Evaluating Investment in Condition Monitoring for Fleet Maintenance

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Abstract: This paper presents an analysis on the value of condition monitoring considering the uncertainties inherent in RUL (Remaining Useful Life) prognosis, the risks entailed by prognostic inaccuracies, and the essential investment prerequisites associated to the implementation of modern digital maintenance approaches. In particularly, we explore this in the context of fleet maintenance using an optimisation model that integrates predictive maintenance with existing preventive maintenance and operational schedules workload balance dynamically. The model presents a novel approach, combining the aforementioned dimensions with a holistic approach, that corresponds to an unsolved gap in literature. The primary objectives of the model application are to ascertain the conditions under which introducing predictive maintenance methodologies generates value, and to identify the junctures where the investment necessary for model implementation becomes economically justifiable. Furthermore, the paper will discuss the long-term benefits that materialise over an extended time horizon. The analysis shows how different levels of RUL prognosis uncertainty affect the fleet allocation to maintenance and operation, and the cost savings that reducing uncertainty means for fleet management. The costs are calculated executing the model in two exemplar cases using Python and Gurobi solver. Based on the savings comparing two uncertainty cases for RUL, companies can estimate the required time to amortise their investment in condition monitoring.

***Keywords*:** Dynamic fleet maintenance, Predictive Maintenance, Condition monitoring investment, Digital Transformation, Asset Management.

1. INTRODUCTION

This paper presents an analysis of the circumstances in which fleet management approaches that include predictive maintenance (Crespo del Castillo et al., 2023; Crespo Márquez et al., 2023; de Pater et al., 2022; Mitici et al., 2023) improve previous maintenance solutions, with an emphasis on the inputs for a predictive maintenance optimisation model. The transition from traditional condition-based to predictive maintenance strategies often entails the requirement for supplementary investments (Rasmekomen & Parlikad, 2016; Zhang et al., 2023). In most cases, the cost savings may not be sufficient to justify the adoption of predictive maintenance solutions (Stern et al., 2017). This is primarily due to the fact that predictive maintenance typically involves monitoring not only the condition of the components but also the condition of various influencing factors (such as weather conditions, asset utilization conditions, asset load, etc.). Consequently, there is a need to identify, and often install, as well as manage, additional data sources that enable the development of advanced predictive models. This paper aims to address this issue by providing an approach to evaluate when it is worth for companies undertaking investments in condition monitoring based on the expected benefits generated from it.

2. UNCERTAINTY IMPLICATIONS FOR DYNAMIC FLEET MAINTENANCE

The utilisation of failure prognosis aims to alleviate the uncertainties inherent in the process by enhancing our comprehension of the stochastic characteristics of failure. However, it is important to acknowledge that the method of prognosis and the underlying data itself introduce their own inherent uncertainties. In reliability engineering, uncertainty refers to the lack of complete knowledge or information about the future behaviour or condition of a system or component (Moubray, 1999). It represents a state where the outcome or result of a particular event or process cannot be precisely determined. Uncertainty can arise due to various factors, including incomplete data, limited understanding of failure mechanisms, variability in operating conditions, and the complexity of the system itself (Jain et al., 2021; Negri et al., 2021). Due to the high uncertainty of some processes and the lack of data, risk-averse maintenance managers implement shorter preventive maintenance intervals that lead to over-maintaining and higher maintenance expenditure (De Rocquingny et al., 2008).

The objective of predictive and condition-based maintenance approaches is to mitigate uncertainty through enhanced knowledge of system behaviour facilitated by data. De Jonge et al. (2015) show that reducing uncertainty does influence the optimal maintenance age and also provides quantifiable cost benefit, when based on data and prognosis algorithms. However, considering that the cost of ignoring the uncertainty is highest in situations where failures are costly (de Jonge & Scarf, 2020), the added value of these algorithms can only be assessed by considering their impact on maintenance decision process (Tseremoglou et al., 2022). Translating and identifying the impact of probabilistic outcomes generated by prognostic models across various systems in a fleet can pose a significant challenge for human decision-makers based on the uncertainty of the prognosis (De Jonge et al., 2015; Tseremoglou et al., 2022; Zhuang et al., 2023). An error in prognosis, when pertaining to an individual asset, may result in the need for corrective maintenance. However, when scaled up to the fleet level, such errors can have more far-reaching consequences (due to dependencies), including critical disruptions to fleet operations and potential penalties, in addition to the costs associated with the corrective maintenance itself (Crespo del Castillo et al., 2023).

Current advances in fleet maintenance management integrate predictive maintenance approaches including RUL prognostics with preventive maintenance (Bougacha et al., 2020; de Pater & Mitici, 2021; 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 model presented in the paper, combines both, measuring the holistic result in terms of cost.

The paper is organised as follows. In section 3 the optimisation model for managing fleet maintenance and operations dynamically is presented. Section 4 applies the model in an analysis that entails two different scenarios of RUL prognosis uncertainty. Section 5 presents the results discussion and section 6 the conclusions.

3. DYNAMIC FLET MAINTENANCE OPTIMISATION MODEL

This section summarises a model based on (Crespo del Castillo et al., 2023) to optimise fleet maintenance management dynamically based on the RUL prognosis (predictive maintenance), preventive maintenance limitations, operation constraints, and balancing the workload allocation to minimise fleet operating costs.
The location of asset $j \dots F$ to operations on a day $h \dots H$ is characterized by the binary matrix **X** ($x_{j,k}$). The allocation of assets to predictive maintenance is represented by the binary matrix **Y** ($y_{j,k}$).

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

The objective function is a minimisation of the total maintenance costs (Equation 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). 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 9). The cost of corrective maintenance (C_{CM}) (Equation6) is the cost of a failure (C_{Cl}) times the probability of failure P_f (Equation 10). The cost of lost RUL (C_{LR}) (Equation 4) is calculated as the cost of lost RUL usage multiplied by the days of life usage lost (Equation 8). Equation 11 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). The cost of lost operation (C_{op}) (Equation 5) is a cost penalisation defined when there are not sufficient assets available for operation to satisfy the client demand (Petchrompo et al., 2020) (Equation 5).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 9).

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

$$C_{PM} = C_{FI} \times N_{FI} \tag{2}$$

$$C_{PdM} = C_{FPdM} \times N_{PD} \tag{3}$$

$$C_{LR} = C_{LU} \times N_{LR} \tag{4}$$

$$C_{op} = C_A \times N_{op} \tag{5}$$

$$C_{CM} = P_f \times C_{CI} \tag{6}$$

$$N_{PD} = \sum_{j=1}^{m} \sum_{k=1}^{K} (y_{j,k} - y_{j,k-1}) \tag{7}$$

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

$$N_{op} = \left(Av_k - \sum_{j=1}^{m} x_{j,k} \right) \quad \forall \, k \tag{9}$$

$$P_f = \boldsymbol{f} \left(\sum_{k=1}^{K} \delta_j \, x_{j,k} \, (1 - y_{j,k}) \right) \tag{10}$$

In Equation 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.
Assigning an asset to operation has an impact on its degradation. In this model, the degradation per day of the planning horizon is assumed to be a constant δ. 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 assetduring 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 $\left(\left(\sum_{k=1}^{K} \delta \, x_{j,k} \, (1 - y_{j,k})\right)\right)$ (Equation 8). 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).

The 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. It is also present in Equation 15 ensuring that the asset cannot be in maintenance and operation at the same time.
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 asset 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.

$$\sum_{j=1}^{m} x_{j,k} \leq Av_k \qquad \forall\, k \tag{11}$$

$$y_{j,k} - y_{j,k-1} \leq 1 - x_{j,k} \qquad \forall\, k\, \forall\, j \tag{12}$$

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

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

$$y_{j,k} \geq y_{j,k-1} \qquad \forall\, k\, \forall\, j \tag{15}$$

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

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

4. SCENARIOS FOR COMPARISON

Regarding fleet maintenance, depending on the level of technological investment and maturity, different levels of information are available to define the remaining useful life of a component before functional failure. If a company has not invested in condition monitoring, it will result in a wider uncertainty in RUL estimation as the uncertainty inherent to the stochastic process is only informed by historical data of failure and replacement. The inherent uncertainty of the fleet management process is considered, considering the stochastic nature of failure when managing the fleet with preventive and corrective maintenance. This uncertainty affects the allocation of assets within the fleet, determining their state as either in operation, idle, or under preventive maintenance. Additionally, the impact of failure, along with the associated risk, influences decision-making processes. In some cases, there may be a tendency towards over-maintenance as a precautionary measure to ensure safety, and there will be more corrective maintenance due to the lack of data.

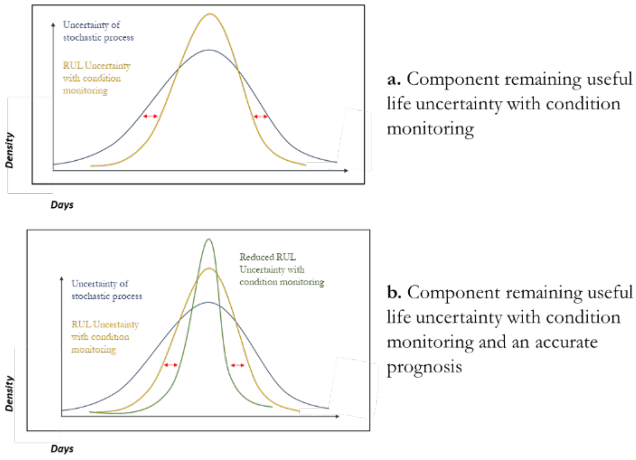

Figure 1: Possible prognosis uncertainty scenarios for implementing fleet maintenance models.

Condition monitoring devices allow the introduction of near-real-time data into the decision-making process, allowing to generate prognosis of life resulting in a RUL estimation with less uncertainty. The first scenario as shown in Figure 1(a) represents the case of any company that has made a certain investment on PHM and gained the capability of detecting anomalies and prognosing failure. The uncertainty is supposed to be reduced from the decision making process. This reduction in uncertainty can lead to a more reliable fleet management approach, where decisions are based on a better understanding of failures and more accurate allocation of fleet resources. As technologies improve and become more mature, the quality and quantity of data will allow to generate improved RUL prognosis with less uncertainty, constituting a continuous process of improvement. The second scenario shown in Figure 1(b) illustrates the same company that already utilizes certain RUL prognostics but makes an investment in PHM technologies to enhance and improve the quality of prognostics.
The following analysis evaluates the transitions between two scenarios and aims to assess the benefits and drawbacks associated with these transitions, including the potential impact on cost reduction, operational efficiency, and overall fleet management performance. In the case of the paper we illustrate the transition between scenarios (a) and (b) presented in Figure 1.

Current scenario analysis: The first step is the evaluation of the current state (Figure 2 Scenario (a)). The aim of the analysis is to calculate the costs of fleet operation for a certain planning horizon. This is done running the model presented in section 3. The model is run with the mode of the RUL of the distributions representing the prognosis (in this case, a Weibull distribution with parameters shown in Figure 2 Scenario (a)).

Future scenario analysis: The model is run with the RUL prognosis with reduced uncertainty, generating the optimal allocation for the same period of time. This solution has an associated cost (expected to be smaller than the previous) and an investment to achieve the RUL quality improvement.
To illustrate the analysis we propose a transition from a scenario (a) (Table 1) to a scenario (b) (Table 1) RUL

distributions with the same mode but with higher accuracy in the second scenario. The notion of improvement in the prognostics refers to a reduction in the standard deviation of the distribution, resulting in decreased dispersion across the entire spectrum and a closer proximity to the mode (Gorjian Jolfaei et al., 2022; Li et al., 2018).The two scenarios are run using Weibull distributions with the same mode but different parameters of shape and scale (β, η), for the same anomalies detected in the assets as it can be seen in Table 1.

Table 1: RUL prognostics Weibull distributions

Scenario **a**	Weibull parameter **β**	Weibull parameter **η**	Scenario **b**	Weibull parameter **β**	Weibull parameter **η**
Asset 1	35	2	Asset 1	25	5
Asset 2	35	2	Asset 2	25	5
Asset 3	35	2	Asset 3	25	5
Asset 4	35	2	Asset 4	25	5
Asset 5	21	2	Asset 5	15	4
Asset 6	21	2	Asset 6	15	4
Asset 7	21	2	Asset 7	15	4
Asset 8	8	2	Asset 8	8	6
Asset 9	8	2	Asset 9	8	6
Asset 10	8	2	Asset 10	8	6

Decision evaluation: The last step of the analysis is the comparison of present and future state and quantifying the difference of fleet maintenance costs for the same planning horizon and preventive maintenance calendar. Furthermore, the change from one scenario to the other implies an investment that has to be considered. Then, from one scenario to another, the cost savings and fleet have to justify the investment made to either include predictive tools or improve them in fleet maintenance scheduling.

Once defined the two scenarios of RUL uncertainty, the rest of inputs that are constant for both scenarios are described following. The application of cost savings is conducted for the planning horizon of 30 days comparing the results of both objective functions. The fleet is composed by 10 assets and has to fulfil a demand of 8 assets available for operation (Av_k) every day. The opportunistic slots to perform predictive maintenance ($OP_{j,k}$) are a binary matrix presented in Figure 2 and represented as pink boxes in Figure 3 and 4, as assignments of the asset to preventive maintenance in the planning horizon.

$$
OP_k = \begin{pmatrix}
0&1&0&0&0&0&0&1&0&0&0&0&0&0&1&0&1&0&0&0&0&0&1&0&0&0&0&0&0&1\\
0&0&0&1&1&1&0&0&0&0&0&0&0&1&0&0&0&0&1&1&1&0&0&0&0&0&0&0&1&0\\
0&0&0&1&0&0&0&0&0&0&0&0&1&0&0&0&0&0&1&0&0&0&0&0&0&0&0&1&0&0\\
1&0&0&0&0&0&1&0&0&0&0&0&0&0&1&1&0&0&0&0&0&1&0&0&0&0&0&0&0&1\\
0&0&1&0&0&0&0&0&0&0&0&1&0&0&0&0&0&1&0&0&0&0&0&0&0&0&1&0&0&0\\
0&0&0&0&0&0&0&0&0&1&1&0&0&0&0&0&0&0&0&0&0&0&0&0&1&1&0&0&0&0\\
0&0&1&0&0&0&0&0&0&0&0&0&0&1&0&0&0&1&0&0&0&0&0&0&0&0&0&0&1&0\\
1&0&0&0&0&0&0&0&1&0&0&0&0&0&0&1&0&0&0&0&0&0&0&1&0&0&0&0&0&0\\
0&1&0&0&0&0&0&0&0&0&0&1&0&0&0&0&1&0&0&0&0&0&0&0&0&0&1&0&0&0\\
0&0&0&0&1&0&0&0&0&0&0&0&1&0&0&0&0&0&0&1&0&0&0&0&0&0&0&1&0&0
\end{pmatrix}
$$

Assets (F)

Days (H)

Figure 2: Preventive maintenance schedule thar represents opportunities for performing PdM

The objective function (Equation 1) has cost parameters that are inputs for the model. These costs are presented in Table 2 and remain stable for both scenarios.

Figure 4: Cost input magnitudes for the model run in monetary units

$\boldsymbol{C_{CI}}$	7000
$\boldsymbol{C_{RU}}$	100
$\boldsymbol{C_{PdM}}$	250
$\boldsymbol{C_{A}}$	2000

Finally RUL_j represents the RUL mode used to calculate the days lost of RUL usage. Is the same for both cases: RUL_j = [24, 24, 24, 24, 14, 14, 14, 7, 7, 7]

5. EXPERIMENTAL RESULTS

The allocation of the fleet is a result of the model run with the aforementioned inputs and the varying RUL distributions input presented in Table 1 and Table 2. The blue boxes represent the asset allocation to operation, the pink ones the schedules preventive maintenance ($OP_{j,k}$), yellow ones PdM carried out in a preventive maintenance opportunity ($OP_{j,k}$), and the white boxes represent the idle state that means that the asset has neither maintenance or operation allocation.

The optimisation results for scenario (a) are presented in Figure 3 and Figure 4 for scenario (b). The cost of the solution for scenario (a) is 13394 monetary units.

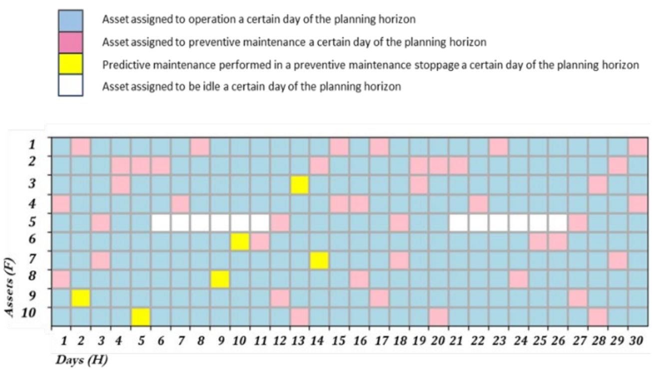

Figure 3: Scenario (***a***) fleet allocation

In the case of scenario b (Figure 6), the risk of failure is smaller when the values are not proximal to the mode, meaning PdM is scheduled later in the planning horizon or even not performed. The cost is also smaller at 8115 monetary units. When the prognosis is less accurate, there is a higher probability of failure, amplifying the corrective maintenance cost from early stages of the planning horizon. This is due to the fact that the probability of failure of scenario (a) Weibull is higher from earlier, and it is multiplying the cost of failure (C_{Cl}) (Equation 6). Consequently, to minimise cost, the asset must be maintained earlier in the current state than in the future state to achieve a comparable cost. An example is the comparison of Asset 9 PdM scheduling that is performed in day 2 in scenario (a) (Figure 3) and in day 12 in scenario (b) (Figure 4). It can also be seen that Asset 3 undergoes PdM the 13th day in scenario (a) whereas in scenario (b) due to the reduced risk and workload balance, it does not undergo PdM. Additionally, this implies that due to the earlier PdM scheduling in scenario (a), the solution is generating higher lost RUL costs. Looking at Asset 9 again, in Figure 3 we can observe that it only consumes 1 day of RUL and in Figure 4 it consumes 5 days RUL compared to the expected 7 in the mode RUL_j.

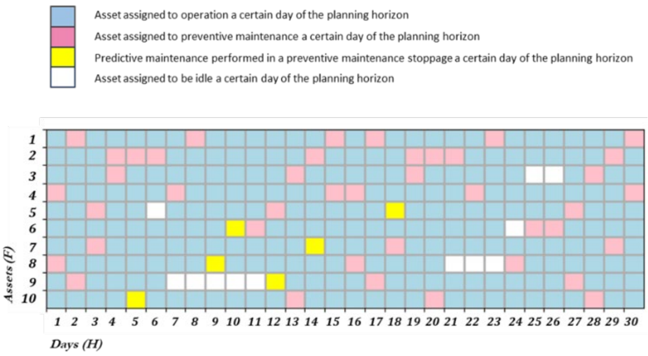

Figure 4: Scenario ***(b)*** (improved Weibull accuracy) fleet allocation

From this analysis, we can infer that prognostics with higher uncertainties imply higher costs as the risk of failure is higher and the interventions are doing earlier causing also higher lost RUL usage. It could also be deduced that, when there is a high level of trust in prognostic models and their predictions, organisations may depend on these forecasts to make decisions about when to perform maintenance or replace components, assuming a reduction in uncertainty. However, if the assumed accuracy of the prognostic models is not realised, errors in predictions can result in suboptimal maintenance practices, increased downtime, and potentially higher costs. Hence, quantifying the uncertainty of prognostics is critical as it provides a measure of the risk, and reducing the uncertainty implies reducing the risk until the values of the RUL distribution are close to the mode.

As previously stated, the cost of the solution presented in scenario (a) (Figure 3) is 13394 monetary units, and the cost of the solution for scenario (b) (Figure 4) is 8115 monetary units. This is a difference of 5279 monetary units, that represent the savings from case (a) to case (b) due to the improvements in prognosis accuracy.

If we could repeat the experiments with a longer preventive maintenance calendar, and simulating an average number of PdM detections that we have every month, we could repeat this comparison for a wider number of months, generating an estimated time that it would take to amortise the investment. It could also be done using the historical preventive maintenance schedules and detections of PdM, comparing how the improved RUL would have performed in the previous months and calculating the accumulated savings. That would also provide an estimation of the time required to return the investment based only in maintenance costs savings. If the required investment and the estimated quality of the prognosis are known, then the time needed to achieve a positive ROI (Return on Investment) can be evaluated to make an informed decision on whether to invest or not. In certain instances, the technology may not have reached a sufficient level of maturity, and its implementation could entail substantial costs. Alternatively, the cost savings may not be deemed substantial enough, considering a particular level of prognostic quality attained. On the other hand, the company could define a certain time frame that is acceptable to generate a positive ROI for condition monitoring or set a limiting budget for investment. Using these metrics, the model can be executed with various levels of prognostic quality to establish the corresponding required prognosis quality and yearly cost savings. This process aids in assessing the realism of these perspectives and can assist in making informed choices among condition monitoring devices and algorithm providers who offer services under specific conditions.

6. CONCLUSIONS

Due to the importance of the RUL prognostic inputs for this model and most of fleet predictive maintenance decision-making models in literature, this paper analyses the impact on the solution of the optimisation. It can be appreciated that the investment in condition monitoring is simplified as an input, however, the quantification of this investment is a complex task. When a company undergoes a transition by incorporating additional monitoring to the existing or enhancing the existing prognosis through algorithms or devices, the analysis is relatively straightforward since the majority of the technological infrastructure is already in place. However, the evaluation is more complex when the different between scenarios involves the shift to the digital paradigm. By the correct quantification of the investment and the expected return times, companies could use the proposed approach to evaluate the feasibility of their expectations. Further work will be analysing the investment required to improve the precision of the RUL and evaluate the time that it would take for the company to amortise this investment in PHM technologies.

The ultimate objective of the paper is unveiling the circumstances in which the application of these type of maintenance models outrun other approaches, and when is worth to apply them based on the nature of their inputs. In order to answer these questions the paper presents an analysis method to evaluate different scenarios of RUL inputs and quantify when is beneficial for companies to undertake a certain investment in PHM technologies. From a theoretical perspective, the novel optimisation model provides a RUL precision dependent solution, that illustrates the difference between costs. So on, the cost magnitudes could be variated and fixed to any value that represents the fleet environment under study. Based on these inputs, the model could be used to evaluate when these fleet management approach generates value for the business depending on the inputs. Further work will be a sensitivity analysis of the model results distribution depending on deeper input values variation.

Incorporating predictive maintenance models into the decision-making process is a vital component of digitalisation efforts when it comes to fleet maintenance in industrial practice. By incorporating these models with the adequate input, businesses can move closer to achieving the goal of digitalisation, which is to optimize asset management and create a more streamlined and effective system.

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