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Simulating dynamic RUL based CBM scheduling. A case study in the railway sector

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ABSTRACT

This paper uses continuous time computer simulation tools to analyze the maintenance scheduling problem of a fleet of assets that is subjected to a CBM (Condition-Based Maintenance) program for critical components under a maintenance 4.0 environment. Detection of component anomalies, their diagnosis and prognosis are considered as built-in capabilities of the organization. Once the remaining useful life (RUL) of a component at risk is known, the organization must react and determine when the component's on-condition maintenance can be released. Maintenance on-condition activities are released controlling a variable named accumulated excess of anomalies over the CBM capacity constraint. When the existing CBM capacity is not enough to service all the components with their lowest possible RUL, components could be replaced with a higher RUL, as few times as possible, to ensure the largest component́s lifecycle. The paper explores the implications of different CBM capacity levels modelling a cost function. Cost function factors considered are cost of lost RUL, cost of CBM capacity, cost of overdue CBM and cost of asset unavailability due to overdue CBM. Empirically, the paper shows how capacity can be optimized to minimize this cost function. Once all different possibilities to schedule CBM activities are modeled, together with the cost of the selected CBM strategy, the paper compare results with those obtained for a base case where the organization could detect anomalies in components but not schedule CBM activities according to their RUL limitations and the maintenance organization capacity constraints. The paper demonstrates the different benefits of this opportunistic CBM task scheduling, according to assets stops for their predetermined PM activities. The tool that is developed has been tested in the railway sector, for a fleet of trains. Interesting results are obtained for different strategies, and they are discussed to understand possible implications of changes in the different factors and parameters of the problem.

1. Introduction and research background

As defined by (Zhao et al., 2022), a fleet is considered a set of multiple homogeneous assets that fulfil the same function together for a larger service requirement and have the same intervention options. Therefore, the inspection and maintenance actions performed on them are considered the same for the assets in the fleet (Petchrompo and Parlikad, 2019). Furthermore, the fleet fulfills a certain demand of operation, balancing the workload between the assets of the fleet. This workload balance is critical in maintenance and service scheduling (Petchrompo et al., 2020; Petchrompo and Parlikad, 2019) and could be done by managing the health of multiple assets to balance based on condition and client demand. Finally, even assets are considered identical, if there are identical assets but with different ages and characteristics associated with them, the asset prioritizing decision based on the criticality can be added to this list (Muller et al., 2008).

The replacement of many predetermined maintenance tasks with CBM tasks represents a significant change in the scheduling on maintenance interventions. Predetermined maintenance is preventive maintenance that is performed according to set time intervals or with a defined number of operating units, but without prior analysis of the condition of the item. CBM, however, is preventive maintenance that includes a combination of physical condition assessment, analysis, and possible subsequent maintenance actions. Condition assessment can be performed by operator observation and/or inspection, and/or testing, and/or condition monitoring of system parameters, etc., performed according to a schedule, on request or on a continuous basis. (EN 13306:2018 Maintenance Terminology). Asset's condition inspections

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are growing, frequently becoming on-line inspections, and the maintenance service is accomplished based on the status of the asset. The fact is that many maintenance interventions will be planned and scheduled dynamically. Thus, understanding how assets conditions deteriorate, in an accurate manner, will help importantly to define (dynamically) the best moment for intervention (Liu et al., 2017).

Scheduling maintenance of a single asset based on its health is an assessed problem with many solutions, but when it scales to the fleet or multi-unit level, different aspects of the problem as operational (fleet scheduling) also condition the management of the assets. As the problem is scaled from the single asset, the precision in representing the asset's condition, identifying what failure mode causes degradation, and how it evolves, loses level of detail. On the other hand, most models only consider fixed maintenance schedules when assigning assets to operation. There is a need to scale the level of detail considered for dynamic maintenance scheduling as a critical constraint to schedule the allocation of resources (Sanhueza et al., 2020; Zaccaria et al., 2018; Zhong et al., 2019).

Another interesting point is presented by (Sanhueza et al., 2020) proposing a PHM (Prognostics and Health Management) framework for fleets of geographically distributed assets. The paper is focused on maintenance management, especially on the restriction that maintenance resources availability constitutes for managing the fleet more effectively. The other insight of the paper, is the fact that it evaluates the potential failure impact on fleet production/service loss, linking condition prognosis with operation/service. On a similar line (Van Horenbeek et al., 2013) proposes a solution to keep decision makers updated with a relevant synthesis of information from both global health of the fleet and the status of maintenance efforts. This comes as a combination from monitoring and modelling of the fleet, as a knowledge scheme for PHM management and CBM in the PHM framework. The combination of both aspects is essential to solve scheduling of maintenance as a constraint for fleet operation scheduling. Although it is conceptualized, it cannot be found to be an end-to-end solution, from data from the field and maintenance, for higher levels of fleet management. The complexity of this problem is also explored by (El Moudani and Mora-Camino, 2000). They add the importance of not only maintenance and assignation, but also the dependence on crew, operation demand, number of assets in the fleet, and the capabilities to carry out maintenance on an aircraft fleet.

1.1. Dynamic fleet RUL base scheduling

From the aforementioned papers it can be observed that existing approaches either focus on condition management of monitored assets or problems associated with capacity and scheduling restrictions, but not on the merge of both. The most advanced approaches to manage fleet maintenance introduce anomaly detection, and life prognosis, for the definition of maintenance activities and scheduling of operation (Atamuradov et al., 2017). A similar idea can be concluded from (Martínez-Galán Fernández et al., 2022) emphasizing on the difficulty of scheduling based on the RUL of different components of each asset combined with other operational factors. The authors highlight the importance of the RUL evolution about risk and precision, and the importance of defining a periodicity of dynamic solution recalculation (something not standardized). (Bougacha et al., 2020; Dersin, 2018; Mira et al., 2020) highlight the importance of dynamic recalculation of maintenance (and the planning horizon) focusing on the fact that fleets are managed with a RUL index for each asset defined by the most critical component, but assets could be broken down in subsystems with their components and RULs with different criticalities. (Herr et al., 2020) propose an optimization model to manage the fleet considering the remaining useful life of components monitored, and the operational requirements, that even providing an insightful application, does not consider predetermined maintenance capacity restrictions, studying predictive RULs isolated. On the same line, as CBM is not merged with predetermined preventive, there is not a clear definition of what resources are for preventive, and what capacity is left for performing condition-based interventions on practice. A similar approach using the RUL prognosis is presented by (de Pater and Mitici, 2021; Lee and Mitici, 2021; Lee et al., 2022) adding the complexity of grouping maintenance in an opportunistic way to optimize usage and considering limitations of spare parts. (de Pater et al., 2022) present an integration of RUL prognostics into maintenance planning a dynamic predictive maintenance scheduling framework considering imperfect RUL prognostics. An integer linear program is used to schedule aircraft fleets for maintenance, with the same focus as the aforementioned works. (Hernández et al., 2022) propose an agent-based model to prioritize usage and maintenance, considering the dynamics of traffic and asset deterioration due to the operational usage, with the same lack of capacity constraints for maintenance. (Petchrompo et al., 2020) propose managing fleets by dynamically scheduling maintenance actions over the planning horizon with a similar optimization algorithm, and presenting significant results, however the genetic algorithm application simplifies maintenance restrictions. These papers resume the most advanced solutions for managing fleets of assets based on their condition, and a gap can be found when integrating this new paradigm with the existing predetermined preventive plans, and the resources available to do so.

1.2. Risk and cost considerations

Some approaches present a risk and cost analysis, in order to find a trade-off between them, with comprehensive evaluations of equipment performance, operation, and maintenance (Alves da Silva et al., 2019; Ge et al., 2012; Zhao et al., 2022). These studies are not applied for fleets with predictive maintenance policies integrated but used to provide a way to manage risk of multiple assets and the associated possible costs. It must be said that there is not a uniform way of formulating costs for maintenance, and even the risk evaluation is detailed, the cost is heterogeneously presented. (Rane, Potdar, and Rane, 2021) link the same argument with the importance of defining the levels of risk, or areas of acceptable risk, for evaluating the prognosis or other calculations to define security rules.

Defining the uncertainty of the prognosis, the levels of risk associated, and policies of acceptable areas depending on possible cost savings is essential to integrate data-driven models within classic optimization approaches. On this line (Jain et al., 2021) present a cost model considering both the preventive, predictive and possible corrective costs of maintenance in a more detailed way, considering the effect of uncertainty. The same view is supported by (Bougacha et al., 2020; Hernández et al., 2022). What can be concluded, is the fact that the evaluation in terms of cost is dependent on the type of maintenance, the system, the components, and specially the type of failure mode within the types of maintenance. This will be specific for each case and company, so focusing on the analysis of risk will provide a universal understanding and decision-making support, that can be then translated to costs depending on the company, resources, type of maintenance, and type of assets and subcomponents representing the case.

1.3. State of the art challenges and findings

Previous work exposed covers the application of CBM programs to fleet management domain, data-driven prognosis of failure, and the quantification of possible maintenance decisions in terms of cost for the organization. From the state-of-the-art analysis some conclusions arise:

- CBM models that use RULs to manage fleets do not integrate predetermined maintenance with the new predictive approach, hence, the limitations of capacity and resources that companies have at maintenance workshops are not considered.
- Capacity and resources are considered for scheduling of operation or preventive maintenance but not the CBM capability. Apart from the forecasting capability, for most of the models that manage fleet based

on condition, only spare parts availability is considered in particular cases.

- The approaches that consider a CBM cost evaluation in detail are not scaled to the fleet level, and most modern dynamic fleet maintenance models do not evaluate the costs of maintenance in detail. In the reviewed papers maintenance costs are generalized using constants related to global execution and not deeply defined by the capacity and depot resources involved.
- The techniques applied to develop fleet maintenance approaches cover from genetic algorithms, system dynamics, or discrete event simulation, to Monte Carlo simulation. These approaches do not provide an optimal solution, but a recommendation of the areas and scenarios that present the widest benefit to the organization, as the dimensions of the problems under study make solver-based optimization problems not manageable operationally, due to computation times. This makes simulation-based solutions one of the most relevant areas, also because they allow the decision maker to experiment with multiple decision scenarios and their impact.

According to previous conclusions, in this work a continuous time system dynamics simulation modelling work is done to:

- Integrate the scheduling of CBM activities together with the predetermined maintenance activities using RUL.
- Introduce the consideration of capacity for CBM activities, capacity to be added to the one designed for preventive predetermined activities.
- Consider different levels of risk in components according to their RUL, circumstance that is used to allocate CBM capacity in a convenient way, according to the risk of the component.
- Identify the different costs of operations that must be considered to optimize CBM capacity and the corresponding preventive maintenance work programs.
- Estimate, in a practical way, the possibilities of such a model to evaluate the opportunity cost of using this type of techniques in industry, assuming the model can be applied to components of assets in any industrial sector.
- Apply findings to a case study in the railway sector, for which information is available to the research team.

In the sequel, the paper is organized as follows: Section 2 presents the problem describing the current scenario and boundaries. Section 3 introduces the reader to the methodology and software used in the study. In Section 4 a model for CBM activities scheduling based on RUL, and existing CBM capacity, is formulated. This model results, will be compared to results of a Base Case model that is presented in Section 5, assuming capacity for anomalies detection but no RUL considerations when scheduling CBM. Section 6 presents inputs considered in the case study and results obtained for different capacity & cost factors. Then these results are compared against the base case model to estimate opportunity costs. This comparison is done using Montecarlo analysis. Conclusions of the case study are presented at the end of the Section, and Section 7 contains the conclusions of the paper.

2. Introduction to the problem

This case study is about the dynamic scheduling of maintenance activities for a fleet of assets' critical components, within a maintenance 4.0 scenario.

Maintenance 4.0 scenario means that, for each component considered, a set of algorithms will be in place, providing anomalies detection, diagnosis, and prognosis (Remaining Useful Life: RUL), for the existing components' failure modes.

In this paper, a statistical approach is followed to estimate the RUL (in this case of any bearing of a train), once a positive (or anomaly detected for a failure mode) appears in a train axle bearing. A positive (according to the Procedure for the Design and Implementation of CBM Plans in the company) is defined as the occurrence of an absolute error (AE) of prediction greater than 10ºC between the actual bearing temperature and the one predicted by the artificial neural network (ANN) designed for detection, when the train is running at more than 90 km/h (i.e., $AE \geq 10$ºC, $TS \geq 90\ km/h$) and for more than one minute. RUL is defined as a random variable that, estimated from the appearance of the first positive, offers a good prediction of the life of the element until its replacement due to a classified failure model (for instance: over temperature or noise in the bearing). This replacement is nowadays performed after the activation of the safety alert in the train monitoring and control system (TCMS) and/or because of a certain inspection (probably during a weekly train inspection in the workshop). The safety alert is triggered when the temperature difference between the four bearings of the same axle is higher than 25 °C — ($Tmin$-$Tmax$) $\geq$ 25 °C — and this condition is maintained for more than 1 min. Company's RUL analyses foresee the recommended time of bearing replacement, after its first positive, even without prior inspection, according to statistical estimates. The calculation is applicable to any bearing regardless of its position in the train. The data used comes from the record of bearing replacements that could be traced, and linked to the recorded equipment monitoring data, and the predictions of bearing failures made with artificial intelligence algorithm.

Workshop capacity is assumed to be constrained, and the model will find out different possibilities to balance capacity utilization, through opportunistic maintenance based on current number of components at risk.

This paper shows only a part of this problem's complexity compared to the real world, offering tools and methodologies that can be used to identify opportunities of improvement for its resolution.

In this case study the time horizon for the analysis will be set to P time periods, where a period t, is defined as the time between two consecutives asset predetermined preventive maintenance activities (PM), established according to existing certified maintenance programs meeting current asset's requirements for O&M and safety. Many times, these predetermined activities may also be related to legal requirements and therefore are somehow fixed beforehand.

When the asset arrives at the workshop for a predetermined PM, condition-based maintenance activities can also be carried out on selected components. These activities will consume specific workshop resources dedicated to these CBM programs and capacity constraints may sometimes appear.

The problem is to determine what are the components, following a CBM program, that must be maintained in each period t and the most important thing: what is the capacity level of the workshop minimizing the cost associated to a component CBM policy.

To accommodate the release of CBM activities to the existing CBM capacity and to the RUL of the component, a very innovative part of the model is the introduction of a variable named accumulated excess of anomalies over the CBM capacity constraint (later named $AEx(j,k)_t$)). When the existing CBM capacity is not enough to service all the components with their lowest possible RUL, this variable helps to determine the components to be replaced with a higher RUL, as few times as possible, to ensure the largest component́s lifecycle.

To determine CBM capacity optimizing cost, a cost function is defined considering the following cost factors: Cost of lost RUL, cost of CBM capacity, cost of CMB overdue and cost of asset unavailability due to CBM overdue.

A constant CBM capacity is established in the workshop for a certain system and planning horizon. Anomalies in systemś component will appear, and the RUL of those failure modes will be known and inputs to the problem. Anomalies will be introduced in the model as random Boolean variables, that take value 1, when an anomaly is detected for a component during a certain period t, and 0 otherwise. To simplify formulation, it is assumed that there is a given schedule and only one asset of the fleet visit the workshop every period (day) for a pre-

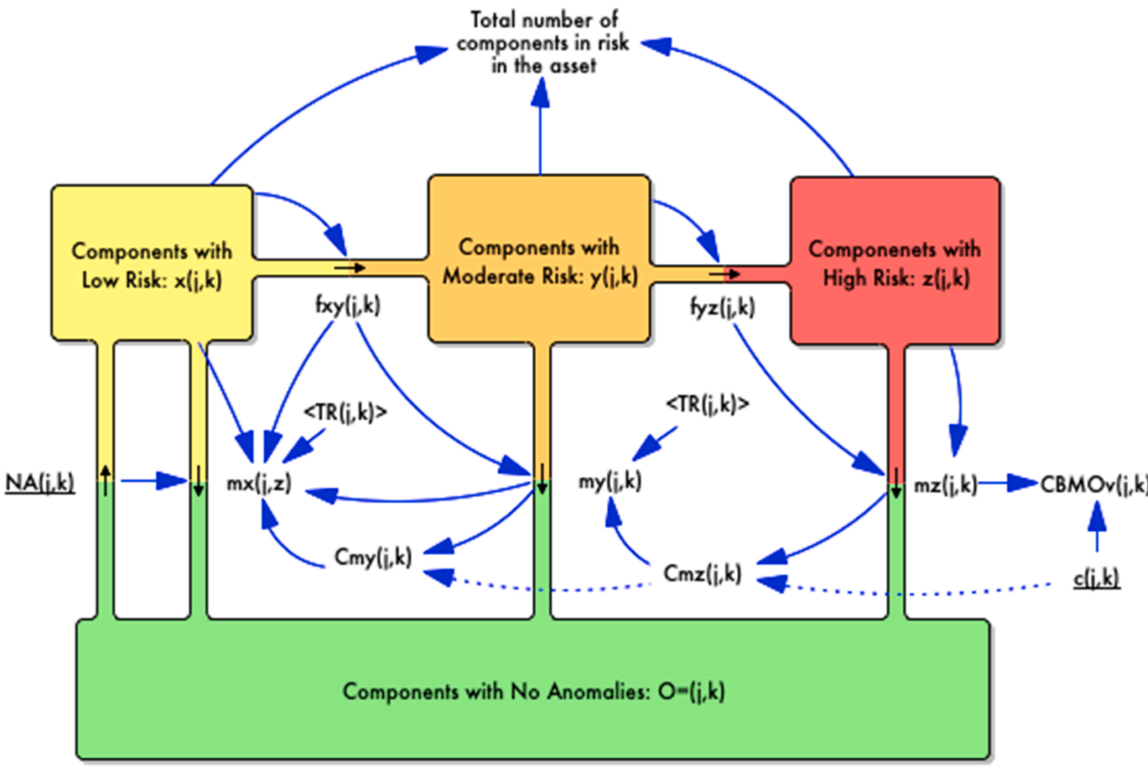

Fig. 1. Basic Stock and Flow component variables considered.

determined PM and at that time CBM activities can be carried out to those systems of that asset with problems.

In the case study that is developed for rolling stock assets, i.e., railway vehicles in the rail transport industry, the "useful life" considered for the RUL is the expected life of the component prior to the intervention of the existing vehicle safety system (named TCMS: Train Control & Monitoring System in the paper), which provides a back-up for safety. The TCMS intervention implies, generally, penalties in asset operation contracts due to stops or speed reductions to control potential failures presence.

3. The simulation methodology and the software

In this paper a continuous time dynamic simulation approach is adopted, the modelling methodology followed has been System Dynamics (SD) (see a complete list of approaches in (Alrabghi and Tiwari, 2015), and the model will be written using difference equations (Marquez, 2010). It is assumed that the change in the system occurs at discrete points in time and that each variable at time $t+1$ will be a function of the current values:

$$x_{t+1} = f(x_t)$$

Notice that $f(x_t)$may be either a linear or a nonlinear function, and that for the equation to be solved the initial value of the variable x_0 should be known. It is also assumed that the time of the simulation will be advanced in fixed time increments and that all system variables will be recalculated at each time increment.

An important assumption for this paper is that the time increment of the simulation matches the time step for assets to undergo fix predetermined preventive maintenance (PM) activities. The schedule of these activities is assumed to be known well in advance the CBM activities must be released.

Some of the system dynamic tools such as the stock and flow diagrams (SFDs) will provide a graphical representation of the model and variables typology immediately (Stearman, 2000) and the software package used for the implementation of the model equation is version 9.3 of Vensim ®, a registered trademark of Ventana Systems Inc. The reader is addressed to (Tesfamariam and Lindberg, 2005) and (Orji and Wei, 2015) to see similar innovative uses of SD models even integrated with other modelling methodologies.

4. Modelling cbm scheduling based on RUL and CBM capacity

In System Dynamics models, two basic types of variables are used: stock or levels and flows or rates. Stock variables will remain constant unless flow variables modify them. To easy the formulation of the flow variables and to give the modeler higher flexibility, auxiliary variables are used. An auxiliary variable may appear in the equation of a flow variable, and can be a function of a stock, of a flow or/and of another auxiliary variable.

In the following sub-Sections, the different parts of the model are introduced. This introduction of the model structure has been divided into three parts or sub-models: the assets condition, the workshop capacity control and utilization, and the cost function.

4.1. The assets condition

Assets conditions will be modelled using stock variables, that are defined at a given time t and will remain constant unless flow variables modify them. Flow and auxiliary variables are defined for a period t. A period t is defined as the period between times $t-1$ and t. As mentioned above, at time t an asset predetermined PM takes place.

In this paper, for modelling purposes and without losing any generality, it is assumed that a component is equivalent to a system, since the same capacity will be used to deal with all components of a system. Also, it is assumed that four different and possible system conditions exist, these conditions correspond to different levels of risk of a system: no-anomaly, low-risk, medium-risk, and high-risk. Low, medium, and high-risk levels consider that an anomaly has been detected in the system. To model systems under these circumstances (e.g., bearings) placed

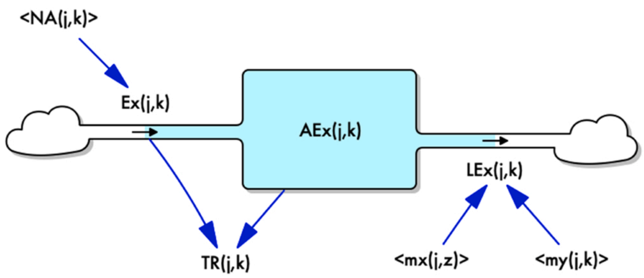

Fig. 2. Accumulated excess capacity modelling and control.

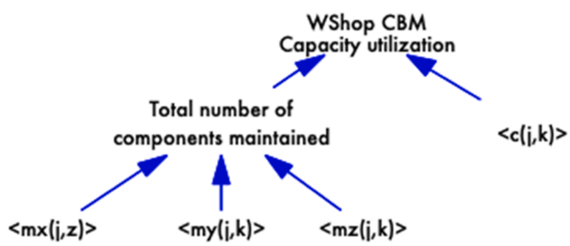

Fig. 3. Obtention of the workshop CBM capacity utilization.

in assets (e.g., trains) the following notation for the stock variables is considered:

$x(j,k)_t$: Number of low-risk components in system *j*, asset *k* at time *t*.

$y(j,k)_t$: Number of medium-risk components in system *j*, asset *k* at time *t*.

$z(j,k)_t$: Number of high-risk components in system *j*, asset *k* at time *t*.

$O(j,k)_t$: Number of no-anomaly components in system *j*, asset *k* at time *t*.

What is the reason for this notation and selection of variables? This comes out from previous works in models developed for axle bearings (Crespo Márquez et al., 2020). For many of these components, when an anomaly is detected, their RUL is set to 30.000 kms, while the train predetermined PM (named IS, taken from the Spanish *inspección semanal* or weekly inspection) are scheduled every 10.000 km (common in many situations where ISs are released on a weekly basis). This would mean that maintenance managers will have three opportunities to do the CBM activity during a train stop for a IS service, once the anomaly is detected, and before the component's RUL expires (when the bearing is in yellow, in orange or in red in Fig. 1).

The RUL estimates are applied to any train bearing, per bearing failure mode, and the adopted RUL is based on conservative statistics, i.e., 30.000 kms RUL implies that the train will reach that distance without bearing failure due to the failure mode studied, with a probability higher than 99%. Moreover, the consequence of not reaching that distance, a circumstance that occurs with very low probability, would only imply the intervention of the TCMS (controlling the risk), as was the case prior to the application of 4.0 technologies to preventive

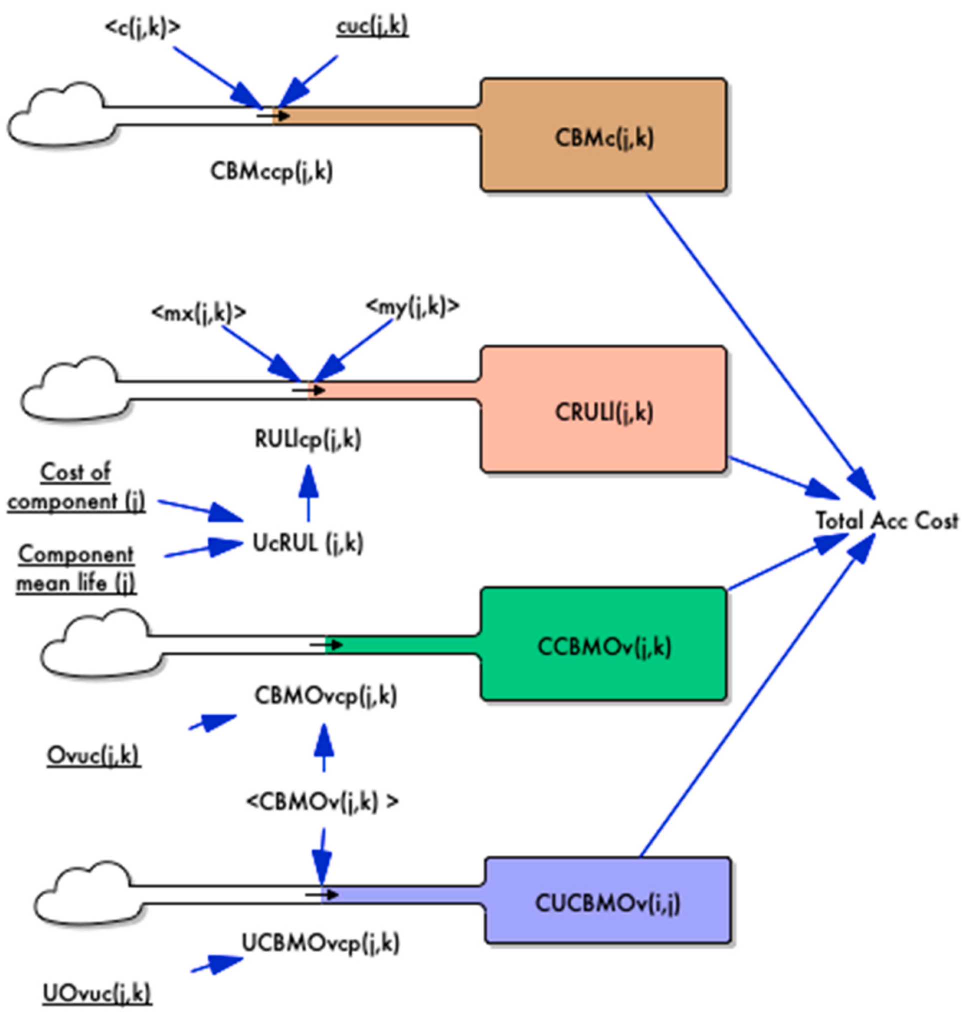

Fig. 4. Stock & flow diagram of the cost factors and total accumulated cost.

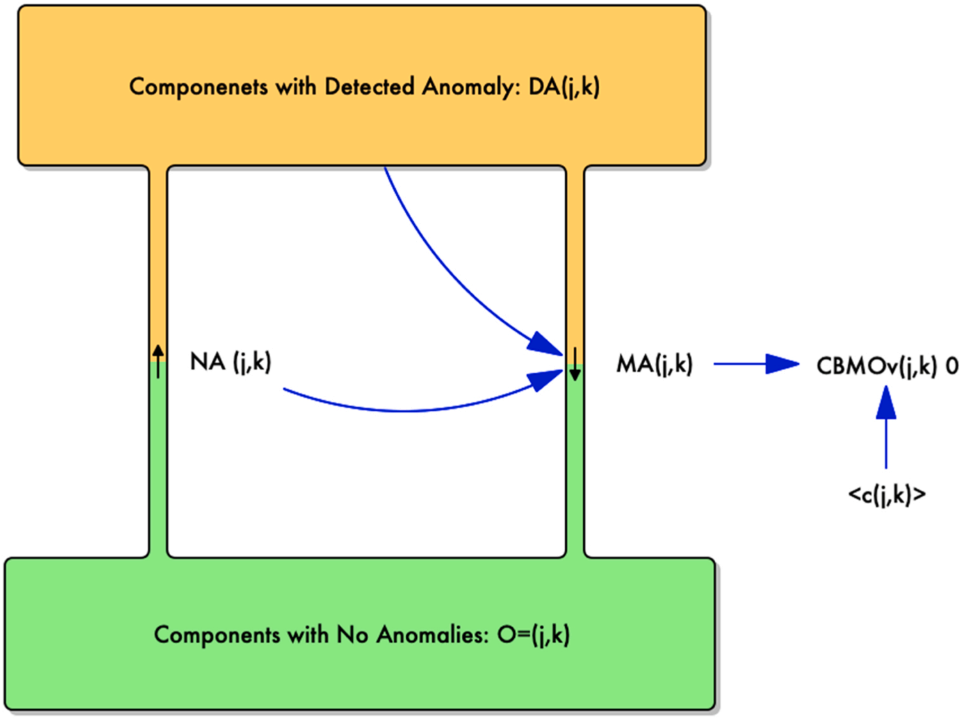

Fig. 5. Complete stock & flow diagram of the status of components in the system.

maintenance management and CBM.

Fig. 1 shows a SFD of the assets condition model, boxes are representing stocks and arrows linking the stocks represents the flows or transitions that take place in one time step. The rest of the variables are auxiliary variables. In the following paragraphs the formulation of these variables is explained.

The balance equations of the variables defining the system j, at risk in asset k (stock variables), are as follows (see Fig. 1):

$$x(j,k)_t = \left\{ \begin{array}{c} x(j,k)_{t-1} + NA(j,k)_t - mx(j,k)_t - fxy(j,k)_t, fort > 0 \\ x_0, fort = 0 \end{array} \right\} \quad (1)$$

$$y(j,k)_t = \left\{ \begin{array}{c} y(j,k)_{t-1} + fxy(j,k)_t - my(j,k)_t - fyz(j,k)_t, fort > 0 \\ y_0, fort = 0 \end{array} \right\} \quad (2)$$

$$z(j,k)_t = \left\{ \begin{array}{c} z(j,k)_{t-1} + fyz(j,k)_t - mz(j,k)_t - fxy(j,k)_t, fort > 0 \\ z_0, fort = 0 \end{array} \right\} \quad (3)$$

$$O(j,k)_t = \left\{ \begin{array}{c} O(j,k)_{t-1} - NA(j,k)_t + mx(j,k)_t + my(j,k)_t + mz(j,k)_t, fort > 0 \\ O_0, fort = 0 \end{array} \right\} \quad (4)$$

Obviously:

$$O(j,k)_t + x(j,k)_t + y(j,k)_t + z(j,k)_t = n, \forall t \quad (5)$$

Transition from no-risk or optimal condition level to low-risk levels are given by the number of positives (anomalies detected) found in a period t, see Eq. 1. This is considered input data to the model, and the flow variable $NA(j,k)_t$ will be randomly generated according to de average age of the fleet of components.

$$NA(j,k)_t = \sum_{i=1}^{i=n} a(i,j,k)_t \quad (6)$$

Where $a(i,j,k)_t$ is an auxiliary variable representing the detected anomalies in component i, of system j, of an asset k at period t. This will be an input to the problem, that can be replicated for a certain series of random numbers.

Transitions of components from a given risk level to the higher one are modelled with flow variables $fxy(j,k)_t$ & $fyz(j,k)_t$. Transition of components at low, medium, and high-risk level, to the "no anomaly" level, because of their maintenance in period t, are modelled with variables $mx(j,k)_t$, $my(j,k)_t$ and $mz(j,k)_t$.

Components not maintained (replaced in many cases), at a given risk, during one period, will move to the higher risk level in the subsequent period, i.e.:

$$fxy(j,k)_t = x(j,k)_{t-1} \quad (7)$$

$$fyz(j,k)_t = y(j,k)_{t-1} \quad (8)$$

The model assumes that all components reaching the highest risk admissible level in a period t will be serviced in that period, i.e.:

$$mz(j,k)_t = z(j,k)_{t-1} + fyz(j,k)_t \Rightarrow z(j,k)_t = 0, \forall t \quad (9)$$

Then notice that the only way to lower this accumulated excess of anomalies would be to increase capacity, or to replace components with lower risk levels $(my(j,k)_t \& mx(j,k)_t)$. Therefore, to model these flow variables $(my(j,k)_t \& mx(j,k)_t)$ a certain capacity control must be established first.

4.2. *The CBM workshop capacity control and utilization*

In this paper we are concerned about the CBM capacity to service components of the system j of an asset k (named $c(j,k)$) when the asset visits the workshop every time step, to undergo a predetermined PM maintenance. We assume there is a certain CBM capacity per system in the workshop per visit of the asset, that can be used whenever the asset has a component in risk. For instance, a time step in the model can be a week, and a different asset k will visit the workshop a different day of the week.

CBM capacity is a model parameter and must be balanced to service all components and have them running before their RUL expiration. $c(j,k)$ can be defined as the maximum number of components of system j that can be maintained during an asset k predetermined PM stop. Ideally, the intention is expressed in Eq. 10:

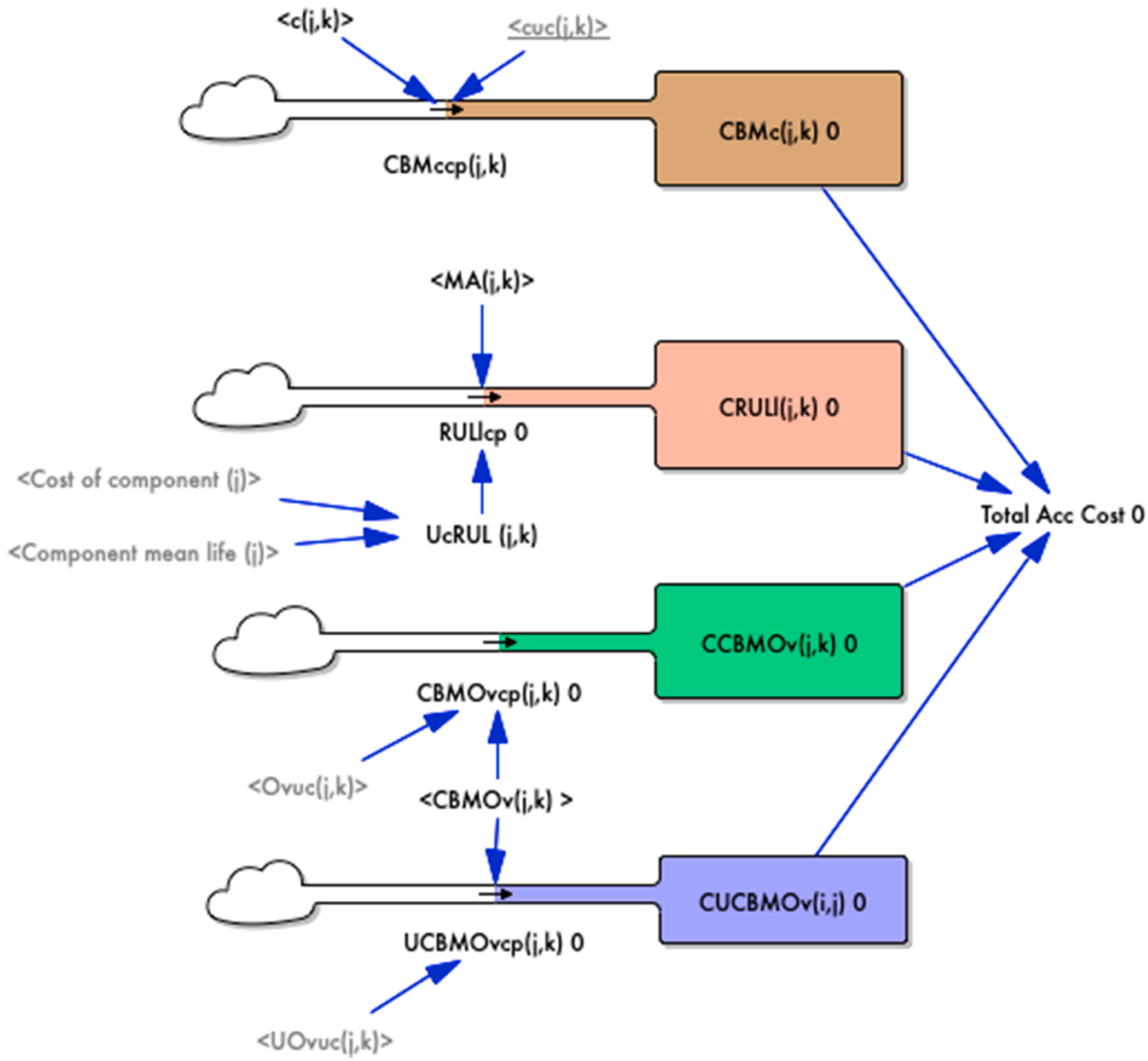

Fig. 6. SFD of the cost factors and total accumulated cost for the base case.

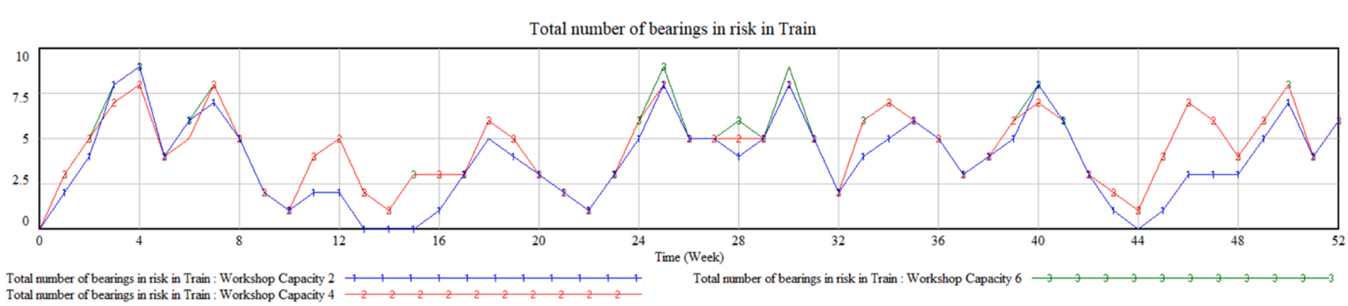

Fig. 7. Bearings running at risk under different depot capacity options.

$$mx(j,k)_t + my(j,k)_t + mz(j,k)_t \le c(j,k), \forall t, j, k \tag{10}$$

Nevertheless, due to the stochastic nature of $NA(j,k)_t$, – and also because many components could increase in risk level, with a higher probability, at certain number of running hours or kilometers – there must be a control of anomalies and capacity, since during a certain period it could happen that $NA(j,k)_t > c(j,k)$.

To control maintenance activities over components of systems with different risk levels, the existing accumulated excess of anomalies, over the CBM capacity, registered (now denoted $AEx(j,k)_t$) must be formulated and controlled (see Fig. 2).

$$AEx(j,k)_t = \left\{ \begin{array}{c} AEx(j,k)_{t-1} + Ex(j,k)_t - LEx(j,k)_t, fort > 0 \\ AEx_0, fort = 0 \end{array} \right\} \tag{11}$$

Let $Ex(j,k)_t$ denote a flow variable representing the difference between anomalies detected and existing CBM capacity in a period t. That is the excess of component experiencing anomalies compared to the ones that the maintenance depot could service, with the existing CBM capacity, in one predetermined PM stop:

$$Ex(j,k)_t = Max(NA(j,k)_t - c(j,k), 0) \tag{12}$$

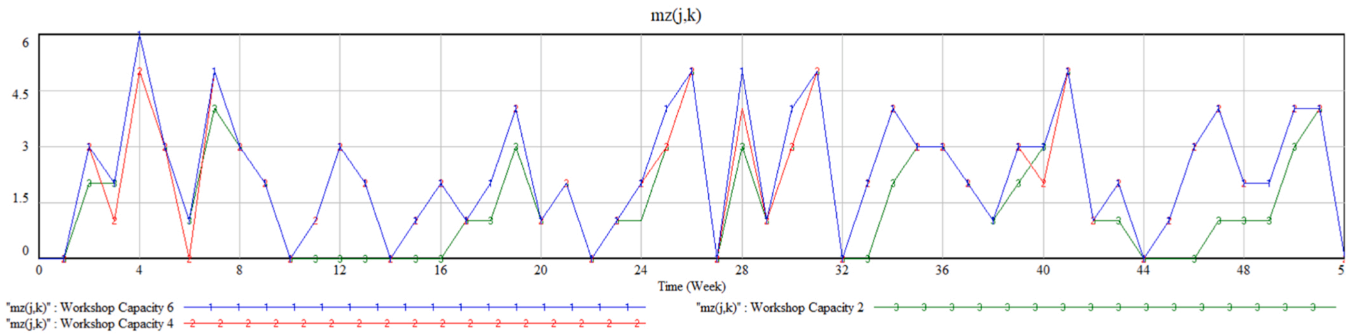

Fig. 8. High risk bearings maintained under different workshop CBM capacity options.

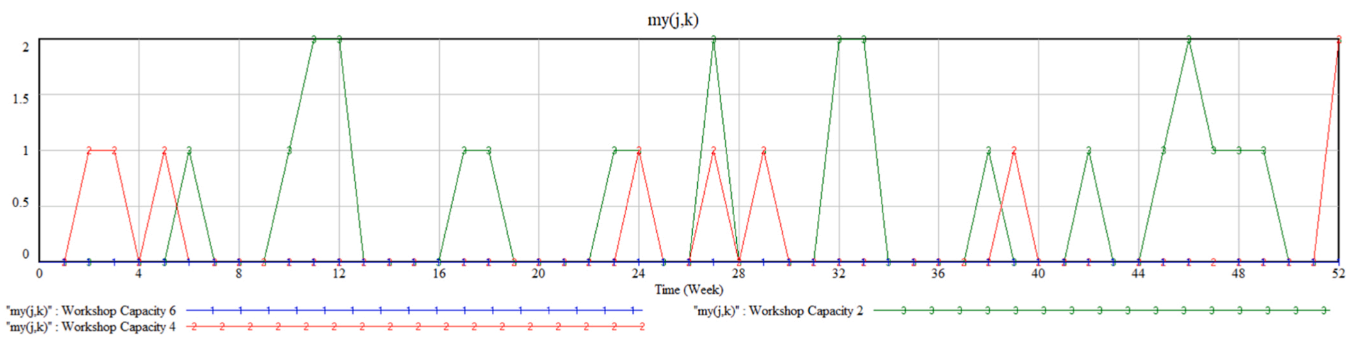

Fig. 9. Medium risk bearings maintained under different workshop CBM capacity options.

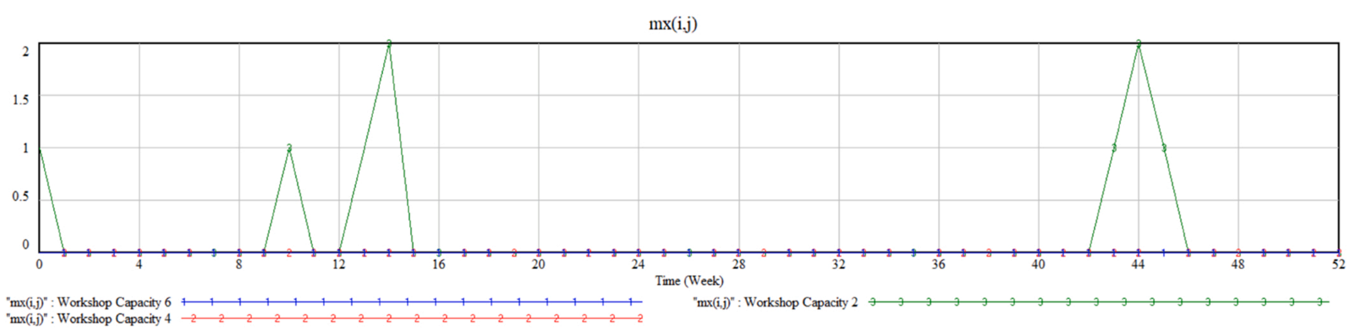

Fig. 10. Low risk bearings maintained under different workshop CBM capacity options.

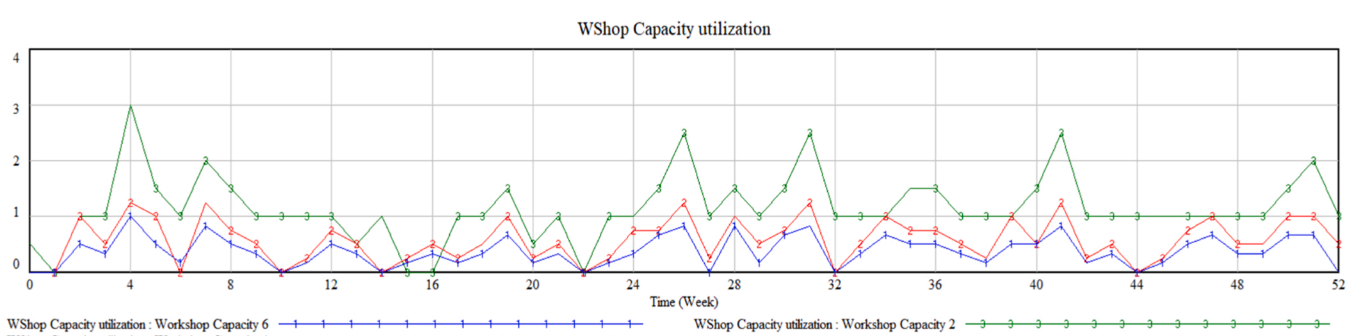

Fig. 11. Workshop capacity utilization with the three simulated scenarios.

In case that $Ex(j,k)_t > 0$, this will force the maintenance organization to act, and to replace components before they reach their highest admissible risk level, corresponding to their lowest RUL or their longest useful lifecycle. Otherwise, capacity could not be enough to service all the components. At the same time, the idea is that lower risk components could be replaced as few times as possible to lengthen their useful lives. The number of possible maintenance interventions on components not reaching their highest risk level would be (see Fig. 2):

$$LEx(j,k)_t = my(j,k)_t + mx(j,k)_t \tag{13}$$

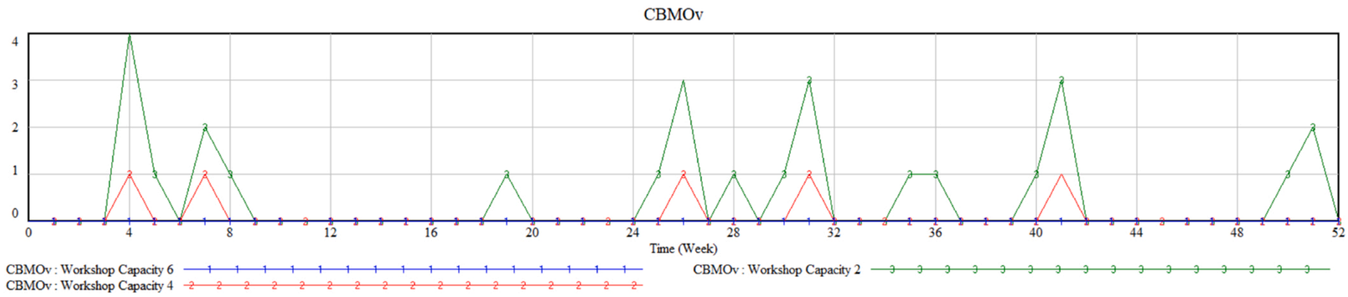

Fig. 12. Workshop extra capacity needed for CBM activities.

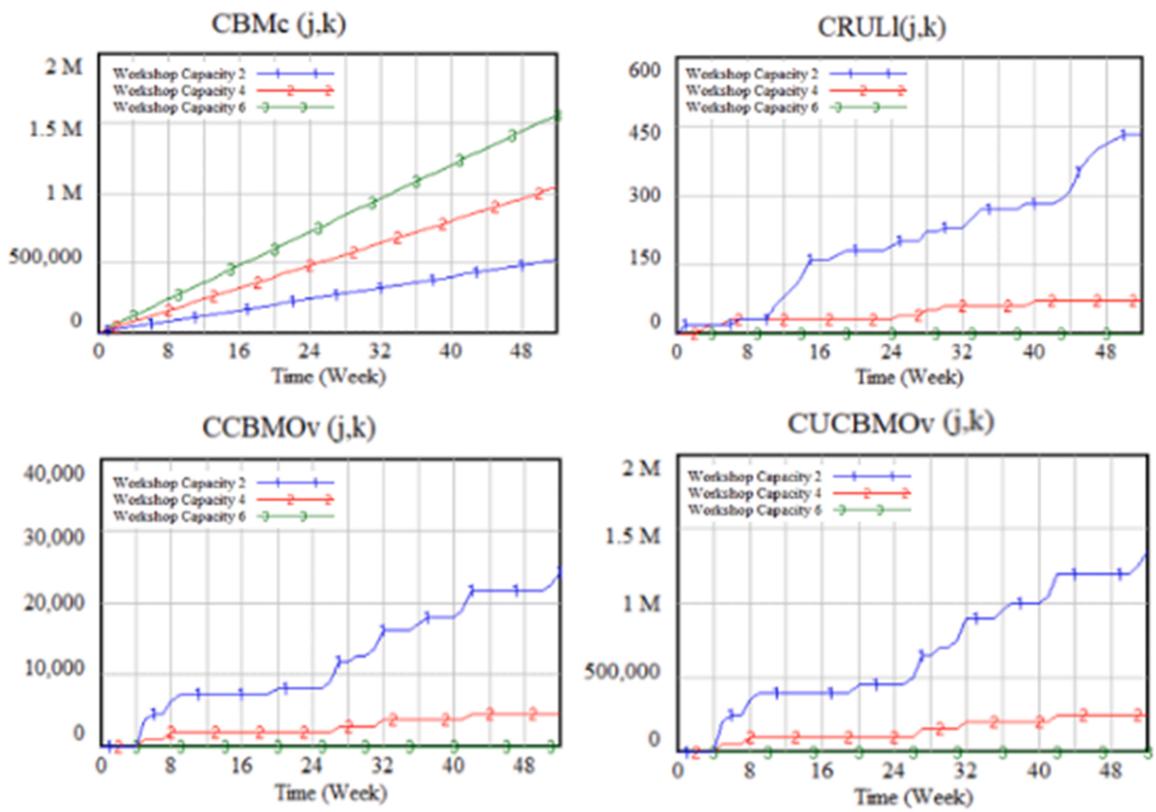

Fig. 13. Sample comparison of results (in €) obtained per cost factor and for just one simulation when CBM capacity level is set to 2, 4 and 6 bearings/period.

The total components to maintain (to replace in the case of come components like bearings) with low or medium risk levels, during a given period t, can be determined as follows (see also Fig. 2):

$$TR(j,k)_t = AEx(j,k)_{t-1} + Ex(j,k)_t \tag{14}$$

Then, to complete the formulation of flow variables in Fig. 1, CBM activities for components with lower risk levels (or higher RUL components), can be calculated as presented in the following Equations:

$$my(j,k)_t = Min(fxj(j,k)_t, MIN(Cmz(j,k)_t, TR(j,k)_t)) \tag{15}$$

With$c(j,k) - mz(j,k)_t \geq 0$

$$mx(j,k)_t = MIN(NA(j,k) + x(j,k) - fxy(j,k), Min(TR(j,k)_t - my(j,k)_t, Cmy(j,k))) \tag{16}$$

With$c(j,k) - mz(j,k)_t - my(j,k)_t \geq 0$Where $Cmz(j,k)$ and $Cmy(j,k)$ are auxiliary variables considered to model the remaining CBM capacity available to service components with higher RUL.

$$Cmz(j,k)_t = MAX(c(j,k) - mz(j,k)_t, 0) \tag{17}$$

$$Cmy(j,k)_t = Cmz(j,k)_t - my(j,k)_t \tag{18}$$

If, despite the redeployment of the CBM to higher RUL components, the capacity set to undertake this type of activities is insufficient to perform all the planned activities in a certain period for predetermined PM, it would be mandatory to stop the asset and then apply its main-

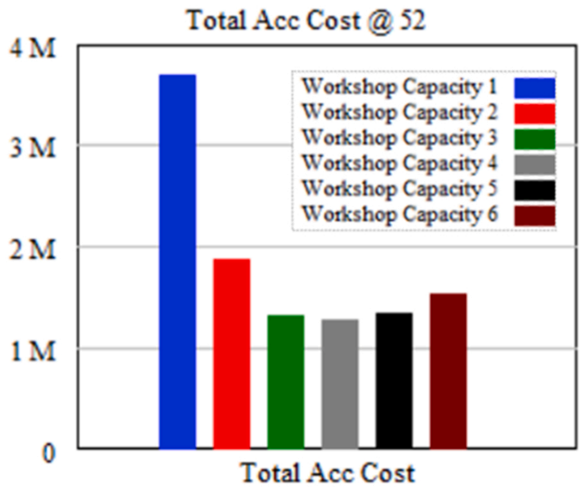

Fig. 14. Sample comparison of results obtained per the variable Total Accumulated Cost and for just one simulation when CBM capacity level changes from 1 to 6 units.

tenance to avoid unacceptable risk levels. This number of CBM overdue activities ($CBMOv(j,k)$) would cause an asset treatment very similar to a corrective activity, the costs of this work (later named *CBMOv unit cost*) would then be higher than normal CBM service, especially because of extra asset unavailability.

$$CBMOv(j,k) = MAX(mz(j,k) - c(j,k), 0) \tag{19}$$

Finally, it is simple to calculate the CBM capacity utilization of the workshop as the fraction as in Eq. 20 (see Fig. 3).

$$WSCapU(j,k) = Min((mx(j,k) + my(j,k) + mz(j,k))/c(j,k); 1) \tag{20}$$

Notice that the variable is cap to 1 in cases we may reach the capacity and there are CBM activities overdue.

This model formulation is rather simple and does not take into consideration, so far, relationships among systems generating opportunistic maintenance options. Nor the fact that different workshops could have different capacity. It is just built to see how workshop capacity may impact the scheduling of maintenance operations when CBM programs are in place.

4.3. The cost function

Once the model can estimate the number of components to have a CBM, at different risk levels, in each period t, the next step is to model a function of cost of our CBM strategy, that will then help to determine a suitable capacity level to that purpose.

In Section 3 is mentioned that the cost function factors considered in this work are: the cost of the CBM Capacity, the cost of lost RUL, the CBM overdue activities cost and the cost of unavailability due to. In the following paragraphs these factors are modelled as stock variables (see Fig. 5), accumulating cost over the planning horizon.

The *cost of CBM capacity* ($CBMc_t$)is obtained accumulating the cost of the designed capacity level per period over the planning horizon.

$$CBMc_t = \left\{ \begin{array}{c} CBMc_{t-1} + CBMccp_t, for t > 0 \\ 0, for t = 0 \end{array} \right\} \tag{21}$$

$$CBMccp_t = c(j,k)_t \bullet cuc \tag{22}$$

Where cuc is the capacity unit cost per period and $CBMccp_t$ is the CBM capacity cost per period.

The *cost of Lost RUL* ($CRULl_t$) is the cost of the amount of operating hours (or kms or another suitable unit of RUL measure) lost by the component because of an early forced CBM because of capacity constraints. It is estimated accumulating the cost of the RUL per period ($RULLcp_t$) over the planning horizon.

$$CRULl_t = \left\{ \begin{array}{c} CRUCLl_{t-1} + RULLcp_t, for t > 0 \\ 0, for t = 0 \end{array} \right\} \tag{23}$$

With

$$RULLcp_t = (mx(j,k)_t \bullet 2 + my(j,k)_t) \bullet UcRUL(j,k) \tag{24}$$

con

$$UcRUL(j,k) = CostofComponent/Componentmeanlife \tag{25}$$

Notice that in Eq. 24, it is considered how the sooner the component is maintained the more RUL is lost, i.e., maintaining a component with lower risk in our example, causes doble RUL lost than maintaining a component with moderate risk. Eq. 25 shows how the higher the cost of the component and the lower its mean life, the greater the unit cost of RUL.

The *CBM overdue activities cost* ($CCBMOv_t$) is the cost service the train when an anomaly is active, no RUL is left, and there is no CBM capacity available during the next predetermined maintenance inspection.

$$CCBMOv_t = \left\{ \begin{array}{c} CCBMOv_{t-1} + CBMOvcp_t, for t > 0 \\ 0, for t = 0 \end{array} \right\} \tag{26}$$

With

$$CBMOvcp_t = CBMOv(j,k)_t \bullet Ovuc(j,k) \tag{27}$$

Finally, the *Cost of Unavailability due to overdue CBM* ($CUCBMOv_t$)is one of the most important cost factors because is the cost of the services lost because of the train unavailability required to carry out CBM overdue activities.

$$CUCBMOv_t = \left\{ \begin{array}{c} CUCBMOv_{t-1} + UCBMOvcp_t, for t > 0 \\ 0, for t = 0 \end{array} \right\} \tag{28}$$

With $CUpp_t$ representing the cost of unavailability due to overdue

Table 1
Sensitivity results of total accumulated cost (€) for the RUL and the base case simulations after 200 simulation replications.

Case	Scenario	Count	Min	Max	Mean	Median	StDev
RUL Information is available	: CBM Capacity 1	200	1.787 M	4.536 M	2.997 M	2.958 M	523,177
	: CBM Capacity 2	200	876,56	2.302 M	1.458 M	1.437 M	260,275
	: CBM Capacity 3	200	830,94	1.595 M	1.159 M	1.137 M	149,623
	: CBM Capacity 4	200	1.04 M	1.498 M	1.203 M	1.193 M	97,212
	: CBM Capacity 5	200	1.3 M	1.504 M	1.353 M	1.351 M	52,848
	: CBM Capacity 6	200	1.56 M	1.662 M	1.571 M	1.56 M	22,859
Base	: CBM Capacity 1	200	2.400 M	4.946 M	3.608 M	3.571 M	485,138
No RUL information available	: CBM Capacity 2	200	1.234 M	3.271 M	2.281 M	2.304 M	379,344
	: CBM Capacity 3	200	934,44	2.208 M	1.573 M	1.546 M	256,635
	: CBM Capacity 4	200	1.042 M	1.806 M	1.339 M	1.322 M	155,504
	: CBM Capacity 5	200	1.302 M	1.659 M	1.385 M	1.353 M	77,211
	: CBM Capacity 6	200	1.562 M	1.715 M	1.578 M	1.562 M	29,106

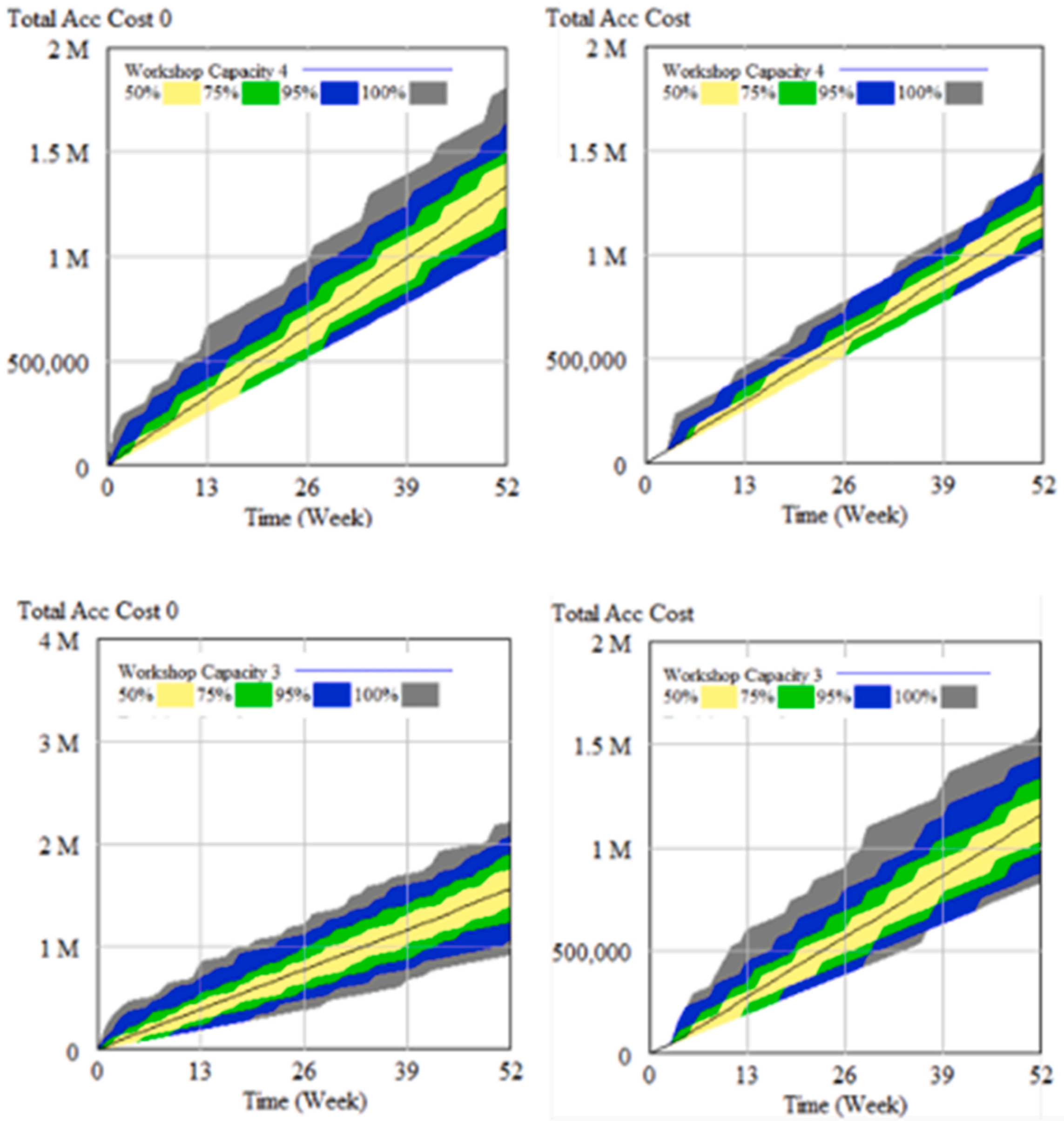

Fig. 15. Comparison of RUL and base case CBM scheduling using sensitivity analysis for Total Acc Cost and for two capacity scenarios (top: CBM capacity=4; down: CBM capacity = 3). Base case results (left) and RUL case results (right). The line represents mean value.

CBM per period

$$UCBMOvcp_t = CBMOv(j,k)_t \bullet UOvuc(j,k) \tag{29}$$

The Total Accumulated cost (*Tot Acc Cost*$_t$) is modelled as an auxiliary variable that just sums all four previously mentioned stock variables (see Fig. 4).

5. Base case scenario modelling for results comparison

In this work we are defining a base case scenario to be modelled, and to compare its results against the ones obtained for the RUL base scheduling model defined in Section 5. This base case scenario considers that the organization has the technology to identify anomalies in asset components, but no capabilities to schedule CBM according to their RUL exist. Therefore, the maintenance organization carries out the CBM activity in the next predetermined PM inspection, and if there is no capacity available, the CBM activity will be considered overdue, and asset will be stopped and serviced. This often happens in early stages of CBM comprehensive strategy introduction for most of the components. In fact, at that moment the organization considers only two risk levels for assets' components (see Fig. 5): with a detected anomaly or without it. in fact, this scenario is the first step taking place between the introduction of a CBM program and the achievement of a full predictive maintenance.

The model assumes that all components where an anomaly is detected will be maintained in the next inspection stop, therefore:

$$MA(j,k)_t = DA(j,k)_{t-1} + NA(j,k)_t \Rightarrow DA(j,k)_t = 0, \forall t \tag{30}$$

If the capacity set to undertake CBM in a predetermined inspection is exceeded, it would be mandatory to stop the asset and then apply its maintenance to avoid unacceptable risk levels (to have an anomaly is now considered a call for action of maintenance). The number of CBM overdue activities (in this case named $CBMOv(j,k)0$) would also cause an asset operational stop and a higher cost than normal is calculated in Eq. 31:

$$CBMOv(j,k)0 = MAX(MA(j,k)_t - c(j,k), 0) \tag{31}$$

The different cost flows for the base case total cost calculations are obtained in Eqs. 32–35.

$$CBMccp0_t = CBMccp_t = c(j,k)_t \bullet cuc \tag{32}$$

$$RULLcp0_t = \left(MA(j,z)_t \bullet 2\right) \bullet UcRUL(j,k) \tag{33}$$

$$CBMOvApp0_t = CBMOv(j,z)0_t \bullet Ovuc \tag{34}$$

$$CUpp0_t = CBMOv(j,z)0_t \bullet UOvuc \tag{35}$$

The corresponding stock variables for this base scenario and the total accumulated cost of the base case is presented in Fig. 6, and they are obtained similarly to the ones in Fig. 4.

6. Model simulation inputs and case study results

For this paper, the simulation models are considering the following inputs:

A ratio of fleet anomalies detection distributed as $N(\mu,\sigma,\min,\max) =$ N(2,2,0,8); A CBM analysis for only one system (or component: bearing in this case study) considered for a fleet of 14 assets (trains, in our case study); A time step defined as the interval between two weekly inspections (named IS), representing 10.000 kms. of operation. A cost of the component (bearing) of 1000 Euro and an average mean life of the component of 1000,000 kms (100 periods).; A capacity for CBM services, once the train is stopped for a predetermined PM, which may vary between 1 and 6 systems to be serviced.

In terms of cost, the cost of CBM Capacity per period and unit is *cuc* = 1000€ /period & unit, the cost of RUL lost is *UcRUL*= 10 €/period & unit, resulting from dividing the cost of the component (1000 €) by the component mean life (100 periods). The cost of *CBMOv* Overdue is *Ovuc* = 2000€ per activity, and the cost of *CBMOv* unavailability has been stablished in *UOvuc* = 10000€ per activity. Notice that these different cost factors can vary significantly for different case studies.

The RUL of the components has been considered as 30.000 kms or 3 predetermine PM inspections (3 ISs).

6.1. Model results for cbm activities when changing capacity

Graphical results provided by the tool, despite being a very simple model, help to understand implications in the number of bearings in risk when changing workshop CBM capacity. The lesser the capacity the higher number of bearings in risk (see Fig. 7).

In Figs. 8–10, different results are obtained for different CBM workshop capacity options. The higher the capacity of the depot the lesser the number of bearings maintained with lower levels of risk.

Fig. 11 shows depot's capacity utilization under the two simulated scenarios. Notice that the scenarios for CBM Capacity equal to 2 and 4 bearings/period, would not be technically feasible according to bearings maintenance demand assuming maximum capacity utilization set to 1.

Therefore, in case of workshop CBM capacity = 2 and CBM capacity = 4, CBM activities would result overdue, and a train stop would be immediately required. The extra capacity demand per period in the workshop is presented in Fig. 12.

6.2. Cost factors results for different capacity levels

Different CBM capacity options will result in different costs in the different factors considered. Finding a proper balance understanding the implication of a single option is a must. Fig. 13 shows an example of the cost factors when setting a CBM capacity of 2,4 and 4 bearings/period in the workshop.

In Fig. 14, the Total Accumulated Cost when varying workshop CBM capacity is presented. Notice that for this simulation replication, a workshop CBM capacity of 3 or 4 bearings/period provides the best results. In fact, Table 1 shows doing Montecarlo analysis for 52 weeks, that a capacity of 3 offer a better average cost in the 200 simulations but the capacity 4, similar in average cost, has a much smaller StDev. In fact, this is the same result that the analyst can get for the optimal capacity when selecting a larger planning horizon (to diminish the effect of randomness in anomalies generation) and minimizing the total accumulated cost of the simulation. To do this Vensim uses a direct search technique based on a Modified Powell Method (see other examples in (Marquez et al., 2003)).

6.3. Comparing against base case scenario

In this Section of results, a couple of scenarios to do Montecarlo simulation and analysis for cost results are selected. More precisely, a seed for the generation of components anomalies has been modified in 200 replications of the experiment. Table 1 shows the results of total accumulated cost for the RUL case model (Section 5 of the paper) and the base case model (Section 6 of the paper) simulations, in the six different scenarios studied (workshop CBM capacity varying from 1 to six bearings/period). As the reader can see, results for the RUL case (in Section 5) are better that for the base case because (see Table 1):

1. For the same capacity the RUL case always obtains a lower cost
2. For the optimum capacity in each one of the cases (in green in Table 1), the RUL case model reaches the lowest result in the mean total accumulated cost and its StDev.

For a better appreciation of the consequences of the introduction of the scheduling methodology according to the components RUL (Section 5 model), Fig. 15 shows the sensitivity analysis for the variable Total Acc Cost 0 (base case model in Section 6) in the left hand side of the figure and the variable Total Acc Cost (RUL case model in Section 5) in the right hand side when the CBM capacity is 4 (top) and 3 (bottom). These where the two scenarios highlighted in Table 1, showing the best results for each case (CBM Capacity=3 for the RUL case and CBM Capacity =4 for the base case).

6.4. Conclusions of the case study

This case study shows that practical simulation tools can be useful when dealing with the problem of scheduling CBM activities. The best options could be identified as well as the cost of opportunity of not using these tools for this purpose. Complexity can be added, when required, to the case study, and other different maintenance opportunistic options and rules can be identified, optimized, and implemented. However, and given the dynamic nature of the problem, the simpler the business rules the easier their implementation at the shop floor.

7. Conclusions

In this paper a system dynamic simulation model has been built to schedule CBM activities in an operational context in which it is known the RUL of components presenting anomalies for systems within a fleet of assets, and where there can be a capacity constraint to carry out CBM activities per system. The model also contains a financial part that calculates the different costs generated for each one of the simulated scenarios. A Montecarlo analysis has been introduced to compare cost results for each CBM capacity scenario and assuming available, or not, the information about the RUL of the components presenting anomalies. When the information about the RUL is not available, the strategy followed has been to carry out the CBM activities in the next possible predetermined PM or to stop the asset if capacity is not available at that time.

Most important conclusions of the work and presented results, are the following:

1. When considering the components RUL, a proper scheduling control requires modelling the accumulated excess of anomalies, over the CBM capacity. This makes possible the utilization of the CBM capacity available to service components with higher RUL, in an opportunistic manner.
2. The model helps the analyst to explore and select suitable CBM capacity scenarios, among those feasible for a project, comparing their impact on each cost factor and on the total accumulated cost.
3. It has been tested how the strategy of maintaining component with higher RUL (lower risk) offer good results in CBM capacity constrained scenarios, compared to a CBM strategy that would release the CBM activity as soon as anomalies are identified.
4. The modelling effort helps also to measure the level of improvement that can be reached with a given strategy for a certain scenario. For instance, in the paper case study, average improvements of 10% in the total accumulated cost were reached while important reductions in StdDev were appreciated.
5. This modelling effort and the analysis of the RUL base CBM scheduling strategies can be easily extended to fleets in any other sector in the industry where maintenance/industry 4.0 technologies apply.

Declaration of Competing Interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests Adolfo Crespo del Castillo reports administrative support, equipment, drugs, or supplies, travel, and writing assistance were provided by Talgo. Adolfo Crespo Marquez reports equipment, drugs, or supplies and travel were provided by Junta de Andalucía Consejería de Educación.

Data Availability

No data was used for the research described in the article.

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