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 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 complement. 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 stand point, 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 from 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 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 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 (Linnéusson 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 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 with this study mainly focuses on the fourth point above, however, with the predecessor points as 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 caracteristics for how two categories of equipment at one production unit, representing equipment with low and high criticallity, may be most benefitially developed, 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 decsion-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.
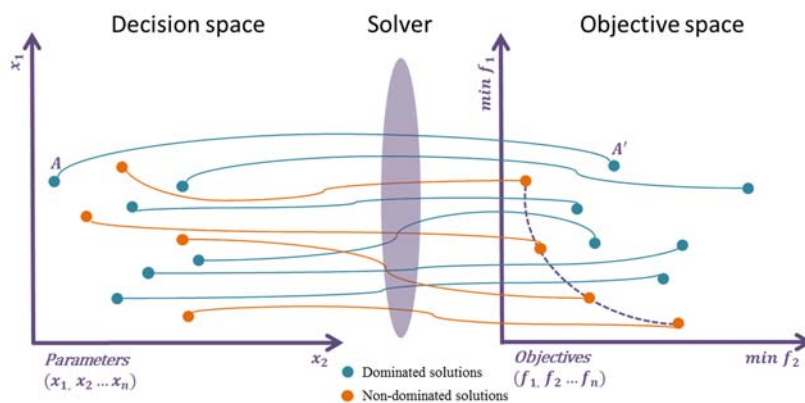

Figure 1. Concept of Non-domination, Decision and Objective Space, from (Aslam, 2013).

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 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 (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 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.
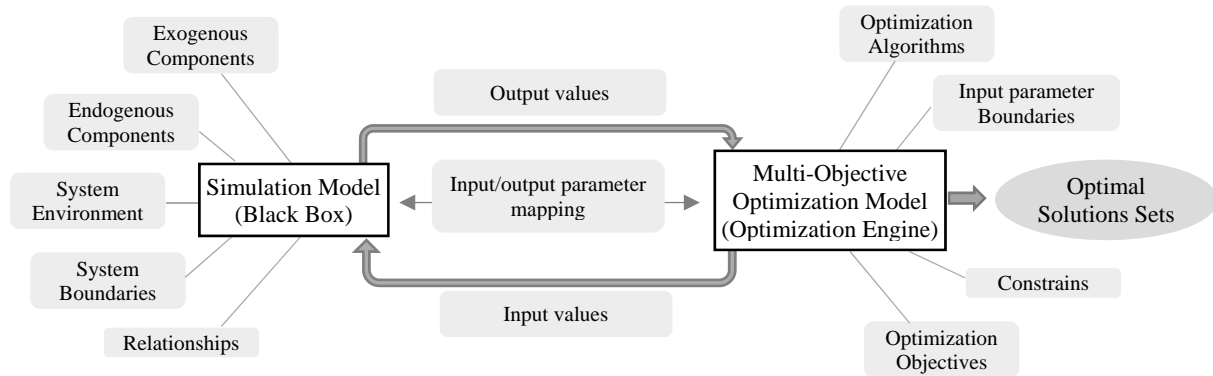

Figure 2. A general simulation-based optimizing process, adapted from (Aslam, 2013).

The applied procedure for the MOO-SD analysis presented in this paper has followed according to Figure 3. Where Step 1 is the ordinary modelling 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 amount 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 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 purpose to learn from how important knowledge about present condition before conducting a 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.
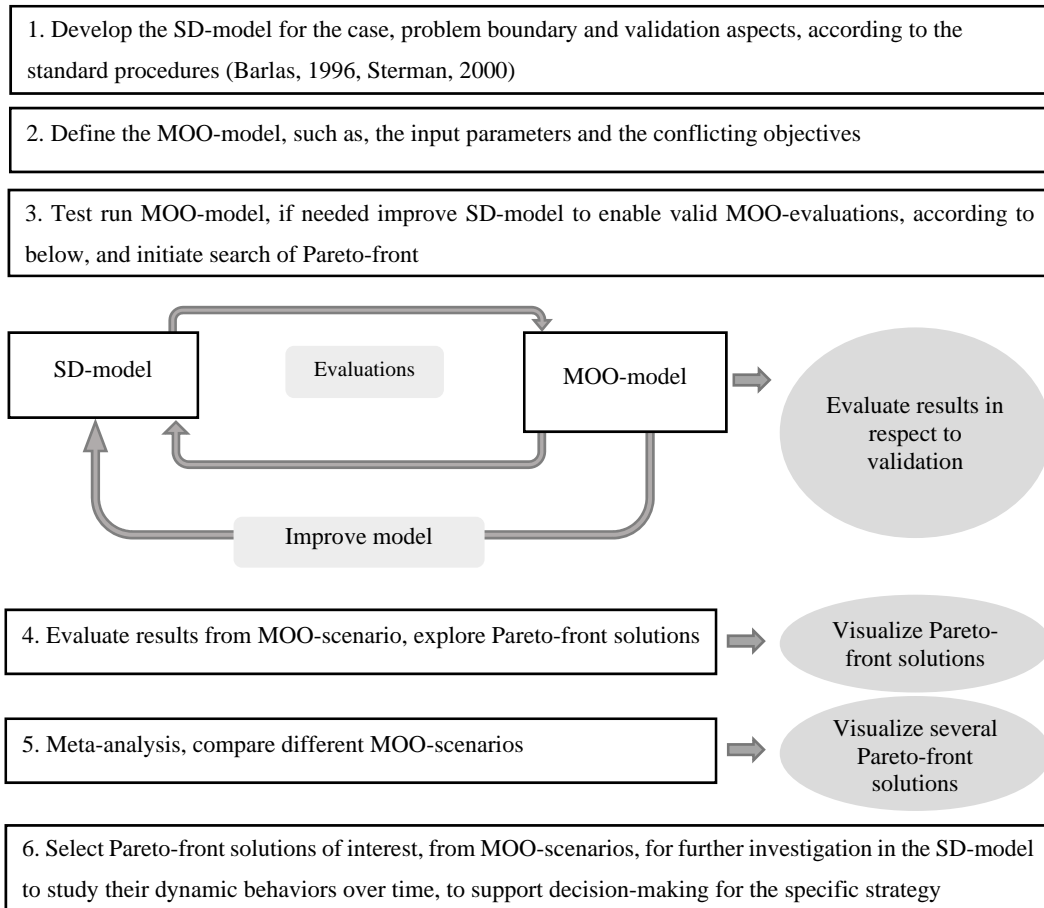
1. Develop the SD-model for the case, problem boundary and validation aspects, according to the standard procedures (Barlas, 1996, Sterman, 2000)

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

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

SD-model   Evaluations   MOO-model   Evaluate results in respect to validation

Improve model

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

5. Meta-analysis, compare different MOO-scenarios   Visualize several Pareto-front solutions

6. Select Pareto-front solutions of interest, from MOO-scenarios, for further investigation in the SD-model to study their dynamic behaviors over time, to support decision-making for the specific strategy

Figure 3. The general procedure for a MOO-SD analysis.

The maintenance performance model

For a full model presentation, see (Linnéusson et al., 2017b), in appendix the complete structure with corresponding model equations is provided. Figure 4, represents an overview of the model, illustrated using five general parts.
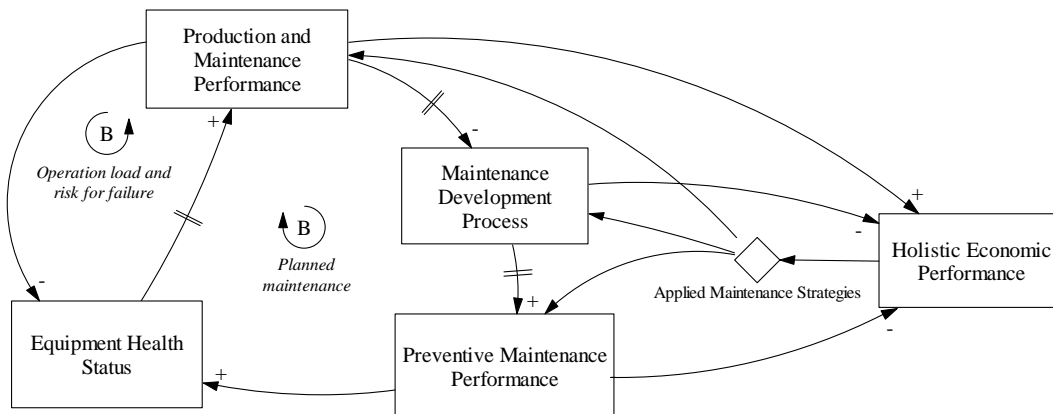
Production and Maintenance Performance

B   Operation load and risk for failure

B   Planned maintenance

Maintenance Development Process

Applied Maintenance Strategies

Holistic Economic Performance

Equipment Health Status

Preventive Maintenance Performance

Figure 4. Overview of the maintenance performance SD-model.

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 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 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 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 on 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 modelling have covered the studies of procedures of the industrial partners and relevant literature. Thus, the overall model behavior has, to some extent, been considered justified, also including the testing of assumptions with help of industrial maintenance experts. Furthermore, the application of MOO, in 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 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 criticallity, where the consequences from a breakdown in respect to downtime, quality, safety, cost, etc., have been analyzed, placing equipment into its category of criticallity. This categorization is then used as 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 criticallity. 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 chaged 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 exchange of more parts than the one causing the breakdown in the first place, thus it is represented by the criticality of the certain pice 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 1. Input parameter data for the MOO-scenarios

Input parameter:	Range:	Step:
numberRepairMen	4 – 50	1
numberMaintenanceEngineers	0 – 30	1
fractionPMiFromRCA	0 – 1	0.05
fractionCBMiFromRCAhelp	0 – 1	0.05
goalFractionCBMoverPM	0 – 1	0.05
inspectionInterval	4 – 52	2
goalCBMsensors	0 – 500	25

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

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 the 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.
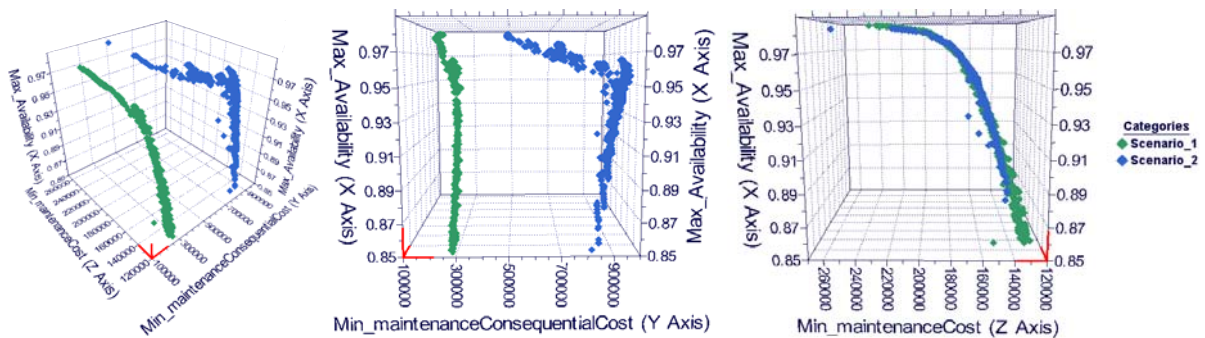

Figure 5. 3D-scatter plots of the same graph, from left: the 3D xyz-axis perspective, the xy-axis perspective, xz-axis perspective.

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 x-axis, and is compared to its trade-off to availability on 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 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.
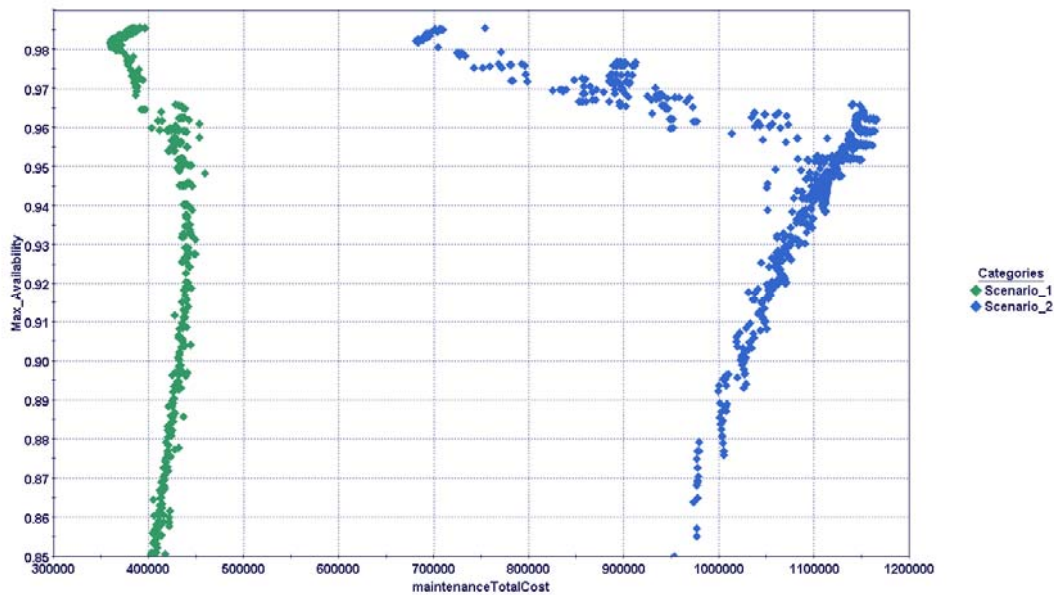

Figure 6. 2D-scatter plot over trade-off objectives.

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 modelled 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 indicates 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 an 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 being more or less easy to accomplish in the implementation.
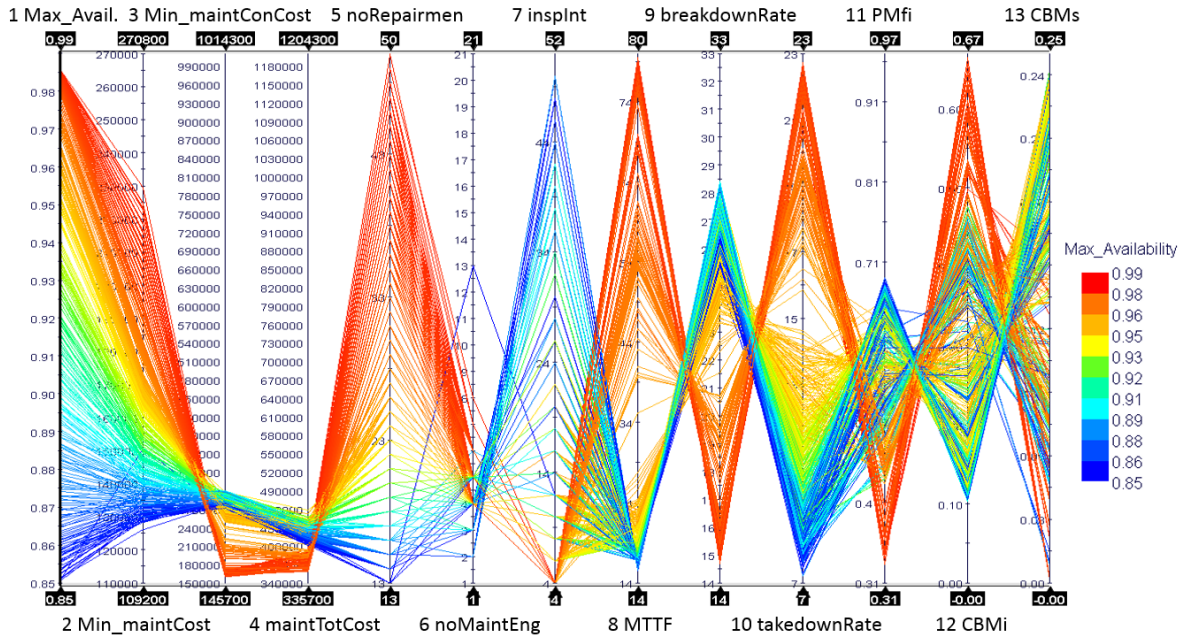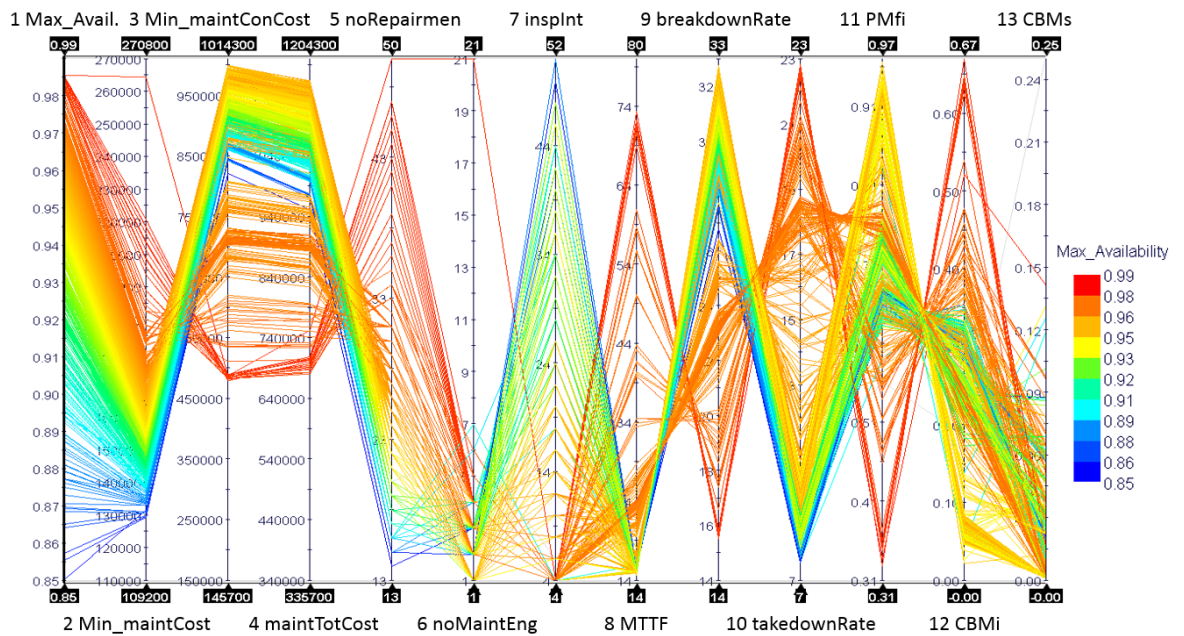

Figure 7. Parallel coordinate heat map over S1.

Figure 8. Parallel coordinate heat map over S2.

Figures 7 and 8 visualize the specific solutions represented by the lines through all parameters in the parallel coordinate plot. It enables fast overview of how the different solutions perform in respect to the

selected parameters. These plots exhibits the generalized patterns of, for instance, that to attain the higher availability solutions for both S1 and S2 it requires more repairmen, but remarkably, S2 solutions presents less repairmen 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 repairmen 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 from 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 these 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 exists 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 a 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 a 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 reveals 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 a 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 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.

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Appendix Model structure

STRATEGY DEVELOPMENT OF
MAINTENANCE PERFORMANCE IN
PRODUCTION
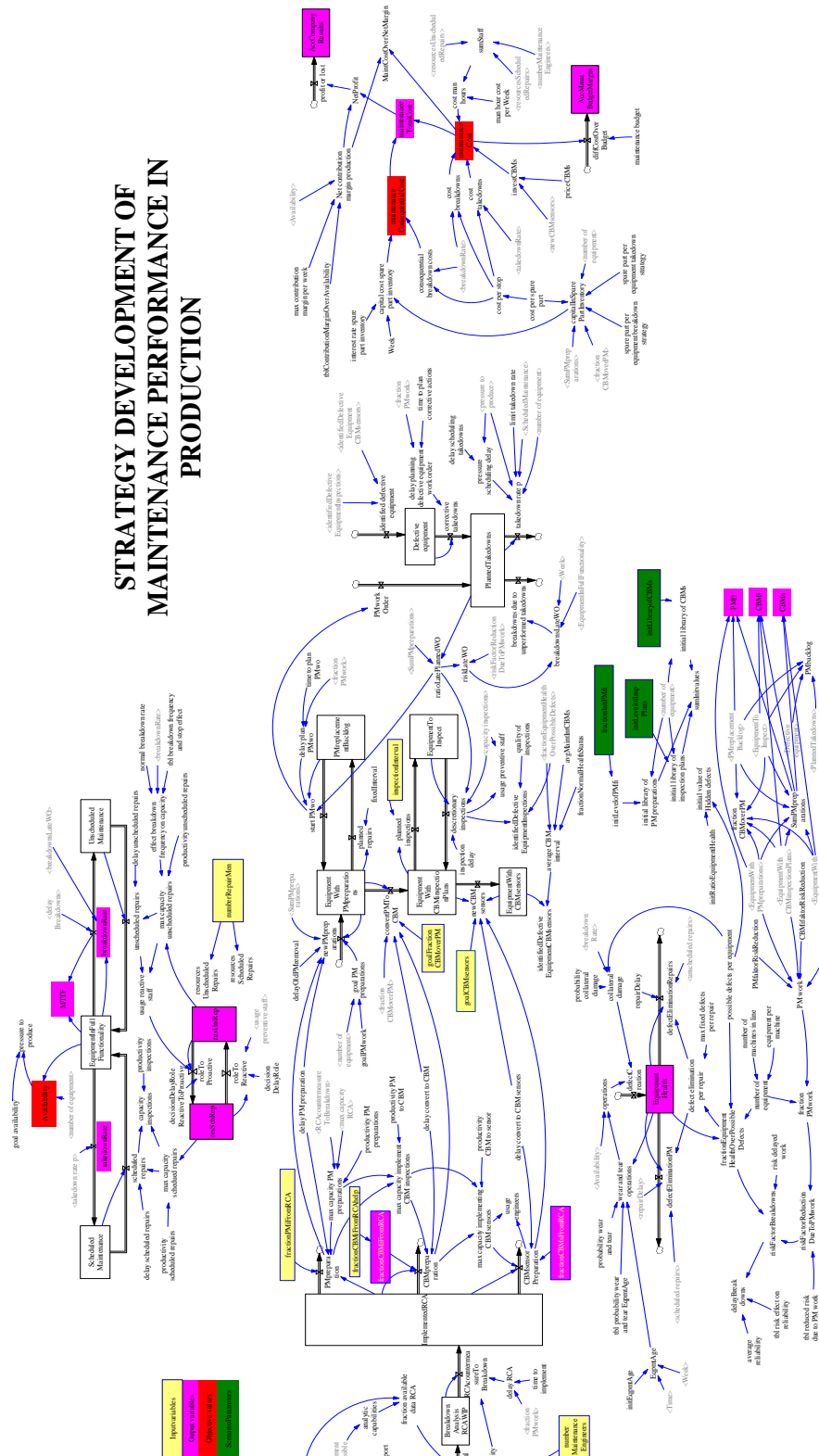
Appendix Model equations

identifiedDefectiveEquipmentInspections = discretionary inspections * fractionEquipmentHealthOverPossibleDefects * 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

EquipmentWithCBMsensors= 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

PMfaktorRiskReduction= 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))) / decisionDelayRole
          ~   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
          ~   *4:1 in scenario S1, and 12:1 in scenario S2*

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

newCBMsensors=IF THEN ELSE(goalCBMsensors>EquipmentWithCBMsensors, MIN(CBMsensorPreparation*PM
preparation release, MIN((goalCBMsensors-EquipmentWithCBMsensors)/delay convert to CBM sensors, MAX(0 ,
EquipmentWithCBMinspectionPlans/delay convert to CBM sensors))) , 0)   ~   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

ImplementedRCA= INTEG (RCAcountermeasureToBreakdown-CBMpreparation-CBMsensorPreparation-PMpreparation,1)
          ~   info

AccCompanyResults= INTEG (profit or lost,0)   ~ $

NetProfit=Net contribution margin production – maintenanceTotalCost   ~ $/Week

sumStaff= numberMaintenanceEngineers+resourcesScheduledRepairs+ resourcesUnscheduledRepairs   ~
          people

profit or lost=   NetProfit ~ $/Week

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

AccMaintBudgetMargin= INTEG (diffCostOverBudget,   0)   ~ $

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

numberMaintenanceEngineers=   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 - RCAcountermeasureToBreakdown)*productivity PM preparations
          ~   info/Week

max capacity RCA=numberMaintenanceEngineers*productivity engineers RCA analysis and PM preparations   ~
          info/Week

capitalInSparePartInventory=(spare part per equipment breakdown strategy*(number of equipment-SumPMpreparations) +
spare part per equipment takedown strategy*((1-fractionCBMoverPM) + 0.5*fractionCBMoverPM) * SumPMpreparations) *
cost per spare part ~ $

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

BreakdownAnalysisRCAWIP= INTEG (RCAUsefulData-RCAcountermeasureToBreakdown, 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

maintenanceTotalCost=   maintenanceConsequentialCost+maintenanceCost   ~ $/Week

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

goalFractionCBMoverPM= 0.3   ~   Dmnl

CBMpreparation= MIN(ImplementedRCA*fractionCBMiFromRCA/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

goalCBMsensors= 25 ~ equipment

RCAUsefulData= breakdown report done*fraction available data RCA ~ info/Week

fractionCBMiFromRCA= (1-fractionPMiFromRCA)*fractionCBMiFromRCAhelp ~ Dmnl

productivity PM to CBM= 0.1 ~ Dmnl

SumPMpreparations= PMreplacementBacklog+EquipmentToInspect+EquipmentWithCBMinspectionPlans+EquipmentWithCBMsensors+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 +EquipmentWithCBMsensors) / (PMreplacementBacklog+EquipmentToInspect+ EquipmentWithCBMinspectionPlans+EquipmentWithCBMsensors+EquipmentWithPMpreparations) ~ Dmnl

fractionPMwork= PM work/number of equipment ~ Dmnl

pressure scheduling delay= (delay scheduling takedowns*pressure to produce) ~ Week

riskFactorBreakdowns= fractionEquipmentHealthOverPossibleDefects * (risk delayed work/ riskFactorReductionDueToPMwork) ~ Dmnl

riskFactorReductionDueToPMwork= tbl reduced risk due to PM work(fractionPMwork) ~ 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 scheued 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 CBM=   26   ~   Week

delay convert to CBM sensors=   52   ~   Week

PMreplacementBacklog= INTEG (planned repairs-start PMwo,   0)   ~   equipment

inspectionInterval= 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,?]