequences of machine failures. Conducted with other organization members (i.e. production)
Data requirement	
Data usage	Some OEE data were used. Generally, subjective data collected by talking to people
Usability and updates	Not used to any great extent. Classification updated annually
Maintenance planning	
Ownership and production synergy	Owned by maintenance, but machines classification is carried out in conjunction with operators, production managers and production engineers
Problems in criticality assessment	Too many machines were classified with high criticality. Factors only show critical or not, but not the type of criticality the machine has. AA machines can stop production, but B or C machines can sometimes bring the system to a halt too

Table III.
Results – ED2

4.3 Within-case analysis – ED3

The results for ED3 analysis, where data were collected from a production site that comprised of assembly, foundry and machining lines, are presented in Table IV. Three focus group interviews formed the data set. The results show that in addition to a lack of focus on productivity as an objective for machine criticality assessment, there was also a failure to use data from production. The criticality classification used in ED3 was used to identify critical machines across the entire factory. Furthermore, the criticality assessment was helpful in providing a good understanding with the production organization.

4.4 Within-case analysis – ED4

The fourth case (ED4) comprised of assembly and machining lines, and the results of the analysis are presented in Table V. Similar to ED3 results, productivity as an objective was considered for criticality assessment. In addition, spare parts planning was also excluded from machine criticality classification in ED4. Bottleneck machines not being captured in their existing classification tool came across as a specific problem. There was also a problem with multiple machines being classified as highly critical.

4.5 Within-case analysis – ED5

The results from the analysis of ED5 are presented in Table VI. ED5 comprised of two interviews conducted at the production site, where a production line chosen for the study had machining layout. The results showed that at this site, machine criticality is used mostly for securing spare parts and not much in maintenance planning. The main problems in the classification tool are the lack of trust and poor standardization of the analysis process. As with the other case results, many machines end up with a classification of highly critical.

Objective	
Purpose of assessing criticality	Purpose is to increase quality and availability. Also, to start autonomous maintenance and preventive maintenance projects
Productivity focus	Productivity not linked to criticality assessment
PM and RM use	Not used for PM; PM plan was the same for all machines. Prioritized RM work orders but priorities not based on criticality classification; usually it comes from production
Spare parts planning	Spare parts plan was same for all machines and not determined by classification
Factors and methods	
Factors for assessing criticality	Environment, safety and complexity of machine, difficulty for operator; single flow or parallel flow; MTTR; safety and environment; bottleneck were the factors
Methods for assessing criticality	Used cost deployment to allocate AA, A, B and C classes. Discuss with manager to identify critical machine. Choosing between single and parallel machines. Analysis includes root cause, monthly follow-up MTTR, MTBF, MWT and maintenance cost
Data requirement	
Data usage	Mostly use maintenance technician's experience for decisions. MTBF and MTTR from CMMS
Usability and updates	Shows critical machine for the whole factory. Updated quarterly or annually
Maintenance planning	
Ownership and production synergy	Maintenance owns the classification. Good understanding of production as the two departments work as a team
Problems in criticality assessment	Assembly tends to be more advanced; classification process such that same machine is classified as critical every time

Table IV.
Results – ED3

Objective	
Purpose of assessing criticality	Improve the quality of PM and allocate more maintenance to critical machines, bottlenecks and minimize maintenance costs
Productivity focus	Productivity not linked to criticality assessment
PM and RM use	No PM related use. RM priorities line-based rather than on criticality classifications. This is usually set by production
Spare parts planning	Spare parts not planned using criticality assessment
Factors and methods	
Factors for assessing criticality	Single or parallel machine, spare parts in-house and technician resource availability
Methods for assessing criticality	Cost deployment for classifying machines. Inventory showing type of manufacture, type of software/hardware, status of machine, quality, spare parts availability and knowledge availability
Data requirement	
Data usage	OEE and CD were used
Usability and updates	Rarely used and only shows critical machine location. Updated quarterly
Maintenance planning	
Ownership and production synergy	Maintenance own classification. Usually obtain consensus but production has final say in case of mismatch
Problems in criticality assessment	Need to limit number of machines classified as highly critical. Procedure in CD problematic as method fails to adequately capture bottlenecks. Cost calculations in CD provide wrong results

Table V.
Results – ED4

4.6 Within-case analysis – ED6

Finally, the results of the ED6 analysis are presented in Table VII. These were obtained from two interviews and the chosen production line had a machining layout. The results showed that there was a clear focus on productivity as an objective for

Objective

Purpose of assessing criticality	Preparing spare parts to solve production issues and improve standards
Productivity focus	Productivity not linked to criticality assessment
PM and RM use	PM not planned using classification. RM is executed on a first-come-first-served basis. Technicians sometimes using their experience to prioritize. Allocation of resources carried out from a command center
Spare parts planning	Secure spare parts for critical machines

Factors and methods

Factors for assessing criticality	Environment, spare parts for maintenance, knowledge of technicians and machine status (wear and tear) were the factors
Methods for assessing criticality	A, B, C, D classes. Flowchart guides classification, which is conducted by a group

Data requirement

Data usage	No data used
Usability and updates	Not understood so hardly used. Updated when new equipment is procured

Maintenance planning

Ownership and production synergy	Conducted by staff with a variety of competences, so creates understanding. Clear view and consensus on critical equipment
Problems in criticality assessment	Classification not well standardized. Lack of trust in current classification. Too many machines with high classification

Table VI.
Results – ED5

Objective

Purpose of assessing criticality	Purpose is to ensure availability of machines
Productivity focus	Bottleneck machine gets maintenance allocation
PM and RM use	PM not planned using criticality assessment
Spare parts planning	Spare parts not planned using criticality assessment

Factors and methods

Factors for assessing criticality	Bottlenecks, single or parallel machines and consequence of PM activities
Methods for assessing criticality	Scale used for classification (5 – low, 10 – medium and 15 – high). Conducted with technicians involved in maintenance organization

Data requirement

Data usage	Not much data used
Usability and updates	Maintenance uses it; updated quarterly

Maintenance planning

Ownership and production synergy	Maintenance owns classification. Consensus with other factories globally is the aim, to achieve standardized procedures
Problems in criticality assessment	The model does not correctly identify critical machine

Table VII.
Results - ED6

machine criticality assessment, even if availability remains the main purpose for assessing criticality. Bottlenecks are also used for providing a productivity focus, but data were not used in the assessment. The main problem in ED6 is that the participants felt that the criticality assessment tool does not correctly identify the correct critical machines.

4.7 Cross-case analysis
The cross-case analysis results are presented below:

(1) Similarities:

- Generally, many machines end up being classified as highly critical, i.e. the machines are not differentiated.

- Some sorts of classifications (ABC type) are used.

- The objective of classification tends to focus on increasing machine availability.

- Productivity is not considered an objective in the criticality assessments.

- Data usage ranges from "nothing" to the use of "mean time between failure (MTBF)" and "mean time to repair (MTTR)."

- Subjective group-discussion-type analysis for setting criticality (qualitative approach) even when data are used.

- Maintenance organization responsible for classification.

- Hardly used for maintenance planning activities. PM activities are not based on criticality, whereas RM activities are conducted by random prioritization or on a first-come-first-served basis.

- Technicians (and their experience) seem to make routine maintenance decisions on the shop-floor.

- Criticality classifications rarely updated (quarterly to annually).

- Maintenance organizations use classification tool to achieve consensus with the production organization on critical machines.

- Current classification tools do not identify the correct machines as critical.

(2) Differences:

- Classification tends to work well for assembly and foundry production set-ups, but poorly for machining lines. CD works particularly well on assembly and foundry lines.

- Despite using ABC-type classification, the approach for assessing criticality differs, ranging from scale questions, to flowcharts and CD matrices.

- Same machine classification tools used for spare parts planning. However, some sites use a separate classification tool solely to identify critical spare parts.

- Despite achieving consensus with the production organization on critical machines using the classification tool, decisions or priorities from the production organization override the classification tool, and the maintenance organization must adhere to these.

The results show that the cases have more similarities than differences between them. In particular, current assessment methods that classify large numbers of machines as highly critical creates an issue of trust that militates against their use in maintenance decision making. As multiple unweighted factors are taken into consideration, machines tend to be assessed as critical under one or other of the chosen factors. The lack of focus on productivity can also be attributed to the generic objective of increased availability to which maintenance organizations strive. Subjective assessment methods and decision making based on operator experience are prevalent across the cases as they do not use data from production systems in assessing criticality. However, with regard to the differences between cases, the criticality classification tool works better on certain production flows than others. Production lines with assembly and foundry layout where the production flows are tightly coupled, the criticality assessment tool appears to be used for maintenance decision making and had fewer problems identifying critical machines. Since there are more similarities than differences, it is likely that the problems

with machine criticality assessment prevail across the cases companies. This situation implies that the problems involved in the machine criticality assessment are highly complex.

5. Discussion
This paper presents the problems in machine criticality assessment practice in manufacturing companies and identifies criticality assessment components based on a multiple case study. Six empirical cases were studied, and the results were analyzed within-case and cross-case analyses results. This section synthesizes the results in terms of criticism of existing practices, arguments for achieving smart maintenance planning, and scientific and industrial contributions. Subsequently, discussion on the methodology is presented.

5.1 Existing practices and criticism
On examination of the machine criticality assessment in manufacturing companies, deeper understanding of the existing practices and the problems in its usage were identified. One of the main findings from this multiple case study is the identification of reasons for the manufacturing companies not using their machine criticality assessment tool for planning maintenance. The results strongly indicate improvement opportunities for increasing not only machine efficiency but also the productivity of the system. It was identified that manufacturing companies do not use their classification tools for planning any type of maintenance. A similar phenomenon was observed previously by Gopalakrishnan and Skoogh (2018). The criticality assessment tools were rather simply used only for obtaining consensus with the production organization. Guo *et al.* (2013) state that maintenance work-order prioritizations are often made using the experience and knowledge of maintenance technicians. Reasons such as lack of trust in the existing classification tool and the assumption that maintenance technicians have a better understanding of the current situation within the production system than the criticality assessment tool can provide were identified for not using the tool for maintenance planning. Especially, the untrustworthy attitude comes from the fact that the method for assessment has not been mastered, and multiple machines end up being highly critical. From the findings, it was further narrowed down to the criticisms in existing classification tools: static, conjectural, complex, biased toward the opinions of those assessing criticality and basing the assessment on multiple factors. As demonstrated in many of the cases, this results in a failure on the part of the criticality assessment tool to identify the correct critical machines. Even in the literature qualitative, multiple factor and static approaches are used for assessing criticality (Márquez *et al.*, 2015; Moss and Woodhouse, 1999; Bengtsson, 2011).

Using multiple factors for assessing criticality is common practice. The case companies use multiple factors in an ABC-type assessment to classify machines. More options are provided in the literature: RPN (Márquez *et al.*, 2015), fuzzy logic (Moss and Woodhouse, 1999), a decision-making scale (Antosz and Ratnayake, 2016), logical algorithm (Moore and Starr, 2006), among others. In addition, there are MCDM models for achieving maintenance optimization. However, when it comes to assessing criticality, using multiple factors hides the critical machine's primary criticality criterion. Even though this problem was only observed in ED2, the authors argue that the problem may persist in all cases. The very nature of classification means grouping machines in one class or another. However, when multiple factors are used to arrive at that conclusion, the primary criterion or the combination of factors by which a machine was classified as highly critical can be lost. This situation is the main reason, multiple machines within a system end up being classified as highly critical. The results also show that the main objective of the classification is to increase the availability of critical machines. Therefore, maintenance is planned for

improving machine availability. Since multiple factors are used for assessment, the critical machines will not be solely availability critical. For example, a safety-critical machine will need safety-related maintenance activities to improve availability. Additionally, the availability objective of the criticality assessment implicitly indicates the productivity of individual machines. On the other hand, system productivity cannot be ensured by increasing the availability of individual machines because of the rippling effects. Prioritized maintenance efforts for the critical machines will ensure that the availability is maximized for the critical machines. Therefore, the current maintenance decisions may generate non-value adding maintenance activities, resulting in financial losses and also reducing machine availability with concomitant productivity losses. Resolving this situation is not simply a matter of knowing which machines are critical to a production system, it is also necessary to know their type of criticality.

Furthermore, the results show that when different people conduct criticality assessments, different machines might emerge as critical. In most of the cases, achieving increased machine availability was the main purpose. It can be argued that if increasing machine availability was indeed the main purpose, then the factors chosen should be based on increasing availability. Since this was not the case, it can be argued that the current classification tool lacks a clear purpose. The results repeatedly showed from many cases that data of any kind other than MTBF and MTTR were used for assessment. This indicated that the criticality classification tools are not created based on the actual state of machines production system, i.e. the tool is not fact-based. A criticality assessment which lacks a clear purpose and is not fact-based cannot identify the critical machines. Hence, data-driven tools for maintenance decision support are needed for assessing machine criticality (Ni and Jin, 2012). Another result showed that existing criticality classifications tend to work better in cases where the production site in question had an assembly or a foundry production layout. These cases, in particular, used CD for assessing criticality. Classification then tends to work better because assembly and foundry lines are tightly coupled, meaning that the effects of the failure of a single-machine/station on the rest of the system are easily captured. The participants felt that the tool identified the critical machines at all time. However in the same cases (ED3 and ED4), when machining lines were analyzed criticality classification proved to be less useful, as it was unable to correctly identify the critical machines. Even though the tool is perceived to work well in tightly coupled systems, it is less useful as it is intuitive that a single-machine failure will stop the entire system. In such scenarios, criticality needs to be assessed using machine-level factors to reduce failure on the least reliable machines.

Maintenance planning activity is performed to mitigate the variabilities in production systems so that productivity can be maximized, i.e. a swift and even flow of production is desirable to maintain flexibility and increase productivity (Schmenner and Swink, 1998). This swift and even flow can be achieved by taking a systems perspective to maintenance planning (factory focus). Based on the current practices and criticisms mentioned above, it can be concluded that a standardized procedure with a clear purpose, data-driven decisions and systems perspective is required to assess machine criticality. From the results obtained in this paper, the current state of machine criticality assessment is modeled and presented in Figure 2. The model shows the generalized state-of-the-art practices in machine criticality assessment, and the problems obtained from the six cases. The bullet point list in-between each of the arrows of the figure describes the attributes of the industrial criticality assessment at each stage. The attributes comprise of the current state as well as the criticism against the criticality assessment.

To sum up the results achieved, maintenance organizations in manufacturing companies lack decision-making support that is needed for the planning of maintenance activities to increase productivity. As shown throughout all cases, the productivity of the system as an

Production system

Machine criticality assessment
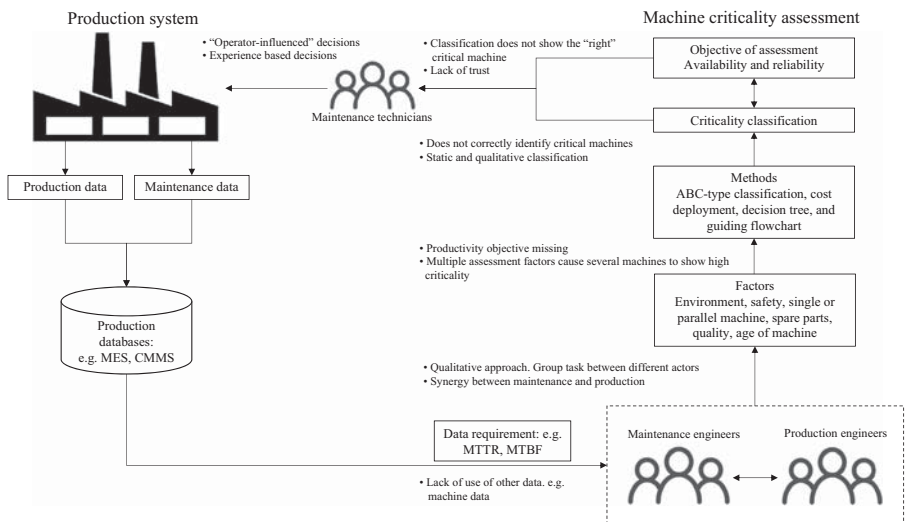
objective is overlooked. However, maintenance planning should not only aim to improve individual machine performance (maximizing availability) but also the productivity of the entire system. Therefore, maintenance organizations require new technologies in the form of data-driven, dynamic decision support, e.g. digitalized tools for smart maintenance planning such as IoT. Moreover, organizational changes are also called for to facilitate approaching maintenance issues from a systems perspective (Ylipää *et al.*, 2017).

5.2 Machine criticality assessment for smart maintenance planning

Digitalized manufacturing has increased expectations on the role of maintenance management in delivering high-performing production systems. There is, however, a wide gap between the expectations on digitalized manufacturing and the future role of maintenance. Bokrantz *et al.* (2017) point out that seven dominant themes will influence the internal environment of maintenance organization in the future. Two among them are fact-based maintenance planning and planning with a systems perspective. This study has particularly addressed these challenges by studying maintenance decision support for smart maintenance planning. This paper has mapped state-of-the-art practices for assessing machine criticality and mapped the gaps in current assessment techniques that hinder the development of high-performance production systems. The results obtained suggest that the focus of maintenance tends to be on solving single-machine problems. The objectives of criticality assessment are therefore related to machine availability and reliability. A large amount of research has focused on single-machine problems, and there is a need to refocus on planning maintenance for multiple machines (Helu and Weiss, 2016; Roy *et al.*, 2016). Because machine downtime can cause rippling effects which lead to idling losses and the machines downstream and upstream. These rippling effects reduce the productivity of the whole system (Skoogh *et al.*, 2011).

On the technical aspect of maintenance organizations, i.e. decision support tools, CMMS have been argued to be obsolete and can no longer support maintenance decision making given the dynamic needs of production systems (Ni and Jin, 2012). The results of this study have exemplified this argument by showing that existing machine criticality assessment techniques are inadequate in terms of identifying critical machines for planning maintenance activities and support effective maintenance decisions.

Production systems are dynamic in nature; naturally, the criticality of the machine in the system as well will tend to change from time to time. Digitalized manufacturing provides opportunities in terms of machine data availability and quality, connectivity through IoT and digital tools. Real-time data analysis of data sets from machines can enable a more accurate and dynamical approach to identify critical machines. Additionally, such an approach can also provide insights into not only which machines are critical but also why they are critical. This kind of decision support can assist maintenance planners/engineers to plan maintenance with greater accuracy based on the needs of the machines. Therefore, a data-driven approach is necessary for assessing machine criticality in order to make fact-based decisions.

Regarding the organizational aspect, industrial practices on and approaches to maintenance issues lack a systems perspective, something that is reflected in this study by the types of goals (e.g. machine availability) and KPIs (e.g. MTTR and MTBF) that are used within maintenance organizations. These are focused on individual machine performance. Even though these measures and goals are important, they alone cannot improve system performance. Therefore, future machine criticality assessment should focus on prioritizing PM and RM maintenance activities on the critical machine for the sake of the whole system (e.g. bottlenecks) at any given point in time. Maintenance organizations tend not to work with bottleneck machines, preferring to consider all machines as on the same level with regard to the throughput of the system. To think in terms of and apply bottleneck-critical based maintenance prioritization is the desired organizational change. Even though the results have shown that classification tools provide synergy between the maintenance and production organizations, incorporating productivity as an objective in the overall maintenance goals will truly enable reaching production synergy. This organizational change (systems perspective) together with the technical advancements (data-driven and dynamic approach) can bring us closer to the smart maintenance planning that is necessary for digitalized manufacturing.

5.3 Scientific contribution
The scientific contribution of the paper is the identification of components for data-driven machine criticality assessment. Traditionally, machine criticality assessment has not been widely studied in research communities. Even though RCM-based approaches such as FMEA are prevalent, these only assess component-level criticality using failure modes (Moubray, 1997). System-level criticality assessments are rare and tend to adopt a static, qualitative, multiple-factor approach (see examples in Márquez *et al.*, 2015; Bengtsson, 2011; Moss and Woodhouse, 1999). However, the results of this study have shed light on the problems faced in companies due to poor criticality assessments. Arguably, the biggest problem is that, despite the efforts expended in creating criticality classifications, these are not used for maintenance planning purposes because they are deemed to be untrustworthy and unable to identify the correct critical machines. Therefore, future criticality assessment needs to be developed in such a way as to resolve these issues. In particular, more empirical research is needed within maintenance (Fraser *et al.*, 2015). With this in mind, the following are identified as the major components of machine criticality assessment that should support maintenance decision making:

- to have productivity as the main objective (systems perspective);
- continuous monitoring of machine states (producing, downtime, idling losses, etc.) to identify criticality;
- data analytics on machine-state data to facilitate real-time decisions;
- define the type of criticality in addition to assessing criticality;

- selecting factors and assessment windows based on needs (e.g. PM needs a larger time window with several factors, whereas RM needs a shorter time window with throughput criticality as the sole factor); and

- machine failure pattern and root cause analysis (predictive and prescriptive maintenance) to decide on type and frequency of maintenance allocation.

Automated decision support that continuously predicts and prescribes critical machines for maintenance decision making is desirable. This decision support will make maintenance efforts selective, fact based and enable faster decisions. Most importantly, it clearly brings the productivity objective into the maintenance organization. It should be noted that achieving automated decision support is not the first step. Problems such as data analytics, data availability, data quality, data security and IT competencies within maintenance organizations need to be addressed before a robust machine criticality assessment tool can be obtained. However, the opportunities provided through digitalized manufacturing, such as IoT tools, fast internet connectivity, etc., will enable this to be rapidly achieved. In particular, the authors intend to develop a framework for machine criticality assessment in the future.

5.4 Industrial contribution
The results of the study, i.e. a deeper understanding of machine criticality assessment practices and struggles in maintenance planning, are of great importance to the maintenance organizations in manufacturing companies. Additionally, as an empirical study, the results achieved are highly relevant to the companies concerned. The results also provide opportunities and methods to improve maintenance planning and seek productivity increase. The main contribution of the research work is the inclusion of productivity as an objective in overall maintenance goals. The components of machine criticality assessment identified in the previous headings suggest that smart maintenance planning offers productivity improvement opportunities without major financial investment to the machines. However, the greatest challenge will be the technical and organizational changes discussed, as these will require the combined efforts of those on both the managerial side and the shop-floor level. Competition and the need for aggressive growth are pushing manufacturing companies toward rapid change, making the results that can be achieved by improving maintenance organizations highly relevant to the current and future marketplace.

5.5 Methodology discussion
The goals of the paper dictated for in-depth understanding of the industrial practices on machine criticality assessment and maintenance decisions supported by the tool. The multiple case study methodology helped in achieving the goals of the paper by enabling in-depth studies at six different production sites from three different companies. Additionally, the six cases had variety in terms of work culture and procedure, different production set-ups and different products being produced. This case study approach provided the advantage of deep learning from six different production sites than compared to that of a large scale questionnaire survey which will not enable in-depth study. Even though case study approach was employed, careful considerations have been made to increase generalizability and validity. Triangulation of different data sources (ED1–ED6) and different data collection methods (interviews and focus groups) ensured that the results obtained were generalizable for discrete manufacturing (Voss *et al.*, 2002; McCutcheon and Meredith, 1993). Furthermore, cross-case analysis was also performed seeking generalization. As a result, a generic model of existing machine criticality assessment and components of machine criticality assessment for increasing productivity were obtained.

6. Conclusion

The advancements in digitalized manufacturing require traditional maintenance practices to transform into smart maintenance which supports the dynamic maintenance needs and increase productivity. This study focuses on the maintenance decision making by studying the machine criticality assessment tool to achieve smart maintenance. Previously, it was found that manufacturing companies work with assessing machine criticality, but it was rendered ineffective for making maintenance decisions. Therefore, the goals of the paper are to map the objectives, uses, methods and data requirements for machine criticality assessment and to identify its components to increase productivity, with the aim of including productivity as an objective for the maintenance organization.

The results were achieved through a multiple case study was conducted with six cases in three multi-national companies. An in-depth understanding of the industrial practices on setting machine criticality, the purpose and problems with it for planning maintenance was identified. Specifically, the study identified that the companies perceive the existing criticality assessment tools to be untrustworthy. The tools did not identify the right critical machines which are crucial for decision making. It was identified that qualitative approach, lack of data usage from machines, static procedure, multiple assessment factors and lack of clear objectives were the main reasons behind this. Furthermore, the results obtained also provide additional reasoning behind operator-influenced and experience-driven decision making instead of fact-based decision making. On analysis of the results, technological (dynamic and data-driven decision making) and organizational (systems perspective) changes that are needed within the maintenance organization were prescribed. Data-driven machine criticality can enable maintenance decisions to be based on facts, whereas approaching maintenance with a systems perspective enables maintenance to focus on maximizing system productivity instead of maximizing availability. By the results achieved, this study describes the components of future machine criticality assessment: to have productivity as the main objective, continuous monitoring of machine states, data analytics, defining the type of criticality for the machine and selection of factors for assessment based on machine needs and including failure pattern and root cause. In conclusion, this study points toward a data-driven machine criticality assessment for making factual maintenance decisions. Such a decision support will be essential for achieving smart maintenance planning, thereby enabling also to fulfill the demands of digitalized manufacturing.

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