Adaptable and Generic Methods for Monitoring and Prognostics of Energy Assets

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ABSTRACT

Monitoring and prognostics of energy assets are crucial for maintaining their reliability and efficiency. Effective monitoring ensures that potential issues are identified early, preventing unexpected failures and optimizing maintenance schedules. However, several challenges complicate this process in real-world scenarios, including poor data quality, low-fidelity and sparse data, the influence of external environmental factors, and diverse operating conditions and asset types. These challenges highlight the need for adaptable and generic solutions that can handle variability and complexity across different energy systems. This Ph.D. project aims to address these challenges by developing scalable, data-driven approaches for monitoring and prognostics. By focusing on creating adaptable and generic frameworks, the research seeks to provide robust solutions for real-world monitoring and prognostic problems for energy assets.

1. PROBLEM STATEMENT

Monitoring and prognostics of energy assets are crucial for maintaining their reliability and efficiency. Effective monitoring ensures that potential issues are identified early, preventing unexpected failures and optimizing maintenance schedules. By continuously tracking the condition and performance of assets, it becomes possible to detect anomalies and signs of wear and tear before they escalate into critical failures. This proactive approach to asset management not only extends the lifespan of the equipment but also minimizes downtime, reduces maintenance costs, and ensures the uninterrupted operation of energy systems. In the context of energy systems, where operational continuity and efficiency directly impact economic and environmental outcomes, the importance of robust monitoring and prognostics cannot be overstated. Ensuring that these systems operate optimally requires a comprehensive understanding of their health and performance, which can only be achieved through effective monitoring and timely prognostics.

However, in real-world scenarios, several challenges complicate this process. Data quality issues, such as low-fidelity and sparsity, can obscure critical information. Additionally, the influence of external factors, such as environmental conditions, can confound sensor data, hiding vital signs of asset degradation or impending failure. In addition, energy systems operate under diverse conditions and include various types of assets, each with unique characteristics and operational requirements. This diversity necessitates monitoring and prognostics solutions that are both generic enough to apply across different scenarios and adaptable enough to cater to specific conditions. The need for such adaptable and generic solutions is paramount to address the aforementioned challenges effectively.

This Ph.D. project focuses on developing such adaptable and generic solutions for the monitoring and prognostics of energy assets. By integrating advanced machine learning techniques with real-world data, my work aims to create robust frameworks that can handle the variability and complexity of actual operating environments. These frameworks are designed to be versatile, capable of processing large-scale data efficiently, and adaptable, adjusting to new data patterns and operational conditions as they emerge.

To ensure the practical applicability and effectiveness of these solutions, my research incorporates real-world case studies. Each case study serves as a testbed to develop and refine the frameworks, ensuring they can address the unique challenges presented by different types of energy assets and operating conditions. The case studies include preemptive failure detection in photovoltaic (PV) inverters, cross-battery state-of-charge estimation for lithium-ion batteries, and novelty detection in connected vehicle systems. These studies highlight the versatility and adaptability of the proposed solutions, demonstrating their potential to enhance the reliability and efficiency of various energy systems.

2. EXPECTED CONTRIBUTION

The primary contribution of this research is to provide solutions tailored for real-world scenarios, addressing the inherent limitations of practical applications such as low data quality and the lack of ground-truth observations. By focusing on the development of general frameworks, this study aims to ensure that the solutions are not only robust and adaptable but also broadly applicable across various types of energy assets. This adaptability is crucial in addressing the diverse operational conditions encountered in the field, which traditional, assumption-heavy models often fail to manage effectively. By avoiding strong assumptions about the problem, such as specific operating conditions or precise data characteristics, the research ensures that the developed frameworks remain flexible and relevant in a wide range of contexts. This approach not only enhances the practical utility of the solutions but also promotes their scalability and ease of implementation in real-world settings.

3. RESEARCH PLAN

This section outlines my research plan, detailing the completed works and the ongoing research for the remainder of my Ph.D. project. The first subsection presents the work performed to date, while the second subsection discusses the future directions and objectives of my research.

3.1. Work Performed

To this point, my research has focused on three distinct case studies: state-of-charge estimation for lithium-ion batteries, preemptive failure detection in photovoltaic (PV) inverters, and novelty detection in connected vehicle systems. These case studies serve as practical applications to develop and validate the adaptable and generic frameworks designed to enhance the reliability and efficiency of energy systems. The specifics of each case study are discussed below.

3.1.1. Cross-Domain State-of-Charge (SOC) Estimation for Lithium-Ion Batteries

Accurate estimation of the state-of-charge (SOC) in lithium-ion batteries (LIBs) is paramount for the safe operation of battery management systems. Despite the effectiveness of existing SOC estimation methods, their generalization across different battery chemistries and operating conditions remains challenging. Current data-driven approaches necessitate extensive data collection for each battery chemistry and operating condition, leading to a costly and time-consuming process. Hence, there is a critical need to enhance the generalization and adaptability of SOC estimators.

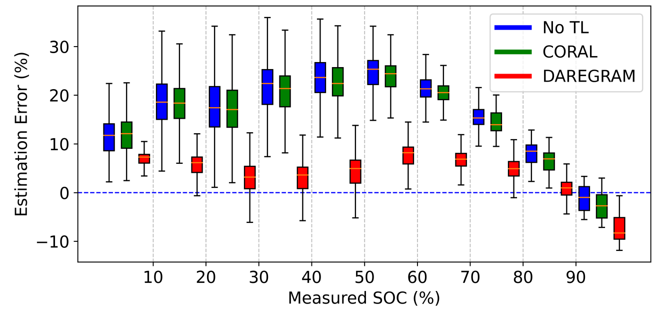

Figure 1. Comparison of Domain Adaptation Methods in SOC Estimation.

In this work, a novel SOC estimation method based on Regression-based Unsupervised Domain Adaptation is proposed. In this study, a "source" battery with labeled data (actual SOCs), and a "target" battery with unlabeled data is utilized to train a deep learning model. This framework minimizes the need for extensive labeled data from each specific battery type by leveraging regression-based unsupervised domain adaptation techniques, such as DARE-GRAM (Nejjar, Wang, & Fink, 2023), to align feature representations across different battery types and conditions.

Figure 1 shows the SOC predictions for a specific battery type without labeled data using different methods: the "No TL" method where the deep learning model is trained solely using the source battery data, CORAL, and DARE-GRAM. The results indicate that the regression-based domain adaptation method (DARE-GRAM) method significantly improved SOC estimation accuracy compared to classification-based approaches such as CORAL (Sun & Saenko, 2016), showcasing robustness and adaptability in varying battery conditions. This work is accepted to be presented at the PHME24 (8th European Conference of the PHM Society) conference.

3.1.2. Preemptive Failure Detection in Photovoltaic (PV) Inverters

This work presents a practical framework for preemptive failure detection in energy systems. The proposed framework comprises three main phases: autonomous sensor data preprocessing, de-confounding external influences, and novelty detection. In the first phase, data cleaning, transformation, calibration, and feature extraction are employed to refine raw sensor data. Removing the influence of external variables such as environmental variables is the main focus of the second phase. The third phase utilizes advanced ensemble methods to detect anomalies indicative of potential failures. This study highlights the importance of preprocessing steps to enhance data quality and demonstrates the framework's effectiveness through a real-world case study on PV inverters.

Validation using real-world PV inverter data demonstrated the framework's effectiveness in identifying inverters ap-

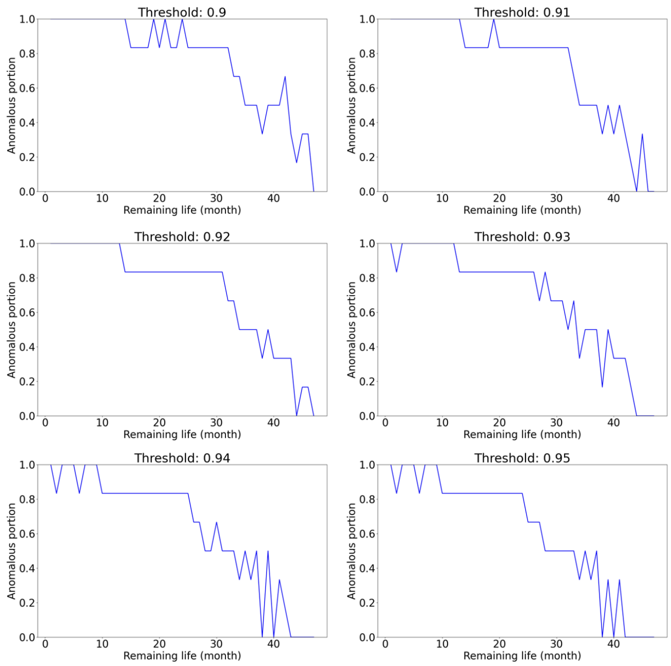

Figure 2. The results of employing the proposed framework for PV inverters preemptive failure detection over different thresholds.

proaching failure, enabling timely maintenance and minimizing downtime. Figure 2 shows the results of employing this framework on a PV inverter case study. The results indicate that the framework successfully detected the upcoming failure of the PV inverters prior to and close to their failures.

3.2. Ensemble Novelty Detection for Monitoring of Connected Vehicle Systems

Shrinking product development cycles and increasing vehicle complexities necessitate a new generation of monitoring and diagnostic algorithms that can demonstrate increased autonomy and adaptivity. Conventional approaches, which make strict assumptions about data fidelity and failure ground-truth availability, face challenges in modern connected vehicle applications. This paper proposes a novelty detection-based autonomous monitoring framework that flags anomalies under sparse and noisy data with limited or no access to ground-truth information. The framework proposes an optional mechanism for extracting age-degrading features and offers a robust approach for fusing the output of heterogeneous novelty detectors to determine the health state of target components. We validate the proposed framework using connected vehicle data for 12-volt battery systems employed by a large fleet of commercial vehicles of a global automotive manufacturer. Results demonstrate the effectiveness of the proposed framework.

3.3. Future Work

Building on the successful development and application of adaptable and generic monitoring and prognostics solutions, my future work will focus on developing an end-to-end model for the maintenance scheduling of energy assets. The motivation for this work arises from the limitations of current condition-based maintenance scheduling approaches, which often rely on strong assumptions that render them inapplicable to real-world problems.

The primary objective of my future work is to develop an end-to-end deep learning model that incorporates sensor data from various energy assets and outputs optimized maintenance schedules. The convergence of machine learning and optimization has recently garnered significant attention from researchers (Kotary, Fioretto, Van Hentenryck, & Wilder, 2021) and (Sadana et al., 2024). One prominent area within this convergence is utilizing machine learning to address combinatorial optimization problems such as the Traveling Salesman Problem (TSP) and the Vehicle Routing Problem (VRP) (Cappart et al., 2023). Drawing inspiration from these studies, my future work aims to connect the uncertainty associated with asset degradation with the development of optimal maintenance schedules. More specifically, the goal of this research is to develop a deep learning model that learns to generate a maintenance policy for a certain time interval by incorporating asset sensor data. The objective of such deep learning model is minimizing the total cost associated with the maintenance activities including preventive maintenance cost, corrective maintenance cost, and also asset downtime cost. The model must also be capable of handling operational constraints.

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