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Review

Battery Health Monitoring and Remaining Useful Life Prediction Techniques: A Review of Technologies

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Abstract: Lithium-ion (Li-ion) batteries have become essential in modern industries and domestic applications due to their high energy density and efficiency. However, they experience gradual degradation over time, which presents significant challenges in maintaining optimal battery performance and increases the risk of unexpected system failures. To ensure the reliability and longevity of Li-ion batteries in applications, various methods have been proposed for battery health monitoring and remaining useful life (RUL) prediction. This paper provides a comprehensive review and analysis of the primary approaches employed for battery health monitoring and RUL estimation under the categories of model-based, data-driven, and hybrid methods. Generally speaking, model-based methods use physical or electrochemical models to simulate battery behaviour, which offers valuable insights into the principles that govern battery degradation. Data-driven techniques leverage historical data, AI, and machine learning algorithms to identify degradation trends and predict RUL, which can provide flexible and adaptive solutions. Hybrid approaches integrate multiple methods to enhance predictive accuracy by combining the physical insights of model-based methods with the statistical and analytical strengths of data-driven techniques. This paper thoroughly evaluates these methodologies, focusing on recent advancements along with their respective strengths and limitations. By consolidating current findings and highlighting potential pathways for advancement, this review paper serves as a foundational resource for researchers and practitioners working to advance battery health monitoring and RUL prediction methods across both academic and industrial fields.

Keywords: lithium-ion batteries; battery health management; battery degradation; state of health estimation; remaining useful life prediction; data-driven techniques; model-based methods; hybrid methods

Academic Editors: Truong Minh Ngoc Bui, Truong Quang Dinh and Mona Faraji Niri

Received: 10 December 2024
Revised: 2 January 2025
Accepted: 15 January 2025
Published: 17 January 2025

Citation: Ahwiadi, M.; Wang, W. Battery Health Monitoring and Remaining Useful Life Prediction Techniques: A Review of Technologies. *Batteries* **2025**, *11*, 31. https://doi.org/10.3390/batteries11010031

1. Introduction

Lithium-ion (Li-ion) batteries have transformed energy storage technology due to their exceptional properties. Their high energy density, efficiency, and long cycle life make them the preferred choice across a wide array of applications, including electric vehicles (EVs), grid storage, aerospace, industrial machinery, and consumer electronics [1,2]. In EVs, for example, Li-ion batteries offer extended driving range and faster charging times, which contribute positively to reduced carbon emissions [3]. Among renewable energy systems, batteries enable more efficient energy storage and power fluctuation management than solar and wind power systems [4]. In consumer electronics, their compact size and long-lasting charge retention support portability and extended use in devices such as smartphones and laptops [5,6]. The high performance of Li-ion batteries is attributed to

their unique electrochemical structure that consists of three main components: an anode, a cathode, and an electrolyte. In general, the anode is constructed of graphite, the cathode is composed of lithium metal oxides, and the electrolyte facilitates the movement of lithium ions between the electrodes [6–8]. During the discharge period, lithium ions release energy by flowing from the anode to the cathode. When the battery is recharged, the ions flow in the reverse direction (from the cathode to the anode) to restore the battery's energy capacity [8,9]. This reversible ion transfer mechanism allows Li-ion batteries to provide high energy density and efficiency [9,10].

However, the electrochemical reaction that provides Li-ion batteries with their high performance also leads to gradual battery power level degradation. Each charge and discharge cycle generates small but irreversible changes to the battery's internal structure, thereby resulting in a steady decline in capacity and efficiency over time [6,11]. Li-ion battery degradation occurs primarily through two mechanisms, known as cycling aging and calendar aging. Cycling aging results from repeated charge and discharge cycling, which gradually wears down electrode materials, increases internal resistance, and changes the battery structure [7,12]. Factors such as high charge/discharge rates, deep discharges, and high temperatures can accelerate this process, potentially further impacting battery performance. In contrast, calendar aging is the natural degradation that occurs over time, even when the battery is not actively cycled. Environmental factors such as temperature and humidity, as well as the battery's state of charge during storage, can significantly influence calendar aging [11,13]. For example, high temperatures accelerate electrolyte decomposition and other internal reactions, which increase internal resistance but reduce capacity. Additionally, keeping the battery at a high state of charge over an extended period can promote the formation of a solid electrolyte interphase layer and reduce ion flow and efficiency [13,14].

Both cycling aging and calendar aging are unavoidable and contribute to the gradual degradation of Li-ion batteries, thereby affecting their long-term performance and reliability. This degradation presents significant challenges, specifically as industries increasingly depend on Li-ion batteries in critical applications such as EVs [5,15]. The longevity and reliability of these batteries are crucial for maintaining optimal performance and avoiding unexpected failures, which can result in costly downtime and, in some cases, pose safety risks. For example, reduced battery capacity in EVs can directly impact driving range and energy efficiency, while in aerospace applications, battery reliability is essential for safety and mission success. In renewable energy systems, where Li-ion batteries store energy from fluctuating sources like solar and wind, battery degradation can reduce storage efficiency and lead to mismatches between supply and demand; this can adversely impact grid stability [9,15]. To address these challenges, advanced monitoring and maintenance strategies are essential to detect early signs of battery degradation, predict the remaining useful life (RUL), and implement appropriate management measures [14,16]. Such strategies are critical for maintaining battery performance and reliability and for supporting the continued integration of Li-ion batteries in demanding applications [15,16].

Accurately predicting the RUL of Li-ion batteries remains challenging due to the nonlinear and complex nature of degradation, which varies significantly with usage conditions, environmental factors and battery design [1,2]. To model this degradation effectively, several battery features are commonly applied for monitoring, including charge capacity, internal resistance, state of health (SOH), voltage characteristics, etc. The demonstration figures in this review paper are generated using real battery data from the National Aeronautics and Space Administration (NASA) Ames Prognostic Center of Excellence to illustrate these features and how they evolve over time as the battery degrades [17]. These metrics serve as essential indicators of a battery's health and degradation state:

- Charge capacity: As shown in Figure 1, charge capacity represents the amount of charge the battery can store and deliver at any given time moment. Tracking the decline in charge capacity over time provides a direct measure of usable energy reduction, which is crucial for predicting the battery RUL. Figure 1 illustrates the trend of decreasing battery capacity over time (i.e., cycles) of three batteries from the dataset in [17], which reflects the normal curves toward eventual battery failure [5,6].
- State of health (SOH): The SOH indicates the battery's health state as a percentage of its original capacity (100% when it is new). This metric provides a clear and quantifiable measure of battery health that reflects how much of the battery's initial capacity remains as it ages. Monitoring SOH is essential for assessing degradation levels and predicting the RUL. In Figure 2, the SOH is calculated based on charge capacity using Equation (1), which illustrates the degradation over time for battery #5 until it reaches its end-of-life threshold, which is usually set at a 30% loss of the initial capacity [6,12]. This trend highlights the gradual decline in the battery's ability to store and deliver energy as it undergoes repeated charge/discharge cycles, thus providing valuable insights into its remaining service life and performance reliability.

$$SOH(\%) = \left(\frac{\text{Current charge capacity}}{\text{Original charge capacity}} \right) \times 100 \quad (1)$$

- Internal resistance: Figure 3 illustrates the progression of internal resistance as a function of the cycle number, highlighting its gradual increase over time. The data used to generate this figure is derived from the measurements of battery #6, providing an example of how internal resistance evolves during repeated charge/discharge cycles. This steady increase in internal resistance is caused by several underlying mechanisms including the breakdown of electrode materials, the formation of a solid electrolyte interphase layer, and the degradation of the electrolyte. These processes collectively reduce the ability of ions to move freely within the battery structure, leading to reduced battery efficiency and diminished power delivery. As internal resistance grows, it results in greater energy losses and increased heat generation, factors that can further impair performance, pose safety risks, and accelerate the degradation process. Therefore, monitoring this resistance trend is essential for understanding how battery performance evolves with age [7,9]. In general, internal resistance is a key indicator of battery health, which provides valuable insights into the battery condition and can help to predict when it will no longer perform effectively. Such predictions are critical for ensuring reliability in applications where consistent performance is essential, including electric vehicles, renewable energy systems, and aerospace technologies.
- Voltage characteristics: Analyzing voltage characteristics helps to detect early signs of battery degradation and to forecast its future performance and lifespan. Figure 4 illustrates the progression of voltage profiles during discharge cycles over time using data from battery #5. The x-axis represents the measurement points within each discharge cycle, while the y-axis shows the corresponding voltage values. A colour gradient is used to indicate the transition from early cycles (blue) to late cycles (red); this is to highlight the battery's aging process over time. In the early cycles (depicted by blue curves), the voltage profiles are higher and more consistent, indicating the battery's ability to deliver energy efficiently. As the battery ages (depicted by red curves), the voltage profiles shift downward and become smoother. This shift indicates a reduction in the battery's energy delivery capacity caused by factors such as increased internal resistance, electrode degradation, and reduced ion mobility. These changes in voltage

behaviour can serve as an early indicator of battery degradation and can be monitored to assess the battery's state of health and predict its RUL [13,14].

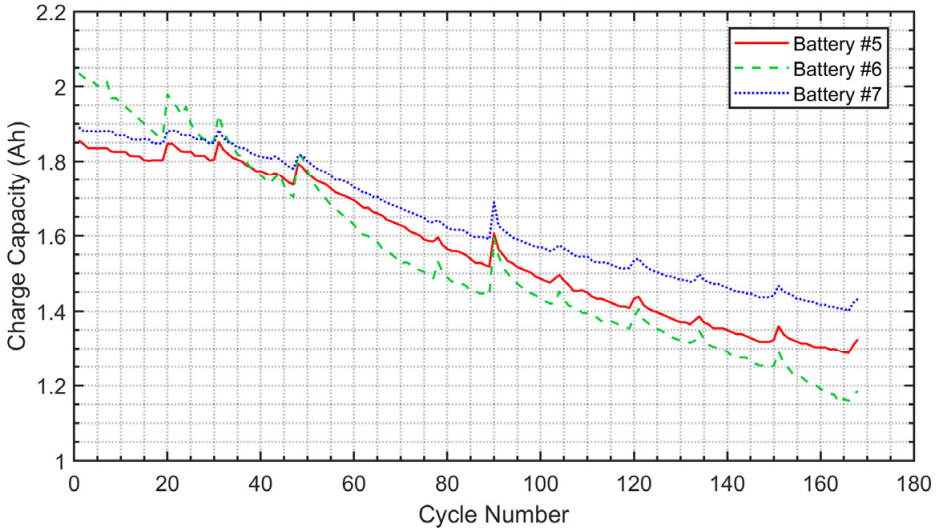

Figure 1. Degradation curves showing charge capacity for batteries #5, #6, and #7.

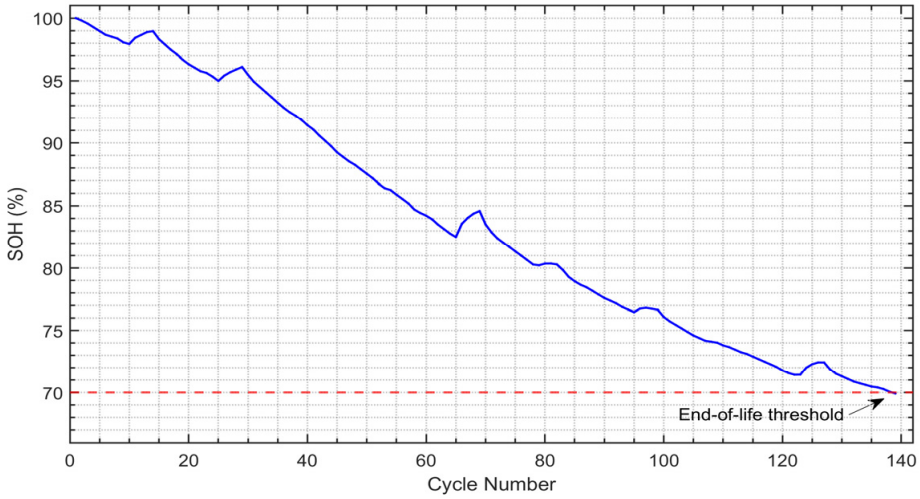

Figure 2. SOH degradation over time, showing progression toward the end-of-life threshold.

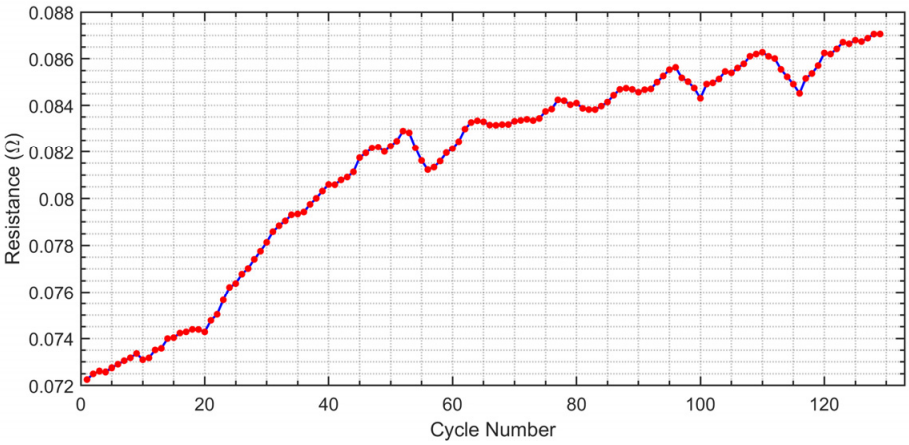

Figure 3. Increase in internal resistance over time indicating gradual battery degradation.

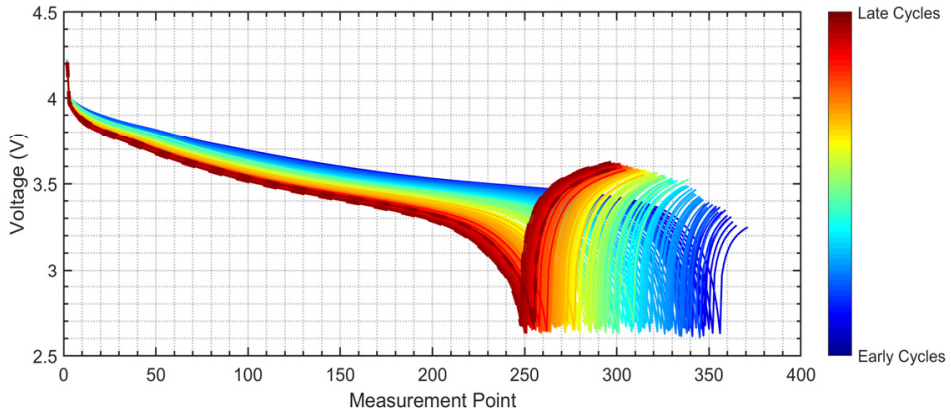

Figure 4. Progression of voltage profiles over discharge cycles, showing a transition from early (blue) to late (red) cycles to indicate declining energy with aging.

Monitoring these features over time provides valuable insights into battery health and performance, allowing more precise predictions of RUL. In general, reliable tracking and modelling of these metrics are essential for developing robust battery health management systems that can predict battery degradation patterns, support timely interventions, and optimize battery life cycles across various applications.

This review paper aims to provide a comprehensive analysis of the main techniques for battery health monitoring and RUL prediction, which provide insights into the state-of-the-art research and identify new initiatives for future exploration and enhancement. Traditionally, three main approaches can be identified for battery health monitoring and RUL prediction: model-based methods, data-driven techniques, and hybrid approaches. Model-based methods use physical or electrochemical models to simulate battery behaviour to offer insights into battery degradation mechanisms and the influence of operational conditions [3,7]. Although such methods offer high interpretability and theoretical grounding, they could have high computational costs and may require detailed battery-specific knowledge. Data-driven techniques leverage historical data and AI/machine learning algorithms to identify degradation patterns and predict RUL. These can provide flexible solutions for complex nonlinear systems without requiring in-depth knowledge of underlying battery chemistry [1,9,15]. Even though these techniques offer reasonable adaptability and flexibility when dealing with nonlinear systems, they rely heavily on large high-quality datasets. Hybrid approaches integrate the strengths of both data-driven and model-based approaches to improve prediction accuracy by incorporating physical understanding and statistical learning, which can tackle certain limitations that surface by using standalone techniques [5,10,15]. These hybrid approaches are robust to some extent and could be more suitable for long-term prediction and complex applications; however, this advantage comes with the cost of increased complexity. Table 1 summarizes the properties of these three approaches, highlighting their key features, strengths, and limitations.

Table 1. Comparison of major approaches to battery health monitoring and RUL forecasting.

Methods	Key Features	Strengths	Limitations
Model-based	Physics-based or equivalent circuit models.	High interpretability; theoretical foundation.	High computational cost; parameter sensitivity.
Data-driven	AI/ML algorithms for trend detection and regression.	Adaptable to nonlinear behaviours; handles noisy data.	Require large datasets; lack physical interpretability.
Hybrid approaches	Combines physical and statistical methods.	Balances accuracy and adaptability.	Higher computational cost; complex integration.

The following sections explore each of these approaches, providing a detailed analysis of their strengths, limitations and opportunities for future advancements.

2. Model-Based Methods

Model-based methods play a crucial role in battery health monitoring and RUL prediction by simulating battery behaviour through physical, electrochemical, or equivalent circuit models. These methods provide detailed insights into degradation mechanisms, the effects of operational conditions, and dynamic system behaviours [18,19]. A significant advantage of model-based methods is their ability to integrate theoretical knowledge with practical adaptability, which is essential for advancing battery management systems and ensuring the long-term reliability of energy storage solutions. Model-based approaches are also highly adaptable to varying operational environments, such as shifts in load, temperature, and usage behaviours, which enhance their applicability in real-world scenarios [1,20]. By including uncertainty quantification in their estimates, these methods could potentially deliver more robust state estimation and RUL prediction, even when the system is exposed to unpredictable or dynamic conditions [20–24].

The main types of models applied in this approach are the electrochemical models, semi-empirical models, and equivalent circuit models (ECMs). Each type of model has its own unique strengths and limitations and is suitable for specific aspects of battery health monitoring.

(a) Electrochemical models: These provide a physics-based framework for simulating internal battery processes including ion movement, reaction rates, and the formation of a solid–electrolyte interphase (SEI). These models are highly detailed and can offer detailed insights into phenomena such as Li-ion intercalation and capacity fade, which allow more accurate assessments of SOH and degradation mechanisms [25–30]. However, they require extensive computational resources and highly accurate parameter inputs associated with electrolyte properties, reaction rates, thermal effects, etc. These requirements make them less practical for real-time applications [6,25–27]. Additionally, the inherent complexity of these models often necessitates simplifications to make them computationally feasible, which, in turn, can reduce prediction accuracy under specific conditions [12,25–27].

(b) Semi-empirical models: These could bridge the gap between theoretical analysis and practical applications by combining experimental data with simplified physical equations. These models can be effectively applied to estimate SOH and RUL with reduced computational demands, rendering them more suitable for real-time applications [29–31]. For example, models that combine empirical capacity degradation curves with simplified mathematical formulations have demonstrated reliable performance in real-world scenarios [2,25–27,32]. Nonetheless, semi-empirical models often lack the precision needed to capture underlying electrochemical processes or to predict performance under extreme conditions. This limitation reduces their applicability in scenarios requiring detailed degradation analysis [26,27,32].

(c) Equivalent circuit models: These represent battery behaviour using simple electrical components such as resistors, capacitors, and voltage sources. They are computationally efficient and require minimal setup data, which makes them ideal for integration into battery management systems for real-time SOH estimation [26,30,33,34]. Studies have demonstrated their ability to accurately model battery behaviour during constant discharge or low-intensity charging cycles [2,6,12,27]. However, their simplified approach creates challenges in capturing a battery's complex physical and chemical processes such as ion diffusion and reaction rates. This oversimplification can result in inaccuracies under high-rate charging/discharging conditions or extreme temperatures [2,26,32].

While model-based methods provide the theoretical framework for understanding battery behaviour, they require appropriate estimation techniques to handle noisy, uncertain, and incomplete data. Tools like the Kalman Filter (KF) and Particle Filter (PF) are essential for improving the reliability and accuracy of these models. These estimation methods enable model-based approaches to infer unobservable system states (e.g., degradation indicators and damage parameters) that are critical for understanding and predicting battery health and performance [6,20,22,35].

2.1. Kalman Filter (KF) Algorithms

The KF is a widely used estimation method for dynamic system analysis, including battery health monitoring and RUL prediction. KF is highly effective at estimating hidden system states by combining system models with noisy measurements, which can provide optimal state estimation for linear and Gaussian systems [13,30,36].

In general, KF operates recursively in two primary steps, prediction and update, utilizing the transition and measurement models to estimate the hidden states of dynamic systems. In the state representation, the true state of the system at time k, denoted by x_k, the KF provides an estimated state, $\hat{x}_k|_{k-1}$, through prediction, and then refines it to $\hat{x}_k|_k$ during the update step by incorporating measurement data. The goal is to minimize the error between the true state x_k and its estimate $\hat{x}_k$ over time [30,37–39].

During the prediction step, the transition model, as described by Equation (2), predicts the system state at the next time step using the previous state and control input:

$$\hat{x}_k\Big|_{k-1} = A_k \cdot \hat{x}_{k-1|k-1} + B_k \cdot c_k \tag{2}$$

where $\hat{x}_k|_{k-1}$ denotes the predicted state estimate at time k, $\hat{x}_{k-1}|_{k-1}$ represents the updated state estimate from the previous time step, A_k is the state transition matrix, B_k is the control input matrix, and c_k represents the control input.

To account for process noise, the predicted error covariance is calculated by:

$$P_{k|k-1} = A_k \cdot P_{k-1|k-1} \cdot A_k + Q_k \tag{3}$$

where $P_{k|k-1}$ denotes the predicted error covariance matrix, $P_{k-1|k-1}$ represents the updated error covariance matrix from the previous step, and Q_k is the process noise covariance matrix representing the uncertainty introduced by the process noise.

During the update step, the measurement model, as described by Equation (4), relates the predicted state to observed data:

$$z_k = H_k \cdot x_k + v_k \tag{4}$$

where z_k represents the observation (measurement) at time k, H_k denotes the measurement matrix mapping the state to the observation space, and v_k is the measurement noise. Using the measurement, the Kalman gain, computed by Equation (5), determines the weight of the correction:

$$K_k = P_{k|k-1} \cdot H_k^T \cdot \left(H_k \cdot P_{k|k-1} \cdot H_k^T + R_k\right)^{-1} \tag{5}$$

where K_k denotes the Kalman gain at time k, and R_k is the measurement noise covariance matrix. The state estimate is then updated using Equation (6):

$$\hat{x}_{k|k} = \hat{x}_{k|k-1} + K_k(z_k - H_k \cdot \hat{x}_{k|k-1}) \tag{6}$$

where the term $z_k - H_k \cdot \hat{x}_{k|k-1}$ is the measurement residual that represents the difference between the actual measurement and the predicted measurement. Finally, the updated error covariance is given by Equation (7):

$$P_{k|k} = (I - K_k \cdot H_k)\, P_{k|k-1} \tag{7}$$

where $P_{k|k}$ denotes the updated error covariance matrix and I is the identity matrix.

As described by Equations (2)–(7), the standard KF works by recursively updating finite-dimensional parameters, minimizing the state error covariance to make precise state estimations over time. Its ability to consistently refine predictions makes it an essential technique in applications requiring accurate, real-time monitoring of dynamic systems [30,37,38]. A number of studies have utilized KFs for battery health monitoring and management. For example, the study in [40] implemented a KF with local linearization, combining open-circuit voltage (OCV) measurements and Coulomb counting for State-of-Charge (SOC) estimation. This approach demonstrated low estimation errors while maintaining low computational complexity. Further advancements related to model mismatches were proposed in [41], where a KF-based approach incorporated a bias term into the state vector to account for errors such as OCV drift and sensor inaccuracies. The findings demonstrated this method's ability to improve accuracy in SOC predictions. KFs have also been applied to large-scale battery systems, as shown in [42], where they were employed in Battery Energy Storage Systems (BESS). This work demonstrated the KF's capability to handle the increased complexity of large-scale configurations and achieve accurate SOC estimates. In addition, the study in [43] utilized a KF integrated with an enhanced electro-thermal coupling model to estimate internal battery temperatures. This approach highlights the KF's capability to accurately estimate the internal thermal state of batteries to ensure safety and performance. The study in [44] introduced an adaptive KF filtering method that integrated SOC estimation with corrections for initial SOC errors in electric vehicle battery packs. This method demonstrated significant reductions in SOC estimation errors compared to traditional approaches. Further adaptive KF methods were proposed in [45,46]. While these studies highlight the KF's ability to address operational challenges, handle model uncertainties, and manage large-scale systems, KFs are known to have limitations in modelling systems with nonlinear or non-Gaussian characteristics. These limitations may affect their performance when dealing with the complex and nonlinear behaviours of Li-ion batteries, especially under time-varying operational conditions [19,20].

Improved KF techniques have been widely explored in various studies to address the challenges associated with handling nonlinear systems. One well-known enhancement is the extended KF (EKF), which provides a solution to the nonlinearities inherent in battery systems [37,38]. By linearizing nonlinear dynamic state-space models through the first-order Taylor series expansion, the EKF enhances the standard KF framework for application in systems with nonlinear behaviours. This linearization is performed at each time step around the current state estimate, which can provide real-time updates of both state variables and error covariance matrices [11,38,47]. To improve the reliability and adaptability of the EKF in modelling battery systems, several advancements have been proposed. For instance, an adaptive EKF method was suggested in [48], which dynamically adjusts the measurement noise covariance using a forgetting factor and a variable sliding window length. This approach addresses uncertainties in model parameters and initial noise covariance matrices, resulting in enhanced SOC estimation accuracy under dynamic conditions. Another advancement was highlighted in [49], where a dual EKF was employed to simultaneously estimate SOC and battery model parameters, utilizing charging voltage curves to reduce computational demands. This approach effectively mitigates measurement noise and achieves high SOC estimation accuracy. Additionally, the study in [50] proposed

a simplified EKF tuning method that uses a single parameter instead of complex covariance matrix adjustments. This approach provided accurate SOC and model parameter estimates while lowering computational requirements. Other improvements include modifications to Jacobian matrix computations, where alternative linearization methods or adaptive updates are implemented to mitigate errors in highly nonlinear systems [51,52]. Furthermore, adaptive noise covariance tuning methods have been suggested to dynamically adjust process and measurement noise parameters based on real-time operational data, improving filter robustness under time-varying conditions [53,54]. Hybrid filtering techniques, such as combining EKF with complementary approaches, have also been employed to address non-Gaussian noise and complex nonlinearities [55,56].

Despite these advancements, EKF faces notable challenges in modelling highly nonlinear or non-Gaussian systems. Its reliance on the first-order Taylor series expansion introduces reducing estimation accuracy when the nonlinearities exceed certain thresholds of approximation. Furthermore, the Gaussian noise assumption in the posterior probability density function (PDF) can degrade performance in real-world scenarios where noise deviates from Gaussian distributions; this highlights the need for more advanced approaches [47,57]. The Unscented KF (UKF) has been proposed to minimize linearization errors in EKFs by utilizing a deterministic sampling method known as the unscented transform [38,57]. This technique computes a set of sigma points to approximate the state distribution, which allows the UKF to better handle nonlinearities compared to the EKF [37,38]. To further enhance the adaptability and accuracy of UKFs in battery system modelling, various advancements have been proposed. For instance, adaptive UKF is suggested by integrating noise covariance estimation techniques (e.g., the Sage–Husa method) to address the challenges of unknown or inaccurate noise statistics and to improve state estimation under time-varying operational conditions [58,59]. Additionally, computational enhancements like the square root UKF have been suggested to reformulate the covariance update in a square-root form to reduce computational complexity [60].

To further address stability and robustness limitations in UKFs, an optimization multi-interest adaptive UKF has been introduced to tackle stability and robustness limitations in traditional UKFs, which maintains accuracy even when the error covariance matrix becomes a non-positive definite [61]. Similarly, the study in [62] presented an improved adaptive UKF that employed singular value decomposition (SVD) instead of Cholesky decomposition to handle non-positive definite error covariance matrices. This method demonstrated enhanced SOC estimation accuracy and stability under dynamic conditions, even with inaccurate initial SOC values. Additionally, a customized UKF was proposed in [63] for SOC estimation, incorporating dual nonlinear transformations to better handle rapid current fluctuations and non-Gaussian noise. This method also included a conformable noise covariance matching technique, which reduced estimation errors and enhanced robustness under challenging operational conditions. Another study in [64] presented a modified multi-innovation UKF that utilized both forward and backward innovations for SOC estimation. By fixing the multi-innovation window length and adjusting historical innovations, this method improved robustness, reduced sensitivity to noise, and achieved consistently low estimation errors. Furthermore, innovative approaches such as combining UKF with data-driven techniques have been explored to improve the UKF so as to enhance SOH estimation and prediction accuracy [65–67]. While the UKFs improve the EKFs to some extent in handling nonlinear systems, future research could focus on improving the adaptability and efficiency of the UKF to make it more suitable for real-world battery health management applications. This could involve combining the UKF with other optimization techniques to adjust system parameters in real time and improve efficiency, especially for systems with limited resources such as low computational power,

restricted memory, or constrained energy availability. While EKFs and UKFs address many limitations of standard KFs, future research should focus on integrating them with machine learning for tuning, hybrid frameworks for robustness, and optimization for resource-constrained systems. Figure 5 highlights how KF methods evolve to address challenges such as nonlinearities, noise characteristics, and computational costs while outlining future directions for advancing battery health monitoring and RUL prediction.

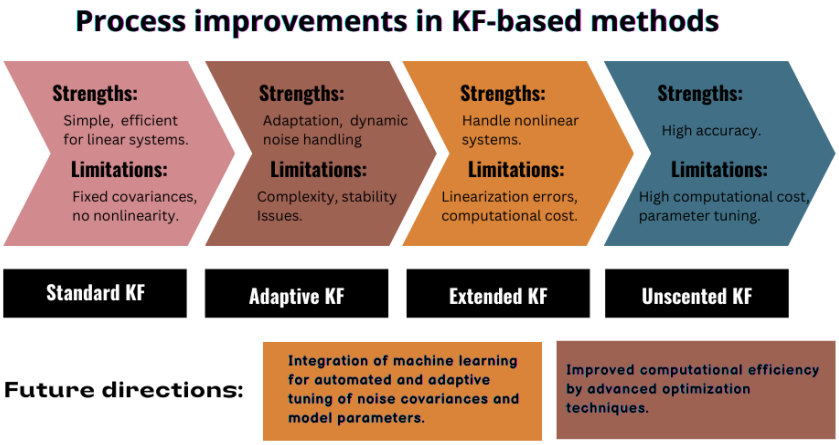

Figure 5. Illustration of the advancements in KF-based methods and their future directions.

2.2. Particle Filter (PF) Algorithm

PF techniques have unique capabilities in addressing challenges associated with nonlinearities and non-Gaussian noise, limitations that the KF and its improved versions are unable to effectively manage. This makes PFs particularly suitable for applications in Li-ion battery health management [9,13]. PFs are sequential Monte Carlo methods used for state estimation in dynamic systems. They operate by numerically implementing the recursive Bayesian framework through Monte Carlo simulation, allowing for inference in the state space [1,3]. They operate within a dynamic state-space framework that consists of two main components: the transition model and the measurement model [19,36–38].

The transition model, as described by Equation (8), can predict the system state at the next time step k based on the current state:

$$x_k = f(x_{k-1}, u_{k-1}) \tag{8}$$

where $f(.)$ denotes the state transition function of the dynamic system; u_k represents the process noise.

The measurement model is represented in Equation (9), which links the predicted state to the observed data y_k that are affected by measurement noise v_k:

$$y_k = h(x_k, v_k) \tag{9}$$

where $h(.)$ is the measurement function mapping the state space to the observation space at the time step k.

PFs estimate the PDF of system states by employing a set of N-weighted particles $\{x_k^i, w_k^i\}_{i=1}^N$, where each particle represents a potential state of the system [19,36]. The posterior PDF, which reflects the probability of the state x_k given all observations up to time k, is approximated by these weighted particles. The posterior density is estimated as:

$$p(x_k|y_{1:k}) \approx \sum_{i=1}^{N} w_k^i \delta(x_k - x_k^i) \tag{10}$$

where x_k represents the state variable of the system at time step k, x_k^i is the i-th particle, w_k^i represents the weight of the i-th particle, and δ is the Dirac delta function [38].

PFs are flexible and adaptable to modelling a wide range of system dynamics including the nonlinear aging processes of Li-ion batteries [6,11]. PFs have been employed to predict battery capacity degradation and internal resistances, which are crucial indicators of SOH and RUL prediction [19,23,68,69]. For example, research conducted at the NASA Prognostics Center of Excellence [70] could be among the first to apply the PF for predicting the RUL of Li-ion batteries. The PFs are used to estimate parameters in an exponential growth model describing electrolyte and charge transfer resistances based on electrochemical impedance spectroscopy measurements. Similarly, an empirical capacity model was developed in [71] to incorporate Coulombic efficiency and relaxation effects, with PF to estimate model parameters for future capacity prediction. These studies can highlight the ability of PF to effectively capture complex battery behaviours and degradation patterns.

Subsequent research [72] compared PF with other estimation techniques, including the UKF and nonlinear least squares, for battery health monitoring and RUL prediction. The findings demonstrate that PF outperforms these related methods, particularly in scenarios involving nonlinear degradation, due to its advanced capability to manage uncertainties and nonlinearities. In another study, PFs were employed to estimate parameters in Brownian motion-based degradation models for SOH estimation and RUL prediction [73]. The results show that PF has high adaptability for tracking stochastic degradation processes, and it outperforms the related methods like GPR and EKF in terms of estimation accuracy. Further advancements in PF applications included the integration of discharge-rate dependency into prognostic models in [74], which could demonstrate PF efficacy in handling time-varying loads and discharge conditions. However, although PFs have these demonstrated strengths, they are not without limitations. One major issue is sample degeneracy, which arises as the PF iterates and propagates its particles over time. This phenomenon occurs when most particles carry negligible weights, leaving only a few significantly contributing to the approximation of the posterior PDF [75,76]. Sample degeneracy becomes especially severe when the likelihood function peaks sharply around specific values, leading to mismatches between particle distribution and true posterior. Consequently, the particle set becomes less representative of the system's actual state, which can, in turn, degrade the filter performance [19,37,38]. To quantify the severity of sample degeneracy, the effective sample size (ESS) is often used as a metric. ESS provides an estimate of the number of particles that effectively contribute to state estimation at each time step [38,77]. When the ESS value drops beyond certain thresholds associated with specific applications, it indicates that sample degeneracy is severe and has degraded PF accuracy [76,78].

To address sample degeneracy, the resampling step process is introduced in [38]. This process replicates particles with higher weights and removes those with lower weights, thereby refocusing the particle distribution on regions of higher probability. While resampling can mitigate sample degeneracy, it introduces another challenge: sample impoverishment [76,79]. Sample impoverishment occurs when the diversity of the particle set decreases due to redundant samples from duplicated high-weight particles, as illustrated in Figure 6. This reduction in diversity limits the filter's ability to thoroughly explore the state space, which is critical for comprehensively exploring and accurately capturing the true system dynamics in complex systems such as Li-ion batteries. Over time, this loss of diversity can lead to less accurate state estimates, thereby highlighting the need for innovative strategies to balance resampling and maintain particle diversity [78].

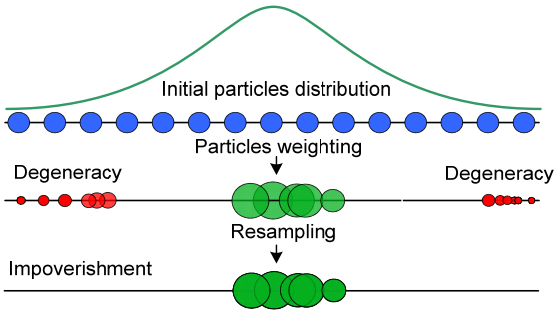

Figure 6. Influence of resampling on particle diversity, contributing to impoverishment.

Several improvements have been proposed to address these PF limitations in nonlinear system prognostics. A common strategy involves optimizing the proposal distribution to ensure that particles accurately reflect the true posterior distribution [80–82]. For instance, a study in [83] introduced the Gaussian PF, using a Gaussian approximation of the posterior distribution to lower the mismatch between the proposal and the true posterior. An auxiliary PF was presented in [84] for RUL estimation by incorporating an auxiliary variable to guide particle selection and regulate particle weights to better approximate the target distribution in the state space. The unscented PF was introduced in [85] by combining UKF with PF, an approach that attempts to leverage UKF state estimation to raise particle diversity and enhance particle generation. A spherical cubature PF was suggested in [86] to propagate particles through a nonlinear system model so as to refine the state distribution approximation and reduce sample degeneracy. Despite these advancements, optimizing the proposal distribution often results in increased computational complexity, as more particles are required to maintain accuracy [87]. Moreover, maintaining particle diversity remains challenging, particularly in highly dynamic or noisy environments, leading to sample impoverishment and reduced estimation accuracy [20,76].

Another approach focuses on regularization techniques to improve the diversity of particles and reduce sample degeneracy by smoothing the posterior PDF density and conducting resampling based on continuous distribution. The research in [88] introduced a regularized PF that employs kernel density estimation to smooth particle distribution after resampling. This approach spreads particles more uniformly in system space to maintain particle diversity. An extension of this method is the regularized auxiliary PF presented in [89], combining regularization with the auxiliary PF framework while applying a regularization step after resampling on the auxiliary PF to enhance particle diversity. Similarly, an adaptive kernel auxiliary PF was suggested in [90] that integrates adaptive kernels into the auxiliary PF framework to dynamically adjust the kernel bandwidth and enhance the representation of the posterior distribution. A mixture-regularized Rao–Blackwellized PF was suggested in [91]; it integrates a mixture-based regularization technique with Rao–Blackwellization and utilizes batter proposal densities and clustering to enhance the importance sampling. While regularization techniques help to improve particle diversity, they also face several specific challenges. For example, these methods can be computationally intensive due to the need for continuous resampling and kernel adjustments, especially in high-dimensional spaces. In highly nonlinear and dynamic applications like Li-ion batteries, the effectiveness of regularization can be mitigated, as smoothing processes may fail to adequately capture sharp changes in posterior distributions [76,82].

Recent research has increasingly focused on integrating AI techniques into PF frameworks to deal with sample degeneracy and impoverishment for enhancing PF performance. Several AI-driven methods have been proposed to optimize particle placement so as to concentrate particles in high-likelihood regions of the posterior space. These approaches aim to overcome the limitations of traditional resampling techniques by incorporating

intelligent search mechanisms to improve state estimation and RUL predictions. For example, a quantum particle swarm optimization-based PF was introduced in [92] to leverage a global search mechanism to guide particles toward optimal regions before resampling in order to improve particle diversity. An artificial fish swarm algorithm-based PF was proposed in [93] to mimic fish behaviours such as foraging and clustering to better explore the state space. It works to optimize particle weights for improving the RUL prediction of Li-ion batteries. An adaptive genetic algorithm PF presented in [94] integrates a genetic algorithm with PF to enhance battery fault diagnosis and RUL prediction. The genetic algorithm adapts the PF by optimizing particle distribution to improve particle diversity and mitigate sample degeneracy. A mutated PF technique was proposed in [19] in which a mutation step is adopted in the PF process to adjust particles to explore new state spaces for achieving a better representation of the posterior distribution and improving the PF performance. A neural network-integrated PF was introduced in [95], employing machine learning models to analyze battery aging characteristics and dynamically adjust model parameters for enhanced performance. In [96], a hybrid approach combined PF with radial basis function neural networks to facilitate real-time neural network training. Additionally, ref. [97] introduced a PF based on a Takagi–Sugeno fuzzy model, using fuzzy logic and clustering methods to manage non-Gaussian noise and complex nonlinear behaviours through an importance density function. Despite their potential to mitigate particle degeneracy and enhance PF performance, these AI-driven approaches come with notable challenges. For instance, overfitting during parameter optimization is still a prevalent challenge, particularly in methods that rely on machine learning techniques [98,99]. High computational demands present another critical limitation, as the complex algorithms of swarm intelligence-based and hybrid methods increase computational loads, which may restrict their use in real-time monitoring scenarios [76,81,100]. Furthermore, these techniques are usually sensitive to noisy environments or rapidly shifting operational conditions [6,20,76]. Moreover, the dependence on normalized particle weights for recognizing and handling low-weight particles can also negatively impact estimation accuracy, when particles concentrate in regions of low likelihood [78,82]. These limitations highlight the necessity for further advancements to develop adaptive, computationally efficient, and noise-robust AI-PF techniques, thereby improving reliability in battery SOH monitoring and RUL prediction. Figure 7 outlines the key strategies developed to address PF challenges, highlighting their strengths and challenges. It also emphasizes future directions for advancing PF methods, such as AI integration for adaptive tuning and the development of lightweight frameworks for real-time applications.

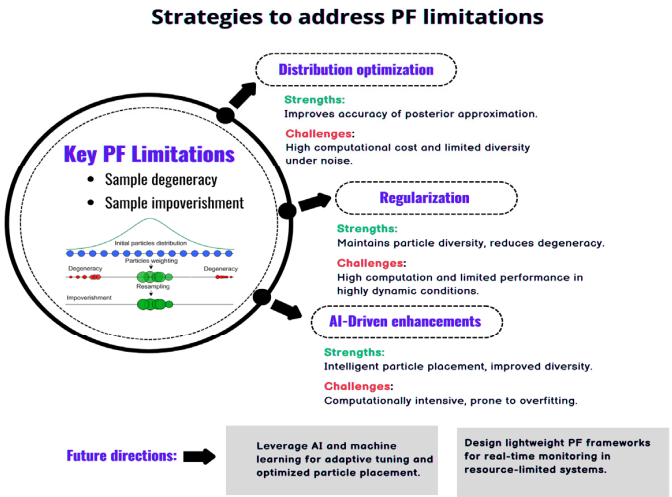

Figure 7. Illustration of strategies addressing PF limitations, strengths and challenges.

3. Data-Driven Techniques

Data-driven techniques have gained significant attention in battery health monitoring and RUL prediction due to their adaptability and capability to learn complex nonlinear degradation behaviours directly from data [1,8]. By analyzing patterns in historical and real-time battery data, these techniques can identify degradation trends and predict RUL using machine learning (ML) and artificial intelligence (AI) methods [2,6,9]. This makes data-driven methods particularly valuable, as they can infer insights into battery health directly from data without requiring in-depth knowledge of the underlying battery chemical processes [2,10,15]. Generally, data-driven techniques can be categorized into traditional statistical ML algorithms and soft-computing techniques; each category can offer unique strengths in capturing battery degradation characteristics and RUL predictions.

3.1. Traditional Statistical Machine Learning Algorithms

Traditional statistical ML algorithms usually employ supervised learning, where models are trained using historical battery data to track degradation features and predict battery health states [1,18]. These algorithms are well-suited for small to medium-sized datasets and provide models that are interpretable to some extent for predicting SOH and RUL. Common methods include support vector regression (SVR), relevance vector machine (RVM), and Gaussian process regression (GPR) [2,16,22]. SVR is a method designed to address regression problems and predict values by finding a line (or curve) that best fits the data within a specified margin of error. It uses mathematical functions called kernels to transform the data into a higher-dimensional space, allowing it to handle complex relationships and identify patterns that may not be obvious in the original data [22,101]. Even though RVM is similar to SVR, it adopts a probabilistic approach. This probabilistic framework allows the model to provide confidence measures for its predictions. The method uses fewer data points (referred to as relevance vectors) to make predictions, rendering it simpler and faster compared to SVR. The ability of RVM to quantify uncertainty makes it particularly valuable in applications where it is essential to understand the reliability of predictions such as battery health monitoring [102]. Because GPR is a nonparametric regression technique that assumes that the data originate from a Gaussian distribution, this method can model complex and nonlinear trends. In addition to providing point predictions, GPR also offers confidence intervals. These features make GPR especially effective in systems where it is important to understand uncertainty such as battery health monitoring under varying operational conditions [103]. Table 2 provides a comparative overview of these methods, highlighting their key features, strengths and limitations.

Table 2. Comparison of traditional statistical ML algorithms for battery RUL estimation.

Methods	Key Features	Strengths	Limitations
SVR	Regression (e.g., RUL or SOH trends).	High accuracy; adaptable with kernel optimization.	Sensitive to parameter selection; lacks uncertainty quantification; complex for real-time applications.
RVM	Regression with probabilistic outputs.	Adaptable to nonlinear behaviours; uncertainty quantification.	Sensitive to kernel selection; computationally intensive.
GPR	Regression with uncertainty quantification.	Handles nonlinear trends; confidence intervals.	High computational cost; scalability issues due to covariance matrix inversion.

The following subsections explore each of these traditional statistical ML methods, providing comprehensive insights into their operational principles, recent advancements addressing their limitations, and potential directions for future improvements.

(1) Support vector regression (SVR):

SVR is an extension of support vector machines (SVM) specifically designed for solving regression problems which is widely applied in predicting battery RUL [22]. The SVR maps input data through kernel functions to capture the complex, nonlinear relationships present between battery aging indicators [6,7]. However, the performance of SVR can be significantly influenced by challenges in selecting optimal parameters, such as the penalty factor and kernel width, which are critical for balancing model accuracy and generalization [10,15]. Recent research has explored various optimization algorithms to address these limitations and improve the accuracy and robustness of SVR models for battery RUL prediction [8,13,14]. For example, a study in [104] introduced an SVR model that was optimized using the artificial bee colony (ABC) algorithm to tune kernel parameters. This optimization dynamically selected the penalty factor and kernel width to enhance the SVR capacity to model battery degradation. The model utilized experimental capacity degradation data from NASA battery datasets, where earlier cycles were used for training and later cycles were applied for testing. The validation results demonstrated that the ABC-SVR model could improve prediction accuracy and stability compared to traditional SVR methods across various degradation stages.

The study in [105] introduced an SVR model enhanced by an improved ant lion optimization (IALO) algorithm. This approach addressed parameter selection challenges by using IALO global optimization capability, which could reduce trapping by local optima. This model used health indicators that were correlated with battery SOH degradation, such as the duration of constant current and constant voltage modes, average discharge voltage, and time of equal voltage drop. The validation results demonstrated that the IALO-SVR approach outperformed traditional SVR methods and maintained robust performance under diverse operational conditions. Similarly, the particle swarm optimization (PSO) algorithm was applied in [106] to optimize the kernel parameters of SVR. This approach focused on capturing the global degradation trend while mitigating the effects of local fluctuations and noise in the data. The validation results revealed that this model outperformed several other data-driven methods and demonstrated its robustness in scenarios with regeneration phenomena and measurement noise. Despite these improvements, SVR performance still depends on selecting the proper parameters, which can be time-consuming but cannot guarantee efficacy [107]. In addition, the use of support vectors could increase complexity and reduce efficiency in real-time applications [108]. Furthermore, its deterministic predictions do not include uncertainty quantification, thereby limiting its applications in scenarios that require confidence measures [109].

(2) Relevance vector machine (RVM):

Unlike SVR, the RVM is a Bayesian extension of SVM designated for both regression and classification tasks. RVM offers advantages over both SVM and SVR such as probabilistic predictions and sparse model representation and uses fewer relevance vectors compared to the number of support vectors typically required. These features make RVM an attractive tool for predicting the RUL of batteries, as it can effectively handle nonlinear relationships and quantify prediction uncertainties [102]. However, RVM also faces challenges, such as sensitivity to kernel parameter selection and inaccuracy in long-term predictions. Several enhanced RVM frameworks were proposed in recent studies to address these limitations so as to improve battery health monitoring and RUL prediction. For example, a study in [110] introduced an RVM-based model combined with a modified degradation model and a Hausdorff Distance-based curve similarity measure to improve prediction accuracy. The modified degradation model reconstructed phase space to capture long-term dependencies in degradation data, while the Hausdorff Distance measured selected degradation curves

that closely matched real-world behaviour. The effectiveness of this approach was validated by using online battery datasets, showing significant improvements in RUL prediction in comparison with traditional RVM models.

In [111], a multi-kernel RVM (MK-RVM) was proposed to predict the cycling aging of Li-ion batteries. The model combined Gaussian and sigmoid kernels to capture both local variations and global trends in battery degradation data, and a PSO algorithm was used to optimize the kernel parameters and reduce computational complexity. This MK-RVM method showed enhanced performance in early-life predictions and long-term RUL estimation. A bat algorithm-optimized RVM model was proposed in [112] for online SOH estimation and RUL prediction. The bat algorithm was employed to optimize wavelet kernel parameters to improve the model's ability and capture complex degradation trends. Although these advancements in RVM offer benefits, RVM still has limitations related to parameter selection sensitivity, as its predefined parameters can limit adaptability to highly nonlinear and complex degradation patterns [113]. Additionally, its uncertainty quantification still lacks sufficient flexibility and robustness in tracking battery degradation features [102].

(3) Gaussian process regression (GPR):

GPR is a nonparametric, probabilistic regression technique known for its ability to capture complex, nonlinear degradation trends while providing confidence intervals for battery RUL prediction. Recent studies have enhanced GPR frameworks to improve predictive performance and adaptability across diverse battery degradation scenarios. For instance, a study in [114] introduced an approach using multiple GPR models for Li-ion battery SOH prediction. This method adopts various GPR models to train multiple batteries, whereas their respective outputs are integrated using weight factors corresponding to prediction uncertainties. By using multiple models, the approach effectively captured variations across different operational conditions. The effectiveness of this approach was validated using NASA datasets, and noticeable accuracy improvements were demonstrated under various operational conditions. In [115], GPR combined with differential thermal voltammetry (DTV) analysis was used for SOH estimation. This study utilized DTV curves to extract unique features, such as peak positions and valley values, which were then mapped to SOH estimation using GPR. The test results highlighted how integrating electrochemical analysis with probabilistic regression could improve SOH prediction reliability and accuracy under real-world application conditions.

Another study in [116] applied GPR to address challenges associated with random charging conditions and missing data. This method reconstructed missing battery health indicators, such as charging time sequences within specific voltage intervals, using a GPR probabilistic framework. Validation with real-world battery datasets demonstrated its robustness in handling irregular charging patterns and training using incomplete datasets, effectively demonstrating its adaptive capability in battery health monitoring and RUL prediction. Additionally, this method showed potential in reducing dependence on large training datasets, making it suitable for implementation in real battery management applications. While these enhancements could address certain challenges, GPR still has some limitations, including high computational costs when applied to large datasets; this is due to its dependence on covariance matrix inversion, which scales exponentially with the increase in data size [103]. Additionally, while GPR performs well under specific conditions, it may not be applicable for applications with extremely high-dimensional or highly variable datasets [117]. Furthermore, GPR requires careful kernel design and parameter selection, which can limit its adaptability in highly dynamic and unpredictable degradation scenarios [115,116].

In general, each ML method has its own unique strengths and specific challenges in battery health monitoring and RUL prediction. While traditional statistical ML algorithms, such as SVR, RVM, and GPR, provide foundational methods for battery health monitoring, their limitations in adaptability, uncertainty handling, and scalability require more systematic research efforts [9,110]. Soft-computing techniques could address these challenges, to some extent, by incorporating adaptability, reasoning under uncertainty, and dynamic rule learning, making them well-suited for highly nonlinear and dynamic battery degradation scenarios [2,3,8].

3.2. Soft-Computing Techniques

Soft-computing techniques represent a class of flexible and adaptive methods designated to manage the complexities, uncertainties, and nonlinearities in battery degradation and health monitoring [1,8,15]. Unlike traditional statistical ML algorithms that often depend on clearly defined features and fixed structures, soft-computing methods can adjust dynamically to changing conditions and handle data that may be incomplete or noise-affected [2,9,118]. These techniques are useful for modelling the complex processes involved in Li-ion battery degradation and predicting battery SOH and RUL [14,119,120].

Among the various soft-computing techniques, artificial neural networks (ANNs) and adaptive neuro-fuzzy inference systems (ANFISs) stand out as two of the most widely used and studied methods due to their proven effectiveness in handling complex, nonlinear problems. While this section focuses on these two techniques, other methods, such as evolutionary algorithms, deep learning, and extreme learning machines have also demonstrated promising performance; they have also been explored in related works [9,15,25,120–133]. In general, ANNs are computational models inspired by the structure and functioning of the human brain. They consist of interconnected layers of neurons, each processing input data to extract patterns and relationships. ANNs are particularly effective in modelling complex and nonlinear relationships directly from data. This adaptability makes them valuable for applications such as battery health monitoring, where varied and dynamic data patterns must be analyzed. However, ANNs face challenges such as sensitivity to overfitting and high computational requirements during training, which have driven the development of various advancements in order to improve their performance.

On the other hand, ANFISs combine the learning capabilities of ANNs with the interpretability of fuzzy logic. This combination allows ANFISs to produce rule-based predictions while effectively handling uncertainty, which is a critical aspect of battery health monitoring under varying operational conditions. By integrating fuzzy if-then rules with ANN optimization, ANFISs can model nonlinear behaviours and provide interpretable outputs. However, despite its strengths, an ANFIS can become computationally intensive when dealing with large datasets or complex rule sets. Additionally, its performance is highly influenced by the quality of initial rules and membership functions, which can impact its overall effectiveness. Table 3 provides a comparative overview of these two methods, highlighting their key features, strengths, and limitations.

The following subsections provide a comprehensive discussion of these two techniques, exploring their recent advancements in overcoming limitations and highlighting potential directions for future enhancements.

(1) Artificial neural networks (ANNs):

ANNs are widely used for Li-ion battery health monitoring and RUL prediction due to their ability to model complex, nonlinear relationships [1,3,134]. By analyzing historical battery data, ANNs can identify degradation patterns and predict important battery health indicators such as SOH and RUL [10,22]. Generally, ANNs consist of interconnected layers with the ability to model time-series data and track battery aging trends [12]. However,

ANNs face several challenges in real-world applications, such as sensitivity to noisy or dynamic data, overfitting, and limited interpretability [135,136]. Several new approaches have been proposed in the literature to tackle these challenges in battery health monitoring.

For example, traditional ANNs require substantial computational resources and time for retraining, especially as the size dataset grows; this presents challenges for real-time battery health monitoring and RUL prediction. To address this limitation, the study in [137] introduced an incremental learning strategy to dynamically update the ANN model as new data becomes available. This approach can eliminate the need for retraining the entire network; it can also allow continuous model refinement and reduce computational costs. This method not only maintains prediction accuracy but can also ensure the adaptability of the model to evolving battery conditions, rendering it suitable for practical applications. The work in [138] introduced temporal convolutional networks (TCNs) to address training complexity. TCNs used dilated and causal convolutions to capture both local and long-range dependencies in time-series data. By utilizing a non-recurrent architecture, TCNs can reduce training complexity while maintaining computational efficiency and improving model stability. The test results demonstrated that TCNs perform better in computation efficiency and accuracy than traditional NNs, especially in scenarios with complex degradation trends and in situations with noisy data.

The noisy and dynamic nature of real-world battery data presents another critical challenge for ANNs, especially when operating conditions vary. To tackle this challenge, the study in [137] proposed a hybrid approach combining complete ensemble empirical mode decomposition with adaptive noise (CEEMDAN) and long short-term memory (LSTM) networks. The CEEMDAN was employed to denoise raw data to ensure that the most relevant features were retained for analysis, while the LSTM networks were applied to capture temporal dependencies within the data to improve the modelling of time-series behaviour. This approach demonstrated its effectiveness by removing noise from the input data and showed improved prediction accuracy even under time-varying and dynamic conditions. Additionally, an approach combining state-space models with ANNs was proposed in [136] to model dynamic degradation processes in noisy environments. In this approach, state-space models were used to generate a comprehensive dataset to represent the system's dynamic behaviour since ANNs learn by using this dataset to predict complex nonlinear degradation trends. Deep layers were also added to the ANN to model and capture subtle degradation patterns to improve adaptability. This approach demonstrated clear improvements in prediction accuracy and reliability under challenging operational scenarios.

Another critical challenge in ANNs is overfitting. Overfitting is a particularly problematic issue in Li-ion battery applications, where datasets are often imbalanced or collected under controlled conditions that do not fully represent the diverse and dynamic real-world operating scenarios. This can reduce the usefulness of ANNs in battery health monitoring, where real-world datasets often differ from simulated training data. Researchers have employed several techniques to address this limitation, such as using regularization techniques, diverse datasets, and adaptive training. These approaches aim to improve the generalization capabilities of ANNs to ensure that they perform well across a wide range of operating conditions. For example, the study in [137] applied dropout layers to address the overfitting problem by randomly deactivating a fraction of neurons during training. This approach reduces the model's dependency on specific neurons and can improve its ability to generalize across unseen data. In addition, weight normalization was applied to stabilize gradients during backpropagation to ensure smoother training and reduce the risk of overfitting. The test results indicated that these techniques could improve the model's performance and achieve higher generalization accuracy by mitigating overfitting in the

modelling. In [136], ANNs were trained using datasets from multiple battery chemistries and operational conditions in order to ensure that the model did not overfit the specific characteristics of a single dataset. By exposing the model to diverse usage patterns, the ANNs generated appropriate robustness and generalization capabilities, which makes ANNs applicable for batteries with differing aging behaviours.

The "black-box" nature of ANNs is another notable limitation, as it often makes their predictions difficult to interpret. This lack of transparency can limit their use, especially in safety-critical applications like battery health monitoring. Future research could be undertaken to develop advanced techniques to enhance ANN interpretability and usability in real-time battery monitoring applications.

(2) Adaptive neuro-fuzzy inference system (ANFIS):

The ANFIS has gained significant attention in Li-ion battery health monitoring and RUL prediction due to its unique ability to integrate the strengths of ANNs with those of fuzzy logic. By combining the learning capabilities of ANNs with the interpretability of fuzzy systems, the ANFIS has demonstrated high proficiency in capturing nonlinear relationships and managing uncertainty, which makes it effective for applications in modelling complex and dynamic battery behaviours [139,140]. The ANFIS integrates fuzzy if-then rules with an ANN learning algorithm to optimize membership functions and rule parameters. This hybrid approach facilitates the accurate modelling of battery parameters, such as SOH, and capacity degradation [139]. Additionally, the interpretability of fuzzy logic provides designers with valuable insights into the relationships between inputs and predictions, which is crucial for safety-critical applications [139,140]. To enhance the performance of the ANFIS in real-world scenarios, researchers have focused on optimizing its structure, improving its robustness to noise, and reducing computational complexity.

To address computational complexity, several optimization algorithms have been proposed to reduce the size and complexity of fuzzy rule sets while maintaining modelling accuracy. For example, the study in [141] used fuzzy c-means clustering and subtractive clustering to optimize the structure of the ANFIS model by identifying the most relevant input features and reducing the number of fuzzy rules. This approach not only improved computational efficiency but also enhanced the prediction accuracy for battery SOH estimation. The work in [142] employed an improved quantum-behaved particle swarm optimization algorithm to fine-tune the parameters of the ANFIS model. It also introduced an adaptive dynamical control mechanism to balance local and global searches so as to ensure faster convergence. This approach demonstrated high performance in training the ANFIS in nonlinear system modelling and time series prediction.

On the other hand, real-world battery data usually contain significant noise due to sensor inaccuracies, environmental condition fluctuations, and changing operational conditions. To address this challenge, preprocessing techniques have been integrated with ANFIS models to enhance data quality. For instance, the study in [143] applied an online self-learning ANFIS approach to adapt to changing battery behaviours, handling data variability and noise by updating its parameters in real time. By continuously refining its membership functions and model parameters in real time, the system could filter out transient noise and focus on capturing meaningful patterns in the data. This adaptive capability ensured a more accurate battery state prognosis, even under fluctuating and noisy operating conditions. The ANFIS also faces challenges of overfitting or underperformance, especially when datasets are small or imbalanced. Researchers have tackled this issue by employing different types of training datasets and cross-validation methods to improve the modelling generalization capabilities. The study in [18] expanded the training set size by generating diverse variations of the data, so as to force the ANFIS model to learn from a

broader range of operating scenarios. This approach could improve the model's robustness and reliability in predicting across various battery chemistries and usage patterns.

Although the ANFIS has demonstrated promising results in battery health monitoring and RUL prediction, there remains potential for further advancements. For example, integrating hybrid architectures with deep learning methods could enhance prediction accuracy and adaptive capability. Developing and using more efficient online optimization algorithms could make the ANFIS more suitable for use in battery health monitoring and management systems. Furthermore, exploring high-efficiency evolutionary algorithms to automate the generation and tuning of fuzzy rules could increase the efficiency and accuracy of ANFIS models.

Table 3. Key characteristics of ANNs and ANFIS techniques for battery prognostics.

Methods	Key Features	Strengths	Limitations
ANNs	Multilayer architecture for modelling nonlinear data relationships.	Adaptable to nonlinear and time-series data; capable of learning directly from raw data; suitable for large datasets with diverse features.	Prone to overfitting with small datasets; high computational cost during training; limited interpretability.
ANFIS	Combines ANN learning capabilities with fuzzy rule-based reasoning.	Provides interpretable rules and clear reasoning for predictions; handles uncertainty; suitable for systems requiring dynamic rule updates.	Computational complexity increases with large datasets or many fuzzy rules; performance depends on the quality of initial rules and membership functions.

4. Hybrid Approaches

Hybrid approaches have become a more popular solution for battery health monitoring and RUL prediction. Relying on a single method, such as model-based filtering or a data-driven technique, is usually insufficient to deliver the required comprehensive requirements in processing accuracy and adaptive capability. This is due to the complex nature of battery degradation, uncertainties over time, and the limited availability of high-quality data [144,145]. Hybrid approaches can tackle these challenges by integrating the advantages of multiple methods while overcoming the limitations of individual techniques, to some extent. Although hybrid methods have their own limitations, researchers aim to achieve a good balance of accuracy, reliability, and adaptability, all important factors for real-world applications in battery management systems [146,147]. One main advantage of hybrid approaches is their ability to handle time-varying operating conditions in battery systems, including varying temperatures, charging rates, and usage patterns, all of which can significantly affect battery performance and degradation. Hybrid methods can adjust their properties to adopt these dynamic conditions to achieve more accurate SOH monitoring and RUL predictions [148]. Furthermore, hybrid approaches are more effective in capturing and modelling the dynamic behaviours of the complex and nonlinear degradation patterns of batteries than using an individual method [87,149]. Another clear strength of hybrid approaches is their ability to perform well even with limited datasets. On the other hand, by combining physics-based models with data-driven methods, hybrid frameworks can properly handle the challenges of incomplete or low-quality (noisy) data while still delivering reasonably reliable results [87]. These properties make hybrid approaches a valuable tool for advancing battery health monitoring and RUL prediction. This review summarizes the properties of some of the latest hybrid frameworks and discusses their potential for further improvements in battery health prediction. Figure 8 provides a visual

summary of how hybrid approaches integrate the strengths of model-based and data-driven methods for real-world battery management applications.

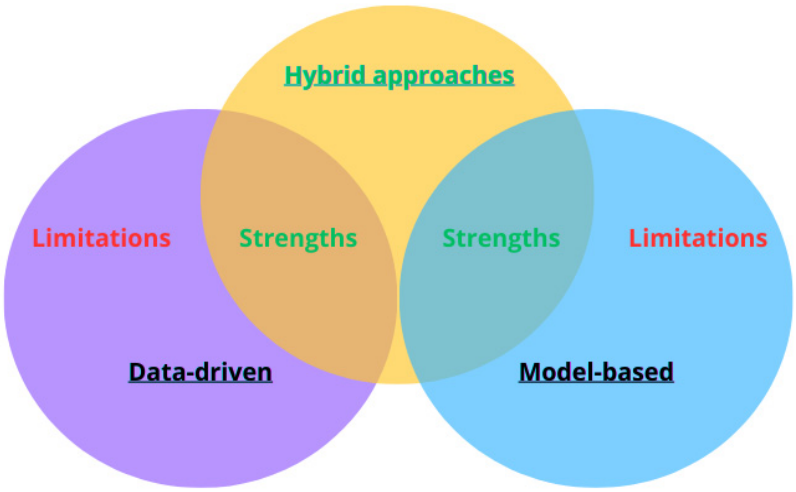

Figure 8. Illustration of how hybrid approaches combine the strengths of model-based and data-driven approaches.

Some hybrid frameworks combine model-based methods with data-driven techniques to address the limitations of model-based methods, particularly during the prognostic period when no new measurements are available. Model-based approaches, such as those relying on PF, are particularly effective in providing a physics-based insight into system dynamics. However, they are inherently limited in their ability to update the PDF during periods without new data, which can lead to reduced accuracy in long-term predictions. By integrating a data-driven method, a hybrid framework introduces the adaptability to predict system behaviour, even in the absence of real measurements. This can ensure that the model remains reliable and accurate over extended prediction horizons. For example, a hybrid framework proposed in [35] integrates a nonlinear autoregressive (ND-AR) time series model as an observer for a regularized PF. This combination allows the regularized PF to leverage the predictive capabilities of the ND-AR model to compensate for the absence of new measurement updates during the prognostic phase. Similarly, a hybrid strategy presented in [149] combines an unscented PF with an optimized multiple kernel relevance vector machine (OMKRVM). In this framework, the unscented PF estimates system conditions, while the OMKRVM corrects residual prediction errors to improve the prediction accuracy and robustness for Li-ion battery degradation. Recent work in [87] further extends the PF approach by incorporating an evolving fuzzy predictor into an enhanced PF structure. This integration addresses the absence of measurement data during the prognostic phase by dynamically modelling degradation trends so as to improve prediction accuracy and adaptability.

Another significant purpose of hybrid frameworks is to model and predict complex, long-term degradation dynamics in Li-ion batteries under time-varying operating conditions. Unlike frameworks that primarily rely on measurement updates, these hybrid approaches integrate physics-based models with data-driven techniques to capture the nonlinear and time-varying degradation trajectories that are critical for accurate capacity and RUL predictions. For instance, a novel hybrid framework was proposed in [150], where the physics-based Arrhenius degradation equation was combined with a Transformer-based deep learning model. This framework effectively bridges degradation mechanisms with statistical temporal features, allowing for more accurate RUL predictions even under variable and noisy operating conditions. Furthermore, its use of a coordinate ascent method for

parameter optimization could further enhance its prediction accuracy. Similarly, a hybrid approach introduced in [151] integrates variational modal decomposition (VMD), PF, and Gaussian process regression (GPR) for improving prediction accuracy. The VMD algorithm decomposes capacity data into an aging trend sequence and residual sequences, which are independently modelled using PF and GPR. This method can improve generalization, reduce prediction errors, and provide efficacy in handling the nonlinear degradation of battery systems. Another example in [152] provides a hybrid feature extraction method with the combination of physics-based electrochemical model insights with data-driven clustering and deep learning. This approach employs hybrid features generated from k-means clustering for data augmentation and training, which could provide accurate capacity degradation trajectory prediction across various battery types.

Some hybrid frameworks are also developed to enhance computational efficiency in battery health monitoring and RUL prediction. These frameworks integrate simplified models and advanced optimization techniques to reduce computation time without sacrificing prediction accuracy. For example, a hybrid framework proposed in [153] combines convolutional neural networks (CNNs), long short-term memory, and deep neural networks (DNNs). This approach utilized data preprocessing and optimization methods to lower computational costs and make it suitable for real-time applications. Another hybrid strategy was introduced in [154], where a northern goshawk optimization algorithm was used to optimize VMD and improve battery RUL prediction reliability under noisy conditions. These hybrid frameworks could help address some of the key challenges in achieving both accuracy and adaptability for battery health monitoring and RUL prediction. By integrating the strengths of various methods, they offer a reliable and flexible approach that can adapt to varying conditions, making them a potentially suitable choice for real-world battery management applications.

While hybrid frameworks offer many advantages, they also have some limitations. One key challenge is the increased complexity of integrating multiple methods, which can lead to higher computational costs and difficulties in implementation. Another limitation is the lack of interpretability of errors in most hybrid approaches, especially those that rely heavily on data-driven methods like deep learning. Future research could focus on improving the reasoning transparency of hybrid frameworks, incorporating more efficient optimization algorithms, and designing models that are easier to implement and require fewer computational resources. Enhanced interpretability can be achieved by integrating explainable AI techniques into data-driven components.

5. Conclusions

This review paper has comprehensively analyzed the related main techniques for battery health monitoring and RUL prediction in Li-ion batteries. It has explored the strengths and limitations of model-based, data-driven, and hybrid approaches. Model-based methods utilize physical and electrochemical models to provide theoretical insights into battery degradation principles. These methods are highly interpretable but often involve significant computational costs and sensitivity to parameter tuning, particularly under dynamic or high-intensity operating conditions. Data-driven techniques use AI and machine learning to adaptively model the complex nonlinear battery degradation behaviours. While these methods demonstrate strong adaptability and flexibility, they rely heavily on large, high-quality datasets and lack the physical interpretability inherent in model-based methods. Hybrid frameworks combine the strengths of both approaches to achieve enhanced predictive accuracy and robustness, particularly in long-term prediction and diverse operating conditions. However, these advantages come at the cost of increased complexity and computational demands.

This study has highlighted significant advancements, including improvements in computational efficiency, adaptability to real-world scenarios, and predictive accuracy achieved through innovative methodologies. It also discussed the challenges faced by the related techniques in computational complexity, noise sensitivity, and the need for real-time adaptability. Future research should focus on developing simpler, faster, more transparent, and robust techniques to enhance battery health monitoring and management applications. For instance, model-based methods could incorporate adaptive mechanisms to better handle dynamic operating conditions, while data-driven approaches should aim to reduce their dependence on extensive datasets to build reliable models and achieve high-accuracy results. Hybrid methods, on the other hand, could benefit from optimized computational frameworks to improve resource efficiency and scalability. Advancing these methodologies will be critical to meeting the growing demand for more reliable and efficient battery health management systems.

Author Contributions: Conceptualization, M.A.; methodology, M.A. and W.W.; validation, M.A. and W.W.; formal analysis, M.A. and W.W.; investigation, M.A. and W.W.; resources, W.W.; data curation, M.A.; writing—original draft preparation, M.A.; writing—review and editing, M.A. and W.W.; supervision, W.W.; funding acquisition, W.W. All authors have read and agreed to the published version of the manuscript.

Funding: This project received partial support from the Natural Sciences and Engineering Research Council of Canada (NSERC), eMech Systems Inc., and Bare Point Water Treatment Plant in Thunder Bay, ON, Canada.

Data Availability Statement: Not applicable.

Conflicts of Interest: The authors declare no conflicts of interest.

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