Intelligent Prediction of Aircraft Engine Remaining Useful Life through Deep Learning Techniques

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Abstract
The aviation industry places critical emphasis on safety, reliability, and maintenance efficiency. One of the most important aspects of aircraft health management is the prediction of the Remaining Useful Life (RUL) of engines, which enables timely maintenance, minimizes downtime, and prevents unexpected failures. Traditional maintenance schedules based on fixed intervals or threshold limits often fail to account for varying operational conditions, leading to inefficiencies and increased costs. To address these limitations, this study proposes a deep learning–based predictive model for estimating the RUL of aircraft engines using time-series sensor data.
The proposed system utilizes data from the NASA C-MAPSS (Commercial Modular Aero-Propulsion System Simulation) dataset, which includes multivariate sensor readings from multiple engine units operating under different conditions and fault modes. After preprocessing and normalization, the time-series data are fed into advanced deep learning architectures such as Long Short-Term Memory (LSTM) and Convolutional Neural Networks (CNNs) to capture both temporal dependencies and degradation trends. The model is trained to map sensor signal patterns to RUL values, learning complex nonlinear relationships without manual feature engineering.
Experimental results demonstrate that the hybrid CNN-LSTM model achieves superior performance, reducing prediction error compared to traditional regression and shallow machine learning methods. The system effectively forecasts degradation trajectories, offering precise RUL predictions even under variable operational environment
Keywords: Deep learning, prediction, aircraft engine

INTRODUCTION

In the aviation industry, the reliability and operational safety of aircraft systems are paramount. Among all critical components, aircraft engines are subject to the most demanding operational and environmental conditions, including high pressure, temperature fluctuations, and continuous mechanical stress. Predicting the Remaining Useful Life (RUL) of these engines is a central goal in predictive maintenance, as it enables operators to anticipate failures, schedule repairs proactively, and optimize maintenance resources. Early and accurate RUL estimation not only enhances flight safety but also significantly reduces maintenance costs and unscheduled downtime.

Traditional maintenance strategies such as corrective maintenance (reactive repair after failure) and preventive maintenance (scheduled service based on predefined intervals) are often inefficient. These approaches overlook the unique degradation patterns of individual engines, which vary based on flight conditions, environmental exposure, and operational stress. Consequently, there is an increasing demand for Condition-Based Maintenance (CBM) and Prognostics and Health Management (PHM) systems that use real-time sensor data and data-driven models to predict component degradation dynamically.

As there was no need for additional sensor values that were significant to an aircraft's engine condition over the previous decades, aircraft engines were constructed with the bare minimum of sensors. Predictive maintenance is now accessible for all 21 of the new sensors that have been installed in an aircraft engine, saving time and money by preventing the need for Unneeded repair. These sensors, which are connected to the aircraft engine, offer agood amount of historical data that really reveals the location of the engine. These huge volumes of data may be kept on locked servers or in the hard drives of aeroplane engines, making it simpler to find and use when needed. As a result, the maintenance service may be found close by, use the data saved in the system, and perform maintenance checks as needed, cutting down on the manual time needed togo work on the engines. Recurrent neural networks (RNN) and long short-term memory are deep learning techniques we employ to predict the present remaining usable life (RUL) of the aircraft engine (LSTM). The previous method enables us to model the data set using time stamps, which implies that data from sixty timestamps in the past is matched to data from the present. A long short term memory (LSTM) neural network is required for improved accuracy because it continuouslyscans and updates itself with all of the input. The most effective neural network methods for forecasting data points are also founded on this. The first estimate is the remaining usable life (RUL), which is also dependent on how many cycles the aircraft engine has run. It seems obvious that long short term memory was created to prevent difficulties with long short term dependent. For time series prediction with real-time data processing, LSTM networks are appropriate.

This research focuses on developing and evaluating a deep learning–based framework for RUL prediction of aircraft engines. The proposed approach leverages the combined strengths of CNN and LSTM architectures: CNN layers extract local degradation features from sensor sequences, while LSTM layers capture temporal dependencies across time steps. The integration of these layers allows the system to learn both short-term signal fluctuations and long-term degradation trends.

LITERATURE SURVEY

So every business that uses machinery must agreement to allow its assets. Predictive maintenance is a technique for planning maintenance that is based on computing an equipment's failure time. Creating the prediction can be executed by analysing the data from the equipment'smeasurements [1]. Advanced sensors that are integrated into the aircraft's electronics are utilized to offer the data that shows the status of the aircraft. The application of precise RUL data-driven prediction modelsfor an aircraft based on DL techniques is facilitated by such data [2]. The aero engine is a highly advanced and costly industrial product.For aero engines,detailed defect location and estimation can result to the right maintenance activities that will stop breakdowns and minimisefinancial losses [3]. Because the internet ofthings technology gets better gradually, companies are able to monitor the health of engine parts and built-in systems by gathering sensor signal data [4]. As most lives depend on the aircraft, engine maintenance is crucial. Thus, we need often check the continuity [5]. When a component rapidly degrades over time after been under heat stress and high temperatures, failure results [6]. The proposed model uses a particle filter to forecast the posterior values of capacitanceand resistance, which are ageingpredictors. The suggested model, incontrast to prior prognosis techniques,forecasts the RUL while taking into account ageing variables such as temperature and voltage; these tests have been done under wider range conditions[7]. The condition monitoring system is based on a model of a wind turbine power curve, so it diagnoses anomalous turbine behaviour to use the deviation-caused power of the turbine [8]. The research uses machine learning to provide a prediction framework for an aircraft's remaining life cycle (RUL) based on the whole life cycle data and deterioration parameter data (ML). For the goal of assessing the engine's lifetime, a Deep Layer Recurrent Neural Network (DL-RNN) model is given[9].The size and quantity of anomalies may vary wildly for each type of error withthe tends to spread the late fracture. With current system reliability methods, it is possible to predict the likelihood of failure of a component with many anomaly kinds as long as the failure probabilitiesassociated with each anomaly are known [10]. despite the fact that the aero engine model can be used in a variety of instances, key reliability-related phenomena still lack the labelled requesteddata to train a fully supervised model [11]. The remaining useful life (RUL) of a turbo engine is the period from the present to its failure, and its modelling techniques aredivided down as follows: Model-based techniques, commonly referred to as the physics of failure methodology, comprise data-driven techniques, hybrid techniques, and model-based policies [12]. Estimating the PEMFC's parameters is a difficult task due to multiple variables, like temperature and ageing, which cause parameter drift and decrease the performance of the entire energy system [13]. The safety of turbofan engines in aeroplanes should be the primary focus. With advances in material and control technologies, which have lowered the amount of aircraft breakdown forced on by loose connections, the management of turbofan engine malfunctions has become key for passenger safety [14]. With complex operations, hybrid errors, and loud noises, LSTM artificial neural network are used toproduce good diagnostic and prediction performance [15]. The rate of change in simulation flow and efficiency points to anotherwise unknown problem with negative effects that worsen as moment. Although the defects' rates of change were picked at random, they were still restricted to an upper limit [16].It is indicated that an adaptive skew-Wiener model, which is far more flexible than conventional stochastic process models, be used to depict the decaying drift of industrial devices. The degradation trajectory is commonly defined utilizing stochastic system models [17]. A hybrid convolutional-recurrent neural network (CNN-RNN) approach is provided for the RUL estimation. Toforesee the RUL, this approach uses a trained hybrid network without a threshold. The model's prediction accuracyis further raised by arranging, adding, and classifying data [18].

EXISTING SYSTEM

Regime In the past year, results were madeusing a machine learning approach to detect a different algorithm to supervised training and learns from the data. In supervised learning, the input variable(sensor values) is a part of the data set, which is then divided into the sets to train and test using which the RUL was predicted. A training set is employed to train the machine learning algorithm, whilea test set helps test the validity of the algorithm.

PROPOSED SYSTEM

To high performance of our application, we included LSTM neural networks in the proposed scheme. In order to put together our data set so that each row comprises 60 values references to the original data sets, this LSTM technique implies time stamps (steps) to look on to the past data. The visual sees the LSTM neural network diagram for the proposed approach.

SYSTEM ARCHITECTURE

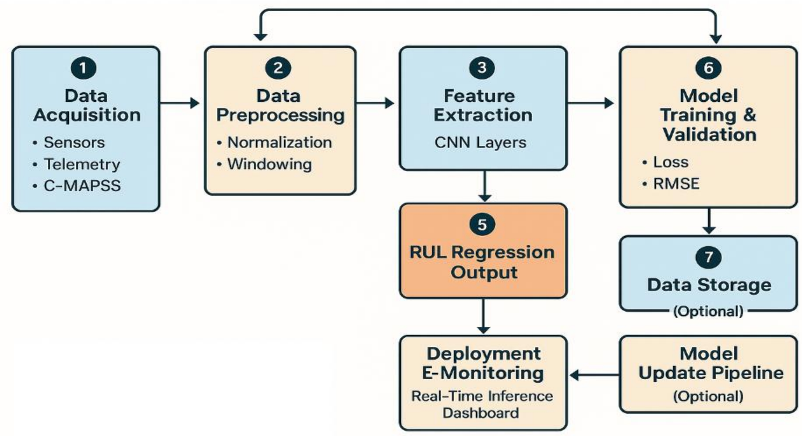
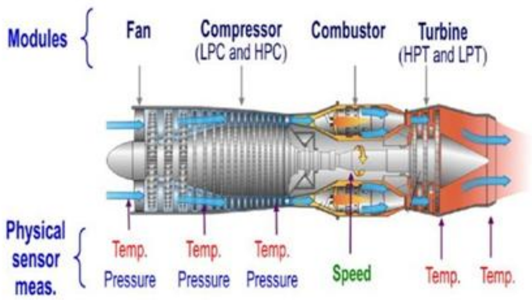


Fig.1. Proposed system

The study's suggested predictive maintenance platform consists of the sensor module and analytical system. The core role of the sensing module was torecord and upload the operational state of the test platform for further monitoring andanalysis. The analytical system was able toanalyse the data efficiently and swiftly, making model updates for failure predictions. On the criterion of both the historical recorded data and the real-time sensor data, it contains suggestions for the maintenance of the test platform in the future.



EXPERIMENTAL STUDY

Dataset.

The dataset most frequently used in the literature for preventative maintenance in plane health systems is the NASA Turbofan Engine Corruption Simulation dataset. The dataset consists by NASA engineers to use the commercial simulation programme C-MAPSS. Simulated conditions include temperatures between -60 and 103 degrees Fahrenheit, altitudes between 0 and 40,000 feet, and Mach numbers between 0 and 0.9. Engine core speed, fan speed, fan inlet pressure, High Pressure Turbine (HPT) exit temperature, High Pressure Compressor (HPC) pressure, and engine-pressure ratio were the parameters of diesel engines involved in the experiments. There are a total of 21 onboard sensors buried throughout the engine to measure its assets, comparing temperature, pressure, and speed.

Sample training data

~20k rows,
100 unique engine id

id	cycle	setting1	setting2	setting3	s1	s2	s3	…	s19	s20	s21
1	1	-0.0007	-0.0004	100	518.67	641.82	1589.7		100	39.06	23.419
1	2	0.0019	-0.0003	100	518.67	642.15	1591.82		100	39	23.4236
1	3	-0.0043	0.0003	100	518.67	642.35	1587.99		100	38.95	23.3442
…	…										
1	191	0	-0.0004	100	518.67	643.34	1602.36		100	38.45	23.1295
1	192	0.0009	0	100	518.67	643.54	1601.41		100	38.48	22.9649
2	1	-0.0018	0.0006	100	518.67	641.89	1583.84		100	38.94	23.4585
2	2	0.0043	-0.0003	100	518.67	641.82	1587.05		100	39.06	23.4085
2	3	0.0018	0.0003	100	518.67	641.55	1588.32		100	39.11	23.425
…	…										
2	286	-0.001	-0.0003	100	518.67	643.44	1603.63		100	38.33	23.0169
2	287	-0.0005	0.0006	100	518.67	643.85	1608.5		100	38.43	23.0848

Sample testing data

~13k rows,
100 unique engine id

id	cycle	setting1	setting2	setting3	s1	s2	s3	…	s19	s20	s21
1	1	0.0023	0.0003	100	518.67	643.02	1585.29		100	38.86	23.3735
1	2	-0.0027	-0.0003	100	518.67	641.71	1588.45		100	39.02	23.3916
1	3	0.0003	0.0001	100	518.67	642.46	1586.94		100	39.08	23.4166
…	…										
1	30	-0.0025	0.0004	100	518.67	642.79	1585.72		100	39.09	23.4069
1	31	-0.0006	0.0004	100	518.67	642.58	1581.22		100	38.81	23.3552
2	1	-0.0009	0.0004	100	518.67	642.66	1589.3		100	39	23.3923
2	2	-0.0011	0.0002	100	518.67	642.51	1588.43		100	38.84	23.2902
2	3	0.0002	0.0003	100	518.67	642.58	1595.6		100	39.02	23.4064
…	…										
2	48	0.0011	-0.0001	100	518.67	642.64	1587.71		100	38.99	23.2918
2	49	0.0018	-0.0001	100	518.67	642.55	1586.59		100	38.81	23.2618
3	1	-0.0001	0.0001	100	518.67	642.03	1589.92		100	38.99	23.296
3	2	0.0039	-0.0003	100	518.67	642.23	1597.31		100	38.84	23.3191
3	3	0.0006	0.0003	100	518.67	642.98	1586.77		100	38.69	23.3774
…	…										
3	125	0.0014	0.0002	100	518.67	643.24	1588.64		100	38.56	23.227
3	126	-0.0016	0.0004	100	518.67	642.88	1589.75		100	38.93	23.274

Sample ground truth data

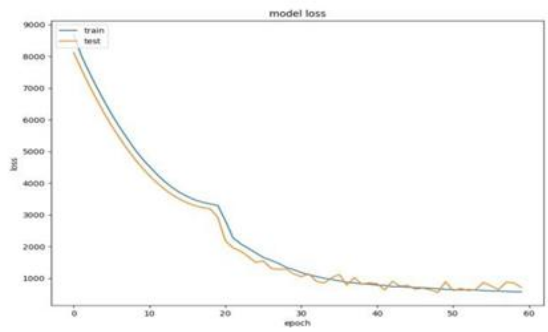
100 rows

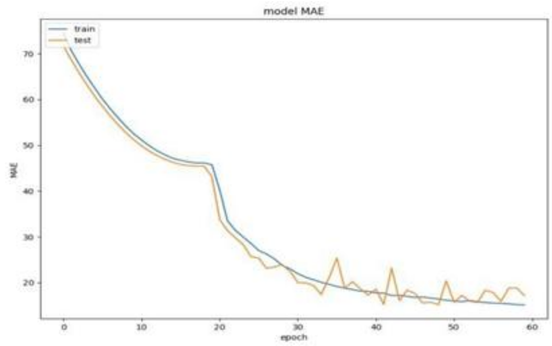
RUL
112
98
69
82
91

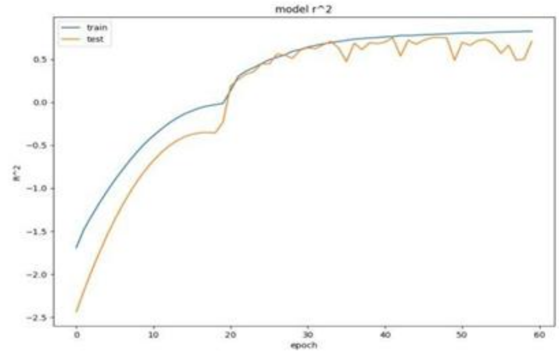
Results and Discussion

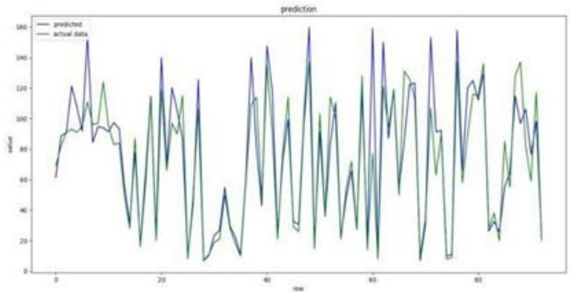
The suggested system architecture involves a number of essential structures, such as the number of input nodes and hidden layers. the hyper parameters of the DNB model as well as the number of hidden layers. The primary structural factors to be considered for producing the suggested model were listed via experimental trials with the goal of obtaining the best RUL prediction performance.

The following images display the trend between actual and predicted data as well as the mean absolute error, R2, and loss function:

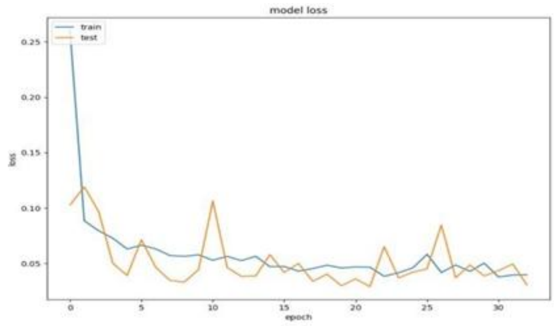


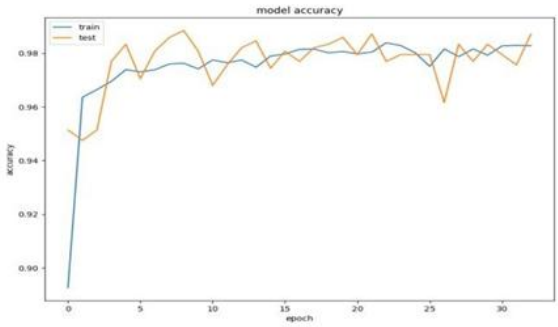


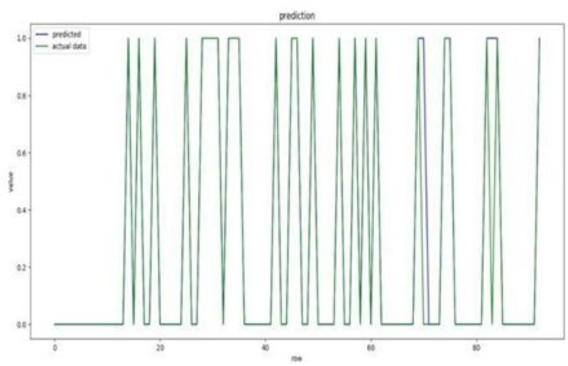




The following picture show trend of loss function, Accuracy and Actual data compared to predicted data:







CONCLUSION

Deep learning techniques have become widely attractive in engineering use in the last decade, particularly in data analysis for reliability evaluation, which was previously inefficient so it actually needed both expert knowledge of the studied system or the limitations of traditional PHM techniques. There are still many obstacles for reliability related, data-drivenapplications to maintain improving the estimate of signs of health that can send an accurate diagnostic for systems andfacilities. This finding indicates a deep learning way to predict the health of complex systems using large amounts of machine data. The method was taught by the framework using a special topology tileneural network, and it was verified using two separate sets of data. Using the C- MAPSS and Challenge datasets, the proposed framework is validated through the training and testing of several models. The proposed approach is also reliable in predicting how hard both datasets will be usable. The superiority of the proposed topology is illustrated by a comparison of SCG algorithms.

REFERENCES

[1] Vimala Mathew, Tom Toby, Vikram Singh, B Maheswara Rao, M Goutham Kumar, "Prediction of Remaining Useful Lifetime(RUL) of Turbofan Engine using Machine Learning" 2017 IEEE International Conference on Circuits and Systems(ICCS 2017). IEEE 2017.

[2] Dong Dong, Xiao-Yang Li, Fu-Qiang Sun "Life Prediction of Jet Engines Based on LSTM-Recurrent Neural Networks" School of Reliability and Systems Engineering, Science and Technology on Reliability andEnvironment Engneering. IEEE 2017.

[3] Mei Yuan, Yuting Wu and Li Lin "Fault diagnosis and Remaining useful life estimationof aero engine using LSTM neural network" 2016 IEEE/CsAA International Conference on Aircraft Utility System(AUS).

[4] Olgun Aydin, Screen Guldamlasioglu "Using LSTM Networks to Predict Engine Condition on Large Scale Data Processing Framework" 2017 4th International Conference On Electrical and Electronics Engineering.

[5] Zhi Lv, Jian wang ,Guigang Zhang, Huang Jiyang "Prognostic Health Management of Condition-Based Maintenance for Aircraft Engine Systems.

[6] Okoh, C.; Roy, R.; Mehnen, J.; Redding, L. "Overview of Remaining Useful Life Prediction Techniques in Through-Life Engineering Services." *ProcediaCIRP* **2014**, *16*, 158–163.

[7] El Mejdoubi, A.; Chaoui, H.; Sabor, J.; Gualous, H. "Remaining Useful Life Prognosis of Supercapacitors under Temperature and Voltage AgingConditions." *IEEE Trans. Ind.Electron.* **2018**, *65*, 4357–4367.

[8] Dhiman, H.S.; Deb, D.; Carroll, J.; Muresan, V.; Unguresan, M.-L. "Wind Turbine Gearbox Condition Monitoring Based on Class of Support Vector Regression Modelsand Residual Analysis." *Sensors* **2020**, *20*, 6742

[9] Lan, G.; Li, Q.; Cheng, N. "RemainingUseful Life Estimation of Turbofan Engine Using LSTM Neural Networks." In Proceedings of the IEEE CSAA Guidance, Navigation and Control Conference (CGNCC), Xiamen, China, 10–12 August 2018

[10] Enright, M.P.; McClung, R.C. "A Probabilistic Framework for Gas Turbine Engine Materials ith Multiple Types of Anomalies." *J. Eng. Gas Turbines Power* **2011**, *133*, 082502.

[11] Zhang, B.; Wang, D.; Song, W.; Zhang, S.; Lin, S. "An Interval-Valued Prediction Method for Remaining Useful Life of Aero Engine." In Proceedings of the 2020 39th Chinese Control Conference (CCC), Shenyang, China, 27–29 July 2020.

[12] Goebel, K.; Saxena, A. "Turbofan Engine Degradation Simulation Dataset. In *NASAAmes Prognostics Data Repository*; NASA Ames Research Center: Moffett Field, CA, USA, 2008."

[13] Chaoui, H.; Kandidayeni, M.; Boulon, L.; Kelouwani, S.; Gualous, H. "Real-Time Parameter Estimation of a Fuel Cell for Remaining Useful Life Assessment. *IEEETrans." Power Electron.* **2021**, *36*,7470–7479.

[14] Hong, C.W.; Lee, C.; Lee, K.; Ko, M.-S.; Kim, D.E.; Hur, K. "Remaining Useful Life Prognosis for Turbofan Engine Using Explainable Deep Neural Networks with Dimensionality Reduction." *Sensors* **2020**, *20*, 6626.

[15] Yuan, M.; Wu, Y.; Lin, L. Fault diagnosis and remaining useful life estimation of aero engine using LSTM neural network. In Proceedings of the IEEE International Conference on Aircraft Utility Systems (AUS),Beijing, China, 10–12 October 2016.

[16] Saxena, A.; Goebel, K.; Simon, D.; Eklund, N. Damage propagation modeling for aircraft engine run-to-failure simulation. In Proceedings of the 2008 International Conference on Prognostics and Health Management, Denver, CO, USA, 6–9 October 2008.

[17] Huang Z., Xu Z., Ke X., Wang W., Sun Y. "Remaining useful life prediction for anadaptive skew-Wiener processmodel. *Mechanical Systems and Signal Processing*." 2017;87:294 –306.

[18] Zhang X., Dong Y., Wen L. Remaining useful life estimation based on a new convolutional and recurrent neural network. Proceedings of the IEEE 15th International Conference on Automation Science and Engineering; August 2019; Vancouver,Canada. pp. 317–322.