

THESIS FOR THE DEGREE OF DOCTOR OF PHILOSOPHY

**Data-Driven Decision Support for Maintenance
Prioritisation**
Connecting Maintenance to Productivity

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ABSTRACT

Productivity is an important factor in the global competitiveness of manufacturing companies. Most industrialised countries around the globe have started initiatives to transform their manufacturing companies through digitalisation and thus achieve competitiveness. Digitalisation has drastically increased expectations that production systems will have substantially higher productivity increments, increased automation and greater resource efficiency. This makes maintenance management strategically important to manufacturing companies. However, the traditional approach to maintenance has been to maximise machine availability. Machine availability does not necessarily mean machine utilisation. Machines are under-utilised because the ripple effects of breakdowns result in idling losses and subsequent loss of productivity. Therefore, there is a need for transformation in the maintenance organisation, moving from a component focus to achieving a systems perspective for solving maintenance problems.

The purpose of this thesis is to enable the successful transformation of maintenance organisations, so that they contribute directly to increased productivity and cost-effectiveness. In order to transform maintenance organisations, particularly the maintenance decision support needs to be fact-based. Therefore, the aim of this thesis is to investigate maintenance prioritisation decisions as well as develop and validate maintenance decision support that enables productivity to increase. The investigation of the current industrial practices led to identifying the gaps between practice and research (RQ1). Based on the identified gaps, a maintenance prioritisation decision support to increase productivity was developed (RQ2). The results were achieved by employing a mixed-methods research approach in the form of five empirical studies, which were conducted using surveys, interviews, experiments and case studies.

The gaps identified in maintenance prioritisation practice and research provided maintenance and productivity improvement potentials: (i) Low OEE figures (avg. 51.5 percent) indicate that maintenance needs to focus on improving the operational efficiency and availability of machines, (ii) Most companies prioritise their maintenance activities according to production operator influence or based on maintenance technicians' experience. So, facts-based decision support tools are needed and (iii) On further examination of the decision support, the criticality classification was found to be static, subjective, using multiple factors and lacking a clear goal. In order to develop a new decision support for maintenance prioritisation, the maintenance priorities and data requirement were assessed. It was identified that system throughput increased when maintenance of bottleneck machines was prioritised and many companies generate automated data from machines that can be used to develop decision support. A data-driven machine criticality assessment framework was developed and validated using industrial cases. The framework provided guidelines on using the data and what maintenance decisions can be made.

The data-driven criticality assessment supports maintenance engineers and planners in making tactical and operational maintenance decisions that are dynamic, fact-based and factory-focused, with the goal of increasing productivity. This thesis provides a pathway for maintenance organisations to transform from their narrow focus (solving machine-level problems) to achieving a systems perspective (solving the maintenance problems of the whole production system). By connecting maintenance to productivity, maintenance organisations can help manufacturing companies compete in global production, especially within digitalised manufacturing.

Keywords: productivity; maintenance prioritisation; machine criticality; bottleneck; data-driven decision support; maintenance management

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Maheshwaran Gopalakrishnan
Gothenburg, August 2018

LIST OF APPENDED PAPERS

Paper I

Ylipää, T., Skoogh, A., Bokrantz, J., & **Gopalakrishnan, M.** (2017). Identification of maintenance improvement potential using OEE assessment. *International Journal of Productivity and Performance Management*, Vol. 66 Issue: 1, pp.126-143.

Contributions: Gopalakrishnan contributed with data analysis and writing of introduction, results and discussion chapters of the paper.

Paper II

Gopalakrishnan, M., & Skoogh, A. (2018). Machine criticality based maintenance prioritization: Identifying productivity improvement potential. *International Journal of Productivity and Performance Management*, Vol. 67 Issue: 4, pp.654-672.

Contributions: Gopalakrishnan initiated the paper, designed the study, collected data, analysed data and wrote the paper.

Paper III

Gopalakrishnan, M., Skoogh, A., Salonen, A., & Asp, M. (2018). Machine criticality assessment for productivity improvement – Smart maintenance decision support. Under 2nd review in the *International Journal of Productivity and Performance Management*.

Contributions: Gopalakrishnan initiated the paper, designed and conducted the multiple case study. Data were analysed and the paper was written by Gopalakrishnan.

Paper IV

Gopalakrishnan, M., Skoogh, A., & Laroque, C. (2016). Buffer utilization based scheduling of maintenance activities by a shifting priority approach – A simulation study. *Proceedings of the 2016 Winter Simulation Conference*. Washington, DC, USA. pp. 2797-2808.

Contribution: Gopalakrishnan initiated the paper, designed the study, and developed the new buffer utilization approach for setting priority. The simulation experiments and writing of the paper were done by Gopalakrishnan.

Paper V

Subramaniyan, M., Skoogh, A., & **Gopalakrishnan, M.** & Hanna, A. (2016). Real-time data-driven average active period method for bottleneck detection. *International Journal of Design & Nature and Ecodynamics*. Vol. 11 No. 3, pp. 428-437.

Contribution: Gopalakrishnan initiated the paper and participated in designing the study, data analysis, modelling and writing together with Subramaniyan.

Paper VI

Gopalakrishnan, M., Subramaniyan, M., & Skoogh, A. (2018). Data-driven machine criticality assessment – Maintenance decision support for increased productivity. Submitted to *Production Planning and Control*.

Contribution: Gopalakrishnan initiated the paper, designed the multiple case study, collected and analysed the data and wrote the paper. Further, Gopalakrishnan developed the data-driven criticality assessment.

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LIST OF ABBREVIATIONS

CBM – Condition Based Maintenance
CMMS – Computerised Maintenance Management System
CPS – Cyber Physical System
DSS – Decision Support System
FMEA – Failure Mode and Effects Analysis
ICT – Information and Communication Technology
IoT – Internet of Things
KPI – Key Performance Indicator
MCDM – Multi-criteria Decision Making
MOW – Maintenance Opportunity Window
MES – Manufacturing Execution System
MTBF – Mean Time Between Failure
MTTR – Mean Time to Repair
OEE – Overall Equipment Effectiveness
PHM – Prognostics and Health Management
PM – Preventive Maintenance
PPA – Productivity Potential Assessment
RCM – Reliability Centred Maintenance
RM – Reactive Maintenance
TPF – Total Factor Productivity
TPM – Total Productive Maintenance

1 INTRODUCTION

This chapter presents the importance of, and need for, the research work conducted in this thesis. It presents the background, role of maintenance, research problem and challenge before framing the purpose, aim, and research questions of the thesis.

1.1 Background

“Productivity isn’t everything, but in the long run it is almost everything. A country’s ability to improve its standard of living over time depends almost entirely on its ability to raise its output per worker” (Krugman, 1994, p. 11)

Every country, every organisation, every industry, every company strives for productivity, particularly the manufacturing industry. Manufacturing industries around the world are in a highly competitive environment, hitherto unseen. To excel in such a competitive environment, major countries around the globe have started initiatives to transform their manufacturing companies through digitalisation. Digitalisation or digitalised manufacturing can be characterised by technological advancements such as the Internet of Things (IoT), big data, automation and cyber-physical systems (CPS). Germany has begun digitalisation and made recommendations through its Industry 4.0 strategic initiative for securing German manufacturing (Kagermann et al., 2013). The United States has an initiative known as Smart Manufacturing aimed at using high technologies to expand the revival of manufacturing (Kang et al. 2016). Korea also is driving a similar technological development to those of the US and Germany (Kang et al. 2016). Developing economies such as China and India have also devised strategies for increasing global competitiveness in manufacturing. For example, the Make in India initiative aims to build best-in-class manufacturing infrastructure and foster global manufacturing competitiveness (Srirang, 2015). However, developing countries have an export-led growth model for their manufacturing initiatives (Raghuram 2015). Finally, in Sweden, where the research in this thesis was conducted, the government has launched its Smart Industry initiative, a strategy for new industrialisation in Swedish manufacturing (Ministry of Enterprise and Innovation, 2016).

The history of industrialisation can be characterised by the pursuit of productivity gains and the dramatic innovations made during those times to support productivity (Schmenner, 2015). Similarly, the new era of industrialisation, this time through digitalisation, also seeks productivity gains to compete in global manufacturing. The productivity of any process rises with the speed of material flows and falls when there is a variable increase in either demand on the process or actual process stages (Schmenner, 2001). The main focus of study in this thesis is the variation arising from the process stages. Industrial equipment cannot go on functioning forever, flawlessly producing goods (Moubray, 1995). Therefore, maintenance of equipment is extremely important in order to repair and restore the equipment to its original condition for smooth functioning. Traditionally, maintaining industrial equipment was deemed a sub-function of production which provides equipment uptime (Gits, 1992). However, maintenance management has undergone so many changes in the last half century that it has become a strategically essential part of the business objectives of manufacturing companies (Pintelon & Parodi-Herz, 2008; Garg & Deshmukh, 2006). Thus, maintenance plays a major role in smooth functioning and effective production systems.

1.2 Role of Maintenance in Production Systems

A production system is a combination of machines and people organised in a particular order to transform raw materials into a product (Bellgran and Säfsten, 2009). Production system configuration affects the production rate (in other words, the throughput of the production system). Specifically, the effect of machine downtime on expected throughput differs according to system configuration (Koren et al., 1998). For example, a single machine failure in a serial line configuration without buffers leads to stoppage of the entire production system, as other machines in the system are either blocked or starved (idling losses). However, when a machine fails in a parallel configuration, only a part of the system loses

its productive capacity (Ni & Jin, 2012). Even though maintenance operations are conducted on individual machines, they have the potential to enhance or diminish the productivity of the entire system.

Historically, maintenance management was reactive in nature, however, preventing machine failures is highly desirable. In terms of safety, environment, productivity and reliability of a production system, it is better to conduct preventive maintenance (PM) than reactive maintenance (RM). Incidental maintenance tasks are also conducted to improve the state of the machines, such as coolant filling or tool replacement. However, complete elimination of machine failures is not possible. Hence, management of preventive and reactive maintenance is very important to the efficient running of the production system. Maintenance is also one of the largest cost centres in a production system. Research into maintenance costs shows that a large proportion of production costs is attributed to maintenance (Muthu et al., 2000; Dekker, 1995). For example, Dunn (1987) says that 15-40 percent of production costs are for maintenance. In research, the term “maintenance management” has been largely synonymous with preventive maintenance management. Maintenance concepts were developed to manage maintenance preventively and reduce/eliminate failures. Major examples include reliability-centred maintenance (RCM), focusing on increasing equipment reliability (Moubray, 1997); and total productive maintenance (TPM), focusing on achieving “zero errors” and “zero breakdowns” (Nakajima, 1998). Several preventive maintenance management models also focus on the optimisation problem (Garg & Deshmukh, 2006). Currently, predictive maintenance is highly sought after as foreknowledge is desirable when planning proactive maintenance (Kans & Galar, 2017; Karim et al., 2016). Machine failures are inevitable, irrespective of innovations and technological advancements, so it is important to study and manage both PM and RM.

Fluctuating market demands and a need for high-volume and mixed products from production systems have created complex scheduling problems. A demanding production schedule makes maintenance scheduling a problem (Löfsten, 1999). Maintenance and production scheduling are usually two separate processes in manufacturing companies, characterised by conflicting with one another (Rishel & Christy, 2007). However, production cannot be ensured without maintenance on the machines. Due to rising demand for volume and variety, companies are moving to increase automation in their production systems.

With digitalisation (and particularly the increasing trend towards automation), production systems are expected to work completely autonomously with little interference from humans. An automated production system is expected to produce continuously, but cannot repair itself when it fails. Human intervention is needed if autonomous production is to work. Therefore, the more autonomous the production system becomes, the more crucial human intervention becomes in ensuring the efficiency of production systems (Bokrantz, 2017). Autonomous production does not mean eliminating human experts. On the contrary, expert human intervention is crucial to smooth operation. Thus, maintaining machines in a production system is complex and needs dynamic management (Ni & Jin, 2012). This means maintenance managers are confronted with very complicated and diverse maintenance needs in a highly demanding business context (Pintelon & Parodi-Herz, 2008).

1.3 Research problem – Unutilised machine state

Although maintenance managers are confronted with complex decision-making, maintenance organisations are viewed as simply there to provide machine availability and reliability in a cost-effective and safe manner. However, the importance of maintenance has been increasing steadily over the years. Various studies have discussed the growing importance of maintenance and argued for a broader scope and definition of maintenance; one that goes beyond assuring traditional machine reliability and availability and embraces a holistic, company-wide approach (Peng, 2012; Dunn, 2003; Coetzee, 1999; Al-Najjar, 1996; Sherwin, 2000; ISO, 2003).

Even so, maintenance theory has long been developed, but there are fewer studies on maintenance practice (Fraser et al., 2015). This has led to a gap between maintenance research and current industrial

practice (Sherwin, 2000; Bokrantz et al., 2017). This gap is exemplified in industrial practices, where maintenance planning is done very much in isolation (without considering the whole factory). Even in research, system-level problems are rare (Helu & Weiss, 2016). Therefore, “*how to maintain more than one equipment at the same time?*” is an important question that needs addressing (Roy et al., 2016). This is the principle research problem which the research in this thesis strives to solve. The research problem is visualised in Figure 1, showing current practices, the necessary transformation and future desirable state.

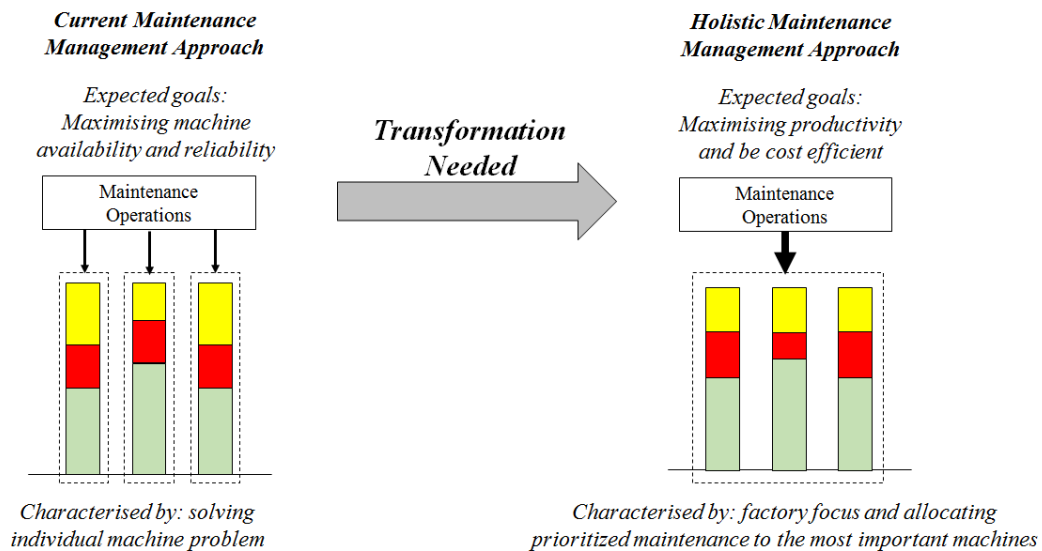


Figure 1. Maintenance approach transformation.

The machine failures and system configuration mean that machines in the production system are not used to their full capacity. The direct machine downtimes, setup time, planned preventive maintenance times and scheduled breaks are contributors to reduced machine capacity. The most desirable machine state is the machine utilisation; the time when the machine is producing. However, there are unutilised times during a machine’s life-cycle (unutilised machine state). These are the periods in a machine’s life-cycle when they are in perfect working condition but cannot be used in production. The unutilised machine state is shown in Figure 2 using a sample use case. The production line in the Figure comprises twelve serially connected machines. It also shows the periods spent by each machine during a production run as follows:

- (i) The green part shows the machine utilisation, the time when the machines are producing.
- (ii) The grey part indicates total machine downtime; when a machine was being repaired or awaiting repair.
- (iii) The red part indicates machine idling losses, in other words the unutilised machine state. This particular machine state offers hidden opportunities for maintenance improvement. The research in this thesis focuses on mitigating unutilised machine periods.

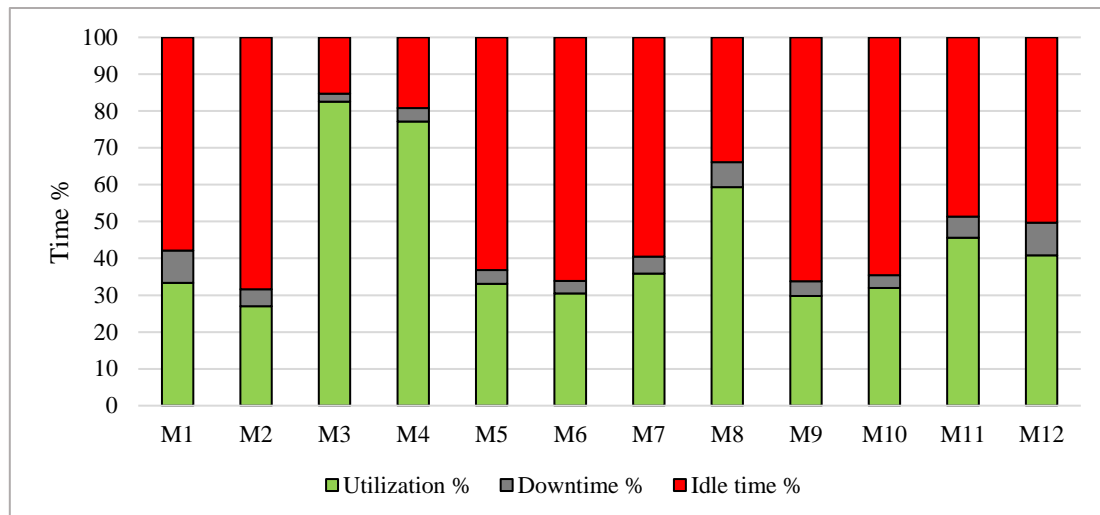


Figure 2. Unutilised machine state.

The unutilised machine states are caused by the fact that they are blocked and starved. Idling losses are counted as production disturbances (Bokrantz et al., 2016), but the maintenance organisations are usually not responsible for mitigating these losses as they are not maintenance-related. These losses constitute lost production time and hence productivity is reduced. It is noteworthy that the amount of time the machines are idle is not the same for all machines in the production line. This implies that each machine affects productivity at different levels. Increasing the availability and reliability of any machine is a good way to reduce machine downtime, but does not necessarily reduce the idling loss of that machine. Therefore, knowing how critical each machine is to the whole system is important if availability and reliability are to be increased. This, in turn, means that equal maintenance efforts should not be provided for all machines, as each one has different needs. In other words, prioritised maintenance efforts are needed.

Maintenance prioritisation decisions can increase system productivity, when they are based on information transferred across hierarchical levels of control and management (Ni & Jin, 2012). Few maintenance tools can provide decision-making information across hierarchical levels. Some examples in the literature include: Guan et al. (2011), for condition based maintenance and Li et al. (2007), for bottleneck detection for maintenance prioritisation. Bengtsson (2011) provides a practical example in the form of a machine classification tool. Prioritisation is a crucial task in a production system, particularly when there are more maintenance work orders than personnel. It can be argued that most manufacturing companies have this situation.

On the one hand, current maintenance prioritisation are practiced randomly or ad-hoc, based only the experience of maintenance technicians, maintenance resource allocation may potentially be wasted. This increases production downtime and eventually causes productivity and monetary losses (Ni & Jin, 2012). On the other hand, maintenance decision-making is a complex task, as it depends on the current health condition of the machine, health degradation, maintenance scheduling, production rates and targets and maintenance costs (Koren & Ulsoy, 2002). These factors cannot be judged on experience alone. Thus, help decision makers need help in basing their maintenance prioritisation decisions on facts. Real-time data collected from machines must be used to analyse its current state plus that of the production system as a whole. Data-driven decision-making has gained importance and been studied in the context of supporting maintenance decisions. Examples include using data-driven models for diagnostics and prognostics of a machine's health (Roy et al., 2016) and detecting bottlenecks (Li, Chang & Ni, 2009). However, research efforts are needed to support manufacturing companies in solving problems of prioritising maintenance operations and in their decision support.

1.4 Research Challenge

The central research problem has been identified as the unutilised machine state causing production losses and the need for maintenance decision support. This work is devoted to improving the maintenance management of manufacturing companies so that maintenance organisations can make their companies competitive in global production. Maintenance organisations have the potential to increase productivity without compromising safety, environment, and reliability standards by approaching maintenance from a systems perspective. Driving this research is a vision of future production systems that are highly resource-efficient and productive due to a transformation in maintenance management.

1.5 Purpose and Aim

The purpose of the thesis is to enable successful transformation of maintenance organisations which contribute directly to increased productivity and cost-effectiveness. “Transformation” here means moving from a component focus to achieving a systems perspective for solving maintenance problems; connecting maintenance to productivity. In order to transform maintenance organisations, particularly the maintenance decision support needs to be facts-based.

Therefore, the aim of this thesis is to investigate maintenance prioritisation decisions as well as develop and validate maintenance decision support that enables productivity to increase. This aim is achieved by identifying the gaps between maintenance prioritisation research and industrial practice and developing solutions to bridge them. The research work focuses on improving maintenance decisions by using facts, i.e. data-driven decision support.

1.6 Research Questions

Two Research Questions (RQ) have been framed:

RQ1: What are the gaps between current industrial practices and research in maintenance prioritisation?

Maintenance prioritisation is a complex task and there are usually more maintenance activities than available personnel. Industrial practice is reportedly well behind research when it concerns managing maintenance effectively. Therefore, identifying the gaps between research and practice in maintenance prioritisation is an important first step. It is necessary to pinpoint these gaps so that potential maintenance and productivity improvements can be identified. This will also encourage identification of the right decision support when prioritising maintenance.

RQ2: How can maintenance prioritisation be supported to increase productivity?

RQ2 was framed on the basis of the RQ1 findings and deals with how decision support for maintenance prioritisation can be established. In other words, potential maintenance and productivity improvements are the input for assessing, developing and validating fact-based decision support for maintenance prioritisation.

1.7 Outline of the thesis

The thesis is structured into six chapters, the content of which is described in Table 1.

Table 1. Thesis outline.

Chapter	Description
1. Introduction	This chapter presents the importance of, and need for, the research work conducted in this thesis. It presents the background, role of maintenance, research problem and challenge before framing the purpose, aim, and research questions of the thesis.
2. Methodology	This chapter begins by presenting the rationale for the chosen methodology. It includes the overall research approach and design, followed by the specific research methods used in each study.
3. Frame of Reference	The frame of reference provides the theoretical foundation of the thesis. The theory on productivity is established, followed by the maintenance theory. The theoretical foundation of maintenance includes a historical overview, maintenance in digitalised manufacturing, problems in maintenance research and decision support for maintenance prioritisation.
4. Results and Synthesis	The results section presents the individual findings of RQ1 and RQ2. The results come from the five empirical studies, which yielded the appended papers. The results sections are followed by a synthesis section for each RQ, in which the RQs are answered.
5. Overall Discussion	This chapter synthesises the answers to RQ1 and RQ2, to explain how maintenance was connected to productivity. It also presents discussions on the scientific and industrial contributions, methodology and future challenges.
6. Conclusion	This chapter provides the key conclusions of the thesis.

2 METHODOLOGY

This chapter begins by presenting the rationale for the chosen methodology. It includes the overall research approach and design, followed by the specific research methods used in each study.

2.1 Researcher's worldview

Research conduct is guided by a set paradigm (a structured path of enquiry). A paradigm may be considered an acceptable worldview and can therefore be defined as “a basic set of beliefs that guide actions” (Guba, 1990, p. 17). The author's philosophical worldview is problem-centred, focusing on real-world practice and the consequences of action. Specifically, it adopts a real-world, problem-centred approach to conducting research. The best depiction of such a worldview would be to call it a “pragmatic” one. It comes out of actions and consequences, focuses more on the research problem and uses many different research approaches to solve it (Creswell, 2013). The author does not see the world as absolute unity, but agrees to the social, historical, and political contexts in which the research takes place. The author's upbringing and surroundings have shaped this worldview and are particularly helpful in studying production systems. Problems in production systems need solutions which are bound to the above contexts. This pragmatic worldview means the scientific framework for conducting research is based on answering “what” and “how” in regard to the intended consequences. So, this worldview helped the author see the reality of the production system, based on subjective as well as objective considerations.

A discrete production system is a complex environment of multiple entities interacting with one another. Maintaining equipment is an important function in a production system that is just as complex and involves multiple entities interacting to provide continuous production. The author believes that because of the complexity of the maintenance problem and its importance in aiding production, maintenance research should take an enlarged viewpoint, rather than isolating individual machine-level problems. Maintenance on individual machine-level problems has been largely focused on the past (Li, Ambani & Ni, 2009; Helu & Weiss, 2016). The author's set of beliefs stem from the researcher's background and the environment in which the research is conducted. The author's background is in production engineering and many years spent learning about production system improvements. Right from the beginning of the PhD studies, the entire research group has taken a holistic approach to its research activities. Naturally, these experiences have shaped the author's thought process towards applying the same in maintenance research. Based on the researcher's beliefs, a holistic approach was chosen for conducting research into maintenance. The lack of a holistic approach within maintenance, and the need for it, has been established (Tsang et al., 1999; Bengtsson, M., & Salonen, 2009; Coetzee, 1999; Jin et al., 2016). The author is therefore confident that a holistic approach to maintenance research is in dire need and that it will add value to manufacturing industries and scientific communities alike.

Another important decision made by the author in this research process was to conduct empirical research. In manufacturing industries, it is reported that there is a substantial gap between maintenance theory and practice (Bokrantz et al., 2017). One of the common problems in maintenance research community is the lack of empirical research (Fraser et al., 2015). Hence the theoretical solutions that have been developed have not always translated into industrial applications. Maintenance is an applied research field and its strategic importance brings competitiveness to manufacturing companies (Fraser et al., 2015). Thus, there is a need for empirical maintenance research to solve real-world problems. All the studies conducted within this thesis are empirical; designed and conducted in an industrial setting.

Industrial and scientific contributions. Stemming directly from its holistic approach and empirical research, the results of the thesis address both the industrial and scientific communities. The findings are compared with contrasting literature to build validity and similar literature to sharpen generalisability of the research (Eisenhardt, 1989). The results are also explained using existing theories, to elevate their significance and add knowledge to the maintenance management field. Thus, the intended audience of the research is maintenance practitioners in manufacturing companies and research practitioners

working in maintenance and productivity management. One of the principle contributions to both communities is that the research has addressed the narrowing gap between maintenance research and industrial practice.

The research process conducted in this thesis appears in Figure 3, which depicts the research framework, and interconnection between the researcher’s worldview, research design and research methods. It also shows the path taken by the author, from worldview to specific research method, for each of the studies.

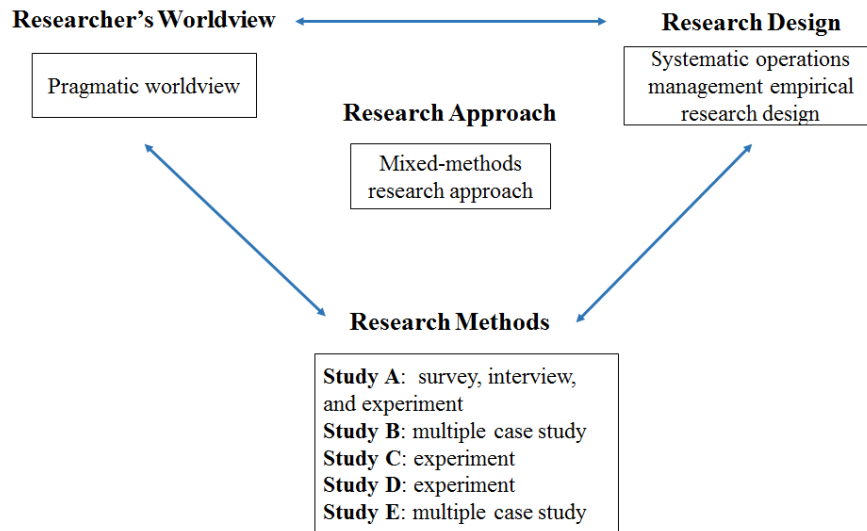


Figure 3. Research framework of this thesis (adapted from Creswell (2013)).

2.2 Research approach

Because of the purpose and aim of the research, plus the need for a complete understanding of the research problem, a mixed-method (qualitative and quantitative) research approach was selected, (Creswell, 2013). The research questions were framed based on this mixed-methods approach (Onwuegbuzie & Leech, 2006). The following paragraphs describe the rationale for the mixed-methods approach chosen to answer each of the research questions. This is followed by a description of the aims of each research study and how they contribute to answering each of the RQs. The timeline of the empirical research studies and appended papers are presented in Figure 4.

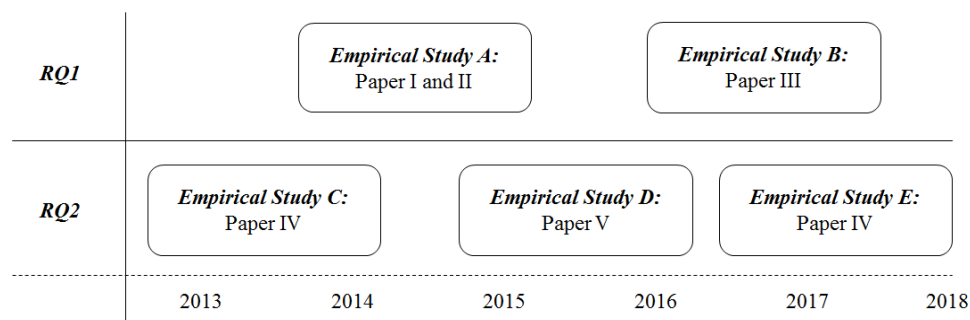


Figure 4. Timeline of empirical studies and appended papers.

RQ1: What are the gaps between current industrial practices and research in maintenance prioritisation?

Wide-ranging enquiries (mapping across different companies) and in-depth enquiry (rationale as to why such a phenomenon exists) are needed, to determine the gaps between research and industrial practice regarding maintenance prioritisation. An explanatory sequential mixed-method research approach was used to answer RQ1 (Creswell, 2013); this explains the rationale behind the “*what*” question (Forza, 2002; Onwuegbuzie & Leech 2006). Study A (Paper I and parts of Paper II) uses a quantitative research

approach conducted across multiple companies to identify the phenomenon of maintenance prioritisation and determine the improvement potential. This knowledge laid the groundwork for an in-depth enquiry into why such a phenomenon occurs. Study B (and parts of Paper II) adopts a qualitative research approach (conducted across a selection of companies) to explain in detail the observed phenomenon of maintenance prioritisation and identify productivity improvement potential.

RQ2: How can maintenance prioritisation be supported to increase productivity?

An embedded mixed-method research approach was used to answer RQ2 (Creswell, 2013). Normative, exploratory, experimental research was conducted (McCutcheon & Meredith, 1993; Onwuegbuzie & Leech, 2006) by way of examining transformation (transforming maintenance prioritisation decisions into an effectively managed increase in productivity). This explains the rationale behind the “how” question. Studies C and D use quantitative data in an experimental research approach which assesses the potential for maintenance prioritisation productivity. Study E, however, employs a multiple-case research method, using both qualitative and quantitative research approaches to develop maintenance prioritisation decision support. The contribution of each of the papers appended to the RQ is shown in Figure 5.

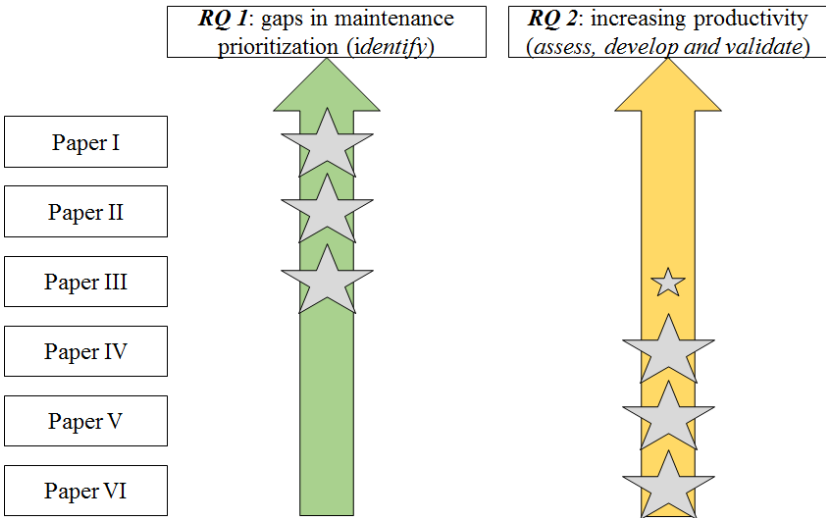


Figure 5. Results contribution of appended papers to each RQ.

2.3 Research design

A systematic, operational management, empirical research design has been adopted from Flynn et al. (1990) for the research activities of the thesis (Figure 6). Based on the aim of the thesis, a theory-building activity was conducted relating to criticality-based machine maintenance prioritisation. Theory verification is not one of the aims of this thesis, but a simulation verification (Paper IV) and interview study (Paper VI) were conducted to evaluate the effects of criticality-based prioritisation. The existing frameworks, widely-acknowledged problems and author’s philosophical assumptions in the field of maintaining production systems (see Section 2.1) form the basis of, or premise for, the theory-building in the thesis (Glasser and Strauss, 1967). Every effort has been made to ground the results of this thesis in these principles, so that its theories adhere to the components and principles of maintenance prioritisation decision support (Flynn et al., 1990).

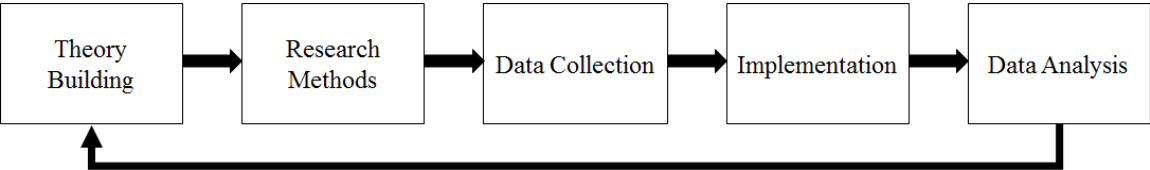


Figure 6. Research design, adopted from Flynn et al. (1990).

After determining a theory-building process, the research design was selected. This selection determined the choice of research methods, followed by data collection, implementation and data analysis (Figure 6). The research design was chosen individually for each study, yielding the appended papers.

2.4 Selection of research design

The research design followed in each study is presented in this section, including the chosen research methods, implementation and data analyses. The research method for the appended papers is provided in greater detail in the papers themselves. The summary of methods in each paper appears in Table 2.

Table 2. Research methods and summary of studies.

Empirical study	Appended papers	Research method	Data collection
Study A	Paper I	Survey	Secondary OEE data
	Paper II	Survey, interview and experiment	Questionnaire and empirical machine data
Study B	Paper III	Multiple case study	Questionnaire and archives
Study C	Paper IV	Experiment	Empirical machine data
Study D	Paper V	Experiment	Empirical machine data
Study E	Paper VI	Multiple case study	Questionnaire, empirical machine data, and maintenance data

Study A: The aim of Study A was to map the current industrial and theoretical practices and identify gaps between them. Gaps were pinpointed by identifying potential maintenance and productivity improvements. A survey method was employed in this study to map the current industrial state (Forza, 2002). The study was conducted in two parts, with one focusing on the individual OEE figures of machines in manufacturing companies (yielded Paper I) and the other focusing on individual maintenance prioritisation practices in manufacturing companies (yielded Paper II). A survey research method for descriptive research was used in the first part of the study. A total of 124 OEE calculations were made, collected from 98 different companies in Sweden between 2006 and 2012. The data collection was not conducted by the authors but by participants from the 50 industrial workshops. Hence, the OEE figures obtained are secondary data. The companies were a mixture of discrete and process industries of different sizes. However, once poor data had been discarded, the authors conducted the data analysis for the 94 OEE datasets. The OEE analysis used the definitions and formula provided by Nakajima (1988). The OEE data was compiled in Excel and a further analysis made, using Monte-Carlo simulation, to find the relative importance of the various components of OEE.

In the second part of Study A, an explanatory sequential mixed-methods approach was chosen to map the maintenance prioritisation practices in manufacturing companies (Creswell, 2013). This comprised a survey, interviews and an experiment in conducting descriptive research. The mixed-methods approach was implemented by using the (i) quantitative data collection and analysis and (ii) qualitative data collection and analysis. The quantitative data includes a literature analysis and a Web-based questionnaire survey, which received 76 responses from 71 different companies. The invitation was sent to selected respondents via e-mail and an open invitation listed publicly on the website and newsletter of the Sustainability and Maintenance Global Centre (SMGC). A response rate of 75 percent was achieved.

The qualitative data included four in-depth, semi-structured, face-to-face interviews, as described by Tong et al. (2007). The interviewees were selected from the largest manufacturing companies in Sweden. The companies were also part of the Web-based questionnaire survey. The interviewees included three maintenance managers and one maintenance strategist. Interview data was manually coded and analysed to gain in-depth knowledge on phenomena observed in the quantitative data. Simulation experiments were also conducted to evaluate the results in the quantitative and qualitative

data. An empirical use-case was selected from one production line at a company which had participated in both the Web-based survey and semi-structured interviews.

Study B: The aim of Study B was detailed mapping of the machine criticality assessment, identifying its components so as to increase productivity. An embedded, multiple-case study approach was chosen for this study, yielding a highly detailed level of enquiry (Yin, 2013). Six different cases were chosen from six production sites operated by three global manufacturing companies. Data collection was carried out in the form of interviews, focus groups and from archival records (Yin, 2013). A total of eight interviews and five focus groups were conducted across these cases. In all but one case, these interviews and focus groups were conducted face-to-face.

The data analysis used predefined codes, obtained from previous literature on machine criticality assessment. The identified codes were the components of machine criticality assessment emerging from the literature. Accordingly, the interviews and focus groups were transcribed and coded using NVIVO qualitative analysis software. A twofold data analysis was also conducted: (i) within case analysis, with cases analysed individually to achieve the goals on a case level and (ii) cross-case analysis, which revealed the similarities and differences between the cases. The cross-case analysis was also useful in seeking generalisations (Voss et al., 2002). Moreover, the data was gathered from more than one data source in each case. This helped increase the generalisability and validity of the results that had been produced (McCutcheon & Meredith, 1993). Study B yielded the appended Paper III.

Study C: The aim of Study C was to evaluate different prioritisation strategies for maintenance activities, with the goal of increasing throughput. An experimental research method was chosen for this study. The effect of machine criticality-based maintenance prioritisation was analysed experimentally. For the simulation study, an industrial use-case with empirical data was chosen and simulation methodology followed (Banks et al., 1996). Verification and validation of the simulation experiment followed the steps suggested by (Rabe et al., 2008). The prioritisation of repair maintenance work orders was used for analysis. The different prioritisation strategies were adopted from various bottleneck detection methods, using active-period methods (Roser et al., 2003b) plus a buffer utilisation method (an improved version of the queue-length method (Roser et al., 2003a)). The identified bottleneck machines were given higher priorities when executing repair work orders. The improvement in throughput of the use-case was analysed in comparison to a first-come-first-served basis of executing repair orders. Study C yielded the appended Paper IV.

Study D: The aim of Study D was to investigate and develop an algorithm for data-driven decision support for maintenance and production improvement. Experimental research was conducted to investigate and develop algorithms. The algorithm was developed for bottleneck detection and an average active period method chosen (Roser et al., 2001). During the testing phase, a hierarchical process model called the Cross-Industry Standard Process for Data Mining (CRISP-DM) methodology was used (Chapman et al., 2000). The algorithms that were developed were tested on two use-cases from two different manufacturing companies. Real-time machine data was collected from manufacturing execution systems (MES) at each of the case companies. The algorithms were then applied to the real-world MES data. Data preparation (cleaning) was conducted as a test stage. The application of the algorithm to real-world MES data helped in evaluating the applicability. Study D yielded the appended Paper V.

Study E: The aim of Study E was to develop and validate a framework for assessing data-driven machine criticality with a focus on productivity. A multiple-case, case-study approach was chosen (Yin, 2013). Four empirical cases were chosen from the three multinational manufacturing companies. The research was conducted in two phases: Phase 1: development and Phase 2: validation. Firstly, a key informant was identified in each case for setting up the study, data collection, and implementation. In Phase 1, machine data from the MES system, maintenance data from computerised maintenance management systems (CMMS) and a criticality assessment tool from CMMS was collected. This had to be done in a

cyclic process, as data collection could not be carried out in a single transaction. The data was analysed to assess the correlation between criticality assessment and maintenance data, particularly PM maintenance planning and machine downtimes. The results were compared to the actual working states from the MES data. Additionally, a cross-case analysis was conducted to identify similarities and differences between cases. This part of the research method was used to develop a generic, data-driven, maintenance decision support framework for discrete production systems.

In Phase 2, a simulation and interview study was conducted within each case to validate the generic framework. The Phase 1 results from each case were used as input to the simulation model, to validate the framework. Four focus group interviews were conducted with selected respondents at each of the case sites. Respondents belonged to the production and maintenance organisations of the chosen cases. The Phase 1 results and simulation results were presented to these respondents. Based on the focus group interviews, the framework and results obtained were further evaluated and validated. The interviews were transcribed and coded in NVIVO qualitative data analysis software. Upon cross-case analysis, some main themes emerged from the qualitative data. This was used to explain the Phase 1 and 2 results. Study E yielded the appended Paper VI.

2.5 Research Quality

The research conducted aimed at increasing the practical applicability for industry (usefulness) and strict research process (rigour). However, the limitations of the research impact the quality of the findings. Thus, during the research process of this thesis, there has been a constant striving to improve its research quality. Since a mixed-methods research approach was being followed, combined quantitative and qualitative research criteria were used to safeguard research quality (Bryman et al., 2008). The research quality of the quantitative research was affected by internal and external factors plus content validity (Yin, 2013). Internal validity was increased by comparing the findings with previous research and theory in Papers I and V and by comparing the findings with the literature analysis in Paper II. External validity was increased by collecting several data sources from various locations in Papers I and II, whereas in Papers V and VI, generic maintenance decision support was developed and validated in different industrial cases. Lastly, in Paper IV, content validity was increased by face validating the simulation experiment with experts at the university (Onwuegbuzie & Johnson, 2006).

With respect to the qualitative research, its quality is affected by validity, reliability, replicability and generalisability (Bryman et al., 2008). Contrary to the general view of case studies, a single case study can generate generalisable results (Flyvbjerg, 2006). Hence, the use of multiple case studies in Papers III and VI can greatly increase generalisability. Data triangulation (multiple data sources obtained from various companies) in Papers II, III and VI also helped increase generalisability, replicability, and reliability (Creswell, 2013). Validity was ensured in Papers II and VI when the results achieved through quantitative data were validated using the qualitative data (Eisenhardt, 1989). The reliability of the data was also ensured in Papers II, III and VI by structuring and coding the qualitative data.

The data from different sources in this thesis also provided various individual lessons; triangulating this varied data helped provide coherent justification for maintenance prioritisation decision support. Each of the appended papers presented its transparency of procedure, case selection procedure and any negative results. Peer debriefing of research process and results were also conducted throughout the PhD studies, allowing constructive criticism and verification of the author's research practices.

3 FRAME OF REFERENCE

The frame of reference provides the theoretical foundation of the thesis. The theory on productivity is established, followed by the maintenance theory. The theoretical foundation of maintenance includes a historical overview, maintenance in digitalised manufacturing, problems in maintenance research and decision support for maintenance prioritisation.

3.1 Productivity Theory

The performance of a production system can be defined in different ways. However, the most common way to assess performance is by measuring productivity. The term “productivity” is often misunderstood and used interchangeably with “performance” (Tangen, 2005). A simple definition of productivity is as a ratio of outputs to inputs (Chew, 1988; Coelli et al., 2005). Therefore, productivity means getting more output from a given set of inputs. This is a major goal in achieving economic development and growth, irrespective of the type of businesses. Schmenner (2015) says that productivity depends on many things, such as the technology used, equipment capital, quality of materials, process quality, product design, efficient allocation/scheduling of resources, workforce education and training and, lastly, management itself. Productivity in an industrial context can be measured in terms of labour productivity, capital productivity, material productivity and total factor productivity (TFP). TFP is a measure which includes all factors of production; the others are partial measures (Coelli et al., 2005). There is no manufacturing company with the highest performance, i.e. the ratio of inputs and outputs is equal to one. This is because of variability in the production system. According to Factory Physics, the law of variability states that “*increasing variability will always degrade the performance of the production system*” (Hopp and Spearman, 1996 p. 309).

Factory Physics also states that variability in production stems from many different sources. Process variability is caused by setups, random failures, quality problems and varying cycle times. Flow variability is caused by process selection, system design and management decisions. Variabilities can be categorised as good or bad. Good includes product variety, technological change and variation in demand. Bad variabilities include setups, machine failures, quality problems and engineering changes (Hopp and Spearman, 1996). Even though any type of variability affects production efficiency, good variability is better for business. This is not the case for bad variability. Hence, one way of attaining smooth production is to “*control*” bad variability. Variability control is actually crucial to improving production system performance (Hopp and Spearman, 1996). So, to improve production system performance, the management strives for smooth production flow. Production smoothing (*heijunka* in Japanese), a key just-in-time (JIT) philosophy, is a tactical planning decision for reducing production rate variability in the final stages of manufacturing (Walleigh, 1986). This reduction in variability is focused only on the final stages of manufacturing, so as to create stable demand for other manufacturing operations in the preceding stages. However, smooth production flow is required throughout the manufacturing operation if high production system efficiency is to be achieved.

Productivity can be enhanced by improving the method (M), the performance (P) and the utilisation (U) at different levels in a company, such as plant productivity (Saito, 2004). For example, the method can be improved by increasing automation, the performance can be improved by reducing cycle time and utilisation can be improved by swift implementation of the intended method. Almström and Kinnander (2011) express the relationship between these three factors as:

$$Productivity = M \times P \times U$$

Almström and Kinnander (2011) developed productivity potential assessment (PPA) to illustrate productivity potential based on shop-floor performance in manufacturing industry. The PPA specifically takes the utilisation factor to assess productivity potential, using different levels as parameters. Level 1 deals with productivity of a single unit, such as labour or a machine. For example, the efficiency of machines is assessed using an OEE measure and manual labour through value-adding and non-value-adding measures. Level 2 consists of parameters to control the operations. Level 3 is the ability of the

company to run production. Maintenance comes in level 3, with downtime as the specific assessment criterion. The results of PPA implementation showed a wealth of productivity potential in Swedish industry (Almström & Kinnander, 2008). Although productivity can be increased using different factors, as mentioned above, this thesis pursues productivity only by controlling machine downtime and maintenance activities. The pursuit of productivity in this thesis also lies in utilisation (U) of the above-mentioned formula, but improvement is approached without the influence of M or P, e.g. without increasing automation or reducing any machine parameters.

Productivity of a machine is measured using the OEE figure (Almström & Kinnander, 2011) and is often used as a maintenance performance indicator (Kumar et al., 2013). The definition of OEE is the ratio between the times spent on producing goods of the required quality to the planned production time (Nakajima, 1988). Nakajima (1988) provided a formula for calculating a machine's OEE using the following components:

$$OEE = Availability \times Operational\ efficiency \times Quality\ rate$$

Furthermore, the pursuit of productivity is well explained by the theory of “*swift, even flow*” (Schmenner, 2015). The theory of swift, even flow can explain the historical innovations in production systems. In other words, everything in the pursuit of productivity from creating a factory for production through to continuous flow, to moving assembly lines, to lean production, to current innovations in digitalised manufacturing. Even though the progression has not been a steady one, the ultimate goal has always been the advancement of productivity (Schmenner, 2015). The productivity of any process increases with the speed of materials flowing through it, but decreases with variability in process or demand (Schmenner, 2001). The principle behind the swift, even flow involves reducing variations in production. As a result, materials can move swiftly when there are no bottlenecks impeding the flow (the throughput time) and materials can move evenly when variability in demand and/or process is narrowed (Schmenner & Swink, 1998). The main suggestion for productivity advancement is to have “*factory focus*” (Schmenner, 2015; Schmenner & Boo Ho, 1990). Factory focus enables identification of system bottlenecks and non-value-adding work to remove them (variability control). This theory is consistent with the “*theory of constraints*”. This theory states that “*the machine which impedes the throughput of the entire system is a bottleneck machine*” (Goldratt and Cox, 1992). Therefore, identifying and controlling bottlenecks can improve system throughput. The purpose of this research is to allow maintenance to enable productivity increases, with the production rate (or throughput) being the measure used to evaluate productivity.

3.2 Historical overview of maintenance management

Maintenance is a multi-disciplinary field with the primary role of supporting a production process. Maintenance is often seen as a sub-process to an integrated, overall production process (Gits, 1992). European Standard (WI 319-003) defines maintenance as:

“A combination of all technical, administrative and managerial actions during the life-cycle of an item, and intended to remain it in, or restore it to a state in which it can perform the required function”

Maintenance activities can be basically defined as PM, when the aim is to prevent failures from happening and RM, when the aim is to repair a machine failure as quickly as possible. The majority of maintenance research has looked at PM. Maintenance evolution is defined in terms of three generations, moving from reactive maintenance towards predictive maintenance (Peng, 2012; Moubray, 1997). The first generation (pre-1950) was characterised by reactive-type maintenance as production activities mostly involved manual work with the help of simple tools. Only during the Second World War did the scientific approach to maintenance emerge through operations research (OR) (Peng, 2012). In particular, during this time, maintenance moved from reactive to preventive and maintenance was planned using OR methods, such as statistics. It was the second and third generations (1950s to 2000s) which saw the

introduction of important maintenance concepts, such as reliability centred maintenance (RCM), total productive maintenance (TPM), condition based maintenance (CBM) and so on (Pintelon & Parodi-Herz, 2008). Another major standard for industrial maintenance is asset management. According to ISO 55000, asset management is defined as “*the coordinated activity of an organisation to realise value from assets*” (ISO, 2003). Because maintenance has been known to work well as a support function of production, maintenance in industry has traditionally been important in securing and improving the reliability and availability of individual machines in the system.

Since those three generations of maintenance, research has increasingly described the next phase of maintenance in terms of greater responsibilities. Writing about the post-maintenance era from the perspective of the semiconductor industry, Peng (2012) proposes new alternatives for equipment maintenance which go beyond traditional maintenance management principles. Dunn (2003) provides arguments on what will shape the fourth generation of maintenance. Dunn expands the traditional technical focus of maintenance managers and speaks more in terms of cross-functional professionals. A process-orientated holistic approach for improving companies’ productivity was described by Alsyouf (2007). Ahlmann (2002) also argues for managing maintenance as a process rather than a traditional maintenance department and its functions. Another piece of research by Dunn (1998) describes the fourth generation of maintenance as having greater emphasis on safety, integrating functional requirement, equipment design and maintenance and using information technology. A service perspective on maintenance was also presented, which changes the role of maintenance within life-cycle management (Takata et al., 2004). Maintenance concepts such as TPM (Nakajima, 1998), total quality maintenance (TQMmain) (Al-Najjar, 1996), terotechnology (Sherwin, 2000), RCM (Moubray, 1997) and value-driven maintenance (VDM) (Haarman & Delahay, 2013) all discuss a greater role for maintenance than would be the case in PM and basic RM. These concepts adopt a more holistic approach to solving equipment-related problems. However, maintenance organisations in manufacturing companies are still working to supply equipment reliability and availability.

Technological advancements, particularly the industrial use of computers, have also influenced the field of maintenance. CMMS were introduced in the 1980s, for ease of planning and following up maintenance activities. Since the 2000s, more and more functions have been digitalised, leading maintenance towards becoming an integrated function with other organisations. E-maintenance (one of the most researched maintenance areas) has emerged and it has been argued that the digitalisation of maintenance constitutes a revolutionary change (Muller et al., 2008). In particular, recent developments have led to next phase of the manufacturing era: digitalised manufacturing.

3.3 Maintenance in digitalised manufacturing

Digitalised manufacturing has been described as a paradigm shift in manufacturing from automated manufacturing to intelligent manufacturing (Thoben et al., 2017). Digitalised manufacturing is best explained in terms of a convergence between the virtual and physical worlds (Monostori et al., 2016; Hermann et al., 2016; Kagermann et al., 2013). This convergence is made possible by CPS systems, with physical and engineering systems connected via the IoT (Henning, 2013). This connection provides monitoring, control, coordination and integration between all the systems on the shop-floor and enables “smart factories” (Thoben et al., 2017; Kang et al., 2016; Hermann et al., 2016). Expectations of digitalised manufacturing are very high; specifically substantial productivity improvements, increased automation and higher resource efficiency (Monostori et al., 2016). Such high expectations will need a drastic increase in extraordinary maintenance management (Bokrantz et al., 2017). Bokrantz et al. (2017) also state that business as well as scientific literature on digitalised manufacturing hardly mentions maintenance, or limits it to an increase in predictive maintenance and maintenance services. Thus, industrial maintenance management faces a daunting task if it is to meet the expectations of digitalised manufacturing. From the outset, there seem to be more problems for maintenance management than opportunities within digitalised manufacturing.

Currently, predictive maintenance is a highly desirable research topic and rightly so. Predictive maintenance and prescriptive maintenance aim to answer “*what will happen in the future?*” and “*what needs to be done?*” (Karim et al., 2016). Continuing on this theme, Maintenance 4.0 is a concept that utilises advances technologies for predictive analytics, particularly those involving data collection, analysis, visualisation and maintenance decision-making (Kans & Galar, 2017). A framework for a cloud-based approach (using the largest information content) aims to improve on condition-based predictive maintenance (Schmidt et al., 2014). Proactive maintenance is also discussed with the aim of eliminating failures (Dunn, 2003). A well-known application called Watchdog Agent (a tool for predicting machine failures and performance) was developed by the Centre for Intelligent Maintenance Systems. This tool stems from the field of prognostics and health management (PHM). PHM is a set of technologies covering everything from failure mechanisms to system life-cycle management, by means of health monitoring, diagnostics, prognostics and maintenance techniques (Jin et al., 2016). A similar concept is E-maintenance, which enables monitoring and management of production plants and physical and engineering systems using sensors and databases (Muller et al., 2008). Another major (and growing) area is big data and data analytics. These allow systematic processing of information, so that uncertainties can be understood and more informed decisions made (Lee et al., 2014). The foundations and technologies required for maintenance in digitalised manufacturing was presented by Roy et al. (2016). They identify the knowledge and skill base required in future maintenance as component and system-level degradation science and assessment and modelling using big data analytics. Maintenance research into digitalised manufacturing focuses heavily on the *technical advancements*, but there are other aspects to it. When a new technology or new practice is deployed, a change will definitely be needed in the *organisational* area. Studies focusing on the organisational changes needed in digitalised manufacturing are rare. One such study has created scenarios on the equipment, plant, company and extra-company levels by considering the hard (technological) as well as soft (social) dimensions of improving maintenance management preparedness for the changes wrought by digitalised manufacturing (Bokrantz et al., 2017).

3.4 Maintenance decision support

A full explanation on the fundamentals of maintenance is presented in a book by Mobley (2004). The maintenance engineering handbook by Mobley et al. (2008) also provides the basics of maintenance and its functions. Maintenance research is a relatively young research field and is becoming increasingly popular. However, over the years, the development of maintenance practice has lagged somewhat behind current requirements; some concepts being used are 30 years out of date (Sherwin, 2000). Therefore, it is important that research into maintenance management treats it as a “profit contributor” rather than a “necessary evil”. There have been extensive prior reviews of existing maintenance management models (Sherwin, 2000; Garg & Deshmukh, 2006; Pintelon & Parodi-Herz, 2008). These maintenance management models include maintenance optimisation models, maintenance techniques, maintenance scheduling, maintenance performance measurement, maintenance information systems, and maintenance policies (Garg & Deshmukh, 2006). Even the concept of customised maintenance has been developed to incorporate data in a company using information and communication technology (ICT) (Waeyenbergh & Pintelon, 2002). Another piece of research was presented in this area, detailing a methodology for selecting an optimal mix of maintenance approaches (Roy & Ghosh, 2010). The emphasis is on linking tactical and operational planning across all decision-making levels, which will enable world-class maintenance to be realised (Pintelon & Parodi-Herz, 2008). The means to achieve this integration is by interdepartmental management decision-making, aided by IT and allowing the co-planning of production with maintenance, renewal of machinery and performance improvement (Sherwin, 2000). Much of the research has argued what the future of maintenance needs to be and how. However, all these maintenance models, concepts and IT tools are intended to support maintenance decision-making, so that companies can achieve performance efficiency and profitability. In other words, maintenance management frameworks allow decision-making processes to manage maintenance (Márquez et al., 2009).

Maintenance decision-making means assessment and selection of the most efficient maintenance approach for companies (Al-Najjar & Alsyouf, 2003). These decision support tools should aid individuals in making decisions more easily, using problem recognition (Santana, 1995). Decision support systems (DSS) are needed for effective maintenance operations, as existing CMMS are inadequate for the demands of dynamic maintenance (Ni & Jin, 2012). The cost of maintenance is already substantial. For example, 15-40% of total production costs are attributed to maintenance (Löfsten, 1999). An even higher figure, 15-70% of total production costs are attributed to maintenance departments (Muthu et al., 2000). These figures are only expected to rise, given the likely future technological advancements within manufacturing companies (Blanchard, 1997). Maintenance costs a lot, but the cost of poor maintenance (CoPM) is even higher (Salonen & Deleryd, 2011). Hence, a maintenance decision support system cannot afford to make erroneous decisions, as this will only worsen the situation. Research into maintenance decision-making has indicated that decision analysis capabilities are often missing in existing CMMSs and that data collected in these systems is under-utilised (Rastegari & Mobin, 2016). However, the main point of supporting maintenance decisions is to provide fact-based decision-making.

Data-driven decision-making can facilitate fact-based maintenance decisions. Big data, particularly data analytics, has the potential to enable data-driven decision-making (Davenport et al., 2012). A systematic literature review of big data in manufacturing has highlighted process and planning as the most prominent research area of contribution so far (Donovan et al., 2017). However, current maintenance decisions are hardly fact-based. Data-driven decision-making is one of the areas for future maintenance development, as shown in the projections for future maintenance planning (Bokrantz et al., 2017). In general, the fact that data-driven decision-making is not fully used industries can partly be attributed to data quality issues. Extensive research is being conducted to ensure data quality, as good data can dramatically increase the size and scope of improvements in companies (Wang et al., 1995; Batini et al., 2009). Particularly within maintenance organisations, shop-floor-level maintenance prioritisation decisions are often taken based on the knowledge and experience of maintenance technicians (Guo et al., 2013; Yang et al., 2007). This is a major problem which needs to be addressed immediately. On the positive side, a handful of data-driven decision-making research studies into maintenance planning are ongoing (Guan et al., 2011; Li & Ni, 2009; Li et al., 2009; Yang et al., 2007).

3.5 Problems in maintenance research

One of the criticisms of maintenance is the gap between theory and practice (Bokrantz et al., 2017; Sherwin, 2000). Bokrantz (2017) describes this as the “gap of incompatibility”. Many problems contribute to this gap and this section presents problems relevant to this thesis.

Firstly, the OEE measure is discussed. This is considered to be predominantly a maintenance measure (Muchiri et al., 2011), as originally presented by Nakajima (1988). The average OEE figures range from 40 to 65%, which is very low considering current demands on production systems (Ingemansson, 2004; Hedman et al., 2016; GoodSolutions, 2012; Ljungberg, 1998). The low OEE figures have also been monitored over time, from 2004 to 2016. Availability, operational efficiency and quality are the components of OEE (Nakajima, 1988). Maintenance organisations focus only on improvements in the availability of individual pieces of equipment. Direct machine downtimes are responsible for low availability, but can also cause ripple effects in other machines in terms of blockage and starvation (idling losses, for example) (Andersson & Danielsson, 2013). A great deal of production time is wasted by these “idle machines states” (Roser et al., 2014; Chiang et al., 1999; Gu et al., 2015). Such losses cause productivity to be lost across the whole system.

Secondly, systems-level maintenance problems are discussed. Maintenance efforts are distributed between reactive, preventive, and improving activities. However, a study in aerospace industry shows that the majority of the efforts are reactive and not preventive (Sandberg et al., 2014). Historically, the relationship between maintenance and production has been characterised by conflict (Rishel & Christy, 2007). Joint production and maintenance planning is important for maintaining high levels of

productivity and production system performance (Wong et al., 2013). One very good way to achieve a joint planning approach is to have a common goal, such as productivity. Maintenance organisations do not focus on increasing productivity; they have a tradition of practicing single-loop learning, in other words maintaining individual machines in their specified state. This is reflected in the key performance indicators (KPI) used by maintenance, specifically mean time between failures (MTBF) and mean time to repair (MTTR). These are individual machine KPIs. Maintenance research has focused largely on machine-level problems while systems-level maintenance problems are ignored in research (Jin et al., 2016; Roy et al., 2016). In PHM research for example, the following types of study are commonplace: machine tool spindles (Vogl & Donmez, 2015), cutting tool wear or breakage (Amer et al., 2007), machine tool feed axis systems (Vogl et al., 2015). To focus on system-level maintenance problems, performance measures should be linked to the organisation's strategy. This allows useful information to be gathered for making effective decisions (Tsang et al., 1999). Indeed, a top-down approach is prescribed as the means to achieve effectiveness and efficiency in maintenance functions (Coetzee, 1999).

Lastly, empirical studies are lacking in maintenance research. Maintenance is an applied research field and maintenance decisions are strategically important to the competitiveness of every organisation (Fraser et al., 2015). The gap between theory and practice is considerable and the current situation needs to be improved (Pintelon & Parodi-Herz, 2008). Therefore, in this thesis, an empirical research approach was chosen to solve the "real-world" problems of maintenance management, as proposed by Fraser et al. (2015).

3.6 Maintenance prioritisation

Maintenance operation prioritisation is an important task in achieving effective production systems (Levitt, 1997). Prioritisation maintenance tasks has been identified as one of the decision support tools in creating effective maintenance operations (Ni & Jin, 2012). Prioritising RM tasks for bottleneck machines has been shown to increase throughput, when compared to the first-come-first-served method of executing maintenance tasks (Yang et al., 2007; Li & Ni, 2009; Li et al., 2009). A dynamic, bottleneck-based prioritisation of RM tasks showed even better throughput improvement than static bottleneck prioritisation (Wedel et al., 2016; Langer et al., 2010). Prioritising bottlenecks will reduce the downtime of the machine that is impeding system throughput (Li et al., 2009). The key to successful throughput increase is prioritisation based on bottlenecks. Hence, identifying and working with bottlenecks is an important task for maintenance organisations. Since productivity is not a maintenance goal, it may be assumed that bottleneck detection is not practiced in companies. Bottleneck identification involves system-level analysis of the production system; the machine level alone cannot do this.

The principle concept underpinning most bottleneck identification methods is identifying idling losses in machines. For example: the sum of blockage and starvation times can be used to identify bottlenecks (Chiang et al., 1998). Additionally, utilization method (Law and Kelton, 2000); active period method (average and percentage) (Roser et al., 2002; Roser et al., 2003b); inter-departure time variance method (Betterson & Silver, 2012) are also used for bottleneck detection using idling losses. In addition to idling losses, the buffer queue length (Lawrence & Buss, 1994) and production rate sensitivity (Kuo et al., 1996) can be used to identify bottlenecks. Traditional bottleneck analysis methods are simulation-based. However, data-driven bottleneck detection methods (in which bottlenecks are identified directly from online machine data) are also becoming popular (Li, 2009; Li et al., 2007; Li, Chang & Ni, 2009). This thesis mostly uses the active period method of bottleneck analysis, as well as buffer-based bottleneck detection. It is therefore important to clarify the meaning of "active period". The active period is the sum of all machine states, except blocked and starved ones (Roser et al., 2001). The machine with the highest active period percentage/average/current longest is determined to be the bottleneck (both static and dynamic) (Roser et al., 2003b).

Maintenance prioritisation in research is heavily focused on RM task prioritisation. However, prioritisation means much more than that. Some of the other research activities in this field include:

prioritising sustainable maintenance strategies (Pires et al., 2016), cost-based criticality (CBC) strategies for maintenance prioritisation (Moore & Starr, 2006), maintenance criticality analysis (MCA)-based prioritisation for improving machine availability (Silvestri et al., 2014) and multi-criteria decision-making (MCDM)-based maintenance priorities for risk reduction and cost minimisation (Roy & Ghosh, 2010). Marquez et al. (2009) in their maintenance management framework, create priorities for assets in planning maintenance strategies. The maintenance strategy includes designing of preventive maintenance plans. Preventive maintenance can also be planned and scheduled according to priority. PM can be planned using maintenance opportunities during production time; known as maintenance opportunity windows (MOW) (Chang et al., 2007). Passive and active MOWs can be identified by identifying the critical downtime of each machine in the system (Gu et al., 2015; Ni et al., 2015). Such PM planning is also a prioritisation technique in which critical downtime is identified using bottleneck analysis. Hence, when PM is planned during the MOWs, the bottleneck machines are assured of being least/not affected (Gu et al., 2013). Accordingly, in this thesis, “maintenance prioritisation” relates to PM as well as RM tasks.

3.7 Machine criticality assessment

Maintenance prioritisation for machines leads to improved production efficiency. However, this only holds true if the right machines are prioritised. In the previous chapters, it was evident that bottlenecks need prioritisation. It was also evident that maintenance organisations do not have productivity as a goal. Hence, there is major scope for improvement in this maintenance planning niche. Industrial practice and academia have been working on machine criticality assessment as a decision support tool for maintenance prioritisation (Bengtsson, 2011). Therefore, this thesis aims to achieve productivity by enabling better maintenance decision support, namely machine criticality assessment. Generally, criticality assessment deals with identifying priorities for machine-level problems. Originating within the RCM concept, failure mode and effects analysis (FMEA) analyses individual machine failure modes and uses that to generate a risk priority number (RPN) for maintenance planning (Moubray, 2007). There are several varieties of machine-level criticality assessment for guiding maintenance planning (Yeh & Sun, 2011; Yang et al., 2006; Yang et al., 2010). Another type of criticality analysis is used for spare-parts planning (Stoll et al., 2015; Sun, 2013; Jiang et al., 2011; Olde Keizer et al., 2017). Additionally, there is NORSOK, a standard for preparing and optimising maintenance activities for plant systems. NORSOK standard Z-008 provides requirements and guidelines for criticality-based maintenance and consequence classification of maintenance activities and is used for plant systems and equipment in the Norwegian petroleum industry (NORSOK, 2011). This thesis aim at systems-level decision support for maintenance. Hence, both machine component criticalities and spare-part criticalities are not included.

Machine criticality assessment studies are rare. One of the earliest studies on this topic defines machine criticality as choosing preventive maintenance policies with the aim of prioritising maintenance, instead of using a first-come-first-served basis (Flynn, 1989; Banerjee & Flynn, 1987). A variant of FMEA is used to assess machine criticality. FMECA (where C = criticality) uses the FMEA analytical basis but assesses machines. Many different FMECA models are present in the literature - for different purposes (Bertolini & Bevilacqua, 2006b; Pelaez & Bowles, 1994; Costantino et al., 2013; Moss & Woodhouse, 1999). Using architectural hierarchical planning (AHP) to determine the logic is another method of assessing machine criticality (Bertolini & Bevilacqua, 2006a; Suryadi, 2006; Antosz & Ratnayake, 2016). Production systems are complex and machines can become critical in more than one factor. MCDM is another means of assessing criticality, in which multiple factors are analysed to assess criticality (de León Hijes & Cartagena, 2006). TOPSIS is a widely-used tool for MCDM (Rastegari & Mobin, 2016), also used to assess criticality (Selim et al., 2015). Machines are also classified and grouped according to their criticality. A frequent grouping method is ABC classification. Machines classified under A are at the highest level of criticality, those under B are medium criticality and those under C are low-level or no criticality (Marquez, 2007; Márquez et al., 2009) In Marquez et al. (2009), an ABC classification for assessing machine criticality is presented with the aim of meeting availability targets. Factors such as redundancy, utilisation factor, quality impact and age of machines are used in

another ABC classification (Bengtsson, 2011). An empirical model derived from three different case studies for an ABC-type classification uses different factors such as machine working time, machine failure, breakdown time, changeability, stability and influence on safety and environment (Stadnicka et al., 2014; Ratnayake et al., 2013).

Goals of improving machine availability and reliability (machine-level maintenance improvements) are very evident in much of the machine criticality assessment literature. System-level analysis, such as bottleneck analysis, is not discussed in the literature. Another important point is the use of qualitative data (such as maintenance technician experience) for assessing criticality (Marquez et al., 2015). This suggests a lack of fact-based decisions in maintenance operations. Additionally, dynamic criticality assessment is rarely mentioned. However, it is obvious that production systems are dynamic and so are their maintenance needs (Ni & Jin, 2012). In the parallel field of computer systems, a patent exists for criticality classification of computer assets, with the aim of prioritising security incidents (Kingsford, 2008). This classification replaces manual asset classification with automated classification, based on usage, with dynamic updates when criticality changes. This patent may serve as a lesson for maintenance management of production systems, when it comes to applying fact-based, updated assessments of machine criticality.

4 RESULTS AND SYNTHESIS

The results section presents the individual findings of RQ1 and RQ2. The results come from the five empirical studies, which yielded the appended papers. The results sections are followed by a synthesis section for each RQ, in which the RQs are answered.

4.1 Overview

Five empirical studies were used to answer RQ1 and RQ2 of the thesis. In total, they yielded the six appended papers. Figure 7 shows an overview of how the empirical studies are interconnected. Studies A and B are connected sequentially to the answer to RQ1. The results from RQ1 served as direct input to the studies conducted to answer RQ2. Studies C, D and E were connected sequentially to answer RQ2.

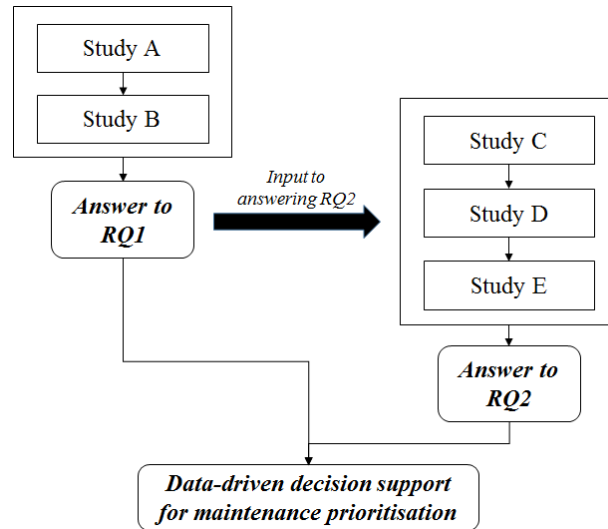


Figure 7. Overview of how the results answer the RQs.

4.2 Results – RQ1

The aim of RQ1 was to identify the gaps in current industrial practices and conduct research into maintenance prioritisation. Two empirical studies (A and B) helped answer RQ1. Study A yielded Papers I and II, while Study B yielded Paper III. All papers are appended to this thesis.

4.2.1 Study A: Part I – Maintenance improvement potential using OEE assessment

A broad approach was taken in Study A by mapping a wide range of maintenance problems. The first part of Study A aimed at identifying maintenance improvement potential, using OEE assessment within a manufacturing industry. A total of 94 OEE values were obtained for the final analysis. The findings include various equipment losses in OEE, such as planned stop time, unplanned stop time, setup losses, utilisation losses, speed losses and quality losses. The availability, operational efficiency, and quality rate are the main components of OEE and the above losses were used to calculate them. The average loss figures and average OEE are presented in Table 3. The average OEE was reported as low (51.5 percent), meaning that the machines were not being utilised to satisfactory limits. From the OEE data, it was also found that the operational efficiency was the lowest-ranked component, followed by availability and quality.

Table 3. Average OEE results, with components.

OEE components (%)	Average
Planned stop	6.6
Availability	78.9
- unplanned stop	9.6
- setup losses	11.5
Operational efficiency	67.1
- utilisation	80.2
- speed rate	86.1
Quality rate	96.9
OEE	51.5

A Monte-Carlo simulation experiment was conducted to analyse the relative importance of the components of the low OEE figure. A tornado analysis was also carried out using the distributions of each component for 1,000 simulation runs (Figure 8). From the analysis, it was observed that the largest impact in the OEE figure was due to the operational efficiency component, which includes utilisation and speed losses. This has the potential to make the OEE vary between 18 and 82 percent, based on the simulation, whereas the availability component causes the OEE to vary between 32 and 65 percent. The quality rate had the lowest impact. The analysis highlighted an opportunity to prioritise the OEE component for improvement. Paper I presents detailed results of this part of the study.

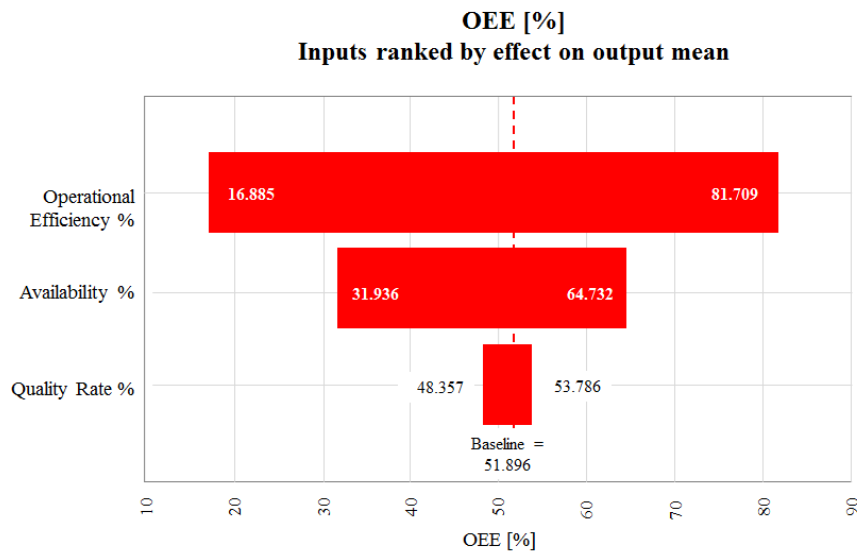


Figure 8. Effects of components on OEE.

4.2.2 Study A: Part II – Current-state mapping of machine-criticality-based maintenance prioritisation

Following the mapping of the maintenance improvement potential, Part II of Study A mapped the current theoretical and practical state of machine-criticality-based maintenance prioritisation. The aim of Part II of the study was to identify potential productivity improvement based on maintenance prioritisation. In particular, the connection between maintenance prioritisation and decision support was studied. An explanatory, mixed-method research design was used. Data from a literature analysis and web-based questionnaire survey served as quantitative data and semi-structured interviews served as qualitative data. A simulation experiment was also conducted to evaluate potential productivity.

The literature analyses for machine criticality assessment and maintenance prioritisation were conducted separately. The results of the criticality assessment literature analysis are tabulated in Table 4. The analysis of the machine criticality assessment literature shows that assessment has a variety of purposes. Only about half the literature chosen for the analysis argues in favour of prioritising maintenance activities for critical machines. A content analysis revealed a number of themes; these are listed as sub-areas in the table. Multiple factors are commonly used to assess criticality and no explicit method was followed to identify criticality here. Some common analytical methods are: classification, bottleneck and FMEA/FMECA.

Table 4. Machine criticality assessment – literature analysis.

<i>Total number of literature sources selected for analysis</i>		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 prioritisation		12

The maintenance prioritisation analysis was conducted in similar fashion to the criticality assessment one. The results are presented in Table 5 and, as it shows, not all prioritisation literature chosen for the analysis argues for machine-criticality-based prioritisation. Priorities for maintenance activities were also based on multiple factors, as illustrated by the sub-areas that emerged. This was followed by an analysis of bottleneck machines and risk. Regarding the purpose of prioritising maintenance, the literature mostly discusses productivity and cost benefits.

Table 5. Maintenance prioritisation – literature analysis.

<i>Total number of literature sources selected for analysis</i>		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

Another quantitative dataset was obtained through the web-based survey. Questions were asked about the level of companies' work to establish machine criticality, their basis for establishing criticality and their level of maintenance prioritisation. 35 percent of the companies establish criticality levels to a relatively high degree or very high degree (Figure 9 (i)). However, 67 percent of the companies prioritise maintenance work orders to a relatively high or very high degree (Figure 9 (ii)). Moreover, "ABC classification" was found to be the primary basis for setting the criticality level. The second most prominent answer for setting criticality level was "operator influence".

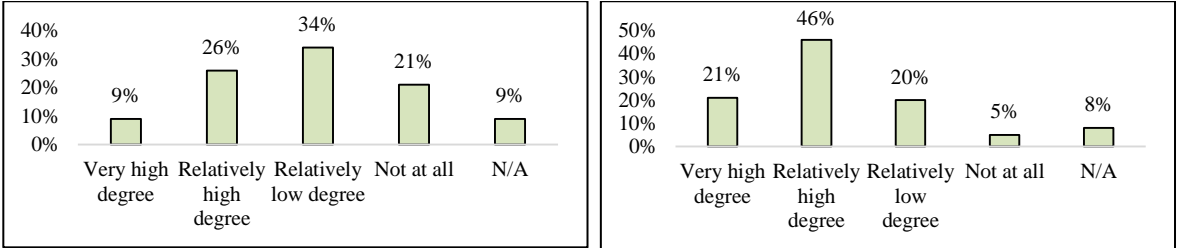


Figure 9. (i) Establishing criticality levels and (ii) Setting maintenance priorities.

Following the quantitative data collection and analysis, it became apparent that the machine-criticality-based maintenance prioritisation phenomenon existed on an overall level across many companies. Four semi-structured interviews were held with the survey participants, to follow-up and explain the phenomenon that had been observed. The interview study aimed to gain a deeper knowledge of industrial practices concerning machine-criticality-based maintenance prioritisation. The results of the interview data analysis are summarised below.

Machine criticality:

- There were indications that criticality assessment was used to set equipment priority numbers during installation. However, others indicated that criticality classification was part of the technical specification for the machines.
- All interviewees indicated an ABC-type criticality classification for their machines. However, the methods for setting criticality differ in each company.
- The criticality classification was not helpful in identifying what is critical in the companies' production systems, as each interviewee gave different answers when asked. When the question was narrowed down to machines, they answered "bottleneck machine".

Maintenance prioritisation:

- All participating companies prioritised their maintenance activities. However, the priorities were set by different departments. The criticality classifications were not used for setting priorities. It is noteworthy that criticality levels were printed on each work order.
- PM work orders were generally planned during production shutdown, whereas RM work orders were prioritised by the maintenance technicians who set the work orders.
- One excerpt from an interview sums up the maintenance prioritisation practice well: "for reactive maintenance work orders, it is up to each maintenance technician to prioritise" and "if we use the criticality classification for prioritising? 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's) not. So that's pretty much how we control and plan."

Lastly, a simulation experiment was conducted to test the impact of the maintenance priorities, based on machine criticality. The purpose of maintenance priorities was to increase productivity in the production system and so bottleneck machines were identified, in order to prioritise maintenance. Bottlenecks are identified by their active-period percentage (Roser et al., 2003). The impact on throughput was tested using two aspects: (i) prioritising maintenance for bottleneck machines and (ii)

maintenance prioritisation for different machine failure patterns (sensitivity analysis). For the first aspect, prioritising work orders achieved a throughput increase of about 5.1 percent, compared to a first-come-first-served basis of executing maintenance work orders. The results obtained were statistically significant, returning 95 percent (non-overlapping) confidence intervals. For the second aspect, a sensitivity analysis was conducted by varying the failure rate of the all the machines. The results are presented in Figure 10.

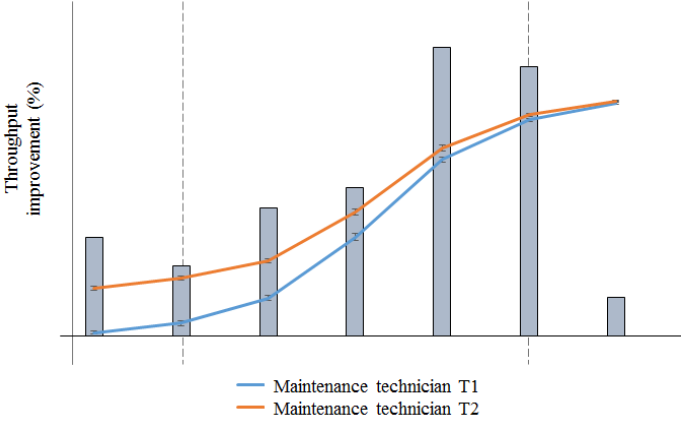


Figure 10. Sensitivity analysis of maintenance prioritisation by varying failure rates.

By increasing and decreasing the actual failure rates by a factor of two, the corresponding throughput increase and maintenance technician were analysed. As can be seen from the figure, utilisation of technicians increases exponentially. The throughput improvement also increases in the middle but is almost negligible in the case of either extremely high or extremely low failure rates. The results of this part of the study are presented in detail in appended Paper II.

4.2.3 Study B – Current-state mapping of the machine criticality assessment tool

As with Study A, Study B also aims to provide a current-state mapping of the industrial and theoretical practices for identifying potential improvements. The goals of Study B were to map state-of-the-art industrial processes for machine criticality assessment and identify components to increase productivity. The mapping covered the objective, method, data requirement and intended use of the decision support tool. The research design adopted for this study was an embedded, multiple case study. Six different cases were chosen from six different production sites, across three global manufacturing companies. Data was collected in the form of interviews, focus groups, and archival records. The qualitative data was analysed in two ways: (i) each of the six empirical datasets (ED) was analysed individually to provide within-case knowledge and (ii) a cross-case analysis was conducted to find the similarities and differences between cases. The generalised model for machine criticality assessment was then created, based on the results obtained.

Firstly, Table 6 presents the within-case analysis results. All six EDs are analysed individually. The aims of this study dictated that the analysis should be based on the headings of “Objectives of machine criticality”, “Factors and methods”, “Data requirements” and “Maintenance planning”. Additionally, the previous literature on machine criticality dictated that the codes should be analysed under each of the headings. Please see the appended paper for details on the rationale behind the choice of headings and codes.

Table 6. Within-case results of the six cases.

	<p>Objectives</p> <p>Purpose of assessing criticality Productivity focus PM and RM use Spare parts planning</p> <p>Factors and methods</p> <p>Factors for assessing criticality Methods for assessing criticality</p> <p>Data requirement</p> <p>Data usage Usability and updates</p> <p>Maintenance planning</p> <p>Ownership and production synergy Problems in criticality assessment</p> <p>Objective</p> <p>Purpose of assessing criticality Productivity focus PM and RM use Spare-parts planning</p> <p>Factors and methods</p> <p>Factors for assessing criticality Methods for assessing criticality</p> <p>Data requirement</p> <p>Data usage Usability and updates</p> <p>Maintenance planning</p> <p>Ownership and production synergy Problems in criticality assessment</p>	<p>Critical from customers' point of view (i.e. production). Clear connection with production. Working with production organisation. Used to prioritise PM and deferred work orders, plus RM. Separate classification for spare-parts planning.</p> <p>Safety and environment, quality, back-up solution, production, MTBF, MTTR and repair costs were the factors. Levels of criticality are AA, A, B, C. A decision tree is used to make decisions for above factors.</p> <p>MTBF and MTTR were used. Very useful and updated annually.</p> <p>Maintenance owns the classification and there is good consensus with production. Over half the machines are classified AA; data quality becomes an issue.</p> <p>Developing autonomous maintenance for critical machines, prioritising condition-based maintenance, long-term spare-parts planning, mapping repair crew competences for the factory. Productivity not linked to criticality assessment. Used to plan PM. RM is prioritised but not based on the classification. Critical areas are set for prioritisation usually set during morning meetings. However, RM work is prioritised over other types of maintenance. Used for long-term spare-parts planning.</p> <p>Safety, environment, redundancy, utilisation, quality and age were the factors. 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 organisation members (i.e. production).</p> <p>Some OEE data was used. Generally, subjective data collected by talking to people. Not used to any great extent. Classification updated annually.</p> <p>Owned by maintenance, but machines classification is carried out in conjunction with operators, production managers and production engineers. 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.</p>
<p>ED 1</p>		
<p>ED2</p>		

	<p>Objective</p> <p>Purpose is to increase quality and availability. Also, to start autonomous maintenance and preventive maintenance projects.</p> <p>Productivity not linked to criticality assessment.</p> <p>PM and RM use</p> <p>Spare-parts planning</p> <p>Factors and methods</p> <p>Environment, safety and complexity of machine, difficulty for operator; single flow or parallel flow; MTTR; safety and environment; bottleneck were the factors.</p> <p>Used cost deployment (CD) to allocate AA, A, B, C classes. Discuss with manager to identify critical machine. Choosing between single and parallel machines. Analysis includes root cause, monthly follow-up MTTR, MTBF, Mean Waiting Time (MWT) and maintenance cost.</p>	<p>Data requirement</p> <p>Mostly use experience for decisions. MTBF and MTTR from CMMS.</p> <p>Shows critical machine for the whole factory. Updated quarterly or annually.</p> <p>Maintenance planning</p> <p>Maintenance owns the classification. Good understanding of production as the two departments work as a team.</p> <p>Assembly tends to be more advanced; classification process such that same machine is classified as critical every time.</p>
ED3	<p>Objective</p> <p>Improve quality of PM and allocate more maintenance to critical machines, bottlenecks; minimise maintenance costs.</p> <p>Productivity not linked to criticality assessment.</p> <p>No PM related use. RM priorities line-based rather than on criticality classifications. This is usually set by production.</p> <p>Spare parts not planned using criticality assessment.</p> <p>Factors and methods</p> <p>Single or parallel machine, spare parts in-house, technician resource availability.</p> <p>Cost deployment for classifying machines. Inventory showing type of manufacture, type of software/hardware, status of machine, quality, spare parts availability and knowledge availability.</p>	<p>Data requirement</p> <p>OEE and CD were used.</p> <p>Rarely used and only shows critical machine location. Updated quarterly.</p> <p>Maintenance planning</p> <p>Maintenance own classification. Usually obtain consensus but production has final say in case of mismatch.</p> <p>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.</p>
ED4	<p>Data requirement</p> <p>OEE and CD were used.</p> <p>Rarely used and only shows critical machine location. Updated quarterly.</p> <p>Maintenance planning</p> <p>Maintenance own classification. Usually obtain consensus but production has final say in case of mismatch.</p> <p>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.</p>	<p>Objective</p> <p>Purpose is to increase quality and availability. Also, to start autonomous maintenance and preventive maintenance projects.</p> <p>Productivity not linked to criticality assessment.</p> <p>PM and RM use</p> <p>Spare-parts planning</p> <p>Factors and methods</p> <p>Environment, safety and complexity of machine, difficulty for operator; single flow or parallel flow; MTTR; safety and environment; bottleneck were the factors.</p> <p>Used cost deployment (CD) to allocate AA, A, B, C classes. Discuss with manager to identify critical machine. Choosing between single and parallel machines. Analysis includes root cause, monthly follow-up MTTR, MTBF, Mean Waiting Time (MWT) and maintenance cost.</p>

	<p>Objective</p> <p>Purpose of assessing criticality</p> <p>Productivity focus</p> <p>PM and RM use</p> <p>Spare-parts planning</p> <p>Factors and methods</p> <p>Factors for assessing criticality</p> <p>Methods for assessing criticality</p> <p>Data requirement</p> <p>Data usage</p> <p>Usability and updates</p> <p>Maintenance planning</p> <p>Ownership and production synergy</p> <p>Problems in criticality assessment</p>	<p>Preparing spare parts, to solve production issues and improve standards.</p> <p>Productivity not linked to criticality assessment.</p> <p>PM not planned using classification. RM is executed on a first-come-first-served basis. Technicians sometimes using their experience to prioritise. Allocation of resources carried out from a command centre.</p> <p>Secure spare parts for critical machines.</p> <p>Environment, spare parts for maintenance, knowledge of technicians, machine status (wear and tear) were the factors.</p> <p>A, B, C, D classes. Flow chart guides classification, which is conducted by a group.</p> <p>No data used.</p> <p>Not understood so hardly used. Updated when new equipment is procured.</p> <p>Conducted by staff with a variety of competences, so creates understanding. Clear view and consensus on critical equipment.</p> <p>Classification not well standardised. Lack of trust in current classification. Too many machines with high classification.</p>
ED5		
	<p>Objective</p> <p>Purpose of assessing criticality</p> <p>Productivity focus</p> <p>PM and RM use</p> <p>Spare-parts planning</p> <p>Factors and methods</p> <p>Factors for assessing criticality</p> <p>Methods for assessing criticality</p> <p>Data requirement</p> <p>Data usage</p> <p>Usability and updates</p> <p>Maintenance planning</p> <p>Ownership and production synergy</p> <p>Problems in criticality assessment</p>	<p>Purpose is to ensure availability of machines.</p> <p>Bottleneck machine gets maintenance allocation.</p> <p>PM not planned using criticality assessment.</p> <p>Spare parts not planned using criticality assessment.</p> <p>Bottlenecks, single or parallel machines, consequence of PM activities.</p> <p>Scale used for classification (5 - low, 10 - medium, 15 - high). Conducted with technicians involved in maintenance organisation.</p> <p>Not much data used.</p> <p>Maintenance uses it; updated quarterly.</p> <p>Maintenance owns classification. Consensus with other factories globally is the aim, to achieve standardised procedures.</p> <p>The model does not correctly identify critical machine.</p>
ED6		

Secondly, the cross-case analysis was conducted, the results of which appear in Table 7. Generally, the similarities across cases are greater than the differences. The main outcome of this analysis is that the current industrial practices for assessing machine criticality are complex. Improvement is needed to support maintenance prioritisation.

Table 7. Cross-case analysis.

Similarities
<ul style="list-style-type: none"> • Generally, many machines end up being classified as highly critical, i.e. the machines are not differentiated. • Some sort of classification (ABC type) is 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 use of “MTBF and MTTR”. • Subjective group-discussion-type analysis for setting criticality (qualitative approach) even when data is used. • Maintenance organisation responsible for classification. • Hardly used for maintenance-planning activities. PM activities not based on criticality, whereas RM activities are conducted by random prioritisation 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 organisations use classification tool to achieve consensus with the production organisation on critical machines. • Current classification tools do not identify the correct machines as critical.
Differences
<ul style="list-style-type: none"> • 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 flow charts and cost deployment 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 organisation on critical machines using the classification tool, decisions or priorities from the production organisation override the classification tool and the maintenance organisation must adhere to these.

Lastly, aided by the results from the six EDs and cross-case analysis, a generalised model was created of the current industrial practice on machine criticality assessment. Figure 11 shows this generalised model and the criticality assessment procedure. At each stage, the attributes of the industrial criticality assessment are exemplified in a bullet point list between each of the figure’s arrows. These attributes comprise the current state and criticism of the criticality assessment. The results of this study are presented in detail in appended Paper III.

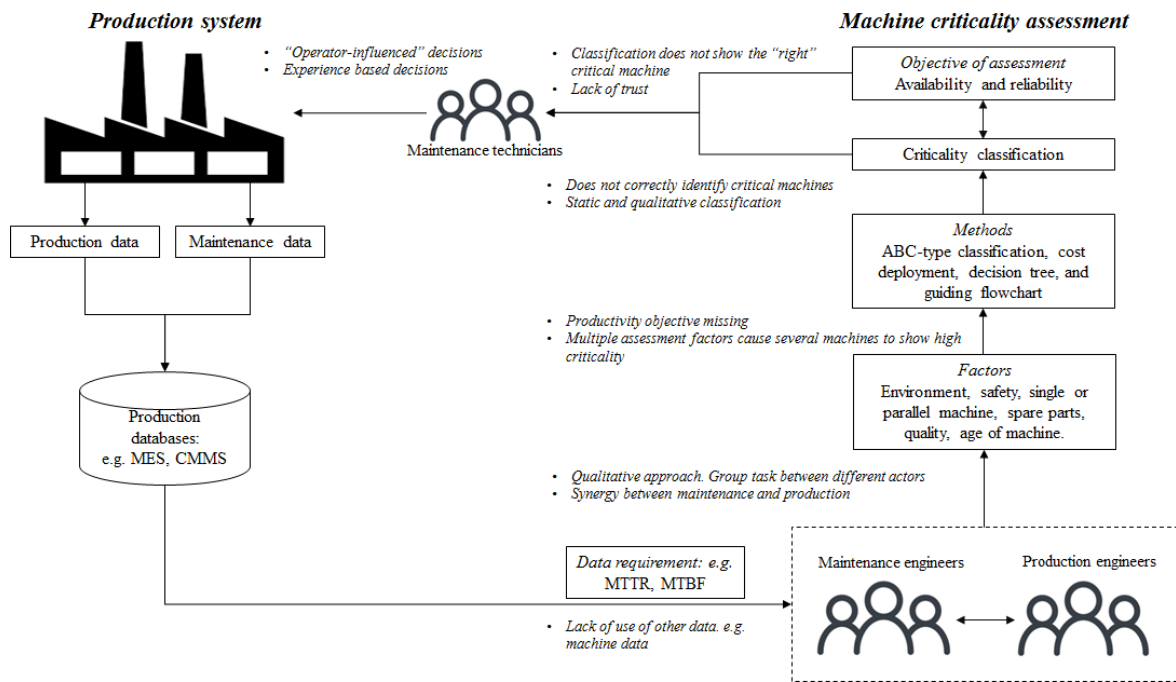


Figure 11. Generalised model of machine criticality assessment.

4.3 Synthesis of RQ1 results

Two empirical studies were conducted to answer RQ1. These studies identify and map the maintenance prioritisation gaps between research and practice, from having a broad approach, to maintenance problems, to specific maintenance prioritisation decision support. They included OEE-based maintenance improvement potential, identification of potential productivity from maintenance prioritisation and a detailed mapping of the current machine criticality assessment. The results of this section are discussed and synthesised to answer RQ1.

4.3.1 Systems perspective on maintenance

An OEE figure is a measure that shows how effectively a machine works. Findings from Part I of Study A showed that the average OEE of machines (across 94 different companies) was 51.5 percent. Similarly low OEE figures were reported about two decades back (Ljungberg, 1998), with world-class figures expected to be around 85 percent (Blanchard, 1997). Hence, the OEE figures in manufacturing companies have not improved for several decades and advancements in maintenance have had little to no effect on the effectiveness of machines. To identify the reasons for low OEE, the three components (availability, operational efficiency and quality) were studied in detail. Findings showed availability (average 78.9 percent) and operational efficiency (average 67.1 percent) to be the components that reduce OEE. The data showed that operational effectiveness had the highest impact on OEE. Even though maintenance do not focus on increasing operational efficiency, OEE is attributed as a maintenance KPI (Muchiri et al., 2011). However, maintenance is mainly responsible for the availability component of OEE, as availability losses are caused by machine downtime. Idling losses, minor stoppages and speed losses (used to calculate operational efficiency) are generally not attributed to maintenance.

Therefore, the OEE of machines cannot be fully improved through “traditional” maintenance practices, which equates to machine-level improvements. These include aiming to repair broken machines or machine parts to make them work to their designed specifications, in other words a reactive rather than a preventive mind-set (Sandberg et al., 2014). Such a mind-set is reflected in the most frequent maintenance KPIs, such as MTTR and MTBF, as these are measured in individual machines. Such machine-level improvements will certainly improve machine availability, but do not mean improved productivity in the system. Productivity potential lies not only in availability, but also in the operational

efficiency of the OEE figure. Study A showed operational efficiency to have the highest impact on OEE. Thus, increasing operational efficiency will provide more of an increase in productivity than availability. Specifically, the average idling losses (unutilised machine state) of the machines contributes 20 percent of the total production time (average machine utilisation is about 80 percent). Idling times do not contribute to production, even when machines are not down. Idling losses are caused by production system variations, particularly those brought about by the ripple effect of a machine's failures on other machines.

As a result, maintenance management should approach maintenance problems holistically and not just for individual machines. In other words, *a systems perspective on maintenance*. A general argument in manufacturing companies is that there is more maintenance work than can be covered by the available maintenance personnel. This is why reactive maintenance work orders sometimes differ. Maintenance planning practices also reveal that many companies have been forced to shut down their entire production line to carry out PM on machines; a direct loss of valuable production time. The OEE figures mask this problem and do not capture the productivity improvement potential. The PM time (measured as planned stoppages) is not even considered in OEE calculation (Nakajima, 1988). Including them thus further dents the already poor OEE figures. With the increasing complexity of machines and variety of products being made, there are bound to be more machine failures and better PM of machines will be needed. In scenarios such as these, it would be criminal to prioritise machine maintenance without knowing which ones are critical. Therefore, prioritisation is important and inevitable if maintenance management is to be effective.

Subsequently, the thesis moved from a broad approach to maintenance to specific investigation of maintenance prioritisation; identifying gaps in maintenance prioritisation practice and the support needed to carry them out effectively. The findings of Part II of Study A showed the correlation between industrial practice of maintenance prioritisation and setting criticality levels. In particular, it showed that maintenance prioritisation was practiced quite extensively by companies but that not many had set criticality levels for their machines. This practice called into question the credibility of their priorities. It was found that maintenance prioritisation decisions were situation-dependent, according to the experience of the maintenance technicians. These results provide additional explanation for the poor OEE figures observed in Part I of the study (the lack of a systems perspective on maintenance). However, maintenance organisations can solve this problem by using a systems perspective to approach maintenance (Roy et al., 2016). Systems-level decision support is therefore needed so that maintenance organisation can identify critical machines. This is particularly the case when productivity is being targeted. The system-level critical machines are the ones impeding system throughput; in other words, the bottlenecks (Chiang et al., 1999; Li, Chang & Ni, 2009). The decision support should therefore allow maintenance to focus on throughput-critical machines in order to prioritise reactive, preventive and improvement maintenance activities.

4.3.2 Machine criticality assessment

Machine criticality assessment is a means of decision support for prioritising maintenance activities on the most critical machines (Marquez, 2007; Antosz & Ratnayake, 2016). Naturally, in order to practice effective maintenance prioritisation, it was necessary to study machine criticality assessment tools in detail. The results of Paper II also showed that existing criticality assessment tools in manufacturing companies were not used for maintenance prioritisation. A common industrial practice for assessing machine criticality was by classification. Classification enables machines to be grouped into different classes of criticality (Bengtsson, 2011). An ABC-type classification was used by the companies in which the studies were conducted. A typical ABC classification determines criticality using multiple factors, such as, quality, safety, environment and delivery (Márquez et al., 2009) and a decision tree or analysis to award criticality scores. This is usually conducted cross-functionally with other organisations in the company. Finally, the scores are used to classify the machines according to a scale, in which machines

classified A are highly critical, machines classified B are medium and those classified C are low/non-critical machines. There can sometimes be several levels of criticality rather than just A, B, and C.

The general findings on criticality assessment in Study A and detailed findings on it in Study B have shown that this type of classification tool is problematic in terms of: (i) Losing the type of machine criticality. This is because multiple factors are used and can mask the primary factor which makes the machines critical, (ii) Static classification. Because the tool is created cross-functionally with other organisations, it tends to be done less frequently. (iii) Non-factual, as the classification methods suggest that data is hardly used and subjective scores were used to assign criticality. Many companies use MTTR and MTBF data, at best. This makes the criticality classification tool complex and untrustworthy. Accordingly, the knowledge of maintenance technicians and influence of operators take precedence in prioritising maintenance activities. This means repair activities were not prioritised based on any classification. However, the most interesting finding was that even PM planning is not based on the classification tools. Paper III showed that the tool was only used to obtain consensus with the production organisation. Such consensus was questionable because it did not lead to a synergy; there is no joint production-maintenance planning in practice.

Another problem with the classification tool is the lack of a clear objective. Previous research shows that maintenance prioritisation based on machine criticality aims to achieve improved reliability of critical machines (Márquez et al., 2009). However, the same research article suggests the use of multiple factors beyond the reliability measurements. Hence, it is possible that a safety-critical machine might end up being A-classified and that prioritised maintenance efforts are made, making it highly reliable. Additionally, with multiple factors, there are more chances of multiple machines being critical in one way or the other. As the results of Study B indicated, many machines end up being highly critical (A-classified). Having many critical machines may also make them less likely to be used, as it can be interpreted that the tool is not working well or that the machines need alarmingly high levels of maintenance.

The current classification tools are not always problematic as it has been shown to work better in closely-linked production lines. In Study B, the interview and focus group results from the foundry and assembly showed that when failures in one station cause a stoppage, the entire production line stops. In such a production layout the ripple effects are easily predictable, with or without a classification tool. However, preventive maintenance may still need prioritising for machines with the highest failure frequency. Reducing the downtime of these machines can effectively improve the downtime of the whole production line.

To sum-up the discussions thus far, improvements in maintenance management are needed as revealed by the low OEE figure. In particular, maintenance organisations lack decision support tools which can aid maintenance planning and increase productivity. The existing CMMS and its maintenance management tool are outdated, as the needs of maintenance management are dynamic and complex (Ni & Jin, 2012). There is an immediate need for modern, digitalised tools which can support dynamic needs and tap into potential productivity.

4.3.3 Productivity potential

An overview of the current maintenance prioritisation practices was mapped from the results of Studies A and B. It identified potential maintenance improvement using OEE assessment and gaps in maintenance prioritisation practices, specifically problems with the machine criticality assessment tool. This synthesis allows potential productivity to be identified. Maintenance management may be primarily responsible for providing the technical availability and reliability of machines in a system, but a system-level view of maintenance management can aid increased productivity in that system.

The main finding was a lack of proper machine criticality assessment in maintenance prioritisation decisions. In other words, a robust criticality assessment allowing maintenance prioritisation to be

conducted effectively. Hence, the key to potential productivity lies in the way criticality assessment is defined and used. Two important changes facilitate a robust criticality assessment and bring about increased productivity. They are: (i) technological advancement and (ii) organisational change.

Firstly, the principle problem of current practices is a lack of fact-based decision-making. A technological advancement (such as data-driven decision support) is needed to solve this. Criticality will then be identified based on the actual state of the machines rather than subjective assessments. Continuously updated assessments are also needed, to capture changes in the production system. Digitalised manufacturing provides opportunities in terms of machine data availability, digital tools and cyber-physical systems (Monostori et al., 2016). Real-time data analysis of datasets from machines can enable a more accurate and dynamic approach to identifying critical machines. Moreover, the reason for a machine being critical can be determined when data is used.

Secondly, the machine-level maintenance approach needs to be challenged and maintenance organisations should incorporate a systems-level approach. Criticality assessment should support prioritisation of PM, RM and improvement maintenance activities at any given time, for bottlenecks affecting the whole system. The results of Papers II and III have clearly shown that maintenance organisations do not work to solve bottleneck problems in maintenance, as these are considered production problems. With industrial digitalisation at full speed, manufacturing companies now have plenty of opportunities to modernise and digitalise their maintenance decision support. However, technological changes alone cannot lead to productivity. A desirable organisational change would be to think in terms of, and apply, system-level decisions to maintenance prioritisation. This organisational change (combined with technological advancements) can truly help in the drive to meet the targets and expectations set by digitalised manufacturing.

The above has helped identify the components of criticality assessment for fact-based decision-making. They are:

- For productivity to be a prime objective (systems perspective).
- Continuous monitoring of machine states (producing, downtime, idling losses and so on) to identify criticality.
- Analytics of machine data (MES) facilitating real-time decisions.
- Defining the type of criticality as well as assessing criticality.
- Selecting factors and assessing time windows based on needs (for example, PM needs a longer window with several factors, whereas RM needs a shorter window with throughput-criticality as the sole factor).
- Machine failure pattern and root-cause analysis (predictive and prescriptive maintenance) to decide on type and frequency of maintenance intervention.

Automated decision support can continuously predict and prescribe critical machines for maintenance decision-making. This decision support will make maintenance efforts selective and fact-based while enabling faster decisions. Most importantly, it clearly brings the productivity objective to the maintenance organisation.

4.3.4 Answer to RQ1 and connection to RQ2

The combined results of the two empirical studies (A and B) show major potential for increasing productivity within the manufacturing industry by improving maintenance prioritisation practices. The gaps between current industrial practice and research in maintenance were identified and these form the answer to RQ1.

RQ1: What are the gaps between current industrial practices and research in maintenance prioritisation?

The divide between industrial practice and research was identified using current-state mapping. Gaps were identified in the form of improvement potential. Firstly, the maintenance improvement potential:

- *The OEE of machines in manufacturing companies was found to average 51.5 percent, whereas world-class figures are expected to be 85 percent.*
- *The traditional objective of maintenance is maximising availability, with a predominantly reactive approach to maintenance.*
- *The availability component (avg. 78.9 percent), which the maintenance organisation assumes responsibility for improving, does not impact the OEE figure as much as the operational efficiency component (avg. 67.1 percent). Therefore, maintenance needs a systems perspective to focus on improving operational efficiency.*

Secondly, productivity improvement potential:

- *Maintenance operations were observed being prioritised in most companies, but most companies do not set criticality levels for their machines. However, theoretical analysis shows that maintenance operations are mainly prioritised for bottleneck machines, to increase productivity.*
- *The main finding of the gap analysis was that maintenance prioritisation decisions were taken without correctly assessing machine criticality. Therefore, developing maintenance prioritisation decision support was identified as the solution to address the gap.*
- *Existing tools in companies (such as criticality classification) lack fact-based decision-making, are static and lack a systems perspective.*

Based on the answer to RQ1, data-driven machine criticality assessment was identified as the maintenance decision support needed for maintenance management to improve productivity. Specifically, the RQ1 results showed that maintenance organisations need to shift part of their focus from technical availability to operational efficiency. Naturally, the next step of the thesis was to assess, develop and validate the decision support. The results of RQ1 were therefore used as a direct input to answer the question “how can maintenance prioritisation be supported to increase productivity?” (RQ2).

4.4 Results – RQ2

The aim of RQ2 is to assess, develop and validate machine criticality assessment. Three empirical studies (C, D, and E) contributed to answering RQ2. Of the papers appended to this thesis, Study C yielded Paper IV, Study D yielded Paper V and Study E yielded Paper VI.

4.4.1 Study C – Evaluation of maintenance priorities

Study C aimed to increase system throughput by using different maintenance prioritisation methods. Its main focus was a new method of prioritisation developed by continuously monitoring buffer levels in the production system to detect throughput-critical machines. This method is an extension of the queue-length method of detecting bottleneck machines (Lawrence & Buss, 1994; Roser et al., 2003b). The method proposes continuous monitoring of buffer levels and calculates the buffer utilisation to dynamically update machine priorities (buffer utilisation = number of parts in the buffer at any given time, divided by buffer capacity). The highest priority is given to the machine subsequent to the buffer with the highest utilisation, while low priorities are given to machines subsequent to buffers with low utilisations. The method was also compared to static and dynamic bottleneck-based maintenance prioritisation, for comparing the effectiveness of the different priorities in increasing throughput. The throughput increment was calculated by comparing prioritised maintenance execution with the first-come-first-served basis of executing maintenance activities.

Table 8 presents the results of the buffer utilisation and machine states. Machines M3 to M6 and M7 to M11 were individually repaired by two different maintenance technicians. Machines M1 and M2 are not included as they were designed to be non-bottlenecks in the production system. These results are therefore separated in the table. The buffer utilisation figures in the table show which machines were bottlenecks in the system and their corresponding machine states. This comparison validates the active-period percentage method of bottleneck machine detection. The buffer utilisation (B5 is highest) and

active-period percentage (M7 is highest) both show machine M7 to be the primary bottleneck of the system between M7 and M11. However, the buffer utilisation values for machines M3 to M6 are close together, as are the machine utilisation values. Therefore, the primary bottleneck of the production line may not be between machines M3 and M6. This phenomenon suggests that buffer utilisation is an indicator of machine utilisation in a production system.

Table 8. Buffer and machine state results from the reference model.

Buffers	Utilisation %	Machine	Utilisation %	Downtime %
B2	90.0	M3	47.7	16.7
B3	91.0	M4	50.2	14.7
B4	88.9	M5	49.4	21.4
-	-	M6	50.6	19.4
B5	58.3	M7	60.4	11.5
B6	44.6	M8	52.6	19.0
B7	29.2	M9	44.1	18.3
B8	14.3	M10	24.5	0.3
B9	37.6	M11	32.7	14.6

The method was put to test in the simulation model and compared to the first-come-first-served basis of executing maintenance work orders. The prioritised simulation model produced a 3.5 percent increase in throughput. The results are also compared to the other types of prioritisation methods for increasing productivity. Figure 12 shows the throughput increment of the static priority model (active-period percentage method) and dynamic priority model (momentary bottleneck method), plus the buffer utilisation with respect to the reference model (first-come-first-served). As the graph shows, the static prioritisation increases throughput by 5 percent, but the momentary bottleneck increases by 2.2 percent. However, the new method proposed (which is also a dynamic prioritisation) improves throughput by 3.5 percent.

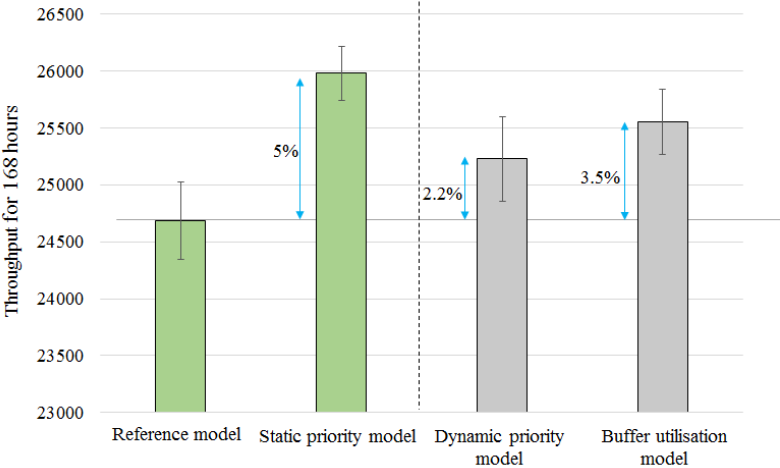


Figure 12. Comparison of different prioritisation schedules.

Due to the nature of the production system, the bottleneck shifts from time to time. Therefore, dynamic maintenance prioritisation increases throughput better than static priorities. However, to achieve the highest possible throughput improvement, it is important to identify the right level of priority-shifting. Therefore, this paper proposed the buffer utilisation approach. This approach has produced a higher throughput increment than the dynamic approach, but a lower throughput increment than the static bottleneck approach. This means that the proposed method is arguably not setting the necessary level of dynamics for shifting priorities. Nevertheless, it is an effective approach, as it improves throughput

substantially and with much less data requirement for critical machine analysis than the static and momentary bottleneck detection methods. The appended Paper IV presents the results of this study in detail.

4.4.2 Study D – Assessment of real-time machine data for developing decision support

Study D aimed to assess real-time data from machines in manufacturing companies and develop data-driven decision support. The resulting data-driven algorithm to detect bottlenecks was tested on real-time shop-floor machine data captured by MES systems. The average active period bottleneck detection method was used to develop the algorithm. The method uses machine-state data by capturing the corresponding time stamps of those states, as recorded by MES. The results of the study yielded appended Paper V of this thesis.

The algorithm requires inputs in terms of interval period (time period for bottleneck analysis), time interval (shift timing of each production day) and machine states (active and inactive periods of machines). The average active period of the machines is calculated using the following formula proposed by Roser et al. (2001).

Let $A = \{a_1, a_2, \dots, a_{n-3}, \dots, a_n\}$ be a set consisting of each active period duration of the machine, i , where i is the machine index. The average active period of A_i is denoted by \bar{A} and the standard deviation is denoted by σ with confidence interval of 95 percent.

$$\bar{A} = (a_1 + a_2 + a_3 + \dots + a_{n-3} + \dots + a_n) / n \quad (1)$$

$$\sigma = \sqrt{\frac{\sum_{i=1}^{i=n} (a_i - \bar{A})^2}{n-1}} \quad (2)$$

$$CI = t_{\alpha/2} \frac{\sigma}{\sqrt{n}} \quad (3)$$

Based on the data requirement, the step-by-step procedure of the algorithm is as follows:

- Step 1: specify time period for which the calculation is to be made (specification of d and D).
- Step 2: specify shift timings of the day (specification of t and T).
- Step 3: classify states of the machine in terms of active and inactive states
- Step 4: If $d \leq D$, then check whether $t \leq T$
- Step 5: check whether the machine is active at the time instant t .
- Step 6: store active periods in the matrix.
- Step 7: continue until $t > T$ and $d > D$.
- Step 8: calculate mean active period according to eqn. (1)
- Step 9: calculate standard deviation according to eqn. (2)
- Step 10: calculate confidence interval at 95% according to eqn. (3)
- Step 11: carry out Steps 3 to 10 for all machines and compare the results.

Where:

- d = start day of the period
- D = end day of the period
- t = start time instant of the production shift
- T = end time instant of the production shift
- j = increment variable for time instant
- n = increment variable for the number elements in the set
- $\{a\}$ = active period set; ($a_1, a_2, a_3, a_4, \dots$)

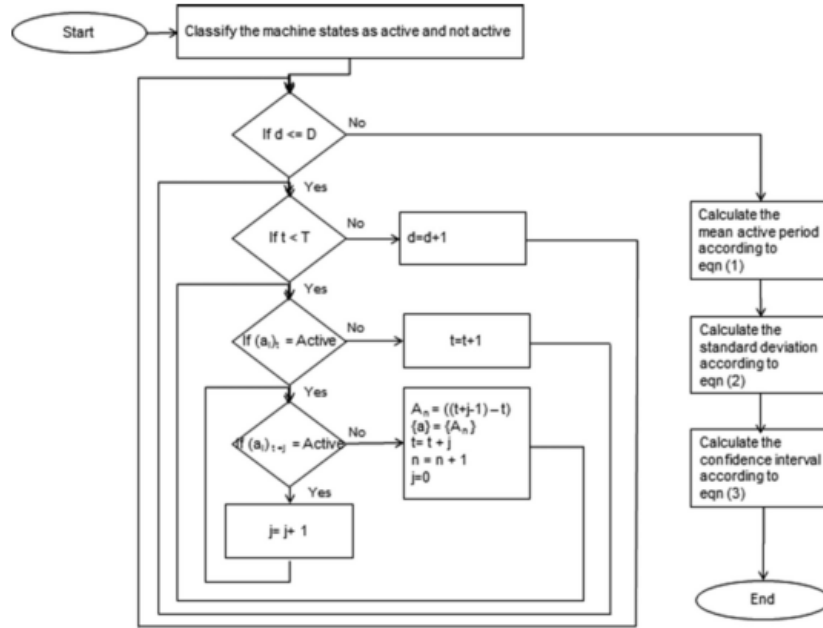


Figure 13. Flow-chart of the data-driven average active period algorithm.

The proposed algorithm was tested on real-time MES data from an industrial use case. There are 17 machines, M1 to M17, in the chosen production line with buffers in-between. The testing phase consists of: (i) data preparation, (ii) modelling and (iii) evaluation. Firstly, MES data was collected for 44 scheduled production days; 748 production hours in total. The MES data, in the form of time stamps, were cleaned for overlaps. Secondly, the modelling was conducted using the developed algorithm. The machine states were classified as either “active” or “inactive”. When the proposed algorithm was applied to the classified machine states, the average active period of each machine with a 95% confidence interval was revealed, as shown in Figure 14. Lastly, the bottleneck machines are evaluated based on the modelling. As the figure shows, machine M17 has the largest average active period across all machines but the confidence interval overlaps with machine M2 (approx. 3.6 percent overlap). This indicates that machines M2 and M17 combine to form a group of primary bottlenecks for the chosen period, as a single primary bottleneck cannot be identified. Appended Paper V presents the results of this study in detail.

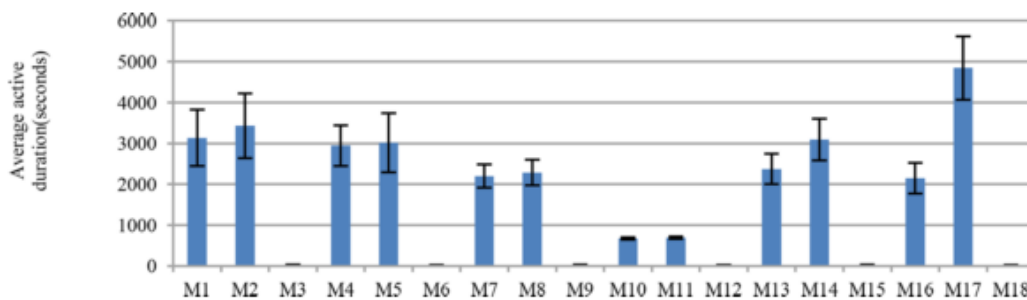


Figure 14. Average active period duration of machines.

4.4.3 Study E – Development and validation of data-driven machine criticality assessment

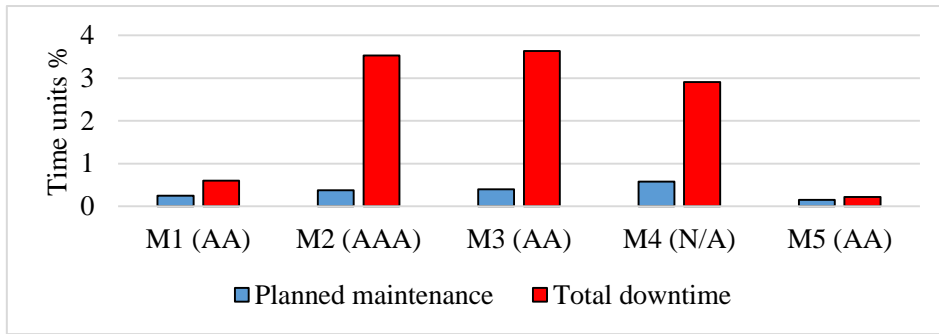
Study E aimed to develop and validate a framework for data-driven machine criticality assessment. A multiple case study methodology was used in this study, to develop and validate the framework in an industrial setting. Four empirical cases were chosen and data on their maintenance plans, criticality classifications and machine states was gathered for analysis. A case-level analysis and within-case analysis were conducted, to develop a generic framework for assessing criticality. A simulation study

(to validate the proposed framework) and an interview study (to evaluate the overall results) were also then conducted within each case. Data from the CMMS and MES systems was used in the study, for the framework development. Appended Paper VI was written based on the study outcomes. A summary of the case study results appears below. For detailed results of the analysis, see appended Paper VI.

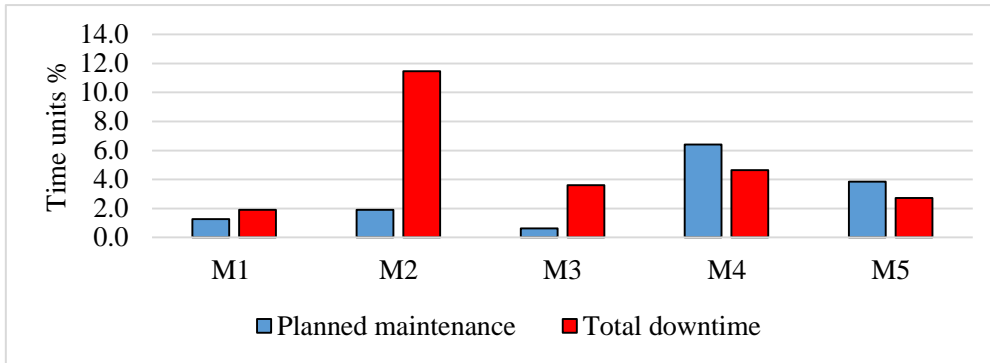
Case study results

Firstly, maintenance data from the CMMS system was analysed to evaluate maintenance planning practices and their correlation to the classification. A summary of the four cases is presented in Figure 15. In all cases, the amount of PM activities performed for the chosen timespan differed across machines, but the preventive maintenance plan was the same for all of them. The amount of planned PM was apparently the same for all machines considered, across the entire PM cycle. On the other hand, total machine downtime was not the same across all machines and showed considerable variation. The amount of PM conducted on a machine also had no impact on the amount of machine downtime.

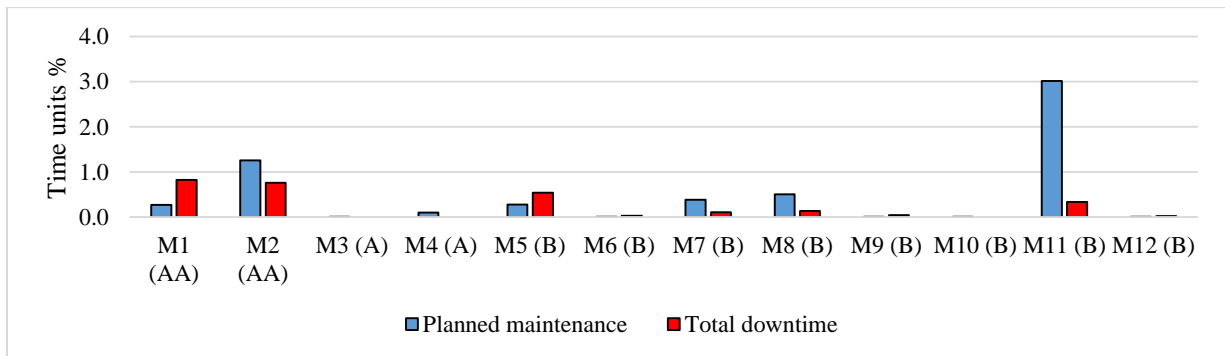
Case A had a criticality classification which in this case used classes AAA, AA, A, B and C. The classes corresponding to the machine chosen for analysis can be seen next to the machine names in Figure 15 (a). With the exception of machine M4, which was not classified, all machines were classified as having high criticality levels. Neither the PM plans nor total downtimes had any correlation to the machine criticality classes. Case B used a prioritisation classification to classify machines and all machines in the chosen production line had the highest priority. Specifically, machines M4 and M5 spent more time on PM but had less total downtime (Figure 15 (b)). The machines in Case C were also classified for criticality by classes AA, A, B, and C. Unlike Case A, not all machines were classified as highly critical. Figure 15 (c) shows that machines M1 and M2 are classified as AA, M3 and M4 are classified A and the rest of the machines are classified B. In this case, several machines spent more time on PM stops than machine downtime. Despite having a criticality classification, Case D was not used for any maintenance-related activities. Like the previous case, many machines spent more time on planned maintenance stops than machine downtime (Figure 15 (d)).



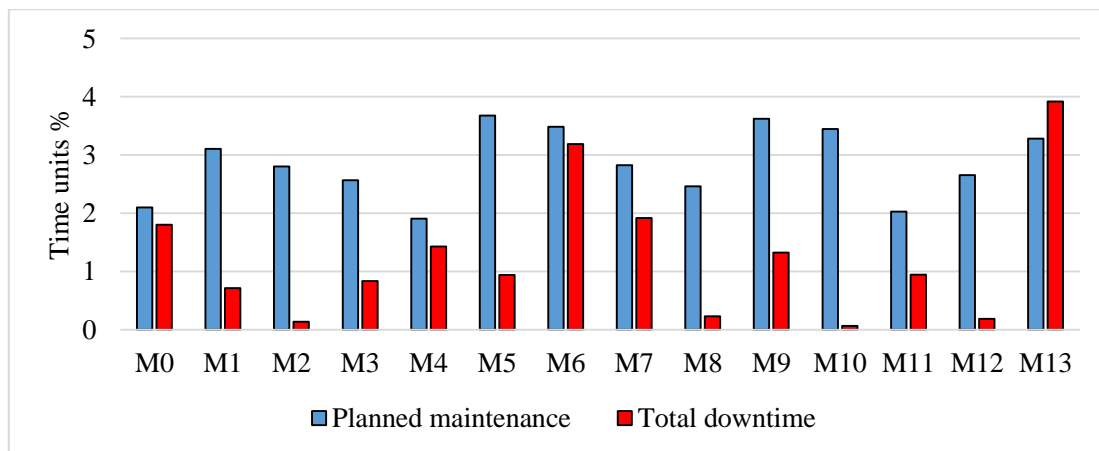
(a) Case A.



(b) Case B



(c) Case C.



(d) Case D.

Figure 15. Summary of CMMS data analysis of industrial cases.

Secondly, the MES data was used to analyse the bottleneck machines in the chosen production line of each case. Case A did not have automated data collection, so real-time MES was not available. Instead, bottleneck analysis was conducted by using the product variants' data and cycle-time data plus the maintenance data from CMMS. The results are presented in Table 9, which shows that machine M1 has the highest active period. This represents the primary bottleneck for the machine in question. However, a comparison with the active periods of other machines shows M3's active period to be as high as M1's. Hence, the grey-shaded lines in the table indicate probable bottleneck machines. Although M1 is the primary bottleneck, examining the total downtime of the machines shows that M1 is actually a cycle-time bottleneck, whereas M3 has a much higher total downtime stop.

Table 9. Bottleneck analysis of Case A.

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

Machine data from Cases B, C, and D had MES was used for bottleneck analysis and diagnostics statistics were also prepared. The results of all three cases are summarised in Table 10. The machines with the highest active period were the bottleneck machines; M2 in Case B, M2 in Case C and M6 in Case D. A group of bottlenecks was also identified from the diagnostics analysis. A T-test value was used at 95% confidence interval to find the active period overlap, which indicates probable bottlenecks. The grey boxes show the probable bottlenecks in each case. The error percentages (machine downtime from the MES data and total machine downtime from CMMS) were compared in Cases B, C and D on the group of bottleneck machines. It was observed that in Cases B and D, the MES data showed more machine downtime than the CMMS data. In case C, where all machines had low total downtime, the MES and CMMS data did not vary greatly.

Table 10: Summary of the bottleneck analysis results (Cases B, C, and D)

Descriptive Statistics				Diagnostics Statistics			
Active states as a % of active time							
Industrial Case B							
Machine	Active period (%)	Standard error (%)	T-test value	Producing (%)	Error (%)	Part changing (%)	Others (%)
M1	52.47	0.84	11.19				
M2	66.41	1.1		72.4	26.5	-	1.1
M3	42.76	0.82	20.92				
M4	64.19	0.99	-0.73	87.1	11.3	-	1.5
M5	60.04	1.12	3.24				
Industrial Case C							
M1	93.3	1.22	-1.62	94.8	1.1	2.9	1.2
M2	94.31	0.57		94.8	0.5	3.1	1.6
M3	92.21	1.1	-0.43	94.8	0.8	3.6	0.9
M4	93.04	0.69	-0.93	94.5	0.5	3.1	2
M5	86.11	1.87	5.14				
M6	86.77	1.13	4.99				
M7	82.08	0.85	9.89				
M8	81.35	0.86	10.62				
M9	86.38	1.13	5.37				
M10	85.09	1.53	6.39				
M11	85.82	1.25	5.85				
M12	88.77	1.22	2.92				
Industrial Case D							
M1	74.38	0.65	7.44				
M2	72.66	0.64	9.6				
M3	75.36	0.55	6.91				
M4	72.75	0.57	10.24				
M5	69.88	0.65	13.02				
M6	80.41	0.49	-	88.41	11.59	-	-
M7	78.22	0.54	3.01				
M8	75.03	0.68	6.44				
M9	80.28	0.46	0.2	89.79	10.21	-	-
M10	76.69	0.49	5.39				
M11	73.24	0.6	9.29				
M12	65.28	0.71	17.57				
M13	61	0.49	28.15				

Cross-case analysis

The individual case study results so far were analysed cross-case to identify similarities and differences between them. The analysis showed more similarities than differences in the way the study companies managed maintenance (Table 11). The main similarities included: standard PM packages for all machines; forced production stop of entire line to carry out PM activities; lack of use of the classification tool for planning; experience-based RM work order prioritisation; CMMS data providing lower machine downtime than MES data. Other than the data format in the MES system, the differences were not significant.

Table 11. Cross-case analysis results.

Similarities
<ul style="list-style-type: none">• Same PM activities across all machines during one cycle. Calendar-based scheduling.• Hardly any connection between criticality classification and maintenance planning, including PM and RM.• Repair activities random or prioritised on shop floor according to experience.• Many cases showed multiple machines end up being classified as high.• Total downtime for the bottleneck machines were high.• No match between downtime in CMMS data and the machine stop time in MES data. MES data showed more machine stop time.• Maintenance data collection mostly not automated. Maintenance work orders were entered manually in CMMS systems.• Maintenance data describes type of failure and root cause (if available), whereas MES data only has time stamps of machine states.
Differences
<ul style="list-style-type: none">• Active periods of machines differed between the cases. Cases A, B and D had much lower active periods for their machines than Case C.• Case C had much less total downtime across machines compared to other cases.• MES data formats differed between the cases.

Results of simulation and interview study

Simulation studies and interview studies were used to validate the framework that had been developed. In each case, the production lines were modelled in a simulation environment. Two maintenance approaches were employed: (i) industrial practice of maintenance management, with PM executed during forced production stops and RM executed on a first-come-first-served basis and (ii) proposed data-driven decision support, in which PM was during MOWs and RM was based on bottleneck prioritisation. The results of the simulation showed (Figure 16) that production line throughput increased substantially when maintenance decisions were based on data-driven machine criticality assessments.

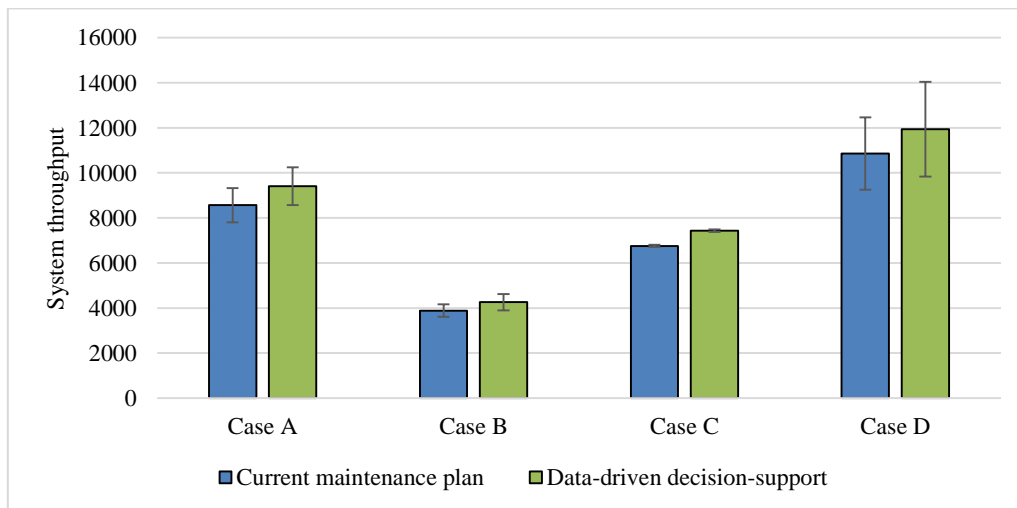


Figure 16. Results of the simulation experiments for all cases.

A focus group interview study was conducted within each case to evaluate the results and proposed framework. Once the results had been presented to the participants, an open-ended questionnaire was used for data collection. The interview data was then analysed as a cross-case analysis, with four major themes emerging from it. The results are presented in Figure 16. The themes provided generalised problems in maintenance planning and data quality. Significantly, the proposed framework was greeted with a largely positive response. The results of this study are presented in detail in appended Paper VI.

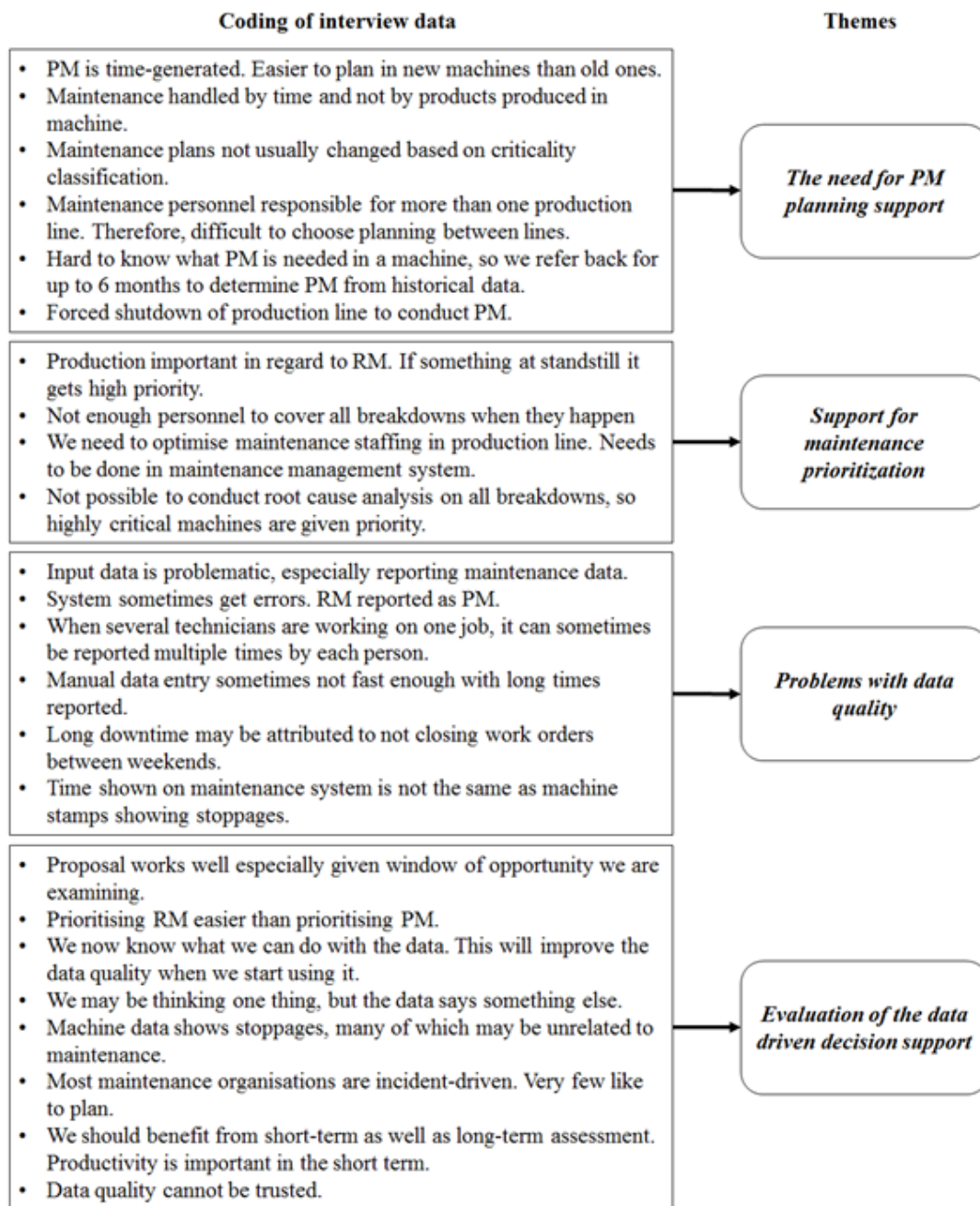


Figure 17. Interview data analysis.

4.5 Synthesis of RQ2 results

RQ1 findings were used as direct input to answer RQ2. In turn, the RQ2 results were gathered using three empirical studies to assess, develop and validate decision support for maintenance prioritisation, with the aim of increasing productivity. The studies evaluated the different maintenance prioritisation approaches, assessed real-time industrial data for developing decision support and provided a framework for data-driven machine criticality assessment. This section discusses and synthesises the results in answer to RQ2.

4.5.1 Importance of maintenance prioritisation

The findings in Study C assess different maintenance priorities and provide quantitative proof (significant throughput increment when bottlenecks are prioritised) for maintenance prioritisation. They showed that, in comparison with executing work orders on a first-come-first-served basis, production line throughput increased when repair work orders for bottleneck machines were prioritised (including

different prioritisation methods). Obviously, the percentage improvement will vary according to different circumstances (different failure rates, production layouts and so on). Previous research has also shown that maintenance prioritisation increases throughput (Li & Ni, 2009; Li et al., 2009; Wedel et al., 2016). There are several established methods for detecting bottleneck machines, such as the active period method (Roser et al., 2003b), longest queue method (Lawrence & Buss, 1994), inter-departure time variance (Betterton & Silver, 2012) and turning point method (Li, Chang & Ni, 2009). Similarly, in Paper IV three different types of bottleneck detection method were used: active-period percentage (static), momentary bottleneck detection using active period (dynamic) and buffer utilisation (dynamic)-based bottleneck detection. All these methods increased throughput. Dynamic prioritisation can increase system throughput even more than static prioritisation (Li et al., 2009; Langer et al., 2010). The author concurs with the literature on dynamic prioritisation, despite the findings of Paper IV. These show the throughput increment to be lower when momentary bottleneck prioritisation was used instead of static prioritisation. The rationale behind the comparatively low increase was due to the timeframe for changing machine priorities. By definition, momentary bottleneck detection deals with rapid changes in bottlenecks across short time intervals. These short changeover times make executing maintenance work orders difficult. Additional studies are therefore needed so that the optimal timeframe for dynamic prioritisation can be identified. Regardless of the varying results of different prioritisation methods, throughput-criticality (bottleneck)-based maintenance prioritisation will increase system productivity. However, identifying the throughput-critical machine is not easy.

The findings in RQ1 showed that maintenance organisations do not work with bottleneck detection and are still prioritising maintenance. Hence, it is interesting to know what happens when machines are wrongly prioritised. Additional simulation experiments were conducted, using the same industrial use case but purposely choosing wrong machine priorities (prioritising a non-bottleneck machine and deprioritising a bottleneck machine) to determine the most adverse effect. It was identified that system throughput went even lower than for first-come-first-served maintenance. Maintenance decisions on the shop floor are made based on the experience of maintenance technicians (Guo et al., 2013; Yang et al., 2007). Additionally, it was found that hardly any kind of data was used for prioritisation decisions. This practice is very risky and manufacturing companies may already be compromising their productivity just by choosing to execute the wrong repair first. Indeed, to avoid lost productivity, they might be better off without any type of maintenance prioritisation.

Consequently, the next question that needs answering is: is maintenance prioritisation always relevant? The results of Part II of Study A have answered this with a resounding “yes”. The answer came by varying the failure rate of machines (see Figure 10 in Section 4.1). Maintenance prioritisation is irrelevant in the case of extremely high failure rates, as the system becomes completely unreliable or at extremely low failure rates, because the system becomes highly reliable. Although an extremely low failure rate is desirable, more often than not companies will end up falling between extremely low and extremely high failure rates. It is in these situations that maintenance prioritisation based on throughput-critical machines has always increased throughput more than would be the case with a first-come-first-served work order.

4.5.2 Machine criticality assessment framework

It is evident that machine criticality assessment is desirable, as prioritising maintenance can increase productivity. However, the wrong priorities can potentially reduce it. Hence, maintenance prioritisation decisions need to be based on facts. Traditional bottleneck detection methods are primarily simulation-based (Lawrence & Buss, 1994; Roser et al., 2003b; Betterton & Silver, 2012). Although simulation modelling can provide reliable bottleneck detection, it requires more time and additional modelling efforts are needed to update it each time. A data-driven approach using data analytics can solve the problems of bringing about the necessary fact-based, faster and dynamic decision support for maintenance prioritisation. To assess the use of industrial machine data (from MES systems), machine event logs were gathered over a set period of time. Paper V proposed a data-driven algorithm for

bottleneck detection, using the average active period. That algorithm was applied to the collected data; it directly identified the system's bottleneck machine with no simulation model needed. The proposed algorithm is also scalable in time (rolling time window) and thus dynamic updates on bottleneck machines can be obtained. Due to this scalability, PM and improvement activities can be planned and not just RM ones. Another advantage is that the data (machine states) for such an algorithm are readily available in modern companies and an algorithm such as this can be automated using existing MES systems.

Maintenance prioritisation in literature generally leans towards RM work order prioritisation based on short-term bottleneck mitigation, such as Langer et al., 2010). Whereas, only a few articles discuss PM prioritisation. However, this thesis considers RM, PM and improvements for maintenance prioritisation. PM planning is generally for long-term mitigation, but PM scheduling involves short-term decisions. There may also be several types of PM designed and planned for a single machine, to prevent a specific type of failure. So, PM planning also needs fact-based decision support, for scheduling and for choosing PM types. The results of RQ1 showed the problems in planning due to the use of multiple factors in criticality assessment. From the case study results in Paper VI, PM was found to be planned according to a calendar and then conducted during forced production shutdown. Moreover, a generic PM plan was followed for all the machines. This makes it hard to know what the machine needs and whether the necessary PM was carried out. Even PM planning needs to be approached from a systems perspective, so that critical machines are improved first and to a better standard. This may also lead to improved productivity.

The PM and RM practices in the corporate cases also highlighted additional information about the problems faced, especially in the decision-making process. Firstly, the amount of time spent on downtime had little connection to planned PM activities. Secondly, the companies' criticality/prioritisation classifications were not used for any maintenance planning activities. Thirdly, maintenance organisations used CMMS data for maintenance-related analysis and MES data was not used. The results of two out of the four cases showed the total stop time in the MES system to be higher than the total downtime in the CMMS system. It was also observed that maintenance data collection was not automated like MES data collection. This implies that the MES data represented the state of machines in production much better than the CMMS data. Lastly, a group of bottlenecks was detected in the MES data. Obviously, maintenance organisations had not used that information, so they were treated no differently. Thus, subjective decisions were made about PM and RM activities but with no productivity goal. This was also observed in the results of Study B.

It was therefore important that decision support development should address the above problems. In particular, the components of data-driven criticality assessment for the development were taken into consideration (see Section 4.3.3). In addition, the design factors of the criticality assessment were identified in Study E. On studying current maintenance practice and existing classification tools, (i) data availability and data analysis were identified as important factors on the analytics part and (ii) choosing the right maintenance decision, its time-frame and type of maintenance effort were identified as the main factors in decision making part. By carefully addressing the gaps identified in RQ1 and using the design factors, a generic data-driven machine criticality assessment framework was developed. This framework provides guidelines for maintenance organisations to work with machine criticality assessment and use it to prioritise tactical and operational maintenance activities. The framework, presented in Figure 18, consists two parts: (i) the analytics part provides guidelines on the methods of assessment and data required for assessment and (ii) the decision-making part provides guidelines for the list of maintenance actions in the assessment which can be supported. The criticality assessment process has a clear purpose: to support maintenance decisions which bring about a *productivity increase*.

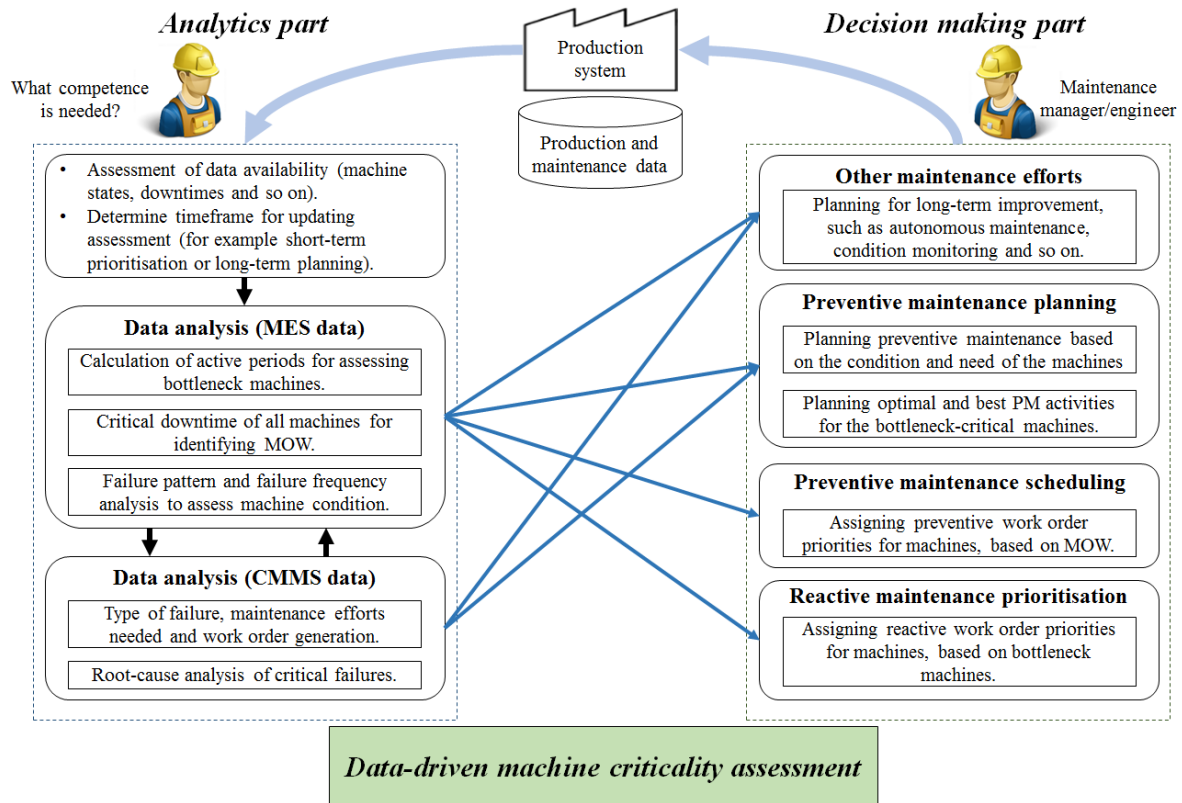


Figure 18. Data-driven machine criticality assessment framework.

The analytics part starts off by assessing the data availability and determining the timeframe for analysis. The timeframe is determined to obtain the level of dynamic assessment (*dynamic approach*). For example, prioritising short-term repair work will need criticality to be assessed in short time intervals, whereas planning PM for a machine needs a longer time interval for criticality assessment. As seen from the findings of Studies B, C and D, manufacturing companies capture data from their machines. Decision-making data is crucial to the framework (*fact-based decisions*) and MES data, in particular, is available in most companies. However, it was observed that this data is not used by maintenance organisations. The framework proposes gathering MES data as well as the traditional CMMS data (which the maintenance organisations do use). This is a novel approach in assessing machine criticality assessment, using both MES data and CMMS data for assessment. By nature, MES data provides the time stamps for machine states, in other words, machine data in context of other machines (*systems perspective*). Once the data is gathered, the actual data analysis needs to begin.

The guidelines show that MES data should be used to assess active periods, critical downtime and the failure pattern and frequency of machines. The longest active period of the machines indicates the bottlenecks in the system (Roser et al., 2001). The critical downtime of each machine in the system provides maintenance windows of opportunity (Ni et al., 2015; Gu et al., 2015). The failure pattern and frequency can be coupled with the CMMS data analysis to learn more about the machine-level information. The CMMS data can provide information on the type of failures, maintenance efforts needed, work order generation and root causes. The analytical part ensures the assessment not only identifies critical machines but also gives the reason for their criticality.

Analysis is only one half of the decision support tool. The tool should also determine which decisions can be supported, so the decision-making half provides the list of maintenance decisions that the assessment can support (Figure 18). The findings showed that companies do not trust their classification tools as a basis for their maintenance decisions. However, the proposed framework provides facts about the machines which add certainty to maintenance decisions. The maintenance prioritisation decisions

that the framework can support include: machine priorities for reactive maintenance work orders, based on bottleneck machines; scheduling PM activities on MOWs, instead of forced production system shutdowns; PM plans tailored to the needs of each machine, instead of generic PM plans for all machines. Other types of maintenance efforts can also be prioritised. For example, investment in autonomous maintenance (or plan-condition monitoring and the like) can be made in the right critical machine. The decision support process is cyclic in nature. In other words, machines must be monitored continuously and their criticalities re-assessed dynamically alongside changes in production systems.

Naturally, the most important part of the framework is the human decision-maker. The data-driven criticality assessment enhances the decision-making quality of maintenance engineers and managers, so that they can run an effective production system (Santana, 1995). It is clear that the stakeholders in the decision-making part are maintenance engineers and managers. However, the identity of the stakeholders in the analytics part is uncertain. The current maintenance organisations may lack the necessary competences to execute the analytics. Studies are needed to identify and analyse the competence gap (Antosz, 2018; Bokrantz et al., 2017). Nevertheless, by using the proposed data-driven approach, maintenance organisations can move from focusing only on the technical availability of machines (machine-level improvement) to focusing on their availability and operational efficiency (system-level improvement). Once both are improved, a well-performing production system can be achieved, leading to world-class OEE figures of 85 percent.

4.5.3 Validation of the framework

The next step in the development process is validation. Although the criticality assessment that has been developed is rooted in an industrial set-up, it is important to validate the tool and achieve generalisability and credibility. A simulation study and interview study were conducted to validate the framework that had been developed. The simulation model was used in the case studies of Study E, using real-time data (machine as well as maintenance data). Once the RM (for bottlenecks) and PM (scheduling during MOWs) had been prioritised, the findings showed increased productivity compared to the first-come-first-served basis of executing maintenance work orders. The simulation results were further presented to selected participants in each case company, for individual evaluation. The main results of the interview study were: additional reasons for the current maintenance management practices, problems with data quality, evaluations of the developed framework and productivity improvement potential based on their own data. Overall, the data-driven tool was given positive feedback and a potential industrial application was agreed.

However, criticisms of the proposed maintenance management framework were also identified. Firstly, senior management and the production organisation have different requirements and expectations of the maintenance organisation. Maintenance is considered to be a support function to production, providing availability of machines (machine level) (Gits, 1992). It was not perceived as supporting and aiding, or making a contribution to, productivity (systems level) (Roy et al., 2016; Helu & Weiss 2016). An organisation change of attitude towards maintenance (and making productivity a maintenance goal) is required going forward. Secondly, data quality problems hindered the application of such a tool (which is heavily rooted in data). Extensive research is being conducted to ensure data quality, because good data can dramatically increase the size and scope of improvements in companies (Wang et al., 1995; Batini et al., 2009). Additionally, different organisations are responsible for different data. The author proposes that the best way to ensure data quality is to start working with existing data and collaborate by data-sharing, with the ultimate goal of improving data quality.

The synergy with production shown in Study A is not the ideal synergy that the company needs. However, when maintenance organisations start to provide fact-based decisions and contribute to increased productivity, then true synergy between maintenance and production will be achieved. This could easily lead to: mutual systems-level maintenance and production planning; better sharing of data and decisions within organisations; increased but cost-effective productivity. Joint production and maintenance planning is important high levels of productivity and performance in production systems

are to be upheld (Wong et al., 2013). The validation of the decision support that has been developed provides maintenance organisations with opportunities for smart maintenance work. This can enable digitalised manufacturing to function efficiently and become highly productive.

4.5.4 Answer to RQ2

The findings of Studies C, D and E were combined to assess, develop and validate maintenance prioritisation decision support to increase productivity. This formed the answer for RQ2, as summarised below.

RQ2: How can maintenance prioritisation be supported to increase productivity?

Assessment of maintenance priorities and real-time data:

- *Prioritising maintenance to critical machines increases productivity. This finding was exemplified in several industrial use-cases by prioritising maintenance work orders to the bottleneck machines. For example in one case, a productivity increase of 5 percent was achieved.*
- *Productivity increase was achieved without any additional financial investments to the machines in the production system.*
- *The results showed that currently available real-time machine data is already enough to develop decision support tools that can support maintenance prioritisation decisions.*

Development and validation of decision support:

- *Facts-based maintenance decision leads to productivity increases, so a data-driven machine criticality assessment framework has been developed in this thesis for supporting maintenance prioritisation decisions.*
- *The framework provides data analytics guidelines and a list of maintenance decisions that can be made. On applying the proposed framework, maintenance organisations will improve not only the availability but also the operational efficiency of their machines, which will lead to overall production system improvement.*
- *The framework that was developed fulfilled the data-driven criticality assessment principles: (i) systems perspective, (ii) dynamic, (iii) fact-based and (iv) productivity focus.*

The conclusion is that facts-based maintenance prioritisation decisions can increase productivity. Maintenance prioritisation decisions can become factual when supported by data-driven machine criticality assessment.

5 OVERALL DISCUSSION

This chapter synthesises the answers to RQ1 and RQ2, to explain how maintenance was connected to productivity. It also presents discussions on the scientific and industrial contributions, methodology and future challenges.

5.1 Maintenance prioritisation for swift, even flow

This thesis has developed a data-driven machine criticality framework for supporting maintenance prioritisation decisions. The main goal of this prioritisation was to pursue increased productivity. The results achieved do not require improvements to the method (M) or performance (P), but only in the utilisation (U) of the productivity formula (Almström & Kinnander, 2011). The productivity potential shown in the results of this thesis are not the only potential; obviously, improving the M and P factors could increase that even further. However, the main takeaway is that productivity can be improved by controlling machine breakdowns and maintenance activities.

The pursuit of productivity is the reason for innovation in production systems, especially through swift, even flow (Schmenner, 2015). The principle goal of achieving productivity gains is to reduce variation in production, because increased variability will always degrade the performance of a production system (Hopp & Spearman, 1996). Machine downtime and preventive maintenance time are important bad variations in a production system. Although machines spend a small percentage of their time on downtime and planned maintenance, these have serious effects on the production system. Of course, the costs associated with maintenance are high (Muthu et al., 2000). However, these small variations (machine failures) in a single machine have the potential to cause ripple effects across other machines (as idling losses) in the production line. The compounding idling losses of multiple machine failures cause even greater variations in production flow and eventually leads to reduced productivity. Prioritising maintenance activities based on machine criticality allows these variations to be reduced. This reduction in variation is explained in two scenarios: (i) RM prioritisation and (ii) PM windows of opportunity.

First scenario. Machine idling losses are the unutilised machine states during which a machine is either blocked by upstream machines or starved by downstream ones. Therefore, idling losses represent hidden potential for productivity improvement. The theory of constraints says that the machine with the lowest idling losses (the one impeding the entire production line) is the bottleneck machine (Goldratt & Cox, 1992). To exploit the idling losses, throughput-critical machines were identified and maintenance activities prioritised (the results of Studies A, C and E used this approach in simulation experiments). Basically, this process controls the bottleneck in the system. Firstly, the reduction in variation is explained for RM work order priorities. Figure 19 shows variations in machine idling losses in the left-hand machine states bar chart, while the right-hand machine states bar chart shows these states after prioritisation. For simplicity and ease of understanding, the figure shows only three machines in a production line.

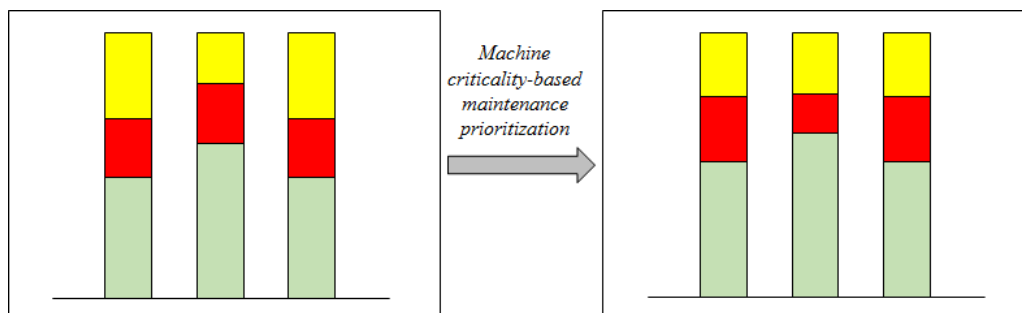


Figure 19. Controlling variations through RM prioritisation.

The centre machine in the left-hand bar chart is the bottleneck machine, because it has the lowest idling losses (or highest active period). Naturally, when maintenance work orders are prioritised for this

machine, the mean downtime of the machine (red bar) reduced. In other words, the maintenance technician did not wait for a repair when the bottleneck machine failed. Consequently, because bottleneck machine have higher priority, the non-bottleneck machines must wait longer for repairs. Still, regardless of the varying changes in mean downtimes, the utilisation of the machines (green bar) has increased. These changes can be viewed in the right-hand bar chart. This increase in machine utilisation makes the production flow swiftly and evenly through the production line. Additionally, it can be seen from the figure that idling losses (yellow bars) have also changed. The non-bottlenecks have reduced their idling losses while the bottleneck machine increased theirs. This means that machine criticality has reduced upon maintenance prioritisation.

Second scenario. The variation reduction in production flow is explained for PM scheduling. Figure 20 represents the maintenance windows of opportunity available during planned production time. Like the previous graph, a three-machine production line is shown, with the added addition of PM time (blue bar). Currently, PM activities are conducted outside production hours (forced entire production stop) and are scheduled periodically, based on calendar time. There are active and passive maintenance windows of opportunity during production (Ni et al., 2015; Gu et al., 2015). The windows of opportunity lie in the machines' idling losses. As represented in the bar chart, the PM planning needs to identify the critical downtime of each machine and allocate PM activities during the machines' idling time. This ensures the bottleneck machines are not affected for production. The figure shows this by moving the PM time (blue bar) to the machine idling time (yellow bar). Scheduling PM in MOWs can also improve production flow by enabling swiftness and evenness, thus increasing productivity.

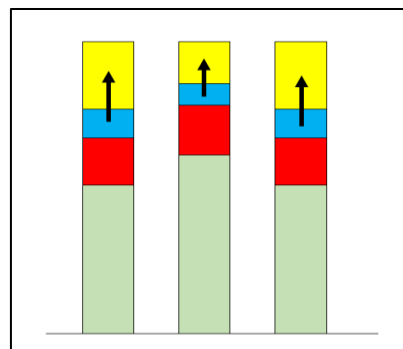


Figure 20. Controlling variations through PM opportunity windows.

To truly reap the benefits of the swift, even flow afforded by maintenance prioritisation requires fact-based maintenance decisions and a focus on productivity. The findings of this thesis have shown that most maintenance organisations have neither. Manufacturing companies therefore have their work cut out to improve the work procedures and increase productivity. The outcome of the thesis has shown that manufacturing companies can solve these challenges by using the data-driven decision support that has been developed. The solutions have also been provided with current maintenance and production data.

5.2 Connecting maintenance to productivity

Traditional maintenance management is considered a support function of production (Gits, 1992). Specifically, maintenance has been focused on solving single-machine problems (Helu & Weiss, 2016; Roy et al., 2016), providing machine availability and ensuring machine reliability. The conclusions of this thesis challenge that traditional view of maintenance. Study A pointed out that, because of the single-loop problem, machines are not utilised to their maximum capacity, (for example, low OEE figures of 51.5 percent were noted). In particular, maintenance management is not involved in improving the operational efficiency of machines (67.1 percent); it is only involved in improving machine availability (78.9 percent). One of the factors used to calculate operational efficiency is the idling losses of machines (the ripple effect of machine failures). The ripple effect of machines in complex production is often overlooked, especially by maintenance organisations. This argument, combined with the

arguable overload of maintenance work in manufacturing companies, has made maintenance prioritisation important and inevitable for achieving production system efficiency (Ni & Jin, 2012).

The results of RQ1 indicated that maintenance prioritisation was mostly conducted at shop-floor level, either by operator influence or based on the experience of maintenance technicians. The RQ2 results highlighted how having the wrong priorities can potentially reduce system throughput to even lower levels than with a first-come-first-served work order. Therefore, the central problem is a lack of decision support for maintenance prioritisation. Assessing machine criticality can help support maintenance prioritisation decisions (Stadnicka et al., 2014; Antosz & Ratnayake, 2016). The RQ1 and RQ2 results have lent overwhelming evidence to the fact that existing criticality assessment tools are not fact-based, are static and importantly, do not have productivity as an assessment goal. This means the existing tool is of no use to the dynamic needs of maintenance operations (Ni & Jin, 2012). Based on what was learned from Papers II and III, a dynamic, data-driven machine criticality assessment was developed in Paper VI. One of the fundamental differences between the new assessment and the existing one that companies use is the inclusion of productivity as a goal.

Including productivity as a maintenance goal is a highly necessary organisational change for smart maintenance. Initiatives such as Industry 4.0 have increased industrial digitalisation and brought about “smart factories” (Thoben et al., 2017). These initiatives have accelerated companies’ growth and set high expectations for drastic productivity improvements (Bokrantz et al., 2017). Therefore, production systems of smart factories need transformed maintenance management that focuses not only on availability (machine level) but also operational efficiency (system view). However, business and scientific literature on digitalised manufacturing hardly mentions maintenance, or limits it to increasing predictive maintenance and maintenance services (Bokrantz et al., 2017). Therefore, the conclusions of this thesis are vital in achieving the above-mentioned drastic expectations. The bottom-line of this thesis is that fact-based maintenance decisions are crucial to increasing productivity.

5.3 Data-driven decision support

Maintenance decision-making means assessing and selecting the most efficient maintenance approach for companies (Al-Najjar & Alsyouf, 2003). A framework for machine criticality assessment has been developed (Figure 18), through a synthesis of the results achieved in this thesis. From these findings, it can be said that companies have so far invested in assessing criticality mostly in terms of safety, environment and quality. Moreover, the approach to multiple factors thus far has been static and subjective. These criteria are probably less dynamic, but the author argues that they are data-critical. The framework suggests that productivity should be afforded greater importance than other factors. Assessing criticality in terms of productivity data definitely assumes major importance; this also needs updating.

A maintenance decision support system cannot afford to make erroneous decisions because this can only worsen the situation. Maintenance decision-making research has indicated that decision analysis capabilities in existing CMMSs are often missing and that the data collected in these systems is under-utilised (Rastegari & Mobin, 2016). Thus, the novel approach proposed in the framework was to use (MES) data from machine states and (CMMS) maintenance data for criticality assessment. The existing subjective approach can be transformed into a fact-based one. This data-driven, dynamic approach can lead to continuous identification of machine criticality and support maintenance decisions on the operational (PM scheduling, RM prioritisation) and tactical (maintenance improvement activities, such as autonomous maintenance) levels. By linking tactical and operational planning through all decision-making levels, world-class maintenance can be realised (Pintelon & Parodi-Herz, 2008).

Previously published literature on maintenance prioritisation has also discussed the productivity focus and bottleneck-based prioritisation (Langer et al., 2010; Li et al., 2009). The main contribution of this thesis is not in developing new methods of maintenance prioritisation, but rather studying how manufacturing companies might benefit from existing methods. Data-driven decision-making is

identified as an area of future maintenance development, as shown in the projections for future maintenance planning (Bokrantz et al., 2017). Therefore, the results of this thesis are niched to enable companies to adopt data-driven decision-making.

Clearly, the framework that has been developed comes with some limitations, one of which is problems with data. It is possible that some companies do not have the necessary type of data for this framework (as seen from Case A in Study E). Whereas, many other companies have data quality issues (other cases in Study E). Ensuring data quality is an important area for future research, as good data can dramatically increase the size and scope of improvements in companies (Batini et al., 2009). Improving data quality is a continuous process and companies should start using data for decision-making to push for higher data quality. For example, through a pilot project, companies can learn the value of using data. Even companies without data can move towards facts-based decisions through a static approach to bottleneck analysis and MOW analysis by using only the mean cycle time, MTTR and MTBF data from the machines. In such conditions, an updating criticality assessment is difficult to achieve and all analysis was manual.

However, digitalised manufacturing is in full flow and technological advancements that comes with it make automated data collection more likely. The framework serves as a platform to enable other decision-making options. Aided by data analytics and good quality data, the decisions proposed in this framework can be further used for predictive and prescriptive maintenance action as well (Karim et al., 2016). However, further research is also needed to increase the reliability and accuracy of the results achieved by data analytics.

A common misunderstanding is that digitalisation can be achieved purely through technological advancement. However, smart maintenance does not mean implementing smart tools, such as modernised ICT tools. These technological advancements may provide great opportunities (in terms of support for easier and faster decision-making, or platforms for collaboration and data sharing and so on (Monostori et al., 2016)), but it is important to use them to create highly productive and reliable production systems. There is a need for technological advancements backed up by an organisational drive to focus on problem-solving.

The results of RQ1 and RQ2 brought about the data-driven machine criticality framework. The overall results of the thesis were synthesised to show the transformation of the maintenance organisation from its current state to its desired future state, as shown in Figure 21. The figure explains the transformation (such as supporting increasing productivity and achieving cost-effectiveness) by mapping the guidelines in the framework to the principles of data-driven criticality assessment.

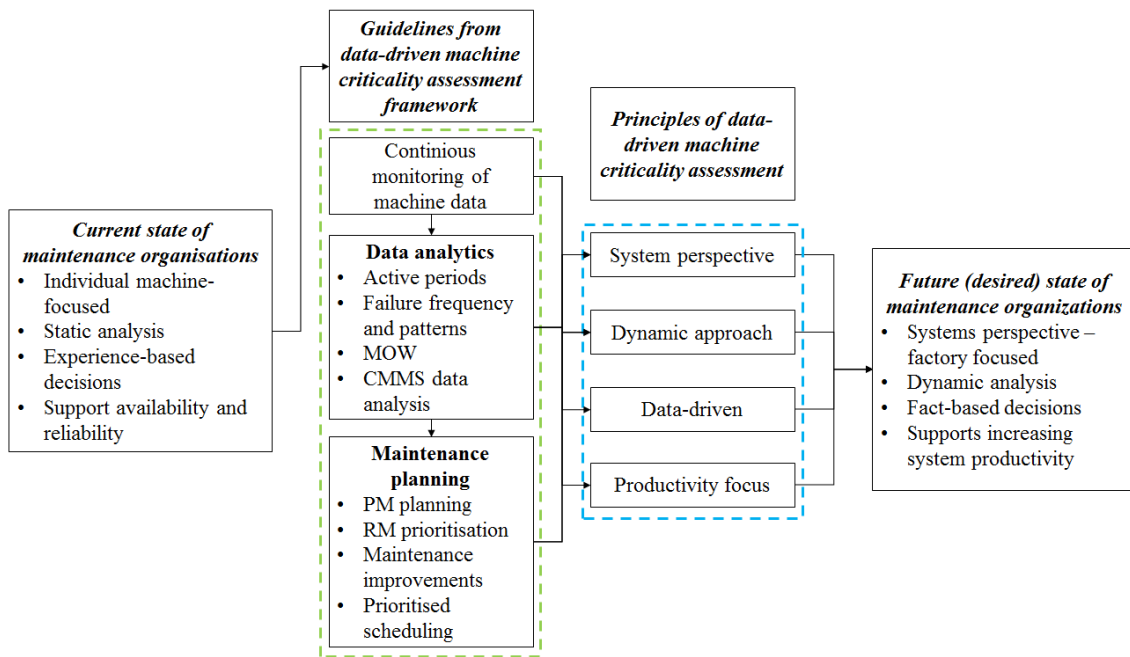


Figure 21. Synthesis of results, showing transformation of the maintenance organisation.

The framework ensured that machine criticality assessments fulfilled the principles of data-driven maintenance decision support:

- Systems perspective – shifting the focus from individual machines to system-level problems.
- Dynamic approach – machine criticality changes with time. Continuous monitoring ensures dynamically updated priorities and offsets the dynamic nature of production systems.
- Fact-based – using real-time machine (MES) data ensured the decisions would also be made in real-time. In other words, relevant and correct decisions based on the machine’s needs.
- Productivity focus – most importantly, having productivity as a maintenance goal ensures the maintenance organisation contributes to increased productivity (maximising availability as well as just the operational efficiency of machines).

5.4 Scientific and industrial contributions

This research aimed to increase practical usefulness for industrial application and research process aimed for scientific rigour. Naturally, the results of this thesis make valuable contributions to the scientific and industrial communities. The empirical data results also make this research highly relevant, an uncommon occurrence in the maintenance field (Fraser et al., 2015).

Firstly, for the research community, the results of Studies A and B (answering RQ1) address existing problems in maintenance management. The empirical findings of Paper I provide additional support for the low OEE figures in companies that had been observed for decades. The empirical findings of Papers II and III provide additional aid to the poor-quality maintenance planning and decision support (an important maintenance related-problem that researchers worldwide are trying to solve). These results are also highly pertinent because studies of machine criticality assessment is of major relevance but sparsely studied by the maintenance research community. There is a paucity of studies which adopt a holistic approach to maintenance problems. Studies C, D, and E (in answering RQ2) provide a scientific contribution in terms of identifying the principles of machine criticality assessment, usage of real-time data for maintenance planning and development of data-driven assessment. The most important contribution of this thesis is establishing the connection between maintenance and productivity. Maintenance research very rarely focuses on improving system productivity. This thesis identifies potential productivity improvements hidden within maintenance problems and provides solutions.

Secondly, the thesis provides practical industrial contributions to maintenance managers and engineers in manufacturing companies. Maintenance is an applied research field and the empirical research in this thesis attempts to solve “real-world” problems. The problems identified, solutions presented and experiments conducted were deeply rooted in industrial practices. Primarily, the results show cost-effective maintenance management methods which will improve productivity. The results of Studies A and B cover the gaps in maintenance practice. These can be used as direct input by maintenance organisations, to plan and prioritise their maintenance effectively. The results from the development of data-driven machine criticality assessment (Studies D and E) show that fact-based decision-making can be achieved by using the real-time MES and maintenance data that is already available in the companies. The solutions in the proposed framework provide guidelines for increasing productivity without additional investment in the companies’ production systems. The knowledge gained through this research work can help companies successfully transform their maintenance organisations so that they contribute directly to increased productivity and cost-effectiveness. Specifically, it can reduce the gap between maintenance theory and industrial practice.

5.5 Methodology discussion

Pursuing a PhD is a continuous learning process. The author’s worldview and research approach have enabled him to conduct research into maintenance management that pursues productivity. It has also helped enhance the quality of the research. However, due to the continuous nature of the process, the research quality was not consistent across all studies. Nevertheless, it can be confidently said that the research quality in this thesis increased constantly over the years (see Chapter 2, Figure 4 for the timeline of empirical studies and appended papers).

As a researcher who has described his worldview as pragmatic (see Section 2.1), the author believes in multiple realities given the particular time and problem (Creswell, 2013). Therefore, the ability of a pragmatic researcher is determined by trying different approaches and learning what works best in solving problems. One example is the author’s approach to simulation-based maintenance decision support during the initial years of his PhD studies. This meant that many of the initial publications centred on simulation experimentation methodologies (Study C). However, in more recent years, the author’s view of maintenance decision support changed to a data-driven approach, because this approach can provide even quicker and more accurate decisions. Mainly, these decisions can be achieved using real-time data (Studies D and E). This meant that approximations and optimisations were not needed, as the whole population was used. This learning is evidenced in the later papers, which focus more on achieving data-driven decision support for maintenance decisions.

Each study had some methodological limitations. In Study A, secondary data was collected for OEE calculations in Paper I by educating industrial participants. The participants could not be controlled in the way they reported on bottleneck machines. However, this was compensated for by the large sample size. In Paper II, four interviews were conducted; more participants might have increased the generalisability, but these interviews were only used to explain the phenomena that had been observed. Study B was conducted with a large quantity of qualitative data, but available data was a function of which companies were involved in the research project. The participating companies are all large automotive manufacturers; no small and medium-sized enterprises (SME) were included in the study. SMEs represent a large section of Swedish industry. However, care was taken to ensure the chosen cases were different from each other, to increase the quality of results. In Studies C and D, the maintenance prioritisation approach and bottleneck detection algorithm were trialled in one (Study C) and then two (Study D) industrial use-cases; more use-cases would have been desirable. Even so, the results from a smaller number use-cases were still relevant as, they verified the maintenance prioritisation methods and usability of real-time industrial data. Lastly, in Study E, the data-driven criticality assessment was validated through a simulation experiment rather than by applying it to an industrial setup. Validating the framework in an industrial setup required a level of resources not available to the author. This was

overcome by using the additional interview study. It ensured that the data analysis results, simulation results and framework were presented to the industry participants for evaluation.

Additionally, the individual limitations of each study were overcome by triangulation (Creswell, 2013). The findings were combined to increase the validity, reliability and generalisability of the results achieved. Data and method triangulation, transparency, peer debriefing of the research process and presentation of negative results (Paper IV) also helped enhance the research quality of the thesis (Creswell, 2013). The appended papers also explain their limitations and how these were overcome, in their respective methodology and methodology discussion sections.

5.6 Future research

Maintenance practice is lagging behind maintenance research and the gap between them is increasing (Bokrantz et al., 2017). Notwithstanding the productivity improvement opportunities and advancements presented in this thesis, a number of challenges await manufacturing companies and research communities in the future. These challenges all have different priorities and so this section presents the short and long-term challenges that face the research community and manufacturing companies.

5.6.1 Short-term challenges

One of the immediate challenges facing companies is the lack of maintenance planning decision support tools. Maintenance decisions are frequently not fact-based and influenced by human guesswork based on experience or ad hoc decisions. Companies need smart maintenance decision support systems to manage the dynamic maintenance needs (Ni & Jin, 2012). This thesis has provided a machine criticality decision support tool for prioritising maintenance. For such a tool to be used in practice, the availability and quality of companies' data becomes a core issue. The best way to address this is to start working with the available data and push on towards the high-quality data that is needed. Moreover, in this thesis, machine-level data analytics have also proved to be important to planning maintenance. Aside from data, maintenance needs to have productivity as its goal.

On the research front, immediate help is needed to develop and evaluate decision support systems for maintenance management. Although many maintenance management models are available, the lack of empirical research has reduced their usability (Fraser et al., 2015). As a next step, the results of this thesis (particularly, data-driven machine criticality assessment) can be used for industrial application by developing algorithms. These algorithms can use existing CMMS data to provide data-driven decision support. However, additional studies are needed to evaluate and achieve generic algorithms, irrespective of the data-types. Data analytics and machine learning can help achieve this. As a further step, PM planning can also be incorporated into the data-driven criticality assessment. Based on the outcome of the criticality assessment, individual PM packages for each machine can be worked out, depending on their criticality. However, support from component-level assessments is needed.

5.6.2 Long-term challenges

Ensuring data quality is a long-term challenge to manufacturing companies. Studies have shown that good data can dramatically increase the size and scope of improvements in companies (Wang et al., 1995; Batini et al., 2009). Therefore, working continuously with companies will help in achieving fact-based decisions that are more accurate and reliable. Specifically, the classification of machine components and its connection with machine criticality assessment needs to be addressed. This correlation can be used to address the type of maintenance (PM or improvement) needed by critical machines. Cross-functional work in companies has also been discussed for a long time. Maintenance operation is cross-functional and, hence, collaborative decision-making is particularly desirable in production organisations. Maintenance managers need to move on from their traditional technical focus and become more cross-functional professionals (Dunn, 2003). Another important long-term challenge is the competences of maintenance personnel. The data analytics part described in the framework cannot be performed by current maintenance personnel. Additionally, this thesis provides arguments for approaching the maintenance problem from a system perspective. Collaboration from outside the

companies is also desirable, as working with machine suppliers can ensure even better maintenance planning.

Data analytics and machine learning approaches have begun being used for maintenance management, so that predictive and prescriptive maintenance planning can be carried out. This offers plenty of future opportunities for maintenance research. However, sensor-level analytics and machine-level analytics need to complement each other, if they are to address maintenance needs effectively. As a continuation to the findings of this thesis, the criticality assessment can be further complimented by failure pattern assessment. The failure pattern and production planning can provide detailed knowledge of machine criticality, in terms of the type of product variants being made. This information can be used for predictive and prescriptive maintenance. Such detailed information from the data can be used for effective control of maintenance variations.

Another interesting area of future research would be to advance the findings of this thesis by applying the technological opportunities provided by CPS. The physical and engineering systems can be connected through IoT (Hermann et al., 2016; Monostori et al., 2016) and data can be collected and analysed automatically to provide decision support.

6 CONCLUSIONS

This chapter provides the key conclusions of the thesis.

The aim of the thesis was to investigate maintenance prioritisation decisions as well as develop and validate maintenance decision support that enables productivity to increase. Traditionally, maintenance is viewed as a sub-function of production, aimed at maximising availability. However, digitalised manufacturing has forced maintenance to be viewed from a broader perspective to support higher productivity and resource efficiency. In particular, maintenance should address unutilised machine states which are not usually associated with maintenance. Therefore, a transformation in maintenance organisations is needed to move from a component focus to achieving a systems perspective to solve maintenance problems. This thesis has provided data-driven decision support for maintenance prioritisation in order to connect maintenance to productivity. Two research questions guided the research in this thesis to achieve its aims. The main conclusions are summarised in Figure 22.

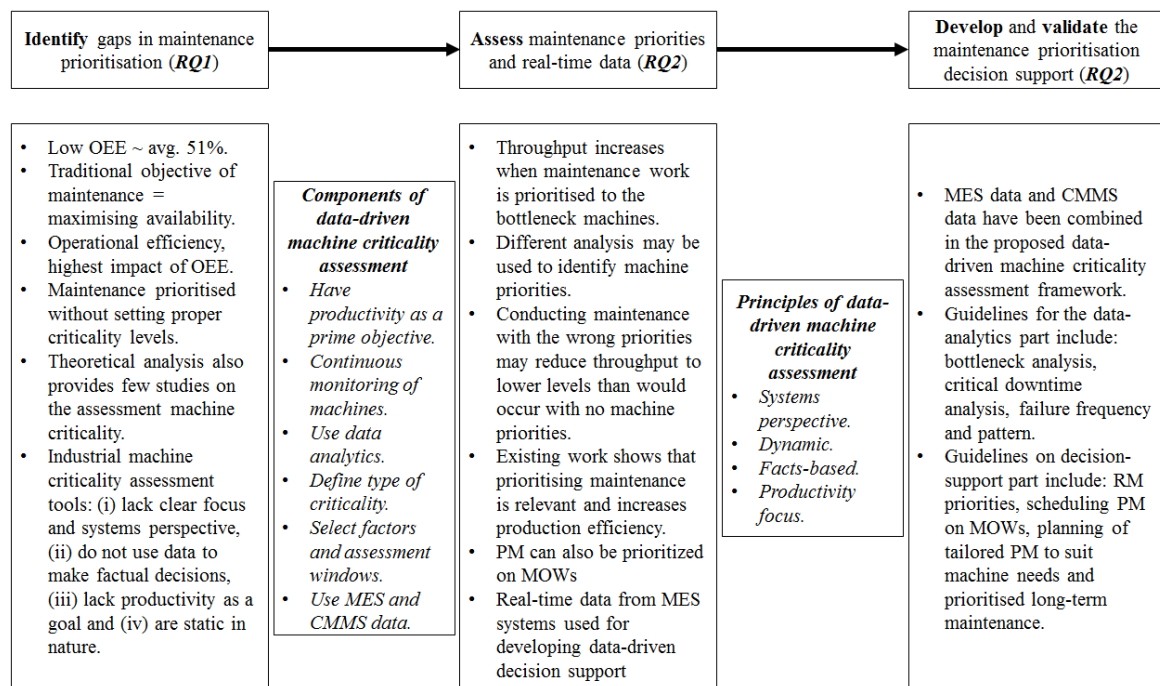


Figure 22. Summary of answers to RQs.

RQ1 was used to identify the gaps in maintenance prioritisation between industrial practice and research in the form of potentials for improvements in maintenance and productivity. The RQ1 results show that current maintenance practices are narrowly focused and do not employ facts-based decision making. The results were used to identify the components of a data-driven criticality assessment. RQ2 guided the research to develop a solution for maintenance decision support to increase productivity. The real-time machine data was assessed for usability and prioritisation decisions were assessed for effectiveness. Subsequently, with the help of criticality assessment principles, a data-driven machine criticality assessment framework was developed and validated. It provided guidelines for data analytics and suggested maintenance prioritisation decisions to be supported.

The research work presented in this thesis increases knowledge of maintenance prioritisation and its decision support system. It provides a pathway for the maintenance organisation transformation from having a narrow focus (solving machine-level problems) to achieving a factory-focus (solving maintenance problems from a systems perspective). The thesis concludes that by applying the obtained results, maintenance organisations can contribute directly towards increased productivity and cost-effectiveness. Thus, this can enable companies to be competitive in global production, especially within digitalised manufacturing.

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