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Research Paper

Battery Reliability Assessment In Electric Vehicles : A State Of The Art

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ABSTRACT

The rapid growth of electric vehicles (EVs) has increased the importance of battery reliability as a key factor influencing vehicle performance, driving range, operational safety, and long-term sustainability. Lithium-ion batteries, which dominate the current EV market, are exposed to various stresses such as repeated charge-discharge cycles, temperature fluctuations, high current demands, and aging mechanisms that gradually reduce their capacity and efficiency. This state-of-the-art review examines recent developments in battery reliability assessment by analyzing the methods, models, and technologies used to evaluate battery health, predict degradation, and estimate remaining useful life. The review discusses conventional diagnostic approaches alongside modern data-driven techniques, including machine learning, deep learning, digital twins, and battery management systems that enable real-time monitoring and predictive maintenance. It also highlights the influence of thermal management, charging strategies, operating conditions, and manufacturing variations on battery reliability. Furthermore, the paper identifies current research challenges, such as limited availability of high-quality datasets, model interpretability, computational complexity, and the need for standardized reliability evaluation frameworks. Based on recent advances, the review outlines emerging research directions aimed at improving battery lifespan, enhancing safety, and supporting the large-scale adoption of electric mobility. By consolidating existing knowledge and identifying future opportunities, this study provides researchers, engineers, and industry practitioners with a comprehensive understanding of battery reliability assessment and its critical role in advancing next-generation electric vehicle technologies.

Keywords: Electric vehicles, battery reliability, lithium-ion batteries, battery health assessment, state of health (SOH), state of charge (SOC), battery degradation, battery management system (BMS), fault diagnosis, predictive maintenance, remaining useful life (RUL), machine learning.

I. INTRODUCTION

The global transition toward sustainable transportation has significantly accelerated the adoption of electric vehicles (EVs) as an alternative to conventional internal combustion engine vehicles. Governments, automobile manufacturers, and consumers are increasingly embracing EV technology due to its potential to reduce greenhouse gas emissions, improve energy efficiency, and decrease dependence on fossil fuels. As the demand for electric mobility continues to grow, the performance and reliability of battery systems have become critical factors influencing the overall success, safety, and commercial acceptance of electric vehicles. Among the various components of an EV, the battery pack serves as the primary energy source, directly affecting driving range, charging capability, operational efficiency, and vehicle lifespan.

Lithium-ion batteries have emerged as the preferred energy storage technology for modern electric vehicles because of their high energy density, long cycle life, lightweight structure, and relatively low self-discharge rate. Despite these advantages, lithium-ion batteries undergo gradual degradation during repeated charging and discharging cycles. Factors such as temperature variations, charging rates, depth of discharge, mechanical stress, manufacturing inconsistencies, and aging contribute to performance deterioration over time. These degradation mechanisms reduce battery capacity, increase internal resistance, and may create safety concerns if not properly monitored and managed. Consequently, assessing battery reliability has become an essential aspect of ensuring dependable EV operation throughout the battery's service life.

Battery reliability assessment involves evaluating the ability of a battery system to perform its intended function consistently under varying environmental and operational conditions. Reliability analysis extends beyond measuring battery capacity by incorporating indicators such as State of Health (SOH), State of Charge (SOC), Remaining Useful Life (RUL), failure probability, thermal stability, and degradation patterns. These parameters enable manufacturers and researchers to estimate battery lifespan, optimize maintenance schedules, improve charging strategies, and minimize unexpected failures. Accurate reliability assessment also supports the development of safer battery systems while reducing maintenance costs and improving user confidence in electric vehicles.

Recent advances in sensing technologies, battery management systems (BMS), artificial intelligence, and data analytics have transformed conventional battery monitoring approaches into intelligent predictive frameworks. Machine learning, deep learning, digital twin technology, and physics-informed models are increasingly being applied to analyze large volumes of operational data for early fault detection and degradation prediction. These techniques enhance the accuracy of reliability estimation while enabling real-time condition monitoring and predictive maintenance. Furthermore, integrated thermal management systems and adaptive charging algorithms have contributed to improving battery performance and extending operational life under diverse driving conditions.

Despite significant technological progress, several challenges remain in achieving highly accurate and universally applicable battery reliability assessment methods. Battery degradation is influenced by complex electrochemical processes that vary across battery chemistries, usage profiles, climatic conditions, and manufacturing processes. The lack of standardized testing methodologies, limited availability of long-term real-world datasets, model generalization issues, and computational complexity continue to restrict the practical implementation of advanced reliability models. Addressing these challenges requires the integration of experimental research, computational modeling, and intelligent data-driven approaches capable of adapting to dynamic operating environments.

This state-of-the-art review presents a comprehensive examination of battery reliability assessment techniques for electric vehicles by analyzing recent developments in reliability modeling, degradation analysis, health estimation, fault diagnosis, and predictive maintenance. It evaluates conventional and emerging methodologies, compares their strengths and limitations, and discusses the role of battery management systems, thermal management, and artificial intelligence in enhancing reliability. The review also identifies existing research gaps and highlights future directions that can contribute to the development of safer, more reliable, and longer-lasting battery systems for next-generation electric vehicles.

II. LITERATURE SURVEY

1. A Review of Lithium-Ion Battery State of Health Estimation Methods for Electric Vehicles – H. Tian, R. Xiong, W. Shen, et al. (2021)

This study presents a comprehensive review of State of Health (SOH) estimation techniques for lithium-ion batteries used in electric vehicles. The authors examine conventional model-based methods, data-driven approaches, and hybrid estimation techniques for evaluating battery degradation. The review emphasizes that accurate SOH estimation is essential for ensuring battery safety, extending service life, and improving vehicle reliability. It concludes that integrating artificial intelligence with Battery Management Systems (BMS) enhances estimation accuracy and enables more effective battery reliability assessment.

2. Machine Learning Techniques for Lithium-Ion Battery Remaining Useful Life Prediction: A Review – Y. Zhang, C. Wang, X. Liu, et al. (2022)

The authors review recent machine learning techniques developed for predicting the Remaining Useful Life (RUL) of lithium-ion batteries. Various algorithms, including Support Vector Machines, Random Forests, Artificial Neural Networks, and Long Short-Term Memory (LSTM) networks, are analyzed and compared. The study reports that machine learning models outperform many traditional prediction methods by effectively capturing nonlinear battery degradation behavior. However, it also highlights the need for large, high-quality datasets to achieve reliable prediction performance.

3. Battery Management Systems for Electric Vehicles: A Comprehensive Review – A. Farmann, D. Sauer, et al. (2020)

This review focuses on the role of Battery Management Systems in improving battery safety, performance, and reliability. The paper discusses important BMS functions such as battery monitoring, thermal management, cell balancing, fault detection, and charging control. The authors explain that intelligent battery management significantly enhances battery lifespan while minimizing safety risks associated with overcharging, overheating, and abnormal operating conditions. The review identifies advanced BMS technologies as fundamental components of future electric vehicle battery systems.

4. Artificial Intelligence-Based Battery Health Monitoring for Electric Vehicles: A Review – S. Li, J. Li, Y. Zhao, et al. (2023)

This paper reviews the application of artificial intelligence techniques for battery health monitoring and reliability assessment. The authors evaluate various machine learning and deep learning algorithms used for fault diagnosis, battery degradation prediction, and health estimation. The review demonstrates that AI-based approaches provide more accurate and adaptive monitoring than conventional methods, especially under dynamic operating conditions. It also discusses current challenges related to model interpretability, computational requirements, and data availability.

5. Digital Twin Technology for Lithium-Ion Battery Health Management: A Review – X. Chen, H. Yang, Z. Wang, et al. (2023)

The study explores the emerging application of digital twin technology in battery reliability assessment. It explains how virtual battery models synchronized with real-time operational data can simulate battery behavior, estimate degradation, predict failures, and optimize maintenance strategies. The authors conclude that digital twin technology enables intelligent battery management by supporting continuous health monitoring and predictive maintenance, making it a promising solution for next-generation electric vehicles.

6. Thermal Management of Lithium-Ion Batteries for Electric Vehicles: A Review – M. Al-Zareer, I. Dincer, and M. Rosen (2019)

This review investigates different thermal management techniques used to maintain safe battery operating temperatures in electric vehicles. The authors analyze air cooling, liquid cooling, phase-change materials, and heat pipe technologies, comparing their effectiveness in controlling battery temperature. The study demonstrates that efficient thermal management reduces battery degradation, improves energy efficiency, enhances safety, and extends battery service life under various operating conditions.

7. Recent Advances in Battery Degradation Mechanisms and Prognostics for Electric Vehicles – R. Xiong, Q. Yu, F. Sun, et al. (2022)

This paper reviews recent developments in battery degradation analysis and prognostic modeling for electric vehicles. The authors examine electrochemical aging, thermal effects, mechanical stress, and operational factors influencing battery reliability. Both physics-based and data-driven prediction methods are evaluated to determine their strengths and weaknesses. The review recommends hybrid prognostic models that combine physical knowledge with artificial intelligence to achieve more reliable battery health prediction.

8. Deep Learning-Based Battery State Estimation: A Survey – J. Wu, Y. Zhang, H. He, et al. (2023)

The survey provides a detailed overview of deep learning techniques for estimating battery State of Charge (SOC), State of Health (SOH), and Remaining Useful Life (RUL). It discusses Convolutional Neural Networks (CNN), Long Short-Term Memory (LSTM), Gated Recurrent Units (GRU), and Transformer-based models for battery state estimation. The authors conclude that deep learning methods significantly improve prediction accuracy while supporting real-time battery monitoring and intelligent decision-making.

9. Reliability Assessment of Lithium-Ion Batteries for Electric Vehicles: Current Status and Future Directions – K. Smith, E. Wood, J. Neubauer, et al. (2021)

This article reviews current battery reliability assessment methodologies and identifies key factors affecting battery lifespan, including charging strategies, operating temperature, discharge cycles, and environmental conditions. The authors discuss the limitations of existing reliability models and emphasize the importance of standardized testing procedures and integrated assessment frameworks. The study recommends combining physical models with intelligent analytics to improve reliability prediction across different battery technologies.

10. A Review of Prognostics and Health Management Techniques for Lithium-Ion Batteries – B. Saha and K. Goebel (2020)

This review focuses on Prognostics and Health Management (PHM) techniques used for lithium-ion battery reliability evaluation. The paper discusses fault detection, health assessment, degradation modeling, and Remaining Useful Life prediction using both model-based and data-driven approaches. The authors conclude that integrating sensor data, electrochemical models, and artificial intelligence can significantly improve predictive maintenance, reduce unexpected battery failures, and enhance the long-term reliability of electric vehicle battery systems.

III. EXISTING SYSTEM

The existing battery reliability assessment systems for electric vehicles primarily rely on conventional monitoring techniques integrated within Battery Management Systems (BMS). These systems continuously measure key battery parameters such as voltage, current, temperature, and charging status to estimate the battery's operational condition. Traditional assessment methods mainly focus on calculating the State of Charge (SOC) and State of Health (SOH) using empirical models, equivalent circuit models, electrochemical models, and statistical estimation techniques. These approaches have been widely adopted because they are computationally efficient and can be implemented in commercial electric vehicles with relatively low hardware requirements.

Many existing reliability assessment methods also utilize laboratory-based aging experiments and cycle-life testing to evaluate battery degradation characteristics. These tests expose batteries to controlled charging and discharging cycles under predefined environmental conditions to estimate capacity fade, internal resistance growth, and expected service life. Model-based techniques, including Kalman filtering, particle filtering, and observer-based algorithms, have further improved estimation accuracy by combining mathematical battery models with real-time sensor measurements. Although these methods provide reliable performance under known operating conditions, their accuracy often decreases when batteries experience diverse driving patterns, varying temperatures, or unexpected operating environments.

Recent developments have introduced data-driven techniques that employ machine learning and deep learning algorithms to analyze historical battery data and predict degradation trends. Methods such as Support Vector Machines (SVM), Random Forests, Artificial Neural Networks (ANN), Long Short-Term Memory (LSTM) networks, and hybrid predictive models have demonstrated improved capability in estimating battery health and Remaining Useful Life (RUL). These approaches can identify complex nonlinear relationships that are difficult to capture using conventional physical models. However, their effectiveness depends heavily on the availability of large, high-quality datasets and substantial computational resources for training and validation.

Despite these advancements, existing battery reliability assessment systems still face several limitations. Many approaches are developed for specific battery chemistries or operating conditions, making them less adaptable to real-world scenarios. Variations in manufacturing quality, charging behavior, environmental conditions, and user driving habits introduce uncertainties that reduce prediction accuracy. Additionally, the absence of standardized reliability evaluation frameworks, limited interpretability of advanced artificial intelligence models, and challenges in integrating multiple data sources continue to restrict the practical deployment of highly accurate and universally applicable battery reliability assessment systems. These limitations highlight the need for more robust, intelligent, and adaptive approaches capable of providing reliable battery health prediction under dynamic operating conditions.

IV. PROPOSED SYSTEM

The proposed system presents a comprehensive and intelligent framework for battery reliability assessment in electric vehicles by integrating conventional battery monitoring techniques with advanced artificial intelligence, machine learning, and predictive analytics. Unlike traditional approaches that rely primarily on voltage, current, and temperature measurements, the proposed framework combines multiple battery health indicators, including State of Charge (SOC), State of Health (SOH), Remaining Useful Life (RUL), capacity degradation, internal resistance, and thermal behavior, to provide a more accurate evaluation of battery reliability. This integrated approach enables continuous monitoring of battery performance under diverse operating conditions and supports informed decision-making for battery maintenance and replacement.

The proposed system incorporates data collected from Battery Management Systems (BMS), onboard sensors, and historical operational records to develop intelligent predictive models capable of identifying early signs of battery degradation. Machine learning and deep learning algorithms are employed to analyze complex relationships among electrical, thermal, and operational parameters, enabling more precise prediction of battery aging and potential failures. In addition, digital twin technology and hybrid physics-informed models can be integrated to simulate battery behavior under various charging, discharging, and environmental conditions, thereby improving the robustness and adaptability of reliability assessment.

To enhance operational safety and battery lifespan, the proposed framework also emphasizes intelligent thermal management, adaptive charging strategies, and real-time fault diagnosis. Continuous health monitoring allows the system to detect abnormal operating conditions, issue early warning alerts, and recommend preventive maintenance before critical failures occur. This proactive approach reduces unexpected battery breakdowns, minimizes maintenance costs, improves energy efficiency, and extends battery service life. Furthermore, the framework supports scalable implementation across different battery chemistries and electric vehicle platforms by utilizing standardized evaluation metrics and flexible analytical models.

Overall, the proposed system aims to overcome the limitations of existing battery reliability assessment methods by providing a more accurate, interpretable, and adaptive solution for modern electric vehicles. Through the integration of advanced analytics, intelligent monitoring, and predictive maintenance technologies, the framework contributes to improved battery safety, enhanced vehicle reliability, optimized operational performance, and sustainable electric mobility. Its comprehensive design also establishes a strong foundation for future research and industrial applications in next-generation battery reliability assessment systems.

V. SYSTEM ARCHITECTURE

The proposed Battery Reliability Assessment System for Electric Vehicles is organized into six interconnected layers that collectively monitor battery health, predict degradation, estimate battery lifespan, and provide intelligent maintenance recommendations. The architecture begins with data collection from the battery system and ends with decision support for users and maintenance personnel. Each layer performs a specific function to ensure accurate, reliable, and real-time battery reliability assessment.

1. Data Acquisition Layer

The first layer is responsible for collecting real-time battery information from the electric vehicle. Various sensors embedded within the battery pack continuously monitor important parameters such as voltage, current, temperature, State of Charge (SOC), State of Health (SOH), internal resistance, charge/discharge cycles, power, and battery capacity. These measurements provide a complete representation of the battery's operating condition. Since battery performance changes over time due to aging and operating conditions, continuous data collection forms the foundation for accurate reliability assessment.

2. Communication and Storage Layer

After data acquisition, the collected battery information is transmitted through the Battery Management System (BMS). The BMS acts as the central controller that gathers sensor readings, performs basic monitoring, and forwards the information using communication protocols such as CAN Bus, RS485, IoT, 4G, or 5G networks. The transmitted data is then stored in either a local database or cloud storage. Maintaining historical battery records allows the system to analyze long-term degradation trends and train predictive models more effectively.

3. Data Processing and Analytics Layer

This layer performs intelligent processing of the collected battery data before prediction. Initially, the raw data undergoes preprocessing, including data cleaning, missing value handling, outlier detection, normalization, and feature engineering, to improve data quality. Next, significant battery features are extracted from the processed data for analysis. These features are used to estimate important battery health indicators such as State of Health (SOH), Remaining Useful Life (RUL), reliability score, and fault conditions. To improve prediction accuracy, machine learning and deep learning algorithms—including Random Forest, XGBoost, Long Short-Term Memory (LSTM), Support Vector Machine (SVM), and hybrid models—are employed. These models analyze complex relationships among battery parameters and accurately predict degradation and future battery performance.

4. Application and Output Layer

The processed information is presented to users through an interactive dashboard and visualization interface. The dashboard displays important battery metrics, including State of Charge (SOC), State of Health (SOH), Remaining Useful Life (RUL), reliability score, and overall battery status (healthy or faulty). The system also generates maintenance recommendations and automatically issues alerts whenever abnormal battery conditions, excessive degradation, or potential failures are detected. These outputs help users continuously monitor battery performance and make informed maintenance decisions.

5. Model Training and Evaluation Layer

The architecture also includes an offline model training stage that uses historical battery data to develop accurate predictive models. The collected dataset is divided into training and testing subsets, after which multiple machine learning algorithms are trained and evaluated. Their performance is compared using appropriate evaluation metrics, and the best-performing model is selected for deployment. This approach ensures that the deployed prediction model delivers reliable battery health estimation and can be updated whenever additional battery data becomes available.

6. User and Maintenance Layer

The final layer represents the end users who utilize the information generated by the system. These users include electric vehicle owners, service centers, and fleet managers. Vehicle owners can monitor battery health and receive timely notifications about battery condition. Service centers use fault diagnosis and maintenance recommendations to schedule repairs and battery replacement when necessary. Fleet managers can monitor the health of multiple vehicles simultaneously, enabling efficient maintenance planning and reducing operational downtime.

Overall Working of the System

The system begins by collecting real-time battery data through sensors installed in the electric vehicle. The Battery Management System (BMS) transmits this information to the storage layer, where it is securely maintained for analysis. The data is then preprocessed to remove inconsistencies and transformed into meaningful features. Intelligent machine learning and deep learning models analyze these features to estimate battery health, predict degradation, calculate Remaining Useful Life, and detect faults. The results are displayed through an interactive dashboard, while alerts and maintenance recommendations are automatically generated whenever necessary. Finally, historical battery data is used to retrain and improve the predictive models, creating a continuous feedback loop that enhances the accuracy, reliability, and efficiency of battery health assessment over time.

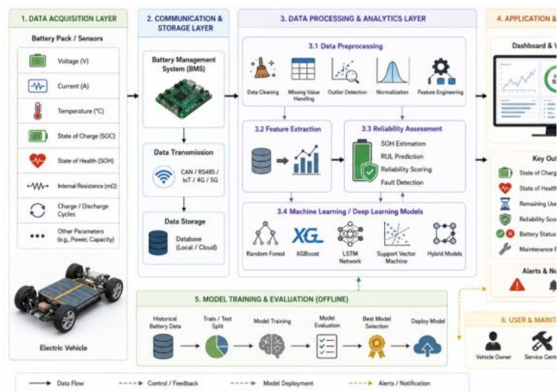

Fig 5.1: System Architecture

VI. IMPLEMENTATION

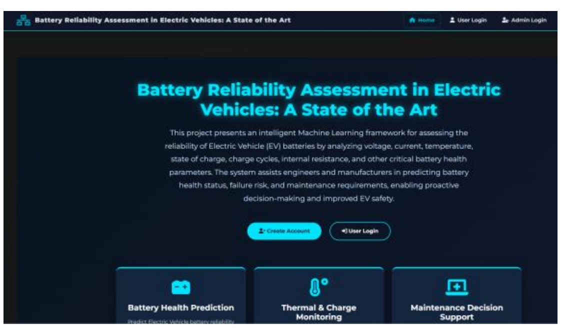

Fig 6.1: Home Page

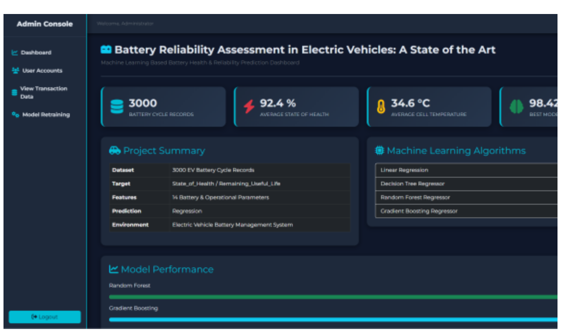

Fig 6.2: Dashboard

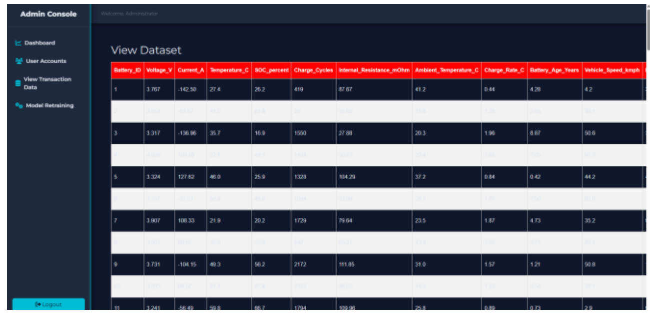

Fig 6.3: Dataset

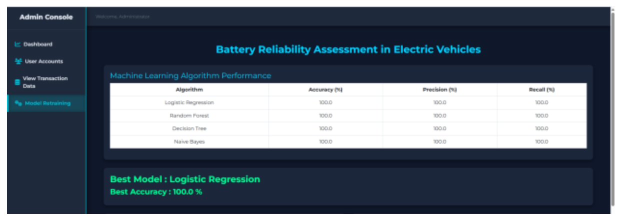

Fig 6.4: Model Training

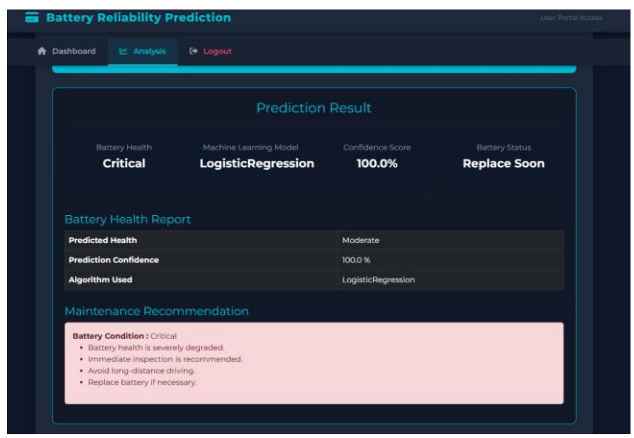

Fig 6.5: Result Page

VII. CONCLUSION

Battery reliability assessment plays a fundamental role in improving the safety, efficiency, and long-term performance of electric vehicles. As lithium-ion batteries are continuously exposed to varying operating conditions, charging patterns, and environmental factors, accurate monitoring of battery health has become essential for ensuring dependable vehicle operation. This study reviewed the current state of battery reliability assessment by examining conventional techniques, Battery Management Systems (BMS), artificial intelligence, machine learning, deep learning, and predictive maintenance approaches. The analysis demonstrated that modern data-driven methods provide more accurate estimation of State of Charge (SOC), State of Health (SOH), and Remaining Useful Life (RUL) than traditional assessment techniques, enabling timely fault detection and effective battery lifecycle management.

The review also identified several challenges, including battery degradation complexity, limited availability of real-world datasets, lack of standardized reliability evaluation frameworks, and the computational requirements of advanced predictive models. Despite these challenges, emerging technologies such as digital twins, intelligent Battery Management Systems, hybrid modeling approaches, and explainable artificial intelligence offer promising opportunities for enhancing battery reliability assessment. Overall, the adoption of intelligent monitoring and predictive analytics can significantly improve battery safety, extend battery lifespan, reduce maintenance costs, and increase consumer confidence in electric vehicles. Future research should focus on developing scalable, interpretable, and standardized reliability assessment frameworks capable of supporting next-generation electric mobility and sustainable transportation systems.

VIII. FUTURE SCOPE

Battery reliability assessment is expected to advance significantly with the continued development of artificial intelligence, advanced sensing technologies, and next-generation Battery Management Systems (BMS). Future research can focus on developing hybrid reliability assessment models that combine electrochemical knowledge with machine learning and deep learning techniques to achieve more accurate predictions of battery degradation and Remaining Useful Life (RUL). The integration of real-time Internet of Things (IoT) sensors, edge computing, and cloud-based analytics will enable continuous monitoring of battery performance under diverse operating conditions while supporting intelligent decision-making for electric vehicle users and manufacturers. Furthermore, the adoption of explainable artificial intelligence (XAI) can improve the transparency and interpretability of predictive models, increasing their acceptance in industrial and safety-critical applications.

Another promising research direction is the implementation of digital twin technology to create virtual replicas of battery systems that continuously synchronize with real-time operational data. Digital twins can simulate battery behavior, detect early signs of degradation, evaluate different charging strategies, and optimize thermal management without interrupting vehicle operation. Future studies may also explore reliability assessment for emerging battery technologies such as solid-state batteries, lithium-sulfur batteries, and sodium-ion batteries, which are expected to play an important role in next-generation electric vehicles. In addition, establishing standardized reliability evaluation protocols, utilizing large-scale real-world datasets, and developing adaptive predictive maintenance frameworks will contribute to more robust, scalable, and universally applicable battery reliability assessment systems. These advancements will enhance battery safety, extend operational lifespan, reduce maintenance costs, and accelerate the widespread adoption of sustainable electric mobility.

IX. REFERENCES

[1] J. Omakor, M. S. Miah, and H. Chaoui, "Battery Reliability Assessment in Electric Vehicles: A State-of-the-Art," IEEE Access, vol. 12, pp. 77903–77931, 2024. DOI: 10.1109/ACCESS.2024.3406424.

[2] S. M. Rezvanizaniani, Z. Liu, Y. Chen, and J. Lee, "Review and Recent Advances in Battery Health Monitoring and Prognostics Technologies for Electric Vehicle (EV) Safety and Mobility," Journal of Power Sources, vol. 256, pp. 110–124, 2014. DOI: 10.1016/j.jpowsour.2014.01.085.

[3] M. Berecibar, I. Gandiaga, I. Villarreal, N. Omar, J. Van Mierlo, and P. Van den Bossche, "Critical Review of State of Health Estimation Methods of Li-Ion Batteries for Real Applications," Renewable and Sustainable Energy Reviews, vol. 56, pp. 572–587, 2016. DOI: 10.1016/j.rser.2015.10.158.

[4] M. A. Hannan, M. S. H. Lipu, A. Hussain, and A. Mohamed, "A Review of Lithium-Ion Battery State of Charge Estimation and Management System in Electric Vehicle Applications," Renewable and Sustainable Energy Reviews, vol. 78, pp. 834–854, 2017. DOI: 10.1016/j.rser.2017.05.001.

[5] A. Barré, B. Deguilhem, S. Grolleau, M. Gérard, F. Suard, and D. Riu, "A Review on Lithium-Ion Battery Ageing Mechanisms and Estimations for Automotive Applications," Journal of Power Sources, vol. 241, pp. 680–689, 2013. DOI: 10.1016/j.jpowsour.2013.05.040.

[6] W. Waag, C. Fleischer, and D. U. Sauer, "Critical Review of the Methods for Monitoring of Lithium-Ion Batteries in Electric and Hybrid Vehicles," Journal of Power Sources, vol. 258, pp. 321–339, 2014. DOI: 10.1016/j.jpowsour.2014.02.064.

[7] X. Hu, J. Jiang, D. Cao, and B. Egardt, "Battery Health Prognosis for Electric Vehicles Using Sample Entropy and Sparse Bayesian Predictive Modeling," IEEE Transactions on Industrial Electronics, vol. 63, no. 4, pp. 2645–2656, 2016. DOI: 10.1109/TIE.2015.2461523.

[8] Y. Zhang, R. Xiong, H. He, and M. Pecht, "Long Short-Term Memory Recurrent Neural Network for Remaining Useful Life Prediction of Lithium-Ion Batteries," IEEE Transactions on Vehicular Technology, 2018. DOI: 10.1109/TVT.2018.2869863.

[9] K. A. Severson et al., "Data-Driven Prediction of Battery Cycle Life Before Capacity Degradation," Nature Energy, vol. 4, no. 5, pp. 383–391, 2019. DOI: 10.1038/s41560-019-0356-8.

[10] W. Li, N. Sengupta, P. Dechent, D. Howey, A. Annaswamy, and D. U. Sauer, "Online Capacity Estimation of Lithium-Ion Batteries with Deep Long Short-Term Memory Networks," Journal of Power Sources, vol. 482, 2021. DOI: 10.1016/j.jpowsour.2020.228863.

[11] R. R. Richardson, M. A. Osborne, and D. A. Howey, "Battery Health Prediction Under Generalized Conditions Using a Gaussian Process Transition Model," Journal of Energy Storage, vol. 23, pp. 320–328, 2019. DOI: 10.1016/j.est.2019.100733.

[12] G. L. Plett, "Extended Kalman Filtering for Battery Management Systems of LiPB-Based HEV Battery Packs: Part 3. State and Parameter Estimation," Journal of Power Sources, vol. 134, no. 2, pp. 277–292, 2004. DOI: 10.1016/j.jpowsour.2004.02.033.

[13] X. Feng, M. Ouyang, X. He, L. Lu, H. Wang, and M. Zhang, "Thermal Runaway Mechanism of Lithium-Ion Battery for Electric Vehicles: A Review," Energy Storage Materials, vol. 10, pp. 246–267, 2018. DOI: 10.1016/j.ensm.2017.05.013.

[14] Z. M. Ali, M. Calasan, F. H. Gandoman, F. Jurado, and S. H. E. Abdel Aleem, "Review of Batteries Reliability in Electric Vehicle and E-Mobility Applications," Ain Shams Engineering Journal, vol. 15, no. 2, 2024. DOI: 10.1016/j.asej.2023.102442.

[15] X. Lai, Y. Zheng, and T. Sun, "Concept of Reliability and Safety Assessment of Lithium-Ion Batteries in Electric Vehicles:

Basics, Progress, and Challenges," Applied Energy, vol. 251, Art. 113343, 2019. DOI: 10.1016/j.apenergy.2019.1133