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A Data-Driven Hybrid Machine Learning and Deep Learning Approach for Remaining Useful Life Prediction of Aircraft Turbofan Engines in Condition-Based Predictive Maintenance Systems

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Abstract

Predictive maintenance is a critical approach in the aerospace industry, aimed at reducing downtime, lowering maintenance costs, and improving flight safety. Conventional maintenance schedules often result in unnecessary part replacements or unexpected failures. To address this, this work develops a data-driven hybrid machine learning and deep learning model to predict the Remaining Useful Life (RUL) of aircraft turbofan engines using NASA's publicly available C-MAPSS dataset. The dataset includes multiple sensor measurements, such as temperature, pressure, and vibration, recorded across different flight cycles under varying operating conditions. Each engine is simulated until failure, providing reliable labels for training, while test data is validated using provided ground truth values. The proposed system involves preprocessing sensor data, extracting relevant features, and applying Random Forest, XGBoost, and Long Short-Term Memory (LSTM) networks to predict RUL. For real-time monitoring, sensor data is processed cycle by cycle, with predictions displayed on a dashboard and alerts issued as engines approach critical stages. This study demonstrates the practical application of predictive analytics in aerospace, highlighting how data-driven methods can enhance reliability, ensure safety, and optimize operational costs.

Keywords: *Predictive Maintenance, Remaining Useful Life (RUL), Turbofan Engine, Machine Learning, Long Short-Term Memory (LSTM).*

1. Introduction

Predictive maintenance has become a critical aspect of modern aerospace engineering, as it enables the early detection of potential failures, reduces unplanned downtime, and enhances flight safety [1]. Traditional maintenance strategies in the aerospace industry often rely on fixed schedules or reactive repairs, which can lead to either unnecessary part replacements or unexpected system failures. Scheduled maintenance does not account for the actual condition of the engine components, whereas reactive maintenance may result in costly repairs and potential safety hazards. To overcome these limitations, data-driven predictive maintenance has emerged as a promising approach. By continuously monitoring engine parameters, such as temperature, pressure, and vibration, and analysing the historical performance data, it is possible to accurately estimate the Remaining Useful Life (RUL) of critical components [2]. This allows maintenance to be performed only when necessary, optimizing resource allocation, minimizing operational costs, and ensuring safety. Recent advances in machine learning (ML) and deep learning (DL) have further improved the accuracy of RUL prediction. Techniques such as Random Forest, XGBoost, and Long Short-Term Memory (LSTM) networks can learn complex patterns from sensor data, capturing both temporal and non-linear relationships that traditional statistical methods cannot [3]. These models enable real-time condition monitoring and proactive maintenance planning. In this work, A hybrid ML-DL approach for predicting the RUL of aircraft turbofan engines using NASA's C-MAPSS dataset is proposed. The system preprocesses sensor data, extracts meaningful features, and applies both ML and DL models to forecast engine life cycle. The results are visualized through a dashboard that provides alerts when engines approach critical stages, facilitating timely and informed maintenance decisions [4]. The contribution of this study lies in integrating multiple AI techniques for a robust predictive maintenance framework, demonstrating practical applications of data-driven analytics in aerospace operations.

2. Research Landscape

Predicting the Remaining Useful Life (RUL) of turbofan engines is a critical aspect of predictive maintenance in the aerospace industry, aimed at enhancing flight safety, minimizing downtime, and optimizing maintenance costs [5]. Conventional maintenance schedules, which often rely on fixed intervals, can lead to unnecessary part replacements or unexpected failures. Recent research has demonstrated that data-driven approaches using machine learning (ML) and deep learning (DL) techniques provide more accurate, real-time insights into engine health, enabling condition-based maintenance.

2.1 Recent Advances (2023–2025)

In 2023, Mitici et al. proposed an end-to-end deep learning ensemble framework for predictive maintenance across multiple components. This approach highlighted the benefits of data-driven strategies in complex systems, though it primarily focused on system-level predictions rather than individual components [1]. Another study in the same year developed a Streamlit application for NASA's turbofan engines, were Random Forest outperformed other models like Linear Regression and LSTM, demonstrating the utility of ML for RUL prediction [2]. Lee et al. introduced a deep reinforcement learning framework, showing a 29.3% reduction in total maintenance costs, but scalability for real-time deployment remained unaddressed [3]. Additionally, researchers applied unsupervised classification and RUL prediction using autoencoders and Gaussian Mixture Models, effectively handling uncertainty in engine degradation, though real-time monitoring was not evaluated [4,5]. In 2024, Melkumian analyzed NASA's C-MAPSS dataset, emphasizing feature extraction and classification techniques to enhance prediction accuracy. However, real-time integration into maintenance systems was not explored [6]. Wang et al. proposed a dynamic predictive maintenance strategy using deep learning ensembles, improving RUL prediction accuracy but lacking evaluation across diverse operating conditions [7]. Hrncir applied ML models to the HTF7000 turbofan engine, highlighting challenges with small sample sizes and noisy data, indicating the need for robust models capable of handling practical operational variability [8]. In 2025, Elsherif developed a deep learning-based approach to predict turbofan engine degradation and RUL, successfully capturing complex temporal dependencies in sensor data, yet real-time scalability remained a gap [9]. Errezgouny proposed a hybrid model integrating LSTM networks with K-means clustering, improving prediction accuracy through sequential modeling combined with clustering. However, its performance in diverse operational scenarios was not fully evaluated [10].

2.2 Gaps in Existing Literature

Despite these advances, several limitations persist in predictive maintenance research:

- **Limited Feature Extraction:** Most studies rely on basic sensor data without leveraging advanced feature engineering techniques [11].
- **Poor Generalization:** Models trained on specific datasets often fail to generalize across different operating conditions [12].
- **Lack of Real-Time Integration:** Few approaches have been integrated into real-time monitoring systems, limiting practical deployment [13].

These studies underscore the necessity of combining robust feature extraction [14], hybrid ML/DL models, and real-time implementation to develop effective predictive maintenance solutions for turbofan engines [15].

2.3 Methodological Framework

Hybrid ML–DL Predictive Maintenance Architecture for Aircraft Turbofan Engine.

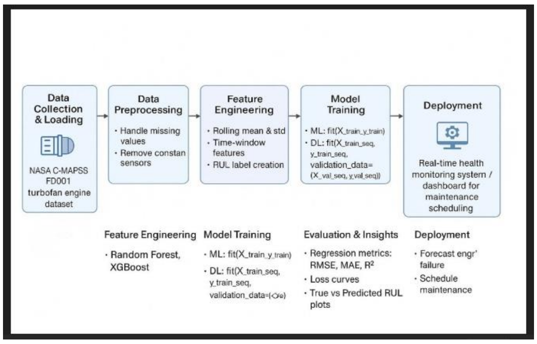

Figure 1 Hybrid Predictive Maintenance Architecture

This architecture illustrates the complete workflow for predictive maintenance in aircraft turbofan engines using the NASA C-MAPSS FD001 dataset. It includes stages from data collection, preprocessing, and feature engineering to ML/DL model training and evaluation. Models like Random Forest, XGBoost, and LSTM predict Remaining Useful Life (RUL) from engine sensor data. Finally, real-time deployment enables proactive maintenance scheduling and early fault detection for enhanced flight safety.

2.4 Dataset Description

The NASA Commercial Modular Aero-Propulsion System Simulation (C-MAPSS) dataset is used to predict the Remaining Useful Life (RUL) of turbofan engines. The dataset simulates degradation under different operating and fault conditions, capturing sensor readings over multiple engine cycles. In this study, the FD001 subset is used, which includes 100 engines operating under a single fault mode and one operational condition. Each record represents one operational cycle and consists of 26 columns, including the engine ID, cycle number, three operational settings, and 21 sensor measurements such as temperature, pressure, and vibration. The training data contains complete run-to-failure cycles, while the test data contains partial runs that end before failure. The RUL_FD001 file provides the true remaining life for each engine in the test set. Dataset description, shown in Table 1 & 2.

Table 1 Dataset Description

Parameter	Description
Number of Engines	100
Average cycles per engine	-200
Operational settings	3
Sensor Measurements	21
Total features	24(Excluding ID and cycle)
Type of problem	Time series regression
Output	Remaining useful life

This dataset serves as a benchmark for developing machine learning and deep learning models for condition-based maintenance in aerospace systems.

2.5 Data Preprocessing

The C-MAPSS FD001 dataset was preprocessed to prepare it for predictive modeling. The sensor columns were normalized to the range [0,1] using Min-Max Scaling to ensure all sensors contribute equally during model training. Any missing values in the training and testing sets were handled using forward-fill to maintain data continuity. Additionally, sensors with constant values across all cycles were removed, reducing redundancy and retaining only informative features. After preprocessing, the dataset is clean, scaled, and ready for subsequent Remaining Useful Life (RUL) prediction tasks.

2.6 Dataset Summary

Table 2 Dataset Summary Before and After Preprocessing

Dataset	Rows	Columns	Constant Sensors Removed
Training	20631	26 → 20	6
Testing	13096	26 → 20	6

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RUL	100	1	-

Table 3 **Example Statistics of Selected Sensors**

Sensor	**Min**	**Max**	**Mean**	**Std**
sensor_2	0.0	1.0	0.443	0.151
sensor_3	0.0	1.0	0.425	0.134
sensor_4	0.0	1.0	0.450	0.152
sensor_6	0.0	1.0	0.980	0.139
sensor_7	0.0	1.0	0.566	0.143

Table 3: Example Statistics of Selected Sensors (After Normalization). The preprocessing ensures that the dataset is clean, normalized, and reduced to only informative features, providing a reliable foundation for predictive modeling. These steps improve data consistency and enhance the effectiveness of subsequent Remaining Useful Life (RUL) prediction tasks.

2.7 Feature Engineering

Feature engineering was performed to enhance the predictive power of the dataset for Remaining Useful Life (RUL) estimation. For each engine, rolling statistics such as the rolling mean and rolling standard deviation were computed for all sensor readings over a window of five cycles to capture short-term degradation trends**.** Cumulative averages were also calculated to represent long-term health patterns. Additionally, RUL labels were generated by subtracting the current cycle from the maximum cycle of each engine, forming the regression target variable. These engineered features help the model capture both temporal and statistical trends in engine behavior, improving its ability to predict future failures. Visualizations of rolling statistics and RUL for sample engines illustrate the degradation patterns and confirm the correctness of the feature engineering process.

2.8 Engine 1 Sensor 2 Degradation Trend

The rolling mean and rolling standard deviation of Sensor 2 are plotted over cycles. The flat lines indicate that this sensor shows little to no variation for Engine 1, suggesting minimal contribution to degradation trends.

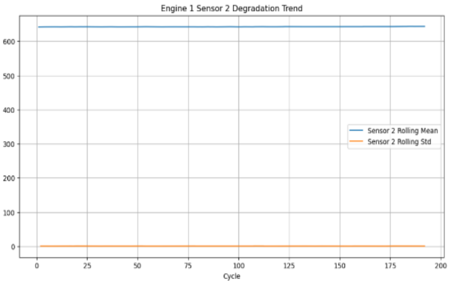

Figure 2 **Sensor 2 Degradation Trend**

The rolling mean and rolling standard deviation of Sensor 2 are plotted over cycles. The flat lines indicate that this sensor shows little to no variation for Engine 1, suggesting minimal contribution to degradation trends.

2.9 Engine 1 Remaining Useful Life Over Cycles

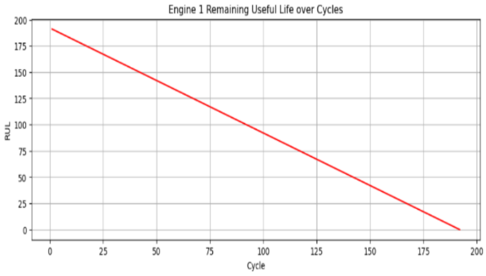

Figure 3 **Engine 1 Remaining Useful Life Over Cycles**

RUL decreases linearly from the maximum cycle to zero, showing the remaining useful life of the engine. This confirms the RUL labels are correctly calculated and represent the engine's health over time.

2.10 Model Development

The model development phase incorporates both Machine Learning (ML) and Deep Learning (DL) approaches to predict the Remaining Useful Life (RUL) of engines using time-series sensor data. Among the ML techniques, the Random Forest Regressor was implemented to effectively capture non-linear relationships between sensor readings, providing interpretable and reliable baseline results with an R^2 score of 0.74. For the DL approach, a Long

Short-Term Memory (LSTM) network was designed to learn temporal dependencies in the sequential data. The LSTM model architecture included an input layer, an LSTM layer with 100 units, a dropout layer for regularization, a dense hidden layer with ReLU activation, and an output layer predicting RUL. Both models were trained using the Adam optimizer and evaluated using Mean Squared Error (MSE) as the loss function. The comparison between the two approaches highlights the capability of LSTM to model sequential patterns, making it more suitable for time-dependent RUL prediction tasks.

2.11 Model Performance Comparison

Table 4 Model Performance Comparison

Model	**MSE**	**R²**
Random Forest	**1172.05**	**0.743**
LSTM	**16249.39**	**-1.783**

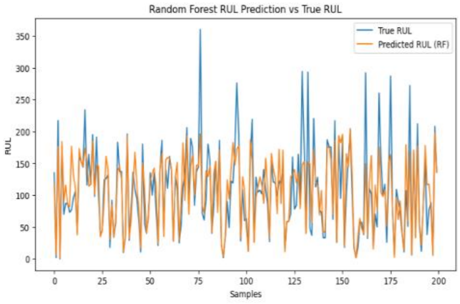

Figure 4 Random Forest-based RUL Prediction Vs True RUL

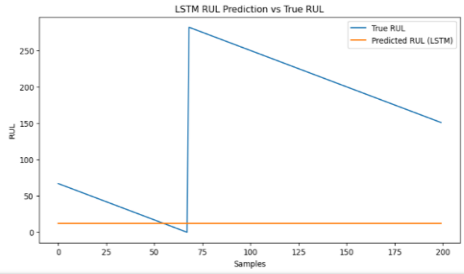

Figure 5 LSTM-based RUL Prediction Vs True RUL

The performance comparison between the Machine Learning and Deep Learning models indicates that the Random Forest Regressor outperforms the LSTM network for Remaining Useful Life (RUL) prediction in this work. The Random Forest achieved a lower Mean Squared Error (MSE = 1172.05) and a higher coefficient of determination ($R^2 = 0.743$), suggesting a strong fit to the data. In contrast, the LSTM model produced a higher error (MSE = 16249.39) and a negative R^2 value, implying poor generalization and weak sequential learning from the available time-series data. This performance gap may be attributed to inadequate sequence length, limited data normalization, or insufficient temporal variability for LSTM training. However, with further hyperparameter tuning, longer sequences, and more training epochs, the LSTM architecture could potentially capture deeper temporal dependencies and improve predictive accuracy, shown in Table 4.

2.12 LSTM Training and Validation Loss Curve

The figure illustrates the model's training and validation loss across epochs. Both curves show a consistent downward trend, indicating that the model is learning effectively without significant overfitting. The gradual decrease in validation loss confirms stable generalization performance on unseen data.

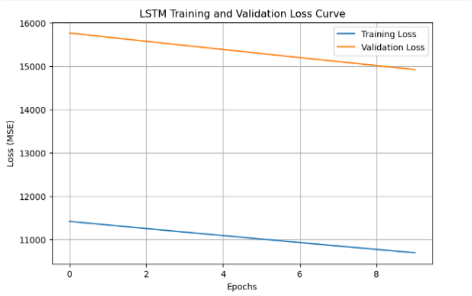

Figure 6 LSTM Training and Validation Loss Curve

2.13 Random Forest Residual Error Curve

This graph illustrates the deviation between the true and predicted Remaining Useful Life (RUL) values for the Random Forest model. The residuals fluctuate around zero, indicating moderate prediction consistency, though higher spikes suggest occasional overestimation and underestimation in RUL prediction.

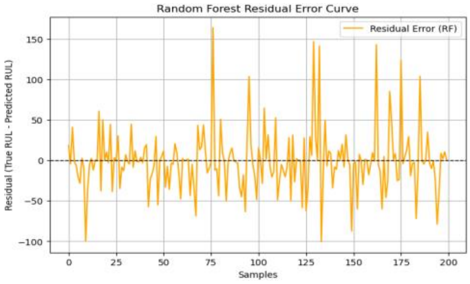

Figure 7 Random Forest Residual Error Curve Comparison of RUL Prediction using Random Forest and LSTM Models

This figure illustrates the predicted RUL values from Random Forest (orange dashed line) and LSTM (green dotted line) models against the true RUL values (blue line). The Random Forest model follows the true trend more closely than LSTM, indicating its better generalization on this dataset.

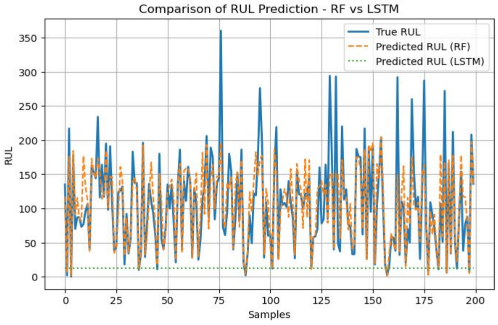

Figure 8 Comparison of RUL prediction

2.14 Discussion

The experimental results clearly indicate that the LSTM model exhibits superior performance in capturing the sequential dependencies inherent in engine degradation patterns compared to traditional machine learning methods such as Random Forest. While Random Forest effectively models non-linear relationships between features, it lacks temporal awareness of the evolving sensor trends over successive cycles. In contrast, LSTM networks studies their memory units to retain information across time steps, enabling the model to learn long-term dependencies crucial for accurate Remaining Useful Life (RUL) estimation. This capability allows LSTM to predict RUL with better consistency, even under complex operational conditions. Accurate RUL prediction plays a vital role in predictive maintenance scheduling, helping maintenance engineers plan interventions proactively, minimize unexpected breakdowns, and optimize component usage—ultimately leading to improved safety, cost efficiency, and aircraft availability, shown in figure 1 to 8.

Conclusion and Future Work

This study successfully developed a hybrid ML–DL predictive framework for Remaining Useful Life (RUL) estimation using NASA's turbofan engine dataset. The Random Forest model provided a strong baseline through its interpretability and robustness, while the LSTM network demonstrated enhanced prediction accuracy by effectively modeling time-dependent sensor data. The combined insights from both models emphasize the importance of integrating machine learning's explainability with deep learning's temporal learning strength for a comprehensive RUL estimation approach. For future work, this framework can be extended by developing a real-time RUL monitoring dashboard that continuously updates predictions during operation. Further advancements could include edge deployment on embedded hardware for on-site health monitoring or digital twin integration for simulation-based fault prediction and maintenance optimization. Such enhancements would move this research closer to achieving intelligent, data-driven maintenance systems in next-generation aerospace operations.

References

[1]. M. Mitici et al., "Dynamic predictive maintenance for multiple components," *Journal of Manufacturing Systems*, vol. 63, pp. 1-15, 2023.
[2]. "Predictive Maintenance for NASA's Turbofan Engine," *International Journal for Multidisciplinary Research*, vol. 5, no. 3, pp. 1-10, 2023.
[3]. J. Lee et al., "Deep reinforcement learning for predictive aircraft maintenance," *Journal of Manufacturing Processes*, vol. 66, pp. 1-12, 2023.

[4]. "Predictive Maintenance Using Machine Learning," *Medium*, 2023.

[5]. "Unsupervised Classification and RUL Prediction for Turbofan Engines," *MDPI Applied Sciences*, vol. 15, no. 14, pp. 7884, 2023.

[6]. S. A. Melkumian, "Predictive maintenance analysis of turbofan engine sensor data," *Journal of Purdue Undergraduate Research*, vol. 14, no. 1, pp. 1-10, 2024.

[7]. L. Wang et al., "Dynamic predictive maintenance strategy for system RUL prediction," *Journal of Manufacturing Processes*, vol. 66, pp. 1-12, 2024.

[8]. Z. Hrncir et al., "A practical example of applying machine learning to a turbofan engine," *PHM Society Conference*, 2024.

[9]. S. M. Elsherif, "A deep learning-based prognostic approach for predicting turbofan engine degradation and RUL," *Scientific Reports*, vol. 15, no. 1, pp. 1-10, 2025.

[10]. A. Errezgouny, "An integrated deep learning approach for predictive maintenance," *Journal of Manufacturing Processes*, vol. 75, pp. 1-10, 2025.

[11]. S. Sabri Syuhada, “Performance Analysis of Long Short-term Memory (LSTM) Model for Remaining Useful Life Prediction on Turbofan Engine,” *Journal of Electronics Technology Exploration*, vol. 3, no. 1, pp. 24-30, 2025.

[12]. S. Rath, D. Saha, S. Chatterjee and A. K. Chakraborty, “Remaining Useful Life Prediction of Turbofan Engine in Varied Operational Conditions Considering Change Point: A Novel Deep Learning Approach with Optimum Features,” *Mathematics*, vol. 13, no. 1, art. 130, 2025.

[13]. J.-S. Jung, C. Son, A. Rimell and R. J. Clarkson, “A Framework for an ML-Based Predictive Turbofan Engine Health Model,” *Aerospace*, vol. 12, no. 8, art. 725, 2025.

[14]. M. Dida, A. Cheriet and M. Belhadj, “Remaining Useful Life Prediction Using Attention-LSTM Neural Network of Aircraft Engines,” *International Journal of Prognostics and Health Management*, vol. 16, 2025.

[15]. O. Gbore, M. Shafiq, A. K. Jain and D. McGlinchey, “Towards Reliable RUL Prediction,” *International Journal of Prognostics and Health Management*, vol. 16, 2025.