© March 2025 | IJIRT | Volume 11 Issue 10 | ISSN: 2349-6002

Lithium Batteries RUL And SOH Prediction – Literature Review

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***Abstract*—Lithium batteries have established themselves as a fundamental element of modern energy storage solutions, driving advancements in both personal electronics and electric mobility. To ensure the battery's reliability, safety, and cost-effectiveness it is vital to accurately predict the Remaining Useful Life (RUL) and State of Health (SOH). This study provides an in-depth analysis of current literature on lithium battery RUL and SOH prediction methodologies, factors used. It explores various approaches such as data-driven models, physics-based techniques, and hybrid methods, highlighting their applications, strengths, and drawbacks. This review also highlights recent achievements in machine learning and artificial intelligence regarding battery life prediction methods. Issues face such as data accessibility, computational demands, and model generalizability, alongside recommendations for future research opportunity are provided in this paper.**

***Index Terms*—Lithium Battery, RUL, SOH, Lifespan prediction,**

I. INTRODUCTION

Lithium batteries rechargeable or non-rechargeable energy storage device that uses lithium as the primary component in its electrochemical composition. These are important components in electric vehicles (EVs), electronics and renewable energy systems owing to their high energy density, lightweight construction, high operating storage, No memory effect, durability, and long lifespan.

However, Despite the advantages of lithium battery it faces issues like, safety and reliability issues, like system failures, malfunctions causing fires etc. Over time the battery faces difficulties like capacity degradation due to repeated charge and discharge cycles, a phenomenon linked to aging occurred by irreversible chemical reactions, such as lithium deposition and electrolyte decomposition directly effecting on their longevity and performance.

A lithium battery to have long lifespan and perform well, there is a need for effective health management systems. The capacity degradation effects Remaining Useful Life (RUL) of the battery and reliability. This degradation is quantified using metrics such as State of Health (SOH), which displays the power capability and battery's energy.

II. LITERATURE REVIEW

2.1. Planning the reasearch

We have collected the papers by focusing on specific keywords as mentioned above such as "RUL", 'SOH", and "Lithium battery life predictions", etc. Additionally, we manually searched for several additional papers to support our research and review process. Our primary goal was to gather a comprehensive set of papers that would enable us to address the following research questions that we planned for deep analysis of the paper collected:

RQ1: What factors and methods that are used in predicting RUL and SOH?

RQ2: What are the key issues faced while predicting?

RQ3: What is the future scope for developing?

By acquiring detailed answers to the above questions, we aim to gain a comprehensive understanding of the processes in each paper. This thorough analysis will ultimately lead us to conclusions regarding the best methodologies and factors used to determine RUL and SOH alongside highlighting the issues occurred during process.

2.2. Conducting the research

After carefully planning on how to collect the papers, we established specific selection and exclusion criteria to determine which papers should be included and excluded. We initially gathered up to 42 papers from various reputable platforms such as IEEE, ResearchGate, IJAER, Academia, IJITEE, and others. We also applied our selection criteria to classify these papers systematically. The selection criteria are as follows:

Selection Criteria	Excluded Criteria
Paper must have the keywords specified.	Papers with no significant resulted shall not be included.
Paper must cover RUL/SOH	Papers before 2010 shall not be included

2.3. Analysis

The eligibility of each paper for inclusion in our research was meticulously analyzed and reviewed in this stage determining their suitability for our research and literature review. The 42 papers collected from various websites, went through rigorous analysis process, we assessed each paper's eligibility. Out of the total collected, 7 papers were focused on Low Quality of Research, Papers with methodological flaws, or poor choice of factor selection which may not provide reliable or valid findings, hence were removed.

Additionally, 3 papers that failed to present conclusive results were excluded. Later we identified 2 papers discussed that discussed the importance of Battery lifetime prediction without detailing the methods or factors involved in prediction process. So, we decided to exclude them as our review aims to focus on the methodologies, factors used. We also caught additional 1 paper, despite being published after 2010, discussed outdated methods from the 2000s and it was excluded to ensure the inclusion of the most recent advancements and trends. This rigorous selection process resulted in a total of 29 papers deemed eligible for in-depth review and analysis.

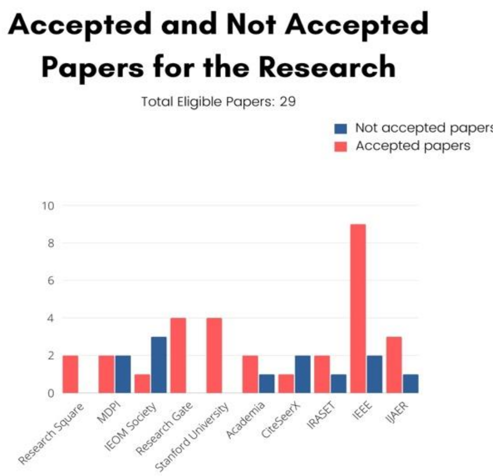

Fig. 1. Bar chart representation of the eligible papers

III. REMAINING USEFUL LIFE (RUL)

RUL stands for Remaining Useful Life, which refers to the anticipated period of functionality or number of cycles left that a battery can operate effectively before needing maintenance or replacement. It is crucial in predictive maintenance, and reliability engineering, optimize maintenance schedules, controlling costs, and aiding organizations in reducing downtime. Sectors such as electric vehicles, aerospace, and renewable energy storage systems, understanding and predicting the RUL of lithium batteries plays a vital role in enhancing the system efficiency and extending battery longevity.

Variety of factors play a major role in determining and predicting lithium battery’s RUL, these factors can be classified into operational, environmental, and design-related.

3.1. Operational Conditions:

This operational conditions explores how was the battery used during its lifetime, which includes:

3.1.1. Depth of Discharge (DoD): The percentage of the battery's capacity used during every cycle, is DoD. Excessive DoD’s exert additional strain on the battery, hastening degradation and diminishing its lifespan, whereas maintaining a moderate DoD range promotes longer durability.

3.1.2. Charge and Discharge Rates: The rate at which a battery charges and discharges is taken into account here. The higher the C-rates of a battery the excessive heat is generated within the battery, causing capacity degradation, and damaging the battery's lifespan. While C-rates that are low or moderate remain not damaged and have a prolonged lifespan.

3.1.3. Cycle Count: The total number of charge and discharge cycles a battery undergoes also contributes to the battery's capacity and lifetime. The greater number of cycles, there will be a gradual decline in the battery's capacity. A battery's longevity is largely defined by the maximum cycles it can perform before its performance deteriorates beyond a usable threshold.

3.1.4. State of Charge (SoC) Range: Keeping a battery fully charged or deeply discharged for longer time period, might accelerate battery's degradation. For long-term health, maintaining a moderate SoC range is more advisable.

3.2. Environmental Influences:

This Environmental Influences explores the external factors that influenced the battery during the battery's use and storage, which includes:

3.2.1. Temperature: The temperature the battery was kept in is very crucial as high temperatures accelerates the chemical reactions within the battery, leading to faster capacity and structural degradations. Whereas at low temperatures, can cause harm to batteries, the mobility of lithium-ion decreases, reflecting in performance fall and causing stress on the battery's components.

3.2.2. Humidity: When batteries come into contact with excessive moisture or humidity the metallic parts of the batteries tend to corrode, leading to performance degradation, reducing efficiency and increasing the chance of malfunction.

3.2.3. Vibration and Mechanical Stress: If the applications are exposed to vibrations and shocks such as electric vehicles or aerospace products, may face physical damage, decreasing efficiency and lifespan.

3.3. Design-Related Influences:

This Design-Related Influences explores the design and manufacturing choices made during a battery's production, which includes:

3.3.1. Electrode Materials: The materials used for the anode and cathode, which will influence in determining the battery's capacity, cycle life, and performance rates.

3.3.2. Electrolyte Composition: The stability and composition of the electrolyte affect ion transport and overall battery efficiency.

3.3.3. Cell Balancing: In battery packs with multiple cells, imbalances between cells can cause uneven degradation. Proper design, including balancing circuits, helps maintain uniform performance and extend the pack's overall lifespan.

3.3.4. Thermal Management Systems: A well-designed thermal management system prevents overheating and ensures uniform temperature distribution within the battery, reducing thermal stress and prolonging life.

3.3.5. Battery Form Factor and Packaging: The physical design of the battery, including its size, shape, and protective casing, influences its ability to withstand environmental stress and mechanical wear.

IV. STATE OF HEALTH(SOH)

SOH, which stands for State of Health plays a vital role in evaluating the performance and longevity of batteries. Compared to the initial state of battery i.e., before the usage battery, it provides a comprehensive measure of the battery's ability to deliver its original capacity and performance right now. Accurate SOH estimation is key to maintaining the safety and functionality of battery-driven technologies like electric cars, renewable power systems, and handheld gadgets.

The factors influencing the State of Health of a battery can be classified into physical, chemical, and environmental factors:

4.1. Physical Factors:

This Physical Factors related to the structural, or mechanical properties that impact the battery, which includes:

4.1.1. Charge/Discharge Cycles: The number and depth of charge/discharge cycles the battery went under play a crucial role in determining a battery's lifespan. The more the dee cycles and high discharge rates the faster capacity fade, while shallow cycles lead to slower aging.

4.1.2. Current Rates (C-rates): The internal chemistry is influenced by the rate at which a battery is charged or discharged. Lithium plating in lithium-ion batteries can take place if C-rates are higher, leading to capacity loss and safety concerns.

4.2. Chemical Factors:

This Chemical Factors related to the internal chemical reactions and processes that occur within the battery, which includes:

4.2.1. State of Charge (SOC) Range: Continuous operation at extreme SOC levels (near 0% or 100%) accelerates degradation due to stress on the electrode materials.

4.2.2. Aging Mechanisms: Both calendar aging and cycle aging effect aging of a battery. Calendar aging refers to the natural degradation of the battery over time, even when not in use, while cycle aging is directly related to operational use.

4.3. Environmental Factors:

This Environmental Factors related to the external conditions that influence a battery, which includes:

4.3.1. Temperature: Surrounding Temperature influence the battery's performance. Excessive heat speeds up the degradation, whereas low temperatures increase internal resistance and reduce capacity.

4.3.2. Humidity: The Higher the humidity level the higher the moisture ingress, causing corrosion or even short circuits.

4.3.3. Mechanical Vibrations: Environmental stresses, such as impacts or vibrations, can compromise the battery housing or internal connections.

V. METHODOLOGIES

To Accurately predict State of Health (SOH) and Remaining Useful Life (RUL) of batteries, different approaches, different methodologies have been developed, such as data-driven, model-based approaches, and hybrid approaches to achieve the best results.

5.1. Data-Driven Model:

Data-driven models rely on historical and real-time data to identify patterns and trends in battery performance instead of their internal physical and chemical processes. The flexibility and ability to handle complex, nonlinear systems make this model popular.

5.1.1. Machine Learning (ML) Techniques: Machine learning algorithms such as Support Vector Machines (SVM), Artificial Neural Networks (ANN), and Random Forests are widely in use to predict SOH and RUL.

These models use voltage, current, temperature, and charge/discharge cycles etc. as input and analysis on the patterns to learn correlations between them and predict future performances. These models can adapt to varying battery chemistries and operating conditions. They do not require detailed knowledge of internal battery mechanisms, making them versatile.

5.1.2. Deep Learning (DL): Advanced DL techniques, such as Convolutional Neural Networks (CNN) and Recurrent Neural Networks (RNN), are gaining prominence in battery health management due to their ability to learn complex, non-linear relationships, and temporal patterns from large-scale data.

Feedforward Neural Networks (FNN), These are the simplest type of neural networks, used primarily for SOH prediction when the data is non-sequential. FNNs can model complex relationships but lack temporal modeling capabilities. RNNs, including their advanced variants like Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU), are highly effective for capturing temporal dependencies in sequential battery data. They excel in RUL prediction by learning from time-series inputs like voltage and temperature profiles during charging and discharging cycles. CNNs are increasingly used for battery health prediction when the data can be represented as spatial or sequential features, they extract local features and patterns efficiently.

5.2. Model-Based Techniques:

Model-based techniques are rooted in the fundamental physical and chemical principles governing battery behavior. These models are designed based on detailed mathematical representations of internal processes, making them highly interpretable and reliable.

5.2.1. Equivalent Circuit Models (ECM): ECMs simplify battery behavior into electrical components like resistors, capacitors, and inductors. These models are computationally efficient and suitable for real-time applications. By analyzing the parameters of an ECM, such as internal resistance or capacitance, SOH can be inferred.

5.2.2. Equivalent Circuit Models (ECM): Physics-Based Models: These models provide a deeper understanding of the degradation mechanisms in batteries, such as lithium plating, solid electrolyte interphase (SEI) growth, and electrolyte degradation. The Doyle–Fuller–Newman (DFN) model is a prominent example, capturing electrochemical dynamics at a granular level. However, these models are computationally intensive and require precise calibration.

5.2.3. Electrochemical Impedance Spectroscopy (EIS) Models: EIS-based models leverage impedance measurements across different frequencies to infer SOH. They provide insights into battery degradation but often require specialized equipment for data acquisition.

5.3. Hybrid Approaches:

Hybrid approaches integrate data-driven and model-based methods to combine their strengths and mitigate their individual limitations. These methods aim to enhance predictive accuracy, robustness, and interpretability.

5.31. Model Parameter Estimation with ML: In this approach, data-driven methods are used to estimate parameters of a model-based framework dynamically. For example, ML algorithms can predict the internal resistance or capacity fade of a battery, which is then fed into an ECM or physics-based model to improve RUL and SOH estimation.

5.3.2. Residual Modeling: Hybrid methods often use physics-based models to generate baseline predictions, while data-driven models predict residuals or deviations from the baseline. This combination can improve accuracy without sacrificing interpretability.

5.3.3. Fusion of Predictions: Another approach involves independently generating predictions from model-based and data-driven methods and fusing them using techniques like weighted averaging or Bayesian frameworks. This ensures robustness by accounting for complementary strengths of each method.

5.3.4. Physics-Guided Neural Networks: These are advanced hybrid methods where physical constraints or model equations are embedded directly into the architecture or loss function of neural networks. This ensures that predictions adhere to physical laws while benefiting from the flexibility of neural networks.

VI. KEY ISSUES AND LIMITATIONS

Data-driven methods have demonstrated significant promises for RUL and SOH predictions, but they are not without drawbacks.

6.1. *Dependence on High-Quality Data:* Data-driven models require large volumes of high-quality, labeled data for effective training. However, obtaining such data for batteries is often costly, time-consuming, and impractical. Poor-quality or incomplete datasets can lead to inaccurate predictions.

6.2 Generalization Challenges: Machine learning (ML) and deep learning (DL) models often struggle to generalize across different battery chemistries, manufacturers, and operating conditions. A model trained on one dataset may fail to perform effectively on another due to differences in degradation patterns, environmental factors, or operational use cases.

6.3. Vulnerability to Overfitting: Overfitting is a common issue in data-driven approaches, especially when working with small datasets. Models that overfit learn spurious relationships in the training data, leading to poor performance on unseen data.

6.4. High Computational Requirements: Deep learning methods, such as LSTM and CNN models, require significant computational resources for training and inference. This makes them less suitable for real-time applications or scenarios with limited computational power, such as embedded systems in battery management units.

6.5. Lack of Long-Term Prediction: Data-driven models often focus on short-term predictions and may not capture long-term degradation trends effectively. Extrapolating beyond the range of available data can lead to unreliable RUL estimates, especially for batteries operated in conditions not represented in the training set.

Model-Based Techniques provide valuable insights into the physical and chemical processes of batteries, but they are not without challenges:

6.6. *High Complexity and Computational Burden*: Physics-based models, such as the Doyle–Fuller–Newman (DFN) model, involve solving complex partial differential equations (PDEs) that describe electrochemical processes. This can be computationally expensive, making real-time applications difficult. Simplified models, like ECMs, reduce complexity but sacrifice accuracy and detail.

6.7. Parameter Sensitivity: These are highly sensitive to the accuracy of their parameters, such as internal resistance, capacity, and reaction rates. These parameters often vary across battery types and degrade over time, necessitating frequent recalibration. Errors in parameter estimation can significantly impact the reliability of RUL and SOH predictions.

6.8. Incomplete Representation of Aging Mechanisms: Although physics-based models aim to capture battery degradation mechanisms, they may fail to represent all contributing factors comprehensively. For example, phenomena like electrolyte decomposition or structural changes in electrodes are often oversimplified or ignored. This can result in reduced accuracy in RUL and SOH predictions.

Hybrid approaches aim to combine the strengths of data-driven and model-based methods, but their integration introduces several unique Limitations

6.9. Increased Complexity: Hybrid methods inherently combine the complexities of both data-driven and model-based approaches. Developing a cohesive framework requires careful integration and fine-tuning of both components, which can be time-consuming and computationally expensive.

6.9.1. Computational Overhead: Hybrid models often involve running both data-driven algorithms and physics-based simulations simultaneously. This significantly increases computational demands, particularly in real-time applications, where rapid predictions are required.

6.9.2. Challenges in Balancing Components: One of the key difficulties in hybrid approaches is finding the right balance between the data-driven and model-based components. Over-reliance on one component can undermine the benefits of the other, reducing overall performance. For example, excessive dependence on data-driven methods may lead to poor generalization, while overemphasis on model-based methods may limit adaptability.

6.9.3. Data and Model Integration: Integrating data-driven outputs with model-based predictions can be challenging, especially when the two components operate on different timescales or rely on different data sources. Ensuring consistency between these components requires sophisticated algorithms and careful validation.

6.9.4. Scalability Concerns: While hybrid approaches show promise in controlled environments, scaling them for real-world applications involving diverse battery chemistries, operating conditions, and environmental factors remains a significant challenge.

Hence, every method has its own challenges and limitations. Data-driven approaches excel in flexibility but suffer from data dependency, interpretability issues, and computational requirements. Model-based methods provide interpretability but are hindered by complexity, sensitivity, and rigidity. Whereas Hybrid approaches offer a promising middle ground but face challenges in integration, complexity, and scalability.

Each method has its trade-offs, and choosing the right approach depends on the specific application requirements, data availability, and operational constraints. Addressing these limitations is critical for advancing battery health management technologies.

VII. FUTURE SCOPE AND DEVELOPMENT

The field of RUL and SOH prediction for batteries is evolving rapidly, driven by advances in materials science, computational modeling, and artificial intelligence. However, significant Limitations remain, and there is scope for future development to enhance the accuracy, reliability, and practicality of these methods. Below are key areas where advancements are anticipated:

7.1. Development of High-Quality, Diverse Datasets: The performance of data-driven and hybrid approaches depends heavily on the availability of large, high-quality datasets. Future efforts should focus on creating comprehensive datasets that encompass various battery chemistries, configurations, and real-world operating conditions.

7.2. Enhanced Physics-Informed Machine Learning: Integrating domain knowledge into data-driven models, often referred to as physics-informed machine learning, offers a promising pathway for improving prediction accuracy and robustness. Combining the physical interpretability of model-based methods with the pattern-recognition capability of machine learning can help address uncertainties and reduce computational demands.

7.3. Cross-Disciplinary Collaboration: The challenges in RUL and SOH prediction require collaboration between fields like materials science, electrical engineering, computer science, and data analytics. Future advancements will benefit from, Unified Frameworks.

7.4. Improved Handling of Uncertainty: Accounting for uncertainties in both model parameters and operational conditions is critical for reliable RUL and SOH predictions. Techniques like Bayesian inference and Gaussian processes can quantify uncertainty in predictions, offering confidence intervals rather than point estimates. Combining multiple models to reduce prediction variability and improve robustness against unseen data.

The future of RUL and SOH prediction lies in the convergence of advanced data-driven techniques, robust physical modeling, and real-time systems integration. By addressing current limitations and leveraging emerging technologies, researchers can develop predictive frameworks that are accurate, reliable, and scalable, paving the way for safer and more efficient energy storage solutions in the coming decades.

VIII. CONCLUSION

Lithium-ion batteries have become indispensable in modern energy storage systems, powering everything from portable electronics to electric vehicles and renewable energy grids. Accurate prediction of battery Remaining Useful Life (RUL) and State of Health (SOH) is critical to ensuring reliability, safety, and efficiency in these applications. This paper provided a comprehensive literature survey of the existing methodologies for RUL and SOH prediction, focusing on data-driven, model-based, and hybrid approaches, alongside their key issues, limitations, and future potential.

Given the rapid advancements in lithium-ion battery technology and the growing demand for energy storage, accurate RUL and SOH prediction is more important than ever. The insights from this literature survey provide a foundation for future research, highlighting the need for innovative, interdisciplinary approaches to overcome current limitations and unlock the full potential of predictive battery health management. This review underscores the critical role of RUL and SOH prediction in driving the transition toward sustainable, efficient, and safe energy systems, paving the way for groundbreaking developments in the field.

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