

Dynamic Fleet management: integrating predictive and preventive maintenance with operation workload balance to minimise cost

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Abstract

The optimization of fleet maintenance management is of utmost importance to ensure the efficient and reliable operation of asset fleets. Traditional maintenance strategies are often reactive or rely on predetermined schedules, which can lead to inefficient resource allocation and increased operational costs. The advent of digital technologies has allowed the integration of predictive maintenance into fleet management. This paradigm shift towards a more data-driven approach enables fleet management to dynamically respond to issues identified through sensors and algorithms that detect anomalies and provide prognostic insights regarding the remaining useful life of components. However, a notable deficiency exists in the integration of predictive maintenance with calendar-based preventive maintenance and fleet operational allocation, thereby impeding value creation for businesses. This paper presents an optimisation model to address this issue by incorporating preventive and predictive maintenance while simultaneously striving to balance the workload to meet operational demand and mitigate potential penalties resulting from failure to meet these demands. The paper also examines the role of component criticality as well as the precision of the RUL (Remaining Useful Life) prognosis. Through the experiments conducted, it has been demonstrated that the allocation of the fleet is subject to change depending on the level of criticality of monitored components. These findings reveal the potential risks and penalties that could arise from an insufficient definition of failure impact severity when integrating predictive maintenance with existing preventive approaches and operational workload balance. Additionally, the experiments underscore the impact of RUL distributions precision on total operating costs, showing the confidence intervals through a sensitivity analysis.

1 Introduction

A fleet is a group of assets that share similar technical features, common maintenance facilities, interventions, and resources, as well as work under similar operating conditions (Petchrompo & Parlikad, 2019). Fleet management is then defined as the coordinated activity of overseeing and organizing a fleet of assets to ensure they are operating safely and efficiently, and fulfilling the operational demand (Birolini et al., 2021; Schulze Spüntrup et al., 2020). Although there has been a flurry of research activities over the past several years on predictive maintenance, not much attention has been given to its application in the context of fleet management. In particular, current literature that explores predictive maintenance in the context of existing operations and maintenance practices is sparse.

Although the performance of the individual assets in a fleet can be thought of as independent, when considering the performance of the fleet as a whole (Erguido et al., 2022; Petchrompo et al., 2020), it is clear that there exists a dependence between the assets due to common spare parts, shared maintenance workforce, inspection tools, and repair facilities (Petchrompo & Parlikad, 2019; Salvador Palau et al., 2019). Moreover, since the condition of most components depend on their usage, there is an opportunity to reduce maintenance costs if the operational workload is effectively shared between the assets in the fleet (Framinan et al., 2019; Frisch et al., 2021).

This paper contributes to this under-explored area by presenting an optimisation model that minimise the costs associated with fleet management by integrating three activities: (i) calendar-based preventive maintenance; (ii) predictive maintenance; and (iii) allocation of operation workload. Further, recognising that algorithms that predict the remaining useful life (RUL) is far from perfect, this paper explores how such an integrated approach for fleet management is affected by the precision of RUL prediction. Finally, the paper provides insights on how the criticality of the components influences the decisions, and hence the fleet management costs.

The paper is structured as follows. Section 2 reviews the literature to set this paper in the context of existing research. Section 3 presents the definition of the problem statement. Section 4 includes the definition of the optimisation model divided into decision variables, objective function, and constraints. Once the model is defined, Section 5 presents the design of experiments to evaluate the model performance and application. Section 6 presents the results and the associated discussion, and section 7 contains the conclusions and proposals for further work.

2 Research background

The aim of this section is two-fold: (i) to describe the state-of-art research in fleet maintenance; and (ii) to identify the gaps and shortcomings of existing work. The purpose of doing so is to set the context of the research presented in this paper and highlight the key contributions of this work.

The focus of this paper is on the fleet management level. Proposed models in the literature have been applied from networks of assets (Hernández et al., 2022; Xia et al., 2021a) to fleets of multiple types as transformers (Alves da Silva et al., 2019), wind turbines (Z. Liu & Lee, 2018; Teng et al., 2020), trains (Bougacha et al., 2020; Dersin, 2018; Herr et al., 2020), aircrafts (de Pater et al., 2022; Lee et al., 2022; Mitici et al., 2023), or vehicles such as cars and lorries (Rawat, 2021; Wang, Limmer, et al., 2022). Fleet management involves dependencies and interactions between all type of assets, and an 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 has service level requirements to adhere to (Lee et al., 2020; Stern et al., 2017), and that it is 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, 2019). The main challenge for dynamic fleet management is integrating existing maintenance approaches with predictive solutions enabled by digitalisation to guarantee certain levels of fleet availability in a more reliable and secure way (Crespo del Castillo et al., 2023). This challenge implies the integration of preventive and predictive maintenance with operation assignation (Crespo del Castillo et al., 2023). Another subsequent need is the study of resources available for maintenance with the same dynamicity as predictive maintenance indicators are evaluated (Mitici et al., 2023; Petchrompo et al., 2020; X. Zhao et al., 2022).

Current advances in fleet maintenance management integrate predictive maintenance approaches including RUL prognostics with preventive maintenance (de Pater & Mitici, 2021; Lee et al., 2022; Mitici et al., 2023). However, integrating the assignation to operation (balancing degradation because of workload), together with preventive and predictive maintenance (considering components' criticality) is an area that has not been deeply explored (Li, 2019) together with its dynamic nature. This divides the main streams of work: solutions that combine predictive and preventive maintenance with fixed operation schedule, or solutions that combine operational assignation with predictive maintenance scheduling.

The most advanced approaches are listed and analysed according to their features in Table 1.

Table 1: Literature relevant papers evaluation

Paper title	Features											Resolution Method
	RUL prognostics definition	Preventive and predictive integration	Operational demand considerations and penalizations	Fleet Workload balance	Resources availability consideration	Cost evaluation	RUL Usage maximisation	Multiple components per asset	Criticality of monitored components considered	RUL prognosis cost influence evaluation	Dynamic rescheduling	
(Herr et al., 2017)	X		X	X			X					MILP - linear programming
(Herr et al., 2020)	X		X	X			X					MILP - linear programming
(van Kessel et al., 2023)		X			X	X					X	MILP - Simulation
(de Pater & Mitici, 2021)	X	X			X	X		X		X	X	ILP - linear programming
(Mitici et al., 2023)	X	X			X	X		X		X	X	MILP - linear programming
(Lee et al., 2022)	X	X			X	X		X				ILP - linear programming
(Lee & Mitici, 2021)	X	X			X			X				Discrete simulation -
(Petchrompo et al., 2020)	X		X	X	X	X						Genetic algorithm -
(Bougacha et al., 2020)		X	X	X	X	X	X					MIP - Genetic algorithm
(Hernández et al., 2022)			X	X	X	X						MILP - linear programming
(Schulze Spüntrup et al., 2020)	X				X		X					MILP - Network framework
(Wang, Limmer, et al., 2022)	X				X	X	X	X			X	evolutionary algorithm
(Muriel et al., 2019)	X				X	X						Discrete Simulation
(Alves da Silva et al., 2019)			X	X	X	X			X			MILP - linear programming
(Z. Zhao et al., 2020)	X		X	X		X					X	Bayesian framework
(Figueiredo-Pinto et al., 2021)	X	X		X				X				GRG Nonlinear method
(Martin et al., 2022)			X	X	X						X	MINLP
(Mira et al., 2020)			X	X	X	X		X			X	ILP - linear programming
(Xia et al., 2021b)		X		X	X	X		X				FM cost saving policy
(Meissner et al., 2021)	X				X	X	X	X				Discrete Simulation
(J. Liu et al., 2022)		X			X	X		X				NLP – Genetic Algorithm
(Deng et al., 2020)					X	X		X			X	Dynamic programming

Within fleet management there is a stream of work that focuses on operation assignment with a simplified maintenance approach (Mira et al., 2020). As said, this stream of work tries to merge predictive maintenance with operation workload balance assignment within the fleet (Herr et al., 2017, 2020; Li, 2019). Balancing the workload allocation is defined in other applications as a way of balancing degradation between systems to guarantee performance, enhancing dynamicity in maintenance strategy (Wang, Li, et al., 2022; X. Zhao et al., 2022). Complex operation assignment (including different types of operation length and degradation) in combination with predictive maintenance has been successfully programmed and has led to maximising the usage of components before replacement (Herr et al., 2020). The main drawback of this approach is the lack of integration between predictive and preventive maintenance (Dersin, 2018; Figueiredo-Pinto et al., 2021; Herr et al., 2017). In some cases (Figueiredo-Pinto et al., 2021) preventive and predictive maintenance are viewed separately, but the resources and stoppages are not managed, merged, or considered.

The other main stream work has focused on dynamic maintenance, integrating predictions of monitored systems with existing preventive maintenance restrictions in companies (de Pater & Mitici, 2021; Lee et al., 2022; Mitici et al., 2023; van Kessel et al., 2023). Especially in the aerospace sector, operation assignment is considered fixed, and maintenance windows are fixed time gaps used by models to minimise costs by scheduling maintenance the best way possible (Lee et al., 2022; Mitici et al., 2023; van Kessel et al., 2023). As a result, availability of the fleet is considered guaranteed in multiple cases; however, some papers include the possibility of not meeting the demand with penalties (Petchrompo et al., 2020; X. Zhao et al., 2022), due to assets' condition or uncertainties in the prognosis (Mitici et al., 2023). Some approaches have focused on the dynamicity of maintenance scheduling, and the capacity of rescheduling based on the resources available in the depots where assets enter for maintenance (Muriel et al., 2019; van Kessel et al., 2023). The most advanced models combine RUL prognostics based predictive maintenance with existing preventive maintenance stoppages to minimise overall maintenance costs (Crespo Márquez et al., 2023; Lee et al., 2022; Mitici et al., 2023). Some even emphasise the resources available to do so (Crespo del Castillo et al., 2023; de Pater & Mitici, 2021). The study of the uncertainty of RUL prognostics on costs (Jain et al., 2021; Mitici et al., 2023) is important to mention, as it extends the analysis to multiple components and relates the quality of the prognosis to the final costs.

In general, most models evaluate their experiments to minimise overall costs, and some maximise component usage before intervention. Even when the evaluation is made based on costs, detailed breakdowns of cost considering preventive and predictive maintenance separately are rare, as are measurements of the overall impact on total cost (Jain et al., 2021; Mitici et al., 2023). Besides, only (Alves da Silva et al., 2019) consider the risk of system impact on costs, however, depending on the level of criticality of the components managed with predictive maintenance, there is an impact of failure on the company (Crespo Márquez et al., 2020; Márquez et al., 2009) and this should be reflected in cost. The total cost of a certain dynamic fleet maintenance decision also depends on the prognosis of RUL of each asset; however, it is not only the summation of individual maintenance decisions (Petchrompo & Parlikad, 2019). When it scales to the fleet, there is a dynamic risk of production loss according to the system aggregate output, that depends on the criticality of the monitored component. Furthermore, the impact of that failure on the company, along with the associated costs, differs depending on the criticality (Besnard & Bertling, 2010). This has not been addressed in previous papers combined with workload balance and the merge of preventive and predictive maintenance opportunistically. The dynamic planning of fleet maintenance has to be achieved by balancing the costs of predictive maintenance, placing emphasis on the difference between preventive, corrective, and lost RUL usage of monitored components.

Regarding the modelling of the solution, most models present either MILP, ILP, MINLP, or simulation approaches (Table 1). The models presented with a more formal optimisation problem are solved using solvers such as Gurobi or CPLEX, and the models developed through NLP or simulation require heuristics such as genetic algorithms to provide admissible solutions. While there

is a clear modelling direction, the dynamicity in solution recalculation and the planning horizon (Figueiredo-Pinto et al., 2021) is still a topic with no clear consensus. Some approaches present the dynamicity of recalculation as a frequency defined by the detection of anomalies, changes in capacity or resources, or changes in the demand for availability.

After the review presented, it can be concluded that the main gap in the literature is the lack of a holistic model that combines the operation (workload balance) and PdM scheduling approach (RUL usage maximisation), with the approach that merges the scheduling of preventive and predictive maintenance (cost minimisation). Besides, integrating in the solution the criticality of the monitored components to see how the cost and allocation of the fleet varies depending on the monitored components, presents an unexplored gap. Furthermore, examining the impact of the precision of the RUL input on the model, along with the aforementioned aspects, would provide insights into the effect of input quality on the variability of model cost results. According to the existing gaps in literature, the research questions are:

Research Question 1: How can the RUL of the fleet assets monitored components be managed optimally while satisfy overall service requirements and existing maintenance constraints?

Research Question 2: How does the allocation of the fleet vary depending on the criticality of the monitored components?

To answer these questions we propose an optimisation model with the focus on optimising the allocation of fleet assets among three options—operation, predictive maintenance, or idle—throughout the planning horizon. The primary goal is to minimise overall operating costs while upholding constraints stemming from predictive maintenance, existing preventive maintenance schedules, the service level agreement, cost of penalties, and safety prerequisites. This is something that has not been solved with this holistic perspective previously, and the main contribution of this paper. Additionally, the paper aims to examine how the criticality of monitored components and the probabilistic distribution of the RUL influence costs and lead to varying solutions at the fleet level.

3 Problem statement

Consider a fleet comprising F assets (where $1 < j < F$), for which the service level agreement mandates the availability of Av_k assets on each day k within a planning horizon of H days to ensure a satisfactory service.

M systems are being monitored on each asset for predictive maintenance with an appropriate anomaly detection and fault diagnostics algorithm. For each monitored system, a predictive analytics algorithm estimates the Remaining Useful Life (RUL) upon anomaly detection. In particular, to reflect the uncertainty in prediction, the output of this algorithm will be in the form of a probability distribution of the RUL. For the purpose of this paper, without loss of generality, we assume that this will be a Weibull distribution. Note that the specific techniques for anomaly detection, fault diagnosis, and RUL prediction are not within the scope of this work.

Utilizing the principle of competing failures, the assets' RUL corresponds to the minimum RUL among its constituent components. The maintenance costs for the asset are determined by the economic impact of failure of the monitored components, which represents the severity of the failure, and hence the criticality of the components, incorporating specific corrective and predictive maintenance intervention expenses. δ_j represents the degradation incurred by an asset j for each day of operation.

The opportunistic preventive maintenance calendar ($OP_{j,k}$) represents the predetermined preventive maintenance inspections that provide the time and resources to perform the predictive intervention of the monitored components with predictive maintenance anomaly. Assets are only taken out of operation for the required predetermined preventive stoppages (Schulze Spüntrup et al., 2020; Stern

et al., 2017), meaning predictive maintenance interventions do not have specific stoppages. Maintenance duration is assumed to be one day. This indicates that the asset will be unavailable for operation during the maintenance period. Disregarding depot transit time for simplicity, it is presumed that an asset requiring inspection on a specific day will remain unavailable for operations throughout that entire day, accounting for the time needed for asset relocation to and from the depot. The problem allows only one predictive maintenance intervention within the planning horizon of H days.

4 Model definition

Sets

J	Fleet of assets = $\{1, \dots, F\}$
D	Days comprising the planning horizon = $\{1, \dots, H\}$

Model Parameters

F	Number of assets composing the system
H	Number of days that compose the planning horizon
δ	Degradation associated with each day the asset is designated for operation
RUL_j	Remaining Useful Life of each asset $j \in J$ at the beginning of the planning horizon
Av_k	Daily demand of assets available for operation each day of the planning horizon $k \in D$
$OP_{j,k}$	Feasible preventive maintenance opportunities (stoppages) to conduct CBM interventions for each asset each day $j \in J$ and $k \in D$
O_k	Number of opportunities available depending on the feasible preventive slots for each asset in a day $k \in D$

Cost Parameters

C_T	Total Cost of fleet operation
C_{PM}	Preventive Maintenance Cost
C_{PdM}	Predictive Maintenance Cost
C_{CM}	Corrective Maintenance Cost
C_{FI}	Fixed Preventive Maintenance costs (Dependant on the defined preventive schedule)
N_{FI}	Number of fixed Preventive Maintenance stoppages scheduled
C_{PD}	Cost of Predictive Maintenance (PdM)
C_{FPdM}	Fixed Cost of PdM intervention (Defined parameter by company and component criticality and value)
N_{PD}	Number of PdM Interventions performed
C_{LR}	Cost of Lost RUL (Defined parameter by company and component criticality and value)
C_{LU}	Cost of unit of lost RUL usage
N_{LR}	Days lost of RUL usage
C_{CI}	Cost of Corrective intervention (Defined parameter by company and component criticality)
P_f	Probability of Failure
C_{op}	Cost of not satisfying the demand of assets available for operation (Lost operation)
N_{op}	Number of lost operations (Availability – Assets allocated to operation)
C_A	Cost of each lost operation not satisfying each unit of demand (Availability – Assets sent to operation)

Decision Variables

$x_{j,k}$	Binary decision variable indicating if the asset $j \in J$ is assigned to operate on a certain day of the planning horizon $k \in D$
$y_{j,k}$	Binary decision variable indicating if the asset $j \in J$ is assigned to conduct a predictive intervention in a preventive maintenance inspection opportunity on a specific day of the planning horizon $k \in D$

Auxiliary Variables

$e_{j,k}$	Continuous variable used to linearise non-linear expressions for $j \in J$ and $k \in D$
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Decision variables:

The allocation of asset j to operations on day k is characterized by the binary matrix $\mathbf{X}(x_{j,k})$ that has the value 1 when the asset is allocated to operation and 0 if not. The allocation of assets to predictive

maintenance is represented by the binary matrix $\mathbf{Y}(y_{j,k})$, as depicted below. The value is 1 if the asset is scheduled to PdM a certain day of the planning horizon, and 0 if not. Then, if the value of both matrixes is 0, the asset is either scheduled to preventive maintenance, or idle in the depot if there is not preventive maintenance that day.

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

Objective function:

The objective function is a minimisation of the total operating costs (Equation 1).

$$\text{Min } C_T \rightarrow C_T = C_{PM} + C_{PdM} + C_{op} + C_{CM} + C_{LR} \quad (1)$$

Preventive maintenance cost (C_{PM}) depends on the predetermined preventive maintenance calendar and is calculated by multiplying the cost of a preventive maintenance unit execution per the number of preventive maintenances scheduled (N_{FI}) for a planning horizon (Equation 2).

$$C_{PM} = C_{FI} \times N_{FI} \quad (2)$$

Predictive maintenance costs (C_{PdM}) (Equation 3) are composed of the cost of performing PdM (C_{FPdM}) multiplied by the number of times it is executed (N_{PD}) (Equation 4). In Equation 4.7 it is ensured that the number of PdM interventions (N_{PD}) is the summation of the number of PdM conducted, which is restricted to a maximum of one each asset (Equation 15) for the time horizon under consideration for the optimisation model.

$$C_{PdM} = C_{FPdM} \times N_{PD} \quad (3)$$

$$N_{PD} = \sum_{j=1}^m \sum_{k=1}^K (y_{j,k} - y_{j,k-1}) \quad (4)$$

The cost of corrective maintenance (C_{CM}) (Equation 5) is the cost of a failure (C_{CI}) times the probability of failure P_f (Equation 6). Equation 6 represents the probability of failure associated with the counter of degradation because of operation, meaning the probability that the monitored component has to fail every time a day of operation is assigned to the asset. The probabilistic distribution type and the parameters that define it are considered as inputs, as they can vary depending on the component or failure mode under study. The probability of failure P_f is dependent on the monitored component and its RUL probabilistic distribution. The value of the probability of failure is calculated using the accumulated density function of the distribution for a certain number of accumulated days of asset operation since the anomaly is detected (Jain et al., 2021). Assigning a train to operation has an impact on its degradation. In this model, the degradation per day of the planning horizon is δ .

$$C_{CM} = P_f \times C_{CI} \quad (5)$$

$$P_f = f\left(\sum_{k=1}^K \delta_j x_{j,k} (1 - y_{j,k})\right) \quad (6)$$

The cost of lost RUL (C_{LR}) (Equation 7) is calculated as the cost of lost RUL usage multiplied by the days of life usage lost (Equation 8). The cost of lost RUL is calculated by multiplying the cost of each RUL unit lost (C_{LU}) with the number of RUL units lost per train during the planning horizon due to an early intervention (earlier than the full value of the RUL). This is calculated as the difference between the RUL and the counter of degradation until the PdM intervention ($(\sum_{k=1}^K \delta x_{j,k} (1 - y_{j,k}))$) (Equation 8).

$$C_{LR} = C_{LU} \times N_{LR} \quad (7)$$

$$N_{LR} = \sum_{j=1}^m C_{LU} \times (RUL_j - \left(\sum_{k=1}^K \delta_j x_{j,k} (1 - y_{j,k}) \right)) \quad (8)$$

The cost of lost operation (C_{op}) (Equation 9) is a cost penalisation defined when there are not sufficient assets available for operation to satisfy the client demand (Petchrompo et al., 2020) (Equation 9). The cost of not satisfying the demand of assets available for operation (C_{op}) is calculated as the cost of each day of lost operation multiplied by the number of days of lost operation (N_{op}) (Equation 10). The number of lost operations (N_{op}) is calculated as the difference between the demand for availability required, and the assets available or assigned to operation (Equation 9).

$$C_{op} = C_A \times \sum_{k=1}^K N_{op_k} \quad (9)$$

$$N_{op_k} = \left(Av_k - \sum_{j=1}^m x_{j,k} \right) \quad \forall k \quad (10)$$

Costs parameters vary depending on the criticality of the system/component considered. High criticality components are components or equipment whose failure could result in injury or loss of life (Moubray, 1999). Medium criticality and medium-high criticality components are components or equipment whose failure could result in significant production losses, environmental damage, or regulatory violations (Moubray, 1999). Low criticality components are components with low frequency of failure and no significant impact on operation. Thus, the cost of fixed corrective intervention (C_{CI}), the cost of unit of RUL lost (C_{LU}), and the fixed cost of PdM intervention (C_{FPdM}) increase with criticality, and ranges of criticalities and cost are structured accordingly.

Constraints:

The following constraints can be derived from the problem statement.

Regarding the availability constraint, the model can assign assets up to the demand for availability or less (Equation 4.11). This way, the model is not forced to satisfy the demand; however, the decision to not satisfy the demand has an associated cost present in the objective function.

$$\sum_{j=1}^m x_{j,k} \leq Av_k \quad \forall k \quad (11)$$

Following, constraints referred to the assignment of PdM are listed. Variable $y_{j,k}$ is defined using step functions (Equations 12 - 16) as a restriction to force the model to allow only one maintenance intervention per asset during the planning horizon. Equation 16 ensuring that the asset cannot be in maintenance and operation at the same time.

$$y_{j,k} - y_{j,k-1} \leq 1 - x_{j,k} \quad \forall k \forall j \quad (12)$$

$$\sum_{j=1}^m (y_{j,k} - y_{j,k-1}) \leq \sum_{j=1}^m OP_{j,k} \quad \forall k \quad (13)$$

$$\sum_{k=1}^K (y_{j,k} - y_{j,k-1}) \leq 1 \quad \forall j \quad (14)$$

$$y_{j,k} \geq y_{j,k-1} \quad \forall k \forall j \quad (15)$$

$$y_{j,k} - y_{j,k-1} \leq OP_{j,k} \quad \forall k \forall j \quad (16)$$

Regarding the opportunistic slots to perform predictive maintenance ($OP_{j,k}$), in (Equation 13) it is ensured that the number of assets maintained based on condition can be as many as the summation of opportunities of preventive maintenance that day (the train is not stopped for condition based

predictive maintenance solely, buy opportunistically in the preventive maintenance schedule). Equation 17 restricts that if the asset is under preventive maintenance, it cannot be sent to operation, and Equation 16 restricts predictive maintenance actions to be performed only in preventive opportunities. The output of the model, together with the total operating cost of the fleet, is the assignment of assets to operation ($x_{j,k}$), preventive maintenance opportunity ($OP_{j,k}$), predictive maintenance ($y_{j,k}$), or idle state ($y_{j,k} = 0 \ \& \ x_{j,k} = 0 \ \& \ OP_{j,k} = 0$), for each asset each day of the planning horizon.

$$x_{j,k} \leq 1 - OP_{j,k} \quad \forall j, \forall k \quad (17)$$

To solve the model using a linear programming solver, the optimisation model has to be linearised. The objective function in the optimization model presents a challenge requiring resolution for linearization: it involves a product of two decision variables, $x_{j,k}$ and $y_{j,k}$. To address this, we introduce a continuous variable, $e_{j,k}$ (Herr et al., 2017). The modified objective function is expressed in Equation (18), alongside the related constraints (19) - (20).

$$\begin{aligned} & \sum_{j=1}^m \sum_{k=1}^K C_{FPdM} \times (y_{j,k} - y_{j,k-1}) \\ & + \sum_{j=1}^m C_{LU} \times \left(RUL_j - \left(\sum_{k=1}^K \delta_j(x_{j,k} - e_{j,k}) \right) \right) \\ & + \sum_{j=1}^m C_{CI} \times f \left(\sum_{k=1}^K \delta_j(x_{j,k} - e_{j,k}) \right) \end{aligned} \quad (18)$$

$$e_{j,k} \leq x_{j,k} \quad \forall j, \forall k \quad (19)$$

$$e_{j,k} \leq y_{j,k} \quad \forall j, \forall k \quad (20)$$

$$1 - x_{j,k} - y_{j,k} + e_{j,k} \geq 0 \quad \forall j, \forall k \quad (21)$$

$$e_{j,k} \geq 0 \quad \forall j, \forall k \quad (22)$$

$$e_{j,k} \in \mathbb{R} \quad (23)$$

5 Experiments

This section defines the experiments used to validate and explore the model application.

5.1 Design of experiments

The experiments can be divided into two dimensions that are interesting to explore, as the impact of different criticalities, and the impact of varying RUL probabilistic distributions, on the cost optimisation solution.

The criticality experiments consist of executing the model with three different criticality considerations for all the monitored components and see how the fleet allocation changes depending on the constant parameters of cost.

The final experiments explore the variation in the cost solution based on the RUL input as the other parameter (with criticality and costs associated) that strongly influences the solution of the model. The intention of this experiment is quantifying the sensitivity of the cost solution when executing the model multiple times clustering the RUL from a more or less spread probabilistic distribution and keeping the rest of inputs fixed. This experiment aims to understand how a RUL input can guarantee certain confidence intervals of cost using the model based on them.

5.2 Criticality experiment

Criticality is derived by assigning a numerical value to both the probability of asset failure (indicating a higher value with increasing probability) and the severity of functional loss consequences across various asset categories (Crespo Márquez, 2022; Moubray, 1999). This process should be strategically defined by companies, as the prioritization of maintenance activities is based on the quantified risk arising from asset failure. According to this definition, criticality influences the model cost parameters referred to as the cost of corrective maintenance intervention and its impact (C_{CI}), the cost of lost RUL (C_{LRUL}), and the cost of the PdM intervention (C_{PdM}). However, the cost that impacts the model more significantly is the cost of corrective maintenance. The cost parameters associated with the management of their maintenance are defined in Table 2. Depending on the type of system or component, and depending on the company, these values vary, so we propose just an exemplar or simplified case to illustrate the magnitudes.

Table 2: Values of cost (economic units) constants proposed for criticality of the components

	Low Criticality (1)	Medium Criticality (2)	High Criticality (3)
C_{CI}	100	7000	15000
C_{RU}	1	100	200
C_{PdM}	50	250	250

To assess the model and see the influence of criticality on the results, the model was run for three scenarios implying the three possible criticalities. The values of the cost parameters varied according to Table 2, and the cost of lost operation penalisation was the same for all experiments, namely $C_A = 2000$ economic units. The remaining input was the same for the three criticality experiments. The availability demand was the same for all days of the planning horizon and had a value of $Av_k = 8$ assets. The degradation was $\delta_j = 1$, meaning that every day of operation the asset degraded one unit of remaining useful life, and on all days the asset degraded the same amount. The preventive maintenance stoppages that represent the opportunities for performing PdM opportunistically ($OP_{j,k}$) is represented as a binary matrix (Equation 24) that reflected value 1 when the day represented an opportunity and 0 if it did not.

$$OP_{j,k} = \begin{pmatrix} 0 & 1 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 1 & 1 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 1 & 1 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 1 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 \\ 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 \end{pmatrix} \quad (24)$$

Finally, the RUL of each of the assets had to be defined and was the same for all three criticalities. The probabilistic distributions used for these experiments used the Weibull distribution $F(t, \beta, \eta) = Weibull(t, \beta, \eta)$, where β is the shape parameter, also known as the Weibull slope, and η is the scale parameter. Out of the Weibull distribution representing each asset, we sampled a value which became the asset's RUL. In the three criticalities experiment, all three cases used the same sample. The focus of this experiment was to see the fleet assignation of the model to minimise cost depending on the criticality, so the RUL would remain the same. The Weibull parameters used are presented in Table 3. The Weibull parameters were selected to generate a certain number of RULs within the planning horizon, and some for longer, as well as at different lengths to enrich results.

Table 3: Weibull parameters values for experiment one

	Weibull parameters	
	β	η
Asset 1	15	4
Asset 2	25	3
Asset 3	38	8
Asset 4	25	3
Asset 5	8	6
Asset 6	15	4
Asset 7	45	5
Asset 8	15	4
Asset 9	25	3
Asset 10	8	6

We consider the RUL sampled for the experiment the mode of the distributions in Table 3 ($RUL_j = [15, 23, 44, 40, 6, 15, 40, 15, 34, 9]$), that are used for calculating the lost RUL in Equation 10.

The optimisation model was run for the three criticality values represented by the cost parameters. The aim of this experiment was to compare the assignment to maintenance of the fleet and the workload balance depending on the criticality of the monitored components. The experiment also aimed to evaluate when the model did or did not perform PdM and when it assigned PdM to the planning horizon, depending on the criticality. For this experiment, all monitored components required the same criticality (low, medium, or high in the three model runs).

5.3 Evaluation of RUL probabilistic distribution influence on costs

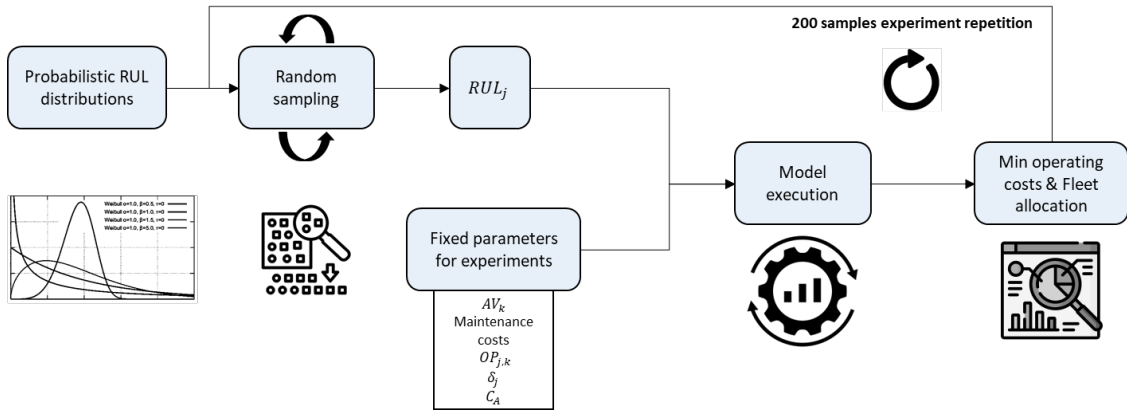


Figure 1: Flow of the experiment that evaluates RUL distribution influence on cost

In order to evaluate the influence of the Weibull uncertainty on costs, this experiment was designed as described in Figure 1. Firstly, as we want to evaluate the sensitivity to RUL variation, we assume fixed the rest of input parameters to the model. The criticality of monitored components is set to be medium. The flow of the experiment process begins with the selection of the RUL distribution, then sampling the value of the RUL_j for each experiment from the distribution. Once defined the values of RUL_j we execute the optimisation model and get the results of cost associated to these inputs. We cluster randomly the RUL_j 200 times from the distribution of each asset, generating a sensitivity analysis of the range of variability of the cost with certain probabilistic distributions. These values are evaluated in order to provide confidence intervals of the cost value. The experiment is completed repeating this process with two distributions sets. The first one has most of the values are distributed around the mode (Weibull parameters 1 in Table 4) and the second has a wider spread of values (Weibull parameters 2 in Table 4). The values of the mode of the two distributions are approximately

the same in both cases for the same assets. For example asset 4, the mode of the distribution with (25,5) is approximately the same as with (30,4).

Table 4: Weibull parameters values for experiment two

Weibull parameters 1			Weibull parameters 2		
	β	η		β	η
Asset 1	25	5	Asset 1	30	4
Asset 2			Asset 2		
Asset 3			Asset 3		
Asset 4			Asset 4		
Asset 5	15	4	Asset 5	16	2
Asset 6			Asset 6		
Asset 7			Asset 7		
Asset 8			Asset 8		
Asset 9	8	6	Asset 9	10	3
Asset 10			Asset 10		

6 Discussion

6.1 Criticality of monitored components influence on fleet allocation

The model was run with three ranges of cost parameters at low (Figure 2), medium (Figure 3) and high (Figure 4) criticalities (Table 2). In the solutions, the blue colour means that the asset is allocated to operation, pink denotes that there is a preventive maintenance stoppage, yellow signifies that predictive maintenance is performed during a preventive stoppage, and white indicates that the asset is idle.

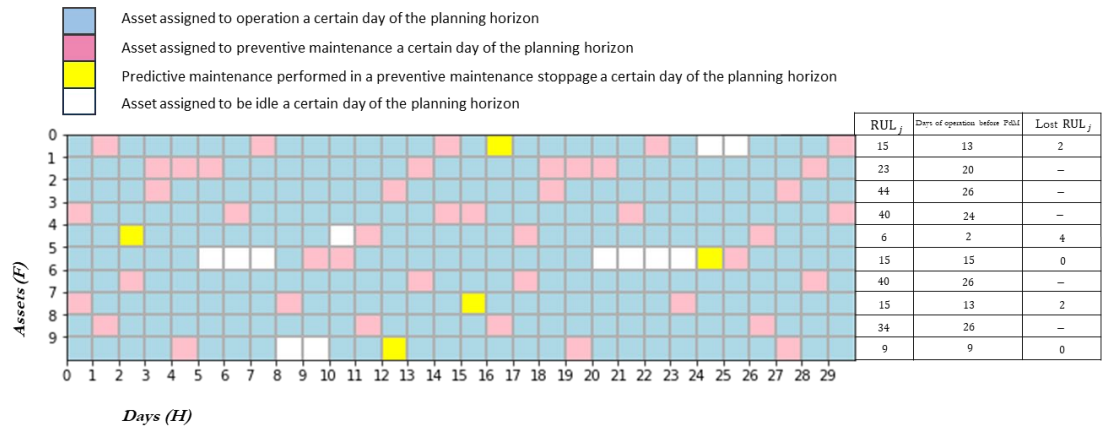


Figure 2: Model assignment to predictive and preventive maintenance, operation, and idle state for low criticality monitored components

Figure 2 shows that in the low criticality case, if the RUL of an asset has the same duration or higher than the planning horizon, predictive maintenance intervention is not performed. When predictive maintenance is performed, the model minimises the cost by maximising the RUL usage as the cost of corrective maintenance is low for the company, because it does not imply safety consequences or asset stoppage and penalties.

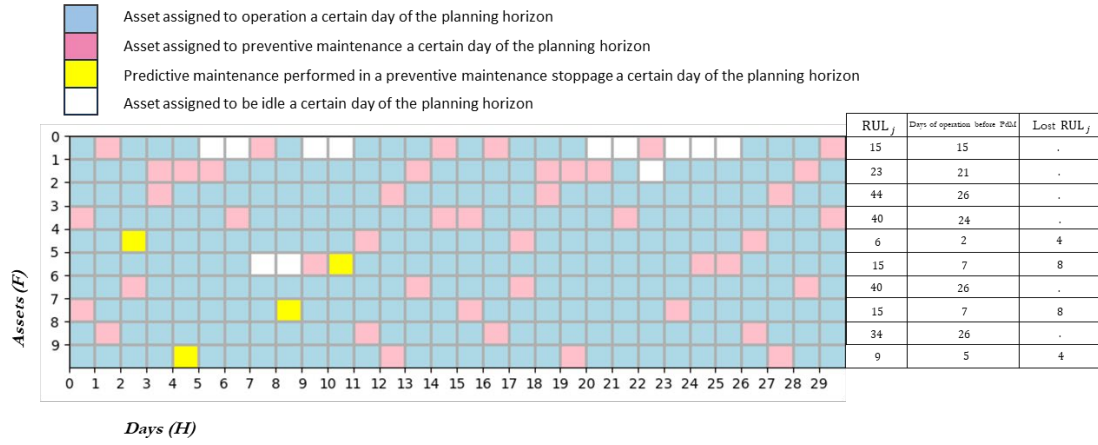


Figure 3: Model assignment to predictive and preventive maintenance, operation, and idle state for medium criticality monitored components

In the case of medium criticality (Figure 3), significant changes can be appreciated. First, the assets that had a RUL smaller than the planning horizon and a predictive intervention in Figure 2 have the intervention, but earlier than the low criticality case. This is due to the cost minimisation objective, as the cost of possible correctives is high, and the days of RUL usage gained are not as valuable as the possible penalty associated with corrective maintenance and the associated penalisation. It is also worth noting that asset one, which has a predictive intervention in Figure 2, does not undergo predictive maintenance in Figure 3. This is because the earlier intervention of the other assets allows the model to balance the workload and allocate that train to be idle more days than in Figure 2. It can be argued that in this case it consumes the RUL of the asset, but it also considers that the end of the period means a preventive stoppage for the same asset. Therefore, the planning horizon used by an optimisation model will always imply the optimisation only considering a certain period. The solution can be recalculated as any event occurs, or if the maintenance schedule changes, or there are new anomalies detected, but the solution will be always performed for a certain planning horizon being agnostic to the periods that follow.

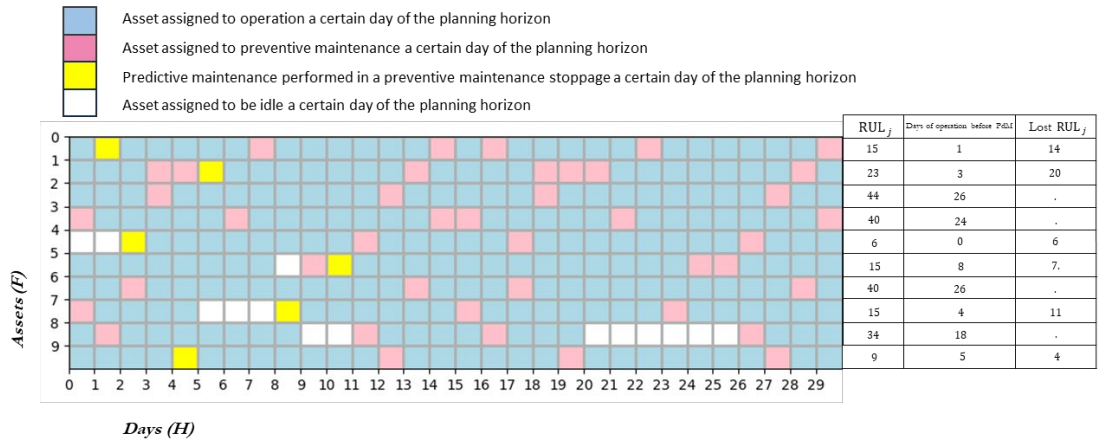


Figure 4: Model assignment to predictive and preventive maintenance, operation, and idle state for high criticality monitored components

In the case of high criticality (Figure 4), the significant rise in corrective maintenance cost conditions the solution. High criticality means that the failure of the component has severe consequences for the organisation. Accordingly, when the component criticality is high, and its RUL is within the planning horizon, the predictive maintenance intervention is performed in the first available preventive maintenance opportunity. Due to the length of the planning horizon for the example and the dimensions of the RUL, gaining 5 or 10 days of component usage is not economically viable compared to the risk that the fleet manager is undertaking considering the cost of the corrective, and

the massive impact that it can have. it can be deduced that in the case of high criticality, the model decides if the predictive maintenance is performed or not, but in case it is, it is performed in the first possible slot.

Other insights that can be deduced as part of the results analysis are as follows:

- Depending on the criticality, planning horizon, and RUL of each asset, the model decides whether or not and when to perform predictive maintenance. With RULs that are wider than the planning horizon the model allocates the asset to everyday operation and does not perform predictive maintenance independently of the criticality. When the RULs are within the planning horizon, the model performs predictive maintenance either as soon as possible at high criticality, or as close as possible to the RUL value at low criticality, while at medium criticality, the model balances between more possibilities.
- The effects of cost saving are more significant if the planning horizon and RULs are longer. With a wider decision horizon, the model is able to minimise costs considering more opportunities for performing predictive maintenance, and in the case of high criticality, the intervention is not performed the first day possible as it would lose a considerable RUL eventually. However, if the RUL usage gains are low and the criticalities are medium or high, the RUL usage is always depreciable compared to the cost of the risk of failure.
- Dynamic fleet management policies need to be defined considering the criticality of the monitored components in order to achieve significant cost savings. In the literature, these models are used with generic components which is not accurate, as experiments show different solutions for different criticalities.
- In certain instances (like the experiments analysed), it is consistently feasible to fulfil the demand, whereas in other cases, the model does not meet the demand, thereby avoiding the potential for corrective measures when the criticality is assessed as medium or high. Nonetheless, if the cost associated with not meeting the demand is substantial, it may be admissible for the assets to undergo failure. However, this scenario is limited to low criticality components, as such failures would not result in the asset being taken out of operation. However most of the monitored components are of medium to high criticality due to the investment that monitoring implies.

6.2 RUL influence on costs experiment

In this section, the impact of the RUL prognostics input on the minimal cost solution is evaluated. Together with the criticality cost parameters, the RUL input is the most relevant input to the model. Due to this fact, this section provides a sensitivity study of the variation of cost depending on the probabilistic distribution that represents the RUL inputs. Even the model is run using an integer value for each RUL, and that value could either be a sample, or the mode of the distribution. Generating random samples from the distributions representing the RULs and seeing the variation of the expected cost, we can define confidence intervals based on the distributions as inputs and evaluate the quality of the prognosis. The impact of criticality and its implications were evaluated in the previous section, but, for the purposes of this section, the impact is fixed at medium criticality for all the experiments.

The first step in this section is characterising the experiments defined in section 4.1. The Weibull distribution defined for each asset is shown in Table 4. Apart from the random sampling, we use three limits as references to analyse dispersion: mode, lower bound (LB), and high bound (HB). The model is run, and the cost calculated, using the mode, the LB (5%), or HB (95%), that represent two standard deviations each side of the mode. The cost using the mode is the expected cost, while the other two are extreme cases used to define intervals. In addition, we wanted to clarify that we applied the model with a fixed medium level of criticality, based on the values provided in Table 1. We arrived at this decision after conducting criticality experiments in the previous section and gaining valuable insights into how it impacts fleet allocation and cost minimisation. In the low criticality case, the

model focuses on maximising RUL usage to minimise costs, as it has lower corrective maintenance costs and a higher tolerance for risk. As a result, uncertainty has a lesser impact. Conversely, when there is high criticality, due to the high risk aversion resulting from the high impact of failure. Finally, medium critical components present an intermediate case that balances workload and PdM performance in a more flexible way.

The results of running the model with LB, HB, mode, and the 200 samples in Figure 5 for the first Weibull parameters. It is worth noting the concentration of data points around the mode cost, and the low dispersion between them. In this case, the confidence intervals for the cost are:

95 % Confidence cost interval: (16119.693995350597, 16432.975258380742)

99 % Confidence cost interval: (16011.029627097716, 16541.639626633627)

As it can be seen in the confidence intervals, there is a narrow range of cost dispersion that can be expected from the model if it is run with the distributions on Weibull parameters set 1 (Table 4.4), meaning a variation of approximately 500 economic units over 1600 units of cost (99%) in a month.

In comparison, the distributions with wider spread values (Table 4) generate significantly different results (Figure 6) as the dispersion of values and the probability of failure from early stages increases.

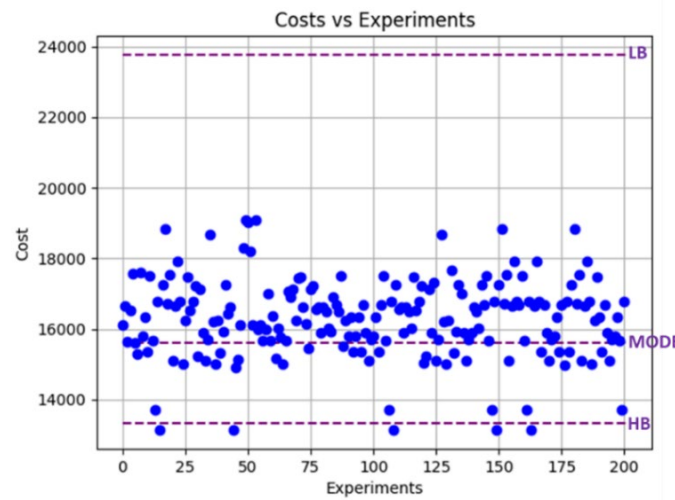


Figure 5: Cost results of the model for two hundred samples with three reference values for Weibull parameters 1

Cost values are distributed in Figure 6 within a larger spectrum and with less density than in Figure 5. The results can reach more extreme cost values as the sampled RUL are disparate in multiple sampling cases. The confidence intervals for the expected cost are:

95 % Confidence cost interval: (15717.1505, 16727.0531)

99 % Confidence cost interval: (15207.3759, 17236.8276)

The difference in cost between the limits of the 99% confidence interval yields 2000 economic units for 30 days. The variation represents around 13% of the cost, and a difference of 1500 economic units with the previous case, caused by distributions with wider spread values.

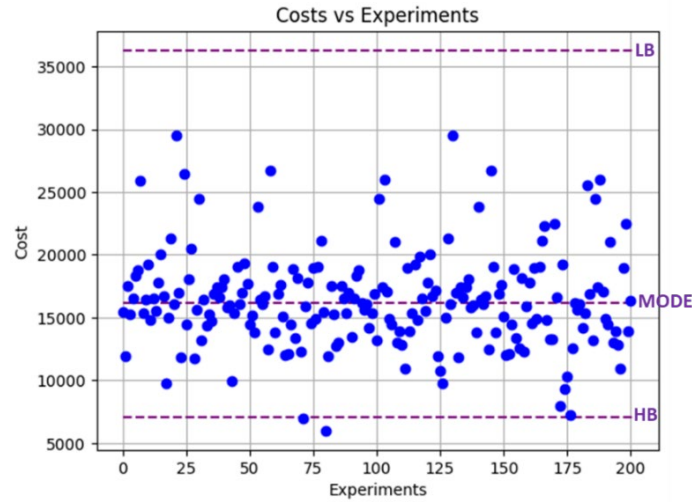


Figure 6: Cost results of the model for two hundred samples with three reference values for Weibull parameters 2

When considering this case of 10 assets over a 30-day period, the difference in cost is significant. However, this impact will be amplified when applied to a larger number of components and a longer planning horizon. Industrial companies today have access to vast amounts of data, but this often results in inaccurate predictions and a high degree of variability in experiment intervals. Such variability can lead to unreliable information that complicates decision-making. The range of expected cost variation implies a level of risk that may be unacceptable or not worthwhile for companies. Once the necessary technologies are in place and data is being collected, the model presented can be used to analyse the variability of possible costs. This analysis could help companies decide whether to manage their fleets dynamically by combining predictive and preventive maintenance or to invest in improving RUL precision.

7 Conclusions and further work

The optimisation model introduced in this paper provides a solution to effectively manage fleets by integrating predictive and preventive maintenance, as well as fleet workload balance. Furthermore, the proposed approach presents an evaluation of maintenance costs deconstructing PdM costs as in the most advanced models in the literature and integrating the results with penalisation when a fleet does not meet the demand. In addition, the proposed solution differentiates between the criticality of the components managed using predictive maintenance and provides the most accurate solution depending on the impact of the component failure on the business. Finally, to highlight the importance of prognostics quality and current data limitations, the paper proposes a sensitivity analysis of expected minimal cost depending on the RUL input. It can be of significant help to decision makers in deciding when to start integrating predictive models into maintenance management, depending on their accuracy and the variability on cost that trusting these technologies can imply for a company.

This research also demonstrates the importance of the preparation work required by industrial companies before changing their fleet management into a dynamic and data driven paradigm. Studying the criticality and hierarchisation of their assets, systems, and components is essential to manage them predictively. The impact of failure on operation, safety, and business radically changes depending on the criticality, the costs of performing maintenance activities, and the value of the lost RUL. If predictive maintenance is managed without these considerations, risk is not being carefully considered; hence, the strategy is not representing realistic costs. These conclusions are extendable to the technology adoption and prognosis of life associated with anomaly detection. Companies need to ensure the quality and quantity of data collected when making decisions that rely on it. In the results section, it can be observed that inaccurate distributions representing RUL led to wider confidence intervals in cost, which in extreme cases means wide cost variations. Besides, it must be

also highlighted the model flexibility to adapt to different sectors and industries by tuning the degradation and preventive maintenance inputs, as well as the operation that could be conditioned or obliged certain days.

Regarding future research, it would be particularly interesting to apply the model to a fleet considering multiple components monitored in each asset. This would save wider maintenance costs and maximise stoppage time usage. Another direction for future work could be to evaluate fleets combining the criticalities of monitored components, to see the variation of fleet allocation and costs, and to analyse the insights of a real case. Finally, it would add value to conduct a deeper uncertainty analysis of the prognosis and propagation of these uncertainties and their impact on cost.

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