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A Comparative Survey Of Machine Learning Techniques For Remaining Useful Life Prediction In Aero Engines

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ABSTRACT

The accurate prediction of an aero engine's Remaining Useful Life (RUL) is essential not only for safety enhancement but also for the maintenance optimization that eventually reduces operational costs within the aviation sector. Traditionally, models based on physics require enormous expertise in a specific domain and do not scale appropriately with data complexity. Recent breakthroughs in machine learning and deep learning facilitate the development of data-driven models that capture non-trivial temporal multivariate dynamics in sensor measurements and hence allow for more precise RUL predictions at greater scalability. This survey covers a broad spectrum of ML and DL methodologies applied to aero engine prognostics, including RNNs, CNNs, LSTM networks, Transfo rmers, and hybrid architectures. The authors review feature engineering methods as well as data preprocessing techniques, transfer learning, and model evaluation. The paper ends with a highlight on the state-of-the-art challenges like data insufficiency, generalization capability, and model interpretability; then pays ways to future tracks in predictive maintenance via intelligent systems.

Keywords: Remaining Useful Life (RUL), Aero Engine Prognostics, Machine Learning, Deep Learning, Predictive Maintenance, Time Series Forecasting, CNN-LSTM, Transformer Networks, CMAPSS Dataset, Feature Engineering.

I. INTRODUCTION

Turbo engines are, by far, the most sophisticated and critically safety-engineering system of modern aircraft that require strict monitoring and control throughout their life cycle. The impact resulting from premature engine failure – which could range from operational delays to catastrophic incidents – underlines the need for accurate and timely Remaining Useful Life (RUL) estimation. Predictive maintenance is enabled by RUL prediction because it allows the operators to foresee failures and intervene prior before the fault propagates to a critical level. Hence, while on one hand, the safety and reliability of aircraft are enhanced, on the other, maintenance costs as well as downtime are considerably reduced. The traditional approaches towards RUL estimation have mainly focused model development efforts onto physics-based models specifically aimed at modeling physical processes of degradation over time for components within engines through models derived from thermodynamic principles, fluid dynamics, and material science. Although these models are precise under carefully controlled situations, they are usually bounded by their reliance on in-depth domain expertise, large- scale calibration, and inability to mimic to diverse operating conditions and realities of the world. The advent of Machine Learning (ML) and Deep Learning (DL) has enabled data- driven prognostics, with models learning degradation patterns through direct interaction with histories and real-time sensor data. In contrast to physics-based techniques, data-driven methods are capable of processing large-scale, high-dimensional, and non-linear data without the need for in-depth understanding of the physical processes involved. This makes them particularly attractive for intricate systems such as aero engines, where numerous interacting variables control component wear and performance. Over the last few years, researchers have used a vast range of ML and DL algorithms for RUL prediction. Earlier research used conventional ML approaches like Linear Regression, Support Vector Machines (SVMs), and Random Forests that were decent in performance when used with meticulous feature engineering. Nonetheless, these models tended to underperform with temporal dependency in time-series data, which is critical to model degradation trends.

More advanced DL architectures have since been proposed to correct this. Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks are particularly built to learn temporal patterns and hence are successful in capturing sequential sensor data. Likewise, Convolutional Neural Networks (CNNs) have been used in modified forms to learn spatial and temporal features from multivariate signals. Latest developments include Transformer-based models and hybrid architectures combining CNN, LSTM, and attention mechanisms, which have achieved state-of-the-art performance by learning well the long-term dependencies and intricate feature interactions. Through integrating current research, the paper seeks to act as a guide for researchers and practitioners developing intelligent predictive maintenance systems, providing knowledge on best practices, trends, and directions in aero engine RUL forecasting.

II. LITERATURE SURVEY

In the last decade, significant research efforts have focused on extending the Remaining Useful Life (RUL) of aero engines using machine learning and deep learning techniques. Researchers have explored a wide range of approaches, from conventional machine learning (ML) algorithms to advanced hybrid deep learning models, to improve prediction accuracy and reliability.

Early studies primarily adopted classical ML methods such as Linear Regression, Decision Trees, and Support Vector Machines (SVMs) for predictive maintenance tasks [8], [9]. These models demonstrated acceptable performance when combined with careful feature engineering but often struggled to capture the complex temporal dependencies present in multivariate time-series data.

With the advancement of sensor technology and the availability of large datasets such as NASA's C-MAPSS, deep learning (DL) models have gained prominence. Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks have shown strong capabilities in modeling sequential dependencies in sensor data, thereby improving prediction accuracy over traditional ML approaches [7]. Convolutional Neural Networks (CNNs) have also been adapted to extract spatial and temporal features from sensor signals, while more recent approaches have utilized Transformer architectures for long-term dependency modeling [6].

Hybrid and ensemble approaches have been proposed to exploit the strengths of multiple models. For example, CNN-LSTM-Attention frameworks have been developed to integrate spatial, temporal, and attention-based feature selection, significantly enhancing model robustness [5]. Similarly, Transfer Learning and Domain Adaptation techniques have been introduced to address the challenge of limited labeled data and improve generalization across different engine types [1], [11].

Recent studies have also emphasized the importance of data preprocessing and label generation. Methods such as noise filtering, normalization, and change-point detection have been used to produce high-quality training data, improving model stability and predictive performance [2], [10].

Moreover, researchers have highlighted that carefully designed label smoothing and degradation modeling strategies lead to more realistic and robust RUL predictions [3].

Overall, literature trends indicate a shift from purely physics-based and standalone ML models toward data-driven hybrid deep learning solutions capable of handling high-dimensional, noisy, and heterogeneous sensor data. These advancements pave the way for more accurate, interpretable, and real-time deployable predictive maintenance systems.

III. CHALLENGES AND FUTURE DIRECTIONS

Forecasting the Remaining Useful Life (RUL) of aero engines using machine learning continues to present multiple open challenges that future research must address. One of the primary concerns is **data quality and availability**.

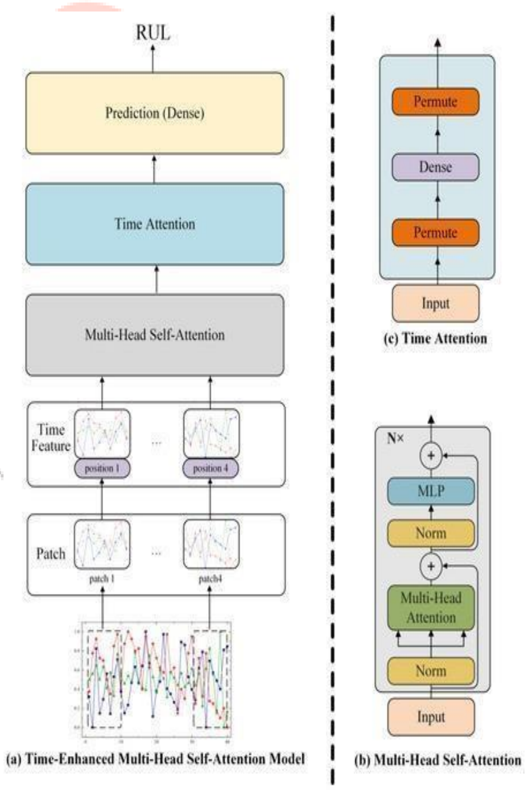
Sensor data from aero engines are often noisy, incomplete, or inconsistent, which affects model reliability. Morerver,robust preprocessing pipelines, including noise reduction, data imputation, and adaptive filtering, are needed to improve model inputs and make training data representative of real-world conditions.

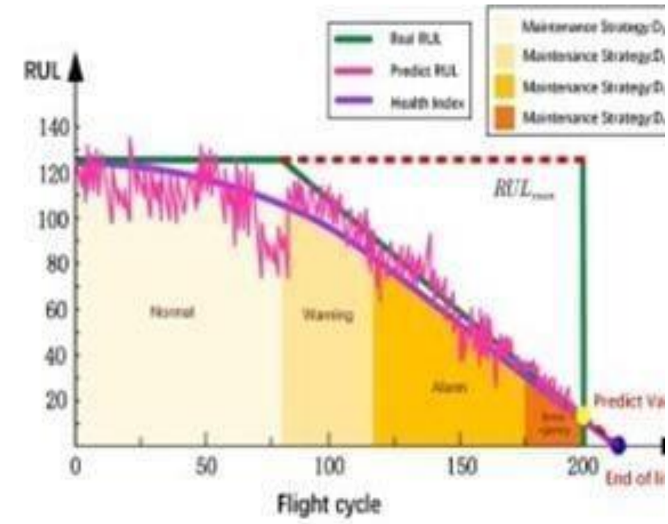
Another key challenge lies in **label generation and degradation modeling**. The true RUL of an engine is rarely observed until failure, and simplistic piecewise-linear labeling can misrepresent the actual wear process. Future approaches may focus on smarter label generation strategies, incorporating physics-informed degradation curves or probabilistic labeling to better capture uncertainty and variance across engines.

Model generalization and transferability also remain open issues. Most models are trained on a single dataset (such as NASA's C-MAPSS), limiting their applicability to different engine types or operational environments. Transfer learning, domain adaptation, and meta-learning approaches can help models learn from one engine type and adapt to another with minimal retraining, which structures also showed improved efficiency and clarity of the analysis. Models using transfer learning [11] demonstrated good performance with few labeled datasets because the models can share knowledge learned from similar or related datasets of engines is essential for real-world deployment.

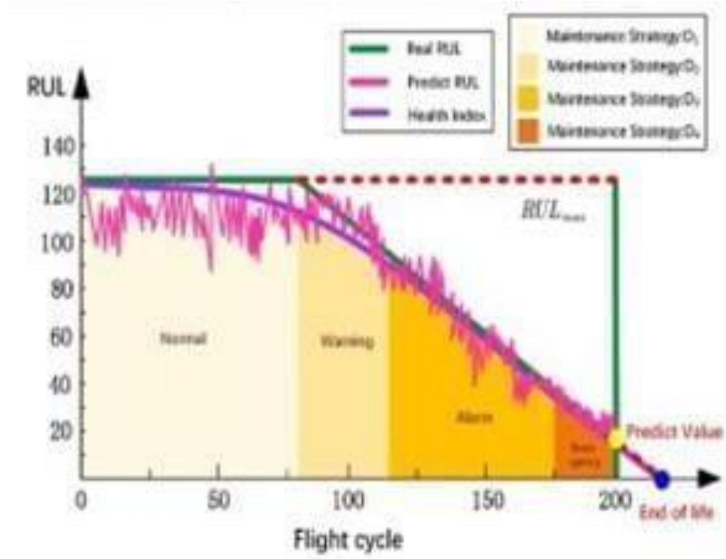
Finally, **computational efficiency and interpretability** are crucial future directions. While deep learning models like CNN-LSTM with attention achieve state-of-the-art results, they are often computationally heavy and act as "black boxes." Future research should focus on lightweight architectures optimized for real-time inference and incorporate explainable AI (XAI) techniques to highlight which features or time steps influence the RUL prediction most. This will build trust among aviation engineers and make these systems viable for operational use.

By tackling these challenges, future work will make RUL prediction more robust, interpretable, and deployment-ready, ultimately improving aviation safety and reducing maintenance costs.

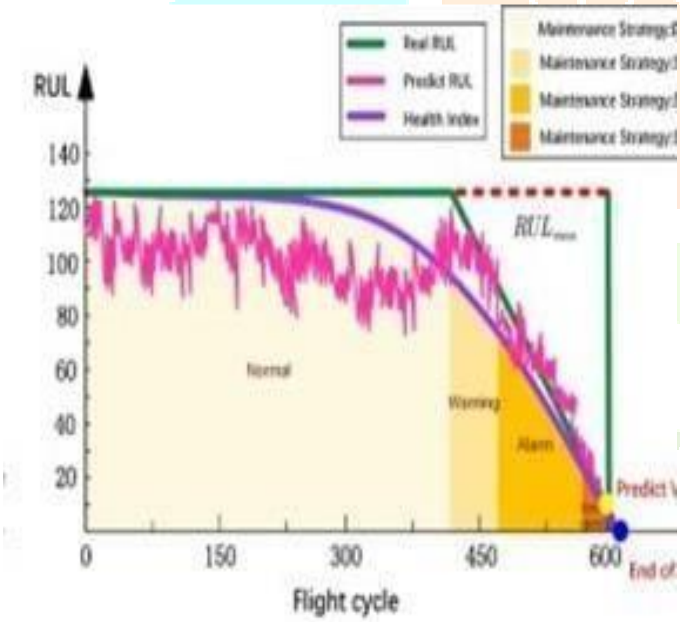




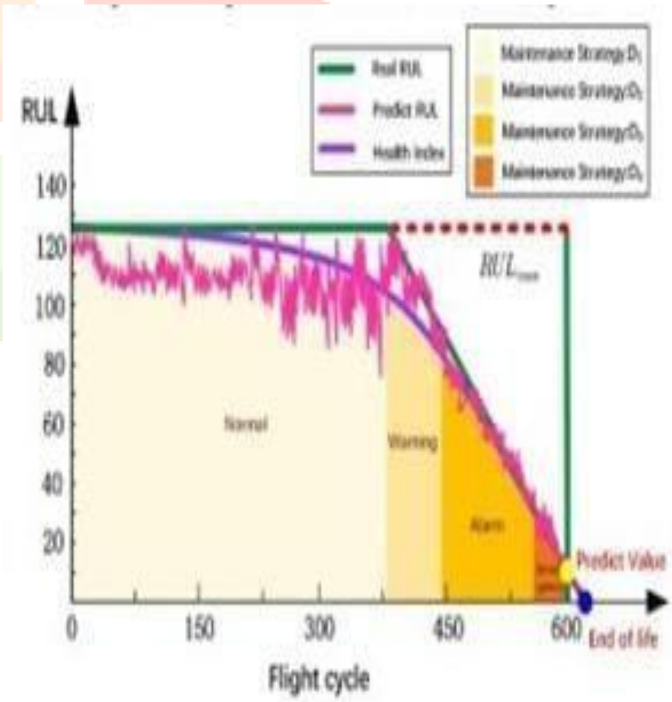
(a) RUL prediction plot for FD001 dataset #76 engine



(c) RUL prediction plot for dataset FD003 #92 engine



(b) RUL prediction plot for FD002 dataset #45 engine



(d) RUL prediction plot for dataset FD004 #134 engine

Year	Author(s) & Title	Methodology	Key Findings
2025	Zha, W. – An aero-engine remaining useful life prediction model based on feature selection and the improved TCN	Temporal Convolution Network (TCN) with feature selection	Enhanced RUL prediction accuracy by incorporating feature selection techniques. (ScienceDirect)
2025	Elsherif, S.M. – A deep learning-based prognostic approach for predicting turbofan engine degradation and remaining useful life	Deep Learning Techniques	Proposed a deep learning-based approach for RUL prediction, improving prognostic accuracy. (Nature)
2024	Deng, S. – Prediction of Remaining Useful Life of Aero-engines Based on CNN-LSTM-Attention	CNN-LSTM with Attention Mechanism	Introduced a hybrid model combining CNN, LSTM, and attention mechanisms for RUL prediction. (SpringerLink)
2024	Barry, I. – Advanced Multi-Model Prediction of Aircraft Engine Remaining Useful Life with Random-Sampling Based Class Balancing and Voting-Based Features Selection	Multi-Model Ensemble	Developed an ensemble approach incorporating class balancing and feature selection for RUL prediction. (ScienceDirect)
2024	Peringal, A. – Reliable Prediction of Remaining Useful Life for Aircraft Engines	Long Short-Term Memory (LSTM) Network	Utilized LSTM networks for reliable RUL prediction in aircraft engines. (AIAA Journal)
2023	Alomari, Y. – Advancing aircraft engine RUL predictions: an interpretable integrated approach of feature engineering and aggregated feature importance	Feature Engineering & Machine Learning	Proposed an interpretable approach combining feature engineering and machine learning for RUL prediction. (Nature)
2023	Li, Y. – Remaining useful life prediction of aero-engine enabled by fusing knowledge and deep learning models	Knowledge Fusion & Deep Learning	Integrated knowledge-based methods with deep learning for enhanced RUL prediction. (IDEAS/RePEc)
2022	Zhou, Z. – An aircraft engine remaining useful life prediction method based on prediction vector angle minimization and feature fusion gate improved transformer	Transformer with Feature Fusion	Introduced a transformer-based model with feature fusion for RUL prediction. (ScienceDirect)
2021	Chen, J. – Aero-engine remaining useful life prediction method with multimodal data fusion and ensemble transfer learning	Multimodal Data Fusion & Transfer Learning	Proposed a method combining multimodal data fusion and transfer learning for RUL prediction. (ScienceDirect)
2020	Gan, F. – Remaining useful life prediction of aero-engine via GCSU layer	GCSU Layer Integration	Developed a model incorporating GCSU layers for improved RUL prediction. (ScienceDirect)

1V. RESULTS AND DISCUSSION

A wide variety of machine learning models for Remaining Useful Life (RUL) prediction has been tried and tested in the literature using benchmark datasets such as NASA's C-MAPSS turbofan engine dataset. This section summarizes typical results, comparisons of models, and implications of different methods for prediction accuracy and robustness.

Performance Metrics :

Below are some examples of common evaluation metrics: RMSE, or root mean squared error, is the square root of the squared mean differences between the actual and expected RUL values. A model with lower RMSE is deemed more accurate. RMSE could also be thought of as a more objective measure of accuracy. The Mean Absolute Error, or MAE, is the mean of the absolute differences between the actual and expected RUL score. Function: to more accurately reflect the real cost of maintenance errors, a one of a kind evaluation metric was created with differing penalties for early and/or late predictions.

Comparative Analysis of Models :

Conventional ML models, such as Support Vector Machines and Random Forests, can offer limited accuracy in terms in accommodating temporal dependencies in sensor data, resulting in high RMSE values. In contrast, models based on Deep Learning, such as LSTM and CNN-LSTM combinations, in most studies, outperform classical models as they integrate temporal and spatial features. Specifically,
[6] and [14] shows RMSE improvement of 10-30 % compared to the baseline ML approaches.

Attention mechanisms with LSTM and CNN-LSTM

Discussion on Challenges and Observations Data Quality and Labeling:

The accuracy of RUL Predictions relies heavily on sensor data and the way it is labeled. Unorganized or even contradictory data can confuse model training, which is why preprocessing and label smoothing is an important step to take during training.

Model Complexity vs. Interpretability:

More complex and elaborate architectures can increase accuracy, but they are simply black boxes, which do not give any reasoning to why a certain decision was made. We can use attention mechanisms to see

Model Complexity vs. Interpretability:

More complex and elaborate architectures can increase accuracy, but they are simply black boxes, which do not give any reasoning to why a certain decision was made. We can use attention mechanisms to see which features are more important for prediction as a way of somewhat easing that black box element.

Generalization Across Engines: Most models are trained using one part of a dataset, such as C-MAPSS, and will only check predictive ability based on that dataset. Therefore when new (different) engines or operational environments are encountered, this can be a challenge - could transfer learning or domain adaptation techniques solve this? More research is needed in this area

Real-Time Deployment: Often seen as the biggest detriment, the computational cost of deep models can make real-time prediction more challenging. Also, for practical implementations, what can be done to ensure models are built to yield faster inference times without sacrificing accuracy.

IV. CONCLUSION

Academic and industry interest is increasing as the development of machine learning modes and models progresses to predicting the useful remaining life (RUL) prediction of aero engines generally represents an important potential in analysis, particularly for predictive maintenance, and through improved operational / aviation safety. This survey has tracked the considerable evolution of machine learning techniques, ranging from traditional machine learning models, and hybrid deep learning models that incorporate CNN-LSTM with attention depending on the sensor data that potentially capture the underlying spatial- temporal dependencies in the sensors.

There are still key barriers to predictors of aero engines; in the area of data quality, label uncertainty, and ensuring that models developed for one engine type have any generalizable value in a different engine type. Just as the transfer of learning in this area, transfer learning, and feature engineering can provide some initial moderating effect on addressing limited labelled data and combined both approaches seem to be useful when managing with uncertainty around limited labelled data. Research must refocus on the development of high-performance, interpretability, and computational efficiencies to address mechanistic control for fit for the particular context of real-time industrial application, with rapid expansion of the datasets to ensure diversity of operational conditions is representative.

In summary, there is a great opportunity for the use of machine learning methodologies within aero engine health monitoring to improve maintenance decisions, reduce maintenance downtime, and improve safety for the aviation sector.

V. REFERENCE

[1] Qi Liu, Zhiyao Zhang, Peng Guo, Yi Wang, and Junxin Liang proposed a multiscale deep transfer learning architecture for aircraft engine RUL prediction, leveraging domain knowledge for better accuracy with limited data. Journal of Computational Design and Engineering, 11(1): 343–355, February 2024.

[2] Kıvanç Esenoglu, Ertan Inalga, and Erdal Esen introduced a deep learning model with change-point detection-based labeling and feature engineering to improve label quality and prediction accuracy. Applied Sciences, 13(12): 7186, 2023.

[3] Xiaoteng Liu, Lingxi Xiong, Yiming Zhang, and Chuntao Luo developed an SAE-TCN model for turbofan engine RUL prediction, improving long-term temporal dependency modeling. Aerospace, 8(1): 75, January 2021.

[4] Wenting Zha and Yusheng Ye proposed an improved temporal convolutional network (TCN) with feature selection, enhancing noise robustness and model generalization. Franklin Open, 1(1): ch1, 2024.

[5] Cheng Feng, Yufeng Chen, Qing Chen, Zhaohui Tang, Lingling Li, and Weihua Gui presented a temporal-spatial feature fusion framework for turbofan engine RUL prognosis, combining multiple signal domains. Sensors, 21(1): 418, May–June 2023.

[6] Wang Hai-Kan, Cheng Yi, and Song Ke proposed a joint TCNN–Transformer hybrid model for RUL estimation, capturing long-term dependencies effectively. Computational Intelligence and Neuroscience, Article ID 5185938, 2021.

[7] Thakkar Unnati and Hitesh Chaurasia applied deep recurrent neural networks (RNNs) for RUL prediction, effectively modeling sequential data. Actuators, 11(1): 67, January 2022.

[8] Das Neetha, Divya R., Gagana R., Meghala N. V., and Saanchitha K. applied traditional ML algorithms trained on NASA's C-MAPSS dataset to predict turbofan engine life, highlighting the importance of data preprocessing. IJARCCE, 9(3): 1596–1601, March 2022.

[9] Kamalkumar Y. P., Veda Keerthi A., Navaneetha Kannan A., Yogesh T., and Kirubagari B. proposed a supervised ML-based predictive maintenance framework for turbofan engines. IJFMR, 5(3): 1–7, May–June 2023.

[10] Bai Y. and Bi J. developed a deep learning methodology for RUL prediction, focusing on improved feature representation and achieving higher accuracy than classical ML approaches. Geoscience Frontiers, 11: 503–509, November 2019.

[11] Zhang Y., Mo Y., Liu J., and Zhang J. designed a deep feature fusion approach with an enhanced Echo State Network (ESN), improving generalization on noisy datasets. Scientific Reports, 12: 10191, April 2022.

[12] Sezhe Deng and Jian Zhou developed a CNN–LSTM–Attention hybrid model for predicting the remaining useful life of aero engines. Their work demonstrated that combining convolutional layers, temporal modeling, and attention mechanisms significantly improved prediction accuracy and interpretability. August 19, 2024.

[13] Michael Kimotho, Xudong Liu, "Aircraft Engine Remaining Useful Life Prediction Using Machine Learning," Proceedings of the 32nd International FLAIRS Conference, pp. 37–42, 2019.

[14] Li, X.; Ding, Q.; Sun, J.-Q. Remaining useful life estimation in prognostics using deep convolution neural networks. Reliab. Eng. Syst. Saf. 2018, 172, 1–11.

[15] Maulana, F.; Starr, A.; Ompusunggu, A.P. Explainable data-driven method combined with bayesian filtering for remaining useful lifetime prediction of aircraft engines using nasa cmapss datasets. Machines 2023, 11, 163 .