

# Transformer based Predictive maintenance of degrading turbofan Engines

## Background

Prognostic Health Management (PHM) aims to predict the remaining useful life (RUL) of a degrading component/system using monitoring data (prognostics). Availability of such data from run-to-failure experiments enables data-driven prognostic solutions, advancing predictive maintenance (PDM). We propose a metric to assess data-driven prognostic algorithms, considering their impact on downstream PDM decisions. This metric is defined with respect to specific decision settings and corresponding PDM policies governing maintenance actions. Two common decision settings are considered: component replacement planning and component ordering-replacement planning, with evaluation based on long-term expected maintenance cost per unit time using available run-to-failure datasets. Different versions of transformer NN architecture serve as data-driven prognostic algorithms in a case study on turbofan engine degradation, examining their joint effect with PDM policies on the metric. Specifically, we explore two PDM policies: a simple heuristic policy and a modified policy based on full RUL distribution, alongside transformer algorithms such as Informer, Spacetimeformer, and Autoformer. These transformers are chosen for their open-source availability and unique features. Informer[1] introduces ProbSparse attention, focusing on dominant queries while avoiding fixed sparsity patterns. Autoformer[2] replaces scaled dot-product attention with the Auto-Correlation module, emphasizing time-series similarity through autocorrelation and time-delay aggregation. Spacetimeformer[3] integrates temporal and spatial attention methods, enhancing the model's understanding of spatial-temporal relationships in data representation.

## Objectives

The main goal is to do a evaluation of the metric  $M$  in conjunction with a prognostic model such as transformer architecture and a PDM policy for planning replacement as a function of different  $C_p/C_c$  cost ratios and compare the results with the LSTM prognostic classifier.

## Methodology

Turbofan engine performance degradation histories due to wear and tear were generated numerically using the C-MAPSS simulator. The simulator replicates engine behavior under various flight conditions, introducing performance degradation in one module via an exponential degradation model.

- Data comprises 14 input variables defining simulation configuration, 21 output variables capturing system response during or post-flight, and 3 variables detailing engine operation modes.

The procedure would be as follows:



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1. Literature review: possible impact of different prognostic algorithms that are suggested in the Background
2. Gather The Remaining useful life (RUL) prediction by applying prognostic algorithms on C-MAPSS data.
3. PDM policies evaluation form the basis for estimation of proposed matric.
4. The metric can further serve as a decision-oriented objective function for optimizing simple heuristic PDM policies or for 'prognostic algorithm' hyperparameter tuning.

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### References

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- [2] Wu, Haixu, et al. "Autoformer: Decomposition transformers with auto-correlation for long-term series forecasting." Advances in Neural Information Processing Systems 34 (2021): 22419–22430.
- [3] Grigsby, Jake, Zhe Wang, Nam Nguyen, and Yanjun Qi. "Long-range transformers for dynamic spatiotemporal forecasting." arXiv preprint arXiv:2109.12218 (2021).
- [4] Kamariotis, Antonios, Konstantinos Tatsis, Eleni Chatzi, Kai Goebel, and Daniel Straub. "A metric for assessing and optimizing data-driven prognostic algorithms for predictive maintenance." Reliability Engineering & System Safety 242 (2024): 109723.