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Data-Driven Prognostics Incorporating Environmental Factors for Aircraft Maintenance

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Key Words: condition-based maintenance, prognostics, aircraft maintenance, RUL, environmental data

SUMMARY & CONCLUSIONS

During flights aircraft continuously collect data regarding operations, health status and system condition. Data-driven approaches typically applied to system specific sensor data provide a way to predict failures of aircraft systems. However, it is believed that some systems deteriorate faster when subjected to particular environmental conditions, such as humidity or dust. In this study, we consider an aircraft system which is suspected to experience degradation due to humidity during ground operations. We apply a Random Forest approach to sensor data only and a combination of sensor data and environmental data from airports to estimate the system's remaining useful life. To our knowledge this is the first paper addressing the problem of integrating environmental data in prognostics for aircraft systems using raw sensor data. The method is validated on a data set provided by an airline that includes the per-second sensor data of 11 different sensors for roughly 12,300 flights, as well as 15 removals. Meteorological data for airports worldwide is obtained from the Meteorological Aerodrome Reports database. The results show that incorporating environmental data in prognostics has a potential towards more accurate prediction models.

1 INTRODUCTION

Nowadays, aircraft systems are maintained in two ways: either a run-to-failure policy is applied or a time-based preventive maintenance is followed to regularly assess or correct the systems health status. With an increasing number of sensor data collected for several aircraft systems, over the last years data-driven prognostics has gained attention. Implemented in a condition-based maintenance framework those methodologies provide the means to predict the future health state of a system and to estimate the remaining useful life of technical systems [1].

Aircraft systems operate under different varying operational and environmental conditions that can accelerate or decelerate the degradation process [2]. For systems prone to faster degradation under varying conditions, using environmental and operational data in addition to multiple sensor signals has the potential to provide more accurate prognostic models. There exist several data-driven prognostic methodologies that can be used in such cases.

Statistical approaches that fit available data to a probabilistic model to construct a remaining useful life (RUL) estimation model have been widely used for prognostics [3] and provide a relatively straight forward way to use data from various sources. In cases when either the exact causes of failures are not known, sensor data are not able to capture degradation symptoms or there are various failure modes and only for some of those a physical description or statistical model of the failure behavior can be obtained, machine learning approaches are a good alternative. Among those are artificial neural networks (ANN) [4], support vector machines [5], auto encoders [6], tree based methodologies such as Random Forests [7], convolutional neural networks (CNN) [8], and recurrent neural networks (RNN), for example, long short-term memory (LSTM) networks [9].

The existing methodologies yield promising results towards the prediction of remaining useful life. However, several issues remain: First, while neural networks have a great potential in predicting even quite complex failure mechanisms, they are hard to tune and they lack interpretability. Tree-based approaches provide for both, capturing the complexity of the degradation behavior and interpretability [10]. Moreover, they have the potential to handle a large number of input variables and are adaptive [11]. Second, most of the proposed methodologies are applied to simulated data sets. Third, associated therewith, often it is taken for granted to use input data from a single source.

In this paper we aim at estimating the RUL for an aircraft system for which the degradation is believed to be linked to the outside temperature and humidity during ground operations, i.e. when the aircraft is located at an airport. We propose a Random Forest based framework to incorporate environmental data in addition to sensor data. The aim of this paper is to answer, with respect to the aircraft system under consideration, the following question: Does incorporating environmental data result in more accurate predictions than training a machine learning model using sensor data only?

The rest of the paper is organized as follows. Section 2 presents the failure prognostics framework used for the RUL estimation. In Section 3, the approach is applied to the above mentioned aircraft system and first results are presented. The results, limitations and remaining challenges are discussed in Section 4. Finally, conclusions are made in Section 5.

2 FAILURE PROGNOSTICS FRAMEWORK

The prognostics framework, as illustrated in Figure 1, consists of four main steps: The data collection, the data pre-processing, fitting a model for the remaining useful life estimation, and evaluating the model performance on the test set. Two setups are distinguished: Setup 1, building a model based on sensor data only and Setup 2, that provides a way to incorporate environmental data into the model.

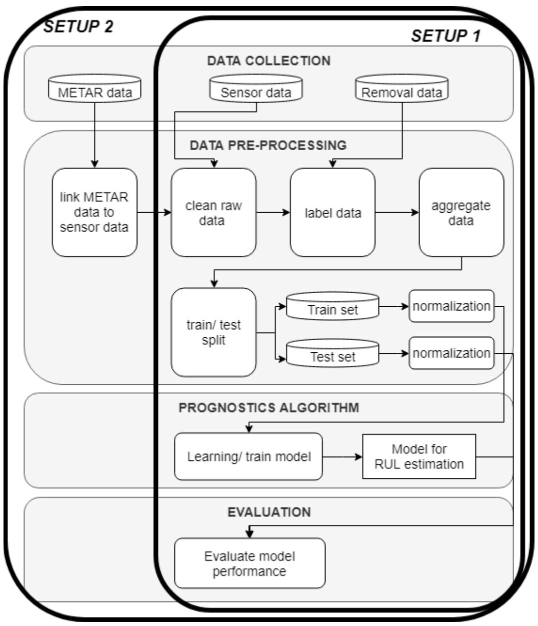

Figure 1: Prognostics Framework for Setup 1 (without taking into account environmental data) and Setup 2 (considering sensor and environmental data in the prognostics).

2.1 Problem Formulation

The notation introduced in this Subsection is similar to the notation used in [12]. Assume that the system observed has in total K components, one of which is denoted by $k \in \{1, \cdots K\}$. Each component k is a run-to-failure component, i.e. it runs for $T_k \in \mathbb{N}$ flight cycles before it fails. A flight cycle is defined as an entire flight including the ground operations, i.e. from engine turn on until engine turn off. There are sensors installed on each component, taking measurements each second. Additional data, like operational or environmental conditions can be added to this data for each flight cycle, so that in the end there are N measured values for every component at each point in time. Those are in the following referred to as features. With this, the features for component k at flight cycle t are given by

$$X_k^t = (x_k^{t1}, \cdots, x_k^{tN}) \in \mathbb{R}^N. \quad (1)$$

Hence, for every component k the according data is

$$X_k = \{X_k^t : t \in \{1, \cdots, T_k\}\} \quad (2)$$

Our goal can be formulated as follows: For component $k \in \{1, \cdots K\}$ at time $t \in \{1, \cdots, Tk\}$, given features up until time t, i.e. $(X_k^1, \ldots, X_k^t) \in \mathbb{R}^{t \times N}$ estimate the remaining useful life at time t, denoted by $RUL_k(t)$. Our assumption is that the degradation of the system starts after a certain time of usage and then degrades linearly. Therefore, the target value of the RUL is calculated using the piece-wise linear function

$$RUL_k(t) := min\,(MAXLIFE, T_k - t) \quad (3)$$

with $MAXLIFE \in \mathbb{N}$. Up to this point, we haven't applied a prognostic algorithm yet. However, our aim is to build a machine learning model based on given training data, that is able to estimate on a test data set, the remaining useful life for a specific component k at given times. How this is done will be explained in more detail in the following subsections.

2.2 Data Collection

During each flight, per second sensor data is collected and sent to a central database whenever the aircraft arrives at an airport. The failure data is obtained from the removal data set that contains the time of installation and removal of the aircraft component. In addition to the sensor data and the removal data set, environmental data from airports is used in Setup 2. It is retrieved from the Meteorological Terminal Aviation Routine Weather Report (METAR) data platform [13] and contains the temperature and dew point for every airport. Those two variables are used to obtain the absolute humidity and an approximation of the relative humidity [14] for flight phases during which the aircraft is located at an airport.

2.3 Data Pre-processing

The data pre-processing consists of several steps: In Setup 2, the first step is to add the humidity data retrieved from the METAR data to the sensor data. The second step in Setup 2, which is the first step in Setup 1, is to clean the raw data. Next, the sensor data and the fault data are linked to create a labelled data set. Then, the data is aggregated per flight phase and split into a train and test data set. The removal data set is added to the sensor data to provide failure labels. The observed component is maintained under a run-to-failure policy, i.e. it is replaced once it has failed. Airlines have a time horizon of a few days before they have to do a maintenance action on this component, which means that once a failure has happened, the removal might take place a few days later. Flights that occur after the time of the failure and the removal of the component are assumed to not contain information about the components degradation and are therefore removed. To remove noise from the raw sensor data, the per-second data is aggregated per flight phase by sum, mean, maximum and minimum. The data is split into K data sets, each containing data corresponding to one component, in such a way that 20% of all components and their corresponding sensor data are contained in the test set and the rest in the train set.

2.4 The Random Forest Algorithm

This subsection introduces the prognostics algorithm used in our case study, the Random Forest Algorithm. Random Forests were introduced by Breiman [15, 16] based on the concept of bagging, where ensemble trees are grown by a random selection (with or without replacement) from the examples in the training set. Due to their interpretability, the fact that they are easy to tune and their flexibility with regards to handling various types of input data, as pointed out in Section 1, we decided to apply a Random Forest approach to estimate the RUL of the studied aircraft system. The estimation of the RUL for component k at time t is denoted by $RUL_{Estimated,k}((\mathrm{X}_k^1, \dots, \mathrm{X}_k^t), t)$. The Random Forest model is fitted on the training samples. For the implementation we use the scikit-learn package in Python [17]. A random grid search is performed to find the best performing set of hyper parameters.

2.5 Evaluation

The performance of the trained models is evaluated using the means squared error (MSE) and the mean absolute percentage error (MAPE). The error of estimating the RUL of the k-th component at time t is given by

$$E_k(t) = RUL_{Estimated,k}(t) - RUL_k(t). \quad (7)$$

When predicting the remaining useful life of a component k until the time step T, the model outputs $RUL_{Estimated,k}((X_k^1, \dots, X_k^t), t)$ for $t \in \{1, \cdots, T\}$. The according true values are the values of the piecewise-linear RUL function as introduced in Subsection 2.1, i.e. $RUL_k(t)$ for $t \in \{1, \cdots, T\}$. The MSE is then given as

$$MSE = \frac{1}{T}\sum_{t=1}^{T}(E_k(t))^2, \quad (8)$$

As a second metric, we use the MAPE, defined as

$$MAPE = \frac{100}{T}\sum_{t=1}^{T}\frac{|E_k(t)|}{RUL_k(t)}. \quad (9)$$

Note that the MAPE weights errors with the true RUL. The closer the component gets to the end of its life the smaller we want the errors in the RUL estimation to be.

3 CASE STUDY: PREDICTING FAILURES FOR AN AIRCRAFT COMPONENT

In the case study, the prognostic frameworks with the two setups presented in Section 2 is applied to an aircraft system to predict at any time t during its life, the RUL of that component.

3.1 Description of the aircraft component and its degradation behavior

The methodology is applied to predict failures of the aircraft system. It consists of four redundant subsystems, referred to as sys1, sys2, sys3 and sys4. On each of the subsystems, nine sensors are installed that take measurements related to the system health. In addition two sensor measurements reported on aircraft level are used as an input. Failures of the four subsystems are assumed to be independent. Operators observed that system failures seem to be linked to the environment in which the aircraft is located, especially during ground operations. Therefore the temperature and humidity values at airports are added to the above presented sensor data. A model is trained for every subsystem separately on sensor data related to that system.

Table 1: Available data points (i.e. flight phases) and failures for each subsystem

	Sys 1	Sys 2	Sys 3	Sys 4
Data points	171422	186911	182905	190719
Flights	12244	13395	13065	13623
Failures	5	2	6	2
Data points per failure	28570	62509	26129	63573

The aggregated data sets each contain around 180000 flight phases in total, which corresponds to around 12300 flights performed by 18 different aircraft. The number of failures for each of the components varies between two failures for sys2 and sys4 and six failures for sys3. The exact number of flight phases, failures and average number of entries per failure is given in Table 1.

3.2 The experimental setups

The main objective of the research is to find out if the accuracy of the predictions increases when incorporating environmental data in addition to sensor data in the deep learning framework. Therefore two setups corresponding to the two previously introduced frameworks as shown in Figure 1 are considered: In Setup 1, only raw sensor data is used as an input for the Random Forest algorithm and in Setup 2, environmental data is added to do the prognostics. Each of the four subsystem has a number of failures, *numfailures*, i.e. components $k \in \{1, \cdots, numfailures\}$. For each component the corresponding data is given as stated in Equation (1) in Subsection 2.1.The hyper-parameters of the Random Forest algorithm, found using a random grid search (Subsection 2.5) and set as follows: The number of trees is set to 200, the minimum number of samples required to split an internal code is set to 10 and the minimum number of samples required to be a leaf node to 2.

Table 2: Resulting scores for four subsystems on the test set in Setup 1 (without taking into account environmental data) and Setup 2 (including environmental data)

Sub-system	*MSE (Setup 1)*	*MSE (Setup 2)*	*MAPE (Setup 1)*	*MAPE (Setup 2)*
Sys 1	419.44	282.6	$5.87 * 10^6$	$4.23 * 10^6$
Sys 2	326.87	312.24	$2 * 10^6$	$1.97 * 10^6$
Sys 3	122.71	315.38	$2.21 * 10^6$	$5.96 * 10^6$
Sys 4	599	543.1	$1.12 * 10^7$	$1.11 * 10^7$

In addition to that, the maximum depth of a tree is set to 100 for all subsystem, except for Subsystem 3, for which it is set to 10 and bootstrap samples are used when building trees for all subsystems but Subsystem 3. The scores for the trained model for each subsystem in Setup 1 and Setup 2 are summarized in Table 2.

Setup 1: Estimates based on sensor data only. In Setup 1 the prognostic models are based on sensor data only. As mentioned in Subsection 3.1 there are nine sensors installed directly on each subsystem and two additional sensor values from the aircraft used, which results, with the four aggregations done (Subsection 2.3) per flight phase, in $N = 44$ features in total. As highlighted in , the MSE ranges from 122.71 for Subsystem 3 to 599 for Subsystem 4. The MAPE is much higher with values between $2 * 10^6$ for Subsystem 2 and $1.12 * 10^7$ for Subsystem 4. The estimated RUL and the true RUL on the test set are shown in Figure 2. For Subsystems 1 and 4, as shown in Figures 2a and 2d, no trend is visible and the RUL does not decrease towards the end of the systems life. For Subsystem 2, in Figure 2b, there is a visible decay of the RUL during a range of flight cycles between 2000 and 3000 flight cycles, but the component keeps operating up until around 4500 flight cycles. Afterwards, the RUL increases for a short amount of time before it becomes in general lower for the remaining system life. And for Subsystem 3, in Figure 2c, there are only slight variations in the RUL, one small decrease for a very short amount of time between flight cycle 4000 and 5000 and a slightly lower RUL towards the end of the system life.

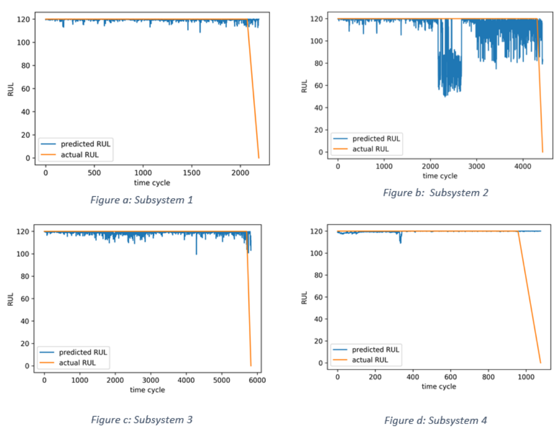

Figure 2: Estimated and true RUL for the models for the four subsystems in Setup 1

Setup 2: Predictions incorporating environmental data

In Setup 2 the prognostic models are based on sensor data and environmental data. This means that, in addition to the previously $N = 44$ features used, 4 features related to the temperature and humidity at airports are included before the aggregation, which means that in total we end up with $N = 60$ features. In this case, as can be seen in , the values of the MSE are closer together, for Subsystem 1 to 3 the MSE is around 300, only Subsystem 4 has a higher MSE of 543.1. The lowest MAPE is the one for the model of Subsystem 2 with 1.97*106 and the highest one is again the MAPE of Subsystem 4, which has a value of 1.11*107. Again, the estimated RUL and the true RUL on the test set are shown in Figure 3. For Subsystem 1, in Figure 3a, there is a small decrease of the RUL estimate over time and towards the end of life of the system, it decreases more remarkably. Similarly as in Setup 1, for Subsystem 2, in Figure 3b, there is a visible decay of the RUL during a range of flight cycles is visible, after which the RUL increases a bit before it stays lower for the remaining system life. For Subsystem 3 and 4, as displayed in Figures 3c and 3d trends are not so clearly visible. For Subsystem 3, similarly as for Subsystem 1, the RUL decreases a little close to the end of life. This is not the case for Subsystem 4, for which no trend is visible at all and the failure is not recognized as such.

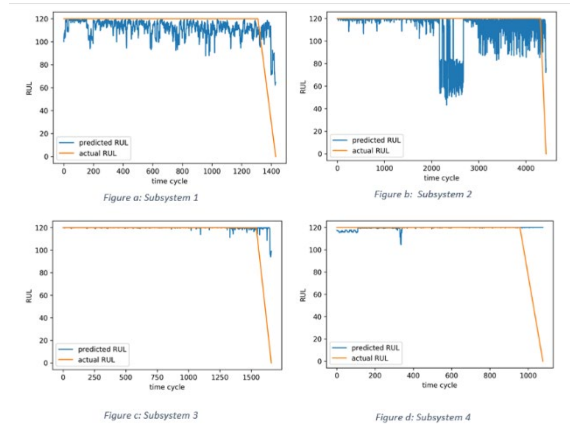

Figure 3: Estimated and true RUL for the models for the four subsystems in Setup 2

4 DISCUSSION

The case study presented in Section 3 shows that for the observed aircraft system, incorporating environmental data into the prognostics results in, in terms of MSE and MAPE, better RUL estimates than those based on sensor data only. Although the model yields promising results, there are limitations still existing and improvements to be made as pointed out in Subsection 4.2. First, in Subsection 4.1, we will have a closer look at the results, explanations for certain behavior and findings made.

4.1 Discussion of the results of the case study

Overall, the results vary a lot between the subsystems but also within the subsystems for different setups. The most visible RUL estimate trends are obtained for Subsystem 2 (Figures 2b and 3b). Here, from the failures, the model seems that a certain combination of feature values leads to degradation. On the test set, this behavior happens in a range of flight cycles not at the end of but in the middle of the system life. Although the RUL increases afterwards, it stays lower than before until the failure. A reason could be that there is one or there are multiple features indicating some sort of degradation reaching a critical value at a certain point. After reaching this value, the aircraft might have switched to using another subsystem as described in Subsection 3.1. Another explanation for this can be the indirect assumption made of only one failure mode for each subsystem. However, it is easily possible that failures differ quite a lot and features that indicate a degradation behavior for one failure do not show the same behavior for another failure. When including environmental data, the results improve in most cases, especially for Subsystem 1. In Setup 1, the RUL estimation model was not able to predict anything from the test data (Figure 2a). Opposed to that, in Setup 2, the RUL estimation model of Subsystem 1 shown in Figure 4a looks like the most promising model obtained and the only one that manages to recognize a major decay in the RUL towards the systems end of life.

4.2 Limitations and Further Research

From the observations highlighted in the previous Section 4.1, it becomes clear that although the RUL estimates are better when incorporating environmental data in prognostic models, most of the models are not able to detect a clear degradation trend in the test data and identify faulty behavior. In the following we point out limitations in more detail and provide some suggestions for improvements.

Firstly, some issues may arise from the underlying data. Features describing the degradation might not be given directly; data is aggregated per flight phase and represented using statistical properties; a relatively small number of failures is available for each subsystem To address these, the following measures can be taken: 1) Apply visualization and dimensionality reduction techniques suited for multivariate data such as t-SNE [18], principal component analysis (PCA) or Kernel PCA [19], providing a way to identify anomalies or distinguish operating conditions; 2) to prevent loss of information, one could simply not use aggregations at all, but train the Random Forest approach directly on per second data to capture all the contained information. Alternatively, operating conditions could be distinguished by means of existing methodologies for this purpose, e.g. clustering and group data accordingly; 3) The paucity of failure data could be addressed through over- or undersampling.

The issues that arise from the underlying data, can also be addressed by means of methodology. More complex techniques such as deep learning techniques or ensembles of machine learning techniques as e.g. presented in [12] or [9] could yield better results to describe complex, non-linear system behavior. Another way of improvement is to work on a more flexible approach entirely that can identify periods of faulty behavior. Several techniques exist in literature, most of them based on the idea of applying unsupervised learning techniques, such as auto encoders, to find patterns in healthy data and use those for the prognostics [6, 20].

So far, the framework is only evaluated in terms of performance metrics. A more fundamental evaluation would be to compare its performance to that of existing approaches with the capability of using environmental data as an additional input, such as Proportional Hazard Models [21]. In addition to that, using different machine learning methodologies and comparing their performance to the performance achieved with the Random Forest approach used in this paper could provide a way of validating the framework. Another way to evaluate the approach is by applying it to known data sets, like the C-MAPSS data [22] to verify that known performance benchmarks are reached or exceeded.

Finally, the framework is tested in a case study for a single aircraft system. A further direction of research is therefore to work on the generalization of the approach, which can help to further substantiate the evaluation.

5 CONCLUSION

In this paper a framework is presented to incorporate environmental data in addition to sensor data in a Random Forest approach and estimate a systems remaining useful life. The main hypothesis is that the accuracy of the prognostic model increases when using environmental data as an additional input. To test this hypothesis, the framework is applied in a case study in two different setups, one in which only sensor data is used for the prognostics and one in which both, sensor data and environmental data are used to train the RUL estimation model. It turns out that incorporating environmental data in failure predictions indeed results in better estimates than those based on sensor data only. Therefore, the framework has potential for generalization.

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REFERENCES

1. Diez-olivan, j. Del ser, d. Galar and b. Sierra, "data fusion and machine learning for industrial prognosis: trends and perspectives towards industry 4.0," information fusion, vol. 50, p. 92–111, 2019.
2. L. Ellefsen, v. Asoy, s. Ushakov and h. Zhang, "a comprehensive survey of prognostics and health management based on deep learning for autonomous ships," ieee transactions on reliability, vol. 68, p. 720–740, 2019.
3. X. S. Si, w. Wang, c. H. Hu and d. H. Zhou, "remaining useful life estimation - a review on the statistical data driven approaches," european journal of operational research, vol. 213, p. 1–14, 2011.
4. N. Gebraeel, m. Lawley, r. Liu and v. Parmeshwaran, "residual life predictions from vibration-based degradation signals: a neural network approach," ieee transactions on industrial electronics, vol. 51, p. 694–700, 2004.
5. V. N. Vapnik, "an overview of statistical learning theory," ieee transactions on neural networks, vol. 10, p. 988–999, 1999.
6. G. Michau, y. Hu, t. Palmé and o. Fink, "feature learning for fault detection in high-dimensional condition monitoring signals," proceedings of the institution of mechanical engineers, part o: journal of risk and reliability, 2019.
7. S. Yang, x. Di and t. Han, "random forests classifier for machine fault diagnosis," journal of mechanical science and technology, vol. 22, p. 1716–1725, 2008.
8. X. Li, q. Ding and j. Q. Sun, "remaining useful life estimation in prognostics using deep convolution neural networks," reliability engineering and system safety, vol. 172, p. 1–11, 2018.
9. G. Huang, h. Z. Huang and y. F. Li, "a bidirectional lstm prognostics method under multiple operational

conditions," ieee transactions on industrial electronics, vol. 66, p. 8792–8802, 2019.

10. S. Ten zeldam, a. De jong, r. Loendersloot, t. Tinga, s. Ten zeldam, a. De jong, r. Loendersloot and t. Tinga, "automated failure diagnosis in aviation maintenance using explainable artificial intelligence (xai)," phm society european conference, vol. 4, p. 1–11, 2018.
11. Wu, c. Jennings, j. Terpenny, r. X. Gao and s. Kumara, "a comparative study on machine learning algorithms for smart manufacturing: tool wear prediction using random forests," journal of manufacturing science and engineering, transactions of the asme, vol. 139, p. 1–9, 2017.
12. L. Jayasinghe, t. Samarasinghe, c. Yuen, j. Chen, n. Low and s. S. Ge, "temporal convolutional memory networks for remaining useful life estimation of industrial machinery," arxiv preprint arxiv:1810.05644, 2018.
13. Meteorological aerodrome reports (metars) - awc, 2020.
14. M. G. Lawrence, "the relationship between relative humidity and the dewpoint temperature in moist air: a simple conversion and applications," bulletin of the american meteorological society, vol. 86, p. 225–233, 2005.
15. L. Breiman, "bagging predictors, url: https://link.springer.com/article/10.1007%2fbf00058655," machine learning, vol. 24, p. 123–140, 1996.
16. L. Breiman, "(impo)random forests(book)," machine learning, p. 5–32, 2001.
17. F. Pedregosa, g. Varoquaux, a. Gramfort, v. Michel, b. Thirion, o. Grisel, m. Blondel, p. Prettenhofer, r. Weiss, v. Dubourg, j. Vanderplas, a. Passos, d. Cournapeau, m. Brucher, m. Perrot and e. Duchesnay, "scikit-learn: machine learning in {p}ython," journal of machine learning research, vol. 12, p. 2825–2830, 2011.
18. L. V. D. A. G. H. Maaten, "visualizing data using t-sne.," journal of machine learning research, vol. 9, no. 1, pp. 2579-2605, 2008.
19. B. A. S. A. K.-r. M. Schölkopf, "nonlinear component analysis as a kernel eigenvalue problem.," neural computation, vol. 10, no. 5, pp. 1299-1319, 1998.
20. W. Yu, i. I. Y. Kim and c. Mechefske, "remaining useful life estimation using a bidirectional recurrent neural network based autoencoder scheme," mechanical systems and signal processing, vol. 129, p. 764–780, 2019.
21. W. J. C. Verhagen, l. W. M. De boer and r. Curran, "component-based data-driven predictive maintenance to reduce unscheduled maintenance events," advances in transdisciplinary engineering, vol. 5, p. 3–10, 2017.
22. D. K. Frederick, j. A. Decastro and j. S. Litt, "user's guide for the commercial modular aero-propulsion system simulation (c-mapss)," 2007.
23. A. K. S. Jardine, d. Lin and d. Banjevic, "a review on machinery diagnostics and prognostics implementing condition-based maintenance," mechanical systems and signal processing, vol. 20, p. 1483–1510, 2006.
24. Y. Wu, m. Yuan, s. Dong, l. Lin and y. Liu, "remaining useful life estimation of engineered systems using vanilla lstm neural networks," neurocomputing, vol. 275, p. 167–179, 2018.

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