# From Prediction to Prescription: A Framework for Prescriptive Maintenance

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**ABSTRACT**

Industries need a maintenance strategy that not only predicts failure but also optimises machine operating conditions to maximise the lifespan. This work addresses this by introducing a new prescriptive maintenance strategy. This framework provides actionable recommendations to optimise the machine's useful lifespan. It uses an ensemble of bagged decision trees for a predictive model. Next, diverse new mathematical functions are derived to construct an array of operational settings that realistically account for all possible operational profiles. Using an array, the model can predict a machine's remaining life. Finally, it prescribes operating conditions that maximise machine lifespan, providing decision-makers with guidance for maintenance.

**KEYWORDS:** Predictive Maintenance; Prescriptive Maintenance; Optimisation.

## 1. INTRODUCTION

Existing Prescriptive Maintenance (PxM) solutions, while effective at predicting the Remaining Useful Life (RUL) of a machine, are limited because they don't dynamically optimise machine parameters. Moreover, these do not provide actionable recommendations to support operational decision-making [1, 2]. Current methods focus on failure prediction but do not consider how alternative operating profiles would affect the machine's future life [3, 4]. Hence, there is a gap in recommending the ideal operational conditions for a machine at any given level of degradation [5]. Accordingly, for the first time, we propose a novel PxM framework that combines machine learning, simulations, and optimisation with prescriptive recommendation capabilities. The framework predicts machine degradation and identifies the operating conditions that maximise the machine's RUL, enabling proactive operational decision making. Additionally, it is designed to be flexible, enabling applications across industries using the same underlying methodology. First, a new Predictive Maintenance (PdM) model is built as an ensemble of bagged decision trees that maps the relationship between operating condition and machine degradation. Next, to analyse all feasible permutations of a machine's operational profiles, an array of operational settings is constructed. A case-specific rulebook with dedicated rules for each machine's operating environment is applied to ensure the array contains only realistic, operationally feasible profiles. The resulting operational profiles are then evaluated using the PdM model to simulate the RUL for each scenario. The framework optimises and prescribes the operating conditions that maximise the machine's RUL.

## 2. METHODOLOGY

Figure 1 illustrates the proposed PxM framework. The PdM model used to estimate the RUL is developed using NASA's turbofan engine degradation dataset [6]. The dataset comprises measurements from 218 engines, including three operational settings recorded throughout their degradation. An ensemble of bagged decision trees is trained on subsets of the dataset to learn the relationships among operational conditions and engine degradation, enabling RUL prediction at any stage of an engine's life cycle. Bagging is chosen here because it learns a robust nonlinear relationship between operating conditions and RUL. While the dataset provides sufficient differentiated data fields, the operational settings for engines are interrelated and do not reflect the independent nature of industrial datasets on tool use, machine productivity, etc.

### *2.1. Operational Settings Array Construction*

Mathematical functions are derived from the multivariate historical database. Herein, to predict RUL across all possible operational settings, a multi-dimensional array is constructed based on the step size for each setting. For each operational setting, the difference between the maximum and minimum value is divided by the smallest increment size. Then the array is filled by varying each operational setting individually to obtain all evaluation scenarios of machine processing; i.e., redundant possibilities determined by the domain case's rulebook are removed. This rulebook is flexible and can be adapted for any industrial applications. For instance, if the altitude operational setting on the engine as 'X' would mean the actual altitude as 0, it renders all the multi-array elements containing combinations with that operational setting as 'X' redundant, as the engine running at ground is usually

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a meaningless operation. These redundant combinations of operational settings are identified and removed by the case-specific rulebook.

*2.2 RUL Optimisation:*

To generate recommended settings to maximise remaining useful life for a given machine, the machine's current age is used as the final parameter in all possible combinations of settings within the operational settings array. The array is then applied to the PdM function to generate a simulated operational environment, with each entry associated with an RUL value. The PxM model prescribes the combination of operational conditions that prescribes the highest RUL.

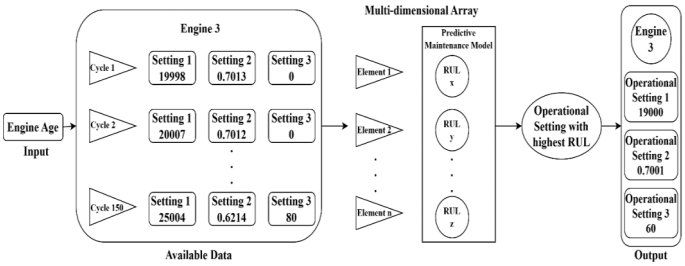



**Figure 1.** Proposed prescriptive maintenance framework.

## 3. RESULTS AND DISCUSSION

The predictive performance of the PdM model is evaluated using the Mean Arctangent Absolute Percentage Error (MAAPE), Root Mean Square Error (RMSE) and computation time. Applying the PdM model across 18 test units yields a MAPPE of 25%. The RMSE of the ensemble of bagged decision trees yields (0.09063) better results than alternatives such as Gaussian Process Regression (0.0915) and Neural Networks (0.0915), at a fraction of the computational time (6 times less than Neural Networks). The functionality of the PxM model is demonstrated using engine 211, which has the median overall life of the 18 engines analysed, making it the best representative of the group. Using the prescribed settings increased the engine's remaining useful life by 8% (after 170 cycles) compared to the original settings. While the RUL improvements from the PxM remain in the low single digits for the first two quartiles, from the third quartile onward, the value addition becomes notable. By the fourth quartile, a 16% improvement is observed, resulting in significantly longer lifespans. These results demonstrate the applicability of the proposed framework.

## 4. CONCLUSION

This study develops a novel PxM framework that enables maintenance managers to determine the optimal operating condition to maximise RUL. The main contributions are: a PdM model constructed from a collection of bagged decision trees, and a scalable technique for developing operating environments that uses a domain-specific screening process to discard infeasible operating profiles. Simulations of all possible working conditions are used to recommend those that maximise RUL. To sum up, this delivers actionable recommendations, enables comparison across different operating scenarios, and provides a generalisable approach that can be easily deployed at an industrial scale.

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