

Web-Based Tool for Predicting the Remaining Lifetime of Aircraft Components

Mr. M .Sivakumar¹, A. Keerthiga², L. Pooja³, N. Poojashree⁴, M. Pragathi⁵

Assistant Professor, Department of ECE, Adhiyamaan College of Engineering, Hosur, Tamilnadu, India¹,

UG Students, Department of ECE, Adhiyamaan College of Engineering, Hosur, Tamilnadu, India^{2,3,4,5}

ABSTRACT: Reliability Safety and economy of engines is very important. To ensure flight safety and decrease the expense of support during airplane engine activity, a prognostics and managing the board framework that centers around shortcoming analysis, wellbeing appraisal, and life forecast is acquainted with take care of the issues. Predicting the remaining useful life (RUL) is the utmost significant information for making conclusions about aircraft engine process and maintenance, and it relies largely on the selection of performance degradation features. The decision of such highlights is profoundly huge, yet there are a few shortcomings in the present calculation for RUL expectation, prominently, the failure to get propensities from the information. Particularly with airplane engines, separating useful degradation features from multi sensor information with complex connections is a key specialized issue that has obstructed the execution of degradation assessment. To take care of these issues, deep learning has been proposed in recent years to exploit multiple layers of nonlinear data preparing for self-learning of different features unsupervised. We in this paper propose a deep learning approach where the RUL of an aircraft engine can be predicted based on a SAE (stacked sparse auto encoder) and logistic regression. The SAE (stacked sparse auto encoder) is used for extracting features such as performance degradation from multiple sensors present in the aircraft engine and to fuse multiple features through multilayer self-learning. To predict the remaining useful life (RUL) logistic regression is being used. In most cases prediction performance and features extraction are significantly impacted by the hyperparameters of the Deep learning, which are determined base on expert experience. We introduce grid search method in this paper for RUL prediction model of the proposed aircraft engine where hyperparameters of the engine will be optimized.

KEYWORDS: Aircraft, RUL, SAE, Deep learning.

I. INTRODUCTION

The core component of the aircrafts are its engines. The major accidents and casualties are always caused due to the failure of its engines. So, the performance of aircraft is vital for safety and the reliability of engines. Since aircraft engines are complex so it is very difficult to maintain the safety and reliability of aircraft engines. When the working time of the aircraft increases, the failure rate of the engine also increases. The engine failures are mainly due to the aging of engine as well as environment and the variable loading. So, to prevent catastrophic failure of the aircraft it is necessary to detect the cause of the engine degradation and to predict engine life time. The traditional maintenance is either purely reactive in the field of aircraft maintenance, (fixing or replacing an aircraft engine component after it fails) or completely proactive (With no input from the aircraft engine itself assuming a certain level of performance degradation and whether maintenance is actually needed or not but maintaining the aircraft engine on a routine schedule). Wasteful and inefficient scenarios and both are not conducted in real time. prognostics and health management (PHM) is gradually replacing these maintenance strategies based on fault diagnosis, performance degradation assessment and the predicted remaining useful life of the aircraft equipment and the need to prevent faults in advance. The forecasting of engine

components/systems breakdown or when the performance will reach to an unacceptable level involves Prognostics managing performance deterioration processes or faults in the aircraft engine Existing System.

[1] C. Okoh, R. Roy, J. Mehnen, L. Redding reports the findings of a recent assessment of the works relative to the practice of prognostics in support of TES qualified IPSS. The methods used to find out the RUL of gas turbine components are also assessed. The study collects data from semi-structured meetings with scholars and experts to recognize types of degradation mechanisms for aero-engine parts as part of a continuing case study, the goal of which is to classify such failures and recognize the root problems. The efficient prediction of RUL for manufactured parts inside the Industrial Product Service System is a main factor the viable service delivery. Thus, the preferences are: embolden swift MRO choice making and improved availability of dependable parts for use. It decreases regular repair cost. It improves working effectiveness. This paper finds the core degradation mechanisms (not entirely) which can affect engine parts. The Remaining Useful Life simulation and modelling tools and methods, the plotting of dilapidation mechanisms versus the prediction methods have been emphasized. This is tied with mapping the method against data type to qualify the selection of the related modelling procedure. In the final examination, it is however seen that TES is a tactical approach within a work performance system which allows, simplifies and supports IPSS results. These devices can be fixed inside the TES architecture to assist or help developer to make instant and improved maintenance decisions.

[2] Daniel Azevedo et al. in their work, a Condition Based Maintenance (CBM) approach is followed where the system state is evaluated using data gathered from the aircraft sensors that comprise the dataset. Using the sensors various data, faults are identified and the Remaining Useful Lifetime (RUL) is predicted for each aircraft engine, also called as test unit. A test component is a set of working cycles achieved during a flight. The RUL Remaining Useful Lifetime corresponds to the amount of cycles of use from the present moment, to the point in which the module becomes totally inoperable, perhaps due to degradation or a failure which happened in the system or in an exact subsystem. For the RUL prediction, Artificial Intelligence, more precisely Machine Learning approaches are used. With training datasets, the machine learning algorithms will discover and learn from the input data and then create a model. The approaches for prediction are broadly separated in model-based systems and data-driven procedures. The model-based procedures use physical understanding in order to project the RUL. This infers that the human knowledge concerning the prediction matter is essential and historical data is not required. The biggest drawback in using these procedures is the need of professional knowledge in order to develop the models. With regard to data-driven models, as the name infers, these are built on historical data. Data is usually characterized in time series and it should echo the system state as the models are developed based thereon. The swiftness and ease in the execution are the key advantages of this type of procedures. The need of huge quantities of data and low volume of oversimplification, due to data reliance of the models, are the main drawbacks.

[3] Zhongzhe Chen, Shuchen Cao, Zijian Mao proposes this paper. As the key power source for aircrafts, the dependability of an aircraft engine is very important for guaranteeing the safety of aircrafts. Prognostics and health management (PHM) on an aircraft engine can not only increase its safety, preservation strategy and availability, but also decrease its operation and maintenance costs. Residual useful life (RUL) assessment is a main methodology in the research of PHM. According to supervised routine data from the engine's different locations, how to asses RUL of an aircraft engine by using these data is a tough challenge for guaranteeing the engine veracity and safety. In this paper, an agenda for RUL assessment of an aircraft engine is presented by using the whole lifecycle data and performance degradation objective data without failures based on the concept of similarity and supporting vector machine (SVM). Moreover, a new position of health pointer is presented for the aircraft engine based on pre-processing of fresh data. Finally, the proposed process is confirmed by using 2008 PHM data challenge competition data, which shows its efficiency and pragmatism. The RUL prediction of an aircraft engine can not only progress its safety, maintenance, and availability, but also decrease its working and maintenance costs. This paper presents two methods to estimate the RUL of an aircraft engine under various conditions. The first method implements a modified similarity-based scheme for assessing the RUL of the aircraft engine with ample run-to-failure data of referenced examples. The second method utilizes depreciated

data of models without up-to-failure data to assess the RUL of the operating sample with less degraded performance data than the reference systems. The two methods are utilized for RUL approximation of an aircraft engine. The model prediction accuracy shows these two methods are efficient and appropriate for RUL assessment of aero engines.

[4] Condition-based maintenance (CBM) is a program to maintain aircraft engines that recommends maintenance choices based on the information gathered using condition monitoring. It has three main stages: data acquisition, data processing and maintenance decision-making. Diagnostics and prognostics are two important features of a CBM program. Study in the CBM area increases rapidly. Hundreds of papers in this domain, including theory and practical implementation, appear every year in educational journals, conference seminars and technical reports. Andrew K.S. et al. presents this paper where they propose and evaluate the recent study and developments in diagnostics and prognostics of aircraft systems implementing CBM with stress on models, algorithms and skills for data processing and upkeep decision-making. Realising the growing trend of using numerous sensors in condition monitoring, the authors also discuss various techniques for many sensor data fusions. In this paper, authors attempted to explain recent study and development in aircraft engine diagnostics and prognostics implementing CBM. Different techniques, models and algorithms have been studied following the three main stages of a CBM program, viz. data acquisition, data processing and maintenance decision-making, with stress on the last two steps. Diverse techniques for multiple sensor data fusion have also been debated.

II. PROPOSED SYSTEM

Prognostics method based on a stacked sparse autoencoder is proposed to endorse self-learning of multilayer features and to predict the RUL of an aircraft engine. Deep learning, a new technique that has been put forward in the proposed system, it can be used to extract various features from data, which means the process could express data at different levels of abstraction. Deep learning is an end-to-end machine learning system. Original signal can be automatically process and identify discriminative and trend feature in the input data layer by layer, and then, directly output the classification result. The whole procedure of feature learning and regression model training is built on optimizing a general objective function. In contrast, traditional machine learning processes are separated into several discontinuous data pre-processing stages, such as manual feature learning and classifier or regression model training, and every step is built on optimizing a separate objective function.

There are many deep learning procedures: deep neural networks (DNNs), deep belief networks (DBNs), and convolutional deep neural networks (CNNs), and so on. The SAE (stacked sparse autoencoder) (SAE) is one of the most frequently used deep neural network approaches. SAE contains of multilayer autoencoder such as denoising autoencoder, sparse autoencoder, and so on. Sparse autoencoder is on the foundation of autoencoder and presented sparse constraint condition to aid the expression code as sparse as possible. Denoising autoencoder can learn to eliminate the noise which is added to the original input data and extract more robust expression of the input data. For this reason, SAE can efficiently capture the significant factor of input data, gather more helpful and robust features of data, and then realize outstanding performance in pattern recognition and machine learning.

A. MERITS OF PROPOSED SYSTEM

- The SAE, a type of deep learning model is able to identify the tendency of the system to grow but also sufficiently robust to noise.
- Proposed method is effective at predicting the RUL of an aircraft engine.
- Proposed method has significance for enhancing the safety of aircraft engines.
- Reduced maintenance cost by prognosticating and managing the health of aircraft engines for fire.

III.METHODOLOGY

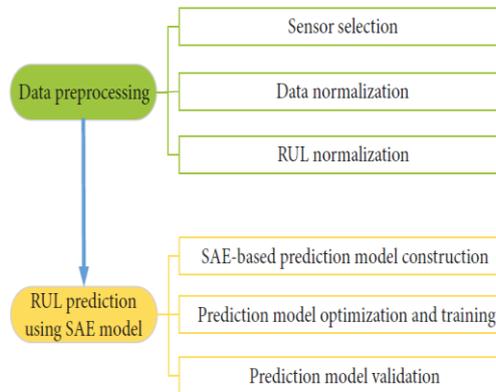


Fig 1. Training method of aircraft engines

A. Data Pre - processing. Selection of sensors that are sensitive to performance degradation and standardization of sensor data with different dimensions are the primary tasks necessary to obtain a high RUL prediction accuracy. Three steps are needed to pre-process the data.

B. Sensor Selection. Different sensors in an aircraft engine have very different responses to the performance degradation process. Some sensors show unclear tendencies because of noise or insensitivity to degradation trends. Choosing insensitive parameter data may reduce the RUL prediction accuracy. To improve the performance of the prediction model, sensors that are more sensitive to the performance degradation process are chosen as inputs to the RUL prediction model. A method called slope analysis is proposed for sensitivity measurement.

C. Data Normalization. The linear function that best preserves the original performance degradation pattern of the aircraft engine is chosen to map the data for each selected sensor to [0, 1].

D. RUL Normalization. The proposed prediction method outputs a result in the range from 0 to 1. In the training stage of the prediction model, the RUL of each cycle of aircraft engine should also be normalized to [0, 1] using a linear function. The test outputs of the prediction model need to be inversely mapped from [0, 1] to the real RUL.

IV.EXPERIMENTAL RESULT

In the procedure of engine performance degradation, the performance data from various sensors increasingly variate over time, and the data indirectly represent the degradation propensity of the engine's performance. However, the sensitivity of various parameters to degradation varies in time. Figure 9 shows the degradation propensity of different performance parameters. According to Figure, data from seven of the sensors (1, 5, 6, 10, 16, 18, and 19) display no tendency, so the sensitivities of the outstanding parameters to engine performance degradation are examined. The results of the 14 performance parameters for which the sensitivity study is directed are shown in Table 3. To decrease the computational difficulty, the data from the first six sensors (4, 7, 8, 11, 12, and 15) in the sensitivity position are taken. By studying and analyzing related information about the RUL of engines, parameters T24 and T30 are also selected as objects of study.

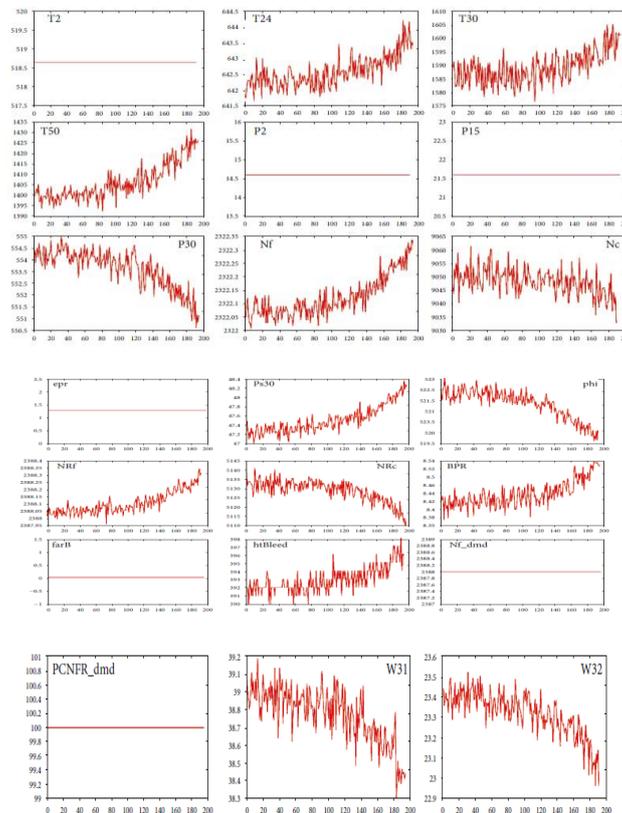


FIGURE 9: Engine degradation tendencies using the data from different sensors over time.

Table 1. Training based on data visualization

Through this selection process of the DNN hyperparameters by use of a grid search, the experimental results display that the process is efficient, with a precision rate of up to 83.82% and an suitable rate of up to 86.32% of position first (shown in Table 6). Associated with the accuracy of the 2008 PHM data challenge engine life prediction, prediction accuracy is 84.19% (shown in Table 7), and the RUL prediction accuracy is fairly close. However, there are six kinds of working state and 218 training and test sets in the FD005T dataset, which were used in the data challenge. Then, comparing the method proposed here and the 2008 PHM data challenge provides only a relative comparison. The correctness of the RUL predictions got in here is suitable in the field of engine prediction, and the results are satisfactory. Table 8 shows the first seven top parameter arrays obtained by the grid search process. Based on the first seven optimal parameters Table 6 shows the life prediction results. In the 2008 PHM data challenge Table 7 shows the seven most accurate engine life predictions.

TABLE 3: Operation regime of the aircraft engine.

Rank	Sensor	Sensitivity
1	Ps30	2.63785E-05
2	phi	2.58711E-05
3	P30	2.45237E-05
4	T50	2.43431E-05
5	BPR	2.35888E-05
6	Nf	2.30928E-05
7	NRf	2.25432E-05
8	W32	2.17608E-05
9	W31	2.13999E-05
10	htBleed	2.1267E-05
11	T24	2.1055E-05
12	T30	1.9856E-05
13	Nc	1.1581E-05
14	NRc	5.86587E-06

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TABLE 6: Life prediction results for the first seven optimal parameters.

Rank	Accuracy rate	MAPE	Acceptable number	Acceptable rate
1	83.82%	16.18%	82	86.32%
2	83.67%	16.33%	81	85.26%
3	83.67%	16.33%	80	84.21%
4	83.66%	16.34%	80	84.21%
5	83.65%	16.35%	80	84.21%
6	83.62%	16.38%	81	85.26%
7	83.61%	16.39%	81	85.26%

TABLE 7: Engine life prediction accuracy of the 2008 PHM data challenge.

Rank	Score	MAPE	Accuracy rate
1	512.12	15.81%	84.19%
2	740.31	18.92%	81.08%
3	873.36	19.19%	80.81%
4	1218.43	20.15%	79.85%
5	1218.76	33.14%	66.86%
6	1232.27	32.90%	67.10%
7	1568.98	36.75%	63.25%
8	1645.77	30.00%	70.00%
9	1816.60	26.47%	73.53%
10	1839.06	27.72%	72.28%

Table 2. Engine life prediction accuracy data

Rank	Sensor	Sensitivity
1	P30	2.63785E-05
2	phi	2.58711E-05
3	P30	2.45237E-05
4	T50	2.43431E-05
5	BPR	2.35888E-05
6	Nf	2.30928E-05
7	NRf	2.25432E-05
8	W32	2.17608E-05
9	W31	2.1399E-05
10	htBleed	2.1267E-05
11	T24	2.1055E-05
12	T30	1.9856E-05
13	Nc	1.1581E-05
14	NRc	5.86587E-06

Table 3. Operation regime of the aircraft engine.

Parameter name	Parameter value
Input layer	16
Learning rate of NN model	0.5
Number of training cycles	300

Parameter name	Min	Step	Max
Hidden layer 1 of SAE	4	2	16
Hidden layer 2 of SAE	2	2	8
Learning rate of SAE	0.3	0.2	1

Table 4. SAE obtained using the grid search method.

Home	Aircraft Test Result	Contact
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Life prediction results for the first seven optimal parameters:

Rank	Accuracy rate	MAPE	Acceptable number	Acceptable rate
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Table 5. Life prediction results.

Home	Aircraft Test Result	Contact
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9	1816.60	26.47%	73.53%
10	1839.06	27.72%	72.28%

Table 6. Engine life prediction result.

Home	Aircraft Test Result	Contact	About
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The first seven optimal parameter arrays obtained by the grid search method:

Rank	Input layer	Hidden layer 1	Hidden layer 2	Output layer	Learning rate of SAE model
1	16	10	2	1	0.9
2	16	10	2	1	0.5
3	16	8	2	1	0.3
4	16	8	2	1	0.5
5	16	12	2	1	0.9
6	16	10	2	1	0.7
7	16	12	4	1	0.5

Table 7. Optimal parameter obtained by grid search method.

V. CONCLUSION

In this project, a new data-driven method to engine prognostics is devised based on deep learning that can extract effective nonlinear features by themselves and decrease manual intervention. The SAE, a type of deep learning model, is not only able to extract the tendency of the structure to evolve but also adequately robust to noise. The grid search algorithm is used to automatically select the hyperparameters of the SAE. The process of predicting an aircraft engine's remaining useful life (RUL) is applied to the 2008 PHM data challenge dataset to validate the effectiveness of the proposed method. The experimental results, which show a satisfactory prediction accuracy and acceptance rate for all the samples, show that the process is effective at predicting the RUL of an aircraft engine. To reduce the cost of maintenance of aircraft, it also has significance for enhancing the safety of aircraft engines and prognosticating and managing the health of aircraft engines.

REFERENCES

- [1] C. Okoh, R. Roy, J. Mehnen, L. Redding. "Overview of Remaining Useful Life Prediction Techniques in Through-Life Engineering Services." 2014 Elsevier.
- [2] Daniel Azevedo, Bernardete Ribeiro, Alberto Cardoso, "Online Simulation of Methods to Predict the Remaining Useful Lifetime of Aircraft Components." 2019 IEEE.
- [3] Zhongzhe Chen, Shuchen Cao, Zijian Mao, "Remaining Useful Life Estimation of Aircraft Engines Using a Modified Similarity and Supporting Vector Machine (SVM) Approach." 2018 Energies.
- [4] Andrew K.S. Jardine, Daming Lin, Dragan Banjevic, "A review on machinery diagnostics and prognostics implementing condition-based maintenance." 2006 Elsevier.
- [5] Lukun Wang, Xiaoying Zhao, Jiangnan Pei and Gongyou Tang, "Transformer fault diagnosis using continuous sparse autoencoder." 2016 Springer Open.
- [6] Fatih Camci and Ratna Babu Chinnam, "Health-State Estimation and Prognostics in Machining Processes." 2010 IEEE.
- [7] Kishore K. Reddy, Soumalya Sarkar, Vivek Venugopalan, Michael Giering, "Anomaly Detection and Fault Disambiguation in Large Flight Data: A Multi-modal Deep Auto-encoder Approach." PHM Society, Denver, Colorado, 2016.
- [8] Dragan Djurdjanovica, Jay Leeb, Jun Ni, "Watchdog Agent—an infotronics-based prognostics approach for product performance degradation assessment and prediction." 2004 Elsevier.