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Machine learning-driven prognostics for lithium-ion batteries: enhancing RUL prediction and performance in smart energy storage systems

Bodapati Venkata Rajanna[1], Aaluri Seenu[2], Kondragunta Rama Krishnaiah[3], Anantha Sravanthi Peddinti[4], Nelaturi Nanda Prakash[5], Bandreddi Venkata Seshukumari[6], Giriprasad Ambati[7], Shaik Hasane Ahammad[8], Chakrapani Srivardhan Kumar[9], Allamraju Shubhangi Rao[10]

[1]Department of Electrical and Electronics Engineering, MLR Institute of Technology, Hyderabad, India
[2]Department of Computer Science and Engineering, Shri Vishnu Engineering College for Women, Bhimavaram, India
[3]Department of Computer Science and Engineering, R K College of Engineering, Kethanakonda, India
[4]Department of Electronics and Communication Engineering, Aditya University, Surampalem, India
[5]Department of Electronics and Communication Engineering, Chalapathi Institute of Engineering and Technology, Guntur, India
[6]Department of Information Technology, VNR Vignana Jyothi Institute of Engineering and Technology, Hyderabad, India
[7]Department of Electrical and Electronics Engineering, VNR Vignana Jyothi Institute of Engineering and Technology, Hyderabad, India
[8]Department of Electronics and Communication Engineering, Koneru Lakshmaiah Education Foundation, Guntur, India
[9]Department of Electrical and Electronics Engineering, School of Engineering, Malla Reddy University, Hyderabad, India
[10]Department of Electrical and Electronics Engineering, Presidency University, Bangalore, India

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ABSTRACT

In the evolving landscape of energy systems, batteries play a critical role in enabling hybrid and stand-alone renewable energy storage solutions. Precisely estimating battery life and remaining useful operational life will go a long way in enhancing the efficiency of the system with assured reliability in smart power storage devices. This report comprehensively surveys advanced approaches in the management of batteries through state-of-the-art artificial intelligence tools-support vector machines, relevance vector machines (RVM), long short-term memory (LSTM) models, and bayesian filters-that are being used with a view to enhancing remaining useful life (RUL) estimates and making real-time system health monitoring capabilities possible. Modeling approaches surveyed include state estimation, capacity, and thermal management, while discussing their applicability to lithium-ion batteries. The review also explores publicly available battery datasets, feature engineering strategies, and hybrid diagnostic frameworks. A technoeconomic perspective is provided to assess system performance in renewable-integrated power grids. This paper aims to consolidate current knowledge, provide comparative insights into the strengths and limitations of different approaches, and highlight open research challenges to guide future developments in smart AI-enabled battery systems that support sustainable and resilient energy infrastructure.

Corresponding Author:

Bodapati Venkata Rajanna
Department of Electrical and Electronics Engineering, MLR Insitute of Technology
Hyderabad, India
Email: rajannabv2012@gmail.com

1. INTRODUCTION

Due to decline in fossil fuels, there is need for usage of more renewable energy resources with storage devices to meet the load demand during peak and off-peak times. Hence, batteries are used for storing the excess energy supplied by renewable sources in hybrid systems [1]. Batteries with high energy density, fast charging, wide operating temperature range, low self-discharging rate, and life cycle longevity can be employed in electric vehicles (EVs), portable electronics, biomedical devices, and for applications in industrial and transportation sectors with rising concerns in climate change, energy security, and sustainable development [2]. Lithium-ion batteries are widely used in industry due to their extended lifespan, high energy density, and small size, however they also have disadvantages like deterioration and safety concerns. Recent studies have stressed the need of accurate RUL estimates in applications such as electric vehicles and renewable energy systems.

Methods of battery life modeling, health monitoring, and RUL forecasting are discussed in terms of statistical, electrochemical, and machine learning [3]. This review addresses battery state estimation, data sets, and residual useful life predictions methods; developing battery management systems (BMS) and RUL prediction methods for enhancing the understanding of battery aging patterns in actual operation. Data acquisition and comprehensive Li-ion battery data resources focuses on the collection of battery data for the purpose of creating a machine learning-based prognostics and health management systems model revolving around public data repositories [4].

Health monitoring and feature extraction involves much more than collecting data, as it bolsters the functionality and precision of machine learning models by parsing raw data and refining the criticality of the extracted health indicators. Many researchers have attempted to develop dependable methods for health indicator detection to estimate the remaining useful life (RUL) of Li-ion battery cells accurately [5]-[7]. This value reflects the total number of charge-discharge cycles a battery cell can sustain before requiring replacement.

The remainder of this paper is organized as follows: Section 2 reviews BMS parameter estimation methods, section 3 discusses RUL prediction approaches, section 4 presents intelligent ML techniques for RUL and SOH, section 5 includes dataset resources and feature engineering strategies, section 6 synthesizes comparative insights and critical synthesis, section 7 analyzes performance optimization strategies in BMS, section 8 outlines future research directions and open challenges, and section 9 includes conclusion and future work of the paper. Furthermore, this paper reviews some existing techniques and provides a comparison of different machine learning methodologies based on advantages, disadvantages, and issues that remain unsolved, thus encouraging further contributions in AI fields.

2. BATTERY MANAGEMENT SYSTEM (BMS) PARAMETER ESTIMATION

Because of the complex design and nonlinear behavior of these cells, sophisticated algorithmic techniques are necessary in lithium-ion battery management systems enhancement. Calculating SOC and SOH with good accuracy is greatly important in effective BMS operations. The current segment starts by introducing basic ideas regarding SOC and SOH estimations and later provides an insight into some state-of-the-art developments being made using machine learning techniques together with advanced sensor innovations. The emphasis is on estimating SOC and SOH, highlighting any significant challenges and possible advantages identified for an informative understanding of how these components enhance battery efficiency, safety, and lifespan.

2.1. Examining the SOC and SOH estimate

The popular SOC estimation methods include lookup tables, coulomb counting, the artificial intelligence algorithms of neural nets, statistical learning through SVMs, electrical simulations using ELMs, physical theories utilized in EMF models, the experimental methodologies of ICA and DVA analyses, and machine-learning-based strategies involving datasets to make predictions [8]. State-of-charge and state-of-health estimation based on the newest methodology applies acoustic-ultrasonic stress waves in combination with piezoelectric sensors and strain gauges in order to closely monitor and understand the interrelation between these two parameters better. The degradation mechanisms affect the life span and the retention capacity of the battery; intrinsic qualities are reduced by active material loss, aging of the electrical conductance, and exhausted lithium inventory, probably initiating dendritic growth that may lead to self-discharge [9]. Differential analysis, voltage fitting algorithms, and AI for sensor data interpretation are among the various techniques applied to E-SoH, which provides important information about battery degradation while enhancing predictive maintenance in future battery control mechanisms.

2.2. SOP, SOE, and SOT estimation review

State of charge (SOC), state of health (SOH), state of power (SOP), state of energy (SOE), and state of time (SOT) should all be estimated by a thorough BMS [10]. SOP stands for useable power, SOE for available energy, and SOT estimationwhich is related to battery temperatureis less studied. While multi-state joint estimating is still a crucial research topic, hybrid estimations that include SOE and SOP have been examined.

2.3. SOS estimation review

With safety-oriented state (SOS) estimation improving efficiency and reliability, system safety is now crucial in battery management systems (BMS). Risks includingfires, explosions, and electrolyte leaks are addressed by improvements in SOS techniques, such as thermal runaway assessments. Internal short circuit tests used in thermal runaway investigations identify impacts and electrical failures as the primary causes of thermal runaway. Better safety and reliability performance are made possible by the combination of SOS with SOC, SOH, SOP, SOT, and SOE. The primary contributing factors are temperature, mechanical deformation, voltage, current, and temperature.

- Temperature: Because high temperatures increase the risk of thermal runaway in addition to fires and explosions, they harm other materials as well as the solid electrolyte interphase (SEI) layer. Low temperatures cause lithium to accumulate on negative electrodes, leading to internal short circuits and reduced capacity.
- Current: High current causes Joule heating in the battery, which, if improper management strategies are used, can lead to thermal runaway. Lithium plating and internal short circuit generation are both more likely to occur during the charging process.
- Voltage: Heat and fumes are produced when the electrolyte and positive electrode are overcharged, causing damage to both. The process of deep discharging cells raises the risk of short circuits by encouraging the growth of copper dendrites.
- State of charge (SOC): When a battery fails, high SOC values increase the likelihood of heat-related energy releases.
- State of health (SOH): Although aging processes cause structural failure and lithium plating circumstances that increase failure potential, older batteries' initial lower charge reduces their hazard.
- Electromechanical imbalance: The electromechanical imbalance occurs because of the change in pressure of the batteries due to different charge cycles, which results in decreasing performance and safety.
- Internal impedance: The increasing thickness of the SEI is one of the factors that contributes to the internal resistance within batteries, decreasing their energy storage capacity and general performance. This process amplifies ion loss within batteries, lowering their storage capability and efficiency levels. The most significant causes of malfunction in the LIB systems are overheating, malfunction of electronic stability control systems, and breakdown of insulation. A number of state-of-the-art methodologies will have to be researched, diagnosed, and simulated in emergency responses to enhance security and longevity. As energy storage demands continue to increase, batteries will ensure enhanced safety and efficiency through the development of protocols as changing circumstances are monitored.

3. APPROACHES FOR PREDICTING REMAINING USEFUL LIFE (RUL)

Estimating how much longer lithium-ion batteries will work safely without replacement defines a significant role in risk mitigation during usage, reduces maintenance costs, and enhances overall performance during operations. This section adopts a structured approach by first reviewing the basic theories underlying the modeling of reliability under uncertainty, including model-based, data-driven, and hybrid approaches. Then, it identifies contemporary research in this area by covering modern approaches such as dynamic filtering techniques, probability model approaches, and cognitive computing-based approaches. This section reviews the gaps in the current techniques and states the unsolved problems that need to be overcome to have practical applications in real-life situations. Precise estimation of a lithium-ion battery system performance involves state-of-health and RUL assessment that helps original equipment manufacturers decide on timely replacement cycles for associated data. The accurate estimates avoid malfunctioning of cell phones and improve overall device performance. Various predictive modeling techniques are adopted for resource utilization level estimation, including but not limited to methodological frameworks like theory-based and empirical model approaches developed directly from datasets, and hybrid techniques that merge elements of each category.

3.1. Model-based approaches

The model-driven approach relies on the use of equations modeling battery behavior to predict the remaining operational lifetime. These models are based either on mechanical laws or chemical reactions to model system wear and degradation phenomena, which denote performance loss. The update of state variables with sensor information increases knowledge of system degradation by analysis. However, using models requires the simulation of complex nonlinear chemical processes quite accurately, which is often difficult owing to practical issues. When there is a discrepancy between what the model predicts about batteries and the actual performance that leads to incorrect forecasts.

3.2. Data-driven approaches

The prediction of remaining useful life, using statistical techniques derived from large datasets of past bicycle usage patterns, is achieved by using advanced artificial intelligence models. Methods such as artificial intelligence models, which are trained on data, include algorithms for recognizing trends in measurements of electrical signals that include amplitude and frequency and thermal conditions. These methods identify complex nonlinear phenomena without requiring an extensive understanding of the underlying chemical processes. Success critically relies on available data sets that are adequate and diverse. Lack of general applicability to wide ranges of chemical systems, operating conditions, or other contexts is one of the main limitations. Remaining useful life-maintenance scheduling identifies how much longer each battery, EV, and machine will continue functioning before replacement. Applications include AI tools, statistical modeling, physical strategy approaches, and hybrids.

3.3. Methods based on statistical models

The models utilizing system information from the past predict the initial stages and progressions in wear-out scenarios. Their approach presents an analytical technique based on the statistical analysis of the performance metrics from the past, with no sole reliance on chronological assessments but instead utilization of comprehensive datasets through time. However, while these statistical models are immensely capable of dealing with abundant historical information, they lack flexibility in handling unexpected operational scenarios. They are also not capable of modeling complicated nonlinear changes as effectively as machine learning approaches.

3.4. Hybrid approaches

Theoretical knowledge obtained by modeling, together with the empirical observations by experimentation, enhances the precision in the predictions while making them more reliable. It is desirable to consider the metrics derived from physical models as input variables for artificial intelligence algorithms. Understanding and flexibility in problem-solving scenarios are increased when both traditional physics-based approaches and machine learning techniques come together. Their methods often outperform those from pure models alone in terms of precision and dependability. However, these hybrid architectures require significant computational power and resource-intensive tasks during both training and testing; they are, therefore, not feasible for practical use in real-time embedded battery management systems. Sensor information and degradation patterns are used to estimate remaining useful life. Here, the methods work by selecting relevant features, initiating a prediction when necessary, and assessing the condition of the system. Kalman filters and Bayesian approaches result in better performance in terms of accuracy.

3.5. Filter-based approaches

RUL of LIBs is essential to avoid breakdowns and ensure security since it offers an idea at what point a battery will start visible degradation in its performance. Risks are at a minimum when appropriate upkeep strategies are supported by correct predictions from precise RUL models. Though incapable of measuring the direct wear of a battery, remaining useful life estimates give important insights into the state of health of the battery. Other valuable techniques that are most helpful in further perfecting the models of remaining useful life prediction, with better accuracy in signal processing through filtering operations and validation of information in the isolated units, include adaptive filters, artificial intelligence strategies, probabilistic algorithms, and cell-level data analysis, among other methods [11]. These filter methods, including the Unscented Kalman filter and its variants, enhance estimation accuracy due to the lower levels of noise and dynamic adaptation ability in treating non-linear features of battery behavior. However, these systems require careful preliminary setup and parameter tuning for efficient performance and might also hinder effective use within limited microcontroller-based battery management system applications.

3.5.1. Adaptive filter techniques

Filters that are capable of mitigating signal disturbances form the basis of the prediction of remaining useful life in many applications. For the purpose of LIBs RUL prediction, the filter approach has undergone several major modifications:

- Unscented Kalman filter (UKF)

This paper proposes a novel approach for the SOH assessment through integrating impedance health features with an UKF. A state prediction model computes the SOH based on the number of times the cells are cycled, whereas a measurement prediction model forecasts the expected health indicator (HI) using the SOH estimation. As impedance measurements become available over the battery's life, the filter updates the estimates depending on the difference between expected and measured HI. Three model structures are examined and contrasted: feedforward neural networks (FNN), polynomial regression (PR), and Gaussian process regression (GPR). The suggested approach is validated using two open-source datasets totaling 51 cells. Dataset 2 contains 21 NMC111 cells aged using various methods, whereas dataset 1 has 30 NMC811 cells aged using a preset protocol at six universities.

Although the estimator can accurately estimate the SOH. With little dependency on the SOC level at which EIS is performed, the GPR models produce the lowest estimation error among the three model structures, with 1.4% for dataset 1 and 1.7% for dataset 2. This demonstrates how adaptable the estimator is to aging mechanisms and cell-to-cell differences [12]. To improve the precision and stability of battery SOC estimation, the UKF model is augmented with a FOLPF algorithm and presented. The suggested method's applicability and resilience are examined in HPPC information for several battery kinds [13]. The unscented Kalman filter (UKF) is widely used for nonlinear state estimation in battery management. The state and measurement models can be expressed as in (1) and (2).

The UKF (equations (1) and (2), Algorithm 1) is advantageous for handling nonlinear battery dynamics and provides accurate SOC/SOH estimation compared to linearized filters such as the extended Kalman filter.

$$x_{k+1} = f(x_k, u_k) + w_k \tag{1}$$

$$z_k = h(x_k) + v_k \tag{2}$$

Where $f(x_k, u_k)$ is the nonlinear state transition function, x_k is the state vector of the battery at time step k, u_k is the control input vector at time step k, $h(x_k)$ nonlinear measurement function, w_k and v_k denote process and measurement noise, respectively.

Algorithm 1. UKF for SOC/SOH estimation
1) Initialize state x_0, covariance P_0
2) Generate sigma points from (x_k,P_k)
3) Propagate sigma points through f (x,u)
4) Compute predicted mean and covariance
5) Update with measurement z using $h(x)$
6) Return updated state estimate x_{k+1}

The symbols used in (1) and (2) and Algorithm 1 are summarized in Table 1 for clarity. In the context of lithium-ion battery management, the state vector typically represents SOC and SOH, the control input corresponds to applied current or excitation, and the measurement vector includes terminal voltage and temperature readings.

Table 1. Definitions of variables in UKF state-space model

Symbol	Definition	Typical battery context
x_k	State vector at time step k	SOC, SOH, internal resistance, capacity
u_k	Control input vector at time step k	Applied current (charge/discharge), excitation
z_k	Measurement vector at time step k	Terminal voltage, current, temperature
$f(x_k, u_k)$	Non-linear state transition function	Governs how states evolve with dynamics
$h(x_k)$	Non-linear measurement function	Maps states to measurable outputs
w_k	Process noise (zero-mean, covariance Q)	Uncertainty in state evolution
v_k	Measurement noise (zero-mean, covariance R)	Sensor noise and disturbances
Q	Process noise covariance matrix	Tuning parameter (system dynamics uncertainty)
R	Measurement noise covariance matrix	Tuning parameter (sensor accuracy)
P	Estimation error covariance matrix	Confidence in filter's state estimate

In the UKF framework, three types of covariance matrices are used: process noise covariance (Q), measurement noise covariance (R), and estimation error covariance (P). While Q and R characterize uncertainties in the system and measurements, respectively, P is updated iteratively within the filter to represent the evolving confidence in the estimated states.

– Unscented particle filter (UPF)

Predicting the battery management system's remaining usable life (RUL) is critical [14]. This paper describes a remaining useful life (RUL) prediction approach for lithium-ion batteries with a dual filter, data-driven, model-based fusion algorithm. One distinguishing aspect of the framework is the concurrent online iteration of bifurcated fusion algorithm filters, which update both the battery's state of capacity degradation and the parameters of the LSSVM model. The unscented particle filtering (UPF) is used in ratio measurement equations to process fusion algorithms, which in turn supply the LSSVM model with virtual future measurements. In UPF processing, the uncertainty of the prognostic result is expressed by a probability density function (PDF) [15].

– Spherical cubature particle filter (SCPF)

A thevenin model is developed and a linear Kalman filter (LKF) is applied to estimate parameters in real-time. The results show that the convergence of LKF outperforms rheonomic least squares (RLS) and RLS with forgetting factor (RLS-FF) [16]. Also, instead of a 9th order polynomial fit, the equilibrium potential equation (EPE) is used to describe the OCV versus SoC relationship. An accurate model of the tested battery and a fast SoC estimation approach are required to improve the estimation accuracy of SoC [17]. The experiments were conducted on prismatic LiFePO4 batteries at room temperature under the New European Driving Cycle and Urban Dynamometer Driving Schedule.

It has been discovered that WMICKF exceeds both the multi-innovation CKF and the standard cubature Kalman filter in performance. WMICKF achieves a SoC estimation error of less than 1% (0.91%), which is lower than CKF's 1.30% and MICKF's 2.71%. The proposed technique is thoroughly tested by determining the mean absolute error (MAE), root mean square error (RMSE), and coefficient of determination (R-square). Furthermore, the resilience of WMICKF is demonstrated for a variety of noise disturbance types and initial SoC faults [18]. A 48 V system offers a low-cost vehicle electrification option that can decrease CO2 emissions by 15% to 20% while preserving the current automotive architecture. Charging and discharging cycles have stringent charging and discharging criteria, elevation for BMS in terms of accurate state estimation.

The first contribution of this paper is down to a multi-scale co-estimation approach in parameters of state of charge and state of health of 48 V battery system. First, we construct a framework for multi-scale estimate based on main features and parameters of the battery. Second, we derive the internal resistance of the battery using the equivalent circuit model with recursive least squares. Battery charge and capacity estimation are performed using advanced filtering techniques like cubature Kalman filter and H-infinity. The embedded BMS with high accuracy requirements also benefits from reduced computation resource demands through multi-timescale co-estimation approaches.

The evaluation of the method's approach consists of performing several simulations based on standard driving cycles. The outcomes are then analyzed alongside results produced from other industry approaches. Outcome results that validate the suggestion's approach is better than all other competing approaches by a mean absolute error 0.64% in capacity estimation and 0.88 in SOC.

4. INTELLIGENT ML TECHNIQUES FOR RUL AND SOH

4.1. Artificial intelligence (AI)

Figure 1 illustrates AI-based techniques that simulate degradation trends from observable data using machine learning. By determining failure thresholds and extrapolating degradation trends from past performance data, they forecast RUL. The architecture integrates multiple machine learning techniques, including artificial neural networks (ANN), support vector machines (SVM), relevance vector machines (RVM), deep neural networks (DNN), and hybrid AI approaches (ML combined with physics-based models), feeding into a centralized prediction engine for accurate battery diagnostics.

4.2. Methods based on physics

For systems such as batteries, physics-based approaches are helpful because they replicate the physical and chemical processes that lead to system deterioration. However, internal conditions are difficult to observe directly. As a result, modeling nonlinear processes such as battery degradation remains a challenge.

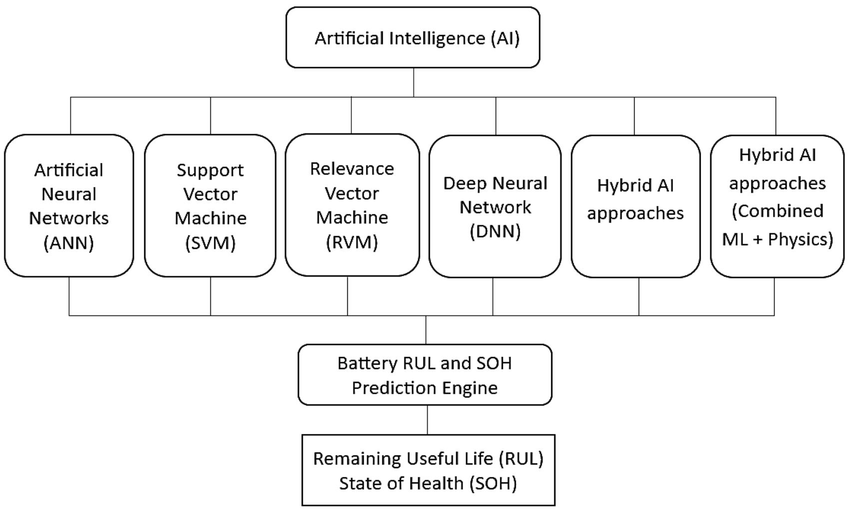

Figure 1. AI-based model for predicting battery remaining useful life (RUL) and state of health (SOH)

4.3. Hybrid methods

Also, combining different approaches still yields better performance: for example, by boosting the reliability of the estimates under load; an advanced machine learning system that deploys specific health metrics in conjunction with hybrid ensemble models made up of random vector functional links and extreme learning machines can achieve superior accuracy. The RUL model has its advantages but also limitations. In practical terms, traditional methods merged with analytical ones increase the reliability of prediction substantially as technology evolves. Complexities in batteries require more sophisticated methodologies such as machine learning and AI as important tools for their remaining useful life estimations and predictions of future states with high accuracy. The first section introduces an investigation on typical intelligent algorithms such as ANNs, SVMs, RVMs, and DNNs. Then it shows recent developments in each and relative efficiencies when benchmarked against different sets of data points. Last but not least, this section summarizes limitations regarding high data requirements, high computational resources, and low interpretability; at the same time, it reflects on its potential to significantly impact the future of battery management systems. The sophisticated processing of data and the creation of prediction algorithms concerning the remaining useful life (RUL) of lithium-ion batteries (LIBs) relies greatly on intelligent systems, especially those that utilize artificial intelligence (AI). These methods optimize accuracy and reliability of predictions with data from multiple sources. We will discuss executive AI-based approaches for RUL estimation as depicted in Figure 2.

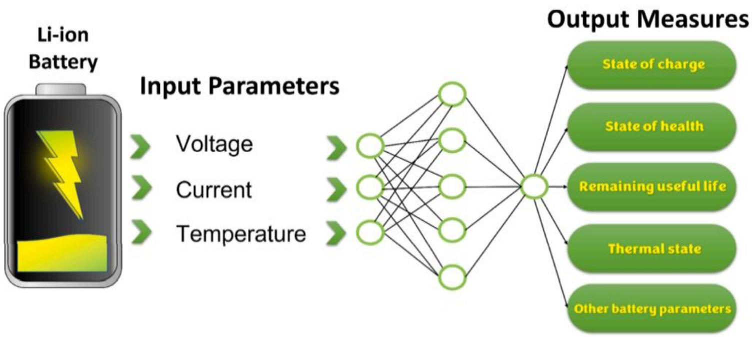

Figure 2. Different parameters evaluation for Li-ion battery using ANN

4.4. Artificial neural networks (ANNs)

Lithium-ion batteries cannot be evaluated with closed-form equations using measurable factors from outside the system. There exist many mathematical and electrical circuit models which aim to explain the working principles of lithium-ion batteries. All of these models have been shown to be somewhat inaccurate, overly sophisticated, and reliant on numerous operating conditions. This is why researchers have been studying the implementation of machine learning (ML) techniques that estimate the state of a battery from easily measurable parameters like discharge current, output voltage, surface temperatures of the cell and corresponding environment temperatures. Additionally, AI and ML strategies have been applied in the manufacturing processes of Li-ion batteries, performed processes related to recycling to assemble new battery packs for several subsequent uses, as well as predicting the mass of Li-ion batteries and their remaining useful life (RUL).

Artificial neural networks (ANN) that co-estimate the power and charge status have achieved significant success. These models are comprised of interconnected networks of nodes that simulate neurons in a human brain and are connected with signals analogous to biological synapses. Neural networks seek to replicate a human brain’s learning and reasoning processes by modifying the previously established weighted connections while trying to find relationships between system parameters during the learning phase. As reported in [19], artificial neural networks are trained on real-time data to predict the states of Li-ion batteries.

4.5. Support vector machines (SVM)

For efficient monitoring of battery management systems, the SOH and RUL of lithium-ion batteries (LIBs) need to be accurately assessed. Due to the complex internal chemical changes and nonlinear degradation of LIBs, direct evaluation of SOH and RUL is near impossible [20]. The TWSVM approach is used to tackle these difficulties and estimate SOH and RUL. In order to ascertain the most prominent drivers of degradation in battery performance, the constant current charging time of a lithium battery is treated as a health indicator (HI). Decomposition is performed using VMD and the importance of random forest features is used to compute the feature correlation scores [21].

Moreover, the global searching capability of COA is boosted through application of the differential evolution method along with good point set theory. SOH and RUL prediction models are created by optimizing TWSVM parameters using the improved convolution optimization algorithm (ICOA) [22]. Finally, the proposed models are validated using data from NASA and the CALCE lithium-ion batteries. Experimental results show that the suggested models achieve a relative error in RUL prediction ranging from -1.8% to 2%, with RMSE and MAPE for SOH and RUL prediction of no more than 0.007 and 0.0082, respectively. The proposed model outperforms existing models in terms of robustness and fit [23]. Support vector machines (SVM) is powerful for classification and regression in battery SOH/RUL estimation. Their optimization problem is formulated as shown in (3) and (4).

$$\min_{w,b,\xi} \frac{1}{2}\|w\|^2 + C\sum_{i=1}^{n}\xi_i \quad (3)$$

$$y_i(w \cdot \phi(x_i) + b) \geq 1 - \xi_i, \xi_i \geq 0 \quad (4)$$

The (3) and (4) and Algorithm 2 illustrate the standard SVM framework applied in SOH/RUL estimation. These formulations enable robust predictions even under small dataset conditions.

Algorithm 2. SVM for SOH/RUL prediction
1) Input training data $\{x_{i,}y_i\}$ for $i = 1, \dots . n$
2) Select kernel function $K(x_i, x_j)$
3) Solve quadratic optimization problem → obtain α_i (Lagrange multipliers)
4) Identify support vectors (samples with $\alpha_i > 0$) and compute weights
5) For a new sample x, predict:

$$f(x) = sign(\Sigma\alpha_i\, y_i\, K(x_i, x) + b) \quad (5)$$

In the dual formulation of SVM, α_i represents the Lagrange multiplier associated with the i^{th} training sample. Non-zero α_i corresponds to support vectors that define the decision boundary. The decision function $f(x)$ is then given by (5) as shown in Algorithm 2, which combines α_i labels y_i , and the kernel similarity function.

The variables used in the SVM optimization problem (equations (3), (4), and (5) and Algorithm 2) are summarized in Table 2. Both x_i and x_j represent training samples, where $\phi(x_i)$ and $\phi(x_j)$ denote their nonlinear transformations into a higher-dimensional feature space. The kernel function $K(x_i, x_j)$ computes their similarity in this space without explicitly evaluating $\phi(\cdot)$.

Table 2. Definitions of variables in SVM model

Symbol	Definition	Context in battery SOH/RUL estimation
x_i	Input feature vector of the i^{th} training sample	Measured battery data (voltage, current, temperature, and cycle count)
x_j	Input feature vector of the j^{th} training sample	Used when computing pairwise similarities in kernel space
y_i	Output label of the i^{th} sample	Target variable (e.g., SOH class, RUL value)
w	Weight vector (model parameters)	Defines the separating hyperplane in feature space
b	Bias term	Shifts the decision boundary from the origin
ξ_i	Slack variable for the i^{th} sample	Allows margin violations/misclassification tolerance
C	Regularization (penalty) parameter	Balances margin maximization and misclassification
$\phi(x_i)$	Nonlinear feature mapping of input x_i	Transforms each raw input into a higher-dimensional space
$\phi(x_j)$	Nonlinear feature mapping of input x_j	Used together with $\phi(x_i)$ when computing kernels
$K(x_i, x_j)$	Kernel function defined as $K(x_i, x_j) = \phi(x_i) \cdot \phi(x_j)$	Computes similarity in transformed space without explicit mapping
n	Number of training samples	Size of the available battery dataset
α_i	Lagrange multiplier for the i^{th} training sample (non-zero only for support vectors)	Weight assigned to support vector in decision boundary calculation

4.6. Relevance vector machines (RVM)

Although it does not necessitate a thorough understanding of the battery's complex electrochemical processes, the data-driven approach is unsuccessful for state of charge (SOC) fluctuations induced by fast changes in battery current. Currently, the majority of data-driven filtering research focuses on neural network-based algorithms, with little attention paid to the relevance vector machine (RVM) algorithm, which has the advantage of being able to manage small sample sizes, high sparsity, and probabilistic distributions. Motivated by this assumption, the current paper presents a novel fusion strategy, the Coulomb_AKF_OIRVM (CFR) algorithm, which intricately combines the optimized incremental RVM (OIRVM) with the Coulomb counting technique [24]. According to the test results, the CFR technique has a remarkable ability to generalize across a wide range of operating cycles and temperatures, demonstrating great estimation accuracy and durability. The experimental and public datasets had mean absolute error, maximum absolute error, determination coefficient, and average root mean square error of 0.85%, 0.25%, 0.2%, and 0.2%, respectively.

4.7. Deep neural networks (DNN)

To use lithium-ion batteries successfully and safely, the state of health (SOH) and remaining usable life (RUL) must be accurately evaluated. Because of their good nonlinear fitting, adaptability, and self-learning capabilities, neural networks are commonly employed to estimate the SOH and RUL of lithium-ion batteries. Convolutional neural networks (CNN) are efficient at extracting key features, whereas recurrent neural networks (RNN) are excellent at recording time information in series data; however, because CNN lacks the ability to learn time associations, traditional series models that combine CNN and RNN may result in information leakage. In this paper, we provide a unique parallel architecture that combines long short-term memory (LSTM) and temporal convolutional networks.

When compared to sequential CNN-RNN techniques, this synergistic architecture considerably improves the accuracy of SOH and RUL estimation for lithium-ion batteries by allowing the simultaneous extraction of spatial degradation features via TCN and dynamic temporal dependencies via LSTM. RUL estimation comparison, we evaluate the series and parallel models on publicly available battery data from Oxford University and the National Aeronautics and Space Administration (NASA). In datasets 1 and 2, SOH estimation precision improved totally by more than 29% and 37% respectively. Parallel models, with the assumption that an acceptable increment in time consumption can be allowed, may be as effective as series models for RUL estimation [25].

Even though DNNs can learn complex nonlinear relationships, they often face problems while processing temporal sequences due to issues of vanishing gradients. To get around this limitation, long short-term memory units of the recurrent neural networks were used in this work. the long short-term memory network is appropriate for state of health and remaining useful life estimation of the batteries, considering their various temporal relationships in the deterioration processes.

4.8. Long short-term memory (LSTM) networks

As in section four, we focus on deep neural networks. Seven excel at modelling complex nonlinear relationships but often find it difficult to model sequences due to the problem called vanishing gradients, which impairs their ability to learn long-term dependencies. To overcome this problem, researchers developed RNNs; however, these standard models suffer from unstable gradient issues during learning. Long short-term memory networks are an extension of RNNs where memory cells and gating mechanisms allow the network to choose whether or not to keep information from previous steps. This makes LSTMs particularly well-suited for battery state of health (SOH) and remaining useful life (RUL) prediction, where both short-term fluctuations (e.g., charge/discharge cycles) and long-term degradation trends must be modeled simultaneously. The governing equations of the LSTM cell are presented in (6)-(14), followed by the algorithmic implementation as shown in Algorithm 3 and detailed variable definitions as shown in Table 3.

$$f_t = \sigma\left(W_f[h_{t-1}, x_t] + b_f\right) \tag{6}$$

$$i_t = \sigma(W_i[h_{t-1}, x_t] + b_i) \tag{7}$$

$$\widetilde{C_t} = \tanh(W_c[h_{t-1}, x_t] + b_c) \tag{8}$$

$$C_t = f_t \odot C_{t-1} + i_t \odot \widetilde{C_t} \tag{9}$$

$$o_t = \sigma(W_o[h_{t-1}, x_t] + b_o) \tag{10}$$

$$h_t = o_t \odot \tanh(C_t) \tag{11}$$

$$\widehat{y_t} = f\left(h_t; W_y, b_y\right) \tag{12}$$

$$\widehat{y_t} = W_y\, h_t + b_y \tag{13}$$

$$\widehat{y_t} = Softmax\left(W_y\, h_t + b_y\right) \tag{14}$$

Algorithm 3. LSTM procedure for battery SOH/RUL prediction
1. Input time-series training data $\{x_t, y_t\}$ for t = 1,…,T
2. Initialize LSTM parameters: weights $\{W_f, W_i, W_o, W_c, W_y\}$, biases $\{b_f, b_i, b_o, b_c, b_y\}$, hidden state $h_0$000, and cell state C_0
3. For each time step t = 1,…, T:
   a. Compute forget gate: $f_t = \sigma\left(W_f[h_{t-1}, x_t] + b_f\right)$
   b. Compute input gate: $i_t = \sigma(W_i[h_{t-1}, x_t] + b_i)$
   c. Compute candidate cell state: $\widetilde{C}_t = \tanh(W_c[h_{t-1}, x_t] + b_c)$
   d. Update cell state: $C_t = f_t \odot C_{t-1} + i_t \odot \widetilde{C}_t$
   e. Compute output gate: $o_t = \sigma(W_o[h_{t-1}, x_t] + b_o)$
   f. Update hidden state: $h_t = o_t \odot \tanh(C_t)$
4. After final time step t, use hidden state h_t for prediction $\hat{y}_t = f\left(h_t; W_y, b_y\right)$
For regression (SOH/RUL): $\hat{y}_t = W_y h_t + b_y$
For classification: $\hat{y}_t = Softmax\left(W_y h_t + b_y\right)$
5. Train the network by minimizing loss function L($\hat{y}$,y) between predicted output $\hat{y}_t$ and ground truth y_t
– Mean squared error (MSE) for regression
– Cross-entropy loss for classification
  Update weights and biases using backpropagation through time (BPTT) with optimizer (e.g., Adam, SGD)
6. For inference, feed new input sequence $\{x_t\}$ into trained LSTM to predict SOH or RUL

In summary, LSTM networks offer significant advantages over conventional ANN and DNN architectures when applied to battery prognostics. Cellular state and control processes inform the use of Long Short-Term Memory networks in spotting fluctuations over small timescales coupled with longer-scale patterns indicative of equipment deterioration, which constitute the main basis for precise SOH and RUL estimations. Unlike static models that rely on hand-designed features, LSTM networks inherently learn sequential patterns from the data without explicit preprocessing, further improving robustness to perturbations and nonlinear dynamics. This is what enables generalization under variant cycling conditions, making them suitable for practical applications of battery management systems. However, challenges such as high computational cost and training time remain, motivating the exploration of lightweight LSTM variants and hybrid approaches in future work.

Table 3. Definitions of variables in LSTM model

Symbol	Definition	Context in battery SOH/RUL estimation
x_t	Input vector at time step t	Battery measurement data at time t (voltage, current, temperature, and cycles)
h_{t-1}	Hidden state from previous time step $t-1$	Captures temporal dependencies from past battery states
h_t	Hidden state at current time step t	Output feature representation for prediction (SOH or RUL)
C_{t-1}	Cell state from previous time step $t-1$	Long-term memory carrying degradation history
C_t	Updated cell state at time step t	Stores long-term degradation features
$\widetilde{C}_t$	Candidate cell state (proposed update before gating)	Represents new degradation information to be integrated into memory
f_t	Forget gate activation vector	Controls what fraction of past cell state is retained
i_t	Input gate activation vector	Controls how much new input information enters the cell
o_t	Output gate activation vector	Controls how much of the cell state is exposed to hidden state
$\hat{y}_t$	Predicted output at time step t, computed from hidden state h_t	Estimated SOH (%) or RUL (remaining cycles)
y_t	Ground-truth label at time step t	Actual SOH or RUL from dataset
W_f, W_i, W_o, W_c	Weight matrices for forget, input, output, and cell gates	Learned parameters mapping $[h_{t-1}, x_t]$ to gate activations
W_y	Weight matrix of final output layer	Maps hidden state h_t to prediction $\hat{y}_t$
b_f, b_i, b_o, b_c	Bias vectors for forget, input, output, and cell gates	Learned parameters that shift activations
b_y	Bias vector of final output layer	Shifts final prediction output
$\sigma(\cdot)$	Sigmoid activation function	Normalizes gate outputs between 0 and 1
$\tanh(\cdot)$	Hyperbolic tangent activation function	Scales values between –1 and 1 for nonlinearity
$\odot$	Element-wise multiplication	Combines gate activations with states

5. DATASETS AND FEATURE ENGINEERING

Standardized datasets play a critical role in enabling ML-based prognostics and health management of lithium-ion batteries. Several widely used datasets include NASA, CALCE, Oxford, and MIT repositories, which provide experimental data across different chemistries, charging protocols, and degradation conditions. Lithium-ion and lithium cobalt oxide batteries are just some of the many batteries with publicly accessible datasets, including some collected by NASA and CALCE. SNL-NASA, CALCE-MIT, and Oxford datasets along with the MIT datasets give experimental data on the types of batteries, new charging methods, the depth of discharge, and performance over time in both cyclic and static aging tests.

6. COMPARATIVE INSIGHTS AND CRITICAL SYNTHESIS

6.1. Comparative analysis of machine learning techniques

To enhance clarity and provide a quick overview of different intelligent methods, a comparative analysis is summarized in Table 4. This table highlights the main advantages, limitations, and application suitability of commonly used machine learning approaches for lithium-ion battery management. A detailed comparative summary of the performance characteristics of key ML models is provided in Table 5.

Besides the qualitative comparison in Table 4, we further give a quantitative-style comparative summary in Table 5 about the widely used machine learning models. The table compares the performances of each model in multi-dimensions, including but not limited to accuracy, robustness, data requirements, computation cost, and suitable application scenarios. Combining both qualitative and quantitative perspectives, the analysis provides readers with a much clearer view of the trade-offs involved in selecting appropriate models for specific battery management applications.

Table 4. Comparison of machine learning techniques for battery management systems

ML technique	Advantages	Limitations	Suitable applications
Artificial neural networks (ANN)	Strong nonlinear modeling capability; learns directly from raw sensor data	Prone to overfitting; requires large training datasets	SOC and SOH estimation, multi-parameter prediction
Support vector machines (SVM)	High accuracy with small datasets; robust to noise	Limited scalability for large datasets; kernel selection is critical	SOH and RUL classification
Relevance vector machines (RVM)	Provides probabilistic outputs; effective for sparse and small datasets	Slower training; limited adoption in large-scale BMS	SOC and RUL estimation under limited data
Deep neural networks (DNN, including CNN, LSTM)	Captures spatial–temporal features; highly accurate for sequential battery data	Computationally expensive; low interpretability	RUL prediction, real-time diagnostics with large datasets
Hybrid models (physics + ML)	Incorporates domain knowledge; improves generalization and robustness	Higher complexity; requires extensive training	Safety-critical BMS, edge deployment in EVs and grids

Table 5. Comparative summary of machine learning models for lithium-ion battery SOH and RUL estimation

Model	Accuracy	Robustness	Data needs	Computation	Suitable use case
ANN	High	Moderate	Large	Medium	SOH estimation
SVM	Moderate	High	Medium	Low	RUL prediction
RVM	High	High	Small	Medium	Sparse datasets
LSTM	Very High	Moderate	Large	High	Time-series RUL

6.2. Flow diagram of ML techniques in battery management

Complementing the information given in the comparison table, Figure 3 presents a flow diagram, where machine learning approaches have been categorized according to the type of input data and their corresponding output parameters. The flow diagram depicts the general process of applying machine learning techniques in the battery management system. The process starts from the input data sources, including direct sensor measurements like voltage, current, and temperature, which are supplemented with historical datasets that represent long-term cycling and aging behavior of lithium-ion batteries. These inputs are processed through several machine learning models including ANN, SVM, RVM, DNN, and hybrid approaches that integrate physics-based knowledge with data-driven learning. The outputs of these models correspond to the key battery management parameters, including SOC, SOH, RUL, and SOS. By connecting input data to predictive models and essential output states, the diagram shows how machine learning provides a structured framework for accurate diagnostics, prognostics, and optimization in advanced battery systems.

6.3. Narrative synthesis

Comparative analysis and flow mapping in Table 1 and Figure 3 show that although machine learning techniques have so far remarkably advanced lithium-ion battery management, each approach carries its unique strengths and limitations that influence its suitability for practical deployment. A critical synthesis of these methods identifies three key dimensions of comparison, namely predictive accuracy, computational feasibility, and interpretability.

6.3.1. Model-based vs. data-driven approaches

Model-based methods can interpret the degradation physics but depend strongly on precise electrochemical modeling that is often challenging to implement for changing operating conditions. On the other hand, the data-driven approaches, including ANN and SVM, can circumvent explicit physical modeling and have demonstrated high accuracy in cases where sufficient datasets are available. However, their reliance on data quality limits their transferability across different chemistries and to real-world conditions.

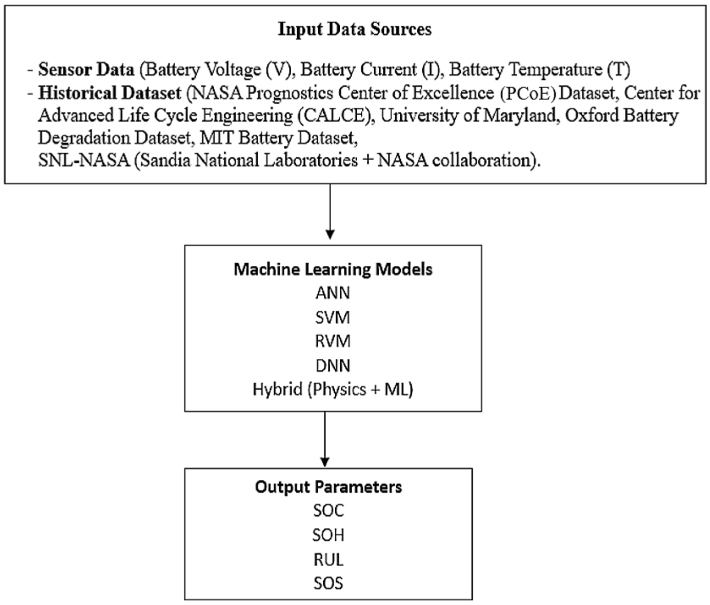

Figure 3. Flow diagram of machine learning techniques applied in battery management systems

6.3.2. Filter-based approaches

Adaptive filtering approaches, including unscented Kalman filters (UKF), unscented particle filters (UPF), and spherical cubature particle filters (SCPF), introduce robustness against noise and uncertainty associated with sensor data. Though these approaches come in very useful in real-time estimations, they generally require careful tuning of parameters and may impose computational burdens whenever deployed for large-scale BMS applications.

6.3.3. Intelligent ML methods

Thus, neural networks, in particular deep learning architectures, such as CNN and LSTM, have shown excellent performance in capturing nonlinear dynamics and temporal dependencies for RUL prediction and SOH estimation. However, their high computational demand and low interpretability remain significant barriers to embedded hardware implementation. On the other hand, lightweight methods like SVM and RVM work well with small datasets and offer probabilistic interpretations but fail to scale on complex high-dimensional degradation data. Hybrid physics-ML approaches embed domain knowledge into data-driven models, which results in an improvement of generalization and robustness. However, complex training requirements, apart from model development complexity, limit the real-time applicability of such methods.

6.3.4. Performance optimization strategies

Thermal management, cell balancing, and calibration techniques help prolong the life of a battery and improve its safety. While these techniques are indeed useful in a lab or controlled environment, integrating them with ML-driven predictive models in a compact, energy-efficient manner is still an active area of research. Non-invasive diagnostic techniques such as neutron imaging offer valuable insights into battery behavior, but are not yet practical for widespread commercial use in BMS.

6.3.5. Cross-cutting challenges

Three open issues that will be critical in the next generation of smart BMS arise from this comparative review:

- Generalizability: Most ML models perform very well on benchmark datasets but fail when applied to different battery chemistries, manufacturers, or operating conditions.

- Computational feasibility: Advanced ML and hybrid models are too resource-intensive, often beyond the capability of most embedded BMS hardware.
- Explainability and safety: In safety-critical applications such as electric vehicles and grid-scale storage, predictions need to be not only accurate but also interpretable for diagnostics and regulatory compliance.

6.4. Synthesis

No single methodology is sufficiently universal. Model-based approaches provide insight but come with restricted adaptability, while data-driven approaches provide accuracy but lack interpretability, and hybrid approaches improve robustness at high complexity. The most promising direction seems to develop lightweight, explainable, and hybrid ML models that balance accuracy with interpretability and computational feasibility. Such frameworks, supported by standardized datasets and benchmarking protocols, will reliably enable AI-enabled BMS in electric vehicles, renewable-integrated grids, and other mission-critical applications.

7. PERFORMANCE OPTIMIZATION IN BMS

The different aspects involved are thermal management, capacity management, imaging, calibration, and BMS.

7.1. Thermal management of batteries (BTM)

The low thermal conductivity of phase change materials makes them suitable for a battery thermal energy management system since they can give improved performance and better cycle life [8]. Battery temperature can degrade performance and cause localized damage owing to uneven distribution inside the battery pack. Maintain temperature homogeneity within and between cells to ensure the longest cycle life. The thermal energy management unit should be in the range of [9]. Minor temperature changes occur within cells and modules. The product's tiny, lightweight design, dependability, low cost, and ease of use make it an attractive option. Also provides a brief analysis of control variables in active cell balancing and discusses optimization strategies for battery management systems (BMS) [10].

7.2. Management of capacity

The studies make use of electrochemical impedance spectroscopy for Li-Tec 40 Ah batteries and online capacity estimation. Current profiles combined with health indicators are used to present online condition assessment. These indicators further enable probabilistic remaining useful life (RUL) prediction.

7.3. Imaging using battery neutrons

Neutron imaging is considered a critical non-destructive technique in the handling of Li-ion batteries. It provides highly accurate monitoring of the dynamics of lithium concentration, aging, and degradation. It is also used to diagnose capacity fading during discharge.

7.4. Calibration of voltage and current

Accurate voltage and current calibration is important for efficient battery management. It enables effective detection of Li-ion voltage and the factors affecting battery lifespan. This, in turn, improves condition assessment and enhances battery management techniques.

8. FUTURE RESEARCH DIRECTIONS AND OPEN CHALLENGES

Despite the significant developments in machine learning-enabled battery management, several open challenges persist before these methods can be reliably adopted into commercial BMSs. The following key research directions can help address the current limitations to further develop next-generation AI-enabled energy storage solutions.

8.1. Standardized and diverse datasets

Most of the existing ML models are trained on laboratory datasets such as NASA, CALCE, and Oxford, which may not reflect the variability of real-world operating conditions. There is a pressing need for standardized, large-scale, openly shared data sets that include diverse chemistries, duty cycles, environmental conditions, and failure modes. Benchmarking frameworks should be developed in order to enable fair performance comparison across methods.

8.2. Lightweight and embedded-friendly algorithms

Most of the advanced ML models, especially deep neural networks, are computationally expensive and not suitable for real-time embedded systems. Future work will be geared towards lightweight architecturespruning, quantization, and edge AI models. These approaches aim to balance predictive accuracy with low memory and energy requirements, enabling effective deployment in electric vehicles, drones, and stationary storage.

8.3. Explainable and trustworthy AI

Safety-critical applications require accuracy but also necessitate interpretable outputs to support diagnostics and fault detection, among other aspects. Research in XAI applied to battery management is at an early stage. Physics-informed ML, attention mechanisms, and feature attribution techniques improve the transparency of AI predictions and will foster trust in AI forecasts.

8.4. Physics–ML integration

Hybrid models that integrate electrochemical insights into ML are much promising in enhancing generalization and robustness. Further efforts on investigating physics-informed neural networks, grey-box modeling, and cosimulation frameworks that exploit the strengths of both approaches are warranted. This direction may also reduce the amount of data required for training while preserving interpretability.

8.5. Transfer learning and domain adaptation

The properties of batteries vary widely depending on the different manufacturers, chemistries, and operating environments. Transfer learning, domain adaptation, and federated learning may enable models trained on one dataset to generalize across conditions without requiring retraining from scratch. This can accelerate the practical use of ML models across a wide range of applications.

8.6. Integration with performance optimization

Future BMS will need to go well beyond estimation and prediction toward actively optimizing battery performance in real time. This implies a deeper integration of RUL and SOH prediction models with thermal management, balancing, and calibration strategies. In order to prolong the life of the battery efficiently while ensuring safety, research will be necessary regarding closed-loop intelligent BMS frameworks.

8.7. Cybersecurity and reliability

As BMS increasingly rely on data-driven algorithms, ensuring resilience against data corruption, cyber-attacks, and sensor malfunctions would be essential. Research should aim at fault-tolerant and secure ML models. These models must be able to maintain stability under adversarial conditions.

8.8. Summary

The path ahead needs a multidisciplinary combination of data science, controls engineering, materials science, and embedded hardware design. Addressing these challenges would lead to future BMS. This evolution will lead to intelligent, trustworthy, and energy-efficient systems that enable widespread use of electric vehicles and renewable energy storage.

9. CONCLUSION

The following review details the machine learning methods developed to estimate battery SOH and RUL in a structured manner. Amongst them, LSTM networks have indeed shown superior performance on modeling timeseries degradation patterns, while SVM provided computational efficiency for smaller datasets. Hybrid approaches such as LSTM+Kalman filtering further improved robustness against noise. By consolidating mathematical formulations, comparative insights, and the publicly available dataset analysis, this work offers a comprehensive reference to both researchers and practitioners. The critical evaluation of model strengths and limitations brings up both the opportunities and practical challenges in deploying ML-based prognostics in real-world BMS.

Stability and reliability in a range of battery-powered applications necessitate an accurate RUL forecast. Numerous internal and external elements, including electrochemical processes, battery material, temperature, techniques, and battery age, have an impact on the RUL forecast. Significant effort has been done to create reliable and accurate RUL prediction techniques in order to overcome these problems. Here is a quick rundown of the main conclusions: i) Lithium-ion battery RUL prediction has been widely tested utilizing a range of model-based, data-driven, and hybrid methodologies. The analysis considers numerous elements, including categories, approaches, traits, contributions, benefits, drawbacks, and research gaps. The findings indicate that model-based approaches can be utilized to extensively investigate internal battery aging, and data-driven approaches can be applied to earlier battery data to predict RUL. Furthermore, hybrid models produce better results than single models; nevertheless, in order to produce suitable results, the hybrid models need a powerful computer for model training and have a complex model structure; ii) The evaluation looks closely at important implementation variables such data collection, data resources, data features, data preprocessing, computational capacity, and model features. The elements that affect RUL implementation are examined. From data collection to the RUL prediction results, prediction is essential. Therefore, for satisfying performance and results, appropriate selection of various implementation aspects should be carried out; iii) Battery aging, battery profile, model framework, model operational, and real-world battery data concerns are among the major limitations and challenges mentioned. It has been found that the problems listed below reduce the RUL prediction framework's accuracy. Consequently, advanced to solve the current problems, a strong framework for doing the RUL prediction should be created; iv) Finally, many key recommendations and opportunities for improving RUL prediction techniques are offered. The identified future initiatives and possibilities would contribute to improving the precision and effectiveness of RUL prediction. The thorough review's in-depth research, model evaluation, difficulties, and prospects will be extremely useful to scholars, governments, and enterprises all around the world. Developing and conducting additional research on predicting the RUL of lithium-ion battery storage systems. Furthermore, the information provided would aid in improving battery performance and delivering sustainable energy with high dependability and efficiency, hence lowering greenhouse gas emissions and contributing to the achievement of the SDGs and global decarbonisation targets. Beyond consolidating the existing methods, this review presents a critical comparison of approaches and outlines the open research challenges, thereby guiding the development of next-generation AI-enabled battery systems.

Future research should be directed toward integrating machine learning models with edge computing platforms for real-time, low-latency battery management systems. There is an urgent need for standardized datasets and benchmarking protocols to ensure comparability across different algorithms and reproducibility of research results. It will be crucial to develop lightweight, computationally efficient, interpretable ML models that are deployable in resource-constrained embedded BMS hardware. Hybrid methods, combining ML with physics-based models or filtering techniques, hold strong promise for improving both accuracy and robustness across a wide range of operating conditions.

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Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Bodapati Venkata Rajanna	✓	✓	✓	✓	✓	✓		✓	✓	✓			✓	
Aaluri Seenu	✓	✓	✓	✓	✓	✓		✓	✓	✓			✓	
Kondragunta Rama Krishnaiah		✓				✓		✓	✓	✓	✓	✓		
Anantha Sravanthi Peddinti	✓		✓	✓			✓			✓	✓		✓	✓
Nelaturi Nanda Prakash		✓				✓		✓	✓	✓	✓	✓		
Bandreddi Venkata Seshukumari	✓		✓	✓			✓			✓	✓		✓	✓
Giriprasad Ambati	✓		✓	✓			✓			✓	✓		✓	✓
Shaik Hasane Ahammad		✓				✓		✓	✓	✓	✓	✓		
Chakrapani Srivardhan Kumar	✓	✓	✓	✓	✓		✓	✓	✓			✓		
Allamraju Shubhangi Rao	✓	✓	✓	✓	✓	✓		✓	✓	✓			✓	

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo: **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper. Authors state no conflict of interest.

DATA AVAILABILITY

The authors have confirmed that the data supporting the findings of this study are available within the article.

REFERENCES

[1] Z. Wang, Q. Zhai, and L. Shen, "Degradation modeling and RUL prediction in dynamic environments using a wiener process with an autoregressive rate," *IEEE Transactions on Reliability*, vol. 73, no. 2, pp. 912–921, 2024, doi: 10.1109/TR.2023.3319497.

[2] S. Bamati and H. Chaoui, "Lithium-ion batteries long horizon health prognostic using machine learning," *IEEE Transactions on Energy Conversion*, vol. 37, no. 2, pp. 1176–1186, 2022, doi: 10.1109/TEC.2021.3111525.

[3] M. Catelani, L. Ciani, R. Fantacci, G. Patrizi, and B. Picano, "Remaining useful life estimation for prognostics of lithium-ion batteries based on recurrent neural network," *IEEE Transactions on Instrumentation and Measurement*, vol. 70, 2021, doi: 10.1109/TIM.2021.3111009.

[4] S. Wang, R. Zhou, Y. Ren, M. Jiao, H. Liu, and C. Lian, "Advanced data-driven techniques in AI for predicting lithium-ion battery remaining useful life: a comprehensive review," *Green Chemical Engineering*, vol. 6, no. 2, pp. 139–153, 2025, doi: 10.1016/j.gce.2024.09.001.

[5] M. Samykano, "Advancing battery thermal management: future directions and challenges in nano-enhanced phase change materials-based systems," *Progress in Materials Science*, vol. 148, 2025, doi: 10.1016/j.pmatsci.2024.101388.

[6] H. Togun *et al.*, "A comprehensive review of battery thermal management systems for electric vehicles: enhancing performance, sustainability, and future trends," *International Journal of Hydrogen Energy*, vol. 97, pp. 1077–1107, 2025, doi: 10.1016/j.ijhydene.2024.11.093.

[7] V. S. Rao, G. S. Sajja, V. B. Manur, S. Arandhakar, and V. B. M. Krishna, "An exploratory study on intelligent active cell balancing of electric vehicle battery management and performance using machine learning algorithms," *Results in Engineering*, vol. 25, 2025, doi: 10.1016/j.rineng.2025.104524.

[8] B. Yao *et al.*, "State-of-charge estimation for lithium-ion batteries based on modified unscented Kalman filter using improved parameter identification," *International Journal of Electrochemical Science*, vol. 19, no. 5, 2024, doi: 10.1016/j.ijoes.2024.100574.

[9] W. Zhang, R. Ahmed, and S. Habibi, "State-of-health estimation for lithium-ion batteries based on electrochemical impedance spectroscopy measurements combined with unscented Kalman filter," *Journal of Power Sources*, vol. 625, 2025, doi: 10.1016/j.jpowsour.2024.235450.

[10] S. Fu *et al.*, "State of charge estimation of lithium-ion phosphate battery based on weighted multi-innovation cubature Kalman filter," *Journal of Energy Storage*, vol. 50, 2022, doi: 10.1016/j.est.2022.104175.

[11] Z. Ning, Z. Deng, J. Li, H. Liu, and W. Guo, "Co-estimation of state of charge and state of health for 48 V battery system based on cubature Kalman filter and H-infinity," *Journal of Energy Storage*, vol. 56, 2022, doi: 10.1016/j.est.2022.106052.

[12] X. Li, Y. Ma, and J. Zhu, "An online dual filters RUL prediction method of lithium-ion battery based on unscented particle filter and least squares support vector machine," *Measurement: Journal of the International Measurement Confederation*, vol. 184, 2021, doi: 10.1016/j.measurement.2021.109935.

[13] A. G. Olabi *et al.*, "Artificial neural network driven prognosis and estimation of lithium-ion battery states: current insights and future perspectives," *Ain Shams Engineering Journal*, vol. 15, no. 2, 2024, doi: 10.1016/j.asej.2023.102429.

[14] L. Yang, H. Ma, Y. Zhang, and W. He, "Joint estimation of SOH and RUL for lithium-ion batteries based on improved twin support vector machine," *Energy Engineering: Journal of the Association of Energy Engineering*, vol. 122, no. 1, pp. 243–264, 2025, doi: 10.32604/ee.2024.057500.

[15] C. Wang, X. Zhang, X. Yun, and X. Fan, "A novel hybrid optimized incremental relevance vector machine and filtering technique for state of charge estimation of lithium-ion batteries," *Journal of Energy Storage*, vol. 90, 2024, doi: 10.1016/j.est.2024.111908.

[16] S. Zhu *et al.*, "State of health and remaining useful life estimation of lithium-ion battery based on parallel deep learning methods," *International Journal of Electrochemical Science*, vol. 20, no. 5, 2025, doi: 10.1016/j.ijoes.2025.100988.

[17] A. Jossen, "Fundamentals of battery dynamics," *Journal of Power Sources*, vol. 154, no. 2, pp. 530–538, 2006, doi: 10.1016/j.jpowsour.2005.10.041.

[18] 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.2015.11.042.

[19] Y. Zhang, R. Xiong, H. He, and M. G. Pecht, "Long short-term memory recurrent neural network for remaining useful life prediction of lithium-ion batteries," *IEEE Transactions on Vehicular Technology*, vol. 67, no. 7, pp. 5695–5705, 2018, doi: 10.1109/TVT.2018.2805189.

[20] K. Liu, Y. Shang, Q. Ouyang, and W. D. Widanage, "A data-driven approach with uncertainty quantification for predicting future capacities and remaining useful life of lithium-ion battery," *IEEE Transactions on Industrial Electronics*, vol. 68, no. 4, pp. 3170–3180, 2021, doi: 10.1109/TIE.2020.2973876.

[21] Z. Du, L. Zuo, J. Li, Y. Liu, and H. T. Shen, "Data-driven estimation of remaining useful lifetime and state of charge for lithium-ion battery," *IEEE Transactions on Transportation Electrification*, vol. 8, no. 1, pp. 356–367, 2022, doi: 10.1109/TTE.2021.3109636.

[22] B. Chinomona, C. Chung, L. K. Chang, W. C. Su, and M. C. Tsai, "Long short-term memory approach to estimate battery remaining useful life using partial data," *IEEE Access*, vol. 8, pp. 165419–165431, 2020, doi: 10.1109/ACCESS.2020.3022505.

[23] Y. Wu, Q. Xue, J. Shen, Z. Lei, Z. Chen, and Y. Liu, "State of health estimation for lithium-ion batteries based on healthy features and long short-term memory," *IEEE Access*, vol. 8, pp. 28533–28547, 2020, doi: 10.1109/ACCESS.2020.2972344.

[24] S. Cui and I. Joe, "A dynamic spatial-temporal attention-based GRU model with healthy features for state-of-health estimation of Lithium-Ion batteries," *IEEE Access*, vol. 9, pp. 27374–27388, 2021, doi: 10.1109/ACCESS.2021.3058018.

[25] S. A. Hasib *et al.*, "A comprehensive review of available battery datasets, RUL prediction approaches, and advanced battery management," *IEEE Access*, vol. 9, pp. 86166–86193, 2021, doi: 10.1109/ACCESS.2021.3089032.

BIOGRAPHIES OF AUTHORS

Bodapati Venkata Rajanna is currently working as an associate professor in Department of Electrical and Electronics Engineering at MLR Institute of Technology, Hyderabad, India. He received B.Tech. degree in electrical and electronics engineering from Chirala Engineering College, JNTU, Kakinada, India, in 2010, M.Tech. degree in power electronics and drives from Koneru Lakshmaiah Education Foundation, Guntur, India, in 2015, and Ph.D. in electrical and electronics engineering at Koneru Lakshmaiah Education Foundation, Guntur, India, in 2021. His current research includes, dynamic modeling of batteries for renewable energy storage, battery management systems (BMS) for electric vehicles and portable electronics applications, renewable energy sources integration with battery energy storage systems (BESS), smart metering and smart grids, micro-grids, automatic meter reading (AMR) devices, GSM/GPRS and power line carrier (PLC) communication, and various modulation techniques such as QPSK, BPSK, ASK, FSK, OOK, and GMSK. He can be contacted at email: rajannabv2012@gmail.com.

Aaluri Seenu received his B.Tech. degree in computer science and engineering from Kakatiya University, India, and the M.Tech. and Ph.D. in computer science and engineering from JNTUH and ANU, respectively. Currently, he is a professor in the Department of Computer Science and Engineering at SVECW. His research interests include data mining, neural networks, cybersecurity, secure software development, data protection strategies, multimedia encryption, cloud computing infrastructures, algorithm analysis, ethical hacking, network security protocols, emerging programming languages, and artificial intelligence in security frameworks. He is affiliated with Shri Vishnu Engineering College for Women. He can be contacted at email: aaluriseenu@svecw.edu.in.

Kondragunta Rama Krishnaiah is a highly qualified person, an efficient and eminent academician. He is an outstanding administrator; a prolific researcher published 95+ research papers in various national and international journals, and a forward-looking educationist. He has guided several students for their M. Tech and Ph.D. degrees and also authored 5 textbooks. He worked in prestigious K L (Deemed to be) University for 11.5 years and has contributed his service for NBA accreditation in May 2004, Aug 2007 with 'record rating', ISO 9001:2000 in 2004, Autonomous status in 2006, NAAC accreditation of UGC in 2008, and University status in 2009. Later on, he worked as principal at Nova College of Engineering and Technology, Vijayawada, for a period of 3.5 years and NVR College of Engineering and Technology, Tenali for a period of 1.5 years. He took charge as the principal, RKCE, Vijayawada in December 2015. Under his able leadership, the college is rising towards a bright future with high academic values and the college got accredited by NAAC with "A" Grade and obtained UGC "Autonomous Status" from the academic year 2024-2025. He has received "Appreciation Award" for the senior principals from JNTUK, Kakinada, in the year 2024. He can be contacted at email: kondraguntark@gmail.com.

Anantha Sravanthi Peddinti received M.E. degree from University College of Engineering, OU. Currently working as an associate professor in ECE Department at Aditya College of Engineering and Technology, Surampalem, AP, India. Her research interest area is image processing. She can be contacted at email: sravanthi.angara@acet.ac.in.

Nelaturi Nanda Prakash received the B.Tech. degree in electronics and communication engineering from Lovely Professional University, Jalandhar, Punjab, India, in 2015, and M.Tech. degree from Koneru Lakshmaiah Education Foundation, Vaddeswaram, Guntur, India in 2017, respectively. He is currently working as an assistant professor in Department of Electrical and Electronics Engineering at Chalapathi Institute of Engineering and Technology, Guntur, India. He has published several papers in international conferences and journals in the field of image processing. He can be contacted at email: nandaprakashnelaturi@gmail.com.

Bandreddi Venkata Seshukumari is an associate professor in the Department of Information Technology at VNRVJIET, with a brilliant academic career devoted to teaching and research. She has received a Ph.D. (CSE) and M.Tech. (CSE), and B.Tech. (CS and IT) from JNTUH. She has 20 years of teaching experience and 10 years of dedicated research experience. She has published 30 papers in reputed journals such as ACM, Elsevier, Springer, and Inder Science. She has been in various departmental roles such as HOD, M.Tech., and several administrative roles, proving herself committed to the development of her students. She can be contacted at email: seshukumari_bv@vnrvjiet.in.

Giriprasad Ambati received a B.Tech. degree in electrical and electronics engineering from V.R. Siddhartha Engineering College, Vijayawada, AP, India, in 2000, an M.Tech. in power systems from JNT University Hyderabad, AP, India, in 2005, and a Ph.D. from JNTUH University Hyderabad, TS, India, in 2019. He has 23 years of teaching experience. He has been working as an assistant professor in the EEE Department, VNR VJIET, since 2017. He has published 32 papers in international journals, 15 papers at international conferences, and 3 papers in National conference papers. He did a project on a Network analyzer from AICTE worth 23 lakhs. He is a member of IEEE and a lifetime member of ISTE, MIE, IAENG, and IFERP. His areas of interest are gas-insulated substations, power systems, smart grids, electric vehicles, power quality, and electromagnetic fields. He can be contacted at email: giriprasad_a@vnrvjiet.in.

Shaik Hasane Ahammad (student member, IEEE) received his B.Tech. and M.Tech. degrees in electronics and communication engineering from Jawaharlal Nehru Technological University, Kakinada, in 2011 and 2014, respectively. He completed his ECE Ph.D. from KLEF Deemed University, which is located in Vaddeswaram, Guntur, Andhra Pradesh. He is an active researcher in the fields of machine learning, computer vision, and biomedical image analysis. His work often brings together theory and practice, which leads to improvements in intelligent systems and medical diagnostic tools. He has guided many postgraduate and doctoral students in their research. Apart from this, He has also been quite active in organizing international conferences, FDPs, and research workshops. He can be contacted at email: ahammadklu@gmail.com.

Chakrapani Srivardhan Kumar earned his B.Tech. degree in electrical and electronics engineering from JNTU Hyderabad, Telangana. He obtained his M.Tech. in power electronics from JNTU Hyderabad. A Ph.D. was completed at the Sathyabama Institute of Science and Technology in Chennai. Currently employed as an Associate Professor at Malla Reddy University, Hyderabad. His research interests include applications of power electronics in energy systems, as well as battery systems management. Also, he organized the resource person for faculty development programs on EV technology funded by Malla Reddy University, Hyderabad. He has published 25 papers in several international journals. He can be contacted at email: srivardhankumar4813@gmail.com.

Allamraju Shubhangi Rao has been functioning as an assistant professor at the MLR Institute of Technology in Hyderabad, within the Electrical and Electronics Engineering Department. Her undergraduate and master's degree, specializing in electrical engineering and control systems, were obtained from RGPV, Bhopal. Having taught at various engineering colleges for a total of nine years, she specializes in electrical machines, control systems, and related fields. She has published a number of articles in esteemed indexed journals and has presented in multiple conferences. In addition, she has given expert talks at many webinars. She can be contacted at email: shubhir5789@gmail.com.