TOWARDS STRATEGIC DEVELOPMENT OF MAINTENANCE AND ITS EFFECTS ON PRODUCTION PERFORMANCE

A hybrid simulation-based optimization framework

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Industrial Informatics
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DOCTORAL DISSERTATION

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ABSTRACT

Managing maintenance in manufacturing within an economical short-termism framework and taking the consequential long-term cost effects into account is hard. The increasing complexity of managing maintenance and its impact on the business results calls for more advanced methods to support long-term development through effective activities in the production system environment. This problem-based design science research has evolved into the novel concept of a hybrid simulation-based optimization (SBO) framework which integrates multi-objective optimization (MOO) with system dynamics (SD) and discrete-event simulation (DES) respectively. The objective is to support managers in their decision-making on the strategic and operational levels for prioritizing activities to develop maintenance and production performance.

To exemplify the hybrid SBO framework this research presents an SD model for the study of the dynamic behaviors of maintenance performance and costs, which aims to illuminate insights for the support of the long-term strategic development of maintenance practices. The model promotes a system view of maintenance costs that includes the dynamic consequential costs as the combined result of several interacting maintenance levels throughout the constituent feedback structures. These levels range from the applied combination of maintenance methodologies to the resulting proactiveness in production, such as the ratio between planned and unplanned downtime, in continuous change based on the rate of improvements arising from root-cause analyses of breakdowns. The model creation and validation process have been supported by two large maintenance organizations operating in the Swedish automotive industry. Experimental results show that intended changes can have both short-term and long-term consequences, and that the system may show both obvious and hidden dynamic behavioral effects.

The application of MOO distinguishes this work from previous research efforts that have mixed SD and DES. It presents a unique methodology to support more quantitative and objective-driven decision making in maintenance management, in which the outcome of an SD+MOO strategy selection process forms the basis for performance improvements on the operations level. This is achieved by framing the potential gains in operations in the DES+MOO study, as a result of the applied strategy in the SD model. All in all, this hybrid SBO framework allows pinpointing maintenance activities based on the analysis of the feedback behavior that generates less reactive load on the maintenance organization.
SAMMANFATTNING


Arbetet är uppdelat i tre delar inklusive det föreslagna hybridramverket. Först utvecklades en konceptuell SD modell för att studera det dynamiska samspelet (beteendet) mellan att utveckla underhållsprestation och genererade kostnadseffekter, rapporterat i en journalartikel. Därefter integrerades MOO med SD modellen för att utforska meritvärden av SD+MOO för att skapa beslutsunderlag vid val av strategi för hur underhåll ska utveckla sin verksamhet, rapporterat i en journalartikel och två konferensartiklar. Det resulterade i en strategivariablar (SD) och MOO process som ger stöd i att analysera feedbacksamverkan mellan förbättringsåtgärder och underhållsprestation och dess effekt på driftsäkerheten i produktion, samt hur det resulterande beteendet i produktion, där fördelning mellan planerade och oplanerade underhållsinsatser, påverkar hur väl underhåll lyckas kontrollera utrustningarnas hälsostatus. Tredje delen av arbetet beskriver ett koncept för hybridramverket, presenterat i en tredje journalartikel, baserat på de två föregående delarna och föreslår betydelsen av att kombinera det med ett mer detaljerat perspektiv, vilket stöds av DES. Interaktionen mellan dessa perspektiv (SD+DES) behövde definieras och anpassas till möjligheterna en DES+MOO analys ger; att definiera utvecklingspotentialen för produktionssystemet genom välriktade aktiviteter.

Användandet av SD+MOO utforskar optimeringsmål som är i målkonflikt och genererar ett kvantitativt beslutsunderlag av möjliga lösningar. Första delen av hybridramverket är en strategivariablar (SD) och MOO process med tre faser som genererar kunskap om hur en bättre avvägd balans mellan reaktivt och proaktivt underhåll kan skapas och ger en output på bedömd förbättringspotential hos mätetalen medeltid till fel (MTTF) och medeltid för reparation (MTTR). Denna process föder sedan en aktivitetsvalsprocess för underhåll
att identifiera hur förbättringspotentialen ska bäst implementeras utifrån produktionssystemets beskaffenhet. DES+MOO är en väl utforskad metodik inom produktionsoptimering tillgänglig i befintlig mjukvara. Avhandlingen bidrar med hur dess användning kan nyttjas från ett underhållsperspektiv för att stödja och prioritera underhållsplanering av förbättringsaktiviteter för att maximera produktionskapaciteten.

SD modellen i sin tur syftar till att illustrera hur insikter och lärande kan skapas för att ge stöd till den långsiktiga utvecklingen av underhållsarbetet. Där kan mer strategiska frågeställningar inkluderas och anpassningar av modellen kan bidra till att identifiera effektivare sätt att nå ett framtida läge. Modellen behandlar ett överbripande systemperspektiv på underhållskostnader, vilket innefattar uppskattade konsekvenskostnader baserat på flertalet feedbackstrukturer och dess underliggande nivåer. Alltifrån utrustningarnas uppskattade hälsostatus och den aktuella fördelningen mellan olika underhållsmetoder för att underhålla utrustningarna, till den resulterande fördelningen mellan planerade och oplanerade stopp i produktionssystemet. Fördelningen mellan dessa nivåer förändras dynamiskt över tid beroende på arbetssätt, t.ex. hur oplanerade aktiviteter kan minskas men även aktuell användning av resurser. Processen att ta fram exempelmodellen har skett i samverkan med två underhållstunga företag i Svensk fordon industri.

Sammantaget bidrar båda perspektiven SD+DES till en bredare helhetsanalys för att underhåll ska ta ut riktningen för den strategiska utvecklingen och ge stöd på det operativa planet för att satsa på rätt insatser.
ACKNOWLEDGMENTS

Pursuing a Ph.D. brings with it many experiences. Writing can be a joy, and in next moment, a pain. I have enjoyed the creative moments, trying to understand, modeling, experimenting, and actually trying to materialize thoughts into written text. Even so, of all exciting thoughts during this time, few actually got on paper! In the start of my second phase of Ph.D. studies, having a licentiate and work experiences in my baggage, I was eager to get on, yet, obstacles of unthinkable character came into the path. Thank you Mikael Wickelgren for your support at this time. And thanks Lena Aggestam for the many supporting systems thinking conversations we have had. After almost a year a new era began, and at last a potential path for this research could be agreed upon. Amos HC Ng took over as the main supervisor, I have much appreciated our discussions since then, and honesty is a virtue I hold high and I think builds your character, thank you! Tehseen Aslam, repeatedly you have cheered and encouraged me to pursue this work – thanks! I am lucky to have had you on my supervision team.

This work was partially financed by the Knowledge Foundation (KKS), Sweden, through the IPSI Research School. I gratefully acknowledge their provision of research funding and the support of the industrial partners Volvo Car Corporation (VCC) and Volvo Group Trucks Operations (VGTO). I want to thank my industrial mentors during this research: Martin Asp, Roland Gustavsson, Sven Wilhelmsson, and Patrik Rempling. I must say that I have always felt much welcomed at both VCC and VGTO, and that is something to be proud of as companies! It must be that maintenance people are warm and kind people. I would like to especially thank CB at VCC for openly discussions, as well as the group of experts involved in the VCC application study.

The University of Skövde is a great workplace when it comes to colleagues and I hope for a great future for all of you! I miss “fredagsmys” at Klas’ office, we must not forget summer tradition with sauna after a run. Bernard, as our mutual crisis emerged, finalizing the Ph.D., we got more and more involved, it has been fun. Maria Ruiz, thank you for inviting me to Mondragon University, not to mention running in the mountains.

I hope we all will have an interwoven future and which you the best!

Last, but most importantly, the people who sustain over periods of employments and work efforts, my family. The last period of time, working on the thesis, has taken me from you for weekends and after workdays. Thank you for your patience and support: Linda, Elsa, Irma, Birger. You are giving me purpose. And I want to give thanks to the creator who sustains over periods of lives, in His mercy we can rest, thank you for giving me love to endure another day, my family, and the opportunity to work.
The following articles were produced during the course of my studies. For the papers, with me as the first author I not only wrote these articles, but also carried out the modeling, experiments, and analyses. However, in some minor parts, the frame of reference was complemented by others. Moreover, for the journal articles, my supervisors provided support with improving the content throughout the process of revising and finalizing the manuscripts.

**PUBLICATIONS WITH HIGH RELEVANCE**

**Paper 1**

**Paper 2**

**Paper 3**

**Paper 4**

**Paper 5**
PUBLICATIONS WITH LOWER RELEVANCE


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INTRODUCTION
CHAPTER 1
INTRODUCTION

1.1 BACKGROUND
Maintenance considerably increases the budget in manufacturing industries. Even if researchers claim that maintenance has shifted from a strong focus on cost towards being an organizational strategic capacity (Simões et al., 2011), the tradeoff between invested costs and their benefits is still of largest concern for decision makers. Moreover, the value of maintenance is strongly challenged by short-termism and the high pressure on utilization in production from the rise of global competition. Recent developments of increased automation, more expensive equipment, and more complex production systems have increased the capital tied up (Garg and Deshmukh, 2006), and has led to more prevalent consequences from unplanned breakdowns (Swanson, 1997). According to Geary et al. (2006), reactive maintenance potentially leads to increased disruption in real-world supply chains, thus causing excess variance in performance. Logically, the opposite should hold; proactive maintenance should reduce variance in performance via the improved precision of maintenance activities in the production systems. In addition, proactive maintenance policies are considered the required strategy (Pinjala et al., 2006), and the proper maintenance practices are considered to contribute to overall business performance (Alsyouf, 2009). However, identifying proper practices and carrying out sound strategies for the development of maintenance performance is non-trivial. A clear measure of this is the frequently-emphasized gap between theory and practice in the maintenance optimization literature (e.g. Linnéusson et al. (2018), Kym et al. (2015). One aspect of this gap is that little attention has been paid to making model results understandable to practitioners (Dekker, 1996, p.235). Yet, considering the concerns brought up by some maintenance practitioners, Blann (1997) reports on the required shift of paradigm for how organizations focus on maintenance activities, from reactive to proactive, and Woodhouse (2001) identifies the reoccurring inability to manage sustainable implementations of maintenance practices with insufficient organizational capabilities to perform and integrate the conflicting priorities and messages into its equation. According to Baldwin and Clark (1992), capabilities such as identifiable combinations of skills, procedures, physical assets, and information systems are sources of superior performance. It is therefore worth understanding how these capabilities are improved and decreased,
and putting the focus on their long-term significance for the organizational performance (Teece et al., 1997). Baldwin and Clark (1992) describe the importance of the capacity to experiment as a tool in developing the knowledge which leads to organizational learning.

### 1.1.1 THE CHALLENGE OF PROACTIVE MAINTENANCE

<table>
<thead>
<tr>
<th>Strategic domain (Organizational learning)</th>
<th>Differentiate Maximize integrated value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Proactive domain (Organizational discipline)</td>
<td>Don’t just fix it, improve it</td>
</tr>
<tr>
<td></td>
<td>Eliminate defects: maximize equipment availability</td>
</tr>
<tr>
<td>Planned domain (Pre-plan work)</td>
<td>Fix it before it breaks</td>
</tr>
<tr>
<td></td>
<td>Predict, plan, and schedule all work</td>
</tr>
<tr>
<td>Reactive domain (Respond to events)</td>
<td>Fix it after it breaks</td>
</tr>
<tr>
<td></td>
<td>Firefight with each new crisis: spend the necessary</td>
</tr>
</tbody>
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Figure 1.1. Paradigm shifts are needed from reactive to proactive (adapted from Blann (1997)).

The definition of maintenance is “the 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” (EN13306, 2010). This definition reflects not only the substantial information flows which can follow an item, but also the focus on items, which are the objects worked on in the production system. Accordingly, Levitt (2011) argues that the goal of maintenance should also include the development of production performance through proactive maintenance. This is attained by systematically reducing the need for maintenance interventions through improvements that extend the interval between maintenance or improve the design, thus reducing the maintenance need in the first place. In other words, via the elusive actions that lead to fewer and fewer reactive repairs, fewer preventive repairs, more preventive actions which do not require downtime, increased condition monitoring capacities, and better equipment in the first place; thus, better acquisition processes, better knowledge-generating processes, better continuous improvement processes, and so on. Hence, there is a multitude of potential efforts leading to more proactive maintenance, however, these must also be well prioritized and differentiated. According to Blann (1997), maintenance as practice needs to develop and be a strategic tool for improving a company’s competitive edge by increasing throughput and profitability and reducing quality defects. The illustration of maintenance paradigms in Figure 1.1 reveals a scale from reactive to beyond proactive, which is the strategic domain. A domain where the knowledge-generating processes is characterized by organizational learning, based on the capacity to differentiate those activities that maximize the value of maintenance to the strategic business level. Overall, the complexity of the problem is as summed up by Levitt (2011): it is still not clear how long-term maintenance should be managed in a profit-making company.

### 1.1.2 STRATEGIC DEVELOPMENT OF MAINTENANCE

Maintenance practices are very important in supporting production operations and thus creating value for customers. However, the value created by maintenance practices is of an implicit character, while the maintenance costs are explicit and part of standard accounting procedures (Pascual et al., 2008). Maintenance costs are generated both from activities of proactive character and as a consequence of insufficiently
applied practices. Furthermore, when a breakdown is a fact there are additional consequential costs of maintenance (Vorster and De La Garza, 1990) which are implicit and intangible and apparent in other parts of an organization, such as fewer manufactured products, increased production man-hours, or quality issues.

The increasing pressures from global industrialization on manufacturing industries, in terms of higher utilization and tougher external requirements, can make it hard to prioritize the necessary proactive maintenance practices which keep equipment health at the required levels. These higher pressures are squeezing the utmost from the internal social and technical systems which are supposed to deliver value on a daily basis. Previously, the value created could be limited to satisfying customers and creating a self-sustainable business, but today it is also expected to contain the balance of larger economic returns, the environmental consequences from production and products including life-cycle perspectives, and social responsibilities as contained by the concept of sustainable manufacturing (Garetti and Taisch, 2012).

It is in operations that the fruit of the long-term strategic capacity of the maintenance organization is utilized. Yet, at the operational level, the focus tends to change from the strategic view towards how to optimally operate the production system, and is a reality characterized by a stochastic environment. This question of optimal operation has long been investigated by the application of discrete-event simulation (DES) in manufacturing (Alabdulkarim et al., 2013). Recently, utilization of DES has developed into advanced simulation-based multi-objective optimization (MOO) methods (Pehrsson et al., 2016), which have the capacity to pinpoint the bottleneck in a production system; that is, the point where an infinitesimal improvement can have the largest impact on throughput (Ng et al., 2014). While this can be useful in supporting improvements aimed at satisfying the higher utilization requirements, we also need a way to support the strategic development of capabilities in order to achieve a more proactive maintenance behavior.

Maintenance management and strategy researchers have implicitly addressed the necessity of a larger system view that takes both present and future conditions into consideration. According to Sherwin (2000), current maintenance performance measurement systems utilize cost over profit measures, and do not capture the reverberations of today’s actions. Tsang (2000) sought tools that can connect and validate the causal relationships between strategic initiatives and performance results. Vorster and De La Garza (1990) emphasized the need to calculate maintenance costs by including estimations of consequential costs with a reasonable degree, in order to assess maintenance policies and strategy based on more sustainable measures of maintenance performance.

What the statements above have in common is that they ask for a feedback approach in order to allow interpretation of the short-term and long-term consequences of various strategies. Strategy researchers have argued for the application of the feedback approach of system dynamics (SD) simulation to investigate how the growth and decline of multiple capabilities affect performance (e.g. Warren, 2005, Rahmandad and Repenning, 2016). SD is a field of research studying feedback behavior, originating from servo-mechanisms such as information-feedback systems (Forrester, 1960). The suitability of SD as a structural theory for operations management has been outlined by Größler et al. (2008), who also used qualitative SD to explain the dynamics which tend to overload the maintenance department with reactive work instead of proactive activities. According to Thompson et al. (2016), SD provides a conceptual framework essential to the discovery of thinking about things.
CHAPTER 1 INTRODUCTION

SD was developed as a response to the inadequacy of conventional management science, which according to Forrester (1960) had emphasized elementary mathematical formulations to enable analytic solutions with a high degree of oversimplification. In attempts to make maintenance optimization models more relevant, maintenance researchers have criticized previous literature for considering oversimplified models (e.g. Van Horenbeek et al., 2010, Lad and Kulkarni, 2011, Sinkkonen et al., 2013, Alrabghi and Tiwari, 2015). The analytical paradigm seems to have been strong in the field of maintenance optimization. For instance, in an influential review and analysis of maintenance optimization models, Dekker (1996) summarized the limited impact of works on decision making within maintenance organizations, but still remained within the analytical paradigm, not questioning the method or even mentioning simulation. However, the same author did later declare analytical models insufficient to trace the effects from maintenance policies, and called for simulation (Nicolai and Dekker, 2008).

Recently, there has been an emerging trend of using simulation to optimize maintenance costs (Sharma et al., 2011), but according to Alrabghi and Tiwari (2015) the available exemplars are still generally oversimplified and that DES may be better able to mimic the operating conditions of maintenance. The application of DES to evaluate preventive maintenance (PM) is currently underexplored (Alrabghi and Tiwari, 2015, Alrabghi et al., 2017). On the other hand, according to Gunal and Pidd (2010), DES studies do not deal with the feedback behavior which helps explain why certain behaviors arise, and this is a necessary perspective for strategy development supported by SD simulation (Warren, 2005). The application of SD in maintenance is emphasized by several authors (e.g. Crespo Marquez and Usano, 1994, Ledet and Paich, 1994, Repenning and Sterman, 2001, Größler et al., 2008). However, an in-depth literature review conducted as part of this thesis work (see Paper 1) revealed a mix of qualitative and quantitative works, few of which demonstrated simulation models, and only one of which included the equations (Thun, 2006).

Based on the above, we can conclude the following. In order to address the challenge of proactive maintenance, a longer-term perspective is required. Moreover, the strategic capacity of maintenance is a function of multiple capabilities which are developed through time, having the consequence that it is the current achieved condition which defines the potential for optimizing the production system on the operational level. SD is a method for creating a structural theory or hypothesis of the studied system, and has been applied to study reactive and proactive maintenance behavior. Nevertheless, while an SD study incorporates the feedback behavior which helps explain why certain behaviors arise, it cannot investigate complexity on the level of detail required for production systems in order to pinpoint where activities should be carried out. For such endeavors, the application of DES is required. Hence, we need a combined approach in which the strategic development is studied using SD and the complexity of operations is studied using DES.

1.1.3 THE NEED FOR SIMULATION-BASED OPTIMIZATION

The simulation-based methodologies such as DES and SD promote experimenting and learning about the modeled systems, by providing environments for “what if” analyses to explore potential changes. However, in order to efficiently trace which solutions are more beneficial than others, simulation-based optimization (SBO) is needed (e.g. Fu (2015). The concept of MOO (e.g. Deb, 2014) has endowed SBO with the ability to seek not only a single optimal solution with a simulation model but multiple Pareto optimal solutions that have a high spread in the objective space. While there is existing software, such as FACTS Analyzer, which tightly integrates DES with MOO algorithms,
making optimization of production systems straightforward to perform (Ng et al., 2014), this is not the case for the field of SD. Optimization in the SD literature is presented as single-objective optimization (SOO) (e.g. Jones (2014) p. 239 and Dangerfield (2014) p. 48). SOO has its limits to seek tradeoffs because it cannot include several conflicting objectives. In general, studies investigating the integration of MOO and SD models, and the use of such integrations, are less reported (e.g. Duggan, 2005, Duggan, 2008, Hedenstierna, 2010, Dudas et al., 2011, Aslam, 2013).

According to Wang (2002), one major problem in the maintenance optimization literature is the restricted use of the minimized maintenance cost rate as the single optimization criterion. Instead, Wang (2002) argues that the criterion sought should be the tradeoff between maximized reliability and minimized maintenance costs, which requires a simultaneous consideration of both objectives. Although a simultaneous evaluation is attainable using MOO algorithms, according to Alrabghi and Tiwari (2015), they identified a limited number of MOO studies in their state-of-the-art review of SBO in maintenance literature. Still, the application of MOO for maintenance optimization has been emphasized by several authors (e.g. Ilgin and Tunali, 2007, Van Horenbeek et al., 2010, Van Horenbeek et al., 2013, Alrabghi and Tiwari, 2015, Alrabghi and Tiwari, 2016). De Almeida et al. (2015) generally disqualified current maintenance and reliability models on similar basis as other researchers reviewed above, but considered that MOO better represents decision makers’ preferences in the decision problem and also includes the conflicting tradeoffs.

To summarize, SBO using MOO with DES has attained a mature level of application and is supported by existing software, while SD+MOO integrations are on the level of research which have indicated on its applicability.

1.2 AIM AND OBJECTIVES

The overall aim of this research is to support the strategic development of maintenance and its effects on production performance, and thus provide support to maintenance management in developing their practices in symbiosis with operations. The intention is to strengthen the capacity to experiment, which according to Baldwin and Clark (1992) is a vital tool in developing the knowledge which leads to organizational learning. The hybrid nature of the problem, as well as the need not only to study the conditions of operations but also to provide enhanced capacity to analyze strategic problems, calls for a mixed operations research and management science method design in which SD is applied to the high-level strategic questions and DES is used to analyze low-level questions in operations.

The aim can be divided into the following objectives:

O1 To create an SD model which can illustrate the effects on operations of the different strategic development of maintenance operations, in terms of proactive or reactive behavior and estimates of the total maintenance costs.

O2 To explore the applicability of MOO to the abovementioned SD model, and to evaluate the added value and qualification of SD+MOO to support identification of the strategic path in maintenance.

O3 To develop a concept, from a systems perspective, of a hybrid SBO framework for maintenance development which can support identification of the strategic long-term policies which lead to the desired tradeoff results in operations, and also support the specifics of the production system in terms of where maintenance should put effort in order to gain maximum benefit.
The resulting hybrid SBO framework will need to apply SD+MOO to identify where improvements should be made in the maintenance system (i.e., strategic, long-term improvements), and link this with an existing bottleneck improvement tool which applies DES+MOO to identify where improvements should be made in the production system (i.e., operational, short-term improvements). Hence, the hybrid SBO framework will be comprised of different method components to form a particular structure, including the phase structures of contained methods, which aligns with the definition of framework according to Goldkuhl et al. (1998).

1.3 RESEARCH QUESTIONS
In order to achieve the objectives, the following research questions were formulated:

**RQ1** Can an SD simulation model be designed to evaluate and compare strategies for maintenance development, while simultaneously considering maintenance operations in interrelation with operations?

**RQ2** Can MOO be applied to the conceptual SD model of maintenance performance and support in order to explore potential strategies and policies for the strategic development of maintenance?

**RQ3** Is it possible to design a hybrid SBO framework which can support maintenance management in considering both the overall strategic (long-term) and the operational (short-term) perspectives for the strategic development of maintenance?

1.4 SCOPE AND DELIMITATIONS
This research includes studies conducted within automotive manufacturing industries. The initial focus was on economic justification of PM, which developed into a set of questions from the industrial partners that then guided this research.

These questions included high-level issues of explorative character, such as: What are the dynamic effects from more or less planned maintenance in a production line, in the long and the short term? What are the potential effects of neglecting planned maintenance for a period in conditions of either high or low production volumes? Clearly, these questions stem from past experiences where production requirements or economic constraints have suddenly become so urgent that the set-out maintenance principles have had to be temporarily deprioritized, and the consequences have reverberated into the future. Hence, it is the long-term feedback character of these questions that calls for simulation and the use of SD. Furthermore, the focus on searching for an explanation of the interplay between production operations and planned maintenance has excluded other processes which have significance for how proactive and reactive maintenance is generated. For instance, it excludes the acquisition process of new equipment, which is treated in life-cycle costing (e.g. Korpi and Ala-Risku, 2008, Campbell and Reyes-Picknell, 2016) and which defines the subsequent need for maintenance in the utilization phase of the equipment. Similarly, the aspect of process quality has been out of scope, though this is also connected to reactive or proactive maintenance (e.g. Jambekar, 2000) and is an additional cost motivator for PM activities. Hence, the focus on the interplay between maintenance and operations has put many aspects which could have been included outside the scope.

Another high-level question was concerned with the need for identification of optimum levels of maintenance, in terms of maximizing benefits from invested resources, which led to exploring the application of MOO to the created SD model.
The guiding questions also included low-level issues, looking for answers on the operational level, such as: How can we understand where to put the activities in a production line, and what kind of activities should these be? Can this research set maintenance input data for optimizing DES models?

All these questions call for the integration of the aforementioned strategic level questions into this operational level, which has been condensed into the formulated objectives of this research. Thus, the scope of this research excludes the bottom-up perspective and presents a top-down approach in order to scope and differentiate the efforts made by maintenance management. Moreover, the focus of combining knowledge on different levels of maturity in this design science research has implied less focus on exploring and developing each sub-part of knowledge. It has revealed in terms of, for instance; taking the next step as soon the base SD model was developed instead of proposing a more polished model; omitting spending efforts on evaluating the best MOO algorithms for SD+MOO; or showing a real world DES case and instead referring to the generalized method developed by others.

1.5 RESEARCH APPROACH

This thesis work has a problem-based and interpretive research character, generated within the problem solving paradigm of design-science research (Hevner et al., 2004) using a systems thinking approach. This subsection begins by introducing the systems thinking approach and design science, and thereafter relates the applied methodology.

1.5.1 SYSTEMS THINKING AND PHILOSOPHY OF SCIENCE

Systems thinking can be defined as follows:

“The central concept ‘system’ embodies the idea of a set of elements connected together which form a whole, this showing properties which are properties of the whole rather than properties of its component parts. ... The phrase ‘systems thinking’ implies thinking about the world outside ourselves, and doing so by means of the concept ‘system’.” (Checkland, 1981, p. 3).

Systems thinking is a terminology that “has no clear definition or usage” (Forrester, 1994), p. 10). This is apparent from the range of methodologies within this discipline, such as: “cybernetics and chaos theory; gestalt therapy; the work of Gregory Bateson, Russel Ackoff, Eric Trist, Ludwig von Bertallanffy, and the Santa Fe institute” (Senge et al., 1994), p. 89), not to mention soft systems methodology (Checkland, 1981). Systems thinking methods can generally be categorized as systemic approaches to achieving an understanding of a particular system (Flood, 1999). The basic theory of such methods describes how systems are comprised and fundamentally functioning, or how they can be studied. Some systems thinking terminologies provide theories regarding a system’s ontology, for instance:

- The viable systems model (Beer, 1994), a diagnostic tool that can “map the extant organization onto the model, and then ask whether all parts are functioning in accordance with the criteria of viability” (Beer, 1994), p. 155.
- Soft systems methodology (Checkland, 1981), an analysis tool or “learning system” for qualitatively defining systems.
- System dynamics (Forrester, 1961), which uses the fundamental building blocks of systems to explain the “universal structure of real social and physical systems” (Forrester, 1994), p. 13) and to guide the construction of a model of a system for analysis.
Systems thinking is in contrast to reductionism. According to Oates (2006), reductionism is one of the basic techniques within the scientific paradigm of positivism which aims to explain phenomena by dividing reality into elements which are understandable and then creating a theory from the study of these parts. Systems thinking, on the other hand, strives to identify the interconnections between elements within a specific boundary, in order to explore phenomena and better understand reality as it is. It is argued that “systemic thinking begins with an intuitive grasp of existence” (Flood, 1999), p. 83) in order to facilitate balancing mystery and mastery to learn within the unknowable. The choice of boundaries is significant in any such analysis, and should remind us that no understanding can ever be complete (Midgley, 2008). According to Midgley (2008), the fact that everything in the world is directly or indirectly connected to everything else inevitably places the scientific observer as part of the observed world and not separate from it.

The characteristics described above are, according to Oates (2006), typical of the scientific paradigm of interpretivism, which can use the following criteria for evaluating research quality:

- **Trustworthiness** – how much trust we can place in the research?
- **Conformability** – have we been told enough about the study to judge whether the findings relate to the data and experiences in the context of the research?
- **Dependability** – how well is the research process recorded for others to trace it?
- **Credibility** – can the enquiry be considered to have ensured accurately explored findings?
- **Transferability** – although each situation may be unique, is generalization possible and the results transferable?

The interpretive character of this explorative research is supported by simulations and quantitative exploration of multiple optimization results. However, it can be argued that all research is interpretive (Gummesson, 2003) and can be defined accordingly:

“Interpretive approaches with an interactive research strategy perhaps only codify the best of common sense, insights, wisdom, sound judgement, intuition and experience. But the differentiating factors between personal everyday interpretation and opinion is the scholarly demands of being systematic, connected to theory, and be as transparent as possible by publishing the research and making it accessible for the academic community and business.” (Gummesson, 2003), p. 491).

### 1.5.2 DESIGN SCIENCE RESEARCH

Both behavioral science and design science are foundational and complementary to the discipline of information systems, which is positioned at the junction of technology, organizations, and people (Hevner et al., 2004). Whereas both relate to the identified business need, behavioral science addresses research in order to develop and justify theories that can explain or predict phenomena, while design science addresses research in order to build and evaluate artefacts designed to meet that need (Hevner et al., 2004). Moreover, these two sciences seek truth and utility, respectively, which is inseparable from the fact that truth informs design and utility informs theory (Hevner et al., 2004).

Design science addresses important unsolved real-world problems by creating innovative solutions and offering a paradigm shift towards more effectively studying “wicked organizational problems” (Hevner and Chatterjee, 2010), p. 13). According to Oates (2006), design science research often results in a combination of different types
of IT artefacts, such as constructs applied in models, models that aid problem understanding, methods which provide guidance for how the models can be applied, and instantiations which demonstrate the potential implementations.

Nunamaker and Briggs (2012) proposed a definition of the field of information systems research consistent with the applied research of this thesis, as follows:

“Information Systems is the study of the understandings people require so they can create new value, and of the analysis, design, development, deployment, operation, and management of systems to inform these understandings.”

(Nunamaker and Briggs, 2012), p. 20:3).

Moreover, Nunamaker and Briggs (2012) proposed a subsequent functional definition of the term understanding which focuses on the understanding that leads decision makers to execute their decisions with a certain expectation of the outcome. They also argued for broadening the focus on the IT artefact to contain the whole system, and stated that the key foci should be value creation with information, design processes, design products, and designed systems.

This research is, in part, seeking to represent proactive maintenance behavior by focusing on technical aspects of analyzing the symbiosis of maintenance and operations. However, it falls into design science research, rather than behavioral science, due to the larger focus on the design of simulation models and the hybrid SBO framework in order to produce artefacts which can support the understanding required for value creation by generating information for the decision maker. The abovementioned systems thinking philosophical underpinnings and the focus on value creation in design science also define the intentions of this thesis, and the research pursued herein. They have also fundamentally contributed to the end result of proposing a mixed method concept for maintenance development, in order to potentially sustain momentum between the perspectives of strategy and operations.

1.5.3 METHODOLOGY

The applied and explorative design science research reported in this thesis is mapped into the conceptual framework proposed by Hevner et al. (2004) and depicted in Figure 1.2. This framework combines behavioral-science and design-science paradigms for supporting the understanding, execution, and evaluation of information systems research. The framework has been further adapted to the design science research cycles illustrated by Hevner and Chatterjee (2010). Figure 1.3 in the next subsection outlines the research carried out for this thesis, and illustrates how Papers 1–5 contribute to the RQs.
Figure 1.2. A merged adaptation of the information systems framework (Hevner et al., 2004) and the design science research cycles (Hevner and Chatterjee, 2010).

Figure 1.2 depicts the design science research conducted for this thesis, revealing the complex exchanges and developments in which the three design science research cycles of relevance, rigor, and design have manifested during the research process. The relevance cycle was characterized by approaching the problem formulation, which has been a progressive moving target, and define it into the aim and objectives of this thesis. Hence, during the design cycle, developments during the research work were created on the basis of the identified business needs, and during their creation evolved into the final product. Meanwhile, the sub-deliveries were evaluated for usefulness and relevance to the real-world application, as well as to the potential novelty of the contributions to the knowledge base. Hence, the rigor cycle represents the contributions to the knowledge base, characterized by searching the literature and presenting reports to the scientific community. Consequently, the research process of this thesis work has searched relevance and truth in the identification process of the business need and applicable knowledge in order to inform the creation process of the proposed designs and their utility in the appropriate environment. Where additions to the knowledge base have been reported to the scientific community in order to permit assessment and evaluation of the research quality and rigor.

Interactions with the environment took the form of qualitative case studies, meetings, discussions, and model walk-through seminars with the industrial partners, with the aim of identifying and strengthening the relevance of the research. The case studies used qualitative research methods and interviews. Interviews among people with different roles were carried out with a “relatively unstructured and open-ended” character, which is the feature of the interview method in qualitative research (Silverman, 2000), p. 90), that can produce the claim of “understanding experience” of people in the system. The case studies were reported to the scientific community, which then applied data generation methods such as SD simulation experiments and SBO experiments using the SD models developed. Models which can be simulated enable the possibility of evaluating the underlying assumptions to a larger extent than merely
qualitative models (Homer and Oliva, 2001). The SBO experiments, which require quantified models, have generated additional (and exhaustive) amounts of quantified simulation results which add to the capacity to test and evaluate the underlying assumptions.

1.6 OUTLINE OF THESIS AND PAPERS

After this introductory chapter, the thesis is organized as follows. Chapter 2 presents the frame of reference, focusing on maintenance in symbiosis with operations. It offers an orientation in SD, due to its significant base for the subsequent parts of the proposed work, followed by shorter presentations of MOO, DES, and mixed method designs. Chapter 3 provides a summary of the proposed hybrid SBO framework and the main contributions from the included papers. Chapter 4 presents a summary and conclusion of how the RQs are addressed by the thesis work, lists the contributions to knowledge, provides a discussion of the results, and offers suggestions for future work.

Figure 1.3. Overview of the outline of the thesis and how Papers 1–5 contribute to the RQs.

Figure 1.3 presents an overview of the thesis and the main contributions of Papers 1–5 in connection with the objectives and RQs. Paper 1 describes an SD model for maintenance performance that captures both strategic (long-term) and operational (short-term) aspects, based on synthesized knowledge from the maintenance literature, reports on maintenance SD models, and information grounded on the experiences of people at the two industrial partners of this work. The conceptual SD model reported in Paper 1 provided the incentives to pursue the work presented by this thesis. As Paper 1 satisfactorily supports answering RQ1, Paper 2 explores the applicability of MOO to eliciting model information. The technical interface for applying MOO to SD models was developed in previous research (Aslam, 2013). For this thesis, RQ2 is directly addressed by Paper 2, and Papers 3 and 4 extend the work by introducing additional SD+MOO studies. During these experiments, it became evident that Papers 2–4 explore only a fraction of the potential angles of study enabled by SD+MOO. Together with the fact that SD models cannot handle enough detail to guide where in the
production system to intervene with activities, a combination with the DES approach was considered at this stage of research. Paper 5 enhances the method of quantitative SD+MOO studies by exploring the subsequent SD model behavior of selected near-optimal solutions. Paper 5 also proposes how the output from such strategy selection process can be applied to define the improvement ranges in DES+MOO studies, based on how these are carried out in an existing software. Hence, Paper 5 proposes a hybrid SBO framework for applying multiple studies to elicit knowledge for action in the maintenance system.

Subsequently, Figure 1.3 is later revisited in chapter 4 in order to support the description of results and the contributions of the thesis.
FRAME OF REFERENCE
CHAPTER 2
FRAME OF REFERENCE

2.1 MAINTENANCE AND PRODUCTION PERFORMANCE
Maintenance and operations are tightly interlinked; operations produce the value, and maintenance supports operations to achieve the required performance. This subsection considers some aspects which are important for the symbiosis between maintenance and operations in terms of the resulting production performance. It aims to some extent show that the current maintenance operations and the symbiosis with operations are contributing factors to the production performance in operations.

2.1.1 PREVENTIVE AND CORRECTIVE MAINTENANCE
Maintenance is performed on items of an equipment asset. Maintenance actions are either preventive or corrective and are categorized in the terminology standard (EN13306, 2010) according to Figure 2.3.

![Maintenance overview](image)

Maintenance is divided into preventive maintenance (PM), which is maintenance carried out before a fault, and corrective maintenance (CM), which is maintenance carried out after a fault. No matter the level of PM work, CM is needed as a complement in case of unexpected breakdowns (Pintelon and Gelders, 1992). Pre-determined mainte-
nance is PM which applies scheduled activities at a fixed interval based on either calendar time, processing time, or number of units produced. Condition-based maintenance (CBM) is PM that is initiated based on the condition of the equipment; it can be performed on a scheduled basis, using a certain interval, or on request and on a continuous basis. Whether scheduled or on request, the replacement of an item is planned for repair if the item is considered in a poor condition, and continuous CBM uses sensors to detect degradation in items before they fail. Immediate maintenance is CM which must be carried out straight away in order to maintain the equipment, and deferred maintenance is CM which can be addressed partially for the time being, with the actual replacement of the item delayed until the next available time slot for planned maintenance.

The application in practice is not as straightforward as the standard. For instance, an item which would be best suited by applying a pre-determined PM interval using process time in the equipment may instead be using a fixed time interval as a consequence of organizational habit and lack of IT support. In such a case, the required technical support may be the easy part to solve, but the habit of how activities are conveniently planned has a larger effect on the maintenance plan which is actually carried out. Hence, the problem can be an organizational one — ensuring a predictable workload for maintenance — and not lack of technical knowledge. For reasons of simplicity, it is therefore the calendar time interval which is applied, even if this is not the most economical alternative. Moreover, it should not be forgotten that even if an item has a defined PM activity, there is always a probability that it will fail and require CM anyway.

The standard division into PM and CM can play a role in categorization of the maintenance performed in order to follow up the work that is carried out. However, there will always be a gap between the intended PM work and the actual result, due to the margin of error of the uncertainty for the specific items. Moreover, the maintenance may not always be accurate, and merely applying a label of “PM” certainly does not solve the problem of unplanned events. Hence it is necessary to study the cost of maintenance for each item, and to implement its optimal maintenance interval (Figure 2.2), which should be evaluated continuously due to changed working conditions.

![Figure 2.2. Cost minimization graph, based on Smith and Hawkins (2004).](image)
The maintenance approach for a particular item is based on its specific failure behavior, and can be determined by, for example, applying the reliability-centered maintenance (RCM) methodology (Nowlan and Heap, 1978) and designing the maintenance plan on the basis of this (Coetzee, 2006). However, there are also engineering hour costs associated with efforts to optimize maintenance intervals, such as collecting and analyzing data. Better methods can support automating these processes, but implementing such methods also requires an investment of time. The configuration of the production system is important for the cost function, which may imply that items of the same sort need different maintenance activities at different intervals depending on where in the production system they are placed. Overall, it is evident that achieving differentiation in maintenance practices poses a challenge to identifying accurate cost functions which include the complete cost perspective of optimizing maintenance actions. Accordingly, as explained by Dekker (1996), it is very difficult to identify the contribution to company profits from the maintenance budget on the macro level, which in turn makes it hard to motivate any allocation in the maintenance budget for conducting systematic maintenance improvements. An evidence-based asset management approach (Campbell and Reyes-Picknell, 2016) is therefore a well invested work-procedure to interweave into the processes of maintenance, in order to define the tactics of when and how to perform maintenance on a physical asset.

There are varying definitions of maintenance methodologies, actions, policies, types, and so on. Generally, maintenance researchers use their own definitions based on the message they want to bring forth in their articles; some examples of this have been laid out by (Rastegari, 2017). This thesis uses the maintenance methodologies defined by (Tsang, 2002):

- Run-to-failure (RTF)
- Preventive maintenance (PM)
- Condition-based maintenance (CBM)
- Design improvement

RTF includes only the basic routine servicing and primary care, such as cleaning, lubrication, and calibration. Equipment is run until it fails. RTF can be appropriate to use if there are no consequences from breakdowns, or if the costs of the preventive measures to avoid failure exceed the expected benefits.

PM is defined similarly to the above EN-standard and involves replacing items at fixed intervals regardless of condition, based on time or usage. Usually these intervals are drawn from supplier information or past experience, and are seldom optimal (Tsang, 2002), where the intervals can be calculated using time-to-failure-data and cost models. Moreover, PM includes CBM using manual inspections on interval.

CBM consists of maintenance actions using sensors, and includes continuous or intermittent monitoring to increase the precision of detecting imminent failures.

Design improvement, which is not included in the SD model reported here, involves modifications to the design of items in order to improve reliability, enhance maintainability, or reduce the competence need of repair workers.

The process of acquiring new equipment is out of scope for the operational conditions, but what defines and determines the underlying maintenance need of a production system, and so it is wise to invest time and competence in evaluating the tradeoff function of value from new equipment to its life-cycle costs (e.g. Campbell and Reyes-Picknell, 2016).
2.1.2 AVAILABILITY PERFORMANCE

Maintenance is often responsible for the key results concerning availability and mean time to repair (MTTR) in the servicing of operations. This is achieved by instant “fire-fighting” activities, or proactive activities such as PM, often with an intangible connection to the result. The traditional measure of maintenance performance is availability performance (Ljungberg, 2000), also known as dependability performance or operating reliability. This is visualized in Figure 2.3, where the higher horizontal line represents equipment in a functioning state and the lower line represents it in the failed state.

![Figure 2.3. Visualization of measures of availability performance.](image)

The illustration in Figure 2.3 is based on the measures mean time to failure (MTTF), mean waiting time (MWT), and MTTR, which are defined according to Hagberg and Henriksson (2010) and are well fitted to the visualization of the common performance indicators related to operations. Some researchers use mean time between failure (MTBF) to define the time interval during which an item is performing its required function (EN15341, 2007, Nord et al., 1997, Campbell and Reyes-Picknell, 2016), instead of using MTTF as in Figure 2.3. In addition, some consider MTTR to be equivalent to how mean downtime (MDT) is depicted in the figure here (EN15341, 2007, Campbell and Reyes-Picknell, 2016). For the present purposes, it is better to describe MDT as consisting of MWT and MTTR, in line with Hagberg and Henriksson (2010) and (Nord et al., 1997), in order to clarify the different contributions of maintenance to operations.

MTBF in Figure 2.3 can be seen as the overall result of the performance measure of the maintenance organization for the certain equipment. It includes MDT, which depends on MWT, a measure of the supportability of maintenance to address the right maintenance resources with the right material, documentation, and tools for starting a repair, and MTTR, a measure of the capability to repair and standardize equipment. The frequency of MDT follows the average failure rate given in Equation 1, which according to Figure 2.3 and the above reasoning relates to the operating reliability measure of MTTF, as defined by Hagberg and Henriksson (2010) and not use MTBF as (e.g. Campbell and Reyes-Picknell, 2016).

\[
\text{Failure rate } (\lambda) = \frac{1}{\text{MTTF}} \quad \text{Eq. 1}
\]

\[
\text{Availability} = \frac{\text{MTTF}}{(\text{MWT} + \text{MTTR} + \text{MTTF})} \quad \text{Eq. 2}
\]

Accordingly, availability for a defined period can be calculated using Equation 2, supported by Figure 2.3. The availability performance explicitly shows how maintenance
can contribute to an improved measure. For example, according to Hagberg and Henriksson (2010):

- Supportability, measured by MWT, can improve through more and better-skilled repair workers, better prioritization in allocating repair workers to the most critical equipment, higher spare part coverage, and better available documentation and tools in case of emergency breakdowns.

- Maintainability, measured by MTTR, can improve through increased capacity to detect the type of failure, simplification of the reparability of the failed item, and standardization of the applied technical solutions.

- Reliability, measured by MTTF, which can be extended by improving weak equipment designs, increasing the capacity of the repair workers to perform the job, improving the application of preventive maintenance, and using parallelization to decrease sensitivity to disruptions.

Hence, according to the examples above, the service level of maintenance can be improved in both the short term, by adding resources in readiness to help out, and the long term, by improving resources, processes, equipment, and so on.

2.1.3 SERVICE LEVEL AGREEMENT

A service level agreement (SLA) is a procedure for managing the requirements between maintenance and operations (Hagberg and Henriksson, 2010). The SLA includes mutually agreed priorities in order to optimally control maintenance resources based on the current budget and the defined need from operations. It should also specify the requirements that maintenance has for operations, such as timeframes for planned maintenance, the level of maintenance carried out by operators, how deviations are reported, and so on. Often, availability performance measures are applied to follow up the service from maintenance, guiding decision making in where to improve their services.

2.1.4 OVERALL EQUIPMENT EFFECTIVENESS

According to Nakajima (1988), efforts to maximize equipment effectiveness must consider not just availability performance, but also the net operating performance efficiency of a production line and its quality performance. The total productive maintenance (TPM) literature (Nakajima, 1988, Ljungberg, 2000, Nord et al., 1997) therefore argues for using the measure of overall equipment effectiveness (OEE), which includes a more complete equipment performance measure. OEE divides losses into six categories:

1. Equipment faults and breakdowns
2. Setup and adjustments
3. Idling and minor stoppages
4. Reduced speeds and delayed process time
5. Process defects
6. Reduced yields

These categories point to losses which are at the intersection of maintenance and operations. For instance, according to Ljungberg (2000), small and frequent faults which can be fixed with minor effort by operators without escalating to breakdowns belong to category 1. Faults which cannot be solved by the operators and call for maintenance repair workers also belong to category 1. Category 2 may be the responsibility of operations, yet depending on circumstances could also be improved by maintenance activities which improve MTTR. The minor stoppages included in category 3 could be
caused by design decisions which result in a requirement for repeated cleaning, which could perhaps be easily redesigned by maintenance experts, or be part of daily care by operators. Idling effects, which also come under category 3, stem from the configuration of the production system, based on the stochastic dynamics during system operation. In accordance with category 4, as equipment ages and wears, it tends to run slower (Smith and Hawkins, 2004). Moreover, the small and frequent faults may also lead to partial breakdowns which result in the process defects of category 5. Such defects may continue undetected until the quality defect is noticed by the customer, which could be either the next operation or the end customer, a problem which belongs to either maintenance or operations for each specific case.

2.1.5 SHORT STOPS AND ACCELERATING DETERIORATION

Short stops in manufacturing equipment easily become part of normal everyday work (Nakajima, 1988, Nord et al., 1997, Ljungberg, 2000, Bicheno and Holweg, 2016). According to Wireman (2004), many Japanese studies have revealed that the efficiency losses represented by chronic problems are always greater than the downtime losses, and that most of these problems are never measured and therefore remain unnoticed until a breakdown occurs. Normally, in my experience, industries use an arbitrary 10-minute limit to classify stops, with shorter stops classified as minor stoppages and longer stops classified as breakdowns. It is also common for the longer breakdowns to get the most attention, with minor stoppages and shorter breakdowns neglected and excluded in much of the decision making regarding improvements. Many of the problems observed with short stops are acknowledged by TPM and Lean literature, including, for instance, the tendency to neglect minor stoppages and short breakdowns because they are often hidden and are the complex result of several interacting causes (Nord et al., 1997, Ljungberg, 2000); this is especially the case in comparison to the sporadic breakdowns which are often considered obvious and which managers tend to get overly concerned about (Nakajima, 1988). Short stops are by nature hard to measure (Bicheno and Holweg, 2016), as well as being frequent and easy to fix (Ljungberg, 2000), which means that chronic losses due to short stops easily become part of the normal state of operations, including the habit of fixing (Nord et al., 1997). According to Bicheno and Holweg (2016), the amount of short stoppages is surprisingly large when tracked, representing as much as 75% of the losses, and industrial studies have revealed that up to 80% of all losses in Swedish industry may be due to chronic problems (Ljungberg, 2000).

Nakajima (1988) underlines that neither longer breakdowns nor minor stoppages can be ignored, especially in highly automated facilities. The perspective of reliability in the RCM approach, where “the consequences of a failure determine the priority of the maintenance activities or design improvements required to prevent its occurrence” (Nowlan and Heap, 1978) p. 25), may mainly motivate addressing the non-hidden sporadic high hazard losses. According to Nowlan and Heap (1978), p. 27), RCM defines some classes of failures where operational consequences from, for instance, short stops may be hard to identify for the specific context of a production line. However, the advancement of applying RCM in combination with advanced methods such as SBO may support the identification of the significant operational consequences, thus motivating this combined approach for the prioritization of addressing chronic losses. Nowlan and Heap (1978) also describe a class of failures termed the hidden-failure consequences, where a defect in one item does not result in a direct failure, but eventually causes failure in another item if the defect is not detected and corrected in time. A similar aspect is noted by Ljungberg (2000), where small defects causing chronic losses such as short stops may have a larger impact than first thought, contributing to
a cumulative effect where many small failures result in a larger problem. Jardine and Tsang (2013) state that minor defects are considered to eventually cause a complete breakdown. According to Nakajima (1988), the deterioration of equipment has a similar behavior which may even require daily care; neglecting such maintenance accelerates the deterioration, while introducing accurate proactive maintenance will help prevent potential equipment breakdowns. These different above-descriptions are acknowledged as managing the flow of defects, according to Ledet (1999), to address the need to eliminate sources of poor reliability. Blann (1997) and Ledet (1999) have shown by reference to a DuPont study from the 1980s that Japanese companies had higher performance levels as a result of focusing on reducing the defect generators, rather than focusing on maintenance cost to drive the success of maintenance.

The aforementioned reasoning could be grouped into signals of short stops which grow in effect, such as the accumulation of chronic problems into larger impact sporadic problems, and minor defects leading to breakdowns and accelerated deterioration. These signals can be sorted into several of the six big losses in the OEE measure and need to become more explicit in order to be accurately addressed. This could be visualized according to Figure 2.4, where the solid uptime lines shown in Figure 2.3 are chopped into pieces including multiple short stops. This illustrates the different character of short stops to some extent, without attempting to be complete; the question mark may indicate faults that reduce speed, similarly to duration diagrams (Hagberg and Henriksson, 2010), and may also cause quality defects.

![Figure 2.4. Explicit visualization of maintenance performance.](image)

According to the abovementioned characteristics of short stops, these do not call for a maintenance expert but are taken care of by the operators themselves. The availability performance in Figure 2.3 is straightforwardly connected to measuring the service level of maintenance through MWT, MTTR, and MTTF. These measures are often applied for reporting maintenance work into the computerized maintenance management system (CMMS). The illustration in Figure 2.4, which shows the situation including all stops in an equipment, explicitly visualizes the common goal of maintenance and operations. However, applying a mental model (see subsection 2.2.3) based on Figure 2.3 may strongly mislead continuous improvements in maintenance, and if they are applied in the SLA process may risk that short stops are neglected. Furthermore, such a mental model will not support a systems view, but on the contrary may lead to conformity, using the measures of maintenance service level, from maintenance management’s side who fulfill their part, despite the possible fact that operations keep experiencing issues with their equipment. There is a risk that the organization will remain in a limbo of organizational defensive routines (Argyris, 1990), and the true potential to deal with the problem will remain hidden.
2.1.6 CAPABILITY DEVELOPMENT OF PROCESS PERFORMANCE

Repenning and Sterman (2001) have actualized and presented a dynamic theory called “the capability trap”, which covers the problem of the uncredited work of long-term capability improvements in producing the required daily process performance. The model is based on numerous case studies which show that the key to successful management of such dynamics is independent of the choice of improvement tools. Instead, the root cause is a systemic problem, which requires much effort in managing the interaction of tools, equipment, workers, and managers. Thus, the model illustrates considerations on a generic level to learn from. The capability trap model in Figure 2.5 applies the modeling language of SD, and so readers who are inexperienced with the SD modeling language may find it valuable to study section 2.2 first. More in-depth information on the model can be found in the original article (Repenning and Sterman, 2001).

The model in Figure 2.5 illustrates the capability of an asset, such as a process, machine, or working procedure, which together with the time spent working results in the actual performance from that asset.

Time spent on improvement increases the capability, though there will be a delay until the effects of the improvement work will be seen; meanwhile, there is a continuous capability erosion, as machines wear out, working procedures become obsolete, and so on. Maintenance, for instance, spends time on improvements, identifying the root causes of breakdowns and their countermeasures, or systematically updating the current base condition of equipment, in order to avoid unplanned disturbances in operations. These proactive actions are done to invest in increasing the capability and support increasing operations actual performance. In maintenance operations, the performance gap can consist of backlogs of work, such as PM, deferred CM, breakdown analyses, requirement specifications for new acquisitions, and so on.

The model contains a number of balancing loops. The first of these, B1, corresponds to a strategy of working harder, and closes the performance gap through increased pressure on short-term results. The second, B2, corresponds to working smarter. While this is aimed at the same goal as B1, its complete feedback loop is a slow-working one which focuses on increasing the capability. Surprisingly, Repenning and Sterman
(2001) discovered that at the companies they studied, working harder was not an occasional lifeline used when the pressure peaked, but rather the standard operating procedure.

The intended effect of B2 is that working smarter will increase the actual performance and hence decrease the pressure to do work, meaning that more time can be spent on improvements; this captures the essence of the reinvestment loop R1 when the capability is successfully improved through continuous improvements. However, if the pressure to work harder persists, there is a great risk that R1 will instead become a vicious spiral where short-term efforts are prioritized over long-term improvements. Moreover, this spiral is likely to be reinforced to the point where it develops into a permanent state of firefighting and increasing safety stocks and buffers. The habit of shortcuts (B3) can also grow as a consequence of that it is effective to use to increase production throughput on short time, by diverting time from necessary long-term improvements into short-term increased process performance.

The capability trap represents general patterns of behavior that can be identified in many different stances of an organization. Repenning and Sterman (2001) have emphasized that managers tend not to realize how deeply trapped the organization is, and apply countermeasures reinforcing the trap even further. The basis for this is that, in general, people:

- Often look for explanations for a puzzling event in nearby recent events assumed to have triggered it rather than underlying patterns of behavior (Carroll et al., 1998).
- Simplify matters by assuming a single cause for each event and falsely assuming cause and effect to be closely related in time and space (Repenning and Sterman, 2001).
- Underestimate the effect of time delays and omit feedback processes in actions (Carroll et al., 1998, Repenning and Sterman, 2001).

Overall, according to Repenning and Sterman (2002), being in the capability trap leads to self-conforming attribution errors, having the effect of blaming the people instead of acknowledging the capability trap dynamics which are causing the degradation of process performance. Thus, Repenning and Sterman (2001) emphasize the need for a mind shift in managing the capability trap, and provide incentives for generating knowledge about the underlying structure of behavior and implementing improvement efforts based on the conditions of these structures.

### 2.2 SYSTEM DYNAMICS THEORY

The theory of structure, which matured in the 1960s, is represented by four significant hierarchies to represent a system (Forrester, 1968, p 4-1):

- **The closed boundary**
  - The feedback loop as the basic system component
    - Levels (the integrations, accumulations, or states of a system)
    - Rates (the policy statements, activity variables, or flows)
      - Goal
      - Observed conditions
      - Discrepancy between goal and observed conditions
      - Desired action

*The closed boundary*: a philosophical view (feedback thinking) that denotes that what crosses the boundary from outside has a minor effect on the system behavior. The line
of the boundary strictly depends on the problem being modeled; the system elements that generate the mode of the problem must be included.

*The feedback loop:* the basic component of a decision-making process (see Figure 2.6). Decision making depends on the perception of the present system condition, and any decision for change gives rise to a new condition which influences our next decision.

*Levels and rates:* the two classes of variables of an SD model. The levels describe the condition of a system, carry the system’s continuity from the past to the present, and are the source of information for the rate equations.

*Goal, observed conditions, discrepancy between the goal and observed conditions, and desired action:* the four components of the “policy substructure” in systems. As seen in Figure 2.6, these provide the explicit substructure of the rate equation. The goal is the desired state of a level, and so there may be several conflicting goals in a system. The observed condition is the apparent state, the available information of the system at that time, and the information for decision (the true state of a system may be delayed or distorted by conditions in the system). The discrepancy between the goal and observed conditions results in a decision; the desired action to close the gap.

![Figure 2.6. Goal oriented balancing feedback loop comprised of level, rate, auxiliaries, and constants](image)

\[
\text{Level} \,(t) = \text{Level} \,(t - dt) + \text{Rate} \cdot dt \quad \text{Eq. 3}
\]

\[
\text{Rate} = \frac{\text{Desired Action}}{\text{Delay}} = \frac{\text{Discrepancy between Goal and Observed Condition}}{\text{Delay}} = \frac{(\text{Goal} - \text{Level})}{\text{Delay}} \quad \text{Eq. 4}
\]

Equation 3 is the level equation, where the rate accumulates into the level in each time step \((dt)\), and Equation 4 is the rate equation, which is the consequence of defined policies and present level. Hence, the level equations are integrations which accumulate the effects of the rates. Combining Equations 3 and 4 results in feedback between the parameters. The “B” in Figure 2.6 means that it is balancing feedback that governs the loop, and the counter arrow shows its direction.

The building blocks are few in SD – only levels and rates – but their combinations to represent a system are infinite, and provide the tools to map the feedback loops of a system. Levels are also referred to as stocks, and rates are also referred to as flows. Although there can be several inflows and outflows, levels can only be affected by their associated connected rates. Rates are ruled either by another rate or by a rate equation comprised of auxiliaries and constants. Auxiliary variables are commonly included for a pedagogical reason; they allow visualization of the structure between variables and simplify the description of their mathematical relations. Delay and goal are constants,
and are not affected by any other variable, which means that a constant is a variable that represents a boundary in a model. Another aspect of the model boundary is represented by the cloud at the end of the rate arrow, which could include another level inside the model boundary.

2.2.1 DYNAMIC COMPLEXITY

Reality is dynamically complex. The methodology of SD was developed in order to capture these kinds of dynamics of systems, which implies that SD is a language of dynamic systems. This property is an important reason why SD should be used for dealing with the dynamic complexity in manufacturing systems such as maintenance. Sterman (2000), p 22) has given several reasons why dynamic complexity arises, stemming from the facts that systems are:

- **Dynamic**: What at first glance appears to be unchanging is actually varying over a longer time horizon. Change in systems occurs at many scales, and these different scales sometimes interact.
- **Tightly coupled**: The actors in a system interact strongly with one another and with the natural world. Everything is connected to everything else.
- **Governed by feedback**: Because of the tight couplings among actors, our actions feedback on themselves. Our decisions alter the state of the world, causing changes in nature and triggering others to act, thus giving rise to a new situation which then influences our next decisions.
- **Nonlinear**: Effect is rarely proportional to cause, and what happens locally in a system (near the current operating point) often does not apply in distant regions (other states of the system). Nonlinearity often arises from the basic physics of systems, and also arises as multiple factors interact in decision making.
- **History-dependent**: Taking one road often precludes taking others, and hence determines where you end up (path dependence). Many actions are irreversible.
- **Self-organizing**: The dynamics of systems arise spontaneously from their internal structure, generating patterns in space and time and creating path dependence.
- **Adaptive**: The capabilities and decision rules of the agents in complex systems change over time. Evolution leads to selection and proliferation of some agents while others become extinct. Adaption also occurs as people learn from experience.
- **Counterintuitive**: In complex systems, cause and effect are distant in time and space, while we tend to look for causes near the events we seek to explain. Our attention is drawn to the symptoms of difficulty rather than the underlying cause. High-leverage policies are often not obvious.
- **Policy resistant**: The complexity of the systems in which we are embedded overwhelms our ability to understand them. The result is that many seemingly obvious solutions to problems fail or actually worsen the situation.
- **Characterized by tradeoffs**: Time delays in feedback channels mean that the long-run response of a system to an intervention is often different from its short-run response. High-leverage policies often cause worse-before-better behavior, while low-leverage policies often generate transitory improvement before the problem grows worse.

2.2.2 MENTAL MODELS

Complex problems are not just physical regularities that enable the reduction of physical phenomena. When human activity is included, difficulties in separating this activity from its physical surroundings make it hard to define what to include or exclude.
The complexity of human activity around problems is that it is not the problems that appear to the problem-owners but their perception of the problems (Checkland, 1981). The phenomenon of different interpretations by different people is termed “mental models” in the SD literature (Forrester, 1961, Senge, 1990, Doyle and Ford, 1998, Sterman, 2000, Morecroft, 2007). Definitions vary, but in essence, mental models are inner simplifications and models inside people’s heads which allow them to interpret the surrounding environment and phenomena. They can be simple or advanced, depending on experience; they are unchangeable unless there is a willingness to learn; and they guide people’s actions.

Moreover, as model interventions aim to unveil ambiguity of the underlying structures to why the studied problem behavior arises, the modeling process which forms a representation of the real system into the model is as much a learning endeavor as is post-analyzing the model that has been constructed (e.g. Lane, 2017).

2.2.3 QUALITATIVE OR QUANTITATIVE SD
It is argued that the quantification of an SD model has decisive importance for a thorough study (Forrester, 1971, Richardson, 1996, Homer and Oliva, 2001). The qualitative procedure termed “systems thinking” was popularized by Senge (1990), and has been used since the early 1980s (Coyle, 2000). However, there is a lack of guidelines on whether to apply qualitative or quantitative modeling in SD (Richardson, 1996).

Applying qualitative systems thinking is agreed by several SD authors to provide a satisfying analysis for change (e.g. Senge, 1990, Vennix, 1996, Sterman, 2000, Morecroft, 2007). Coyle (2000) goes even further, saying that a qualitative analysis is enough, especially when dealing with uncertainty. However, Homer and Oliva (2001) claim that this is incorrect, and that quantitative modeling provides a more thorough analysis. They also point out that simulation increases the possibility of testing whether uncertainty is affecting the system and makes it easier to judge whether enough data exist to reach correct conclusions. Moreover, an SD model provides testing (validation) of the assumptions about the interacting element’s relations, while a systems thinking model provides a qualitative evaluation of validity only.

This thesis uses quantitative modeling, since the purpose is to enable simulation experimentation. However, as revealed by the literature review in Paper 1, most publications on maintenance-related SD work are not quantitative, or do not present the quantitative results to facilitate replication. According to Forrester (1987), it is almost impossible to understand a system’s nonlinear dynamics without simulation. Quantitative modeling allows us to study the characteristics of the variables which describe the interrelatedness of system components (stocks, flows, and constants) in the form of structure and equations. This is discussed at greater length elsewhere (Linnéusson, 2009).

2.2.4 THE MODELING PROCESS IN SD
The general steps in SD modeling in the literature range from articulating the problem phenomena to implementation. Modeling is highly iterative, and each step may have consequences for the next. For example, an unexpected result in testing the model may lead to refinement of the problem articulation or the dynamic hypothesis.

The key aspects of the modeling process are, in brief (adapted from Sterman (2000):

1. Problem articulation: understand the problem, articulate it, and select the boundary.
2. Dynamic hypothesis: formulate a dynamic hypothesis for how the problem dynamics are endogenously generated from the feedback structure within the selected boundaries. This formulation includes studying the relevant literature on problem phenomena and investigating the situation at the companies being studied.

3. Formulation: build a simulation model based on the dynamic problem and test the hypothesis, including existing ideas from the literature and real-world descriptions based on tacit information. This is a highly intuitive process (Sterman, 2000), and there are no formal descriptions of how to implement system dynamics projects (Linnéusson, 2009). The model includes specifications of structure and decision rules, parameter estimation, behavioral relationships, initial conditions, and tests for consistency with the aim of the model.

4. Testing: examine whether the model reproduces adequately with respect to its purpose. Testing is further treated in the validation subsection below.

5. Policy formulation and evaluation: apply the model to explore possible “what if” scenarios, test their sensitivity to implementation, examine synergy policies, and so on.

2.2.5 GROUP MODEL BUILDING

Group model building (GMB) can be applied to facilitate the modeling process in SD. It uses an approach to managerial modeling (Lane, 1994) that focuses on learning through including the client in the process. Shared understanding among group members is the desired effect, enhancing the results from modeling and improving the conditions for implementation of the solution (Lane, 1994, Andersen et al., 1997). The primary goal of GMB is to engage people “in building a system dynamics model of a problem in order to see to what extent this process might be helpful to increase problem understanding and to devise courses of action to which team members will feel committed” (Vennix, 1996), p3).

2.2.6 VALIDATION OF MODELS

Validation is a part of model testing which builds confidence about how correctly a model mirrors a system. The purpose of a model has the strongest impact on how validation is carried out. Another crucial aspect of validation is that in reality all models are “wrong”, because “all models, mental or formal, are limited, simplified representations of the real world” (Sterman, 2000), p 846). According to Richardson (1996), confidence and validation have been weak areas in SD, lacking appropriate procedures and standards. Finally, validation is a matter of acceptance of the results; however well the tests are passed, this means nothing without acceptance. This has a clear connection to the model ownership, which is emphasized in GMB above.

More technically, SD models are causal-descriptive as well as “statements as to how real systems actually operate in some aspects” (Barlas, 1996), p 185). The model’s internal structure validation, together with its capacity to explain how the behavior arises, is therefore crucial. While correlational black-box models are validated using statistical tests, this is not applicable for validating behaviors in an SD model, due to the problems of autocorrelation and multicollinearity (Barlas, 1996). Moreover, judging the validity of the internal structure of a model is very problematic, and most methods are informal and qualitative in nature (Barlas, 1996), and see e.g. Luna-Reyes and Andersen (2003). Therefore, it is largely the model’s usefulness in explaining problem phenomena that determines its validation, as pointed out by Sterman (2000). In other words, if the model can be considered acceptably relevant and its usage may assist managers’ decision-making in the real world, it supports validation (Bertrand and Fransoo, 2002).
Barlas (1996) presented a general framework for identifying proper validation criteria depending on the type of model, divided into three main types of tests:

1. **Direct structure tests:** Do not use simulation. Compare the model with knowledge about the real system, both information from the system (empirical) and information from generalized knowledge (theoretical).

2. **Structure-oriented behavior tests:** Use simulation in order to study the behavioral results in order to indirectly uncover structural flaws.

3. **Behavior pattern tests:** Evaluates how well the model accurately reproduce the behavior patterns found in the real system.

The **direct structure tests** include:

- **Structure-confirmation test:** Comparing model relations (equations) with existing relationships in the real system (empirical) and with generalized knowledge in the literature (theoretical). This is one of the most difficult tests to formalize and quantify (Barlas, 1996). It is based on qualitative data; the interpretation of how the real system is functioning.
- **Parameter-confirmation test:** Evaluation of how the constants in the model agree with the real system, either empirically or theoretically.
- **Direct extreme-condition test:** Evaluation of each equation in order to avoid incorrect results; for example, a negative inventory value should not be possible.
- **Dimensional consistency test:** Each equation should be dimensionally consistent on both the left-hand side and the right-hand side.

The **structure-oriented behavior tests** include:

- **Extreme-condition test:** Ensures that the model behaves similarly to the real system in an extreme condition.
- **Behavior sensitivity test:** Locates those parameters which are highly sensitive to model behavior, and evaluates whether the real system would behave in a similar way.
- **Modified-behavior prediction:** This can only be performed if there exist historical data covering a modification of the real system. The model can then be tested by applying the same structural modifications as in the real system and seeing if the results are similar.
- **Boundary adequacy test:** This is conducted to ensure that the important aspects of the problem behavior are included in the model. If the model behavior changes significantly when the boundary is modified, then the model needs to include these changes. Consequently, if the behavior is unaffected by a boundary change, it may be excluded. As far as possible, exogenous variables and constants in the model should be modified into endogenously generated ones.
- **Phase relationship test:** Some pairs of variables may show similar behavior in a model; this test examines whether the same phase relationship exists in the real system. Correspondingly, a phase relationship in the real system should also be reflected in the model.

The **behavior pattern tests** emphasize pattern prediction, such as “periods, frequencies, trends, phase lags, amplitudes,...” (Barlas, 1996), rather than event prediction. They do not provide any added information on the validity of a model structure.

SD models have different uses, and their requirements regarding validation may depend on their type. These are divided into:
• Modeling of a real system in order to achieve improved performance (e.g. Forrester, 1961, Sterman, 2000) uses all three stages of validation tests described above (Barlas, 1996).
• Modeling for theory building in order to test or improve it (e.g. Größler et al., 2008, Schwaninger and Hamann, 2005) uses the two first structural tests but typically makes no use of the third (Barlas, 1996).
• When building the simulator model for “management flight simulators” (Sterman (2000), all three stages of the validation test are desirable but other disciplines may be required too, such as cognitive psychology, information systems design, and computer technology (Barlas, 1996).
• Modeling for learning (Lane, 1994) using group model building (Vennix, 1996) mainly uses the two first structural validation tests, since the purpose is learning-oriented and has similarities to models of scientific theories (Barlas, 1996).

2.2.7 SD IMPLEMENTATION ISSUES
In operational management applications of SD, there is often an aspect of the client body. In order to provide good results from modeling, it is valuable if not essential to have a good connection with the client. According to Wolstenholme (1997), operational management might have several different problems with the SD type of modeling:
• Abstract parameters: These can include a high level of aggregation parameters, generally making it difficult for operational management to relate to their own businesses.
• Soft variables: The mix of soft and hard variables in modeling brings the consequence of a culture gap to previously-used methods which are oriented towards hard variables.
• Detail escalation: The tendency for each part of an organization to see itself as the most important means that attention is required in modeling projects in order to keep the model detail/boundary on a suitable level.
• Model ownership: The desire for ownership of the model for future improvements is not included in the modeling process.

According to Richmond (1994), there are difficulties with implementing a modeling project, and several researchers have emphasized the limited support for such endeavors (Forrester, 1994, Rouwette et al., 2002). The unavailability of SD for new users has also been pointed out (e.g. Richmond, 1994, Richardson, 1996), as has the fact that the low use in management is considered to be due to pedagogical flaws in the methodology (Warren, 2005). However, the issues of implementing the SD methodology contain the paradox of both simplicity and complexity. On the building-block level, the methodology is easy to understand; the base elements of system dynamics modeling are elementary. However, when these elements are put together to formalize a whole, the complete structure becomes complex and difficult and can be doubtful to rely on. With these building elements, one can develop many diverse models, generating endless complexity. Hence, one difficult part in modeling is formalizing the model equations which define how the model entities are interconnected. There is no key for judging the soundness of each thought included in the model, besides the modeler’s own creativity and ability to perform the art of modeling (Sterman, 2000), p 87 and 89).

2.3 MULTI-OBJECTIVE OPTIMIZATION
MOO is a discipline that, in contrast to SOO which considers one objective function, evaluates two or more conflicting objectives against each other, and obtains the Pareto
optimal solutions that constitute the Pareto front (Basseur et al., 2006). MOO can be applied using multiple different methods (see, Marler and Arora (2004) and different simulation-optimization methods (see, Figueira and Almada-Lobo (2014). The application of MOO in this thesis have not explored which are the best performing optimization algorithms with SD or DES. A good overview of multi-objective evolutionary algorithms is given by Zhou et al. (2011). Here, the fast elitist non-dominated sorting genetic algorithm (NSGA-II) originally developed by Deb et al. (2002) has been applied. This is probably the best-known population-based metaheuristic algorithm for giving very good approximations of the Pareto front, and according to Zhou et al. (2011) a majority of research and application areas applying multi-objective evolutionary algorithms is sharing more or less the same framework as that of NSGA-II. The intention with genetic multi-objective evolutionary algorithms, is to depict a complete Pareto optimal set, which represents an approximate potential set of solution points, which can be replaced with a potentially better solution (Marler and Arora 2004). The comparison of the solutions utilizes the domination concept, in which a solution \( s_1 \) is said to dominate a solution \( s_2 \) if \( s_1 \) is no worse then \( s_2 \) with respect to all optimization objectives, and is strictly better than \( s_2 \) in at least one optimization objective (Deb, 2001).

Figure 2.7. The concept of non-domination, decision, and objective space, from Aslam (2013).

Figure 2.7 illustrates the concept of decision and objective space, as well as the domination and non-domination of solutions in MOO. The decision space contains the design variables, defined by the input parameters, which are being searched in a MOO problem. Each design variable is mapped to the objective space and evaluated through a solver, which in our case is either an SD or a DES model using the same principle. Thus, a certain solution \( A \) with its inherent values of the design parameters \( x_1 \) and \( x_2 \) is evaluated through the solver, which results in \( A' \) in the objective space representing the fitness or performance of solution \( A \) in terms of the objective functions \( f_1 \) and \( f_2 \).

Simulation models are normally applied in order to represent a complex problem which cannot be solved analytically. Hence, having a simulation model as solver in Figure 2.7 requires considerable exploration of the decision space and therefore each solution is evaluated using search algorithms applied in frameworks called metaheuristics (Figueira and Almada-Lobo, 2014). One such framework is the population-based metaheuristic algorithm, called genetic algorithms, and was originally developed to address deterministic problems (Figueira and Almada-Lobo, 2014), even so the application of MOO to SD models, which are deterministic, is not yet widespread.
Conversely, metaheuristics dominate the optimization routines of the DES software (Figueira and Almada-Lobo, 2014).

As mentioned above, the application of MOO in this thesis delimits to identifying how the created SD simulation model can be explored, focusing on aspects such as defining the optimization objectives, input parameter boundaries, and suitable constraints. The application of MOO follows the general SBO process seen in Figure 2.8, which separates simulation and optimization. Moreover, the SBO process indicates on the potential applicability with any simulation approach, as it regards the model content as black box information, and therefore it is essential to understand what the applied simulation model is considering in order to interpret the consequent optimal solution sets correctly.

![Figure 2.8](image)

**Figure 2.8.** A general SBO process which utilizes a MOO on a simulation model, adapted from Aslam (2013).

### 2.4 DISCRETE-EVENT SIMULATION AND MAINTENANCE

DES can be considered a hard approach with the purpose of mimicking the dynamics of a production system based on the structure of operating units and buffer queues between them. According to Robinson (2014), the philosophical perspective of DES is seeing and defining systems in terms of this queuing structure and the variability that the system is subject to. Each entity is tracked and processed through the structure, which allows modeling of the individual events of the system and their stochastic dynamics. The required input data in DES is heavily standardized (e.g. Law, 2007, Banks et al., 2010). Moreover, according to Pidd (2012), DES could fall into the category of logical models, as opposed to SD, which falls into the category of interpretive models.

A DES study can include a range of complexity, from aggregated to detailed; for instance, all the movements within a production cell could be modeled if this supports the purpose of the study, or it could be considered good enough to apply the process time for the whole unit of that production cell. Nonetheless, any DES study is a tangible study based on the real-world system configuration. Besides operating units and queues, the inputs are data regarding each unit’s availability, which is a function of MTTF and MDT. In the perspective of this thesis, these two measures are key measures delivered from the technical system in united action with the capacities of the maintenance organization, as reviewed in the subsection on availability performance.

The validation criterion for a DES model is how well it performs in comparison with historical data collected from the real-world production system. If these data do not exist, they can be generated by using on-site work sampling methods. Hence, the input data follow a rather subjective procedure. Having built the DES model, repeated tests
with different random distributions enables testing the model’s confidence interval, which reflects the probability that the simulation results are correct for the real system. Moreover, a DES model of a real-world production system enables analyses of the robustness (variability) of the production system and plausible improvements. However, in such a connected system, if any of the input parameters have high variance then the model may be uncertain; because of this, outliers in the real data are often neglected when considering the input data distributions for the model. Applying DES is therefore strongly dependent on the stability of the real system, in terms of mimicking its performance in a satisfying way. Similarly, maintenance activities contribute to keeping variance low and add stability to the real production system.

Depending on the purpose of the study, the staff needed to interact with the operating units could also be included, enabling a deeper analysis of the significance to the system performance of, for instance, the number or required competence levels of operators and repair workers. Such studies will include more soft variables and become more of an interpretive character, and may also include less validation support from existing historical data.

Hence, the application of DES can take numerous forms, as can the support it offers to maintenance development. One option is to apply it to support prioritization of reactive breakdown repairs, and several studies have used DES evaluations to plan reactive maintenance interventions to increase throughput (Gopalakrishnan, 2016). The studies apply the perspective of operations, which is well-studied in the application field of DES, for better maintenance planning of the reactive outcome of the failing equipment. Quite recently, DES has begun to be used to evaluate so-called maintenance strategies (Alrabghi and Tiwari, 2016), which provide frameworks for some general cases of time-based PM, opportunistic maintenance, and periodic CBM. Moreover, SOO has been used to support evaluation of the benefits of the different maintenance strategies. Alrabghi and Tiwari (2016) approach the usage of DES from the maintenance management perspective (e.g. Dekker, 1996, Ding and Kamaruddin, 2015, Alrabghi and Tiwari, 2015) with the intention of allowing the inclusion of a richer complexity of maintenance systems, which they argue previous applications have failed to acknowledge. For example, maintenance systems have been modeled in isolation, only testing one strategy or policy at a time, and have used oversimplified assumptions disconnected from real-world systems. More recently, Alrabghi et al. (2017) used the suggested framework in two case studies, this time applying MOO, and concluded that it is important to consider optimization of maintenance strategies to avoid sub-optimization. However, they also saw unexpected results, such as very few non-dominated solutions, indicating that maintenance cost and production throughput might be non-conflicting. Another finding, and a very interesting one, was that despite the application of SBO “the complexity of maintenance problems makes it difficult to assume a given maintenance strategy is the optimum for each asset in the system” (Alrabghi et al., 2017), p. 206). Overall, the application of DES to evaluate PM is very sparsely explored (Alrabghi and Tiwari, 2015, Alrabghi et al., 2017).

2.4.1 THE SUPPORT FROM MOO+DES TO MAINTENANCE
The application of MOO to DES models as suggested in this thesis contributes to the prioritization of improvements to the production system that maintenance can include in their plans of activities. The application of MOO on DES models has its usage as an effective method to unveil the most critical bottleneck of the production system (e.g. Ng et al., 2014, Bernedixen et al., 2015, Pehrsson et al., 2016). The bottleneck in a production line is the point where an infinitesimal improvement can have the largest impact on throughput (Ng et al., 2014). Ng et al. (2014) and Pehrsson et al. (2016)
argue that numerous methods in the literature, such as utilization of machines, blocking and starving patterns, data-driven approaches, shifting bottleneck detection, and multiple bottlenecks, all share the same deficiency of lacking a suitable level of information to show which improvement action(s) should be taken at the identified workstation or machine. By applying conflicting objective functions, the abovementioned MOO+DES strategy works simultaneously to maximize the throughput (other performance measures are also applicable, such as lead time, buffer levels, etc.) and minimize the sum of applied improvement combinations; thus the evaluated Pareto front results are prioritized in the order of activities to achieve the best results with the smallest number of actions.

Bernedixen et al. (2015) compared the utilization method to the shifting bottleneck detection method, and identified a different potential source of the bottleneck. Testing the suggested improvements from the two approaches revealed a significantly higher improvement for the MOO+DES method (15% compared to 5.9%). A MOO+DES study evaluates potential improvements, such as improved process time, MTTR and availability of the respective machines in the production line. The evaluation process, using MOO, identifies the Pareto front solutions and the improvement activities and where in the production system to implement them. The study of Bernedixen et al. (2015) indicated the need for improving availability rather than process time. Hence, their approach implied different but, as they argue, more precise pinpointed action to increase the throughput.

There is no actual limit to which parameters in a DES model to evaluate in terms of identifying the potential relief of the bottleneck (Bernedixen et al., 2015). It promotes large adaptability to increased usage for maintenance development. Even if the current presented applications of above studies, using DES+MOO to search the priority of improvements, are not directly linked to maintenance, the addressed parameters are strongly related to the performance of maintenance. Where, for instance, the optimization evaluations showing how and where to intervene in the system in Pehrsson et al. (2016), result in that the top five actions are suggesting to improve availability rather than improving any process times.

The application of MOO to DES models according to the above description provides a tool for the maintenance context which allows increased differentiation ability on the level of operations, instead of the level of individual items and equipment at risk. By advancing from studying individual machines and equipment to studying the need of maintenance from a production system perspective introduce a tool which can potentially improve maintenance’s tactical planning capabilities, which according to Pintelon and Gelders (1992) is a way to address the problem of effective resource utilization.

2.5 METHODOLOGICAL ASPECTS OF MIXED METHOD DESIGNS

The mixed approach of SD and DES has been of interest to researchers in recent decades, and many applications in operations research have been reported (Howick and Ackermann, 2011). Reports have also included many different levels of integration; according to Brailsford et al. (2010), the holy grail of achieving the complete mix, drawing on the full potential of both approaches, is continuously coming closer, but may never be fully realized due to the disparate philosophical standpoints of the two approaches. To support reflection on the methodological level, Morgan et al. (2017)
presented a toolkit of designs for mixing the DES and SD methods, which is shown in brief in Figure 2.9.

A literature search for DES+SD maintenance applications produced few results, all with different industrial focus than in this thesis. These included: (1) a performance forecast model for cutting tool replacements in mechanized tunneling projects which also applied agent-based modeling (Conrads et al., 2017), (2) a hybrid model of the availability assessment of an oil field (Droguett et al., 2006), and (3) a thesis on using DES to mitigate the limitations of SD by utilizing DES to represent individual entities and stochastic behavior using a simplified maintenance SD model (Bell, 2015). Paper 5 presents both a literature review of DES+SD applications that apply optimization and the full description of the SD+DES+MOO framework.

From a technical point of view, one reason to mix DES and SD is that this strategy combines the specialization of including feedback in SD with the high degree of details that can be included in DES models (Viana et al., 2014). Even if feedback may be incorporated to some extent in DES models, according to Gunal and Pidd (2010) utilizing DES as a tool tends to focus on the operational level of specific areas, and utilizing DES for policy-level analysis is rare; moreover, the visualization of the feedback behavior does not adequately support the answer to why certain behaviors arise. However, examples of hybrid DES and SD simulation models that do not aim to study the feedback behavior also exist. For example, Abduaziz et al. (2015) applied SD merely to accumulate data from the DES model to trace the environmental load from operations in the automotive industry. Hence, there is a large variation in how DES and SD can be mixed, as depicted in Figure 2.9. This figure is adapted from the work of Morgan et al. (2017), who extensively studied the literature of mixing OR/MS methods and/or mixing DES and SD and made recommendations for further studies. A brief explanation of each of the mixed methods designs shown in Figure 2.9 is provided below.

![Figure 2.9. Mixed method designs, adapted from Morgan et al. (2017).](image)

An isolationist design applies SD or DES without mixing them. A parallel design applies SD and DES, each in isolation, in order to contrast their respective contributions to a commonly studied phenomenon. This allows utilization of their shared paradigm perspectives, focusing on the methodological level of each respective technique
to study the same problem. A *sequential design* applies SD followed by DES, with the first method feeding input to the second. This allows both method models to be fully developed within their paradigm for their specific uses. An *enrichment design* has one primary method which is enriched with techniques from one or more additional paradigms, such as utilizing discrete events in an SD model or continuous behaviors in a DES model. An *interactive design* allows feedback exchange between methods, which relaxes the paradigm restrictions between SD and DES and allows utilization of each method’s benefits in one methodology. The level of interaction can range from the frequent exchange of information between an SD and DES model in one simulation evaluation to a few interactions during an evaluation period. Finally, an *integrated design* incorporates a full integration, with each simulation evaluation including both discrete and continuous time steps and both methods taking one mutual system view.

The framework proposed by Morgan et al. (2017) was developed with applications of DES and SD in mind, and omits the aspect of optimization. Among the techniques illustrated in Figure 2.9, integration is the one to which optimization best applies, as also exemplified by Pidd (2012). According to that optimization is omitted in the mixed method designs framework, it is not possible to fit the proposed hybrid SBO framework which applies SD+DES+MOO into one of the abovementioned designs of mixing SD and DES. The proposed hybrid SBO framework is presented in Figure 4 of Paper 5, including elements of sequential design, elements of potential interaction, and integration of the respective SD+DES method with MOO. According to Pidd (2014), such design could be classified as somewhere between a “loose coupling of different approaches” and “the use of one approach as a precursor to the other”. And may best fit as a sequential design in the framework of Morgan et al. (2017). Although each SD+MOO and DES+MOO integration can be applied without the other method to support practical development, for the purpose of maintenance development they have been integrated into the proposed framework to complement each other and provide a larger system view.

### 2.5.1 A REFLECTION ON CHANGE IN PRODUCTION SYSTEMS USING DES OR SD

According to Tsoukas and Chia (2002), traditional approaches to organizational change consider the current state of operation to be the stable condition, and change to be the exceptional event(s) which we want to perform to improve the system. This corresponds largely to how DES represents the environment of the production system. The DES model represents the stable state of operation, and applying the method of DES+MOO then makes it possible to optimize the minimized improvement changes to implement, changing the configuration to make the system operate more effectively.

However, Tsoukas and Chia (2002) claim that organizational change is continuously taking place through “the reweaving of actors’ webs of beliefs and habits of action to accommodate new experiences obtained through interactions”. They also state that change is the natural condition of organizations, and that this is what makes it hard to see. The ongoing characteristics of change resemble the systems thinking perspective applied in SD simulations, which emphasizes feedback as the basic system component, with a decision-making loop based on the decision makers’ perceived discrepancy between the goal and observed conditions; this is where the desired corrective action should take place (Forrester, 1968). It may be easy enough to manage the ongoing dynamic process of a single decision loop without delayed information, where instant steering is possible. However, this rapidly becomes overly complex in organizational structures where several feedback loops are connected, and the information required for steering may not be at hand. Hence, the driving force of the continuously-evolving
organizational behavior is the multifaceted decision-making of many agents within the system, all of which act on the basis of their own perceptions of knowledge regarding their sub-systems.

Still, in industrial systems, people not only self-adapt and learn in interaction with each other, but also interact with the equipment of the production system. This means, for instance, that insufficient maintenance may build a hidden backlog of defects which eventually has consequences in terms of more frequent breakdowns and more downtime (e.g. Sterman, 2000). In addition, the current state of maintenance operations is influenced by decisions which were made many years earlier but which today have an effect on the rate of equipment degradation (Murthy et al., 2002), p. 288). However, it also means that maintenance operations are continuously shaped by the maintenance strategy, and that this shaping extends many years into the future. The application of DES and SD allows studying different levels of changes that are applied to the production system.
RESULTS
CHAPTER 3
RESULTS

3.1 SUMMARY OF THE HYBRID SBO FRAMEWORK
This section gives an overview of the hybrid SBO framework. The contributions from Papers 1–5 are explicitly included in the overview in Figure 3.1 and presented in the subsequent section.

![Figure 3.1. Map of the phases 1-6 and their interacting processes, which together constitute the hybrid SBO framework.](image-url)
Figure 3.1 illustrates how applying the hybrid SBO framework iteratively generates studies that aim to improve how maintenance acts in the production system environment (PSE). In fact, as the interactions with the PSE in Figure 3.1 reveal, the strategic focus is on improvement of the maintenance system, and the operational focus of maintenance is on improvement of the production system. There are six phases, each color-coded in the figure and described below in brief:

1. Phase 1 illustrates the iterative process of creating the SD model, resulting in deeper studies of the dynamic behaviors, creating learning opportunities and model refinements of the strategic problem of interest. This is preferably conducted in GMB sessions (e.g. Linnéusson and Aslam, 2014). However, in order to be used in the SBO framework, this SD model needs to be related to the performance measures of maintenance operations applied in the subsequent DES model.

2. Phase 2 illustrates the explorative process of SD+MOO, in which MOO becomes a tool for searching the ability of the SD model to answer different questions. It is wise to test different optimization criteria to identify the variables that support seeking the tradeoff solutions of interest. In addition, the rapid exploration of the SD model may give new ideas for testing and implementing new structures to support the desired strategic development more efficiently. Finally, at some point, the “good enough” analysis threshold leads to selecting solutions of interest.

3. Phase 3 illustrates the exploration and selection comparison between the tradeoff solutions generated in Phase 2. Based on the quantified decision basis, which reveals the Pareto frontier of the objective space, the solution(s) of interest is selected. The subsequent study of the SD model allows deeper thought regarding which characteristics and policies drive the successful outputs. This enlarged strategic understanding, which can identify potential drivers of the desired behaviors, is then applied as an input to the maintenance strategy.

4. Phase 4 illustrates the improvement feedback at the production system level from DES+MOO studies. The outputs from these studies are the pinpointed measures that accurately address the next infinitesimal bottleneck; that is, where the maintenance activities should be prioritized.

5. Phase 5 illustrates the interaction of the SD and DES views. The improved behavior in the maintenance system gained from the subsequent strategy selection process results in potential improvements of MTTF and MTTR. The ranges of improvement are applied in the DES+MOO study to identify the first area of focus in the production line. Overall, the DES+MOO method is critical for the framework to pinpoint activities; and even if the framework is not critical for the DES+MOO study itself, the context of the framework provides guidance for more well-planned maintenance activities.

6. Phase 6 involves implementing the lessons that have been learned from the analyses. SD analyses potentially affect how we think about a problem as a consequence of approaching ambiguous aspects, in trying to model them, making them more tangible to address. Hence, insights gained during an analysis may be acted out in the real system in terms of improving various principles, such as a refocus on projects or activities that support improving the organizational capacities to audit, monitor, and estimate equipment health. This phase also includes consideration and evaluation of the results from the tangible study of DES+MOO. These two perspectives altogether defines activities into the maintenance plan, containing aspects of both concrete and policy character.
3.2 SUMMARY OF PAPERS

Paper 1

Paper 1, (Linnéusson et al., 2018a), is the result of the first phase of this research, based on the industrial problem of managing the tradeoff in maintenance management between the short-term and long-term effects of maintenance practices. The paper presents an SD base model for maintenance performance that captures both strategic (long-term) and operational (short-term) aspects, based on synthesized knowledge from maintenance literature, reports on maintenance SD models, and information grounded in an interpretation of the experiences described by employees at the two industrial partners of this research. The research process was an explorative one, formulating a dynamic theory for how maintenance performance is generated using SD.

Paper 1 presents an analysis of simulation experiments using the created SD model, including RTF strategy and some versions of PM strategies. The objective was to identify the base elements which function to produce the required proactiveness in relation to operations, and how they can interact. Further details are provided in the paper. As shown in Figure 3.1, Paper 1 addresses RQ1; this figure also illustrates the contribution of the paper to the SBO framework.

One important aspect highlighted by Paper 1 is the importance of generating knowledge about the operational level for the strategic level, in order to support the development of maintenance practices by formulating wise strategies and policies (Figure 3.2).

![Figure 3.2](image)

*Figure 3.2.* Feedback behavior between strategic and operational levels in maintenance development.

The SD model represents aggregated conditions on the operational level which impact and reverberate onto the strategic level. The core assumption of the model is that the mix of different maintenance methodologies (Tsang, 2002), can detect potential defects with diverse efficiency. Thus, from a holistic perspective, the mix of maintenance methodologies, such as RTF, PM using fixed intervals, and CBM using inspections or sensors, defines the collective capacity of the PM work to identify defects before failure.

The purpose of the model is to support the investigation of the feedback effects from strategies on maintenance performance in interaction with production. Figure 3.3 is a
high level illustration of the model; it represents how the model parts work together for the holistic economic performance. At the aggregated level of this model overview, only the balancing loops (B) are visible, which indicates the exclusion of growth mechanisms in the model. The reinforcing mechanism appears in the interaction between the decision makers and the model, as indicated previously in Figure 3.2 by the feedback behavior between strategic and operational levels in maintenance development. The decision maker applies maintenance strategies to the model, as illustrated by the diamond in Figure 3.3, in order to explore, understand, and act upon the added information gained from utilizing simulation.

In brief each box includes:

- **Production and maintenance performance** defines the availability in production as a consequence of the current operating reliability of the equipment, the performed planned and unplanned maintenance respectively, and staffing.

- **Equipment health status** defines the aggregated equipment reliability as a consequence of the current health and risk level of the equipment. Equipment health is modeled using accumulated defects, generated by operations and eliminated through repairs.

- **Preventive maintenance performance** defines the takedown rate of scheduled repairs, based on the level of applied maintenance methodology, where work order stock, planning and scheduling capabilities, and the pressure to produce take priority over maintenance and result in the actual takedown rate.

- **Maintenance development process** defines the pace of maintenance performance development on the basis of policies, resources, delays, work pressure, and work progress.

- **Holistic economic performance** calculates the total maintenance costs as a consequence of current production and maintenance performance; it includes direct costs and indirect consequential costs of breakdowns, due to the level of planned over unplanned work.

Besides estimations of applied PM work the defect generating and defect eliminating activities need to be modeled. Based on a model which focuses on how equipment defects are caused and affect plant uptime, as in part described in Sterman (2000), the efficiency of the PM work can be measured in terms of its capacity on an aggregated level to control equipment health. Simultaneously, the resulting overall equipment health relates to the breakdown frequency in the production system, which contributes...
to the resulting balance of unscheduled or scheduled maintenance together with the mix of PM work and applied resource policies.

Continuous improvement is included in order to produce development of maintenance which according to Lad and Kulkarni (2011) is often missing in the maintenance modeling literature. This is applied here based on the root-cause analyses of breakdowns improving the mix of PM work provided the corresponding resource policies to support the change. To complete the possibility of evaluating the tradeoff from the strategic development, maintenance costs and estimated consequential costs are included. The structure of the model enables generation of the total costs as an effect of the success of the maintenance practices.

The purpose of using SD was to support investigation of the causal relationships between strategic initiatives and performance results, and to enable analyses that take into consideration the time delays between different actions, in order to support the sound formulation of maintenance policies; which has originated from Tsang (2000). SD was considered an applicable method, as explained in the introduction to this thesis. The literature review in Paper 1 identified works applying SD in maintenance, but there were very few reports covering quantitative models, which are required in order to experiment using simulation. Moreover, previous SD work had not examined the potential of estimating maintenance total costs from the resulting maintenance performance.

The main contributions of Paper 1 are:

- The literature review shows potential and novelty.
- The description of a maintenance performance SD model and simulation experiments enables evaluation of:
  - The operational conditions in maintenance which lead to proactively or reactively achieved availability in operations.
  - The tradeoff between increased resources and improved policies until the delayed consequent effects are seen in terms of proactiveness in operations.
  - The consequent economic effects from the model behavior.
- The open description of the model supports the potential future continuation of this important work by others in the scientific community.

As indicated in the outline of the thesis and papers in Figure 1.3, these aspects provided incentives to progress towards the subsequent objectives rather than identifying more detailed SD models. The SD model described in this paper was considered to satisfy the pre-conditions to study multiple tradeoffs between conflicting objectives in order to conduct strategic development of maintenance and its effects on production performance. It also defined a dynamic cost model, available for further development, to estimate and trade future benefits to the required investment in the present, based on the behavioral effects of applied strategies and policies.

Additional work which is not reported in Paper 1 includes the development of a demonstration, based on the SD model, which places the user in the position of a maintenance manager in charge over a set of policies in order to achieve better maintenance performance. This demonstration is planned to be installed at the innovation arena of ASSAR in 2018.
Paper 2


Paper 2, (Linnéusson et al., 2018b), is the first of three SD+MOO papers to explore the applicability and contribution of MOO to the SD maintenance performance model described in Paper 1, thus addressing RQ2 as depicted in Figure 3.1. The research reported in this paper was therefore explorative in character, creating an SD+MOO platform that was used in the subsequent studies. The template scripts in the “VensimInterface” using the modeFRONTIER software shown in Figure 3.5. Overview of the maintenance SD model and the schematic integration with MOO.

, for the technical integration of MOO and SD, were developed in previous research (Aslam, 2013).

A search of the literature revealed very few SD+MOO examples, and these were generally applied to well-known “textbook models” in order to reveal the potential usability of the integrated approach of MOO and SD. Hence, the explorative research in this work attempted to integrate MOO with a self-developed model, in a process of testing the model’s capacity to search the input decision space. Much effort was placed on interpreting the outcome of the test results, iteratively identifying why unexpected results appeared in order to improve the SD model. Eventually, the SD model was valid enough to produce adequate output from the SD+MOO evaluations. Testing and evaluating different optimization criteria resulted in applying the conflicting objectives of maximized availability, minimized maintenance cost, and minimized consequential maintenance cost; and a set of input parameters were identified which were considered to affect the development towards proactiveness (Figure 3.4). These criteria were re-used in the subsequent experiments reported in Papers 2 and 3.

![Figure 3.4. Illustration of MOO model in the modeFRONTIER software.](image-url)
Below, in Figure 3.5, a slightly evolved overview of the SD model from the previous one is given, including the application of MOO to evaluate near-optimal scenarios for the resource and policy planning. The schematic makes explicit the reinforcing behavior (R1) between proactiveness and keeping equipment health, where increased proactiveness leads to improved health status, and less costs. However, it requires resources and policies to support the development, searching the best tradeoffs between invested resources to the gained effects with help of MOO.

Figure 3.5. Overview of the maintenance SD model and the schematic integration with MOO.

Paper 2 presented three experiments depicted in Figure 3.6, which studied three clearly different points of origin a maintenance organization may begin with when pursuing their strategic development towards a future state. Cat. 1 starts in an RTF condition, Cat. 2 in a mediocre PM condition, and Cat. 3 in a well-developed condition.

Figure 3.6. Scatter plot for the three experiment scenarios in Paper 2.

The experimental results strongly indicate that the current condition of maintenance operations defines the strategic development potentials. The result graph shown in Figure 3.6 sums the total costs ($C_T$), including the maintenance costs ($C_M$) and the maintenance consequential costs ($C_O$). As described in Equation 5, ($C_M$) includes all man-hour costs ($C_h$) and CI investments ($C_CI$) which in this study only includes invest-
ments in CBMs, while $R_{BD}$ and $R_{TD}$ induce equal spare part costs per stop ($C_S$). Equations 6 and 7 specify that $C_Q$ consists of consequential breakdown costs ($C_{QBD}$), which based on (Wireman, 2004) have a factor 4 for each breakdown, and added capital costs from spare part inventory ($C_{CSI}$).

$$C_M = C_h + C_{CI} + C_S \cdot (R_{BD} + R_{TD})$$  \hspace{1cm} \text{Eq. 5}

$$C_Q = C_{QBD} + C_{CSI}$$  \hspace{1cm} \text{Eq. 6}

$$\text{where } C_{QBD} = 4C_S \cdot R_{BD}$$  \hspace{1cm} \text{Eq. 7}

Paper 2 also presents a meta-analysis which uses parallel coordinate heat maps (PCHMs) of the experiment solutions (see example from Paper 3 below) to visualize dependencies between parameters in the SD model, contrasting alternative strategies. This shows, for instance, that the best Cat. 3 solutions use far more maintenance engineers, which increases $C_M$ but assists the development into a more proactive maintenance behavior with much lower $R_{BD}$. Further details are provided in Paper 2.

The main contributions of Paper 2 are:

- The literature review motivates the use of simulation and MOO, and indicates the novelty of the study as probably the first SD+MOO study of a maintenance behavior model.
- The considerable quantifications of near-optimal Pareto front solutions allow visualization of the extensive amount of simulation data of the applied SD model, and thus:
  - Exemplify applicability and reveal the potential of applying SD+MOO to support exploration of the created SD model.
  - Enable study of the dependencies between decision parameters and objective fulfillment in a comprehensive procedure which supports selecting the most beneficial tradeoff solution to inform a maintenance strategy.
  - Strengthen the validity of the work, first by the process of integrating the SD model with MOO, and then by the explicit exposure of the quantified objective space and the input space parameters.
Paper 3


Paper 3, (Linnéusson et al., 2017), is the second SD+MOO paper to explore the applicability and contribution of MOO for the SD maintenance performance model, and also addresses RQ2. Building on the contributions of Paper 2, along with an additional study, this paper emphasizes that there can be no return to the single use of SD, since MOO makes an extensive contribution to exploring system behavior. However, for the practical application, the combined approach of SD+MOO does not replace the SD analysis but rather complements it; an understanding of the underlying model dynamics is fundamental for analyzing the Pareto fronts and PCHMs, and is critical for the facilitation of the selected strategic path for implementation.

The experiments studied two sets of equipment with different levels of criticality. Figure 3.7 depicts the Pareto fronts, with Scenario_1 using \( C_{QBD} = 4C_s \times R_{BD} \), according to Equation 7 and Scenario_2 using \( C_{QBD} = 12C_s \times R_{BD} \). \( C_{0} \) follows similar patterns for both cases, while \( C_{QBD} \) diverges widely. In both cases, the higher availability was only reached by achieving proactive maintenance operations, and the equipment with higher \( C_{QBD} \) had a substantially higher economic potential from such development.

The main contributions of Paper 3 are:
- The applicability of SD+MOO and the contributions of Paper 2 are reinforced.
- Multiple potential strategies can be contrasted by changing one relevant parameter and provide rather diverse tradeoffs for the decision makers.
Paper 4

Paper 4, (Linnéusson et al., 2018c), is the third SD+MOO paper to explore the applicability and contribution of MOO to the SD maintenance performance model, again addressing RQ2. In addition to the contributions of Papers 2 and 3, this paper experiments with the simulation period and presents a strategy selection process for using MOO with SD in maintenance, which is later applied in the SBO framework.

The shortened description of the SD model in Paper 4 focuses on proactive and reactive maintenance dynamics and the related cost consequences, which describe in part the multiple simultaneous feedback transfers between parameters. For a given set of conditions in maintenance operations, this feedback creates the basis for an equilibrium level of equipment health and availability. Equilibrium is changed when resources are added or removed; moreover, continuous improvements change the conditions for the equilibrium state, in order for a more efficient equilibrium to exist.

The quantified SD+MOO results (Figure 3.9) provide insights on how different time frames are conditional to enable more or less proactive maintenance behavior in servicing production. For instance, the one-year time horizon (TH1Y) does not present any proactive maintenance solutions, while proactive behavior is required to achieve the solutions of higher availability in the seven-year (TH7Y) experiment. For the three-year and five-year experiments, their highest availability solutions can be reached either by developing into proactive maintenance operations or by remaining reactive with a larger total cost (see right-hand-side in Figure 3.9).

![Figure 3.9](image)

Figure 3.9. The Pareto front solutions from the four experiments in Paper 4. Left: the performance in availability traded from maintenance costs ($C_M$). Right: the performance in availability traded from maintenance consequential costs ($C_Q$).

The main contributions of Paper 4 could be concluded the following:
- It reinforced the applicability of SD+MOO and the contributions from Paper 2 and 3.
- It further indicated the applicability of the SD model to represent a structural theory for studying maintenance proactive and reactive behavior by using MOO.
- The time horizon is crucial for the strategic development of maintenance.
Paper 5

Paper 5, (Linnéusson et al., 2018d), outlines the proposed hybrid SBO framework and its design. The intention is to facilitate strategic development of maintenance performance by supporting maintenance management in their decision-making on the strategic and operational levels for prioritizing the maintenance plan. As shown in Figure 3.1, Paper 5 addresses the complete SBO framework and hence contributes to RQ3. In supporting RQ3, Paper 5 gives additional support to RQ2 and RQ1 through putting them in the context of a larger systems study (see Figure 1.3). Accordingly, Paper 5 justifies the proposition of the SBO framework by exemplifying the way the SD model and the application of SD+MOO can support the study of long-term strategic questions and the evaluation of potential tradeoffs between conflicting objectives. However, in relation to Figure 3.2 above, an SD study is too aggregated to provide knowledge of where in the production system to intervene. This motivates the use of DES+MOO, which supports pinpointing places in the production system where maintenance can contribute to increased throughput. Hence, in order to provide the last component to conceptually run the SBO framework, Paper 5 exemplifies how the output results from the strategy selection process, using SD and MOO, are defined in order to match the required input to the subsequent DES+MOO study. In addition, a theoretical model of maintenance-driven change in the production system is proposed which motivates the need to mix SD and DES in order to experiment and identify the deliberate changes on the strategic and operational levels. Paper 5 includes a literature review of mixed method designs, which reveals surprisingly few SBO examples. Hence, while the research field of mixed method designs using SD and DES has grown for more than two decades, the combination with MOO is in its early stages. The literature review also shows that applications of hybrid DES+SD in maintenance seem very limited.

Figure 3.10, which is taken from Paper 5, depicts an overview of the hybridization principles. The strategy selection process informs the maintenance strategy and the applicable key performance indicators (KPIs) which are considered to support the desired
behavior in the SD model. The obtained strategy has implications on the level of pro-
activeness and equipment health, which are related output results into the DES+MOO
study in terms of measures such as MTTF and MTTR. Moreover, the selected improve-
ments in the DES+MOO study could be evaluated in a DES study as further input to
the conditions of the SD model. These could regard two aspects that potentially can
change the tradeoff exploration in the SD-MOO study, such as the productivity of the
production system and the generated profit based on that increased productivity.

In summary, the SBO framework supports growing maintenance’ knowledge regard-
ing the operational conditions to support maximizing throughput by accurate activi-
ties, and the knowledge of strategic tradeoffs on the higher aggregation of the mainte-
nance system. This, in turn, supports the iterative knowledge building and organiza-
tional learning needed to shape, manage, and be prepared for future demands. The
main reason to mix SD and DES is in order to take advantage of the disassociated phil-
osophical standpoints of the two approaches, and their complement to each other, ac-
cording to the theory model of maintenance development presented in Paper 5. Ac-
cordingly, SD is utilized for its capabilities to study the ambiguous structures of a de-
cision-making process, which according to Forrester (1961) consist of the conversion
of information into action. By definition, such processes utilize feedback as their key
fundament, and by modeling them we can visualize our interpretation of the struc-
tures. This exposes the structures for more tangible discussions regarding possible
changes to produce better results based on the testing of hypotheses. The application
of DES, as with the effective usage of MOO, produces accurate information to guide
the actions of the maintenance organization, which together produce production sys-
tem level knowledge that effectively facilitates the conversion of relevant information
into more accurate actions. Accordingly, as Forrester (1992, p. 43) puts it, “manage-
ment success depends primarily on what information is chosen and how the conver-
sion is executed”.

The main contributions of Paper 5 are:

- The literature review shows potential and novelty.
- The paper provides a thorough presentation of the hybrid SBO framework, a walk-
through of the various phases, and a description of how the outcome of the SD+MOO
analyses form the basis for the performance improvements in the operations level eval-
uated by applying DES+MOO.
- Simulated SD model behavior from selected SD+MOO solutions is presented.
- The link between SD and DES+MOO is described.
- A theoretical model of maintenance-driven change in the production system is pre-
sented, which:
  - Visualizes three different levels of development on which maintenance can act to
    affect the production system towards higher utilization.
  - Motivates the application of mixing SD and DES in an SBO framework to achieve
    the change momentum towards proactiveness.
CHAPTER 3 RESULTS
SUMMARY AND CONCLUSIONS
CHAPTER 4
SUMMARY AND CONCLUSIONS

4.1 SUMMARY OF THESIS

In order to achieve the overall aim of supporting the strategic development of maintenance based on its effects on production performance, the introductory chapter showed that a hybrid SBO framework is needed. Thus, the core objective of this thesis is to develop a concept of a hybrid SBO framework. This path was not evident in the first part of this interpretive and explorative research; however, as the problems of economically justifying maintenance and attaining proactive maintenance behavior were approached, the path described here came into being. The thesis outlines the challenge of proactive maintenance, which has been considered by many researchers to have significance for both production performance and profitability. Thus, this thesis also pays attention to the problem of the uncredited work of long-term improvements in maintenance in order to produce the required daily process performance which, according to Repenning and Sterman (2001), is a systemic problem that requires much effort in managing the interaction of tools, equipment, workers, and managers. Systemic problems can only be understood by taking a systemic approach (Flood, 1999) supported with systems thinking (Checkland, 1981) to identify what constitutes the whole, based on the connected elements of the system. This design science research therefore began by emphasizing SD as a method for supporting systems thinking. However, SD alone cannot deal with complexity on the operational level of the production system, for which DES is required. Moreover, efficacy in identifying tradeoff solutions is required and therefore tests of applying MOO to explore a created SD model have been performed. In all, the proposed end product of the hybrid SBO framework could be defined on a conceptual level by including the developments of this thesis and others’ work.

The subsection below reviews the support given to the research objectives (O) and research questions (RQ). This is followed by a list of the contributions to knowledge made by this thesis, a discussion of the results, and a reflection on future work.
4.2 CONCLUSIONS

The purpose of the proposed hybrid SBO framework is to support more deliberate changes in maintenance operations. These changes should take a sustainable consideration on the inherent tradeoffs between direct consequences and indirect consequences of the studied problem, and be based on more informed knowledge of the potential system effects on the strategic level integrated with the operational level. Potential applications of the framework include dynamic tradeoff studies of the conflicting objectives of direct and consequence costs contrasted with the gains in availability performance on a relevant time horizon. While management steers towards the identified long-term strategic plans, the operations perspective is supported by analyses pinpointing the most relevant maintenance activities with regard to the production system’s throughput. Hence, the hybrid SBO framework presents a holistic approach to managing change in the maintenance system, assisting maintenance management to formalize strategy, policies to support this strategy, and effective prioritization in the production system. The strengths of the framework are the mutual development of strategy based on identified learning mechanisms such as learning from breakdowns or evaluating the PM work performed, and development of the production system based on accurate bottleneck detection. Overall, the framework offers potential for executing activities on the events level, and delving below the events level into the deeper fundamental layers of the systemic structures which can affect the future capabilities and the future knock-on effects, which eventually reverberate back up to the events level later on.

The description of the aim and objectives of this work can be found in subsection 1.2, and Figure 1.3 illustrates how Papers 1–5 are connected and how each contributes to the objectives. In order to support the aim and core objective, which is defined as the third objective (O3) in subsection 1.2, the two preceding objectives first needed to be fulfilled to a satisfactory degree. Hence, O1 was the first formulated objective to contribute to the aim. O1 is based on the fact that the problem of justifying maintenance has a dynamic character, calling for the necessity to connect the conditions of long-term effects with the corresponding economic consequences from maintenance performance, in order to allow seeking the sustainable strategic tradeoffs between higher initial development costs and lower consequence costs as an effect from a more proactive maintenance behavior with less breakdowns.

The research questions to support the objectives are formulated in subsection 1.3. The work reported in Paper 1 provides an answer to RQ1 by formulating an SD model which, among other things, is capable of producing simulation experiments which show the temporary benefits from adding repair workers and the more permanent benefits from a more proactive PM work. Hence, having been supported by thorough model testing of different hypotheses regarding the consequences of altering various parameters, the SD model was considered to have sufficient capacity to be worth reporting to the scientific community. By providing a sufficient answer to RQ1, Paper 1 supports O1; however the extensive time required to test multiple settings in the SD model to explore proactive and reactive behavior and estimates of the total maintenance costs from different potential strategic developments called for a more efficient search process. As shown in Figure 1.3, this provided incentives for moving towards SBO and the application of SD+MOO.

The work reported in Paper 2 provides an answer to RQ2, which is directly linked to O2, by integrating SD+MOO and successfully generating valuable experiments to elicit knowledge from the application. The results were considered promising to explore potential maintenance strategies using the SD+MOO to search the behavior space of the
model. The search for optimized conflicting objective tradeoffs in the SD model using MOO severely tested the capacity of the SD model to reveal stable and valid solutions. Hence, the procedure for integrating SD+MOO strengthened the SD model in this respect. The exhaustive evaluation procedure, generating more than 50,000 solutions, revealed a large set of solutions on the Pareto front which showed different tradeoff optimal solutions between the different conflicting optimization criteria. This not only supports an answer to RQ2, by exemplifying how MOO can be used to quantitatively explore an SD model by visualizing a rich quantification of the dependencies between parameters of the solution sets, but to some extent also provides support to O1. For instance, the tradeoff curves shown in the scatter plots of Papers 2–4 essentially speak for themselves with respect to whether a proactive or reactive behavior is to be expected in the specific solution representing a certain SD model simulation run; this is illustrated further in Paper 5. Moreover, Papers 3 and 4 give further support to RQ2, and their contributing studies reinforce the support given by Paper 2 to RQ2 and RQ1.

The work presented in Paper 5 provides an answer to RQ3, which is directly linked to O3, by carefully describing the hybrid SBO framework and walking through its various phases. In addition, the strategy selection process is completed in Paper 5 which exemplifies how the exploration of potential strategies and policies using SD+MOO is post-analyzed in the SD model. The reason for post-studying selected optimal tradeoff solutions is to allow a deeper understanding of model behavior and to support discussions among the change agents about the required conditions in maintenance operations to attain the proactive dynamics. Another reason is to create deeper knowledge in order to guide and inform the maintenance strategy. Equally importantly, the selected solution can also represent a reactive strategy, if the conditions for the specific study result in such a tradeoff. Hence, the SBO framework evaluates differentiation of the application of resources based on the conditions on the strategic level to maximize the value of maintenance on long-term (see, e.g., Figure 1.1). Paper 5 also motivates the need for a hybrid SBO framework in order to bridge the lack of detail complexity in SD studies and the inability to differentiate on the operational level. For such studies, there are available tools which integrate MOO+DES in order to pinpoint with high precision the infinitesimal change of configuration of the production system that leads to the largest effect. This would be an invaluable ability for maintenance to integrate into their planning of improvement activities. Hence, it is the combination of the disparate capacities of SD and DES that supports O3, and the design of the proposed hybrid SBO framework which answers RQ3. Consequently, the integration with MOO is essential, as reviewed in Paper 5, since the SD output of the strategic analyses defines the range of potential improvement achievable on the operational level, which corresponds to the input space of the optimization of the DES model. There is also a corresponding effect from implementing the identified activities, based on DES+MOO, which when implemented are having an effect to the strategic perspective in terms of changing a subsequent SD+MOO tradeoff evaluation.

### 4.3 CONTRIBUTIONS TO KNOWLEDGE

The main contributions of this thesis are:

- The creation of a conceptual SD model provides the first step towards a structural theory for studying the dynamics of maintenance operations and its development, by combining maintenance and SD literature, and understanding practitioner experience from qualitative case studies in industry.
• The experiments presented here exemplify the application of SD+MOO to evaluate maintenance strategy, and is considered to explore SD models effectively by exhaustive quantification of the Pareto frontier solutions.

• The novel hybrid SBO framework is designed to be suitable for the strategic and operational development of maintenance, considering its symbiosis with operations, by combining SD, DES, and MOO.

• The design of the hybrid SBO framework for maintenance development presents a unique procedure for combining SD+DES; by the application of SD+MOO, a strategy is selected and corresponding SD model behavior is post-analyzed where two key performance indicators (MTTF and MTTR) define the ranges of improvements explored by the input space search process using MOO of the DES model to pinpoint where in the production system to begin.

4.4 DISCUSSION OF THE RESULTS
This thesis proposes a hybrid SBO framework to support the strategic development of maintenance in relation to its effects on production performance. One part of the framework considers the aspects of strategic (long-term) and operational (short-term) dynamics on an aggregated level. The application of SD was explored to identify a doable theory to manage this, based on other work in the relevant literature and understanding practitioners at the two industrial partners. As work progressed and materialized, the strategic perspective of developing maintenance which includes achieving a more proactive maintenance behavior resulting in increased efficiency of the maintenance operations, the need of dedicating activities into the production system became more important. Before the research even began, the idea of applying DES was considered but discarded due to its limited capacity to include the feedback between long-term and short-term consequences from actions, such as including the behavior of the continuous improvement work in maintenance. However, as a tool, especially integrated with MOO, it is perfectly capable of differentiating actions toward the bottlenecks of a system. Maintenance will benefit from increasing their capability to understand how production systems generate throughput and to plan their improvements based on such information. However, such an operations study fully neglects the strategic perspective of the long-term strategic development of maintenance performance, based on the development of the working procedures in maintenance, which motivates how maintenance structure and carry out their long-term work.

The research process described here provides strong motivation for closing the loop on the higher framework level, from initial studies to the presented framework. Hence, the proposal is an early version structure on which multiple future applications can be formulated. As in any modeling, there are endless possibilities which require much work and time for studies. The process of this research has focused on creating an end product which implements the higher-level vision of how a hybrid SBO framework could be designed in order to support maintenance to better shape their capacities to support operations. This support is provided on several levels; from activities which support a better configuration of the production system (Level One improvements in the theory model in Paper 5), via activities which support better efficiency of maintenance operations leading to more proactive behavior (Level Two improvements), to activities which improve the learning mechanisms of the maintenance system which should be included in the maintenance strategy (Level Three improvements). The focus on creating and describing an applicable framework, in order to explore its tech-
nical design and purpose of usage, has required putting aside studies of too many details. Consequently, the many potential elaborations of the SD base model, which could explore and produce more refined studies on the strategic level, have been omitted in favor of finalizing the design of an applicable and useful hybrid SBO framework. However, it should be added that in parallel with developing the research towards the end product of the hybrid SBO framework, an application study was carried out at one of the partner industries. This work indicated the challenge of introducing SD studies which consider aggregated behavior from a systems thinking perspective, as further elaborated in the end of this subsection.

Hence, with respect to validation of the hybrid SBO framework, the explorative design science research work of this thesis (see subsection 1.5 for more details) can be considered to have shown that the concept of the hybrid SBO framework works, using experiments and simulation. However, testing the framework in full scale has not been fully achieved due to time limitations. The application of DES+MOO which is referred to in this research has been thoroughly tested and evaluated by previous researchers (Pehrsson (2013), and has been integrated into the commercial software package FACTS Analyzer (Ng et al., 2014). Moreover, scripts to integrate Vensim® SD models with the modeFRONTIER® software package have been developed in previous research (Aslam (2013). Hence, the purpose of the exploration of SD+MOO in this research was to test its applicability to a self-developed SD maintenance performance model in order to effectively investigate and explore model performance.

During the research process and as a consequence of the valuable knowledge elicited from the SD+MOO analyses made it possible to consider an improved approach to the operational perspective. By connecting the strategic perspective of identifying guiding principles for maintenance operations with DES and DES+MOO analyses of the production system’s stochastic dynamics, the long-term work in maintenance can be rather tangibly addressed. The work presented in this thesis merely opens the door to future exchanges between these perspectives. For example, as the maintenance care for equipment improves, the variance in operations performance is likely to decrease. Variance is an enemy in production systems, and so the strategic (long-term) work of maintenance could be connected with specific activities in the production system pointed out by the DES+MOO study in which variance most beneficially is reduced first.

The validity of this design science research needs to relate to the evaluation criteria of interpretive research described by Oates (2006) and covered in the introduction to this thesis. The end product contains many parts, ranging from software applications that have existed and been researched for a decade, to creative SD model constructs of aspects that are currently unknown, such as specific degradation of equipment. However, the purpose of an SD model is not to provide ready-made plug-in answers to specifics, but rather to enable systems thinking, questioning, and improved understanding of the different important interrelations of the relevant system. This allows identification of whether current knowledge should be applied on an improved level, or whether certain knowledge is in need of development. Moreover, the application of SD+MOO has vastly improved searching the input and corresponding objective space of the applied SD models, which speaks for increased dependability and credibility of the method to explore SD models on regular basis, and suggests that the SD model has a reasonable structure. With respect to the hybridization of the SBO framework, this research has focused on the link from the strategic perspective, using SD+MOO, to earlier reports of applications of DES+MOO in order to enable more detailed studies.
CHAPTER 4 SUMMARY AND CONCLUSIONS

of maintenance value to operations. The application of SD+MOO is thoroughly addressed in Papers 2–4, in order to explore and reveal its applicability. And the application of DES+MOO has at this pioneer point sufficient capacity to pinpoint activities relevant for maintenance on the basis provided in Paper 5. Hence, with respect to addressing a specific real situation, the weakest part is currently the SD model. At the same time, the SD model created during this work was considered to provide enough incentives for continuing the research. Hence, for the purpose of this thesis, it has served as a “good enough” representation for contributing to exploring the components of the end product of the hybrid SBO framework, and in addition has been considered worthwhile for publication in a high rank journal.

One aspect not addressed by the papers in this thesis is the pedagogical challenge of conducting SD model building projects (e.g. Linnéusson (2009). This is reflected on in Paper 5: “An apparent weakness of the proposed framework is the high level of competence, knowledge, and applicable technical support required to implement it in industry. From our experience, one critical bottleneck is applying SD in maintenance and manufacturing systems development. This introduces the aggregate perspective of seeing one’s processes from a systems perspective, which industrial actors are inexperienced in doing. Moreover, the SD model-building process is highly intuitive and considerable practice is required to manage the high-variability capacity of its modeling language, which allows endless possibilities to model the problem at hand.”

The abovementioned application study at one of the industrial partners was an invaluable source of information. The SD model was walked through and thoroughly discussed, and efforts were made to transform the base model into an application model. In these efforts, we experienced some of the implementation issues described by Wolstenholme (1997), who listed a number of ways in which operational management might have problems with the SD type of modeling, such as:

- Difficulties for the client to relate to aggregated behaviors.
- Difficulty considering variables other than the traditional hard facts.
- A strong tendency towards wanting to increase the model detail and model boundary during modeling in order to better mirror the system.

We also found that the current structure of the information in the maintenance system did not support studying aggregated system behavior. For instance, how many items a production system is actually comprised of to estimate the overall maintenance need, and subsequently transparency in how these items are planned to be maintained with respect to different maintenance methodologies to correctly codify the level of PM work. The contributions from these studies are therefore limited in terms of industrial reports, yet the studies provided invaluable information for the results presented in this thesis.

4.5 FUTURE WORK

The present thesis work opens avenues for numerous future studies in the fields of maintenance management and maintenance policy optimization, as well as many potential industrial studies. Considering the issues with SD mentioned above, our recommendation for practical implementations is to start approaching the framework using DES+MOO, due to its more tangible character and standardized approach. With the emerging digitalization in industry, there will be a natural development of more advanced virtual tools. Support from a maintenance development tool which encompasses the larger system boundary as defined by the hybrid SBO framework presented
here will be necessary to handle the increasing complexities and demand for high utilization. Hence, this work may serve as a reference for future studies that aim to unite the two perspectives of maintenance strategy and operations in order to accomplish sustainable change in production performance by the efforts of maintenance.

Accordingly, future work can be directed towards:

- An application study to evaluate the existing implementation gap of a hybrid SBO framework in practice, in order to distinguish the roadmap and generate proposals of manageable portions to address in future projects.
- Supporting the next step of industrial application of DES+MOO in maintenance; that is, developing a maintenance handbook or tool/methodology for application in order to support the organizational capacity for maintenance to generate activities that are linked to the production performance in operations.
- Exploring the multitude of SD+MOO studies of potential strategic questions that add value to the long-term development of maintenance, by mapping and improving the SD model to include strategic challenges in industrial maintenance, for example:
  - The flows of competence and retirements of the workforce.
  - Implications of increased digitalization of equipment to support carrying out more well-directed maintenance.
  - Identifying potential structures for implementing continuous improvement.
  - Improving the generalizability of the model and its capacity to represent industrial cases.
- Creating generalized descriptions of the maintenance dynamics, based on the SD model, in order to simplify dissemination.
- Creating advanced education material for studying maintenance dynamics, by applying the current structural theory of the SD model, supported by simulation.
- Exploring and exemplifying the corresponding effects of implementing the identified activities, based on DES+MOO, into the strategic perspective in terms of changing the conditions of a subsequent SD+MOO tradeoff evaluation.
- Exploring possible improvements of the validation process through utilizing MOO for systematic parameter exploration of the SD model input space. The purpose of this is to support the pre-evaluation of the precision which is required from input parameters. Thereafter, by knowing the sensitive parameters, these can later demand for better input data and thereby omitting unnecessary work.
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INCLUDED PAPERS
INCLUDED PAPERS

Paper 1

Paper 2

Paper 3

Paper 4

Paper 5
Towards strategic development of maintenance and its effects on production performance by using system dynamics in the automotive industry

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Abstract
Managing maintenance within an economical short-termism framework, without considering the consequential long-term cost effect, is very common in industry. This research presents a novel conceptual system dynamics model for the study of the dynamic behaviors of maintenance performance and costs, which aims to illuminate insights for the support of the long-term, strategic development of maintenance. By novel, we claim the model promotes a system’s view of maintenance costs that include its dynamic consequential costs as the combined result of several interacting maintenance levels throughout the constituent feedback structures. These range from the applied combination of maintenance methodologies to the resulting proactiveness in production, which is based on the rate of continuous improvements arising from the root cause analyses of breakdowns. The purpose of using system dynamics is to support the investigations of the causal relationships between strategic initiatives and performance results, and to enable analyses that take into consideration the time delays between different actions, in order to support the sound formulation of policies to develop maintenance and production performances. The model construction and validation process has been supported by two large maintenance organizations operating in the Swedish automotive industry. Experimental results show that intended changes can have both short and long-term consequences, and that obvious and hidden dynamic behavioral effects, which have not been reported in the literature previously, may be in the system. We believe the model can help to illuminate the holistic value of maintenance on the one hand and support its strategic development as well as the organizational transformation into proactiveness on the other.

Keywords: maintenance performance, strategic development, system dynamics, simulation.

1 Introduction
In manufacturing industries, where equipment is arranged in complex production lines, reliability and maintenance performance are directly connected to process uncertainty (Geary et al., 2006). Hence, the impact of well-developed maintenance performance may extend far beyond the level of focus on equipment, potentially shortening lead times, reducing local production inventories, and thus leading to more lean supply chains. The definition of maintenance is “the 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” (EN13306, 2010). However, researchers,
such as Levitt (2011), argue that the goal of maintenance should also include the development of production performance through pro-active maintenance. Pro-active maintenance policies are considered one of the beneficial strategies required, in order to be a quality competitor in the marketplace (Pinjala et al., 2006). In contrast, according to Geary et al. (2006), reactive maintenance can potentially lead to increased disruption in real-world supply chains, thus causing excess variances in performance.

It is well known that maintenance costs constitute a considerable amount of the production budget. Additionally, according to Wireman (2004), surveys in the United States reveal that approximately one third of the total maintenance expenditures are spent unnecessarily. In addition, considerable amounts of maintenance consequence costs are associated with, for example, equipment downtime (Vorster and De La Garza, 1990), or lack of proper maintenance practices which may, according to Holweg and Bicheno (2002) and Geary et al. (2006), require that extra capital is tied up in the supply chain.

In summary, the fact that maintenance has a considerable direct and indirect economic impact highlights the improvement potential and underlines its strategic importance. Moreover, Tsang (2000) has identified that future maintenance strategy research needs to seek tools to validate the causal relationships between strategic initiatives and maintenance performance results, and it needs to address the inclusion of time delays between actions. Nonetheless, an aggravating fact, according to Dekker (1996), is that maintenance may be difficult to justify at the individual activity level, which can contribute to maintenance often being considered a cost function only. According to Sherwin (2000), the consequence of such a scenario is that the strategic importance of maintenance is neglected. Woodhouse (2001) argues that the short-term cost perspective is the motivation that regulates how assets in maintenance are managed; where known best practice does not align with the strategies implemented. Furthermore, Woodhouse (2001) identifies the limitation to be the organizational capability to perform a sustainable implementation together with how the conflicting priorities and messages should be integrated into its equation.

Hence, one key challenge associated with the untapped economic potential in maintenance seems to be the critical ability to manage the dynamic tradeoffs between saving money, or investing, in the short-term while diminishing, or developing, the maintenance capabilities of the equipment and the organization over time (see, e.g., Repenning and Sterman 2001, Levitt 2011). In order to address this dynamic challenge, which includes investigating how the growth and decline of multiple capabilities affect performance, strategy researchers have argued for the application of system dynamics simulation (see, e.g., Warren 2005, Rahmandad and Repenning 2015). The system dynamics approach seeks to identify the interconnections between parts in relevant system boundaries, in order to gain a better understanding of reality. Thus, simulation in a dynamic systems study, according to Senge and Sterman (1992), enables multiple testing, in order to challenge one’s present mental models, and may generate double loop learning by questioning the underlying values governing the system. Nonetheless, as the literature review presented reveals, while overall maintenance system behavior has been explored using system dynamics, applications regarding the consequential costs of maintenance seem non-existent. Also, there are only a few published works that can be reutilized and support building a model to address this dynamic challenge in maintenance.

The above-mentioned situation presents facts that are familiar to maintenance practitioners, and it therefore requires appropriate academic support. Consequently, this research addresses two key aspects, previously identified, that can facilitate better strategies for action in maintenance: firstly, the need of an improved visualization of the consequential costs of maintenance performance, which is a critical requirement to support higher management’s decision-making (Linnéusson et al., 2015b); secondly, the need to support the development of maintenance in conjunction with production, to replace the short-term “my budget” thinking with a systems perspective (Linnéusson et al., 2015a). On these two key aspects the proposed conceptual system dynamics model is built and therefore aims to
facilitate bridging myopic policies to support the strategic development of maintenance instead. Therefore, this paper, with its problem-based motivation, seeks a systems approach to justify preventive maintenance (PM) activities from a strategic perspective; consequently, the presented model boundary selection (BS) includes the following aspects:

BS1. Equipment health and its interaction with the operating load of production.
BS2. Direct and indirect maintenance resources working reactively or proactively.
BS3. Enable analysis of different applied maintenance methodologies and their optional mix.
BS4. Evaluate processes of continuous improvement of maintenance performance.
BS5. Investigate the total costs of the complete analysis, such as, reactive and proactive tradeoffs.

However, its application does not mean seeking maximized proactivity at any cost, but supports investigating the tradeoffs between invested efforts and their calculated effects. The contribution of this work aims to provide support that counters the demands of short-termism, generated by profit considerations, by applying a systems view to the development of maintenance performance. Therefore, the model is built utilizing the system dynamics simulation technique and focuses on the aggregated behavior of the maintenance system over time, in order to link the impact of strategic policies to their total costs and facilitate the understanding of possible high leverage from such a system view. Thus, the model addresses the strategic maintenance management perspective, where the detailed work will need the utilization of other maintenance approaches, and aims to work as a tool for investigating the potential paths forward for an organization.

As such, the presented model can be regarded as a base model for maintenance performance. It also includes what are considered to be the most basic components required to generate representative behavior and be a showcase that demonstrates how the approach can illuminate the strategic development of maintenance. The model has been inspired by maintenance theory and the operational thinking about “how things are” at two global companies in the automotive industry and thus represents a conceptual structural theory (see, e.g., Grössler et al., 2008, Schwaninger and Grösser 2008). These companies have provided us with real-world knowledge about behavior and supported the model building, testing, and validation aspects. Hence, the presented model is an academic generalization based on the ambition of a sound practical foundation. Because there are only a few published works applying system dynamics in maintenance one objective of this paper is to present such a model which can serve as a basis for future research and development that aims to provide generic and available academic support that is practical enough for use in industry.

The remaining sections of this paper comprise the following: a theory section including a review of works that have applied system dynamics to maintenance; a section that includes a description of the developed system dynamics model and a set of simulation experiments representing possible “What if” scenarios, in order to investigate maintenance performance; a final section that reveals conclusions on the presented work and makes proposals for future research. Although the purpose of the model is not limited to the presented experiments, they serve to reveal, to some extent, the potential use of the proposed approach to investigate the strategic development of maintenance.

2. Development of maintenance performance

Proper maintenance practices are considered to be contributing factors to overall business performance (Alsyouf, 2009). However, investigating what is proper and carrying out sound strategies for the development of maintenance performance and practices is difficult; in addition, the direct and indirect consequences of maintenance practices are hard to evaluate.

In the following, we discuss and present aspects of the strategic development of maintenance. We start with some characteristics of maintenance development and follow with a review of approaches
for modeling maintenance performance. Thereafter, a literature review of research that has applied system dynamics to facilitate the development of maintenance performance is presented.

### 2.1 Characteristics of maintenance development

The effective development of maintenance performance can be established by creating knowledge about the results at the operational level, in relation to customer needs, which may be a production line, together with a high capacity to interpret those results at the strategic level. This may result in soundly formulated policies and strategic activities that keep a positive momentum, to reinforce (R) the development of maintenance, as illustrated schematically in Fig. 1. Conversely, less developed strategic capacities may instead risk a reversal of development and reduce maintenance performance. Furthermore, less developed capabilities at the operational level can impede the generation of profit and knowledge required for improvement, which may further reduce the options for sound decision-making at the strategic level; this also follows the reinforcing behavior (R) in Fig. 1.

![Fig. 1. Feedback behavior between strategic and operational levels in maintenance development.](image)

According to Dekker (1996), the operational level of maintenance is hard to manage and suffers from many unplanned events of a stochastic character which, as they reoccur, interrupt important, advanced-planned activities and altogether allow too little abstract and strategic thinking. This explains, to some extent, a common problem with regard to the dynamics of maintenance which tend to overload the maintenance department with reactive work instead of proactive activities (Größler et al., 2008). Although neglecting maintenance activities can achieve short-term gains, such as reduced costs or more production hours, it may lead to delayed economic consequences resulting from more frequent breakdowns (Sherwin, 2000), reduced equipment capabilities, or less time invested in continuous improvement (Repenning and Sterman, 2001).

Managing the development of maintenance corresponds well with the identified difficulty related to managing improvements. Both have wide ranging system consequences that are hard to overview and which, according to Keating et al. (1999), require active management strategies that deal with how the improvements interact with the current feedback structures. According to Warren (2005), performance reflects the current state of resources at any period of time and successful strategic management requires steering the rates of resources, in order to develop performance over time. Thus, managing the development of maintenance performance needs to consider the current state of resources and their dependencies through the existing feedback structures. At the core of maintenance performance, researchers (Ledet and Paich, 1994, Murthy et al., 2002) advocate the importance of including the feedback generated between the degradation mechanism and the operating load on equipment. Moreover, Murthy et al. (2002) consider that this aspect has been neglected in the maintenance concepts of Reliability Centered Maintenance (RCM) and Total Productive Maintenance (TPM), thus rendering them insufficient in this respect. According to Tsang (2002), the speed of development towards improved efficiency is defined by the current mix of applied maintenance methodologies and continuous ongoing improvement work within the maintenance organization. The development of maintenance performance is, in this respect, path dependent, where historical decisions impact future choices (Sterman, 2000). Thus, one can become stuck in a procedure...
which may require huge efforts to correct; moreover, the next decision may be based on that poor historical assumption, with inferior results.

In conclusion, the characteristics of maintenance development indicate the need of improved support for strategic thinking, since feedback consequences must be monitored and the effect of production on the degradation of equipment and the effect of the applied maintenance approaches all significantly impact the maintenance performance.

2.2 Approaches to modeling maintenance performance

Model approaches to support the development of maintenance performance can be divided into cost models (see, e.g., Komonen 2002, Al-Najjar 2007, Lad and Kulkarni 2011), analytical models, and simulation. While modeling the direct maintenance cost is explicit and part of standard accounting procedures (Pascual et al., 2008), the maintenance consequential costs (Vorster and De La Garza, 1990) are implicit and intangible and apparent in other parts of an organization, such as fewer manufactured products, increased production man hours, or quality issues. Tracing the consequential costs is thus a problem of inherent subjectivity (Vorster and De La Garza, 1990) and almost impossible to achieve using financial accounting (Pascual et al., 2008). Accordingly, several researchers have pointed out that maintenance optimization utilizing analytical modeling, which quantifies maintenance costs and benefits, struggles with practical applicability (for further details see, e.g., Dekker 1996, Alrabghi and Tiwari 2015). Furthermore, according to Lad and Kulkarni (2011), maintenance modeling literature excludes degradation patterns and the effects of continuous improvements. Therefore, maintenance optimization models are often oversimplified and considered unrealistic.

Alrabghi and Tiwari (2015) consider that simulation bridges the limitations of analytical approaches. Additionally, Alabdulkarim et al. (2013) state that current applications of simulation work do not adequately address overall maintenance system behavior and treat sub-systems in isolation. They, therefore, propose that discrete event simulation (DES) has the potential to better include the effects of more efficient maintenance practices in manufacturing. On the other hand, according to Gunal and Pidd (2010), utilizing DES as a tool also tends to focus on the operational level of specific areas and utilizing DES for policy-level analysis is rare. Furthermore, feedback behavior is inadequately visualized, in order to answer why certain behaviors arise.

System dynamics theory has been discussed in the introduction for its capacity to include feedback behavior, which may support the management of strategic development according to the illustration in Fig.1 above. Also, several researchers (Keating et al., 1999, Repenning and Sterman, 2001, Warren, 2005) consider it to be a powerful methodology from the strategic perspective. Researchers have previously claimed the benefits of applications of system dynamics in maintenance (Crespo Marquez and Usano, 1994) and, for further details, Größler et al. (2008) provide a review of how operations management studies based on system dynamics theory can apply to maintenance. However, to our knowledge, there are still no published simulation models that include dynamic tradeoffs between direct and consequential effects, as given by the boundary selection of this study, mentioned in the introduction and reviewed in the next section.

2.3 System dynamics and maintenance development

This section provides a literature review of research that has applied system dynamics to support the development of maintenance performance within a production focus. It has excluded, for example, maintenance of aviation equipment and bus fleet maintenance. The reviewed literature is summarized in Table 1. Six columns are arranged according to: article, whether paper presents simulation results, whether the model structure of the simulation model and the model equations are presented, the purpose of the model, and the paper’s graded relevance to our research together with a short note.
Table 1
List of papers and their contents.

<table>
<thead>
<tr>
<th>Article</th>
<th>Presents simulation results</th>
<th>Presents simulation model</th>
<th>Presents model eq.</th>
<th>Model purpose</th>
<th>Relevance to this research</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. (Ledet and Paich, 1994)</td>
<td>no</td>
<td>partly</td>
<td>no</td>
<td>Analyze the contribution of maintenance to manufacturing.</td>
<td>High. Shares modeling scope, less specific paper, but has had a high impact and contributes to the model in this study.</td>
</tr>
<tr>
<td>2. (Sterman, 2000) p.66-79</td>
<td>no</td>
<td>partly</td>
<td>no</td>
<td>Illustrate a maintenance study in a textbook, with focus on the physics of breakdowns rather than cost minimization.</td>
<td>High. Shares philosophical base, part of the structure of equipment defects is reused, no equations presented.</td>
</tr>
<tr>
<td>3. (Jokinen et al., 2011)</td>
<td>yes</td>
<td>partly</td>
<td>no</td>
<td>Understand customer’s business connected to maintenance, and act as a service sales tool.</td>
<td>Medium. Similarities in scope, model presentation focus on component degradation structure, which is detailed.</td>
</tr>
<tr>
<td>4. (Carroll et al., 1998)</td>
<td>no</td>
<td>no</td>
<td>no</td>
<td>Quantify maintenance value, its direct costs and benefits delivered in terms of increased uptime, fewer breakdowns, etc.</td>
<td>Medium. Text-based paper, focuses on the organizational intervention, indirect model building support.</td>
</tr>
<tr>
<td>5. (Thun, 2006)</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
<td>Support a theoretical discussion of implementing TPM, a one stock model using equipment defects.</td>
<td>Medium. Explicit model, equations open for review. Still, study too aggregated, hard to transfer to this research.</td>
</tr>
<tr>
<td>6. (Repenning and Sterman, 2001)</td>
<td>yes</td>
<td>partly</td>
<td>partly</td>
<td>Explain capability management, includes worse-before-better and better-before-worse behavior.</td>
<td>Medium. Insight paper about proactive and reactive maintenance behavior, however, no material for direct reuse in model.</td>
</tr>
<tr>
<td>7. (Sterman, 2015)</td>
<td>yes</td>
<td>partly</td>
<td>no</td>
<td>Illustrate capability trap for maintenance costs, includes worse-before-better and better-before-worse behavior.</td>
<td>Medium. Discusses maintenance costs based on proactive or reactive behavior, yet, not on applicable detail to support model building.</td>
</tr>
<tr>
<td>8. (Jambekar, 2000)</td>
<td>no</td>
<td>no</td>
<td>no</td>
<td>A systems thinking analysis of the interrelations of maintenance, operations, and process quality.</td>
<td>Medium. Similar modeling scope, provides a qualitative model, low model building support.</td>
</tr>
<tr>
<td>9. (Zuakhiani et al., 2011)</td>
<td>no</td>
<td>no</td>
<td>no</td>
<td>Map the dynamics of overall equipment effectiveness and analyze short and long-term dynamics of maintenance.</td>
<td>Medium. Similar modeling scope, provides a qualitative model and analysis without simulation, indirect model building support.</td>
</tr>
<tr>
<td>10. (Crespo Marquez and Usano, 1994)</td>
<td>no</td>
<td>no</td>
<td>no</td>
<td>Demonstrate medium to long-term benefits of continuous improvements in maintenance.</td>
<td>Low. Relevant topic to our study, but very brief model descriptions and nothing to reuse.</td>
</tr>
<tr>
<td>11. (Beenen et al., 2008)</td>
<td>yes</td>
<td>no</td>
<td>no</td>
<td>A study to improve the corrective maintenance process for a client.</td>
<td>Low. Not in line with this research, by its main focus on reactive work.</td>
</tr>
<tr>
<td>12. (Khorshidi et al., 2015)</td>
<td>yes</td>
<td>yes</td>
<td>partly</td>
<td>Investigate strategies on the basis of RCM.</td>
<td>Low. Model without feedback loops, not relevant to this study.</td>
</tr>
<tr>
<td>13. (Kamath and Rodrigues, 2016)</td>
<td>yes</td>
<td>partly</td>
<td>no</td>
<td>Study effects on production from combining TPM and Total Quality Management.</td>
<td>Low. An overly simple and shallow presentation to judge its relevance.</td>
</tr>
</tbody>
</table>

The articles presented in Table 1 have low, medium, or high relevance to our research. The papers rated low relevance mainly suffer from being too simple or lack model details to support this research. Many of the articles have a medium relevance rating; however, their contributions to this research are limited, in terms of being able to reutilize material. One medium rated paper, the only one found with full model documentation, article 5 in Table 1 (Thun, 2006), applies a model to support theoretical discussions of implementing TPM, and is based on article 2 by Sterman (2000). However, despite its openness, the model’s purpose and aggregation make it difficult to apply in our research. Articles 6 and 7 in Table 1 present general insights regarding the dynamics of worse-before-better and better-before-worse behavior in maintenance. Neither article presents research that is fully aligned with our study. For example, Repenning and Sterman (2001) treat the dynamic problem of intangible capabilities that have a significant effect on system performance, such as the dynamics that lead to cutting corners in work procedures to meet the demands of short-term goals, instead of investing time on improvements which could lead to increased maintenance capabilities. Articles 8 and 9 in Table 1 only apply qualitative system dynamics to analyze and map the interrelations between parts. While such a map provides a vehicle for reasoning about the dynamics between system variables, it does not provide any quantitative analysis to test assumptions or study system behavior. However, articles 8 and 9 align with our research and have thus affected it by their descriptions. This is similar to article 4 in Table 1, where Carroll et al. (1998) provide details of successful change programs facilitated by
system dynamics analysis, going from reactive to proactive maintenance performance. Nevertheless, their presentation consists of plain text, limiting the contribution.

However, and unfortunately, the highly relevant articles 1 and 2 in Table 1 lack presentations of underlying quantitative models to learn from, with respect to modeling. The article by Ledet and Paich (1994) has contributed to and has had a considerable impact on our study. Their modeling effort analyzes the contribution of maintenance to manufacturing by focusing on the behavior behind the performance of variables, such as mean time to failure and mean time to repair, which perfectly align with our research focus. However, their presentation is merely text based with poorly described model structures. Furthermore, in his modeling textbook, Sterman (2000) considers the same study, as the reports in articles 1 and 4 in Table 1, and emphasizes the change in the organization’s efforts, from a maintenance cost focus to defect elimination focus. However, only part of the model is described, without any equations; therefore, only a part has been possible to reutilize.

In conclusion, maintenance behavior has been explored utilizing system dynamics; to date, the amount of published material presents few examples of the quantitative form to learn from. In fact, none of the high-relevant papers in Table 1 that investigate maintenance dynamics provide enough detail to make it directly reusable. Regarding the focus of our paper, the search for applications with respect to the consequential costs of maintenance has failed to find any publications. Thus, our study is justified.

3 Model Description
The description of the model and its parts is a full review of the base model over maintenance performance. The aim of the model is to be a compact presentation, in order to generate the representative behaviors, where some are found in the Simulation experiments chapter, and a showcase that demonstrates how the approach can illustrate the strategic development of maintenance. The aim of the base model is thus towards generalizability. The presented structure should not be case specific, as a specific case may require adapting and extending this model. Modeling is an iterative transformation process of real-world information flows into their feedback structures. It materializes equations describing assumptions of variable dependencies, going back and forth in a continuous learning process through the steps of the modeling process, according to Sterman (2000):

- **Problem articulation**: understand the problem and articulate it, mainly reviewed by the previous chapters, and select the boundary, represented by the boundary selection (BS) points in the introduction.
- **Dynamic hypothesis**: the model includes many such hypotheses regarding the expected implications and behaviors from and within each of the above-mentioned BS points. This includes studying literature on problem phenomena and investigating the situation at the companies.
- **Formulation**: build the simulation model based on the dynamic problem, include existing ideas from the literature and tacit real-world descriptions. This is a highly intuitive process (Sterman, 2000) and there are no formal descriptions of how to implement system dynamics projects (Linnéusson, 2009). Include specification of structure and decision rules, parameter estimation, behavioral relationships, initial conditions, and tests for consistency with the model purpose.
- **Testing**: does the model reproduce adequately with respect to its purpose? See separate validation section.
- **Policy formulation and evaluation**: apply the model to explore possible “what if” scenarios, test their sensitivity and suitability for implementation, examine synergy policies, etc. See the simulation experiments chapter, which can be considered a showcase on application towards policy formulations but, in this study, only achieves the investigation of the strategic development of maintenance performance.
The purpose of the model is to support the investigation of the feedback effects from strategies on maintenance performance in interaction with production. The model is built using the Vensim DSS software, and its complete structure is found in appendix. Fig. 2 is a high level illustration of the model; it represents how the model parts work together for the holistic economic performance. Each model part, represented by a box in Fig. 2, is explained in subsequent sections, using their representations from the system dynamics software. In addition, to support reading the connections between the parts, the boxes from Fig.2 are included. At the aggregated level of the model overview, in Fig. 2, only the balancing loops (B) are visible, which indicates the exclusion of growth mechanisms in the model. The reinforcing mechanism appears in the interaction between the decision makers and the model, as indicated previously in Fig. 1 by the feedback behavior between strategic and operational levels in maintenance development. The decision maker applies maintenance strategies to the model, as illustrated by the diamond in Fig. 2, in order to explore, understand, and act upon the added information gained from utilizing simulation.

Fig. 2. High level illustration of the base model.

In order to comprehend the boundary selection presented in the introduction, the complete model could be divided into the above-mentioned parts, according to Fig. 2, where each box in brief includes:

- **Production and maintenance performance** defines the availability in production as a consequence of the current reliability of the equipment, the performed planned and unplanned maintenance respectively, and staffing.
- **Equipment health status** defines the aggregated equipment reliability as a consequence of the current health and risk level of the equipment. Equipment health is modeled using accumulated defects, generated by operations and eliminated through repairs.
- **Preventive maintenance performance** defines the takedown rate of scheduled repairs, based on the level of applied maintenance methodology, where work order stock, planning and scheduling capabilities, and the pressure to produce take priority over maintenance and result in the actual takedown rate.
- **Maintenance development process** defines the pace of maintenance performance development on the basis of policies, resources, delays, work pressure, and work progress.
- **Holistic economic performance** calculates the total maintenance costs as a consequence of current production and maintenance performance; it includes direct costs and indirect consequential costs of breakdowns, due to the level of planned over unplanned work.
3.1 Production and Maintenance Performance

![Diagram of production and maintenance performance](image)

**Fig. 3.** Structure of the production and maintenance performance part.

The origin of the structure in Fig. 3 is partially from Ledet and Paich (1994). It utilizes equipment as units, which flow between the stocks. The stock in the middle contains the equipment in full functionality and the breakdown rate moves equipment to unscheduled maintenance which waits for an unscheduled repair. The takedown rate moves equipment to scheduled maintenance which waits for a scheduled repair, then restores the equipment to full functionality. The flows are also affected by other parts of the model, illustrated by the boxes in the overview of Fig. 2, the content of which is reviewed in Figures 4, 9, and 10.

\[
\text{Availability} = \frac{\text{Equipment in full functionality}}{\text{number of equipment}}
\]

(1)

Where

\[
\text{Equipment in full functionality} = \text{number of equipment} - \text{Unscheduled maintenance} - \text{Scheduled maintenance}
\]

(2)

\[
\text{breakdown rate} = \frac{\text{Equipment in full functionality}}{\text{delay breakdowns}} + \text{breakdowns due to unperformed takedowns}
\]

(3)

Delay breakdowns = a value that depends on equipment health status and risk management, see equation 11

Breakdowns due to unperformed takedowns = equipment that fails while waiting for a scheduled repair, see figure 9

\[
\text{Unscheduled maintenance}_{t} = \text{Unscheduled maintenance}_{t-1} + (\text{breakdown rate}_{t} - \text{unscheduled repairs}_{t})
\]

(4)

\[
\text{unscheduled repairs} = \text{MIN}(\text{Unscheduled maintenance}_{t}, \text{max capacity unscheduled repairs})
\]

(5)

The takedown rate depends on the result of applied maintenance methodology in preventive maintenance, Fig. 9, planning and scheduling of preventive maintenance, Fig. 10, and on access to equipment, based on pressure to produce; where lower availability limits planned work.

The work in scheduled and unscheduled repairs differs in effectiveness; on average, the stop time for unscheduled repairs in production is longer than for scheduled repairs, since more time is spent on identifying the fault and additional waiting time is required for bringing spare parts or tools, as well as finding instructions or drawings, etc. Resources for scheduled repairs are also used for inspections. The max capacity for unscheduled repairs is not linear, it has a limit to the contribution of the latest added repairman and is affected by the effect of breakdown frequency on capacity.
In this model, any equipment failure reduces production performance, which is not necessarily the case in production systems. Hence, the benefits of PM can be considered even larger when maintenance can be performed outside production hours.

3.2 Equipment Health Status

The structure in Fig. 4 represents the underlying dynamics for equipment health, equation 6 and is based on a maintenance model partly presented in Sterman (2000). It utilizes defects as units and is the basis for modeling the risk of failures in production. Furthermore, it is connected to availability, in Fig. 3, and increased performance will lead to increased equipment load and degradation via operations. Defects are also created by collateral damage from every breakdown. In addition, neglected equipment tends to break down more frequently and is included in wear and tear operations according to equation 10.

\[
\text{Equipment health}_t = \text{Equipment health}_{t-1} + \text{defect creation}_t - \text{defect elimination repairs}_t - \text{defect elimination PM}_t
\]  

(6)

Where initial value at Equipment health_{t=0} = \text{initial value of Hidden defects \times number of equipment} 

(7)

\[
\text{defect creation}_t = \text{operations}_t + \text{collateral damage}_t
\]  

(8)

\[
\text{operations}_t = \text{Availability}_t \times \text{wear and tear operations}_t
\]  

(9)

\[
\text{wear and tear operations}_t = \text{Equipment health}_t \times \text{probability wear and tear}
\]  

(10)

Defects in the stock equipment health are eliminated through scheduled and unscheduled maintenance, for model simplicity, with the same precision, where each repair is proportional to the number of defects; thus, repairs at poor health status are more efficient than at good health status. This relates to whether the equipment replacement is cost effective or not, or whether the equipment is over/under maintained.

Delay breakdowns interfere with the breakdown rate, in Fig. 3. It is a product of risk for failures, according to equations 11-15, and it is assumed that well-performed PM work can reduce such risk, in Fig. 4, based on behavior in model part in Figures 9 and 10. Better implementation of PM procedures enables the improvement of risk management, through better knowledge of actual equipment health. Risk reduction utilizes a table function, Fig. 5, where the input fraction PM work, equation 15, transforms into the output value, equation 14, used in equation 12. Likewise, the delay breakdowns variable, equation 11, utilizes the table function in Fig. 6 to transform risk for failures into a delay,
where the units of the output are years. Hence, excellent PM work and equipment health provide input values towards 0, in Fig. 6, which provide delay output values towards 4 years.

\[
\text{delay breakdowns}_t = \text{tbl risk effect on reliability} \left( \text{risk factor breakdowns}_t \right) \times \text{average reliability}
\]

\[
\left( \frac{\text{risk factor breakdowns}_t}{\text{risk delayed work}} \right) \times \text{fraction equipment health over possible defects}_t \times \left( \frac{\text{fraction equipment health over possible defects}_t}{\text{equipment health}_t} \right) \times \left( \frac{\text{equipment health}_t}{\text{number of equipment}} \right)
\]

\[
\text{delay breakdowns}_t = \text{fraction equipment health over possible defects}_t \times \text{risk delayed work} \times \text{fraction equipment health over possible defects}_t \times \left( \frac{\text{equipment health}_t}{\text{number of equipment}} \right)
\]

\[
\text{fraction equipment health over possible defects}_t = \frac{\text{Equipment health}_t}{\text{number of equipment}}
\]

\[
\text{risk factor reduction due to PM work}_t = \text{tbl reduced risk due to PM work} \times \text{fraction PM work}_t
\]

\[
\text{fraction PM work}_t = \frac{\text{PM work}_t}{\text{number of equipment}}
\]

Fig. 5. Table function tbl reduced risk due to PM work.

Fig. 6. Table function tbl risk effect on reliability.
3.3 Preventive Maintenance Performance

The stock and flow structures in Figures 7 and 8 are inspired by the written description of the manufacturing game (Ledet and Paich, 1994). The structure in Fig. 7 utilizes PM work orders as units and regulates the flow of work orders scheduled in Fig. 8; the output of which is the takedown rate of equipment in production.

The applied maintenance methodologies, in Fig. 7, include three types of PM work orders:

1. PM using fixed intervals, the flow between the stocks equipment with PM preparations and PM replacement backlog generates the rate of PM work orders, in Fig. 8, to be scheduled. Planning, in Fig. 7, is subject to the fraction of PM work, according to equations 16 and 17.
\[
\text{start } PM_{wo_t} = \frac{PM \text{ replacement backlog}_{t}}{\text{delay plan } PM_{wo_t}} \quad (16)
\]
\[
\text{Where } \text{ delay plan } PM_{wo_t} = \frac{\text{time to plan } PM_{wo}}{\text{MIN}(\text{fraction } PM_{wo}, 0.5) \cdot 2} \quad (17)
\]

2. PM using CBM inspection plans, the flow in the middle structure, in Fig. 7, where available resources for discretionary inspections may limit the rate of identified defective equipment, equations 18 and 19, and the workload is based on inspection interval. Hence, policies regarding inspections result in the backlog of PM work orders in the stock equipment to inspect and the corresponding resource demand.

\[
\text{identified defective equipment inspections}_t = \text{descretionary inspections}_t \cdot \text{fraction equipment health over possible defects}_t \cdot \text{quality of inspections}_t
\]
\[
\text{where descretionary inspections}_t = \text{MIN}(\frac{\text{Equipment to inspect}_t}{\text{inspection delay}}) \quad (18)
\]

3. PM using CBM sensors, the amount of PM preparations in the stock equipment with CBM sensors contributes to the rate identified defective equipment in Fig. 8, based on the current status of equipment health.

\[
\text{identified defective equipment CBM sensors}_t = \frac{\text{Equipment with CBM sensors}_t}{\text{average CBM interval}_t} \quad (20)
\]
\[
\text{where average CBM interval}_t = \frac{\text{Week}}{\text{4 \cdot fraction equipment health over possible defects}_t} \quad (21)
\]

Week = constant of 52 weeks in one year.
4 = a constant dividing Week into 4, that represents the interval of identifying defects when equipment health is at its poorest.

One symptom in the planning and scheduling structure, Fig. 8, from insufficient resources in Fig. 2 is a backlog in the stock planned takedowns. The takedown rate \( p \) is a function of planned takedowns and the scheduling delays, according to equations 22-24, where a longer delay may result in an increased rate of breakdowns due to unperformed takedowns, which interfere in Fig. 3, equation 3.

\[
takedown rate \ p_t = \text{IF THEN ELSE}(\text{Scheduled maintenance}_t > \frac{\text{limit takedown rate} \cdot \text{number of equipment}}{\text{pressure to produce}_t},
0, \frac{\text{Planned takedowns}_t}{\text{pressure scheduling delay}_t}) \quad (22)
\]

\[
\text{limit takedown rate} \cdot \text{number of equipment} = \text{if limit of Scheduled maintenance is reached no new PM work orders are scheduled, however, as pressure to produce increases the limit decreases according to equation 23.}
\]

\[
\text{Where pressure to produce}_t = \text{MIN}(\text{MAX}(1, \frac{\text{goal availability}_t}{\text{Availability}_t}), 4) \quad (23)
\]

\[
\text{Where pressure scheduling delay}_t = \text{delay scheduling takedowns} \cdot \text{pressure to produce}_t \quad (24)
\]

\[
\text{delay scheduling takedowns} = \text{constant of 1 Week.}
\]

New PM preparations, Fig. 7, are introduced based on the maintenance development process, the model part in Fig. 9, which governs the rates of ongoing continuous improvement of the current mix of applied maintenance methodologies (Tsang, 2002), in Fig. 7, according to equations 26-31.

\[
\text{Equipment with CBM sensors}_t = \text{Equipment with CBM sensors}_{t-1} + \text{new CBM sensors}_t \quad (25)
\]

\[
\text{Where initial value at Equipment with CBM sensors}_{t=0} = \text{init library of CBM sensor} \quad (26)
\]
3.4 Maintenance Development Process

Information from breakdown reports flows through the structure, in Fig. 9, and represents the development of maintenance practices transforming facts, such as what equipment has failed and why, the costs, how often, etc., into countermeasures based on root cause analysis (RCA). This approach, similar to RCM, aims to generate learning from failures, to improve reliability which, at its best, also suggests evaluating completed PM work orders to reduce potential breakdowns (Nowlan and Heap, 1978). However, in this base model, only breakdowns are used as the basis for improvements, since this method has been mainly performed at our industrial partners. The stock and flow structure considers three states of information transforming into countermeasures: Breakdown

Fig. 9. Structure for maintenance development process part.
reports Backlog, Breakdown analysis RCA WIP (Work in progress), and Implemented RCA, initiated by the breakdown report demand according to equation 32.

\[
\text{breakdown report demand}_t = \text{unscheduled repairs}_t \ast \text{policy fraction report per breakdown} \quad (32)
\]

Where policy fraction report per breakdown = set by decision maker.

The rate of RCA useful data depends on analytic capabilities and the current workload in Breakdown reports Backlog, where analytic capabilities are set proportionally to equipment health as an indicator of the actual capacity to achieve a well-informed report, see equations 33-37.

\[
\text{RCA useful data}_t = \text{breakdown report done}_t \ast \text{fraction available data RCA}_t \quad (33)
\]

Where breakdown report done \( t \) = Breakdown reports Backlog \( t \) / delaytime breakdown report \( t \) \( (34) \)

Breakdown reports Backlog \( t \) = accumulated report workload for repair workers.

delaytime breakdown report \( t \) = 1 week average delay per report.

Where fraction available data RCA \( t \) = useful info in reports \( t \) \* analytic capabilities \( t \) \( (35) \)

Where useful info in reports \( t \) = tbl pressure to close gap (Breakdown reports Backlog \( t \) \* pressure per breakdown report) \( (36) \)

tbl pressure to close gap = Fig. 10 shows the nonlinear dependence between breakdown reports backlog and pressure.

Pressure per breakdown report \( t \) = 1.

Fig. 10. Table function over the consequence of pressure from report backlog on report quality.

\[
\text{analytic capabilities}_t = 1 - \text{fraction equipment health over possible defects}_t \quad (37)
\]

\[
\text{fraction equipment health over possible defects}_t = \text{see equation 13.}
\]

RCA useful data accumulates into Breakdown analysis RCA WIP where maintenance engineers use information to identify RCA countermeasure to breakdown. The speed of development depends on resources, their productivity, and the implementation delay, see equations 38 and 39.

\[
\text{RCA countermeasure to breakdown}_t = \text{MIN}(\frac{\text{Breakdown analysis RCA WIP}_t}{\text{delay RCA}_t}, \text{max capacity RCA}) \quad (38)
\]

Breakdown analysis RCA WIP \( t \) = available information for engineers to analyze.

\[
\text{max capacity RCA} = \text{info per week}, \text{a product determined by resources and their productivity.}
\]

Where delay RCA \( t \) = time to implement MIN(fraction PM work, 0.8) \* 2 \( (39) \)
Longer delay when fraction PM work is below 0.5, and delay is shorter until 0.8.

Information in Implemented RCA develops into improved PM work, depending on available engineering resources and policies of maintenance methodologies, according to equations 40 - 42, where the number of resources available for the specific activity is defined in equations 43-45.

\[
PM \text{ preparation}_t = \min\left(\frac{\text{Implemented RCA} \times \text{fraction PM preparations from RCA}}{\text{delay PM preparation}}, \text{max capacity PM preparations}_t\right)
\]  

\[
CBM \text{ preparation}_t = \min\left(\frac{\text{Implemented RCA} \times \text{fraction CBM preparations from RCA}}{\text{delay convert to CBM}}, \text{max capacity implement CBM inspections}_t\right)
\]  

\[
CBM \text{ sensor preparation}_t = \min\left(\frac{\text{Implemented RCA} \times \text{fraction CBM sensor preparations from RCA}}{\text{delay convert to CBM sensors}}, \text{max capacity implementing CBM sensors}_t\right)
\]  

Where max capacity implementing CBM sensors\(_t\) = (max capacity implement CBM inspections\(_t\) - CBM preparation\(_t\)) \times \text{productivity CBM to sensor}

Where max capacity implement CBM inspections\(_t\) = (max capacity PM preparations\(_t\) - PM preparation\(_t\)) \times \text{productivity PM to CBM}

Where max capacity PM preparations\(_t\) = (max capacity RCA\(_t\) - RCA countermeasure to breakdown\(_t\)) \times \text{productivity PM preparations}

\[3.5 \text{ Holistic Economic Performance}\]

The holistic economic performance structure in Fig. 11 calculates the total maintenance cost, equation 46, based on the behavior of the model, which intersects here through variables illustrated in the structures of Figures 3 and 7. In addition, it totals costs from utilizing direct and indirect resources, spare parts and capital expenditure for spare part inventory, as well as the estimated extra expenses from breakdowns, together with lost contribution margin due to lost production time. Direct maintenance costs, equation 49, are calculated using the same bases for both proactive and reactive work for simplicity reasons; instead, it is the frequency of events, such as breakdown rate and takedown rate that governs its result. Calculating consequential breakdown costs is based on estimates
in Wireman (2004) which are indicated on a cost ratio of 1:5 between planned and unplanned work, implemented according to equation 48.

\[ \text{maintenance total cost}_t = \text{maintenance consequential cost}_t + \text{maintenance cost}_t \]  
\[ (46) \]

\[ \text{maintenance consequential cost}_t = \text{consequential breakdown costs}_t + \text{capital cost spare part inventory}_t \]  
\[ (47) \]

Where consequential breakdown costs\(_t\) = 4 * cost per stop * breakdown rate\(_t\)  
\[ (48) \]

\[ \text{maintenance cost}_t = \text{cost man hours}_t + \text{cost breakdowns}_t + \text{cost takedowns}_t \]  
\[ (49) \]

Unplanned maintenance requires more spare parts, due to higher uncertainty and less preparation time before breakdowns, using five spares per equipment, while PM with fixed intervals uses two spares per equipment and CBM uses one, according to equations 50-51.

\[ \text{capital cost spare part inventory}_t = \frac{\text{interest rate spare part inventory}}{\text{week}} \times \text{capital in spare part inventory}_t \]  
\[ (50) \]

Where capital in spare part inventory\(_t\) = cost per spare part *  
(spare part per equipment breakdown strategy * (number of equipment − Sum PM preparations\(_t\)) + spare part per equipment takedown strategy * ((1 − fraction CBM over PM\(_t\)) + 0.5 *  
fraction CBM over PM\(_t\)) + Sum PM preparations\(_t\))  
\[ (51) \]

Including Net profit, in Fig. 11, can enable estimates of maintenance value. In effect, improved availability leads to a larger net contribution margin, but also an increase of maintenance total cost subject to the efficiency of attained maintenance performance. Estimating Net profit can enable exploring the value of increased performance, see equations 52-55. A similar procedure to calculate value is performed in models by using overall equipment effectiveness (Zuashkiani et al., 2011).

\[ \text{Net Profit}_t = \text{Net contribution margin production}_t - \text{maintenance total cost}_t \]  
\[ (52) \]

Where Net contribution margin production\(_t\) = Availability\(_t\) ∗ max contribution margin per week  
\[ (53) \]

\[ \text{Acc Company Results}_t = \text{Acc Company Results}_{t-1} + \text{profit or loss}_t \]  
\[ (54) \]

Where profit or loss\(_t\) = Net Profit\(_t\)  
\[ (55) \]

In order to include the maintenance manager perspective, the maintenance budget is included, equations 56-57, which is normally based on the maintenance cost excluding consequential costs.

\[ \text{Acc Maint. Budget Margin}_t = \text{Acc Maint. Budget Margin}_{t-1} + \text{diff cost over budget}_t \]  
\[ (56) \]

Where diff cost over budget\(_t\) = maintenance budget\(_t\) − maintenance cost\(_t\)  
\[ (57) \]

3.6 Validation

Any model is a tradeoff between what to include and what to exclude and requires relevant boundary adequacy tests and structure assessment tests (Sterman, 2000). System dynamics models are causal-descriptive as well as “statements as to how real systems actually operate in some aspects” (Barlas, 1996, p.185). The model’s internal structure validation, together with its capacity to explain how the behaviour arises, is therefore crucial. While correlational black-box models are validated using statistical tests, this is not applicable for validating behaviours in a system dynamics model, which are regarded more as white-box learning models, due to the problems of autocorrelations and multicollinearity (Barlas, 1996). Moreover, judging the validity of the internal structure of a model is very problematic, and most methods are informal and qualitative in nature (Barlas, 1996) (see, for
instance, Luna-Reyes and Andersen, 2003). Therefore, it is largely the model’s usefulness in explaining problem phenomena that determines its validation (Sterman, 2000). In other words, if the model can be considered acceptable relevant and its usage may assist managers’ decision-making in the real world, it supports validation (Bertrand and Fransoo, 2002).

Testing model validation is iterative during modeling and is supported, according to Barlas (1996), by using:

- direct structure tests, which compare model with knowledge about the real system (empirical) and generalized knowledge (theoretical),
- structure-oriented behavior tests, which by using simulation studies the behavioral results as a mean to identify structural inconsistencies, and
- behavior pattern tests, which measure the accuracy of reproducing behavior patterns of the real system.

The aim is to identify parameters that endogenously create the problematic behavior in the real system. Modeling for theory building, as proposed here, it uses the two first structural tests but has typically no use of the third (Barlas, 1996). Moreover, for theory building, one vital aspect is that the model enables the explanation of the behavior under study (Schwaninger and Grösser, 2008). Hence, direct structure tests and structure-oriented behavior tests have been part of the modeling process, to continually refine the correspondence between the proposed model and reality. Furthermore, the model has been reviewed in several workshops at industrial partners with maintenance staff in walk-through sessions, strengthening its structural validity.

For the specific model, the essential parts that enable experiments on maintenance methodologies and their implications at a strategic level can be considered in place. These include the following:

a) the dynamics of defects,
b) how defects result in failures and disturb production,
c) how failures are eliminated by using planned and unplanned maintenance respectively,
d) how the development of preventive maintenance evolves from information gained by learning about breakdowns,
e) the total economic consequence, including both maintenance costs and consequential costs, in order to compare the effectiveness of short and long-term activities.

As a supporting detail previously studied behaviors, such as worse-before-better and better-before-worse (see, e.g., Repenning and Sterman 2001), can be considered integrated into the model. For example, see the results of the presented experiments, where better-before-worse behavior is found, in Fig. 12, line 4, from adding repair workers to equipment health, or the worse-before-better behavior of consequential costs in Figures 18 and 23 in proactive maintenance strategies.

The input to the modeling has involved studying procedures of the industrial partners and reviewing relevant literature. With respect to external validation, the model may be regarded as theoretical in character. However, the overall model behavior may, to some extent, be justified, mainly through the knowledge documented in the literature and the testing of assumptions with the help of industrial maintenance experts. By utilizing the maintenance performance model, it was possible to argue for the representation of key dynamics and development processes in a maintenance setting. One important characterization of quantitative system dynamics models is that they are comprised of an explicit set of mathematical expressions based on current assumptions, and are therefore testable and possible to falsify (Schwaninger and Grösser, 2008). Hence, modeling for learning as made by this study, bring the consequence of formalizing assumptions of the real problem, making them more explicit as they are studied. And, due to the learning and knowledge retrieval from testing one’s assumptions it is a continual work, and it is considered that the proposed conceptual model will evolve as future research and applications are extended. Therefore, explicitly presenting the model structure,
4. Simulation Experiments
Simulation enables manipulating the maintenance performance model in multiple procedures. It is, for instance, possible to investigate the effects of processes that can cause delays. For example, such delays can be caused by the scheduling or planning processes (Ledet and Paich, 1994), a high production load that prevents planned maintenance, and strategies that accelerate the maintenance development process, to name a few. However, simulation experiments need to be limited and, in order to isolate consequences from the applied strategy, only a few parameters were changed and other parameters were not manipulated, according to settings in Table 2. The following strategies for maintenance methodologies that have been examined originated in Tsang (2002):

- Run-To-Failure (RTF),
- Preventive maintenance using fixed intervals (PMfi),
- Condition-based maintenance using manual inspections on interval (CBMi),
- Condition-based maintenance using sensors (CBMs).

Table 2. Parameter settings for experiment runs.

<table>
<thead>
<tr>
<th>Maintenance methodology</th>
<th>Experiment runs</th>
<th>resources scheduled repair</th>
<th>resources unscheduled repair</th>
<th>no. maint eng.</th>
<th>goal fraction CBM over PM</th>
<th>init level of PMfi</th>
<th>Insp. int.</th>
<th>fraction PMfi from RCA</th>
<th>fraction CBMi from RCA</th>
<th>fraction CBMs from RCA</th>
</tr>
</thead>
<tbody>
<tr>
<td>RTF</td>
<td>1</td>
<td>23</td>
<td>0</td>
<td>0</td>
<td>0%</td>
<td>5%</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>RTF_step staff</td>
<td>1</td>
<td>18,20,22,24,26,28,30,32,34</td>
<td>0</td>
<td>0</td>
<td>0%</td>
<td>5%</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>PM_100%</td>
<td>6</td>
<td>15</td>
<td>3</td>
<td>0</td>
<td>50%</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>PM_100%_lim staff</td>
<td>1</td>
<td>15</td>
<td>1</td>
<td>0</td>
<td>50%</td>
<td>-</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>-</td>
</tr>
<tr>
<td>CBMi_50%,13w</td>
<td>6</td>
<td>15</td>
<td>3</td>
<td>0.5</td>
<td>50%</td>
<td>13w</td>
<td>0.5</td>
<td>0.5</td>
<td>0</td>
<td>-</td>
</tr>
<tr>
<td>CBMi_50%,4w</td>
<td>6</td>
<td>15</td>
<td>3</td>
<td>0.5</td>
<td>50%</td>
<td>4w</td>
<td>0.5</td>
<td>0.5</td>
<td>0</td>
<td>-</td>
</tr>
<tr>
<td>CBMi_50%,4w_lim staff</td>
<td>1</td>
<td>15</td>
<td>1</td>
<td>0.5</td>
<td>50%</td>
<td>4w</td>
<td>0.5</td>
<td>0.5</td>
<td>0</td>
<td>-</td>
</tr>
<tr>
<td>CBMs_5%,4w</td>
<td>6</td>
<td>15</td>
<td>3</td>
<td>0.5</td>
<td>50%</td>
<td>4w</td>
<td>0.5</td>
<td>0.45</td>
<td>0.05</td>
<td>-</td>
</tr>
<tr>
<td>CBMs_25%,4w</td>
<td>6</td>
<td>15</td>
<td>3</td>
<td>0.5</td>
<td>50%</td>
<td>4w</td>
<td>0.5</td>
<td>0.25</td>
<td>0.25</td>
<td>-</td>
</tr>
<tr>
<td>CBMs_5%,4w_lim staff</td>
<td>6</td>
<td>15</td>
<td>1</td>
<td>0.5</td>
<td>50%</td>
<td>4w</td>
<td>0.5</td>
<td>0.45</td>
<td>0.05</td>
<td>-</td>
</tr>
</tbody>
</table>

The selection of the design of experiments (DOE) was based on the need to represent a spread of general analyses identified together with partners from the automotive industry, where the main PM work is currently carried out using PMfi emerging towards more CBM.

The initial condition applied for the experiments is a state of equilibrium based on the RTF experiment in Table 2. The utilized resources maintain the status quo of the system. The procedure of identifying equilibrium included tuning the initial levels of Equipment in full functionality and the initial level of Equipment health. Then, at equilibrium, the maintenance total cost was calculated and used to calculate the max contribution margin per week, while the maintenance cost was used to calculate the maintenance budget.

The RTF experiment represents the scenario of a company in equilibrium that achieves availability at approximately 60%. The RTF_step staff experiment represents one possible scenario that attempts to improve that situation, by studying the temporal effects of adding resources. The RTF experiments
include some minimum lubrication and services, according to machine specifications, requiring 5% PMi and one PM resource.

All other experiments initially use 50% PMi, with the objective to implement 100% PM according to the fractions in Table 2. The experiments generally represent businesses that are committed to the process of developing maintenance performance, where using fixed intervals is normal and occasionally not enough resources are used. Experiment runs with manual inspections use a goal value representing the condition that 50% of all maintenance activities should be inspections. The tradeoff between more or less frequent inspections is used as a comparison between the two first CBM Experiments. The third CBM experiment uses the best result to test what happens when staff is limited; a relevant implementation scenario. A similar procedure is conducted for CBM6 experiments, according to Table 2.

4.1 Results RTF Experiments

![Defect creation and Equipment health RTF runs](image)

Fig. 12. Equipment health RTF runs

Fig. 12 shows the behavior in the parameters defect creation and Equipment health. The RTF experiment indicates stable behavior where defect elimination is at the level of defect creation. The RTF_step staff experiment, line 4, shows an initial pulse on Equipment health, due to insufficient resources. However, with each step staff increase, an improvement is indicated for a time, then balances back towards line 3; also noticeable is that the effect decreases with each staff increase. The increase in defect creation in RTF_step staff is due to the increased use of equipment; including the feedback of defect creation from operational load (Murthy et al., 2002).

![Availability and MTTF in production RTF runs](image)

Fig. 13. Maintenance in production RTF runs
The temporal effect in parameter MTTF in experiment RTF_step staff, line 4 in Fig. 13, is a result of more frequent repairs having a positive effect on Equipment health. Each step staff increase also leads to a positive effect on availability, line 2, which shows the behavior of a greater initial effect that nevertheless diminishes. This effect is expected in reality, here explained by the model, and reveals why adding staff may be a common procedure but is nonetheless not very successful in the long-term.

Fig. 14. Maintenance costs RTF runs

Fig. 14 illustrates the economic consequences of strategies on maintenance cost and consequential costs. The RTF shows neutral behavior, while RTF_step staff starts at a lower level and gradually increases. Comparing maintenance costs and consequential costs in the experiment RTF_step staff, lines 2 and 4, reveals a minor phase delay of 13-26 weeks, which implies that consequential effects come with a delay to direct costs.

Fig. 15. Accumulated economic results RTF runs

Fig. 15 shows the accumulated economic results. The RTF experiment is neutral and RTF_step staff has an initial positive result for budget due to less staff; however, after two years, costs are greater than the value from maintenance. In RTF_step staff, line 2, there is an initial lack of results due to poor availability, but as availability increases, the company result has a positive outcome until before week 312 when accumulated results start diminishing. Simulation experiments of the model clearly reveal that a reactive strategy using RTF follows the expected behavior associated with lower performance, as in Swanson (2001).
4.2 PMₐ Experiments

**Fig. 16.** Equipment health PMₐ runs

**Fig. 17.** Maintenance in production PMₐ runs

**Fig. 18.** Maintenance costs PMₐ runs
Fig. 19. Accumulated economic results PM_6 runs

Fig. 16 shows that both PM strategies develop poor equipment health, worse than for the RTF scenarios illustrated in Fig. 12. The main explanation is the positive result in improved availability, Fig. 17, and the increase in defect creation, Fig. 16, finding a new equilibrium. Increased availability implies a greater operation load on equipment. However, at the same time, MTTF is improved, see Fig. 18, positively affecting breakdown frequency and reducing defect creation from collateral damage. It can be considered that the time delay to implement PM work is three years. In PM_100%_lim staff, an effect of limiting preventive resources is that the achieved availability is reduced to approximately 95%. Studying Fig. 18 reveals that when the limit intrudes, at about four years, the maintenance cost starts to vary, which is due to the reoccurring backlog of scheduled repairs. It seems that this phenomenon is related to the situation regarding insufficient preventive resources. PM_100%_lim staff shows better economic results, see Fig. 19, and strictly looking at the maintenance budget reveals it is the only successful one. Although, studying the overall result in the accumulated company results of both experiment runs reveals similar behavior.

4.3 CBMi Experiments

Fig. 20. Equipment health CBMi runs

A frequent inspection interval supported by preventive resources, as in CBMi_50%_4w in Fig. 20, shows that it is a forceful approach to reducing the number of hidden defects in the equipment. While CBMi_50%_13w shows a slightly improved behavioral effect, CBMi_50%_4w_lim staff reveals deterioration that is similar to the PM_6 experiments. Defect creation deviates considerably after three years and the effects of the different strategies are apparent.
There is a distinct initial improvement of availability in all experiment runs of Fig. 21. It is clear which one is most beneficial. Furthermore, Fig. 21 reveals that the limit of resources, CBMi_4w_lim staff, eventually has the effect of a setback in which the workload affects the capacity to keep availability at its level. This is also revealed in Fig. 22 line 6, which illustrates that the PM work parameter has a negative development after five years, due to an increasing backlog of PM work. For MTTF in all the experiments, the first three years follow a similar development, thereafter the results differentiate. Although the CBMi_50%.4w experiment indicates strong development after three years, it decreases before 312 weeks, due to a growing PM backlog which increases the risk of breakdowns.

Examining the parameter PM work in Fig. 22 reveals that CBMi_50%.4w_lim staff has the poorest development, which of course would be expected, since fewer resources lead to a larger backlog that eliminates the benefits of PM work. Furthermore, an aggressive strategy of frequent inspections, as in CBM_50%_4w, which has a positive effect on equipment health, also suffers from a PM backlog, compared to CBM_50%.13w in Fig. 22. The fraction CBM over PM for the different experiments shows quite diverse results. Experiment CBM_i_50%.4w reaches the goal of a 0.5 fraction, meanwhile, the other experiments do not.
A decrease of maintenance consequential costs, due to successful PM work, is depicted in CBMi_50%_13w and CBMi_50%_4w on different scales in lines 1 and 2 of Fig. 23; however, it is not shown in CBMi_50%_4w_lim staff. This indicates the importance of having enough resources to support a strategy towards more proactive maintenance.

The economic results, in Fig. 24, follow similar behavior as previous PMi experiments. The experiments demonstrate that it is not possible to sustain the maintenance budget, since applying CBM, requires a larger budget. However, gradually, positive results are revealed from the holistic perspective.

Comparing the CBM experiments shows the benefits of implementing shorter inspection intervals to detect defective equipment. However, conducting frequent inspections also implies that more resources are necessary. All three experimental runs indicate that more frequent inspections provide better results; however, it is not possible to limit resources and at the same time increase inspections.
4.4 CBM, Experiments

Fig. 25. Equipment health CBM, runs

Fig. 26. Monitoring progress of PM work CBM, runs

Explaining the CBM, experiment runs requires the use of only three graphs, since the results reveal similar patterns of behavior as in previous sections. CBMs_5%_4w is the experiment run that stands out in this comparison. Interestingly, experiment runs CBMs_5%_4w_lim staff and CBMs_25%_4w follow similar patterns of behavior in Equipment health and fraction CBM over PM. It seems that both strategies have a similar cause for the consequence of work overload for maintenance engineers. However, a closer examination of the details reveals that for CBMs_5%_4w_lim staff, the main cause is the firm limit on the number of engineers, which slows the progress and restricts the rate of CBM preparations, see Fig. 26. However, for CBMs_25%_4w, the main cause can be found in the greater number of defects identified during the manual inspections, illustrated in the graph of identified defective equipment in Fig. 27. One could propose that a strategy utilizing CBM with more sensors would be the best. However, with current policies, it has been shown that inspections at more frequent intervals provide the higher rate of identified defective equipment.
5. Results and discussion
A review of all the possible strategies in any model is strongly limited by time, thus, only ten experiments were conducted in this study. These investigated three different development goals for the mix of maintenance methodologies, and some resource allocation limits. Nonetheless, the application of the system dynamics model presented in this paper may have provided, through the experiments, some general insights into the strategic development of maintenance performance. For each maintenance methodology, the experiments can be summarized accordingly:

- **RTF**, the experiments enable us to identify, in Fig. 13, that as expected an increase in reactive staff provides an increase in availability performance for the short-term; however, the application of this dynamic study also reveals that availability performance saturates at a lower level after a delay. The experiments reveal that this is due to the fact that the underlying conditions for achieving the sustained improvement of equipment health are not present, Fig. 12. Nor does the RTF methodology show any positive, endogenously created economic development, Fig. 14 and 15.

- **PM_{ri}**, similarly, these experiments enable us to identify, in Fig. 17, that as expected, implementing PM work, using fixed intervals, greatly increases availability performance and does so for a three-year period. Furthermore, the application of this dynamic study reveals that if resources are insufficient during this three-year process, it will go unnoticed and result in reduced availability after this period. This leads to unstable maintenance costs, Fig. 18, and poorer equipment health, Fig. 16. The experiments also reveal that introducing PM_{ri} will appear successful, despite the previously mentioned unimproved equipment health, when the result performance indicators are examined, such as improved MTTF, Fig. 17, and positive economic development, Fig. 19.

- **CBM_{ri}**, the experiments show that implementing CBM using inspections increases availability significantly, Fig. 21, similar to the PM_{ri} experiments. However, with insufficient resources, the positive initial development will diminish in the long-term, indicating noticeable differences in MTTF, Fig. 21. This illuminates the necessity to support the desired development with resources accordingly. The CBM_{ri} experiments also appear successful, if only the economic result parameters are examined, Fig. 24. However, in combination with enough resources, CBM_{ri} is a successful strategy, according to the experiments, and more frequent inspection intervals improve actual health status.

- **CBM_{si}**, the experiments demonstrate that implementing CBM using sensors largely follows previous experiment results. Furthermore, it is shown that insufficient resources do not harm positive development as much as in previous experiments; for instance, compare line 3 in Fig.

![Fig. 27. Identified defective equipment CBM, runs](image-url)
25 with line 6 in Fig. 20. In addition, a less aggressive strategy may be more beneficial, according to the conducted experiments, where a goal of 5% CBMs performs better than 25% CBMs. The experiments also indicate that the main flow of identified defects that are scheduled in the planned maintenance work comes from inspections and not sensors, regardless of the tested CBM strategy, Fig. 27.

As a matter of fact, the experiments reveal that proactive strategies which seem to be successful do not necessarily have a deep impact at a sustainable level. The model makes explicit the importance of the underlying equipment health, which can be considered a basis for the availability in production. Thus, the more effectively maintenance interventions act on true equipment health, the more likely it will gradually improve. In this respect, the experiments reveal that the effect of applying PM_{h} and CBM_{h} is very different, but at the same time sensitive to the level of staff.

6. Conclusions and future directions
There is some noticeable need in industry to evaluate the dynamic effects of applied strategies and policies on maintenance performance, in order to identify sustainable actions that challenge short-termism. The proposed system dynamics model presents a first step towards a structural theory for strategic development of maintenance, considering both strategic (long term) and operational (short term) aspects of maintenance. It is a learning model created based on the difficulty of anticipating the long-term consequences in operations from the decision making regarding resources spent in maintenance. The model includes what is considered the least number of components required to generate representative behavior, in order to illuminate the strategic development of maintenance performance, including equipment health, the operating interaction with production, and total maintenance cost, to support challenging how strategic development is carried out in maintenance organizations.

The literature review of previous work has identified that maintenance behavior has been explored by utilizing system dynamics; however, to date, the amount of published material reveals there are few quantitative examples for academics to learn from. In fact, the highly relevant papers to this study have only provided qualitative results; thus, our study openly presents the simulation model for other researchers to audit and utilize. Furthermore, to our best knowledge, this research is also justified by the fact that there are no studies applying system dynamics considering both the direct and the consequential costs of maintenance.

A selection of experiments is provided to illustrate the application of the model to evaluate the development of maintenance performance. This enables analyzing the combined outcome of the direct and delayed feedback effect of improvements throughout the model structure. Hence, the experiment results illustrate effects in the model derived from changing some of the many possible policy values for the development towards an assumed, better mix of different maintenance methodologies (Tsang, 2002), such as: RTF (Run to Failure), PM_{h} (preventive maintenance using fixed intervals), CBM_{h} (Condition Based Maintenance using inspections), and CBM_{l} (Condition Based Maintenance using sensors). The results show that there are both short-term and long-term consequences from intended changes. One general insight gained from the experiments, indicating the value generated from a dynamic systems study, is the possibility of revealing the double messages in the system: one obvious, and one hidden. This can have the effect that the application of this base model may facilitate the investigation of seemingly obvious strategies, to reveal the dynamics of underlying and hidden conditions, vital for the long-term development. For example, it supports the examination of strategies for the normally hidden behavior of equipment health, and examines the use of obvious strategies which may also have second order consequences, such as the addition of direct resources which have delayed effect according to presented experiments. Therefore, experimenting in the conceptual model may contribute valuable information prior to determining strategy and could also initiate further investigations by the application of the model. The use of a tool
to investigate strategic development in maintenance, by taking into account its consequence on maintenance performance, production performance, and economic performance, can be considered to have a practical value.

An example of insight regards the maintenance budget, which normally defines management maneuverability. One important consideration about maintenance development is how the focus on the maintenance budget may limit the progress of implementing PM work. None of the experiment runs managed to stay on budget. This implies that if the maintenance budget had been the priority in deciding how to develop maintenance in the presented experiments, it would have significantly limited the long-term development! Therefore, it highlights how a dynamic systems study can encourage other strategies than the present procedures of conduct, in order to identify the most beneficial strategy holistically. In addition, it highlights the possibility of addressing economic short-termism by applying the model.

In conclusion, the simulation of the developed model facilitates investigating the development of maintenance performance at the strategic planning level, in order to identify directions for maintenance performance management. The model concerns the overall development of maintenance performance, with respect to the size of the time dependent workload that is generated by production, which is a function of current equipment health and current applied maintenance methodologies. The presented results indicate that such a tool may have the potential to contribute to the struggle within maintenance to justify efforts needed to transform it into proactiveness. This may include applying more precision in the analyses of dynamic consequences than just associating a proactive strategy with improved performance, as otherwise declared (Swanson, 2001). Furthermore, by supporting management in its formation of policies, the extended effects of such a tool may redefine current maintenance strategy and budget processes by illuminating the holistic value of maintenance, including its required development into the equation, instead of letting short-term requirements limit its value.

Future research can take several different directions. For example, it could include production and inventory dynamics to enable studying the effects of preventive maintenance at the supply chain level. Ongoing work includes more detailed investigations and workshops at the companies, which can add feedback structures that adapt the base model to a more specific application study. Another research direction is to strengthen the general insights gained from the simulation experiments. This could involve exploring the use of simulation-based optimization (SBO), where the concept of multi-objective optimization (MOO) has endowed SBO to not only seek a single optimal solution with a simulation model, but multiple Pareto-optimal solutions that have a high spread in the objective space. Except for a few studies, including ours (Aslam, 2013), the use of SBO with SD models has, in general, been much less reported. As a matter of fact, applying MOO on SD models can lead to benefits in identifying optimal solutions based on tradeoffs between several conflicting objectives (Aslam, 2013), such as availability, maintenance costs, and maintenance consequential costs for the maintenance model, to be more specific. Due to the vast possibilities provided by investigating the model's dynamics in order to select a progressive maintenance strategy, integrating such a technique has been initiated and is expected to significantly contribute to model analysis.

Acknowledgements
This work was partially financed by the Knowledge Foundation (KKS), Sweden, through the IPSI Research School. The authors gratefully acknowledge their provision of the research funding and the support of the industrial partners Volvo Car Corporation and Volvo Group Trucks Operations.

References


EN13306 2010. Maintenance - Maintenance terminology, European Standard EN 13306


Units in stocks and flows in the different parts:
1. Equipment, 2. Defects, 3. PM work orders, 4. Information,

2. Equipment health status

3. Applied maintenance methodology and scheduling

4. Maintenance development process

5. Holistic economic performance
Linnéusson G, Ng AHC and Aslam T. (2018) Quantitative analysis of a conceptual system dynamics maintenance performance model using multi-objective optimisation. *This is the Manuscript of an article submitted to the Journal of Simulation on [2018-02-01]. At the time the thesis was published, the manuscript was still under review.*
Quantitative analysis of a conceptual system dynamics maintenance performance model using multi-objective optimisation

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Abstract
This paper presents a quantitative analysis of a conceptual, system dynamics (SD) model by the application of multi-objective optimisation (MOO). The SD model investigates the strategic development of maintenance performance, using a system view of maintenance costs, while the execution of MOO evaluates multiple simulation runs, seeking the simultaneous trade-off solutions of the three conflicting objectives: maximise availability, minimise maintenance costs, and minimise maintenance consequential costs. The study explores three scenarios that represent companies at different states of developed maintenance performance.

The application of this integrated, simulation-based optimisation approach reveals multiple analyses of system behaviour of the SD model, which are presented in a compact format to a decision maker. Actually, notwithstanding the application to a conceptual model, the study results make explicit the nonlinearity between invested maintenance cost and its consequent effects. Furthermore, the approach demonstrates the contribution to the process of strengthening the usefulness of the conceptual maintenance performance model.

Keywords: simulation-based optimisation, system dynamics, multi-objective optimisation, maintenance performance, maintenance costs.

Introduction
For manufacturing industries, maintenance has become a critical capability in order to compete in the marketplace. The increasing levels of technology and automation mean that more capital is tied up in production equipment (Garg and Deshmukh, 2006) and more prevalent consequences occur as a result of unplanned breakdowns (Swanson, 1997). Further, it is known that the cost of maintenance constitutes a considerable part of the manufacturing budget, see, e.g., (Salonen and Deleryd, 2011). However, it is hard to acknowledge the consequential maintenance costs (Vorster and De La Garza, 1990; Pascual et al, 2008) which are considered the larger portion of the total cost. For instance, according to Wireman (2004), downtime costs can be up to 14 times more than the cost of a repair. In order to manage the situation, resources need to be intelligently invested in a proactive maintenance strategy and, according to Sherwin (2000), such a strategy must be well-grounded in top management
by translating it into economic terms. In accordance with Simões et al, (2011), the previously narrow operational perspective of maintenance has now shifted to an organisational strategic perspective. Hence, these recent developments and the increasing complexity of the manufacturing sector seek improved methods that are capable of supporting development towards proactive maintenance actions traded off against their consequent effects. Accordingly, this study reutilises a previously proposed, novel system dynamics (SD) simulation model (Linnéusson et al, 2018). The novelty of the model is based on its promotion of a system's view of maintenance costs that also include the dynamic consequential costs as the combined result of several interacting maintenance levels throughout the constituent feedback structures. According to Bertrand and Fransoo (2002), it can be considered as a conceptual model, since it is more theoretical and academic in nature. Nonetheless, it has been developed to address the practical problem of how to achieve sustainability in the strategic development of maintenance performance in the automotive industry. Furthermore, the model aims to support the situation, described by Woodhouse (2001), that it is the short-term cost perspective that causes the present insufficient management of maintenance assets, where known best practices do not align with the implemented ones. Thus, it can be useful to evaluate the consequences of a maintenance strategy, with respect to generated costs, both short and long-term in character which, according to Pascual et al, (2008), the current inadequate economical efforts cannot handle. Therefore, in order to explore such a model thoroughly, this paper extends the previous work by applying simulation-based optimisation (SBO). While SBO can be used as an effective approach to seeking some optimal solution in an automated manner, see, e.g., (Fu, 2014), the concept of multi-objective optimisation (MOO), see, e.g., (Deb, 2014), has endowed SBO to not only seek a single optimal solution with a simulation model but multiple Pareto-optimal solutions that have a high spread in the objective space. Except for a few studies, including ours that investigated the integration of MOO and SD models (Duggan, 2008; Hedenstierna, 2010; Dudas et al, 2011; Aslam, 2013), its use has, in general, been much less reported. In fact, to our best knowledge, besides our studies, the application of MOO has not previously been applied to maintenance SD models. The presented study, integrating MOO with an SD model, examines the results of three scenarios which represent three disassociated starting points of preventive maintenance that an industrial manufacturer might deal with. MOO enables the critical applicability of the simultaneous evaluation of several conflicting objectives, in which both the decision and objective landscape of maximising availability, minimising maintenance costs, and minimising maintenance consequential costs can be analysed. Essentially for this paper, we first motivate the application of SBO and specifically MOO for maintenance optimisation, as well as the need of an overall method, such as SD, to appropriately address system costs in maintenance from a strategic perspective. Thereafter, an overview of the SD modelling process is provided with the specific contribution from a MOO+SD study to the process. This is followed by an overview of the reutilised and previously presented SD model, a description of the general procedure for a MOO+SD analysis, and the presentation of the three scenarios. The results and analysis section reviews the quantified Pareto-front solutions from which the analyses are drawn. This is supported by two types of visualisation plots; the scatter plots that provide an overview of the possible objective landscape obtained from the trade-off and the parallel coordinate heat maps that enable the comparison of decision parameters in order to fulfil the conflicting objectives.

**Maintenance optimisation and simulation**

Maintenance optimisation (MO) quantifies maintenance costs and benefits (Dekker, 1996). According to Dekker (1996), there are several problems regarding the practical applicability of recent MO research and many current maintenance researchers have also pointed out that the analytical approach is inadequate (Van Horenbeek et al, 2010; Lad and Kulkarni, 2011; Sinkkonen et al, 2013; Alrabghi and Tiwari, 2015). Nicolai and Dekker (2008) assert that many maintenance policies are not analytically traceable and therefore MO requires simulation. Hence, the application of simulation for MO has increased (Garg and Deshmukh, 2006) and is considered an emerging trend, according to
Sharma et al, (2011). In their review, Sharma et al, (2011) sought even more simulation studies on optimizing maintenance costs for different combinations of maintenance activity. However, recently, Ding and Kamaruddin (2015) criticised the practical applicability of current maintenance policy optimisation research and consequently indicated that the latest developments with simulation are insufficient. In fact, despite the emerging development of simulation and SBO in maintenance research, Alabdulkarim et al, (2013) claim that maintenance problems are commonly treated in isolation. Moreover, in their state-of-the-art review of SBO applications in maintenance modelling, Alrabghi and Tiwari (2015) identified that the maintenance literature generally suffers from oversimplified studies that neglect many of the interconnections found in real systems. According to Wang (2002), one major problem that the MO literature exposes is that only using the minimised maintenance cost rate as the single optimisation criterion results in most cases having unacceptably low levels of system reliability. Instead, Wang (2002) argues that the trade-off between maximised reliability and minimised maintenance costs should be the criteria being sought; which requires a simultaneous consideration of both objectives. Although a simultaneous evaluation is attainable using MOO algorithms, according to Alrabghi and Tiwari (2015), a limited number of MOO studies are available in the maintenance literature. For example, several authors recently considered the application of MOO for MO, see, e.g., (Ilgin and Tunali, 2007; Van Horenbeek et al, 2010; Van Horenbeek et al, 2013; Alrabghi and Tiwari, 2015, 2016). However, as a final remark, De Almeida et al, (2015) generally disqualified current maintenance and reliability models for not considering the multi-criteria nature of decision-making. They conclude “there is an inability to translate the multiple objectives of the problem in terms of cost or financial impact” (De Almeida et al, 2015, p.261). Moreover, they see potential in an increased focus on better representing the decision makers’ preferences regarding the decision problem, including the conflicting trade-offs, and using MOO to achieve a more realistic analysis (De Almeida et al, 2015, p.253).

The above-mentioned aspects could be enhanced with a discussion regarding the purpose of MO models, such as, what system level of investigation is under consideration and why is it appropriate? For instance, the discussion in Van Horenbeek et al, (2010) concerns the possibility that the selection of optimisation objectives may lead to sub-optimised solutions. However, they do not discuss how the construct, or boundary of the model, may delimit the investigation. The above review reveals that MO, with its traditional, technical and analytical approach, has resulted in overly extensive simplifications and delimitations of the problems under study. As a response to including a more practical maintenance perspective, Alabdulkarim et al, (2013) specifically emphasise that discrete-event simulation (DES) has the capabilities to replicate the production system and provide more realistic analyses. Moreover, although the above review identifies researchers who point out that the application of MOO is the next step, only a few advocates the need to incorporate the decision maker’s preferences, as De Almeida et al, (2015) do. According to Sterman (2000), this is one of the most important criteria that should be addressed first in a modelling project. Furthermore, to enlighten what we mean by the level of analysis, we provide the following example: Alabdulkarim et al, (2013) promote the application of DES to evaluate different maintenance strategies, in order to support a wider system perspective, rather than the previous analytical MO methods which may provide analyses that are too narrow. However, according to Gunal and Pidd (2010), utilising DES as a tool also tends to focus on the operational level of specific areas. Further, they declare that if the policy-level analysis is of interest, it may not be relevant to utilise DES, nor is feedback behaviour adequately visualised to support the answer to why certain behaviours arise. In order to support the overall view of the policy-level analyses and appropriately address the strategical perspective, several researchers argue for the application of SD, see, e.g., (Keating et al, 1999; Repenning and Sterman, 2001; Warren, 2005; Morecroft, 2007). However, research on the application of SD in maintenance is still overrepresented by qualitative studies, with few published simulation models (for further details see Linnéusson et al, 2018).

A relevant example of applying SD in maintenance is found in Ledet and Paich (1994) where the authors analyse the contribution of maintenance to manufacturing and focus on the relationships that generate the performance of, e.g., mean time to failure and mean time to repair. Hence, SD models
may include the underlying conditions required for the development of an organisation’s maintenance performance. Linnéusson et al., (2018) present a base model of maintenance performance using SD simulation, with a system’s view on maintenance costs, in which short-term benefits and costs can be evaluated for their long-term effects including consequent levels of future costs; based on theory and studies at two large maintenance organisations in the Swedish automotive industry. Their model was subsequently applied to investigate, for example, the impacts of using condition-based maintenance to move from a reactive maintenance approach to more proactive behaviour, which is one of the identified key areas of future research in Alabdulkarim et al., (2013). However, despite the capabilities of addressing the strategical perspective, multiple analyses of SD models to explore the solution space are time-consuming. Therefore, the combination of MOO and SD has been motivated (see, e.g., Duggan, 2008, Aslam, 2013) to quantitatively analyse the trade-off solutions in the objective space.

In conclusion, the above review of MO and simulation can be summarised accordingly. Applying analytical modelling to quantify maintenance costs and benefits is not enough. Furthermore, current simulation contributions do not seem to achieve enough practical relevance, due to their oversimplified system boundaries. MO models have a history of only focusing on maintenance costs, thus, it has been argued that the application of MOO would be better if it included the multi-criteria nature of decision-making. DES is considered applicable at the operational level to support the execution of maintenance but may be insufficient to support understanding the feedback behaviours at the strategic level. Finally, the SD approach may support the formulation of policies to develop maintenance performance for the strategic level, however, few simulation applications on maintenance performance are available and, thus, the applications of MOO on such SD models, beside ours, are non-existent. In summary, it motivates the integrated SBO approach, where the application of MOO potentially supports the exploration of the applied SD model in its aim to support the investigation of the strategic development of maintenance performance using a system’s view to quantify maintenance costs and benefits.

The modelling process in SD

This section presents an overview of the modelling process in an SD project. The description follows the modelling steps according to Sterman (2000):

- **Problem articulation;** understand the problem and articulate it, and select the boundary.
- **Dynamic hypothesis;** formulate a dynamic hypothesis regarding how the problem dynamics are endogenously generated from the feedback structure within the selected boundaries. Such formulation includes studying the relevant literature on problem phenomena and investigating the situation at the studied companies.
- **Formulation;** build a simulation model based on the dynamic problem and test the hypothesis, includes existing ideas from the literature and tacit real-world descriptions. This is a highly intuitive process (Sterman, 2000), and there are no formal descriptions of how to implement system dynamics projects (Linnéusson, 2009). The model includes specifications of structure and decision rules, parameter estimation, behavioural relationships, initial conditions, and tests for consistency with the aim of the model.
- **Testing;** examine whether the model reproduces adequately, with respect to its purpose. SD models are causal-descriptive as well as “statements as to how real systems actually operate in some aspects” (Barlas, 1996, p.185). The model’s internal structure validation, together with its capacity to explain how the behaviour arises, is therefore crucial. While correlational black-box models are validated using statistical tests, this is not applicable for validating behaviours in an SD model, due to the problems of autocorrelations and multicollinearity (Barlas, 1996). Moreover, judging the validity of the internal structure of a model is very problematic, and most methods are informal and qualitative in nature (Barlas, 1996) (see, for instance, Luna-Reyes and Andersen, 2003). Therefore, it is largely the model’s usefulness in explaining problem phenomena that determines its validation (Sterman, 2000). In other words, if the model can be
considered acceptable relevant and its usage may assist managers’ decision-making in the real world, it supports validation (Bertrand and Fransoo, 2002).

- **Policy formulation and evaluation:** apply the model to explore possible “what if” scenarios, test their sensitivity to implementation, examine synergy policies, etc.

In this section, it is relevant to pinpoint and complement the contribution of the MOO application to an SD model. The effective search of the objective landscape mainly supports the *policy formulation and evaluation* step in the modelling process above. However, a MOO study can also be considered to contribute to the *testing* step, further reviewed by step 3 in the schematic illustration of Figure 3. Figure 3 illustrates that the SD model must be able to produce relevant output, on a high spread of input parameters, in order to pass step 3.

**Overview of the conceptual SD model**

This section presents a concise overview of the applied SD model in the MOO analysis. The full model includes a large feedback structure which requires much space for transcription (for the full structure and equations review see Linnéusson et al, (2018), and the appendix where the 1:1 structure is provided). Managing maintenance in the economic short-termism framework is challenging. Therefore, the purpose of the model is to support investigating the causal relationships between strategic initiatives and performance results, as well as enable analyses that take into consideration the time delays between different actions, which Tsang (2000) has sought from future researchers. The model boundary selection (BS) includes, according to Linnéusson et al, (2018), aspects such as:

- **BS1.** Equipment health and its interaction with the operating load of production,
- **BS2.** Enable the analysis of different applied maintenance methodologies and their optional mix,
- **BS3.** Evaluate processes of continuous improvement of maintenance performance,
- **BS4.** Direct and indirect maintenance resources working reactively or proactively,
- **BS5.** Estimate the total costs for the complete analysis, such as reactive and proactive trade-offs.

![Figure 1. Overview of the maintenance performance SD model.](image)

The SD model overview in Figure 1 concisely describes the maintenance performance model, including the boundary selections (BS) above, to clearly point out their relevance to the model with their subsequent descriptions below. Each box in the figure has structures of stocks and flows of a different size, which are the building blocks in SD modelling (accessible in the appendix).

- **BS1** includes the *equipment health* (*EH*) structure and its interaction with the maintenance performance in production (*MPP*), which at any moment in time has a certain *balance of proactive over reactive maintenance in production* (*MPP*). The *EH* is represented by a stock of accumulated defects, whose flows are governed by the result of the *MPP*, where defects are reduced by planned or
unplanned repairs and defects are generated by collateral damage from the breakdown rate in production and the continuous operation load. There is a reinforcing feedback (R1) in these flows of hidden defects, where the poorer EH causes more reactive breakdowns and thus more collateral damage, making EH even poorer. Reversely, better EH leads to less need for reactive maintenance, however, it depends on the support of BS2. Availability (AT) is the result of the MPP, where reactive work and proactive work both aim at retaining equipment at full functionality; however, they do so through different feedback structures in the model, thus, with different effects on total costs (CT).

BS2 supports the improvement of EH by the wise application of preventive maintenance methodologies (PMM). Therefore, with an improved palette of PMM, it supports the efficiency of defect identification where, for instance, condition-based monitoring using sensors (CBM), through its online monitoring, is perhaps more efficient than PM using fixed interval (PMfi). The applied palette of PM methodologies also includes CBM using discretionary inspections by maintenance staff at the interval (CBM). These three methodologies are different in character. They have different planning triggers for work orders and different capabilities for detecting anomalies. For example, PMfi has a fixed average delay for initiating work orders and a fixed number of parts to repair. CBMi, on the other hand, is initiated at the interval and each inspection is performed if the staff is available. This results in a certain number of parts to repair, depending on the level of EH. However, the optimal mix is not evident, as the results of the MOO analysis in this study indicate.

BS3 indicates that the palette of PM methodologies can be improved, while the maintenance development process is a delay structure that transforms information from breakdown reports into countermeasures based on root-cause analyses (RCA) of available information. Different policies for retrieving information and the process to transform it can be formulated, for instance, whether the number of maintenance engineers (SE) affects the flow of RCA. Its delayed output may be new PM preparations, or the development of old ones, changing the mix between PMfi, CBMi, and CBMs and its total relation to all parts of the system. This means any scenario of between 0% to 100% PM work can be subject to experimentation, as well as any of the varying optional mix of the methodologies.

Now the balancing loop B1 can be closed, which describes the continuous improvement generated by the need for increased capabilities to maintain EH at an acceptable level. Poorer EH leads to poorer MPP with a high rate of breakdowns (RBD), for which repairmen document, if known, their causes. Through the analyses of engineers (SE), this eventually results in improved PM preparations of either PMfi, CBM, or CBMs. It also leads to more efficient PM work and has a greater impact on the EH through the more proactive balance of preventive repairs in production.

BS4 nonetheless regards that the dedicated resource planning, to a large extent, decides upon the effective result through the above-mentioned feedback mechanisms. Three types of staff resources are included, engineers (SE) and repairmen (SR) working proactively or reactively. SE are dedicated to their tasks throughout the simulation period, while the SR move between their working pools according to the workload created from the RBD. If RBD persists, SE cannot work proactively, however, if the RBD increases, proactive SE staff will help and support the acute need.

BS5 sums up the total maintenance costs (CT) as a consequence of the palette of PMM, including maintenance costs (CM) of staff and spare parts, investment costs in CBM, and consequential maintenance costs (CQ) from breakdowns and tied up capital in the spare parts inventory. This structure also contains the accumulation of the maintenance budget accomplishment and the accumulated profits throughout the simulation period; the accumulated economic result (ER). As the overview in Figure 1 illustrates, there is no feedback from the CT back to the other structure, hence, the measures in BS5 do not impact any of the endogenously-created dynamics, which could be the case for another system boundary.

Validation of the SD model has considered the normal techniques in SD, applying the formal validation tests according to Barlas (1996):
• Direct structure tests have been followed, which constitute purely qualitative comparisons with the literature and knowledge about the real-world system provided by the study of two large maintenance organisations.
• Structure-oriented behaviour tests have been followed to a large extent. Such tests utilise the quantitative simulation to evaluate the structures’ capability to represent the expected feedback behaviours, by the application of extreme condition tests, behaviour sensitivity tests, and boundary adequacy tests.
• Behaviour pattern tests do not provide added value to validate the model structure (Barlas, 1996), but validates the generated behaviour. However, the conceptual model does not include parameter face values which need an application case where direct input data is taken from the real-world system.

The tests have resulted, to some extent, in justifying the overall model behaviour. They have also included the testing of assumptions, with the help of industrial maintenance experts. Furthermore, the application of MOO has resulted in strengthening the structure-oriented behaviour test, by exploring errors in the model, as mentioned previously and described schematically in Figure 3. Consequently, model equations have been improved, adding some parameters and new structures, compared to the conceptual SD model presented in the study by Linnéusson et al, (2018).

Applying MOO with SD
The simulation principle for evaluating SD models using MOO follows the general SBO-process illustrated in Figure 2, where the “Simulation Model” is regarded as a “Black Box” for the optimisation engine. The SD model was built in Vensim DSS and the MOO simulation model in modeFrontier. The integration of MOO and SD has followed the MOO+SD methodology developed by Aslam (2013), which in detail describes the steps of decision space sampling, global objective space search, and local objective space refinement. This leads to the presentation of optimal solutions which are part of step 4 in the general procedure for a MOO+SD analysis, illustrated in Figure 3. The MOO simulation model utilises the NSGA-II algorithm, and the evaluation process activates and executes multiple runs of the SD model. In the literature, Fast Elitist Non-Dominated Sorting Genetic Algorithm (NSGA-II), developed by Deb et al, (2002), is probably the best-known population-based metaheuristic algorithm for giving very good approximations of the Pareto front. Three major features have rendered the outstanding performance of NSGA-II which make it to be chosen for this work: (1) an elitism principle, based on a $\lambda + \mu$ elitism selection procedure; (2) the calculation of crowding distance value for an explicit and efficient diversity preserving mechanism that eliminates an extra niching parameter used in other MOO algorithms; (3) non-dominated solutions is emphasised by equipping with a fast non-dominated sorting approach that has a complexity of $O(mN^2)$, instead of $O(mN^3)$ like Multi-Objective Genetic Algorithm (Babbar et al, 2003).

Furthermore, the presented optimisation scenarios in this study are the result of applying an initial DOE (design of experiments) with 50 randomised values on the inputs, presented in Table 1, run for 100 generations, totalling 5000 evaluations. The generated initial population of Pareto-front solutions was then used as “a trained DOE”, run for the number of generations that resulted in a final solution set of at least 50,000 evaluations.
This is the Manuscript of an article submitted to the *Journal of Simulation*.

The procedure for the MOO+SD analysis can generally be described according to Figure 3. Step 1 is the ordinary modelling procedure for an SD model. Step 2 includes setting up the optimisation model in the optimisation engine, based on the selected conflicting objectives in the SD model, and output parameters of interest. Step 3 includes evaluating the initial results, which most certainly will require further improvements of the validity of the SD model since the MOO evaluations expose any inability of the SD model to generate a valid answer. When step 3 reveals valid answers, step 4 can start with the aim to generate analysable results, such as the subsequent scatter plots and parallel coordinates in the results and analysis section. Step 5 represents the comparison of several scenarios, as performed in this study. Step 6 represents post-analyses of solutions of interest, where a Pareto-front solution can be analysed in the SD software more deeply, in order to investigate the feedback dynamics of its performance; however, this is not explored further in this paper.

1. Develop the SD model for the case, problem boundary and validation aspects, according to SD-standard procedures (Barlas, 1996, Sterman, 2000).

2. Define the MOO model, such as, the input parameters and the conflicting objectives.

3. Test run the MOO model, if needed, improve SD model to enable valid MOO-evaluations, according to below, and initiate search of Pareto-front.

4. Evaluate results of MOO-scenario, explore Pareto-front solutions.

5. Meta-analysis, compare different MOO-scenarios.

6. Select Pareto-front solutions of interest, from MOO-scenarios, for further investigation in the SD model to study their dynamic behaviours over time, to support decision-making for the specific strategy.
MOO of the maintenance performance model
The MOO scenarios represent companies at different states of developed maintenance performance. Thus, each scenario seeks to evaluate the same input parameters, and the same ranges of these, according to Table 1. The input parameters are selected in the SD model on the basis of their expected effects that can lead to the attainment of a proactive behaviour in maintenance. The aim of each optimisation scenario is to identify the most beneficial development towards a future state in the SD model, which uses a time horizon of 10 years. This is applied using the optimisation objectives of maximising availability, \( \max(A_t) \), minimising maintenance costs, \( \min(C_M) \), and minimising maintenance consequential costs, \( \min(C_Q) \).

Table 1. Input parameter data from SD model in Appendix for the MOO evaluations.

<table>
<thead>
<tr>
<th>Input parameter in SD model</th>
<th>Notation:</th>
<th>Range:</th>
<th>Step:</th>
<th>Note:</th>
</tr>
</thead>
<tbody>
<tr>
<td>numberRepairWorkers</td>
<td>( S_R )</td>
<td>4 – 50</td>
<td>1</td>
<td>Total work pool of repair staff</td>
</tr>
<tr>
<td>numberMaintenanceEngineers</td>
<td>( S_E )</td>
<td>0 – 30</td>
<td>1</td>
<td>Staff dedicated to develop new PM work</td>
</tr>
<tr>
<td>fractionPMiFromRCA</td>
<td>( F_{PM} )</td>
<td>0 – 1</td>
<td>0.05</td>
<td>These two parameters control the distribution between PM, CBM, and CBM_i</td>
</tr>
<tr>
<td>fractionCBMiFromRCAhelp</td>
<td>( F_{CBM} )</td>
<td>0 – 1</td>
<td>0.05</td>
<td></td>
</tr>
<tr>
<td>goalFractionCBMoverPM</td>
<td>( PM_{CBM} )</td>
<td>0 – 1</td>
<td>0.05</td>
<td>Goal for CBM_i + CBM_s over all PM work</td>
</tr>
<tr>
<td>inspectionInterval</td>
<td>( I_i )</td>
<td>4 – 52</td>
<td>2</td>
<td>Interval for inspections for CBM_i</td>
</tr>
<tr>
<td>goalCBMsensors</td>
<td>( PM_{CBM_s} )</td>
<td>0 – 500</td>
<td>25</td>
<td>Goal for CBM_s</td>
</tr>
</tbody>
</table>

The scenarios represent three different initial conditions, to which some companies can relate, which differ accordingly:

- Scenario S1 represents companies applying a Run-To-Failure (RTF) strategy, using \( PM_{fi} \) on 5% of the equipment, including, for example, lubrication and the minimal activities due to warranty requirements.
- Scenario S2 represents companies applying a somewhat mediocre PM performance, with an RTF strategy for 50% of the equipment, and 50% using \( PM_{fi} \).
- Scenario S3 represents companies with highly developed and well performing PM work, with 75% \( PM_{fi} \), 20% of \( CBM_i \), and 5% \( CBM_s \).

Results and analysis
To pursue the analysis, firstly, the scatter plots of the optimised trade-off behaviour between the three conflicting objectives are analysed. Secondly, the parallel coordinate heat maps (PCHM), covering a set of selected parameters, are analysed to identify their patterns of dependence.
Meta-analysis of MOO scenarios using scatter plots

The results, in Figure 4, include four perspectives of the same sets of solutions, where scenario S1 is the category 1 circular dots, scenario S2 is the category 2 x-shaped dots, and scenario S3 is the category 3 triangle-shaped dots. The left-hand-side upper plot has a 3D perspective, including all three optimisation objectives, which the other 2D plots are oriented toward. All Pareto-front solutions for scenarios S1, S2, and S3 are significantly apart. The right-hand-side upper plot reveals a linear dependency between availability ($A_T$) and maintenance cost ($C_M$), where the consequence of increased equipment utilisation leads to a higher $C_M$. Both S2 and S3 exhibit a knee region, characterised by the fact that a small increase in $A_T$ has induced a considerably higher $C_M$. S1 solutions do not have such a ‘knee’ region and reach about $A_T = 0.95$. In the left-hand-side lower plot, especially S2 and S3 solutions reveal a nonlinear characteristic, where increased $A_T$ leads to decreased maintenance consequential costs ($C_Q$), although initially, they follow a near linear dependency on higher $C_Q$ as $A_T$ increases. It means that the high performing solutions probably achieve the availability through a proactive behaviour in the SD model since attaining high availability through a reactive behaviour generates substantial consequential breakdown costs and a larger spare parts inventory. With this in mind, S1 solutions in the $C_Q$-$A_T$ plot on the left-hand-side exhibit a rather linear shape. Interestingly, at about $A_T = 0.95$, there are S2 solutions that perform lower $C_Q$ than the S3 solutions. Nonetheless, the top performing solutions in S3 outperform all others, with respect to $C_Q$. The right-hand-side lower plot reveals the characteristic relation between the performance of $C_M$ and the $C_Q$. Studying S1 in that plot reveals that there is little benefit from increasing $C_M$. However, in S2 and S3, the relation between $C_M$ and $C_Q$ has shown some dramatic changes. In S2, at higher $C_M$ than about 150,000, a further increase of availability causes a steady decrease of $C_Q$ until at about 200,000, where no further benefit is shown. S3 solutions behave similarly, but much more rapidly, with a large gap between Pareto-front solutions on the scale of $C_Q$. 

Figure 4. Scatter plots for the three scenarios.
Hence, the Pareto-front results in Figure 4 clearly reveal the trade-off between the three optimizing objectives: $\max(A_T)$, $\min(C_M)$, and $\min(C_Q)$. Firstly, they can be considered very different in character, as comparing the patterns of solutions for each scenario reveals. Secondly, they exhibit a perception of the possible path to development within each scenario, as indicated in the characteristics of system inertia, depending on the scenario and selected strategies.

Figure 5. 2D scatter plot for the three scenarios.

The 2D scatter plot, in Figure 5, totals the two cost objectives: $C_T = C_M + C_Q$. In S1, $C_T$ increases with higher $A_T$ until 0.94, but when $A_T$ approaches 0.95, $C_T$ is lower for some solutions. S2 solutions clearly produce a nonlinear behaviour, where higher $A_T$ up to about 0.92 is linear. From that area, each increase in $A_T$ leads to a considerable decrease of $C_T$, until a point where a further increase is very expensive. Studying the PCHM in Figure 7 reveals that these solutions are characterised by having fewer breakdowns ($R_{BD}$) and more takedowns ($R_{TD}$). S3 solutions exhibit a behaviour which at first shows that there is a small increase of $C_T$ as $A_T$ increases, then above 0.98, there are radically better solutions with a gap in between; in the PCHM of Figure 8, this appears as two clusters of solutions.

Meta-analysis of MOO scenarios using PCHM
The parallel coordinate heat maps (PCHM) of the scenarios enable a meta-analysis of the results. Each line in the PCHM represents one set of Pareto-front solutions, which enables analysing the dependency between parameter results and distinguishes the characteristics of the solutions from each other. The first four axes in Figure 6 to 8 are the parameters presented in the abobe scatter plots: $A_T$, $C_M$, $C_Q$, and $C_T$ respectively. Thus, the same information is presented in the PCHM-format. For instance, studying the 3D scatter plot 3 in Figure 5 reveals that some solutions in S2 are better than in S3; identify these on the 3rd axis and follow the lines to the breakdown rate ($R_{BD}$) and the takedown rate ($R_{TD}$) axis, where the best S2 solutions have more planned maintenance activities compared to the inferior cluster of solutions in S3. In addition, looking at the accumulated economic results ($E_R$) on the 5th axis in the PCHMs shows that all S1 solutions have a negative result, thus, they may not be worth aiming for with respect to profit. However, S2 and S3 have solutions with positive $E_R$ and in addition S3 has some very high performing solutions. The next two parameters are the staff of repair workers ($S_R$) and maintenance engineers ($S_E$), where S1 solutions require high levels of $S_R$ and $S_E$. S2 solutions are represented on a large range of $S_R$ and more $S_E$ than S1. Furthermore, S3 manages with fewer $S_R$ and
has even more $S_e$. The next parameter, the inspection interval ($I_i$), shows that all solutions for S1 use a short interval, solutions for S2 are represented on the complete range, and S3 solutions are either concentrated on short intervals or long intervals. The performance of S1 solutions, on the $EH$ axis of the equipment health parameter, is on a rather narrow range and on quite a high level of hidden defects, which is its units. For S2, there is a large range spanning from a high to a low level of hidden defects and, for S3, there are two clear clusters of solutions at both ends of the S2 range on $EH$. The next two parameters indicate the result of unplanned and planned maintenance interventions, where S1 solutions have a high breakdown rate ($R_{BD}$), with a narrow range and few takedowns ($R_{TD}$). A similar pattern is found for the poor performing solutions in S2, while the better performing cluster has an opposite relation. For S3, there are clearly two separate clusters that either perform very well, or similar, on the poor performing solutions in S2. The last three parameters in the PCHMs provide information on the distribution between the different maintenance methodologies, namely, $PM_{fi}$, $CBM_i$, and $CBM_s$ respectively. By comparing S1, S2, and S3, three different patterns are obvious. S1 solutions generally use the most $PM_{fi}$, then $CBM_i$, and thereafter $CBM_s$. In S2 solutions, three patterns can be distinguished; first, solutions using more than 50% $PM_{fi}$ which also use about 10% $CBM_i$, and most $CBM_s$. The second clear pattern, which also represents solutions that perform best on $AT$, is solutions that use less than 50% $PM_{fi}$, almost 50% $CBM_i$, or more, as well as a low level of $CBM_s$. The third pattern can be distinguished in the middle of the $PM_{fi}$ axis. These solutions use approximately 50% $PM_{fi}$ and about 40% $CBM_i$, as well as $CBM_s$ on an almost 10% range. S3 solutions, whose results on previous parameters have been very clearly divided into two patterns, are not so different here, where solutions are rather concentrated for both $PM_{fi}$ and $CBM_i$. However, for S3 solutions on the $CBM_s$ axis, some of the best performing solutions on availability differ with a higher level of $CBM_s$, but they also exist on the lower range down to 5% $CBM_s$.

Figure 6. PCHM for scenario 1.
Summary MOO meta-analysis
Generally, the meta-analysis indicates that S1 solutions are more homogenous, whereas S2 and S3 have at least two clusters of behaviour. Studying all the top performing solutions in all the graphs on the different parameters’ axes, $S_E$ is a common denominator, indicating the significance of engineers to the development process of more proactive maintenance. Another aspect is the considerable
diversity of maintenance methodologies (PMfi, CBMi, CBMs) for the solutions. Each scenario exhibits its own separate pattern, indicating the importance of considering the initial condition when choosing the strategy to apply in order to achieve the most successful PM behaviour in production. S1 reveals that a journey towards a proactive maintenance behaviour, with the initial condition of using an RTF strategy, may not provide enough profit, see $E_\alpha$. It means that the profit per production volume needs to be higher for a company in S1 than for a company in S2 and S3. It indicates that companies with inadequately developed and poor performing PM work may be better off by continuing with reactive maintenance. This result could clarify the statement, according to Sharma et al. (2005), that using a breakdown maintenance strategy is a feasible approach in situations with high customer demands and large profit margins. However, as a matter of fact, the MOO analysis reveals that the potential to be proactive is still prominent in such a system that S1 represents, see Figure 6, where solutions with a higher RTD perform best in $A_T$ and $C_Q$. Hence, if profit margins are large enough, the negative spiral of reactiveness can be broken if such a strategy is pursued.

S2 solutions perform on a large range of $C_M$, see Figure 7, where high-cost solutions clearly result in the overall best PM performance, with lowest $C_Q$. S2 represents a company with an initial, mediocre level of maintenance performance and, in order to attain the higher region of $A_T$, the analysis clearly indicates the need for $S_\alpha$. Comparing the high $A_T$ solutions to the low $A_T$ solutions, which have low $C_M$, indicates they definitively suffer from an overbalance toward RBD instead of planned RTD.

S3 reveals that distinctly better performing future states are attainable, see Figure 8. S3 stands out from S1 and S2 by using considerably more engineers ($S_E$), which indicates that the initial conditions may be highly significant for whether the capabilities of $S_E$ can be put into effect or whether doing so is just a waste of resources. Nevertheless, S3 clearly indicates that, when the inertia in the maintenance and production system overcomes the tipping point into a proactive maintenance behaviour, it excels in performance. The characteristics, seen in S3, that generate such proactive maintenance behaviour is keeping the hidden defects in the parameter EH at a low level. The strategy applied in the top performing solution sets is attained by a high RTD based on identified defects mainly through CBMi, followed by a rather high level of CBMi and PMfi on the lowest share. Nevertheless, such a strategy must also be supported by accurate levels of $S_\alpha$ and $S_\epsilon$, to enable the corresponding development of precision activities, based on facts about the equipment and its failure behaviours.

Conclusions and future work
This paper presents a study which applies simulation-based optimisation (SBO), using multi-objective optimisation (MOO) on a conceptual, system dynamics (SD) maintenance performance model. This integration provides a method for the thorough analysis of the trade-offs between conflicting objectives, such as maximise availability, minimise maintenance costs, and minimise maintenance consequential costs.

The study compares three MOO scenarios with different initial conditions of preventive maintenance, which result in a certain performance and behaviour in the model. The results strongly indicate the nonlinearity between maintenance costs and maintenance consequential costs, especially at the higher levels of developed, preventive maintenance performance. The results clearly reveal that the different initial conditions require different strategies for the development of maintenance performance. The use of parallel coordinate heat maps (PCHM) enables the analysis to identify why the scenarios perform differently and explain the characterisation of solutions on the efficient frontiers. The results make explicit the implication of path dependency, regarding the development rate of maintenance performance for the different scenarios. This depends both on the current state and on how policies are formulated on the journey towards an improved future state. Consequently, using MOO with an SD model, as proposed in this paper, exhibits a very rich quantitative analysis to support the decision-making on a possible, future action strategy for the system under study.

The results and insights gained from the conceptual model, described in this paper, cannot be generalised for all practical maintenance situations which require the development of more detailed models of production facilities and complex cost models. However, it is believed that the SBO
framework, using MOO analysis on SD models, is readily applicable to more complex, detailed models for more complicated analyses of maintenance performance. In other words, it can be said that the limitation of the paper is posed by the detailed level of the SD models, but not the SBO framework. Additionally, with respect to validation, a MOO analysis allows an extreme and thorough evaluation of possible simulation runs of the applied SD model, which clearly reveals its capacity to calculate reasonable results. For this study, the applied model had to be improved to show any meaningful results, hence, applying MOO to explore a conceptual SD model has contributed to strengthening its use. As such, this can be considered a positive side effect in the process of achieving increased validation for its applicability.

In this regard, the application of MOO to explore an SD model can be considered a valuable contribution to support the formulation of a maintenance strategy, compared to experimenting in an SD model without knowing whether the experiments are close or far from the optimal trade-offs. Nonetheless, in order to connect strategy and operational execution, future work will investigate the combination with discrete event simulation (DES) to prioritise maintenance activities at the operational level. Combining SD with DES is emerging, and has been promoted, due to its ability to dramatically increase the size of the scenario landscape, as well as exchange the strengths of the two approaches between them, such as feedback into DES and details into SD (Sasdad et al, 2014). In other words, future work will explore a mixed method approach that considers both the planning of the short-term, maintenance tasks and the improvement of long-term strategic planning as in this paper. By integrating the DES and SD modelling approaches using MOO, it will be possible to explore an integrated SBO framework with the potential to address industrial maintenance problems that stretch the interface between strategic and operational levels. Overall speaking, such a framework can allow maintenance to be in charge of its own optimal planning, instead of reacting and following other requirements set by production or poorly defined priorities of activities.

Acknowledgements
This work was partially financed by the Knowledge Foundation (KKS), Sweden, through the IPSI Research School. The authors gratefully acknowledge their provision of the research funding and the support of the industrial partners Volvo Car Corporation and Volvo Group Trucks Operations.

References


Justifying maintenance studying system behavior: a multi-purpose approach using multi-objective optimization

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Abstract
Industrial maintenance includes rich internal dynamic complexity on how to deliver value. While the technical development has provided with applicable solutions in terms of reliability and condition based monitoring, managing maintenance is still an act of balancing, trying to please the short-termism from the economic requirements and simultaneously address the necessity of strategic and long-term thinking. By presenting an analysis to justify maintenance studying system behavior, this paper exemplifies the contribution of the combined approach of a system dynamics maintenance performance model and multi-objective optimization. The paper reveals how insights from the investigation, of the near optimal Pareto-front solutions in the objective space, can be drawn using visualization of the performance of selected parameters. According to our analysis, there is no return back to the single use of system dynamics; the contribution to the analysis of exploring system behavior, from applying multi-objective optimization, is extensive. However, for the practical application, the combined approach is not a replacement – but a compliment. Where the interpretation of the visualized Pareto-fronts strongly benefits from the understanding of the model dynamics, in which important nonlinearities and delays can be revealed, and thus facilitate on the selected strategical path for implementation.

Keywords: maintenance performance, strategic development, system dynamics, simulation, multi-objective optimization

Introduction
Justifying maintenance is not straightforward, if it was, any company would have full control over tradeoffs between money spent in their maintenance organization and their effect on production throughput or service to its customers. Any market, where your products or services compete, there is an upper level for what customers are ready to pay. Having the consequence that for the specific department there is normally a budget limiting the ambition for maintenance development to support production with required dependability. It is of interest, from a practical standpoint, to better understand the underlying structures in maintenance, resulting in its system behavior, and to identify the best trade-off between conflicting objectives, in order to attain strategic development of the maintenance performance. Furthermore, as a consequence of increased competition, the improvement potential becomes harder to gain putting higher demands on future methods for justifying maintenance.
Therefore, this paper presents one approach to economically justify maintenance, focusing on the study of system behavior, by the combined utilization of a system dynamics (SD) maintenance performance model and the simulation-based optimization (SBO) approach of multi-objective optimization (MOO). Where the application of MOO leads to the thorough investigation of the trade-offs between the conflicting objectives of, for instance, the short-term economic requirements, (Sherwin, 2000), and the long-term development needs (Repenning and Sterman, 2001), and thus support the maneuver in systems with different short- and long-run dynamics, addressed in (Rahmandad and Repenning, 2015). Except for a few studies, including ours that investigated the integration of MOO and system dynamics (SD) models (Aslam, 2013, Duggan, 2008), the use of SBO with SD models is in general much less reported. As a matter of fact, the work of Aslam (2013) has exemplified applying MOO on SD models, whereas one is the well-known beer game model of (Sterman, 2000) which has shown possible to draw generalized conclusions through studying the resulting patterns from the extensive amount of different optimal simulation runs (Aslam, 2013); thus MOO can support the identification of innovative principles that make up certain patterns of the non-dominated optimal solutions from the SD model under study. More concretely, for the model applied in this study, it provides a method for the thorough analysis of the trade-offs between conflicting objectives, such as availability, maintenance costs, and maintenance consequential costs.

The applied research work represented by this paper, and the choices of methodologies, has several purposes:

- Firstly, address the practical problem in the automotive industry of attaining sustainability in the strategic development of maintenance performance. This is the fundamental research motivation. To support a sustainable development Linnéusson et al. (2015a) calls for a systems thinking approach to better address maintenance cost modeling; which should include the visualization of consequential maintenance costs; with the purpose to minimize short-term my-budget-thinking and support the long-term development of maintenance performance.

- Secondly, by applying the systems thinking approach, the ambition is to introduce thinking differently, and more holistically, to defeat chronic reactiveness and to contribute to the shift in mind on the added value from maintenance, brought up in (Linnéussson et al., 2015b), where the need to build a maintenance SD model was elaborated on. Because, utterly, what is needed and sought to support, is to transcend current paradigm (Donella, 1999) of short-termism within the maintenance context. Even if such endeavor may be considered too ambitious, working in that direction is considered fundamental in this research.

- Thirdly, visualize system behavior, applications investigating maintenance performance, in for instance (Linnéusson et al., 2017b), have applied SD to analyze such system behavior and expose possible paths towards proactiveness. The model includes the interaction of maintenance in production, studying maintenance performance, based on the efficiency of applied pallet of maintenance methodologies (Tsang, 2002), such as: run-to-failure, preventive maintenance using fixed intervals, condition-based maintenance using inspections, and condition-based maintenance using sensors, and the load on equipment in production including feedback to equipment degradation, inspired by (Ledet and Paich, 1994, Sterman, 2000), and its corresponding effect to the mean delay of breakdowns. It included cost consequences from model behavior which explicitly visualize consequential maintenance costs (Vorster and De La Garza, 1990). Furthermore, continuous development based on breakdowns, similar to the Reliability centered maintenance (RCM) concept was also included.
• Fourthly, increase knowledge elicitation from SD models, the application using the combined approach of SD and MOO (Duggan, 2008, Aslam, 2013) enables extensive evaluation of the decision- and objective space, and their visualization. It has enabled meta-analyses comparing several scenario’s Pareto-fronts to distinguish characteristics based on a starting point in the proactive maintenance work (Linnéusson et al., 2017a). The many SD model evaluations in a MOO study also lead to the merciless verdict on attained internal validation. The reward from its application is vast information of the patterns between parameters with respect to the optimization objectives, see, for example, the parallel coordinate heat maps in Figure 7 and Figure 8.

• Fifthly, support the practical improvement of precision in maintenance’ activities towards proactiveness and higher efficiency. By the application of above-mentioned methods, contributing to the improved evaluation of strategic development, this purpose is supported and can generate policies on the general level of maintenance performance development.

Hence, the purpose of this study mainly focuses on the fourth point above, however, with the predecessor points as a basis, and, with the aim to deliver value to the fifth purpose.

The application of MOO enables this paper to explore the different objective space characteristics for how two categories of equipment at one production unit, representing equipment with low and high criticality, may most beneficially develop, with respect to the underlying SD model. The outcome of the investigation is thus a visualization of the Pareto-front trade-offs between the investigated conflicting objectives and a set of model parameters, supporting the analysis of system behavior for the decision-maker.

Multi-objective optimization
Multi-objective optimization (MOO) is a discipline that has been studied since the 1970s. Its application areas range widely from resource allocation, transportation, and investment decisions to mechanical engineering, chemical engineering, and automation applications, to name a few. In contrast to single-objective optimization, in which only one objective function is considered, MOO considers multiple objective functions simultaneously and seeks to identify a set of optimal solutions which are defined as Pareto-optimal solutions. A solution is considered to belong to the Pareto-optimal set when there is no other solution that can improve at least one of the optimization objectives without deteriorating any other objective. This set of solutions is also known as the Pareto-front when plotted on the objective space. Figure 1 illustrates the concept of decision and objective space, as well as the domination and non-domination of solutions in MOO. The search space of a multi-objective optimization problem is represented by the decision space where the design variables, which are the input parameters, constitute a set of solutions that are evaluated through a solver, which in this work is mainly a simulation model, and mapped to the objective space. Thus, a certain solution A with its inherent values of the design parameters \( x_1 \) and \( x_2 \) is evaluated through the solver which subsequently results in \( A' \) in the objective space representing the fitness or performance of solution A in terms of the objective functions \( f_1 \) and \( f_2 \).
The main concept of MOO is to evaluate two or more conflicting objectives against each other and obtain the Pareto-optimal solutions and the Pareto-front (Basseur et al., 2006). This comparison of the solutions is executed on the basis of the domination concept in which a solution $s_1$ is said to dominate a solution $s_2$ if $s_1$ is no worse than $s_2$, with respect to all optimization objectives, and where $s_1$ is strictly better than $s_2$ in at least one optimization objective (Deb, 2001).

**Applying MOO with SD**

The simulation principle for evaluating SD models using MOO follows the general simulation-based optimizing process as is seen in Figure 2. For this study, the “Simulation Model”, which for the optimization model is regarded as a “Black Box”, has utilized the SD model included in the appendix. The SD model was built in Vensim DSS and the MOO-simulation model in modeFrontier. The MOO-simulation model utilizes the NSGA-II algorithm, and the evaluation process activates and executes multiple runs of the SD model. Using a double quad-core processor enables eight simultaneous evaluations, which implies 1.5-2 hours for about 50,000 evaluations.

![Diagram](image)

*Figure 1. The concept of non-domination, decision and objective space, from (Aslam, 2013).*

![Diagram](image)

*Figure 2. A general simulation-based optimizing process, adapted from (Aslam, 2013).*

The applied procedure for the MOO-SD analysis presented in this paper has followed according to Figure 3. Where Step 1 is the ordinary modeling procedure for the SD model, which in this case used a previously developed model presented in (Linnéusson et al., 2017b). Step 2 includes setting up the optimization model in the optimization engine based on the selected conflicting objectives in the SD model and defines the number of evaluations. Step 3 includes evaluating the initial results, where strange results may indicate on the need of SD model modifications in order to get reasonable output values. This process harshly exposes any inability to generate a valid answer for all evaluations; a process following iterations of model improvements to
provide a more stable and valid SD model. Step 4 can be performed when the SD model can be considered valid enough for its purpose, and provides with the possibility to analyze the results, according to the scatter plots and parallel coordinates presented later. Step 5 may be applied if the analysis benefits from investigating different points of origin, where scenarios with different initial conditions may be explored, with the purpose to learn from how important knowledge about the present condition before conducting an implementation journey towards a future state, as examined in (Linnéusson et al., 2017a). Step 6 represents the possible post-analysis of solutions of interest, however not explored in this paper, where the explored Pareto-front solutions may be further analyzed utilizing the SD model again in order to apply the strengths of SD to facilitate the desired development. Furthermore, in order to conduct the MOO-simulation, in Step 4, the methodology for SD+MOO presented in (Aslam, 2013) has been used, which in detail describes the steps of decision space sampling, global objective space search, and local objective space refinement, which leads to the presentation of optimal solutions.

The maintenance performance model
For a full model presentation, see (Linnéusson et al., 2017b), in the appendix the complete structure with corresponding model equations is provided. Figure 4, represents an overview of the model, illustrated using five general parts.
The structure in Production and maintenance performance part defines the availability as a consequence of the current equipment reliability, defined in the structure found in the Equipment health status box, together with staffing for unplanned or planned maintenance repairs and their respective productivity, similar to the structure in (Ledet and Paich, 1994). Thus, the better equipment health status is, the breakdown frequency decreases, and availability increases, however, the higher availability is it also leads to a higher operational load on equipment which implies a higher risk for a failure. The structure in Equipment health status part defines the aggregated equipment reliability as a consequence of the accumulated defects, generated by the operation load and collateral damage from breakdowns, and their elimination through repairs, inspired by the structure of Equipment defects presented in (Sterman, 2000). Based on the level of Preventive maintenance performance, and the ratio between planned and unplanned repairs, it results in the certain defect elimination, where planned maintenance has the more efficient approach to defect elimination. The planned maintenance is based on the level of applied maintenance methodology, divided between preventive maintenance using fixed interval, and condition-based maintenance using manual inspections, or sensors; which in turn results in different efficiency to detect defects based on which of these three methodologies that are applied. And also, includes the planning and scheduling capabilities, similar to the structure in (Ledet and Paich, 1994), together with a throttle limited by the pressure to produce on behalf of preventive maintenance, if availability is under its goal value. The model also includes a structure for a Maintenance development process which defines the maintenance performance development pace based on policies, resources, delays, work pressure, and work progress of transforming information of why breakdowns occurred into root-cause countermeasures, represented in the model by new preventive maintenance activities. The structure describing the Holistic economic performance box includes, for example, the calculation of total maintenance costs as a consequence of the production and maintenance performance, including direct maintenance costs, and consequential maintenance costs from breakdowns, using a simple principle found in (Wireman, 2004) where the maintenance costs and downtime costs ratio have been empirically considered in the range from 1:2 to 1:14. The Applied Maintenance Strategies diamond in Figure 4 represent where possible policies and strategies for development interact with the model for this study.

Validation has considered the normal techniques in SD, such as the process according to (Barlas, 1996), with direct structure tests, structure-oriented behavior tests, and behavior pattern tests. Inputs to modeling have covered the studies of procedures of the industrial partners and relevant literature. Thus, the overall model behavior has been considered justified, to some extent, also including the testing of assumptions with help of industrial maintenance experts. Furthermore, the application of MOO, with respect to model validation, is very powerful. Any
error in the model will be identified by the evaluation of so many solutions, thus MOO identifies any weak spots leading to anomalies. In this study, it has had the effect of improving model equations in order to correct erroneous behavior, adding parameters, as well as, some new structure.

**MOO simulation scenarios**

The maintenance performance SD model can be applied for different studies using the MOO-technique, for instance, comparing different categories of companies at three different states of applied maintenance methodology, as is presented in (Linnéusson et al., 2017a). This study, however, is an example where MOO is applied to investigate an applicable strategy for two sets of equipment at one production unit, with different characteristics regarding downtime costs. In a structured maintenance, organization equipment is normally divided into different categories of criticality, where the consequences from a breakdown in respect to downtime, quality, safety, cost, etc., have been analyzed, placing equipment into its category of criticality. This categorization is then used as an input value to the preparation of the maintenance planning for the certain piece of equipment, considering activities such as preventive maintenance using fixed intervals (PMfi), condition based maintenance using inspections (CBMi), and condition-based maintenance using sensors (CBMs). Thus the output should be a set of maintenance activities that will prevent failure to the required level of the specific category of criticality. In the real setting, there may be several categories of equipment, not just two as in this example, as provided due to space limitation. Furthermore, in the presented case, for simplicity, in respect to model comparison, only one parameter is changed between the two scenarios, which is the repair cost ratio for a planned and unplanned repair. The downtime cost varies depending on the consequences in production if the stop causes quality issues, or increased damage requiring the exchange of more parts than the one causing the breakdown in the first place, thus it is represented by the criticality of the certain piece of equipment. Therefore, the scenarios for this study are accordingly:

- Scenario S1 includes the equipment of lower criticality, with a cost ratio of 1:4 between the repair cost for a planned and an unplanned repair.
- Scenario S2, includes the equipment of higher criticality, with a cost ratio of 1:12 between the repair cost for a planned and an unplanned repair.

The MOO-scenarios apply the input parameters, and ranges, according to Table 1 below. The input parameters are selected based on their expected effects to attain a proactive behavior in maintenance in the SD model, using a time horizon of 10 years. The same initial conditions are applied, using a Run-To-Failure (RTF) strategy for 50% of the equipment, and the other 50% use PMfi.

<table>
<thead>
<tr>
<th>Input parameter</th>
<th>Range</th>
<th>Step</th>
</tr>
</thead>
<tbody>
<tr>
<td>numberRepairMen</td>
<td>4 – 50</td>
<td>1</td>
</tr>
<tr>
<td>numberMaintenanceEngineers</td>
<td>0 – 30</td>
<td>1</td>
</tr>
<tr>
<td>fractionPMiFromRCA</td>
<td>0 – 1</td>
<td>0.05</td>
</tr>
<tr>
<td>fractionCBMiFromRCAhelp</td>
<td>0 – 1</td>
<td>0.05</td>
</tr>
<tr>
<td>goalFractionCBMoverPM</td>
<td>0 – 1</td>
<td>0.05</td>
</tr>
<tr>
<td>inspectionInterval</td>
<td>4 – 52</td>
<td>2</td>
</tr>
<tr>
<td>goalCBMsensors</td>
<td>0 – 500</td>
<td>25</td>
</tr>
</tbody>
</table>

Each MOO-scenario evaluates the multi-criteria trade-offs between maximized availability, minimized maintenance cost, and minimized consequential maintenance costs. Hence, the
MOO investigation in this paper explores how to strategically address maintenance activities at one production unit having two categories of criticality.

**Results and Analysis**

The optimization has, for each scenario, been run for at least 50,000 evaluations, following the methodology for SD+MOO developed by (Aslam, 2013). As previously described the performed MOO considers three objectives, which suitably can be displayed using a 3D-scatter plot. However, a 3D-scatter plot can be hard to interpret using a 2D-paper. Therefore, Figure 5 reveals three perspectives of the same resulting plots, according to their axes. It means, that the left plot reveals all three objectives in one view. The second plot reveals the trade-off curve between the two objectives availability and the consequential maintenance cost; which are clearly different for the two scenarios. The third plot reveals the trade-off curve between the two objectives availability and the maintenance cost; which clearly shows that scenario S1 and S2 follow near the same trade-off curve on these objectives. Looking at the middle coordinate set, the S2 is the curve with higher consequential maintenance cost, and it exhibits a considerable behavior of lower cost as availability increases.

![Figure 5. 3D-scatter plots of the same graph, from left: the 3D xyz-axis perspective, the xy-axis perspective, xz-axis perspective.](image)

If we are interested in the total maintenance cost, a 2D-scatter plot, as in Figure 6, may be easier to interpret, where the maintenance cost and the consequential maintenance cost are summarized on the x-axis, and is compared to its trade-off to availability on the y-axis. The comparison between the two scenarios, using Figure 6, indicates that solutions on the higher range of availability reach lower total costs. It also reveals that the two scenarios clearly distinguishes in performance, and that scenario S2 have much higher total costs and that they are on a larger spread. It means that the exploration of optimization results make known that equipment treated in S2, represented by equipment with higher criticality, clearly have a high potential for high availability solutions to a radically lower total maintenance cost than to those with lower availability. An analysis on this level may also indicate that the maintenance organization should prioritize on attaining the development suggested by the S2 solutions, and perhaps wait with the equipment included in the S1-analysis.
Parallel coordinate heat map analysis
To better understand the results in the scatter plots we can also present the results utilizing parallel coordinate heat maps, which visually display the performance of selected variables, as is seen in Figures Figure 7-Figure 8. The scales are normalized between the scenarios. Any of the parameters in a Vensim model can be modeled to be an output parameter for analyzing the results, here some parameters of interest are represented. By comparing S1 and S2 results, in Figure 7 and Figure 8 respectively, common and distinguishing patterns can be identified, enriching the analysis to include in a future strategy for maintenance development. For instance, the best performing solutions in both S1 and S2 follows a similar pattern on all output parameters. However, solutions just below top performers on availability, on about availability of 0.96 represented by orange lines, we can see diverging patterns where for S1 amount of maintenance engineers are some more, result on MTTF (mean time to failure) is better, breakdown rate lower, but takedown rate about same as for S2. And, for the last three parameters, the policies for applied maintenance methodologies (PMfi, CBMi, and CBMs) are needed to be selected differently to attain the optimal solution. Thus, by applying the parallel coordinates it enables generating further quantitative knowledge of the patterns of behavior, generated by the SD model, in respect to its trade-off solutions.

The presented analysis reveals it possible to identify the specific strategy to apply for both equipment sets, but also considering S1 and S2 equipment together, where the results clearly indicate that equipment in scenario S2 should be at main focus due to the much larger leverage on cost performance from improved proactive behavior in the maintenance function. Such a conclusion may seem obvious, however, the parallel coordinate heat maps support the differentiation of separate runs, each representing a behavior graph in the SD model, which may require improvements that may be considered is more or less easy to accomplish in the implementation.
Figures 7 and 8 visualize the specific solutions represented by the lines through all parameters in the parallel coordinate plot. It enables a fast overview of how the different solutions perform in respect to the selected parameters. These plots exhibit the generalized patterns of, for instance, that to attain the higher availability solutions for both S1 and S2 it requires more repair workers, but remarkably, S2 solutions present fewer repair workers for the top performing solutions and a lower MTTF average. However, it is also seen that for the top performing solutions, in both S1 and S2, despite higher direct maintenance cost it may be beneficial to apply more repair workers due to the resulting lower maintenance consequence cost, likely, as a consequence from a more proactive behavior in the SD model.
Discussion and Recommendations for Management

According to the results and analysis, it is clear that the more critical equipment has the larger financial potential for improved maintenance performance. It must be understood clearly, that the solutions presented in Figure 5 to 8 are only represented by those solutions that are the best trade-off between the three objectives of maximized availability to the minimized maintenance cost, and the minimized consequence cost from the performed maintenance. It means that the MOO-analysis explores multiple SD model solutions, and selects those on the Pareto-front, and exhibits these. The applied SD model is a model that considers the balancing of the proactive versus the reactively performed maintenance. Therefore, any solution in the plots is the optimal trade-off for the given availability performance that the SD model possibly can express. This paper focuses on illustrating the contribution of applying MOO to the underlying SD model, while the SD model itself is not so deeply reviewed within this piece of paper, this can be further read in (Linnéusson et al., 2017b, Linnéusson et al., 2016).

In order to discuss recommendations to a specific maintenance organization more information to the decision making will be considered. However, as for the contribution of this study, it can be pointed out that, for those equipment considered more critical where consequences of breakdowns are larger, as in S2, there is a clear benefit with respect to total maintenance cost to prioritize management of this equipment. And in respect to selecting key performance indicators, that can guide towards the desired future state for S1 and S2 together, it should also be considered ok to perform on a poorer level on the equipment included in the S1 scenario. While equipment included in the S2-analysis are ok to spoil with higher support even if the direct cost-benefit analysis may be hard to motivate. At the same time, it means that the results from a study like this can explore the possible path for a strategy for the production line at hand. This study has not got into the resulting plots from the specific SD model experiments, where the time delays until efforts pay back are reviewed. This would be the next step for management, to select solutions of interest from the S1 and S2 scenarios and explore their specific behaviors in the SD model, in order to justify the required time delays until the expected and desired effects are attained. Such analysis could be used as a discussion base to draw up their specific strategy for the complete line, and how to specifically treat the equipment in S1 and S2 respectively.

Conclusions

Technically this paper presents a multi-objective optimization (MOO) analysis of a system dynamics (SD) model. Two MOO+SD scenarios are explored. The application area is industrial maintenance, where there exist short-term and long-term procedures to support production through the delivered dependability from maintenance performance, here specifically equipment availability.

Studying the optimization results, they provide a rich visual quantification of the near optimal trade-off solutions between the conflicting objectives of maximizing availability, minimizing maintenance cost, and minimizing consequential maintenance cost, for two different sets of equipment with different criticality. Applying an SD model of the dynamics between short-term and long-term feedback, it enables investigating trade-offs that consider the long-term development of maintenance towards a more proactive behavior. However, the application of MOO to an SD model adds the dimension of simultaneously evaluating multiple objectives, and the visual presentation of multiple solutions on the optimal trade-off between objectives, strongly supporting analysis and the decision making process. As is given by the presented analysis, where two sets of equipment which differ in criticality, in respect to the consequential downtime cost from breakdowns, it enables identifying the specific strategy to apply to the specific equipment set of S1 or S2, but also considering them together, where the results clearly
reveal that equipment in scenario S2 should be at main focus due to the much larger leverage on cost performance from improved proactive behavior in the maintenance function.

At least as for the results presented in this paper, applying MOO to an SD model provides the conclusion of that there is no return back to the single use of system dynamics; since the contribution to the analysis of exploring system behavior, from applying multi-objective optimization, is extensive. However, for the practical application, the combined approach of MOO+SD should not be a replacement to the SD analysis – but should be its complement. Since the interpretation of the visualized Pareto-fronts strongly benefits from the understanding of the underlying model dynamics, in which important nonlinearities and delays can be revealed; critical for the facilitation of the selected strategical path for implementation.

**Future work**

According to the presented purpose with the research work to support the practical improvement of precision in maintenance’ activities towards proactiveness and higher efficiency, the application of MOO+SD contributes to the improved evaluation of strategic development and can generate policies on the general level of maintenance performance development. However, the feedback to the practical implementation perspective, from the higher level strategic development, is also considered key in this work. Where the combination with the operational level, is considered to benefit from including discrete-event simulation (DES). Hence, the work reported in this paper represents the foundation into such stretched analysis, with the potential to inquire for the activities that support the investigated path forward. Combining SD with DES is emerging and has been promoted due to its ability to dramatically increase the size of scenario landscape, and exchange of strengths between the two approaches, such as feedback into DES and details into SD (Sasdad et al., 2014). In other words, future work will investigate a hybrid approach that considers both the short-term, urgent maintenance tasks planning and improvement of long-term strategic planning, by combining DES with SD.

Hence, by integrating the above-said approaches together, future work will consider the proposal of an integrated simulation-based optimization (SBO) framework that can offer the potential to address industrial maintenance problems that stretch the interface between strategic and operational levels. Firstly, key leverage processes from the holistic, organizational maintenance behavior perspective can be identified, using MOO+SD, and presented as input information into a DES model of the production line, guiding on operational level execution in order to obtain best implementation effects. Secondly, the connection between strategy and operational level may require that the optimization criteria in a DES model need to be adapted to the findings on the strategical level obtained in the SD model. Hence, an overall feedback can be established between the strategic and operational level, contributing to more precise efforts and empowering maintenance to form its own strategic planning, to a larger extent, instead of adapting to happenstance. Overall speaking, on a theoretical level, the framework introduces a methodology for addressing industrial maintenance from a holistic perspective. On a practical level, the SBO framework can endow maintenance to get in charge of its own optimal planning, instead of reacting and follow other requirements set by production or poorly defined priorities of activities.

**Acknowledgments**

This work was partially financed by Knowledge Foundation (KKS), Sweden, through the IPSI Research School. The authors gratefully acknowledge their provision of the research funding and the support of the industrial partners Volvo Car Corporation and Volvo Group Trucks Operations.
References


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Appendix Model structure
Appendix Model equations

identifiedDefectiveEquipmentInspections = discretionary inspections * 
frac(EquipmentHealthOverPossibleDefects) quality of inspections ~ equipment/Week
defectEliminationPM= MIN(scheduled repairs*defect elimination per repair, EquipmentHealth/repairDelay) ~ defects/Week
initLevelofInspPlans= 0.001 ~ Dmnl
initLibraryofCBMs= 0.001 ~ Dmnl
descretionary inspections= IF THEN ELSE(ratioLatePlannedWO>=0.1, 0, IF THEN ELSE(capacity inspections>= 2*(EquipmentToInspect/inspection delay), MIN(2*(EquipmentToInspect / inspection delay), capacity inspections), MIN(EquipmentToInspect / inspection delay , capacity inspections))) ~ equipment/Week
start PMwo= IF THEN ELSE(ratioLatePlannedWO>=0.1, 0, PMreplacementBacklog/delay plan PMwo) ~ equipment/Week
breakdowns due to unperformed takedowns= breakdownsLateWO ~ equipment/Week
breakdownsLateWO= riskLateWO*EquipmentInFullFunctionality/Week ~ equipment/Week
ratioLatePlannedWO= PlannedTakedowns/SumPMpreparations ~ Dmnl
breakdownRate= EquipmentInFullFunctionality/ delayBreakdowns + breakdownsLateWO ~ equipment/Week
riskLateWO= ratioLatePlannedWO/riskFactorReductionDueToPMwork ~ Dmnl
fractionInitPMfi= 0.5 ~ Dmnl
fractionNormalHealthStatus= 0.7 ~ Dmnl
resourcesScheduledRepairs= 0.2*numberRepairMen ~ people
numberRepairMen= 10 ~ people
resourcesUnscheduledRepairs= 0.8*numberRepairMen ~ people
average CBM interval= avgMaintIntCBMs / (fractionEquipmentHealthOverPossibleDefects/fractionNormalHealthStatus) ~ Week
defectEliminationRepairs= MIN(unscheduled repairs*defect elimination per repair, EquipmentHealth/repairDelay) ~ defects/Week
avgMaintIntCBMs= 104 ~ weeks
repairDelay= 1 ~ Week
initLevelofPMfi= fractionInitPMfi ~ Dmnl
EquipmentWithCBM sensors= INTEG (newCBMsensors, initial library of CBMs) ~ equipment
initial library of CBMs= initLibraryofCBMs*number of equipment ~ equipment
collateral damage= breakdownRate*probability collateral damage*possible defects per equipment ~ defects/Week
probability collateral damage= 0.25 ~ Dmnl
wear and tear operations= tbl probability wear and tear EqpmtAge(EqpmtAge)*probability wear and tear * MIN(EquipmentHealth, 9000) ~ defects/Week
tblContributionMarginOverAvailability( [(0,0)-(1,1)],(0,1),(0.7,1),(1,0.85)) ~ Dmnl
Not used: EqpmtAge= (initEqpmtAge*Week+Time)/Week ~ Dmnl
max contribution margin per week= 600000 ~ $/Week
Net contribution margin production= Availability * max contribution margin per week * tblContributionMarginOverAvailability(Availability) ~ $/Week
Not used: tbl probability wear and tear EqpmtAge( [(0,0)-(20,4)],(0.1),(10,1)) ~ Dmnl
Not used: initEqpmtAge= 0 ~ weeks
MaintCostOverNetMargin= maintenanceCost/Net contribution margin production ~ Dmnl
maintenanceCost=cost man hours + cost breakdowns + cost takedowns + investCBMs ~ $/Week
priceCBMs= 10000 ~ $/equipment
investCBMs= newCBMsensors*priceCBMs ~ $/Week
CBMifaktorRiskReduction= 0.8 ~ Dmnl
PM work= EquipmentWithCBMinspectionPlans*CBMifaktorRiskReduction +EquipmentWithCBMsensors +EquipmentWithPMPreparations*PMfaktorRiskReduction ~ equipment
goal PM preparations= number of equipment*goalPMwork ~ equipment
delayOldPMremoval= 26 ~ weeks
newPMpreparations= MIN((goal PM preparations - SumPMpreparations)/delay PM preparation, PMpreparation *PM preparation release) - IF THEN ELSE(goal PM preparations< SumPMpreparations, EquipmentWithPMpreparations/ delayOldPMRemoval, 0) ~ equipment/Week
goalPMwork= 1 ~ Dmnl
CBMs= EquipmentWithCBMsensors/SumPMpreparations ~ Dmnl
initRatioEquipmentHealth= 0.7737 ~ Dmnl
PMtotal= SumPMpreparations/number of equipment ~ Dmnl
CBMi= (EquipmentToInspect + EquipmentWithCBMinspectionPlans)/SumPMpreparations ~ Dmnl
initial value of Hidden defects= initRatioEquipmentHealth*possible defects per equipment ~ defects/equipment
PMfactorRiskReduction= 0.5 ~ Dmnl
inspection delay= 2 ~ Week
PMfi= (EquipmentWithPMpreparations + PMreplacementBacklog)/SumPMpreparations ~ Dmnl
decisionDelayRoleReactiveToProactive= 4 ~ weeks
roleToProactive= IF THEN ELSE(resUnsRep<1, 0, IF THEN ELSE(resUnsRep>4:AND:usage reactive staff<0.75, 1, IF THEN ELSE(resUnsRep<4:AND:usage reactive staff <0.5, 1, 0))) / decisionDelayRoleReactiveToProactive ~ people/Week
roleToReactive= IF THEN ELSE(resSchRep<1, 0, IF THEN ELSE(resSchRep>4:AND:usage preventive staff<0.75, 1, IF THEN ELSE(resSchRep>2:AND:usage preventive staff<0.5, 1, 0))) / decisionDelayRoleReactiveToProactive ~ people/Week
max capacity unscheduled repairs= resUnsRep*productivity unscheduled repairs/effect breakdown frequency on capacity ~ equipment/Week
max capacity scheduled repairs= resSchRep*productivity scheduled repairs ~ equipment/Week
resUnsRep= INTEG (roleToReactive - roleToProactive, resourcesUnscheduledRepairs) ~ people
decisionDelayRole= 12 ~ weeks
resSchRep= INTEG (roleToProactive - roleToReactive, resourcesScheduledRepairs) ~ people
fractionCBMiFromRCAhelp= 0.45 ~ Dmnl
fractionCBMsFromRCA= 1 - fractionCBMiFromRCA - fractionPMiFromRCA ~ Dmnl
delaytime breakdown report= 1 ~ weeks
max capacity implement CBM inspections= (max capacity PM preparations - PMpreparation) * productivity PM to CBM ~ info/Week
max capacity implementing CBM sensors= (max capacity implement CBM inspections - CBMpreparation) * productivity CBM to sensor ~ info/Week
usage engineers= IF THEN ELSE(max capacity implementing CBM sensors=0, 1, ZIDZ(CBMsensorPreparation, max capacity implementing CBM sensors)) ~ Dmnl
quality of inspections= 1 ~ Dmnl
cost breakdowns= cost per stop*breakdownRate ~ $/Week
effect breakdown frequency on capacity= tbl breakdown frequency and stop effect(breakdownRate/normal breakdown rate) ~ Dmnl
UnscheduledMaintenance= INTEG (breakdownRate - unscheduled repairs, 0.378*number of equipment) ~ equipment
MTTF= EquipmentInFullFunctionality/breakdownRate ~ Week
EquipmentInFullFunctionality= INTEG (scheduled repairs + unscheduled repairs - breakdownRate - takedownRate, 0.622*number of equipment) ~ equipment
pressure to produce= MIN(MAX(1, goal availability/Availability), 4) ~ Dmnl
consequential breakdown costs= 12*cost per stop * breakdownRate ~ $/Week
planned repairs= EquipmentWithPMpreparations/ fixedInterval ~ equipment/Week
PMWorkOrder= start PMwo ~ equipment/Week
maintenance budget= 100000 ~ $/Week
cost man hours= man hour cost per Week*sumStaff ~ $/Week
RCAcountermeasureToBreakdown= MIN(BreakdownAnalysisRCAWIP/delay RCA, max capacity RCA) ~ info/Week
diffCostOverBudget= maintenance budget - maintenanceCost ~ $/Week
Availability = EquipmentInFullFunctionality / number of equipment ~ Dmnl

delay plan PMwo = time to plan PMwo / (MIN(fractionPMwork, 0.5)*2) ~ Week
time to plan PMwo = 2 ~ Week
corrective takedowns = Defective equipment / delay planning defective equipment work order ~ equipment / Week
delay planning defective equipment work order = time to plan corrective actions / (MIN(fractionPMwork, 0.5)*2) ~ Week
time to plan corrective actions = 1 ~ Week

breakdown report done = Breakdown reports Backlog / delaytime breakdown report ~ info / Week
newCBM sensors = IF THEN ELSE(goalCBMsensors > EquipmentWithCBMsensors, EquipmentWithCBMsensors, MIN(CBMsensorPreparation * PM preparation release, MIN((goalCBMsensors - EquipmentWithCBMsensors) / delay convert to CBM sensors, MAX(0, EquipmentWithCBMinspectionPlans / delay convert to CBM sensors)))) ~ equipment / Week

delay planning defective equipment work order = time to plan corrective actions / (MIN(fractionPMwork, 0.5)*2) ~ Week

time to plan corrective actions = 1 ~ Week

breakdown report done = Breakdown reports Backlog / delaytime breakdown report ~ info / Week
newCBM sensors = IF THEN ELSE(goalCBMsensors > EquipmentWithCBMsensors, EquipmentWithCBMsensors, MIN(CBMsensorPreparation * PM preparation release, MIN((goalCBMsensors - EquipmentWithCBMsensors) / delay convert to CBM sensors, MAX(0, EquipmentWithCBMinspectionPlans / delay convert to CBM sensors)))) ~ equipment / Week

policy fraction report per breakdown = IF THEN ELSE(numberMaintenanceEngineers > 0, AND: resourcesScheduledRepairs > 0, 1, 0) ~ info / equipment

usage reactive staff = ZIDZ (unscheduled repairs, max capacity unscheduled repairs) ~ Dmnl
defectCreation = operations + collateral damage ~ defects / Week

ImplementeRCA = INTEG (RCAcountermeasureToBreakdown - CBM preparation - CBMsensor Preparation - PM preparation, 1) ~ info

Acc Company Results = INTEG (profit or lost, 0) ~ $/Week

Net Profit = Net contribution margin production - maintenanceTotalCost ~ $/Week

sum Staff = numberMaintenanceEngineers + resourcesScheduledRepairs + resourcesUnscheduledRepairs ~ people

profit or lost = Net Profit ~ $/Week

usage preventive staff = ZIDZ (descretionary inspections, capacity inspections) ~ Dmnl

Acc Maint Budget Margin = INTEG (diffCostOverBudget, 0) ~ $/Week

PMpreparation = MIN (ImplementedRCA * fractionPMiFromRCA / delay PM preparation, max capacity PM preparations) ~ info / Week

number Maintenance Engineers = 3 ~ people

productivity PM preparations = 0.5 ~ Dmnl

productivity engineers RCA analysis and PM preparations = 10 ~ info / (Week * people)

max capacity PM preparations = (max capacity RCA - RCA countermeasureToBreakdown) * productivity PM preparations ~ info / Week

max capacity RCA = number Maintenance Engineers * productivity engineers RCA analysis and PM preparations ~ info / Week

capitalInSparePartInventory = (spare part per equipment breakdown strategy * (number of equipment - Sum PM preparations)) + spare part per equipment takedown strategy * ((1 - fractionCBMoverPM) + 0.5 * fractionCBMoverPM) * Sum PM preparations * cost per spare part ~ $/Week

planned inspections = EquipmentWithCBMinspectionPlans / inspectionInterval ~ equipment / Week

spare part per equipment takedown strategy = 2 ~ Dmnl

spare part per equipment breakdown strategy = 5 ~ Dmnl

delay RCA = time to implement / (MIN (fractionPMwork, 0.8)*2) ~ weeks

tbl breakdown frequency and stop effect = ([0,0)-(4,9), (0,1), (1,1), (2,3), (4,9)] ~ Dmnl

normal breakdown rate = 18 ~ equipment / Week

analytic capabilities = 1 - fractionEquipmentHealthOverPossibleDefects ~ Dmnl

Breakdown Analysis RCA WIP = INTEG (RCA Use Data - RCA countermeasure To Breakdown, 0) ~ info

productivity CBM to sensor = 0.5 ~ Dmnl

breakdown report demand = unscheduled repairs * policy fraction report per breakdown ~ info / Week

Breakdown reports Backlog = INTEG (breakdown report demand - breakdown report done, 0) ~ info / Week

maintenance Total Cost = maintenanceConsequentialCost + maintenance Cost ~ $/Week

fraction available data RCA = useful info in reports * analytic capabilities ~ Dmnl

goal Fraction CBM over PM = 0.3 ~ Dmnl

CBM preparation = MIN (ImplementedRCA * fractionCBM from RCA / delay convert to CBM, max capacity implement CBM inspections) ~ info / Week
CBMsensorPreparation = MIN(ImplementedRCA*fractionCBMsFromRCA/delay convert to CBM sensors, max capacity implementing CBM sensors) ~ info/Week
convertPMToCBM = MIN(MAX(0,(goalFractionCBMoverPM*EquipmentWithPMpreparations-fractionCBMoverPM*EquipmentWithPMpreparations)/ delay convert to CBM), CBMpreparation*PM preparation release) ~ equipment/Week
fractionPMiFromRCA = 0.5 ~ Dmnl
tbl pressure to close gap = \[(0,0)-(100000,1),(0,1),(1,1),(5,0.9),(10,0.7),(20,0.5),(100,0.2),(100000,0)\] ~ Dmnl
time to implement = 13 ~ Week
useful info in reports = tbl pressure to close gap(Breakdown reports Backlog*pressure per breakdown report) ~ Dmnl
delay PM preparation = 13 ~ Week
PM preparation release = 1 ~ equipment/info
EquipmentWithPMpreparations = INTEG (newPMpreparations+start PMwo-convertPMToCBM-planned repairs, initial library of PM preparations) ~ equipment
pressure per breakdown report = 1 ~ 1/info
goalCBMpreparation = 25 ~ equipment
RCAUsefulData = breakdown report done*fraction available data RCA ~ info/Week
fractionCBMfromRCA = (1-fractionPMiFromRCA)*fractionCBMfromRCAhelp ~ Dmnl
productivity PM to CBM = 0.1 ~ Dmnl
SumPMpreparations = PMreplacementBacklog+EquipmentToInspect+EquipmentWithCBMinspectionPlans+EquipmentWithCBMpreparations+EquipmentWithPMpreparations ~ equipment
capital cost spare part inventory = interest rate spare part inventory/Week * capitalInSparePartInventory ~ $/Week
interest rate spare part inventory = 0.4 ~ Dmnl
cost per spare part = 2000 ~ $/equipment
cost per stop = 1.25*cost per spare part ~ $/equipment
cost takedowns = cost per stop*takedownRate ~ $/Week
man hour cost per Week = 2400 ~ $/(Person*Week)
Week = 52 ~ Week
maintenanceConsequentialCost = consequential breakdown costs + capital cost spare part inventory ~ $/Week
fractionCBMoverPM = (EquipmentToInspect+EquipmentWithCBMinspectionPlans+EquipmentWithCBMpreparations) / (PMreplacementBacklog+EquipmentToInspect+EquipmentWithCBMinspectionPlans+EquipmentWithCBMpreparations+EquipmentWithPMpreparations) ~ Dmnl
PMtakedown = PM replacement*takedownRate ~ equipment/Week
riskFactorBreakdowns = fractionEquipmentHealthOverPossibleDefects * (risk delayed work/ riskFactorReductionDueToPMwork) ~ Dmnl
riskFactorReductionDueToPMwork = tbl reduced risk due to PM work ~ Dmnl
takedown rate p = IF THEN ELSE(ScheduledMaintenance > limit takedown rate*number of equipment/pressure to produce, 0, PlannedTakedowns/pressure scheduling delay) ~ equipment/Week
PlannedTakedowns = INTEG (corrective takedowns+PMworkOrder-breakdowns due to unperformed takedowns-takedown rate p - breakdowns due to unperformed takedowns, 4) ~ equipment
operations = Availability * wear and tear operations ~ defects/Week
capacity inspections = MAX(max capacity scheduled repairs - scheduled repairs , 0) * productivity inspections ~ equipment/Week
PMbacklog = PMreplacementBacklog+EquipmentToInspect+Defective equipment+PlannedTakedowns ~ equipment
tbl reduced risk due to PM work = \[(0,0.8)-(1,2),(0,1),(0.3,1.05),(0.6,1.4),(0.75,1.9),(1,2)\] ~ Dmnl
defect elimination per repair = MAX(max fixed defects per repair * 
fractionEquipmentHealthOverPossibleDefects , 1) ~ defects/equipment 
delayBreakdowns = tbl risk effect on reliability(riskFactorBreakdowns) * average reliability ~ Week 
fractionEquipmentHealthOverPossibleDefects = EquipmentHealth/(number of equipment*possible defects per equipment) ~ Dmnl 
tbl risk effect on reliability = ((0,0), (2.1,4), (0.4), (0.3,3.6), (0.38,3), (0.45,1.5), (0.5,1), (0.65,0.72), (1.05,0.36), (2.1,0.1)) ~ Dmnl 
productivity inspections = 2*0.8 ~ Dmnl 
risk delayed work = 2 ~ Dmnl 
initial library of inspection plans = initLevelofInspPlans * number of equipment ~ equipment 
initial library of PM preparations = initLevelofPMfi*number of equipment ~ equipment 
limit takedown rate = 0.05 ~ Dmnl 
productivity scheduled repairs = 36 * 0.2 ~ equipment/(Week*people) 
productivity unscheduled repairs = 9 * 0.5 ~ equipment/(Week*people) 
average reliability = 52 ~ Week 
scheduled repairs = MIN(ScheduledMaintenance/delay scheduled repairs , max capacity scheduled repairs) ~ equipment/Week 
unscheduled repairs = MIN(UnscheduledMaintenance/delay unscheduled repairs , max capacity unscheduled repairs) ~ equipment/Week 
probability wear and tear = 0.015 ~ 1/Week 
identifiedDefectiveEquipmentCBMsensors = EquipmentWithCBMsensors/average CBM interval ~ equipment/Week 
identified defective equipment = identifiedDefectiveEquipmentInspections + 
identifiedDefectiveEquipmentCBMsensors ~ equipment/Week 
number of machines in line = 20 ~ machines 
number of equipment = number of machines in line*equipment per machine ~ equipment 
equipment per machine = 25 ~ equipment/machine 
delay scheduled repairs = 0.05 ~ Week 
delay unscheduled repairs = 0.1 ~ Week 
max fixed defects per repair = 8 ~ defects/equipment 
possible defects per equipment = 20 ~ defects/equipment 
goal availability = 0.9 ~ Dmnl 
takedownRate = takedown rate p ~ equipment/Week 
delay scheduling takedowns = 1 ~ Week 
fixedInterval = 52 ~ Week 
EquipmentWithCBMInspectionPlans = INTEG (convertPMToCBM-newCBMsensors-planned inspections+descretionary inspections, initial library of inspection plans) ~ equipment 
delay convert to CMB = 26 ~ Week 
delay convert to CBM sensors = 52 ~ Week 
PMreplacementBacklog = INTEG (planned repairs-start PMwo, 0) ~ equipment 
scheduledInterval = 4 ~ Week 
EquipmentHealth = INTEG (defectCreation-defectEliminationPM-defectEliminationRepairs, initial value of Hidden defects*number of equipment) ~ defects 
EquipmentToInspect = INTEG (planned inspections-descretionary inspections, 0) ~ equipment 
Defective equipment = INTEG (identified defective equipment-corrective takedowns, 1) ~ equipment 
ScheduledMaintenance = INTEG (takedownRate-scheduled repairs, 0) ~ equipment 
FINAL TIME = 520 ~ Week 
INITIAL TIME = 0 ~ Week 
SAVEPER = 13 ~ Week [0,?] 
TIME STEP = 0.015625 ~ Week [0,?]
51st CIRP Conference on Manufacturing Systems

Relating strategic time horizons and proactiveness in equipment maintenance: a simulation-based optimization study

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Abstract

Identifying sustainable strategies to develop maintenance performance within the short-termism framework is indeed challenging. It requires reinforcing long-term capabilities while managing short-term requirements. This study explores differently applied time horizons when optimizing the tradeoff between conflicting objectives, in maintenance performance, which are: maximize availability, minimize maintenance costs, and minimize maintenance consequence costs. The study has applied multi-objective optimization on a maintenance performance system dynamics model that contains feedback structures that explains reactive and proactive maintenance behavior on a general level. The quantified results provide insights on how different time frames are conditional to enable more or less proactive maintenance behavior in servicing production.

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Keywords: strategic development; maintenance performance; proactive maintenance; multi-objective optimization; system dynamics; simulation

1. Introduction

Industrial equipment maintenance includes rich dynamic complexity on how to deliver value. While the technical development has provided with many applicable solutions in terms of reliability and condition-based monitoring, managing maintenance is still an act of balancing, trying to manage the short-term economic requirements and simultaneously address the necessity of strategic and long-term thinking. Nonetheless, one of the contributing facts to seeing maintenance as a cost function only is the aggravating fact that maintenance is hard to justify at the individual activity level [1]. It contributes to that the strategic importance of maintenance becomes neglected [2]. The operational level of maintenance is hard to manage [1], since it suffers from many unplanned events of stochastic nature which, as they reoccur, interrupt important, advanced-planned activities and altogether allow too little abstract and strategic thinking. Therefore, much maintenance literature focus on the operation of maintenance, see, e.g., [3]. However, the economic short-term pressure combined with the character of maintenance on the operational level explain, to some extent, a common problem with regard to the dynamics of maintenance behavior, which according to [4], tend to overload the maintenance department with reactive work. Although the neglecting of preventive maintenance (PM) activities can achieve short-term gains, such as reduced costs or more production hours, it may lead to delayed economic consequences resulting from more frequent breakdowns [2], reduced equipment capability, or less time invested in continuous improvements [5]. At this point, there is no definition of what constitutes all these dynamic consequences from a proactive or reactive maintenance behavior, having subjective economic consequences [6], which makes it hard to apply the accurate strategy to improve. The complexity of production processes make it necessary to build models to support decisions for effective maintenance operations [7]. Yet, studying the dynamics of maintenance behavior seems to be a rather unexplored area in CIRP Annals, and few available studies are identified elsewhere, see, e.g., [8]. This paper is based on the belief that a larger understanding of how to achieve
proactive maintenance behavior in manufacturing operations can be supportive in reducing the knock-on cost consequences in such time-dependent systems. Furthermore, to sustainably implement strategic development of maintenance behavior, it has been argued [9] that despite us knowing the best practices, they do not align with the applied, where the limit is the organizational capabilities to integrate the conflicting priorities and messages.

Hence, abovementioned aspects frame the contribution of this study which presents a set of quantitative analyses that optimize maintenance behavior, testing four different strategic time horizons to their effects on the levels of maintenance proactiveness in the production system. The results are achieved by the application of simulation-based optimization (SBO), using multi-objective optimization (MOO) to a system dynamics (SD) model that studies aggregated maintenance behavior from different policies to the result in production performance. Hence, the experiments are evaluating the conflicting objectives of maximizing availability ($A_f$) in production, minimizing direct maintenance costs ($C_M$), and minimizing the maintenance consequence costs ($C_Q$) as an effect of insufficient maintenance.

The hypotheses of the study is that the time horizon is basis to the success of a sustainable strategic work, where optimizing maintenance performance with a short time horizon is expected to produce more reactive behavior due to larger attention to $C_M$, and using a longer time horizon is expected to produce more proactive behavior due to that the long-term benefits will have the opportunity to be considered in the tradeoff evaluation.

Hence, to search supports to a sustainable implementation, addressed by [9], this paper presents one approach to inform strategic development of maintenance, seeking its economic justification by analyses of the aggregated system behavior. MOO is applied to explore the tradeoffs between the conflicting objectives of, for instance, the short-term economic requirements [2], and the long-term needs in the maintenance system to attain the desired development [5].

Strategy researchers [5,10,11], have argued for SD’s application to investigate how the growth and decline of multiple capabilities affect system performance. SD is applied to identify the interconnections between parts in relevant system boundaries, to support understanding the complex reality. Researchers have previously claimed the benefits of applications of SD to study maintenance behavior, and further details can be found in [4,5], of how operations management studies based on SD theory can apply to maintenance. To our knowledge and recent studies of literature, see [8], there are still no published simulation models, except ours, that include the dynamic tradeoffs in maintenance behavior between the levels of $A_f$, $C_M$, and $C_Q$.

Moreover, few studies have investigated the integration of MOO and SD models, see, e.g., [13,14]. The work of [13] has applied MOO on models from [15], which have shown possible to draw generalized conclusions through studying the resulting patterns from the extensive amount of different optimal simulation runs. Our previous studies have explored the discerned strategies to apply on more of less critical equipment in the production system [16], and how the impact of the starting point of PM work may affect a manufacturing industry’s strategic development of maintenance [17].

In contrast to single-objective optimization, in which only one objective function is considered, the main concept of MOO is to evaluate two or more conflicting objectives against each other and obtain the Pareto-optimal solutions and the Pareto-front [18]. This comparison of the solutions is executed on the basis of the domination concept in which a solution $s_1$ is said to dominate a solution $s_2$ if $s_1$ is no worse than $s_2$, with respect to all optimization objectives, and where $s_1$ is strictly better than $s_2$ in at least one optimization objective [19]. The search space of a MOO problem is represented by the decision space where the input parameters, constitute a set of solutions evaluated through a solver, here an SD model, and mapped to the objective space. Thus, the design parameters are evaluated through the solver which subsequently results in the objective space representing the fitness or performance of a solution in terms of its defined objective functions.

2. The SD+MOO study

The technical procedure for how to achieve Pareto-optimal solutions, using MOO on SD models, have applied the methodology developed by [13]; as in applying the NSGA-II algorithm running at least 50,000 evaluations of the SD model. And, the support to develop maintenance performance through the application of SD+MOO, is more accurately described as a part of a strategy selection process, depicted in Fig. 1. The strategy selection process contains three phases which result in different levels of knowledge to support strategic work in maintenance systems. Hence, this study applies phase two to elicit Meta knowledge of system behavior tradeoffs, elaborately described in [16,17].

### Strategy-selection process

1. Create SD model maintenance behavior
2. MOO study of SD model
3. SD study of MOO results

<table>
<thead>
<tr>
<th>Step</th>
<th>Description</th>
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<tbody>
<tr>
<td>1.</td>
<td>a) Define problem, purpose, and boundary of study</td>
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<td></td>
<td>b) Build / reuse / adapt simulation model</td>
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<td>c) Explore and build model confidence</td>
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<td></td>
<td>d) Knowledge of dynamic system behavior</td>
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<td>2.</td>
<td>a) Identify MOO criteria and conflicting objectives</td>
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<td>b) Objective space exploration</td>
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<td>c) Verify results and improve SD model validation</td>
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<td></td>
<td>d) Perform tradeoff analyses of interest</td>
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<td></td>
<td>e) Meta knowledge of system behavior tradeoffs</td>
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<td>3.</td>
<td>a) Select optimal SD+MOO solution sets of interest</td>
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<td>b) Compare the sets’ dynamic behaviors in the SD model</td>
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<td></td>
<td>c) Study behaviors to inform the strategy guidelines and KPIs</td>
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<td></td>
<td>d) Knowledge of optimal solutions’ dynamic system behavior(s)</td>
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Fig. 1. The phases of the strategy-selection process.

2.1. The SD maintenance performance model

The purpose of the SD model is to serve as the basis for more informed strategies by investigating tradeoffs between short-term and long-term dependencies in the maintenance system. It is a generalized model developed with support from two large maintenance organizations in Swedish automotive industry. It is reviewed with detail explanations in [8], and [16] includes the specific SD model equations from the software. Thus this
The applied mix of maintenance methodologies, such as run-to-failure (RTF), preventive maintenance using fixed intervals (PMfi), and using condition-based maintenance using inspections (CBM) or sensors (CBMs) [20].

- The result generating and defect eliminating activities, resulting in the aggregated equipment health (EH) which relates to the rate of breakdowns ($R_{BD}$) of equipment [15].
- The resulting proactive or reactive effects from above aspects to operations, alongside applied resources such as repair workers ($S_r$), executing unscheduled or scheduled maintenance, inspired by [21].
- The continuous improvements (CI), developing countermeasures based on root cause analyses (RCA) of breakdowns inspired by practices at industrial partners, resulting in improving the applied mix of maintenance methodologies.
- The total maintenance costs ($C_t$), based on direct maintenance costs ($CM$), and estimated maintenance consequence costs ($C_Q$), based on corresponding model behaviors, such as $R_{BD}$, the rate of takedowns ($R_{TD}$), and applied resources. See Eq. 1-4.

![Fig. 2. Maintenance dynamics in the SD model.](image)

Consequently, the cost effects from reactive maintenance behavior consist of $CM$ based on breakdowns and applied resource policies, which is the standard approach to its cost modeling [9]. Yet, breakdowns also generate consequence costs ($C_{QBD}$), which effects are more intangible and apparent in other parts of an organization [22]. Thus estimates as in Eq. 4 must be applied. Additionally, reactive maintenance behavior requires higher levels of spare part inventories due to uncertainty, adding capital costs for $C_{CSI}$. These aspects sum up to the $C_Q$ according to Eq. 3.

Subsequently, the effects from proactive maintenance include a higher $R_{TD}$, which have zero $C_{QBD}$, however, apply an equal level of direct material costs ($C_S$) as breakdowns for each repair, but somewhat shorter repair time, and finally also reduce spare part inventories due to more planned work. On adding costs proactive behavior may apply more costly resources, more $S_R$ and $S_S$, however, if the $R_{BD}$ can be reduced within the time horizon of the investigated strategy there may be requiring fewer $S_r$ on average. On the other hand, to achieve a higher rate of $CI$ to move in the proactive direction also requires more $S_C$, adding to the $CM$. 

\[
C_T = C_M + C_Q \tag{1}
\]

\[
C_M = C_R + C_{CI} + C_S \ast (R_{BD} + R_{TD}) \tag{2}
\]

\[
C_Q = C_{QBD} + C_{CSI} \tag{3}
\]

\[
C_{QBD} = 4 \ast (C_S \ast R_{BD}) \tag{4}
\]
2.2. Defining the SD+MOO experiments

The purpose of the experiments is to enable testing the above-mentioned hypothesis about the importance of the strategic time horizon for the optimal tradeoff between the conflicting objectives in the maintenance performance model. To test the hypothesis, four experiments have been conducted on the same SD model using a different length of simulation time: one, three, five, and seven years. Any other changes are omitted. Furthermore, the experiments have applied the same optimizing objectives: maximize \((AT)\), minimize \((CM)\), and minimize \((CQ)\).

As the above description of the SD model explains, the three objectives are the measures of complex feedback interactions in the model. Hence, the experiments have searched combinations of input parameter values in the SD model within the same parameter ranges for all experiments, see Table 1. Accordingly, the defined experiments explore their respective optimal solutions, given the time frame for the policies to be implemented and acted out through the delays of the modeled system.

Table 1. Input parameter data for MOO evaluations.

<table>
<thead>
<tr>
<th>Input parameters</th>
<th>Range</th>
<th>Step</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Number of (S_E)</td>
<td>4 – 50</td>
<td>1</td>
</tr>
<tr>
<td>2. Number of (S_R)</td>
<td>0 – 30</td>
<td>1</td>
</tr>
<tr>
<td>3. % of (PM) from RCA</td>
<td>0 – 1</td>
<td>0.05</td>
</tr>
<tr>
<td>4. % of (CBM) from RCA</td>
<td>0 – 1</td>
<td>0.05</td>
</tr>
<tr>
<td>5. % of (CBM) with RCA</td>
<td>0 – 1</td>
<td>0.05</td>
</tr>
<tr>
<td>6. Goal % (CBM) of total PM</td>
<td>0 – 1</td>
<td>0.05</td>
</tr>
<tr>
<td>7. (CBM) interval (Weeks)</td>
<td>4 – 52</td>
<td>2</td>
</tr>
<tr>
<td>8. Goal (CBM)</td>
<td>0 – 500</td>
<td>25</td>
</tr>
</tbody>
</table>

Input parameters one and two affect resource policies for \(S_R\) and \(S_E\). More \(S_R\) have an instant short-term effect on \(AT\) in reactive maintenance, see e.g. [8]. And, to achieve proactive maintenance there is need for more staff and time to develop the supportive PM-work required. However, such development has tradeoff costs and delayed effects in the system that may not come into effect during the time horizon applied in the experiment.

Remaining input parameters, three to eight, are parameters in the SD model which explore goals leading to different levels of \(PM_{fi}\), \(CBM_{fi}\), and \(CBM_i\) to guide policymaking for the development of PM-work. In previous studies the resulting output patterns of these mixes have been studied, see e.g. [16,17]. Therefore, this study excludes a further focus on these measures, limiting the study to the inputs of \(S_R\) and \(S_E\).

To close the description of the MOO experiments, some aspects of the initial conditions are mentioned to support interpreting the result graphs. An experiment is affected by its initial levels of \(AT\), \(EH\), and levels of constituent PM-work. In this study, these values are reused from previous studies, based on levels that provided equilibrium behavior using RTF strategy [8], and the assumed starting point of mediocre PM-work as applied in one of the MOO+SD experiments in [17]. It gives an initial \(AT\) at 0.622 and \(EH\) at 0.7737. And, 0.5 of equipment applying \(PM_{fi}\) without any \(CBM_i\) or \(CBM_{fi}\) resulting in an initial fraction of PM-work at 0.25 in the model.

2.3. The SD+MOO results

The presented results are the Pareto-front solutions based on the conflicting objectives of maximizing \((AT)\), minimizing \((CM)\), and minimizing \((CQ)\). Further, solutions with lower \(AT\) than 0.85 are not considered in the analyses.

\(CM\) is generated based on the levels of \(S_R\), \(S_E\) and the \(C_s\) related to \(RTD\) and \(RBD\) throughout the simulation period. The experiments in Fig. 3. reveal that a tradeoff between increased \(CM\), by allocating more resources, do not necessarily provide a linear increase of \(AT\). Yet, up to around \(AT = 0.90\), a nearly linear increase of \(CM\) is shown for all experiments. The one-year time horizon experiment, TH1Y, stands out with clearly more expensive solutions which do not reach above 0.92 in \(AT\), further it depicts a sharp knee region, which means that a small increase on \(AT\) induce a considerable higher \(CM\), while the other experiment solutions depict smoother knee regions.

In sum, the results in Fig. 3. depict that the applied time horizons have tradeoff solutions on different achieved levels of \(CM\) compared to gained \(AT\), providing a spectrum of solutions where the longer time horizon leads to better-achieved objectives.

![Fig. 3. Solutions from the four experiments of the tradeoffs between availability \((AT)\) and maintenance costs \((CM)\).](image-url)

![Fig. 4. Solutions from the four experiments of the tradeoffs between availability \((AT)\) and maintenance consequence costs \((CQ)\).](image-url)
Studying Fig. 4, which compares $A_T$ to the induced $C_Q$, another pattern occurs. The TH1Y solutions reveal a rather linear relation between $A_T$ and $C_Q$. In comparison with the other experiments, TH1Y has no solutions at the higher region of $A_T$ having a clear non-linear pattern of lower $C_Q$. We could expect that these solutions do not include the achievement of proactive maintenance, which is later shown in Fig. 5. Since, attaining a proactive maintenance reduces the $R_{BD}$, resulting in lower $C_Q$. The three-year time horizon experiment, TH3Y, and the five-year horizon experiment, TH5Y, both reveal an unexpected pattern where solutions with higher $A_T$ are found on disparate levels of higher and lower levels of $C_Q$. The solutions in the seven-year time horizon experiment, TH7Y, apart from that pattern slightly, by having a small slope from higher $C_Q$, on the right hand in the graph, to lower, as $A_T$ increases. Moreover, TH7Y reveals a cluster of solutions at the lowest end of $C_Q$ with the highest $A_T$ values.

In sum, the results in Fig. 4 depict that the applied time horizons have tradeoff solutions on different achieved levels of $C_Q$ compared to gained $A_T$, however, they provide a non-linear pattern where some solutions from TH3Y are better than some solutions from TH7Y. Furthermore, the results indicate that applying a longer time horizon can identify tradeoff solutions that have significantly lower levels of $C_Q$.

The parallel coordinate map (PCM), depicted in Fig. 5., visualizes relations between parameters of interest. To have a cleaner figure the TH5Y and TH3Y results are omitted, comparing the most disassociated experiments TH1Y and TH7Y. The PMC visualizes that the TH1Y solutions depict one distinct cluster, with $R_{TD}$ at 4-6 per week, and $R_{BD}$ at 34-36 per week; thus exhibits a ratio of about 90% of reactive maintenance. The PCM reveals such ratio to induce the higher levels of $C_Y$, see Eq. 1., which is the sum of the costs depicted in the two aforementioned graphs, as well as, the higher levels of $C_M$. Hence, the effect of reducing $C_Q$ can be evaluated to the required increase of $C_M$ to achieve the associated results. In TH1Y it means higher levels of allocated $S_E$, while for $S_E$, which reveals a pattern of even distribution is less informative on the optimal choice.

![Fig. 5. Parallel coordinate map of experiments TH1Y and TH7Y.](image)

In contrast, the TH7Y solutions are represented with several clusters in the PCM. Where, for instance, the cluster containing the highest levels of $A_T$ relates to ranges of higher $R_{TD}$, at around 22 per week, and lower $R_{BD}$, at around 18 per week; exhibiting a ratio of around 45% of reactive maintenance on average. Furthermore, tracing the results of these solutions they induce the lowest levels of $C_Y$, but at the same time require the higher levels of $C_M$ and the higher levels of $S_E$; and apply more $S_R$ than the other TH7Y solutions. Moreover, the cluster around $A_T = 0.95$ in the TH7Y solutions, traced to the resource parameters are seen to require fewer repair workers and engineers and thus lower levels of $C_M$, still achieving more proactive levels than the THY1 solutions.

In sum, the results depicted in Fig. 5 reveal that the applied time horizons strongly relate to the achievement of proactive maintenance behavior, measured by the rates of takedowns ($R_{TD}$) and breakdowns ($R_{BD}$).

In this study, the quantified results of the objective space – max($A_T$), min($C_M$), and min($C_Q$) – have been studied, as well as, selected model parameters ($R_{TD}$, $R_{BD}$) which indicate on achieved proactive behaviors in the maintenance SD model, and two input space parameters ($S_R$, $S_E$). In this study, the specific input-policies, besides staffing ($S_E$, $S_R$), are not deeper studied, which could be part of future works. However, the above-analyses of resulting tradeoff solutions indicate that:

- It requires a longer time horizon to act out the effects, based on applied policies, to expose a proactive maintenance behavior.
- A proactive maintenance behavior is conditional to achieve the higher levels of availability ($A_T$) and lower levels of maintenance total costs ($C_T$).

3. Discussion and conclusions

To achieve proactive maintenance behavior it requires the continuous improvement (CI) of preventive maintenance (PM) procedures to balance the underlying maintenance need of the equipment. This study shows that results from strategic development of maintenance do not come into effect on short-term. This work is based on a previously published system dynamics (SD) model of maintenance performance dynamics. The purpose of the SD model is to serve as the basis for a more informed strategic development of maintenance behavior by supporting the investigation of tradeoffs between short-term and long-term dependencies in the system. Hence, it can be considered to represent a structural theory for studying the feedback between interrelating elements of equipment maintenance, such as maintenance need based on reliability and current equipment health, number of repair workers, applied mix of maintenance methodologies, CI of the applied mix, and the corresponding effect in operations based on ratio between scheduled and unscheduled maintenance interventions. Hence, the SD model makes possible addressing the system costs of maintenance as a result of the operational feedback behavior in the system.

To explore the SD model we apply multi-objective optimization (MOO) which generates near optimal Pareto-front solutions. The experiments apply different time frames of one, three, five, and seven years; for which the inputs of staff resources and the corresponding CI effects of the PM-work are searched and evaluated, using MOO, through the SD model’s complex feedback structures with delayed effects.

The SD+MOO experiments have searched the tradeoffs between the conflicting objectives of maximizing availability
(AT), minimize maintenance costs (CM), and minimize maintenance consequence costs (CQ). The results indicate that the levels of achieved proactive maintenance behavior relate to the applied strategic time horizon when searching the appropriate strategy for developing maintenance. For the specific study, it has had the implication that the optimal tradeoff solutions using a one-year time horizon allow low levels of proactiveness, around 10% when the resulting ratio of scheduled maintenance is compared to unscheduled. While quite the reverse is true using a seven-year time horizon, ending up at around 55% on the same measure of proactiveness; which quite the reverse is true using a seven-year time horizon, ending up at around 55% on the same measure of proactiveness; which moreover is exhibiting higher levels of AT and lower levels of CQ. However, both cases partly share the required levels of resources to achieve the associated results.

Hence, the hypothesis that the time horizon is one of the key contributors to the success of sustainable strategic work, in terms of enabling a more proactive strategy, is considered enforced.

Nevertheless, to use these generalized results in a sharp manufacturing case, naturally, the SD model must be adapted until enough confidence is achieved for its specific use. Hence, the applied SD model holds the largest bias in this study. However, at the same time, the results may indicate its supports as a structural theory for studying proactive and reactive maintenance behavior. The results may also support showing how the application of MOO supports exploring the SD model, and its corresponding applicability to support the economic justification of proactive maintenance on an aggregated system behavior level.

As regards future work, the presented application holds many promising uses and enables testing different questions with respect to strategic development of maintenance, and it can induce deeper studies to adapt the SD model to contain more dynamics related to achieving proactiveness, such as, for example, the hiring, training, and retiring of repair workers.

Acknowledgments

This work was partially financed by the Knowledge Foundation (KKS), Sweden, through the IPSI Research School. The authors gratefully acknowledge their provision of the research funding and the support of the industrial partners Volvo Car Corporation and Volvo Group Trucks Operations.

References

A hybrid simulation-based optimization framework supporting strategic maintenance development to improve production performance

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Abstract
Managing maintenance and its impact on business results is increasingly complex, calling for more advanced methods to support long-term development through effective activities in the production system environment. This problem-based research supplements the operations research/management science literature by contributing a novel, hybrid simulation-based optimization (SBO) framework that integrates multi-objective optimization (MOO) with system dynamics (SD) and discrete-event simulation (DES). The objective is to support maintenance management decision making at the strategic and operational levels to prioritize maintenance long-term planning.

The application of MOO distinguishes this research from previous efforts mixing SD and DES, presenting a unique methodology supporting more quantitative and objective-driven decision making in maintenance management. A multiphase process is designed, applying SD+MOO in exploring feedback behaviors to determine why certain near-optimal maintenance behaviors arise. The outcome then forms the basis of potential operations-level performance improvements. In other words, the SD output is utilized as the input decision space of the DES+MOO study, available by a standard software, resulting in the sequence of improvements addressing the primary bottleneck in the production system.

Overall, this hybrid SBO framework allows maintenance activities to be pinpointed based on analysis of the feedback behavior that generates less reactive load on the maintenance organization. On one hand, based on a literature review on related hybrid methods (see section 3), the proposed work can be claimed to be novel; on the other hand, this study is describing a conceptual hybridization based on SD+MOO cases and their application to the DES+MOO software.

Keywords: problem structuring, decision support, system dynamics, multi-objective optimization, discrete-event simulation

1. Introduction
Maintenance considerably increases the budget in manufacturing industries. Even though a cost focus belongs to the past and maintenance has shifted towards being an organizational strategic capacity (Simões, Gomes, & Yasin, 2011), the tradeoff between invested costs and their benefits is still of great concern for decision makers. The value of maintenance is strongly challenged by short-termism and by high pressure for production utilization from the rise of global competition. According to Geary, Disney, and Towill (2006), reactive maintenance potentially leads to increased disruption in real-world supply chains, causing excess variance in performance. Logically, the opposite is valid, i.e., that proactive maintenance should reduce variance in performance by means of more precise maintenance activities in production systems. Recent developments in terms of increased automation, more expensive equipment,
and more complex production systems have increased the capital tied up (Garg & Deshmukh, 2006), meaning that unplanned breakdowns have more serious consequences (Swanson, 1997). Proactive maintenance policies are therefore considered a necessity (Pinjala, Pintelon, & Vereecke, 2006), and proper maintenance practices contribute to overall business performance (Alsyouf, 2009). However, identifying appropriate practices and implementing sound strategies for developing maintenance performance are still non-trivial. Moreover, Woodhouse (2001) recognized the limiting factor in managing the implementation of sustainable maintenance practices to be the organizational capabilities to perform and incorporate conflicting priorities and messages into the equation.

Accordingly, strategic development of maintenance performance requires support to uncover longer-term processes inherent in the complex system of managing assets, in order to deliver shorter-term production performance according to market demand. Researchers in maintenance management and strategy have tacitly addressed the necessity of the larger system view, for example, discovering that: (1) cost-over-profit maintenance performance measurement systems do not capture the repercussions of current actions (Sherwin, 2000); (2) tools are required that can connect and validate the causal relationships between strategic initiatives and performance results (Tsang, 2000); and (3) consequential costs due to applied strategy must be included in the development of maintenance performance (Vorster & De La Garza, 1990). Moreover, in maintenance policy optimization research, analytical models have struggled to find practical applications in industry (Dekker, 1996), and Nicolai and Dekker (2008) declared that such models are insufficient for tracing the effects of maintenance policies. Maintenance modeling has been sharply criticized for oversimplification (Lad & Kulkarni, 2011; Sinkkonen, Martonen, Tynninen, & Kärri, 2013). Therefore, simulation to optimize maintenance cost has been an emerging trend (Sharma, Yadava, & Deshmukh, 2011). Nevertheless, such typical maintenance problems are often oversimplified and treated in isolation, and the maintenance literature generally suffers from equally oversimplified simulation studies (Alrabghi & Tiwari, 2015). In fact, according to Ding and Kamaruddin (2015), production systems are overly complex and current research in maintenance policy optimization does not sufficiently address the matter of practical applicability. According to De Almeida, Pires Ferreira, and Cavalcante (2015), maintenance needs applications of multi-objective optimization (MOO), which could better capture decision makers’ preferences regarding the decision problem and include conflicting tradeoffs.

Consequently, research contributions to the maintenance field should consider both from problem structuring methods using simulation and the application of MOO. Nonetheless, according to Pintelon and Gelders (1992), sound knowledge of operations research/management science (OR/MS) techniques supporting quantitative analysis to make decision making in maintenance management more objective also requires a thorough understanding of maintenance practice and organization. To address the deficiencies of overly narrow simulation applications and allow the consideration of more complex maintenance systems, Alabdulkarim, Ball, and Tiwari (2013) proposed discrete-event simulation (DES) to potentially add to the maintenance field what it has delivered to operational research into manufacturing systems. Applying DES to evaluate maintenance strategies at the operational level has therefore emerged more recently (Alrabghi & Tiwari, 2016), providing frameworks for general cases of time-based preventive maintenance (PM), opportunistic maintenance, and periodic condition-based maintenance (CBM). On the other hand, according to Alrabghi and Tiwari (2015) and Alrabghi, Tiwari, and Savill (2017), the application of DES to evaluate PM has been very little explored. Mainstream DES research mainly supports the reactive improvement of production systems (e.g., Gopalakrishnan (2016), with several studies applying DES evaluations to support the prioritization of reactive breakdown repairs with the objective of increasing system throughput.

On the other hand, according to Gunal and Pidd (2010), DES inadequately visualizes feedback behavior and cannot explain why certain behaviors arise. In conducting studies that explain feedback behavior, the application of system dynamics (SD) has brought insights into industrial systems ever since Forrester (1961) quantitatively explained the bullwhip effect in supply chains and further claimed that simulation could be used to demonstrate that the feedback’s structure can have greater influence on system behavior than its specific parameter values. The suitability of SD as a structural theory for operations management has been advocated by Größler, Thun, and Milling (2008), using qualitative examples illustrating how system dynamics behavior tends to overload maintenance departments conducting reactive rather than proactive activities. However, quantified SD models of maintenance applications and subsequent
documentation are generally rare, according to a recent literature review by Linnéusson, Ng, and Aslam (2018c); except for the approach proposed by the review’s authors, no previous studies enable investigation of the tradeoff between availability, maintenance cost, and maintenance consequential costs.

Nevertheless, SD cannot be used in studying complexity at the detailed level required for production systems and is more suitable for facilitating understanding of why certain dynamic changes arise in systems. Besides, applying DES or SD in studies limits analyses to “what if” scenarios, and calls for the integrated application of optimization to identify the best option. However, single-objective optimization (SOO), commonly applied in SD (e.g., Dangerfield (2014); Jones (2014)), has its limits in terms of seeking tradeoffs and cannot include several conflicting objectives. More specifically, we need SBO, which applies SD integrated with MOO, as proposed by Linnéusson, Ng, and Aslam (2018a), as well as DES integrated with MOO, as previously proposed by Ng, Bernedixen, and Pehrsson (2014), to achieve more complete predictions of the objective landscape to inform decision making at both the strategic and operational levels.

Subsequently, based on the industrial need for maintenance development that seeks support to analyze the longer-term repercussions of current activities, including targeted operational activities to improve overall production system performance, this paper proposes a hybrid SBO framework combining SD and DES studies supported by their respective integration with MOO. The purpose is to synthesize the strengths of each method: SD+MOO helps in identifying the optimized long-term aggregate view of the strategic development of maintenance system behaviors and their simultaneous tradeoffs in terms of both short-term and delayed maintenance costs, whereas DES+MOO helps in identifying activities to maximize utilization from a short-term detailed view of operations. Accordingly, this study aims to support applications of SD+DES mixed-method designs developed in the OR/MS community, which seeks to combine the benefits of both simulation approaches to overcome the deficiencies of each, as suggested by Brailsford, Desai, and Viana (2010). Unexpectedly, as revealed in section 3, the literature review of SD+DES mixed-method designs applying optimization identified remarkably few articles. Specifically, integrating MOO was mentioned in only one paper, by El-Zoghby, Farouk, and El-Kilany (2016), but even so, it was not implemented in the reported experiment. To some extent, this highlights the contribution of the present paper, which uses MOO as a precondition for applying mixed SD+DES to generate the required efficacy.

The paper is organized as follows: section 2 introduces a theoretical model of maintenance-driven change in the production system, including three levels of maintenance development that the SBO framework addresses; section 3 describes the methodological aspects of mixed-method designs, briefly introduces MOO, and reviews the literature on SD+DES mixed-method designs with an emphasis on optimization; section 4 contains the core contents of this paper, describing the SBO framework in which various phases of our proposed approach are illustrated by contributions and exchanges between the methods and the production system environment. Finally, the paper ends with a discussion and conclusions section.

2. A system view of combining SD and DES for maintenance development

Supported by the schema in Fig. 1, we define a theory of maintenance-driven change in production systems taking account of three levels of maintenance development and of how the SD and DES methods can support them. It also explicitly shows why mixing SD and DES can add value to achieve momentum for sustainable change in the applied production system environment.

Maintenance interventions are either, proactive combining PM and systemic procedures, or reactive with run-to-failure at their extreme. Generally, the more proactive the better, since the current level of care upholds current equipment performance; however, the economic justification may not be equally distributed, as this depends on the production system configuration, which can produce significantly nonuniform consequences. According to Warren (2005), performance reflects the current state of resources in any period, so performance development requires the strategic management of steering the rates of resource use. For maintenance, strategy implies controlling the rates of resource use, which in due time leads to proactiveness. Moreover, such control is dependent on many, often ambiguous, accumulations in the system – such as hidden defects in equipment, the quality of developed PM work.
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to address the defects, skill and competence levels of staff, and more – which are affecting the required strategy. It is therefore hard to foresee and trace the consequences of the applied strategies. Operations, on the other hand, are relatively more tangible, though simultaneously extremely complex. Also, operations are often subject to short-term pressures that displace the activities ultimately leading to proactiveness. Therefore, any optimal configuration of operations cannot be attained without the support of a prediction method, such as simulation.

![Diagram](image)

Fig. 1. Theoretical model showing how different levels of maintenance development align with the applied methods.

Fig. 1 outlines a theory of the continuous interactions between activities acting on the longer and shorter terms, visualizing the nature of the ongoing change due to production system maintenance. Fig. 1 contains several semantic items, all of which are meaningful, connected to the defined levels as follows:

**Level One:** The circle represents operations and is where the current results are produced. At this level, change is manifested in activities to optimize the operation of the production system, using current maintenance capabilities to deliver proactive or reactive service to operations.

**Level Two:** The wedge represents maintenance operations. At this level, the current rates of capability change are produced, as in moving towards proactiveness or reactiveness.

**Level Three:** The large arrow represents the maintenance strategy and is where the quality of the current learning mechanisms, generated from perceived knowledge of the real-world system, are generating the changes that improve or degrade the performance.

This figure illustrates how changes at the three levels relate to the importance of maintenance in the production system environment. The ongoing work of maintenance operations (level two) serves as a wedge upholding the current operational performance of production system operations (level one). These components, i.e., maintenance operations and production system operations, continuously move up or down the slope determined by the balance between the entropy-driven deterioration of the maintenance system and “friction” (see, e.g., Levitt (2011)). The “gravity force” of this deterioration can be illustrated using different slopes and is largely defined by the requirements defined in the acquisition of the production system equipment. At the same time, the “friction” slowing this deterioration can be increased by improving the efficiency of currently applied basic maintenance policies (see Pintelon and Gelders (1992) or, in other words, maintenance methodologies (Tsang, 2002), which in the figure is called mix of PM work. Balancing these conditions involves complex feedback among the components of this sociotechnical system. Accordingly, many preconditions at level one are governed by capabilities at level two, which together generate the current availability of the production system. This also means that when conditions change at level one they will affect level two, for example, reducing the timeframes...
for PM work in operations. In the real world, it is tempting to neglect any longer-term consequences of such changes, and applying a DES study would certainly imply using the same input data. Again, in the real world, we know that there are delayed consequences, such as an increasing backlog of PM work and an increasing load on the equipment, potentially resulting in more unplanned breakdown events in operations, but we lack the proper tools to draw such conclusions from the decision-maker perspective. Much can be gained from experimenting in DES studies, for example, considering how maintenance could provide better service operations (see Gopalakrishnan (2016), who addresses level one, and Alrabghi et al. (2017), who address levels one and two by exploring different PM strategies). However, although DES studies at best optimize the use of current maintenance operation capabilities, they cannot evaluate the rates of capability change, as in moving towards proactiveness or reactiveness. Still, DES studies can affect the formulation of a maintenance strategy (level three), but from a limited long-term perspective, explaining the size of the dotted oval shape labeled “DES.”

Certainly, better understanding the consequences of feedback between the operational load, its effect on equipment health, and how the applied mix of maintenance methodologies can support the balance between proactive and reactive interventions in operations would support strategy formulation. Fig. 1 highlights the purpose of using SD, which, according to Thompson, Howick, and Belton (2016), is a conceptual framework essential to thinking about things. SD is therefore applied to make explicit the structures generating level two and three performance, to support the formulation of prudent strategies based on a simulated theory of how organizational change is generated and operated by means of organizational learning (Senge & Sterman, 1992). Furthermore, SD enables analysis of the potential impacts of various strategies for achieving proactiveness, given the current limitations of maintenance operations at the aggregate level, shown by the dotted oval labeled “SD.”

The objective of the hybrid SBO framework incorporating a mixed SD+DES approach is to support all three levels of maintenance development in interaction with operations. As noted, no single method is applicable to all three levels and their diverse characters of change. Moreover, these levels can be addressed with different degrees of precision, so a precondition is integration with MOO to support the evaluation of accurate, optimal tradeoff solutions.

3. Theory and literature review

3.1. Methodological aspects of mixed-method designs

The mixed SD+DES approach has interested researchers in recent decades: many applications have been reported in operations research (Howick & Ackermann, 2011) and many different levels of integration have been reported. According to Brailsford et al. (2010), the “Holy Grail” of achieving the complete mix, realizing the full potential of both approaches, is continuously improving, but may not be attained due to the divergent philosophical standpoints of each approach. To support methodological-level reflection, Morgan, Howick, and Belton (2017) presented a toolkit of designs for mixing the DES and SD methods. Fig. 2 depicts their schema of mixed-method designs to facilitate reflection on how the SD+DES+MOO framework used here was methodologically designed.

From a technical viewpoint, there are two reasons for mixing DES and SD: the feedback control level incorporated in SD and the great detail level that can be included in DES models (Viana, Brailsford, Harindra, & Harper, 2014). Although feedback may be incorporated to some extent in DES models, Gunal and Pidd (2010) have claimed that the use of DES as a tool tends to emphasize the operational level of specific areas, whereas the use of DES for policy-level analysis is rare and feedback behavior is inadequately visualized to support the determination of why certain behaviors arise. However, examples of hybrid DES+SD simulation models not intended to consider feedback behavior also exist; for example, Abduaziz, Cheng, Tahar, and Varma (2015) applied SD merely to accumulate result data from the DES model to trace the environmental load of automotive industry operations. There is great variation in how DES and SD can be mixed, as depicted in Fig. 2. This figure was adapted from Morgan et al. (2017), who extensively studied the literature on mixing OR/MS methods and/or mixing DES+SD, while making recommendations for further studies.
Isolation is applying SD or DES without mixing them. Parallel is applying SD and DES in isolation for the purpose of contrasting their respective contributions to a commonly studied phenomenon, using their shared paradigm perspectives, which then focus on the methodological level of the respective techniques used to study the same problem. Sequential is alternately applying SD and DES, each method supplying input to the other, allowing both methods to be fully developed within their specific use paradigms. Enrichment is when a primary method is enriched with techniques from one or more other paradigms, for example, using DES in an SD model or continuous behaviors in a DES model. Interaction is allowing feedback exchange between methods, relaxing the paradigm restrictions between SD and DES, exploiting both methods’ benefits in one methodology. The level of interaction can range from the frequent exchange of information between SD and DES models in one simulation evaluation to just a few interactions during an evaluation period. Integration, on the other hand, is full integration in which one simulation evaluation includes both discrete and continuous time steps, but with both methods taking a shared system view.

The mixed-method design framework proposed by Morgan et al. (2017), as adapted in Fig. 2, was developed with applications of DES and SD in mind, but lacking the aspect of optimization. Considering the optimization of the techniques in Fig. 2, it applies best to integration, as also described by Pidd (2012), giving rise, according to the discussions above, to a new method or potentially even a new paradigm, depending on the significance of the contribution of optimization to the method. Accordingly, the proposed hybrid SBO framework that applies SD+DES+MOO in a certain procedure depicted later in Fig. 4 is not directly applicable into one of the categorizations of the above-reviewed framework of mixing SD and DES. Considering Fig. 4, one therefore finds elements of sequential design, potential interaction, and integration of the SD+DES+MOO methods in the proposed hybrid SBO framework. According to Pidd (2014), this could be classified as somewhere between a “loose coupling of different approaches” and “the use of one approach as a precursor to the other.” Although each SD+MOO and DES+MOO integration can be applied without the other method to support practical development, for the purpose of maintenance development, they have been combined into our proposed framework to complement each other, giving a broader system view.

3.2. Multi-objective optimization (MOO)

MOO is a discipline that, in contrast to SOO which considers one objective function, evaluates two or more conflicting objectives against each other, and obtains the Pareto-optimal solutions that constitute the Pareto front (Basseur, Talbi, Nebro, & Alba, 2006). The comparison of the solutions utilizes the domination concept in which solution \( s_1 \) is said to dominate solution \( s_2 \) if \( s_1 \) is no worse than \( s_2 \), with respect to all optimization objectives, but \( s_1 \) is strictly better than \( s_2 \) in at least one optimization objective (Deb, 2001).
Fig. 3 illustrates the concepts of decision space and objective space, as well as the domination and non-dominance of solutions in MOO. The decision space contains the design variables (defined by the input parameters) being sought in a MOO problem. Each design variable is mapped to the objective space and evaluated through a solver, which in our case is either an SD or DES model using the same principle. Thus, a certain solution $A$ with its inherent values of the design parameters $x_1$ and $x_2$ is evaluated through the solver, subsequently resulting in $A'$ in the objective space representing the fitness or performance of solution $A$ in terms of the objective functions $f_1$ and $f_2$.

### 3.3. Literature review of works mixing SD+DES+MOO

The current research frontier of work combining DES and SD with optimization is reviewed in this subsection. This topic was briefly mentioned by Pidd (2012), serving only as an example of mixed methods closely integrated with simulation. As mentioned above, this matter was ignored by Morgan et al. (2017), who mainly presented a comprehensive toolkit of designs for mixing DES and SD. Therefore, a Scopus search was conducted using the keywords “discrete event simulation” and “system dynamic*” and “optim*” in titles, abstracts, and keywords. We initially identified 56 items, but on closer examination, found fewer articles that actually mixed DES and SD. Regarding papers with contents related to optimization, a total of six papers could be identified; they are summarized in Table 1 to provide an explicit overview of the state of research combining DES+SD with optimization.

<table>
<thead>
<tr>
<th>Article</th>
<th>Research scope</th>
<th>Level of optimization</th>
<th>Optimization objective</th>
</tr>
</thead>
<tbody>
<tr>
<td>Venkateswaran and Son (2005)</td>
<td>Solving the hierarchical production planning problem using SD and DES coupled with optimization</td>
<td>Inputs to SD model use SOO. DES model applies outputs from SD evaluations, and uses SOO. DES+SD level evaluates.</td>
<td>SD: evaluates SOO input. DES: max. throughput. SD+DES: evaluation.</td>
</tr>
<tr>
<td>Venkateswaran, Son, Jones, and Min (2006)</td>
<td>Proposing an approach for integrating vendor inventory supply chain and production planning</td>
<td>Inputs to SD model use SOO. DES model applies outputs from SD evaluations, and uses SOO. DES+SD level evaluates.</td>
<td>SD: evaluates SOO input. DES: min. tardiness. SD+DES: evaluation.</td>
</tr>
<tr>
<td>Jovanoski, Nove, Lichtenegger, and Voessner (2013)</td>
<td>Providing examples to justify a hybrid simulation approach for managing strategy and production levels</td>
<td>Not implementing; emphasizes optimization</td>
<td>Enable optimal storage capacities and number of salespersons.</td>
</tr>
<tr>
<td>Albrecht, Kleine, and Abele (2014)</td>
<td>Providing computerized decision support for designing changeable production systems</td>
<td>Not implementing; “optimization” is mentioned in title and abstract but not emphasized elsewhere.</td>
<td>DES: evaluates given state. SD: evaluates changeability of the production system.</td>
</tr>
<tr>
<td>El-Zoghby et al. (2016)</td>
<td>Presenting a conceptual framework for a multilevel approach to optimizing an emergency department</td>
<td>A theoretical review of a framework: DES model should use MOO; SD model evaluates and iteratively provides input to the DES fitness computation until satisfactory results are obtained.</td>
<td>Claims to improve multiple objectives; no tradeoff objectives defined; experiments apply what-if analysis.</td>
</tr>
</tbody>
</table>
The above survey of available research applying optimization integrated with any approach mixing DES and SD provided surprisingly few examples. Only the work of Venkateswaran and Son (2005) and Venkateswaran et al. (2006) presented proof-of-concept experiments applying optimization. Regarding MOO, its application in modeling patient flows in emergency departments was emphasized by El-Zoghby et al. (2016) as the most frequently studied topic in healthcare management and therefore had a legitimate place in their framework. Even so, their experiment was merely a what-if analysis and optimization was not used.

Additionally, searching for applications of DES+SD in maintenance produced few results, and with a different industrial focus from that considered here: (1) a performance forecast model for cutting tool replacements in mechanized tunneling projects that also applied agent-based modeling (Conrads, Scheffer, Mattern, König, & Thewes, 2017); (2) a hybrid model of the availability assessment of an oil field (Drogueet, Jacinto, Garcia, & Moura, 2006); and (3) a thesis on how to technically address the limitations of SD, with DES used to represent individual entities and stochastic behavior, using a simplified SD model of maintenance (Bell, 2015).

4. Description of the hybrid SBO framework

Applying the SBO framework to support decision making is not straightforward. It involves many feedback iterations, from the iterative process of developing an SD model, through the knowledge extractions during the various phases, until specific activities can be identified and implemented in the maintenance system. This section first presents a technical introduction to the SBO framework in terms of its most prominent process steps. Subsections 4.1–4.6 present a walkthrough of the various phases of the framework, while subsection 4.7 presents a complete overview of the mixed-method framework in context.

![Fig. 4. The technical SBO framework of mixed-method design.](image)

![Fig. 5. Phases 1–6 and their steps in applying the SBO framework.](image)
each phase that are required in order to implement the results. Examining each phase improves our knowledge of the studied systems – hence, the continuous feedback of study results. Phase 3, which ends the strategy-selection process, has three potential outputs:

1. **Output strategies** – which are the results of phases 1–3 and can be applied as general guidelines for the maintenance system
2. **Input DES+MOO** – the behavior resulting from phase 3, as the measures mean time to failure (MTTF) and mean time to repair (MTTR), which serve as the input decision space for phase 5 (see subsection 4.4)
3. **DES\(_t\)** – the potential changes to the structure of the DES+MOO exploration, which can be applied to subsequent cases

In particular, the interaction between SD and DES is based on the application of SD+MOO, and the outcome itself defines the decision space, which is further searched using DES+MOO. The optimized result is the end product of the activity-selection process, pinpointing the improvement actions in the production system. On the other hand, the effects on system throughput may have implications for parameters in the SD model, so that phase 2 may provide different tradeoff analyses due to the improved conditions.

Placing the application of DES+MOO in the maintenance context allows tactical planning of the improvement of maintenance, which, according to Pintelon and Gelders (1992), addresses the problem of effective resource utilization. This contextualization focuses maintenance attention on the operation conditions, instead of ensuring the health status of isolated equipment, which is the case when criticality due to production system configuration is ignored. Overall, the DES+MOO method is critical for the framework; however, in the reverse direction, DES+MOO can be run independently without the framework, even though its context adds meaning and provides guidance for better-planned maintenance activities.

The application of these studies in the SBO framework should therefore be seen as contributing to the complex management of activities, for the purpose of helping accelerate rather than slow the rate of change towards proactiveness (see Fig. 1). Accordingly, the wider system boundary addressed by the framework does not come with any claims of completeness; rather, a wider system boundary is required to induce greater awareness and more insightful decisions. The framework is based on the belief that, although not everything can be controlled, we need guidance in the uncontrollable environment of complex sociotechnical systems. This approach to reality recalls the systems thinking proposed by Flood (1999), exemplified in the following: “We will not struggle to manage over things – we will manage within the unmanageable.”

### 4.1. Phase 1 – An exemplar SD model

This phase is represented by an SD model as reported and applied in previously published cases; detailed explanations were presented by (Linnéusson et al., 2018c), including analyses based on dynamic model behaviors, and all model equations by (Linnéusson, Ng, & Aslam, 2017), and aspects of model boundary and validity supported by SD+MOO (Linnéusson et al., 2018a). The subsequent results here were generated from the previously reported SD model, yet the description is kept as brief as possible. The model was designed to serve as the basis for better-informed strategies, by enabling the exploration of tradeoffs between short- and long-term dependencies in the maintenance system. It is a generalization, developed with support from two large maintenance organizations in the Swedish automotive industry, that includes the following elements:

- a mix of currently applied maintenance methodologies, such as run-to-failure (RTF), PM using fixed intervals (PMfi), and condition-based maintenance using inspections (CBM) or sensors (CBMs) (Tsang, 2002);
- defect-generating and defect-eliminating activities resulting in an aggregate equipment health (EH) relating to the breakdown frequency (RBD) of the production system (Sterman, 2000);
- the resulting balance between unscheduled and scheduled maintenance, based on the above points together with applied repair workers (SR) (inspired by Ledet and Paich (1994)).
- continuous improvement (CI), based on root-cause analyses (RCA) of breakdowns, changing the mix of maintenance methodologies depending on available maintenance engineers (SE) (inspired by industrial partners); and
- maintenance total costs (CT), based on direct maintenance costs (CM), and estimated maintenance consequence costs (CQ), based on variable behaviors such as RBD, planned takedowns (RTD), inventories, and applied resources, (inspired by how costs are generated).

Fig. 6. is a simplified schematic of the SD model using Vensim DSS software, showing a stock and flow structure for keeping track of the condition of equipment in operations; the remaining structure is simplified into causal loop diagramming (CLD) notations (Sterman, 2000) to support the qualitative explanation of the dynamics.

Reactive maintenance leads to breakdowns (RBD) fixed by unscheduled repairs to restore equipment to its functional condition. RBD not only degrade equipment health (EH), which can lead to more RBD, but also reduce availability (AT), yet, simultaneously a lower level of AT is limiting the impact of equipment deterioration, having a combined effect resulting from two different feedback loops. If the number of repair workers (SR) is kept constant, all this feedback eventually generates an equilibrium performance level. Regarding Fig. 1, this would correspond to the wedge keeping the circle in a fairly stationary position on the slope; accordingly, reactive maintenance corresponds to level two.

Proactive maintenance leads to scheduled repairs restoring equipment to functional condition before failure. The flow of takedowns (RTD) depends on the planned work order backlog and the pressure to produce, giving rise to a growing gap between the targeted and current AT. This gap will delay the proactive work and increase the risk of RBD. The precision with which defects can be identified depends on the applied mix of RTF, PM Ji, CBM i, and CBMS j, represented by the boxed variable “PM work” and the current EH status. At this point, related to Fig. 1, these dynamics correspond to level two, as does reactive maintenance. However, the introduction of new PM work according to the continuous improvement (CI) principle, based on policies set by goal PM work and applied resource policies, changes the mix of maintenance methodologies applied during different periods. As depicted by the dynamics corresponding to level three in Fig. 1, the large arrow shifts the equilibrium towards proactiveness by moving the wedge and circle up the slope.

4.2. Phase 2 – MOO+SD studies
Phase 2 represents a MOO study dependent on the purpose of the SD model, the understanding of the dynamics included, and an idea of what should be studied in the tradeoff analyses. Similarly, as in SD
studies, a large variety of possible tradeoff studies is available when using MOO in an SD model. It is therefore the study at hand that defines the exact criteria to use. The applied MOO criteria identified in step a) define the MOO model, as depicted in Fig. 7.

Fig. 7 shows the parameters of the decision space searched in the SD model, defined in the InputFile, and the searched objectives, defined in the OutputFile. The selection of input parameters is based on knowledge of their effects in the SD model; any constant can be explored, but more parameters increase the dimensionality of the search. It is desirable to include the major steering rates to check which ones affect the model. The outputs include the conflicting objectives, which are evaluated together with possible constraints, and any additional parameters can be mapped outside the evaluation process; this allows multiple post analyses to support deeper understanding of the Pareto-front characteristics. More details about the applied MOO criteria are reported in our previous studies (Linnéusson et al., 2017, 2018a; Linnéusson, Ng, & Aslam, 2018b).

Objective space exploration, step b), involves evaluating how well the integration of MOO and the SD model works. It therefore involves a process of refining the integration through steps a), b), and c), also improving the validity of the SD model through exploring the objective space. Further details of the improved validation of the SD model were presented by Linnéusson et al. (2018a).

Stable conditions are eventually achieved, allowing performance of the tradeoff analysis of interest, i.e., step d). In the abovementioned SD+MOO-related papers, the relationship between the decision space and the same optimization objectives as examined here was already analyzed, though the purposes of this and the previous MOO studies differ greatly. In one of these studies, two experiments were contrasted using a different coefficient for maintenance consequence costs ($C_Q$), representing two categories of critical equipment, to explore the potentially different Pareto frontiers. This resulted in two very different mixes of maintenance methodologies (see Linnéusson et al. (2017); the results indicated that more proactive efforts invested in more critical equipment generated much more potential saving effects, as long as higher availability ($A_T$) was required. Another study explored the MOO results of applying different time horizons in four experiments, exploring the hypothesis that a longer time horizon will allow more proactive solutions in the objective space. For example, Fig. 8 shows the different characteristics of the Pareto front resulting from applying 1-, 3-, 5-, and 7-year time horizons, implying that longer horizons enable solutions with higher performance at lower cost.
The fact that more proactive maintenance behavior is achieved when searching for tradeoff-optimal solutions with a longer time horizon is indicated by the nonlinear development of $C_Q$ in the right-hand-side graph in Fig. 8. At first, all experimental scenarios follow a linear relationship between $C_Q$ and $A_T$, up to a certain threshold. Studying a parallel coordinate map of certain key parameters in the one- and seven-year scenarios, depicted in Fig. 9, clearly reveals that the better solutions are more proactive solutions, as indicated by diverse results concerning $R_{TD}$ and $R_{BD}$.

Moreover, the third study, i.e., Linnéusson et al. (2018a), explored three scenarios of companies at different achieved states of maintenance performance, examining how the starting point in the PM work is very important for the subsequent strategic development of maintenance. The experiments made it clear that the starting point was significant for the potential tradeoffs between the three conflicting objectives, which were carefully compared in a meta-analysis, revealing that different strategies were required for the specific cases. It did not address the one-size-fits-all “fix” of implementing CBM to achieve proactiveness; rather, it spoke for the need to carefully understand one’s starting point in order to identify and select one of the best tradeoff solutions for a specific company.

Overall, SD+MOO enables effective searches of Pareto-front solutions, presenting the spectrum of potential near-optimal tradeoffs in the studied system, though it is important to note that the results are no better than the applied SD model. However, if someone is considering applying SD to explore the conditions that can unlock future potentials of his/her system, the application of MOO provides meta-knowledge of system behavior tradeoffs, i.e., step e), which cannot be identified using SD alone. Furthermore, MOO analyses allow the comparison of tradeoff solutions between conflicting objectives, which cannot be done using SOO.
4.3. Phase 3 – Study of SD model behavior

Phase 3 is illustrated using a MOO experiment optimized using the abovementioned criteria with a simulation period of fifteen years. Three near-optimal tradeoff solutions are selected according to Fig. 10. Solutions 40,992 and 42,962 are at the same level of $A_T$, but perform divergently in terms of $C_T$, while solution 13,785 is the best performing in $C_T$, yet not optimal in $A_T$.

![Fig. 10. Result graph showing selected solutions.](image)

Table 2 presents the input values used to achieve the above solutions. These inputs are used to compare and examine the dynamic behaviors of the solutions of the applied SD model, i.e., steps b) and c), shown in the behavior graphs in Figs. 11–13. Fig. 11 presents the cost results, indicating that solution 13,785, line 3 in the graphs, requires substantial initial costs, both $CM$ and $C_Q$, indicating clear worse-before-better behavior. This behavior is not as apparent in the other solutions, but is somewhat evident in solution 40,992, line 2 in Fig. 11. This information provides a basis for what to expect from policies applied to achieve long-term results, i.e., higher initial costs should be expected.

![Table 2. The decision space generating the selected solutions.](image)

However, to generate sufficient information to provide guidelines and key performance indicators (KPIs), the decision space in Table 2 needs interpretation; in addition, careful investigation is required of the flows and states of the SD model supporting the monitoring of desired progress towards realizing the strategy. For example, the distribution between preventive and reactive work that $SR$ can implement can be studied in greater depth in Fig. 12, which characterizes an initially higher unscheduled workload eventually leading to a shift towards scheduled work, especially in line 3. Still, this is a result of higher levels of the underlying conditions sustaining such proactive behavior. Further examining the hidden defect level of $EH$, the left-hand side of Fig. 13, reveals that the three solutions have divergent effects. However, the hidden defects measure results from other ongoing action flows, such as the flow of $RCA$, the right-hand side of the same figure, which is a flow of implemented countermeasures leading to the improved PM work in the SD model. Efforts to understand the preconditions enabling the flow of $RCA$ countermeasures are worthwhile, as they enable better-informed knowledge of the driving forces of the studied system. In other words, the SD model allows many potential studies of the underlying parameter behaviors to support step c), i.e., formulation of strategy guidelines and KPIs, building support to achieve the turnaround point in the worse-before-better behavior shown in line 3 in Fig. 11.
Step d) is by no means fully approached in the above examples, since the SD model allows multiple investigations of the interrelations in the modeled structures. By means of such studies, information can be generated that builds confidence in and motivation to implement the selected strategy, helps prepare for any potential pitfalls, and provides prudent KPIs for measuring/monitoring important developments considered necessary for the end results. Moreover, phase 3 may prompt study refinements, as indicated in Fig. 4, due to redefined knowledge of the importance of evaluating additional structures supporting the desired development. Accordingly, phases 1–3 are described as supporting the output strategies shown in Fig. 4, applying SD modeling to facilitate identifying the general cause effect structures of maintenance behavior and permit subsequent analyses, making the challenge of strategic development of maintenance less intangible.
4.4. Phase 4 – DES+MOO studies

The bottleneck in a production line is where the infinitesimal improvement with the largest impact on throughput is located (Ng et al., 2014). Ng et al. (2014) and Pehrsson, Ng, and Bernedixen (2016) argued that the numerous methods – such as machine utilization, blocking and starving patterns, data-driven approaches, shifting bottleneck detection, and multiple bottlenecks detection – sharing the same deficiency of lacking sufficient information to determine what improvement action(s) must be taken at the identified workstation or machine. Instead, they apply conflicting objective functions, in which the integration of DES and MOO works simultaneously to maximize the throughput and minimize the sum of improvement combinations. Bernedixen, Ng, Pehrsson, and Antonsson (2015) compared DES+MOO with the utilization method and the shifting bottleneck detection method, which better and more accurately pinpointed the activity for the DES+MOO study, which had a larger effect in their comparison.

A DES+MOO study of a production system, is also dependent on the purpose of the DES model, which in our case is to identify bottlenecks in processing time, availability, and mean time to repair (MTTR). Two suitable studies, i.e., by (Bernedixen et al., 2015; Ng et al., 2014), well represent how the results are generated and what information they provide. Both cases were generated using in-house developed software, the FACTS Analyzer, which provides a tightly integrated MOO-simulation functionality, making the optimization of production systems straightforward (Ng et al., 2014). Further technical details were presented by Pehrsson et al. (2016). Interestingly, the optimization results presented in all the three aforementioned papers largely identify improved availability as the potential solution for increased throughput, and not the traditionally expected processing time. In the industrial case described by Ng et al. (2014), eight of the ten best improvements concerned availability, while the other two concerned processing time. In the industrial case presented by Bernedixen et al. (2015), five of the ten best improvements concerned availability and the other five concerned processing times. However, these studies developed and applied production systems simulation from a production engineering perspective in industrial cases, paying less attention to the maintenance perspective, which needs some further elaboration.

Maintenance is often responsible for key results in terms of availability and MTTR in the servicing of operations. This is achieved by urgent activities, of a “firefighting” nature after the failure of items, or by planned activities based on knowledge about the degradation of specific items. Such planned for PM activities are often having an intangible connection to the results, leading to decisions that delay the preventive care (Repenning & Sterman, 2001). Availability, as applied in the discussed DES studies, applies to the traditional measure of availability performance (Ljungberg, 2000). The upper horizontal line in Fig. 14 shows when the equipment is functioning and the lower line shows the equipment downtime.

![Fig. 14. Visualization of common measures of availability performance.](image)

Fig. 14 is based on the measures mean time to failure (MTTF), mean waiting time (MWT), and mean time to repair (MTTR) as defined by Hagberg and Henriksson (2010), which we believe are best suited for the visualization of common maintenance performance indicators related to operations. For instance, some use the term mean time between failures (MTBF) to define the time interval during which an item is performing its required function (see Campbell and Reyes-Picknell (2016); EN15341 (2007); Nord, Pettersson, and Johansson (1997), instead of using MTTF. Also, some consider MTTR as equivalent to how mean downtime (MDT) is depicted in our figure (see, e.g., Campbell and Reyes-Picknell (2016); EN15341 (2007). We think that it is better to describe MDT as consisting of MWT and MTTR, in order
to clarify the different contributions of maintenance to operations. MTBF, used in Fig. 14, can be seen as the overall measure of maintenance organization performance for a certain piece of equipment. It includes MDT, which depends on MWT, a measure of maintenance supportability to supply the right maintenance resources with the right materials, documentation, and tools to start a repair, and MTTR, a measure of the ability to repair and standardize equipment. The frequency of MDT follows the average failure rate (Equation 1), which, according to Fig. 14 and the above reasoning, relates to the operating reliability measure MTTF, according to (Hagberg & Henriksson, 2010), and not using MTBF as the measure of reliability, as did (Campbell & Reyes-Picknell, 2016).

\[ \text{Failure rate (} \lambda \text{)} = \frac{1}{MTTF} \]  
\[ \text{Availability} = \frac{MTTF}{MWT + MTTR + MTTF} \]  

Accordingly, calculating availability for a defined period follows Equation 2, supported by Fig. 14. A DES study applies the availability measure as an input for a piece of equipment, together with MDT, which jointly define the discrete events of time between failures and time to repair according to their respective statistical distributions. The resulting improved mean reliability measure is MTTF (arising from the maintenance methodologies applied over the period studied in an SD model), considered to generate the corresponding improvement in the input measure of availability in a DES+MOO study with a proportional effect. These definitions mean that if MTTR is reduced and MTTF remains the same, an improved MTTR will lead to a decreased MTBF, which may explain why MTTR is ranked low in the abovementioned studies and why improving MTTF is more beneficial than MTTR. Furthermore, it is clear that the abovementioned studies have applied MTTR as corresponding to MDT, according to our illustration in Fig. 14.

Overall, the available industrial case study examples and the applicability of the ready developed FACTS Analyzer software point towards a practical method for bottleneck detection that facilitates maintenance in prioritizing their activities. It supplies knowledge of where in the production system to intervene, and of which parameters to adjust, by means of improved policies explored using the above-described strategy-selection process. The use of DES+MOO in Phase 4, steps a) to d), could contain more than the aspects mentioned above, but at this point, the activity-selection process (Fig. 4) builds on how these previous studies addressed the potential improvements of the production system.

4.5. Phase 5 – SD+DES interaction study

Using the presented SD model enables easy monitoring of MTTF, since the stock and flow structure represents both the average equipment in full operational functionality and the breakdown rate (see Equation 3). The variable names in Equations 3–5 follow Fig. 6. MTTR, on the other hand, needs some content interpretation, and can be defined differently depending on the applied structure of the SD model. Equation 5 shows how MTTR is applied to obtain the measure presented in Fig. 15, which is based on Equation 4. In this figure it is evident that the resulting measure, based on the time slots of scheduled or unscheduled repairs, is a dimensionless ratio between reactive and proactive maintenance interventions in operations. This means that the development shown in Fig. 15 can be interpreted as the ratio shifting from reactive to proactive for the selected simulation experiments from Fig. 10.

\[ MTTF = \frac{\text{Equipment in operation}}{\text{breakdowns}} \]  
\[ MTTR = \frac{\sum \text{time scheduled repairs} + \sum \text{time unscheduled repairs}}{\sum \text{scheduled repairs} + \sum \text{unscheduled repairs}} \]  
\[ MTTR_{\text{proactive}} = \frac{MTTR}{\text{time per unscheduled repair}} \]  

The phase 5 SD+DES interaction study, consequently applies the combined output of the selected strategy in phase 3, represented by the measures MTTF and MTTRproactive. These measures define the potential percentage improvement of the objects in the DES+MOO study during a period defined in the
specific study. In the example illustrated in Fig. 15, the dotted line indicates an arbitrary three-year period for this purpose. The value of the specific solution is read at the end of the defined period, and the improvement is calculated (see Equation 6), defining the maximum value of the range in the DES+MOO study, according to Table 3.

\[ \Delta \text{MTTF or } \Delta \text{MTTR} = \frac{\text{value at end of time period} - \text{value at start}}{\text{value at start}} \]  

(6)

![MTTF and MTTR graphs](image)

Fig. 15. Output behavior of selected strategies for variables interacting with the DES+MOO study.

The example presented in Fig. 15 implies that the improvement details according to Table 3 are applied in the DES+MOO study of MTTF and MTTR, respectively.

Table 3. Example of calculated improvement ranges in DES+MOO study based on SD outputs.

<table>
<thead>
<tr>
<th>Type of improvement variable in SD model (Fig. 15)</th>
<th>DES+MOO range</th>
<th>Start value</th>
<th>Value at 156 weeks</th>
</tr>
</thead>
<tbody>
<tr>
<td>MTTF line1</td>
<td>0% 0% 0%</td>
<td>13.07</td>
<td>14.73</td>
</tr>
<tr>
<td>MTTF line2</td>
<td>0% 0% 0%</td>
<td>13.07</td>
<td>15.28</td>
</tr>
<tr>
<td>MTTF line3</td>
<td>0% 0% 0%</td>
<td>13.07</td>
<td>26.93</td>
</tr>
<tr>
<td>MTTR line1</td>
<td>0% 0% 0%</td>
<td>1</td>
<td>0.8614</td>
</tr>
<tr>
<td>MTTR line2</td>
<td>0% 0% 0%</td>
<td>1</td>
<td>0.8236</td>
</tr>
<tr>
<td>MTTR line3</td>
<td>0% 0% 0%</td>
<td>1</td>
<td>0.5459</td>
</tr>
</tbody>
</table>

Subsequently, the explored potential strategies result in three experiments for the DES+MOO study, further exploring the production system to identify where improvements in MTTF and MTTR would have the greatest impact. The resulting analyses, which optimize throughput with the fewest implemented improvements, present a prioritized plan for maintenance to consider when planning improvement activities. This specific DES+MOO study is not presented here; to understand its principles in detail, the reader is referred to, for example, Ng et al. (2014) and Bernedixen et al. (2015).

4.6. Phase 6 – Reflections on implementation

The application of SD studies to problems contains a process of approaching ambiguous aspects of the addressed problem boundary and potentially affects how we think about our problems, making them more tangible. Therefore, as insights grow they can be implemented even during the process of identifying policies, guidelines, and KPIs. Above all, although the SBO framework is a learning process based on the strategy-selection process, a strategy can be formulated that the maintenance management is confident in communicating and implementing; see step a) in phase 6 in Fig 5. The expected results of the strategy applied to the measures MTTF and MTTR are then considered and evaluated in a more tangible DES+MOO study. Altogether, the SBO framework defines the activities of the maintenance plan and budget for the coming year, containing both concrete and policy aspects.
Accordingly, the implemented activities are guided by their importance to the throughput of the production system. The condition of the specific pinpointed equipment and the available historical data then determine activities to be implemented to achieve the calculated improvement range (see Table 3). At such specific levels, the guiding principles from the strategy perspective may be less significant, but from the systems perspective, strategy evaluation provides insights into the accumulated flows in the production system generated by all equipment. This means that the two perspectives are interdependent: while the systems perspective supports analyzing the accumulated loads on equipment and resources to reduce the risk of overload and gradually reduce the load, the specific equipment perspective aims to reduce the significance of accumulating the load by means of intelligent prioritization, through the lens of maximizing the production system throughput.

4.7. Concluding summary of the hybrid SBO framework

Fig. 16 presents an overview of the end product of the mixed method. It illustrates the contributions and exchanges between the methods and the production system environment. SD with the integrated use of MOO facilitates the strategy-selection process, exposing and evaluating the tradeoffs between conflicting objectives in both the short and long terms, in order to inform maintenance strategy and the applicable supporting KPIs. The obtained strategy has implications for the levels of proactiveness and equipment health, which are related strategy output results serving as input into the DES+MOO study, which represents the operational level. By applying the potential improvements in the DES+MOO study generated by the applied strategy in terms of measures such as MTTF and MTTR, the optimization of operations provides the prioritized measures that maintenance can include in their plans.

In summary, the SBO framework helps improve our knowledge of maintenance, on the strategic perspective by exploring tradeoffs between long term implications of policies and the short term economic requirements, and regarding the operational conditions that help maximize throughput via accurate activities. This supports iterative knowledge building and organizational learning in order to shape, manage, and be prepared for future demands.

According to the theoretical model of maintenance development presented in Fig. 1, SD and DES are mixed in the proposed SBO framework mainly in order to take advantage of the divergent philosophical standpoints of the two approaches, and of how they complement each other. Accordingly, SD is used for its abilities to illuminate the ambiguous structures of decision-making processes, which, according to Forrester (1961), consist of processes of converting information into action. Per definition, such processes have feedback as their basis; by modeling them, we visualize our interpretations of the structures and treat them in more tangible discussions. We do this before any changes in these structures, with the aim of producing better results based on hypothesis testing. As the application of DES+MOO produces accurate information to guide the actions of the maintenance organization, which together
produce knowledge at the production system level that effectively facilitates the process of converting relevant information into more accurate actions.

Discussion and conclusions
Our findings suggest that system dynamics (SD) simulation studies be applied to address the tradeoff conflict between short-term requirements and their long-term effects through the complex feedback structures of maintenance. Nevertheless, SD alone cannot adequately clarify the complexity of the production system. Therefore, the application of DES is also proposed, enabling identification of where in the production system maintenance should intervene for maximum effect. To achieve analytical efficacy, the mixed-method designs integrate MOO, creating a hybrid SBO framework to support maintenance management, using a mixed OR/MS method design combining SD and DES. MOO has proven ability to exhaustively examine the objective space in SD models and effectively seek optimal configurations in DES models. Actually, each method can be applied without the other to support practical development, but to integrate strategic and operational maintenance development, they have been synergistically used together as proposed here.

Moreover, the integration of SD with MOO not only increases the investigative rigor of the applied models, but also presents Pareto-front optimal tradeoff solutions to the decision maker. The integration of DES and MOO ensures the use of the best known and most effective approach to address the accurate sequence in improving bottlenecks. Our literature review identified few studies that integrated optimization into their proposed mixed SD+DES frameworks, and even fewer that emphasized MOO. It seems as though this unique interaction between SD and DES is highly novel compared with previous research. The resulting analyzed improvement potential, evaluated via a strategy-selection process using SD and MOO, defines the input ranges for optimizing the DES model. Issues concerning the qualitative character of SD modeling and subsequent analyses are therefore limited to the application of SD and do not affect the validity of the DES model.

An apparent weakness of the proposed framework is the high level of competence, knowledge, and applicable technical support required to implement it in industry. From our experience, one critical bottleneck is applying SD in maintenance and manufacturing systems development. This introduces the aggregate perspective of seeing one’s processes from a systems perspective, which industrial actors are inexperienced in doing. Moreover, the SD model-building process is highly intuitive and considerable practice is required to manage the high-variability capacity of its modeling language, which allows endless possibilities to model the problem at hand. We therefore believe that future work to improve the proposed framework should focus on the strategy side, to enhance and facilitate the application of SD in maintenance development. At this point, our efforts have been directed towards integrating the technical elements, ranging from the exemplary SD base model that MOO studies have demonstrated to be useful, to the “headwork” of uniting the two perspectives of maintenance strategy and operations in a suitable mixed method.

Regarding further research, the present work opens avenues for numerous studies in the fields of maintenance management and maintenance policy optimization, primarily in industrial studies. Regarding practical implementation and given the above issues concerning SD, our recommendation is to start approaching the framework using DES+MOO due to its more tangible character and standardized approach. With the emerging digitalization of industry, which will likely follow the common pattern of exponential growth, there will be a natural development of more advanced virtual tools. Support from a maintenance development tool that encompasses the larger system boundary as defined here is required in order to maneuver among the increasing complexities and the demand for high utilization. This work may serve as a reference for future studies endeavoring to unite the two perspectives of maintenance strategy and operations in order to realize sustainable change in production performance via maintenance efforts.

Acknowledgements
This work was partially financed by the Knowledge Foundation (KKS), Sweden, through the IPSI Research School. The authors gratefully acknowledge their provision of research funding and the support of the industrial partners Volvo Car Corporation and Volvo Group Trucks Operations.
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Gary has work experience from various positions in industry, at a research institute, and in academia before pursuing this Ph.D. From his early career in industry, as a graduate from mechanical engineering, it seemed ordinary that decision-making was made without thinking too much about the long-term consequences. Having the possibility at that time to pursue industrial Ph.D. studies therefore applied system dynamics to address reoccurring problems of systemic character for manufacturing systems development, resulting in a licentiate degree. Most recently he has worked as a lecturer at the University of Skövde, teaching project management, lean production, systems thinking, and maintenance. He has experience of working with internal logistics and assembly, continuous improvements, world class manufacturing, change management, and discrete-event simulation, both as production engineer and project manager.