Hybrid Deep Intelligence for Aircraft Engine Remaining Useful Life Prediction

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Abstract. In modern aerospace systems, reliability-centered maintenance promotes the implementation of condition-based maintenance to ensure operational safety and enable precise lifespan estimation of aircraft engines. This study investigates RUL prediction using the FD001(subset of C-MAPSS) of NASA prognostics repository simulated dataset. The FD001 subset comprises nonlinear time-series sensor measurements from turbines under diverse operating states and degradation trajectories.A deep neural state-space modelling framework is proposed to capture the latent degradation dynamics governing engine health evolution. The method explicitly simulates the relationship between observable sensor measurements and concealed state transitions. To enhance the model performance and training stability, the feature selection technique called Shapley Additive exPlanations is implemented to filter the informative sensors, critical prognostic indicator identification, and signal elimination. To capture the nonlinear dynamics of aircraft engines, the LSTM-based state-space model incorporates batch normalization, dropout regularization, and early stopping techniques. The Neural State Space model integrates physics-informed state-space modeling with neural architectures, achieving improved Remaining Useful Life prediction with Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and NASA scoring metrics compared to baseline models.

Keywords: Remaining Useful Life Prediction, CMAPSS dataset, FD001, Predictive Maintenance, Neural State Space Model.

1 INTRODUCTION

In order to enhance predictive maintenance, the aviation sector is increasingly focusing on advanced health monitoring and prognostics techniques for aircraft engines, operational safety and protocols, cutting maintenance expenses and limiting downtime. Effective aircraft engine health monitoring requires a structured framework for systematically tracking engine performance and degradation, detecting incipient faults, and precisely estimating the lifetime of engines, which quantifies the remaining cycle for aircraft engines before a system or components reach failure, using the historical data of turbofan engines. The main propulsion systems found in contemporary military and

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commercial aircraft are turbofan engines. Extreme mechanical, thermal and aerodynamic stresses during operation cause these engines' components to gradually deteriorate over time. Continuous exposure to high temperature, pressure fluctuations, vibration and rotational stress accelerates wear and fatigue, leading to a catastrophic breakdown of the turbofan engine in the aviation industry.

A standard for assessing Remaining Useful Life prediction models for turbofan engines is the NASA Prognostics repository dataset. Under conditions of progressive degradation, it offers complex time series sensor data, including temperature and pressure at fan inlet, LPC outlet, HPC outlet, [1]. The FD001 subset of the NASA C-MAPSS dataset represents aircraft engine degradation under a single operating condition and a single fault mode, making RUL prediction a challenging sequential learning problem and enabling controlled evaluation of prognostic models.

Recent research has increasingly explored deep learning and models and hybrid architectures of deep neural networks [3,4], to model sequential dependencies in sensor recordings. These models exhibit substantially lower prediction error and efficiently learn degradation patterns inherent in multivariate time series data.

Frameworks for Physics-informed machine learning (PIML) have been proposed to combine data-driven learning with domain knowledge in order to overcome these challenges. PIML techniques improve robustness and match predictions with established thermodynamic behavior by incorporating physical limitations and degradation equations into the loss function [2].

Recurrent Neural Networks (RNNs) have become an effective tool to capture the sequential deterioration data. RNN-based architectures have demonstrated improved performance by detecting prolonged temporal evolution in turbofan engine sensor measurements [3]. The proposed model effectively learn degradation patterns embedded in multivariate time-series data and has significantly reduced prediction errors compared to shallow machine learning techniques. Nevertheless, standard RNN architectures suffer from limitations such as gradient instability, limited interpretability and weak generalization under distributional shifts. RNN based approached is the absence of an explicit dynamical system formulation.By analyzing the time-dependent deterioration patterns in multivariate sensor data, deep recurrent and convolutional neural structures share their efficiency [4], which showed RUL estimation by both binary classification and regression problems.

Despite advancements in PIML and deep learning, still there is a significant research gap: the requirement for models that concurrently.

1. Captures the true degradation mechanism (Hidden health state)
2. How degradation evolves over time
3. Represent latent degradation dynamics explicitly
4. Maintain structural interpretability aligned with system physics

In this Study, we implemented a State Space Model that offers a principled mathematical framework for representing dynamical systems through latent state transition and observation equations. The Neural State Space Model enhanced temporal dependency detection. The suggested model's state transition and observed mappings are parameterized using neural networks, enabling the model to learn nonlinear degradation dynamics directly from data. This paper proposes a prediction model of engine's RUL and advancement of the temporal consistency and dynamic interpretability while utilizing deep learning's expressive capabilities to provide a reliable and scalable predictive maintenance solution for aircraft equipment.

2 DATASET DESCRIPTION

The turbofan engine degradation dataset used in this study is sourced from the NASA open data repository and widely used for estimating the remaining useful life of aircraft engines. A big, realistic commercial turbofan engine can be simulated using MATLAB Simulink. The dataset was split into four subgroups (FD001 to FD004) based on the flying situation and fault modes [8]. This paper uses the FD001 subset, which is recorded during flight hours based on engine health and ranging from normal operation to performance failure and encompasses multivariate time series data from 100 unique aircraft engine units. Each unit's operational behavior is captured through readings from 21 sensors and observation of 3 operational settings. The dataset consists of separate training and testing datasets to facilitate model training and performance evaluation. The total number of turbines and sensor measurements per engine is recorded in the training set up until engine failure [4]. The test set includes sensor readings from random operational cycles, and the corresponding estimation of RUL is the target variable for prediction. Each feature and its descriptions are outlined in Table 1.

Table 1. NASA CMAPSS Turbofan Engine FD001

Category	Feature Name	Description
Engine Identifier	Engine ID	Unique identifier of engines
Time cycle recorded	Maximum of cycles	Operational cycle
Operational Settings	3 Operational settings	Operational condition parameters
Sensor Measurements	21 Sensors	Engine sensor readings capturing system health
Target Variable	RUL	Remaining Useful Life(Cycles to failure)

2.1 Performance Evaluation of Prior Methods

{Desribe table here in 3-4 sentecnes}

Table 2. Result Analysis of Related Work

Author	Model	RMSE
Unit Amin, Krishna D. Kumar, 2021[13].	CNN RNN CNN LSTM	15.68 15.92
Shuiyuan Cao, Hanwen Zhang, 2024[18]	Bayesian LSTM	23.4
Jianjing Zhanga, Peng Wanga, Ruqiang Yanb, Robert X. Gaoa, 2018[12].	MLP LSTM BD-LSTM	20.84 18.07 15.42
Rajeev Kumar Guptaa, Jay Nakuma,Punit Guptaa,2025.[9]	Random forest Linear regression Support vector9]	21.468 18.963 17.425
Slawomir Szrama , Tomasz Lodygowski,2024[14].	LSTM LSTM_CMAPPS CNN CNN_CMAPPS	50.23 22.39 50.23 18.38
Priyadarshini Mahalingam , D. Kalpana , T. Thyagarajan b,2025[15]	Exponential Degradation Model	24.60
Xiaoyu Feng, Jinshan Yue,2019[19]	CNN	18.45
Ying Chen, Lubing Wang, Jiawei Xiang, Xufeng Zhao, , 2024[17].	Mixed-integer linear programming (MILP) model	41.33
Abedin Sherifi* Pratt and Whitney,2024[11].	Linear Regression LSTM BLSTM + Dropout	30.5 27.74 26.68
Celestino Ordóñez, Javier de Cos Juez, Javier Roc Fran cisco, 2019[16].	Auto regressive and Support Vector Machine	39.6843

3 METHODOLOGY

Using FD001 subset, this research work takes an organized approach to forecast the RUL to guarantee the aircraft engine's operational parameters and safety. The suggested model's architecture is described below,

3.1 Data collection and Preprocessing

To comprehend the dataset's distribution and structure, a preliminary analysis was carried out [7]. To guarantee data consistency and integrity, this phase involved determining the quantity of attributes, value gaps, forms of data and category distribution. The dataset was preprocessed by handling missing values, removing inconsistent records, and detecting outliers using statistical threshold-based filtering. Normalized the sensor data to a common scale to ensure consistent input to the model. Each dataset includes data from 21 sensors [6], as outlined in Table 3.

Table 3. Sensor Configuration for Prognostic Modeling

Sensors	Description
1	Temperature at the Fan Inlet.
2	Compressor with low pressure and outlet temperature.
3	Compressor with high pressure and outlet temperature.
4	Temperature of the turbine low pressure outlet.
5	Pressure of Fan Inlet.
6	Total Bypass Duct Pressure
7	Total Pressure at the High-Pressure Compressor Outlet.
8	Physical Speed Bypass Duct for Fans.
9	Speed’s Core Engine.
10	Engine Pressure Ratio.
11	Compressor with Outlet Static Pressure and High Pressure.
12	High Pressure Compressor with Outlet Pressure Ratio.
13	Equivalent Fan Speed.
14	Engine Core Speed.
15	Bypass Ratio calculation.
16	Air Ratio Measurement.
17	Extraction of Enthalpy.
18	Fan Speed Request.
19	Equivalent Speed Requested.
20	The elevated pressure Turbine Bleed and Air Flow Rate.
21	Low Pressure Propeller Bleed and Air Flow Rate.

3.2 Data Visualization and Feature Engineering

The sensor’s recorded readings and the visual tool Power Bi are utilized to understand the attribute variations and spot patterns of the sensors. Primary insights are enabled, and pertinent factors are identified using these visuals.

Important factors in the operational lifespan prior to failure are shown by the measurements taken from the unit's maximum cycle. Some units break much earlier at 50 to 150 cycles, while others have longer lifespans, hitting a maximum cycle of 500 to 600 under various operating conditions. Different operating conditions are highlighted by the engine's life span. The broad range of lifetimes improves the dataset applicability for creating reliable deep learning models that forecast the life span of aircraft engines. The maximum cycle of each engine unit is given in the Fig.1.

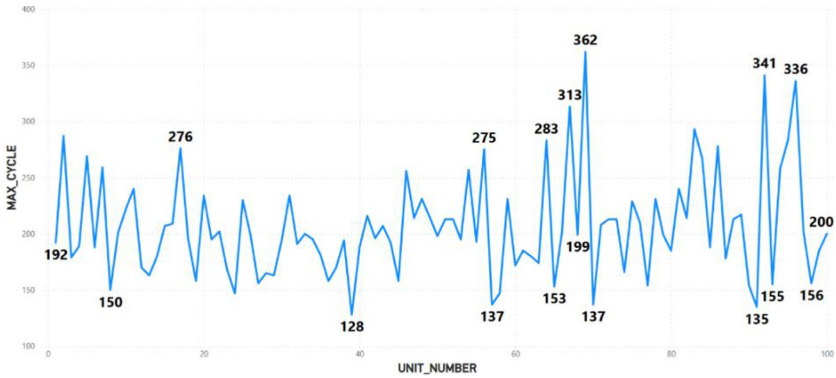

Fig. 1. Distribution of Maximum Cycles Across Engine Units

The representation of trend and pattern in the Sensor measurements of each engine is shown in the Fig 2. The hidden sensor state measurement is visualized using Power Bi. This tells how the sensors are reached the degradation state over time. In this study, SHAP (Shapley Additive exPlanations) [10] was employed to identify informative sensors from the dataset. SHAP analysis was performed to measure each sensor's contribution to the model prediction, and sensors with higher SHAP values were selected as informative, as shown in Fig. 2. By quantifying feature contributions to model output, SHAP enables elimination of redundant or noisy signals, enhancing both interpretability and training performance. It quantifies the marginal contribution of each feature by computing Shapley values, which represent the average impact of including a specific feature across all possible subsets of features.

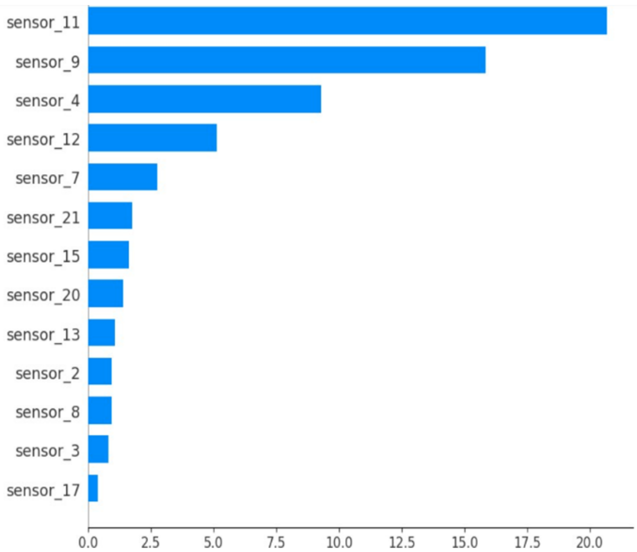

Fig. 2. SHAP-Derived Informative Features for RUL Prediction

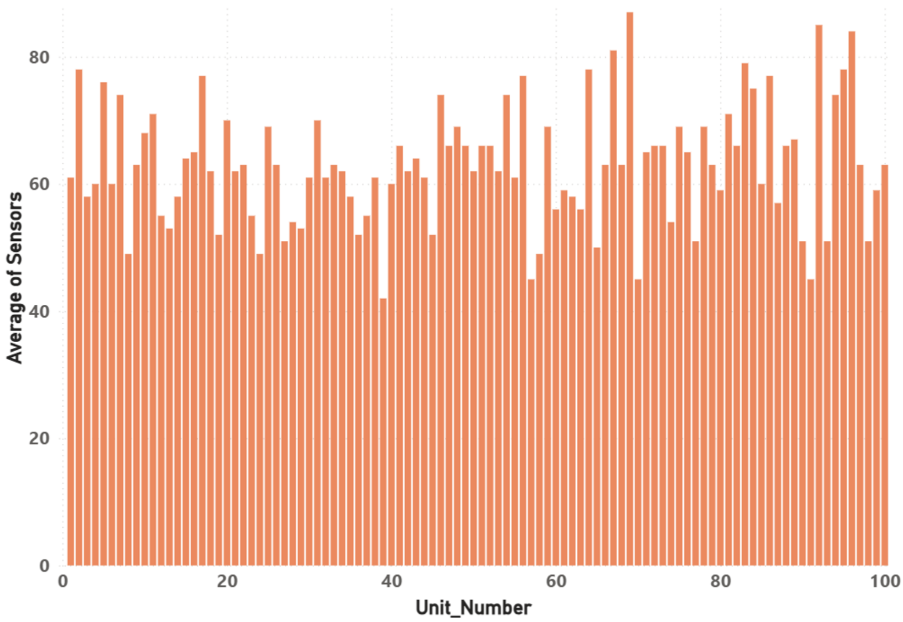

Fig. 3. Aggregated Sensor Feature Visualization

3.3 RUL Calculation

The maximum cycle is computed for each engine by estimating the RUL for every operating cycle.

RUL=Maximum Cycle – Current Cycle

The estimated lifetime for each engine cycle is the target parameter, which is computed using a predefined degradation function. A current cycle number of a particular unit is represented by the RUL computation, which is the high possible of cycles observed for each unit [9].

3.4 Min-Max Scaling

The collected data had been analyzed using standardization and normalizing approaches to enhance training stability and model performance [2]. One essential preprocessing step that guarantees the resilience and efficacy of models is normalization. The procedure entails changing the data attributes scale to a uniform range. This transformation guarantees that, according to the training dataset, it fits within the specified range. This enhanced the model's ability to recognize relationships and patterns in the data, leading to higher prediction performance.

$$x' = \frac{x - x_{min}}{x_{\max} - x_{min}} \tag{1}$$

4 State Space Model (SSM)

The model represents Aircraft engine degradation as a nonlinear stochastic dynamical system where latent health states evolve over time under varying operational conditions. The State Space model represents the internal health or the condition of a system, which explains how the state changes over time and how the sensor measurements rely on that internal change. A State Space Model consists of two equations:

State Transition Equation

$$\mathrm{h_t} = \mathrm{f}\left(\mathrm{h_{(t-1)}}, \mathrm{u_t}, \mathrm{w_t}\right) \tag{2}$$

Where:
h_t - Hidden health state at time t
u_t – Operating conditions + Sensor readings
w_t – Process noise (Uncertainty)

This formula simulates the gradual decline in engine health.

Observation Equation

.
$$\mathrm{y_t} = \mathrm{g}(\mathrm{h_t}, \mathrm{v_t}) \tag{3}$$

Where:
Y_t – Measured sensor values.
V_t – Measures noise. This maps hidden health state and measurable sensor outputs.

This equation estimates the hidden health state and forecasts when the failure threshold is reached, finally, RUL is estimated.

4.1 Neural State Space Model (NSSM)

The predictive performance is improved and upgraded by applying the deep neural network and long short-term memory-based model from the state space model to NSSM, which increased the temporal dependency detection. The proposed model architecture learns the hidden health condition and dynamics from the sensor sequences, while fully connected regression layers assess the aircraft engine's remaining useful life by mapping the learned health status representation.

In SSM, Tracking features and sensor conditions are predetermined using linear or nonlinear parametric forms. In contrast, Neural State Space Model replace these functions with deep neural networks, enabling data-driven modeling of complex nonlinear system dynamics without explicit system assumptions.

$$h_t = f\theta\left(h_{(t-1)}, u_t\right) + w_t \quad (4)$$

Where:

h_t – Hidden health state at time t
h_{t-1} – Previous health state
u_t – Operating conditions + sensor inputs
f_θ – Neural network with learnable parameters θ
w_t – Process noise

$$y_t = g\theta(h_t) + v_t \quad (5)$$

The sensor values are measured by yt, The hidden degradation state is mapped by ht, and the Noise measurement and Neural network health mapping, which is the sensor output, is identified by g and vt.

5 Evaluation and Improvement

The given dataset was used to train the proposed model. Standard LSTM-based performance indicators, including the root mean squared error (RMSE) as well as Scoring function [18], were used to assess the model's ability to predict RUL.NASA Score function is also used as a metric to assess deviation between model predictions and actual observations of the model performance [18]. These models were chosen due to their effectiveness with time series data, considering the time-dependent nature of sensor values. Training sequences were generated using a sliding window technique with a window size of 30 time steps, where each window contains consecutive sensor readings used as input to the model and to reduce the impact of large RUL values during the early degradation stages, the RUL labels were clipped at a maximum threshold of 125 cycles.

Because of the quadratic procedure, the RMSE penalized bigger predicting errors more severely, which is the main scoring statistic used in this study. It is especially appropriate for prognostic applications where major variations from the true RUL can result in serious maintenance risks. Following the creation of the State Space Model, the LSTM network is trained, and hyperparameters are chosen based on each unit in the turbofan dataset. There is a scoring function [19] and an error rate of the root mean square between the true and calculated RUL value. The error metrics display how accurate the model's predictions are in comparison to the actual values.

A score function, RMSE and MAE are computed to assess the estimation outcome and displayed in Table 5.

6 Results and Discussion

A thorough analysis of the RUL forecasting results using our proposed model is presented in this section. Numerous factors affect the model's accuracy. This falls into two different types. The window size and threshold values are among the NSSM hyperparameters, and the parameters related to the initial RUL value. An optimal hyperparameter for the suggested model is chosen using an iterative grid search method based on the lowest RMSE. The model's validation is examined using the RMSE, MAE and NASA Score values shown in the table [5].

By utilizing the causal analysis of the sensor measurements using the SHAP method for feature reduction on the engine dataset by removing the constant and noisy sensors, Core Engine Equivalent Speed, Fuel-to-Air Ratio, Requested Fan Speed, and Requested Fan Equivalent Speed Fig 3.

By investigating the hyperparameter space, this approach increases the model's accuracy and reliability. In order to get the final score and RMSE for the overall model evaluation, the SSM is finally assessed using testing data that are averaged throughout all iterations. The optimal test RMSE of the state space model is assessed by using NSSM, and to improve its performance, hyperparameters like learning rate, batch count and regularization are changed.

Table 4. Performance evaluation of SSM and NSSM

Model	RMSE
State Space Model(SSM)	17.9
Neural State Space Model(NSSM)	13.05

Table 5. Performance evaluation of NSSM

Neural State Space Model	
RMSE	13.05
MAE	9.91
NASA SCORE VALUE	286.44

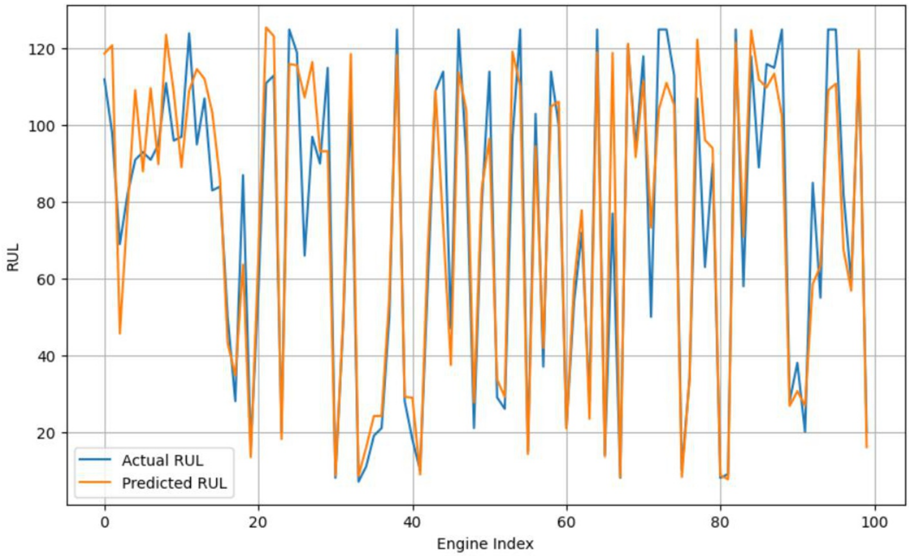

Fig. 4. Visualization of True and Predicted Remaining Useful Life

The proposed Neural State Space Model outperforms the baseline models, including Long Short-Term Memory (LSTM), Convolutional Neural Network (CNN), Recurrent Neural Network (RNN) and Linear regression as demonstrated by lower RMSE, MAE and NASA score values. The Neural State Space model achieved a training RMSE of 13.4 and a test RMSE of 13.05, indicating consistent generalization performance on unseen data, demonstrating best efficiency in forecasting the actual RUL of the aircraft engine. The experimental result suggests that the proposed model has potential applicability for predictive maintenance studies in aviation systems. The performance of my model is visualized in Fig 4.

7 Conclusion

This work implemented a State Space Model and a Neural State Space Model to anticipate the aircraft engine's remaining usable life. The suggested study demonstrates that the LSTM model produces extremely accurate RUL predictions when paired with efficient preprocessing techniques. By removing unnecessary sensors and utilizing a physics-informed model that incorporates domain-specific equations, the model demonstrates more precise alignment between predicted and actual RUL values. The new model's reduced feature space and consideration of physical factors likely contribute to better generalization, decreased prediction error, and enhanced resilience. These findings highlight the importance of physics-informed simulation and feature optimization for predictive maintenance tasks. It became clear form analyzing the data that there are several ways to improve this prognostic statistic. It should be mentioned that forecasting the future is more challenging than forecasting a moment closer to death;

it's crucial to give greater weight to RUL accuracy. In conclusion, anticipatory health monitoring of engines with turbofans has gained popularity due to its effectiveness in improving the engine's system dependability and safety because of the huge dimension and complex attributes of data collected by sensors in RUL prediction. The turbofan engine's maintenance needs have been planned using the Remaining Useful Lifetime forecast. Predictive maintenance makes it possible to foresee failures and schedule repair in advance. This proposed model aims to identify the underlying causes and develop insights that can contribute to enhancing the quality, non-linear degradation tracking and temporal complexity, predictive maintenance, safety and protocols and reliability of the aircraft engine in the aviation industry.

Dataset Access. The FD001 subset data analyzed in this paper is publicly accessible in the NASA CMAPSS(Commercial Modular Aero-Propulsion System Simulation) Prognostic Repository. https://data.nasa.gov/dataset/cmapss-jet-engine-simulated-data.

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