European Journal of Operational Research xxx (xxxx) xxx

Contents lists available at ScienceDirect

European Journal of Operational Research

journal homepage: www.elsevier.com/locate/ejor

Innovative Applications of O.R.

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

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A R T I C L E I N F O

Article history:
Received 20 March 2018
Accepted 19 August 2019
Available online xxx

Keywords:
Problem structuring
Decision support
System dynamics
Multi-objective optimization
Discrete-event simulation

A B S T R A C T

Managing maintenance and its impact on business results is increasingly complex, calling for more advanced operational research methodologies to address the challenge of sustainable decision-making. This problem-based research has identified a framework of methods to supplement the operations research/management science literature by contributing a hybrid simulation-based optimization framework (HSBOF), extending previously reported research.

Overall, it is the application of multi-objective optimization (MOO) with system dynamics (SD) and discrete-event simulation (DES) respectively which allows maintenance activities to be pinpointed in the production system based on analyzes generating less reactive work load on the maintenance organization. Therefore, the application of the HSBOF informs practice by a multiphase process, where each phase builds knowledge, starting with exploring feedback behaviors to why certain near-optimal maintenance behaviors arise, forming the basis of potential performance improvements, subsequently optimized using DES+MOO in a standard software, prioritizing the sequence of improvements in the production system for maintenance to implement.

Studying literature on related hybridizations using optimization the proposed work can be considered novel, being based on SD+MOO industrial cases and their application to a DES+MOO software.

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. A cost focus leads to reactive maintenance, which according to Geary, Disney and Towill (2006), potentially leads to increased disruption in real-world supply chains, causing excess variance in performance. Recent developments in terms of increased automation, more expensive equipment, and more complex production systems have required larger capital tied up in assets (Garg & Deshmukh, 2006), and proactive maintenance policies are therefore considered a necessity (Pinjala, Pintelon & Vereecke, 2006). Nonetheless, identifying appropriate practices and implementing sound strategies for developing maintenance performance are still non-trivial. A clear measure of this is the frequently-emphasized gap between theory and practice in the maintenance optimization literature (e.g. Fraser, Hvolby and Tseng (2015), Linnéusson, Ng and Aslam (2018a). One aspect of this gap is that little attention has been paid to making model results understandable to practitioners (Dekker, 1996, p.235). Moreover, Woodhouse (2001) identifies the organizational capabilities to manage the implementation of sustainable maintenance practices a crucial limiting factor. 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, Pisano & Shuen, 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. System experiments using computer simulation (Forrester, 1961) has amongst other approaches served as such supporting tool. Simulation in manufacturing and business, specifically discrete-event simulation (DES) and system dynamics (SD) simulation as the most common (Jahangirian, Eldabi, Naseer, Stergioulas & Young, 2010), have been considered necessary approaches for the proposed research

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https://doi.org/10.1016/j.ejor.2019.08.036
0377-2217/

Please cite this article as: G. Linnéusson, A.H.C. Ng and T. Aslam, A hybrid simulation-based optimization framework supporting strategic maintenance development to improve production performance, European Journal of Operational Research, https://doi.org/10.1016/j.ejor.2019.08.036

resulting in a hybrid simulation-based optimization framework (HSBOF). Combining operational research (OR) methods to approach complex problems using a larger system view based on problem characteristics is growing, and examples of hybrid models and frameworks for such endeavors are more and more frequently found in OR (Brailsford, Eldabi, Kunc, Mustafee & Osorio, 2018). Hence, this paper presents a conceptual framework to support developing long-term maintenance performance in conflict with the persisting short-term economic pressure from keeping required production performance levels. The framework designed here build on previously reported research studies which has approached the above challenge to support maintenance management in their industrial setting, resulting in a mixed-method framework to inform practice. This paper describes the pieces put together to follow in a rather intricate process: starting with SD modeling to frame the strategic path of attaining the desired level of proactive maintenance, formulating the "why", then, SD is aided by optimization in order to allow evaluating multiple near-optimal tradeoff solutions on the basis of their short- and long-term consequences to the modelled system, ending with the selected SD simulation results affecting the DES study, which integrated with optimization supports identifying the "how" and "where" in the practice. In all, the framework includes several phases of generating knowledge on several levels, allowing opportunities of problem structuring and learning of how maintenance performance is generated, hence can be improved in the context of discrete production systems form a strategic and operational perspective.

The paper is structured as follows. Section 2 presents the necessary background information of challenges in supporting maintenance development and the methods applied in the framework, ending with a brief literature review of hybrid simulations using optimization. Section 3 introduces a theoretical model of maintenance-driven change in the production system, presenting the specific relevance of the methods of DES and SD in the framework including three levels of maintenance development that the HSBOF addresses. Section 4 contains the core contents of this paper, describing the HSBOF by combining previous work into its various phases. In Section 5 we reflect on the HSBOF and future research in a discussion and conclusions section.

2. Background

2.1. Simulation and optimization to support maintenance development

The heritage in maintenance policy optimization research is analytical modeling, see Dekker (1996), and to bridge its insufficiency Nicolai and Dekker (2008) argued for simulation to enable tracing the effects of maintenance policies. Traditional preventive maintenance (PM) policy studies are identified based on simplified, non-realistic assumptions, and do not consider costs with enough viability (Kenné et al., 2007; Lad & Kulkarni, 2011). Simulation is an emerging trend to include more complex dynamics, in order to optimize maintenance cost (Sharma, Yadava & Deshmukh, 2011). Nevertheless, formulations of such typical maintenance problems are often treated in isolation, and the maintenance literature generally suffers from oversimplified simulation studies (Alrabghi & Tiwari, 2015). In fact, current research in maintenance policy optimization does not sufficiently address the matter of practical applicability in production systems (Ding & Kamaruddin, 2015). It could potentially be addressed, according to De Almeida, Pires Ferreira and Cavalcante (2015), by the application of multi-objective optimization (MOO), in order to better capture decision makers' preferences regarding the decision problem and include conflicting tradeoffs in maintenance policy optimization.

To address the deficiencies of overly narrow simulation applications, Alabdulkarim, Ball and Tiwari (2013) proposed DES to potentially add to the maintenance field what it has delivered to OR 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.

On the other hand, according to Gunal and Pidd (2010), DES inadequately visualizes feedback behavior and cannot explain why certain behaviors arise, which is of interest in order to study the strategic development of systems (Warren, 2005). In conducting studies that explain feedback behavior, the application of system dynamics (SD) has brought insights into industrial systems ever since Forrester (1961) 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 applied to maintenance has been advocated by Größler, Thun and Milling (2008). However, quantified SD models of maintenance applications and subsequent documentation are generally rare, according to Linnéusson, Ng and Aslam (2018c); except for their proposed approach, no previous SD studies were identified having investigated the dynamic 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 leading us back to the need of mixing SD with DES.

Subsequently, based on the industrial need for maintenance development this paper proposes the HSBOF with the purpose to synthesize the strengths of each method to support better informed practice. Yet, applying merely simulation 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 simulation-based optimization (SBO), which applies SD integrated with MOO, see, e.g., Bandaru, Aslam, Ng and Deb (2015), Duggan (2008), and Linnéusson et al. (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.

2.2. SD+DES and hybrid simulation modeling

SD is a conceptual framework essential to thinking about things (Thompson, Howick & Belton, 2016), applicable 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). SD models use stocks and flows calculated using differential equations and are generally deterministic (Tako & Robinson, 2010). Using SD focuses much on usefulness and on stakeholder involvement with the utmost purpose to affect people's mental models to achieve change, which if achieved is considered one important proof of validation (Sterman, 2000). DES, on the other hand, represents individual entities in systems viewed as queuing networks (Brailsford, 2014), its suitableness of mimicking production systems on the operational level and excellent handling of stochastic dynamic complexity have naturally resulted in traditionally being used in the manufacturing

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sector (Tako & Robinson, 2010), for which DES is unarguably the most common applied OR method (Jahangirian, Eldabi, Naseer, Stergioulas & Young, 2010). Hence, validation in DES has traditionally focused on statistical performance evaluation between model on high detail level and the real system due to its capability to represent such tangible systems and their stochastic dynamics. For SD validation, there are a set of tests to perform, yet, due to the high level of intuition inbuilt in the process of producing models, they cannot be tested using falsification but if they are useful or not (Sterman, 2000). Applying group model building in comparison to the traditional modeler-client approach, is one approach to facilitate productive discussions of complex problems, see, e.g., building and simulating strategies in manufacturing systems together with managers, (Linnéusson & Aslam, 2014); or modeling business strategies with focus on deeper levels of understanding using rehearsals on developed simulation models (Torres, Kunc & O'Brien, 2017). Such facilitated modeling is less common using DES, yet, there is such recent work which proposes moving away from the traditional approach of DES using solely detailed models to simple less accurate models with purpose of learning and debate on complex problems (Robinson, Worthington, Burgess & Radnor, 2014).

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, achieving the complete mix, realizing the full potential of both approaches may not be attained due to the divergent philosophical standpoints of each approach (Brailsford et al., 2010).

The mixed SD+DES approach has interested researchers in recent two decades and many applications have been reported in OR (Brailsford et al., 2018; Howick & Ackermann, 2011). More recently, Morgan, Howick and Belton (2017) presented a toolkit of designs for mixing the DES and SD methods, identifying five modes of information exchange between simulation methods:

- *Parallel:* SD and DES applied in isolation for the purpose of contrasting their respective contributions to a commonly studied phenomenon, identifying problems which share their use paradigm.
- *Sequential:* 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:* one primary method is enriched with techniques from one or more other paradigms, for example, using discrete events in an SD model or continuous behaviors in a DES model.
- *Interaction:* allows 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:* full integration in which one simulation evaluation includes both discrete and continuous time steps, taking a shared system view.

Brailsford et al. (2018), provided a review of the growing literature on hybrid simulation modeling from an OR perspective. In their life-cycle based framework they present a systematic checklist for hybrid simulation models using DES, SD and agent-based modeling (ABM), unifying around their common four stages of (1) real world problem, (2) conceptual modeling, (3) computer modeling, and (4) solution & understanding. However, outside the scope of both Morgan et al. (2017) and Brailsford et al. (2018) is the fertilization of optimization in a hybrid simulation framework, which in the proposed HSBOF here, is a vital component part of the selection-sequence and knowledge extraction, from the phase of problem structuring in SD modeling to the phase of informing practice; reviewed in Section 4.

2.3. Optimization in hybrid simulation modeling

Optimization is a technique which applies best to integration with a single simulation model (Pidd, 2012). 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 then 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). Moreover, in a MOO study one must identify which parameters, and their respective ranges, are part of the decision space to be explored through the lens of the model and multiple evaluations, resulting in the Pareto-optimal solutions in the objective space.

Hence, unless a fully integrated hybrid simulation model is applied, using SD+DES in a seamless combined time sequence, which according to Brailsford et al. (2010) above may never be developed, the application of optimization requires a sequence of SD+MOO integration and DES+MOO integration respectively, and a sequence of them depending on purpose of usage. Moreover, depending on how decision data from MOO analyses are applied, as in need of interpreting the conflicting tradeoffs between complex decision parameters, it may require a convoluted selection process to manage the distillation of data into valid decision criteria. Accordingly, the proposed HSBOF presented later is not directly applicable into one of the modes of mixing SD and DES in Section 2.2 above by Morgan et al. (2017), but needs to combine several phases into its framework detailed in Section 4.

On the other hand, optimization integrated with either SD or DES in a hybrid simulation model or framework is not so commonly reported. To provide some examples 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, only a total of six papers could be identified actually mixing DES and SD including contents related to optimization; summarized in Table 1.

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, Son, .Jones & Min (2006) presented proof-of-concept experiments applying optimization. Regarding MOO, its application in modeling patient flows in emergency departments was emphasized by El-Zoghby, Farouk, & El-Kilany (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, identifying 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 (Droguett, Jacinto, Garcia & Moura, 2006); and (3) a thesis on how to technically address the limitations of SD, with

Table 1
Examples of SD+DES works using optimization.

Article	Research scope	Level of optimization	Optimization objective
Venkateswaran and Son (2005)	Solving the hierarchical production planning problem using SD and DES coupled with optimization	Inputs to SD model use SOO. DES model applies outputs from SD evaluations, and uses SOO. DES+SD level evaluates.	SD: evaluates SOO input DES: max. throughput SD+DES: evaluation
Venkateswaran et al. (2006)	Proposing an approach for integrating vendor inventory supply chain and production planning	Inputs to SD model use SOO. DES model applies outputs from SD evaluations, and uses SOO. DES+SD level evaluates.	SD: evaluates SOO input DES: min. tardiness SD+DES: evaluation
Wang and van den Heuvel (2011)	Developing a hybrid service-network simulation approach	Not implementing; emphasizes optimization	Tuning towards optimal performance
Jovanoski, Nove, Lichtenegger and Voessner (2013)	Providing examples to justify a hybrid simulation approach for managing strategy and production levels	Not implementing; emphasizes optimization	Enable optimal storage capacities and number of salespersons
Albrecht, Kleine and Abele (2014)	Providing computerized decision support for designing changeable production systems	Not implementing; "optimization" is mentioned in title and abstract but not emphasized elsewhere.	DES: evaluates given state SD: evaluates changeability of the production system
El-Zoghby et al. (2016)	Presenting a conceptual framework for a multilevel approach to optimizing an emergency department	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.	Claims to improve multiple objectives; no tradeoff objectives defined; experiments apply what-if analysis

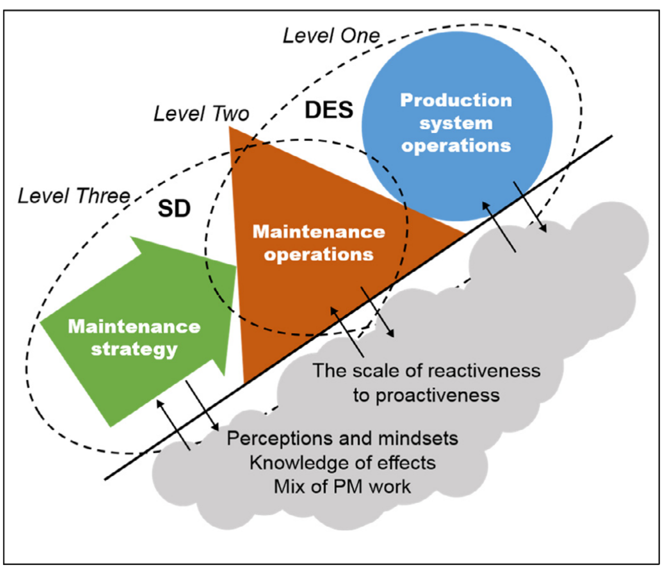

Fig. 1. Generalized model over the different alignments of SD and DES to the levels of maintenance development.

DES used to represent individual entities and stochastic behavior, using a simplified SD model of maintenance (Bell, 2015).

3. 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, 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 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 of production systems, on the other hand, enable a relatively tangible modeling and verification procedure with the physical real-world, though simultaneously extremely complex due to numerous configurations. Also, operations are often subject to short-term pressures that displace the strategic activities ultimately leading to proactiveness. Hence, the need for an overarching framework for operational and strategic views is prominent for achieving better informed practices.

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 produce current results. At this level, change is manifested in activities to optimize the operation of the production system, using current maintenance capabilities which deliver a certain balance of proactive and reactive service to operations.

Level Two: The wedge represents the dynamics of maintenance operations, e.g., the slow-working continuous interaction of equipment and their care. 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 conditions for performance.

Further, the ongoing work of maintenance operations (level two) serves as a wedge upholding the current operational performance of production system operations (level one), balancing the entropy-driven deterioration of the maintenance system, e.g., Levitt (2011), with applied resources. The force of the 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 on production system level involves complex feedback among the components. Accordingly, many preconditions at level one are governed by capabilities at level two, which together generate the current availability and total maintenance costs of the production system. Hence, when conditions change at level one they will affect level two, for example, reducing the time-frames for PM work in operations. In the real world practice, it is tempting to neglect any longer-term consequences of such changes, as well as in applying a DES study. 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 to 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."

SD studies presents the perspective of exploring maintenance behavior, (see Linnéusson et al. (2018c), who address levels two and three by exploring SD to better understand 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). Given the limitations of maintenance operations at the aggregate level, the dotted oval labeled "SD" in Fig. 1 is also including interaction with production operations on the level of generalized availability performance.

Accordingly, the objective of the HSBOF 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 and accordingly requires the application of SD and DES. Moreover, these levels can be addressed with different degrees of precision, so a vital precondition is integration with MOO to support the evaluation of accurate, near-optimal tradeoff solutions. In subsequent section the HSBOF is described, which has evolved from recently conducted studies by Linnéusson et al. (2018a), Linnéusson, Ng and Aslam (2017), Linnéusson, Ng and Aslam (2018b), and Linnéusson et al. (2018c) in order to address the challenge of managing maintenance within the economical short-termism framework and simultaneously consider maintenance consequential long-term costs. The conducted research began with both SD and DES in mind in order to address the above-mentioned complex maintenance dynamics, yet, identified SD and specifically SD+MOO to contain a higher level of novelty, and applicability to study feedback dynamics of possible strategies, than did extending the application area of the already available DES+MOO software. However, as researching the problem unveiled the inability of SD to support with tangible directives to practice, besides suggesting on overarching policies of developing the maintenance management, DES+MOO was considered to complement, hence, a focus of identifying a procedure for aligning the reported SD+MOO approach with existing DES+MOO method initiated this reported research.

4. Description of the HSBOF

Applying the HSBOF, depicted in Figs. 2 and 3, to support decision making is not straightforward. First of all, it is noticed that Fig. 2 includes many potential iterations where its subsequent description takes the point of origin from applying SD first and not DES (Phase 4). However, as indicated by the framework design, Phase 4 and Phase 1 can be independent. Starting with DES and DES+MOO could also be the case, as its output can feedback changes the conditions governing the ratio of proactive maintenance behavior studied in Phase 1. Yet, including the consideration that starting with DES results in that the considered input to the DES+MOO study from the strategy-selection process (Phase 1 to Phase 3) described in Fig. 3 is obsolete.

As depicted in Fig. 2 each phase in the process of applying the framework involves steps of many feedback iterations due to that more and more learning of the problem undertaken is gained. From the initial iterative process of problem structuring with stakeholders, developing an SD model in phase 1, which involves much examination of multiple potential paths to address the modelled problem, see, e.g., (Hämäläinen & Lahtinen, 2016), to the multiple knowledge extractions during the explorative process of getting to phase 2 which results in producing initial results from MOO with SD, thoroughly testing the behavioral space of the designed model, allowing even more choices of paths forward regarding the undertaken study. Even so, the presented decision space in phase 3 involves multiple choices depending on the decision-makers' preferences about strategies to employ, and further DES+MOO studies to conduct in order to identify where in the production system specific activities can be implemented by maintenance.

Fig. 3 complements the technical schematic in Fig. 2 by explaining the steps in each phase that are required. Phase 3, which ends the strategy-selection process, has three potential outputs:

1. DES_{t1} – the potential changes to the structure of subsequent DES+MOO cases
2. Define DES+MOO decision space – based on the behavioral results from phase 3 explained in Section 4.4
3. Strategies, policies, guidelines, key performance indicators (KPIs), etc. – which represents the results of phases 1–3 extracted to general guidelines for the maintenance system

Subsequent subsections include a walkthrough of the HSBOF. It uses a previously reported SD model as basis in order to comprehend the subsequent walkthrough of the various phases of the HSBOF. Hence, Phase 1 illustrates and briefly reviews an example SD model; where detailed explanations were presented by Linnéusson et al. (2018c), and, all model equations and aspects of model boundary and validity supported by SD+MOO are found in Linnéusson et al. (2018a). Phase 2 then describes in short the application of MOO to the SD model. Phase 3 presents how results from studying new experiments (from Phase 2) are selected and analyzed in order to illustrate how results from Phase 3 are integrated into the application of DES+MOO, detailed in the description of Phase 5. And, in the preceding description of Phase 4 a short review of the motivation of DES+MOO studies previously reported from other cases, using an in-house developed software, are found. Finally, Phase 6 presents reflections upon the implementation of the HSBOF in practice.

After the walkthrough, Section 4.7 summarizes the HSBOF in its context underlining its application as a generalizable framework, as regards to the application of developing proactive maintenance performance and the link of the output from the strategy-selection

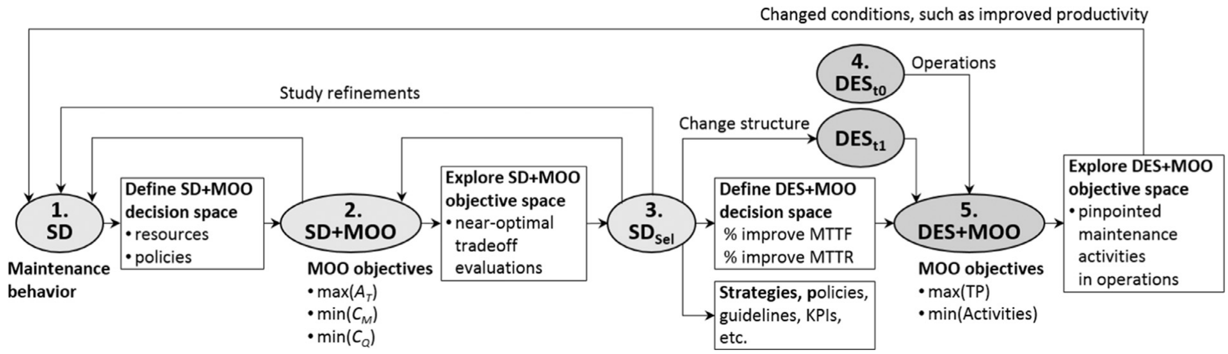

Fig. 2. A technical description of the HSBOF design.

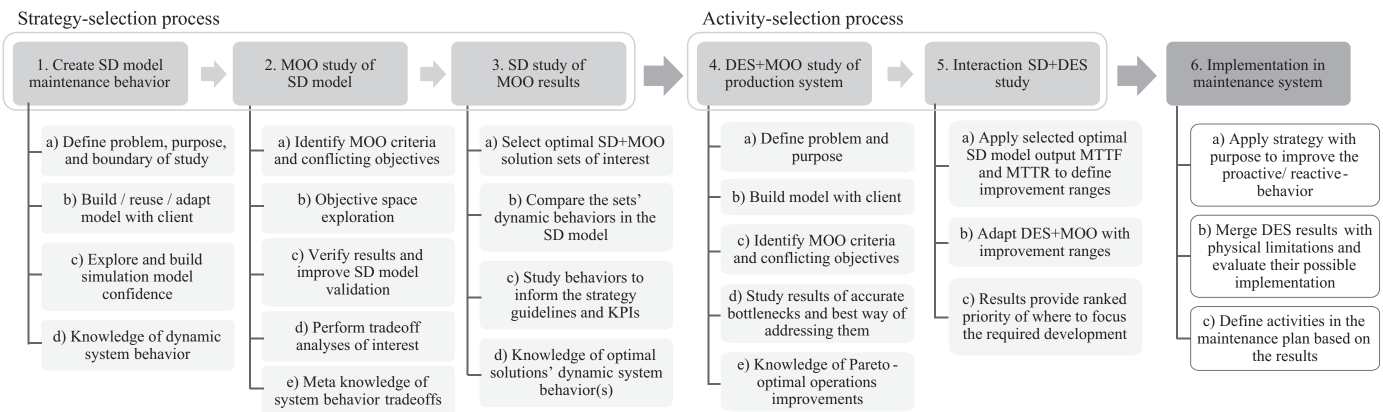

Fig. 3. Phases 1–6 and their steps in applying the HSBOF.

process into the activity-selection process, which is the KPIs of MTTF and MTTR according to Fig. 2.

4.1. Phase 1 – An exemplar SD model

Phase 1, step 1a) to step 1d) in Fig. 2, follows the general model building process in SD and is here illustrated by an SD model designed to serve as the basis for better-informed strategies by enabling the exploration of arbitrary tradeoffs between short- and long-term dependencies in the maintenance system. The applied SD model 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 (PM_{fi}), and condition-based maintenance using inspections (CBM_i) or sensors (CBM_s) (Tsang, 2002);
- defect-generating and defect-eliminating activities resulting in an aggregate equipment health (*EH*) relating to the breakdown frequency (R_{BD}) of the production system (Sterman, 2000);
- the resulting balance between unscheduled and scheduled maintenance, based on the above points together with applied repair workers (S_R) (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 (S_E) (inspired by industrial partners); and
- maintenance total costs (C_T), based on direct maintenance costs (C_M), and estimated maintenance consequence costs (C_Q), based on variable behaviors such as R_{BD}, planned takedowns (R_{TD}), inventories, and applied resources, (inspired by how costs are generated).

Fig. 4. 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 (R_{BD}) fixed by unscheduled repairs to restore equipment to its functional condition. R_{BD} not only degrade equipment health (*EH*), which can lead to more R_{BD}, but also reduce availability (A_T), yet, simultaneously a lower level of A_T is limiting the impact of equipment deterioration, having a combined effect resulting from two different feedback loops. If the number of repair workers (S_R) 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 (R_{TD}) depends on the planned work order backlog and the pressure to produce, giving rise to a growing gap between the targeted and current A_T. This gap will delay the proactive work and increase the risk of R_{BD}. The precision with which defects can be identified depends on the applied mix of *RTF*, PM_{fi}, CBM_i, and CBM_s, 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, similar to 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. These dynamics correspond to level three in Fig. 1, to shift the equilibrium towards higher levels of proactiveness.

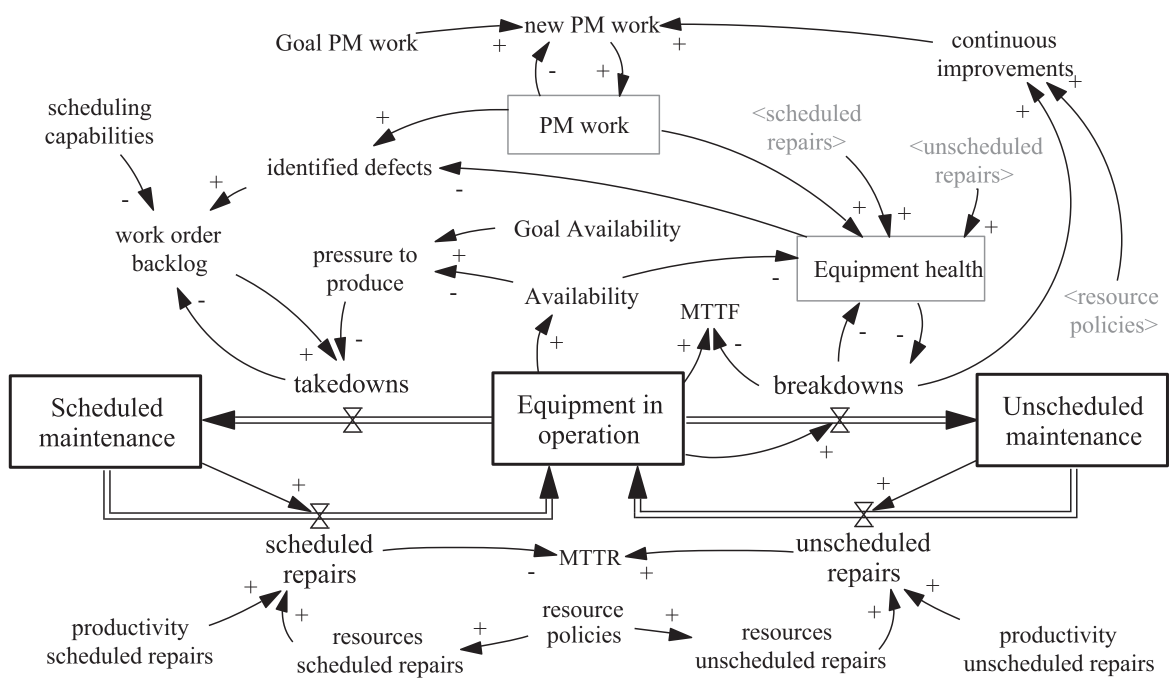

Fig. 4. Schematic of the maintenance dynamics of the SD model, incorporating CLD notations.

4.2. Phase 2 – MOO+SD studies

Phase 2 includes the steps to extract multiple knowledge from the applied SD model using MOO. A MOO study is dependent on the purpose of the SD model, the understanding of the dynamics included in a SD model, and an idea of what should be studied in the tradeoff analyses, since it defines what is found. Similarly, as in any 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 2a) in Fig. 3 define the MOO model, where the exemplar case is depicted in Fig. 5.

Fig. 5 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 must be 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 parameters affecting the major steering rates. The outputs in the exemplar study included the conflicting objectives: maximize availability (A_T); minimize maintenance costs (C_M); and minimize maintenance consequence costs (C_Q), which are evaluated together with suitable constraints.

Objective space exploration, step 2b), involves evaluating how well the integration of MOO and the SD model works. It therefore involves a process of refining the integration through steps 2a), 2b), and 2c), also improving the validity of the SD model, with further details found in Linnéusson et al. (2018a). And, then allows performing the near-optimal tradeoff analysis of interest, i.e., step 2d). Several examples of results on step 2e) are found in previously reported studies which allows to study multiple patterns of potential policies for the near-optimal solutions: (1) experiments using different coefficients for maintenance consequence costs (C_Q) finding different Pareto frontiers of optimal tradeoff solutions suggesting two very different panoramas of strategies for mixing the maintenance methodologies, but for the best A_T solutions points to unities (Linnéusson et al., 2017); (2) experiments explored how different time horizons of 1–7 years will allow more or less proactive behavior and their respective policies, clearly showing imbalance to reactive results using a short-term strategy (Linnéusson et al., 2018b); (3) experiments exploring how three different starting points in the PM work matter substantially for the subsequent strategic development of maintenance, where, for instance, policies in a setting with poorer starting conditions are limited by this fact and added proactive resources fail to be utilized (Linnéusson et al., 2018a).

Overall, SD+MOO enables presenting the spectrum of potential near-optimal tradeoffs in the studied system, yet it is important to note that the results are no better than the applied SD model. However, the application of MOO provides meta-knowledge of system behavior tradeoffs which cannot be identified using SD alone, confirmed by above-mentioned case studies. 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 an SD+MOO experiment optimized using the abovementioned criteria with a simulation period of fifteen years. Three near-optimal tradeoff solutions are selected according to Fig. 6. Solutions 40,992 and 42,962 are at the same level of A_T, but perform divergently in terms of maintenance total costs (C_T), while solution 13,785 is the best performing in C_T, yet not optimal in A_T.

Table 2 presents the resulting input values obtained to achieve the solutions in Fig. 6. These values are then applied in the SD model, i.e., steps 3b) and 3c). Figs. 7–9 illustrate some selected behavior graphs. Fig. 7 presents the cost results, indicating that solution 13,785, line 3 in the graphs, requires substantial initial costs, both C_M 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. 7. 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.

To provide guidelines and KPIs, the configuration of inputs in Table 2 needs interpretation, using careful investigation of the SD

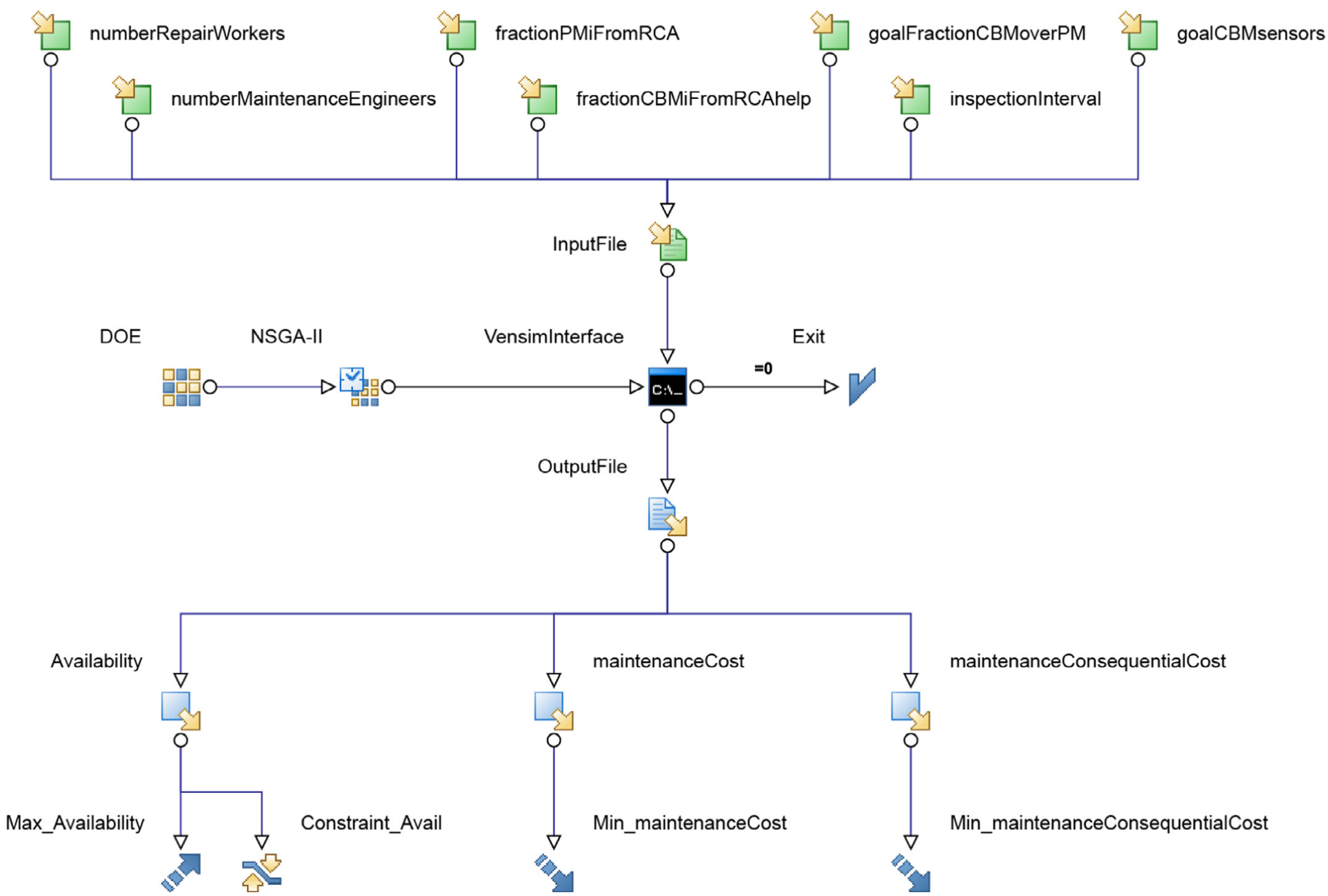

Fig. 5. Diagram of MOO model, from modeFRONTIER software.

Table 2
The configuration of inputs generating the selected solutions.

Input parameters	13,785	40,992	42,962
1. numberRepairWorkers (Number of S_R)	36	22	23
2. numberMaintenanceEngineers (Number of S_E)	5	5	2
3. fractionPMiFromRCA (% of PM_{fi} from RCA)	0.25	0.25	0.35
4. fractionCBMiFromRCAhelp (factor to calculate% of CBM_i and CBM_s from RCA)	0.95	0.4	1
5. goalFractionCBMoverPM (Goal% $CBM_i + CBM_s$ of total PM)	1	1	1
6. inspectionInterval (CBM_i interval (Weeks))	4	6	50
7. goalCBMsensors (Goal CBM_s)	500	150	325

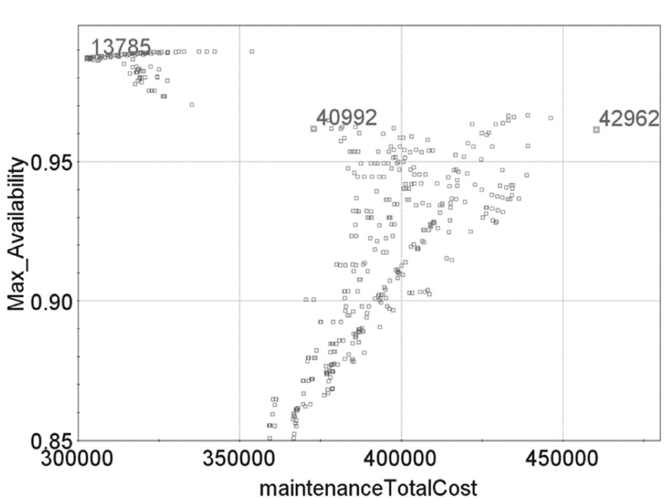

Fig. 6. Result graph over Pareto-front solutions and selected solutions.

model behaviors. For example, the distribution between preventive and reactive work that S_R can implement can be studied in greater depth in Fig. 8, 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. 9, reveals that the three solutions have divergent effects; where 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 behaviors to support step 3c), 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. 7.

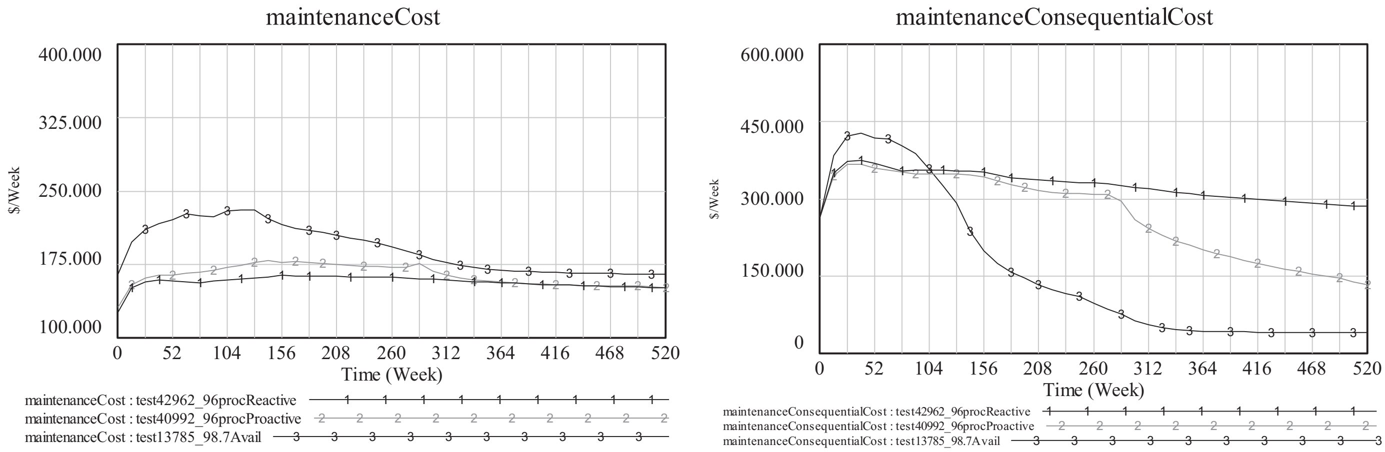

Fig. 7. The resulting maintenance (C_M) and consequential costs (C_Q) of the studied MOO solutions.

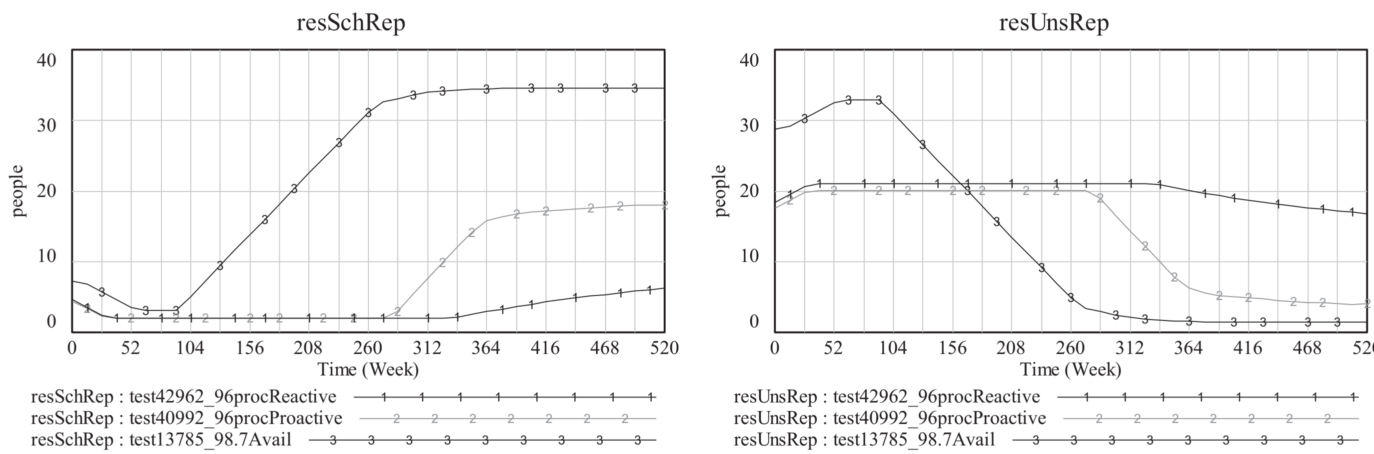

Fig. 8. Distribution over the simulation period of scheduled work to the left, unscheduled work to the right.

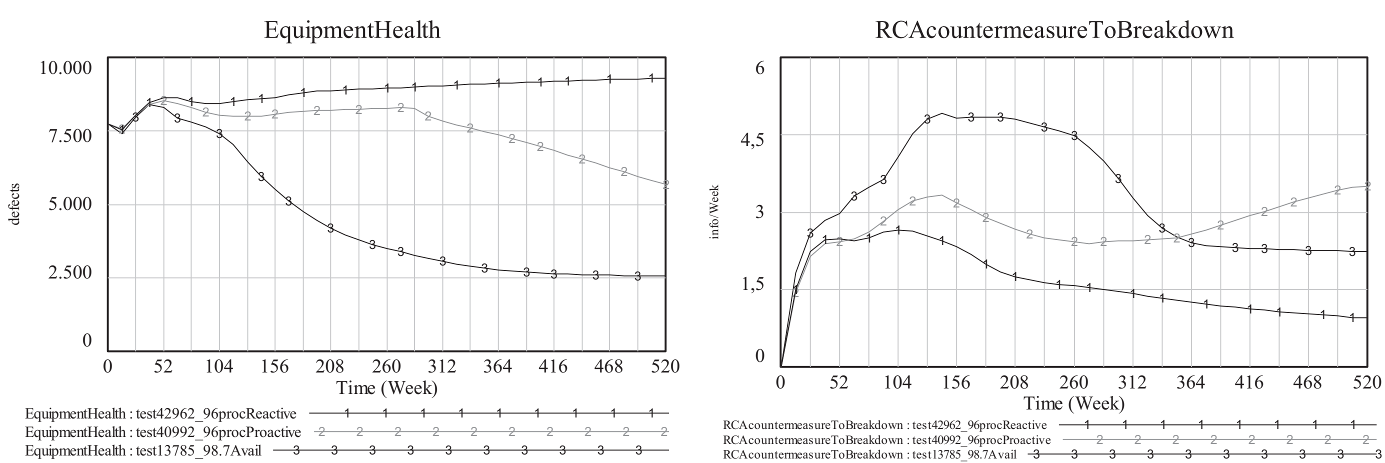

Fig. 9. Resulting *EH* and flow of *RCA* countermeasures to address R_{BD}.

Since an SD model allows multiple investigations of the interrelations in its modeled structures, step 3d) is by no means fully approached by the above example graphs. 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. 2, due to redefined knowledge.

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 – all 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 more accurately pinpointed the activity for the DES+MOO study, which had a larger improvement effect in their comparison.

A DES+MOO study is also dependent on the purpose of the applied 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 DES+MOO 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, for all the three aforementioned papers improved availability was the potential solution for increased throughput, and not the traditionally expected processing time. Availability and MTTR are often maintenance KPIs in the servicing of operations and applies to the traditional measure of availability performance (Hagberg & Henriksson, 2010; Ljungberg, 2000), as defined in Eq. (1). 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); EN_15341 (2010); Nord, Pettersson and Johansson (1997). And, some consider MTTR as equivalent to mean downtime (MDT), see Campbell and Reyes-Picknell (2016); EN_15341 (2010). We think that it is better to describe MDT as consisting of MWT and MTTR, according to Eq. (2), in order to clarify the different contributions of maintenance to operations. MTBF, as defined in Eq. (3), can then be seen as the overall measure of maintenance organization performance for a certain piece of equipment; where MWT is a measure of maintenance supportability to supply the right maintenance resources and materials, documentation, and tools to start a repair; and MTTR is a measure of the ability to repair and standardize equipment. Further, the frequency of MDT follows the average failure rate (Eq. (4)), which relates to the operating reliability measure MTTF.

$$Availability = \frac{MTTF}{(MWT + MTTR + MTTF)} \tag{1}$$

$$MDT = MWT + MTTR \tag{2}$$

$$MTBF = MWT + MTTR + MTTF \tag{3}$$

$$Failure\ rate\ (\lambda) = \frac{1}{MTTF} \tag{4}$$

Accordingly, a DES study which applies the availability measure as an input for a piece of equipment, together with MDT, jointly define the discrete events of time between failures and time to repair according to their respective statistical distributions. The resulting improved long-term mean reliability measure of maintenance performance is MTTF, considered to generate the corresponding improvement of availability in a DES+MOO study.

Overall, the available industrial case study examples and the applicability of the ready developed FACTS Analyzer software point towards a proven practical method that supplies knowledge of where in the production system to intervene, and of which parameters to adjust.

Table 3
Example of calculated improvement ranges in DES+MOO study based on outputs in Fig. 10.

Type of improvement variable in SD model (Fig. 10)	DES+MOO range		Start value	Value at 156 weeks
	min	max		
MTTF line1	0%	12.7%	13.07	14.73
MTTF line2	0%	16.9%	13.07	15.28
MTTF line3	0%	106.0%	13.07	26.93
MTTR line1	0%	−13.9%	1	0.8614
MTTR line2	0%	−17.6%	1	0.8236
MTTR line3	0%	−45.4%	1	0.5459

4.5. Phase 5 – SD+DES interaction study

Using the presented SD model, and its results presented in Section 4.3, enables monitoring of MTTF, since the stock and flow structure represents both the average equipment in full operational functionality and the breakdown rate (Eq. (5)). The variable names in Eqs. (5)–(7) follow Fig. 4. MTTR (Eq. (6)), on the other hand, needs some interpretation. Eq. (7) shows how MTTR is applied to obtain the measure presented in Fig. 10, which is based on Eq. (6). In Fig. 10 the resulting measure is a dimensionless ratio between reactive and proactive maintenance interventions in operations. This means that the development shown in Fig. 10 can be interpreted as the ratio shifting from reactive to proactive for the selected simulation experiments from Fig. 6.

$$MTTF = \frac{Equipment\ in\ operation}{breakdowns} \tag{5}$$

$$MTTR = \frac{\sum time\ scheduled\ repairs + \sum time\ unscheduled\ repairs}{\sum scheduled\ repairs + \sum unscheduled\ repairs} \tag{6}$$

$$MTTRproactive = \frac{MTTR}{time\ per\ unscheduled\ repair} \tag{7}$$

The phase 5 SD+DES interaction study, consequently applies the combined output of the selected strategy in phase 3, represented by the measures MTTF (Eq. (5)) and MTTRproactive (Eq. (7)). These measures define the potential percentage improvement in the DES+MOO study. In the example illustrated in Fig. 10, the dotted line indicates a 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 Eq. (8)), defining the maximum value of the range in the DES+MOO study, according to Table 3.

$$\Delta MTTF\ or\ \Delta MTTR = \frac{value\ at\ end\ of\ time\ period\ -\ value\ at\ start}{value\ at\ start} \tag{8}$$

The example presented in Fig. 10 implies that the improvement details according to Table 3 are applied in the DES+MOO study of MTTF and MTTR, respectively.

Finally, the explored potential strategies, seen in Fig. 10, result in this case in three potential experiments for the DES+MOO study. The resulting analyses, which optimize throughput with the fewest and most rewarding improvements in MTTF and MTTR in the production system, present a prioritized plan for maintenance to consider when planning improvement activities; now based on a desired future state in a three year period. 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).

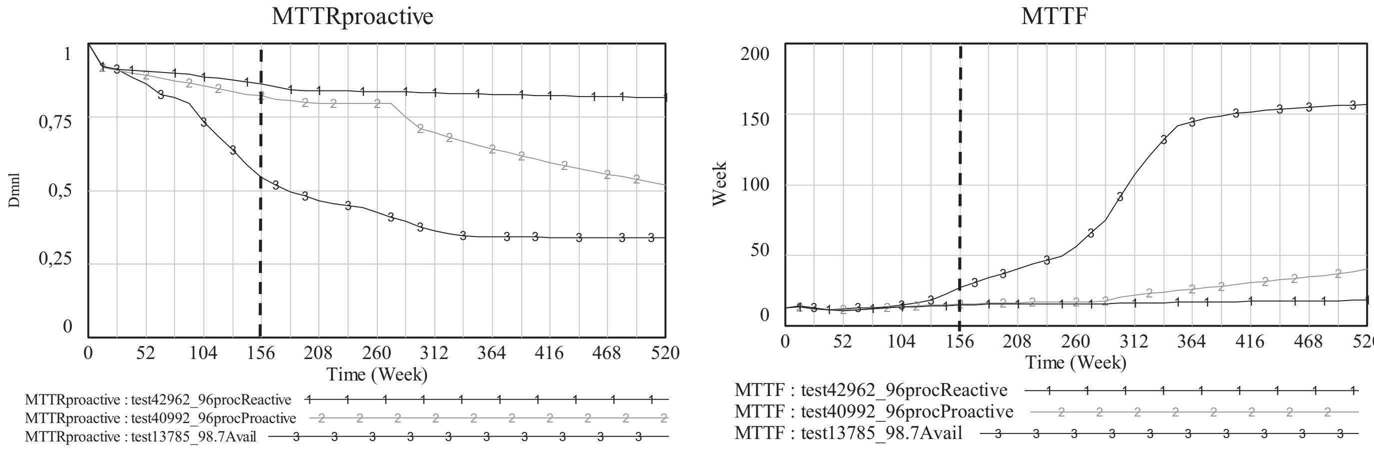

Fig. 10. Output behavior of selected strategies for the variables interacting with the DES+MOO study.

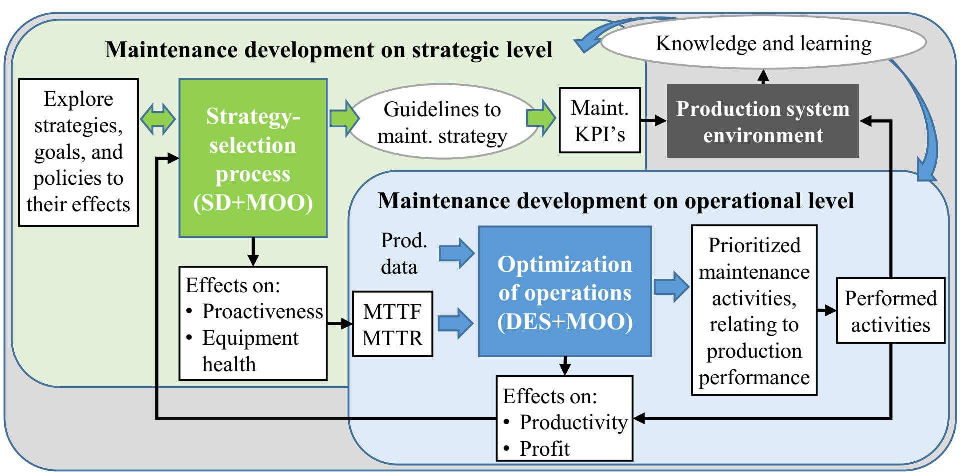

Fig. 11. Overview of the HSBOF in its context.

4.6. Phase 6 – Reflections on implementation

The strength of the application of SD studies to problems contains a process of problem structuring, approaching ambiguous aspects of the addressed problem boundary. A process which potentially affects how we think about our problems, making them more tangible. Therefore, as insights grow applying the framework good ideas can be implemented even during the process of identifying policies, guidelines, and KPIs. Above all, the HSBOF is a learning process based on both the strategy- and activities-selection process. However, the limitation of attaining a relevant SD model to support addressing maintenance dynamics is in itself a challenge, containing potential pitfalls and is restricted to the organizational capability to interpret and model those dynamics. Building a simulation model based on the dynamic problem and test its hypothesis is a highly intuitive process (Sterman, 2000) and there are no formal descriptions of how to implement system dynamics projects (Linnéusson, 2009). Hence, building modeling skills to perform SD studies is also a learning process and it can be hard to retrieve tangible results. Hence, as mentioned in Section 3, the support from the tangible DES+MOO application, which is verified towards the physical production system, is needed to bridge the difficulty of providing accessible advises on activity level. Altogether, the HSBOF defines the activities of the maintenance plan and budget for the coming year, containing both concrete and policy aspects.

Accordingly, the activities studied using DES+MOO are guided by their importance to the throughput of the production system. At such specific levels, the guiding principles from the maintenance strategy perspective may be less significant, but from the systems perspective, such strategy evaluation provides insights on the aggregated level of how to balance the work load and achieve proactiveness; meaning that the two perspectives are interdependent.

4.7. Concluding summary of the HSBOF

Fig. 11 illustrates the contributions and exchanges between the methods of the HSBOF 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 to achieve proactive maintenance behavior. 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 HSBOF helps improve our iterative knowledge building regarding the complexities to manage proactive maintenance in order to be prepared for future demands. Accordingly, SD is used for its abilities to illuminate the ambiguous structures of decision-making processes, which, according to

Please cite this article as: G. Linnéusson, A.H.C. Ng and T. Aslam, A hybrid simulation-based optimization framework supporting strategic maintenance development to improve production performance, European Journal of Operational Research, https://doi.org/10.1016/j.ejor.2019.08.036

Forrester (1961), consist of processes of converting information into action. While the application of DES+MOO produces accurate information to guide the next actions of the maintenance organization at the production system level.

5. Discussion and conclusions

This paper presents a resulting framework from studies implementing system dynamics (SD), and SD with multi-objective optimization (MOO), to support maintenance management to address the difficulty of balancing economic short-term requirements while proactive maintenance behavior have long-term effects on the production system. A complex system in which one decision based on economic budget, easily dis-attached from consequence to the real-world system, can tip the continuous work of excellence performed by maintenance and cause poor availability and high consequential costs. And, at the same time, maintenance can claim budget while not performing excellence because of too large safety margins inducing high maintenance costs caused by lack of knowledge of the complex systems.

Nevertheless, SD alone cannot adequately clarify the complexity of the production system. Therefore, the application of discrete-event simulation (DES) is also needed, enabling identification of where in the production system maintenance should intervene for maximum effect. To achieve this analytical efficacy MOO is applied, creating a hybrid simulation-based optimization framework (HSBOF), in order to support maintenance management. MOO has proven ability to exhaustively examine SD models, presenting Pareto-front optimal tradeoff solutions to the decision maker, and effectively seek optimal configurations in DES models; ensuring the use of the best known and most effective approach to address the accurate sequence of activities in improving bottlenecks. Actually, each method can inform practice separately, but to integrate strategic and operational maintenance development, they have been synergistically used together as argued and proposed here.

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. The other apparent weakness and limitation with the proposed framework, inherent in all SD studies, is the difficulty in attaining relevant models due to its intuitive modeling and testing process (Sterman, 2000). Hence, the strengths of applying SD as problem structuring method should be acknowledged, and herein supported by MOO the relevance of an SD model is unforgivingly examined. We, therefore, believe that future research needs to focus on improving the proposed framework on the strategy side, to enhance and facilitate the application of SD in maintenance development. Moreover, it identifies the need of future studies to retrieve how the application of the HSBOF actually supports and is improving human problem solving and decision making in practice, which is the core of the behavioral OR field (Franco & Hämäläinen, 2016), and fundamental to further explore in order to develop this problem-based research. Besides these, it is believed that the presented work opens avenues for numerous studies in industrial maintenance management, as well as, applications of automated innovation as applied to previous SD+MOO studies (Bandaru, Aslam, Ng & Deb, 2015) could unveil and extract further knowledge of presented studies here. However, our recommendation for industry is to start approaching the framework using DES+MOO due to its more tangible character and standardized approach. With the emerging digitalization of industry there will be a natural development of more advanced virtual tools. And, support from a maintenance development tool that encompasses the larger system boundary as defined here is considered required in order to maneuver among the increasing complexities and the demand for high utilization. Hence, 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

We are very grateful to the anonymous reviewers, whose comments have resulted in considerable improvement to the original version of this paper. 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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Please cite this article as: G. Linnéusson, A.H.C. Ng and T. Aslam, A hybrid simulation-based optimization framework supporting strategic maintenance development to improve production performance, European Journal of Operational Research, https://doi.org/10.1016/j.ejor.2019.08.036