Abstract

In the era of Industry 4.0, Intelligent Predictive Maintenance (PdM) has emerged as a critical enabler for ensuring the reliability, safety, and operational efficiency of industrial systems. Traditional maintenance strategies often suffer from challenges such as unforeseen failures, high downtime costs, inventory management issues, and, in severe cases, loss of life and property. To overcome these challenges, there has been a paradigm shift from reactive approaches to proactive maintenance approaches driven by data-centric solutions, including the Internet-of-Things (IoT), Cloud services, Machine learning, and Deep learning pipelines.

Despite these advancements, the current landscape of data-driven PdM remains fragmented due to several challenges and limitations, such as the heterogeneity of the condition monitoring data, difficulties in extracting meaningful information from sensor signals, limited availability of labeled failure data, model selection and reproducibility concerns, uncertainty quantification in predicted results, and the absence of unified benchmarks for evaluating performance and interpretability across diverse operational conditions. While the existing body of literature has proposed various solutions to address these issues, it remains largely disjointed and lacks a comprehensive, structured framework for designing and developing decision support systems for intelligent PdM.

To address the aforementioned issues, the thesis sets four primary objectives and each of the set objectives are built upon the conceptual framework we identified for the data-driven intelligent PdM system architecture. The first objective proposes an unsupervised early fault detection (FD) algorithm for systems operating under high noise and variable fault signatures. The second objective introduces a probabilistic approach to fault detection with uncertainty quantification, capable of handling multi-fault signatures and multi-sensory data fusion. Finally, the third and the forth objective together presents an interpretable deep learning algorithm for Remaining Useful Life (RUL) prediction that accounts for multiple degradation stages. The PdM system architecture on which the objectives are based, elaborates on the challenges and effective measures proposed for effective PdM deployment. Building on this foundation, the first objective introduces a novel Weighted Adaptive Isolation Forest with Density-Based Partitioning (WAIF-DBP) for unsupervised fault detection. By incorporating density-driven feature selection and entropy-based split optimization into the splitting process of standard Isolation Forests, the proposed method enhances real-time detection in high-dimensional, noisy vibration data. Additionally, it provides a ground truth generation strategy using advanced signal processing to validate results on unlabeled sensor datasets. Statistical testing further confirms its robustness and adaptability across diverse operating scenarios. To improve interpretability and reliability in safety-critical environments, the second objective transitions from unsupervised detection to a supervised Bayesian 1D Convolutional Neural Network (1D-BCNN) for fault detection and diagnosis in bearing systems.

This framework jointly captures epistemic and aleatoric uncertainty, integrates multi-sensor fusion, produces probabilistic outputs, and leverages a novel labelling strategy for unlabeled time-series signals. Experimental validation on benchmark datasets demonstrates not only superior predictive performance but also enhanced interpretability compared to conventional deep learning methods. Extending the theme of uncertainty-aware predictive modelling, the third and fourth objectives together focus on RUL estimation considering multi-stage health state detection. Here, a hybrid methodology combining Savitzky-Golay filtering with Statistical Process Control is proposed to segment vibration trajectories into distinct degradation stages, and then a Bayesian Temporal Convolutional Dilated Attention Neural Network with a Multi-Channel Residual Mechanism (BTCDAN-MCRA) is used to predict the RUL. To quantify the uncertainties in prediction, a Monte Carlo dropout technique is used that provides confidence measures in the predicted results.

Taken together, these four objectives yield contributions on two fronts: first the theoretical developments and, second, the practical applicability. From a theoretical standpoints, this research: (i) builds a structured decision support system for intelligent predictive maintenance, spanning data collection, model development to decision-making, (ii) develops a novel methodology based on Weighted Adaptive Isolation Forest with Density-Based Partitioning for fault detection that bridges the gap between isolation-based FD and density-driven modeling, contributing an approach that is more robust to high-dimensional and noisy data, (iii) designs a dynamic time warping-based framework for sensor-level data fusion for variable signal lengths that enriches data quality and augment signal with multi-fault characteristics, (iv) introduces a hybrid Savitzky-Golay and SPC-based methodology for degradation stage segmentation, and (v) advances Bayesian deep neural architectures for probabilistic predictions and uncertainty quantification in both FD and RUL estimation.

From a practical perspective, the research delivers methods and tools that are directly applicable to industrial contexts. Specifically, (i) the proposed labeling strategy for time-series signals is reproducible with minimal tuning and adaptable across diverse assets, (ii) the proposed FD model, WAIF-DBP achieves close to 99% accuracy along with similar high precision and recall, ensuring reliability across dynamic operating conditions, (iii) the sensor fusion approach effectively handles variable-length signals typical of real-world scenarios, (iv) the probabilistic models provide not only high FD accuracy but also quantify the uncertainties at the micro levels of epistemic and aleatoric components, thereby improving transparency, (v) the health state estimation algorithm demonstrates universality across different vibration datasets with minor parameter adjustments, and (vi) the transformer-based neural network for RUL prediction captures both temporal dependencies and feature interactions, thereby enhancing predictive accuracy and interpretability. Collectively, these contributions provide engineers, maintenance teams, and decision-makers with a comprehensive framework and practical tools to enable

intelligent, data-driven predictive maintenance strategies for asset health management in line with the goals of Industry 4.0.

Keywords: *Predictive maintenance; Fault detection; Fault diagnosis; Remaining useful life prediction; Health state estimation; Prognostics and health management; Uncertainty quantification; Condition monitoring; Decision making; Machine learning; Deep neural network; Statistical Analysis; Bayesian modelling.*