

XAI Implemented Prognostic Framework: Condition Monitoring and Alert System Based on RUL and Sensory Data

Authors : Faruk Ozdemir, Roy Kalawsky, Peter Hubbard

Abstract : Accurate estimation of RUL provides a basis for effective predictive maintenance, reducing unexpected downtime for industrial equipment. However, while models such as the Random Forest have effective predictive capabilities, they are the so-called 'black box' models, where interpretability is at a threshold to make critical diagnostic decisions involved in industries related to aviation. The purpose of this work is to present a prognostic framework that embeds Explainable Artificial Intelligence (XAI) techniques in order to provide essential transparency in Machine Learning methods' decision-making mechanisms based on sensor data, with the objective of procuring actionable insights for the aviation industry. Sensor readings have been gathered from critical equipment such as turbofan jet engine and landing gear, and the prediction of the RUL is done by a Random Forest model. It involves steps such as data gathering, feature engineering, model training, and evaluation. These critical components' datasets are independently trained and evaluated by the models. While suitable predictions are served, their performance metrics are reasonably good; such complex models, however obscure reasoning for the predictions made by them and may even undermine the confidence of the decision-maker or the maintenance teams. This is followed by global explanations using SHAP and local explanations using LIME in the second phase to bridge the gap in reliability within industrial contexts. These tools analyze model decisions, highlighting feature importance and explaining how each input variable affects the output. This dual approach offers a general comprehension of the overall model behavior and detailed insight into specific predictions. The proposed framework, in its third component, incorporates the techniques of causal analysis in the form of Granger causality tests in order to move beyond correlation toward causation. This will not only allow the model to predict failures but also present reasons, from the key sensor features linked to possible failure mechanisms to relevant personnel. The causality between sensor behaviors and equipment failures creates much value for maintenance teams due to better root cause identification and effective preventive measures. This step contributes to the system being more explainable. Surrogate Several simple models, including Decision Trees and Linear Models, can be used in yet another stage to approximately represent the complex Random Forest model. These simpler models act as backups, replicating important jobs of the original model's behavior. If the feature explanations obtained from the surrogate model are cross-validated with the primary model, the insights derived would be more reliable and provide an intuitive sense of how the input variables affect the predictions. We then create an iterative explainable feedback loop, where the knowledge learned from the explainability methods feeds back into the training of the models. This feeds into a cycle of continuous improvement both in model accuracy and interpretability over time. By systematically integrating new findings, the model is expected to adapt to changed conditions and further develop its prognosis capability. These components are then presented to the decision-makers through the development of a fully transparent condition monitoring and alert system. The system provides a holistic tool for maintenance operations by leveraging RUL predictions, feature importance scores, persistent sensor threshold values, and autonomous alert mechanisms. Since the system will provide explanations for the predictions given, along with active alerts, the maintenance personnel can make informed decisions on their end regarding correct interventions to extend the life of the critical machinery.

Keywords : predictive maintenance, explainable artificial intelligence, prognostic, RUL, machine learning, turbofan engines, C-MAPSS dataset

Conference Title : ICAMAME 2025 : International Conference on Aerospace, Mechanical, Automotive and Materials Engineering

Conference Location : London, United Kingdom

Conference Dates : June 28-29, 2025