Performance monitoring and wear comprehension through Neural Network

Thomas BINET[1,3], Hanane AZZAG[1], Mustapha LEBBAH[2], Jerome LACAILLE[3]

1- Sorbonne Paris Nord University - LIPN, UMR CNRS 7030, Villetaneuse - France
2- DAVID Lab, University of Versailles, University Paris-Saclay, Versailles, France
3- Safran Aircraft Engine, Moissy-Cramayel - France

Abstract. In this paper, we present a novel approach to modeling the wear of complex dynamic systems, exemplified by aircraft engines, through the construction of a structured latent space. Unlike traditional methods, our model does not rely on explicit wear data but instead leverages supervised training to minimize the error on observable system parameters. Beyond wear forecasting, this work offers a foundation for unsupervised diagnosis, risk prevention, and the quantification of repair impacts.

1 Introduction

Dynamic system analysis has traditionally relied on methods such as PDEs (partial differential equation), ODEs (ordinary differential equation), and the study of their parameters [1]. While effective, these methods have notable limitations, primarily due to the complexity of the models and the need for extensive human expertise in the physical aspects of the problem. Recently, however, the advent of advanced architectures, such as RNNs (LSTM, GRU) and transformers [2], has made it possible to analyze time series data associated with complex dynamic systems in new ways. This shift has spurred significant interest in the aeronautical industry, particularly in the analysis and simulation of aircraft engine behavior [3, 4]. These efforts are critical for improving engine performance, optimizing maintenance processes, ensuring safety, and supporting sustainability initiatives. A significant number of sensors are embedded within aircraft engines to collect data on engine usage during flights according to specific rules (ACARS). While these data are abundant and notably noisy, they contain valuable insights into engine wear. This aspect is important for Prognostic Health Management (PHM) because, with effective data processing, it may be possible to predict maintenance needs in advance, thereby reducing engine downtime [5]. Recent studies have explored this area, including one focused on continuous flight data [6] and another on the specific case of ACARS [7]. The model in [7] is designed to predict the Exhaust Gas Temperature (EGT) in aircraft turbofan engines, a vital metric for assessing engine efficiency and planning maintenance. Using a neural network structure with recurrent layers and attention mechanisms. This model focuses on predicting EGT during the cruise phase, which is particularly critical for maintaining engine performance. It incorporates two attention mechanisms: one for short-term focus on recent flight data and another for long-term attention to monitor the engine's health state over time. Additionally, the model includes a Gaussian Mixture Model (GMM) to handle performance uncertainties, especially

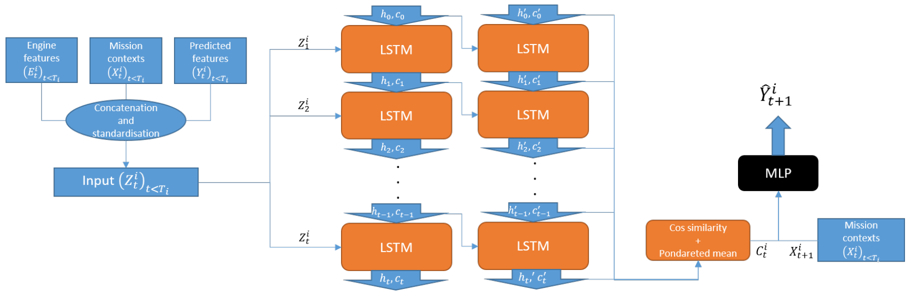


Fig. 1: SV-LSTM architecture. Schema of the computation of prediction $\hat{Y}_t^i$ where i is the engine index and t is the cycle since new (temporal). The loss used is the mean of temporal MSE of each prediction parameter

following maintenance actions like water washes that impact EGT. In this work, we draw inspiration from this prior work building upon the latter to improve the parameter prediction model, aiming to better capture engine wear.

2 Data Driven Simulator

2.1 Methodology

The proposed model named SV-LSTM (State Vector learning by an LSTM architecture), illustrated in Figure 1, adopts an encoder-decoder architecture to encode information about the dynamic system over a time range leading up to the prediction point $t + 1$. We have the choice between several model to capture the temporal dependencies like Transformer [2], Mamba [8] and LSTM architecture. We choose to adopt the LSTM architecture because it's the simpler model between the over, and some work was already made on RUL (remaning useful life) with an LSTM architecture and demonstrate good result [9, 7]. This encoding process generates a state vector within a latent space, which is the foundation for predicting system wear parameters at time $t + 1$. To enhance prediction accuracy, contextual parameters are incorporated. Furthermore, the model integrates an attention mechanism that processes the sequences $(h_i)_{0<i<t+1}$ and $(c_i)_{0<i<t+1}$, ensuring the effective integration of the most relevant temporal features. This architecture introduces a novel methodology for dynamic systems analysis and wear modeling by structuring a latent space aligned with the wear characteristics of complex systems. Unlike traditional approaches, such as supervised methods like survival analysis, which rely on explicit wear data to predict outcomes, this model employs supervised training to estimate key parameters of the dynamic system while constructing a wear indicator in an unsupervised manner, thereby eliminating the dependency on direct wear labels. The table 1 shows a qualitative comparison of the different modules in our model and others.

Key architectural refinements are implemented to optimize the latent space for precise wear assessment. Unlike the approach described in [7], this model

Model	Self Attention	latent vector	output	Loss function	predicted features
model in [7]	MLP & Cos similarity	state & flight	GMM	Likelihood	1
SV-LSTM (ours)	Cos similarity	state	Direct values	MSE	1 or more

Table 1: The comparison between the SV-LSTM model (ours), the model proposed in [7]. Both models use a latent space to predict outputs; however, the SV-LSTM model is more lightweight than the [7] counterpart.

omits the lower attention layer used for building flight context vectors, instead enriching the state vector contexts directly to support effective classification. In addition, analysis revealed that the flight context vector strongly impacts target prediction (notably EGT); however, this component can unintentionally segment engines in the latent space, counteracting the goal of building a cohesive state vector (explained in figure 3). Additionally, the model opts for direct prediction over stochastic approaches, leveraging the inherent variability of the context at each time step to capture stochastic behavior effectively. The model is also expanded to predict multiple target variables, thus enriching the state vector to support various metrics and enable a comprehensive understanding of system health. The loss function is defined as the mean squared error (MSE) between the predicted time series and the target, ensuring precise optimization for wear-related predictions.

3 Experiments

3.1 Dataset

To train our model, we utilize data from LEAP-1A engines obtained through ACARS, providing access to key parameters such as Exhaust Gas Temperature (EGT), fan speed (N1), core speed (N2), and other critical engine and control metrics. This dataset is further enriched with meteorological information from the departure and arrival airports, sourced via METAR and SATAVIA database. This additional data includes METAR reports and pollution metrics, encompassing variables like wind speed and direction, pollution levels across locations, humidity, and other environmental factors, offering a comprehensive dataset to enhance model performance.

3.2 Numerical comparison

To evaluate our model's performance, we compared it against the model proposed in [7], focusing on two key aspects. The first is the prediction accuracy of the target parameters, where the prediction error is quantified using the Root Mean Square Error (RMSE). The second aspect involves analyzing the structure of the latent space formed by the state vectors generated by the model. This analysis is essential for enabling comparisons between engine states, providing valuable insights into engine wear and its progression.

Since our model outperforms the baseline (Figure 2), it allows a meaningful

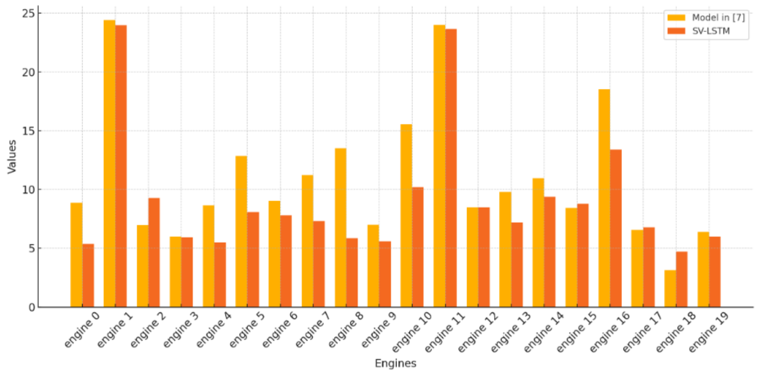


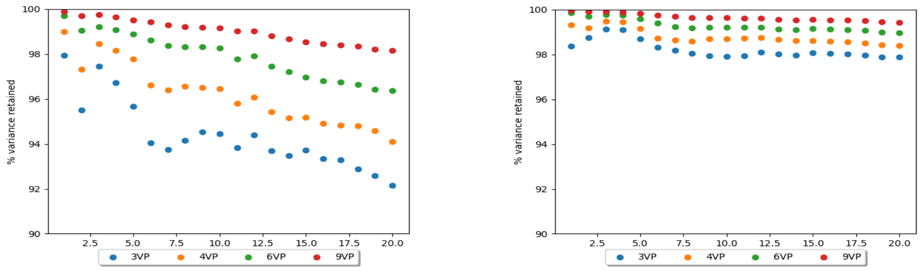
Fig. 2: RMSE of different model (model in [7], SV-LSTM (ours)) for 20 engines. We see that our model outperform the model in [7] by far.

comparison of the latent spaces generated by the models, with the goal of facilitating classification. Specifically, we aim to establish a direct correlation between the position in the latent space and wear in average EGT. The average EGT is calculated by generating EGT values across various contexts in the dataset. This approach is motivated by the fact that all three models are trained to predict parameters for the next time step based on a state vector derived from prior data. Given that wears are inherently continuous phenomena, the model incrementally adapts to capture these trends. However, when a repair occurs, the engine's state undergoes a sudden shift, which the model cannot immediately account for. Consequently, the model requires an acclimation period — approximately 200 flights — to realign with the new engine state. This period, however, can be significantly shortened by resetting the hidden states of the LSTM to zero, effectively reinitializing the model to align with the updated state vector.

Figure 3 demonstrates that the projected space of our model, regardless of the number of components chosen, remains independent of the number of engines used in its calculation. This is a crucial finding, as it suggests that the distribution—at least the portion captured by PCA—is consistent across all engines. This consistency enables all engines to be represented within a unified projection, which significantly streamlines the interpretation and visualization of the state vector.

4 Wear comprehension due to state latent space

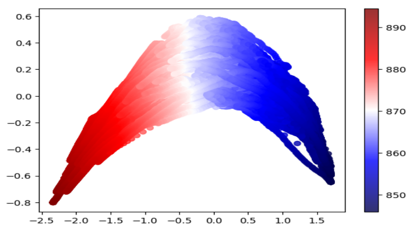
Developing an aircraft engine wear model presents significant challenges, primarily due to the variability of flight conditions. This variability prevents direct comparisons between engines, as each follows a unique wear trajectory. Nevertheless, many engines exhibit common wear types, such as degradation in the HPT module (High Pressure Turbine). By leveraging the predictive model of ACARS



(a) model in [7] (b) SV-LSTM (ours)

Fig. 3: Variance ratio explained comparison between model in [7] (3a) and SV-LSTM (3b), for different data set size (number of engines in dataset) for different number of eigenvalues retained. We see a big decreasing of the explained variance ratio for the figure 3a but not for SV-LSTM model (3b).

parameters, alongside the constructed state vector and the context of the next flight, it becomes possible to establish an analogy between the latent space and the engine wear space. This wear space becomes increasingly detailed as the independence of the predicted parameters improves. The wear space provides two key perspectives: the current engine state (its position within the space) and its dynamics (how the state evolves over time). These insights enable the unsupervised identification of engine wear. Exhaust Gas Temperature (EGT) serves as a particularly effective indicator, though this approach is equally applicable to other variables influenced by wear, provided all other factors remain constant. This methodology facilitates a deeper understanding of engine health and wear trends across various operational contexts.



(a) SV-LSTM (ours)

Fig. 4: Projection onto the first two eigenvectors from the Principal Component Analysis (PCA) applied to the state vector for the SV-LSTM model. The SV-LSTM model produces a straightforward structure where the position in the latent space correlates directly with the average Exhaust Gas Temperature (EGT), serving as a reliable representation of engine wear. This distinction underscores the SV-LSTM model's capability to facilitate meaningful insights into engine health and wear patterns.

Our model provides a clear and interpretable understanding of wear through its structured latent space, in contrast to the model in [7], which exhibits significantly more chaotic behavior. An initial analysis can be performed independently of specific wear types by examining the engine's position within the latent space. This positioning serves as an indicator of the wear level, particularly in terms of Exhaust Gas Temperature (EGT) performance or other target parameters, offering valuable insights into the engine's health and operational efficiency.

5 Conclusion

In this paper, we present a model that constructs a latent space aligned with the wear of complex dynamic systems, achieved without relying on explicit wear data. Instead, the model is trained exclusively by minimizing the prediction error of the observable system parameters. This innovation enables wear forecasting for complex dynamic systems, such as aircraft engines or even living organisms, serving as both a risk prevention tool and a method for quantifying and comparing the effects of repairs on aircraft engines. Furthermore, future experiments could explore the validity of the LSTM component in comparison to alternative architectures, such as transformers or ODE networks, to assess their suitability and potential advantages for this application.

References

[1] Safia Slimani. *Système dynamique stochastique de certains modèles proies-prédateurs et applications.* Theses, Normandie Université ; Université Badji Mokhtar-Annaba, December 2018.

[2] Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N Gomez, Ł ukasz Kaiser, and Illia Polosukhin. Attention is all you need. In I. Guyon, U. Von Luxburg, S. Bengio, H. Wallach, R. Fergus, S. Vishwanathan, and R. Garnett, editors, *Advances in Neural Information Processing Systems*, volume 30. Curran Associates, Inc., 2017.

[3] Sangjo Kim, Kuisoon Kim, and Changmin Son. Transient system simulation for an aircraft engine using a data-driven model. *Energy*, 196:117046, 2020.

[4] Amare Desalegn Fentaye, Valentina Zaccaria, and Konstantinos Kyprianidis. Aircraft engine performance monitoring and diagnostics based on deep convolutional neural networks. *Machines*, 9(12), 2021.

[5] Jean Coussirou, Thomas Vanaret, Jérôme Lacaille, and Safran Aircraft Engines DataLab. Anomaly detections on the oil system of a turbofan engine by a neural autoencoder. In *30th European Symposium on Artificial Neural Networks, Computational Intelligence and Machine Learning, ESANN*, 2022.

[6] Abdellah Madane, Florent Forest, Hanane Azzag, Mustapha Lebbah, and Jérôme Lacaille. From Data to Simulation: Capturing Aircraft Engine Degradation Dynamics. In *ESANN 2024*, pages 537–542, Bruges (Belgium) and online, France, October 2024. Ciaco - i6doc.com.

[7] Raphaël Langhendries and Jérôme Lacaille. Turbofan exhaust gas temperature forecasting and performance monitoring with a neural network model. In *Proceedings of the 32nd European Safety and Reliability Conference (ESREL 2022)*, pages 3095–3102, 08 2022.

[8] Haoyu Ma, Yushu Chen, Wenlai Zhao, Jinzhe Yang, Yingsheng Ji, Xinghua Xu, Xiaozhu Liu, Hao Jing, Shengzhuo Liu, and Guangwen Yang. A mamba foundation model for time series forecasting, 2024.

[9] Yupeng Wei. Prediction of state of health of lithium-ion battery using health index informed attention model. *Sensors*, 23(5), 2023.