A Machine Learning Approach for Spare Parts Lifetime Estimation

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Abstract: Under the Industry 4.0 concept, there is increased usage of data-driven analytics to enhance the production process. In particular, equipment maintenance is a key industrial area that can benefit from using Machine Learning (ML) models. In this paper, we propose a novel Remaining Useful Life (RUL) ML-based spare part prediction that considers maintenance historical records, which are commonly available in several industries and thus more easy to collect when compared with specific equipment measurement data. As a case study, we consider 18,355 RUL records from an automotive multimedia assembly company, where each RUL value is defined as the full amount of units produced within two consecutive corrective maintenance actions. Under regression modeling, two categorical input transforms and eight ML algorithms were explored by considering a realistic rolling window evaluation. The best prediction model, which adopts an Inverse Document Frequency (IDF) data transformation and the Random Forest (RF) algorithm, produced high-quality RUL prediction results under a reasonable computational effort. Moreover, we have executed an eXplainable Artificial Intelligence (XAI) approach, based on the SHapley Additive exPlanations (SHAP) method, over the selected RF model, showing its potential value to extract useful explanatory knowledge for the maintenance domain.

1 INTRODUCTION

Maintenance is a key area within the Industry 4.0 concept. Indeed, equipment maintenance can have a significant impact on the uptime and efficiency of the entire production system (Lee et al., 2019). It is estimated that between 15% and 40% of total production costs are attributed to maintenance. Thus, a good maintenance policy is essential to ensure the efficiency of the industrial system and increase the reliability of equipment (Wang, 2012). Following the fourth industrial revolution, there is an increase in data availability, which leads to opportunities for changing the maintenance paradigm (Susto et al., 2012). The integration between the physical and digital systems of production environments allows more significant volumes of data collection, from different equipments and sections of the plant, enabling a faster exchange of information (Rauch et al., 2020; Borgi et al., 2017). Through analytical approaches, the collected data can potentially provide valuable insights into the industrial process, improving decision making, which can result in a reduction of maintenance costs and machine failures and an increase of the useful life of spare parts (Carvalho et al., 2019).

Several maintenance approaches and strategies have emerged, which can be grouped into three main categories (Susto et al., 2012; Susto et al., 2015):

- *Run-to-Failure* (R2F) or *Corrective Maintenance* which occurs whenever a piece of equipment stops working. It is the simplest maintenance strategy since it is executed as soon as an equipment failure is detected. This approach contributes to higher maintenance costs, given the immediate requirement of labor and parts to repair.
- *Preventive Maintenance* (PvM), *Time-based Maintenance* or *Scheduled Maintenance*, is a type of maintenance that is performed periodically, with a planned schedule, in order to anticipate equipment failures.

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- *Predictive Maintenance* (PdM) is a more recent type of maintenance, which emerged with the modernization of industrial processes and integration of sensors in equipment/production lines. It uses predictive tools (data-driven) to continuously monitor a piece of equipment or process, evaluating and calculating when maintenance is required. It also allows an early detection of failures by typically implementing Machine Learning (ML) algorithms based on historical equipment data.

Most industries opt for a hybrid system that includes a corrective (R2F) and preventive (PvM) maintenance, where the former strategy being executed when a failure is detected and there is no preventive maintenance scheduling. However, these two types of strategies raise have drawbacks. Industries that adopt a R2F maintenance often delay maintenance actions, assuming the risk of unavailability of their assets. As for the PvM maintenance, it might lead to the replacement of spare parts that are far from reaching their end of life (Carvalho et al., 2019). An alternative is to adopt a predictive maintenance (PdM), which can potentially detect a failure before it occurs. Yet, PdM is not a viable option for many industries, since it often requires the implementation of the particular information systems infrastructure, expertise, and customized intelligent software (Jardine et al., 2006).

Within this context, the Remaining Useful Life (RUL) emerges as valuable indicator, typically coupled with predictive maintenance systems, to predict equipment failures. More precisely, RUL estimates the total time (e.g., in days, months or years) that a component is capable of performing its function before justifying its replacement, implying an economic aspect dependent on the context and its operational characteristics (Kang et al., 2021; Okoh et al., 2014).

There are two main approaches for RUL prediction: model-based and data-driven methods (Wang et al., 2020). The model-based relies on statistical estimation techniques to model the degradation process of machines and predict the RUL. On the other hand, data-driven approaches are more accurate since it uses sensor data directly from the equipments and then ML to learn its degradation process, instead of relying on theoretical knowledge about the failure process.(Wang et al., 2020; Li et al., 2020).

RUL equipment/component data-driven prediction remains a key challenge in predictive maintenance, since it requires a data set that covers the entire period from machine operation to failure, which is relatively difficult to acquire and, due to business issues, companies are often reluctant to open their data to the public (Fan et al., 2015). Indeed, most data-driven RUL prediction studies work with private industry data, under different ML algorithm approaches. For instance, (Wu et al., 2017) developed a Random Forest based prognostic methods to predict the tool wear in milling operations. More recently, (Cheng et al., 2020) proposed a data-driven framework for bearing RUL prediction that uses a Deep Convolution Neural Network (CNN) to discover a pattern between the calculated indicator and the bearing vibration signals. Using the predicted degradation energy indicator, a Support Vector Regressor was implemented to predict the RUL of the testing bearings.

Most of the data-driven RUL studies use equipment measurements (e.g., image, temperature levels, equipment functioning time) as the inputs of a ML RUL prediction model (Kang et al., 2021; Okoh et al., 2014). In this paper, we propose a rather different RUL ML prediction approach, in which the lifetime of spare parts is predicted based on corrective maintenance historical records (which are more easy to collect). In particular, we measure the lifetime in terms of the full amount of units produced within two consecutive corrective maintenance actions. As a case study, we consider a recent dataset that includes 18,355 records with RUL measurements that were extracted from an automotive multimedia assembly company. Assuming a regression task modeling, we explore and compare eight distinct ML algorithms, namely Decision Tree (DT), Random Forest (RF), Extra Trees (ET), XGBoost (XB), Light Gradient Boost Machine (LGBM), Histogram-based Gradient Regression Tree (HGBM), a Gaussian kernel Support Vector Machine (SVM) and Linear Support Vector Machine (LSVM). Two categorical preprocessing techniques were employed to handle inputs with a high cardinality of distinct levels: Percentage Categorical Pruned (PCP) and Inverse Document Frequency (IDF). Moreover, the performance of the ML predictive models was evaluated by assuming a realistic Rolling Window scheme, which simulates several training and testing executions through time. Finally, the best RUL prediction model is further analyzed in terms of its extracted knowledge by adopting an eXplainable Artificial Intelligence (XAI) approach (Sahakyan et al., 2021), namely by using SHapley Additive exPlanations (SHAP) (Lundberg and Lee, 2017b), which allows to measure the impact of the adopted industrial inputs in the RUL predictions.

The paper is structured as follows. Section 2 describes the industrial maintenance data, the proposed Machine Learning (ML) approaches and the evaluation methodology. Then, Section 3 presents the obtained results. Lastly, the main conclusions are discussed in Section 4.

2 MATERIALS AND METHODS

2.1 Industrial Data

For this task, 118,776 records of maintenance orders were collected alongside spare parts movements performed at a major automotive multimedia assembly company between April 2004 and May 2021. The data consists of a compilation of maintenance orders for spare parts replacement within the equipment. Furthermore, it was possible to register the type of maintenance for each equipment machine, the technician who performed it, and the part replaced. The exact order can also be associated with several records, depending on the variety of parts used for the maintenance (e.g., maintenance that requires three different spare parts will be represented by three records, one for each part). The order can also be reopened whenever there is a new movement of the part. Moreover, there are six distinct types of movements associated with spare parts: stock entries in maze-supplier, returns of the parts to the supplier, stock out for a maintenance order, and return of the part from maintenance to maze. There are three types of maintenance orders: corrective, preventive and improvement (changes performed on the equipment to introduce improvements).

The data initially supplied did not present any indication regarding the duration of the part, so a strategy of comparing similar records, ordered in time, was adopted to estimate the total production for which a part, for a given equipment, can be subject to before failure. For research purposes, only the movements performed between the maze-maintenance were accounted for, focusing on the records that present outputs of parts for maintenance. The returns of material to the warehouse, on the part of maintenance, were used to make adjustments in the registers, since there were maintenance orders that ended up not replacing parts, and therefore returned in their entirety to the warehouse. Furthermore, an adjustment was made on the dataset to account only for the spare parts whose maintenance was a part replacement, meaning that there is no record of that specific part to return to the warehouse. In addition, we collected a new dataset, containing 4,488,689 daily records, of the number of parts each piece of equipment produced between 00:00h and 23:59h on a day. By comparing the dates of the two maintenance records for the same equipment, with the same spare part, it was possible to associate a quantity produced to that transaction, through the sum of the quantities produced between the period being compared. The following function presents the reasoning followed to calculate the target variable (y):

$$f(x) \cap g(x) = f(x+1) \cap g(x+1) \implies y = \sum_{i=t(x)}^{t(x+1)} Q(i), \tag{1}$$

where f denotes the equipment, g the spare part, t the date when the transaction was held, Q represents the production volume and y the spare part lifetime, in production units. A special attention was paid to specific maintenance orders for each record to ensure accuracy in the target calculation. Since the purpose is to estimate the total lifetime of a part, when comparing two transactions, if the second one corresponds to a preventive maintenance order, the assigned value is 0, and therefore removed from the dataset. As mentioned in Section 1, the preventive maintenance is scheduled, occurring within a specified time limit, regardless of whether or not there is a need for part replacement. Thus, we intended to capture the life of a machine part from the moment it is replaced within the equipment until it fails, thus being labeled as ”corrective maintenance”. Therefore, we only calculated the lifetime whenever the second transaction compared was corrective.

The final dataset contains 18,355 records, over seven distinct features. As shown in Table 1, all attributes are categorical, with the exception of part life. There are 1,189 unique types of equipment, in 73 subtypes, 37 types and three sections, and 3,418 unique spare parts, from 8 different suppliers, one of them being the category ”Not Available” which represents 94.6% of the data. The useful life of the spare part varies from 1 to 17,909,367, having an average value of 506,026.

Table 1: Adopted data attributes (input features)

Context	Attribute	Description
spare part	id	spare part id: 3418 categorical levels
	supplier	supplier code: 8 categorical levels
	technician	technician name : 1709 categorical levels
	lifetime	spare part lifetime: 12020 levels
equipment	id	equipment name: 1189 categorical levels
	type	equipment type: 37 categorical levels
	subtype	equipment subtype: 73 categorical levels
	section	equipment section: 3 categorical levels

2.2 Data Preprocessing

The data preprocessing involved the transformation of categorical values into numerical values. We compared two transformations that were specifically designed to handle large cardinally categorical inputs (which is our case): IDF (Matos et al., 2018) and PCP (Matos et al., 2019). The former transform converts each input into a single numeric value, using a mapping that puts the most frequent levels closer to zero are more distant to each other, while the less frequent levels appear on the right side of the scale (larger values) and closer to each other. The latter transform merges all infrequent levels (10%) into a single "Others" level and then employs the popular one-hot encoding that uses one boolean value per level. All techniques were implemented through the Python library `Cane` (Matos et al., 2020). The categorical encodings were calculated using only training data, storing the training transformation variables in dictionaries such that test data could be coded using the same mapping, ensuring uniformity across sets.

2.3 Regression Methods

We explore eight different ML methods, all with their default parameters (as encoded in the Python language): Decision Tree (DT), Random Forest (RF), Extra Trees (ET), XGBoost (XB), Light Gradient Boost Machine (LGBM), Histogram-Based Gradient Regression Tree (HGBM), Gaussian Support Vector Machine (SVM) and Linear Support Vector Machine (LSVM). The XB, RF, ET, LGBM and HGBM are all based on decision trees. All algorithms were implemented using the `sklearn` Python module, except for XG and LGBM, which were implemented using the `xgboost` and `lightgbm` Python libraries.

DT is one of the most common ML techniques and it assumes a a tree structure by mapping the result of a series of possible node decision choices (Shalev-Shwartz and Ben-David, 2014). One of its advantages is the simplicity with which these structures are built, promoting straightforward interpretation and understanding of their results. However, DT assumes a rather rigid knowledge representation that often results in a lower predictive performance for regression tasks. Thus, other tree-based algorithms, particularly based on ensembles, have been proposed, such as RF (Breiman, 2001). The algorithm was proposed in 2001 and works on a set of decision trees to find the most prominent observations and attributes in all trained trees, looking for the optimal split. Another tree-based ML algorithm is the ET (Geurts et al., 2006), which unlike RF randomly splits the parent node into two random child nodes. The ET creates several trees in a sequential fashion, making the training process slower since both do not support parallel computing. In a more recent approach, XGBoost, which stands for eXtreme Gradient Boosting (Chen and Guestrin, 2016), has emerged, which in addition to requiring less computational effort, is more flexible, allowing distributed computing to train large models, and solve problems in a faster and more accurate way. Another solution to increase the efficiency of DT ensembles is the use histograms as the input data structure. These structures group data into discrete compartments and use these to build feature histograms during training. Feature histograms represent the content of a dataset as a vector, counting the number of times each distinct value appears in the original set. LGBM (Ke et al., 2017) which, compared to the previous algorithms, does not grow at the tree level but chooses the leaf it trusts, can potentially produce a greater reduction in losses. Moreover, it integrates two different techniques called Gradient-Based One-Side Sampling and Exclusive Feature Bundling, thus ensuring faster model execution while preserving its accuracy. HGBM is a `sklearn` implementation inspired by LGBM.

A different ML base-learner is the SVM (Cristianini and Shawe-Taylor, 2000), which was initially proposed in 1992 to classify data points that are mapped into a multidimensional space by using a kernel function. Therefore, the data is represented in N-dimensional space, where N is the number of variables in the dataset. The SVM finds the optimal separation hyperplane, maximizing the smallest possible distance between a boundary space and the objects. In this work, we assume the SVM Regression (known as SVR) method under two kernel functions, linear (LSVM) and Gaussian (SVM). The LSVM is faster to train when compared with SVM but it only produces a linear data separation.

Concerning the XAI component of the project, we adopt the SHAP method (Lundberg and Lee, 2017a), which is based on Shapley (Shapiro and Shapley, 1978) values, an approach widely used in cooperative game theory, in which there is a fair distribution of gains between the different players who cooperated on a given task: more significant effort has a greater reward; less effort has a lesser reward. In an ML context, SHAP calculates for each feature its importance value for a given prediction. In this paper, we assume the SHAP implementation of the `Shapash`[1] Python module.

2.4 Evaluation

A robust Rolling Window (RW) (Tashman, 2000) scheme was adopted for the evaluation phase. As shown in Figure 1, the RW simulates the usage a ML algorithm over time, with several iterations, each with a training and a testing procedure. The RW is achieved by adopting a fixed training window of size W and then perfoming up to H ahead predictions. The window is "rolled " by discarding the oldest S records

[1] https://shapash.readthedocs.io/en/latest/

and adding the more recent S instances. Let D_{L} denote the total length of the available data, then the total number of RW iterations (or model updates, U) is given by:

$$U = \frac{D_{\mathrm{L}} - (W + H)}{S} \tag{2}$$

In this paper, and after consulting the maintenance company experts, we fixed the values $W = 8,000$, $T = 800$ and $S = 800$, which leads to a total of $U = 11$ RW iterations.

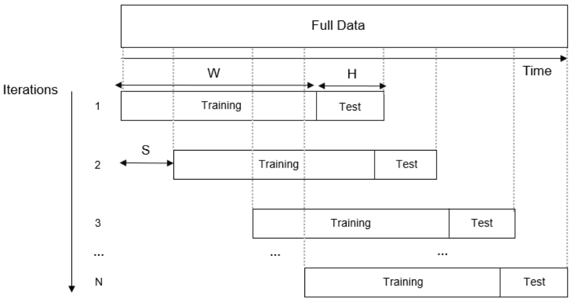


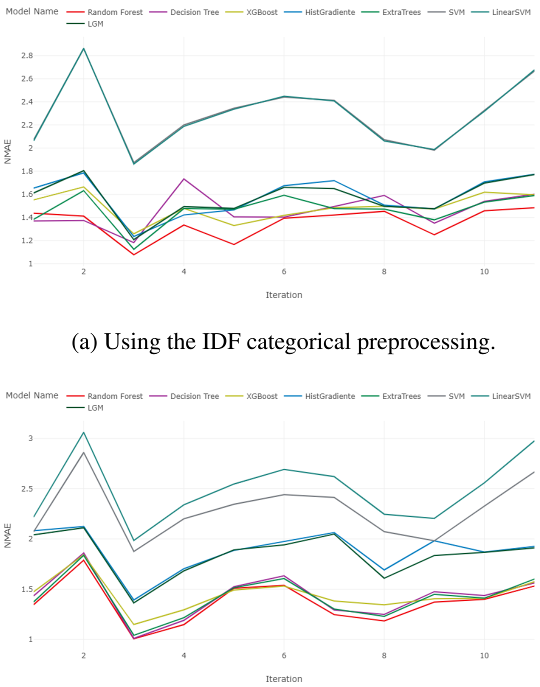
Figure 1: Schematic of Rolling Window (RW) evaluation.

To measure the predictive performance of the models, we adopt to popular regression measures, the Normalized Mean Average Error (NMAE) (Goldberg et al., 2001) and the Coefficient of Determination (R^2) (Wright, 1921). The NMAE expresses, as a percentage, the average absolute error normalised to the scale of real values, and is calculated as (Oliveira et al., 2017): $NMAE = MAE/(y_{\max} - y_{\min})$, where $y_{\max}$ and $y_{\min}$ represent the highest and lowest target values. The lower the NMAE values, the better the forecasts are. The closer to 1 the R^2 value is, the better the model fits the data.

Since the RW produces several test sets, one for each RW iteration, the individual R^2 and NMAE values were first stored. Then, the aggregated results ($u \in \{1,...,U\}$) were obtained by calculating the median values for each metric since it is less sensitive to outliers when compared with the average function. Furthermore, the total computation time, including training and prediction response times, was also recorded in seconds.

3 RESULTS

Table 2 presents the final predictive test results, discriminating by the categorical preprocessing technique applied. In general, both PCP and IDF obtained similar median results, with the NMAE values ranging from 1.36% to 2.49%, and the R^2 varying between -0.15 and 0.76. Regardless of the method, SVM and LinearSVM obtained a poor performance, leading to the highest median values of NMAE and negative R^2 values. Considering the NMAE values, regardless of the categorical transform technique, the RF algorithm stood out from the other ML models, registering the lowest NMAE values (1.39% for IDF and 1.35% for PCP). As for the R^2 performance measure, the highest value in IDF reached 0,76 for the RF model. Going into more detail with IDF, there is a clear dominance of the RF, whether the analysis is based on NMAE or R^2 values. Other models such as ET also achieved good results, maintaining an R2 above 0.7 and a NMAE below 1.5%. For PCP, the scenario is slightly different, with RF standing out for its lower NMAE value, while XB outperformed in terms of the R^2 values.



(a) Using the IDF categorical preprocessing.

(b) Using the PCP categorical preprocessing.

Figure 2: Evolution of the RW NMAE individual values.

For a fine grain analysis, the obtained individual NMAE values for each RW iteration are shown in Figure 2, for the IDF (top graph) and PCP (bottom graph) categorical transformations. The predictive NMAE performance for the distinct ML algorithms is aligned with the results from Table 2. In particular, the RF method (red curve) produces systematically the lowest NMAE values for both IDF and PCP input transformations.

For demonstration purposes, Figure 3 shows the

Table 2: Median prediction results for RW iterations (best values per preprocessing method in **bold**; best global value is underline; the selected model is signaled by using a **bold** and *italic* font).

Preprocessing	Model Name	Total Time(s)	NMAE	R^2
IDF	***RF***	100	**1.39**	**0.76**
	DT	77	1.41	0.67
	XB	359	1.48	0.68
	HGBM	1727	1.65	0.68
	ET	95	1.48	0.72
	SVM	147	2.33	-0.08
	LSVM	88	2.32	-0.09
	LGM	128	1.61	0.67
PCP	RF	870	**1.36**	0.65
	DT	68	1.43	0.63
	XB	592	1.45	**0.70**
	HGBM	2016	1.88	0.48
	ET	1204	1.42	0.63
	SVM	1037	2.30	-0.08
	LSVM	65	2.49	-0.15
	LGM	91	1.85	0.47

regression scatter plot for the IDF and PCP transforms that was obtained during the $u = 7$th RW iteration and for the RF algorithm. Each plot shows the target measured values (x-axis) versus the obtained RF predictions (y-axis), where the dashed diagonal denotes the perfect regression line. Thus, the closer are the predicted points (purple points) to the diagonal line, the better are the predictions and the higher is the R^2 score. For this iteration (u=7), both IDF and PCP transforms provided a high quality result when using the RF algorithm, resulting in very similar R^2 values (0.87 for IDF and 0.88 for PCP).

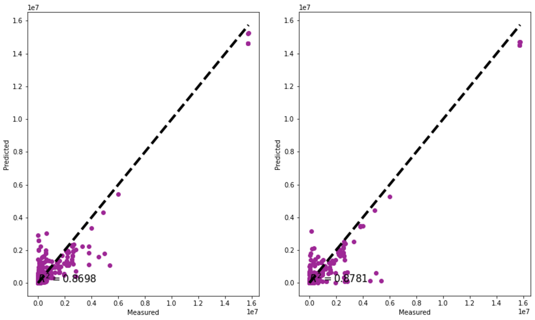


Figure 3: R^2 for RF and RW iteration $u = \mathbf{7}$, using IDF (left) and PCP (right).

In order to select the best RUL prediction method, we also consider the computational effort. As shown in Table 2, the IDF based RF model requires much less effort (it is around 8.7 times faster) when compared with its PCP variant. Given that the IDF RF combination also provided the higher median R^2 score (0.76) and second lowest NMAE median value (1.39%), it was considered the best ML approach as measured when using the RW evaluation.

Next, we have applied the XAI approach to the selected ML model (IDF categorical transform and RF algorithm). In particular, the SHAP method, by means of the `Shapash` Python tool, was executed for the IDF based RF model that was fit during the $u = 7$th RW iteration. The top of Figure 4 displays the overall feature importance for the trained model. There is a clear dominance of the impact of equipment-related attributes on the expected lifetime of a spare part (e.g., `equipment_type`, `equipment_subtype`), representing approximately 80% of the total variable input influence. In contrast, the suppliers (`supplier_code`) have an almost irrelevant impact on the RUL forecasting process, which may be explained due to the high unavailability of data for this data field.

An additional explanatory knowledge that can be provided by analyzing the SHAP method results in terms of the behavior produced by changing a particular input factor in the predictions. Under an interactive process, the maintenance manager can perform several root-cause analyses by executing distinct what-if queries or even a full sensitivity analysis for a particular RUL spare part prediction. For demonstration purposes, we exemplify a a sensitivity analysis for the IDF based RF model trained during iteration u=7 (bottom of Figure 4). In this visualization, we selected a specific spare part RUL prediction, fixing all input variables except the maintenance technician (`technician_name`), which was varied through its range. Then, the obtained SHAP contribution val-

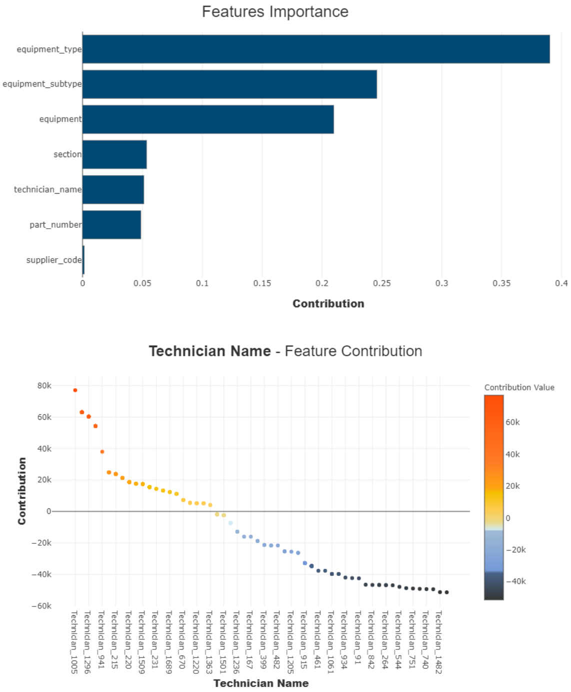


Figure 4: XAI analysis (top – importance of the input features; bottom – sensitivity analysis for a RUL prediction).

ues (in the y-axis) were sorted in a decreasing order. As shown in the bottom of Figure 4, there are some technicians (e.g., #1005, #1296), that produce a positive impact in the RUL, while others tend to decrease the RUL value (e.g., #740, #1482). This extracted knowledge can be used by the manager to support her/his decisions when selecting technicians to perform new maintenance operations. Thus, the SHAP extracted explanatory knowledge can be potentially used to minimize the failure rate in production lines, thus improving the quality of the products and services provided, and reduce the overall maintenance activities costs.

4 CONCLUSIONS

In this work, we assume a novel data-driven RUL prediction approach that only uses corrective maintenance historical records, which are commonly available in assembly industries and thus more easy to collect when compared with specific equipment measurements that require dedicated sensors (e.g., temperature levels). As a case study, we address 18,355 records with RUL measurements that were extracted from an automotive multimedia assembly company. Assuming a regression task, where we predict the RUL in terms of number of produced units, we compare two categorical input transforms (IDF and PCP) and eight ML algorithms (DT, RF, ET, XG, LGBM, HGBM, LSVM and SVM). The experimental evaluation assumed a realistic and robust RW evaluation. Overall, high-quality RUL prediction results were obtained by the IDF input transform when combined with the RF algorithm, obtaining a median NMAE of 1.39% and median R^2 score of 0.76. This ML approach also required a reasonable amount of computational effort, being much faster when compared with the PCP RF variant. The selected model was further analyzed by using the SHAP XAI method for a better understanding in preventing the occurrence of spare part breakdowns. In particular, we have shown how the XAI can be used to extract the relative importance of the input features and also perform a sensitivity analysis, measuring the prediction model effect of changing a selected input variable.

The obtained results were provided to the assembly company maintenance experts, which provided very positive feedback. In particular, the experts valued the high predictive results (NMAE and R^2 values) and the XAI examples. In future work, we intend to implement the proposed IDF based RF algorithm in a real industrial environment, using a friendly interactive tool (e.g., for the XAI analyses) that would allow us to obtain additional valuable feedback on the usefulness of the proposed ML approach to enhance maintenance management decisions.

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