*Grenze International Journal of Engineering and Technology, June Issue*

# Predictive Maintenance of Lithium-Ion Batteries: A Review on Remaining useful Life Prediction Models

Kiran Dashrath Katwale[1] and P. H. Govardhan[2]
[1]Research Scholar, Department of Computer Science and Engineering, Priyadarshini College of Engineering, Nagpur, Maharashtra, India.
[2]Assistant Professor, Department of Computer Science and Engineering, Priyadarshini College of Engineering, Nagpur, Maharashtra, India

***Abstract*— The process of predicting Remaining Useful Life (RUL) for lithium-ion batteries provides an important safety assessment which leads to reduced maintenance expenses and better operational forecasting of battery systems used in portable devices and electric vehicles and renewable energy storage solutions. The operational process of the system suffers from battery degeneration because this process occurs through multiple stages which depend on different operational factors such as temperature and load profile and current operating conditions. The research paper presents a complete evaluation of all existing techniques which use machine learning and deep learning and statistical and physics-based methods and hybrid systems to predict lithium-ion battery Remaining Useful Life. The established methods enable users to monitor system performance through their uncertainty prediction abilities, but the methods fail to deliver precise results under changing environmental conditions. The data-driven machine learning and deep learning models, which include LSTM and transformer-based architectures, demonstrate superior predictive capabilities because they can recognize long-term battery aging patterns from their degradation data. The hybrid approaches lead to better results than the base performance of the models through their combination of CEEMDAN decomposition and incremental capacity analysis signal processing techniques. The review presents detailed information about current research topics which include physics-informed machine learning and transfer learning and system interpretability and uncertainty quantification. The research identifies two major obstacles which need more study, while it emphasizes the need to create models which can explain their decisions and assess uncertainty that can function in actual Battery systems.**

***Index Terms*— Useful Life (RUL), Predictive maintenance, Battery health management, Machine learning, State of Health (SOH) assessment, Deep learning, Data-driven models etc.**

## I. Introduction

### *A. Overview*

The leading energy storage technology currently applied in renewable energy systems, electric vehicles, and also in the newest smart grid applications is the lithium-ion batteries. The exceptional energy storage capacity together with their extended operational lifespan and minimal energy loss during storage periods has established them as the top solution among multiple existing technologies. The increasing dependence on lithium-ion batteries will create major obstacles for achieving safe and reliable operation at affordable costs.

*Grenze ID: 01.GIJET.12.2.220_22*

Batteries lose capacity and develop increased internal resistance during their entire life cycle which results in various problems including unpredicted equipment breakdowns and dangerous situations and increased expenses for operations. In recent years, experts have been actively studying how to accurately determine batteries State of Health (SOH) as well as Remaining Use Life (RUL) [6], [18]. RUL prediction was the process of figuring out how many cycles a battery can endure before it is deemed unfit for use or how long it can be used in its current condition.

Reliable RUL prediction allows for the implementation of predictive maintenance, discourages invasive failures, and provides the right management through the optimal decision in the BMS area. Historically, the methods used to estimate battery health have relied heavily on physics-based and statistical models, including electrochemical models, Wiener process models, and particle filtering approaches [9], [16], [18]. Techniques provide physical interpretability in combination with uncertainty modeling capability. The methodologies require accurate system modeling which leads to two limitations. The methodologies fail to capture nonlinear degradation behavior across various operating conditions. Given the possibility of battery aging statistics and the rise in processing power, data-driven machine learning techniques have emerged as the primary area of interest. Machine learning techniques such as regression models decision trees and ensemble methods have been able to prove their superiority over conventional methods in terms of prediction accuracy. The models depend heavily on feature extraction which humans must create to work with various battery types and usage patterns. The NASA lithium-ion battery aging dataset and other benchmark datasets provide research support through their standardized testing framework which allows for prognosis algorithm evaluation. Researchers will continue to apply deep learning algorithms for battery remaining useful life estimation because these algorithms possess the ability to automatically evaluate intricate non-linear deterioration patterns present in time-based datasets.

Recurrent neural networks, such as LSTM (Long Short-Term Memory) and Gated Recurrent Unit, or G networks, have been frequently used by researchers to create models that examine battery deterioration patterns over long time periods [2] [5]. Transformer-based networks together with attention mechanisms enable prediction accuracy improvements which also help handle noisy datasets because these systems can track extended connections and handle information through superior methods [4],[13]. Deep learning models reach high accuracy performance yet they require extensive labeled data which creates a problem because their operations remain hidden from users thus making them unsuitable for environments where safety features become essential [10].

Hybrid and multi-model solutions have proposed an approach which combines signal processing methods with deep learning systems to overcome limitations that restrict current methods from achieving their full potential. The implementation of Incremental Capacity analysis together with CEEMDAN decomposition methods enables prediction through their ability to create high-quality features that maintain their effectiveness under noisy conditions [1], [8], [19], [20]. In order to enhance generalization and uncertainty awareness, research has evaluated transfer learning in conjunction with conventional survival analysis and physics-informed artificial intelligence frameworks [3], [11], [14]. The methods result in increased computational demands while they lack standard validation methods which would apply to different operational states.

The review recently published is an all-encompassing analysis of RUL prediction methods based on lithium-ion batteries, which fall into four categories: hybrid, deep learning, machine learning, and conventional. In addition to identifying important areas that need more research regarding interpretability, uncertainty quantification, and real-world deployability, the current study employs an organized approach to evaluate existing methods, data sets, performance indicators, and constraints. The review aims to deliver academic researchers and industry experts an accurate organized overview of current battery prognosis systems while the study identifies potential research paths that will lead to the development of reliable understandable scalable battery prognosis systems.

*B. Problem Definition*

- The remaining useful life of lithium-ion batteries requires accurate forecasting because their degradation process follows multiple nonlinear paths which researchers find challenging to understand.
- Limited and Incomplete Datasets: The great majority of the datasets available, such as NASA and CALCE, do not mirror entirely the operating conditions of the real-world which in turn prevents the models from being generalized across the different chemistries, manufacturers, and environments.
- Low Model Transferability: A model that has been trained on one battery type may not necessarily be good when applied to a different cell, chemistry, or usage profile because of the difference in the aging mechanisms.

- Feature Extraction Challenges: The process of identifying the reliable health indicators of the battery such as SOH, internal resistance, and capacity fade is very hard because the sensor data is noisy, irregular, and high-dimensional.
- Most deep learning and machine learning techniques operate as inexplicable systems which create challenges for understanding degradation patterns in safety-critical fields.
- High-precision deep learning models demand extensive computational resources which prevents their implementation on embedded electric vehicle battery management systems.
- The existing models lack uncertainty quantification which creates untrustworthiness for remaining useful life predictions during actual decision-making processes.

## II. Literature Review

### *A. Conventional Battery State Estimation*

Currently, there are two primary ways for determining battery state: using physics-based or statistical degradation models to estimate State of Health and Estimated Useful Life. The initial research work used stochastic processes for battery degradation modeling which included the Wiener process that predicted capacity decline through Gaussian noise patterns [18].

The probabilistic models provide two main benefits which include model explanations and uncertainty prediction capabilities, but they necessitate rigorous assumptions regarding degradation processes. The estimation results became better through the use of particle filter-based methods which maintained ongoing monitoring of State of Health and Remaining Useful Life while dealing with measurement noise problems [9]. The methods need exact state space modeling combined with all prior parameter changes which must be implemented. The NASA Aging Database analysis study showed that traditional estimating techniques lost accuracy when they operated under different testing conditions.

The complete analysis demonstrates that actual Battery Management System (MS) applications cannot use physics-based models because those models fail to adapt to various operational conditions and different battery chemical compositions [6].

### *B. Physics-Informed Machine Learning*

The scientific field of physics-informed machine learning (PIML) develops more trustworthy and broadly usable solutions through its method of combining data-driven models with battery degradation knowledge. The methods use their black-box learning methods together with their operational restrictions and failure patterns and deterioration tracking health indicators. The researchers developed an improved state-of-health assessment system for batteries through their work with NASA aging data which uses machine learning to predict battery cell performance across multiple battery types.

The survival analysis methods create understandable danger situations which measure the probability of remaining operational time by merging machine learning with physical failure concepts [14] [6] The research demonstrated that scientists can use physics-based methods to improve their ability to predict battery performance in untested conditions beyond their existing knowledge. The process of establishing precise physical boundaries faces difficulties because electrochemical aging exhibits complex structural behavior. The system demonstrates advanced prediction capabilities because its interpretability features enable better understanding of its operations.

### *C. Deep Sequential Models for Health Prognosis*

Researchers use deep sequential learning models to evaluate the remaining functional life of lithium-ion batteries because these models can identify complex non-linear degradation patterns which develop throughout the battery's operational period. The recurrent neural network LSTM and GRU models demonstrate their capability to predict capacity decline that occurs during charge-discharge cycles [5]. The DAE-MSCNN-LSTM framework developed by Lv [2] creates better feature extraction capabilities which help to learn temporal relationships and achieve more accurate predictions.

Transformer-based architectures achieve better performance because their attention mechanisms allow systems to monitor remote degradation patterns in challenging acoustic conditions [4]. The DLinear model together with its linear-based deep learning models provides accurate predictions while enabling efficient computational processing [12]. Deep models need extensive data acquisition to attain their best accuracy performance because Ganesh Kumar [10] demonstrated that deep models become unfit for use in safety-critical environments due to their lack of operational transparency.

*D. Hybrid and Multi-Model Fusion Approaches*

The combination of signal processing with optimization and deep learning through hybrid and multi-model fusion methods leads to stronger RUL prediction results. The researchers used CEEMDAN-based signal decomposition to obtain fundamental deterioration elements which they utilized for their forecasting models of). The research project achieved better system stability and lower prediction inaccuracies through its implementation of CEEMDAN together with BiGRU network technology [20]. achieved their RUL estimation goals through the implementation of PSO optimization in their system framework. Autoencoder–CNN–LSTM hybrids improve both temporal learning and spatial feature extraction capacities [2].According to Tarar [15] that hybrid frameworks and ensemble methods delivered better results than single-model approaches in all operating conditions. The methods have two issues because they need complex calculations for their real-time system operation and their working methods still remain unclear.

*E. Signal Processing and Feature Engineering*

The accurate prediction of battery remaining useful life requires both signal processing techniques and feature engineering methods. Researchers use the combination of Increment Capacity (IC) and Differential Voltage (DV) monitoring techniques to discover the most subtle electrochemical degradation patterns [1]. The model uses capacity fade and coulombic efficiency and resistance proxy as health indicators to improve its ability to detect aging patterns [3]. CEEMDAN-based decomposition separates a nonlinear and non-stationary component which leads to better signal quality [8]. Chang [5] demonstrated that statistical features extracted from discharge curves significantly improve machine learning performance. The process of manual feature engineering becomes problematic because it creates difficulties for organizations that want to expand their operations and share their resources among different data environments. Recent studies advocate combining signal processing with deep automatic feature learning to balance interpretability and accuracy [20].

*F. Data Regeneration and Transfer Learning*

Researchers face difficulties in developing reliable RUL models because they lack access to complete battery aging data throughout its entire lifecycle. Researchers solve this issue by combining data regeneration techniques with transfer learning methods. Denoising autoencoders serve as standard tools which improve feature performance when dealing with limited or contaminated data situations [2] [4]. End-to-end deep learning systems enable knowledge transfer between multiple battery types and various data sets while reducing requirements for system installation [11] [12], demonstrated that transfer learning enhances long-term prediction accuracy while decreasing processing expenses. Reviews emphasize that transfer learning is essential for practical BMS applications where collecting complete aging data is infeasible [10]. The main problem exists because source batteries and target batteries exhibit domain differences.

*G. Interpretability, Uncertainty, and Safety*

People achieve satisfaction through the creation of battery RUL models which they use in their safety-critical applications that depend on the most advanced technology available. Probabilistic approaches such as particle filters inherently provide confidence bounds, improving trustworthiness [9]. Survival analysis–based machine learning further enables interpretable failure risk estimation with probabilistic RUL outputs [14] [18], emphasized the importance of stochastic modeling for uncertainty-aware prognosis. Deep learning models function as black boxes which create safety problems and regulatory issues. [6] emphasized that explainable AI together with physics-informed constraints needs to exist for BMS integration to achieve reliable results. Researchers have not yet studied uncertainty-aware deep models which show accuracy improvements because this area remains important for future research.

*H. Research Gap*

The remaining Useful Lifetime (RUL) forecast for lithium-ion batteries has advanced significantly, but there are still a number of unanswered questions. While stochastic and conventional physics-based models are interpretable, they are unable to adequately represent nonlinear degradation under various operating situation [6][18] . Deep learning models like LSTM and Transformer and attention-based networks show high prediction accuracy but need extensive labeled datasets and they fail to provide clear model understanding and uncertainty measurement [2][4][10]. Hybrid approaches that combine signal processing with deep learning methods achieve better accuracy results yet they create higher computational demands which prevent their use in real-time applications [19][20]. The majority of research studies focus on specific datasets which include the NASA Aging Dataset as their only testing material to examine various battery chemistries and usage patterns [3][16]. The field requires additional research to investigate transfer learning and uncertainty-aware frameworks which are essential for creating secure Battery Management Systems. The existing need requires development of a machine learning framework which provides generalizable model interpretation together with uncertainty assessment capabilities and maintains both accuracy and robustness during practical applications.

*I. Comparison of Literature*

TABLE I. COMPARISON OF LITERATURE BASED ON KEY PARAMETERS

| Parameter | Conventional / Statistical Models | Machine Learning Models | Deep Learning Models | Hybrid / Advanced Models |
|---|---|---|---|---|
| Model Type | Physics-based, Wiener process, Particle Filter | Regression, Decision Trees, Random Forest | LSTM, CNN, Transformer, DLinear | CEEMDAN-BiGRU, AE-CNN-LSTM, PSO-BiGRU |
| Accuracy | Moderate, degrades under nonlinear aging | Improved over conventional methods | High prediction accuracy | Very high accuracy with noise robustness |
| Interpretability | High (physically interpretable) | Medium | Low (black-box nature) | Low to Medium |
| Data Requirement | Low to moderate | Moderate | High (large labeled datasets) | High |
| Uncertainty Handling | Explicit (probabilistic) | Limited | Mostly absent | Rarely addressed |
| Generalization Ability | Poor under varying conditions | Moderate | Limited without transfer learning | Improved but dataset-dependent |
| Computational Complexity | Low | Moderate | High | Very High |

## III. RESEARCH METHODOLOGY

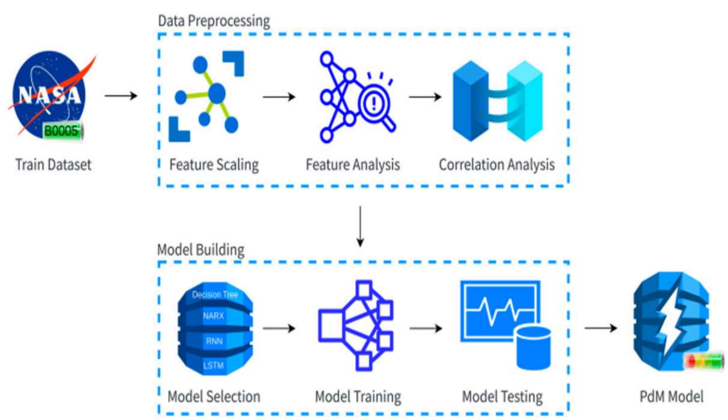


Figure 1. Flow of model building

The Remaining Use Life (RUL) prediction process for a typical lithium-ion battery begins with preprocessing of data and concludes with model development, as shown in Figure 1 Model development Flow. The NASA battery dataset serves as the starting point for this process which provides an overview of the experimental Volt. The experimental procedure includes measuring current and temperature together with capacity measurements during charge-discharge cycles. The first task is to take care of the noise in the raw time-series sensor data which is not always consistent in the observation intervals and to perform feature scaling, so all values are given a fair chance during the training of the model. Then, feature analysis is done based on the computed features through statistical characterizations, like mean, variance, skewness, and kurtosis, which, among others, depict degradation trends.

In addition, correlation analysis is done to determine which features are strongly associated with battery health and to eliminate those that are not clear in order to reduce compute time, thus, making model performance better in prediction. The last phase, model building which works on the basis of data set to create models, unravels the whole selection of algorithms, and their training for RUL prediction. The research team is currently evaluating multiple testing methodologies which include Decision Tree, NARX, RNN, and LSTM for assessment in RUL testing.

The model will complete its training phase to learn degradation patterns through historical battery data which will be then followed by evaluating the accuracy of the model using unidentified data. Standard error measurements, such as root mean square errors (RMSE), Integral Absolute Error (IAE), and Integral Squared Error, will be used in the performance evaluation (ISE).
The comparative results demonstrated that deep learning models which included LSTM models delivered better performance than traditional models because deep learning models maintained long-term temporal reality through their design.

### *A. Challenges and Limitations*

Although there have been notable developments in the field of Remain Useful Life (RUL) forecasting for lithium-ion batteries, there are still a number of obstacles to overcome before these predictions can be used practically in battery management systems. The major problem which requires solution exists because the system cannot handle extensive complex data sets.
The majority of studies until now have relied on laboratory data, including the NASA battery data set, which only provides partial, real-world operating condition simulations.
Battery models cannot be used in all situations because their performance depends on different battery chemistries and manufacturer designs and various operating conditions. The degradation mechanisms present challenges because their complex mechanisms of operation depend on multiple factors which include temperature and load changes and various aging modes and their combined effects with other systems. Machine learning and deep learning based models may show exceptional accuracy, However, their opaque character makes it challenging to comprehend how they generate their outcomes. The electric vehicle sector and aerospace industry pose major safety concerns because they require safety to be maintained at all times.

## IV. INTERPRETATION

Lithium-ion batteries, which have a large energy storage capability and a long battery life, are essential to the basic technology of contemporary energy storage systems, electric cars, renewable energy systems, and consumer electronics. Numerous factors, such as electrochemical reactions, temperature impacts, and The forces of nature that affect battery operation, cause the operating life of batteries in certain applications to deteriorate. Accurately estimating batteries' Remaining Effective Life (RUL) is crucial for operational safety, dependability, and cost-effectiveness.
The most commonly used maintenance strategies employ time-based and condition-based approaches; however, these approaches fail to handle the complex battery degradation processes which occur in nonlinear patterns. The system of predictive maintenance establishes operational efficiencies through its use of advanced battery models and real-time data to predict battery health status with higher precision. The proposed RUL-prediction models include three types of approaches which consist of physics-based methods that simulate the battery components' mechanisms, statistical models that approximate the probabilistic behavior of battery degradation, and data-driven methods such as deep learning and machine learning, which make it easier to identify patterns in both historical and current data.
Every method presents its benefits and drawbacks. The solution to the problem requires researchers to assess which approach delivers optimal results for three criteria. Data scarcity and feature selection problems together with uncertainty quantification challenges and the need to test different battery chemistries remain obstacles yet researchers continue developing advanced hybrid systems that use data-driven approaches. The accurate prediction of RUL establishes the foundation for advanced maintenance planning methods.

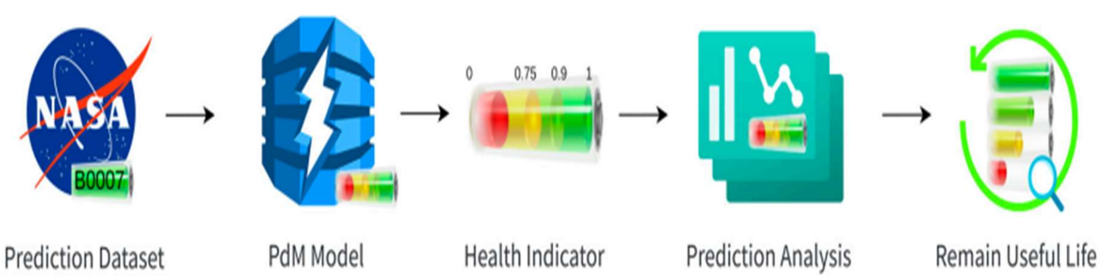


Figure 2. Flow of health indicator and remaining useful life

TABLE II LI-ON BATTERY PREDICTION METHODOLOGY FOR REMAINING USEFUL LIFE: TYPICAL STRUCTURE

| Model Physics- | Description |
|---|---|
| Based Models | Mimic battery reactions using electromechanical theories or equal circuits for elucidation of the material decays. |
| Statistical Models | Apply probabilistic and stochastic methods to estimate RUL from historical battery data. |
| Machine Learning Models | Use SVM, Random Forest, to Gradient Boosting to learn from past data and identify patterns of degradation. |
| Deep Learning Models | For precise remaining useful life estimation researchers should utilize LSTM networks or GRU networks or Transformer networks to capture intricate time-based relationships present in battery data. |
| Hybrid Models | The research work establishes a method for combining physics-based methods with data-driven techniques to achieve both explainable model output and precise prediction results. |

Scientists estimate the Remain Use Life (RUL) of lithium-ion cells primarily using the health markers shown in Figure 2. Scientists must first gather data by keeping an eye on critical battery parameters including current, temperature, voltage, and recharging and recharging cycle information. The data needed for this investigation comes from sensors and the battery management system (BMS). Researchers use appropriate pre-processing methods to extract features from the raw data of the battery management system which includes internal resistance and voltage fluctuation measurements and all essential capacity fade degradation indicators. One or more RUL model predictions are produced by extracting characteristics together with the power source state-of-health data. The RUL prediction process accepts different approaches which include physics-based methods and statistical techniques and machine learning and deep learning methods.

The estimated remaining lifespan or RUL predicted then carries through to the decision module that dictates actions regarding maintenance replacement or scheduling decisions for maintenance or optimization of operations. The system displays processed RUL results on dashboards which show either real-time data or moving averages according to the discharge scenario of the situation while a feedback loop indicates the system will keep running the same process with new data.

## V. FINDINGS

- When it comes to forecasting the Remaining Use Life (RUL) of lithium-ion batteries, machine learning as well as deep learning models outperform both physics-based or statistical approaches.
- The LSTM and Transformer network deep sequential models effectively predict nonlinear and long-term battery degradation using NASA Aging Dataset for their training.
- Incremental Capacity (IC) analysis together with CEEMDAN decomposition methods, serve as signal processing techniques that improve feature quality while making predictions more stable in noisy operating conditions.
- The hybrid models which merge signal decomposition with deep learning methods, produce the most accurate predictions, yet they require more computing power to operate.
- Conventional probabilistic approaches such as particle filters and Wiener process models provide better interpretability and uncertainty handling but show reduced accuracy under dynamic conditions. The use of transfer learning together with end-to-end frameworks enhances battery generalization, yet their usage remains restricted.
- The existing studies demonstrate a gap in creating frameworks that combine uncertainty handling with explainable features, which shows the requirement for secure and trustworthy Battery Management System integration.

## V. CONCLUSION

The report examines the latest advancements in Remaining Usage Life (RUL) projections for lithium-ion batteries. The study investigates four different forecasting approaches which include hybrid estimation and deep learning forecasting and machine learning forecasting and classical forecasting. The initial statistical and physics-based models faced challenges in simulating the nonlinear deterioration process which happened under various operational conditions while they successfully predicted uncertainty outcomes. Machine learning models require large datasets which contain information about degradation processes and aging processes to learn their patterns and build accurate models that can predict RUL intervals when used with deep sequential models which include LSTM and Transformer-based architectures. The combination of deep learning techniques with incremental capacity growth and CEEMDAN signal processing methods produces hybrid systems that achieve maximum performance results.

The progress made so far has not yet solved existing problems. The deep learning techniques that researchers developed face a critical obstacle because they require extensive labeled data but struggle to interpret results and lack mechanisms for assessing uncertainty, which makes their use in Battery Management Systems that need safety features impossible. Scientists need to focus more on finding solutions that enable batteries to function across different battery chemical compositions and various Battery operating conditions. The future needs to concentrate on creating frameworks that use physics knowledge while handling uncertainties and enabling transfer learning because these frameworks will provide systems that balance prediction accuracy with understandable results and efficient computational performance. The framework development work will establish a base which will support dependable predictive maintenance systems together with complete operational life cycle management of lithium-ion battery systems.

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