Tecnológico de Monterrey
Escuela de Ingeniería y Ciencias

Enhancing Aircraft Engine RUL Prediction: Interpretable Models and Bayesian Optimization

Juan Pablo Echeagaray González
School of Engineering and Sciences

Introduction

- **Precision Planning:** Optimizes maintenance schedules, minimizing costs while ensuring maximum efficiency.
- **Elevated Performance:** Enhances operational efficiency and security, elevating the standards for engine maintenance.
- **Sustainability in Practice:** Fosters sustainable operations, aligning with eco-conscious practices for long-term reliability.

Problem Statement

The main goal is to estimate the remaining useful life (RUL) of a fleet of turbofan engines under challenging conditions, defined by high variability and multiple failure modes.

- **Efficient Modelling:** need for lower cost models.
- **Model Interpretability:** understand predictions in critical scenarios.
- **Confidence and prediction intervals:** provide measures of uncertainty.

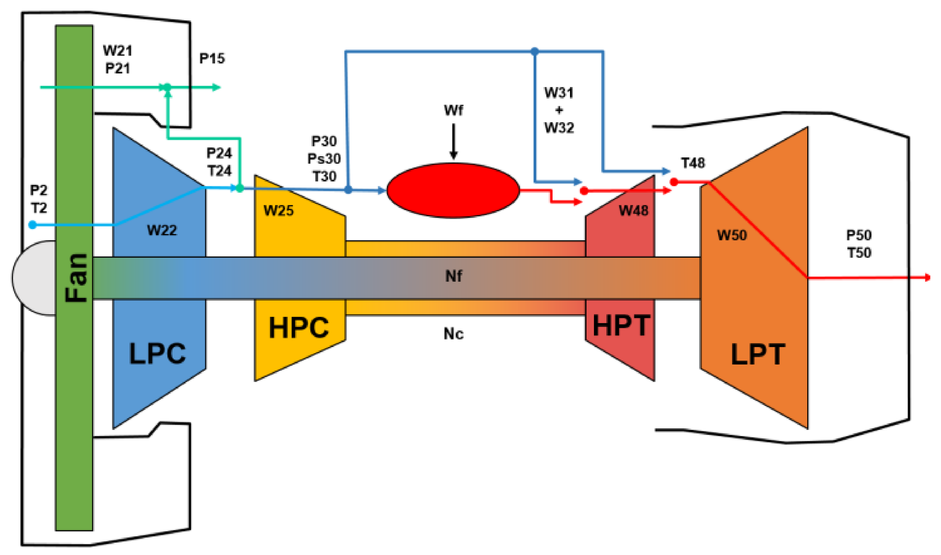


Figure 1. Schematics of a turbofan engine

The effectiveness of the proposed model is measured with the PHMAP 2021 Data Challenge Loss function [1]:

$$
\begin{aligned}
\mathrm{RMSE}(y,\hat{y}) &= \sqrt{\frac{1}{m}\sum_{i=1}^{m}(y_i-\hat{y}_i)^2} \\
\mathit{NASA}(y,\hat{y}) &= \frac{1}{m}\sum_{i=1}^{m}\left[\exp(\alpha\cdot(y_i-\hat{y}_i))-1\right] \\
\alpha &= \begin{cases} \frac{-1}{10} & \text{if } y_i-\hat{y}_i \le 0 \\ \frac{1}{13} & \text{if } y_i-\hat{y}_i > 0 \end{cases} \\
\mathcal{L}(y,\hat{y}) &= \frac{1}{2}(\mathrm{RMSE}(y,\hat{y})+\mathit{NASA}(y,\hat{y}))\,.
\end{aligned} \tag{1}
$$

Methodology

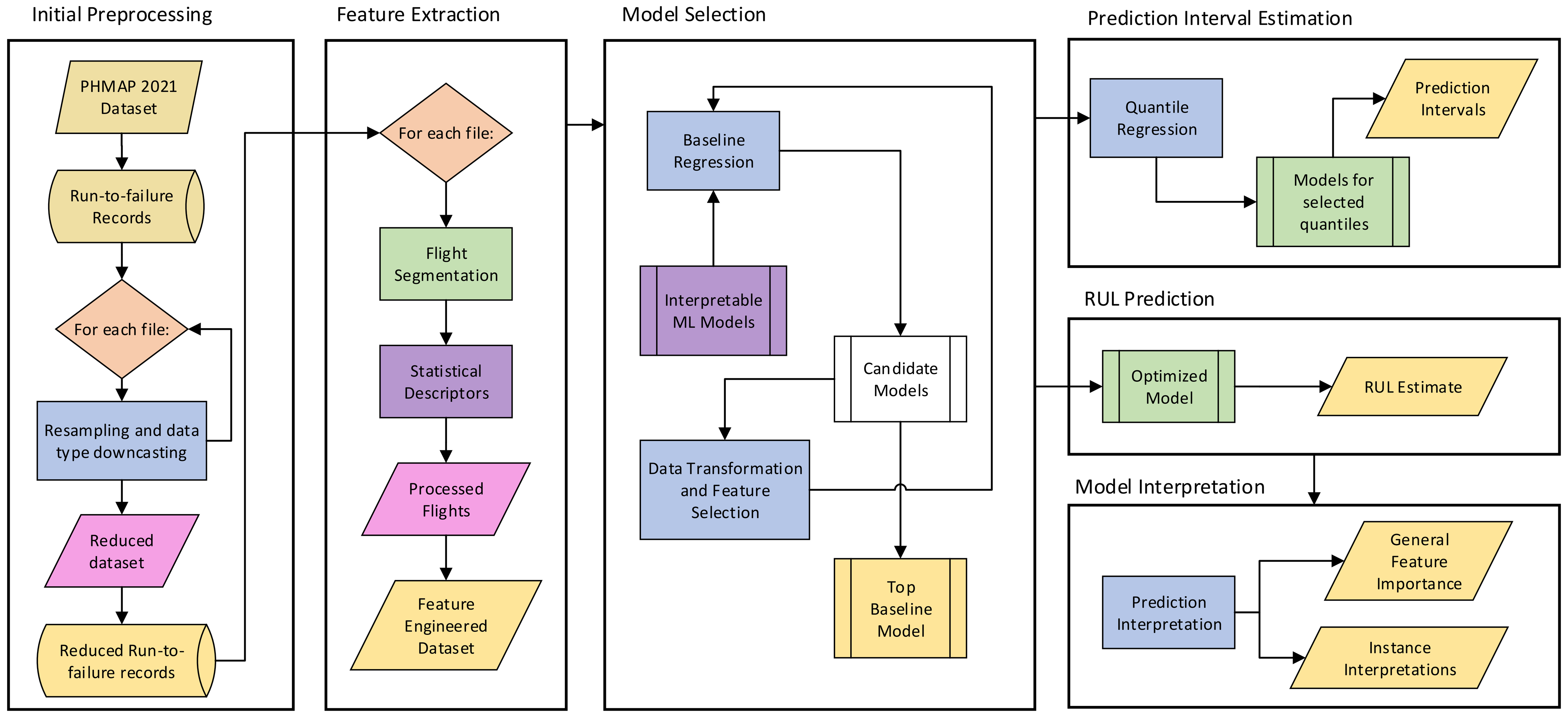
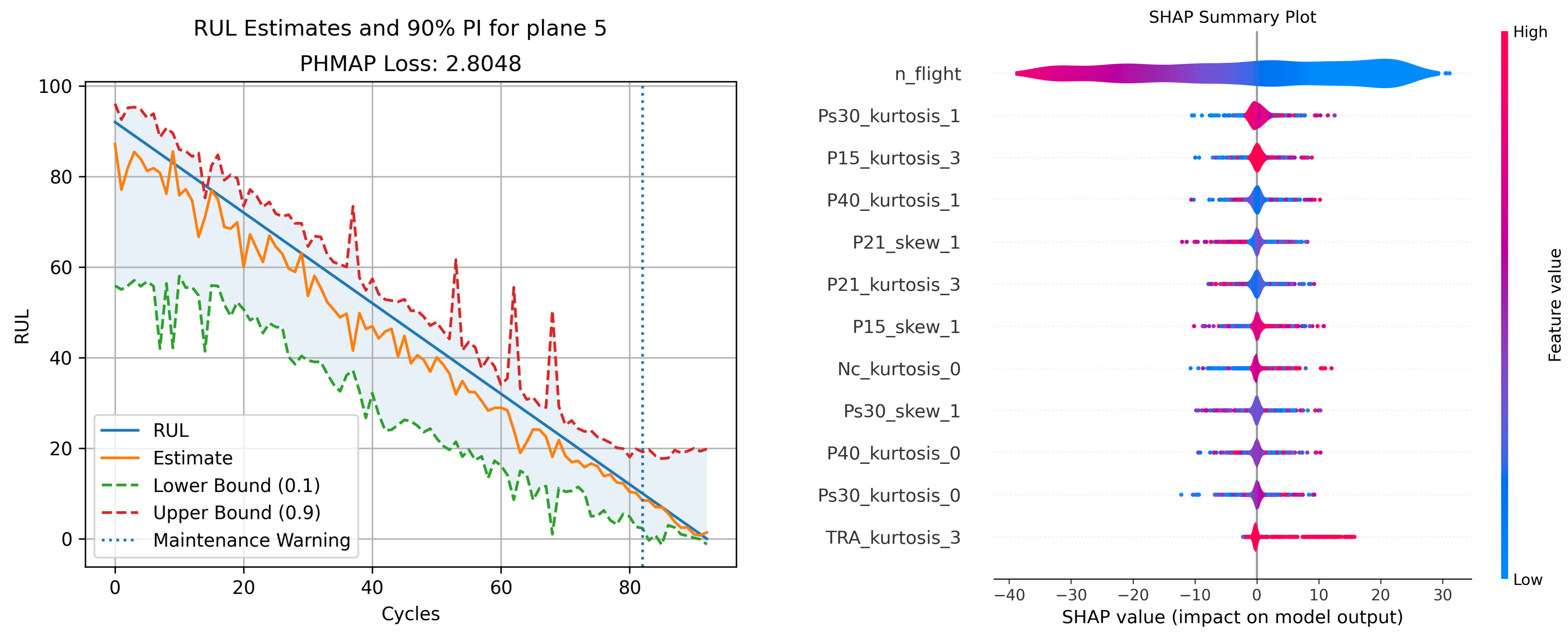


Figure 2. Proposed methodology

Results

- **Model Selection and Optimization:** Employed diverse models such as Linear Regression, SVM, and gradient boosting, with XGBoost chosen for its rapid learning and potential GPU integration after the dominance of gradient boosting.
- **Enhanced Model Performance:** Used *Tree-Structured Parzen Estimators* [2] to optimize XGBoost [3], achieving superior performance to default settings after *500 iterations* across all models.



(a) RUL estimates and prediction intervals
(b) Distribution of Shapley Values per feature

Figure 3. Example of RUL estimates produced and the Shapley Values for the predictions of the dataset

Discussion

Slight decrease in performance but much less compute time for training and inference.

User	Model	Score
IJoinedTooLate [4]	Dilated CNN	3.006
YellowJackets [5]	Inception CNN	3.327
DatrikUS [6]	Stacked DCNN	3.651
*	Bayesian Optimized XGBoost	5.687

Table 1. Comparison of model performances

Conclusions

The research has delivered a comprehensive toolbox for precise model optimization, showcasing performance enhancements over basic models but with a slight trade-off compared to Deep Learning methods.

Future directions involve integrating segmentation algorithms into hyperparameter optimization, modifying feature selection techniques, and further experimentation with hyperparameter optimization processes. These endeavors contribute to the evolving landscape of predictive maintenance methodologies, striving for continuous improvements in both effectiveness and efficiency.

References

[1] M. A. Chao, C. Kulkarni, K. Goebel, and O. Fink, "Phm society data challenge 2021," 2021.

[2] J. Bergstra, R. Bardenet, Y. Bengio, and B. Kégl, "Algorithms for hyper-parameter optimization," *Advances in neural information processing systems*, vol. 24, 2011.

[3] J. Guo, L. Yang, R. Bie, J. Yu, Y. Gao, Y. Shen, and A. Kos, "An xgboost-based physical fitness evaluation model using advanced feature selection and bayesian hyper-parameter optimization for wearable running monitoring," *Computer Networks*, vol. 151, pp. 166–180, 2019.

[4] A. Lövberg, "Remaining useful life prediction of aircraft engines with variable length input sequences," *Annual Conference of the PHM Society*, vol. 13, 12 2021.

[5] N. DeVol, C. Saldana, and K. Fu, "Inception based deep convolutional neural network for remaining useful life estimation of turbofan engines," *Annual Conference of the PHM Society*, vol. 13, 12 2021.

[6] D. Solís-Martín, J. Galán-Páez, and J. Borrego-Díaz, "A stacked deep convolutional neural network to predict the remaining useful life of a turbofan engine," *Annual Conference of the PHM Society*, vol. 13, 11 2021.

Further Information

Catch the Full Implementation and Code Details on GitHub! Scan the QR for in-depth insights and complete access to the implemented methodology and documentation.

SCAN ME