

Remaining Useful Life Estimation of Turbofan Engines with Deep Learning Using Change-Point Detection Based Labeling and Feature Engineering

Abstract

[3]Ensarioğlu K İnkaya T and Emel E . This paper proposes a model for predicting the remaining lifespan of turbofan engines using deep learning predicting remaining lifespan is a challenging problem in engine health monitoring because sensor data requires thorough processing before model training researchers employed a method based on differential feature construction change point detection and then used a hybrid 1D CNN LSTM deep learning model to predict remaining lifespan the model was evaluated using the FD001 C MAPSS dataset the results showed that the proposed model outperformed some machine learning and deep learning models achieving an RMSE of 16 and a score of 437.

Introduction

[3]Ensarioğlu K İnkaya T and Emel E . The paper states that turbofan engines are critical components in aircraft and that predicting their remaining service life helps support predictive maintenance and reduce unexpected failures it also notes that most recent studies in this field rely on data-driven models because sensor data contains crucial information about engine degradation the paper highlights the problem that many studies consistently use piecewise linear labeling assigning the same initial service life value to all engines during their normal operating period this may not accurately represent the state of degradation therefore the paper suggests using change Point Detection to better identify the starting point of degradation for each engine and then using a 1D CNN LSTM model to improve the accuracy of predicting remaining service life.

Related Work

[3]Ensarioğlu K İnkaya T and Emel E. Previous studies in the field of predicting the remaining lifespan of turbofan engines have shown that many studies have used data driven models such as machine learning and deep learning to analyze sensor data and predict remaining lifespan the paper also mentions that some studies used LSTM because it is suitable for handling temporal data while others used CNN to extract features from sensor data some studies relied on methods for classifying or dividing deterioration stages or used methods to extract features before prediction however the problem is that many of the previous methods rely on fixed labels for remaining life or do not adequately utilize the development of new features therefore this paper aims to improve upon previous work by integrating feature engineering with change-point detection-based labeling and a 1D CNN-LSTM model.

Methodology

[3]Ensarioğlu K İnkaya T and Emel E. The C MAPSS FD001 turbofan engine dataset was used to evaluate the proposed model. The methodology focuses on three main steps first new features were constructed from the sensor data using difference-based feature construction to extract clearer information about engine condition changes then change point detection based on piecewise linear labeling was used to identify the starting point of deterioration instead of relying on a fixed value for initial age subsequently a 1D CNN-LSTM hybrid deep learning model was trained the CNN helps extract important features from the data while the LSTM helps understand temporal changes in the sensor data the proposed model was then compared with machine learning and deep learning models both with and without the new features to determine the impact of the processing steps on prediction accuracy.

Results

[3]Ensarioğlu K İnkaya T and Emel E .The results showed that the 1D CNN LSTM model with features built using difference feature analysis achieved the best performance in predicting the remaining service life of turbofan engines on the FD001 set of C MAPSS data. The paper achieved an RMSE score of 16.1 and a Score of 437.2 the results also showed that using feature engineering with change point detection based labeling helped improve prediction accuracy compared to models that did not use these steps the paper stated that the proposed model outperformed some previous machine learning and deep learning models indicating that identifying the point of deterioration and building appropriate features helps improve predictive maintenance results.

Conclusion

[3]Ensarioğlu K İnkaya T and Emel E .The study concluded that integrating change point detection with feature engineering and a 1D CNN LSTM model improves the accuracy of predicting the remaining lifespan of turbofan engines the change point detection method allowed for more realistic remaining lifespan designations compared to using a fixed value for all engines the new features also enhanced the model's ability to understand engine degradation the paper indicated that the proposed model performed well on FD001 data from C MAPSS but its main limitation was its focus on only a single subset therefore future testing of the method on more complex subsets and multiple operating conditions is recommended to improve the model's generalizability.

Paper	All Models	Datasets	Dataset Link	Limitation	Best model	results
Ensarioğlu et al [3]	1D CNN LSTM and comparison with machine learning and deep learning models with and without difference feature	C MAPSS FD001			1D CNN LSTM with difference feature and change point based labeling	RMSE 16.1 and Score 437.2

Ref

[3]Ensarioğlu K İnkaya T and Emel E “Remaining Useful Life Estimation of Turbofan Engines with Deep Learning Using Change Point Detection Based Labeling and Feature Engineering” Applied Sciences vol 13 no 21 Article 11893 2023 DOI 10.3390/app132111893