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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]. Furthermore, 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 instead of proactive activities. Although the neglecting of 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 [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 proactive or reactive maintenance, where the economic consequences are subjective in nature [6], which makes it hard to apply the accurate strategy to decrease them. It is necessary to build models to support decisions for effective maintenance operations because of the complexity of production processes [7]. Yet, studying the dynamics of maintenance behavior seems to be a rather unexplored area in CIRP Annals, with few available studies identified elsewhere, see, e.g., [8]. This paper is based on the belief that a larger

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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 strategical 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, above-mentioned 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 in production, minimizing direct maintenance costs, and minimizing the consequence costs connected to insufficient maintenance.

The hypotheses of the study is that the time horizon is one of the key contributors to the success of sustainable strategic work, where: optimization of maintenance performance using a short time horizon is expected to produce more reactive behavior due to larger attention to direct maintenance costs, 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 availability, maintenance costs, and maintenance consequence costs.

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 preventive maintenance (PM) work may affect a manufacturing industry's strategic development of maintenance [17].

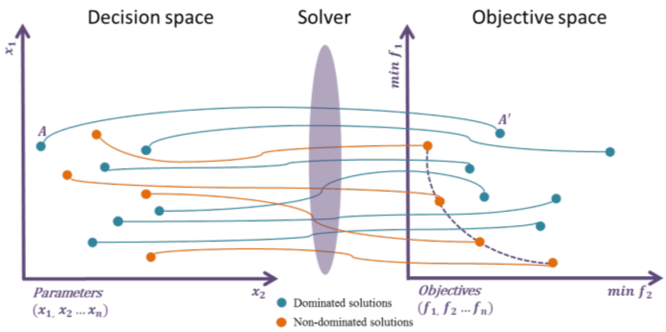

Fig. 1. Concept of Non-domination, Decision and Objective Space, from [13].

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 then 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]. Fig. 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 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, a certain solution A with its inherent values of the design parameters x_1 and x_2 are 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.

2. The SD+MOO study

The technical procedure for how to achieve Pareto-optimal solutions, using MOO on SD models, have applied the method-

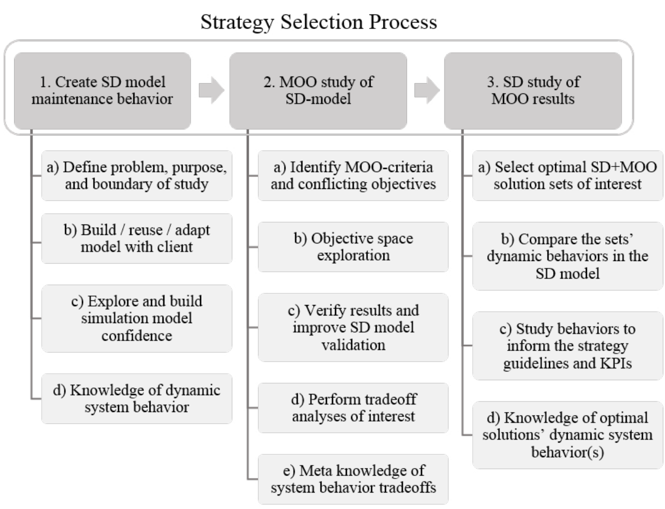

Fig. 2. The phases of the strategy selection process.

ology 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. 2. 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].

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 paper briefly introduces the model and its overall dynamics, which includes the following parts:

- The applied mix of maintenance methodologies, such as run-to-failure (*RTF*), preventive maintenance using fixed intervals (PM_{fi}), and using condition-based maintenance using inspections (CBM_i) or sensors (CBM_s) [20].
- The defect 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 (C_M), 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. 3. illustrates the model parts leading to the maintenance dynamics, and uses the stock and flow structure from the SD model that keeps track of the state of equipment in production as its base. The rest of the SD model is simplified into causal loop diagramming notations [15].

Reactive maintenance dynamics leads to unscheduled maintenance, which in Fig. 3. is depicted as a stock accumulated through breakdowns (R_{BD}) and reduced by unscheduled repairs, which restore equipment into function. R_{BD} leads to deteriorated *EH*, which leads back to more R_{BD}. The continuous level of equipment in the stock of unscheduled maintenance has the effect of reduced availability (A_T) and produce a lower operations load on equipment, thus limits the deteriorating impact on *EH*. Together with the repair workers (S_R), if kept constant, all these feedback eventually generate a new equilibrium level of *EH* and A_T.

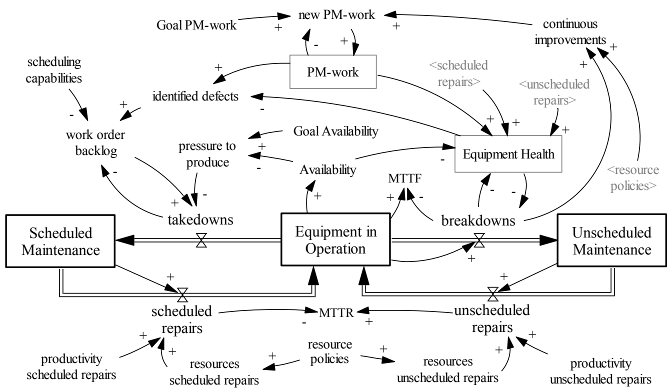

Fig. 3. Maintenance dynamics in the SD model.

Proactive maintenance dynamics leads to the execution of scheduled maintenance, which is a stock accumulated through planned takedowns (R_{TD}) and reduced by scheduled repairs, restoring equipment into function before failure. The R_{TD} depends on the planned work order backlog, which may be limited by the pressure to produce which rises with a growing gap between the goal and current level of A_T; and if so happens it overrules the maintenance plan on short-term, having the consequence of increasing the work order backlog. Thus, a growing backlog will delay the proactive work and meanwhile cause an increased risk of a higher R_{BD} to happen instead. Furthermore, the precision of identified defects depends on the currently applied mix of *RTF*, PM_{fi}, CBM_i, and $CBMS_s$, represented by the boxed variable PM-work, with its current collective capability to proactively monitor the average *EH* status. Hence, new PM-work is prepared based on the policies set by goal PM-work, and the rate of *CI* arising from the *RCA* of breakdowns, which levels depend on the applied resource policies for the number engineers (S_E) to its supports. The resource policies also determine the number of repair workers (S_R) working with scheduled repairs, which should be in balance with the generated activities based on the level of PM-work. Introducing *CI* has the effect of a moving equilibrium between reactiveness and proactiveness.

The resulting behavior in the model in Fig. 3., generates the economic effects according to equations 1-4. Eq. 1 shows how C_T is calculated. Eq. 2 includes total man-hour costs (C_h) and *CI* investments (C_{CI}) which in this study only includes investments in CBM_s, while R_{BD} and R_{TD} induce equal spare part costs per stop (C_S). Eq. 3 describes that C_Q consist of consequential breakdown costs (C_{QBD}), which based on [23] has factor 4 to each breakdown, see Eq. 4, and capital costs from spare part inventory (C_{CSI}).

$$C_T = C_M + C_Q \quad (1)$$

$$C_M = C_h + C_{CI} + C_S * (R_{BD} + R_{TD}) \quad (2)$$

$$C_Q = C_{QBD} + C_{CSI} \quad (3)$$

$$\textit{where } C_{QBD} = 4 * (C_S * R_{BD}) \quad (4)$$

Consequently, the cost effects from reactive maintenance behavior consist of C_M 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 to 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 costive resource policies, more S_R and S_E, 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_E, adding to the C_M.

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 (A_T), minimize (C_M), and minimize (C_Q).
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.

Input parameters	Range	Step
1. Number of S_R	4 – 50	1
2. Number of S_E	0 – 30	1
3. % of PM_i from RCA	0 – 1	0.05
4. % of CBM_i from RCA	0 – 1	0.05
5. % of CBM_s from RCA	0 – 1	0.05
6. Goal % CBM of total PM	0 – 1	0.05
7. CBM_i interval (Weeks)	4 – 52	2
8. Goal CBM_s	0 – 500	25

Input parameters one and two affect resource policies for S_R and S_E. More S_R have an instant short-term effect on A_T 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_i, and CBM_s 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 A_T, *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 A_T at 0.622 and *EH* at 0.7737. And, 0.5 of equipment applying PM_{fi} without any CBM_i or CBM_s 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 (A_T), minimize (C_M), and minimize (C_Q). Further, solutions with lower A_T than 0.85 are not considered in the analyses.

C_M is generated based on the levels of applied resources and the consumed amount of spare parts, related to R_{TD} and R_{BD} throughout the simulation period. According to Fig. 4., all experiments show the expected tradeoff where an increase of invested C_M, by allocating more resources, do not necessarily provide a linear increase of A_T. Yet, to around A_T = 0.90, a nearly linear increase of C_M is revealed in all solutions. The experiment with one-year time horizon, TH1Y, stands out with clearly more expensive solutions which do not reach above 0.92 in A_T, further it depicts a sharp knee region, which means that a small increase on A_T induce a considerable higher C_M, while the other experiment solutions depict smoother knee regions.

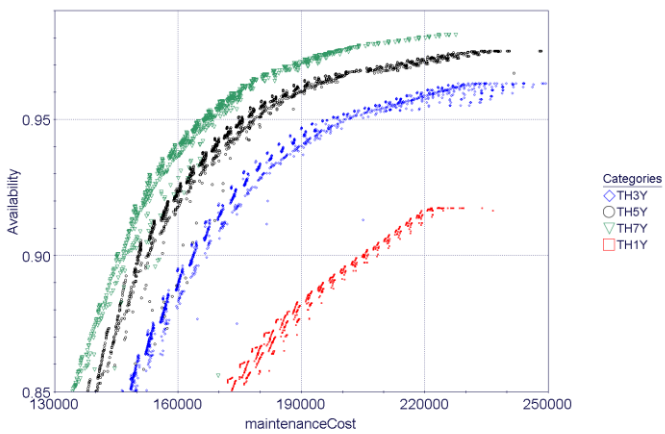

Fig. 4. Solutions from the four experiments of the tradeoffs between availability (A_T) and maintenance costs (C_M).

In sum, the results in Fig. 4. depict that the applied time horizons have tradeoff solutions on different achieved levels of C_M compared to gained A_T, providing a spectrum of solutions where the longer time horizon leads to better-achieved objectives.

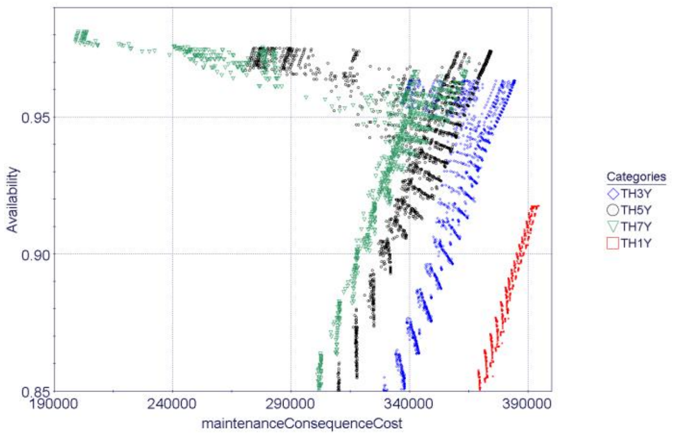

Fig. 5. Solutions from the four experiments of the tradeoffs between availability (A_T) and maintenance consequence costs (C_Q).

Studying Fig. 5. 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. 6. Since, attaining a proactive maintenance reduces the R_{BD}, resulting in lower C_{QBD}.

The experiment with three-year time horizon, TH3Y, and the five-year horizon experiment, TH5Y, both reveal an unexpected pattern where solutions with highest A_T are found on disparate levels of higher and lower levels of C_Q. The solutions in the experiment with seven-year time horizon, 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. 5. 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. 7., 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_T, 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

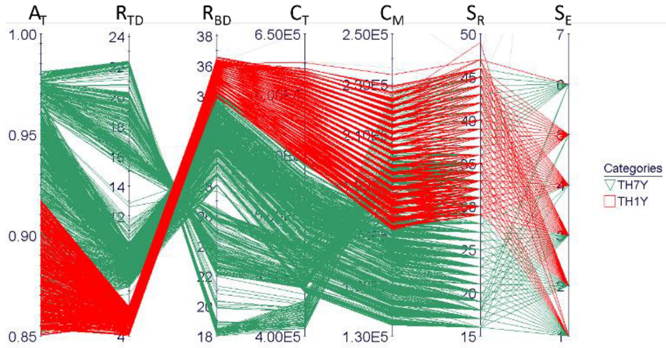

Fig. 7. Parallel coordinate map of experiments TH1Y and TH7Y.

required increase of C_M to achieve the associated results. In TH1Y it means higher levels of allocated S_R, while for S_E, which reveals a pattern of even distribution is less informative on the optimal choice. 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_T, but at the same time require the higher levels of C_M and the higher levels of S_R; and apply more S_E 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. 6. 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 (A_T, C_M, 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_R, S_E), 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, minimize maintenance costs, and minimize maintenance consequence costs. 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 moreover is exhibiting higher levels of availability and lower levels of maintenance consequence costs. 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.

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