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Analysis of Battery SoH Prediction Factors Using SHAP-based Explainable Artificial Intelligence

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Abstract: This paper explores the application of SHAP (SHapley Additive exPlanations)-based Explainable AI (XAI) in predicting battery State of Health (SoH). It reviews the significance of SoH in energy management, the factors influencing battery degradation, and the role of XAI in enhancing the transparency and interpretability of predictive models. The paper discusses the benefits of using SHAP for SoH prediction, compares it with other XAI techniques, and presents case studies demonstrating its effectiveness. The aim is to highlight how SHAP can improve understanding of battery performance, facilitate informed decision-making for maintenance, and ultimately contribute to more sustainable and reliable energy systems.

***Index Terms* -** Battery State of Health (SoH), Explainable AI (XAI), SHAP (SHapley Additive exPlanations), Predictive Maintenance, Battery Degradation, Energy Management, Machine Learning Interpretability

I. Introduction

In recent years, the integration of artificial intelligence (AI) into various technological domains has fundamentally transformed the way data is analyzed and interpreted. This is particularly relevant in the field of energy management, where understanding the state of health (SoH) of batteries is vital for optimizing their performance and lifespan. The significance of this analysis is heightened by the fact that buildings are responsible for a substantial portion of global energy consumption, estimated to account for 40% of total energy use and contributing to significant carbon emissions (AGOSTINELLI et al., 2024). Thus, enhancing our prediction capabilities regarding battery SoH using SHAP-based explainable AI (XAI) not only advances technological efficiency but also addresses pressing environmental concerns. This introductory exploration aims to delineate the factors influencing battery SoH predictions, ultimately guiding sustainable energy practices and fostering innovation within the built environment (Agostinelli et al., 2024).

A. Overview of Battery State of Health (SoH)

The State of Health (SoH) of batteries is a critical parameter that reflects their overall condition and performance, crucial for applications in renewable energy storage, electric vehicles, and consumer electronics. SoH quantifies the batterys capacity to deliver its intended performance compared to its original state, facilitating predictive maintenance strategies for optimal operational efficiency. With the rise of Internet of Things (IoT) technologies, machine learning (ML) models have become instrumental in estimating SoH by analyzing patterns in operational data and identifying anomalies that may indicate degradation or failure. In particular, predictive maintenance leverages these models to estimate the Remaining Useful Life (RUL), thus enhancing decision-making processes regarding battery management. Data preprocessing methods, such as exponential smoothing, and advanced algorithms like Shapley additive explanations (SHAP) are employed to interpret these models, allowing for a nuanced understanding of how various factors influence SoH predictions (CORSETTI et al., 2023), (Gu et al., 2023).

B. Importance of Explainable Artificial Intelligence in Battery Management

As the reliance on battery systems in various industries continues to grow, the need for effective management strategies has become increasingly paramount. Explainable Artificial Intelligence (XAI) plays a critical role in battery management by providing transparency and interpretability to complex predictive models, particularly in assessing battery state of health. By utilizing techniques like SHAP (SHapley Additive exPlanations), stakeholders can understand the factors influencing battery performance, allowing for more informed decision-making and maintenance procedures. Such insights are essential to optimize battery lifespan and efficiency, as highlighted by the integration of data-driven methods in prognostics (Baptista et al., 2024). Moreover, XAI enhances trust in automated systems, mitigating concerns regarding the black-box nature of machine learning models. As evidenced in studies concerning Alzheimers disease diagnostic models, explainability allows for a broader acceptance of AI applications, reinforcing their practical utility in critical domains (Moral A et al., 2021).

II. UNDERSTANDING BATTERY STATE OF HEALTH

The State of Health (SOH) of batteries plays a critical role in determining their performance and longevity, which is particularly essential in applications ranging from electric vehicles to renewable energy storage. SOH assessments provide valuable insights into a batterys ability to retain charge and deliver power efficiently over its lifecycle. The advent of explainable artificial intelligence, particularly through SHAP-based methodologies, enhances the interpretability of predictions related to SOH by elucidating the factors contributing to a batterys health status. By analyzing historical usage and environmental data, SHAP can identify which variables significantly influence battery degradation, thereby enabling more informed maintenance and operational decisions. This understanding is vital for industries aiming to optimize battery efficiency and reliability, as it not only assists in predictive maintenance strategies but also aligns with broader efforts to integrate advanced machine learning techniques into industrial practice (Baptista et al., 2024), (Moral A et al., 2021).

A. Definition and Key Metrics of Battery SoH

The concept of State of Health (SoH) in batteries is foundational to understanding their performance and longevity, reflecting their ability to deliver the required energy output relative to their original specifications. It is quantified through various key metrics, such as capacity fade, internal resistance, and self-discharge rates, which provide insights into the batterys overall efficiency and remaining useful life. Accurately predicting SoH is critical, especially in applications ranging from electric vehicles to renewable energy systems, as it has direct implications on operational efficiency and safety. Techniques employing data-driven methodologies, particularly those leveraging explainable artificial intelligence (AI), have gained traction for their ability to enhance understanding of these metrics. For instance, employing models like Shapley additive explanations allows for the interpretation of complex models, thus revealing how variations in parameters influence SoH predictions, thereby enabling proactive maintenance strategies in battery management systems (Moosavi et al., 2024), (Baptista et al., 2024).

B. Factors Influencing Battery Degradation

The degradation of batteries is influenced by a multitude of factors that can significantly impact their performance and longevity. Among these, the internal resistance and capacity of individual cells are crucial, as manufacturing variances can lead to imbalances within the battery pack, affecting overall functionality. Specifically, the interplay of current, State of Charge, and temperature distributions during discharge cycles can exacerbate degradation, particularly when cells of differing chemistries are mixed, which complicates the self-balancing process of the module (Niri F et al., 2024). Additionally, environmental conditions, such as operating temperature, contribute to thermal gradients that further exacerbate this imbalance, creating a detrimental effect on battery health over time. As Industry 4.0 advances, understanding these variables through innovative collaborative approaches and artificial intelligence applications becomes essential for effective battery management in flexible and cyber-physical systems (N/A, 2022). Hence, a comprehensive analysis of these degradation factors is vital for enhancing battery State of Health predictions.

III. INTRODUCTION TO SHAP (SHAPLEY ADDITIVE EXPLANATIONS)

In the realm of artificial intelligence, SHapley Additive exPlanations (SHAP) serves as a pivotal framework for enhancing model interpretability, particularly in complex systems like battery state of health prediction. By attributing individual feature contributions to model predictions, SHAP provides a detailed understanding of how various factors influence outcomes, which is crucial in the context of battery management systems. This capacity for interpretability aligns with the emerging demands for resilience in energy infrastructure, especially as highlighted by recent events where vulnerabilities in power systems were exposed during extreme weather conditions (Rahman et al., 2024). Moreover, the integration of SHAP into AI-driven analyses augments predictive maintenance strategies, enabling stakeholders to identify critical features affecting battery performance (AGOSTINELLI et al., 2024). Consequently, adopting SHAP not only facilitates more informed decision-making but also addresses the imperative for transparency in AI systems, fostering trust and reliability in energy management applications.

A. Explanation of SHAP and Its Relevance to AI

In the realm of artificial intelligence, SHAP (SHapley Additive exPlanations) provides a robust framework for interpreting model predictions, thereby enhancing the transparency of these models, especially in critical applications like battery state of health (SoH) prediction. By employing cooperative game theory concepts, SHAP assigns each feature an importance value that reflects its contribution to the overall prediction. This interpretability is crucial, as it allows stakeholders to understand the rationale behind specific decisions made by AI models. For instance, in the analysis of SoH prediction factors, SHAP can illuminate how different variables, such as temperature and voltage, influence battery performance, providing actionable insights for maintenance and optimization. Furthermore, Baptista et al. emphasize that the integration of SHAP in prognostics via machine learning can facilitate a deeper understanding of data-driven methods, which are increasingly pivotal for enhancing efficiency across various industries (Baptista et al., 2024). Such interpretive clarity is essential for fostering trust and enhancing user engagement with AI technologies (Moosavi et al., 2024).

B. Benefits of Using SHAP for Battery SoH Prediction

The application of SHAP (Shapley Additive Explanations) in predicting the State of Health (SoH) of batteries presents numerous benefits that enhance both the accuracy and interpretability of AI-driven models. By utilizing SHAP, researchers gain insights into the contributions of various features to the models predictions, thereby illuminating critical factors affecting battery degradation such as temperature, discharge rates, and charging cycles. This interpretability facilitates the identification of underlying issues, as seen in the analysis of induction furnaces and their operational parameters, where specific electrical faults could be tied directly to variations in performance metrics (Moosavi et al., 2024). Moreover, in the context of energy systems prone to disruptions, such as those affected by extreme weather, SHAP can elucidate how different variables influence battery resilience, thereby contributing to effective management strategies and optimized performance (Rahman et al., 2024). Overall, the integration of SHAP not only advances predictive accuracy but also empowers stakeholders with actionable insights for battery maintenance and utilization.

IV. APPLICATION OF SHAP IN BATTERY SOH PREDICTION

The application of SHAP (SHapley Additive exPlanations) in predicting the state of health (SoH) of batteries represents a significant advancement in the field of battery management systems. By leveraging SHAP, researchers are able to gain insights into the intricacies of predictive models, enhancing transparency and trust in machine learning methodologies employed for battery SoH assessment. This aligns with the growing emphasis on data-driven approaches aimed at improving system efficiency and longevity, particularly in industries like energy, where accurate SoH predictions can mitigate failures and optimize maintenance schedules. Notably, the interpretability provided by SHAP is crucial, as it allows engineers to understand the factors influencing predictions, thereby enabling informed decision-making. Such insights are critical in sectors where safety and performance are paramount, as demonstrated in recent studies that utilized SHAP for fault diagnosis in electrical systems, reinforcing its value in complex predictive environments (Baptista et al., 2024) (Moosavi et al., 2024).

A. Case Studies Demonstrating SHAP's Effectiveness

SHAP, or SHapley Additive exPlanations, has demonstrably improved model interpretability, as shown in several studies spanning multiple fields. For example, one early study used a deep neural network to detect faults in induction furnaces. Here, SHAP successfully clarified the complex connections between electrical parameters and fault types; ultimately, this led to a high F-measure of 0.9187 for model accuracy (Moosavi et al., 2024). Likewise, in a medical setting, a two-layer model for Alzheimer's diagnosis and tracking employed SHAP to give doctors easy-to-understand explanations, boosting trust and understanding of complicated machine learning decisions. Diagnostic accuracy reached 93.95% (Moral A et al., 2021). Overall, these examples show that SHAP helps to connect advanced predictive models with real-world uses, especially in the analysis of Battery State of Health prediction factors.

B. Comparison of SHAP with Other Explainable AI Techniques

The field of explainable AI is always changing, and when we compare SHAP to other ways of understanding AI, we see some important benefits. SHAP uses ideas from cooperative game theory to give us a way to see how important different features are, both on a big scale and in specific cases. This method is strong and reliable. Other methods, like LIME, might not be as steady because they use random sampling, which could lead to conclusions that aren't as trustworthy. For example, some studies have used SHAP to predict how Alzheimers disease might progress, and it worked well because it could make decisions that were both accurate and easy to understand (Moral A et al., 2021). Also, in energy management, SHAP has shown that it can explain how important factors affect things while still making good predictions, even better than many older methods (Oladapo et al., 2025). So, SHAP's careful approach not only makes AI models easier to understand but also helps people trust the predictions that AI makes.

V. Conclusion

To summarize, using SHAP-based Explainable AI (XAI) to predict battery state of health (SoH) is really helpful for making energy systems work better and building user confidence. By figuring out what really affects how batteries degrade, this method helps people in charge make smart choices and manage things well. Also, like other studies have shown, we really need our energy systems to be tough, so it's important to get how the predictive models that make them run smoothly work (Rahman et al., 2024). SHAP helps us understand these complicated machine learning programs, and it also makes the energy field more open, especially as we need more power and everything is connected (Agostinelli et al., 2024). In the end, learning more about predicting SoH with SHAP is good for both users and systems, helping battery tech be more sustainable and work great.

A. Summary of Key Findings

The need for precise battery state of health (SoH) predictions is increasingly apparent. This highlights the value of explainable artificial intelligence (XAI) approaches, especially when using SHAP (SHapley Additive exPlanations) methods. Some recent research suggests that certain electrical parameters, voltage and current harmonics for example, do have a significant effect on how well we can predict battery performance. This really showcases how robust these data-driven methods can be. What's interesting is that integrating SHAP to interpret the model helps clarify the complex links between what we put in and what the model predicts. This boosts the transparency of AI when diagnosing batteries. Similar systems used to look at electrical problems in induction furnaces have done well, with an average F-measure of 0.9187. This really points to the potential for using such clear models in different energy applications (Moosavi et al., 2024). These findings go beyond just battery health and can give us broader understanding of how to make power systems more resilient, especially with increasing demands and environmental issues (Rahman et al., 2024).

B. Future Directions for Research in Battery SoH Prediction Using Explainable AI

Looking ahead, as battery state of health (SoH) prediction advances, incorporating Explainable Artificial Intelligence (XAI) will be key for building trust and understanding in models. Right now, quite a few data-centric methods used to predict battery health don't really explain how they arrive at their results, which can be confusing. But by using tools like SHAP (SHapley Additive exPlanations), we can clarify how different things affect a battery's performance. This makes decisions about batteries easier to understand and more dependable for everyone involved. As the battery business works to boost efficiency and make batteries last longer, all while staying safe, this becomes super important. We might even learn something from other fields; for example, Alzheimer’s research uses a mix of different methods to improve how well they diagnose the disease, and we might be able to adapt these ideas for battery management systems (Baptista et al., 2024), (Moral A et al., 2021). If researchers, engineers, and even doctors work together, we could end up with SoH prediction models in the energy world that work better and are easier to understand.

References

Baptista, Márcia L., Henriques, Elsa, Mishra, Madhav, Prendinger, et al. (2024). Using Explainable Artificial Intelligence to Interpret Remaining Useful Life Estimation with Gated Recurrent Unit. https://core.ac.uk/download/639218004.pdf

Alonso Moral, José María, El-Sappagh, Shaker, Islam, Sumaiya M. Riazul, Kwak, et al. (2021). A multilayer multimodal detection and prediction model based on explainable artificial intelligence for Alzheimer's disease. https://core.ac.uk/download/389435200.pdf

Moosavi, Sajad, Palade, Vasile, Razavi-Far, Roozbeh, Saif, et al. (2024). Explainable Artificial Intelligence Approach for Diagnosing Faults in an Induction Furnace. https://core.ac.uk/download/609730177.pdf

Rahman, Farishta (2024). Outage Prediction And Detecting Influential Factors Under Extreme Weather Events Using SHAP Analysis. https://core.ac.uk/download/640769165.pdf

Agostinelli, Sofia, Cumo, Fabrizio, Gugliermetti, Luca (2024). A Future direction of machine learning for building energy management. Interpretable models. https://core.ac.uk/download/599521341.pdf

AGOSTINELLI, SOFIA (2024). Optimization and management of microgrids in the built environment based on intelligent digital twins. https://core.ac.uk/download/599502843.pdf

Faraji Niri, Mona, Fasolato, Simone, Heymer, Robert, Hidalgo, et al. (2024). Unveiling the performance impact of module level features on parallel-connected lithium-ion cells via explainable machine learning techniques on a full factorial design of experiments. https://core.ac.uk/download/603347082.pdf

Oladapo, Bankole I., Olawumi, Mattew A. (2025). AI-driven predictive models for sustainability. https://core.ac.uk/download/651218975.pdf

CORSETTI, ROCCO (2023). Machine Learning-based Approaches for Advanced Monitoring of Smart Glasses. https://core.ac.uk/download/570935117.pdf

Gu, Xinyu (2023). Machine Learning Applications in Time Series Forecasting for Engineering Problems. https://core.ac.uk/download/618458636.pdf