Different Facets of Artificial Intelligence-Based Predictive Maintenance for Electric Powertrains

Ali Serdar[1][0000-0002-9513-2481], Ahu Ece Hartavi Karcı[2][0000-0003-4956-4651], İbrahim Arif[4][0000-0002-7710-935X], Salih Ergün [3,4] [0000-0001-7070-9726], and Alper Kanak [3,4,*] [0000-0003-2541-7753]

[1] AI4SEC OÜ, Talinn, Estonia
[2] University of Surrey, Center of Automotive Engineering, Guildford, UK
[3] Ergünler R&D Co. Ltd., Isparta, Turkiye
[4] Ergtech Sp.Z.o.o., Warszawa, Poland
ali.atalay@ai4sec.eu, a.hartavikarci@surrey.ac.uk, ibrahim.arif@ergtech.eu, salih.ergun@{ergtech.eu, erarge.com.tr}, alper.kanak@{ergtech.eu, erarge.com.tr}

Abstract. Maintenance, traditionally perceived as a reactive cost and a hindrance, poses challenges to efficiency when components succumb to unforeseen breakdowns. In addition to the financial implications, the repair process also incurs substantial time wastage. To overcome these obstacles and achieve enhanced efficiency and cost savings within the manufacturing sector, this paper presents a conceptual study of a technologically advanced predictive maintenance (PdM) approach, particularly in the realm of artificial intelligence-powered digital twins. The effectiveness of these solutions hinges on their data-driven nature, technical feasibility, and acceptance by industry stakeholders.

Keywords: Predictive Maintenance; Artificial Intelligence; Electric Powertrains; Performance Optimization; Operational Efficiency; Sustainability.

1 Introduction

The multifaceted nature of predictive maintenance for electric powertrains entails comprehensive approaches to diagnose the internal physical phenomena of various components within electric vehicle (EV) powertrains. By integrating advanced sensing technologies, data analytics, and machine learning algorithms, predictive maintenance enables real-time monitoring and analysis of key performance indicators, facilitating early detection of faults or abnormalities. This proactive approach not only optimizes the performance, longevity, safety, and reliability of electric powertrains but also mitigates unplanned downtime, lowers maintenance costs, and enhances overall operational efficiency. Through the utilization of multidimensional predictive maintenance strategies, stakeholders in the electric vehicle industry can achieve significant advancements in powertrain maintenance and contribute to the development of sustainable transportation solutions.

This study aims to investigate the facets and benefits of implementing predictive maintenance strategies, specifically focusing on artificial intelligence-based approaches, in the context of electric powertrains. The European Union-funded ESCALATE and OPEVA approach aims to assure the electric vehicle user reaches its current destination to boost customer satisfaction, as it offers not only a safe journey but also promises no more breakdowns before the destination is reached. By examining the multifaceted aspects of predictive maintenance, including advanced sensing technologies, data analytics, and machine learning algorithms, this research aims to explore how these building blocks are brought together to enhance the performance, longevity, safety, and reliability of electric powertrains. Furthermore, the study seeks to evaluate the impact of advanced predictive maintenance on reducing unplanned downtime, optimizing maintenance costs, and improving overall operational efficiency. Through data-driven insights, this study aims to provide valuable insights and recommendations for stakeholders in the electric vehicle industry, contributing to the development of sustainable transportation solutions.

2 State-of-the-Art

Concurrently, extensive research is underway to enhance BMS performance, particularly in terms of predicting battery ageing and ensuring safety. These techniques also aim to predict battery lifespan and detect faults. To address these challenges, James C. Chen et al. [1] propose empirical mode decomposition (EMD), grey relational analysis (GRA), and deep recurrent neural networks (RNN), whilst Y. Che et al. [2] propose optimized health indicators and online model correction with transfer learning for the RUL prediction of lithium-ion batteries.

The practical integration of AI into power electronic applications encompasses deterministic and stochastic environments, data collection and analytics methods, forecasting techniques, and cost-effective algorithms and hardware implementations [3]. In recent years, physics-informed PdM methods aligned seamlessly with the strategy of making AI a frontrunner in e-mobility applications. Among these, Li et al. [4] propose a model to calculate the cumulative fatigue damage of IGBT modules in EVs to evaluate the reliability. Rao et al. [5] propose a novel approach to PdM of power electronics by integrating optical and quantum-enhanced AI techniques.

The electric motor, a pivotal component within the electrical powertrain of electric vehicles powered by batteries, operates under demanding conditions characterized by significant temperature fluctuations, pronounced vibrations and voltage stress stemming from inverter power supply [6]. Wotawa et al. [7] employ model-based, simulation-based and machine learning-based real-time PdM approach for e-motors. Rjabtšikov et al. [8] and Dettinger et.al [9] use a Digital Twin-based approach when dealing with the predictive maintenance of e-motors.

Recent developments [10] employ AIoT-based preventive diagnostic by enabling recommendation and notification prediction for Run-to-Failure maintenance, planned preventive maintenance, and predictive maintenance for EV thermal management system. Yi et al. [11] utilize Long Short-Term Memory (LSTM) based Digital Twin to achieve real-time temperature forecasting and analyze degradation models for lithium-ion batteries. Dettinger et al. [12] introduce a machine learning-based model for fault detection in EV powertrains, employing a Digital Twin. In parallel, Bhatti et al. [13] advocate the application of Digital Twin technology in EVs through their systematic review.

3 Digital-Twin-Powered PdM Services Architecture

Integrating technologies like IoFog, Arrowhead, and Mimosa into predictive maintenance (PdM) for Electric Vehicle (EV) powertrains can significantly enhance real-time data processing, communication, and overall management of maintenance activities by leveraging the capabilities of edge computing, interoperable automation, and standards for enterprise integration respectively. The PdM services are designed to be used as online services, in the form of PdM-as-a-Service, within a digital twin framework as depicted in **Fig. 1**. The framework has a data acquisition and management module which is built on a secure multi-agent system. This module is implemented as a heterogeneous data flow backbone based on an Arrowhead-ioFog-Mimosa architecture (See **Fig. 2**). This module is strengthened with cyber security solutions enabling very fast agent data encryption and person/node authentication. The multi-agent system enables effective data acquisition from EVs, grid infrastructure (i.e., charging infrastructure) and environmental data.

The acquired data can be classified as JSON files and stored in a cloud database, such as MariaDB, as proposed in the digital twin framework. There exist auxiliary backend services such as data and query management services, cloud services management, security and privacy management and Identity Management System (IDMS).

A two-way Kafka-based messaging system is designed to feed the Smart Services Modules which are utilized as Docker containers at the righthand side. The Docker containers receive the classified data in JSON format or other messages or requests from the secure multi-agent system and backend services. When the Digital Twin services including AI-powered PdM solutions produce an output, these outputs are also delivered to the visualization and user interfaces layer through a results gateway, or as feedback to the Secure Multi-Agent System (for instance, in case of an anomaly).

The framework is realized through a layered architecture (**Fig. 2**) that utilizes the combination of Arrowhead [14], Eclipse ioFog [15] and MIMOSA [16] and is composed of i) Edge layer (ioFog), ii) Communication & Automation Layer (Arrowhead), iii) Enterprise integration layer (MIMOSA), and iv) Execution layer.

The **Edge Layer** facilitates decentralized data processing, enabling real-time analysis of powertrain data (such as battery voltage, current, and temperature) directly within the EV or local edge nodes. This layer implements LSTM or other predictive models on the edge for immediate anomaly detection and alerting for powertrain issues. Here ioFog can manage data transmission over the cloud, ensuring only relevant or summarized data is sent, which is vital for efficient bandwidth usage and managing large fleets of EVs. This layer delivers an Edge-AI-based processing that enables localized decision-making, and reduces the need to transmit all raw data to a central server, thus saving bandwidth and enhancing data privacy. Instantaneous actions, such as emergency alerts or minor adjustment suggestions, could be generated directly from the AI models deployed at the edge.

The **Communication & Automation Layer** provides a framework for ensuring interoperable communication between various systems involved in a PdM solution space, such as between EVs, charging stations, and maintenance facilities. This layer is implemented by deploying an Arrowhead framework which is an open-source technology that establishes a standardized and secure interoperability platform for seamless communication and interaction between diverse services and devices. The Arrowhead-based solution facilitates automated workflows that enhance PdM, like scheduling maintenance activities, based on predictive insights while considering logistic and operational constraints.

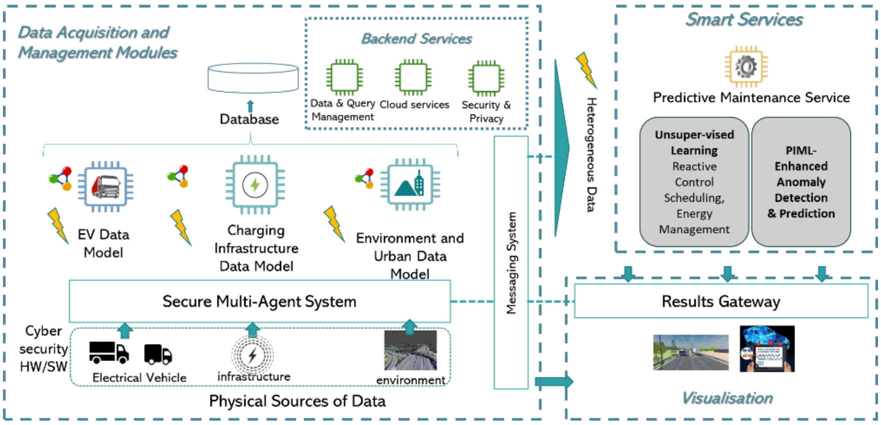

Fig. 1. Proposed Digital Twin Framework

The **Enterprise Integration Layer** is implemented by utilizing the MIMOSA framework which is based on the Open System Architecture for Enterprise Application Integration (OSA-EAI) standard. Implementing MIMOSA standards ensures consistent data handling and interpretation across various entities involved in PdM systems, such as service providers, component manufacturers, and operators. Utilizing MIMOSA's OSA-EAI standards for enhanced data sharing and integration between enterprise systems and field-level entities ensures that PdM insights and actions are cohesively managed and executed across the organization (e.g. fleet operator, vehicle manufacturer).

The **Execution Layer** is the highest level of applications that are actively used by the end users such as maintenance service providers, vehicle operators, etc. The bidirectional arrows between this layer and the Enterprise Integration Layer indicate the cooperative work of service maintenance scheduling and coordination.

The four-layer architecture enables an effective data and action flow between layers. Data flow starts with raw data acquired from edge nodes like edge devices, gateways, smart grids, and/or onboard systems. Processed data and initial insights are transferred between the edge and communication layers. The standardized and structured data are propagated to the enterprise layer along with global insights and alerts. On the other hand, action flows can be instructions for actual maintenance activities that are streamed from the enterprise layer to the execution layer. Feedback, status updates and any corrective actions are exchanged between the execution and enterprise layer.

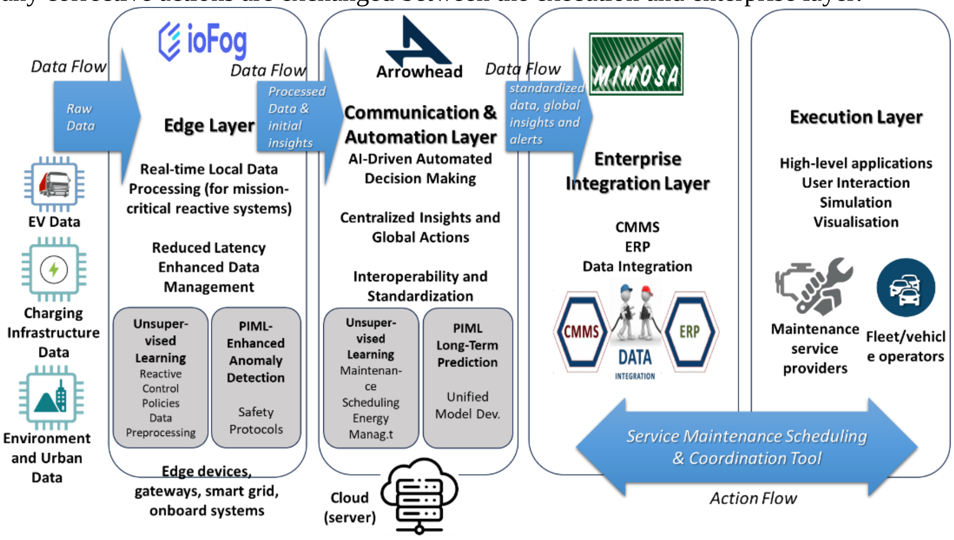

Fig. 2. The layered Digital Twin Architecture

In both edge and communication & automation layers, unsupervised learning (UL) algorithms can be deployed for reactive control and data preprocessing as well as maintenance scheduling and energy management. The proposed architecture at the edge layer implements UL algorithms to develop local control policies that react to real-time data, adjusting operating parameters to enhance performance or mitigate anomalies. The edge layer also enables optimal energy management and creating policies that consider both localized powertrain health and broader energy demands, like grid stability or energy prices. Physics-Informed Machine Learning (PIML) for more effective PdM can also be tacked both at the edge and global level. ioFog can be used to implement PIML for real-time analysis, using physics-based principles to enhance anomaly detection in powertrain components, ensuring that the alerts are not just data-driven but also physically plausible. Here, safety protocols leverage PIML to establish safe operating boundaries for the powertrain, using physics principles to prevent settings or actions that might risk component health or safety. At the automation layer, PIML models can be used for analysing long-term physical degradation patterns in powertrain components, ensuring that PdM strategies are aligned with anticipated wear and tear. A unified model can be developed to integrate physics-based principles with data-driven insights, presenting comprehensive models that ensure predictive insights and prescribed actions that are scientifically substantiated.

4 Conclusion

This paper presents a digital twin framework based on a 4-layered architecture that integrates Edge (ioFog), Communication & Automation (Arrowhead), Enterprise integration (MIMOSA), and Execution layers. IoFog, Arrowhead, and Mimosa are utilized for orchestrating physics-informed PdM and UL for EV powertrains so that organizations can create a robust, efficient, and scalable system. This integration not only enhances real-time data processing and communication but also ensures that the maintenance activities are streamlined, standardized, and optimized for the best possible performance and longevity of EV powertrains.

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References

1. James C. Chen, Tzu-Li Chen, Wei-Jun Liu, C.C. Cheng, Meng-Gung Li, Combining empirical mode decomposition and deep recurrent neural networks for predictive maintenance of lithium-ion battery, Advanced Engineering Informatics, vol. 50, 2021
2. Y. Che, Z. Deng, X. Lin, L. Hu and X. Hu, "Predictive Battery Health Management with Transfer Learning and Online Model Correction," in *IEEE Transactions on Vehicular Technology*, vol. 70, no. 2, pp. 1269-1277, Feb. 2021.
3. Zhao, S., Blaabjerg, F., & Wang, H., An overview of artificial intelligence applications for power electronics. IEEE Transactions on Power Electronics, 36(4), 4633-4658, 2020.
4. Li, Ling-Ling, et al. "Predicting the power module cumulative damage degree in new energy vehicle: Improved Manson model." *Journal of Cleaner Production* 374 (2022): 133945.
5. Rao, P. Srinivasa, et al. "Integrated artificial intelligence and predictive maintenance of electric vehicle components with optical and quantum enhancements." *Optical and Quantum Electronics* 55.10 (2023): 1-19.
6. M. Galea, *et al.,* Reliability-Oriented Design of Electrical Machines: The Design Process for Machines' Insulation Systems MUST Evolve, IEEE Ind. Electronics Magazine, 2020
7. Wotawa, Franz, et al. "Real-Time Predictive Maintenance–Model-Based, Simulation-Based and Machine Learning Based Diagnosis." *AI for Digitising Industry–App.* River Publishers, 2022. 63-81.
8. Rjabtšikov, Viktor, et al. "Digital Twin Service Unit Development for an EV Induction Motor Fault Detection." *Int. Electric Machines & Drives Conference (IEMDC)*. IEEE, 2023.
9. Dettinger, Falk, et al. Machine-Learning-Based Fault Detection in Electric Vehicle Powertrains Using a Digital Twin. No. 2023-01-1214. SAE Technical Paper, 2023.
10. Kumar, Lohith, et al. "Electric Vehicle (EV) Preventive Diagnostic System: Solution for Thermal Management of Battery Packs using AIOT." *13th An. Comp. and Com. Work. & Conf. (CCWC)*. IEEE, 2023.
11. Yi, Yahui, et al. "Digital twin-long short-term memory (LSTM) neural network based real-time temperature prediction and degradation model analysis for lithium-ion battery." *Journal of Energy Storage* 64 (2023): 107203.
12. Dettinger, Falk, et al. Machine-Learning-Based Fault Detection in Electric Vehicle Powertrains Using a Digital Twin. No. 2023-01-1214. SAE Technical Paper, 2023.
13. Bhatti, Ghanishtha, Harshit Mohan, and R. Raja Singh. "Towards the future of smart electric vehicles: Digital twin technology." *Renew. & Sustain. Energy Reviews* 141 (2021): 110801.
14. Delsing, J. (Ed.).: IoT Automation: Arrowhead framework. CRC Press. (2017).
15. Desbiens, F.: Building Enterprise IoT Solutions with Eclipse IoT Technologies: An Open-Source Approach to Edge Computing (pp. 67-101). Apress. (2023).
16. MIMOSA, Open Standards for Physical Asset Management, https://www.mimosa.org/