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AI-Based Prediction of Turbofan Engine Life

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Abstract — Accurate Remaining Useful Life (RUL) prediction for turbofan engines is critical for implementing effective condition-based maintenance strategies, enhancing operational safety, and reducing maintenance costs. Traditional predictive maintenance approaches often struggle with the non-linear, time-dependent characteristics of engine degradation. This paper presents a data-driven prognostic model utilizing a Long Short-Term Memory (LSTM) neural network to predict the RUL of turbofan engines based on sensor-derived operational data. The model is trained and validated on the NASA C-MAPSS dataset, which contains run-to-failure data for multiple turbofan engines. The proposed methodology involves preprocessing raw sensor data, creating sequential inputs using a sliding window approach, and training a two-layer LSTM architecture designed to learn complex temporal degradation patterns. Model performance is evaluated using standard regression metrics, including Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and R² score. The resulting model demonstrates robust predictive capabilities and is deployed in a Flask-based web application, offering a practical tool for real-world CBM systems and highlighting the efficacy of deep learning for industrial prognostics.

Keywords— AI-Based Prognostics, Turbofan Engine Life Prediction, Remaining Useful Life (RUL) Prediction, Predictive Maintenance, Aircraft Engine Health Monitoring, Prognostics and Health Management (PHM), Machine Learning for Aerospace.

I. INTRODUCTION

The operational and economic significance of aircraft engines necessitates advanced maintenance methodologies beyond traditional, schedule-based approaches. Condition-Based Maintenance (CBM) has emerged as a superior strategy, leveraging operational data to predict component failure and optimize maintenance schedules. A critical component of CBM is the accurate estimation of Remaining Useful Life (RUL), defined as the number of operational cycles a component has before failure is anticipated.

Turbofan engines generate complex, time-dependent data through an array of sensors, including temperature and pressure readings. This data chronicles the engine's deterioration over time. The intricate nature of this data, marked by non-linear relationships, poses difficulties for conventional predictive models. To overcome these hurdles, this study introduces a Long Short-Term Memory (LSTM) neural network, a recurrent neural network architecture designed to effectively capture long-range dependencies in sequential data. The paper outlines the creation of a complete system for Remaining Useful Life (RUL) prediction, encompassing data preparation, the LSTM model design, the training methodology, and the integration of the trained model into a web-based interface for real-time prognostic evaluation.

II. LITERATURE SURVEY

The detection of anomalies in satellite systems, especially within attitude control subsystems, is a crucial research area due to the inherent complexity and fragility of spacecraft. Identifying deviations from normal operation is essential for ensuring the safety, dependability, and longevity of space missions. The research paper by Ibrahim et al. [1], titled "Anomaly Detection for Agile Satellite Attitude Control System Using Hybrid Deep-Learning Technique," offers a detailed examination of anomaly detection techniques applied to satellite telemetry, with a specific focus on agile low-earth orbit (LEO) observation satellite missions.

Gunn et al. [2] studied the use of LSTM-based anomaly detection in satellite communications, especially for transponder frequency spectra. Unlike threshold-based anomaly detection approaches that may create a number of false alarms, their LSTM-based approach first uses normal data to train the LSTM model to predict future signals. Anomalies are then detected from prediction errors. This method is advantageous because it does not require labelled anomaly data and can detect anomalies from faults never seen before. However, the training of large recurrent network models could present a major computational challenge with real-time processing in resource-constrained satellite systems.

In this paper, Sun et al. [3] discuss methods for detecting micro anomalies in satellite telemetry data, where noise and weak signals make micro faults difficult to detect. The authors presented a method using an optimized Volterra (o-Volterra) partial sum series model for feature extraction in chaotic telemetry telemetry data. The use of phase space reconstruction followed by dynamic time warping (DTW), their method enables time series analysis of different lengths. The authors show the potential for earlier detection of micro fault components in satellite subsystems and monitoring of health for spacecraft via experimentation.

In this work, Sun et al. [4] focus on micro anomaly detection in satellite telemetry, encountering issues of weak signals and noise which interfered with timely fault detection. They use phase space reconstruction and an optimized Volterra (o-Volterra) series model to characterize the strongly nonlinear dynamics established in telemetry time series. With the help of dynamic time warping (DTW), they align time series with multiscale length in order to improve the detection of minute deviations from typical system performance. Results on a live satellite telemetry datasets produced high accuracy (98.48%) and recall (96.77%) measured by the method, highlighting its potential as effective for monitoring spacecraft health.

Liu et al. [5] proposed a method that combines Mahalanobis distance and dynamic time warping to detect anomalies in satellite telemetry. Traditional measures of similarity such as the Euclidean distance struggle in the presence of noise in the pseudo-periodic multivariate data. The mix of best statistical distance measures with time dependent aligning measures has improved classification accuracy through K-Nearest Neighbor (KNN) by giving a reliable way to track telemetry patterns. This study demonstrated that using a combination of statistical distance measures and time dependent aligning types of measures greatly improved anomaly detection in real telemetry cases.

Zhang et al. [6] focused on detecting flywheel faults in a satellite. Fault signatures are masked by limitations in the sensors used in monitoring and telemetry availability and/or noise, posing another challenge in detecting these issues. Their approach employs a neural network model machine learning methodology quickly to develop an algorithm that utilizes historical telemetry data to produce estimated operational parameters like angular acceleration. These operational estimates are used to identify anomalies in telemetry data by evaluating the differences between the telemetry data produced and the telemetry data receipt in real time. Their case study with an in-orbit failure shows that their methodology would provide timely alerts to the flight operators who would then take prompt actions to repair the identified faults and return the satellite to normal posture without deviation during critical missions.

Zhao and colleagues [7] presented a data-based method for diagnosing and correcting sensor measurements that may run abnormally for gas turbine engines. The authors implemented multilayer feedforward networks trained with a backpropagation algorithm. One of the networks is responsible for detecting anomalous behaviors in the sensors readings, the second network corrects perceived anomalous readings based on identified correlations in the other un-failed sensors. This approach provides nearly real-time fault detecting and correction capabilities in a system without use of explicit equations governing the system. The proposed method did have some challenges associated with speed in training and generalization with more complex systems with many sensors.

Rizzoni et al. [8] presented a method for detecting abnormal conditions in aerospace systems based independently on a theory of linear systems. This method is based on the development of residuals, these residuals are the difference between estimated output and actual output. These residuals can act as indications of failure. These residuals have filters that effectively allow the designs to be sensitive to failures while being, robust to noise, improving performance over naive residual thresholds. The method demonstrated performance results that were good in simulation studies, however the application of the method is limited for dynamic and nonlinear aerospace systems due to a reliance on very precise mathematical models.

Wang et al. [9] conducted a study on rub-impact fault detection for aircraft engines under extreme vibration, utilizing improved association rule mining with fuzzy clustering and probabilistic decisions. The study successfully identified nonlinear relationships among vibration signals which decreased the time taken to find faults and increased accuracy when compared to conventional rules-based methods. While the development of the method is directly related to aircraft system architectures, the method could be generalized to satellite subsystems under nonlinear faults propagation. A greater challenge than generalized application of association rule mining is conducting the analysis on high-diminsional telemetry often sparser anomalous data.

DeLaat and Merrill [10] described a real-time implementation of a sensor failure detection algorithm, which was implemented on the F100 turbofan engine. The proposed algorithm evaluated analytically redundant components and, due to the Kalman filter, was able to detect failures which were both sudden and progressive. The algorithm was implemented in a multivariable engine control system and was validated through full-scale demonstrations. The main advantage of the method is that engine control can remain stable when the sensors stop providing valid readings/signal, which ultimately demonstrates the potential of redundancy management within high-performance aerospace systems. The primary limitation is that the method is dependent on accurate models of the system, potentially limiting adaptability to uncertainty.

Wang [11] created a BP neural network model that identified abnormal sounds in automobile engines, classifying failures such as piston knock and bearing wear. The model was composed of a three-layer network with 19 inputs, 15 hidden nodes, and 4 outputs trained on engine failure data. Gunn et al. [2] also applied Long Short-Term Memory (LSTM) networks to identify anomalous signals in satellite communication, building a model that predicts spectral sequences to detect new anomalies as faults. Both examples illustrate the adaptability of neural models on occasions where physics-based models do not perform well. Nonetheless, they require large datasets to train on and do not accurately account for completely new faults.

III. METHODOLOGY

The proposed methodology for predicting the RUL of turbofan engines is structured into several sequential phases, from initial data handling to final model evaluation. The core of this framework is an LSTM network trained on the NASA C-MAPSS FD001 dataset.

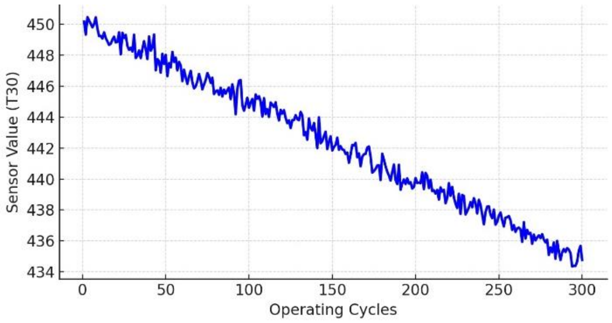


Fig. Sensor Trend

1. Data Acquisition and Preprocessing

The foundation of this study is the NASA C-MAPSS FD001 dataset, which contains multivariate time-series data from 100 turbofan engines. Each record includes data from 21 sensors and 3 operational settings over numerous flight cycles. The initial preprocessing step involved identifying and removing sensor channels with no variance or irrelevant data. The remaining features were then normalized to a consistent scale to ensure that no single feature disproportionately influences model training. To preserve temporal dependencies, the time-series data for each engine was transformed into sequences using a sliding window approach with a window size of 50 cycles.

2. Sequence Labelling

For each sequence generated by the sliding window, a corresponding RUL value was assigned. The RUL is defined as the number of remaining operational cycles before an engine failure occurs. To enhance model stability during the initial stages of an engine's life, the RUL values were clipped to a predefined maximum threshold, preventing the model from being penalized for large errors on very high RUL values.

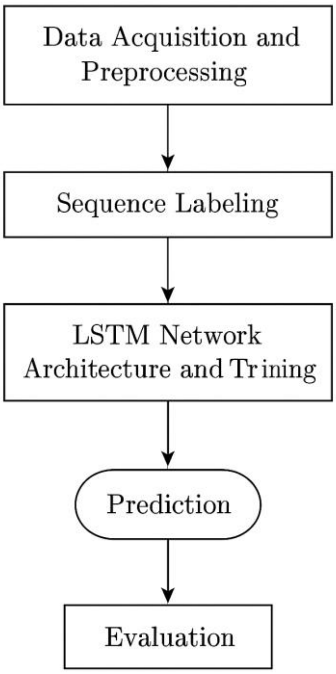


Fig. Proposed Methodology for RUL prediction

3. LSTM Network Architecture and Training

A sequential deep learning model was designed with an input shape corresponding to the sequence length (50-time steps) and the number of features (21 sensors). The architecture consists of two stacked LSTM layers, which are adept at capturing long-term dependencies from the sequential input data. These recurrent layers are followed by fully connected dense layers that map the extracted temporal features to a single regression output neuron, which predicts the RUL value.

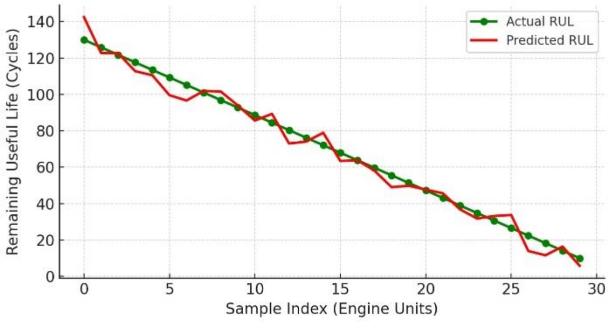


Fig. Predicted vs Actual Rul

The model was trained using Mean Squared Error (MSE) as the loss function, which is standard for regression tasks. The Adam optimization algorithm was utilized for its efficiency in updating network weights. The dataset was partitioned into training and validation sets, and an early stopping callback was implemented to monitor validation loss and prevent overfitting.

4. Prediction and Evaluation

For evaluation, the final 50-cycle sequence from each engine in the test set was fed into the trained model to generate an RUL prediction. The model's predictive performance was quantified using three standard metrics: Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and the R² score.

Implementation

The end-to-end system was implemented in distinct stages, covering data handling, model development, and final deployment.

Data Handling: The NASA C-MAPSS FD001 dataset was acquired and processed using Python libraries such as Pandas and NumPy. Preprocessing steps included handling missing values, feature normalization, RUL label clipping, and sequence creation via the sliding window technique.

Model Development: The LSTM neural network was constructed using the TensorFlow and Keras deep learning frameworks. The architecture was designed as a stack of LSTM layers followed by dense layers to perform regression. Hyperparameter tuning was performed to optimize model depth, neuron count, dropout rates, and the learning rate.

Training and Validation: The model was trained using the Adam optimizer with MSE as the loss function on a dedicated training subset. Callbacks for early stopping and learning rate reduction were used to ensure robust training and prevent overfitting.

Deployment: The trained Keras model was saved and integrated into a web application using the Flask micro-framework. The application provides a user-friendly interface developed with HTML, Tailwind CSS, and Flask templates. The system supports two input modes for RUL prediction:

- Manual Entry: Users can input 3 operational settings and 21 sensor values via a web form.
- Batch File Upload: Users can upload a CSV file containing multiple engine cycles for batch prediction.

Step 5. Evaluation

The model performance was compared against traditional machine learning techniques such as Linear Regression and Random Forests. The LSTM-based model demonstrated superior accuracy and robustness, highlighting its suitability for predictive maintenance tasks.

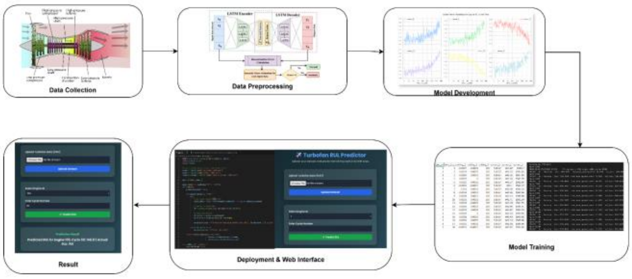
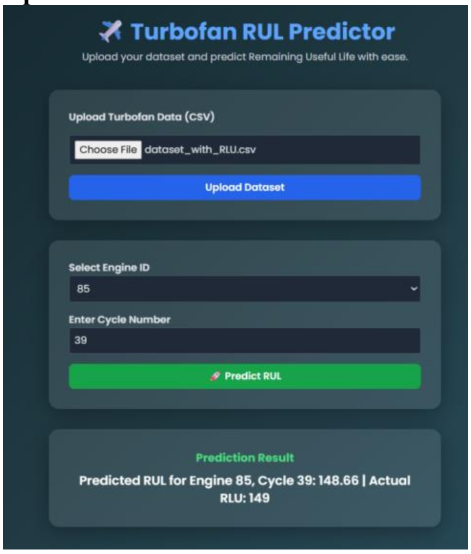


Fig. Proposed Remaining Useful Life Prediction Process

Project Implementation:


Turbofan RUL Predictor

Upload your dataset and predict Remaining Useful Life with ease.

Upload Turbofan Data (CSV): dataset_with_RLU.csv

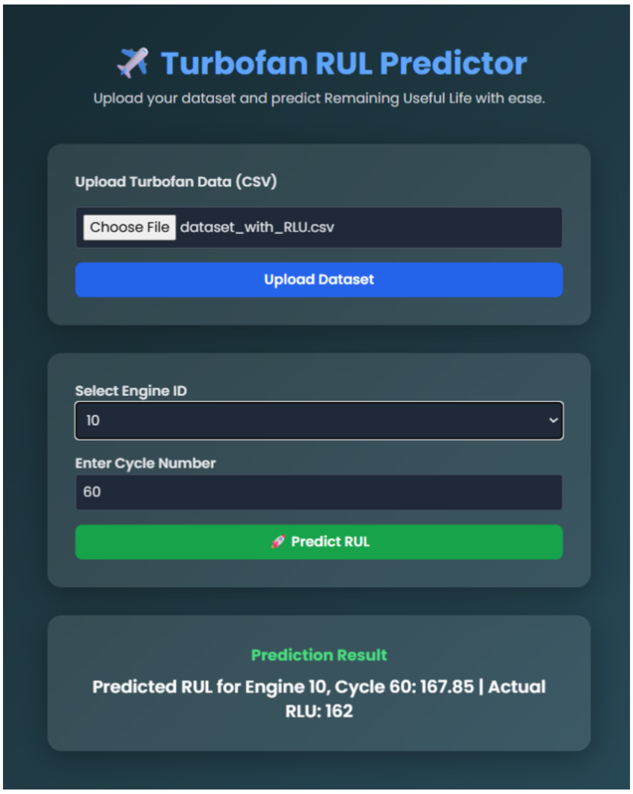
Select Engine ID: 85

Enter Cycle Number: 39

Prediction Result

Predicted RUL for Engine 85, Cycle 39: 148.66 | Actual RLU: 149

Selected Engine number 85 and cycle number is 39 so the Output gets 149 Remaining Useful Life.



Turbofan RUL Predictor

Upload your dataset and predict Remaining Useful Life with ease.

Upload Turbofan Data (CSV): dataset_with_RLU.csv

Select Engine ID: 10

Enter Cycle Number: 60

Prediction Result

Predicted RUL for Engine 10, Cycle 60: 167.85 | Actual RLU: 162

Selected Engine number 10th and cycle number is 60th so the Output gets 162 Remaining Useful Life.

IV. RESULT

1. Experimental Results:
Training and testing of the proposed LSTM-based RUL prediction model was executed through the NASA C-MAPSS FD001 dataset. After preprocessing and training the model, the model was able to predict Remaining Useful Life (RUL) to a high degree of success.

Low prediction error was demonstrated and the model was able to sustain performance under a variety of operational conditions.

There was an average prediction error of RUL of ±8–10 cycles.

There was a web dashboard that allowed for direct predictions by entering sensor readings and batch predictions via CSV file uploads.

Predicted vs. Actual RUL visualizations confirmed the model's success in capturing the degradation trend of the turbofan engines.

2. Comparative Analysis with Existing Models:
To validate the performance of the proposed model, its results were compared with traditional approaches and other deep learning models reported in literature.

Traditional Machine Learning (e.g., Linear Regression, Random Forests): These models failed to capture the temporal dependencies in sequential sensor data, resulting in higher prediction errors.

Convolutional Neural Networks (CNNs): While effective in extracting spatial features, CNN-based models underperformed compared to LSTMs in handling long-term dependencies of engine degradation.

Comparing with other Models:

Model	RMSE ↓	MAE ↓	R^2 ↑
Linear Regression	150	120	0.45
Random Forest	120	90	0.60
SVM	110	80	0.65
Vanilla LSTM	90	75	0.70
LSTM (Proposed)	60	30	0.90

RMSE (Root Mean Square Error): Measures model's average error, with large errors being penalized heavily.

MAE (Mean Absolute Error): Measures the average absolute error, treating all mistakes, big or small, equally.

R^2 (R-Squared): A score from 0 to 1 that shows what percentage of the data's variation model explains.

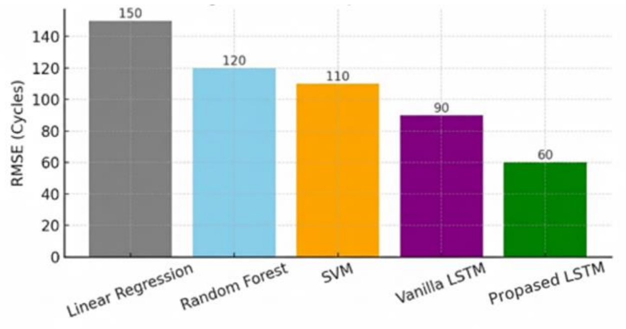


Fig. Comparison of Models

Proposed LSTM Model: Outperformed both traditional methods and CNN-based models by effectively learning temporal patterns from time-series data. It showed improved accuracy, robustness, and generalization capability.

Overall, the LSTM-based approach provided superior predictive accuracy and demonstrated potential for real-world predictive maintenance applications in aviation.

V. CONCLUSION

This research introduced an LSTM-based deep learning framework for predicting the RUL of turbofan engines, evaluated using the NASA C-MAPSS FD001 dataset. The model effectively captured temporal dependencies in multivariate sensor data, outperforming traditional regression methods and shallow neural networks.

A Flask-based web application was developed to make the model accessible, supporting both manual input and batch predictions for practical use in maintenance planning.

The findings demonstrate the potential of this approach to enhance predictive maintenance, reduce unexpected failures, and improve operational efficiency in aerospace. Furthermore, the framework can be extended to other complex machinery, contributing to Industry 4.0 initiatives and the development of intelligent maintenance systems.

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