CHALMERS
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Discrete-Event Simulation in Smart Maintenance

Use of Discrete-Event Simulation in Manufacturing Maintenance Applications and Smart maintenance dimensions

Master's thesis in Production Engineering

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CHALMERS UNIVERSITY OF TECHNOLOGY
Gothenburg, Sweden 2020

MASTER'S THESIS 2020

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Master's Thesis 2020
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Cover: The link between Discrete event simulation and Smart Maintenance identified.

Typeset in LaTeX
Printed by Chalmers Reproservice
Gothenburg, Sweden 2020

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Abstract

Manufacturing companies and industries are striving to maintain failure free production and therefore it is of great importance to have modern tools to assist maintenance activities. The move toward digitalization has brought new advantages and allowed for the transition to smart maintenance (SM).

In this thesis, the use of Discrete-event simulation (DES) for the maintenance of manufacturing applications as well as the link between DES and SM dimensions are researched. With the aim to find the use of DES in manufacturing maintenance applications as well as the link between DES and SM dimensions, literature study was conducted along with interviews to develop both quantitative and qualitative data, then this data is analyzed, and interpreted as a result. The report also encompasses information regarding DES, maintenance types and SM. Results states the use of DES in manufacturing maintenance applications and the link between DES and SM dimensions. Future research agenda also addresses the potential use of DES in maintenance area as well as in SM dimensions that have not yet been assessed by literature.

Keywords: maintenance, maintenance strategies, maintenance optimization, smart maintenance, simulation, discrete-event simulation, manufacturing maintenance applications.

Acknowledgements

We would like to thank everyone that has contributed to this thesis, especially our Supervisor and examiner Torbjörn Ylipää for his guidance and support throughout this work. Further, we would like to thank researchers within Chalmers University of Technology for their contribution to our thesis. Finally, we would like to thank Anders Skoogh, Professor of Production Maintenance and Director of the Production Engineering master's program, for his valuable help and motivation.

Abbas Abbasli & Jeyhun Mammadli, Gothenburg, November, 2020

Acronyms

AI	Artificial Intelligence
C	Complementary
CBM	Condition-Based Maintenance
CM	Corrective Maintenance
DDDM	Data-Driven Decision-Making
DES	Discrete-Event Simulation
DT	Digital Twin
FIFO	First-In First Out
FIT	Flexible Integrated Technology
FMEA	Failure Mode Effect Analysis
GDM	Generic Data Management
GMO	Global Maintenance Order
HCR	Human Capital Resource
ICP	Inventory Control Policy
ICT	Information and Communication Technology
IPV	Information Processing View
KBV	Knowledge-Based View
KSAOs	Knowledge, Skills, Abilities, and Other Characteristics
LCC	Life-Cycle Cost
MFS	Maintenance Float Systems
ML	Machine Learning
MOEAs	Multi-Objective Evolutionary Algorithms
MOO	Multi-Objective Optimization
MTBF	Mean Time Between Failure
MTTR	Mean Time To Repair
OCBA	Optimal Computing Budget Allocation
OEE	Overall Equipment efficiency
OEMs	Original Equipment Manufacturers
PdM	Predictive Maintenance
PM	Preventive Maintenance
RCM	Reliability Centered Maintenance
RMO	Reliability-Based Maintenance Order

RQ	Research Question
S	Substitutable
SD	System Dynamics
SM	Smart Maintenance
SMEs	Small and Medium Enterprises
SMI	Swedish Manufacturing Industries
SMT	Surface Mounted Technology
SP	Spare Parts
TPM	Total Productive Maintenance
UAVs	Unmanned Aerial Vehicles
VBA	Visual Basic for Applications
VMO	Value-Based Maintenance Order

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1

Introduction

The chapter introduces the thesis starting with a background information to the research area. The purpose of the thesis is presented together with research questions that aimed to be answered in this thesis. The subsequent subchapter explains the project delimitations briefly. The chapter is closed by an explanation of the outline of the thesis.

1.1 Background

In ever growing world, manufacturing companies and industries are striving to maintain failure free production and therefore it is of great importance to have modern tools to assist maintenance activities. The move toward digitalization has brought new advantages and allowed for the transition to smart maintenance (SM). Smart maintenance is about leveraging the new technology such as big data applications and the internet of things, to ensure that all the production equipment operates at 100 % efficiency at all times.

Several studies have been conducted on SM, Akkermans et al. (2016) explain SM as a primary term used by practitioners in Swedish manufacturing industry and other European countries. Akkermans at al. (2016) also states that implementation of SM requires more experimentation, collaboration, risk-taking, and speed. R. Foresti et al. (2020) proposes SM in his study as a human-centric approach that evaluates the relation between human resources (HR) and new machines/components, considers human habit and related knowledge level. J. Bokrantz et al. (2019) conducted an empirical, inductive research approach to conceptualize SM by using focus groups and conducting interviews with more than 110 experts from over 20 different firms. The first empirically grounded definition of SM and its four underlying dimensions is explained by combining empirical observation and theoretical interpretations (J. Bokrantz et al. 2019).

Simulation is such a powerful tool that is capable of modelling complex systems such as maintenance activities and can be applied to achieve high performance improvement. The difference and the power of discrete-event simulation (DES) is the ability to mimic the dynamics of a real system (Ricki G. Ingalls, 2011) and offer the possibility to perform analysis and experiments virtually and avoid the risk of potential damages and cost to the real physical world. The use of DES can make potential contributions to the performance of smart maintenance operations.

A lot of research has been conducted in the area of DES and maintenance. Some of these studies indicate how DES can be used in maintenance operations. The studies use DES with the aim of improving productivity, comparing different maintenance planning strategies as well as identifying bottleneck machines (Gopalakrishnan et al. 2014). However, none of these studies has shown how DES can be linked with SM and its dimensions. The research of today is clearly missing the use of DES in SM and its dimensions.

1.2 Purpose and Research Questions

The purpose of this thesis is to investigate how DES is applied in manufacturing maintenance applications as well as how it can be linked to SM dimensions. By studying and analyzing the application areas of discrete-event simulation and the logical steps that constitute the implementation of smart maintenance, it will become feasible to use discrete-event simulation in dimensions of SM with the best way possible. Also, a future research agenda is formulated for the use of DES in complex machines maintenance and SM. To fulfil the purpose of the thesis the following research questions are formed as following:

RQ1: How DES is used in manufacturing maintenance applications?

RQ2: How DES can be linked with Smart maintenance dimensions?

In order to answer the main research questions, the following sub questions will be answered:

SQ1: What are the parameters that improved by the application of DES?

SQ2: How is DES used to detect the problems in manufacturing industries?

SQ3: Which dimensions of SM are closely linked to DES?

SQ4: Can DES be considered as a decision support tool?

There is an unbalance between these two research questions. Because the first research question addresses the use of DES in manufacturing maintenance applications which is in use already, however, the latter looks forward into the future. Using of DES in SM dimensions is a new industrial application and is of high importance for the industry to get guidelines regarding the use of it.

1.3 Delimitations

There are several simulation software which are used in production, but only DES will be the topic of interest in this study. DES has a wide range of application areas; however, the application of DES is delimited to maintenance operations. Therefore, it will not consider the use of DES for production disturbances. The project will not consider the economic sides of using DES in the application of SM either. The project considers the application of DES in manufacturing maintenance applications, the use of DES in the maintenance of complex machines is therefore suggested to be investigated in future research.

1.4 Outline of the Thesis

The report is divided into 6 chapters. After the introduction, chapter 2 begins containing a theoretical framework for the thesis. This chapter includes background information about simulation, DES, several types of maintenance, SM and previous studies on simulation and maintenance. Chapter 3 presents the methodology that are used in this thesis work to obtain the intended results. The results are divided into three parts. First part indicates the findings from the papers regarding the use of DES in maintenance which is the answer to RQ1. Second part illustrates the classification of the papers in terms of SM dimensions and answers to RQ2. The last part shows the result of the interviews. Next chapter presents discussions about the result, methodology that is used and research quality followed by the future research agenda. Finally, conclusions are drawn in the last chapter 6 to summarize the thesis work.

2
Theory

The chapter provides information from the literature regarding background subjects of the project. It helps the reader to get better understanding and insight by providing background information about the topic of interest.

2.1 Simulation

According to Shannon (1975), simulation is "the process of designing a model of a real system and conducting experiments with this model for the purpose either of understanding the behavior of the system or of evaluating various strategies (within the limits imposed by a criterion or set of criteria) for the operation of the system."

Banks et al. (2000) states that "simulation is the imitation of the operation of a real-world process or system over time". Simulation engages the creation of an artificial history of a system and the use of that artificial history to make inferences with the operating characteristics of the real system. The behavior of a system is studied as it thrives over time by developing a simulation model. Once this model is developed and validated, it is time for investigating a wide variety of what if questions about the real-world system. Potential changes to the system can be simulated first in the generated model in order to predict their influence on the system performance. Simulation can also be used to test the systems in the design phase, before such systems are created. Thus, simulation modelling is used as an analysis tool to predict the impact of changes to the existing system or as a design tool to estimate the performance of new systems that are intended to be built (Banks et al., 2000).

2.2 Discrete-Event Simulation

Discrete-event simulation (DES) is about the modelling of a system as it develops over time, where state variables change instantaneously at separate points in time. These separate points in time are the ones that an event occurs, where an event is defined as an instantaneous occurrence that may change the state of the system (Law, A. M, 2007).

DES is traditionally applied for industrial use. There has been a quick development in manufacturing technology as well as DES technologies. Several companies have invested a great amount in new technologies with the purpose of making manufacturing operations flexible. Thus, DES software is the tool for managers to make right decisions. It is the purpose of every production manager to improve productivity by achieving higher throughput rate, shorter lead time, low work-in-process and high utilization of resources. So that with the help of simulation, they are able to evaluate the behavior of manufacturing processes under various given conditions. Also, they can test different "what-if" scenarios in order to identify better physical configurations and operational policies (Aitor Goti, 2010).

The power of the DES is its ability to mimic the dynamics of a real system. Many models, such as high-powered optimization models, can not consider the dynamics of a real system. The ability to mimic the dynamics of a real system gives DES its structure, its function, and its unique way to analyze results (Ricki G. Ingalls, 2011)

2.2.1 Data Requirement in DES

DES models heavily rely on high input data quality and the process which converts the raw data to relevant information that is suitable to adapt for simulation models is called input data management. This process involves identification and collection of relevant input parameters (Skoogh et al. 2012). Skoogh & Johansson (2008) present a methodology in order to secure quality and increase rapidity in DES projects. By suggesting a structured methodology for activities in the input data phase, the objective is to contribute to the work towards more time-efficient and accurate input data management for simulation projects. Including 13 activities, the methodology represents detailed guideline in order to explain how to conduct the crucial process of handling input data. Skoogh et al. (2010) carried out another study regarding data processing in simulation models. The research presents an approach that combines automated raw data collection and automated processing of raw data to simulation information and the objective is to enable efficient reuse of DES models by reducing the time-consumption for input data management. MTConnect and GDM-Tool are combined in the study in order to achieve a push-button solution for input data management in DES. Raw data is directly collected by the machines via MTConnect, processed and prepared for simulation in the GDM-Tool, and finally input to a DES model for further analysis. Skoogh et al. (2012) carried out further study about data requirement for DES project with the aim of automating data processing. Hatami, (1990) discusses the parameters which is used for DES model and the list below covers the most common parameters required for DES stated by him:

- Storage Space Capacity or Buffer
- Machine/Operators Speed
- Processing time
- Set-up Times
- Breakdown Frequency (MTBF)
- Work Schedules
- Material Handling Systems
- Layouts

- Product Flow Mix
- Quality related parameters

2.2.2 Simulation Software – AutoMod

The AutoMod Product Suite is offered by Brooks Automations (Rohrer, 2003). It consists of AutoMod simulation package, AutoStat for experimentation and analysis, and AutoView for making AVI movies of the built-in 3-D animation. AutoMod simulation is mainly used in manufacturing and material handling systems. The strength of the AutoMod Software is that large models can be used for planning, operational decision support and control-system testing (Jerry Banks et. al, 2010).

An AutoMod model includes one or more systems. A system can be a process system, where control logic and flow are defined, or a material movement system that is based on the material-handling templates. A model can consist of any number of systems, and it can be saved and reused as objects in different models (Jerry Banks et. al, 2010).

Each model must contain one process system and can contain several number of movement systems. Processes consist of logic to control the flow of either manufacturing materials or control messages, to deal with resources, or waiting for specified times. Loads can be moved between processes with the help of or without using movement systems (Stanely, 2001).

2.3 Maintenance Planning and Scheduling

Companies are trying to get more profit as much as possible. In order to do this, they avoid the failure of production. They want to have lowest maintenance cost expenditure and good maintenance quality to get maximum profit. Nowadays maintenance is one of the most important considerations in industry, but that was not always the case. Maintenance was considered an inevitable part of production and it was nothing more than a necessary evil in the 1950s (Pintelon & Parodi-Herz, 2008). Today, maintenance plays an important role in terms of companies' competitiveness and it is important regarding sustainable development, including environmental, energy saving, safety and economical aspects (A. Starr et al. 2010). Now, all the organizations are aware of the importance of maintenance and they try to decide which maintenance strategy or concept is suitable for their production. Apart from that, some organizations keep working on maintenance in order to improve or develop new maintenance concepts such as smart maintenance. Manufacturing companies have different maintenance planning and scheduling and this process differs due to organizations' philosophy. As the importance of maintenance varies from company to company, the definition of the maintenance also differs. Maintenance is defined by European standard (BS EN 13306:2010) as: *"Combination of all technical, administrative and managerial actions during the life cycle of an item intended to retain it in, or restore it to, a state in which it can perform the required function"*.

Ylipää et al.(2017) claim that this definition needs to be improved by stating there is a need for change in the maintenance function in the manufacturing industry and current definition of maintenance is too narrow for the future challenges. It is mentioned in the paper that current maintenance needs to evolve from only retaining and restoring equipment back to a designed level to taking a wider responsibility, including improvements and upgrades for extended equipment life-cycles. The aim of the study is to describe the need of maintenance evolutions in the manufacturing industry by using OEE data to quantify the losses and identify the important factors that prevent OEE parameters to become world-class levels.

In order to perform maintenance, detailed planning needs to be made which requires procedures, activities and resources. The maintenance managers should consider the bathtub curve during maintenance planning (Figure 2.1) and know that new machines have a high probability of failure during a couple of weeks due to installation. Then, the probability to fail tends to lower and stay fixed for an extended period of time. Failure probability sharply increases by the time passes after the normal machine life period (Mobley, 2004).

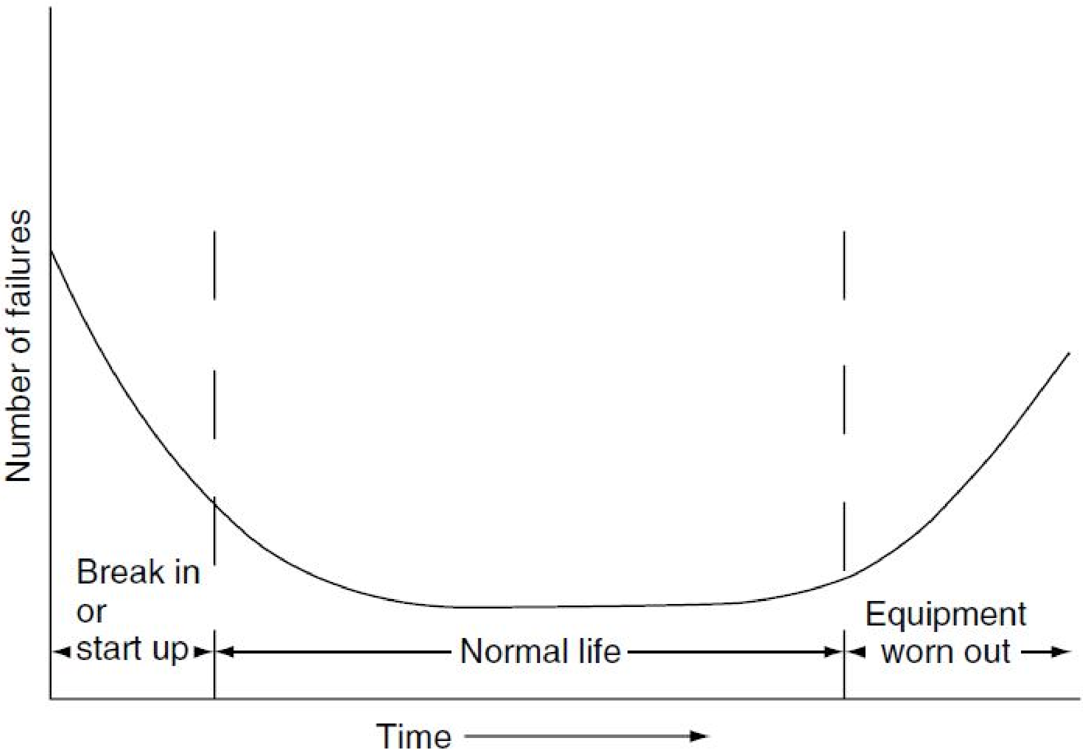

Figure 2.1: Bathtub Curve (Mobley, 2004)

Maintenance is a very broad term and it has wide-ranging terminology. Since there are a lot of maintenance types, not all of them will be covered in the study. Following sub-chapter will provide information about different maintenance strategies and concepts which emerged after maintenance planning and scheduling.

2.3.1 Reactive Maintenance (Corrective Maintenance Actions)

In corrective maintenance, also known as run-to-failure, the component or machine is allowed to fail before the maintenance is initiated (Holmberg, K. et al, 2010). The logic behind the corrective maintenance is simple and straightforward. When a machine breaks, fix it. “If it ain’t broke, don’t fix it” method had been an essential part of maintenance operations since the first manufacturing plant was built. The plant that uses run-to-failure methodology does not spend a bit of money on maintenance until a machine or component fails to function (Mobley, K.R. 2004). This approach is appropriate if the consequences of failure are small such as a light bulb.

Basically, corrective maintenance is appropriate only if it does not matter whether the machine breaks down, or how much time the repair will take or how much it will cost. The only advantages of CM strategy are that the planning is simple and therefore the organization needs to adapt the failure rate and the work is not scheduled until it is really needed. However, it has major disadvantages, for example, failure can occur at inappropriate times, when the plant is at full load. The other disadvantage is that no data are available for the past, present and future conditions of the machine etc. (Holmberg, K. et al, 2010).

Run-to-failure is in fact the most expensive maintenance management method. Few plants use run-to-failure methodology truly because in almost all the cases basic preventive tasks such as lubrication and other types of adjustment are done. The net consequences of reactive types of maintenance are higher maintenance cost and less availability of process machinery. After analyzing the cost of maintenance repairment, it shows that the cost of repairment performed in run-to-failure mode will be three times higher than the same repairment done within preventive mode (Mobley, K.R. 2004).

Lynch, M. (1996) states three reasons why CM is required. Human error is the most common reason that requires the application of CM. Mistakes that are made during setup, programming and production can damage the machine tools. The component failure is considered as the second reason. The mechanical and electrical components that are part of advanced machine tools, some of them are prone to failure and therefore, almost all machine builders provide their users with a list of spare parts that they can use to reduce the number of failures. The last and unforgivable reason is that users are neglecting the preventive maintenance actions that machine builders recommended. All builders provide instructions on how to conduct preventive actions that are aimed at keeping the machine performance at peak.

2.3.2 Preventive Maintenance

Preventive maintenance (PM) is a proactive maintenance strategy. It was developed in the 1960s when companies analyzed some failures on mechanical components and recognized that there is a direct relation between the failures on parts and the time or number of cycles in use. Those failures mainly due to physical wear or age-related fatigue characteristics (Pintelon & Parodi-Herz, 2008). At that time, since it was a new concept, PM was the best strategy for companies.

PM is still used by numerous industrial areas as a main maintenance strategy. Since PM is time driven, it is also known as time-based maintenance. It is applied to avoid any potential failures by replacing components at a particular time. Component life is assumed predictable and maintenance is performed based on a fixed time interval (i.e., couple of hours or days). Regardless of its condition, PM task is required to replace or repair the component/part at a fixed time after installation (A. Starr et al. 2010). For example, a horizontal split-case centrifugal pump should run 18 months before being rebuilt. If PM is performed, the pump needs to be removed and rebuilt after 17 months of operation independent of its condition. Original equipment manufacturers' (OEMs) recommendation or experience of technicians is used when choosing the frequency of PM tasks. Longer equipment lifespan, lower cost, reduced failure rates and higher system availability could be an advantage of PM over corrective maintenance. As the most preferred maintenance strategy, PM is implemented in many marine industries (M. Abbas & M. Shafiee, 2020). There are some PM tasks, Table 2.1 provides information about typical PM activities.

Visual and aural inspection for leaks, noise, looseness and cleanliness
Lubrication of bearings and slides
Adjustment of belts and couplings
Checking electrical connections
Checking performance
Cleaning filters and strainers
Replacing parts at intervals: belts, seals, bearing, etc.

Table 2.1: Typical Preventive Maintenance activities (A. Starr et al. 2010).

Since the PM assumes a component/part that will need maintenance after a particular time, this would result in either unnecessary repairs or terrible failure. The first scenario is, the machine may not need PM after assumed time interval e.g. the pump may not need to be rebuilt after 17 months. In this case the labor and material used for the PM would be wasted. The second scenario is the failure of the machine before the scheduled time interval which would result in a huge economical cost e.g. pump fails before 17 months. In order to prevent those scenarios, PM should be implemented in equipment that has a very predictable life, such as components that are designed to wear (A. Starr et al. 2010).

2.3.3 Predictive Maintenance

Predictive maintenance (PdM) is also considered as a proactive maintenance strategy. Equipment was becoming more complex in the late 1970s and early 1980s. Individual components' failure pattern started to change by introduction of new equipment. There was no longer dominant age-related failure mode and this limited the implementation of PM in order to improve reliability of complex items. At this point, the effectiveness of the PM was under question and was considered more carefully. “Over-maintaining” was the common consideration during that time. Gradual, though not complete, switch to PdM started and new PdM techniques emerged (Pintelon & Parodi-Herz, 2008).

Exhaustive PdM program uses a combination of most cost-effective tools to get actual operating conditions of critical plant systems. Some of the typical tools used for the PdM technology are listed below (M. Smithand & R. Hinchcliffe, 2003):

- Lubricant analysis
- Vibration, pulse, spike energy measurement
- Thermal imaging
- Stress/strain/torque measurement
- Ultrasonic movement sensing
- Nonintrusive flow measurement
- Acoustic leak detection
- Dynamic radiography measurement
- Microprocessors with expert system software
- Hyperbolic moisture detection
- Pattern recognition

PdM schedules all maintenance activities based on these actual data. It is possible to optimize the availability of process machinery and reduce maintenance cost with applying a comprehensive PdM program. PdM utilizes the actual operating condition of plant equipment in order to optimize total plant operation. It also helps to improve product productivity, quality, and profitability of production plants.

PdM could be considered as a condition-driven PM program. Instead of counting on in-plant or industrial average-life statistics to schedule maintenance tasks, PdM utilizes direct monitoring of the machine condition, system efficiency and other parameters to identify actual failure time or loss of efficiency for each machine and system in the factory. Apart from that, PdM provides factual data about the actual condition of each machine and operating efficiency of each process system which help maintenance managers to schedule maintenance activities based on the actual data (Mobley, 2004).

By applying PdM, it is possible to minimize unscheduled breakdowns of equipment in the plant and make sure that the equipment is in good condition. PdM can also detect machine problems early and it gives an opportunity to the maintenance manager to repair machines before it becomes serious and prevent major failures. The actual information obtained from the machines by applying PdM activities enable maintenance managers to achieve optimum reliability and availability from the plant (Mobley, 2004).

2.3.4 Reliability Centered Maintenance

During the last few decades several maintenance methodologies have been developed and one of them is reliability centred maintenance (RCM) which has been the latest technology in maintenance and introduced by the Airline industry in the 1960's. RCM is a process used to determine the maintenance requirements of any physical asset in its operating context. Full definition of the RCM can be expressed as a process which is used to determine what must be done to ensure that any physical asset continues to do whatever its users want it to do in its present operating context (Moubray, 1997).

RCM is undoubtedly a precious maintenance concept that not only considers the equipment itself but also the system functionality. In the RCM concept, reliability is the focus and more attention is paid to safety and environmental integrity than cost (Pintelon and Perodi-Herz, 2008). Since RCM is based on the system functionality failure analysis, it uses features such as failure modes and effects analysis (FMEA) and Fault tree analysis (FTA) (G. Gupta et al., 2016). It also identifies the consequences of the functional failures. RCM takes preventive measures and utilizes a standardized logical resolution based on the identified consequences. Then RCM techniques assign the required maintenance for a system while in its operating condition (Moubray, 1997). RCM process have seven key RCM questions and it should ensure that all are answered reasonably and, in the order, as follows:

- What are the functions and associated performance standards of the asset in its present operating context?
- In what ways does it fail to fulfil its functions?
- What causes each functional failure?
- What happens when each failure occurs?
- In what way does each failure matter?
- What can be done to predict or prevent each failure?
- What should be done if a suitable proactive task cannot be found?

Basically, the RCM process consisted of two methods: the classical RCM and backfit RCM. Both methods are applied for different maintenance situations, but they have similar characteristics at some points. The classical RCM method is a PM approach that critically develops preventive and continuous maintenance strategy in an uncertainty environment where operating data are limited, or in a new asset where no operating data exists at all. On the contrary, the backfit RCM is a PM engineering that is applied where sufficient previous operating data exists. (Tee et al., 2019). RCM leads to exceptional development in maintenance effectiveness, and often achieves so quickly if it is applied properly. The successful implementation of RCM is mainly depending on the meticulous planning and preparation. The key factors to the success of RCM are as follows (Moubray, 1997):

- Decision on which assets are most likely to get benefit from the RCM process, and precisely how they will benefit?
- Assess the resources that is necessary to apply the RCM process to the selected

assets

- In cases where the likely benefits justify the investment, decide in detail who is responsible to perform and who is accountable for the control of each analysis, when and where, and providing for them to receive appropriate training
- Ensure that all operating conditions of the asset is understood clearly

By the application of the RCM methodology the organizations will achieve greater safety and environmental integrity as well as improved operating performance. RCM also achieves greater maintenance cost effectiveness since it pays more attention to the maintenance activities that increase the performance of the plant. Apart from that, longer useful life of expensive items and a comprehensive database will be achieved by the implementation of RCM (Moubray, 1997).

2.3.5 Condition-Based Maintenance

With ever growing modern technology, products have become more complex in shape and structure while better quality and higher reliability are required. This increases the cost of preventive maintenance and eventually, preventive maintenance has become a main source of expenses for many organizations. Therefore, more effective maintenance methodologies such as condition-based maintenance (CBM) are applied to deal with the situation.

(CBM) is a maintenance program that avoids failure by detecting the early deterioration and identifying hidden or potential failures. CBM initiates maintenance when the sign of deterioration in machine condition can be seen. The component or parts of the asset is repaired or replaced with the new one once the monitoring level value exceed the normal (Holmberg, K. et al., 2010)

"(CBM) is a maintenance program that provides a maintenance approach based on the data that is gained through condition monitoring" (Andrew Jardine, 2006). The CBM techniques can be listed as fluid analysis, infrared thermography, voltage and current monitoring, vibration analysis etc. that are designed to actively monitor equipment conditions. However, despite the upward trend in this area as well as the successful history of CBM implementation that are shown in the literature, in reality, many of the CBM methods fail or are not financially justified (Javid Koochaki, 2009). CBM tries to avoid needless maintenance tasks by applying maintenance actions if there is proof of abnormal behaviors of a physical asset. The purpose of this policy is to prevent any unexpected downtime and to reduce maintenance cost by avoiding unnecessary preventive actions (Moubray, 1997).

So that, if properly established and effectively implemented, a CBM approach can make significant reduction on maintenance cost by decreasing the number of unnecessary preventive maintenance tasks (Andrew Jardine, 2006). A CBM program consists of three key steps: (Andrew Jardine, 2006).

1. Data acquisition step (information collecting), to obtain data relevant to system health.
2. Data processing step (information handling), to handle and analyze the data or

signals collected in step 1 for better understanding and interpretation of the data.
3. Maintenance decision-making step (decision-making), to recommend efficient maintenance policies.

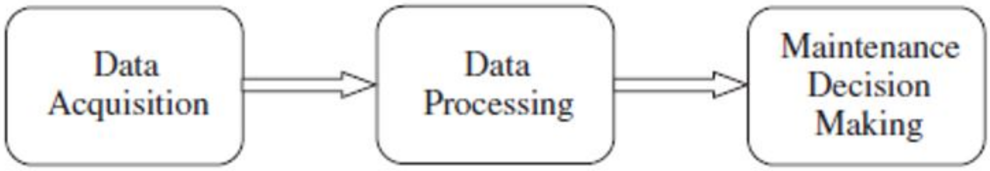

Figure 2.2: Three steps in a Condition-Based Maintenance program

Diagnostics and prognostics are considered as two main aspects in a CBM approach. Diagnostics deals with fault detection, isolation and identification when it occurs. Prognostics deals with fault prediction before it occurs. Diagnostics is an analysis after the event and prognostics is an analysis prior to the event. Therefore, prognostics is considered much more efficient than diagnostics to achieve zero-downtime performance (Andrew Jardine, 2006).

2.3.6 Total Productive Maintenance

The first official definition of Total Productive Maintenance (TPM) was appeared in 1971 by JIPM and Nakajima (1989) and it is defined as the maintenance approach which optimizes the equipment effectiveness, eliminates breakdowns, and promotes autonomous maintenance of operators (J. R. Díaz-Reza et al. 2019). TPM is considered more than just a concept, it is rather considered as a maintenance philosophy. TPM can be defined as an approach to maximize equipment effectiveness of production facilities by involving total participation at all level of organization (Pintelon & Parodi-Herz, 2008). It comprises some methods that are known from maintenance management experience to improve reliability, production, and quality. By changing corporate culture, TPM aims to enhance a company through improving personnel and plant (A. Starr et al. 2010). It is not an easy task to change the culture at a plant and it requires a strong role for machine operators and support from the maintenance department (Willmott and McCarthy 2000). The role of machine operators is very important in TPM and they are required to take over some of tasks which belong to maintenance staff, such as lubrication, cleaning, tightening fasteners, observation of changes in the machine condition. All these tasks are important as well as useful in order to prevent some failure causes at an early stage (A. Starr et al. 2010).

Improving Overall Equipment Effectiveness (OEE) stands at the core of TPM by achieving a new partnership among the production people, maintenance, engineering, and technical services. The aim is zero breakdown and zero defects by improving or eliminating following six big production losses (Mobley, 2002):

- Equipment breakdown

- Setup and adjustment slowdowns
- Idling and short-term stoppages
- Reduced capacity
- Quality-related losses
- Startup/restart losses

TPM is considered as an innovative maintenance approach which holds the potential for improving the effectiveness of production plant. It requires major changes in terms of work culture and radical restructuring of work. Since TPM demands organizational culture change, implementation of TPM is a challenging task, especially in an organizational environment which is typically traditional and unfavorable to the transformation (Tsang and Chan, 2000). Studies have shown that many companies have tried to apply TPM, but less than 10% have been successful (Mora 2002). Therefore, it is very important to foresee the barriers associated with TPM before the adoption and application of it (R. Attri et al, 2014)

2.3.7 Priority-Based Maintenance

Almost all of the manufacturing companies have a couple of machines/equipment within the plant. Prioritization of those machines during the maintenance decision making process is as important task as implementing particular maintenance. Let us consider a situation in which 5 different machines need to be carried out a maintenance. Which machine should be given a priority by the maintenance managers, in which order maintenance should be performed? The right prioritization policy will have positive effects while wrong prioritization will bring a lot of problems. Maintenance prioritization is important in manufacturing systems in order to avoid unnecessary maintenance activities. It is possible to use resources efficiently and minimize the total cost of system operation by developing a good prioritization policy (L. Li & J.Ni. 2009). Maintenance prioritization is considered as an effective decision support tool for maintenance engineers. As a maintenance strategy, prioritization of maintenance differs from company to company. Maintenance prioritization varies on types of organizations as well as what parameters the organizations consider most. Availability, reliability, safety, productivity and so on could be the parameters that manufacturing companies would focus on during maintenance prioritization. For example, reliability is the main focus in organizations such as petrochemical plants, and the maintenance prioritization is given to reliability improvement. Machine criticality plays a crucial role during maintenance prioritization. Priority should be given to critical machines which cause the highest effect for the intended purpose, for example have an impact on quality of a production schedule. There are some methods to detect the critical machines such as Failure Mode Effect Analysis (FMEA) analysis and ABC/ABCD classification (Gopalakrishnan, M., & Skoogh, A. 2018).

Some studies have shown that prioritizing maintenance work orders of bottleneck machines improves productivity (Lu et al., 2011; Li, Chang Ni and Biller, 2009). Improvement of bottleneck machines by giving a higher priority maintenance to machines whose bottleneck impact factor is the highest leads to a higher overall system throughput (L. Li & J.Ni. 2009). It means detection of bottleneck machine(s) is very important and it enables companies to increase productivity. There are some methods to detect bottleneck in production and data driven bottleneck detection by using DES is one of them (L. Li et al. 2009). By using an optimization procedure, companies can make a decision for the best maintenance priority (Yang Z. et al. 2006). Some of the main maintenance optimization models involve fuzzy logic, multi-criteria decision making, analytic hierarchy process and simulation. One of the main criticisms regarding optimization models is that they cannot exactly fill the gap between research and real industrial practice (Gopalakrishnan, M., & Skoogh, A. 2018).

2.4 Smart Maintenance

The history of all maintenance strategies and concepts is very old and almost all of them developed in the 20th century. However, SM is a new maintenance concept and researchers think that it still needs comprehensive research and development. Since SM is a new concept and not well known, there is a limited research article about it. Akkermans et al. (2016) explain the SM as a primary term used by practitioners in Swedish manufacturing industry as well as other European countries. He also states that once SM was a peripheral development, but now it is becoming a core requirement. Akkermans et al. (2016) argues that current maintenance strategies developed by managers, which involve increasing the availability of the assets, extending lifetimes and reducing maintenance cost, will not be sustainable for the next five to ten years. By shifting their focus from cost-cutting to innovation, from maintenance as a utility to maintenance as a competitive capability, organizations will have to embrace ‘SM’, in line with the digital disruption in society. He believes organizations that want to be ’SM’ champions will have to follow the path that all organizations which want to be superior in their digital strategies. According to Akkermans at al. (2016), implementation of ‘SM’ requires more experimentation, collaboration, risk-taking, and speed. Macchi et al. (2017) claim that in order to make progress to implement a SM system, digitization requires to master technology and organization, implying SM is a transition towards new technologies (J. Bokrantz et al. 2019). R. Foresti et al. (2020) develop a method to reduce training time and cost for smart management. He proposes “SM” in his study as a human-centric approach that evaluates the relation between HR and new machines/components, considers human habit and related knowledge level.

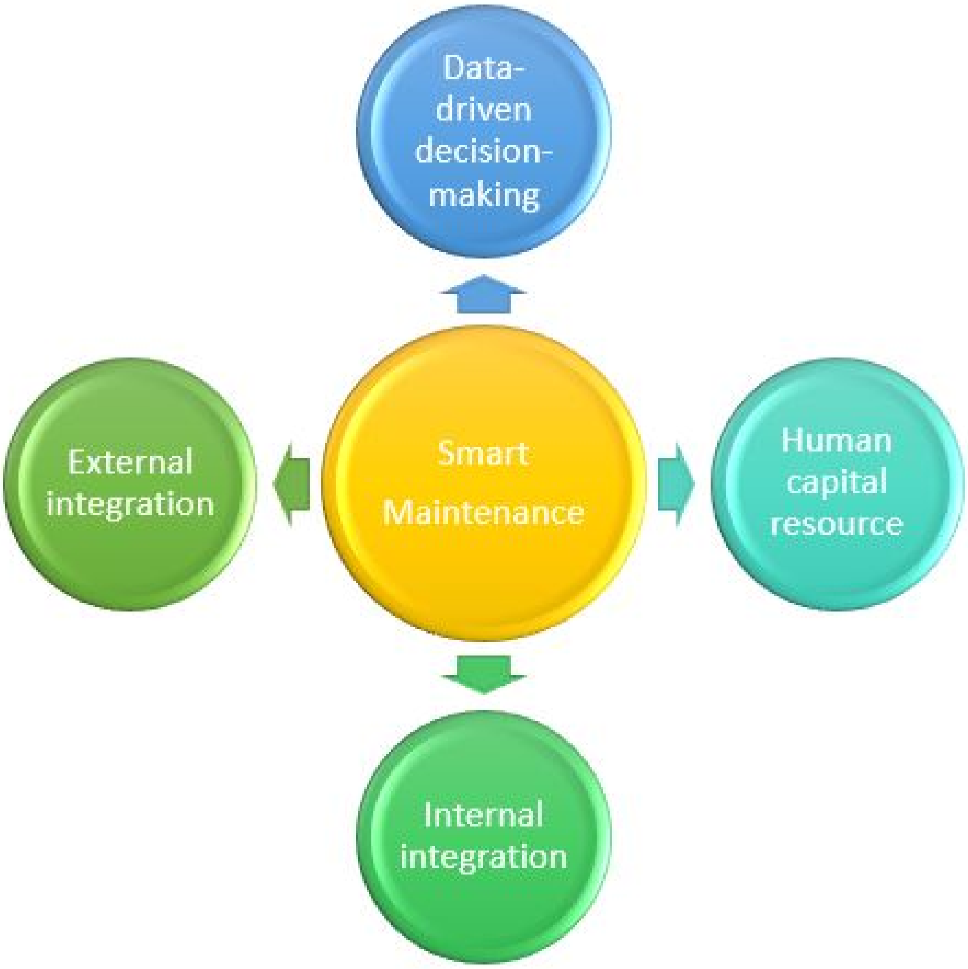

Figure 2.3: Smart Maintenance concept developed by J. Bokrantz et al. (2019)

J. Bokrantz et al. (2019) present an empirical, inductive research approach in order to conceptualize SM by using focus groups and conducting interviews with more than 110 experts from over 20 different firms. By combining empirical observation and theoretical interpretations, he explains the first empirically grounded definition of SM and its four underlying dimensions which are Data-Driven Decision-Making, (DDDM) Human Capital Resource (HCR), integral integration, and external integration. SM is defined as 'an organizational design for managing maintenance of manufacturing plants in environments with pervasive digital technologies' in the paper. Findings from the article map a new directions for contemporary and future maintenance research by examining the original data through the lens of many general theories. Figure 2.3 illustrates the SM concept together with its four dimensions. Moreover, J. Bokrantz et al. (2020) conducted a study with the aim of developing a psychometric instrument that measures the four dimensions of SM. J. Bokrantz et al. (2019) argue that the four dimensions constitute what SM is and they are parameters that hold casual power, thus play the central role. Apart from this, there is a relationship between all those four dimensions and SM can be achieved if and only if all four dimensions are achieved. All the dimensions are explained in detail below.

Data-driven decision-making. (DDDM) is defined as 'the degree to which decisions are based on data' (J. Bokrantz et al. 2019). Quick advancement in Machine learning (ML) and Artificial Intelligence (AI) as well as the falling prices of technologies (e.g. sensors) have increased the chances and facilitate the process of collecting, analyzing and interpreting data to make better decisions.

J. Bokrantz et al. (2019) state that old time-based preventive maintenance plans can be discarded if it is possible to get more understanding from data and then decisions can be made based on the real conditions of equipment. While processing raw data to the useful information, four categories have been identified: data collection, data quality, data analysis and decision-making. The first three categories – data collection, quality and analysis, are the means to make proper decisions. J. Bokrantz et al. (2019) add that it is not possible to base decisions on non-existing data, no algorithm or machine can transform useless data into sharp, intelligible data, and there is no learning from data without analysis. However, having or analyzing high quality data does not automatically lead to decisions that are driven by data. Too often data remains unused, or analyzes are not considered sufficiently insightful, and therefore, decisions are made based on intuition and experience. The key point of truly understanding the successful value creation from data is to learn how it drives decision-making.

J. Bokrantz et al. (2019) describe that data-driven decisions consist of two main categories: decision automation and decision augmentation. Decision automation is about how computers or advanced algorithms such as ML systems execute the decision-making procedures that were previously done by humans. The crucial part is to make decisions automatically and thereby, the equipment informs when a maintenance is required before the component or machine fails. Conversely, decision augmentation shows what is complimentary between human intuition and algorithm. Empirical studies from the article (J. Bokrantz et al. 2019) get the idea from participants that expert knowledge can not be discarded just because you have better possibilities for measurement. The real value comes from the interplay between data and human experience.

Despite the fact that some decisions will be more effective with complementary human judgement, the informants are more likely to delegate decision tasks to ML systems. So that data and algorithms are considered the reliable one and that is what needs to be acted upon. As a result, J. Bokrantz et al. (2019) conclude that universal solutions are lacking, and task allocation is considerably challenging. Some decision tasks suit for automation while others are only fit for augmentation.

Human capital resource (HCR) is defined as a 'unit capacity based on individual Knowledge, Skills, Abilities and Other characteristics (KSAOs) that are accessible for unit-relevant performance' (J. Bokrantz et al. 2019). Sveiby (2001) states that knowledge is considered as the organizations' primary intangible source of value and this knowledge is possessed by human capital of a companies' individual employees. As a source of value creation within maintenance, humans and their implicit as well as explicit knowledge will remain a critical resource (J. Bokrantz et al. 2019). HCR contributes to the pursuit of the goal of maintenance functions. This dimension is based on human capital of the individual maintenance employees and it is also influenced by the interaction as well as relationship between them. Advancement in technology increases the need for both generic and specific KSAOs. SM individuals are required to have both generic and specific skills which are social, business and technical skills and specific types of analytical and Information and Communication Technology (ICT) skills respectively (J. Bokrantz, 2019).

J. Bokrantz et al. (2019) add adaptability skills to the mentioned skills above and explain each of them. Social skills reflect the individuals' communicating and collaborating capability with internal as well as external parties. Business skills refer to the capability to translate maintenance terms into accounting terms, e.g. understand how downtime or idling time would affect organization financially. Technical skills are important in terms of application of maintenance fundamentals. Analytical skills reflect an understanding of data collection, analysis and so on. It also involves basic data analytics skills and communicating with data scientists for advanced tasks. ICT skills refer to the capability of using information systems proficiently which are integrated into the production. Finally, adaptability skills refer to the capability to adapt to technological change, continuous learning, and quickly developing the skill in new tasks.

Internal integration is defined as 'the degree to which the maintenance function is a part of a unified, intra-organizational whole' J. Bokrantz et al. (2019). This has been considered as a challenge throughout the history of time: Maintenance functions must collaborate with production and other functions in the plant. When the maintenance function cooperates with other functions, the flow of data, information and knowledge across functional borders becomes easier to process. As it is stated in the DDDM section, the cheapening prices of technologies facilitates the process of collecting, analyzing and interpreting data. So that ML decreases the prices for predictions and changes the demand to complementary HCR.

J. Bokrantz et al. (2019) emphasize that the distinctive characteristic of SM is how maintenance functions connect to the internal plant organization. It comes up with three categories regarding the integration of maintenance with production and the rest of the organization. The first category is about the significance of information flow and states that production monitoring systems could reach lots of data in maintenance systems such as stop times and so on. If this information is shared and combined, there are many interesting conclusions that can be drawn. However, it also states that it is too narrowing to focus solely on data and information, dimension is also about knowledge integration. Then it explains that workers in the plant have different competencies and these competencies are far from each other, there is no natural connection in between. It is all about how you come together and get benefit from that knowledge. There is a great capital of knowledge in the plant, but it is not used in the right way.

Secondly, J. Bokrantz et al. (2019) states that there is a need for cross-functional collaboration. It is impossible to succeed without collaborating with production. If it is not firmly anchored with them, it will never work. It is needed to break down the obstacles between functions and involve more teamwork, faster communication, close connection and better coordination. So that, increasing level of integration leads to maintenance to be an active speaking partner and contributes to the development of production system, equipment acquisition and the design of IT plant infrastructure.

Lastly, it is realized that spreading the information flow enables consensus and reduces the conflicts across the functions. J. Bokrantz et al. (2019) emphasize the importance of joint decision making, where shared data tells the sole truth, more facts lead to less conflicts. So that if maintenance and production do not compromise on something, the common data about the issue will provide consensus and make joint decisions. Therefore, it can be said that consensus on data is consensus on decisions, which makes it possible to collaborate and synchronize maintenance with other processes.

Internal integration is different from external integration. Information Processing View (IPV) states that organizations with both integrated and differentiated subunits have great capacities for information processing because information can be transferred across subunits and organizations can use such information for decision making. Knowledge-Based View (KBV) comprehends knowledge different from data and information, but the perspective for integration is similar. Because of differentiation, individuals are supposed to be specialized in specific areas of knowledge (J. Bokrantz et al., 2019).

Interdependence is considered as the fundamentals of integration. Internal integration of maintenance functions with production and other organizations emerges two types of interdependence: sequential and reciprocal. In sequential interdependence the contributions of sub-units must be added in a predetermined sequence while in reciprocal interdependence the contributions are mutually dependent to each other. (J. Bokrantz et al., 2019).

External integration is defined as ‘the degree to which the maintenance function is a part of a unified, inter-organizational whole’ (J. Bokrantz et al. 2019). Along with the internal integration, maintenance function also interacts with its external environment. External integration enables maintenance function to access data, information, and knowledge residing outside the boundaries of the plant. Organizations should be clearly acknowledged that along with distribution of SM to beyond the walls of the plant, large parts of data, information and knowledge could be successful. That will encourage them in terms of establishing organizational structures which enable the maintenance function to absorb external, heterogenous, and distributed resources (J. Bokrantz et al. 2019). Maintenance function must extend their organizational links to external parties, such as suppliers, partners and etc. in order to get benefit from technological progress, innovation, and knowledge that develops well faster outside the plant. External integration involves people (e.g. communicating and collaborating with suppliers), processes (e.g. coordinate buyer-supplier activities) and technology (e.g. share data with those of the suppliers) (J. Bokrantz, 2019). The idea behind this dimension is that value is intended to return to each party in the form of more relevant knowledge and better product if sharing is established in networks. Apart from that, it enables an efficient flow of valuable products and services by establishment of these links with strategic partners (J. Bokrantz et al. 2019).

As it is mentioned before, there is a relationship between the four dimensions of SM. Table 2.2 shows the two primary relationships between the dimensions which are substitutable (S) and complementary (C). Substitutable (S) refers to where one replaces the other; complementary (C) refers if doing (more of) any one of them increases the returns to doing (more of) the other (Milgrom & Roberts,1995). Each dimension is shown in both a row and a column (Table 3.2). Grey colored part of the table can be neglected since the structure is symmetric and based on pairs of interactions.

Table 2.2: Relationships between the four dimensions of Smart Maintenance (J. Bokrantz et al. 2019)

	(1)	(2)	(3)	(4)
(1) Data-driven decision-making		S, C	C	C
(2) Human capital resource			C	C
(3) Integral integration				C
(4) External integration				

First of all, relationship between DDDM and HCR (1,2) are both substitutable (automate) and complementary (augment) since ML primarily substitutes for the human's prediction task whilst complementing judgement. Computers, especially ML, substitute human for some tasks while complementing another task within an occupation. Secondly, there is a complementary relationship between DDDM and internal and external integration (1,3 & 1,4). Internal and external integration increase an information-processing capacity of organization and the increased capacity enhances the ability of organizations to collect, interpret and synthesize information that can be used for decision-making. Thirdly, there is also a complementary relationship between HCR and internal and external integration (2,3 & 2,4). Organization role is to integrate specialists' knowledge since different organizational sub-units have different stocks of knowledge which reside within the HCR. Therefore, by integrating the HCR internally with other functions within the organization as well as externally with suppliers and networks, value can be leveraged. Finally, internal integration complements the external integration (3,4) since internal integration strengthens the effect of external integration. It is possible to achieve a high performance by firstly achieving integral integration, then external integration. By the emergence of networks and ecosystems, the internal organization can no longer be separated from the factors outside the boundaries of the plant.

2.5 Previous Studies on Simulation and Maintenance

According to Haarman and Delahey (2004), it is difficult for maintenance managers to explain the benefits of maintenance. Due to its ability to model stochastic changes over time, DES has been applied to a wide range of applications area (Alabdulkarim et al. 2011). There are several examples regarding the use of DES for improving service and maintenance operations (Ali et al. 2008). This section will cover the researches which represent the study regarding the use of DES in maintenance applications. Table 2.3 is retrieved by quantitative study and presents the selected articles about how DES has been used in manufacturing maintenance applications.

Table 2.3: Classification of articles

Author & year	Title & content
Abdullah Alrabghi & Ashutosh Tiwari (2014)	**State of the Art in Simulation-Based Optimization for Maintenance Systems.** The research is mainly focusing on PM and optimizing PM frequency that will lead to the minimum cost.
Abdullah Alrabghi et al. (2017)	**Simulation-Based Optimization of Maintenance Systems: Industrial Case Studies.** The study contributes to the field of simulation-based optimization of maintenance. Stochastic Discrete Event-Simulation models were developed and connected to a Multi-Objective Optimization engine.
Alabdulkarim et al. (2013)	**Application of Simulation in Maintenance Research** Assess potential contribution that simulation (DES) can make to better understand the performance of maintenance operation.
Alabdulkarim and Ball (2014)	**Selecting the Appropriate Product Monitoring Levels for Maintenance Operations: A Simulation Approach** DES used as a tool to assess maintenance systems and was applied to a utility company by showing a comparison between reactive, diagnostic, and prognostic maintenance strategies
Alabdulkarim et al. (2011)	**Rapid Modeling of Field Maintenance using Discrete Event Simulation** DES is used to understand the impact of difference maintenance strategies in the field of maintenance
Alabdulkarim et al. (2014)	**Influence of Resources on Maintenance Operations with Different Asset Monitoring Levels: A Simulation Approach** DES model was developed to mimic complex maintenance operations with different monitoring levels (reactive, diagnostics, and prognostics). The model was created to understand and assess the influence of resources (labour and spare parts) on a maintenance operation
Alabdulkarim et al. (2015)	**Assessing Asset Monitoring Levels for Maintenance Operations: A Simulation Approach** Develop a dynamic modelling approach using DES to assess cost effective maintenance systems in order to provide a better understanding of the behaviour of complex maintenance operations

Ali Azadeh et al. (2013)	**An Integrated Simulation-Analysis of Variance Methodology for Effective Analysis of CBM Alternatives** An integrated simulation-analysis of variance methodology to analyze the cost-effectiveness of condition-based maintenance (CBM) alternatives: a discrete event simulation is used to analyze each alternative and calculate the total system cost
Ali et al. (2008)	**Optimized Maintenance Design for Manufacturing Performance Improvement Using Simulation** Presents optimized maintenance design using simulation to analyze the capability of auto part manufacturing production system
Alrabghi & Tiwari (2015)	**A Novel Framework for Simulation-Based Optimization of Maintenance Systems.** Simulation tool is used to provide adequate level of details to optimize maintenance systems
Altuger & Chassapis (2009)	**Multi Criteria Preventive Maintenance Scheduling through Arena Based Simulation Modelling.** DES is used to assess different preventive maintenance scheduling and to incorporate simulations as a decision-making support tool to the evaluation and decision process when selecting a preventive maintenance technique.
Amodeo et al. (2008)	**Simulation Based Optimization of a Train Maintenance Facility.** Coupling of DES with multi-objective optimizer is used for optimization of maintenance scheduling policies.
Azadeh et al. (2015)	**Condition-Based Maintenance Effectiveness for Series Parallel Power Generation System - A Combined Markovian Simulation Model.** Markovian discrete-event simulation model is developed to estimate the reliability and costs of the system with the aim of comparing the effectiveness of CBM with other two maintenance policies: Corrective maintenance CM and Preventive maintenance PM.
Bazargan & McGrath (2003)	**Discrete Event Simulation to Improve Aircraft Availability and Maintainability.** DES modeling was used to examine performance measures such as aircraft cycle times and mechanic labor utilization.
Cao et al. (2013)	**Optimizing Maintenance Policies Based on Discrete Event Simulation and the OCBA Mechanism.** System costs (availability) are estimated by the discrete event simulation technique and the Optimal Computing Budget Allocation (OCBA) mechanism is implemented to try to find the optimal maintenance policies for the system.

Choudhari & Gajjar (2018)	**Simulation Modeling for Manpower Planning in Electrical Maintenance Service Facility.** Present DES model for manpower planning in electrical maintenance service facility and evaluates different scenarios to improve resource utilization while meeting the desired service level.
Curtis Iwata & Dimitri Mavris (2013)	**Object-Oriented Discrete Event Simulation Modelling Environment for Aerospace Vehicle Maintenance and Logistics Process.** A DES model is being developed for maintenance and logistics analysis using an object-oriented programming language.
Erik Johansson & Mats Jägstam (2010)	**Maintenance Planning Using Simulation-Based Optimization.** A genetic algorithm for simulation-based multi-objective optimization is used to examine the possible planning options.
Peito et al. (2011)	**Simulation as a Decision Support Tool in Maintenance Float Systems.** Arena simulation language is used to contract a Maintenance Float Systems (MFS).
Gary Linnéusson et al. (2019)	**A Hybrid Simulation-Based Optimization Framework Supporting Strategic Maintenance Development to Improve Production Performance.** Discrete event simulation (DES) is used with system dynamics (SD) to support maintenance development.
Gopalakrishnan et al. (2014)	**Simulation-Based Planning of Maintenance Activities by a Shifting Priority Method.** Integrate dynamic maintenance strategies into scheduling of reactive maintenance using DES.
Gopalakrishnan et al. (2013)	**Simulation-Based Planning of Maintenance Activities in the Automotive Industry.** Investigate how different maintenance strategy affect production performance and use DES to improve productivity by selecting the best maintenance strategy.
Greasley (2000)	**Using Simulation to Assess the Service Reliability of a Train Maintenance Depot.** DES is used as tool to ensure a reliable service is delivered over time by analysing maintenance depot.
Guido Guizzi et al. (2019)	**An Integrated and Parametric Simulation Model to Improve Production and Maintenance Processes: Towards a Digital Factory Performance.** An integrated parametric simulation model is used to enhance the production and maintenance process.

Hani et al. (2006)	**Simulation Based Optimization of a Train Maintenance Facility Model Using Genetic Algorithms.** DES is developed in order to evaluate the performance of a train maintenance facility. Coupling DES with a multi objective optimizer based on a genetic algorithm simulation-based optimization method is introduced.
James et al. (2018)	**A Simulation-Based Optimization Approach Evaluating Maintenance and Spare Parts Demand Interaction Effects.** The study utilizes empirical maintenance data to generate a framework where Pareto analysis is employed to identify critical subsystems, while expert input is incorporated to derive model variables such as availability, repair time and costs that significantly impact the performance of this system.
Khebbache-Hadji et al. (2012)	**Genetic Algorithm Used in Simulation Model: Application in a Maintenance Process.** Integration of simulation model with genetic algorithm of a maintenance system in order to optimize the number of failures repaired and the stopping time of the machines.
Koochaki at al. (2011)	**Evaluating Condition-Based Maintenance Effectiveness for Two Processes in Series.** A simulation model was developed to explore the effects of production context using traditional performance indicators (costs and availability of each piece of equipment) and a more comprehensive metric (line efficiency).
Louit and Knights (2013)	**Simulation of Initiatives to Improve Mine Maintenance.** A discrete simulation model is constructed to represent the mine maintenance system. The aim is to show that significant improvement can be achieved through initiatives designed to reduce the frequency of unplanned failures and the times necessary to repair them.
Ma et al. (2012)	**Modeling the Impact of Prognostic Errors on CBM Effectiveness Using Discrete-Event Simulation.** DES model is built to improve the system performance under CBM policy by evaluating and comparing a simple system performance under three maintenance policies including CBM, run-to-failure maintenance and scheduled preventive maintenance.

Oyarbide-Zubillaga et al. (2008)	**Preventive Maintenance Optimisation of Multi-Equipment Manufacturing Systems by Combining Discrete Event Simulation and Multi-Objective Evolutionary Algorithms.** DES is combined with multi-objective evolutionary algorithms (MOEAs) and study focuses on preventive maintenance optimisation in manufacturing environments, with the objective of determining the optimal preventive maintenance frequencies for multi-equipment systems under cost and profit criteria.
Pablo et al. (2019)	**A Simulation-Based Modelling Approach to Jointly Support and Evaluate Spare Parts Supply Chain Network and Maintenance System.** Investigation on a simulation-based modelling methodology to support the decision-making process related to the Spare Parts Supply Chain which is a supporting system for maintenance operations.
Packianather et al. (2018)	**Predictive Maintenance in a Manufacturing Environment Through FIT Manufacturing and Discrete Event Simulation.** Manufacturing process has been modelled by process mapping and utilised by DES under flexible integrated technology (FIT) manufacturing constraints to study the behaviour of the manufacturing system. DES is used for increasing productivity and predictive maintenance.
Painter et al. (2006)	**Using Simulation, Data Mining, and Knowledge Discovery Techniques for Optimized Aircraft Engine Fleet Management.** DES is used to determine impact of candidate aircraft engine maintenance decisions in terms of life-cycle cost and develop a maintenance parameter to determine the LCC implication of maintenance decision made in a given context.
Paolo Pagani et al. (2019)	**A logistical Simulation Tool to Quantitatively Evaluate the Effect of Different Maintenance Solutions on the Total Maintenance Downtime for Fusion Reactors.** A logistical simulation tool is used across the time to simulate the occurrence of maintenance activities.
Ragini Waman Joshia et al. (2019)	**Simulation and Analysis of Preventive Maintenance Scheduling Techniques for Fruit-Roll Packaging Line.** A simulation model is used to analyze Preventive maintenance (PM) scheduling techniques to reduce downtime and associated costs.

Roux et al. (2008)	**Development of Simulation and Optimization Platform to Analyse Maintenance Policies Performances for Manufacturing Systems.** Integrating the optimization algorithms and the DES methods is used to analyse maintenance strategies performances for manufacturing systems in which operating characteristics deteriorate with use and whose lifetime and repair duration are random.
Sahar Tahvili et al. (2014)	**Solving Complex Maintenance Planning Optimization Problems Using Stochastic Simulation and Multi-Criteria Fuzzy Decision Making.** The study explores the use of stochastic simulation, genetic algorithms, and other tools for solving complex maintenance planning optimization problems based on discrete event simulation.
Scholl et al. (2012)	**A Multi-Stage Discrete Event Simulation Approach for Scheduling of Maintenance Activities in a Semiconductor Manufacturing Line.** DES is used planning and scheduling of extended (several days) maintenance activities at two stages. The first stage of maintenance activity planning is conducted with a transient long-term simulation model with the focus on evaluating the effect of maintenance activity on the expected fab performance while the second stage of the planning is initiated several days before the start of the maintenance activities.
Semaan and Yehia (2019)	**A Stochastic Detailed Scheduling Model for Periodic Maintenance of Military Rotor-Craft.** Develop a stochastic detailed schedule for a preventive/scheduled/periodic maintenance program of a military aircraft by using DES.
Sharda and Bury (2008)	**A Discrete Event Simulation Model for Reliability Modeling of a Chemical Plant.** DES model is developed to identify and understand the effect of different failures on the overall production capabilities and analyse the impact of change policy on production losses.
Taiwo Joel Omoleye et al. (2018)	**Impact of Resources and Monitoring Effectiveness on Prognostics Enabled Condition-Based Maintenance Policy.** The investigation focuses on CBM implementation from a new perspective by using an Excel-based interface integrated with ARENA® based Discrete Event Simulation (DES) to assess and analyze the impact of resources and monitoring effectiveness on the key critical phases in CBM policy. The paper identifies how the influence of resources and monitoring effectiveness affect asset availability and overall cost.

Tan et al. (2019)	**WITNESS Simulation of Preventive and Corrective Maintenance for Surface Mounted Technology (SMT) Line.** Discrete Event Simulation (DES) is used) to study the effect of Corrective Maintenance (CM) and Preventive Maintenance (PM) strategies to the availability. Each machine availability and system availability were verified with the simulation model.
Thomas Dietrich et al. (2017)	**A Discrete Event Simulation and Evaluation Framework for Multi UAV System Maintenance Processes.** The research presents a novel simulation framework for mobile robotic systems with the focus on energy maintenance and node replacement strategies.
Won Young Yun et al. (2008)	**Simulation-Based Maintenance Support System for Multi-Functional Complex Systems.** An object-oriented simulation model is developed to estimate the reliability, availability, and maintainability of the multi-functional system with complex structures.

A. Ingemansson et. al (2002) conducted a survey about the use of DES in the manufacturing industry. The aim is to give a current view of the use of DES in the industry. According to the survey, 79% of the companies that have adopted the technology stated that DES facilitates the decision-making process. The study also suggested that the application of DES can expand to other areas such as activity-based management, coordinate commitment between market and production and as a link between design and manufacturing. The comprehensive survey showed the usefulness of DES according to company responses. All the responses to the survey questions regarding the usefulness of DES from the companies can be summarized briefly. So that the majority of responses indicated that DES facilitates the decision-making process, improves availability of equipment and achieves cost reduction. Apart from that, the following are also extracted according to the respondent's answer (A. Ingemansson et. al 2002).

- DES is a proper tool to visualize the problem
- DES is a faster working method compared to other methods
- DES gives a relevant support for the actual decision of a project
- It is easier to prepare a model that corresponds with the real world and perform the actual simulation
- It is less effortless to use the output data from the simulation and apply it on the real world

Gopalakrishnan et al. (2014) present a study regarding application of DES in maintenance operations. The study aims to improve productivity and compares different maintenance planning strategies for manufacturing industries by using DES. DES is used to identify bottleneck machine(s) and the priority is given to that machine during maintenance. The paper compares shifting and static bottleneck priorities data that is gained from DES and the result shows that static priority model increases productivity about 5.1% while an improvement of about 1.31% for shifting priority model is observed. Similar study is conducted by Gopalakrishnan et al. (2013) with using of DES shows that it is possible to increase productivity even more up to 11% by changing operators' responsibilities or all operators work as a team. Another study regarding bottlenecks is conducted by Paolo Pagani et al. (2019), a discrete logistic simulation tool is used for the maintenance process of Hot Cell and the Cask in order to investigate maintenance times. The result of the simulation tool showed that maintenance time is decreasing with increasing number of resources and resources are more interdependent than expected. Increasing the number of resources which is currently bottleneck will turn another resource into a bottleneck.

Choudhari and Gajjar (2018) present a simulation model in order to improve resource utilization while fulfilling desired service level. The proposed simulation model helps maintenance personnel to decide the optimum number of resources to fulfil the agreed performance level that is expected by different stakeholders. The study shows the capability of the simulation as an effective decision support tool in modelling, evaluating, and choosing the alternative scenario to enhance the performance of electrical maintenance service systems. Simulation model also shows the time that is spent for value-added and non-value added activities and this enables maintenance managers to take actions in order to decrease the time spent for non-value added activities.

Scholl et al. (2012) performed a study about planning and scheduling of extended (several days) maintenance activities by conducting multi-stage DES approach. The study combines two approaches which are long/mid-term and short-term simulation for PM planning in a semiconductor water fab environment. Based on assessment of cycle time impact of the extended PM activities, the long/mid-term simulation model is used to identify the time period in which PM can be performed. The short-term simulation model is then used to identify the day within the week that PM can be carried out, upon identifying the week for PM. Simulation-based multi-stage approach for maintenance activity scheduling and associated benefits as well as challenges is explained in the paper. Ragini Waman Joshia et al. (2019) have also studied the various preventive maintenance (PM) scheduling techniques for fruit-roll packaging line and built a simulation model to analyze these techniques to reduce downtime and associated cost. DES is used for building simulation models to analyze different maintenance approaches. The failure times for CM and scheduled PM that is collected over the years by maintenance technicians is used as an input to the simulation. The article explains three techniques which are Global Maintenance Order (GMO), Value-based Maintenance Order (VMO) and Reliability-based Maintenance Order (RMO) for PM scheduling. The result of the simulation model showed that VMO is the most suitable technique for scheduling PM which reduces downtime and cost better than others.

Alabdulkarim et al. (2011) carried out a study and showed the potential that DES has in helping to understand the impact of different maintenance policies in manufacturing maintenance. The article presents the design and use of built-in logic modules to show different maintenance policies by using simulation. The paper shows the ability of DES to model complex operations such as field maintenance. Apart from this, in the study DES is used as a decision tool to decide what maintenance policy should be applied. Further, information regarding how changing of maintenance strategy affects the asset availability is explained in this article. Likewise, Alabdulkarim and Ball (2014) conducted a study which shows the ability of DES to compare different product monitoring levels. Then, this capability is applied in case study to examine whether the higher monitoring level causes higher product availability. The study identifies overall maintenance systems performance on the performance of products supported in the field using DES. DES is chosen as a tool to assess maintenance systems and the result shows comparison of three different scenarios which are reactive, diagnostics, and prognostic. Differences in the product dynamic performances can be identified by DES in complex maintenance operations while application of different monitoring levels.

Oyarbide-Zubillaga et al. (2008) present a study with the aim of combining DES with Multi-Objective Evolutionary Algorithms (MOEAs). The research is focused on PM optimisation and the objective is to determine the optimal PM frequencies for multi-equipment systems under cost and profit criteria. DES+MOEAs is used in order to introduce the effect of maintenance activities into cost and profit and maintenance intervals optimisation based on cost and benefit criteria. The study shows how generation of events and calculation of benefit and costs is performed in relation to maintenance. Cao et al. (2013) also conducted a study regarding maintenance optimisation based on cost criteria. DES and Optimal Computing Budget Allocation (OCBA) is implemented to try to find out the optimal maintenance policies for the system with the objective of maximizing the system availability while keeping the maintenance cost at acceptable level. PM and CM is considered in the simulation model and those two maintenance policies are compared in terms of cost associated with them. Simulation is a developing tool to include more complex dynamics, for the purpose of optimizing maintenance cost.

Gary Linnéusson et al. (2019) also carried out a study regarding the use of DES to optimize cost and states that DES is not adequate to visualize feedback behavior and unable to explain the reasons of certain behaviors that arise which are of great interest in order to study strategic development of systems. The need of explaining that behaviors bring out the application of System Dynamics (SD) which brings insights into industrial systems. However, the application of SD merely is not enough to study complexity at the detailed level required for a production system and that emerged the need of mixing SD with DES. The study identifies the application of SD+DES in maintenance produces a few results: it gives a performance forecast model for tool replacement, the model of availability assessment and a thesis on how to technically address the limitations of SD. To support maintenance development the integration of DES with Multi Objective Optimization (MOO) is required to achieve more complete predictions of the object to provide decision makers with details at both the strategic and operational level.

Ali Azadeh et al. (2013) analyzed the cost-effectiveness of CBM alternatives with respect to different levels of influencing factors. DES is used to analyze each experiment and calculate the total system cost. The study explains the idea of using DES is associated with two main principles of designing any experiments, which are randomization and replication. Randomizations means the errors that happen during conducting an experiment is attributed to the uncontrollable factors such as experience of the operators, working conditions, work instructions etc. Replication refers to the independent iteration of experiment under the same condition which provides a strong and more reliable results and inferences. Real implementation of the experiment requires a lot of time and investment. On the other hand, the circumstances for the experiment do not remain the same due to the long running time of experiment. So that robust simulation enables the generation of completely random errors within the experiment and repeating the experiment without concerning the time and cost.

Peito et al. (2011) developed a simulation model for Maintenance Float System (MFS) using DES. This model allowed the estimation of average system availability and total maintenance cost. In the DES model, a control system for repair and overhaul requests is generated. Managing the maintenance queue is based on the First In First Out (FIFO) rule, except the case when the total number of maintenance requests exceeds the number of maintenance crews. In this case, machines requiring repair action have priority over machines requiring overhaul.

Alabdulkarim et al. (2014) develop DES model to support maintenance operations decision makers in choosing the appropriate asset monitoring level for their particular operations and DES was created to understand and assess the impact of resources (labor and spare parts) on a particular maintenance operation. The paper examines the effects of different levels of spare parts (ranging from deficient inventory to a plentiful spare inventory) and labour on the asset availability by using a DES approach. The DES model is developed to compare different monitoring levels (reactive, diagnostics, and prognostics) using different levels of spare part policies and the expected output of this simulation is to understand the effect of different monitoring levels on the overall system performance. Another study is carried out by Alabdulkarim et al. (2015) also shows the effects of different spare parts policies on different monitoring levels by using DES. In order to provide a better understanding of the behaviour of complex maintenance operations, a dynamic modelling approach using DES is developed in the study.

Taiwo Joel Omoleye et al. (2018) have done similar research that focuses on CBM implementation by using an Excel-based interface integrated with simulation based on DES. The main aim of the study is to investigate the impact of resources (spare parts and maintenance workers) and monitoring effectiveness (imperfect condition monitoring, imperfect diagnostics, and imperfect prognostics) that affect asset availability and overall cost by using DES. A modelled DES tool and Visual Basic for Application (VBA) codes was created by Taiwo Joel Omoleye et al. (2018) to get the different monitoring levels which are Classic CBM, Diagnostics-enabled CBM and Prognostics-enabled CBM. The study emphasizes the importance of maintenance resources such as spare parts and maintenance personnel in the effective execution of maintenance systems.

Importance of spare parts is also mentioned in Pablo et al. (2019). The study suggested a simulation-based modelling approach helps to evaluate Spare Parts Supply Chain performance along with its impact on the Maintenance System. The joint modelling and performance evaluation for Maintenance System and Spare Parts Supply Chain enables the assessment and selection process of Spare Part inventories such as supplying process, decisions for transport and maintenance operations. The proposed simulation model is built based on Preventive and Corrective maintenance strategies and considers the existence of three small warehouses for each of the SP, where each warehouse contains inventories which are considered to serve specific SP requirements for maintenance activities. Then, based on the Inventory Control Policy (ICP) that is assumed for each SP, the orders are determined and submitted to independent suppliers for each SP. Thereby, based on the DES model the research suggests and develops a quantitative methodology to assist the planning and control of the Spare Parts Supply Chain network.

3
Methodology

This chapter presents the methodology used for the thesis. It begins with research strategy and followed by research design. Then description of data collection is presented, and the chapter closes with research ethics.

3.1 Research strategy

According to Bryman and Bell (2015), research strategy is a general orientation when conducting a research. Quantitative and qualitative research is considered two main clusters and those clusters are different regarding a few areas stated by Bryman and Bell (2015).

Quantitative research is a strategy that focuses on numbers, monetary terms, and percentages during data collection (Krishnaswami, 2010). It is a research strategy that revolves around numbers (Bryman and Bell, 2015). Apart from this, quantitative research enables researchers to use statistical tools which help to draw conclusions collectively and at an individual level (Krishnaswami, 2010). The role of a theory in relation to the research is deductive approaches. It means that the researcher builds a hypothesis based on existing theory and rejects or confirms it at the end of data collection and analysis (Bryman and Bell,2015).

By contrast, qualitative research is a strategy that focuses on words rather than numbers when collecting and analysing data (Bryman and Bell, 2015). It puts more emphasis on subjective assessment of attitude behaviour, impressions, opinions and so on (Krishnaswami, 2010). The role of theory in relation to research is an inductive approach. It means that firstly researchers collect the data and then build a theory which helps him/her explain the patterns examined from the data (Bryman and Bell, 2015). A combination of quantitative and qualitative research, where researchers draw conclusions based on both approaches, is called mixed method research (Creswell & Clark, 2017). Denscombe (2010) explains mixed methods as the use of many different research methods in a research project.

Mixed method research improves researcher's confidence in the accuracy of findings through the application of different methods to examine the same subject. It can also improve the findings of research by providing a clearer and more complete picture of the topic that is of interest. (Martyn Denscombe, 2014). However, O'Gorman and MacIntosh (2015) do not agree with this statement using mixed method research would only lead to confusion and misunderstanding of results.

There is another research approach that analyse research problems with different perspectives, but also gather different materials of research projects without confusion and called triangulation of methods. Unlike using many different research methods in mixed research, as the name implies, the main idea of using triangulation in mixed method research is to work on and combine three perspectives in order to get key findings. By validating findings in terms of authenticity and checking bias in research methods, triangulation allows the researcher to get improved accuracy (Denscombe, 2010). Since it prevents misunderstanding and confusion during research, triangulation mixed research is the research strategy used for the thesis. Literature review, qualitative and quantitative data or research are three methods which are used as three perspectives of triangulation mixed method and it is depicted in Figure 3.1

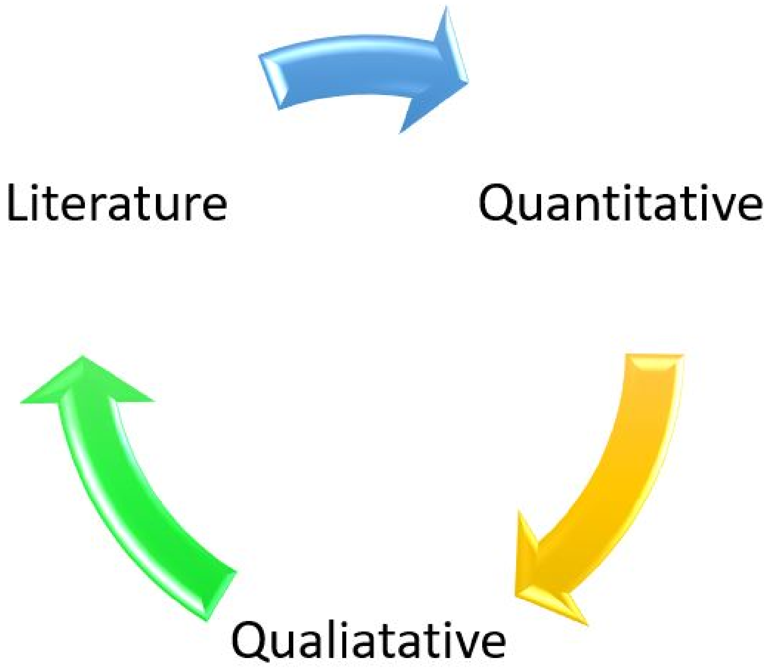

Figure 3.1: Illustration of the research methodology.

As it can be seen from Figure 3.1, literature study, qualitative and quantitative research or data collection will be three main combined perspectives throughout the research.

3.2 Research design

Saunders, Lewis & Thornhil (2016) argue that in order to meet different types of purposes, research can be designed as followings: exploratory, explanatory, evaluative purpose or a combination of the three. In order to determine which study type is suitable, it is needed to go through research questions. There are three types of studies as followings: Exploratory studies are suitable when the researcher needs to get a deeper understanding of a problem or phenomenon. Explanatory studies are useful when the researcher wants to understand the relationship between variables in a given situation, e.g. relationship between mean and standard deviation. Descriptive studies focus on getting an accurate profile of events, situations or persons which needs a clear picture of the topic in advance.

Since the thesis is of a research nature and its focus is on a literature review and the purpose is to conduct exploratory study. The reason to conduct exploratory study is that there is a certain need of knowledge and researchers should gain a deeper understanding and insight about the topic of interest which requires a comprehensive literature review.

3.3 Methods

This section presents data collection methods. It starts with literature study and finishes with interviews.

3.3.1 Literature study

Literature study helps researchers to collect background information about the topic. Since the thesis is of an exploratory nature literature study plays a very important role for the study and it needs to be conducted properly. The literature study is conducted in order to see what is already researched and known in the topic of interest, which types of research methods were used previously, what concepts and theories are relevant among others. A comprehensive literature study is conducted in order to get a better and deeper understanding of the problem. Previous research knowledge is examined through the literature study and is presented in the theory section of the report. The main purpose of the literature study was to find previous studies that presents the use of DES in manufacturing maintenance. Also, to identify how DES can be linked with SM dimensions which is a quite new concept for the industry. Apart from gaining insight about the study, the researchers use the literature in order to make appropriate assumptions. Literature study is conducted using different search engines in order to increase range of knowledge. The search for relevant literature will be conducted through Chalmers Library databases such as Scopus, ScienceDirect etc. and Google Scholar.

Relevant information is gained by searching for appropriate keywords in databases such as maintenance, maintenance strategies, maintenance optimization, smart maintenance, simulation, discrete-event simulation, manufacturing maintenance applications.

Review of titles is a first step when narrowing down the research. If the title is relevant to the study, reviewing the abstract helps researchers in order to decide whether to read the whole article. After reading abstract, articles that seem relevant to study are chosen for full-text review.

3.3.2 Interviews

Interviews were appropriate to conduct because there is a value to gather deeper information from persons with relevant roles or experience (Denscombe, 2014). In order to deeper understand the use of DES in maintenance and SM dimensions, the qualitative data were collected in the form of face-to-face semi-structured interviews. Qualitative data which are collected in the form of interviews are one of the data collection methods that uses selected people's answers to researchers' questions as a source of data. The first thing needs to be considered in this regard is the possibility of having access to potential interviewees. Since the project is about the application of DES in smart maintenance, people were intended to be selected from certain areas where they have done similar tasks in these respected fields. As it is explained in section 1.2 the use of DES in manufacturing maintenance applications is a new industrial application, therefore, only three people were found to be interviewed. So that, two PhD students and one researcher were chosen to be interviewed. The interviews were intended to be held through the Zoom software considering the current quarantine regime.

The interview procedure was carried out in four stages: In the first phase, the aim of the interview study was defined. The right way of performing the interviews as well as the information that is required to be gathered were defined to achieve the aim of the study. In the second phase, interview questions were developed considering the purpose and research questions of the study. In the third stage, gained information was transcribed. Finally, gained data was documented in a way that is understandable and reasonable. Here are the main interview questions:

IQ1: What is the application area of DES in maintenance? How DES is used in maintenance area?
IQ2: How can you define SM and what can you say about its four dimensions?
IQ3: How smart maintenance will change the future production system? What are the benefits and drawbacks of smart maintenance from a production system perspective?
IQ4: When it comes to the SM dimensions, which one do you think is more important and why? Or do you think all of them have the same importance? What can you say about the relationship between these four dimensions?
IQ5: How DES can be used in Smart maintenance dimensions? How it is possible to relate each dimension with DES? Which dimension can be improved better with the application of DES?
IQ6: Can DES be considered as a decision support tool?

Before starting the interviews, the aim of the study was clearly expressed and consent for recording the interview was gained. The interview time was kept to one hour. To make sure that any valuable information was not missed as well as not being distracted by taking note are the main benefits of recording the interview. Also, recording the interview did not disturb the interviewees and it is feasible to double-check the provided information (Denscombe, 2014).

According to Martyn Denscombe (2014), interviews are divided into three types according to what extent the sequence of questions and answers stick tightly to an agenda. The first one is a structured interview where the researcher has a predetermined list of questions. The questions are structured in such a way that encourage the respondent to offer limited-option responses. This interview method standardizes the process of data collection that is especially useful when conducting a great number of interviews that involve computer-assisted personal interviewing with many interviewers inputting responses directly into mobile devices. The second type of an interview that is suggested by Denscombe (2014) is called semi-structured interviews. The questions are prepared in advance as it is in the structured interview, however, the topic can be addressed in a flexible way. So, the interviewee can freely develop ideas and speak more broadly on the issue resulting in more open-ended answers. Unstructured interviews are the third way of conducting an interview. The role of interviewers is basically to introduce a topic, but the focus is not to find answers to a set of predetermined questions. The idea is to give the interviewee a freedom to think and develop their own ideas rather than shaping the discussion by the questions that the researcher has already in mind (Martyn Denscombe, 2014). It is important in the beginning to decide on whether a standardized interview or more a flexible approach suits best to the purpose of a research project.

The semi-structured interview is decided to be conducted in this project. This approach enables researchers to develop the interviews and refers to the questions from previous interviews. The notes were taken during the interviews to provide better interaction, at the same time the interviews were recorded by the permission of interviewees since the reviewers do not want to miss any valuable information. Interviewees have been provided with relevant information about the project before the interviews are conducted. All the interviews were transcribed from audio recording and used for the result chapter.

The purpose of the interviews is to gather the information and get deeper insight to the previous research within the areas of DES, maintenance and smart maintenance. Therefore, interviewees were chosen to have experiences from respected fields. Interview questions have been formulated with the aim of determining the use of DES in manufacturing maintenance applications as well as identifying the link between DES and SM dimensions. The interview questions also aims to gather information from the researchers that would validate the literature findings in this regard. The interviewees' details are presented in table 3.1 below. After conducting the interviews saturation is an important concept which is defined as data adequacy. In contrast to quantitative research, in qualitative research the signal of saturation should be determined by researcher proclamation and by evaluating adequacy and comprehensiveness of the result (J. M. Morse, 1995).

Table 3.1: List of interviewees and their expertise

Interviewees	Area of knowledge	Background
Researcher 1	Maintenance Management Data-driven Decision support for maintenance Planning and Prioritization	KTH Royal Institute of Technology
Researcher 2	Smart Maintenance - maintenance in digitized manufacturing	Chalmers University of Technology
Researcher 3	Implementation of Smart Maintenance within industry	Chalmers University of Technology

3.3.3 Data analysis and validation

This subsection explains the methods used to process and analyze data throughout the data collection process.

3.3.3.1 Triangulation

Triangulation is a multi-method approach for data collection and analysis in qualitative research. The main idea of triangulation method is that the phenomena is understood best when a combination of multiple approaches are applied for the study (Lisa M. Given, 2008). This multi-method approach allows researchers to identify and explore different dimensions of the studied topic, and thereby it strengthens their findings and enriches their interpretations. Triangulation method can be used in four basic ways: triangulation of methods, investigator triangulation, theory triangulation, and triangulation of data sources (Lisa M. Given, 2008).

Triangulation of methods and triangulation of data sources are the two approaches that are used in this project. Triangulation of methods is when conducting a project, researchers combine various methods such as interviewing and observation in variable times and in various places in order to get the data about the studied topic from different perspectives. Thus, to explore different dimensions of the topic, authors combined various methods such as interviews as well as literature study. Researchers can also vary the methods that are used in each type of approach: for example, they can use a combination of conversational interviewing and structured interview questions, methods that would give complementary data. So that, authors also varied the methods that is used in interview process by using the combination of conversational and structured type of interview questions. Triangulation of Data Sources is about increasing the credibility research findings by using a variety of data sources. For example, researchers may gather data from interviews, written documents and other similar projects. Each type of data source provides various evidence and insights to the studied topic (Lisa M. Given, 2008). To give more insights and increase the credibility of research findings some data is gathered from similar projects. Since the using of DES in SM dimensions is a new industrial application, there is not sufficient literature findings regarding this topic yet. There are not many qualified people from the industry either, therefore, only 3 people were chosen to be interviewed in this regard.

Multiple methods were combined to get a deeper insight and understanding of a researched topic. This method aids the triangulation of data sources that comprises interviews. Each approach contributes to understanding the studied phenomena deeply and effectively.

3.3.3.2 Data saturation

Saturation is defined as data adequacy which is the key to excellent qualitative work. It can also be explained as collecting data until no new information is obtained (J. M. Morse, 1995). In qualitative research, there are no guidelines to estimate the size of data that is required to reach saturation compared to those where formulas used in quantitative research. During the literature study, after full-text review of certain number of articles, no new information is obtained. The literature findings became to give the same information over and over regarding the use of DES in maintenance. Thereby, data saturation is achieved. Interview result also gave the same information in this regard.

As opposed to quantitative research, in qualitative research, the research seems to give the signals of saturation by evaluating the adequacy and comprehensiveness of the result. Although initially qualitative data appears diverse and disconnected, in the saturation process, it forms patterns and themes and begins to make sense. However, the book states that there are no specific rules for the estimation of the amount of data required for each category but it emphasizes the importance in the initial stages of analysis, the researcher must give equal attention to each group in the analytic coding procedure. Frequency in the occurrence of any specific incident must be disregarded, since saturation involves eliciting all forms and types of occurrences, prefer variation over quantity (J. M. Morse, 1995). In this thesis, saturation of data is also achieved when it comes to the application of DES in SM. There is not any specific rule to estimate the amount of data required for saturation in qualitative research, the aggregated interview result, variation as well as clear analysis of that data gave the signals of saturation .

It is the fact that researchers may report some information repeatedly and report other aspects of the studied topic less frequently, which is inconsequential. It is rather important for the researchers to “know it all”, than to hear the things repeatedly over which could make a false sense of saturation. The quantity of the data is not important in the saturation process, what is more important is the richness of the data, not the number of times stated (J. M. Morse, 1995). Qualitative research is based on variation and has two aspects: first, how does the researcher decide on the completeness of the result and secondly, how does the researcher know when enough data is enough? The faster saturation will be achieved by being tighter and more restrictive on the data and narrowing and delineating the domain. In this project, saturation approach is used in the whole process of collecting and analyzing data.

3.4 Research ethics

When dealing with the research ethics eleven principles stated by Bryman and Bell and some of them are discussed which are *harm to participants, informed consent, privacy invasion, confidentiality, anonymity and deception* (Bryman and Bell, 2007). The first one is harming to participants which refer to the potential to cause harm throughout the research process and there is a need to ensure physical and psychological well-being either of research participants, the researcher, or others. The second one which is informed consent is about fully informing of research participants such as stakeholders about the interviews. By sending the details of the interview before the meeting is scheduled allows them to have enough time to decide about their participation in the interview.

The third one is privacy invasion where there is a need to protect privacy of research subjects. It is about asking the project sponsor for permission to take photos or filming inside the factory and products. Confidentiality is a requirement to ensure the privacy of research data whether relating to individuals or organizations. The purpose is to protect the information that is provided by research participants from other parties. Anonymity involves concealing the names of an individual such as interviewee or an organization in order to protect their identity. Deception which refers to trapping the stakeholders or the potential cheating through the research process, either through lies or misleading behavior (Bryman and Bell, 2007).

4

Results

This chapter presents the results gained from literature review. The findings from the theory enable reviewers to answer research questions.

4.1 Using of DES in maintenance

After conducting quantitative research, findings regarding the use of DES in manufacturing maintenance application will be presented in two different graph forms. One of the graphs will illustrate year distribution of relevant articles and another will present information regarding the use of DES in manufacturing maintenance applications.

Year allocation of relevant articles retrieved by quantitative study is of great importance due to how many articles intended to present DES in maintenance during corresponding years. To do so, it is possible to analyze whether the use of DES in maintenance is an increasing tendency. Schematic view of year distribution of papers has been illustrated in Figure 4.1.

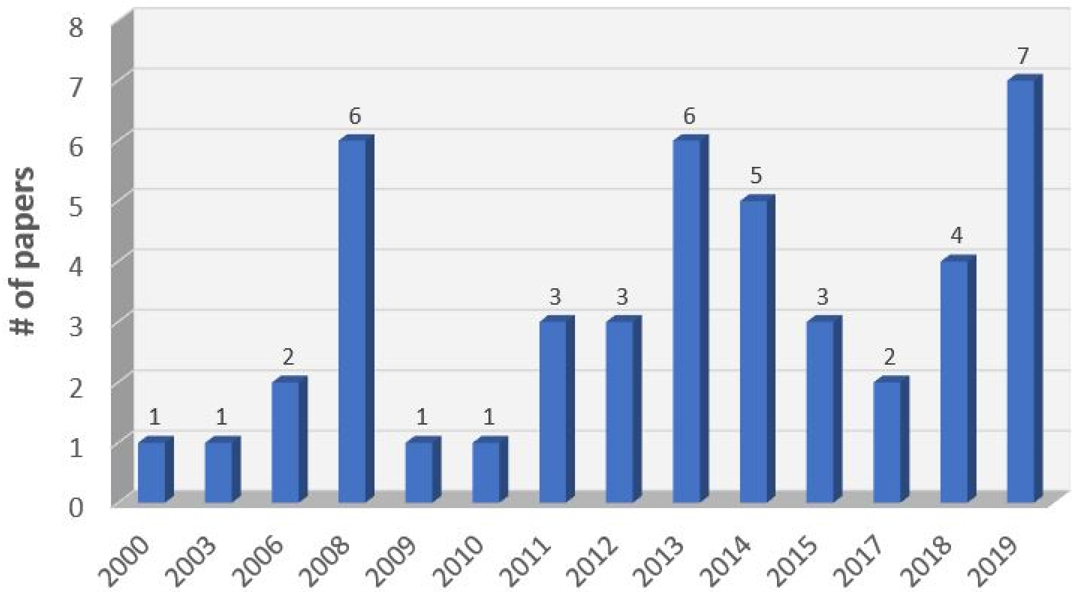

Figure 4.1: Year allocation of papers.

Based on the chart, it can be said that research about the use of DES in maintenance has started at the beginning of the twenty-first century and it was not a popular research field until 2013. However, in 2008 there have been quite many studies regarding the topic. The number of research papers regarding the topic of interest between 2013 and 2019 is 50% more than the papers between 2000 and 2012. This means there has been a 50% increase of studies during the last six years compared to twelve years passing after the starting of study. Moreover, compared with all the times, there have been no more studies conducted than last year. After analyzing the figure 4.1, it is clear that the topic of interest is an increasing tendency.

The other graph presents the parameters that DES studies focused on regarding maintenance. The graph provides valuable information and answers to one of the research questions. After conducting quantitative research and full-text review of related articles, the papers were allocated in terms of maintenance application. It is found out that DES was used in the papers for six specific purposes in terms of maintenance and authors decided to call it as six maintenance parameters which are various maintenance strategies, availability, productivity, cost, maintenance planning and scheduling, and spare parts. Figure 4.2 illustrates the parameters that are estimated with the help of DES in various projects. Before analyzing the graph, it should be mentioned that one paper may provide information about more than one parameter.

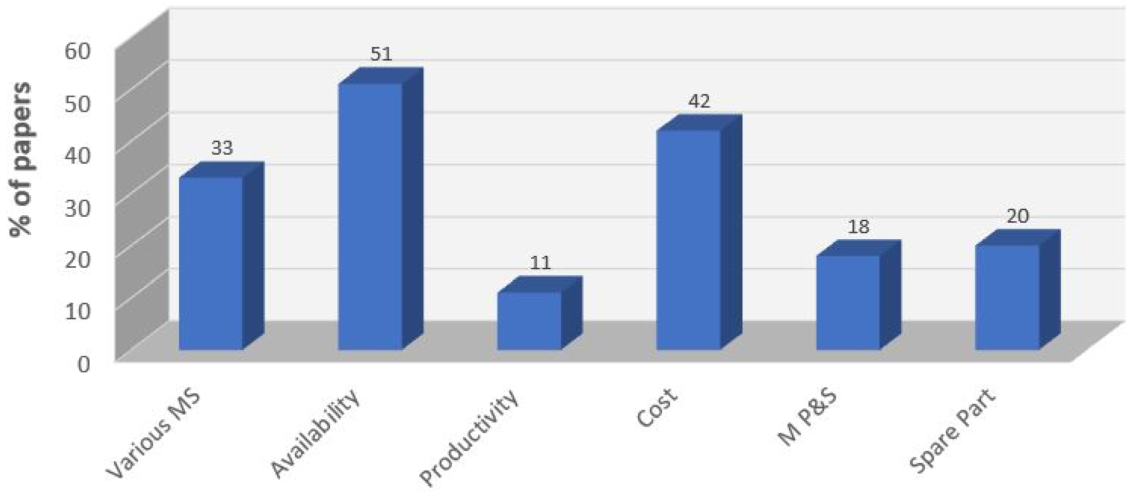

Figure 4.2: Maintenance parameters used in DES

As it can be seen from the graph, DES is used in 33% of papers in order to compare different maintenance strategies or policies for organizations and this parameter is the third most examined element that is used in DES projects. 51% of all papers present DES to improve or investigate availability within the organization and the availability is the most considered parameter in DES projects. Quantitative research shows that availability is examined in the DES project as two different factors which are people (maintenance personnel, labor, and crew) and technology (maintenance equipment, machine, component) availability. Among the availability considered papers, 35% of papers investigate the people availability while 87% of papers focused on availability of technology. It should be mentioned that one paper may include both availability factors. The least mentioned parameter among all is productivity. 11% of articles considered improving productivity while using the DES method. DES is used in 42% of articles in order to compare or investigate cost and the cost is the second most considered parameter in DES projects. Maintenance planning and scheduling and spare parts are very close parameters as a percentage which are 18% and 20% respectively. 18% of papers consider planning and scheduling of maintenance activities with the help of DES method. Lastly, DES is used in 20% of paper in order to compare or examine different spare part methods.

The result of papers by 51% showed that DES is mainly used to investigate availability within the organization. In Alabdulkarim et al. (2011), DES is used to show how changing of maintenance strategy affects the asset availability. To compare different product monitoring levels, Alabdulkarim and Ball (2014) has done a study to show the ability of DES in this regard. Cao et al. (2013) used DES with OCBA to find out the optimal maintenance policies for the system with the objective of maximizing the system availability while keeping the maintenance cost at acceptable level.

As it can be seen from the figure 4.2, cost is the second most considered parameter that is investigated by means of DES. DES model can be developed to test different strategies and analyze the system's behavior. As Alabdulkarim et al. (2013) stated, DES has the potential to calculate maintenance operation cost, especially to address the cost-efficiency of introducing product monitoring (sensing) technologies for product located within customer locations as the case in production service system. Gary Linnéusson et al. (2020) study used SD and DES together to optimize cost. On the other hand, by the application of SD+DES in maintenance gives a performance forecast model for tool replacement and the model of availability assessment. Ali Azadeh et al. (2014) also showed that DES can be used to analyze the cost-effectiveness of CBM alternatives with respect to different levels of influencing factors. Here DES is used to analyze each experiment and calculate the total system cost.

The study of Gopalakrishnan et al. (2014) showed how DES can be used to improve productivity and compared different maintenance planning strategies for manufacturing industries. To improve productivity, DES is also used to identify bottleneck machine(s), and during maintenance priority is given to that machine. Paolo Pagani et al. (2019) also conducted a study regarding bottleneck detection a discrete logistic simulation tool is used to investigate maintenance times. According to the result of the study maintenance time is decreasing with increasing number of resources. To improve the resource utilization as well as achieving higher level of availability, Choudhari and Gajjar (2018) presented a simulation model.

Scholl et al. (2012) achieved to plan and schedule maintenance activities by conducting multi-stage DES approach. Combination of long/mid-term and short-term simulation approaches are used for PM planning. Alabdulkarim et al. (2015) used DES to show the effects of different spare parts policies on different monitoring levels. Spare parts management is an important component in the maintenance system and has a considerable impact on cost and availability. Taiwo Joel Omoleye et al. (2019) study focused on to investigate the impact of resources (spare parts and maintenance workers) and monitoring effectiveness (imperfect condition monitoring, imperfect diagnostics, and imperfect prognostics) that affect asset availability and overall cost by using DES. Pablo et al. (2019) emphasized the importance of spare parts and the study suggested a simulation-based modelling approach helps to evaluate Spare Parts Supply Chain performance along with its impact on the Maintenance System.

During the study of the six parameters DES is also found to be used as a decision support tool in the literature. According to the study of A. Ingemansson et. al (2002) survey, 79% of the companies stated that DES facilitates the decision-making process. The survey states that DES enables to visualize the problem and faster compared to other methods. With the help of DES, it is easier to build a model that corresponds with real world and perform the actual simulation.

In manufacturing industries DES is used for bottleneck detection. DES model is also used to show the time that is spent for value-added and non-value-added activities and thereby maintenance managers can take actions in order to reduce the time spent for non-value added activities.

4.2 Classification of the papers in terms of SM dimensions

After investigating how DES is used in manufacturing maintenance applications, classification of the previously conducted articles in terms of the SM dimensions is performed. Since the definition of SM dimensions (section 3.4) is provided in theory chapter and it is fully understood by the researchers, that knowledge helped the researchers to classify the papers regarding SM dimensions. All the papers were tried to be classified in terms of SM dimension during the full-reviewing process. The link between SM dimensions and DES was carefully identified. It should be mentioned that one paper might have been linked to more than one dimension. The classification of the previous studies regarding SM dimensions is illustrated in figure 4.3.

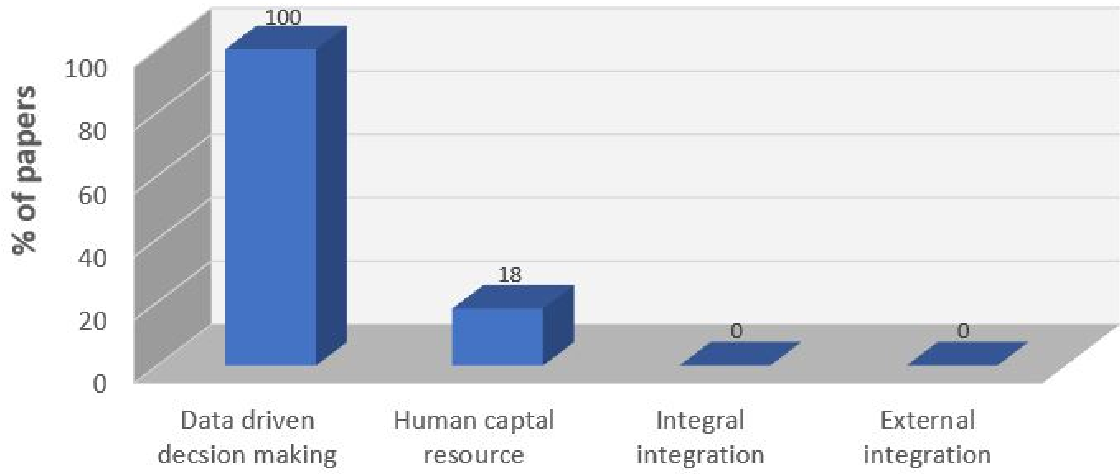

Figure 4.3: Classification of previous papers in terms of four dimensions

As it is mentioned before (section 2.2.1), DES requires data in order to create a model and the model is used to make decisions based on the data. So, it is possible to say that DES projects cannot be modeled without data. Verification of this statement can be shown in figure 4.3. As it is depicted in the figure, all the reviewed papers can be linked with the DDDM dimension of SM since the data is used to create simulation models. After examining all the articles, it can be said that the DDDM dimension is highly linked with DES. Researchers want to clarify which kind of data is used for the DES project in the studies since another part of this finding will be discussed broadly in the discussion chapter. In some articles, data is collected by computerized data sources from the company shop floor while some papers mention that data is gained based on the manager's experience and interview with production personnel. It is mentioned in more than half of the articles that historical data is considered as the data used for the DES model. So, the first findings from the studies shows that DES is very closely related to DDDM.

Among all the examined studies, there is only 18% of them which can be linked with the HCR dimension of SM and the link will be explained in this part. DES is presented in some articles to investigate how would different labor level affect the maintenance strategy (Alabdulkarim et al. 2015 & Alabdulkarim et al. 2014) while DES is used in some articles to understand and assess the effect of different levels of labor availability on different maintenance monitoring level (Alabdulkarim and Ball, 2014 & Alabdulkarim et al. 2011). By considering the stochastic nature of complaint arrival and processing time there is a study (Choudhari and Gajjar, 2018) aimed to decide appropriate staffing levels while meeting the desired customer service level. Moreover, another study (Louit & Knights, 2013) investigated the workload for each simulated event and decided whether to increase current labor. In addition, with using DES on a system-wide level, the objective of one of the papers (Taiwo Joel Omoleye et al. 2018) is to assess the impact of resources including workers on CBM. Lastly, there is a study (Peito et al. 2011) which discusses the optimal number of maintenance crews using DES.

As it is illustrated in figure 4.3, linking of internal as well as external integration with DES could not be possible for this study. There were not any articles to be found to mention the link between those dimensions and DES.

4.3 Interview results

The semi-structured interviews were conducted with three researchers whose research area focus are Maintenance Management and SM. The first interviewer's research is mainly focused on Maintenance Management more specifically - Data-driven Decision support for maintenance Planning and Prioritization. The other two interviewers' research are more focused on how to conceptualize SM and how SM can be implemented easily in the organizations.

The result of the interviews has been summarized in four subchapters. The input from the interviewers gives more insight to the problem by defining SM, its dimensions as well as the relationship between these dimensions and answers two research questions of this project.

4.3.1 Defining SM, its dimensions, and the role of SM in industries

One of the researchers has been working for a long time together with Swedish Manufacturing Industries (SMI). SMI has shown a need for more clear, collective vision and concept, as well as terminology, so they can work with. SMI particularly thinks from a sustainability perspective and decided to call the idea about future maintenance as SM. After SMI decided to call it SM, then researchers proceeded with this study, created the concept and came up with four dimensions of SM.

The research field of maintenance is mainly technology oriented, therefore research papers can define SM from a technological aspect. However, the researchers have defined SM from more a realistic perspective by considering people and organization. One of the researchers stated that SM is a modern version of TPM. It is similar to TPM and it is sort of a model for the entire maintenance function. Indicating the difference between SM and other maintenance types helped to better understand SM. According to his explanation, for example, RCM is more of a planning method, PdM is maintenance policy which is extremely narrow, but TPM is something that is more realistic. So, the idea is that SM is similar to TPM, but in a new environment. According to other researchers, all types of maintenance, corrective and preventive are still part of SM. SM is not a completely new operational concept, it is not like new TPM, which is still used. SM asks companies to change the way they do the business, for example change the way they work with respect to data (DDDM) or sharing of the data (Internal and external integration). That is what SM brings to the table. SM is about how maintenance is done at an organizational level, that is the case. As one interviewer mentioned "You would do proactive maintenance, predictive maintenance or high-end machine learning applications without doing SM.

At the same time, you may not achieve really high technological advancement but still be smart in some way." As a concept SM is about how organizations work, whereas on the other side there are a lot of technological advancements. Just because organizations have technological advancement does not mean it is automated or smart in the way of organizing their organizations. Organizations can be smart with not the zero use of technology but optimized use of technology. There is no limit at what stage companies should stop to claim to become SM,it depends on the company. Maybe simpler applications still are enough to achieve what is required at a given plant. Technology matters for the specific part of SM such as, for example data driven decisions, data analytics, data analysis or ML.

According to the last interviewer, SM itself is not an improvement of any maintenance type such as TPM or RCM. When companies want to work with SM, they take a lot of initiatives to develop different ML projects to increase DDDM and they educate the workers to increase HCR. So, TPM or RCM are the maintenance types that companies have first and then ready to level up their maintenance by trying the SM concept.

When it comes to the SM dimensions and its importance, each researcher has amplified the fact that all four dimensions of SM are necessary to achieve a high level of performance. These dimensions are closely connected and improvement in one dimension will have an improvement in another dimension in some way. One is not more important than the other. There is no SM unless all four dimensions are achieved. One of the researchers also stated that all four dimensions need to have SM, but in general saying, the competence is needed first, then internal integration, and then it can be improved better by DDDM and to be the best external integration can be applied.

4.3.2 The application of DES in manufacturing maintenance applications

DES is a great tool to test production systems behaviour. It is not necessarily used for decision making, but it is a great tool for testing maintenance strategies as well as allocating resources. The available data on the shop floor can be used to simulate production line and it can be used for bottleneck detection. One of the researchers stated that they have already reached a point right now that they could completely skip DES and still reach bottleneck analysis and maintenance opportunity windows directly from the data. DES is used as a tool to verify the results, but at the same time engineers could also choose what happens in the production system if the decisions are changing. System dynamics can be well analyzed in DES because direct data cannot capture system dynamics. DES can also be used to investigate the potential role of implementing new technology into production and what could be done from a maintenance perspective. The interviewer mentioned that by collecting a lot of data about the machines or equipment, it is possible to predict which part is about to fail, so workers can order spare parts in time and thereby it eliminates the risk of failure at the plant.

The interviewers did not mention any particular parameters that are not found in our research. When the six parameters that are the result of quantitative study were introduced it was acknowledged by all interviewers. They stated that researched parameters which are various maintenance strategies, availability, productivity, cost, maintenance planning and scheduling, and spare parts sound quite reasonable that indicating the use of DES in the manufacturing maintenance application.

4.3.3 The application of DES in SM dimensions

How DES can be used in SM dimensions is one of the research questions for this project. One interviewer explained that DDDM is the obvious one that could be improved better with the help of DES. Because that is where DES uses data for some sort of decision making, it could be a bottleneck or maintenance prioritization, availability, or spare part. HCR can also be improved with DES. It is also possible to simulate the value chain internally as well as externally in the factory. Different scenarios can be simulated to see how data can be shared internally and externally. However, that can not be done by using DES, agent-based simulation would be the right choice for that purpose.

The other interviewer stated that DES can be considered as some sort of decision making tool if it is used on a daily basis by maintenance engineers. They can simulate the HCR in order to see what kind of manpower is needed or to calculate the time consumption for the repairs. So, they could simulate to see the time spent on repairs or is there any errors in the repairs that could be reflection of low skill for example. Then, they can estimate the effect and come to the conclusion that if higher skill in the maintenance employees would be achieved the repairs could have been done quicker.

On the other hand, the interviewer also stated that a simulation model is not data driven when it is used in practice. Because DES creates the model and it is not being fed directly with the real time data. In fact, that is possible with DES now, but it is not how DES typically used. It is possible to take some form of distribution and historical data, but then it is needed to make assumptions about the input values for the different resources. Then experiment can be done with this model and possible to make a decision with it. Data driven means creating a model from the data and that is mainly what ML does. ML uses algorithms to create a model from data, but in DES the model is created and then the data is estimated with data from the production system. In many cases, assumptions are made based on historical data, something from their suppliers or people just make it up. The researcher emphasized that it is possible for the simulation model to be integrated with an information system where the simulation model can be fed and upgraded automatically and that is the time DES becomes more data driven.

Last researcher mentioned that DES has a positive impact on all dimensions somehow. If you educate the workers to analyze the simulation result, it clearly improves HCR. Also, DES can be used as a communication tool to improve internal and external integration. Instead of explaining to the workers the reason why investing on certain machines, engineers can run simulation models and get data in order to provide fact-based arguments which makes it easier to communicate with the economy department or management level.

All in all, DES could be used as a decision support tool if the model can be fed with real time data continuously. Also, DES becomes a DDDM tool in case of using it on a daily basis as a manufacturing engineering tool and automatically upgrading the model with data all the time.

4.3.4 How SM will reshape the future production system, pros and cons

The company that has SM means a company has a smart way of working, or they are working toward improving productivity or competitiveness. It will change the nature of work. The way of working will be changed completely for both customers as well as service providers. One interviewer stated that there will be more interaction between the manufacturing company and the equipment manufacturers as well as manufacturing companies and customers that they provide. Some particular jobs of employees will be replaced by technology as well.

SM will definitely challenge humans and employees will need to be updated and trained continuously with the latest technology. Digitalization first does skills requirement, so that maintenance employees that are going to work in SM organizations need to have higher skill. SM is also an opportunity for maintenance workers to develop themselves which can be highlighted as the positive side of it. The benefits of SM are quite clear, if a company possesses SM, it can reach its high level of performance. Obviously, the companies that possess SM have a much more aligned goal with the rest of organizations.

All interviewers highlighted that extremely high performance of maintenance does not necessarily lead to high production performance, it is important to find the optimum, the right amount of maintenance maximizes the output, conversely superfluous amount of it will end up with reduction in productivity. Over maintenance is a kind of loss. Maintenance in most cases is a tradeoff between productivity and cost and cost could be considered as a main drawback of maintenance. SM cost does not just consist of the investment in technology or technical infrastructure to be able to work in a smart way. In general, lots of people are needed to work in SM which emerges as an integration cost. It takes a lot of efforts to work together with all other departments, companies, as well as suppliers, and that is always associated with cost in the organizations. Sophisticated maintenance costs a lot of money and the point is to figure out whether that is worth investing in terms of productivity.

Engineers could be careful of what is required for the particular plant or what is necessary for them rather than seeing some other plant doing something else and trying to compete. Because introducing new technology changes the work in an organization.

The thing is to make sure that plants have the right technologies for the intended outcome. Not all the companies should aim to reach the same level of technology. All companies can apply SM concept, but they need to decide whether it is worth it in terms of productivity.

5

Discussion

The chapter discusses the result of this thesis and the methods used to answer the stated research questions. The quality of research will also be discussed and future research agenda will close this chapter.

5.1 Using of DES in maintenance

The result of this thesis shows that DES is an important tool to be used in the maintenance area. Application of DES in the maintenance area is becoming more of interest by the authors and the researchers are more focusing on the topic as the years pass by. In order to provide precise answers to research questions the following sub questions have been answered:

SQ1: *Which are the parameters that improved by the application of DES?*
Answer: Various maintenance strategies, availability, productivity, cost, maintenance planning and scheduling, and spare parts.
SQ2: *How is DES used to detect the problems in manufacturing industries?*
Answer: DES is mainly used for bottleneck detection in many organizations.

The result of quantitative study shows that DES is used to estimate six parameters which are various maintenance strategies, availability, productivity, cost, maintenance planning and scheduling, and spare parts. The identification of these six parameters is the answer to the first research question of this thesis. Classification of the parameters by the years indicates that the use of DES in the maintenance area has been increased in the recent years. According to the result of study DES is mostly used to improve three parameters which are availability, cost, and various maintenance strategies.

Quantitative research (figure 4.1) enables researchers to announce that there will be much more studies conducted about the use of DES in maintenance in the future since this topic is an increasing tendency. This research project has identified the use of DES in manufacturing maintenance applications but authors are also curious to know how DES could be applied for specific machine maintenance, for example, for turning or grinding machines. Does DES have a potential to be used for certain machine maintenance? This view is decided to be addressed and discussed in future research agenda.

5.2 Classification of the papers in terms of SM dimensions

DDDM and HCR are the two dimensions of SM that can be improved with the use of DES. Both the outcome of the quantitative study and interviews indicates that DES is most closely related with DDDM and can also be linked with HCR. However, there are no literature findings on the use of DES in internal and external integration. This topic has been discussed with interviewers as well.

SQ3: *Which dimensions of SM are closely linked to DES?*
Answer: Data-driven decision-making is closely linked with DES. Human capital resource is also linked to DES.

First findings from the papers show that DDDM and DES are closely linked. It is a controversial topic to discuss whether DES is a decision support tool or not. DES in and of itself is a tool and that does not lead to any sort of improvement, the point is how to use it which determines the outcome. DES is a best tool for certain decisions. It could be used anywhere within the maintenance framework because it could simulate basically anything that has data. It can be used to study the effects of different maintenance strategies, what happens when using run to failure, predictive or preventive maintenance so there is endless opportunity. If DES is used for bottleneck detection, it is possible to find bottleneck over time. Then, it is considered as a historical bottleneck, but in real time bottleneck changes. So, it might need another tool to predict which machine will be bottleneck in the next hours. DES can help with basics somehow, but it might not be sufficient. One of the interviewers stated that automotive companies do not use DES as a decision support tool in maintenance, but used it at some level, not necessarily for making decisions, but doing some tests for example. It is possible to set up different scenarios and test these scenarios to see the effect and decide on what is best fit to project purpose.

As the name implies, DDDM dimension of SM means that the decision making process is based on the data which requires a data-driven simulation. Data-driven simulation is a model that can be completely parameterized so data can be input and adjusted externally from the simulation which allows a user to build, run, and update simulation models without the need to do any programming (Goodall, P. et al. 2019). Interview results match with this information and shows that data-driven simulation should be based on real-time data in the plant. As it is mentioned in the result chapter (section 4.2), previous studies show that none of the DES projects decisions are based on real time data in the plant and findings from the interviews and papers match in this regard and indicates that most of the DES project based on historical data. So, it is possible to say that DES could be considered as a decision support tool as long as the model is being fed with real time data from the plant.

SQ4: *Can DES be considered as a decision support tool?*
Answer: DES could be used as a decision support tool if the model is being fed

with real time data continuously from the plant.

The reason the DDDM dimension of SM requires real-data is that real data always shows the current process and anomalies in the plant. So, the decisions can be made based on the current anomalies. Real-time data is concerned with the area of digital twin (DT). DT is the connection between the physical model and the corresponding virtual model. This connection is established by generating real-time data using sensors (Bacchiega and Gianluca, 2018). Companies that have a DT can do experiments and feed it with real data and then come up with solutions. In this regard, DES with real-time data is similar to DT. Fuller et. al, 2019 states that DT is a digital representation of a physical item or assembly using integrated simulations and service data. The digital representation holds information from multiple sources across the product life cycle. This information is continuously updated and is visualized in a variety of ways to predict current and future conditions, in both design and operational environments, to enhance decision making.

Feeding the model with real time data from the plant is another issue and the possibility of building a DES model based on real-time data for daily-base should be studied and this will be discussed further on the future research agenda subchapter. During the literature study and interviews historical data has been mentioned in decision making. It is also a polemic issue to use historical data for decision making. Based on the historical data, the organization at least knows the MTBF and MTTR values of machines as well as what type of breakdowns it was. So, they might anticipate the future failures based on that data. The point is that making decisions based on historical data is better than not using data at all. But of course, it is not as precise as the real data. The main problem with historical data is that if the company works with continuous improvement to change the production system then the historical data becomes outdated and can no longer be valid for the entire system. But in some cases it might be good enough to make a decision based on historical data.

Findings from some papers show that DES can be linked with the HCR dimension of SM. It is possible to build a DES model and show that how different maintenance strategies would require different labor levels. Also, availability of the maintenance crew can be investigated in terms of different maintenance policies. DES is a great tool to visualize the whole factory and to see how this factory is running. It enables to see the full buffers as well as bottlenecks. It gives common understanding to the factory, so that when workers and operators see the model on the screen running they can see the problem easily such as where they have a bottleneck or where the buffer is full.

There are no literature findings on the use of DES in internal and external integration. One of the interviewers has stated that simulation has the potential to be used to get common understanding between different departments to see what is going on in the factory. When everybody communicates and collaborates, then things work well. That is one part of internal integration. Using of DES in internal and external integration also needs further research and that can be discussed further on future research agenda subchapter too.

Since the SM concept looks quite hard and costly to implement, some of the companies, especially small and medium enterprises (SMEs), might avoid building SM concept. The Implementation of the SM concept depends on the companies. Each of four SM dimensions has a non-zero value, meaning that each of four dimensions exist in the company to some extent. So, the companies have SM to some extent and it can be applied in any factory. The main consideration when implementing an SM concept is that the companies should investigate whether it is worth applying it in terms of productivity and if they are ready to embrace the changes that the SM concept will bring together, such as internal and external collaboration. The companies should investigate before that if this concept will be more or less effective depending on the nature of the plant. For example, in a very small plant maybe it is not worth being really good at SM or in a very big plant it might be very beneficial or might be the opposite.

5.3 Methodological discussion

Triangulation of methods and triangulation of data sources are used for research questions. As a triangulation of methods, authors vary the methods by using a combination of conversational interviewing and semi-structured interview questions. To increase the credibility of findings data is collected from interviews, written documents, and similar projects as a triangulation of data sources.

This multimethod approach allows researchers to identify and explore different dimensions of the studied topic, and thereby it strengthens their findings and enriches their interpretations (Lisa M. Given, 2008). The study of RQ1 was mainly based on quantitative study enabled to explore the research area broadly. When exploring the application area of DES in maintenance, the research was continued until the articles gave the same information over researched topics. However, the study for RQ2 was based on both interviews and quantitative study.

Semi-structured interviews were conducted as a source of qualitative data. The questions were prepared prior to the interviews and the knowledge areas of interviewees were considered in these questions. To better conduct the interviews and to get effective inputs from the interviewees, the questions were updated after every interview based on the input of latest interviewees. Combining the interview results with quantitative study provided clear explanations and deeper insights to the researched topic.

Data saturation is used for data adequacy which can be explained as collecting data until no new information is obtained (J. M. Morse, 1995). While evaluating the adequacy of collected data, the richness of information by all interviewees and relevance of this information to quantitative data gave the signal of saturation. The result might have been stronger if there were more researchers working with SM concepts. However, in general the inputs were reasonably adequate for basing the analysis on.

5.4 Quality of research

Literature study and interviews are the main foundation of the results in this project. The data that is collected through interviews is affected by personal opinions of interviewers and therefore are not always accurate. In order to resolve this uncertainty, triangulation (triangulation of methods and triangulation of data sources) is used to increase the credibility of the collected data. Some parts of interviews and theory were compared and combined to strengthen the result. Data saturation is used to make sure that sufficient amount of data was collected. There were not any specific guidelines for when to terminate data collection in qualitative research, but data collection carried on until no new information was obtained.

5.5 Future Research Agenda

In the light of discussed considerations, the authors have attempted to determine which directions might be productive for future research on the use of DES in maintenance area and SM dimensions in order to address the potential use of DES in maintenance area and SM dimensions that have not yet been assessed by literature. The research agenda described in this section is based on and directly derived from the analysis of the theory part and interview result.

The authors have identified four main research areas for further development in the future to better use in the areas of maintenance and SM. These areas are reported in Figure 5.1. The first research area pays attention to the use of DES in single complex machines, while the second one focuses on real data collection and field study to provide new data sets for the use of DES in SM dimensions. The subsequent two research areas investigate the use of DES as a data driven tool as well as how DES can be used to simulate internal and external integration in SM.

<table>
<tr><th colspan="2">MAINTENANCE</th><th colspan="2">SMART MAINTENANCE</th></tr>
<tr><td>HISTORICAL DATA</td><td>REAL TIME DATA</td><td>SMART MAINTENANCE DIMENSIONS</td><td>ADVANCE TECHNOLOGY AND SENSORS</td></tr>
<tr><td colspan="2">RESEARCH AREA 1
USE OF DES FOR THE MAINTENANCE OF SINGLE COMPLEX MACHINES SUCH AS CARS</td><td colspan="2">RESEARCH AREA 2
REAL DATA COLLECTION, FIELD STUDY AND INTERVIEWS TO PROVIDE NEW DATA SETS FOR THE APPLICATION OF DES IN SM DIMENSIONS</td></tr>
<tr><td colspan="4">RESEARCH AREA 3
DISCRETE EVENT SIMULATION AS A DATA DRIVEN SIMULATION TOOL</td></tr>
<tr><td colspan="4">RESEARCH AREA 4
THE LINK BETWEEN DES AND INTERNAL AND EXTERNAL INTEGRATION</td></tr>
</table>

Figure 5.1: Four future research areas in Maintenance and Smart Maintenance.

Research area 1: Use of DES for the maintenance of single complex machines such as cars.

This research area investigates the use of DES for the maintenance of single complex machines such as cars. Throughout the study the use of DES has been discussed in certain articles for several purposes. Young et. al, (2008), developed an object-oriented simulation model to estimate the reliability, availability, and maintainability of the multi-functional system with complex structures. A complex system can be defined with a complex structure that performs several functions as a multi-functional complex system.

Curtis Iwata & Dimitri Mavris, (2013) study showed how the vehicles and parts are modeled as simulation objects and these parts have characteristics such as a descriptive name, the spending time in operation, and a label indicating whether a part is broken or not. The steps of the maintenance process, such as assessing for broken parts and replacing them, are modeled as functions that change the characteristics of the simulation objects (Curtis Iwata & Dimitri Mavris, 2013). However, almost no study has been dedicated to study the use of DES in single complex machines. Therefore, this needs to be addressed in future research. In this research area, this study direction is proposed:

Proposition 1.1. PdM strategy should be applied to get actual operating conditions of specific parts of complex machines or cars by using DES. The research should aim to minimize the unscheduled breakdowns of complex machines.

PdM provides factual data about the actual condition of each machine and operating efficiency of each process system which help maintenance managers to schedule maintenance activities based on the actual data (Mobley, 2004). PdM schedules maintenance activities based on actual data. It will be interesting to research how PdM will get actual data with the help of DES.

Research area 2: Real data collection, field study and interviews to provide new data sets for the application of DES in SM dimensions.

The literature analysis on theory part has shown how DES is used in the maintenance area. Content classification of papers indicates that DES is most closely linked with DDDM dimension. Certain number of papers also stated the relation between DES and HCR. This research area would help in the study of how DES can be linked with all dimensions of SM. Field studies and interviews could give credible information on how all dimensions can be improved with the help of DES. In this research area, two main topics are proposed:

Proposition 2.1. Data on how SM concepts and its dimensions are perceived in organizations should be collected and analyzed.

Industrial data collections as well as interviews are needed to provide managers with the SM concept, its benefits and value and how it could improve maintenance to a new level. These data are also necessary to indicate SM dimensions and the relations between them. To achieve these results, future research efforts should be directed toward field studies and interviews based on real and reliable data sets from industries. Certainly, industrial data sets should be analyzed properly in order to deduce correct features to use. A researcher, J. Bokrantz et al. (2019) provides an empirical study to show how SM can impact industrial performance. However, this study is the only one dedicated to study and conceptualizing SM. More research is needed on the SM concept.

Proposition 2.2. How DES can be linked with all dimensions of SM? How could these dimensions be improved with the aid of DES?

Maintenance engineers who use DES no matter what the aim is can help with their knowledge to the development of these kinds of studies that should use DES in SM dimensions. Gopalakrishnan et al. (2014) present a study regarding application of DES in maintenance operations. The study aims to improve productivity and compares different maintenance planning strategies for manufacturing industries by using DES. Scholl et al. (2012) also conducted a multi-stage DES approach to study planning and scheduling of extended maintenance activities. Similar studies are also done by many researchers and studied the use of DES in maintenance. However, use of DES in all dimensions of SM are lacking. This area needs to be addressed in future research.

Research area 3: DES as a data driven simulation tool.

DES is used for the modelling of a system and it can test different "what-if" scenarios in order to identify better physical configurations and operational policies (Aitor Goti, 2010). The power of the DES is its ability to mimic the dynamics of a real system and this ability gives DES its structure, its function, and its unique way to analyze results (Ricki G. Ingalls, 2011). However, DES uses historical process data to analyze the results. Using historical process data can reduce the inaccuracies within the input data which may quickly become outdated and inaccurate (Goodall et. al, 2019).

It is needed to investigate how DES can be used as a data driven simulation model so data can be input and adjusted externally from the simulation. Data-driven simulation is an approach where the simulation is completely parameterized by providing data through a set of data inputs, allowing a user to create, and run a simulation model without the need to do any programming (Wang et. al, 2011). Future efforts need to address the use of DES as a data driven tool so that the model can be fed with real-time data continuously from the plant. Feeding the model with real-time data continuously will be the challenging task but it will reduce the inaccuracies and give more credible results for sure.

Research area 4: The link between DES and internal and external integration.

During this study DES has been found to be linked with two dimensions of SM which are DDDM and HCR. However, no research finding has shown the relation between DES in internal and external integration. This topic has been discussed in the interviews as well and decided to be addressed in future research. One of the interviewee stated that DES can be used as a communication tool to improve internal and external integration. Instead of explaining to the workers the reason why investing on certain machines, engineers can run simulation models and get data in order to provide fact-based arguments which makes it easier to communicate with the economy department or management level. The application of DES in internal and external integration will provide common understanding in the factory and will facilitate the communication for sure. To achieve these results and further, future research efforts should be directed towards the use of DES in internal and external integration.

6
Conclusion

The purpose of this thesis was to investigate how DES can be applied in manufacturing maintenance applications and how it can be linked to SM dimensions. To provide precise answers to research questions, four sub questions have been aimed to be answered during the study. The conclusions drawn from the work carried out are presented below:

SQ1: *Which are the parameters that improved by the application of DES?*
Answer: Various maintenance strategies, availability, productivity, cost, maintenance planning and scheduling, and spare parts.

SQ2: *How is DES used to detect the problems in manufacturing industries?*
Answer: DES is mainly used for bottleneck detection in many organizations.

SQ3: *Which dimensions of SM are closely linked to DES?*
Answer: Data-driven decision-making is closely linked with DES. Human capital resource is also linked to DES.

SQ4: *Can DES be considered as a decision support tool?*
Answer: DES could be used as a decision support tool if the model is being fed with real time data continuously from the plant.

By the analysis of the relevant articles retrieved by quantitative study has shown that the use of DES is an increasing tendency during the last couple of years. The researched six parameters which are various maintenance strategies, availability, productivity, cost, maintenance planning and scheduling, and spare parts indicate the use of DES in the manufacturing maintenance application. Interview result also support these six parameters and reinforced the fact that by collecting a lot of data about the machines or equipment, it is possible to predict which part is about to fail, so workers can order spare parts in time and thereby it can eliminate the risk of failure at the plant. Improving productivity in most cases first requires to find bottleneck machine in the system which is one of the main use of DES in manufacturing industries.

The analysis of retrieved articles also showed how DES can be linked to SM dimensions. Examination of the articles has shown that DDDM is highly linked with DES. According to some articles, data is collected by computerized data sources from the company shop floor while some papers mention that data is gained based on the manager's experience and interview with production personnel. Half of the articles also states that historical data is considered as the data used for the DES model. Also, 18% of the articles shows that there is a link between DES and HCR dimension of SM. DES is used to assess the effect of different levels of labor availability on different maintenance monitoring level. There are not any tangible findings from the literature to prove the link between DES and internal/external integration, however, based on the interview result, DES can be used as a communication tool to improve internal and external integration. All in all, DES could be used as a decision support tool if the model can be fed with real time data continuously. Future research agenda is also given to address the potential use of DES in maintenance area and SM dimensions that have not yet been assessed by literature.

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