

Physics Informed Machine Learning techniques for condition monitoring of drivetrains

Evenela Maria Dima^{1,2}, Konstantinos Gryllias^{1,2}

¹ *Department of Mechanical Engineering, KU Leuven*
evenelamaria.dima@kuleuven.be
konstantinos.gryllias@kuleuven.be

² *Flanders Make @KU Leuven*
Celestijnenlaan 300, Box 2420, 3001 Leuven, Belgium

ABSTRACT

Drivetrains play a central role in a wide range of industrial applications, including wind energy, aerospace, and agricultural machinery. Their reliability has a direct impact on system availability, safety, and maintenance costs. Within this context, Predictive Maintenance (PdM) has emerged as a key strategy to anticipate failures, reduce unplanned downtime, and optimize maintenance operations.

Despite significant advancements in condition monitoring technologies, gearbox components remain among the most critical elements in terms of reliability. In wind energy applications, for example, turbines frequently experience premature failures associated with bearing related damage mechanisms, which prevent them from achieving their expected service life and lead to high maintenance costs and downtime. In aerospace systems, gearbox integrity is even more critical, as demonstrated by strict regulatory requirements imposed by aviation authorities. These include repeated inspections of main gearboxes and monitoring of metallic debris in lubrication systems, underlining the importance of early fault detection and reliable prognostic capabilities. These challenges reflect a strong industrial need for methodologies capable of predicting failures in a robust and reliable manner.

However, developing reliable prognostic tools remains challenging. In condition monitoring, traditional machine learning approaches have typically relied on a multi-step pipeline, where features are manually extracted from sensor data, often in the time, frequency, or time–frequency domains, and then used as input for classification or regression models. While this approach allows for some level of interpretability and control, it strongly depends on expert knowledge and can be-

come difficult to scale when dealing with complex systems or high-dimensional data (Lei et al., 2020).

More recent developments in deep learning have addressed part of these limitations by enabling end-to-end learning directly from raw signals. Architectures such as convolutional and recurrent neural networks can automatically identify relevant patterns and features, significantly improving performance in fault diagnosis tasks. However, these methods introduce new challenges. Their effectiveness is strongly dependent on the availability of large amounts of labelled data, which are typically not available in industrial contexts (Fu et al., 2024). Faulty conditions are rarely observed, resulting in limited and often unbalanced datasets, which further reduce model reliability. As a consequence, deep learning models may achieve high accuracy under controlled conditions but fail to generalize when applied to real-world scenarios.

Overall, purely data-driven approaches tend to perform well within the range of observed data but often struggle with extrapolation and may generate predictions that are not physically meaningful (Fu et al., 2024). This lack of robustness and interpretability represents a key limitation, particularly for predictive maintenance applications in safety-critical systems.

To overcome these limitations, recent research has focused on the integration of physical knowledge within machine learning models. In this context, Physics-Informed Neural Networks (PINNs) have emerged as a promising framework for combining data-driven learning with prior knowledge of the system (Karniadakis et al., 2021). These models allow the incorporation of physical constraints, such as governing equations, directly into the training process, either by embedding them into the network structure or by enforcing them through the loss function (Shen et al., 2024; Kim, Choi, & Kim, 2022; Zhang, Gong, & Xuan, 2021).

Evenela Maria Dima et al. This is an open-access article distributed under the terms of the Creative Commons Attribution 3.0 United States License, which permits unrestricted use, distribution, and reproduction in any medium, provided the original author and source are credited.

In addition, the integration of physics and data-driven components can be achieved at different levels. One possibility is to design parts of the neural network architecture based on the underlying physical model (Ni, Ji, Halkon, Feng, & Nandi, 2023; Chen, Li, Liu, & Li, 2023; Yucasan & Viana, 2020). Alternatively, physics-based and data-driven models can be arranged sequentially, allowing the data-driven component to capture the aspects of the system that are not fully described by the physical model. In this way, the overall model is encouraged to produce predictions that are consistent not only with the observed data but also with the expected physical behaviour of the system.

This class of approaches is particularly well-suited for industrial applications, where the amount of available data is limited. By constraining the learning process using physics-based knowledge, these models can achieve improved generalization even in small-data regimes. Moreover, they tend to be more robust to noise and missing data, and they offer better extrapolation capabilities.

The present research aims to develop and validate a hybrid methodology for fault detection and prognostics in drivetrains, in which physics-informed components are used to describe relatively well-known mechanisms, such as bearing and gear fatigue life, while data-driven components are employed to capture phenomena that are difficult to model explicitly, such as lubricant degradation. The validation of the approach will be carried out using experimental data collected from dedicated in-house drivetrain test rigs.

The main expected contributions to the field of Prognostics and Health Management (PHM) can be summarized as follows:

- The development of a hybrid modelling framework combining physics-based layers with data-driven layers, with the objective of improving fault detection and prognostic performance while ensuring robustness and interpretability in realistic industrial conditions;
- A structured approach to link oil degradation to the detection of wear damage in gearboxes, along with an evaluation of the benefits of integrating oil condition monitoring with other techniques, such as vibration analysis, thereby fostering a closer integration between tribology and PHM in gearbox applications.

To achieve these objectives, the research is structured into the following main activities:

1. **Literature review:** A comprehensive review of existing work will be carried out across three key areas: machine learning and deep learning for condition monitoring, signal processing techniques and feature extraction, and tribology, with emphasis on contact and lubrication. The aim is to identify current limitations and define a solid basis for the proposed methodology.
2. **Deep learning:** Different neural network architectures will be investigated. Particular focus will be placed on their suitability for modelling phenomena that are difficult to describe analytically, such as lubricant degradation. Various configurations will be implemented and compared, and explainability techniques will be used to interpret the learned features and assess their physical relevance.
3. **Tribology and contact analysis:** The study will examine contact interactions in drivetrains, focusing on the relationship between loading conditions, lubrication, and damage mechanisms. Special attention will be given to identifying measurable quantities that can capture the evolution of damage at the contact level. In parallel, different oil sensing technologies will be analyzed to determine their effectiveness in monitoring lubricant condition.
4. **Signal processing and feature extraction:** A detailed investigation of signal processing techniques will be performed, covering time-domain, frequency-domain, and time-frequency approaches. Cyclostationary analysis will be explored in depth, given its relevance for rotating machinery. Existing health indicators will be evaluated to identify the most informative features for the application.
5. **Experimental validation:** The proposed methodology will be validated on dedicated drivetrain test rigs. Accelerated life tests will be conducted to generate representative faulty data under controlled operating conditions. Multiple sensor types, including accelerometers, temperature sensors, and oil sensors, will be used. The collected data will be used to evaluate the performance of the proposed approach in terms of fault detection capabilities and prognostic accuracy under realistic conditions.

The validation of the developed methodology will rely on experimental data collected from a dedicated test rig specifically designed to conduct accelerated life tests to induce faults in gears under controlled operating conditions.

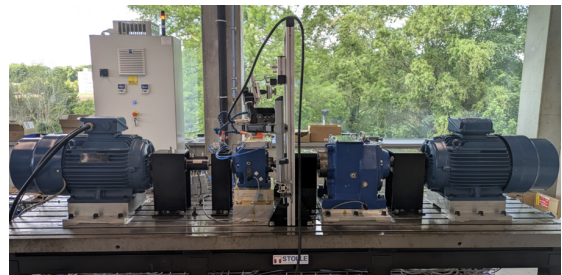


Figure 1. Back-to-back gearbox test rig

The setup consists of a back-to-back configuration with two parallel-shaft helical gearboxes and is designed to induce the development of typical gear faults, with particular emphasis

on pitting, as well as other damage modes such as spalling and tooth cracking.

A key feature of the setup is the possibility to directly observe the evolution of the damage. The gearbox has been modified to provide optical access to the critical component, and a high-speed camera is used to capture images during operation. This leads to the generation of a dataset in which visual information is synchronized with sensor measurements, facilitating the identification of fault initiation and evolution.

The test rig is also equipped with oil sensors that provide information on lubricant condition, including temperature, cleanliness level, humidity, and particle concentration through a particle counter. These measurements are relevant for analysing the role of lubrication in the damage process. Additional sensors will be integrated in the near future to measure viscosity, oxidation and contamination level, as well as water content, further supporting the objectives of this research.

In summary, this work presents the main limitations of current condition monitoring approaches, and highlights the need for methodologies capable of dealing with limited data while ensuring physical consistency. PINNs have been introduced as a suitable framework for addressing these challenges. The proposed hybrid approach, together with the role of contact mechanics and tribology, has been outlined as a central element of the research. Additionally, a dedicated test rig has been introduced to support the validation of the proposed methodology under controlled conditions. Finally, a structured research plan has been defined, with the objective of developing a robust framework for fault detection and prognostics in drivetrains, contributing to the advancement of PHM.

ACKNOWLEDGMENT

The authors gratefully acknowledge the European Commission for its support of the Marie Skłodowska Curie program through the Horizon Europe DN PATRON project (GA 101120172). Views and opinions expressed are however those of the authors only and do not necessarily reflect those of the European Union. The European Union cannot be held responsible for them.

REFERENCES

- Chen, D., Li, Y., Liu, K., & Li, Y. (2023). A physics-informed neural network approach to fatigue life prediction using small quantity of samples. *International Journal of Fatigue*, 166. doi: 10.1016/j.ijfatigue.2022.107270
- Fu, X., Fang, Y., Xu, Y., Xu, H., Ma, G., & Peng, N. (2024). Current status of research on fault diagnosis using machine learning for gear transmission systems. *Machines*, 12(10). doi: 10.3390/machines12100679
- Karniadakis, G. E., Kevrekidis, I. G., Lu, L., Perdikaris, P., Wang, S., & Yang, L. (2021). Physics-informed machine learning. *Nature Reviews Physics*, 3. doi: 10.1038/s42254-021-00314-5
- Kim, S., Choi, J.-H., & Kim, N. H. (2022). Data-driven prognostics with low-fidelity physical information for digital twin: physics-informed neural network. *Advanced Engineering Informatics*, 54. doi: 10.1016/j.aei.2022.101803
- Lei, Y., Yang, B., Jiang, X., Jia, F., Li, N., & Nandi, A. K. (2020). Applications of machine learning to machine fault diagnosis: A review and roadmap. *Mechanical Systems and Signal Processing*, 138. doi: 10.1016/j.ymssp.2019.106587
- Ni, Q., Ji, J. C., Halkon, B., Feng, K., & Nandi, A. K. (2023). Physics-informed residual network (piresnet) for rolling element bearing fault diagnostics. *Mechanical Systems and Signal Processing*, 198. doi: 10.1016/j.ymssp.2023.110449
- Shen, S., Lu, H., Sadoughi, M., Hu, C., Nemani, V., Thelen, A., ... Kenny, S. (2024). M-band wavelet network for machine anomaly detection from a frequency perspective. *Mechanical Systems and Signal Processing*, 217. doi: 10.1016/j.ymssp.2024.111489
- Yucesan, Y. A., & Viana, F. A. C. (2020). A physics-informed neural network for wind turbine main bearing fatigue. *International Journal of Prognostics and Health Management*, 11(1). doi: 10.36001/ijphm.2020.v11i1.2594
- Zhang, X., Gong, J.-G., & Xuan, F.-Z. (2021). A physics-informed neural network for creep-fatigue life prediction of components at elevated temperatures. *Engineering Fracture Mechanics*, 258. doi: 10.1016/j.engfracmech.2021.108130

BIOGRAPHIES



Evenela Maria Dima received her Bachelor degree in Mechanical Engineering from Sapienza University of Rome, Italy and her Master's degree in Mechatronic Engineering from the University of Modena and Reggio Emilia, Italy. In 2025, she joined the Condition Monitoring research group in the Department of Mechanical Engineering at

KU Leuven, Belgium as a Ph.D. researcher. Her research interests lie in the areas of condition monitoring, deep learning and tribology.



Konstantinos Gryllias received the Diploma and Ph.D. degrees in Mechanical Engineering from the National Technical University of Athens, Greece, in 2004 and 2010, respectively. He is currently a Professor of Vibro-Acoustics of Machines and Transportation Systems with the Department of Mechanical Engineering, KU Leuven, Belgium. He also serves as the Manager of the University Core Lab Flanders Make@KU Leuven Motion

Products, Belgium. His research interests include condition monitoring, signal processing, prognostics, and health management of mechanical and mechatronic systems.