**Editorial: Special Issue on Physics-Informed Machine Learning Enabling Fault Feature Extraction and Robust Failure Prognosis**

The use of machine learning (ML) techniques has resulted in fairly high accuracy in diagnosing faults and predicting failures for a wide range of engineered systems. Nonetheless, production-scale adoption of ML-based predictive maintenance has in part been impeded by challenges resulting from poor generalization of purely data-driven ML models. While these models can work well on often small quantities of fault/failure scenarios that a training dataset has captured, they may fail to perform on so-called *out-of-distribution* cases that are not well-represented in the training dataset but are encountered in real-world system operations. Such behavior makes ML models unusable in high-value systems where bad predictions have serious consequences on costs or safety. Moreover, data-driven ML models may fail to provide any physical interpretation of identified fault features or final predictions. Only limited research has been carried out so far to adapt ML models to out-of-distribution cases and to offer physical interpretability. More fundamental and applied research is needed to address these problems. Advances in the understanding of how to incorporate physical knowledge into data-driven ML models have the promise of making these models generalize better to unseen, out-of-distribution cases while at the same time explaining underlying physics.

This special issue consists of 17 papers creating new theoretical foundations and models/algorithms of physics-informed ML for fault diagnosis and failure prognosis. According to the applications of interest, these papers can be broadly categorized into four groups: (1) physics-informed ML for machinery health monitoring, encompassing fault diagnosis and failure prognosis; (2) physics-informed ML specifically for the battery health monitoring domain, The scope encompasses (a) state-of-health (SOH) estimation, (b) degradation diagnosis, and (c) degradation prognosis; (3) physics-informed ML for prognosis as applied to various engineered systems that represent rotating components and machinery; and (4) physics-informed ML for other engineering applications. A summary of these papers is provided in Sections 1 to 4. This editorial is concluded in Section 5, where we analyze the general themes of these 17 papers and discuss potential topics for future research surrounding physics-informed ML for diagnosis and prognosis.

## 1. Physics-Informed ML for Machine Health Monitoring

In the paper titled *Deep convolutional generative adversarial network with semi-supervised learning enabled physics elucidation for extended gear fault diagnosis under data limitations*, Zhou et al. attempted to answer the question of how to achieve highly accurate fault diagnosis with only small labeled data available for model training [1]. Their solution to this challenge was synthesizing a deep convolutional generative adversarial network (DCGAN) which allowed exploiting rich fault signatures in much bigger unlabeled training data. These fault signatures could be representative of "unseen" faults in real-world fault diagnosis practice that differ substantially from known faults in labeled training data. The authors experimentally validated the effectiveness of a trained DCGAN in improving fault classification accuracy over a supervised multi-class classifier using vibration measurements from a laboratory-scale gear system.

Chen et al. presented a physics-informed hyperparameter optimization approach for long short-term memory (LSTM) recurrent neural networks in their paper titled *Physics-informed LSTM hyperparameters selection for gearbox fault detection* [2]. Their approach centered on replacing a conventional validation mean squared error with the discrepancy between healthy and faulty states, with faulty data simulated based on the physics of gear faults. The proposed approach was demonstrated for gear fault classification using two laboratory-scale gearbox test rigs. This work shed some key insights into how physical knowledge can be leveraged to optimize the hyperparameters of a neural network.

Kim et al. presented a new deep learning method for gearbox fault diagnosis involving a health-adaptive time-scale representation and a convolutional neural network in their paper titled *A health-adaptive time-scale representation (HTSR) embedded convolutional neural network for gearbox fault diagnostics* [3]. The unique element of their method is the so-called multiscale convolutional filters used to process input signals as the first feature extraction step (followed by a standard convolutional neural network). These carefully designed filters allow the resulting health-adaptive time-scale representation to capture fault-related information in various temporal and frequency ranges. This method was applied to diagnose faults in a two-stage spur gearbox and a planetary gearbox.

In the paper titled *Physics-informed deep learning for signal compression and reconstruction of big data in industrial condition monitoring*, Russell and Wang presented a physics-informed deep learning framework to compress and reconstruct vibration signals for cloud-based diagnosis and prognosis in industrial settings [4]. Their key idea is to train a deep neural network architecture called deep convolutional autoencoder using a combination of a conventional mean squared error loss term and two newly proposed loss terms, namely local structure loss and physics-informed loss. These additional loss terms helped improve signal reconstruction fidelity in ways relevant to machine condition monitoring. Performance improvements were demonstrated using publicly available bearing fault and milling data sets.

Wang et al. designed a new physically interpretable neural network for machine health monitoring, specifically focusing on improving the interpretability of extreme learning machines [5]. This paper was titled *Fully interpretable neural network for locating resonance frequency bands for machine condition monitoring*. The physical interpretation was realized by (1) adding three signal processing operations, i.e., a wavelet transform, square envelope, and Fourier transform, as the first three "hidden" layers so that extraction of repetitive transients caused by rotating faults was physically interpretable and (2) setting hidden units in a conventional layer to classic sparsity measures, which are kurtosis, negative entropy, Gini index, and reciprocal of smoothness index, for quantifying the cyclo-stationarity of repetitive transients. Overall, the fully physically interpretable neural network was interpretable from signal preprocessing and machine health estimation perspectives. Results showed that this fully interpretable architecture could automatically tune optimal wavelet parameters to locate informative frequency bands for machine health monitoring.

In the paper titled *A hybrid physics-informed neural network for main bearing fatigue prognosis under grease quality variation*, Yucesan and Viana addressed the problem of grease condition monitoring by combing physics-based and data-driven models within a hybrid physics-informed neural network [6]. The physics-based models captured bearing fatigue damage accumulation under given loads and grease state; the data-driven model allowed quantifying grease damage, known to accelerate bearing degradation. A unique contribution of this work was estimating grease damage accumulation using a data-driven neural network in place of poorly understood physics of grease degradation. The authors demonstrated their hybrid physics-informed neural network for bearing fatigue prognosis via numerical experiments on a wind park consisting of 100 wind turbines.

## 2. Physics-Informed ML for Battery Health Monitoring

The goal of *A convolutional neural network model for SOH estimation of Li-ion batteries with physical interpretability* by Lee et al. was to understand the contribution of each temporal feature to SOH forecasting by trained ML models on a per-instance basis [7]. These ML models were convolutional neural networks known to be capable of automating the process of extracting useful features from high-dimensional input data. Classification activation maps were used to quantitatively analyze temporal features' importance in producing a final SOH prediction for a future cycle. The proposed interpretable ML method was demonstrated using capacity degradation data of 379 automotive lithium-ion cells, focusing on early SOH prediction.

Greenbank and Howey studied the construction of piecewise-linear models for battery capacity forecasting and end-of-life prediction [8]. In their paper titled *Piecewise-linear modelling with automated feature selection for Li-ion battery end-of-life prognosis*, a piecewise-linear regression approach was used in combination with automated feature selection to predict a cell's capacity trajectory up to the cell's end of life. When evaluated on a public aging dataset consisting of 169 automotive lithium-ion cells, the proposed piecewise-linear modeling approach yielded competitive prediction accuracy comparable to Gaussian process regression, which was expected to be computationally more expensive than the proposed approach.

Shi et al. developed a physics-informed machine learning method for capacity forecasting and remaining useful life prediction under different operating conditions in their paper titled *Battery health* *management using physics-informed machine learning: Online degradation modeling and remaining useful life prediction* [9]. Here, the physics-informed machine learning method consisted of a physics-based calendar and cycle aging model connected with an LSTM layer to discover the relationship between linear model estimation and practical battery degradation. The beauty of the physics-based model was that it allowed accounting for the effects of operating and health conditions on battery degradation so as to predict battery capacity fade. The proposed physics-informed machine learning method was demonstrated to be effective using a publicly available battery aging dataset published by the NASA Ames Prognostics Center of Excellence. Results showed that the physics-informed machine learning method was more accurate in predicting capacity fade under different operating conditions than two baseline methods based on convolutional neural networks and bi-directional LSTM recurrent neural networks.

In the paper titled *Physics-informed machine learning model for battery state of health prognostics using partial charging segments* [10], Kohtz et al. combined a 1D physics-based battery model with a Gaussian process regression surrogate model in order to estimate detailed physical information from relatively easy to measure voltage data. Specifically, they were able to match measured voltage curves during charging to modelled curves and thereby predict solid electrolyte interphase (SEI) thickness from partial charging segments. (Anode SEI growth is one of the main degradation mechanisms in Li-ion cells.) Results were demonstrated on a publicly available battery aging dataset from NASA.

## 3. Physics-Informed ML for General-Purpose Prognosis

In the paper titled *Time-varying trajectory modeling via dynamic governing network for remaining useful life prediction*, Zhou et al. addressed whether data-driven methods could produce RUL trajectories consistent with physical intuition [11]. Their solution was first formalizing RUL prediction as a time-varying trajectory modeling problem and then solving this problem by a dynamic governing network that directly mapped time series measurements to an RUL estimate whose trajectory had a smoothness property compliant with the physical intuition of system degradation while improving generalization over conventional deep learning methods. The proposed method was demonstrated using two publicly available run-to-failure datasets: the new NASA CMAPSS (N-CMAPSS) aircraft engine dataset and the Xi'an Jiaotong University and Changxing Sumyong Technology Co., Ltd. (XJTU-SY) bearing dataset. This work shed light on improving the trajectory smoothness and generalization performance of direct mapping approaches to RUL prediction.

Nguyen et al. studied a combination of physics and fuzzy logic within generative adversarial networks (GANs) for failure prognosis [12]. In their paper titled *Physics-infused fuzzy generative adversarial network for robust failure prognosis*, a physics-based aggregation was added to a fuzzy logic model to improve GANs' regression capabilities relevant to a prognostic task. The proposed PhyzzyGAN approach was demonstrated on two publicly available run-to-failure datasets, the Center for Intelligent Maintenance Systems (IMS) bearing dataset and the NASA CMAPSS aircraft engine dataset, with two observations: (1) PhyzzyGAN produced higher accuracy in RUL prediction than standard GANs, GANs with only physics, and GANs with only fuzzy logic; and (2) PhyzzyGAN also exhibited higher robustness to the training data size than standard LSTM recurrent neural networks.

## 4. Physics-Informed ML for Other Engineering Applications

In the paper titled *Physics-informed ensemble learning for online joint strength prediction in ultrasonic metal welding*, Meng and Shao aimed to solve the narrow operating window problem and disturbance problem of ultrasonic metal welding, and they proposed a hierarchical physics-informed ensemble learning framework to fully explore the utility of physical knowledge and online sensor data in accurately predicting ultrasonic metal welding joint strength [13]. Their framework decomposed joint strength variability into two parts: a physics-informed global trend and a data-driven residual. Besides, discrete wavelet transform was used to develop an efficient feature extraction scheme to intelligently extract low-dimensional signatures from high-dimensional sensor data. Two case studies were provided to verify the effectiveness of the proposed physics-informed ensemble learning.

Zhang et al. studied how to incorporate physics and domain knowledge when designing Gaussian process regression models for HVAC system performance prognosis [14]. Their paper titled *Physics-guided Gaussian process for HVAC system performance prognosis* presented a physics-guided Gaussian process that used a mean function and kernel functions customized to capture known degradation characteristics of an HVAC system. Results from a case study on chiller performance prognosis suggested that incorporating physics and domain knowledge can help improve prediction accuracy and data efficiency and reduce predictive uncertainty.

Nelson et al. took a step toward combining data-driven and physics-based methods for high-rate state estimation in their paper titled *Multi-step ahead state estimation with hybrid algorithm for high-rate dynamic systems* [15]. They presented a hybrid algorithm called a neural state estimator that consisted of (1) an ensemble of LSTM recurrent neural networks for multi-step ahead time series prediction and (2) a model reference adaptive system for state estimation. Their algorithm was applied to high-rate structural health monitoring and demonstrated using acceleration data collected from the Dynamic Reproduction of Projectiles in Ballistic Environments for Advanced Research (DROPBEAR) testbed and an accelerated drop tower shock testbed. This work provided insight into achieving state estimation with zero timing deadline overshoot by using predicted time series as an input for a state estimator, particularly relevant to high-rate structures.

Another interesting engineering application of physics-informed ML was the discovery of governing equations (PDEs) from measurement data collected from a dynamical system. In the paper titled *Parsimony-enhanced sparse Bayesian learning for robust discovery of partial differential equations*, Zhang and Liu presented a parsimony-enhanced sparse Bayesian learning method that promoted parsimony (penalizing the complexity of model terms) in addition to promoting sparsity (minimizing the number of model terms) as by conventional sparse Bayesian learning [16]. Comprehensive demonstrations covering PDE discovery in various engineering applications showed that the proposed method could identify governing PDEs of a parsimonious form and reduce the risk of overfitting an unnecessarily complex model to data.

The availability of streaming data enabled sequential decision-making for rare failure prediction. Dangut et al., in their paper titled *Application of deep reinforcement learning for extremely rare failure prediction in aircraft maintenance*, presented a unique application of deep reinforcement learning where unplanned aircraft maintenance actions were predicted using operational data from aircraft central maintenance system logs [17]. Using a reward system that favored predictions leading to correct diagnosis and penalizes those leading to false diagnosis, the authors showed how deep reinforcement learning offered a better alternative to standard model training strategies in the presence of extremely imbalanced classification datasets. Another uniqueness of this work was the methodology demonstration on a real-world aircraft central maintenance system dataset collected from a fleet of long-range and short-aisle aircraft families.

## 5. Summary and Outlook

The above-discussed articles gave a selective snapshot of the current research themes in physics-informed ML for fault diagnosis and failure prognosis. These articles cover a range of different ML techniques, including shallow and deep neural networks [1,3,4,6,7,11-13,17], GANs [1,12], recurrent neural networks [2,6,9,15], extreme learning machines [5], Bayesian linear regression [8], Gaussian process regression [10,14], gradient boosting machines [13], sparse Bayesian learning [16], and reinforcement learning [17]. The large variety of ML techniques highlighted the diversity of the approaches and that the methodology of choosing a specific technique to solve an engineering problem is still an art form. Indeed, the choice of a physics-informed ML approach is often application-dependent, influenced by many factors, such as the form and fidelity of available physics, the size and representativeness of training data, and the connections between physics and data.

The proposed approaches can be categorized into two general groups:

(1) physics-informed ML model architectures, such as (a) multi-fidelity delta learning using physics-informed co-kriging [10], (b) physics-informed designs of basic building blocks of ML models [11,12,14], (c) using physically meaningful models or signal processing techniques as

preprocessing steps for standard ML models [3,5,9], (d) hybrid of physics-based and ML models that collaboratively capture underlying physics [6] or fulfill prediction tasks [13,15];

(2) physics-informed loss functions, such as (a) a physics-informed validation loss for neural network hyperparameter optimization [2] and (b) a physics-informed training loss for neural network training [4].

Despite tremendous advances, physics-informed ML research in the field of diagnosis and prognosis is still in its infancy. There are several exciting avenues for future research.

- First, modeling physics of fault and degradation is a must-have for physics-informed ML; however, many engineering applications do not have well-understood physics or require complex physics-based degradation models that are difficult to calibrate/validate in the first place. Thus, a deeper and more rigorous understanding of physics and new ways to build high-fidelity physics-based models would go a long way in facilitating the wide-scale adoption of physics-informed ML. Further, when only low-fidelity physics-based models are available, it is important to investigate whether and how incorporating such imperfect physics can help ML models extrapolate to out-of-distribution samples as well as the impact on the uncertainty of the prediction.
- Second, publicly available datasets have substantially and positively impacted physics-informed ML research by providing common platforms for performance benchmarking. For example, several papers in this special issue used open-source fault datasets for diagnosis, such as the Case Western Reserve University bearing dataset, or run-to-failure datasets for prognosis, such as the IMS bearing dataset and the NASA CMAPSS and N-CMAPSS aircraft engine datasets. However, there is still a great need for run-to-failure datasets containing large quantities of system units tested under wide ranges of operating conditions representative of field use. Although collecting run-to-failure data can be very time- and cost-intensive, such efforts will be essential to creating and validating physics-informed ML approaches for failure prognosis that are suitable for industry-scale adoption.
- Third, the papers in this special issue mostly demonstrated their methods using data from numerical simulations or lab-scale experiments. A big gap needs to be filled by efforts dedicated to robustness evaluation and field validation. For example, physics-informed ML models and algorithms for failure prognosis can be built into cloud-based predictive modeling platforms for managing large fleets of aging engineering assets. Large volumes of monitoring data from the field can be used to update and refine these models and algorithms over time and on an as-needed basis. Efforts like this will play a key role in translating physics-informed ML from research to commercialization.

The guest editor team wants to thank all reviewers for their voluntary efforts. The constructive review feedback from the reviewers has allowed the authors to improve the quality of their work. We also thank the Editor-in-Chief, Prof. John Mottershead, for his insightful suggestions and timely review coordination throughout the solicitation, review, and publication processes and Ms. Christy Jacob for the administrative support.

**References**

1. Zhou, K., Diehl, E. and Tang, J., 2023. Deep convolutional generative adversarial network with semi-supervised learning enabled physics elucidation for extended gear fault diagnosis under data limitations. *Mechanical Systems and Signal Processing*, *185*, p.109772.
2. Chen, Y., Rao, M., Feng, K. and Zuo, M.J., 2022. Physics-Informed LSTM hyperparameters selection for gearbox fault detection. *Mechanical Systems and Signal Processing*, *171*, p.108907.
3. Kim, Y., Na, K. and Youn, B.D., 2022. A health-adaptive time-scale representation (HTSR) embedded convolutional neural network for gearbox fault diagnostics. *Mechanical Systems and Signal Processing*, *167*, p.108575.
4. Russell, M. and Wang, P., 2022. Physics-informed deep learning for signal compression and reconstruction of big data in industrial condition monitoring. *Mechanical Systems and Signal Processing*, *168*, p.108709.

5. Wang, D., Chen, Y., Shen, C., Zhong, J., Peng, Z. and Li, C., 2022. Fully interpretable neural network for locating resonance frequency bands for machine condition monitoring. *Mechanical Systems and Signal Processing*, *168*, p.108673.
6. Yucesan, Y.A. and Viana, F.A., 2022. A hybrid physics-informed neural network for main bearing fatigue prognosis under grease quality variation. *Mechanical Systems and Signal Processing*, *171*, p.108875.
7. Lee, G., Kwon, D. and Lee, C., 2023. A convolutional neural network model for SOH estimation of Li-ion batteries with physical interpretability. *Mechanical Systems and Signal Processing*, *188*, p.110004.
8. Greenbank, S. and Howey, D.A., 2023. Piecewise-linear modelling with automated feature selection for Li-ion battery end-of-life prognosis. *Mechanical Systems and Signal Processing*, *184*, p.109612.
9. Shi, J., Rivera, A. and Wu, D., 2022. Battery health management using physics-informed machine learning: Online degradation modeling and remaining useful life prediction. *Mechanical Systems and Signal Processing*, *179*, p.109347.
10. Kohtz, S., Xu, Y., Zheng, Z. and Wang, P., 2022. Physics-informed machine learning model for battery state of health prognostics using partial charging segments. *Mechanical Systems and Signal Processing*, *172*, p.109002.
11. Zhou, Z., Li, T., Zhao, Z., Sun, C., Chen, X., Yan, R. and Jia, J., 2023. Time-varying trajectory modeling via dynamic governing network for remaining useful life prediction. *Mechanical Systems and Signal Processing*, *182*, p.109610.
12. Nguyen, R., Singh, S.K. and Rai, R., 2023. Physics-infused fuzzy generative adversarial network for robust failure prognosis. *Mechanical Systems and Signal Processing*, *184*, p.109611.
13. Meng, Y. and Shao, C., 2022. Physics-informed ensemble learning for online joint strength prediction in ultrasonic metal welding. *Mechanical Systems and Signal Processing*, *181*, p.109473.
14. Zhang, J., Liu, C. and Gao, R.X., 2022. Physics-guided Gaussian process for HVAC system performance prognosis. *Mechanical Systems and Signal Processing*, *179*, p.109336.
15. Nelson, M., Barzegar, V., Laflamme, S., Hu, C., Downey, A.R., Bakos, J.D., Thelen, A. and Dodson, J., 2023. Multi-step ahead state estimation with hybrid algorithm for high-rate dynamic systems. *Mechanical Systems and Signal Processing*, *182*, p.109536.
16. Zhang, Z. and Liu, Y., 2022. Parsimony-enhanced sparse Bayesian learning for robust discovery of partial differential equations. *Mechanical Systems and Signal Processing*, *171*, p.108833.
17. Dangut, M.D., Jennions, I.K., King, S. and Skaf, Z., 2022. Application of deep reinforcement learning for extremely rare failure prediction in aircraft maintenance. *Mechanical Systems and Signal Processing*, *171*, p.108873.