Dynamic fleet maintenance management model applied to rolling stock

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Abstract

This paper presents a model for optimising fleet maintenance management with a particular application to train rolling stock fleets. The proposed model produces a joint schedule for train operations and opportunistic predictive maintenance activities with an aim to maximise operational useful life. The model opportunistically allocates predictive maintenance interventions to existing preventive maintenance schedule considering the estimated remaining useful life (RUL) of critical components whilst ensuring fleet availability to meet operational demands as well as resource and time constraints at the maintenance depots. The proposed methodology is described in three phases: (i) definition of the operating context and maintenance resources; (ii) evaluation of feasible opportunistic maintenance timeslots; (iii) optimal maintenance and operations scheduling. The optimisation model, developed as a Mixed Integer Linear Programming problem, is applied to a real industrial case study on a fleet of high-speed trains in Spain. The results show significant improvement in the utilisation of operational life of components compared to the current policies used by the company. Although the model was developed with particular consideration to the train fleets, it can be adapted for other sectors such as bus fleets and airlines with similar operational constraints.

Notation

$\boldsymbol{PM}$	Number of preventive maintenance inspection types	$\boldsymbol{I_m}$	Number of failure modes monitored for each system m
$\boldsymbol{S}$	Number of specialities of maintenance	$\boldsymbol{PC}$	Percentage of corrective maintenance in hours, estimated to add to the preventive maintenance inspection time
$\boldsymbol{N}$	Number of maintenance depots	$\boldsymbol{F}$	Number of assets composing the fleet
$\boldsymbol{M}$	Number of monitored systems	$\boldsymbol{H}$	Number of planning horizon days
$\boldsymbol{T_{x,y}}$	Hours of resource for each speciality of maintenance y required per preventive maintenance inspection type x, with $x = 1 \dots PM$ and $y = 1 \dots S$.	$\boldsymbol{PIW_{j,k}}$	Weekly preventive maintenance inspections (0/1) per train j and day k, with $j = 1 \dots F$ and $k = 1 \dots H$.
$\boldsymbol{R_y^n}$	Units of resources (Operators) per speciality of maintenance y available at each maintenance depot n, with $y = 1 \dots S$ and $n = 1 \dots N$.	$\boldsymbol{PIB_{j,k}}$	Biweekly preventive maintenance inspections (0/1) per train j and day k, with $j = 1 \dots F$ and $k = 1 \dots H$.
$\boldsymbol{MT_{x,y}^n}$	Total maintenance time required per speciality of maintenance y, at maintenance depot n, with $x = 1 \dots PM$, $y = 1 \dots S$, and $n = 1 \dots N$.	$\boldsymbol{PIM_{j,k}}$	Monthly preventive maintenance inspections (0/1) per train j and day k, with $j = 1 \dots F$ and $k = 1 \dots H$.
$\boldsymbol{ST_x}$	Total train stoppage time, at the depot, per preventive maintenance inspection type x, with $x = 1 \dots PM$	$\boldsymbol{PT_{x,y}^n}$	Time available for predictive maintenance at a certain preventive maintenance inspection type x and speciality of maintenance y. in a certain depot n with $x = 1 \dots PM$, $y = 1 \dots S$, and $n = 1 \dots N$.
$\boldsymbol{CT_{x,y}^n}$	Corrective maintenance time per preventive maintenance inspection type x and speciality of maintenance y, at maintenance depot n. with $x = 1 \dots PM$, $y = 1 \dots S$, and $n = 1 \dots N$.	$\boldsymbol{MS_{i,y}^m}$	Required speciality of maintenance y time required to do a predictive intervention for a certain monitored system m and a specific failure mode alarm i, with $i = 1 \dots I$, $y = 1 \dots S$, and $m = 1 \dots I$.

$\boldsymbol{\delta_j}$	Degradation associated with each day each asset is designated to operation	$\boldsymbol{A_k}$	Daily demand of assets available for operation each day of the planning horizon $k = 1 \dots H$
$\boldsymbol{IW_{j,k}}$	Feasible preventive weekly inspections (opportunities) to carry out predictive maintenance per train j and day k, with $j = 1 \dots F$ and $k = 1 \dots H$.	$\boldsymbol{IB_{j,k}}$	Feasible preventive biweekly inspections (opportunities) to carry out predictive maintenance per train j and day k, with $j = 1 \dots F$ and $k = 1 \dots H$.
$\boldsymbol{IM_{j,k}}$	Feasible preventive monthly inspections (opportunities) to carry out predictive maintenance per train j and day k, with $j = 1 \dots F$ and $k = 1 \dots H$.		

1 Introduction

The increased prevalence of digitalisation in today's industry allows a comprehensive understanding of the value of the assets for the organisation (Márquez et al., 2009), and a radical change in maintenance by improving the capability to detect anomalies in the operational behaviour of critical assets, and to predict their Remaining Useful Life (RUL). In this context, Prognostics and Health Management (PHM) (Haddad et al., 2011; Li, 2019; UNE, 2018) and predictive maintenance cover all activities from data acquisition and processing, to maintenance decision-making advisory as output (anomaly detection, failure mode diagnosis, and prognosis) (Crespo Márquez et al., 2020, 2023; Guillén et al., 2016; Kaur et al., 2018; Scarf, 2007). It is important to note that PHM espouses a wider view of 'health management' as opposed to a focus on maintenance, which means decisions such as workload determination and operational scheduling based on the asset condition must go hand-in-hand with maintenance decisions.

This paper focuses particularly on the rail sector, where it is estimated that condition-based and predictive maintenance could lead to an overall reduction of at least 10 to 15% in maintenance costs (Stern et al., 2017), providing a comprehensive pathway for growth, especially for OEMs and rail network operators. Even though this change of paradigm will mean future savings by establishing more efficient approaches, there are important existing limitations that need to be addressed. These limitations relate to safety, policy, and a lack of implementation strategy for moving from a focus on individual assets to a holistic perspective of the entire fleet. Even though new predictive approaches generate better health indices and prognostics for a single asset, they are rarely translated into proper fleet maintenance management frameworks (de Jonge & Scarf, 2020; Kim et al., 2022; Lee et al., 2022; Mitici et al., 2023). Managing a fleet dynamically based on data-driven prognosis is far from being implemented (Stern et al., 2017), representing a challenge and clear research direction.

This paper presents an approach to dynamically optimise the maintenance of assets in a fleet based on the predicted RUL of critical components considering operational performance requirements and maintenance capacity constraints. In the context of existing literature on the topic, the key novelties of the work presented in this paper are:

- An approach for opportunistically combining predictive and preventive maintenance so asset stoppages are reduced, considering not only the RUL, but also the associated maintenance resources required for predictive interventions. The approach dynamically manages the RUL from the systems that are monitored, existing limitations for maintenance resources in each depot, the preventive maintenance calendar, and operation availability demand.
- A scheduling optimisation model to allocate assets of the fleet to operation, maintenance (predictive and preventive), or being idle, maximising the usage of components useful life before intervention.

The structure of the paper is as follows. Section 2 presents the review of literature and relevant background work, especially regarding fleet management and dynamic maintenance of fleets. Section 3 presents the proposed model to manage the maintenance of the fleet dynamically, composed of three stages. The fourth section illustrates the application of the model by applying it to a fleet of trains manufactured and operated by Talgo in Spain. The results are presented in the following section. The sixth section is the discussion of the paper's value-adding points and limitations, and the final section concludes the paper and presents further work suggestions.

2 Literature Review

This section aims to provide a brief review of relevant literature in fleet maintenance to set the context for this research and to present the key gap that it addresses.

Research on fleet maintenance falls within the broader area of 'multi-unit systems' (Petchrompo & Parlikad, 2019), which deal with a system composed of multiple assets that share common characteristics or a single-asset system composed of multiple components operating together. Fleet management literature focus on aspects of managing of a group of identical or similar assets that together aim to provide a pre-determined level of service or function. Typically fleet management problems considered in the literature assume that the same intervention options are available for all the assets within the fleet (Monnin et al., 2014; Rawat & Lad, 2015).

A key aspect in fleet management is the consideration of resource constraints while determining intervention (e.g., maintenance, inspection, upgrade) schedules of the assets. Due to the shared nature of resources (e.g., budget, spares, personnel) (van Kessel et al., 2023), it might not be feasible for the interventions to be carried out at their 'optimal' time based on individual asset requirements. In such situations, prioritisation of the interventions based on the urgency of the intervention and criticality of assets becomes a necessity (Muller et al., 2008). This will require careful consideration of risks, since the ultimate outcome will be 'sub-optimal' for the individual assets, possibly increasing the risk of failure and degraded performance (Dhada et al., 2020; Jain et al., 2021; Salvador Palau et al., 2019; Zhou et al., 2022).

Another critical issue to consider within fleet maintenance are to define the broader dependencies and interactions between the assets in a fleet, and their impact on maintenance decisions. On the outset, it may seem that each asset in a fleet is independent in terms of its degradation and performance. However, considering that the fleet often will have service level requirements to adhere to (Herr et al., 2017; Lee et al., 2022; Stern et al., 2017), and that the fleet will often be managed by a common set of resources (e.g., maintenance personnel, spares, budget), such dependencies are important to consider to improve fleet performance (Van Horenbeek et al., 2013). For example, balancing the workload of assets in the fleet is important to ensure that asset availability is not compromised either while scheduling maintenance or due to unexpected failures (Monnin et al., 2014; Petchrompo & Parlikad, 2019b). In doing so, often it is impractical to assume that the assets are identical, since the assets (or their constituent components) will be of different ages and characteristics, and most definitely would have gone through different usage loads and patterns (Jamshidi et al., 2018; Li, 2019; Petchrompo et al., 2020). Combining maintenance and operations scheduling dynamically is an area of research that has been attracting increasing attention due to predictive maintenance approaches and incorporating data to decision making. Fleet managers cannot ignore the fact that their maintenance decisions will impact both company service and financial performance (Bivona & Montemaggiore, 2005), so their decisions have to be based on the indexes built from data precedent from the field in real-time. However, the complexity of multiple-assets maintenance implications makes this task very difficult, and that cannot be solved by using past data to statistically plan the actions to do (Bivona & Montemaggiore, 2005).

In the context of maintenance management, the attribute of dynamism can be defined as the capacity of maintenance activities to undergo continuous recalculation based on data that captures any form of alteration transpiring in the managed assets (Bouvard et al., 2011; Y. Wang et al., 2022). When the idea of dynamic maintenance is scaled to the fleet level, different aspects of the problem as operational (fleet scheduling) also condition the management of the assets. As the problem is scaled from a single asset, the precision in representing the asset's condition, identifying what failure mode causes degradation, and how it evolves, loses level of detail (Guillén et al., 2016; Márquez et al., 2009). 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).

The lack of detail regarding the failure modes and their prognostics scaling a fleet level, and managing preventive and predictive maintenance limitations together, constitute gaps in literature when it comes to dynamic fleet maintenance. Scaling the level of maintenance detail to fleet decision making is critical to translate health and condition indicators into decisions. Integral solutions start from anomaly detection, diagnosis, and prognosis at the asset level (the CBM data and the importance of the failure mode) and converts prognosis results into actionable insights that optimize operational plans together with the rest of the business constraints (Liu & Lee, 2018). On a similar line (Monnin et al., 2014) propose a solution to keep decision makers updated with a relevant synthesis of information from both the global health of the fleet and the status of maintenance efforts, but it is not translated into dynamic maintenance decisions.

On the lack of solutions combining preventive and predictive maintenance with operation assignment, some models consider fixed maintenance schedules when assigning assets to operation (El Moudani & Mora-Camino, 2000), but not including data driven prognostics. (Agostino et al., 2020) focus on the flexible operational scheduling using discrete simulation, but only assessing preventive maintenance in different scenarios, not considering condition-based maintenance. On the other hand, other papers focus on estimate RUL prognostics and data-driven approaches for the assets of the fleet, but the scalation to manage at fleet-level does not consider the existing preventive maintenance approaches (Van Nguyen et al., 2019). A similar idea can be deduced from (Martínez-Galán Fernández et al., 2022) making emphasis on the difficulty of scheduling based on the RUL (due to risk and precision) of different components of each asset combined with other operational factors, and defining a periodicity of dynamic solution recalculation (something not standardised). (Dersin, 2018; Mira et al., 2020) make emphasis on dynamic recalculation of maintenance (and the planning horizon) by 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. This will generate the case for opportunistic maintenance policies dynamically combined with PHM, considering that not every component is critical for the assets' performance (Dersin, 2018).

Some of the advanced modelling approaches (Herr et al., 2017; Perez Hernandez, M., Puchkova, A., Kumar Parlikad, 2022; Petchrompo et al., 2020) do not consider restricting preventive and systematic maintenance in contract, law, or policy, meaning a realistic solution is necessary to meet mandatory inspections. In the aforementioned stream of approaches mentioned, the fleet of trains is scheduled according to the actual state of health of systems as an outcome of local PHM programmes and solved using a linear programming approach (Herr et al., 2017). This conception evolves from traditional CBM or preventive maintenance by considering the degradation level prognosis, systems usage, and the impact of missions on multiple assets systems health. However, the authors (Herr et al., 2017) recognise the limitations of constraints that are not realistic, particularly constraints related to the maintenance capacity. A similar approach applied to networks can be found in (Perez Hernandez et al., 2022). Using an agent-based model, the authors consider the dynamics of data traffic and asset deterioration in a data packet transport network. Finally, (Petchrompo et al., 2020) present a value-based approach to managing fleets by dynamically scheduling maintenance actions over the planning horizon, with a strategy which has been demonstrated to offer considerable maintenance cost savings and significantly prolong the average asset. However, they highlight the limitations of data for defining a dynamic condition-based model and the rising complexity as the assets have multiple stakeholders in many cases, and shared maintenance resources. In terms of resources limitation (van Kessel et al., 2023) propose a novel model to manage dynamically maintenance scheduling considering the maintenance limitations and existing resources (with an extensive resource classification), but do consider it isolated from the assignation to operation and the degradation depending on operating conditions. A similar application can be appreciated at (Wang et al., 2022) but considering only predictions and resources for maintenance, and not the preventive schedule that can be updated depending on changing conditions. It has to be added to this complexity, that CBM would manage not all systems or components of an asset. Based on the reliability and criticality of the component, it is not worth investing in monitoring because it does not add real value to the business managing them further than just on systematic bases.

On the other hand, another stream of advanced modelling solutions (de Pater & Mitici, 2021; Lee et al., 2022; Mitici et al., 2023) considers the slots of maintenance stoppages of the fleet, but do not balance the operation workload between the assets of the fleet depending on their condition. In the approaches within the aerospace sector (de Pater & Mitici, 2021; Lee et al., 2022; Mitici et al., 2023), operational assignment is considered a fixed input, and decision making is limited to maintenance performance depending on the available slots. Maintenance windows serve as designated time intervals utilized by models to optimize cost reduction through efficient maintenance scheduling (van Kessel et al., 2023) . Consequently, fleet availability is generally perceived as assured across various scenarios. Nevertheless, certain studies acknowledge the potential for demand not being met, or meeting the demand in a more efficient manner balancing the assets assignment to operation (Li, 2019; Li et al., 2018; Petchrompo et al., 2020). On this line, a novel approach in literature (Mitici et al., 2023) integrates preventive maintenance with data-driven RUL prognostics and depot resources, with integer linear programming. However, the authors do not integrate the assignation to operation, and characterising the degradation because of the type of operation. Hence, future strategies for dynamic fleet management should focus on merging preventive and predictive maintenance approaches based on the capacity and resources available, depending on the system and failure mode, and together with operation workload balance.

3 Problem statement

Consider a fleet consisting of F trains, and the service level agreement requires A_k trains on each day k to be available for running a satisfactory service. It is assumed that due to operational constraints, the fleet has to adhere to the service level agreement.

M systems are being monitored on each train for PHM with an appropriate anomaly detection and fault diagnostics algorithm that we assume will correctly identify the fault as one of I_m possible failure modes of system m. For each of the system being monitored, it is assumed that an appropriate predictive analytics algorithm is implemented to produce an estimated remaining useful life (RUL) upon detection of an anomaly. Applying the logic of competing failures, the RUL of each train is taken to be the RUL of the constituent component with the lowest RUL. For the purpose of this paper, the technique(s) used for anomaly detection, fault diagnosis and the prediction of RUL is not within the scope of discussion, but we assume that they are accurate. Moreover, we assume that due to safety constraints, once a fault is detected and diagnosed, the train will need to be maintained before the predicted RUL. It is assumed that the critical component of train j degrades at a constant rate δ_j for each day of operation. Each ‘day’ is translated to an average value of kilometres or any other metric that represents the daily counter of degradation.

Each train has an associated preventive maintenance schedule determined by regulatory and performance requirements. The schedule consists of three different types of train stoppages – weekly, fortnightly, and monthly, and this schedule is considered to be fixed. In order to simplify their planning process, train operating companies specify a pre-determined fixed time at the depot for each type of maintenance. For instance, the weekly stoppages are primarily for inspection and the length of the stoppage would be shorter than the fortnightly and monthly ones, where additional maintenance/part replacement activities may be carried out. Regardless of the time at the depot, for simplicity, it is assumed that a train that needs to undergo an inspection on a particular day will not be available for operations that entire day considering the time taken for moving the train to the depot and back.

Each type of maintenance uses a certain number of person-hours of maintenance personnel with different specialties (e.g., mechanical, electrical). Let S be the number of different specialties involved in train maintenance. Similarly, predictive maintenance to address each failure mode of the monitored systems will also take a certain number of person-hours of maintenance personnel with different specialties. In order to minimise operational disruptions, the predictive interventions will need to be carried out opportunistically during the existing preventive maintenance timeslots.

In terms of maintenance facilities, there are N maintenance depots. Each maintenance depot n has R_y^n workers with speciality y, where $y = 1 \dots S$ available on each day assigned to each train scheduled for preventive maintenance. The preventive maintenance schedule pre-allocates each train to a particular maintenance depot. The planning horizon for the decision-maker is H days.

The problem addressed in the paper is to determine the optimal allocation of each train in the fleet to one of three possible options – operation, predictive maintenance, or idle – for each day in the planning horizon such that the usage of the monitored components is maximised while satisfying the constraints placed by the limited depot resources, pre-existing preventive maintenance schedules, the service level agreement, and the safety constraints. Thus, this model evolves from (Herr et al., 2017, 2020) and (Perez Hernandez et al., 2022) but adds more realistic maintenance environment complexity and capacity constraints. The number of predictive maintenance interventions within the planning horizon is limited to one since the focus is on the component with the lowest RUL. This is one of the limitations of the current model, which will be addressed in future work.

4 Methodology

The methodology presented in this section offers an approach to generate the fleet operations and maintenance schedule dynamically, where the dynamicity is characterised by the periodicity of recalculation of the results. The detection of an anomaly is the event that triggers the recalculation, and the model will generate a revised maintenance and operations schedule dynamically as anomalies are detected in the monitored systems.

This decision process is divided into three phases as shown in Figure 1:

(i) Definition of the Operating Context and Maintenance Resources. This involves the characterisation of the fleet, performance requirements, information about the maintenance depots, current preventive maintenance schedules and any operational constraints regarding how the fleet will be managed. This is an ‘offline’ activity that will be carried out prior to implementation of PHM. It is envisaged that this will need to be updated on a regular basis as the operating context changes.

(ii) Evaluation of feasible opportunistic predictive maintenance timeslots. This phase examines the existing preventive maintenance schedule and identifies those timeslots for which opportunistic predictive maintenance is feasible considering the resources necessary to carry out the intervention and the resource availability at the depots.

(iii) Predictive maintenance and operations scheduling. The final phase of the process is to generate an optimal schedule for the operations and predictive maintenance of each train in the fleet considering the constraints and performance requirements.

Each of these phases will now be described in the following sub-sections.

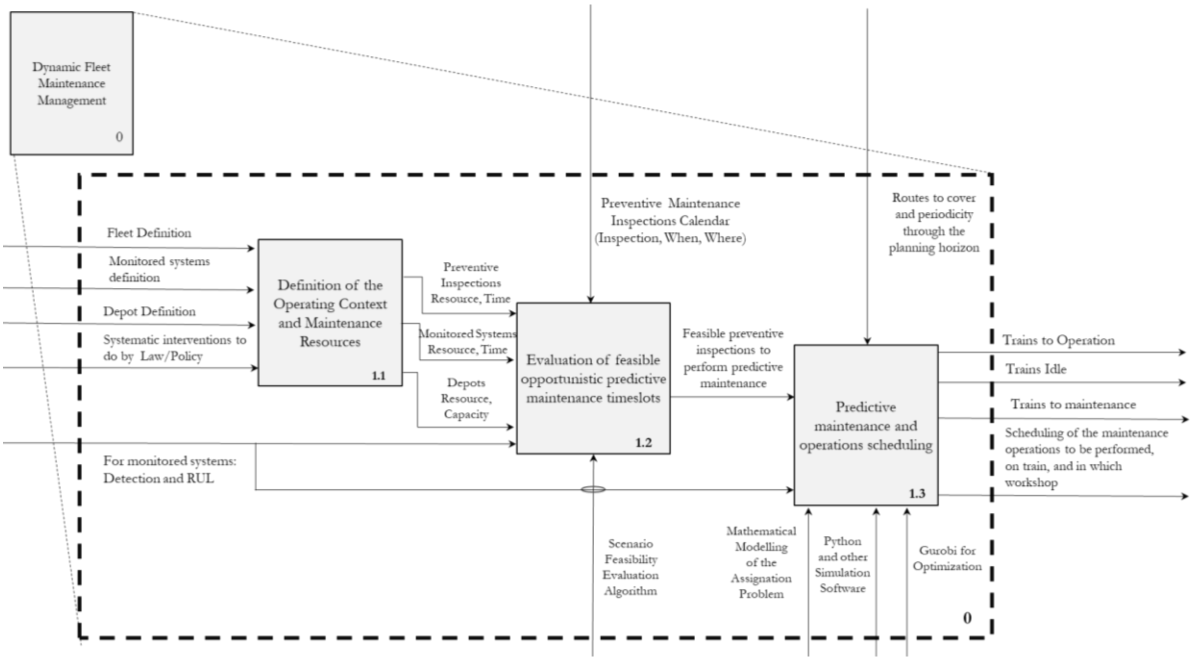

Figure 1: Methodology for dynamic maintenance and operations scheduling

4.1 Definition of the operating context and maintenance resources

This step characterises the fleet, monitored systems, current inspection and maintenance schedules, and depots. This involves gathering the following information:

- Fleet and train-related information
  - Number of assets in the fleet and their characteristics (model, age, and average mileage that each train does every day)
  - Service level agreement, expressed in terms of train availability
  - The systems and failure modes of the train that are monitored for PHM
  - Time and resources (number and speciality of personnel, duration of task) necessary to conduct predictive interventions for each system and failure mode involved.
- Depot-related information
  - the different depots in which the fleets are inspected and maintained
  - the capacity and number of personnel at the depots
  - types of specialities available at each depot
- Periodicity of existing preventive maintenance/inspection
- Planning horizon for scheduling

4.2 Evaluation of feasible opportunistic predictive maintenance timeslots

This phase is divided into two steps (see Figure 2). The first step characterises the existing maintenance schedule and evaluates the resource availability at each depot, and the second step identifies the set of feasible opportunistic predictive maintenance timeslots for each train considering the resource availability.

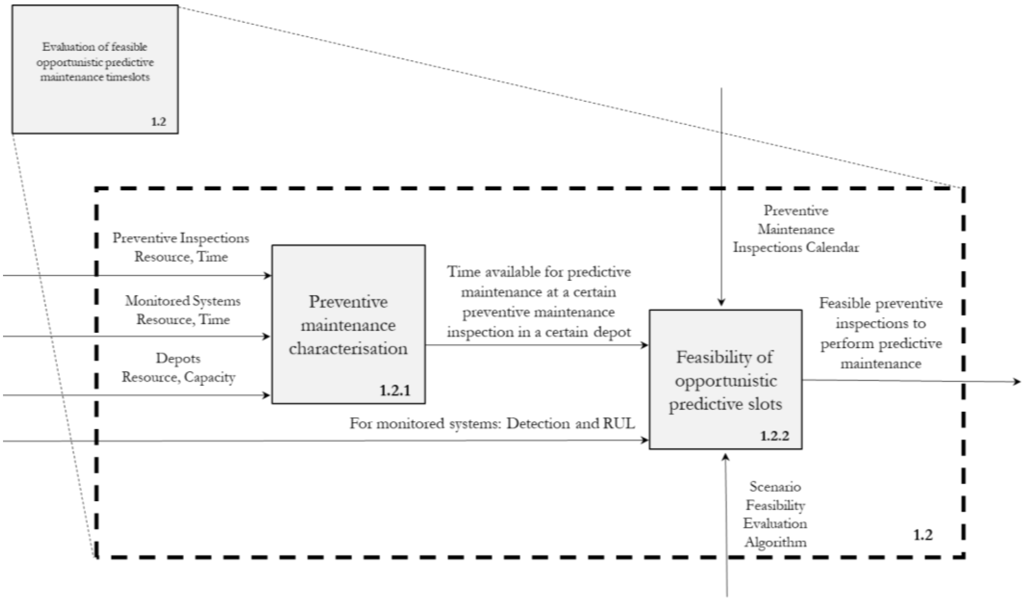

Figure 2: Representation of process 1.2

4.2.1 Preventive maintenance characterisation

The purpose of this step is to determine the time (in hours) of each speciality available for predictive maintenance at each depot. This will then be used in the following step to determine the feasibility of allocating a predictive maintenance activity for each train during its scheduled preventive maintenance timeslot. Note that the preventive maintenance schedule pre-allocates each train to a particular depot.

Recollect that there are three types of preventive maintenance scheduled for each train – weekly, fortnightly, and monthly. Let ST_x be the pre-determined train stoppage time for preventive maintenance type x.

Now, let $T_{x,y}$ be the person-hours required per speciality y for maintenance type x, where $x = 1 \dots PM$. Therefore, the time (in hours) required per speciality y for maintenance type x, at maintenance depot n, $PT_{x,y}^n$ can be calculated as shown in equation (1).

$$MT_{x,y}^n = \frac{T_{x,y}}{R_y^n} \tag{1}$$

Let us also consider that each train stoppage will also consume some time $CT_{x,y}^n$ for carrying out necessary corrective maintenance activities. Without loss of generality, we allocate a fixed percentage PC of each speciality for corrective maintenance. Therefore, the time taken for corrective maintenance $CT_{x,y}^n$ is given by equation (2).

$$CT_{x,y}^n = \frac{T_{x,y}}{R_y^n} \times PC \tag{2}$$

Assuming that the personnel of different specialities can work on the train in parallel to other specialities, the time available for performing predictive maintenance $PT_{x,y}^n$ during each pre-scheduled maintenance type stoppage x, for a certain speciality y at depot n is calculated as in equation (3).

$$PT_{x,y}^n = ST_x - \left(MT_{x,y}^n + CT_{x,y}^n\right) \tag{3}$$

4.2.2 Feasibility of opportunistic predictive slots

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Algorithm 1 Feasibility of preventive opportunities evaluation
procedure
for x ⟵ 1, PM & y ⟵ 1, S & n ⟵ 1, N do
    for i ⟵ 1, I & m ⟵ 1, M do
            if x = 1 then
                    for j ⟵ 1, F & k ⟵ 1, H do
                            if PT^n_{x,y} ≥ MS^m_{i,y} then
                                    if PIW_{j,k} = n then
                                            IW_{j,k}=1
                            else    if PIW_{j,k} = n then
                                            IW_{j,k}=0
                            end if
                    end for
            else if x =2 then
                    for j ⟵ 1, F & k ⟵ 1, H do
                            if PT^n_{x,y} ≥ MS^m_{i,y} then
                                    if PIB_{j,k} = n then
                                            IB_{j,k}=1
                            else    if PIB_{j,k} = n then
                                            IB_{j,k}=0
                            end if
                        end for
                    end for
            else if x =3 then
                    for j ⟵ 1, F & k ⟵ 1, H do
                            if PT^n_{x,y} ≥ MS^m_{i,y} then
                                    if PIM_{j,k} = n then
                                            IM_{j,k}=1
                            else    if PIM_{j,k} = n then
                                            IM_{j,k}=0
                            end if
                    end for
            end if
    end for
end for
end procedure
```

This step determines the feasibility of carrying out predictive maintenance on a train that has generated an alarm pertaining to a failure mode i from a monitored system m (Algorithm 1). Let $MS^m_{i,y}$ be the number of hours of a certain speciality y necessary to carry out the predictive maintenance intervention. Clearly, it will be feasible to carry out predictive maintenance opportunistically during a preventive maintenance timeslot if and only if equation (4) is satisfied.

$$PT^n_{x,y} \geq MS^m_{i,y} \tag{4}$$

The values of $PT^n_{x,y}$ are considered as a data master that has been previously parametrised (4.2.1), and the value of $MS^m_{i,y}$ comes from the anomaly detection and directly enters the system for evaluation previous to the optimisation model execution. The process consists of an evaluation of the feasibility of performing a certain predictive intervention during a possible preventive maintenance inspection ($PIW_{j,k}$, $PIB_{j,k}$, $PIM_{j,k}$) slot for a certain planning horizon H (Algorithm 1). The values in the matrixes is 0 when a preventive maintenance is not performed, and n (value of the integer associated to each depot) when there is preventive maintenance on a certain day k for a certain asset j.

Once the anomaly appears, the equation (4) is calculated, defining in which inspection and depot is it possible to schedule predictive maintenance. This means, generating a relation between inspection x, and depot n, of feasible or not feasible for a certain detection. The evaluation is done in the possible preventive maintenance matrix (Figure 3). Every time a value is different to 0, the value of n, is changed to 1 if the equation (4) is satisfied for depot n, and it is changed to 0 in any other case. This way, the Boolean matrix of feasible slots for scheduling predictive on preventive interventions is created (Figure 3) and is an input to the optimisation model presented in section 4.3.

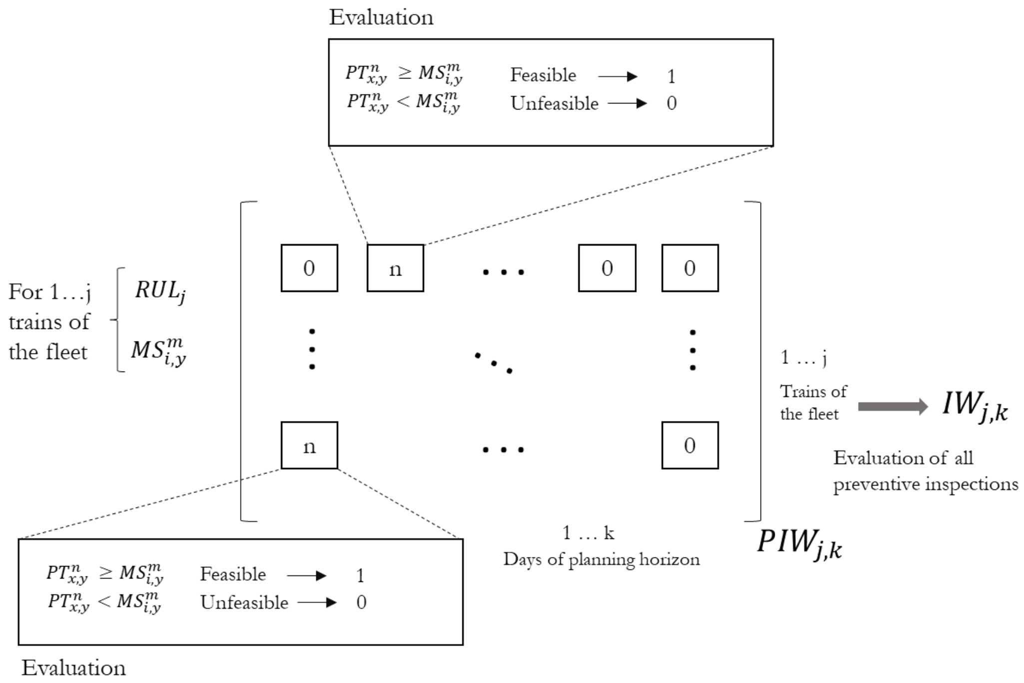

Figure 3: Evaluation of preventive inspections feasible for performing predictive maintenance opportunistically

4.3 Predictive maintenance and operations scheduling

The purpose of this model is to optimise train allocation to operation or maintenance based on demand, the prognostics of the remaining useful life, and the preventive maintenance slots planned in specific depots. The optimisation model, which is formulated as a Mixed Integer Linear Program (MILP), is illustrated as follows.

Decision variables:

The assignment of train j to operations on day k is described by the binary matrix $\boldsymbol{X}$ and the assignment of trains to predictive maintenance is described by the binary matrix $\boldsymbol{Y}$ illustrated as follows.

$$\boldsymbol{X} = \begin{bmatrix} x_{1,1} & \cdots & x_{1,H} \\ \vdots & x_{j,k} & \vdots \\ x_{F,1} & \cdots & x_{F,H} \end{bmatrix} \qquad \boldsymbol{Y} = \begin{bmatrix} y_{1,1} & \cdots & y_{1,H} \\ \vdots & y_{j,k} & \vdots \\ y_{F,1} & \cdots & y_{F,H} \end{bmatrix}$$

When the train is not assigned to operation or predictive maintenance, it is considered to be idle unless it is on a scheduled preventive maintenance date.

Objective function:

The objective of the optimisation model is to maximise the useful life of the components. In other words, the objective is to minimise the difference between the predicted RUL and the accumulated degradation due to operation. This is formally stated as follows.

$$\min \sum_{j=1}^{F} \left| RUL_j - \left(\sum_{k=1}^{H} \delta_j \, x_{j,k} \, (1 - y_{j,k}) \right) \right| \tag{5}$$

Constraints:

The constraints of the optimisation model are given by equations (6)-(14).

$$\sum_{j=1}^{F} x_{j,k} = A_k \;\; \forall \, k \tag{6}$$

$$y_{j,k} - y_{j,k-1} \leq 1 - x_{j,k} \;\; \forall \, j, \forall k \tag{7}$$

$$\sum_{k=1}^{H} (y_{j,k} - y_{j,k-1}) \leq 1 \;\; \forall \, j \tag{8}$$

$$y_{j,k} \geq y_{j,k-1} \;\; \forall \, j, \forall k \tag{9}$$

$$y_{j,k} - y_{j,k-1} \leq IW_{j,k} + IB_{j,k} + IM_{j,k} \;\; \forall \, j, \forall k \tag{10}$$

$$x_{j,k} \leq 1 - IW_{j,k} \;\; \forall \, j, \forall k \tag{11}$$

$$x_{j,k} \leq 1 - IB_{j,k} \;\; \forall \, j, \forall k \tag{12}$$

$$x_{j,k} \leq 1 - IM_{j,k} \;\; \forall \, j, \forall k \tag{13}$$

$$\sum_{j=1}^{F} (y_{j,k} - y_{j,k-1}) \leq \sum_{j=1}^{F} (IW_{j,k} + IB_{j,k} + IM_{j,k}) \; \forall \, k \tag{14}$$

$$x_{j,k} \in \{0,1\} \tag{15}$$

$$y_{j,k} \in \{0,1\} \tag{16}$$

Equation (6) ensures that the model assigns the number of trains to the operation necessary to satisfy the demand according to the service level agreement. Equation (7) will ensure that each train is not allocated to operations and maintenance on the same day. Equations (8) and (9) defines the variable, $y_{j,k}$ as a step function to force the model to allow only one maintenance intervention per train during the planning horizon. This guarantees that once $y_{j,k}$ becomes 1, its value remains 1, not allowing to allocate another predictive intervention in the same planning horizon.

Equation (10) ensures that the train is assigned to predictive maintenance only on those days that are identified as feasible according to section 4.2.2. Equations (12) and (13) will ensure that the model will not send the train to operation on days where a preventive maintenance is scheduled. Finally, equation (14) ensures that the number of predictive maintenance interventions assigned each day is less than or equal to the opportunities available depending on the feasible preventive slots for each train that day.

The objective function has two issues that need to be addressed in order to make the optimisation model linear: (i) it has an absolute value function; and (ii) it contains a product of the two decisions variables $x_{j,k}$ and $y_{j,k}$. In order to linearise the objective function, we introduce two new continuous variable, $e_{j,k}$ and W_j (Herr et al., 2017) . The revised objective function is given (23) with the associated constraints (18)-(25).

$$\min \sum_{j=1}^{F} W_j \tag{17}$$

$$RUL_j - \left(\sum_{k=1}^{H} \delta_j \left(x_{j,k} - e_{j,k} \right)\right) \leq W_j \quad \forall j \tag{18}$$

$$-\left(RUL_j - \left(\sum_{k=1}^{H} \delta_j \left(x_{j,k} - e_{j,k} \right)\right)\right) \leq W_j \quad \forall j \tag{19}$$

$$W_j \in \mathbb{R}^+ \quad \forall j \tag{20}$$

$$e_{j,k} \leq x_{j,k} \quad \forall j, \forall k \tag{21}$$

$$e_{j,k} \leq y_{j,k} \quad \forall j, \forall k \tag{22}$$

$$1 - x_{j,k} - y_{j,k} + e_{j,k} \geq 0 \quad \forall j, \forall k \tag{23}$$

$$e_{j,k} \geq 0 \quad \forall j, \forall k \tag{24}$$

$$e_{j,k} \in \mathbb{R} \tag{25}$$

In the next section, we show how this methodology is applied to a real industrial case study.

5 Case study

In order to demonstrate the applicability of the methodology, we apply it to a case study of rolling stock fleet in Spain. Talgo is a Spanish railway company that manufactures trains and also offers train maintenance services. Talgo has implemented PHM solutions through the deployment of sensors on critical systems and machine learning algorithms to detect and classify faults as well as estimate the RUL as described in (Crespo Márquez et al., 2020, 2023; Martínez-Galán Fernández et al., 2022). This has been developed for some systems to allow sufficient time to perform maintenance before serious failures can develop, which increases safety, reliability, and availability.

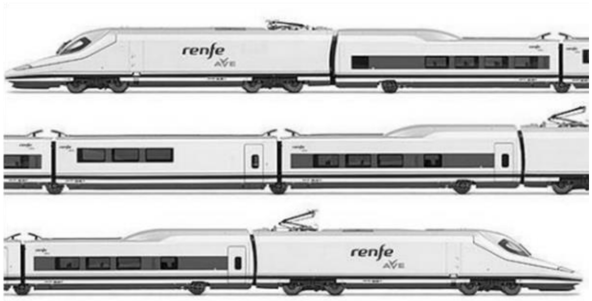

Figure 4: End-to-end main route of the case and train model Talgo 112

The case selected for the application is part of the high-speed service between the cities of Madrid (STC) and Málaga (MLG) (Figure 4). We will now apply the different phases of the methodology to this case study.

5.1 Definition of the Operating Context and Maintenance Resources

The fleet is composed of 24 trains of which 20 trains are needed daily for operation to satisfy the operator's demand. It is assumed that each train operates for an average of 1000 km every day.

We focus on the Bearings and HVAC systems that are monitored through their PHM programme, which monitors two failure modes from each of those systems. Three specialities – Air Conditioning, Electric, and Mechanical – are necessary to carry out the necessary maintenance activities. The number of person-hours of each speciality required for each of the failure modes are shown in Table 1.

Table 1: Failure modes and maintenance hours required ($MS_{i,y}^{m}$)

		Air Conditioning (HVAC)	Electric	Mechanical
Bearings	Failure Mode 1	0	0	5.1
	Failure Mode 2	0	0	7.2
HVAC	Failure Mode 1	4.5	0	0
	Failure Mode 2	5.5	3	0

The RUL is the estimated time of equipment operation until failure, and it is estimated for any point located from the detection of an anomaly on the equipment. The RUL is determined by estimating the distribution function of the PF interval (Figure 5) as a Weibull distribution, $Weibull(t, \beta, \eta)$. The Kolmogorov-Smirnov test was used as a goodness-of-fit test of the Weibull (Aslam, 2020). Different Weibull distributions were used for different failure modes and monitored systems (Zhang et al., 2014). In recent years, machine learning approaches that use recurrent neural networks (e.g., WTTE-RNN) have been used to estimate the Weibull parameters of time to failure, which allows a probabilistic estimation of remaining useful life based on condition-monitoring data(Dhada et al., 2023; Palau et al., 2018)

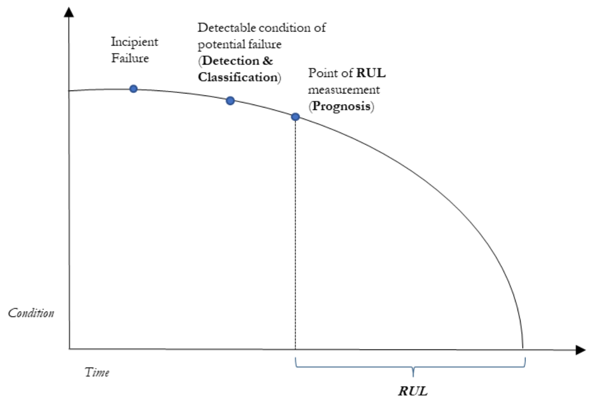

Figure 5: P-F Curve and Estimated time to failure (RUL)

There are two depots, each with a certain number of personnel for each speciality as shown in Table 2.

Table 2: Number of operators or units of resources for each speciality in each depot

	Air Conditioning (HVAC)	Electric	Mechanical
Sta Catalina (STC)	5	8	7
Málaga (MLG)	4	6	5

The existing preventive maintenance schedule is given in Figure 8. 10% of the time is reserved for corrective interventions and added to the existing preventive maintenance time. The planning horizon for this case study is taken as 15 days.

	Day1	Day2	Day3	Day4	Day5	Day6	Day7	Day8	Day9	Day10	Day11	Day12	Day13	Day14	Day15
Train 1			IW - MLG					IW - MLG						IW - MLG	
Train 2		IW - STC						IW - STC							IW - STC
Train 3		IM - STC	IM - STC	IM - STC							IW - STC				
Train 4	IM - MLG	IM - MLG	IM - MLG	IM - MLG	IM - MLG	IM - MLG	IM - MLG					IW - MLG			
Train 5				IW - STC						IW - STC					
Train 6					IW - STC						IW - STC				IW - STC
Train 7						IW - STC						IW - STC			
Train 8									IW - MLG						
Train 9		IW - STC						IW - STC							IW - STC
Train 10					IW - STC						IW - STC				
Train 11		IB - MLG					IW - STC					IW - MLG			
Train 12	IM - STC	IM - STC				IW - STC							IW - STC		
Train 13						IW - STC								IW - STC	
Train 14						IW - MLG						IB - STC			
Train 15				IW - MLG						IW - MLG					IW - MLG
Train 16				IW - STC								IW - STC			
Train 17	IB - STC						IW - STC								IW - STC
Train 18							IW - STC						IW - STC		
Train 19				IW - STC									IW - STC		
Train 20				IW - STC							IW - STC				
Train 21					IW - STC					IM - STC	IM - STC	IM - STC			
Train 22	IW - MLG					IM - MLG	IM - MLG	IM - MLG					IW - STC		
Train 23	IW - STC					IM - STC	IM - STC	IM - STC							IW - MLG
Train 24				IW - STC						IB - STC					IW - STC

Figure 6: Preventive maintenance calendar

This matrix is decomposed into three matrixes according to the three types of preventive maintenance ($PIW_{j,k}$, $PIB_{j,k}$, $PIM_{j,k}$) with a 0 value when there is no preventive maintenance, and a value of 1 when maintenance is done in Madrid, and 2 when maintenance is done in Málaga.

5.2 Feasibility of opportunistic predictive slots

The matrix presented in Figure 6 is divided into the three maintenance schedules $PIW_{j,k}$, $PIB_{j,k}$, and $PIM_{j,k}$. $PT^n_{x,y}$ is calculated for all possibilities considering the two depots and their resources, the specialities (HVAC, electric, mechanical), and the preventive maintenance types (Table 3).

Table 3: Time available for predictive maintenance in each depot for the three specialities and preventive maintenance types

$PT^n_{x,y}$ STC	Air Conditioning (HVAC)	Electric	Mechanical
IS	6,23	3,05	5,26
IB	9,19	7,12	8,20
IM	16,75	4,68	11,17

$PT^n_{x,y}$ MLG	Air Conditioning (HVAC)	Electric	Mechanical
IS	5,93	2,13	4,61
IB	8,72	6,22	7,31
IM	15,54	1,10	8,16

Table 4 shows the anomalies detected on each train sub-system and the associated RUL.

$PT^n_{x,y}$

$PT^n_{x,y}$

Table 4: Anomaly detections in the fleet in the fleet

	System	Type of failure	RUL
Train 1	BEARING	1	24
Train 2	BEARING	1	10
Train 3	BEARING	2	12
Train 4	HVAC	2	8
Train 5	BEARING	1	13
Train 6	HVAC	1	11
Train 7	HVAC	1	6
Train 8	HVAC	1	23
Train 9	HVAC	2	10
Train 10	BEARING	1	20
Train 11	HVAC	1	4
Train 12	BEARING	2	11
Train 13	BEARING	1	14
Train 14	BEARING	2	7
Train 15	HVAC	1	6
Train 16	HVAC	1	14
Train 17	HVAC	1	4
Train 18	BEARING	1	13
Train 19	BEARING	1	14
Train 20	HVAC	1	13
Train 21	HVAC	2	12
Train 22	Bearing	2	5
Train 23	HVAC	2	9
Train 24	HVAC	1	6

The number of hours of a certain speciality necessary to carry out the predictive maintenance intervention $MS_{i,y}^{m}$ is given in Table 1. Then for every train j, the feasible predictive maintenance slots during the planning horizon are identified according to Algorithm 1. An example of the evaluation can be seen in Figure 7. The full results for $IW_{j,k}$, $IB_{j,k}$, $IM_{j,k}$ are shown in Figure 8.

	CBM Alarm System	Tye of alarm	RUL
Train 4	HVAC	2	8

	Air Conditioning (HVAC)	Electric	Mechanical
Time required for predictive intervention	5,5	3	0

PIM	Option 1	Option 1	Option 1	Option 1	Option 1	Option 1	Option 1								
Train 4	IM - MLG	IM - MLG	IM - MLG	IM - MLG	IM - MLG	IM - MLG	IM - MLG	Day 8	Day 9	Day 10	Day 11	Day 12	Day 13	Day 14	Day 15
	n=2	n=2	n=2	n=2	n=2	n=2	n=2	0	0	0	0	0	0	0	0
PIW												Option 2			
Train 4	Day 1	Day 2	Day 3	Day 4	Day 5	Day 6	Day 7	Day 8	Day 9	Day 10	Day 11	IW - MLG	Day 13	Day 14	Day 15
	0	0	0	0	0	0	0	0	0	0	0	n=2	0	0	0

	Time available for Mechanical	Time available for Electrical	Time available for Air Conditioning	Time required for Mechanical	Time required for Electrical	Time required for Air Conditioning	Feasible?
Option 1	23,06	15,97	35,71	0	3	5,5	YES
Option 2	4,61	2,13	5,93	0	3	5,5	NO

Figure 7: Example of feasibility evaluation in train 4 in the $PIW_{j,k}$, $PIM_{j,k}$ matrices

IW	Day1	Day2	Day3	Day4	Day5	Day6	Day7	Day8	Day9	Day10	Day11	Day12	Day13	Day14	Day15
Train 1	0	0	1	0	0	0	0	1	0	0	0	0	0	1	0
Train 2	0	1	0	0	0	0	0	1	0	0	0	0	0	0	1
Train 3	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0
Train 4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Train 5	0	0	0	1	0	0	0	0	0	1	0	0	0	0	0
Train 6	0	0	0	0	1	0	0	0	0	0	1	0	0	0	1
Train 7	0	0	0	0	0	1	0	0	0	0	0	1	0	0	0
Train 8	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0
Train 9	0	1	0	0	0	0	0	0	0	0	0	0	0	0	1
Train 10	0	0	0	0	1	0	0	0	0	0	1	0	0	0	0
Train 11	0	0	0	0	0	0	1	0	0	0	0	1	0	0	0
Train 12	0	0	0	0	0	1	0	0	0	0	0	0	1	0	0
Train 13	0	0	0	0	0	1	0	0	0	0	0	0	0	1	0
Train 14	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Train 15	0	0	0	1	0	0	0	0	0	1	0	0	0	0	1
Train 16	0	0	0	1	0	0	0	0	0	0	0	1	0	0	0
Train 17	0	0	0	0	0	0	1	0	0	0	0	0	0	0	1
Train 18	0	0	0	0	0	0	1	0	0	0	0	0	1	0	0
Train 19	0	0	0	1	0	0	0	0	0	0	0	0	1	0	0
Train 20	0	0	0	1	0	0	0	0	0	0	1	0	0	0	0
Train 21	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0
Train 22	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0
Train 23	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Train 24	0	0	0	1	0	0	0	0	0	0	0	0	0	0	1

IB	Day1	Day2	Day3	Day4	Day5	Day6	Day7	Day8	Day9	Day10	Day11	Day12	Day13	Day14	Day15
Train 1	0	0	0	0	0	0	0	0	0	0	0		0	0	0
Train 2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Train 3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Train 4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Train 5	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Train 6	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Train 7	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Train 8	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Train 9	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0
Train 10	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Train 11	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0
Train 12	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Train 13	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Train 14	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0
Train 15	0	0	0	0	0	0	0	0	0	0	0		0	0	0
Train 16	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Train 17	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Train 18	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Train 19	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Train 20	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Train 21	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Train 22	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Train 23	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Train 24	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0

IM	Day1	Day2	Day3	Day4	Day5	Day6	Day7	Day8	Day9	Day10	Day11	Day12	Day13	Day14	Day15
Train 1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Train 2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Train 3	0	1	1	1	0	0	0	0	0	0	0	0	0	0	0
Train 4	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0
Train 5	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Train 6	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Train 7	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Train 8	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Train 9	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Train 10	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Train 11	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Train 12	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0
Train 13	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Train 14	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Train 15	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Train 16	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Train 17	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Train 18	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Train 19	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Train 20	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Train 21	0	0	0	0	0	0	0	0	0	1	1	1	0	0	0
Train 22	0	0	0	0	0	1	1	1	0	0	0	0	0	0	0
Train 23	0	0	0	0	0	1	1	1	0	0	0	0	0	0	0
Train 24	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Figure 8: $IW_{j,k}$, $IB_{j,k}$, $IM_{j,k}$ preventive maintenance intervention opportunities to perform predictive

5.3 Predictive maintenance and operations scheduling

The optimisation model was run in Python, together using the Gurobi optimizer (Gurobi Optimizer version 9.5.2 build v9.5.2rc0) as the solver, and the Gurobipy library for Python. Due to the nature of the inspections in Talgo, IW does not consume operational time as it is done at night, so equation (11) is eliminated from the optimisation model for the case study. The solver optimises the solution for a model with 3639 rows, 1104 columns and 24024 nonzero. It explored 66 nodes with 4140 simplex iterations in 0.73 seconds. The optimal value of the objective function corresponds to 10 lost days of RUL across the fleet.

Together with the value of the objective function, the model produced the outputs of the decision variables $x_{j,k}$ (Figure 9), $y_{j,k}$ (Figure 10). The results show the train's daily assignment for operation, highlighted in blue, the predictive maintenance allocation shown in yellow, and idle status in white (Figure 11). The pink highlighted cells indicate the trains that are not in operation since they are undergoing a preventive maintenance. Also, Figure 11 also shows the type of inspection (*IW, IB, IM*) and the location (STC, MLG) based on the existing preventive maintenance schedule. The days that are in blue with the code IW-OP mean the train undergoes a weekly inspection, but it is assigned to operation the same day, as it is not consuming operational time.

$x_{j,k}$

	Days														
Train	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**
1	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
2	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	0.0	1.0	1.0	0.0	0.0	0.0	0.0
3	1.0	0.0	0.0	0.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
4	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
5	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	0.0	1.0	1.0	1.0	1.0	0.0	1.0
6	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	0.0	1.0	1.0	1.0	1.0
7	1.0	1.0	1.0	1.0	1.0	0.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
8	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
9	1.0	1.0	1.0	1.0	1.0	1.0	1.0	0.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
10	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
11	1.0	0.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
12	0.0	0.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	0.0	1.0	0.0	1.0	1.0	1.0
13	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	0.0	1.0
14	1.0	1.0	0.0	0.0	1.0	1.0	1.0	1.0	0.0	1.0	0.0	0.0	1.0	1.0	1.0
15	1.0	1.0	1.0	0.0	0.0	1.0	1.0	1.0	0.0	0.0	1.0	1.0	1.0	1.0	1.0
16	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	0.0
17	0.0	1.0	0.0	1.0	1.0	1.0	0.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
18	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	0.0	1.0	0.0
19	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	0.0	1.0	1.0
20	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	0.0	0.0
21	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	0.0	0.0	0.0	1.0	1.0	1.0
22	1.0	1.0	1.0	1.0	1.0	0.0	0.0	0.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
23	1.0	1.0	1.0	1.0	0.0	0.0	0.0	0.0	1.0	1.0	0.0	1.0	0.0	1.0	1.0
24	0.0	1.0	1.0	1.0	0.0	1.0	1.0	1.0	1.0	0.0	1.0	1.0	1.0	1.0	1.0

Figure 9: Solution for $x_{j,k}$

$y_{j,k}$

	Days														
Train	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**
1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
2	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.0
3	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
4	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
5	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
6	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.0	1.0	1.0	1.0	1.0
7	0.0	0.0	0.0	0.0	0.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
8	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
9	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
10	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
11	0.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
12	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
13	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
14	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.0	1.0	1.0	1.0
15	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.0	1.0	1.0	1.0	1.0	1.0
16	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
17	0.0	0.0	0.0	0.0	0.0	0.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
18	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
19	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
20	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
21	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
22	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
23	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
24	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.0	1.0	1.0	1.0	1.0	1.0

Figure 10: Solution for $y_{j,k}$

RUL	Fleet	Day1	Day2	Day3	Day4	Day5	Day6	Day7	Day8	Day9	Day10	Day11	Day12	Day13	Day14	Day15
24	Train 1			IW - OP					IW - OP						IW - OP	
10	Train 2		IW - OP						IW - OP	IDLE		IDLE	IDLE	IDLE	IDLE	IW - OP
12	Train 3		IM - STC	IM - STC	IM - STC							IW - OP				
8	Train 4	IM - MLG	IM - MLG	IM - MLG	IM - MLG	IM - MLG	IM - MLG	IM - MLG	IDLE			IW - OP				
13	Train 5				IW - OP					IDLE	IW - OP					IDLE
11	Train 6					IW - OP						IW -STC				IS - OP
6	Train 7						IW -STC						IW - OP			
23	Train 8									IW - OP						
10	Train 9		IW - OP						IB-STC							IS - OP
20	Train 10					IW - OP						IW - OP				
4	Train 11		IW-MLG					IW - OP					IW - OP			
11	Train 12	IM - STC	IM - STC				IW - OP							IDLE-IS		IDLE
14	Train 13						IW - OP								IW - OP	IDLE
7	Train 14	IDLE				IDLE				IDLE		IDLE	IB-STC			
6	Train 15			IDLE	IDLE						IW-MLG					IW - OP
14	Train 16				IW - OP								IW - OP		IDLE	
4	Train 17	IB -STC				IDLE		IW -STC								IW - OP
13	Train 18							IS - OP						IDLE		IDLE
14	Train 19				IW - OP									IW - OP	IDLE	
13	Train 20				IW - OP							IW - OP		IDLE	IDLE	
12	Train 21					IW - OP					IM - STC	IM - STC	IM - STC			
5	Train 22						IM -MLG	IM -MLG	IM-MLG					IW - OP		
9	Train 23	IW - OP				IDLE	IM - STC	IM - STC	IM - STC		IDLE		IDLE			
6	Train 24			IDLE	IDLE					IDLE	IB-STC					IW - OP

Figure 11: Figure 13: Solution illustration combining the variables and preventive maintenance calendar

Figure 11 also shows the days that the train is idle. Such cases are in twofold. The first one represents the train is not operational because it is at the depot for preventive maintenance. The second case indicates when the train is idle because it is not assigned for normal operation or predictive maintenance.

5.4 Evaluation of results in comparison to existing company policies

The output of this research is compared against two existing policies in use by the company depending on the fleet. The first policy represents the case of most fleets that do not have sufficient data to estimate RUL. The second policy considers that the company generates the RUL estimations with insufficient data points in terms of quality or quantity. The proposed policies represent the reality in practice and underline the data limitations and possible impact of this research.

5.4.1 Policy 1

The first policy illustrates the case where the company does not have sufficient data to estimate the RUL. Here, the company assumes that failure mode 2 of the bearings imply immediate stoppage of the train as soon as possible. We assume for quantifying the results that it can be done the first day of the planning horizon (Figure 12). This case is not considering the speciality resources at each depot, as without considering the time that the intervention will take, the stoppage will be done, since the consequences of failure are not permissible. It could even imply not supplying the trains needed for operation, or the need of providing more trains from reserves, but will be still better than the consequences of failure.

	Preventive
	predictive performed in preventive maintenance inspection
Critical syst & FM	predictive maintenance performed when a critical FM is detected in critical system of the train

Monitored System	Alarm/FM		Day1	Day2	Day3	Day4	Day5	Day6	Day7	Day8	Day9	Day10	Day11	Day12	Day13	Day14	Day15	Lost RUL
BEARING	2	Train 1	Critical syst & FM		IW - MLG					IW - MLG						IW - MLG		24
BEARING	1	Train 2		IW - STC						IW - STC							IW - STC	9
BEARING	2	Train 3	Critical syst & FM	IM - STC	IM - STC	IM - STC							IW - STC					12
HVAC	2	Train 4	IM - MLG	IM - MLG	IM - MLG	IM - MLG	IM - MLG	IM - MLG	IM - MLG									8
BEARING	1	Train 5				IW - STC						IW - STC						10
HVAC	1	Train 6					IW - STC						IW - STC				IW - STC	7
HVAC	1	Train 7						IW - STC						IW - STC				1
HVAC	1	Train 8									IW - MLG							0
HVAC	2	Train 9		IW - STC						IB - STC							IW - STC	9
BEARING	1	Train 10					IW - STC						IW - STC					16
HVAC	1	Train 11		IB - MLG					IW - MLG					IW - MLG				3
BEARING	2	Train 12	IM - STC	IM - STC				IW - STC							IW - STC			10
BEARING	1	Train 13						IW - STC								IW - STC		9
BEARING	2	Train 14	Critical syst & FM					IW - MLG						IB - STC				7
HVAC	1	Train 15				IW - MLG						IW - MLG					IW - MLG	3
HVAC	1	Train 16				IW - STC								IW - STC				11
HVAC	1	Train 17	IB - STC						IW - STC								IW - STC	4
BEARING	1	Train 18							IW - STC						IW - STC			7
BEARING	1	Train 19				IW - STC									IW - STC			11
HVAC	1	Train 20				IW - STC							IW - STC					10
HVAC	2	Train 21					IW - STC					IM - STC	IM - STC	IM - STC				8
BEARINGS	2	Train 22	IW - MLG					IM - MLG	IM - MLG	IM - MLG					IW - STC			5
HVAC	2	Train 23	IW - STC					IM - STC	IM - STC	IM - STC							IW - MLG	9
HVAC	1	Train 24				IW - STC						IB - STC					IW - STC	3
																	Total	196

Figure 12: Policy 1 representation

Figure 14:

In order to compare the existing policies to the model solution, we compare the days of lost RUL for each case. Policy 1 will imply losing 196 days of RUL of the components. This is calculated as the summation of all the days lost of RUL in each train because of maintaining the limiting component before the end of the useful life. It is calculated subtracting to each RUL the day when predictive maintenance was carried out (Figure 12), and then lost RUL of all trains are summed.

5.4.2 Policy 2

This second policy illustrates the case where the company generates RUL predictions, but these only fit statistical distributions that do not accurately represent the useful life due to poor quantity and quality of data. Depending on the variance in asset data, distribution parameters would not be stable until certain amount of data describing the asset’s working regime is obtained (Salvador Palau et al., 2019). Due to this situation, in Policy 2 the company does not trust the predicted value of the RUL, and therefore allocates the predictive maintenance intervention in the first preventive maintenance slot if the RUL value is within the planning horizon.

To compare with previous policy and the model solution, the days of lost RUL are calculated using the days when predictive was conducted (Figure 13), and the same RUL. The results are 150 days of lost RUL. This policy, compared to policy 1, reduces workshop visits, and extends the lifetime of train components, without compromising reliability.

RUL			Day1	Day2	Day3	Day4	Day5	Day6	Day7	Day8	Day9	Day10	Day11	Day12	Day13	Day14	Day15	Lost RUL
24	BEARING	Train 1			IW - MLG					IW - MLG						IW - MLG		0
10	BEARING	Train 2		IW - STC						IW - STC							IW - STC	9
12	BEARING	Train 3		IM - STC	IM - STC	IM - STC							IW - STC					11
8	HVAC	Train 4	IM - MLG	IM - MLG	IM - MLG	IM - MLG	IM - MLG	IM - MLG	IM - MLG									8
13	BEARING	Train 5				IW - STC						IW - STC						10
11	HVAC	Train 6					IW - STC						IW - STC				IW - STC	7
6	HVAC	Train 7						IW - STC						IW - STC				1
23	HVAC	Train 8									IW - MLG							0
10	HVAC	Train 9		IW - STC						IB - STC							IW - STC	9
20	BEARING	Train 10					IW - STC						IW - STC					0
4	HVAC	Train 11		IB - MLG					IW - MLG					IW - MLG				3
11	BEARING	Train 12	IM - STC	IM - STC				IW - STC							IW - STC			10
14	BEARING	Train 13						IW - STC								IW - STC		9
7	BEARING	Train 14						IW - MLG						IB - STC				2
6	HVAC	Train 15				IW - MLG						IW - MLG					IW - MLG	3
14	HVAC	Train 16				IW - STC								IW - STC				11
4	HVAC	Train 17	IB - STC						IW - STC								IW - STC	4
13	BEARING	Train 18							IW - STC						IW - STC			7
14	BEARING	Train 19				IW - STC									IW - STC			11
13	HVAC	Train 20				IW - STC							IW - STC					10
12	HVAC	Train 21					IW - STC					IM - STC	IM - STC	IM - STC				8
5	Bearing	Train 22	IW - MLG					IM - MLG	IM - MLG	IM - MLG					IW - STC			5
9	HVAC	Train 23	IW - STC					IM - STC	IM - STC	IM - STC							IW - MLG	9
6	HVAC	Train 24				IW - STC						IB - STC					IW - STC	3
																	Total	150

Figure 13: Policy 2 representation

5.4.3 Discussion

In comparison with the existing company policies, the solution proposed in this paper results in a much lower loss of component usage (10 days). This savings can be translated to monetary impact using a certain cost per day or km depending on the company and component.

This maintenance management policy can improve scheduling efficiency by reacting dynamically to the PHM alarms and corresponding RUL predictions. If there are no opportunities for performing predictive maintenance upon a certain fault detection, the maintenance calendar will have to be adapted either by adding a new slot, increasing the stoppage, or providing more resources at the depots. This way, maintenance schedulers can react dynamically generating new feasible schedules when needed (Figure 14).

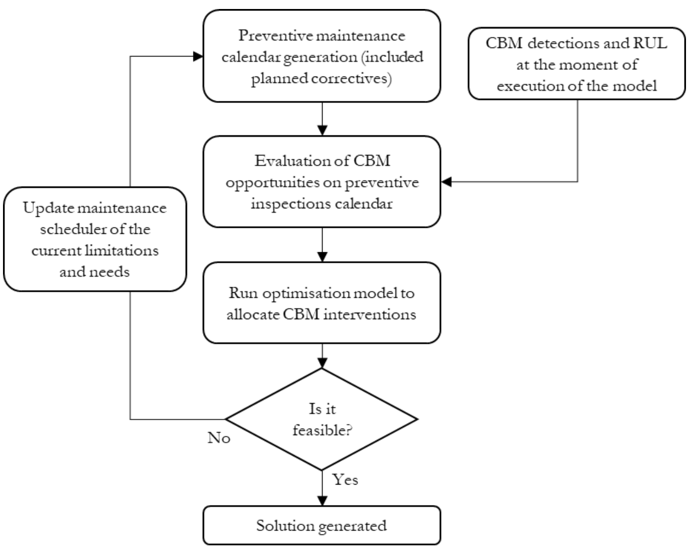

Figure 14: Flow of decision making for model application

6 Conclusions and Further work

This paper presents a novel and structured strategic approach to manage the maintenance of fleets of valuable industrial assets. It consists, firstly, of an initial exposition of the objectives and a deep literature review to illustrate the limitations of state of the art. Then the methodology explains the structured model stages to manage the fleet, defining the required inputs and tools, the existing limitations, and the expected outputs of every stage. Next, the evaluation of predetermined preventive maintenance inspections, and the possibility of performing CBM interventions on them is defined. Once the anomalies are detected, the model evaluates which of them could be intervened on which day of their opportunities in the planning horizon. Finally, the optimisation model is presented to allocate the assets of the fleet to maintenance, operation or idle. Then the practical case of an application that acts as proof of concept is defined, and the methodology applied, showing that the usage of components with this simulated RULs are increased, something that will be even more significant as the planning horizon is made wider.

The next step will be modelling considering different levels of risk in the prognosis of RUL and considering how this maximisation of usage could be translated to cost depending on component criticality. Another further challenge is to develop a strategy to combine predictive maintenance with preventive maintenance in a dynamic way, so preventive maintenance becomes more dynamic and data-driven, and how this will affect business decision making and the periodicity of it. Additionally, a significant further challenge is defining the quality and quantity of data required to develop more accurate prognostics, that will allow to have more accurate and trustable results of this work's model application. Finally, the dynamicity of maintenance decision making driven by data will allow to offer more efficient services and higher fleet reliability, and this would need to be proven with further applications on wider problems integrating data from multiple levels of companies.

Declaration of Competing Interest

The authors of this paper declare no conflicts of interest that could be inherent in their submissions.

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