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Review

A Critical Review of AI-Based Battery Remaining Useful Life Prediction for Energy Storage Systems

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Abstract

This paper provides a comprehensive review of recent advances in remaining useful life prediction for lithium-ion battery energy storage systems. Existing approaches are generally categorized into model-based methods, data-driven methods, and hybrid methods. A systematic comparison of these three methodological paradigms is presented, with hybrid methods further divided into filter-based hybrids and data-driven hybrids, followed by a comparative analysis of remaining useful life prediction accuracy. The literature analysis indicates that data-driven hybrid methods, by integrating the strengths of physical mechanism modeling and machine learning algorithms, exhibit superior robustness under complex operating conditions. Among them, the hybrid framework combining long short-term memory networks with an eXtreme Gradient Boosting model optimized by the Binary Firefly Algorithm demonstrates the highest stability and accuracy in the reviewed studies, achieving a root mean squared error below 2% and a mean absolute percentage error below 1%. Future research may further enhance the generalization capability of this framework, reduce computational cost, and improve model interpretability.

Keywords: lithium-ion battery; remaining useful life prediction; prediction method; data-driven method; hybrid approach

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1. Introduction

In the current era marked by dual challenges of environmental degradation and resource depletion, nations worldwide have prioritized the exploration and application of novel energy sources as a critical pathway toward achieving long-term sustainable development. Lithium-ion batteries have become a cornerstone energy source in diverse fields such as electric vehicles (EVs), renewable energy storage systems, portable electronic devices, and aerospace applications, which can be attributed to their high energy density, prolonged cycle lifespan, and minimal self-discharge characteristics [1–3]. Amid the accelerating global transition toward low-carbon energy structures, data from the International Energy Agency (IEA) projects that the global lithium-ion battery market will expand exponentially from United States Dollar (USD) 45 billion in 2020 to over USD 250 billion by 2030, accompanied by rapid technological iteration [4]. However, the inherent capacity degradation and performance deterioration of lithium-ion batteries during prolonged charge–discharge cycles pose significant threats to operational safety and economic viability [5,6]. For instance, capacity fade in EV traction batteries may reduce driving range and elevate thermal runaway risks [7], while performance degradation in grid-scale energy storage systems substantially increases lifecycle maintenance costs [8–10]. As a critical component of battery management systems (BMSs) [11–13], accurate prediction of remaining useful life (RUL) for lithium-ion batteries has become paramount to ensuring long-term operational safety and reliability [14–16]. This capability enables proactive maintenance strategies and informed decision-making regarding battery retirement or repurposing, thereby optimizing resource utilization and minimizing environmental impacts throughout the battery lifecycle.

Understanding the intrinsic aging mechanisms of lithium-ion batteries first requires clarifying their structural configuration. Fundamentally, these batteries are composed of a graphite anode [17], a metal oxide cathode [18], an electrolyte [19], and a separator [20]. Their aging phenomena arise from multifaceted factors, fundamentally originating from the cumulative effects of irreversible side reactions within the electrochemical system during cycling and storage [21,22]. The degradation pathways are governed by multi-scale mechanisms, including electrode material phase transitions, thickening of the solid electrolyte interphase (SEI) layer [23], lithium dendrite growth [24], and active material loss [25], as illustrated in Figure 1 [26,27]. These interrelated processes collectively drive performance deterioration through structural and compositional changes at the electrode-electrolyte interfaces, ultimately manifesting as capacity fades and impedance rises over the battery's operational lifespan.

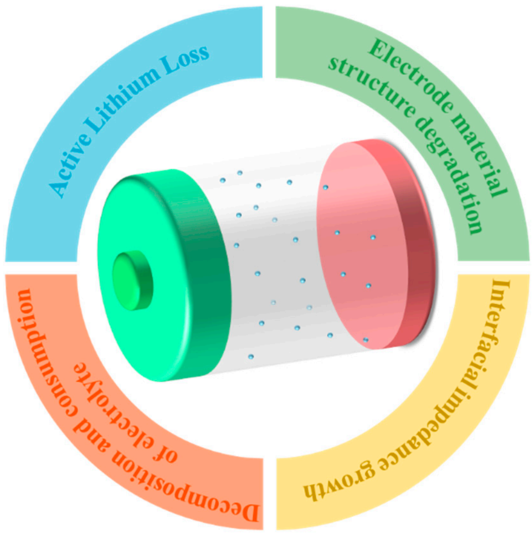


Figure 1. Mechanism of capacity attenuation of lithium-ion batteries.

These degradation mechanisms are closely associated with battery design parameters (e.g., cathode/anode material ratios [28], electrolyte composition [29]) and are significantly influenced by external operating conditions, including charge–discharge rates [30], temperature [31], state of charge (SOC) fluctuations [32,33], and depth of discharge (DOD) [34]. Ouyang et al. [35] demonstrated that high-rate charging/discharging induces substantial capacity fade, revealing multidimensional impacts of high-rate operations on lithium-ion battery performance through accelerated electrode polarization and mechanical stress. Zhang et al. [36] systematically elucidated the limitations of lithium-ion batteries under extreme temperatures, emphasizing the critical role of electrolyte behavior mechanisms, particularly the trade-offs between ionic conductivity and thermal stability at extreme low and high temperatures. These findings underscore that lithium-ion batteries remain functionally analogous to "black boxes," as their internal states resist direct measurement through conventional sensors. Mehta et al. [37] further validated the nonlinear degradation characteristics arising from multi-factor coupling through advanced mathematical modeling, highlighting the necessity to establish cross-scale correlation models bridging microscopic mechanisms and macroscopic performance for RUL prediction [38–40]. While traditional physics-based electrochemical models (EMs) can characterize specific aging mechanisms, their capacity to model full lifecycle degradation behaviors often relies on oversimplified assumptions, resulting in limited prediction accuracy under real-world complex operating conditions.

The swift progression of Internet of Things (IoT) technologies, coupled with advancements in artificial intelligence (AI) algorithms, has introduced data-driven methods as a transformative paradigm for battery RUL prediction. By leveraging sensor networks integrated within battery modules, researchers can continuously acquire real-time operational data—encompassing parameters such as voltage, current, and temperature [41,42]. These comprehensive datasets, when coupled with sophisticated feature extraction methodologies, like electrochemical impedance spectroscopy [43–45] (EIS) and incremental capacity analysis [46,47] (ICA), facilitate the development of degradation indicators that accurately mirror the battery's state of health (SOH) [48,49]. By leveraging such data, traditional machine learning (TML) models (e.g., support vector regression, random forests) and deep learning (DL) architectures (e.g., long short-term memory networks, convolutional neural networks) can autonomously uncover aging patterns from historical data, thereby circumventing the need for explicit modeling of complex electrochemical mechanisms [50–52]. Consequently, the development of hybrid prediction frameworks that synergistically integrate mechanistic interpretability with data-driven adaptability has emerged as a critical research frontier [53]. However, there is a dearth of comprehensive reviews that systematically delineate data-driven methodologies for achieving accurate prediction of the RUL of lithium-ion batteries.

This article initiates its analysis through an examination of aging mechanisms and their influencing factors, progressively expanding into a detailed exploration of RUL prediction tasks across multiple scales. The structure of the chapter is organized in the following manner: Section 2 elucidates the foundational theories underlying RUL prognosis for lithium-ion batteries; Section 3 provides a systematic categorization of current RUL prediction methodologies; Section 4 conducts a comparative analysis of multi-scale prognostic approaches; and Section 5 briefly summarizes the conclusions of the entire study and reveals the future development direction and challenges faced by lithium battery RUL prediction.

2. Definition of Remaining Useful Life

The RUL of lithium-ion batteries is defined as the number of charge–discharge cycles remaining from the present time until the battery reaches its end-of-life (EOL) stage. Throughout the operational lifecycle, repeated cycling inevitably causes progressive degradation of the battery's actual capacity [54,55]. It is widely accepted that a battery is considered to have reached its EOL when its actual capacity declines to 70–80% of the nominal capacity [56]. Accordingly, the RUL can be quantified as the number of additional charge–discharge cycles required for the capacity to decrease from its present level to the EOL threshold [57]. The schematic principle of RUL determination is illustrated in Figure 2.

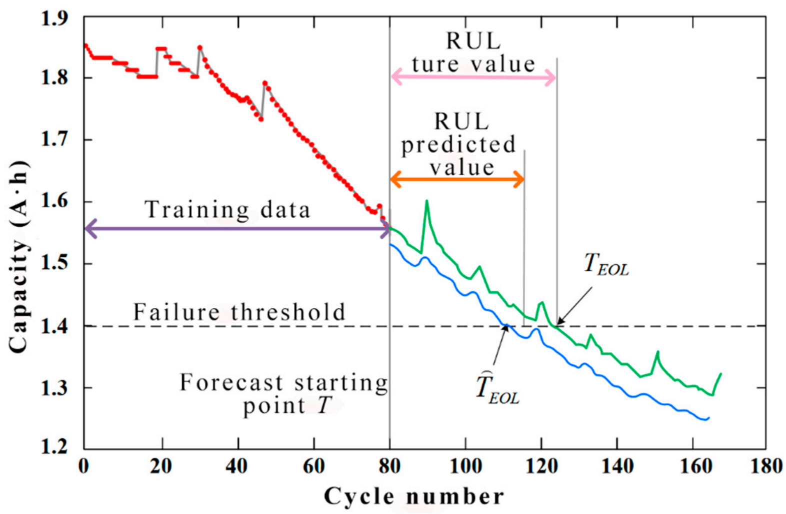


Figure 2. Calculation principle of battery RUL.

In the figure, T represents the cycle index at the initial assessment point, and T_{EOL} denotes the cycle index corresponding to the actual EOL state. Therefore, based on the above definitions, the true RUL value T_{RUL} can be mathematically expressed as follows:

$$T_{RUL} = T_{EOL} - T \tag{1}$$

Similarly, the predicted RUL value, $T_{\hat{RUL}}$ is determined by estimating the future EOL cycle number, $T_{\hat{EOL}}$ based on the available training data and forecast models. Therefore, this predicted value is given by the difference between the estimated EOL cycle number, $T_{\hat{EOL}}$ and the current cycle index T. This relationship is expressed in Equation (2):

$$T_{\hat{RUL}} = T_{\hat{EOL}} - T \tag{2}$$

By using these two equations, both the actual RUL and the predicted RUL values can be calculated, enabling accurate estimation of the RUL of the battery based on both actual and forecasted operational conditions.

3. Discussion on the Classification of Methods for RUL Prediction

Currently, numerous mature strategies for predicting the RUL of lithium-ion batteries have been developed. These strategies can be systematically classified into three major categories: physics-based model-driven approaches, data-driven machine learning frameworks, and hybrid prediction architectures [58–60]. As illustrated in Figure 3, RUL prediction methodologies have been extensively investigated and applied across various contexts.

Model-driven approaches employ mathematical formalisms, such as differential equations or state-space formulations, to construct degradation representations, often coupling with empirical degradation models to characterize the system's evolution trajectories [61]. In contrast, data-centric methodologies leverage advanced machine learning architectures and statistical analysis of historical operational datasets to identify degradation patterns specifically tailored to application-specific operational contexts [62–64]. Finally, hybrid models synergistically combine multiple approaches, capitalizing on the individual strengths of different methodologies to enhance prediction robustness and accuracy.

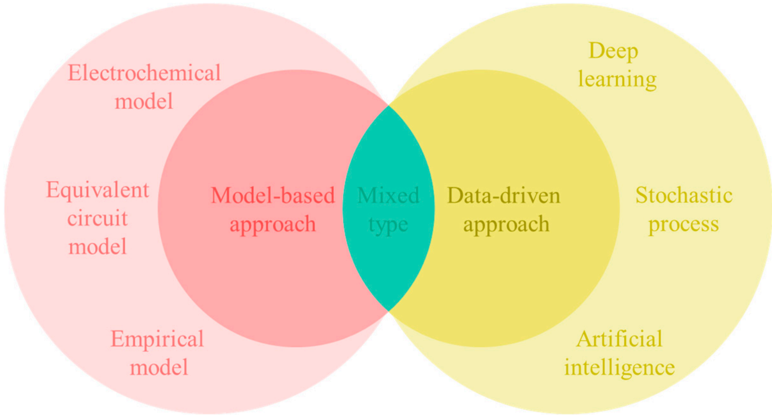


Figure 3. RUL prediction method for lithium-ion batteries.

3.1. Model-Based Approaches for RUL Prediction

Physics-informed modeling paradigms for lithium-ion battery RUL prognostics employ differential equation frameworks to mathematically characterize the coupled physical–electrochemical degradation mechanisms governing battery operational dynamics. These models account for a spectrum of features influencing battery performance and health, including current, voltage, cycling patterns, temperature, aging mechanisms, and usage profiles [65,66]. By evaluating battery states and simulating their performance evolution over time, these methods enable precise and reliable predictions of RUL [67,68], making them indispensable tools for managing the lifecycle of lithium-ion batteries across diverse applications [69]. Established model-driven paradigms are generally categorized into three classes: physics-based EMs [70], lumped-parameter equivalent circuit models (ECMs) [71], and recursive state-space filtering architectures. As summarized in Table 1, these methodological frameworks exhibit distinct trade-offs between computational complexity, predictive accuracy, and adaptability to varying degradation mechanisms inherent in lithium-ion battery aging processes.

Table 1. Methodological strengths and limitations of model-driven approaches for lithium-ion battery RUL prognostics.

Group	Method	Advantage	Disadvantage	Reference
Electrochemical Model (EM)	Pseudo Two-Dimensional (P2D)	High-precision simulation capability High prediction accuracy	High computational complexity Rely on experimental data	Tao et al. (2024) [72]
	Single-Particle Model (SPM)	High computational efficiency Parameter identification is simple	Limited applicable scenarios Poor adaptability to dynamic working conditions	Madani et al. (2025) [73]
Equivalent Circuit Model (ECM)	Rint	Simple structure Easy to implement Low calculation complexity	Two polarization phenomena are ignored Low accuracy Dynamic performance	Tao et al. (2024) [74]
	Thevenin	Relatively simple structure Relatively low calculation complexity	Relatively low model accuracy in the low SOC region	Wang et al. (2023) [75]
	Second-Order RC	Relatively high model accuracy	Relatively complex structure	Xia et al. (2023) [76]
	Partnership for a New Generation of Vehicles (PNGV)	Relatively high model accuracy Loading effects considered Excellent dynamic performance	Relatively long computational time Relatively complex structure	Vasta et al. (2023) [77]
	Gaussian Negative Log-Likelihood (GNL)	High model accuracy Self-discharge effect considered	Long computational time	Nuroldayeva et al. (2023) [78]

Table 1. *Cont.*

Group	Method	Advantage	Disadvantage	Reference
Filtering Model (FM)	Kalman Filter (KF)	High computational efficiency Suitable for real-time applications	Applies only to linear systems	Fahmy et al. (2025) [79]
	Particle Filter (PF)	Can handle nonlinear and non-Gaussian noise	Suitable for offline or high-performance computing scenarios	Li et al. (2022) [80]
	Adaptive Filter (AF)	Adapt to the change in system parameters Improve the prediction accuracy	Necessary to design a suitable adaptive algorithm	Shrivastava et al. (2023) [81]

3.1.1. Electrochemical Model-Based RUL Prediction

EMs represent a physically grounded approach to lithium-ion battery modeling by simulating ion transport mechanisms, electrochemical reaction kinetics, and processes such as SEI formation, thereby elucidating the physicochemical phenomena within batteries. These models deliver high predictive accuracy for RUL estimation and performance evaluation [82,83]. However, the inherent complexity of EMs imposes substantial demands on computational resources and high-precision input parameters, limiting their feasibility for real-time applications. To reconcile algorithmic efficiency with predictive fidelity, simplified variants of the P2D model and SPM have been widely adopted [84]. These streamlined frameworks reduce computational burdens through structural reconfiguration while retaining the ability to model temporal battery behavior. Although simplifications may compromise predictive accuracy under specific conditions, these models remain extensively utilized in BMSs for real-time state estimation and lifespan prediction, providing theoretical support for optimizing battery performance and extending operational longevity.

At the specific application level, Chen et al. [85] formulated a multi-scale prognostic architecture for commercial high-capacity $LiFePO_4$/graphite lithium-ion cells by coupling a P2D EM with a semi-empirical degradation kinetics model accounting for SEI layer formation parasitics. The resultant framework provides actionable design guidelines for advanced cell optimization through a mechanistic understanding of coupled aging mechanisms. Mo'ath et al. [86] employed the SPM to directly determine degradation parameters from voltage-capacity datasets, facilitating accurate characterization of degradation pathways and prognostic modeling of capacity loss trends. Subsequently, the parameterized capacity estimates were integrated into a stochastic prediction framework to formulate an RUL prediction model. The P2D and SPM models exhibit high fidelity in elucidating the electrochemical–thermal coupling mechanisms within batteries. However, these models rely on solving multidimensional partial differential equation systems. They also require complex parameter calibration. In addition, their real-time computation often encounters bottlenecks. Owing to these limitations, researchers have adopted reduced-order modeling approaches based on macroscopic equivalent circuit topologies.

3.1.2. Equivalent Circuit Model-Based RUL Prediction

The terminal voltage of lithium-ion batteries is governed by the interplay between electrode potentials and internal resistance, with its temporal variations reflecting the dynamic interaction of these components. These variations encapsulate critical information about battery performance degradation. ECMs for lithium-ion battery RUL prediction utilize resistor–capacitor networks integrated with controlled voltage sources to characterize the electrochemical response mechanisms governing battery degradation processes [87,88]. These models enable real-time assessment of SOC and SOH while facilitating RUL prediction based on voltage and current data [89,90]. ECMs are widely adopted in industrial applications for real-time monitoring and prognostics due to their computational efficiency, parameters with clear physical interpretations, and adaptability to online evaluation [91].

Common ECM architectures, as illustrated in Figure 4, include the Rint model, the Thevenin model, the second-order RC model, the PNGV model, and the GNL model.

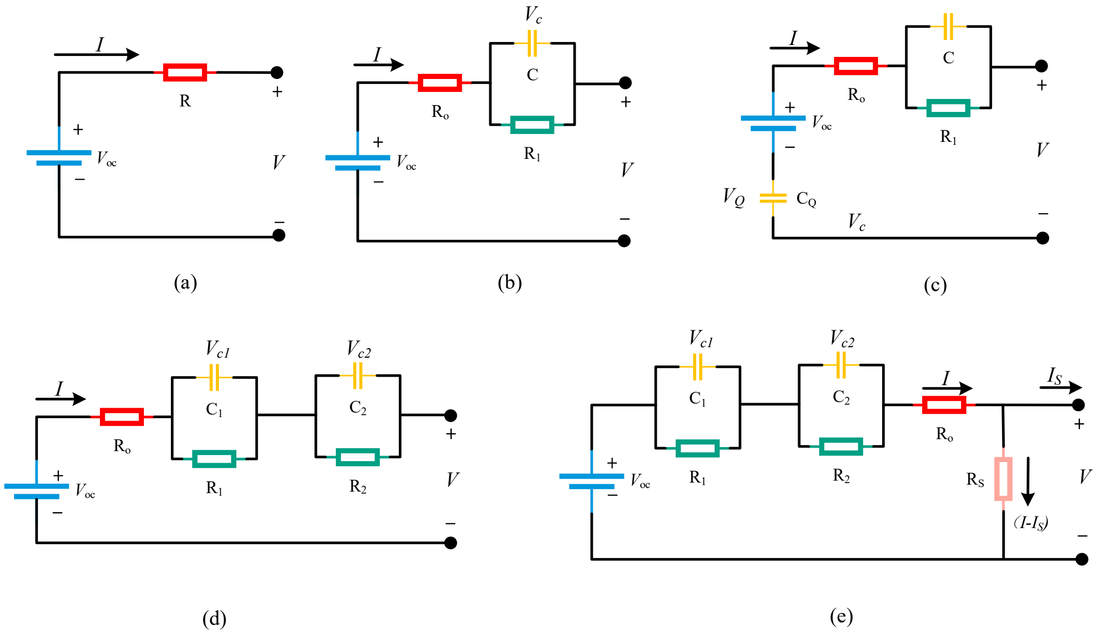


Figure 4. Common Types of ECMs. (**a**) Rint ECM; (**b**) Thevenin ECM; (**c**) PNGV ECM; (**d**) Second-order RC ECM; (**e**) GNL ECM.

Although ECMs efficiently model battery dynamic characteristics by simplifying electrochemical–thermal coupling processes into resistive–capacitive networks, their lack of description of long-term degradation mechanisms, such as lithium-ion deposition and SEI film thickening, means that ECMs alone cannot accurately predict the remaining lifespan of lithium-ion batteries. To address this, researchers typically couple ECMs with filtering methods, such as KF and PF, to construct joint state-observer frameworks. These frameworks enable real-time correction of aging parameters, such as capacity decay and internal resistance growth, thereby retaining the real-time capabilities of ECMs while overcoming mechanistic limitations. As a result, ECM-based approaches achieve accurate prediction of battery health throughout the lifecycle.

3.1.3. Filtering Model-Based RUL Prediction

State-space filtering methodologies enable real-time tracking and prediction of battery degradation states through dynamic state-space model formulations, incorporating adaptive noise attenuation mechanisms while preserving prediction accuracy. These inherent advantages have facilitated their pervasive implementation in real-time battery state-of-health monitoring systems across diverse operational scenarios [92–94]. Commonly utilized filtering models include KFs, PFs, and AFs. Wu et al. [95] proposed an improved method based on the unscented KF to optimize particle filtering. Using a resampling particle weighting strategy, they effectively improved prediction accuracy. Experimental verification showed that this method can significantly reduce the width of the predicted probability density function distribution and enhance the robustness of the prediction results. Xu et al. [96] developed an optimized gray PF architecture for lithium-ion battery RUL prognostics, with rigorous experimental evaluations confirming the model's superior predictive performance through accelerated aging datasets collected in high-temperature environments. Although combining ECMs with filter models and their improved versions can reduce the amount of computation required, they still struggle to provide accurate RUL prediction data under complex operating conditions [97]. Therefore, future efforts should focus on integrating filter models with data-driven methods to enhance the accuracy and adaptability of lithium-ion battery RUL prediction.

3.2. RUL Prediction Based on the Data-Driven Approach

In tandem with the exponential proliferation of AI technologies, data-driven methodologies for RUL prognostics have emerged as a focal area of contemporary research endeavors. Data-driven techniques, when compared with traditional physics-based prognostic approaches, eliminate the need for in-depth exploration of complex battery aging mechanisms [98–100]. Instead, they automatically establish input–output mapping relationships through algorithm optimization and training datasets to achieve predictive capabilities, as illustrated in Figure 5.

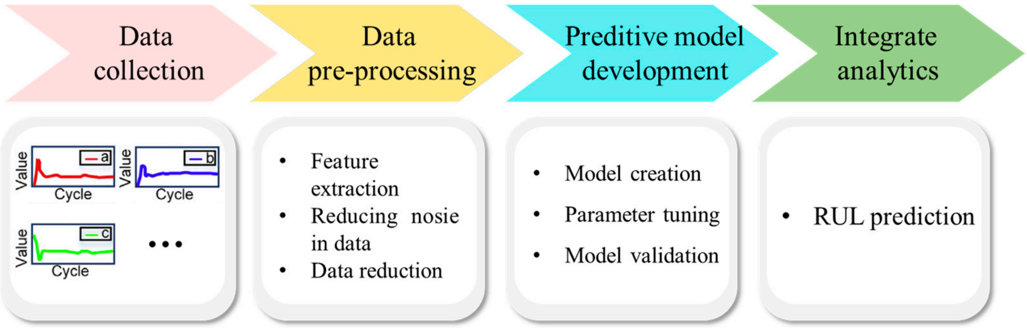


Figure 5. Flowchart of data-driven RUL prediction for lithium-ion batteries.

Furthermore, when handling high-dimensional nonlinear systems, data-driven methods demonstrate notable advantages. Their technical frameworks can be systematically categorized into three major classes: stochastic process-based methods, TML methods, and DL methods [101]. The specific implementations of these methodologies will be comprehensively elaborated in subsequent sections.

3.2.1. Stochastic Process Methods for RUL Prediction

Rooted in statistical foundations and fused with advanced mathematical constructs, stochastic process-based methodologies leverage probabilistic frameworks to characterize the intrinsic uncertainties and randomness embedded within lithium-ion battery degradation mechanisms [102]. By incorporating statistical and mathematical frameworks, these approaches effectively capture the complexity and variability of battery degradation processes, thereby enabling more accurate and reliable RUL predictions [103,104]. Currently, the most widely implemented stochastic process methods include the Wiener process, the Gamma process, and the Markov process. A comparative analysis of the advantages and limitations of different stochastic process methodologies is systematically presented in Table 2.

Table 2. Advantages and disadvantages of different stochastic processes.

Method	Advantage	Disadvantage	Reference
Wiener Process	Facilitate the theory analysis and real-time computing Suitable for modeling continuous evolution phenomena	Only applicable to continuous diffusion processes Parameter sensitivity	Xu et al. (2021) [105]
Gamma Process	Suitable to describe the irreversibility of the process of degradation Flexible time evolution	High computational cost Additional parameters need to be introduced for time-varying systems	Keshun et al. (2023) [106]
Markov process	Suitable for multi-stage aging modeling Excellent uncertainty description capability	Difficulty in capturing continuous, nonlinear degradation trends Unsuitability for modeling sudden degradation	Zhang et al. (2023) [107]

Xu et al. [95] established an aging model for lithium-ion batteries under time-varying temperature conditions based on the Wiener process. They proposed a two-step unbiased estimation method that combines maximum likelihood estimation with genetic algorithms, and they performed online updating of stochastic parameters within a Bayesian framework. This approach derives the probability density function of the RUL for lithium-ion batteries under time-varying temperature conditions, thereby demonstrating significant improvements in prediction accuracy. Keshun et al. [106] introduced a gamma stochastic process combined with state-space modeling to analyze lithium battery capacity degradation, incorporating support vector regression for parameter calibration. This methodology not only achieves exceptional prediction precision but also significantly reduces computational complexity, and it demonstrates practical advantages for industrial applications. Zhang et al. [107] integrated battery degradation characteristics by combining a nonlinear drift-driven Wiener process with a Markov chain switching model through a fuzzy system. The online updating strategy of this framework was validated through simulations, and the results demonstrated enhanced adaptability and robustness. However, its nonlinear representation capability requires further enhancement when handling abrupt operational anomalies. Chen et al. [108] developed a neural network-represented Wiener process degradation model that strengthens nonlinear fitting capabilities while enabling real-time monitoring of lithium battery capacity fade patterns. The proposed architecture markedly improves reliability in nonlinear system evaluation. Furthermore, learning-based methods have been employed to dynamically calibrate process parameters, thereby enhancing the model's adaptability and prediction accuracy. Overall, these studies collectively highlight the versatility of stochastic process-based methodologies in capturing degradation dynamics and improving the prediction accuracy of the lithium-ion battery RUL.

3.2.2. Traditional Machine Learning Methods for RUL Prediction

Currently, the most widely employed TML methodologies in this domain include artificial neural networks (ANNs), support vector machines (SVMs), relevance vector machines (RVMs), and Gaussian Process Regressions (GPRs). These approaches leverage feature identification and analysis to estimate the system's RUL, thereby enabling preventive maintenance implementation before battery failure [109–111]. Figure 6 illustrates the flowchart of the machine learning-based process for predicting the RUL of lithium batteries.

ANNs can be structured with multiple layers, each containing numerous neurons or nodes. The activation value of each neuron within a given layer is mathematically determined through activation functions, which implement a nonlinear transformation based on the weighted sum of input signals propagated from all constituent neurons in the immediately preceding layer [112,113]. Ansari et al. [114] developed a multi-channel input configuration based on ANNs, demonstrating that its prediction accuracy for RUL significantly outperformed single-channel input configurations. Tang et al. [115] employed mean substitution and normalization substitution methods to extract HIs and applied the Pearson correlation coefficient for optimal feature selection. Based on these selected features, they constructed ANNs incorporating temporal sequence morphology, time-dependent features, and sequence transformation features, thereby enhancing prediction accuracy. Pugalenthi et al. [116] developed a hybrid architecture that integrated a neural network with an adaptive Bayesian inference mechanism. This architecture enabled accurate RUL prognostics for electronic components through dynamic parameter calibration. Lin et al. [117] proposed a Gray Neural Network combined with the Systematic Gray Model using a PF algorithm for RUL prediction. Their method achieved a maximum absolute error of no more than 14 cycles, highlighting the effectiveness of ANN-based approaches in improving prognostic accuracy for lithium-ion batteries.

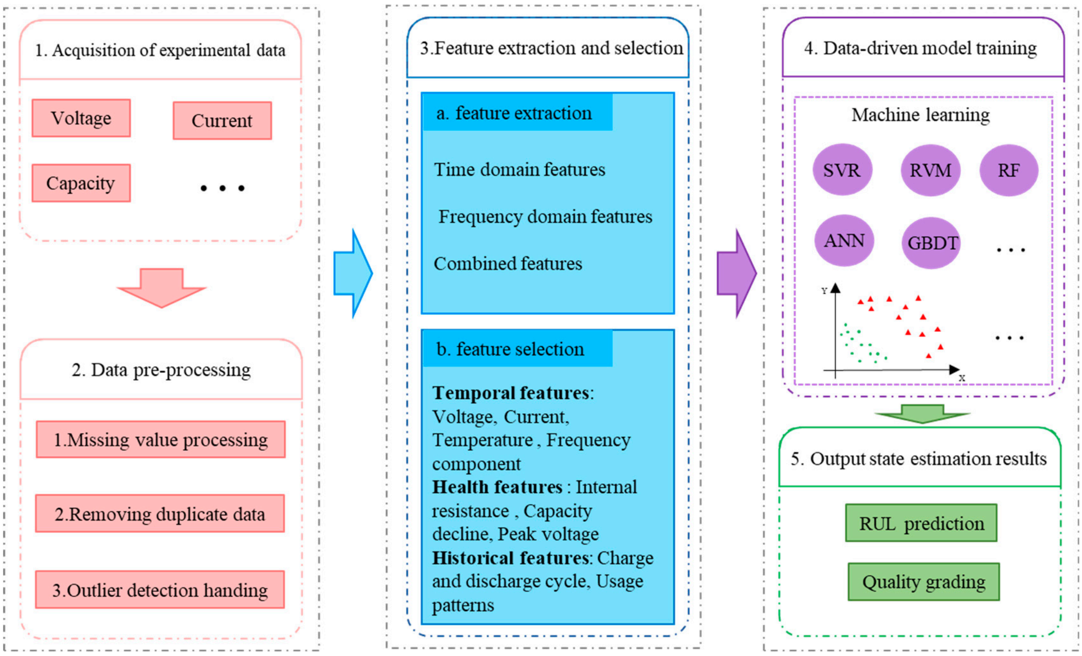


Figure 6. Flowchart of TML-based RUL prediction for lithium-ion batteries.

SVMs are a class of supervised learning algorithms applicable to both regression and classification tasks. They can be applied to develop models based on feature extraction from operational data of lithium-ion batteries, which enables accurate prediction of their RUL [118,119]. The precision of lithium-ion battery RUL prediction holds paramount significance for BMSs, and ongoing advancements in data mining methodologies substantially enhance predictive capabilities for RUL assessment. Li et al. [120] proposed a hybrid framework integrating SVM regression with PF for RUL prediction, achieving uncertainty reduction in predictive outcomes. Li et al. [121] integrated the least squares support vector machine (LSSVM) model into the unscented particle filtering (UPF) framework, serving as its measurement model to generate anticipatory virtual measurements for the hybrid UPF-LSSVM algorithm. Collectively, these developments highlight the pivotal role of SVM-based methods in advancing RUL prognostics of lithium-ion batteries.

RVMs share fundamental similarities with SVMs. RVMs employ Bayesian methods to compute the weights required for probability density function estimation, are characterized by high sparsity, and enable probabilistic predictions [122]. Chen et al. [123] integrated Broad Learning Systems (BLSs) with RVMs to enhance long-term prediction capability and generalization performance in RUL prediction, achieving a root mean squared error (RMSE) of 0.01. Guo et al. [124] adopted a modified RVM combined with an improved Hausdorff distance-based capacity degradation model, generating multiple degradation curves and selecting the optimal fitting curve to extrapolate to the failure threshold for RUL prediction, thereby improving prediction stability. Jiang et al. [125] enhanced the learning efficacy and generalization performance of RVMs through the formulation of a hybrid-feature kernel architecture. By integrating the Particle Swarm Optimization (PSO) algorithm, they optimized the kernel hyperparameters and weighting coefficients, thereby enabling precise early-stage RUL prediction. Jia et al. [126] proposed a hybrid methodology integrating sample entropy with RVMs, where wavelet denoising and linear weighting techniques were applied to reduce noise and mitigate weighting biases in multi-entropy inputs, achieving accurate and robust RUL predictions. Overall, RVM-based methods, especially when combined with optimization algorithms and hybrid architectures, have demonstrated strong potential for improving the accuracy, robustness, and stability of RUL prediction models.

GPR is a probabilistic approach established within the Bayesian statistical framework, utilizing a kernel function to define the covariance between degradation states at any two temporal points. Given training data, it predicts future degradation trajectories and quantifies their associated uncertainty through posterior distributions. Xing et al. [127] proposed a hybrid prognostic strategy integrating principal component analysis, HIs, and enhanced GPR. This hybrid model achieved high-precision RUL prediction by effectively integrating data-driven features with probabilistic prediction frameworks while significantly enhancing adaptability to diverse operating conditions. The approach provides an engineering-applicable solution for lithium battery lifespan prediction. In another study, Wei et al. [128] developed a GPR-neural network fusion method for lithium battery RUL prediction, demonstrating robust performance with RMSE values below 1.2% for capacity estimation and prediction accuracy exceeding 98% across four distinct operating conditions. This methodology offers an efficient solution for battery prognosis under complex operational scenarios. Table 3 summarizes the characteristics of predicting the RUL of lithium-ion batteries using TML approaches. Collectively, these studies highlight the potential of GPR-based hybrid frameworks to deliver efficient and reliable solutions for lithium-ion battery prognosis under complex operational scenarios.

Table 3. Characteristic analysis of TML for RUL prediction.

Method	Advantage	Disadvantage	Ref.
ANN	Deal with highly nonlinear problems High flexibility and strong scalability	Requires large amounts of training data Prone to getting stuck in local optima Poor interpretability	Olabi et al. (2024) [129]
SVM	According to the structural risk minimization criterion Strong generalization ability	Sensitive to parameter selection Slow training speed and high computational cost on large-scale datasets	Xiong et al. (2023) [130]
RVM	Adaptive nuclear selection Quantify uncertainty Multi-task learning and scene transfer	Model training complexity is relatively high Sparsity may be unstable in certain scenarios Limited applicability in practical deployment	Zhang et al. (2024) [131]
GPR	Flexibly approximating intricate nonlinear degradation trajectories Robust small-sample learning capability	High computational complexity, difficult to scale with large sample sizes Sensitive to kernel function selection, highly dependent on modeling experience	Jia et al. (2020) [132]

TML methods have demonstrated strong practicality and flexibility in the prediction of the RUL of lithium-ion batteries. ANNs, with their multilayer structures and nonlinear activation functions, are well-suited for modeling complex feature relationships and integrating temporal morphology with multidimensional health indicators [133,134]. SVMs exhibit robust generalization capabilities under small-sample conditions and are often combined with filtering techniques to enhance prediction stability [135,136]. RVMs, while maintaining model sparsity, provide probabilistic outputs, making them suitable for scenarios requiring both high precision and uncertainty quantification [137]. GPR, grounded in Bayesian theory, provides excellent confidence interval estimation and is particularly effective for the long-term prediction of degradation processes [138]. These methods not only excel in predictive accuracy and uncertainty modeling but also exhibit strong potential for integration and scalability. Future developments may emphasize hybrid model construction, multi-channel data processing, dynamic model updating, and enhanced domain adaptability, thereby further improving the performance of traditional machine learning methods for RUL prediction under complex operational conditions.

3.2.3. Deep Learning Methods for RUL Prediction

DL methods offer highly accurate and flexible solutions for the prediction of the RUL of lithium-ion batteries through end-to-end modeling, automatic feature extraction, and powerful time series modeling capabilities. These approaches demonstrate significant advantages, particularly in addressing complex scenarios such as nonlinear degradation [139], varying operating conditions, and the fusion of multi-source data [140–142]. In the specific context of RUL prediction for batteries, diverse Deep Neural Network (DNN) [143] architectures based on Recurrent Neural Networks (RNNs) [144] have been widely adopted. These include long short-term memory (LSTM) [145,146] networks, Gated Recurrent Unit (GRU) [147] models, and convolutional neural networks (CNNs). Figure 7 illustrates a flowchart for predicting the RUL of lithium-ion batteries based on deep learning.

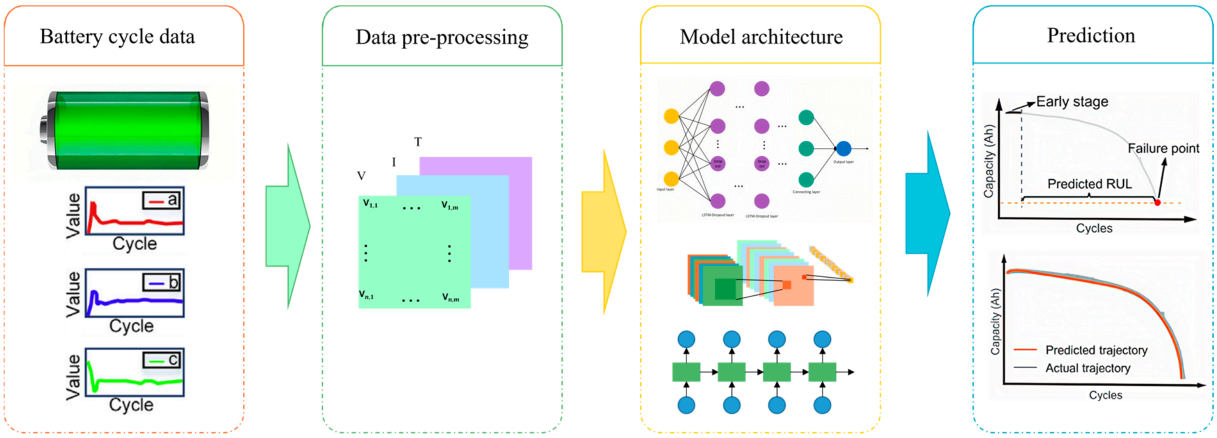


Figure 7. Flowchart of DL-based RUL prediction for lithium-ion batteries.

LSTM networks utilize gating mechanisms to regulate information flow, thereby addressing the vanishing gradient problem. An LSTM comprises three gating units: the input gate, output gate, and forget gate. LSTM networks can achieve accurate early-stage RUL prediction using only 20–25% of a battery's full lifecycle degradation data [148–150]. Current research on LSTMs focuses on four core areas: gated structure optimization, algorithm fusion, ensemble learning, and transfer learning [151,152]. Park et al. [153] implemented an enhanced LSTM algorithm for multi-channel RUL prediction, significantly reducing the number of model parameters while improving generalization capability. Ouyang et al. [154] developed an ensemble forecasting architecture by coupling a Whale Optimization Algorithm (WOA)-tuned Variational Mode Decomposition (VMD) module with an LSTM network. This approach resulted in a mean absolute cycle deviation of 1 cycle, an RMSE $\leq$ 0.69%, and a mean absolute percentage error (MAPE) < 0.43% across experimental evaluations. Li et al. [155] introduced a novel methodology combining Iterative Transfer Learning (ITL) and Mogrifier LSTM for lithium-ion battery RUL prediction, which overcomes data length constraints during training and enhances prediction reliability.

The GRU model, evolved from the LSTM architecture, integrates gating mechanisms to streamline its structural complexity. While preserving comparable functional capabilities to LSTM, GRUs have emerged as a widely adopted alternative for RUL prediction in recent years, owing to their simplified architecture and reduced computational demands [156]. RouhiArdeshiri et al. [157] proposed a deep learning model based on GRU-RNN, achieving a mean RMSE of approximately 2%, which outperformed LSTM and SVM methods by factors of 1.34 and 8.32, respectively. Wei et al. [158] developed a hybrid model integrating Monte Carlo (MC) dropout with GRU, not only improving prediction accuracy but also enabling effective characterization of RUL prediction uncertainty. Ardeshiri et al. [159] proposed a modified Least Squares Generative Adversarial Network architecture for lithium-ion battery RUL prognosis, integrating a GRU-structured generator and a multilayer perceptron-based discriminator. Through adversarial training, the framework captured the underlying probabilistic distribution of temporal degradation trajectories. It also mitigated the vanishing gradient problem and implemented adaptive penalty weighting for large deviation instances. Feature engineering employed a hybrid selection strategy combining statistical metrics-based filtering and a random forest-based feature importance ranking protocol. Experimental evaluations on benchmark datasets reported a normalized error metric of 2.63% with a maximum absolute deviation of 0.02 charging cycles, demonstrating enhanced long-term prediction stability compared to baseline models.

CNNs dominate computer vision paradigms. They have also demonstrated comparable efficacy in sequential data feature representation. In practical implementations, CNN architectures typically serve as the front-end processing component. They utilize trainable convolutional filters to progressively abstract spatial hierarchies, transitioning from localized receptive fields to global contextual structures [160,161]. Hong et al. [162] employed a dual-convolutional neural network architecture to achieve dimensionality reduction in input data. They subsequently integrated the derived feature representations with engineered domain-specific features through a hybrid feature fusion strategy. Hsu et al. [163] employed a dual-convolutional neural network architecture to achieve dimensionality reduction in input data, subsequently integrating the derived feature representations with engineered domain-specific features through a hybrid feature fusion strategy. They used a DNN to predict battery RUL and achieved an MAPE of 6.46% with only one cycle of test data. Xiong et al. [164] introduced a semi-supervised learning paradigm for capacity degradation estimation, in which raw EIS measurements were directly processed through a CNN architecture for unsupervised feature extraction. This end-to-end pipeline enabled capacity estimation without requiring paired capacity annotations during the feature learning phase. Table 4 summarizes the characteristics of various DL approaches applied to lithium-ion battery RUL prediction.

Table 4. Characteristic analysis of DL methods for RUL prediction.

Method	Advantage	Disadvantage	Ref.
LSTM	Control the information flow that has long been relied upon Eliminate gradient explosion	Complex structure, lengthy training time Numerous parameters, prone to overfitting High computational cost	Reza et al. (2024) [165]
GRU	Simple structure and high calculation efficiency Strong anti-noise robustness	Limited capacity in capturing very long-term dependencies Risk of underfitting in complex prediction tasks	Guo et al. (2023) [166]
CNN	Local information extraction Multi-level feature abstraction Multi-data channel fusion	Insufficient ability to model long-range temporal dependencies High computational demand with large-scale data	He et al. (2024) [167]

In summary, traditional machine learning methods and deep learning approaches each exhibit distinct advantages and limitations in the prediction of lithium-ion battery RUL. The former demonstrates strong generalization capability and interpretability under small-sample conditions, whereas the latter excels in modeling complex nonlinear degradation patterns and integrating multi-source data. Nevertheless, under varying operating conditions (e.g., temperature fluctuations, cycling rate differences, and dataset size), the choice of an optimal algorithm differs significantly. To facilitate intuitive comparison and practical model selection, the optimal machine learning methods under different prediction conditions are summarized in Table 5.

Table 5. Classification and characteristics of machine learning methods under different prediction conditions.

Prediction Condition	Preferred Methods	Characteristics	Ref.
Small sample size	RVM, GPR	RVM and GPR perform well with limited data and provide uncertainty quantification, but suffer from high computational cost	Chen et al. [123] Jia et al. [132]
Large sample size	ANN, SVM	ANN learns complex nonlinear mappings given sufficient data; SVM is robust for medium-to-large datasets but sensitive to kernel and parameter selection	Olabi et al. [129] Xiong et al. [130]
Time series forecasting	LSTM, GRU	Capable of capturing long- and short-term dependencies in sequential battery data; well-suited for degradation trajectory modeling, though computationally expensive	Wang et al. [150] Rouhi et al. [157]
Multidimensional mixed features	ANN, SVM	The ANN can automatically extract features from high-dimensional data; the SVM handles nonlinear relationships effectively in structured feature spaces	Tang et al. [115] Jafari et al. [118]
Nonlinear degradation modeling	ANN, CNN	The ANN is powerful in learning complex nonlinear degradation patterns; the CNN automatically extracts features from curves or spectrograms	Olabi et al. [129] He et al. [167]
RUL prediction	LSTM, GRU, GPR	LSTM/GRU model long-term cycling trends; GPR provides probabilistic predictions with confidence intervals for reliability assessment	Park et al. [153] Jia et al. [132]
Safety prediction	CNN, SVM	The CNN extracts abnormal patterns from voltage/temperature signals; the SVM is widely used for anomaly classification in battery safety monitoring	Hong et al. [162] Xiong et al. [130]

4. Fusion-Based RUL Prediction Using Multi-Scale Methods

Hybrid prediction methods represent a predominant research direction in the current field of RUL prediction. Model-based filtering techniques and purely data-driven methods often struggle to balance prediction accuracy with adaptive capability. Hybrid approaches, by integrating the strengths of multiple techniques and mitigating their individual limitations, provide an effective solution to these challenges [168–170]. Although hybrid strategies have inherent constraints, researchers aim to optimize the trade-off among predictive accuracy, system reliability, and online adaptability—factors that are critical for practical battery management system deployment. Such frameworks can dynamically respond to varying operational conditions (e.g., temperature fluctuations, charge–discharge rates, and usage patterns), thereby delivering more precise RUL predictions. Moreover, compared to single-method solutions, hybrid architectures demonstrate superior efficacy in capturing the dynamic characteristics of complex, nonlinear degradation processes and maintain robust predictive performance, even when data are scarce [171]. As illustrated in Figure 8, the procedural framework of the RUL fusion method exemplifies how such integration systematically unifies empirical insights and data-driven analytics to achieve robust cross-domain adaptability.

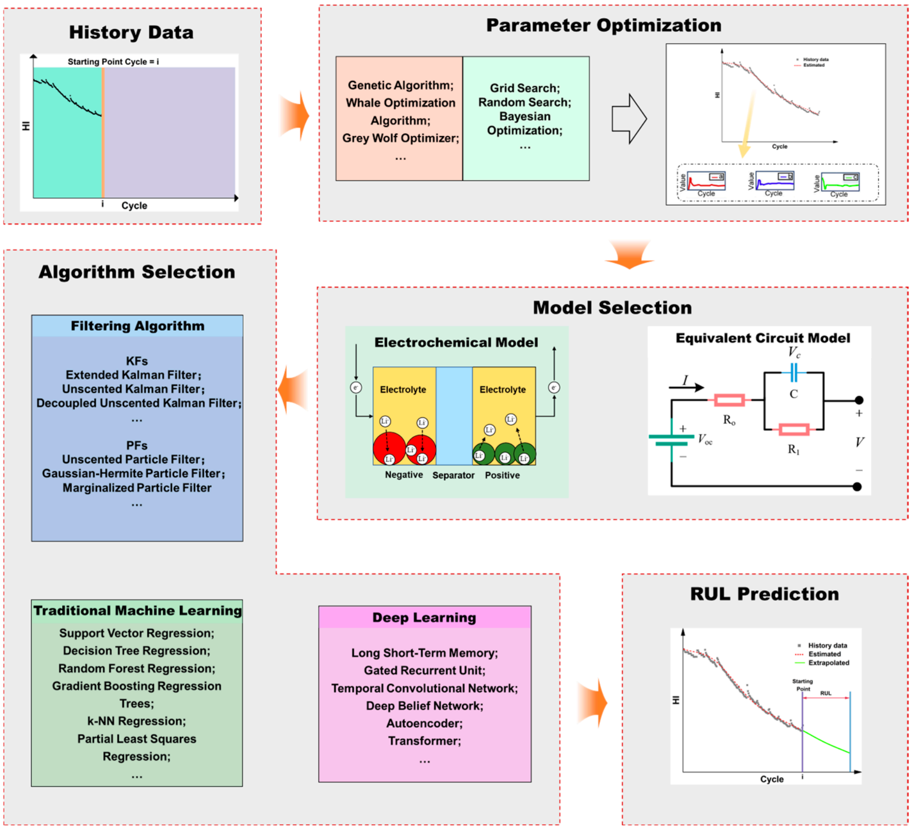


Figure 8. Flowchart of fusion-based RUL prediction for lithium-ion batteries.

This section provides a systematic comparison of contemporary hybrid methodologies for lithium-ion battery RUL prognosis, with particular emphasis on their methodological attributes and prognostic performance. The taxonomy of fusion-based approaches is divided into two principal categories. The first category applies filtering techniques, including KF [172] and PF [173] paradigms, along with their adaptive variants. As demonstrated in Table 6, a comparative overview summarizes the methodological attributes and performance advantages of hybrid filtering implementations for RUL prediction.

Table 6. Comparison of filtering algorithms for fusion-based RUL prediction.

Method	Characteristic	Datasets	Criteria	Ref.
Improved WOA+PF	Superior ability to resist noise	NASA (B5, 6, 7, 18) Oxford (Cell1, 2, 3, 6, 7, 8)	RMSE = 0.089 MAPE = 0.067	Duan et al. (2023) [174]
Improved PSO+PF	Strong ability to resist environmental interference	NASA (B5, 6, 7, 18) CALCE (CS2-34, CS2-36, CS2-37)	RMSE = 0.0164 MAPE = 0.00324	Pang et al. (2024) [175]
Capacity Regeneration Point (CRP)+PF+Autoregressive Integrated Moving Average (AIMA)	Effectively addresses capacity regeneration interference to improve RUL prediction accuracy	NASA (B5, 6, 7, 18)	RMSE = 0.0157 MAPE = 0.0185	He et al. (2024) [176]
Gray+Ensemble Kalman Filter (EnKF)	Adaptable to varying Requires minimal historical data, low modeling costs	NASA (B5, 6, 7, 18)	RMSE = 0.016 MAPE = 0.0077	Li et al. (2025) [177]
Electrochemical–Thermal model (ECT)+Unscented Kalman Filter (UKF)	Improve the accuracy of the prediction Enhance the generalization ability of the model	NASA (RW13, 14) Self-made dataset: 18,650 $LiFePO_4/C$	RMSE = 0.0132 MAPE = 0.0273	Ren et al. (2024) [178]

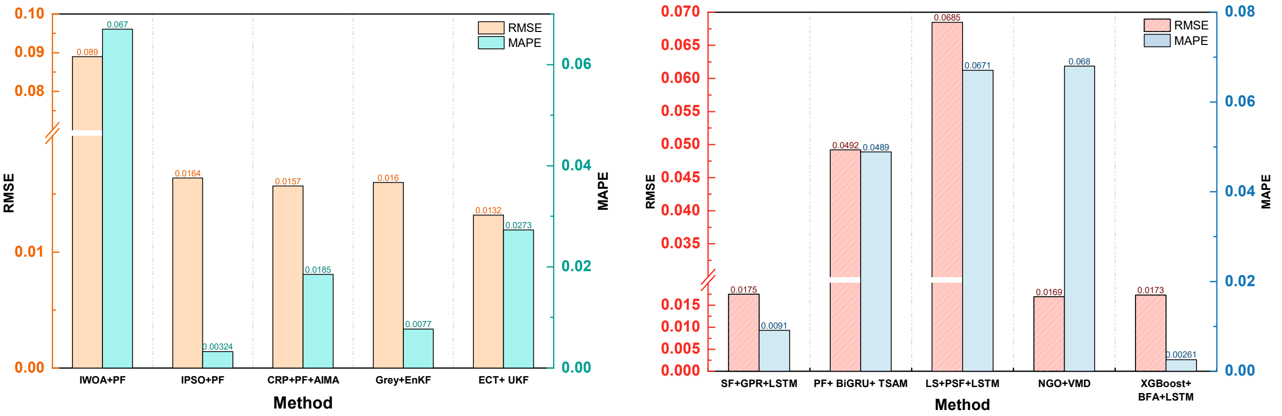
The above-mentioned hybrid methods each have distinct focuses in terms of model construction, feature extraction, and optimization strategies, but they generally share the following common characteristics and differences. Duan et al. [174] proposed a variable-forgetting-factor online sequential extreme learning machine (VFOS-ELM) combined with a PF-based online sequential extreme learning framework, which, through the improvement of the whale extreme random tree optimization algorithm and feature selection, effectively balances learning speed and model simplicity. He et al. [176] proposed a CRP-PF-ARIMA model integrating Wasserstein distance, particle filtering, and AIMA with error compensation to address capacity regeneration in lithium-ion battery RUL prediction. Validated on the NASA dataset, it achieved ≤5% error and about 70% higher accuracy than existing methods. Li et al. [177] proposed a hybrid approach of piecewise gray modeling and EnKF error compensation, which reduces prediction bias from capacity regeneration and ensures accuracy, efficiency, and practicality in lithium-ion battery RUL prediction. Ren et al. [178] enhanced the accuracy of multi-physics coupling prediction by coupling ECT, electrochemical–thermal, and SEI film formation models, supplemented by UKF parameter iteration. Collectively, these approaches highlight the diverse innovations of hybrid methods while emphasizing their shared potential in improving RUL prediction reliability.

The second type of hybrid methodology relies on intelligent algorithms, particularly machine learning approaches [179]. Table 7 presents the characteristics and advantages of integrating different data-driven algorithms for RUL prediction.

Table 7. Comparison of different data-driven algorithms for fusion-based RUL prediction.

Method	Characteristic	Datasets	Criteria	Ref.
Singular Filtering (SF)+GPR+LSTM	Accurately quantify the remaining capacity of lithium batteries at extremely low temperatures	Self-made dataset	RMSE = 0.0175 MAPE = 0.0091	Wang et al. (2023) [180]
PF+Bidirectional Gated Recurrent Unit (BiGRU)+Temporal Attention Mechanism (TSAM)	Based on historical data, offline modeling is carried out to achieve the quantitative representation of battery capacity in the time series dimension	NASA (B5, 6, 7, 18)	RMSE = 0.0492 MAPE = 0.0489	Zhang et al. (2024) [181]
Lebesgue Sampling (LS)+Parallel State Fusion (PSF)+LSTM	Addresses early-cycle lithium-ion battery RUL prediction challenges	MIT (M#1, 2, 3, 4) Tongji (T#1, 2, 3, 4)	RMSE = 0.0685 MAPE = 0.0671	Lyu et al. (2023) [182]
Northern Goshawk Optimization (NGO)+Variational Mode Decomposition (VMD)	Effectively extract multi-scale useful information and significantly reduce the complexity of battery capacity sequences	NASA (B5, 6, 7, 18) CALCE (CS2-33, CS2-34, CX2-33, CX2-34)	RMSE = 0.0169 MAPE = 0.068	Li et al. (2024) [183]
eXtreme Gradient Boosting (XGBoost)+Binary Firefly Algorithm (BFA)+LSTM	Deep exploration of the relationship between battery health indicators and RUL degradation	NASA (B5, 6, 7, 18)	RMSE = 0.0173 MAPE = 0.00261	Jin et al. (2025) [184]

Compared with the first category of methods, Wang et al. [180] introduced a multi-time scale SF-GPR-LSTM framework, and Zhang et al. [181] developed the PF-BiGRU-TSAM system. Both frameworks underscore the strengths of deep learning for temporal pattern recognition and context-aware feature extraction, while further enhancing capacity estimation and RUL prediction performance by incorporating multidimensional physical characteristics and interactive data-driven approaches. Lyu et al. [182] proposed the LS-PSF-LSTM strategy, and Li et al. [183] designed the NGO-VMD approach, which, respectively, optimizes error control and model robustness from the perspectives of sample selection and noise suppression. Meanwhile, Jin et al. [184] combined LSTM with a BFA-optimized XGBoost model to demonstrate the synergistic potential of metaheuristic optimization in feature selection within a gradient boosting framework. Collectively, these intelligent algorithm-based hybrid methods highlight the growing importance of deep learning and optimization strategies in achieving accurate and reliable RUL prediction. A comparative analysis of the RMSE and MAPE values in Figure 9a,b shows that data-driven fusion algorithms offer a significant advantage in predictive performance.



(**a**) (**b**)

Figure 9. Comparative analysis of RMSE and MAPE for lithium-ion battery RUL prediction under different algorithms: (**a**) filtering algorithms for fusion-based RUL prediction; (**b**) data-driven algorithms for fusion-based RUL prediction.

These data-driven methods achieve markedly higher prediction accuracy compared to fusion schemes that incorporate filtering techniques. Moreover, the data-driven fusion algorithms show enhanced generalizability across diverse application scenarios, effectively expanding their applicability. This comparison validates the effectiveness of data-driven strategies in the design of fusion algorithms and provides a quantitative foundation for methodological selection in related research fields. Future research should aim to reduce model complexity and online computational costs while maintaining high RUL prediction accuracy. Researchers should also incorporate explainable AI technologies to enhance transparency in decision-making and strengthen engineering credibility. In addition, the integration of multimodal sensing and contextual information can enable collaborative modeling of degradation mechanisms based on multi-source data. Finally, future studies should improve uncertainty quantification and adaptive correction capabilities to better meet the dynamic monitoring and risk-warning requirements of real-world operating conditions.

5. Conclusions and Prospects

5.1. Conclusions

This review systematically analyzed mainstream approaches for predicting the RUL of lithium-ion batteries, including model-based, data-driven, and hybrid methods. Model-based approaches offer mechanistic interpretability but suffer from high computational demands and parameter sensitivity under dynamic conditions. Data-driven techniques excel at capturing nonlinear degradation behaviors and adapting to diverse environments but rely heavily on large-scale datasets and lack physical interpretability. Hybrid architectures that integrate physical models with data-driven approaches overcome the inherent limitations of the two individual categories and significantly improve prediction accuracy and system stability in complex operating scenarios. This review categorizes various fusion approaches within hybrid architectures and systematically compares their prediction performance using RMSE and MAPE as evaluation metrics. The analysis results indicate that, among the hybrid methods compared in this paper, the LSTM network and the BFA-optimized XGBoost hybrid framework achieve the best performance, with a root mean square error of less than 2% and a mean absolute percentage error of less than 1% for RUL prediction accuracy. Future research can further improve these hybrid algorithms, thereby laying a solid foundation for the safe and efficient operation of energy storage systems.

5.2. Prospect

Building on this research, future studies should focus on enhancing the efficiency and interpretability of hybrid models. Optimization algorithms, such as PSO, can be introduced to establish iterative training frameworks, further improving the efficiency of feature selection and model parameter tuning. By incorporating explainable artificial intelligence methods to address the "black box" nature of algorithms, we can gain deeper insights into battery degradation mechanisms. Simultaneously, this approach still holds significant room for improvement in scalability and real-time deployment. Real-time updates and dynamic optimization of battery state can be achieved through the synergy between XGBoost and EKF, strengthening the coupling between physical mechanisms and data features. Future research should also focus on overcoming bottlenecks in multimodal data fusion and edge intelligence deployment. By exploring transfer learning and domain adaptation techniques, models trained for specific battery types or states can be effectively applied to other scenarios, reducing the need for extensive retraining. This enhances prediction reliability under extreme environments and dynamic loads, ensuring continuous and dependable battery health monitoring in practical applications.

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