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Review article

Recent advancement of remaining useful life prediction of lithium-ion battery in electric vehicle applications: A review of modelling mechanisms, network configurations, factors, and outstanding issues

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ABSTRACT

The remaining useful life (RUL) prediction of lithium-ion batteries (LIBs) plays a crucial role in battery management, safety assurance, and the anticipation of maintenance needs for reliable electric vehicle (EV) operation. An efficient prediction of RUL can ensure its safe operation and prevent both internal and external failures, as well as avoid any unwanted catastrophic events. However, achieving precise RUL prediction for electric vehicles presents a challenging task due to several issues related to intricate operational characteristics and dynamic shifts in model parameters throughout the aging process, battery parameters data extraction, data preprocessing, and hyperparameters tuning of the prediction model. This phenomenon significantly impacts the advancement of electric vehicle technology. To address these challenges, this study offers a comprehensive overview of various RUL prediction methods, presenting a comparative analysis of their outcomes, advantages, drawbacks, and associated research constraints. Emphasis is placed on the necessity of a battery management system (BMS) to ensure the safe and reliable functioning of LIBs. The review delves into crucial implementation factors, including battery test bench considerations, data selection, feature extraction, data preprocessing, performance evaluation indicators, and hyperparameter tuning. Additionally, the issues and challenges related to RUL prediction approaches such as; thermal runaway, material selection, cell balancing, battery aging, relaxation impact, training algorithms, data acquisition, and hyperparameter tuning were outlined to provide an in-depth understanding of the recent situations. The outcome of this review comprehensively examines various methods for predicting the RUL of LIB in EV applications, offering insights into their advantages, limitations, and research challenges. Recommendations for future trends in LIBs technology comprise enhancing prognostic accuracy and developing robust approaches to guarantee sustainable operation and management.

1. Introduction

Due to the pressing need to mitigate carbon emissions and combat climate change, EVs have emerged as a promising solution, with LIBs playing a pivotal role in their widespread adoption (Napa et al., 2024; Foo et al., 2024; Rouhi et al., 2022a; Bin et al., 2021). LIBs, renowned for their longevity, high energy density, low cost, low self-discharge, and suitability across various applications, including EVs, electronic devices, stationary battery storage system integrated power grid, the automotive industry, medical equipment, and other applications (Xue et al., 2020a), (Ghadbane et al., 2024), making them integral to efforts aimed at reducing reliance on fossil fuels and promoting sustainable energy solutions. However, the limited lifespan of LIBs (LIBs), particularly their efficient service time, is widely acknowledged. As LIBs are utilized, their performance gradually deteriorates due to intricate internal electrochemical reactions, encompassing impedance growth, active material loss, dendrite formation, inner short-circuits, and other factors. Moreover, the performance deterioration process comprises calendar and cyclic aging processes, which endangers compatibility with other energy sources. The impacts of aging on the negative electrodes of a battery lead

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to SEI growth and capacity decline as shown in Fig. 1(a). Fig. 1(b) illustrates the key battery degradation mechanism of the LIB cell. The effect of uncertainty on cell spreading during linear and nonlinear aging as shown in Fig. 1(c) in battery systems also hamper the battery

performance. Furthermore, as LIBs undergo repeated charging and discharging cycles, their performance gradually diminishes until they reach the end-of-life (EOL) stage. This deterioration gives rise to various issues, including a decrease in capacity and a reduction in driving distance. The real-life battery degradation of Tesla is shown in Fig. (d). Once the maximum discharging capacity of an LIB drops to approximately 70–80% of its rated capacity, it surpasses the capacity failure threshold, rendering it unsuitable for use in EVs (Chen et al., 2022a). If the battery be employed in EVs beyond its EOL, it would inflict further operational damage and potentially lead to catastrophic events due to accelerated degradation of power and capacity. Hence, the development of an accurate technique for estimating the RUL and capacity degradation mechanism of batteries becomes imperative for reliable BMS. The field of battery maintenance has advanced significantly in the last few years. Although conventional maintenance approaches such as reactive and scheduled maintenance have been applied, they are not well suited to handle the intricate behavior of battery systems. Scheduled maintenance ignores the system's true state and is carried out on a regular basis or according to usage hours (Zhu et al., 2017). This method can result in excessive maintenance costs even though it lowers failure rates. Reactive maintenance also known as corrective maintenance, on the other hand, reacts to anomalies or failures, but because of its simplicity, it may lead to dangerous unexpected failures (Levitin et al., 2024). These conventional approaches fall short in complicated battery systems where safety is critical. Among these advancements, the development of data-driven and hybrid methods stand out as one of the most promising. However, these approaches encounter challenges such as; battery features extraction, data preprocessing, data sampling,

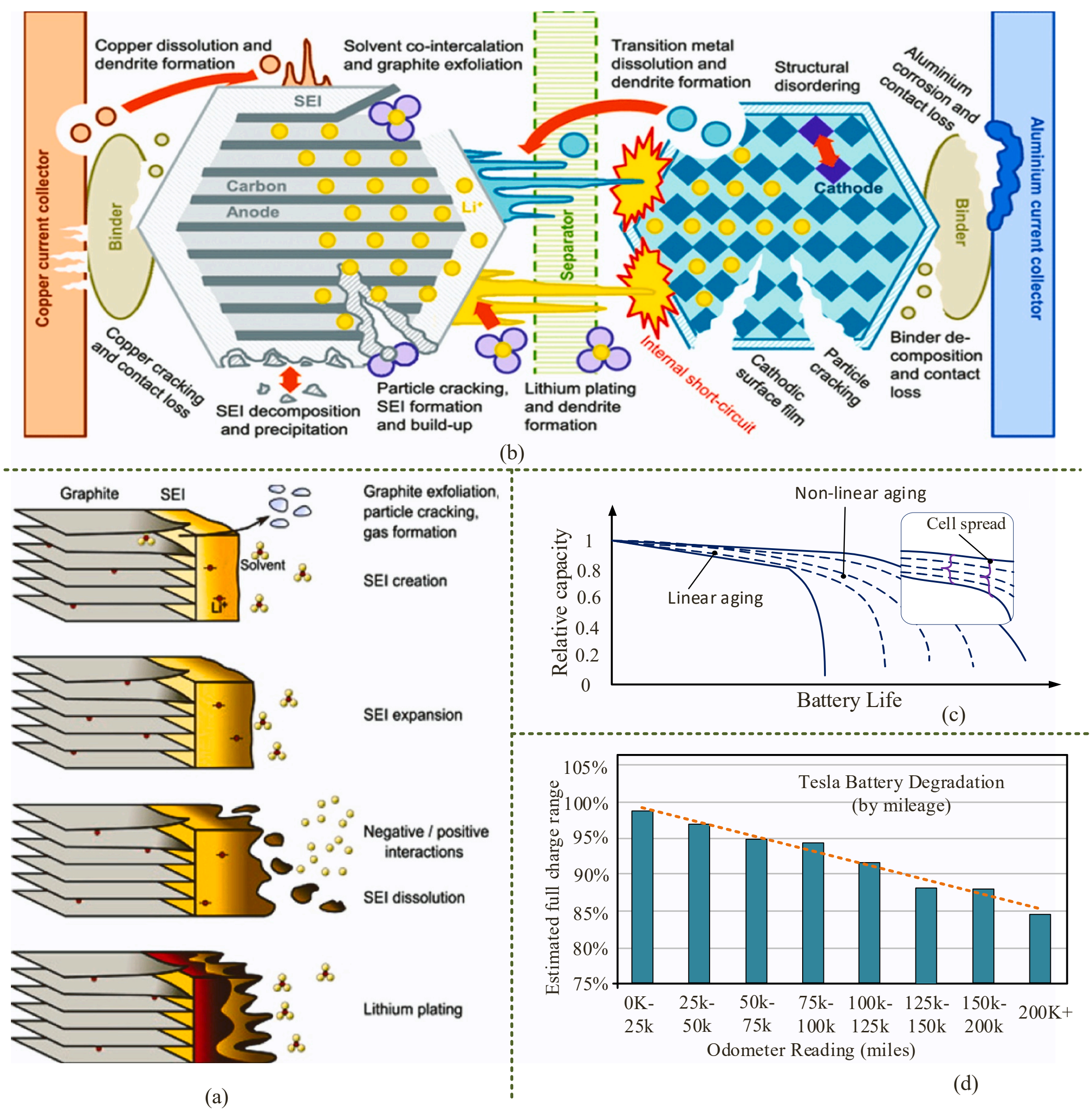

Fig. 1. (b) Degradation mechanism of LIB cell. (d) Degradation of Teshla battery by mileage (NimbleFins, 2023). According to the survey, the average Tesla battery keeps more than 90% of its original range up to 100,000 miles, and it still retains more than 80% of the initial range after 125,000 miles.
(a) (a) Aging impacts on the negative electrode of a battery: capacity decline and SEI growth, reproduced with permission from (Barré et al., 2013), Elsevier 2013, copyright. (b) Deterioration in Li-ion cells is produced by a variety of chemical and physical factors that influence the cell's components: electrolytes, electrodes, separators, and current collectors, reproduced with permission from (Birkl et al., 2017), Elsevier 2017, copyright. (c) (c) The effect of uncertainty on linear and nonlinear battery system aging, reproduced with permission from (Reza et al., 2023), Elsevier 2023, copyright.

hyperparameter tuning, and so on. Therefore, it is imperative to develop an comprehensive review analysis based on recent technological advancement of RUL prediction methodologies highliting outcomes, advantages, drawbacks, and associated research constraints.

To effectively handle a large number of batteries within the battery pack of an EV, safeguard both the individual batteries and the battery pack from potential damage, maintain the batteries within suitable voltage and temperature ranges, and maximize their overall lifespan to meet vehicle requirements, the implementation of a BMS becomes indispensable. The standard BMS comprises both hardware and software components, working in tandem to achieve optimal management and control of battery operation. Through the monitoring of LIB data acquisition, cycle charge-discharge management, and monitoring temperature, the BMS aims to minimize battery failures (Shen, 2021). Key functionalities of the BMS include battery balance management, protection against overcurrent and overvoltage situations, data acquisition and storage, temperature control, as well as battery state estimation and prediction, among others (Xu and Shen, 2021), (Ali et al., 2019).

In the existing body of literature, numerous approaches have been conducted to forecast the RUL and determine future battery capacities accurately. These approaches can be broadly classified into three distinct classes: model-based methods and data-driven approaches (Wang et al., 2023a; Yao and Han, 2023; Liu et al., 2023; Xu et al., 2023a). In the field of model-based techniques, researchers explore the degradation processes of LIBs using electrochemical mechanism models, empirical models, or equivalent circuit models (ECMs). Electrochemical mechanism models generally concentrate on three elements connected with the internal attenuation mechanism: lithium loss, active material loss in the positive electrode, and active material loss in the negative electrode (Tian et al., 2021). Liu et al (Liu et al., 2019a). presented an enhanced capacity degradation model based on the electrochemical mechanism to forecast battery cycle life. However, the model suffered from complexity, sensitivity to parameters, and scalability issues. Moreover, the key battery parameters such as; voltage, temperature, and impedance which has great impact on reliable capacity degradation model were not considered. ECMs, on the other hand, utilize circuits to simplify the process of battery operation, establishing a mapping function between ohmic/polarization resistance and capacity attenuation to examine the degradation process (Lyu et al., 2021). Empirical degradation trends of LIB capacities make it easier to construct models such as exponential and polynomial models (Birkl et al., 2017). To update the model parameters, adaptive filter techniques are commonly utilized (Zhang et al., 2022a), (Yue et al., 2020). While model-based methods offer good interpretability, they are prone to generating significant errors in predicting RUL due to the approximation of the degradation mechanism. In order to forecast the RUL of batteries, Guha et al (Guha et al., 2017). proposed a method based on the internal resistance growth model and particle filtering approach. However, the method faced problem for capturing the dynamic behavior of LIBs, which make it difficult to estimate anticipate RUL under different operating scenarios and aging processes. Data-driven techniques, on the other hand, rely on discovering hidden correlations among characteristics or features, latent mappings between outputs and inputs, or interactions between features and attributes, without the requirement for a mathematical model to estimate battery RUL (Zhang et al., 2019a). Because of the increased volume of available data and developments in graphics processing units, the accuracy of prediction outcomes utilizing data-driven methodologies has substantially improved. An RNN technique for the RUL prediction was established by Ansari et al (Ansari et al., 2021). by taking into account a number of operating profile characteristics.The use of multichannel profiles resulted in a high prediction accuracy, but choosing the right hyperparameters required time and human expertise. Furthermore, there has been significant progress in research related to RUL prediction using deep learning (DL) models and hybrid models (Yue et al., 2020; Guha et al., 2017; Zhang et al., 2019a; Ansari et al., 2021). However, achieving optimal performance with these models necessitates the availability of suitable training datasets and the fine-tuning of hyperparameters (Liu et al., 2024). In order to extract the global degradation trend from predicted capacity degradation curves, Liu et al (Liu et al., 2024). developed a hybrid methodology that integrates signal decomposition and deep learning. Specifically, a gated recurrent unit-fully connected model infers the degradation trajectory and remaining useful life, while convolutional neural networks predict maximum discharging capacity for each cycle. However, the proposed method was computationally complex and used time consuming trail end error method to determine the hyperparameters.

Few review studies have offered a complete overview of the methods for estimating RUL for LIBs in EV applications. Shao et al (Shao et al., 2023). developed a review article based on stochastic filtering methods for energy storage components RUL prediction, where storage components failure mechanisms were clarified. However, this research did not provide a detailed discussion of the data-driven methods and future research directions were not highlighted. A review by Zhao et al (Zhao et al., 2023)., was presented to examine RUL and state estimation where data-driven and hybrid methods are briefly discussed. Moreover, the key issues and challenges for the RUL and state estimation, and future research direction were not discussed. Hu et al (Hu et al., 2020). provided an in-depth evaluation of several strategies for RUL prediction, including obstacles and future research work, although sophisticated DL approaches were not included. In another review, Wang et al (Wang et al., 2021). presented adaptive DL algorithms for the prediction of RUL. However, the review's scope was limited to the investigation of DL approaches. Wu et al (Wu et al., 2016). synthesized RUL prediction techniques using data-driven methodology. However, only four issues with RUL estimation for LIBs were thoroughly discussed. To summarize, the majority of the aforementioned review papers primarily concentrated on examining model-based and data-driven techniques for predicting RUL. However, a thorough investigation encompassing various RUL prediction methodologies along with the key issues and challenges with effective future research direction, has yet to be explored in its entirety.

To address this knowledge gap, this review presents a novel contribution by providing a comprehensive analysis of estimation techniques for predicting RUL. Furthermore, the review highlights the key factors and challenges associated with RUL estimation strategies. The review includes these cutting-edge contributions:

- A thorough explanation of the functionality requirements and the necessity of implementing a BMS to ensure the secure and reliable operation of LIBs in EV applications.
- An in-depth analysis of various RUL prediction methodologies, characteristics, major findings, benefits, drawbacks, and research gaps.
- Essential implementation factors such as experimental setup for a battery test bench, data preparation, and hyperparameters for battery DL algorithms to execute various RUL prediction methodologies are highlighted.
- The main limitations, issues, and challenges of the existing research are identified.
- Selective suggestions and future directions for developing sustainable RUL prediction methodologies for LIBs in EV applications are provided.

The rest of the papers are organized as follows: Section 2 presents the overall reviewing procedure. Section 3 presents the details of BMS. The several RUL estimation strategies including the model-based method, data-driven method, and fusion-based method are highlighted in Section 4. Section 5 presents the typical implementation factors to execute various RUL prediction methodologies. The key issues and challenges for RUL prediction are addressed in Section 6. Finally, Section 7 concludes with effective future research suggestions.

2. Review methods

The objective of this review is to consolidate all available information, perform an analysis, and deliver a comprehensive evaluation of RUL prediction strategies applied to LIBs in EV applications. To achieve this, the Scopus databases were utilized to explore pertinent studies. The suitable sources were collected and referenced adequately, encompassing materials from Scopus, IEEE Xplore, Science Direct, and Google Search. Relevant articles are searched for using specific searches employing key terms related to lithium-ion batteries, remaining useful life, and electric vehicles. Due to limited resources, the review only considered papers published in English. Several articles, conference papers, and book chapters were identified, but careful selection was made based on variables such as the study's title, originality, structure, abstract, and contributions. This selecting process's outcome is provided in four steps. To begin, a thorough examination of the importance of BMS was demonstrated for the safe and efficient operation of LIB. Second, several RUL prediction methodologies were thoroughly examined. Third, provided a through discussion of the key implementation factor for RUL prediction. Fourth, a thorough discussion of the various challenges and issues involved with RUL prediction methodologies was

held. Finally, a conclusion is presented, along with prospective pathways for improving RUL prediction methodologies. Fig. 2 depicts a graphical depiction of the selection procedure and review findings.

2.1. Selection procedure

- During the initial screening process, 411 papers were gathered based on the keywords (lithium-ion battery and remaining useful life, and electric vehicle) from a diverse range of platforms such as Scopus, Science Direct, IEEE Xplore, and Google search.
- The second review and screening step effectively discovered a total of 275 publications by implementing precise criteria such as proper titles, year limits, an English language filter, article content analysis, and examination of each paper's contribution.
- The third searching was performed based on the impact factor, the number of citations, and the procedure of review.
- Finally, 168 articles from prominent scientific publications, conference proceedings, book chapters, and web pages were taken for final review and discussion.

2.2. Review findings

- A detailed discussion of the BMS components and their impact on the battery performance was thoroughly presented.
- The classification of the several RUL prediction methodologies and network configurations along with their pros and cons were provided.
- The critical implementation components, such as experimental setup for a battery test bench, data preparation, and hyperparameters for battery DL algorithms, were thoroughly examined to execute several RUL prediction approaches.
- The concerns and limitations of LIB RUL prediction modelling approaches in EV applications were investigated.
- Specific future directions for further improving the RUL prediction modelling technique in the respective disciplines were proposed to boost accuracy, robustness, and adaptability.

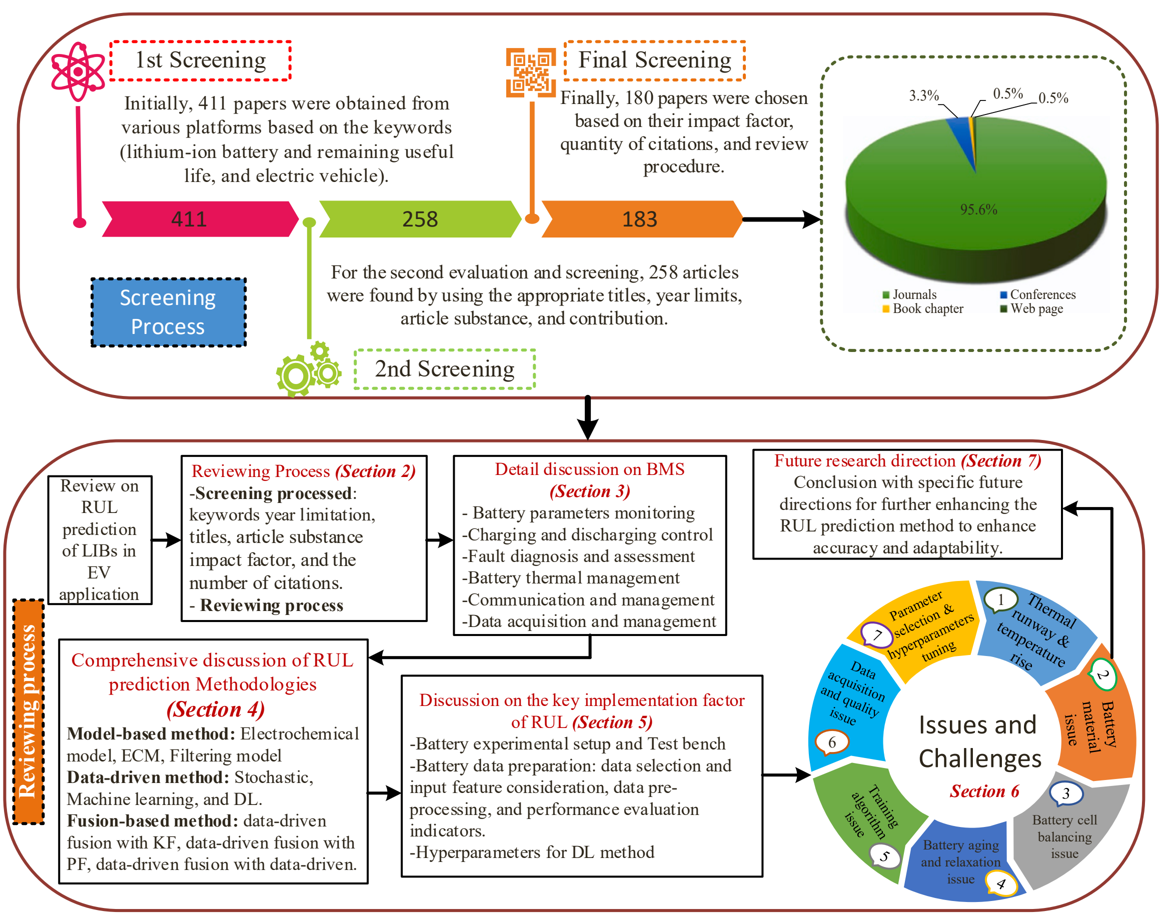

Fig. 2. Graphical representation of the selection procedure and review findings.

3. Battery management system

The BMS is an electronic system responsible for monitoring and controlling various aspects of LIB's operation to ensure safe and efficient performance (Ramkumar et al., 2022). Throughout the battery's lifecycle, the BMS plays a critical role in managing and safeguarding the battery. Properly designed BMSs manage the battery's charging-discharging cycles and monitor its state to identify safety issues and enhance performance. Currently, the BMS is extensively employed by automotive companies, colleges, and universities. The definition of BMS varies across different applications, but it generally refers to an advanced management scheme that locally controls and optimizes the efficiency of individual or multiple battery modules while minimizing degradation (Gabbar et al., 2021). While a comprehensive BMS has been successfully implemented in portable electronic devices like cell phones and notebooks, its integration into EVs is still in the early stages. This is due to the significantly larger number of batteries in EVs compared to portable devices, along with the higher power, voltage, and current requirements of EVs, which make BMS implementation more complex. Fig. 3(a) illustrates the BMS operation inside the EV. A BMS design typically encompasses various components, including monitoring, charge-discharge control, battery protection, thermal management, power management, communication and networking, fault diagnosis, and assessment, as well as data storage and acquisition (Wang et al., 2023a). Fig. 3(b) provides an

overview of the BMS functions, illustrating the key aspects of its operation and control. By incorporating these components, a well-designed BMS ensures the efficient and safe performance of the battery system. The following subsection provides the comprehensive discussion of the BMS functionality requirements.

3.1. Battery parameters monitoring

The monitoring of critical system states that significantly impact performance and safety is the primary function of a BMS. These states encompass cell voltage, terminal voltage, current, electrolyte temperature, SOC, and SOH. Through the use of sensors or suitable battery models, the BMS actively monitors and prevents potentially hazardous situations, such as battery overcharge, over-current, and overheating, ensuring the safe operation of the battery system (Simeone et al., 2018), (Alwis and Goh, 2009). For instance, Vijaya et al (Vijaya Gowri et al., 2023). proposed an innovative IoT-enabled battery management system, utilizing a microcontroller circuit and liquid cooling, to monitor and regulate Lithium-ion battery parameters in electric vehicles. This system offers real-time monitoring and alerts, enhancing battery performance and safety. However, a limitation lies in the reliance on continuous sensor monitoring, which may lead to increased power consumption and potential system strain. EVs utilize a series of interconnected LIB cells within a pack, each exhibiting unique behavior during runtime. Exposing the battery cells and membrane to such hazardous conditions can potentially result in permanent damage, adversely affecting their structural integrity and overall performance. To ensure optimal performance, continuous monitoring of these battery cells is essential for assessing their condition. It is also crucial to continuously monitor the voltage and current levels of Li-ion battery cells, as deviations from the expected values can lead to system failure or burnout, necessitating protection against over-current/over-voltage, and under-current/under-voltage conditions (Pratap Singh et al., 2022).

3.2. Charging and discharging control

The BMS plays an important role in prolonging the lifespan of a battery by efficiently supervising its charging and discharging

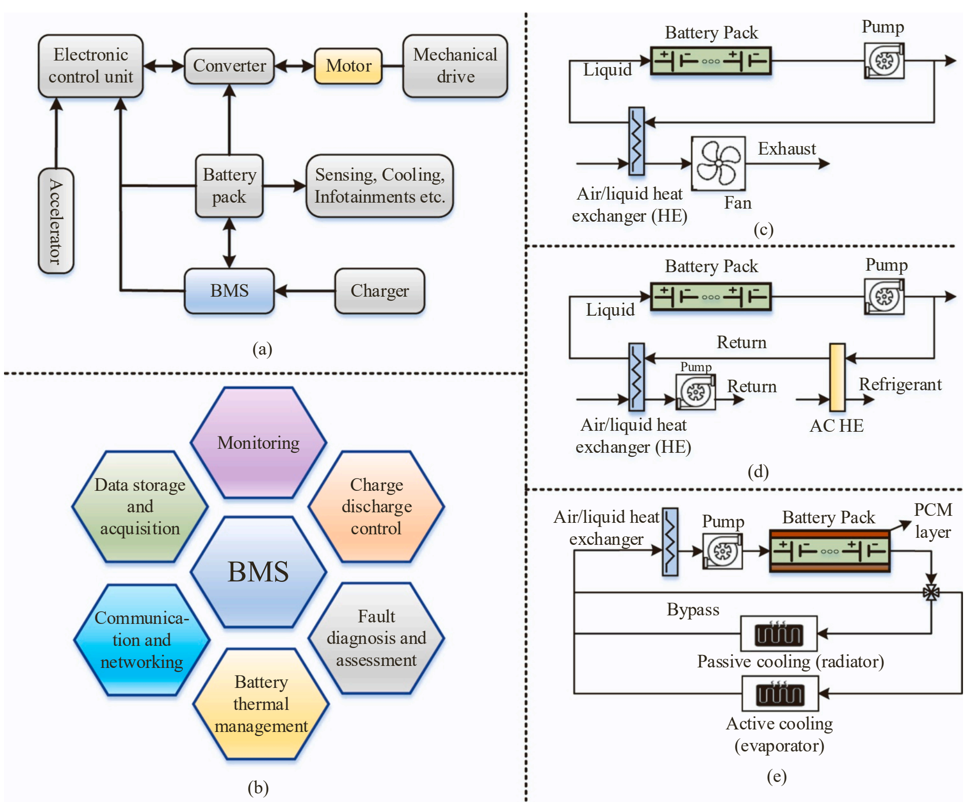

Fig. 3. Battery management system (a) in EV operation and (b) functionality requirements. Schematic of (c) active cooling/heating, (d) passive cooling, and (e) hybrid cooling with PCM system.
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operation. Overcharging and undercharging can lead to cell explosions and damage the chemical properties of battery cells, ultimately reducing their lifespan, decreasing discharge time, and increasing memory effect. The use of an efficient charge equalization controller can minimize overcharging and undercharging abnormalities and improve LIB's overall performance, enabling it to power an EV more effectively (Wang et al., 2016). This management process involves regulating the SOC range and cycle count, and it seamlessly collaborates with the EMS to control parameters such as input current, input/output power limitations, the initiation of the pre-charge sequence, and the utilization of diverse charging modes, among other functions. Hannan et al (Hannan et al., 2017). presented a novel battery charge equalization algorithm for lithium-ion batteries in electric vehicles (EVs), enhancing performance and safety by balancing cell voltages. Real-time testing confirms the algorithm's efficiency and scalability up to 100 cells, although additional components increase costs. However, the study lacks in-depth consideration of real-life charging and discharging conditions, which may impact algorithm performance in practical EV applications. Various control technique has been introduced to optimally charge and discharge the LIBs such as; CC-CV (constant current-constant voltage) control, reflex control, and low-power DC-DC (direct current-direct current) converter, random charging, discontinuous current mode PI (proportional-integral) control, and optimization based controller (Yu et al., 2016; Yao and Thinzar, 2023; Hoque et al., 2017a, 2017). Ouyang et al (Ouyang et al., 2022). presented a multi-objective optimal charging strategy for LIBs in EV, integrating user demand, cost optimization, and safety constraints. By employing a coupled electrothermal model, the proposed approach intelligently adjusts charging current based on user demand and electricity pricing, reducing electricity fees and energy loss. However, the study acknowledges a limitation in not optimizing economic costs related to battery degradation, with future research aimed at refining battery aging modeling for improved charging algorithms.

3.3. Fault diagnosis and assessment

The BMS performs continuous monitoring of sensor signals and estimated system states using battery models to proactively detect potential faults and generate warning signals. These faults may include data acquisition issues, networking and communication failures, programming errors, electric connection errors, and isolation problems, among others. To effectively address these faults, the BMS employs fault diagnosis technology, which consists of a system database, communication networks, an intelligent control program, and other technical measures, enabling the assessment, diagnosis, and appropriate response to faults based on their severity (Sun et al., 2023), (Zheng et al., 2020). Zhang et al (Zhang et al., 2023a). presented a method for early detection and assessment of soft internal short-circuit faults in LIB packs, utilizing incremental capacity curve analysis and the local outlier factor method. Simulation and real-world vehicle data validate the effectiveness of the approach in identifying faulty cells and assessing fault severity. However, the study acknowledges limitations in considering only state of charge differences and intends to explore internal resistance and capacity differences in future research for more comprehensive fault diagnosis.

3.4. Battery thermal management

To maintain the battery pack temperature within the specified range and minimize temperature variations between cells (Chen et al., 2015), (Xue et al., 2020b), it is crucial to have an effective battery thermal management system (BTMS). The BTMS serves the dual purpose of managing and dissipating the heat generated during electrochemical reactions in the cells, ensuring the safe and efficient operation of the battery pack. There are several alternatives for selecting an appropriate battery thermal management system (BTMS) in a battery system, which include three primary techniques: passive, active, and hybrid methods, as shown in Fig. 3(c), (d), and (e), respectively. Among these techniques, the active BTMS stands out as it requires an external energy source to enhance heat transfer. Despite its need for additional power, the active technique offers several noteworthy advantages such as; no moving parts, noise-free, no chemical reaction inside, longer lifetime, reliable, and low maintenance costs (Shi et al., 2017). However, it is important to note that this technique exhibits lower efficiencies and necessitates additional power, thereby limiting its effectiveness and suitability for commercial applications. Incorporating techniques that operate without the need for additional heating or cooling sources, passive methods represent a category of BTMSs with distinctive characteristics. Notably, passive BTMSs are renowned for their energy efficiency, affordability, as well as their ability to provide reliable and durable performance over an extended period (Khan et al., 2017). Nevertheless, these methods do have certain drawbacks, including low thermal conductivity and the potential for leakage. Yue et al (Yue et al., 2022). introduced a passive BTMS using thermally enhanced water adsorbents and copper foam significantly reduces LIB temperatures during discharge. Compared to other cooling methods, it achieves superior cooling performance with zero energy consumption, ensuring temperature uniformity and safety in electric vehicles. However, the study lacks detailed analysis of the system's performance under extreme conditions or long-term use, which may limit its applicability in real-world EV scenarios.Recognizing the advantages offered by both active and passive systems, hybrid techniques have emerged as a viable solution for achieving a balanced approach. By combining two or more of the aforementioned alternatives, hybrid BTMSs aim to leverage the benefits of both active and passive systems. As a result, these hybrid systems offer superior thermal management for battery packs compared to either passive or active systems (Akinlabi and Solyali, 2020). However, it is essential to acknowledge that the complexity and cost associated with hybrid techniques restrict their applicability primarily in the context of EVs. Cen et al (Cen et al., 2018). presents a novel lithium-ion BTMS that utilizes air conditioning refrigerant of EV for direct battery pack cooling. Through specialized module design and control mechanisms, the system maintains the pack temperature below 35°C even in extreme 40°C ambient conditions, with minimal temperature variation of less than 4°C during tests. Refrigerant circuit optimization significantly impacts temperature uniformity within the pack, highlighting the importance of design for cooling efficiency. Future research will focus on further improving temperature uniformity through module structures and dynamic temperature adjustments.

3.5. Communication and networking

EV system necessitates seamless communication with both the vehicle subsystems and the inter-networking systems. This communication is crucial for optimizing performance within the EV and facilitating a range of functions, such as online monitoring, program downloading, updating, calibration, and controlling modifications specifically tailored for the BMS (Habib et al., 2023). Furthermore, the identification of optimal EV charging stations and accurate prediction of drive range relies on the integration of the controller area network and global positioning system. These systems enable online estimations of the SOH and the battery storage system, thereby facilitating reliable and real-time assessments. Kunitachi et al (Kumtachi et al., 2017). developed a wireless sensor network method for enhancing vehicle comfort and convenience, particularly focusing on battery management systems (BMS) for electric vehicles. Through computer simulations, the proposed method achieves high packet arrival ratios within a short time frame for BMS and crew sensor networks. However, performance degradation is observed when multiple applications are simultaneously running, suggesting a limitation in maintaining delay constraints under heavy network traffic.

3.6. Data acquisition and storage

Data storage and data acquisition constitute integral components of a comprehensive BMS, enabling efficient management and vigilant monitoring of battery pack performance (Kong et al., 2017). The process of data acquisition involves the systematic collection of information from an array of sensors, measurement hardware, processors, and software seamlessly integrated within the BMS. This inclusive approach facilitates the aggregation and storage of crucial data originating from the battery storage system, encompassing parameters such as current, voltage, and temperature. Moreover, the amassed data within the BMS undergoes meticulous processing through functional and control algorithms, facilitating sophisticated analysis and informed decision-making.

Conversely, data storage entails the establishment of a dedicated memory or storage system within the BMS to ensure the retention of acquired data for future utilization, extensive analysis, and diagnostic purposes (Kulkarni et al., 2016). The preserved data reserves offer invaluable insights into the historical performance of the battery, revealing patterns of usage, identifying anomalies, and highlighting prevailing trends over a span of time. Consequently, this reservoir of information emerges as a precious asset for evaluating battery health, optimizing system operations, and guiding discerning decisions on maintenance protocols, performance enhancements, or potential replacements.

4. RUL prediction methods

To guarantee the reliable functioning of a LIB system, it is necessary to have a mechanism in place to evaluate the SOH of the system and estimate its RUL. This can assist manufacturers in deciding when to remove or replace reference information related to the battery. Additionally, it is important to note that having an accurate assessment of the SOH and RUL can help prevent unexpected battery failures and optimize the performance of the system. Currently, there are many established strategies for predicting the RUL of LIBs, which have been summarized and divided into various categories including model-based, data-driven, and hybrid-based RUL prediction models. The RUL prediction approaches have been thoroughly examined, as shown in Fig. 4. The model-based technique uses mathematical modelling to build the degradation and empirical models to represent the deteriorating path of an associated system. Data-driven models, on the other hand, use machine learning (ML) and historical data techniques to determine the degradation model for various applications. Lastly, the hybrid model incorporates numerous approaches that take full advantage of the individual advantages of distinct model approaches.

4.1. Model-based method

Model-based approaches for predicting the RUL of LIBs use mathematical models that explain the physical and chemical phenomena that happen inside the battery during its operation. These models consider a wide range of characteristics that can impact battery performance and health, such as cycle, temperature, aging, and usage patterns. These methodologies can provide precise and trustworthy estimates of the battery's RUL by evaluating the battery's state using the model and simulating its performance over time, making them important tools for managing the life cycle of LIBs in diverse applications. The commonly used model-based approaches are mainly categorized into the electrochemical model (EM), ECM, and filtering model which is comprehensively described in the following subsection. A detailed analysis of various model-based methods of LIBs for RUL prediction has been presented in Table 1. Fig. 5 presents the schematic of several EM and several ECM structures.

4.1.1. Electrochemical model

The EM is a method for assessing the law of battery performance degradation and is based on the electrochemical process occurring inside a LIB. This model considers the intricate relationships between the materials and the electrolyte present in the battery and utilizes partial differential equations to depict the movement of lithium ions and electrons inside the battery, along with the chemical reactions that take place at the electrodes. The model can also consider temperature, aging, and cycling history, among other aspects that affect battery performance. EMs, on the other hand, can be computationally expensive and demand large amounts of data for modeling, as well as a high level of skill in electrochemical processes and numerical simulation. However, electrochemical models are frequently employed in the field of battery management and are considered to be highly accurate in forecasting battery performance and RUL. The EM can estimate the RUL of the battery and provide insights into its performance characteristics by modelling its behavior over time. To improve real-time battery state estimation, numerous studies have attempted to simplify and reconstruct various electrochemical models. At present, the pseudo-two-

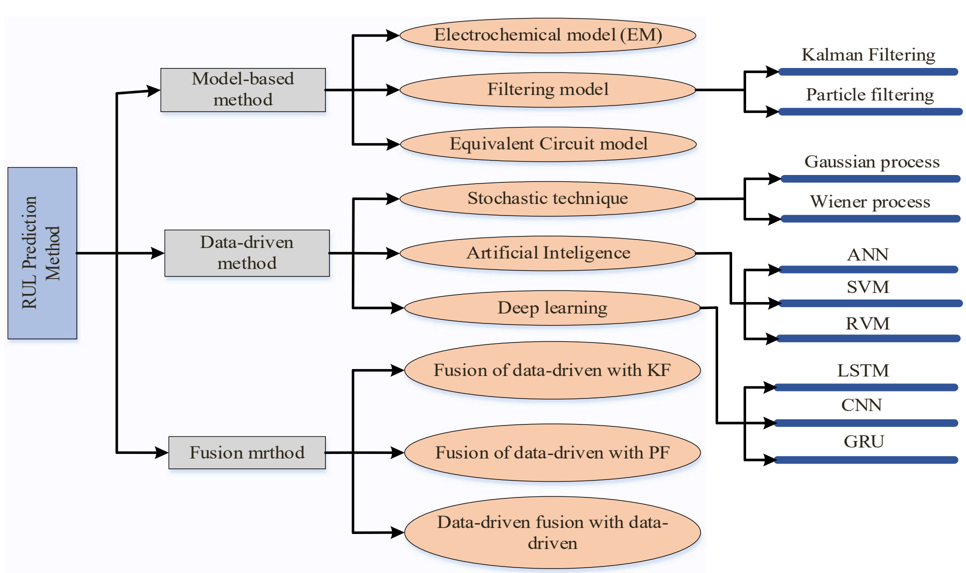

Fig. 4. RUL prediction method for LIBs.

Table 1
A comparison of various model-based methods for LIB RUL prediction in EV application.

Group	Method	Database	Battery cell	Advantages	Disadvantages	Accuracy
EM	P2D (Liu et al., 2020)	Experimental data	Panasonic NCR18650BD	Provides a deeper understanding of battery complex physical and chemical phenomena and sensitivity analysis.	Require significant computational resources and limit their practicality for large-scale simulation or real-world application.	RMSE less than 1.1026
	SPM (Khodadadi Sadabadi et al., 2021)	Experimental data	LMO-NMC	Simple design and requires less parameter calibration which makes it feasible; computationally efficient.	The SPM's simplicity comes at the expense of lower detail and accuracy; Insufficient battery aging information; less applicability.	Maximum RUL pdf STD was 3.82 kAh.
ECM	Rint (Wu et al., 2022)	Experimental data	$LiFePO_4$	Simple architecture and parameter calculation.	The dynamic process of the battery cell cannot be characterized.	MAE was less than 1.6 W.
	Thevenin (Ding et al., 2019)	Experimental data	Ternary lithium battery	Statistic and dynamic characteristics of LIB battery cells can be calculated.	Sensitive to battery aging and temperature.	Parameter identification error was lessthan 1%.
	Second-order RC (Xia et al., 2023a)	CALCE and Sandia National Laboratory	$LiCoO_2$, Panasonic NCA	The influence of complex parameter adjustment processes and measurement noise can be eliminated.	Lack of flexibility, limited accuracy, and limited applicability.	The highest RUL projected AE for CALCE was within 10.
	PNGV (Wang et al., 2017)	Experimental data	$LiNi_xCo_yMn_{1-x-y}O$	Addressing the temperature influence, good battery application to different operating conditions, and enhanced precision.	Model accuracy reduces due to the series resistor's cumulative errors and is not efficient for polarization response.	The RMSE was less than 0.0192 for all operating conditions.
Filtering model	High-order EKF (Wang and Wen, 2022)	NASA	18650 battery cell	Well-suited for modelling LIBs complex behaviour and allows recursive estimation.	Requires mathematical formulation, which increases the model complexity, and obtaining accurate initial values can be difficult.	The prediction accuracy improved from 66.13% to 97.67%.
	UKF (Miao et al., 2013a)	Experimental data	18650 battery	Able to solve the problem regarding particle degradation and the impact of singular values of PF. Easier to implement than EKF.	Did not able to describe the non-monotonic degradation trends and showed volatility. Did not consider the uncertain environment.	Relative error reduced from 4.34% to 0.36% for battery no. 2.
	PF-KS (Hu et al., 2015)	Not mentioned	Lithium-ion battery cell	Simple and high precision.	High mathematical calculation.	The error range was less than 0.002.
	UPF (Miao et al., 2013b)	CALCE	$LiCoO_2$	Able to effectively fit the true situation; provide proposal distribution.	Sensitive to model errors and noise and computationally complex.	Error less than 5%

dimensional (P2D) model and the single particle model (SPM) are two of the most prominent electrochemical-based models as shown in Fig. 5(a) and (b), respectively. To enable RUL prediction using EMs, all of these models are reconstructed to decrease computing complexity while preserving acceptable model accuracy. Doyle et al. developed a P2D model for LIBs in 1993, combining the concentrated solution theory and the porous electrode theory. Its predictions are reasonably reliable and generally agree with experimental evidence (Oca et al., 2021). The article proposed (Liu et al., 2020) a P2D model for predicting the LIBs calendar aging as well as evaluating the rate of SEI growth. To reduce the computational times, Zhang et al (Zhang et al., 2000). proposed the SPM in 2000, which is a simplified version of the P2D model. The primary characteristics of the SPM are its simplicity, low computational requirements for the solution, and versatility in serving various purposes such as life modeling online estimation of LIBs (Lacroix et al., 2016b). Its main disadvantage is that for thick electrodes and large discharge rates, it must be tuned according to electrolyte characteristics. To solve this problem, an improved version of SPM called enhanced single particle model (eSPM) was proposed in (Khodadadi Sadabadi et al., 2021) to predict the RUL of LIB cell. Various MPM as shown in Fig. 5(c) have also been suggested to address the challenges posed by particles of different sizes, properties, and varying contact resistance (R_c) in LIBs that have LiFePO4 electrodes (Farkhondeh and Delacourt, 2012), (Safari et al., 2011).

4.1.2. Equivalent circuit model

ECMs for RUL prediction of LIBs are electrical models that depict the electrochemical behavior of the battery using a series of resistors, capacitors, and voltage sources. The ECM can assess the battery's state of charge (SOC) and state of health (SOH) and anticipate the battery's RUL by measuring the voltage and current. Therefore, by creating a mathematical model using circuit analysis tools, the mechanism of battery degradation may be explained (Hu et al., 2020). ECMs are frequently employed in industry because of their computational efficiency and simplicity, which make them suited for real-time applications. However, its parameters have a distinct physical meaning and can be evaluated online, which can reflect the battery properties (Shao et al., 2023). Nowadays, the internal resistance battery model (Rint), Thevenin model, second-order RC model, PNGV, and GNL model are widely used ECMs (Shao et al., 2023). In 1994, the Rint concept was implemented in ADVISOR as shown in Fig. 5(d) (Johnson, 2002). Since the lithium battery's terminal voltage is controlled by the electrode voltage and resistance during charging and discharging, the terminal voltage curves acquire the information included in the electrode voltage curve. As a result, the Rint ECM can be calculated using Eq. 1.

$$V = V_{oc} - IR_0 \tag{1}$$

where V denotes the terminal voltage, I denotes the current, R_0 denotes the ohmic resistance, and V_{oc} denotes open circuit voltage. The structure of this model is very simple thus easy parameter calculation. However, this model is unable to characterize the dynamic behavior of the LIB cell.

To solve this issues Thevenin model (Barletta et al., 2022) and second-order RC (Xia et al., 2023b) ECM are widely used as shown in Fig. 5(e) and (f), which also consider the polarization reaction of the battery. However, temperature variations and battery aging have a considerable influence on the model's accuracy. The dynamic behavior of the Thevenin model and second-order RC model can be calculated using Eqs. 2, 3, and 4, respectively.

$$V = V_{oc} - IR_0 - U_c \tag{2}$$

$$I = \frac{U_c}{R_1} + C \quad \frac{dU_c}{dt} \tag{3}$$

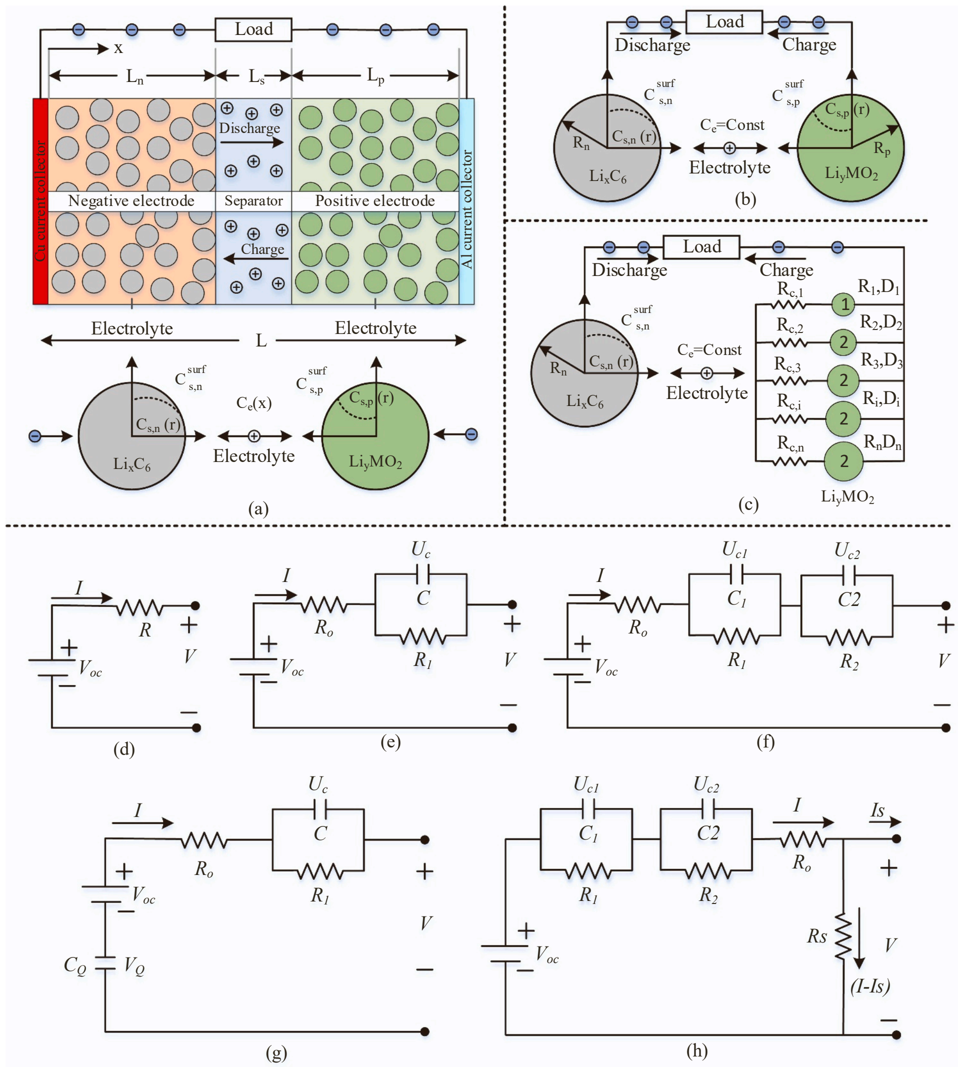

Fig. 5. Schematic of several EM (a) P2D model, (b) SPM, and (c) Multiple particle model (MPM). Several ECM structures (d) Rint model, (e) Thevenin model, (f) Second-order RC model, (g) PNGV model, and (h) GNL model.
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$$V = V_{oc} - IR_0 - U_{c1} - U_{c2} \tag{4}$$

where U_c, U_{c1}, and U_{c2} are the polarization voltages. The influence of temperature changes was considered in (Nelson et al., 2002) for lithium-ion PNGV batteries as shown in Fig. 5(g). It is a series connection between a capacitor and the Second-order RC model that simulates how fluctuations in SOC induced by the time integral of current affect the battery's open-circuit voltage (Pa, 2019). However, the accumulated error of the series capacitor decreases the model's accuracy and makes it insensitive to polarisation responses. The PNGV ECM can be calculated using Eqs. (5) and 6, respectively.

$$V = V_{oc} - IR_0 - U_c - V_Q \tag{5}$$

$$V_Q = \frac{1}{C_Q} \tag{6}$$

where C_Q denotes the battery capacitance and V_Q denotes the battery capacitance voltage. On the other hand, GNL ECM, as illustrated in Fig. 5 (h), takes into account the self-discharge component (W. Y.-W. et al., 2018). However, this model is very complex, which increases the complexity of calculation and parameter adjustment. The GNL ECM can be evaluated as:

$$V = V_{oc} - IR_0 - U_{c1} - U_{c2} \tag{7}$$

$$V = (I - I_s).R_s \tag{8}$$

4.1.3. Filtering model

To estimate the RUL of LIBs and get an accurate picture of the battery's state over time, filtering methods are widely used to eliminate sensor data noise. There are several filtering methods, such as Kalman filtering (KF) and Particle filtering (PF) approaches that can be utilized. In this section, we will explore some of the frequently used filtering methods for predicting RUL.

Kalman filtering - The KF is a frequently utilized filtering technique in predicting the RUL of batteries. An estimator utilizes a system model and a series of measurements to determine the state of a system. The KF is especially advantageous when dealing with noisy data, as it can minimize the impact of measurement noise and generate a more accurate assessment of the system's state. Another major benefit of the KF is its low computational requirements, as it only needs to consider the system state at the previous moment and potential measurements to acquire an optimal estimation of the current state. However, the KF's actual implementation may be limited due to the need for a precise system model and accurate measurements, as well as the assumption of

Gaussian noise and system model. Furthermore, if the covariance matrix is not well-behaved, the filter may experience numerical instability problems. Different optimized KF techniques have been developed to enhance the performance of the traditional methods through improved algorithms or parameters. Wang et al (Wang and Wen, 2022). presented a real-time update high-order extended KF (EKF) method for predicting the RUL of LIBs in EV. This method overcomes the limitations of existing methods by improving prediction accuracy and extending the prediction period. The proposed approach combined models and data and established a state model that described the dynamic energy attenuation model's parameters. Through iterative recursion, a state model's multi-step prediction equation was established, and the efficacy of the method is demonstrated via digital simulations. Duan et al (Duan et al., 2019). established a novel extended Kalman PF (EKPF) to estimate the RUL of LIBs. The first standard PF was used to analyze the problem. The PF algorithm was optimized as a sampling density function using EKF. Chen et al (Chen et al., 2015). suggested a new approach for predicting the RUL of LIBs by combining the unscented KF (UKF) and minimum sampling variance resampling with the standard PF. The purpose of this method was to tackle the problem of unreliable and inaccurate predictions caused by particle degeneracy and impoverishment that occurs in the standard PF after a few iterations. The proposed technique was tested on four different battery datasets from NASA, and the results showed that it was highly reliable and accurate in predicting the RUL of the batteries. Xue et al (Xue et al., 2020b). developed an integrated algorithm for LIBs RUL prediction that combined AUKF and genetic algorithm to optimize support vector regression (SVR), with a minimum accuracy of 0.933. They used evolutionary algorithms to optimise the essential parameters of SVR for multiple-step prediction and then proposed the adaptive unscented KF (AUKF) technique for automatically adjusting the method's noise covariance and the observed noise covariance.

Particle filter - PF algorithm idea comes from the Monte Carlo approach, which is a popular filtering technique that used RUL prediction of LIB. The method uses a set of particles to estimate the probability distribution of a system's state. The particles represent many alternative system states and their corresponding weights, which are modified at each time step depending on fresh sensor measurements. The PF method is capable of dealing with non-linear and non-Gaussian systems, making it suited for RUL prediction in LIBs. The approach, unlike the KF, does not require a detailed system model. However, finding the right number of particles can be challenging, and the computing burden can be significant, particularly in complex battery systems. Hu et al (Hu et al., 2015). combined PF with Kernel Smoothing (KS) to predict the RUL of LIBs, enabling the simultaneous estimation of the degradation model's deterioration status and unknown parameters. The results indicated that the proposed method outperformed the traditional PF method. Ye et al (Ye et al., 2023). proposed an improved PF based on the chaotic PSO algorithm (CPSO-PF) to predict the LIBs remaining operation life, which is important for ensuring the reliability and safety of EVs. By employing CPSO to drive the previous distribution of particles into a high likelihood probability, the CPSO-PF technique overcomes the difficulties of particle degeneracy and impoverishment. Xie et al (Xie et al., 2019). established a hybrid algorithm for predicting the RUL of LIBs that combined the PF with the extended unbiased finite impulse response (EFIR) filter. The method first created a state space model for capacity degradation and then uses the EKF algorithm to estimate model parameters. Then, a regularized PF is used to make preliminary predictions, which are further diagnosed and repaired using the EFIR filter and diagnostic method. According to the experimental results, the suggested technique achieves steady and reliable RUL prediction results. Yang et al (Yang et al., 2022). introduced a novel approach to predict the RUL of LIBs that combines several methods, including unscented PF (UPF), optimal combination strategy (OCS), and particle resampling. The UPF played a key role in generating the proposal distribution of particles, while OCS was strategically employed during the resampling process to enhance the distribution and diversity of particles. The proposed method was found to be effective in predicting battery RUL and superior and more robust than conventional methods.

4.2. Data-driven method

Data-driven methodologies have developed as powerful tools for LIB's RUL prediction in recent years. The data-driven framework makes use of past data to forecast the degradation pattern of the battery. By examining previous data, such as power usage and environmental conditions, the data-driven framework can find patterns and trends that can be utilized to anticipate the battery's future performance and health. Data-driven techniques do not need to investigate the battery's specific failure process, avoiding the development of complex physicochemical models. Furthermore, as compared to model-based methods, the data-driven technique is simpler and much more practical, and it can manage complex systems. Data-driven methods are broadly classified into three categories such as; stochastic technique, ML technique, and DL technique. In the following subsection, all these methods are broadly described. Table 2 presents a comparative analysis of several data-driven methods of LIBs for RUL prediction.

4.2.1. Stochastic technique

Stochastic process methods utilize statistical principles and incorporate other mathematical concepts. Stochastic process approaches apply probability theory to model the uncertainty and randomness of LIB degradation. The integration of statistical and mathematical principles enables stochastic process approaches to capture the complex and variable character of battery degradation and deliver more precise and reliable RUL predictions. Stochastic techniques are broadly classified into Gaussian process regression (GPR) and wiener process.

Gaussian process regression Gaussian process regression (GPR) emerges as a potent solution when confronted with arduous regression quandaries, encompassing challenges arising from high dimensionality, scanty sample sizes, and nonlinearity. Unlike neural networks and support vector machines (SVMs), GPR boasts numerous advantages, such as its facile implementation, the automated acquisition of hyper-parameters, and the provision of probabilistic outputs. Additionally, GPR can model the underlying distribution of the data rather than simply projecting a point estimate. This probabilistic output can provide useful insights into the uncertainty of the forecasts, allowing for better decision-making. Xing et al (Xing et al., 2023). introduced a new approach for forecasting the RUL of LIBs using principal component analysis (PCA), a health indicator (HI), and improved GPR (IGPR). The HI was retrieved from the cycle curve of battery voltage while charging and utilized to forecast the RUL using the PCA-IGPR networks. The results showed that the proposed PCA-IGPR model had higher prediction accuracy compared to traditional GPR and SVR, with RMSEs of 0.34%, 0.67%, and 0.53% and MAPEs of 0.59%, 1.17%, and 0.96%. Pang et al. established (Pang et al., 2021) a novel approach that combines GPR and incremental capacity analysis (ICA) to predict the RUL of LIBs. The proposed method utilized the IC curve to extract HIs and established a framework of RUL prediction with uncertainty based on ICA and GPR. The outcomes revealed a remarkable precision and dependability of the suggested approach, substantiated by its ability to generate probabilistic outputs. Nonetheless, it is worth noting that the method's applicability to diverse battery types may be limited, warranting additional testing and investigations to foster the development of a more precise and universally applicable battery degradation model. Li et al (Li et al., 2020). established a multi-time scale architecture that calculates short-term SOH and predicts the batteries long-term RUL. The framework utilized incremental capacity analysis to extract four features, which were used as inputs to a GPR model to create a short-term aging model. Nonlinear regression was then used to predict the battery SOH and long-term RUL. The predicted MAE and RMSE for RUL were less than 26 cycles, and the majority of the RUL prediction errors occurred

Table 2
A comparison of various data-driven methods for LIB RUL prediction in EV application.

Main group	Sub-group	Method	Database	Battery Cell	Key Findings	Research gaps	Prediction accuracy
Data-driven	Stochastic technique	Multiple GPR (Liu et al., 2019b)	NASA and CALCE	18650 battery cell and $LiCoO_2$	Able to attain more reliable and accurate prediction considering capacity regeneration phenomenon with uncertainty.	GPR and health indicators parameters are needed to optimize for improving the adaptability at real-time applications and several operating conditions.	The RMSE of NASA batteries was lower than 10 cycles.
		Two-stage WP Shen et al., (2021)	Experimental data	NCR18650B lithium-ion battery cell	Considered the effect of variable discharge current and provide the PDF of RUL. Able to describe the degradation process uncertainty.	Did not able to capture the complex physical and electrochemical process of the battery.	RMSE was less than 3.13% for B1 and B2 batteries.
	Machine Learning Algorithm	ANN (Zhang et al., 2019b)	NASA	18650 battery cell	The structure was really simple. As a result, the approach provided significant advantages in terms of cost savings and ease of usage.	Prediction performance may be affected by the changes in operating conditions and battery model.	Relative error rates for SOH prediction were less than 3%.
		SVR (Zhao et al., 2018)	NASA and CALCE	18650 battery cell and $LiCoO_2$	Models relationship between capacity and health indicators and SOH and RUL was determined.	The confidence interval of the prediction results and probability distribution can be considered for further study.	RMSE was less than 1.52% for NASA batteries.
		RVM (Liu et al., 2015)	NASA	18650 battery cell	Capable of assessing performance decline and estimating the RUL of LIBs.	Future research will concentrate on quantifying and reducing prognostic uncertainty.	RMSE was less than 0.0196 for battery no.5 in all cases.
	Deep learning algorithm	Anti-noise adaptive LSTM (Wang et al., 2023b)	Experimental data and NASA	18650 battery cell	Delivers high-precision prediction results considering ambient temperature, current rate, and other factors.	Various factors including charge/discharge ratio, air humidity, and pressure that may affect the battery degradation rate will be addressed further.	RMSE value of 0.60434%.
		GRU (Wei et al., 2022)	-	Lithium-ion	Provides reliable RUL estimation with Uncertainty.	Inefficient to handle irregular sample data and sensitive to hyperparameters.	MAE was below 1.55%.
		CNN (Zhang et al., 2022b)	MIT and Stanford	$LiFePO_4$/graphite A123 APR18650M1A cells	Provides high accuracy and reliability for battery RUL prediction considering sparse and random segment data.	The PDF of the prediction and uncertainty can be considered for future research.	Achieved a low test error of 4.15%

within the range of 5–20 cycles. The fuzzy evaluation GPR (FE-GPR), proposed by Kang et al (Kang et al., 2020)., employs fuzzy evaluation to pre-process observation data, which is then combined with the GPR method's characteristics. The GSA approach optimized the classification node by effectively combining GSA and historical data, resulting in strong data extraction capabilities and accurate RUL prediction. The combination of GPR and finite element methods has significantly improved the precision of predicting high-level small sample data, achieving a regression analysis value of 0.739. Liu et al (Liu et al., 2019b). developed a novel RUL prediction approach using multiple GPR models and indirect HIs to solve the capacity unmeasurable issue in batteries. Measurable HIs were extracted from the charging process, and three GPR models were built based on the HI versus cycle number data. The prediction results were added to the multidimensional GPR model, validated by two datasets, and showed accurate RUL prediction. Future work will concentrate on optimizing the HIs and improving the GPR model efficiency for better battery RUL prediction. Tagade et al (Tagade et al., 2020). developed a deep Gaussian process approach for LIB health monitoring, modelling inter-node correlations using Gaussian processes and matrix-variate Gaussian distributions. Using partial charging and discharging sequence data, the algorithm accurately evaluated battery capacity and forecasted EOL via statistical association with elapsed time. While obtaining excellent prediction accuracy, the complexity of computation and training period was increased, necessitating additional efforts to optimize model parameters in the future.

Wiener process - Recently, there has been a lot of interest in using statistics-based data-driven methods, such as the WP, for battery RUL prediction. The WP is a type of diffusion process that is driven by Brownian motion and is well-suited for describing non-monotonic degradation processes that exhibit discontinuous increases or decreases in trend. Xu et al (Xu et al., 2021a). developed a novel method RUL prediction method for LIBs under varying temperature conditions. The method included a stochastic deterioration rate model that relied on the Arrhenius temperature method, an aging model founded on the WP, and a two-step unbiased estimating approach based on maximum likelihood estimation and genetic algorithm (GA). The method was validated through a case study, which demonstrated its effectiveness in accurately predicting RUL with smaller uncertainty. Tang et al (Tang et al., 2014). established a novel method for estimating the RUL of LIBs based on the WP with measurement error. The method employed a truncated normal distribution for estimating deterioration status and an MLE method for estimating population-based parameters, with an approach for real-time parameter modification. Numerical examples and a case study were used to demonstrate the effectiveness of the proposed method, though future research is needed to apply this method to batteries with nonlinear degradation trends. Eq. 9 can be used to express the RUL degradation model as described in the existing literature.

$$Y(t) = X(t) + \varepsilon = \delta t + \sigma_B B(t) + \varepsilon \tag{9}$$

where the degradation stage with measurement error is represented by $Y(t)$, while $X(t)$ represents the degradation step without measurement error. The measurement error is denoted byε, and δ represents the drift parameter. The diffusion parameter is denoted byσ_B, and $B(t)$ represents the standard Brownian motion. Zhang et al (Zhang et al., 2023a). presented a model to predict the RUL of industrial products based on the degradation process and dynamic environmental impacts. The model utilized a nonlinear Wiener process with a random time-varying covariate, modeled with an Ornstein-Uhlenbeck process and linked to the degradation rate by an exponential form covariate-effect function. The proposed model was validated with Monte Carlo simulations and applied to two datasets, showing superior performance in RUL prediction compared to existing models. Shen et al (Shen et al., 2021). developed a two-stage Wiener process model for accurately predicting the RUL of LIBs. They then used the UPF algorithm to post-update the

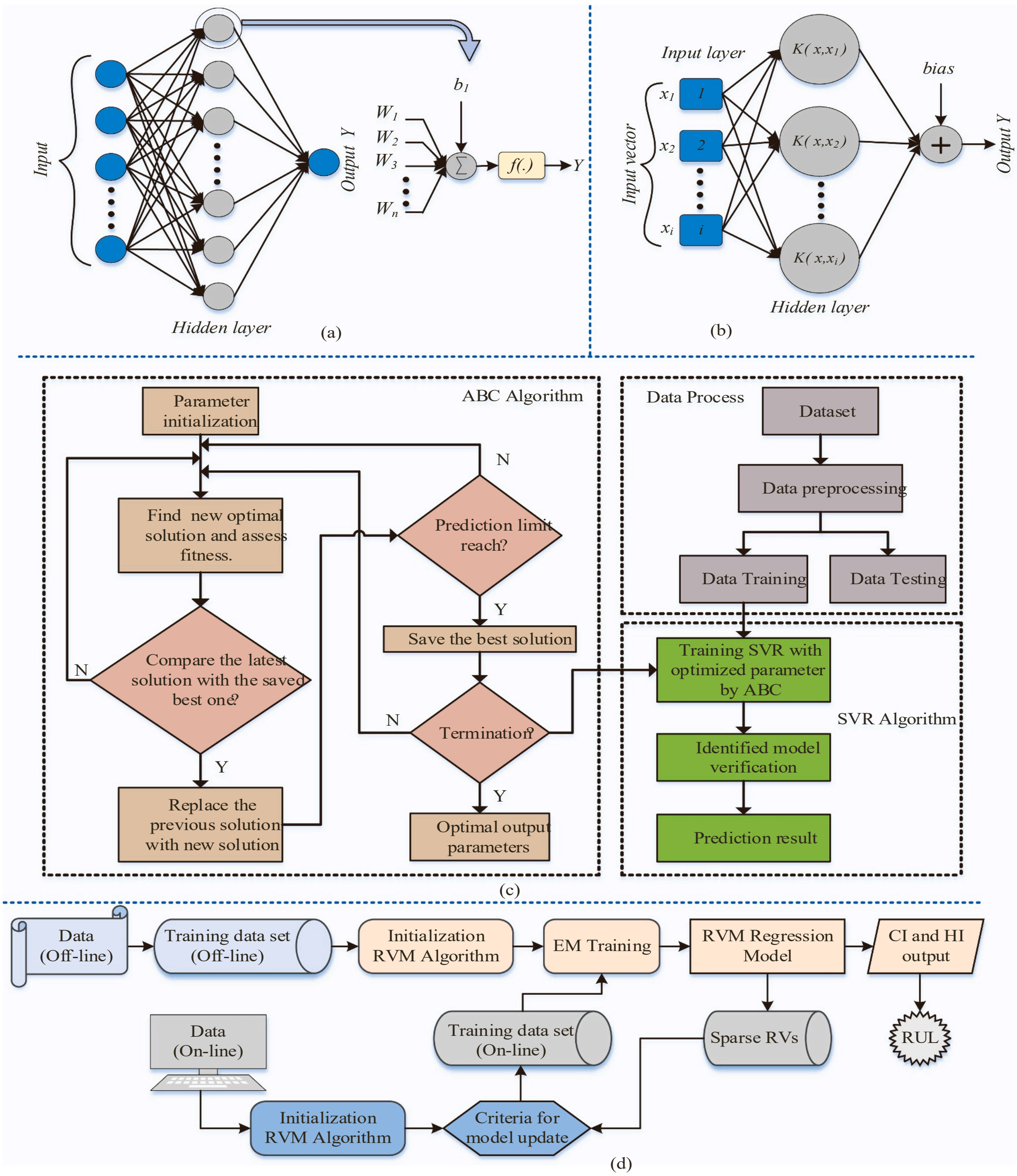

Fig. 6. The basic architecture of (a) artificial neural network (ANN) (Liu et al., 2021) and (b) support vector machine (SVM) (Zakaria et al., 2014). (c) Flowchart of the ABC-based SVR method (Wang et al., 2019a). (d) RUL estimation framework based on the incremental RVM technique, reproduced with permission of (Liu et al., 2015), Elsevier 2015, copyright.

model parameters and RUL distribution, resulting in high prediction accuracy and robustness. By introducing an odor-less PF algorithm, they were able to adaptively update all model parameters and RUL allocation based on the latest online measurements.

4.2.2. Machine learning algorithm

Artificial intelligence (AI) methods frequently use monitoring data to construct a degradation model for a certain variable. This model is then used to determine the RUL by extending the variable's behavior up until the moment of failure. This strategy entails applying AI to study and predict the lifespan of a system or component by analyzing real-time data about its performance and behavior, and it doesn't require knowledge of the electrochemical processes that occur within the battery. The method often entails collecting huge volumes of data about the system being monitored, such as temperature, pressure, vibration, and other important factors. This data is then evaluated using ML methods such as artificial neural networks (ANNs), SVMs, and relevance vector machines (RVMs) to identify patterns and correlations that can be used to anticipate the system's behavior over time. Based on these estimates, the system's RUL can be anticipated, enabling preventative maintenance or replacement before failure occurs. The basic architecture of the ANN and SVM are shown in Fig. 6(a) and (b), respectively. Fig. 6(c) and (d) presents the flowchart of ABC-based SVR method and incremental RVM technique for RUL prediction, respectively.

Artificial neural network - An ANN can have numerous layers, each of which contains multiple neurons or nodes. A logistic regression is used to calculate the value of each neuron in a given layer based on the values of all neurons in the previous layers. Zhang et al (Zhang et al., 2019b). introduced a new online synthesis approach for assessing battery SOH and RUL under constant current discharge. The method combined partial incremental capacity and ANN and employed the use of advanced filter and correlation analysis techniques. The proposed model achieved high prediction accuracy with MAE and RMSE of RUL being less than 4 cycles and 6 cycles respectively, and the relative error rate of SOH not exceeding 3%, indicating strong generalization ability. Wu et al (Wu et al., 2019). presented a new method for forecasting the RUL of LIBs by combining a neural network (NN) to model battery degradation trends and a bat-based PF to update the NN model's parameters. The experimental results showed that the suggested method outperforms traditional methods in terms of modelling the battery's deterioration trend and achieving higher RUL prediction accuracy. Further research could broaden the prediction method to more realistic applications and create a general degradation model by investigating the interaction between the degradation model and the operating conditions. Pugalenthi et al (Pugalenthi et al., 2022). developed a predictive maintenance solution using neural networks and adaptive Bayesian learning to estimate the RUL of electronic devices. The proposed approach included weight regularization using particle roughening as a regularization method in the Bayesian framework to address issues with particle weight decay. The model was tested using LIB capacity degradation data and demonstrated improved performance compared to conventional methods, with RMSE values and execution time used as metrics for evaluation.

Support vector machine - SVM are supervised learning algorithms that can be utilized for regression and classification applications. SVMs can be used to develop a model that predicts the RUL of a LIB based on features extracted from the battery's operating data. The RUL of LIBs is critical for BMS, and data mining technology is improving its ability to estimate RUL. Nevertheless, the classic single-radial basis kernel function utilized by SVM has poor generalization and can result in inaccurate RUL prediction. Gao et al (Gao and Huang, 2017). presented a novel multi-kernel SVM (MSVM) based on polynomial and radial basis kernels, optimized using the particle swarm optimization algorithm. When compared to traditional single-kernel SVM, the PSO-MSVM model exhibits higher prediction accuracy, stronger generalization performance, shorter training time, and lower computational costs. Wang et al (Wang et al., 2019a). proposed an approach for predicting the RUL of LIBs that combines artificial bee colony (ABC) with SVR where the kernel parameters of the SVR were optimally selected using the ABC algorithm. The flowchart of the proposed method is presented in Fig. 6(c). The results showed that the proposed method was accurate and stable, with RMSEs less than 0.05 and all unit's average values less than 27%. Future work will focus on improving prediction accuracy and extending the model structure with multi-kernel SVR for prediction. Li (Li et al., 2015) et al. developed an improved grey prediction model that uses a trigonometric function to transform the original data sequence and enhance its smoothness. The model integrated the improved grey model with SVM and selected the optimal model parameters using genetic algorithms. The model was tested using battery life data and compared to traditional grey models and SVMs, and the results showed that the grey SVM model was superior, with a root mean square error of only 3.18%. Dong et al. presented (Dong, 2021) a method for forecasting the RUL of LIBs using the Dempster-Shafer theory (DST) and the SVR-PF. When data is scarce, the model improves forecast accuracy. The suggested method modifies the basic probability assignment of DST at each iteration, boosting the importance of high-confidence prediction methods in the

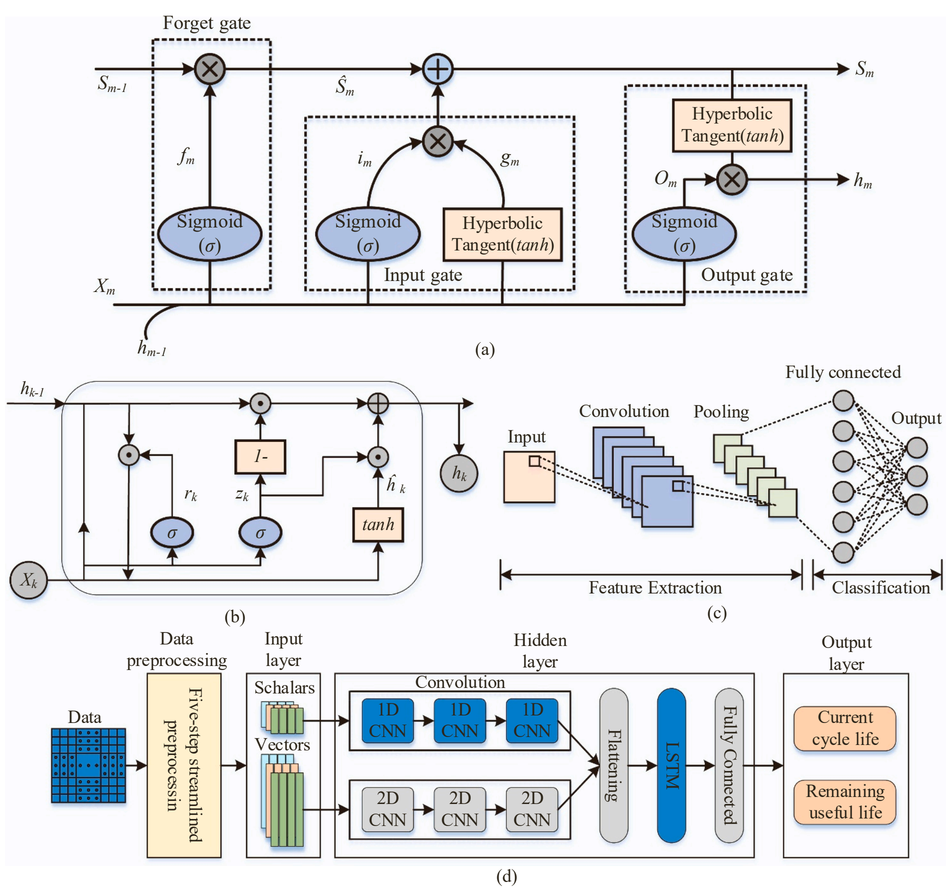

Fig. 7. DNN architecture (a) long short-term memory (LSTM), (b) gated recurrent unit (GRU) (Rouhi et al., 2022b), and (c) convolutional neural network (CNN). (d) Battery life prediction framework using CNN.
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combined findings and resulting in more accurate predictions. The suggested method can also be used to combine prediction findings from several independent data sources, and simulation results and comparisons with existing methods demonstrate its usefulness.

***Relevance vector machine (RVM)* -** Tipping (2000) created an ML method called RVM (Tipping and House, 2000), which is similar to SVM. RVM uses the Bayesian approach to calculate the necessary weights for PDF computation. This technique is characterized by a high degree of sparsity and can make predictions based on probability. Liu et al (Liu et al., 2015). employed the RVM approach to evaluate performance degradation and predict the RUL of LIBs. However, the tiny sample size along with the poor precision of multi-step forecasting limits its potential in sparse RVM approach battery RUL prediction. To address these concerns, the study presented a versatile and successful online training approach in the RVM approach to improving prediction ability, as well as an incrementally optimized RVM approach through efficient online training to improve operating efficiency and computational complexity. The proposed method was evaluated on a NASA battery data set and demonstrated satisfactory performance in battery RUL estimation. Fig. 6 (d) illustrates the framework of the incremental RVM technique for RUL prediction. Guo et al (Guo and He, 2022). established an integrated RUL prediction method, called ORV-MDMHD, for predicting the RUL of LIBs with high accuracy, especially for long-term predictions.To increase the performance of RVM regression, the method combines a modified degradation model with the Hausdorff distance and optimal relevance vectors (RVs). The results demonstrated that the suggested method produces more stable and accurate LIB RUL forecasts, particularly for long-term predictions. Nan et al (Nan et al., 2022). presented an RVM-grey predictive model (GM) algorithm based on dynamic window size to achieve a more accurate prediction of the RUL of LIBs with limited data. The method integrates the benefits of the RVM method and the GM method to give trend prediction as well as output probability prediction. NASA lithium-ion battery data were used to validate the suggested technique, which demonstrated higher prediction accuracy than PF and CNN. The proposed approach should be improved for more complex battery operating situations and implementation in a BMS controller. Jiang et al (Jiang et al., 2023). developed a data-driven model for predicting the RUL of LIBs, which is essential for battery health management and preventing unexpected failures. To estimate kernel and weight parameters, the model employed a multi-kernel RVM and a PSO approach. A similarity criterion of battery capacity curves was used to screen offline data to train the model. The results showed a maximum RUL prediction error of 25.58%, 12.15%, and 8.93% for different battery operating points (BOP), which can be reduced to 5.35% with more similar aging data utilized for training. Additionally, the model provided accurate capacity prediction with a maximum absolute percentage error (MaxAPE) within 3.25%.

4.2.3. Deep learning

A deep neural network (DNN) for LIBs RUL prediction is a kind of ML approach that employs multiple layers of artificial neurons to identify patterns and relationships in data on the health and degradation of LIBs. In contrast to the ANN's simple activation function, the DNN can perform operations such as convolutions or multiple activations in a single neuron. For battery RUL prediction, various DNNs based on recurrent neural networks, including the long short-term memory (LSTM), gated recurrent unit (GRU) model, and convolutional neural network (CNN), have been widely used. The architecture of these DNNs is shown in Fig. 7(a), (b), and (c), respectively. Fig. 7(d) presents the Battery life prediction framework using CNN.

***Long-short term memory* -** The data on the aging of LIBs is a type of time series data that is well-known and can be effectively handled by Recurrent Neural Networks (RNNs) due to their unique structure. However, using backpropagation as a training method for RNNs may cause gradient problems such as "vanishing" or "exploding," where the network weights become extremely small or large, limiting their ability to learn long-term associations (Zhang et al., 2021). To address these issues, an LSTM block is typically added to the hidden neurons of the RNN, which includes three gates (input gate, forget gate, and output gate) to modify and retain crucial information over a long time without diminishing gradients. The advantage of using the LSTM architecture is its ability to modify the gates to preserve important data, as well as its capacity to maintain information over a long period without being affected by diminishing gradients. Wang et al (Wang et al., 2023b). presented an improved anti-noise adaptive LSTM neural network, which used a dual closed-loop observation approach to accurately predict the RUL of LIBs. The network incorporated an adaptive state parameter feedback correction strategy and multi-parameter optimization to handle varying current rates, ambient temperatures, and other influencing parameters. Compared to existing methods, the proposed model showed a significant reduction in errors and an increase in R-squared, making it a promising solution for industrial applications of LIBs. Zhao et al (Zhao et al., 2022). developed a novel data-driven approach that combines LSTM and a broad learning system (BLS) to predict the RUL and capacity of LIBs. The BLS first produced feature nodes and applied the enhancement mapping to create enhancement nodes, and the resulting nodes were concatenated as the input layer of the LSTM. The results showed that the method proposed in this study guarantees the precision of the prediction while reducing the training data to only 25% of the whole degraded data.

***Gated recurrent unit* -** Another commonly used RNN is GRU which is usually used to predict sequences, such as the RUL of LIBs. Compared to the more complex LSTM, the GRU offers a lower computation cost, which has contributed to its widespread usage in studies involving time-based data (Hannan et al., 2021). Given that capacity and RUL prediction relies on data such as voltage, temperature, and current that are recorded over time, models like the GRU that are designed for sequence processing hold great potential for providing accurate and reliable predictions. However, the GRU's gating mechanism is simpler than that of the LSTM, which may limit its capacity to identify complicated patterns in some circumstances. Ardeshiri et al (Rouhi et al., 2022a). introduced a least-squares generative adversarial network with a GRU generator and a multi-layer perceptron discriminator to predict the RUL of LIBs. Through adversarial training, the network learned the probability distribution of future values, addressing the vanishing gradient problem and penalizing huge errors more severely. Time-domain features were employed, which were chosen using statistical formulas and the random forest algorithm, and experimental data were used to validate the model, which had a prediction error of 2.63% and an absolute error of 0.02. Wei et al (Wei et al., 2022). presented a new machine-learning approach for estimating LIB's RUL using GRU with error compensation (EC) and dropout Monte Carlo technology for reliable RUL prediction with uncertainty quantification. The method included establishing an equal charging voltage time and using variational mode decomposition to reduce the influence of the capacity regeneration phenomenon, adopting phase space reconstruction with C-C technology for optimal input sequence, and using the GRU with EC for RUL prediction. The method achieved higher accuracy with a mean absolute error below 1.55% and reliable RUL prediction with probability distribution compared to existing methods.

***Convolutional neural network* -** CNN is also a popular DL technique, widely used in speech processing, computer vision, face recognition, natural language processing, and time-series prediction (Gu et al., 2018). It is understood that a CNN is capable of automatically extracting hidden features from the input data and mapping it to the corresponding labels without any additional pre-processing. However, CNN can be computationally expensive, necessitating a large amount of computing power as well as time to train and test. Nowadays, CNNs have been widely used for capacity and RUL prediction of LIBs (Chen et al., 2022b; Tan and Liu, 2022; Ma et al., 2023a). Zhang et al (Zhang et al., 2022b). introduced a new model called Hybrid Parallel Residual CNN for predicting the RUL of LIBs in practical applications. The model used a

Table 3
A comparison of various fusion-based methods for LIB RUL prediction in EV application.

Main group	Sub-group	Method	Database	Battery Cell	Key Findings	Research gaps	Prediction accuracy
Fusion Method	Data-driven fusion with KF	RVM-KF (Song et al., 2018)	NASA and Satellite battery dataset	18650 battery cell and lithium-ion battery cell	Able to improve poor long-term prediction performance and handle LIB dynamic features.	The RVM algorithm re-training process can be optimized in future research to reduce the computational burden.	The RMSE of NASA batteries was lower than 0.0641.
		UKF-RVM-CEEMD (Chang et al., 2017)	CALCE and NASA	$LiCoO_2$ and 18650 battery cell	Achieved more robust and accurate results compared to the individual RVM and UKF methods.	The prediction results from robustness were very much sensitive to historical data.	The highest accuracy indicator (AI) was 97.72%.
	Data-driven fusion with PF	PF-LSTM (Xue et al., 2023)	NASA	18650 battery cell	Obtained robust prediction performance with PDF of the posterior and prior distribution of battery RUL and capacity.	The disruptions caused by the capacity regeneration phenomena have a significant impact on forecast errors.	RMSE value of 6.059231.
		SVR-PF (Dong et al., 2014)	NASA	18650 battery cell	The RUL value was provided, and the RUL probability distribution was updated for the EOL cycle.	Future studies will entail investigating physical models for various types of batteries.	RMSE value was less than 1.75×10^{-3} R_e
	Data-driven fusion with data-driven	CEEMDAN-BiGRU (Tang et al., 2023)	CALCE and NASA	$LiCoO_2$ and 18650 battery cell	Provides reliable RUL prediction under several operating conditions.	The prediction probability distribution and uncertainty consideration can be analyzed.	MAE of less than 4%.
		CNN-LSTM-DNN (Zraibi et al., 2021)	NASA and CALCE	18650 battery cell and $LiCoO_2$	Provided more accurate prediction results compare to individual CNN, LSTM, and DNN methods.	Inefficient to handle irregular sample data and sensitive to hyperparameters.	RMSE improved from 25.91% to 83.15% for NASA batteries.

residual network to extract hidden features effectively and could achieve online prediction using only sparse data, making it suitable for conditions with random charging processes. The proposed method was validated using a public dataset and demonstrated a low test error of 4.15%, indicating its potential for accurately predicting RUL in real-world scenarios. However, diverse aging mechanisms and capacity degradation mechanisms at an early cycle stage were not considered. To address this issue, Chen et al (Chen et al., 2022a). presented a new DL-based method for predicting the RUL of LIBs under multiple cycle profiles as shown in Fig. 7(d). The method used a hybrid neural network and a five-step pre-processing approach to construct the input data. CNNs and LSTM networks were employed to extract features and learn time-sequential relationships. The proposed model had strong generalization capability and achieved high accuracy with a mean absolute percentage error of only 1.47% and 2.85% in early lifetime prediction and RUL prediction, respectively.

4.3. *Fusion methods*

The fusion method, when integrated with various other techniques, aims to overcome the limitations of individual methods and enhance the accuracy of diagnosis and prediction by utilizing all available data more effectively. Furthermore, the fusion approach can assist in discovering elements that individual methods may overlook or disregard, which could be critical in establishing a diagnosis or prognosis. Recently, there has been a lot of interest in research on estimating the RUL of LIBs employing fusion methodologies based on model-based and data-driven procedures. There are two main types of fusion methods: those that use filtering techniques like KF, PF, and their variations, and those that rely on intelligent algorithms such as ML. Table 3 provides an overview of various fusion-based methods of LIBs for RUL prediction.

4.3.1. *Data-driven fusion with KF*

In terms of data-driven fusion with KF, Xue et al (Xue et al., 2020b). introduced an algorithm that combines AUKF and GA-optimized SVR to improve the accuracy of RUL prediction of LIBs. Song et al (Song et al., 2018). highlighted the importance of accurately estimating the RUL of LIBs in spacecraft and presented an iterative updated approach to improve the long-term estimation performance of RVM. The approach involved optimizing the RVM estimator with a physical degradation model using the KF, adding the optimized estimator to the training set as an online sample, re-training the RVM model, and dynamically adjusting the coefficient matrix and relevance vectors for next iterative prediction. The proposed method was demonstrated to achieve better performance for RUL estimation using both satellite battery data and commercial battery test data. Zheng et al (Zheng and Fang, 2015). developed short-term capacity estimation algorithms based on the KF and RVR methodologies. They created a framework that was continually updated with suitable RVR prediction information. However, for future research, they suggest incorporating long-term capacity prediction into their work. Chang et al (Chang et al., 2017). introduced a hybrid technique for RUL prediction of LIBs that combined the UKF, complete ensemble empirical mode decomposition (CEEMD), and RVM. The method employed an error-correction approach, analyzed the decomposition results of the raw error series obtained by CEEMD, and employed RVM regression to estimate the prognostic error for correcting the UKF's prognostic result. The experimental results showed that the suggested hybrid technique for RUL prediction of batteries with varied rated capacity and discharging currents was highly reliable.

4.3.2. *Data-driven fusion with PF*

In comparison to KF, more researchers prefer the PF technical framework's fusion method. Jafari et al (Jafari and Byun, 2022). combined a KF with a PF and used extreme gradient boosting (XGBoost) for RUL prediction. The proposed method showed improved accuracy compared to other methods with RMSE and MAE were 0.0173% and

0.0179%, respectively. Chen et al (Chen et al., 2022c). demonstrated a grey neural network (GNN) model that combines the grey model and the BPNN to predict online capacity using new HIs. The sliding-window grey model was utilized to track the battery's degradation trend, and the trend equation was used as the state transition equation of the PF algorithm to build the GNN fused sliding-window grey model based on the PF framework for battery RUL prediction. Experimental result demonstrated that the proposed GNN algorithm can effectively estimate degradation capacity with MAE less than 2.2%. Xue et al (Xue et al., 2023). offered a hybrid prognostic framework for the dynamic classification of SOH and long-term RUL prediction that incorporates a two-phase clustering scheme and a PF-LSTM algorithm. The framework was exhibited and compared to various adaptive learning and ML methods for LIB degradation modelling and RUL prediction. The results revealed that the hybrid PF-LSTM technique offered robust prediction performance as well as an accurate characterization of equipment deterioration states, which may be used to develop predictive maintenance action recommendations. Dong et al (Dong et al., 2014). proposed a fusion technique combining SVR and PF for lithium battery RUL prediction, and the experimental results achieved are superior to the standard single PF.

4.3.3. Data-driven fusion with intelligent algorithms

Nowadays, researchers around the world have become interested in the hybridization of intelligent algorithms based on data-driven models. Tang et al (Tang et al., 2023). developed a hybrid RUL prediction model for LIBs that combined complete ensemble empirical mode decomposition with adaptive noise (CEEMDAN) and a bi-directional GRU (BiGRU) to address capacity regeneration and model adaptability under various operating conditions. The suggested solution employed CEEMDAN to mitigate the impact of capacity regeneration and an improved grey wolf optimizer (IGOW) to maintain the BiGRU network's reliability. The experimental results revealed that the suggested method outperformed previous methods and achieved good accuracy with only 30% of the training set. In terms of the DL hybrid technique, Fan et al (FAN et al., 2019). proposed an approach that involves the use of the Forgetting Online Sequential Extreme Learning Machine (FOS-ELM) along with the Hybrid Grey Wolf Optimizer (HGWO) algorithm and attention mechanism. To enhance the accuracy of the method, noise from the raw data was removed using Variational Mode Decomposition (VMD), and FOS-ELM parameters were optimized through the HGWO algorithm. Zraibi et al (Zraibi et al., 2021). suggested an RUL prediction framework based on CNN-LSTM-DNN. Despite hybrid techniques produce better results than a single model structure, the model's complexity rises, requiring high computational power and human efforts.

5. RUL prediction implementation factors

Several execution strategies can have a significant impact on the estimation accuracy of data-driven based RUL prediction methods. The following part discusses the critical implementation procedures of RUL estimation for LIBs.

5.1. Battery experimental setup and test bench platform

The extraction of battery data including current, voltage, cycle, impedance, and capacity, which are critical for RUL prediction, is strongly reliant on the battery test bench (BTB). The BTB typically includes necessary components such as a sufficient power supply, load, programmable controller, and a host computer integrated with battery test system software. Popular BTB models in BMS include the Digatron BTS, Arbin BT2000, and NEWARE CT-4008 T-5V12A-S1 (Hossain Lipu et al., 2022). However, it is vital to remember that each BTB has unique characteristics, such as data extraction, data preprocessing, response time, and performance, which differ between models. Xu et al (Xu et al., 2023a). proposed a hybrid method to predict the battery health where A123 ANR26650M1B commercial LFP/graphite cells were chosen for aging tests and examined with a battery test equipment (NEWARE CT-4008 T-5V12A-S1). The ambient temperature was maintained using SUYIDA GDW-100 L programmable thermostat. Kong et al (Kong et al., 2022). created a battery test bench for battery health prognostics that included an Arbin BT2000 battery tester with cylindrical BAK 18650 battery samples, a temperature chamber, a Vötsch incubator, and a host computer. An NCR18650PF battery cell was tested by Chemali et al (Chemali et al., 2018). using Digatron BTS which includes a host PC, a thermal chamber, and a cell cycler. An Arbin BT-5HC test equipment with a heat chamber and a host computer for data storage and processing was used by Zhang et al (Zhang, 2018). to develop an LSTM-based DL approach for RUL prediction.

5.2. Battery data preparation

Battery data preparation includes data extraction, input feature selection, data pre-processing, and evaluation matrices which have a significant impact on the model training for RUL prediction. A comprehensive discussion of the battery data preparation is illustrated in the following subsection.

5.2.1. Data selection and input feature consideration

The RUL prediction entails the acquisition of relevant data from trustworthy sources such as NASA, CALCE, and MIT Stanford. NASA and CALCE are widely acknowledged as the key providers of battery datasets for RUL prediction. From the NASA database, the most popular datasets are B005, B006, B007, and B0018 which are widely used to predict the RUL (Zhu et al., 2023), (Xia et al., 2023c), whereas from CALCE database CS2–35, CS2–36, CS2–37, and CS2–38 datasets are the mostly used for battery health prognostics (Zhang et al., 2023b). Three battery datasets such as; NASA, MIT, and CALCE were used to demonstrate the effectiveness of the proposed method for battery health estimation by Jin et al (Jin et al., 2022). Ma et al (Ma et al., 2023b). proposed a fusion-based LIB health prognostic model where the NASA dataset was used as the source domain data, and the MIT dataset was chosen as the target domain data. The quality and effectiveness of data-driven models for SOH, SOC, and RUL estimation are largely dependent on input features. SOC is typically calculated by analyzing voltage, current, and temperature measurements acquired at constant or variable room temperatures. Several data-driven SOC estimation approaches make use of three critical parameters: current, voltage, and temperature (Xiao et al., 2019), (Huang et al., 2019). In contrast, determining SOH and RUL requires taking into account additional elements like current, voltage, temperature, impedance, and capacity (Park et al., 2020).

5.2.2. Data pre-processing

Data pre-processing assumes paramount importance in the overall process and encompasses a multitude of vital facets, encompassing data cleansing, filtering, formatting, normalization, and reduction. Before model input, data cleansing is executed to eradicate unwanted noise characteristics and inadequate information residing within the database. Moreover, data normalization and averaging procedures are implemented to expedite data transformation, thereby promoting faster convergence of the training model by constraining the data within specific bounds. Xu et al (Xu et al., 2023b). utilized the Savitzky-Golay filter to remove unwanted noise from the incremental capacity data without destroying the main data features. The data normalization technique was used by Xiao et al (Xiao et al., 2019). to improve model training convergence time. The datasets were scaled to a range of 0–1 using this technique. In (Park et al., 2020), the capacity degradation data was first cleansed by replacing the abnormal values with the average of highly correlated data. After data cleansing, min-max normalization was performed to replace the current, voltage, capacity, and temperature data on the same scale. To increase the prediction accuracy of LSTM for SOH and RUL estimation, Qu et al (Qu et al., 2019).

used CEEMDAN for noise reduction from raw data.

5.2.3. Performance evaluation indicators

Several indicators of error are used to assess the efficacy of SOH, SOC, and RUL prediction using data-driven methods. These include mean square error (MSE), mean absolute error (MAE), mean absolute percentage error (MAPE), correlation coefficient (R^2), and standard deviation. These statistical measures can be quantitatively stated as follows (Hannan et al., 2020):

Zhao et al., (2023)

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|Y' - Y_{actual}|$$

Hu et al., (2020)

$$MSE = \frac{1}{N}\sqrt{\sum_{i=1}^{N}(Y' - Y_{actual})^2}$$

Wang et al., (2021)

$$MAPE = \frac{100\%}{N}\sum_{i=1}^{N}\left|\frac{Y_{actual} - Y'}{Y_{actual}}\right|$$

Wu et al., (2016)

$$R^2 = 1 - \frac{\sum_{i=1}^{N}(Y_{actual} - Y')^2}{\sum_{i=1}^{N}(Y_{actual} - Y_{mean})^2}$$

Ramkumar et al., (2022)

$$SD = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}\left(Y'_{error} - Y'_{error_{mean}}\right)^2}$$

where Y_{actual} presents the actual data, Y' presents the predicted value, Y_{mean} presents the mean of C_{bat}, $Y'_{error_{mean}}$ represents the average error value, and N presents the observation number.

5.3. Hyperparameters for DL methods

The selection of hyperparameters during training has a substantial impact on the performance of DL models, which include elements such as the number of hidden layers and cells, learning rate, activation function, weight initialization, batch size, gradient decay factor, number of epoch, and many more. To obtain the output, the function provides weight to the inputs and guides them via the hidden layer and cells using an activation function. In (Ren et al., 2021), the author employed 7 hidden layers with varying numbers of neurons to predict the RUL of LIBs. The learning rate is the rate at which a network is tuned by evaluating the step size at every iteration while attempting to minimize a loss function. Song et al (Song et al., 2019). introduced the CNN-LSTM technique with a learning rate of α= 0.01 to evaluate the SOC of LIB, whereas for SOH estimation Qu et al (Qu et al., 2019). used α=0.02. Weight initialization is another important factor for the development of the DL model which helps to prevent activation layer output from being exploded or vanishing. In a DL approach, the number of epochs represents the whole iteration of datasets in both the forward and backward directions, reflecting the times the learning algorithm processes the entire training dataset. It is critical to assign an adequate number of epochs to avoid under-fitting and overfitting concerns. The batch size is the number of data samples that are sent across a network in a single iteration. A careful batch size selection would prevent slow learning, uneven gradient descent, and loss oscillation. In (Zhou et al., 2020), the TCN model was used for RUL prediction, with a batch size of 128 and 1000 iterations.

The search space expands exponentially as the number of hyperparameters grows. Furthermore, each hyperparameter affects the others. As a result, manually adjusting particular hyperparameters without taking into account others frequently results in inferior solutions. Furthermore, the ideal hyperparameters can vary significantly from one data set to the next (How et al., 2022). Therefore, optimally selecting the hyperparameters is very important to increase the prediction performance of the DL model. The hyperparameter tuning can be conducted in several ways such as grid search, random search, Bayesian optimization, and metaheuristic optimization (Yang and Shami, 2020). Because of the large search space, traditional hyperparameters optimization (HPO) techniques like grid search (GS) and random search (RS) are impractical. Furthermore, when you consider how long it takes to train only one model, employing GS and RS as a search method takes an extraordinarily lengthy time (Hossain and Timmer, 2021). Bayesian optimization (BO) (Snoek et al., 2012) is a popular reprocessing approach in HPO situations. In contrast to GS and RS, BO uses previous findings to establish future assessment spots. The BO model balances exploration and exploitation by finding attractive locations while preventing early convergence in less studied areas. BO outperforms GS and RS by effectively identifying ideal hyperparameter combinations based on previously evaluated values, and using a surrogate model is often less expensive than evaluating the entire objective function (Seeger, 2004). However, because BO is based on previous evaluations, combining it with parallel sequential approaches can be difficult. Metaheuristic algorithms (Gogna and Tayal, 2013) are a class of algorithms that are heavily used to solve optimization problems and are inspired by biological theories. Metaheuristics are different from traditional optimization methods in that they can solve non-convex, non-continuous, and non-smooth optimization problems. Population-based optimization techniques are a form of metaheuristic algorithm that includes particle swarm optimization (PSO) (Zhu et al., 2022), genetic algorithm (GA) (Karmawijaya et al., 2022), bat algorithm (BA) (Karmawijaya et al., 2022), differential search algorithm (DSA) (Hossain Lipu et al., 2023), and gravitational search algorithm (GSA) (Hossain Lipu et al., 2019). The strategies used to create and select populations are the fundamental variations between different POAs. POAs are easily parallelizable since a sample of N individuals may be assessed in parallel on a maximum of N threads or processors (Gressling, 2021).

6. Issues and challenges for RUL prediction

Since battery performance degrades over time owing to a variety of internal and external causes, estimating RUL for LIBs under varied operating situations has become a key challenge. Several issues and challenges such as; battery thermal runaway and temperature rise, battery material selection, cell balancing, aging and relaxation effect, training algorithm, data acquisition and quality, and feature selection and hyperparameters tuning are highly responsible for battery performance dealing and inefficient RUL prediction. The summarized of the most possible issues and challenges for RUL prediction are illustrated in Fig. 8(a) The researchers offered several battery models to estimate RUL; however, each model suffers from a lack of data for real-world EV applications. Furthermore, to accurately assess battery conditions, a lack of accuracy, difficult calculation, and high computation cost have become key concerns. Fig. 8(b) and (c) show the battery thermal runway and their characteristic curves within a battery cell, respectively. Moreover, the battery aging effect on resistence and capacitance at varying temperature are shown in Fig. 8(d) and (e), respectively.

6.1. Thermal runway and temperature issue

Thermal runway is defined as an uncontrolled and self-accelerating rise in temperature within a battery cell, which can result in a chain reaction of heat creation and, in extreme cases, lead to explosions or fires. The discharge of stored energy in the battery causes this occurrence, which is frequently linked to over-charging, over-discharging, internal

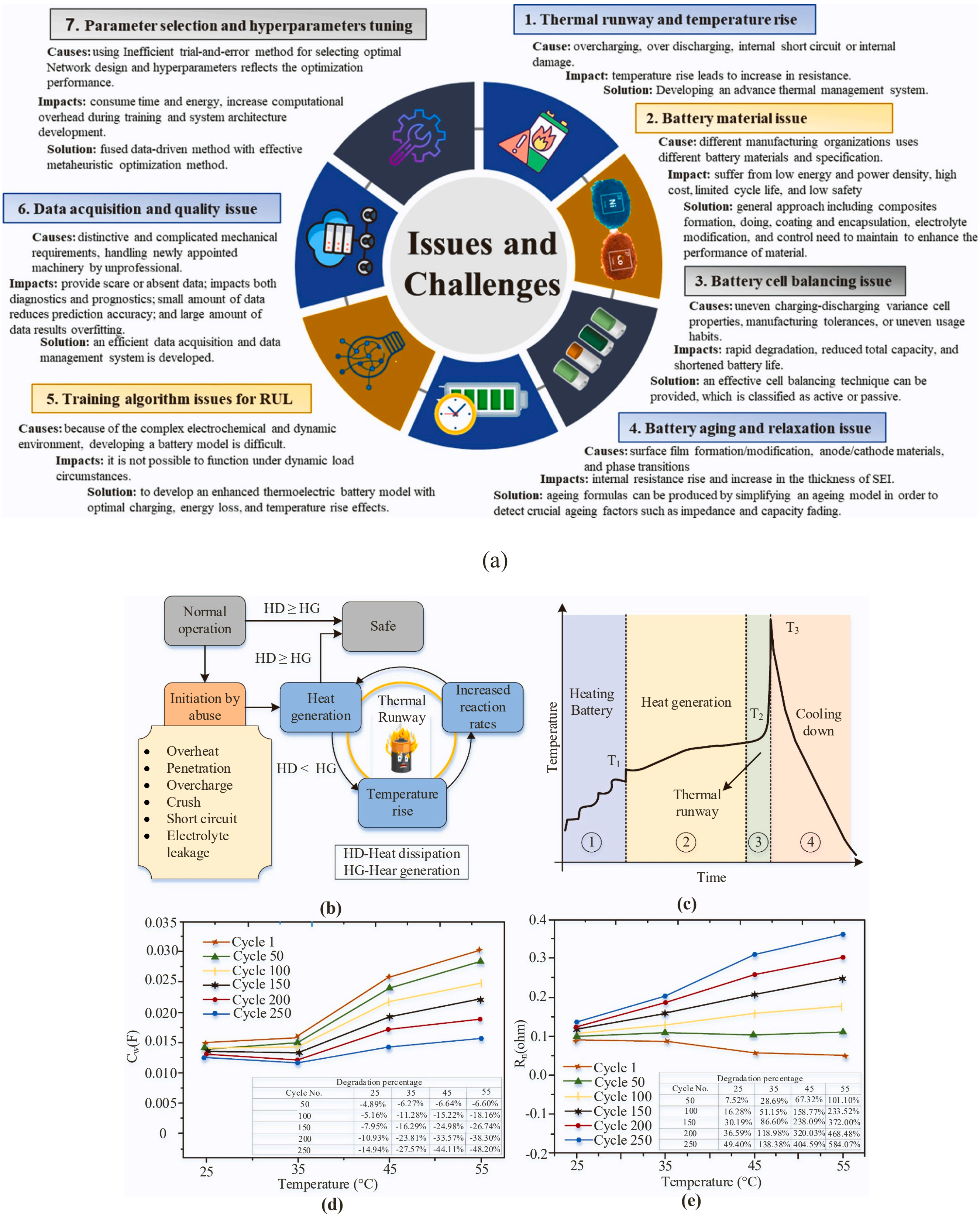

Fig. 8. (a) Challenges and effective solutions for RUL prediction of LIBs. (b) Thermal runway procedure within a single battery cell, reproduced with permission of (Bugryniec et al., 2020), Elsevier 2020, copyright. (c) LIBs thermal stability test (T_1 denotes the self-heating initial temperature, T2 denotes the critical temperature, and T3 denotes the sample maximum temperature during TR), reproduced with permission of (Mallick and Gayen, 2023a), Elsevier 2023, copyright. (d) Aging effect on battery capacitance at different temperatures, reproduced with permission of (Leng et al., 2015), Springer Nature 2015, copyright. (e) Aging effect on battery resistance at varying temperatures. Reproduced with permission of (Leng et al., 2015), Springer Nature 2015, copyright.

short circuits, or physical damage. At higher temperatures, the cell elements break down exothermically (Mallick and Gayen, 2023b). The process of the thermal runway within the particular cell is shown in Fig. 8(b). When the cell's self-heating rate surpasses the level at which heat can be dispersed, the temperature of the cell rises exponentially and its stability falls as shown in Fig. 8(c). Due to the loss of stability, all remaining electrochemical and thermal energy is released into the environment or neighboring cells. There has been numerous research on the temperature stability of LIBs. Among the most recent research, Feng et al (Feng et al., 2019). identified that during TR at high temperatures, the redox reaction between the cathode and anode was the dominant source of heat. Lopez et al (Lopez et al., 2015). investigated TR propagation into cell-to-cell and reported that TR propagation in a battery cell is reduced as the inter-cell distance in a battery pack is increased. Battery temperature is an important factor in evaluating the prediction performance of RUL using various DL algorithms. The RUL prediction accuracy varies under different temperature conditions. Xu et al (Xu et al., 2021b). assessed the RUL of LIBs using the Wiener process under varying temperature conditions. The results illustrated that the relative error of the proposed method is controlled within 1.93%, whereas the max error of the other two methods (without considering time-varying temperature) is up to 7.04% and 7.26%, respectively. Han et al (Han et al., 2021). validated the performance of the proposed fusion method based on data-driven and mechanism modelling using the battery aging data obtain from NASA and CALCE. The results indicated that the MAE and RMSE of the RUL for LIBs were both less than 20 and 25 cycles under constant temperature conditions, respectively, whereas, for non-constant temperature conditions they were determined to be less than 3.30 and 3.60 cycles, respectively.

6.2. Battery material issue

Predicting the RUL of LIBs is a difficult task, owing to material difficulties inherent in these batteries. Several prominent organizations, including NASA, MIT Stanford, and CALCE, have done significant studies using various battery materials and deterioration profiles to evaluate the accuracy of RUL prediction. NASA, for example, uses lithium nickel-cadmium aluminum (LiNCA) cell chemistry, whereas MIT employs lithium-ion phosphate (LFP)/graphite cells, and CALCE uses lithium cadmium oxide (LCO) (Fei et al., 2023). Furthermore, the minimum charge current in the NASA and CALCE battery datasets is set at 20 mA and 0.05 A, respectively. Liu et al (Liu et al., 2023). proposed an improved sparrow search algorithm-based LSTM method for RUL prediction using NASA and CALCE battery data. The results indicated that compared with the CALCE dataset the proposed method achieved high accuracy with the NASA dataset. The results indicate that varying battery profiles influence model training. As a result, the RUL forecast accuracy with varied battery profiles requires more investigation.

6.3. Battery cell balancing issue

The RUL of the battery pack is greatly impacted by battery cell balancing, making it an essential factor in LIB systems. Cell imbalance occurs when individual cells in the battery pack exhibit significant differences in their capacity or SOC. These imbalances can stem from various sources, including inherent variations in cell properties, manufacturing tolerances, or disparities in usage patterns (Diao et al., 2019). Cell imbalance can occur in uneven charging and discharging of cells, which can result in rapid degradation, reduced total capacity, and shortened battery life (Ouyang et al., 2020). Four main problems caused by cell imbalance in LIB packs are undercharging, overcharging, underdischarging, and overdischarging (Samanta and Chowdhuri, 2021). These problems lead to capacity degradation, thermal instability, permanent loss of capacity, and even chemical explosion. Effective cell balancing techniques are essential for minimising the negative consequences of cell imbalance and enhancing LIB performance.

To maintain optimal battery operation, active intervention mechanisms, passive and active balancing techniques, play crucial roles in equalising cell voltages and SOC levels. Passive balancing is the process of dissipating excess energy and guaranteeing voltage equalisation during charging and discharging cycles by using passive components, such as balancing resistors, across individual cells (Thiruvonasundari and Deepa, 2023). On the otherhand, active balancing technique uses integrated BMS or specific circuitry to facilitate energy transfer between cells by actively adjusting SOC levels to attain balance (Samanta and Chowdhuri, 2021), (Zhang et al., 2020). LIB systems may achieve increased reliability, longevity, and performance by resolving cell imbalance. It is imperative to acknowledge that cell balancing strategies need to be carefully customised to particular application demands, taking into account variables like pack size, cell chemistry, and operational circumstances.

6.4. Battery aging and relaxation effect

Battery aging is a natural and unavoidable phenomenon in which the performance of battery cells steadily degrades over time, even under normal operating settings. Danzer et al (Danzer et al., 2015). identified that surface film formation/modification, anode/cathode materials, and phase transitions all play important roles in electrode aging. Internal resistance rises due to changes in the structure of anode and cathode materials, in addition to an increase in the thickness of the solid-electrolyte interphase (SEI). It is also worth mentioning that as temperatures rise, the aging process accelerates. Leng et al (Leng et al., 2015). investigated the impact of aging behavior for LIBs at temperatures ranging from 25 to 55°C. As shown in Fig. 8(d) and (e), the results show that the value of capacitance and resistance varies gradually as the number of aging cycles increases. Battery aging issues significantly affect the DL method accuracy for RUL prediction. Shi et al (Shi et al., 2022). developed a physics-informed ML approach, notably the PI-LSTM model, which combines a calendar and cycle aging (CCA) model with an LSTM layer to successfully account for degradation pattern predict RUL under varying operation conditions.

The relaxation effect is a major phenomenon found during LIB degradation. When a battery rests for a longer period of time, its capacity regenerated, resulting in greater available capacity for the next cycle (Xu et al., 2019). This relaxation effect has a significant impact on the deterioration behavior of LIBs and is regarded as a critical factor in accurately forecasting their RUL (Wu et al., 2016). As a result, more study is required to develop RUL prediction methods that account for the relaxation effect, to improve the safety and reliability of LIBs.

6.5. Training algorithm issues for RUL

While several models for predicting RUL have yielded promising findings, they also exhibit certain limitations (Ansari et al., 2022). The PF-based method, for example, is ideal for high-dimensional systems and simple to apply, but it requires a powerful computer processor and produces inconsistent results. The KF model, on the other hand, is lightweight and fast but predicts poorly. Data-driven models provide fast training but require expert input to identify optimal hyperparameters. DL models acquire great accuracy and self-learning capabilities, but they require a large amount of training data. To solve these limitations, hybrid models have arisen; nevertheless, they introduce computational complexity and necessitate expert knowledge. As a result, more study is required to successfully address the model selection difficulty in RUL prediction.

Additionally, LiB technology integrates data science to correlation analysis between material properties and performance, extending beyond RUL prediction. Researchers can investigate the complex connections between material properties, like electrode composition, porosity, and morphology, and LiB performance metrics, like capacity, cycling stability, and rate capability, by utilising advanced analytics and machine learning techniques (Qiu et al., 2022). Employing extensive datasets that include electrochemical characteristics, battery performance, and material attributes, data-driven methodologies enable the identification of crucial correlations and insights that guide material choice, design enhancement, and performance forecasting.

6.6. Data acquisition and quality issue

The accuracy and efficiency of data-driven battery RUL prediction algorithm highly rely on the data acquisition and quality of the data. In the field of LiBs technology, data acquisition presents a difficult challenge due to the scarcity or absence of event data, especially in newly commissioned equipment (Lei et al., 2018). This challenge is compounded by the intricate mechanical requirements and diverse material properties associate in LiBs, such as electrode materials, porosity, electrolytes, and separators.To handle this issue physics-based models are suitable since all other data-driven approaches require sufficient data to train and estimate the battery RUL. The data-collecting process for equipment prognostics moves into a big-data scenario as the number of monitored machines and installed sensors expands, bringing both benefits and constraints (Meeker and Hong, 2014). The fundamental problem in this setting is successfully obtaining relevant information from huge data resources in a timely way, which impacts both diagnostics and prognostics. The quality of data highly relies on three main factors such as; data precision, data abundance, and data variety (Ren and Du, 2023). For example, a small amount of data reduces the precision of the DL algorithm, whereas a large volume of data results in massive computing expenses and severe overfitting concerns. The collecting of a huge volume of data over a period of time is a time-consuming and arduous operation. Furthermore, the data quantity for different EV cycles fluctuates, displaying a variety of voltage and current value patterns. While larger data sets can produce better results, this strategy requires longer training intervals and more computational complexities, which may result in overfitting concerns (Najafabadi et al., 2015).

RUL prediction in LIBs is hampered by data acquisition and quality issues that are largely influenced by the correlation between data science and battery material properties. Researchers can perform in-depth analyses to identify the complex relationships between LiBs performance metrics and material (Lang et al., 2024). Because of this correlation, more accurate data acquisition strategies that are specifically designed to capture important information related to RUL prediction can be developed. Correlation analysis insights can also help choose input feature choices and improve data quality by guaranteeing that collected data closely matches the underlying mechanisms controlling battery degradation.

6.7. Parameter selection and hyperparameters tuning issue

The performance of a data-driven algorithm for RUL prediction is influenced by a variety of elements, including the model architecture, input features, training procedures, and hyperparameters. However, in addition to these factors, it is crucial to examine the correlation analysis using data science methodologies between material properties and LiBs performance. In prediction algorithms, choosing the best model architecture and optimising hyperparameters are crucial because they greatly affect algorithmic performance (Yang and Shami, 2020).The number of hidden layers in a model increases the computing overhead during training and deployment. At the moment, architecture selection is mostly based on the inefficient trial-and-error method, which consumes time and energy. Alternative methods, like singular value decomposition, can be used to find the optimal number of hidden layer neurons, resulting in a more effective and accurate decision-making process. In the case of selecting optimal hyperparameters, a standardized algorithm for diverse problems is yet to be developed. As a result, hyperparameters are frequently fine-tuned through a trial-and-error procedure until sufficient results are reached. Recently several optimization techniques including PSO (Zhang et al., 2023c), whale optimization algorithm (WOA) (Zhu et al., 2022), ABC (Wang et al., 2019b), GSA (Qinfeng et al., 2021), etc. have been widely used to find the hyperparameters battery state estimation. However, the convergence behavior, learning accuracy, and execution duration of various optimization techniques differ. Furthermore, the optimization process comprises several parameters and steps, necessitating not only human expertise and comprehensive knowledge but also significant computing costs and lengthy training periods. Therefore, a fusion of appropriate optimization algorithms with data-driven methods needs further research to improve the RUL prediction performance.

Considering these factors, an essential way towards for improving the effectiveness and dependability of LiBs technology is the incorporation of correlation analysis between material attributes and LIBs performance within the larger framework of data-driven methodologies (Wang et al., 2022). Through establishing the complex connections between material properties and battery performance, researchers can extract substantial information that will guide parameter choice and hyperparameter optimisation, ultimately improving the predictive power of data-driven algorithms in LIB application.

7. Conclusion and future research directions

Accurate RUL prediction is critical for guaranteeing the dependability and safety of battery systems, especially in the context of EVs. However, achieving high accuracy in RUL prediction remains a difficult challenge due to the complicated operating features and dynamic changes in model parameters during the aging process. This review study provides a thorough overview of several model-based, data-driven, and fusion-based methodologies for forecasting the RUL of LIB. The classifications, techniques, characteristics, contributions, benefits, drawbacks, and research gaps were all examined. Model-based methods allow for in-depth research of internal battery aging, whilst data-driven methods use past battery data for RUL prediction, and fusion models outperform individual models but require complicated structures and considerable computational resources for training. Moreover, this research emphasizes the importance of building a BMS to support the safe and reliable operation of LIBs. The review also explores essential implementation factors that influence RUL prediction, such as battery test bench, data selection and input feature extraction, data preprocessing, performance evaluation indicators, and hyperparameters tuning. It also discusses a variety of issues and challenges related to RUL prediction methodologies, including thermal runway, material selection, cell balancing, battery aging and relaxation influence, training algorithm, data collecting, and hyperparameters tuning. This study provides valuable recommendations, prospects, and enhancements for researchers trying to build robust and successful methods for forecasting the RUL of LIBs by offering a comprehensive overview of the existing literature and finding gaps in current research. This advice and insights will help to design appropriate strategies for the long-term operation and management of LIBs.

Following the review, a myriad of critical and insightful recommendations have been suggested to push future technological breakthroughs in RUL estimates for LIBs in EV applications. Among these suggestions are:

- RUL prediction for lithium-ion batteries focuses on individual cells, but battery packs (comprising series and parallel-connected cells) pose challenges due to material variability, manufacturing discrepancies, and temperature-induced aging. Inaccuracies stem from charge unbalancing during operation. Converter and controller circuits help mitigate this issue, yet deeper investigation into battery pack inconsistencies is necessary for more precise RUL prediction.
- To acquire a better understanding of the underlying degradation mechanisms, future research should focus on building more advanced battery models and physics-based techniques. By capturing

complicated battery behaviors, improved electrochemical models and multi-physics simulations may contribute to more accurate RUL predictions.

- Various battery testing configurations have been utilized for LIB RUL prediction, however, data quality is hampered by issues such as electromagnetic interference (EMI), apparatus inaccuracy, and unwanted noise. It is crucial to build a sophisticated battery testing system since malfunctioning sensors and EMI can make it difficult to validate RUL prediction algorithms in laboratory settings. To overcome this issue, a number of techniques have been proposed, including the wavelength transform and the recursive total least squares method.
- With recent advancements in DL techniques, the demand for high computational resources for effective model training has become evident. To improve the RUL prediction model's training capacity, powerful processors like Intel Xeon CPUs and graphics cards including the GeForce GTX series are required. Large datasets and intricate DL algorithms may be processed quickly and effectively thanks to these resources, which makes it easier to create reliable and accurate RUL prediction models. Furthermore, investigating new hardware developments and developing technologies might enhance the effectiveness of model training and boost forecast accuracy in battery management applications.
- Since choosing the appropriate hyperparameters is essential for precise model performance, the existing 'trial and error' approach is laborious and mainly depends on human experience. This methodology may result in complex calculations and poor forecasts. Future studies should investigate the application of metaheuristic optimisation methods for hyperparameter selection in order to address these issues. Algorithms used in metaheuristic optimisation effectively search the hyperparameter space for the ideal combination to enhance model performance. We can improve battery RUL prediction efficiency and accuracy by implementing these strategies.
- The adoption of hybrid models has produced promising results, including higher RUL prediction accuracy as compared to single-model frameworks. Hybrid models have been shown to perform better by fusing two models together or combining an optimisation method with a single model. But incorrectly combining multiple models might result in inadequate results, overfitting, and more computing complexity. The viability and practicality of creating an intelligent hybrid model especially for lithium-ion battery RUL prediction must thus be investigated. Through the integration of complementary qualities from several models or techniques (such as data-driven and physics-based approaches) into a coherent framework, hybrid methods have the potential to improve RUL prediction accuracy while reducing the drawbacks of individual models. Additional investigation into intelligent hybrid models may yield insightful information and lead to improved battery management techniques.
- RUL prediction is fundamentally uncertain due to a variety of factors. Future research should focus on advanced probabilistic modeling techniques, such as Bayesian inference or Monte Carlo simulations, to comprehensively capture and quantify uncertainties associated with RUL estimates. Decision-makers may come to informed decisions about replacing batteries and maintenance by accounting for uncertainties.
- As the adoption of EVs grows, it is critical to examine the environmental impact of battery production and disposal. Future studies should concentrate on building RUL estimate models that adhere to circular economy concepts, permitting battery reuse and recycling while maximizing battery usable life.

Incorporating these ideas into RUL estimates would be a significant contribution, providing academics and manufacturers with useful information for future EV development. In summary, undertaking extra research to improve network configuration and methodology for RUL prediction in LIBs can promote EV market sustainability. Furthermore, encouraging the rise of EVs through improved production and recycling methods for LIBs can benefit the global environment by reducing CO2 and GHG emissions. This study primarily concentrates on the application of LIBs in EV application, with future research exploring the important area of stationary energy storage applications, thereby acknowledging the value of broader investigation.

CRediT authorship contribution statement

M A Hannan: Writing – review & editing, Visualization, Validation, Supervision, Resources, Project administration, Formal analysis, Conceptualization. **T M Indra Mahlia:** Writing – review & editing, Validation, Software, Funding acquisition. **Pin Jern Ker:** Writing – review & editing, Visualization, Software, Project administration, Funding acquisition. **M Mansor:** Validation, Supervision, Resources, Project administration, Funding acquisition. **M. Mannan:** Writing – original draft, Software, Investigation, Formal analysis. **M. S. Reza:** Writing – original draft, Software, Methodology, Investigation, Formal analysis, Data curation.

Declaration of Competing Interest

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

Data Availability

No data was used for the research described in the article.

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