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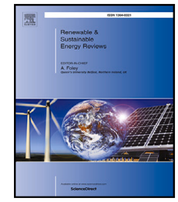

Machine learning in state of health and remaining useful life estimation: Theoretical and technological development in battery degradation modelling

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ABSTRACT

Designing and deployment of state-of-the-art electric vehicles (EVs) in terms of low cost and high driving range with appropriate reliability and security are identified as the key towards decarbonization of the transportation sector. Nevertheless, the utilization of lithium-ion batteries face a core difficulty associated with environmental degradation factors, capacity fade, aging-induced degradation, and end-of-life repurposing. These factors play a pivotal role in the field of EVs. In this regard, state-of-health (SOH) and remaining useful life (RUL) estimation outlines the efficacy of the batteries as well as facilitate in the development and testing of numerous EV optimizations with identification of parameters that will enhance and further improve their efficiency. Both indices give an accurate estimation of the battery performance, maintenance, prognostics, and health management. Accordingly, machine learning (ML) techniques provide a significant developmental scope as best parameters and approaches cannot be identified for these estimations. ML strategies comparatively provide a non-invasive approach with low computation and high accuracy considering the scalability and timescale issues of battery degradation. This paper objectively provides an inclusively extensive review on these topics based on the research conducted over the past decade. An in-depth introductory is provided for SOH and RUL estimation highlighting their process and significance. Furthermore, numerous ML techniques are thoroughly and independently investigated based on each category and sub-category implemented for SOH and RUL measurement. Finally, applications-oriented discussion that explicates the advantages in terms of accuracy and computation is presented that targets to provide an insight for further development in this field of research.

1. Introduction

Battery energy storage system (BESS) is the key for the transport electrification and have been widely used in automobile, aviation, and other relevant industrial fields [1]. The usage of BESS as a main power source in electric vehicles (EV), has a significant potential to provide needed energy storage to contribute to the reduction of fossil fuel reserve. It acts as a promising technology for reducing the environmental impacts of transportation [2]. The rapid development of the industries related to cell-phones, computers, power-tools and EVs has increased the demand for power batteries [3]. In recent years, battery technology has made significant progress in many areas, such as improved energy density and power density, which is of great importance to energy storage and plays a key role in many real-world applications [4]. Particularly, the battery pack acts as a key component, and is quite critical to the power performance, operation and economy of EVs. It is, therefore, important to accurately manage the battery pack to extend its lifespan, improve its reliability and lower its cost [5]. EVs operate on batteries that have a limited life span and charging efficiency, and thus energy consumption is highly dependent on the condition of batteries [6]. Among different kinds of batteries, lithium-ion (Li-ion) battery is the fastest developed and proved to be the most promising technology for energy storage [7]. Over the last few decades, the significant advancements in Li-ion batteries have attracted significant recognition due to their high energy density, low maintenance, and efficient performance. The reliability and safety evaluation of Li-ion batteries has become an important issue for battery technology manufacturers, in particular for future applications' performance [8].

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Applications employing Li-ion batteries face difficulties in terms of battery degradation which occurs both over time and due to usage. The degradation depends on the battery chemistry, environmental conditions, and operating patterns [9]. The aging-induced degradation in battery capacity and power is inevitable which reduces its performance and service life, and even gives rise to some safety hazards. Battery degradation take place in every condition, but in different proportions as usage and external conditions interact to provoke degradation. Curbing degradation has been recognized as one of the sustainable approach for battery resource management, as the extension in battery life decreases costs and environmental burdens that comes along with the production of new batteries [10,11]. From the perspective of the battery operation, the degradation model needs to be developed, especially to evaluate the influence of the key parameters on battery health and life and to curb the degradation. Understanding the operation fundamentals and modelling the degradation of Li-ion batteries assists explicate operations that can extend battery lifetime [12]. It is essential to precisely estimate the battery health, and model the battery degradation and aging mechanism to establish the requisite operational performance and optimize the battery design and management of Li-ion batteries.

State of health (SOH) and remaining useful life (RUL) are the most vital parameters of Li-ion battery to evaluate the contemporary battery health condition and the battery performance [13]. These parameters are largely associated with the battery degradation model as they track the actual performance of batteries in operation, indicate the current capacity of a Li-ion battery to store and dispense energy, and describe the extent of degradation and aging [14]. While incorporating the accurate RUL prediction and SOH estimation, the ongoing or a sudden degradation of the battery is evaluated, and is therefore critical to model the battery degradation. Devising the battery degradation model based on SOH and RUL estimation is vital to ensure the safety and reliability of batteries [15]. Gaining more knowledge through battery degradation model can eventually result in the development of cost-effective and long lasting batteries. Therefore, it is always desirable to monitor the underlying degradation using SOH and RUL estimation to be able to track the actual performance and carry out health diagnosis and prognosis.

Several SOH and RUL estimation methods have been evaluated and proposed in the literature. A recent summary on methods for Li-ion battery SOH estimation can be found in [16]. RUL prognosis, which depicts when a battery will fail or when it will reach a level that cannot ensure satisfactory performance; the methods of its estimation have also been studied extensively in different studies [17]. Battery SOH estimation and RUL prediction have already developed as a expansive area of research, with several reviews and approaches outlined and discussed in the literature [13,18,19]. Recent advancements in data-driven methods have raised interest in machine learning based battery health estimation [20,21]. The feasibility and cost-effectiveness of data-driven techniques to deal with the challenges of real-time battery health management has boosted progress in battery health estimation and prediction in real-world applications [22]. Among the data-driven techniques, machine learning (ML) has recently emerged as a favourable modelling approach for SOH and RUL estimation and battery degradation modelling, due to substantial availability of battery data and enhanced computation capabilities [23]. Different ML models are employed in various studies depending on the data attributes, input features and target variables, experimental conditions, battery design, and prediction accuracy to have a bigger picture view of the ML based SOH and RUL estimation.

Several studies have been published for SOH and RUL estimation which are summarized in Table 1. There are significant limitations that are found in literature in the relevant SOH and RUL prediction based review studies. Battery SOH and RUL prediction has progressed as a significant area of research with different machine learning approaches discussed in literature and gaining more knowledge about battery degradation model through these aspects can eventually result in the development of efficient and reliable batteries. The major research gaps in the existing SOH and RUL estimation based review studies, and the contributions of this review study are represented in Fig. 1. The novelty and contributions of this study are summarized as:

- The review article discusses about the relationship between the battery degradation modelling, and SOH and RUL estimation as there is a lack of clarification of the relationship between these aspects in the current research status, and very few studies marks out the relationship of the battery degradation with SOH and RUL.
- This review study upgrades the current literature by comprehensively reviewing the machine learning methods used for SOH and RUL estimation and battery degradation modelling as there are very few studies that partially review the machine learning based degradation models, and SOH and RUL estimation techniques.
- This review article describes and summarizes the State-of-the-art ML based SOH and RUL estimation methods, their classifications, characteristics, evaluation processes and applications as there is a paucity of discussion in terms of characteristics, evaluation processes and applications in the existing studies.

The framework for systematic review of our research study is illustrated in Fig. 2. The framework consists of the external factors causing the battery degradation, which are used as features in the ML methods for battery degradation modelling, and SOH and RUL estimation. The factors include cycling time, voltage range, current rate, state of charge (SOC), temperature, depth of discharge (DOD), and energy storage time. These factors are also used as features and parameters in the machine learning methods for battery degradation modelling, and SOH and RUL estimation.

This review study is envisaged to apprise the relevant academic research and battery technology sector regarding the state-of-the-art ML-based battery degradation modelling and SOH and RUL estimation techniques. These techniques would aid in achieving sustainability, particularly in the EV sector. The global environment would benefit from the improved production and recycling procedures of Li-ion batteries in the EV sector. Engineers and researchers can use suitable machine learning approaches to estimate SOH and RUL based on specific requirements, and can gain ideas for how to improve these techniques. This study is a useful resource for assisting in the design and operation of battery health estimation and remaining life prediction systems, as well as informing the research community on factors relevant to battery dependability and life improvement. Thus, this review study amplifies the progress in machine learning based battery degradation modelling and battery health estimation on all energy storage technology primed levels.

The review article is divided into 7 sections. Section 2 describes the implementation of review methodology, while the definition of SOH and RUL, and their relationship with battery degradation is discussed in Section 3. Battery degradation analysis and modelling using data-driven approaches, and the main factors affecting Li-ion battery performance and life degradation are described in Section 4 while Section 5 provides a detailed and comprehensive review to the current SOH and RUL prediction methods and framework based on machine learning models. Section 6 discusses the characteristics of the existing ML methods in order to find the most suitable adaptive models for Li-ion battery SOH and RUL estimation. Furthermore, it details the current challenges and discusses future directions related to ML based battery degradation modelling. The final section provides the conclusion of this review article.

2. Review methodology

This review is carried out in the context of the machine learning techniques for battery degradation modelling based on thorough content analysis. The review process is conducted using the state-of-the-art

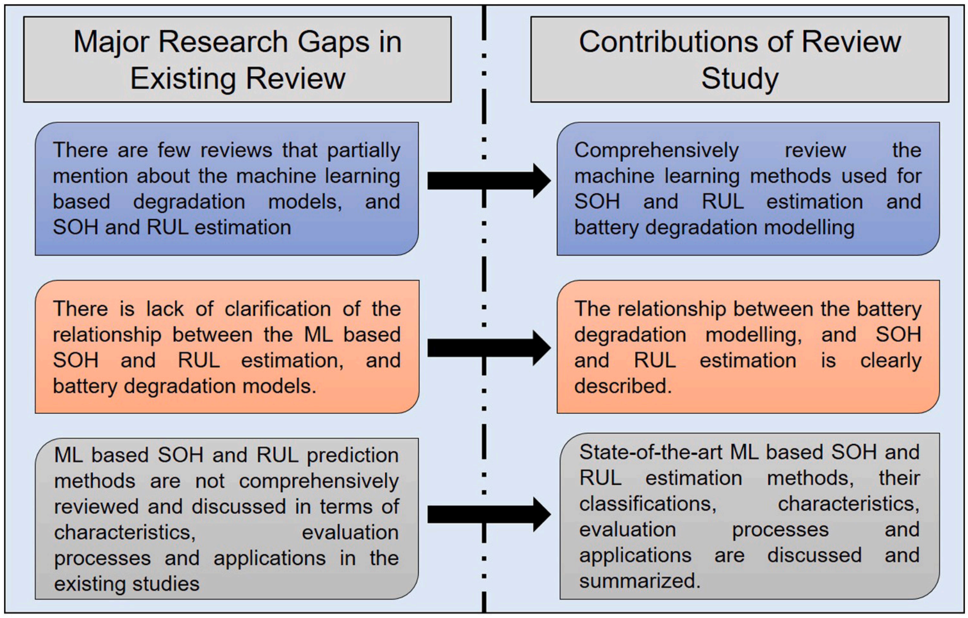

Fig. 1. Existing gaps vs. contributions.

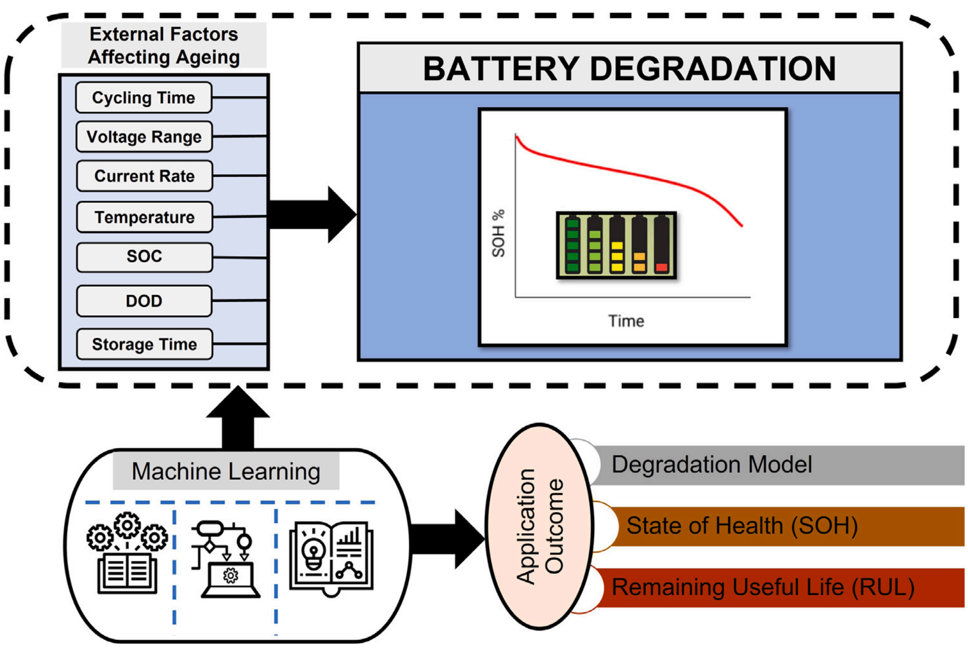

Fig. 2. Framework for systematic review of ML based battery degradation modelling, and SOH and RUL estimation.

studies published in Nature, Elsevier, IEEE, Springer and conference publications. The review consists of the analysis and evaluation of the studies published in the last 10 years. This is to make sure that all the relevant aspects and techniques of machine learning used for SOH and RUL estimation, and battery degradation modelling are covered in this review study. The keywords which are used to search for relevant articles include: data-driven techniques and Li-ion battery degradation, ML and Li-ion battery aging and degradation, ML and Li-ion battery SOH, ML and Li-ion battery RUL, utilization of battery degradation models and applications. More than 500 articles were found from the preliminary search. 300 articles have been selected by filtering and analysing the title, abstract, keywords, and the relevant topics. Finally, 250 articles are listed down based on the impact factor, citation count, and review process. Based on these articles, the review study mainly discusses three aspects. Firstly, the relationship between SOH, RUL and battery degradation modelling is established. Secondly, the ML methods to estimate SOH and RUL are comprehensively reviewed. Lastly, the ML based SOH and RUL estimation methods, their classifications, characteristics, evaluation processes and applications are discussed.

3. SOH and RUL as critical measures of battery degradation

SOH and RUL are the most crucial parameters to model the Li-ion battery's degradation [32]. SOH estimation and RUL prediction have developed into a prominent research theme, which is particularly aimed for enhancing battery reliability and prolonging battery life. The battery degradation effects are usually represented by the change of the battery electrical performance, especially the capacity and power. Generally, battery SOH, and RUL are influenced by the usable capacity, available energy and power, which degrades with the battery aging.

Table 1
Evaluation of relevant review papers.

Topic	Reference	Content
State of health and remaining useful life estimation methods for Li-ion battery in electric vehicles	Lipu et. al. [24]	Discussed different estimation models to predict SOH, and RUL in a comparative manner Identified the classifications, characteristics, and evaluation processes with advantages and disadvantages for EV applications. Investigated the issues and challenges with technological development of SOH, and RUL estimation for Li-ion batteries.
Battery state of health monitoring methods for smarter battery management system	Xiong et. al. [25]	Systematically reviewed the state of health estimation methods. Analyzed battery aging process and provided theoretical support for model-based methods. Explained the methods for determining the health state of the battery. Analyzed the strengths and weaknesses of methods.
State of health estimation for Li-ion batteries	Tian et. al. [26]	Provided a discussion on the aging reasons for Li-ion batteries. Introduced the SOH prediction method based on the classification framework. Analyzed the key benefits and drawbacks of each method.
Calendar aging prediction of Li-ion batteries	Liu et. al. [27]	Evaluated three mainstream types of modelling techniques for calendar aging prediction of Li-ion batteries. Developed an experimental setup to collect calendar aging under different storage temperature and SOC levels. Prediction performances of the models are studied and evaluated in terms of the model accuracy, generalization ability and uncertainty management.
State of health estimation methods of Li-ion batteries for real applications	Berecibar et. al. [28]	Battery SOH monitoring methods are reviewed Different SOH estimation approaches are classified into specific groups. Accuracy, strengths, and weaknesses of SOH estimation methods for the use in online BMS applications are reviewed.
Prognostics and health management (PHM) methods of Li-ion batteries	Meng et. al. [15]	Approaches related to battery prognostics and health management are evaluated. Considered the selection of the battery PHM approach according to the data availability, and degradation mechanisms. Contributed the perspectives on approach selection, health management, performance evaluation, uncertainty treatment, application economics, as well as environmental issues.
Data-driven health estimation and lifetime prediction of lithium-ion batteries	Li. et. al. [29]	Data-driven battery health estimation techniques are reviewed The feasibility and cost-effectiveness of DDM techniques are studied with battery health in real-world applications. Challenges of real-time battery health management and potential next-generation techniques are also discussed.
Li-ion battery aging mechanisms and diagnosis method for automotive applications	Xiong et. al. [25]	Summarized mechanisms and diagnosis of Li-ion battery aging. Explained the influence of different external factors on the aging mechanism. Discussed the widely-used methods for aging diagnosis Discussed the challenges in the quantitative diagnosis and on-board diagnosis on battery aging.
State estimation for advanced battery management	Hu et. al. [30]	Presented an overview of existing methods, key issues of the battery state estimation domain. Elucidated various battery states estimation. Discussed technical challenges, and future trends of the battery state estimation.
Battery health monitoring and prognostics technologies for electric vehicle (EV) safety and mobility	Rezvanizaniani et. al. [31]	Summarized battery prognostics and health management (PHM) techniques. Presented the approaches to monitor battery health status and performance. Elaborated the evolution of prognostics modeling methods.
Li-ion battery degradation	Han et. al. [12]	Provided comprehensive review of key issues of the battery degradation among the whole life cycle. Reviewed battery internal aging mechanisms for understanding the battery fade characteristic. Discussed the influence factors affecting battery life from the perspectives of design, production, and application Presented the battery system degradation mechanism.

The SOH diagnostics manifest the performance degradation and helps in taking preventive measure to avoid possible accidents [33]. With the increasing demand for Li-ion batteries, the SOH estimation plays an vital part in battery RUL prognostics as a capacity indicator. Appropriate and robust prognostics algorithms of SOH and RUL estimation are necessarily needed that can address the battery degradation challenges as well as improve the performance and optimize the battery operation. Fig. 3 depicts the relationship between SOH, RUL and battery degradation modelling, and illustrates a combined framework of SOH estimation and RUL prediction which is used to establish the model of battery degradation mechanism. It describes the factors impacting battery degradation, and battery failure which are used for SOH estimation modelling. The SOH diagnostics and estimation assists in modelling the battery RUL by evaluating the time or cycles remaining to reach 80% SOH. Exploring, and modelling the degradation behaviour of batteries hence requires accurate estimation of SOH, and RUL.

The battery aging and degradation models are depicted and evaluated in the context of battery health and remaining capacity in several studies [34–36]. The stable operation of EV is ensured by the systematic application of accurate and robust SOH and RUL estimation methods for Li-ion batteries. Nevertheless, the performance of Li-ion battery varies due to charging–discharging behaviour, temperature fluctuation and degradation [15]. Different studies consider battery degradation, SOH estimation, and RUL prediction as either being fully identical or completely distinct. Apart from the dissimilarities, dependencies, and relations between these aspects, there is an associated confounded notions, obscurity in their modelling concepts and unclear definitions for these terms. The clarification related to the origins and definition of these aspects, and evaluation of the relationship between them is provided in the following sections.

3.1. Relationship of SOH with battery degradation

The most intuitive external characteristics of battery degradation are capacity fade and/or power fade, which are mainly associated with battery SOH. SOH is defined as the current status of battery health to supply specific power and energy compared with its ability to deliver power when it was in an initial state. It is mathematically formulated

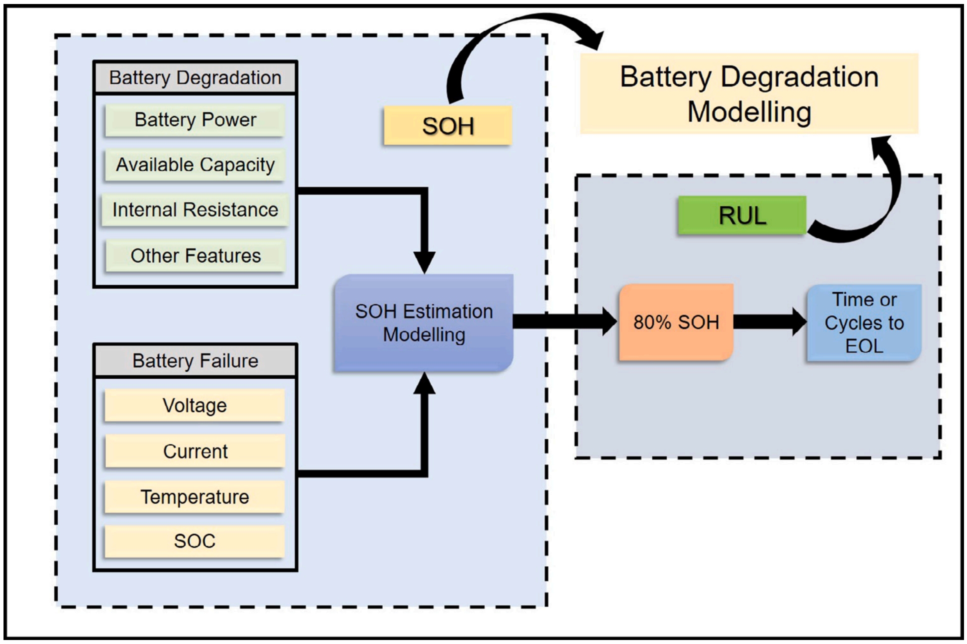

Fig. 3. Relationship between SOH, RUL and battery degradation modelling.

by dividing the actual capacity with nominal capacity, as shown in the following equation [37]

$$SOH = \frac{C_{actual}}{C_{nom}} \tag{1}$$

where C_{actual} and $C_{nominal}$ represent the actual capacity and the nominal capacity, respectively.

In addition, the battery degradation mode includes the internal resistance increase, which also used to define the SOH for battery cells and packs. The internal resistance increase may directly lead to the battery power fade of the battery, and decreases in battery available capacity. Generally, the decrease of capacity and increase of internal resistance evaluates the SOH. As the Li-ion batteries start degrading due to the degradation of the active material and other electrochemical phenomena, the internal resistance starts increasing and the capacity starts decreasing with time [38]. Therefore, internal resistance is also considered an important indicator that identifies degradation process, and evaluates SOH. Since the internal resistance of the battery increases as the battery SOH decreases, SOH can be evaluated from the perspective of the internal resistance of battery using the following equation [39]:

$$SOH = \frac{R_{eol} - R}{R_{eol} - R_{new}} \tag{2}$$

where R_{eol} is the internal resistance at the end of battery life, R_{new} represents the internal resistance of new battery, and R indicates the current internal resistance of battery. Organizing a framework to form the linkage between battery SOH and battery degradation is necessary for battery degradation modelling as battery SOH is a estimation of battery degradation in comparison to a new battery. Capacity and internal resistance, in particular, are exclusive indicators which are used to define battery SOH, and identify the process of battery degradation [40]. Various research studies have also used distinctive features of battery degradation to describe SOH, such as internal resistance, and power density [41,42]. The information related to capacity and internal resistance is advantageous for the BMS to regulate the battery performance, ensuring battery reliability, and avoiding energy shortages, and system faults of the battery. The parameters also give information on the capability of the battery to fulfil the power requirements during use [43,44]. SOH depicts the battery degradation state and informs about the battery replacement. When the capacity of the battery degrades to 80% of original capacity, it is considered impracticable for vehicular applications and needs replacement. The battery SOH degrades with aging following different rates that depend on storage and use conditions [24,26]. Predicting the real values of battery health states makes it possible to avoid battery overcharging and undercharging [45]. Given that some of the battery's internal parameters also determine the health status, therefore characteristic features like battery capacity and internal resistance are not the only predictors of battery SOH. In practical terms, monitoring the SOH also allows to investigate the parameters like voltage, current, temperature, and SOC, which eventually helps in establishing a realistic degradation model.

3.2. Relationship of RUL with battery degradation

The RUL is very useful for the battery health management, and particularly important for the battery degradation evaluation process. Considering the nonlinear degradation characteristics of the battery, it is important to realize the accurate RUL prediction based on aging mechanism and corresponding battery life model under different fading stages. Generally, RUL of a battery is determined by evaluating the time remaining to reach the estimated end of life (EOL) [17]. The EOL is the time and the number of charge–discharge cycles when the battery reaches the failure threshold. RUL is indicated by the following formula:

$$RUL_{\alpha} = CC_{EOL} - CC_{\alpha} \tag{3}$$

where CC_{α} is the present cycle, and C_{eol} is the cycle at the EOL. RUL of the battery at cycle α is obtained by estimating the cycle number of EOL i.e., CC_{EOL}.

The mechanism of degradation and RUL estimation correlate closely to the operating state and reliability of the Li-ion battery. Successful RUL prediction for batteries is highly desired; it allows for more controllable failure prevention, so that functional maintenance can be carried out at the suitable time without permanently degrading the battery [46]. RUL describes the degradation-inherent relationship and the trend based on data. AI methods use monitoring data to fit a degradation model, and estimate RUL through extrapolating the characteristics variables. RUL is typically associated with performance degradation and predefined failure threshold, which determines the remaining number of available cycles of Li-ion battery to the replacement threshold. There is a strong relatedness between RUL and battery degradation, since the distinctive features required to model the battery degradation are similar to that can be used for RUL prediction. Liu et al. devised the battery degradation model and estimated the RUL simultaneously using operating parameters of Li-ion batteries [47]. Another study based on experimental outcomes identified degradation patterns by forecasting RUL and SOH. Additional studies also devised the battery degradation model by evaluating and predicting the RUL prognostics [48,49]. As a result, it is established that there is a strapping connection between the battery degradation model and RUL estimation and we can evaluate both at the same time using the characterization parameters. It also is clear from the literature evaluation that many RUL prediction methods are also applicable to battery degradation modelling.

4. Battery degradation analysis and modelling

Li-ion batteries are susceptible to aging, which decreases its performance. One critical degradation characteristic is the loss of energy quantified by the decrease in capacity. The major issue takes place due to the degradation in capacity over time and it is one of the key indicators of the SOH [50]. Furthermore, accurately measuring and predicting SOH is very important in a BMS to have a sound estimate of the battery performance. One of the important aspects of battery degradation modelling is not only to give a measure of the current capacity, but also to detect and analyze the aging mechanisms causing the capacity fade. Understanding the cause of capacity fade and degradation mechanisms in Li-ion batteries is critical to address the challenges of longevity and safety. It is also important to make accurate RUL predictions, and improve the functioning of the battery [28,51]. Several studies have been proposed to analyze rudimentary cause and effect relation of the battery degradation. The majority of research studies concur that capacity fading can be represented by the variation in internal resistance and other parameters of equivalent circuit models (ECMs) [52]. In recent years, battery life and health estimation methods exacted from incremental capacity (IC) [53,54], differential voltage (DV) [55,56], open circuit voltage (OCV) [57,58], and sample entropy of discharging voltage curves have been suggested [59].

Battery capacity is regarded as a criterion for determining the relationship between the ampere-hours charged or discharged from the battery and voltage difference prior to and following the respective usage. Therefore, determining this relationship is a fundamental principle of almost all methods of capacity estimation and battery aging. Due to the interaction of number of factors, aging phenomena is extremely difficult to report. Fig. 4 depicts the coupling factors that cause degradation of batteries. The factors include calendar aging, cycle aging, environmental conditions, components and manufacturing faults [60]. These factors are further subdivided into various critical parameters like temperature, SOC, humidity, mechanical stress, charging and discharging current, and electrodes and electrolyte degradation. All of these factors are mainly employed for analysing and modelling the degradation of batteries. Various studies approached to analyze the battery degradation by investigating these factors. A particular study based on extended accelerated aging tests on Li-ion batteries which include storage and cycling is undertaken for the detailed analysis of battery aging under the influence of temperature, voltage and SOC on battery aging using the differential voltage method [61]. Another study investigates the cycling aging behaviour under the influence of DOD, C-rate and Ah-throughput, and compares degradation under constant operation conditions with non-constant operations through a semi-empirical model dynamic validation [62]. Some studies modelled the battery capacity and consequent aging on the basis of the OCV and SoC relationship for the given battery type [63,64], while some proposed to model the capacity fade by employing its correlation with the increase in battery resistance, which is considered as an attempt to model a universal battery degradation that would reflect both the change in the battery impedance and capacity [65]. Furthermore, in some studies, degradation occurring in Li-ion batteries is evaluated by the performance of the battery under both rest and cycling conditions, using the long-term storage or cycling data [66,67]. In one study, a particular methodology is presented to identify the aging mechanisms associated with capacity loss in a Li-ion battery. A model was proposed that relates changes in the capacity of active material and the stoichiometric operating window in each electrode to the aging mechanisms [50]. In another study, a unique battery degradation model is proposed using a synthetic strategy based on specific electrode behaviour with the right adjustments of the loading ratio and the extent of degradation. This method differs significantly from traditional empirical methods, and it has a mechanistic knowledge of battery aging processes and failure mechanisms, allowing it to perform high-fidelity simulations that address route dependency in battery degradation [68]. A concise review study is undertaken by the authors of [69], who presented the failure mode and error analysis (FMEA) method to categorize degradation mechanisms of Li-ion batteries, and analyzed their causes and effects. In another study, the impact of Li-ion battery impedance on battery aging is investigated. It exploits the battery resistance to extensively evaluate the battery degradation [70].

Battery aging models have a key significance in the development of a Li-ion battery RUL prediction method. A multi-variable analysis of a detailed series of accelerated lifetime experiments is presented in a study to evaluate RUL, and a semi-empirical aging model coupled with an impedance-based electric thermal model is used to simulate the dynamic interaction between battery aging and thermal as well as electric behaviour [71]. Another study devised the method for estimating battery RUL by directly measuring the capacity loss in real time. It proposed the excitation response level (ERL) as a battery health indicator to describe the voltage variation over different lifetimes based on the current and voltage under the actual load curve. This approach made it effective to quantify the battery degradation characteristics [72]. Nonetheless, due to various factors as depicted in Fig. 4, the extent of aging and degradation of Li-ion batteries substantially varies. Thus, a suitable and robust algorithm for battery degradation modelling, and SOH and RUL estimation is imperative that considers all the associated parameters and factors to precisely model the degradation of Li-ion battery.

4.1. Battery degradation model using data driven approaches

A variety of methods have been developed for battery degradation modelling and battery SOH estimation. These methods can be roughly classified into four domains: Physics-based models [73], empirical models [74], data-driven methods (DDMs) [20,75], and hybrid methods [76]. The key benefits and drawbacks of these domain models are represented in Fig. 5. The methods associated with the aforementioned domains have been implemented in various studies, and the outcomes of these studies are used to describe the benefits, and drawbacks of different modelling techniques. Table 2 highlights the domain and the associated modelling techniques along with the summary of their respective advantages, and drawbacks. The domain of Physics-based approaches comprises of equivalent circuit models (ECM), electrochemical models, and filter-based models. Empirical models, and probabilistic models refers to the domain of mathematical models, while statistical models and machine learning methods refer to the DDM domain. Hybrid method's domain comprises of the combination of DDMs, filtering techniques and empirical models.

Off all the methods, data-driven methods are becoming one of the most distinguished approaches for establishing battery degradation models, battery health estimation and life prediction due to their flexibility and model-free characteristics [77]. DDMs incorporate specialized battery tests containing all the degradation influencing factors, and these factors are then linked to the battery health to establish a

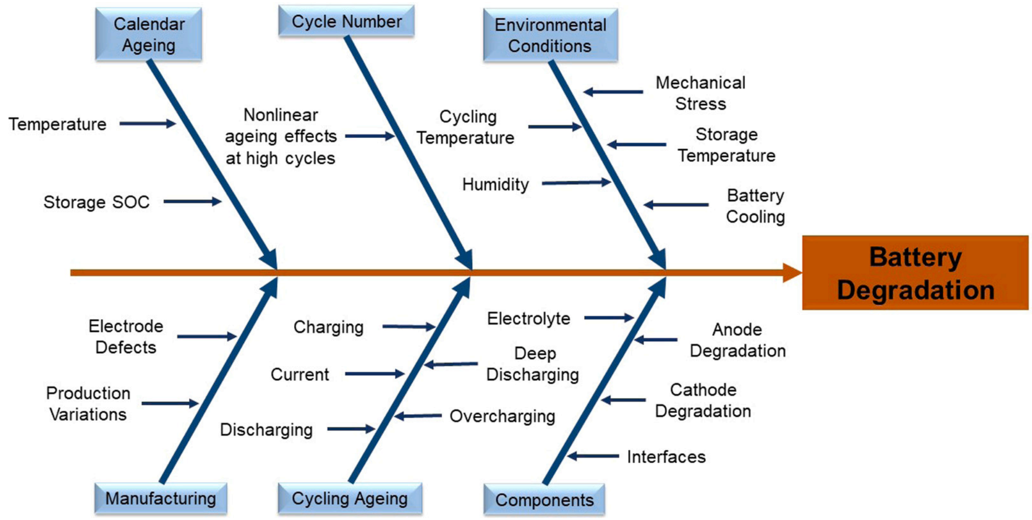

Fig. 4. Factors impacting battery degradation.

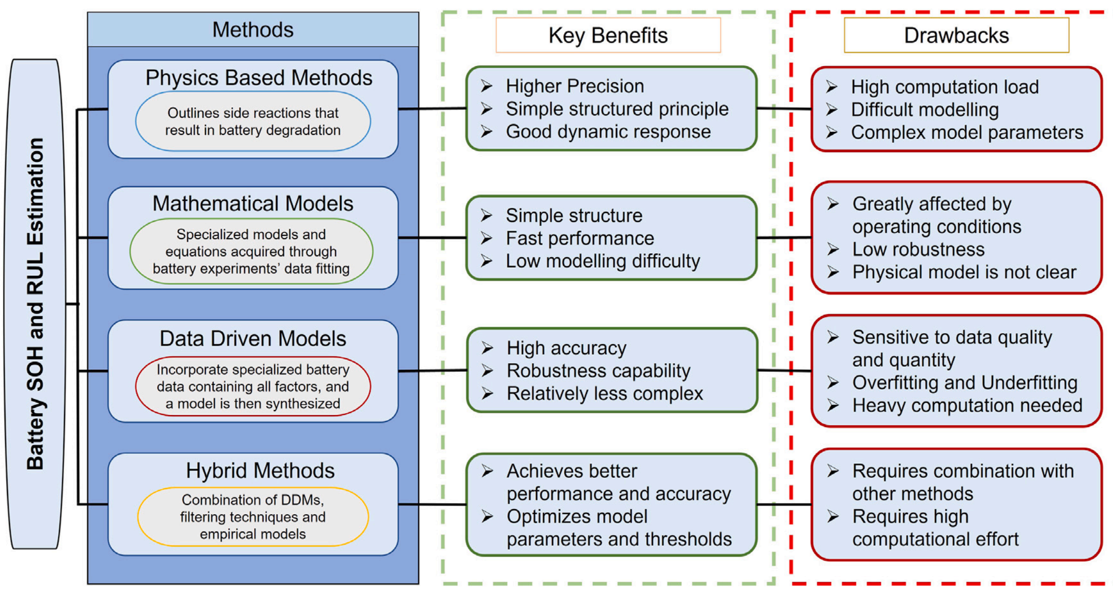

Fig. 5. Methods for battery degradation modelling, and SOH and RUL estimation.

battery degradation model. However, the efficacy of these methods are heavily dependent on the characteristics and volume of data [78,79].

Several data-driven techniques are notably applied in the battery degradation models and battery health estimation and prediction, which are categorized as differential analysis, lifetime estimation models, and machine learning methods. Differential analysis (DA) has proven to be a useful tool to analyze voltage, surface temperature and strain data under different aging states due to the correlation between the SOH and electrical, thermal and mechanical behaviours of a battery [29,80]. Lifetime estimation models have become another well-known technique which makes use of the predefined experimental conditions and devise the fitting model using the collected data. These models have high computational efficiency and greater accuracy when subjected to similar operating conditions [41,81]. Machine-learning (ML) methods are among the most admired data-driven techniques for SOH estimation and RUL prediction due to their adaptability and non-linear problem solving capability. Functional tests on battery aging are conducted to generate a suitable training dataset which incorporates multiple factors affecting battery health. A principal relation is then established by mapping the factors to the battery health and remaining life using different ML techniques [82,83].

5. Battery degradation modelling using machine learning

Characterizing and simulating battery degradation mechanism is unscalable. The SOH and RUL of a battery frequently span many charge/discharge cycles, resulting in two relevant timescales, making predictions particularly difficult. The challenges associated with degradation can be summarized as the need for a function that takes the current state of the battery as an input and predicts future behaviour. A promising strategy for overcoming this obstacle is the data-driven modelling [91]. Combined with machine learning techniques which are flexible, models are able to make predictions without prior knowledge of the system because they have an efficient fitting function with no underlying physical knowledge.

ML techniques have grown in popularity as a result of their enormous potential for achieving high accuracy at a low computation cost. ML techniques – including neural network, support-vector machine, random forest and regression techniques – predicts and estimates battery SOC, SOH and RUL [82,92]. Recent advances in DDMs have assisted in devising the models for degradation diagnosis, and subsequently the SOH, RUL, battery degradation can be accurately predicted

Table 2
Summary of the various battery degradation modelling techniques.

Domain	Modelling techniques	Advantages	Drawbacks	Ref.
Physics based approaches	Equivalent circuit model	Simple structured principle Good dynamic response characteristics	Prediction depends on ECM structure. The model error increases continuously	Ng et. al. [82] Dai et. al. [52]
	Electrochemical model	Higher precision. Quantify the aging state inside battery.	Parameter identification is difficult. No accurate internal aging mechanism.	Wang et. al. [6] Barre et. al. [84]
	Filter based models	Robust degradation estimation. Dynamically tracks and predicts the health. Deals with the uncertainty of external factors.	Complex, and higher computation. Rely heavily on the model accuracy.	Song et. al. [85] li et. al. [86]
Mathematical models	Empirical models	Simple mathematical structure. Fast performance calculations.	The physical model is not clear. Affected by external factors. Affected by operating conditions.	Pelletier et. al. [74]
	Probabilistic models	Low modelling difficulty. Handles several aspects for modelling. Wide range of applications.	Require experimental pre-validation Relies on model accuracy. Depends on computational time.	Feng et. al. [87]
Data-Driven Models (DDMs)	Statistical models	Simple to use, and has high accuracy. No complexity involved.	Low update efficiency of the model Requires comprehensive data.	Nuhic et. al. [88] You et. al. [21]
	Machine learning models	Accurate. Robust. Applicable for modelling of non-linear systems.	Depends on the data quality. Depends on the data quantity. Requires higher computation.	Ng et. al. [82] Severson et. al. [89]
Hybrid methods	Combination of DDMs, filtering techniques, and empirical models	Achieves better performance and accuracy. Optimizes model parameters and thresholds.	Complexity is increased. Requires higher computation.	Li et. al. [29] Wu et. al. [90]

without modelling a physical mechanism [83]. Qualitative changes are apparent in Li-ion battery degradation process. However, it is challenging to identify quantitative features that are linked to degradation. The data-driven based prognostics approach resolves this by performing real-time, non-invasive measurements without on the battery modelling a physical process, and utilizing statistical machine learning to link those results to battery health and degradation [92,93]. Fig. 6 illustrates the primary workflow required for the machine learning application to the battery degradation modelling. The first step is the data collection of quantifiable battery parameters which include temperature, current and voltage recorded during operation, which can be operated as the inputs for the model training. The features of the degradation process are extracted in the second step. The following step is to train a machine learning model to describe the relationship between battery degradation, SOH estimation, and extracted features. After the model has been trained, the final step is to put it into actual usage. Feature extraction is a crucial step that has a significant impact on SOH estimation and battery degradation model performance, so having more relevant and accurate feature input data will lead to more accurate models. To highlight the content and features of various ML algorithms for battery degradation model from the perspective of SOH and RUL estimation, a comparison of studies is illustrated in Table 3.

A framework of the ML based battery degradation model development for online application is illustrated in Fig. 7, which uses battery parameters to establish a degradation model. The aging model can then be integrated with online application in which real-time battery data parameters act as inputs for the pre-established lifetime estimation model to estimate the SOH and RUL of the battery. To establish the battery degradation model, ML methods can be used for both SOH estimation and RUL prediction, but there is a significant difference between these two aspects in terms of input parameters and the expected outcome [110]. As described in Fig. 6, the input features for SOH estimation are retrieved from the BMS and the output is the estimated SOH. However, the ML methods for RUL prediction generally require the estimated SOH parameters as the input to predict RUL of the battery.

There are a wide range of machine learning models, which can be classified into two categories: supervised and unsupervised learning. Supervised learning is the most seasoned approach used in the majority of ML studies for battery SOH and RUL estimation [23,82]. Furthermore, it is methodically observed that all battery SOH estimation and RUL prediction problems can be characterized as the regression problems, as they represent the output in the form of numerical SOH and RUL values and therefore the methods described in this study refer to the regression type.

5.1. SOH estimation using machine learning approaches

In recent years, battery degradation state recognition for battery SOH estimation has attracted intense interests, and therefore, many approaches are put forward, among which the data-driven approaches have gained much attention. One of the main benefits of data-driven approaches for Li-ion batteries degradation model development and SOH estimation is that they can be applied as black-box models, as they are capable of learning the behaviour of the battery based on monitored data and thus do not demand battery chemical modelling and knowledge. DDMs are also used to model the relationship between battery health, performance and environmental parameters during operation [31]. Among DDMs, machine learning approaches such as an artificial neural network (ANN), support vector machine (SVM), and Relevance Vector Machine (RVM), as well as other intelligent algorithms, are used to extrapolate the estimated SOH, and map the relationship between the battery degradation, health indicators and battery SOH through learning from a historical database [47,111]. The SOH is calculated by ML methods using features that are sensitive to battery degradation. This calculation necessitates the collection and examination of data throughout the battery operation. It has the advantage of not requiring extensive battery behaviour tests and simulations and it allows for greater adaptability to various features and battery types. However, on the other hand, ML techniques have a drawback of carrying out high end computation, which makes online model operation on a real-world application like EV more complex [112]. Various studies have been conducted for SOH estimation using appropriate machine learning methods including linear regression, random forest, SVM, fuzzy logic, neural networks and Gaussian processes [24,25,85]. Thus, in the following sub-sections, we present an state-of-the-art research status of machine learning techniques based SOH estimation in detail, for battery degradation model development.

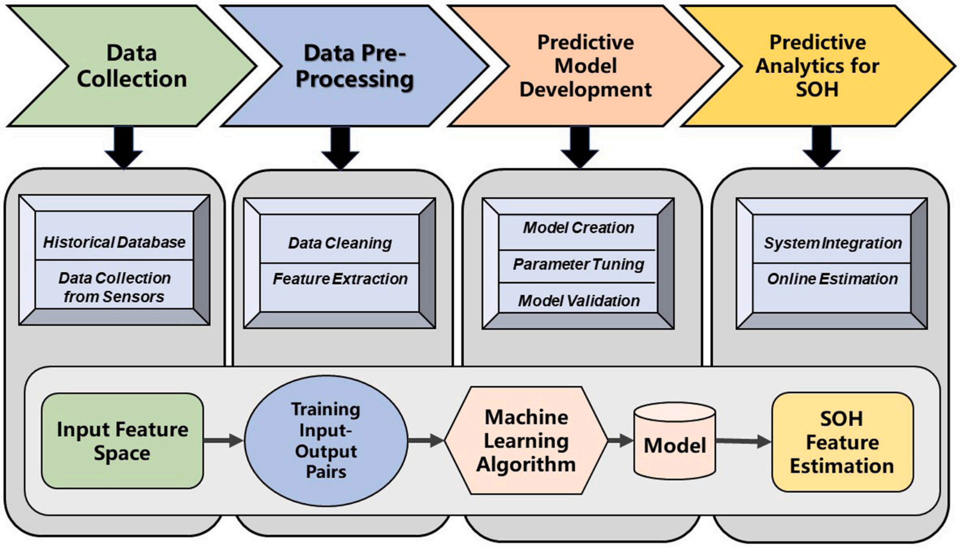

Fig. 6. Generic workflow for battery degradation and SOH/RUL prediction models using ML techniques.

Table 3
Machine learning algorithms for battery degradation modelling.

Methods	Estimation parameter	Content and features	Refs
ANN	SOH	Uses maximum available capacity to indicate the SOH based neural network.	[21]
	RUL	Uses battery capacity and applies neural networks to estimate the RUL.	[94]
SVM	SOH	Provides battery health capacity model	[95]
	RUL	Provides accurate practical information about the battery's expected life.	[96]
RVM	SOH	Estimates the battery health and remaining capacity using capacity fade trend.	[97]
	RUL	Employed as a time-series prediction model to predict the RUL of the battery.	[98,99]
Fuzzy Logic	SOH	Establishes the dynamic prediction model and calculates SOH.	[26]
GPR	SOH	Generates the mapping between different factors and forecasts battery SOH.	[33,100]
	RUL	Realize the RUL prediction by incorporating prognostics with prior information and uncertainty.	[101]
ARMA	SOH	Evaluates SOH by taking battery capacity as the representing parameter.	[76]
	RUL	Uses SOH estimation to characterize RUL.	[102,103]
LSTM	SOH	Establishes the SOH prediction model-based on a sliding window.	[104]
	RUL	Predicts RUL and EOL with better generalization.	[105]
Bayesian networks	SOH	Devise the battery degradation model over repetitive cycles to estimate SOH.	[106]
	RUL	Evaluates RUL by quantifying the uncertainties in predicting the end of life cycles.	[107]
Hybrid methods	SOH	Optimizes the combination of different methods and achieves better performance for accurate SOH estimation.	[86,108]
	RUL	Predicts the RUL of the battery by combining ML methods with different adaptive techniques.	[109]

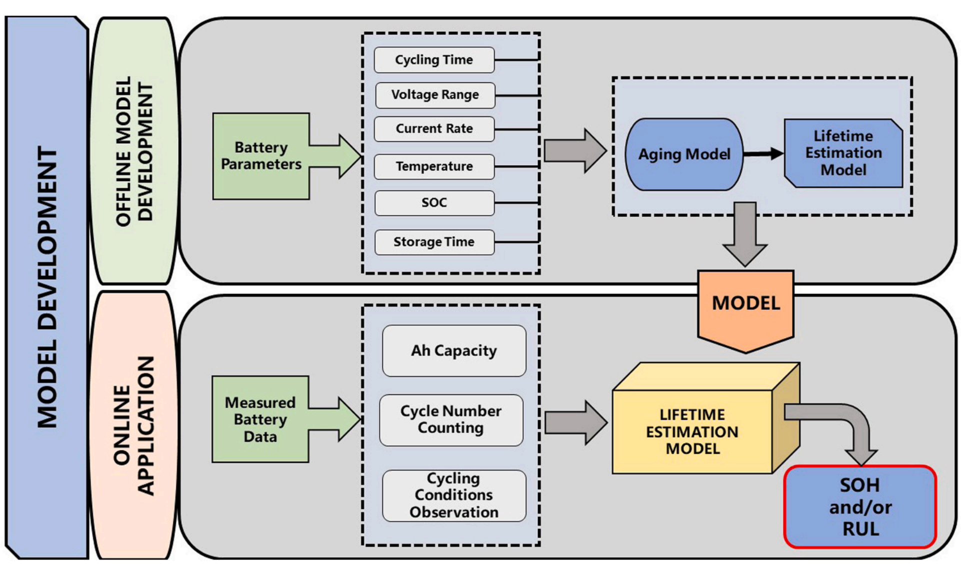

Fig. 7. Conceptual diagram for ML based battery lifetime estimation, and degradation model.

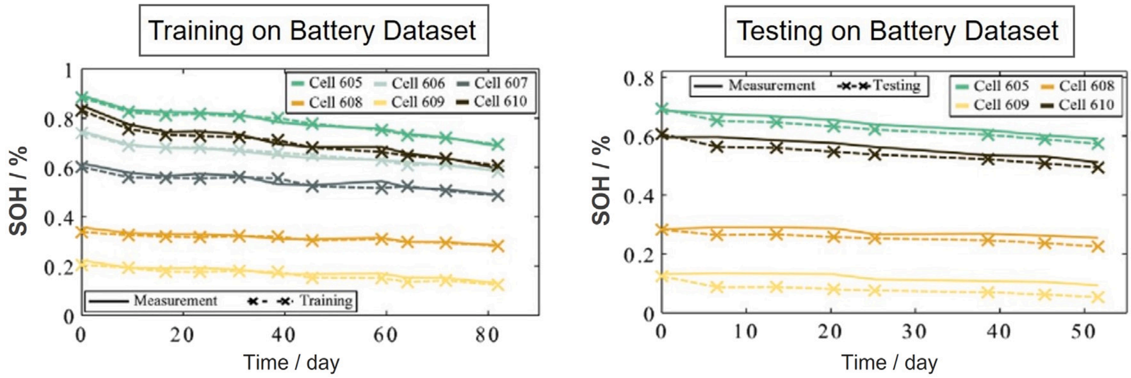

Fig. 8. SOH estimation results by applying SVM for the conventional battery data [88].

5.1.1. Support vector machines

SVM is an effective ML technique which is applied to solve nonlinear issues like battery health estimation, by transforming the data into a higher feature space, where a problem becomes linear. Kernels are generally used in SVM to aid in evaluating nonlinear problems with a lower-feature space, by transforming them into a linear problem with higher feature space [29]. It has the advantage as an adaptable method which can reasonably model complex problems when provided sufficient data. SVM makes predictions based on the following function [113]:

$$y(x) = \sum_{n=1}^{N} \omega_n K(x, x_n) + \varepsilon \tag{4}$$

where ω_n are the weights of the model connecting feature space to output whereas K(·) is a kernel function. The battery SOH and RUL estimation problems primarily fall under the regression category and when SVM is applied for regression tasks like battery SOH and RUL estimation, it is named support vector regression (SVR) [114]. SVR is a useful tool for nonlinear regression problems and it deals with data in a high dimension space by using linear quadratic programming techniques which gives the optimal properties to regression results [115]. Given the capability of SVR to describe the nonlinear correlation of input and output data, it is suitable for prediction tasks [116]. Several studies applied SVM algorithm for the estimation of SOH under the influence of different environment and load conditions. The summary of the SVM based SOH estimation and degradation modelling studies is given in Table 4. Nuhic et al. demonstrated an unique data-driven strategy that incorporates the influence of environmental, ambient, and load variables, as well as the operating history, to include diagnosis and prognostics of battery health for automotive applications [88]. The SVM method is used to estimate the SOH from the perspective of capacity. The study accurately predicted SOH with less than 0.0007 mean square error (MSE) in real driving conditions, considering temperature change, SoC, and C-rate. The results of SOH estimation with the SVM by using the conventional battery dataset are shown in Fig. 8. Klass et al. devised a method for applying standard battery tests to an SVM-based battery model. To estimate capacity, typical EV battery usage data is collected and SVM technique is applied to it. The resultant SOH estimation shows good accuracy under typical EV operation settings, allowing for online battery degradation modelling [117].

Many studies are being conducted on improving the performance of the SVM algorithm by fusing it with other algorithms, in addition to the simple SVM algorithm. Dong et al. considered a novel technique by merging SVM and adaptive particle-filter (PF) algorithm for SOH estimation [95]. Chen et al. proposed a fixed size LS-SVM model based on the arbitrary entropy to estimate SOH. The authors first chose a voltage range, then used the discharge time of the voltage interval as the model's input variable and SOH as the model's output variable. Finally, with LS-SVM, the Bayesian framework is employed to estimate the important parameters, considerably speeding up computation and modelling [118]. Ma et al. used feature fusion and SVR, and proposed a methodology for Li-ion battery SOH prediction. During the discharge phase of Li-ion batteries, the authors used a sliding window to extract features [116].

5.1.2. Gaussian process regression

ML techniques which include regression methods have received increasing attention in Li-ion battery health estimation, because of their model-free characteristics [122]. Generally, the battery health estimation problems are primarily evaluated using the regression techniques as it can be used to supplement existing mathematical approaches with strong potential for battery degradation model development. Due to its non-parametric nature, which allows for greater flexibility in capturing complex nonlinear relationships and its ability to directly quantify the uncertainty in the predictions, Gaussian process regression (GPR) is an effective technique for dealing with complicated battery aging prediction problems [27,123]. It can predict the behaviour of any system by using an appropriate combination of Gaussian processes to model its behaviour. It has finite variable sets, each of which has a Gaussian distribution [124]. The Gaussian process $f(x)$, which is constructed using the mean function $m(x)$ and the co-variance function, can be obtained by extending the multivariate Gaussian distribution to infinite dimensions $k(x_i, x_j)$. The co-variance function $k(x_i, x_j)$, also known as the kernel function, is utilized to capture the similarity between distinct inputs, which is extremely sensitive to GPR performance predictions. The GPR method delivers a probability distribution of possible battery SOH predictions through following function [82,125]:

$$m(x) = E(f(x)) \tag{5}$$

$$k_f(x_i, x_j) = E[(f(x_i) - m(x_i))(f(x_j) - m(x_j))] \tag{6}$$

GPR-based DDMs have been successfully used in the literature for SOH prediction by extracting certain features as inputs [100,126]. The summary of all the GPR based SOH estimation and degradation modelling studies is given in Table 5. Zhang et al. established a method which uses the GPR through proper co-variance functions or the optimal combination for battery state. GPR is applied on the training data to determine the ultra-parameter, and the model is used to predict the latter cycle capacities within the test data with MAE and RMSE less than 0.01, and 0.014, respectively [127]. Deng et al. employed typical data-driven methods, including LR, SVM, RVM, and GPR, to predict battery SOH. A novel feature extraction method is proposed to extract health indicators (HIs) which can be used as input features. The estimation results of these methods are compared under different operating conditions for the three types of batteries. Among them, the GPR depicts the best performance, and its MAE and RMSE are lower

Table 4
Summary of the SVM based SOH/RUL estimation and degradation modelling studies.

Refs	Battery chemistry	SOH/ RUL estimation	Data calculation	Operation mode	Stress factors considered	Evaluation index	Estimation error
Nuhic et al. [88]	High power LIBs	SOH and RUL	Matrix operation	Online	Temperature, SOC, DOD, C-rate	MSE	$<8 \times 10^{-4}$
Chen et al. [118]	LiFEPO4/Graphite	SOH	Matrix operation	Offline	Temperature, C-rate	RMSE, MARE	0.32%, 0.2279%
Anton et al. [119]	LiFePO4	SOH	Radial Basis Function (RBF), and Polynomial kernel	Offline	Temperature, C-rate, SOC	MARE	3.61%
Dong et al. [95]	Second generation Li-ion battery	SOH and RUL	Probabilistic Distribution Functions	Online	Temperature, Current, Voltage and Internal impedance	RMSE	$<2.5 \times 10^{-3}$
Klass et al. [117]	Automotive Li-ion battery	SOH	Langrangian Multipliers, RBF-kernel	Online	Temperature, C-rate, SOC	RMSE	<0.85%
Song et al. [85]	Li(NiCoMn)O2/Graphite	SOH	Langrangian multipliers, and Matrix operation	Online	C-rate, SOC, Temperature	RMSE	<4%
Ng et al. [120]	Moderate power LIBs	RUL	Probability estimates, and Logistic models	Offline	Temperature, Current, Voltage and Impedance	RMSE	0.27
Liu et al. [7]	LiCoO2	SOH	Kernel principal algorithm	Online	Temperature, Voltage, Current, C-rate	MAE	<5%
Mansouri et al. [121]	UAV Li-ion battery	RUL	LASSO and Langrangian Multipliers	Online	Voltage, DOD	MAPE	1.2%

than 1% and 1.3%, respectively [128]. A study by Kailong et al. modelled Li-ion battery SOH and aging prediction through an experimental setup, which is established to collect aging data at various storage temperatures. The GPR model is well trained using its corresponding training solution based on this database, and the model's prediction performances are analyzed and assessed in terms of model accuracy, generalization capacity, and uncertainty management. Results for both training and testing phases of this study are shown in Fig. 9 [27]. Richardson et al. effectively modelled the underlying degradation of the Li-ion battery by accurately forecasting the battery SOH using GPR, having RMSE less than 0.05. The researchers also employed a systematic kernel function to fit complex aging patterns, and combine Gaussian processes with knowledge of degradation mechanisms [100].

SOH estimation using GPR in combination with different techniques has also been considerably undertaken in various studies. Liu et al. used a combination of Linear Gaussian Process Functional Regression (LGPFR) and multi-step-ahead prognostics for Li-ion battery SOH estimation. An improved Quadratic Gaussian Process Functional Regression (QGPFR) is also applied in order to realize multiple-step-ahead prognostics to reflect SOH, including capacity fade and local regeneration [33]. Fig. 10 displays the mean prediction of the two models in detail. The prognostics results are proven to reflect the self-recharge phenomenon as fixed cycles, which differ from actual regeneration cycles. This is because the study's co-variance function is chosen in a smooth and consistent manner. Yu et al. presented a consolidated multiscale logic regression (MLR) and GPR ensemble for SOH estimation [45]. Systematic multiscale GPR modelling method is also proposed in some studies to accurately solve the SOH estimation problem [129]. He et al. suggested a multiscale GPR modelling approach to determine the SOH of Li-ion batteries [130]. Other combined approaches, such as GPR and multiscale GPR algorithms, are considered to be more complicated than GPRNN (Gaussian process regression with neural network) models. GPRNN models have the ability to provide real-time prognostics. Zhou et al. also proposed the GPR with GPRNN as its variance function to evaluate and predict the SOH of batteries. By comparing quantitatively with basic GPR, combination LGPFR, combination QGPFR, and the multiscale GPR, experimental results show that the GPRNN may be used effectively for Li-ion battery health estimation. The proposed models' RMSE and MAPE have been decreased to less than 1% [131].

5.1.3. Neural networks

Artificial intelligence is envisioned to establish solutions to the accurate aging estimation and prediction models. Artificial neural networks (ANN) are particularly suitable for complex non-linear problems and achieves better accuracy. The structure of ANN consists of artificial neurons arranged in input, output and hidden layers as shown in Fig. 11. The input layer takes the pre-processed data and operates as a directing medium to the hidden layers. In the hidden layers, each neuron acts as mathematical model for governing the output based on the input, and represented by a weighted linear combinations [113,134]. NNs are widely used in self-learning and adaption and, they do not rely on the electrochemical scenarios taking place inside the battery. The mapping association between characteristic parameters and the lifetime of Li-ion battery degradation is established using neural networks. NN has a robust algorithm that estimates SOH accurately under a variety of battery states, dynamic loads, and temperatures [135].

Various studies used ANN to explore its extensive applications in battery degradation modelling and SOH estimation [136–138]. A summary of the neural networks based SOH estimation and degradation modelling studies is given in Table 6. Two types of ANN including as recurrent neural networks (RNN), and feed-forward neural networks (FFNN), have been mainly applied for SOH estimation. FFNN and RNN are promising methods to express the input and output correlations in the battery aging data. The structures of FFNN and RNN are visually represented in Fig. 11. The battery degradation process typically comprises several cycles, and the degradation information among these cycles is greatly dependent and correlated. Thus, it is worthwhile to derive these dependencies and correlations for accurate estimation. In a study, authors applied a systematic approach based on the ANN for battery SOH estimation [139]. In another study, based on the historical distribution of data collected over one year of experiments on Li-ion battery cells using ten different driving cycle profiles, the researchers developed a real-time SOH estimating method utilizing FNN [21]. Pan et al. presented a FFNN based method which takes voltage, time, voltage boost points and battery degradation curve data as input under different cycle numbers, while battery SOH is taken as an output variable for prediction [94]. To calculate SOH, FNN with time-delayed input data is employed in a study, which is referred as an input time-delayed neural network (ITDNN). The NN successfully represented the dynamics and memory effects of a battery by using time delayed inputs. The battery terminal voltage, current, time-delayed signals, and ambient temperature are used to calculate SOH [140]. Yang et al. proposed a simple method estimating battery's SOH based on three-layer back propagation (BP) neural network. Based on a BP neural network, the study employed maximum available capacity to determine the battery SOH. The parameters of the first-order equivalent

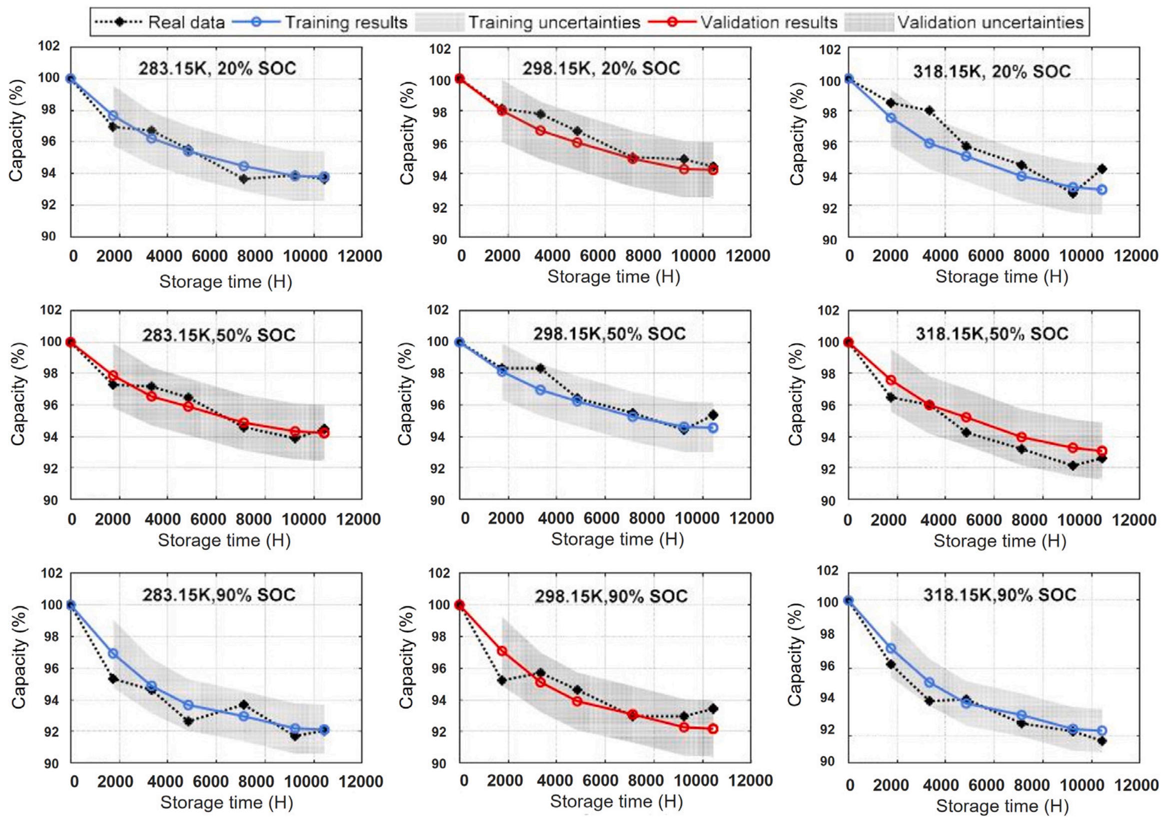

Fig. 9. Training and testing data results using GPR model [27].

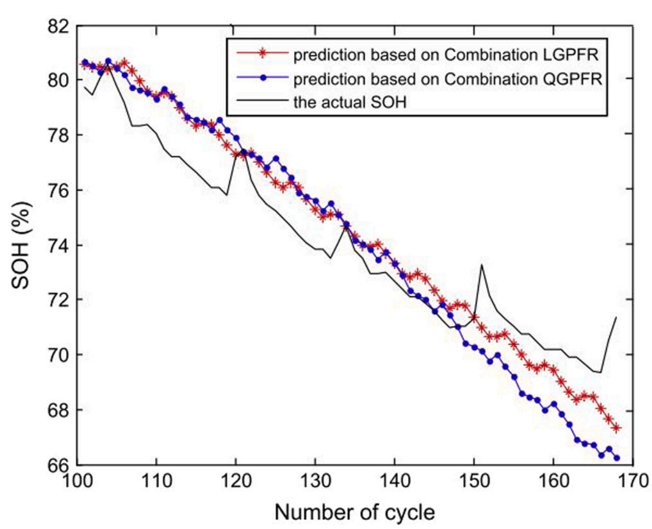

Fig. 10. Battery health prognostics compared with LGPFR and QGPFR [33].

circuit model (ECM) are identified using a direct parameter extraction method. To estimate SOH, a three-layer BP neural network is then devised, with inputs being the first-order ECM parameters and outputs being the current value of SOH [141].

RNNs have been widely used to process sequential data in artificial intelligence applications, and it is also one of most promising method for battery health prediction. SOH estimate entails following a gradual battery degradation process using battery data with dynamic characteristics. As a result, using an RNN to tackle SOH estimate is an intrinsic strategy. Associative memory feature, voltage, current, temperature, and time-delayed voltage and current are the key inputs of the RNN.

In literature, RNN has been widely used as a more effective technique than the FFNN for SOH estimation. For example, Chaoui et al. presented simple RNN based approach, where the dynamically driven RNN is built to estimate both the SOC and SOH of Li-ion batteries [111]. A more practical RNN based approach is presented in another study, in which batteries support real-world driving patterns. The study proposed to trace SOH using measurable EV data, such as current and voltage. A degradation model is designed a model based on a RNN, which is highly suited to handling the sequential data. The validation provides very robust and flexible results under various EV driving conditions, with the average error lower than 2.46% over all of the experiments [152]. Authors of an another study created an RNN to forecast the SOH of

Table 5
Summary of the GPR based SOH/RUL estimation and degradation modelling studies.

Refs	Battery	SOH/RUL estimation	Operation mode	Stress factors considered	Evaluation index	Evaluation error
Liu et al. [33]	Li-ion IFP18650	SOH	Offline	Charging/Discharging voltage, current and temperature	MAPE	0.016
Yin et al. [132]	LIBs	RUL	Offline	Charging/Discharging voltage, current and temperature`	MAE	0.0067
He et al. [130]	Li-ion IFP18650	RUL	Online	Charging/Discharging voltage, current and temperature	MAPE	<0.98%
Richardson et al. [100]	Li-ion IFP18650	SOH	Online	Temperature, Current, Voltage	RMSE	<0.025
Peng et al. [101]	LIBs	RUL	Online	Temperature, Current, Voltage	Accuracy	2.2%
Yu state et al. [45]	Li-ion IFP18650	SOH	Online	Temperature, Charging/Discharging voltage and current, and EOL criteria	RMSE	0.0168
Yang et al. [129]	Li-ion IFP18650	SOH	Online	Temperature, Voltage, Current	RMSE	<0.0345
Li et al. [133]	Li-ion IFP18650	RUL	Offline	Temperature, charge/discharge and impedance	RMSE	0.0130
Zhou et al. [131]	Li-ion IFP18650	SOH	Offline	Temperature, Charge/Discharge Current, and Voltage	MAPE & RMSE	<1%
Richardson et al. [122]	LiNCO/Graphite & Li-ion IFP18650	RUL	Online	Temperature, C-rate, Charge/Discharge Voltage, Current	RMSE	<3%

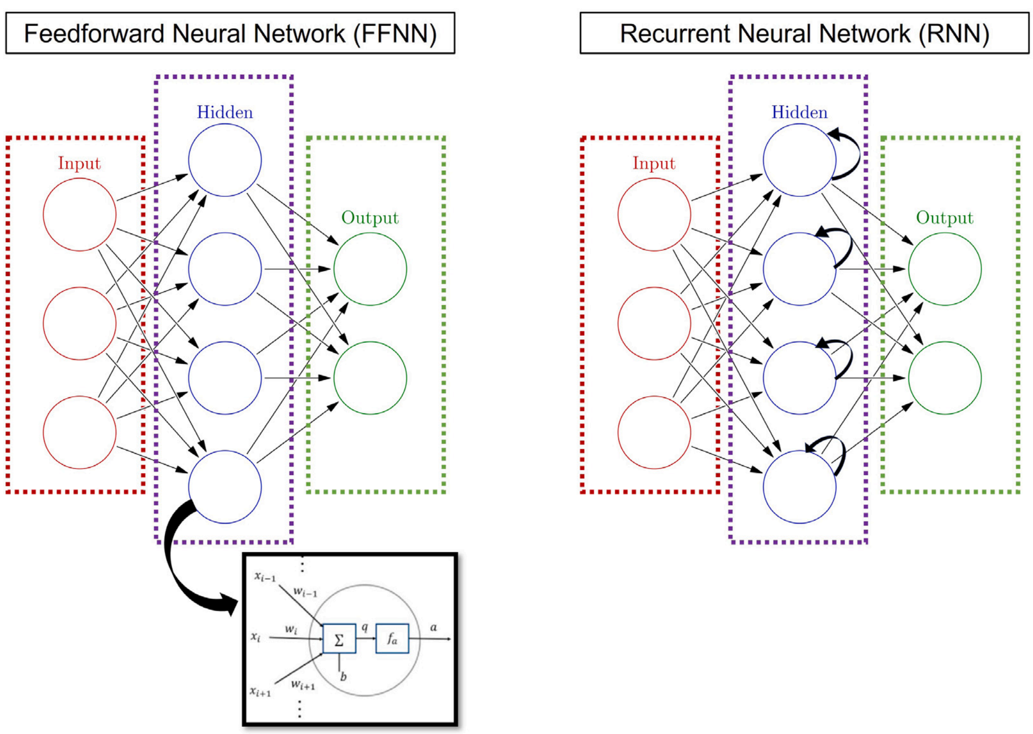

Fig. 11. A visual representation of FFNN and RNN. The neurons are represented as circles [134].

a Li-ion battery based on both battery capacity fade and rise in its equivalent series resistance in a practical investigation. As illustrated in Fig. 12, a battery data input is utilized to train RNNs capable of estimating battery capacity and equivalent resistance, which are then merged to estimate SOH. The RNNs are trained and evaluated utilizing cell temperature, current, SOC fluctuation, and previous time step capacity and resistance. When compared to experimental data, the SOH estimator model produced an accurate prediction of the battery SOH, with an MSE of less than 1% [142].

Long short-term memory (LSTM) is a sub-type of RNN architecture that is created to address the RNN's long-term dependency. LSTM has feedback connections, unlike normal FFNN. In comparison to the RNN architecture, it has input gates, forgetting gates, and output gates. LSTM has been utilized in a number of research to estimate and predict SOH. Qu et al. used LSTM to create a prediction model for SOH and predict SOH using a sliding window, whose basic model formula is provided below [104]:

$$SOH^{e}_{t+1} = f([SOH^{o}_{t}, SOH^{o}_{t-1}, \dots, SOH^{o}_{t+1-s}]) \tag{7}$$

where SOH^{e}_{t+1} and SOH^{o}_{t+1} is the estimation value, and observation value at step t, respectively and s is the length of the sliding window.

In real environments and applications, LSTM is also used to forecast SOH. Chen et al. for example, provided a SOH estimation approach for EV battery life prediction using LSTM. The prediction model with LSTM is built using the discharge time under constant current, the number of charging and discharging cycles, and the charging capacity [118]. In one study, the authors utilized an LSTM to predict the battery SOH, which was trained using a 2.3 Ah LFP cell dataset simulated from an electrochemical model of the cell at various SOHs. Cell capacity fluctuation, voltage, current, and temperature are all employed to train

Table 6
Summary of the neural networks based SOH/RUL estimation and degradation modelling studies.

Refs	NN method	Battery	SOH/RUL estimation	Operation mode	Stress factors considered	Evaluation index	Evaluation error
Eddahech et al. [142]	RNN	LiNixCoy-AlzO2/Graphite	SOH	Online	Temperature, SOC, Current	MSE	0.462
Zhang et al. [143]	RNN	Li(Ni, Co, Al)O2	RUL	Offline	Temperature, C-rate, SOC	Prediction error	0.2 to 0.25
You et al. [21]	FFNN	Li-ion 18650 3.1 Ah	SOH	Online	Temperature, C-rate, Current, Voltage	RMSE	0.0677
Wu et al. [139]	FFNN	LiFePO4	SOH	Offline	Temperature, SOC, C-rate	MAE	0.81%
You et al. [144]	RNN	Li-ion IFP18650	SOH	Online	Temperature, C-rate	RMSE	<2.46%
Chaoui et al. [111]	DDRN	LiFePO4 &LTO	SOH	Offline	Temperature, SOC, Voltage, Current	RMSE	<0.42%
Hussein et al. [145]	ANN	Li-ion battery 3.6-V/16.5-Ah	SOH	Offline	Temperature, SOC, C-rate	Prediction error	<0.1613
Wu et al. [138]	FFNN	Li-ion IFP1865140	RUL	Online	Temperature, C-rate, SOC	Prediction error	<5%
Li et al. [146]	CNN	LiPO4/graphite	RUL	Offline	Voltage, and Temperature	MAE	13.7
Lin et al. [147]	RNN	LiFePO4	SOH and RUL	Online	Temperature, C-rate	Accuracy	>90%
Choi et al. [148]	FFNN/CNN	Li-ion IFP18650	RUL	Offline	Temperature, C-rate	MAPE	1.03%
Bai et al. [149]	ANN	Li-ion IFP18650	SOH	Offline	Temperature, C-rate	MAPE	<2.75%
Zhou et al. [150]	ANN	Li-ion Polymer Battery	SOH	Offline	Temperature, C-rate	Normalized root-mean-square-error (NRMSE)	<10%
Wang et al. [151]	ANN	LiFePO4	SOH	Offline	Temperature, C-rate, SOC	RMSE	<0.012
Pan et al. [94]	FFNN	LiNMC battery	SOH	Online	Temperature, C-rate, SOC, Voltage, Current	RMSE	0.0280

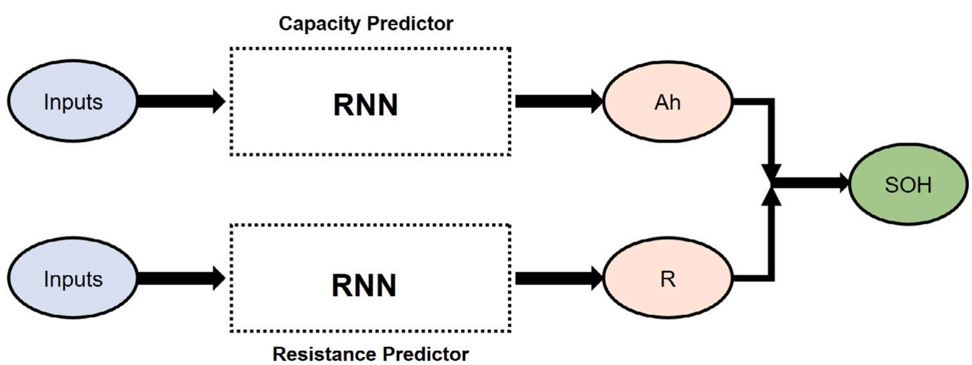

Fig. 12. SOH estimation architecture using RNN [142].

the LSTM. Simulating an aging mechanism with high currents and temperature inputs yielded the dataset used to train the model. The SOH is only calculated during charging profiles from the model-generated dataset [153].

All Neural Network methods offer the advantage to be very quickly adapted to the nonlinear battery data, and it is not required for them to model the battery in all of its details. They must, however, be trained over a large number of cycles.

5.1.4. Fuzzy logic and integrated learning methods

Fuzzy logic is a behaviour-based bionic reasoning technique designed to address complicated reasoning problems involving fuzzy phenomena [154]. It is an adaptive machine learning technique which can be used for SOH estimation. It processes the measured data of complex and nonlinear systems using a fuzzy rule set and offer the possibility to globalize data, which is an advantage for battery aging and SOH estimation [155,156]. For example, Ali et al. improved the accuracy of the SOH estimation based on two parameters' measurements embedded with a fuzzy logic system operating under a large scale of temperature and current [157]. A study used cycle number, voltage drop, and internal resistance as inputs, while the SOH is used as an output. The dynamic prediction model is built using the T–S fuzzy control, and the SOH is calculated to model battery degradation [92]. In another study, fuzzy logic is used to estimate SOH where the input is maximum capacity and resistance [158]. Neuro-fuzzy (NF) system is also proposed in a study, to develop an online machine health prognostic system. The study determines NF technique to be more reliable and robust health condition predictor than RNN as it can capture the system dynamic behaviour quickly and accurately [159].

Besides the discussed methods, there are a variety of additional ML techniques that are used for estimating battery SOH [82]. These methods are referred as ensemble methods and integrated learning algorithms. They employ a number of different approaches to learning, as well as certain principles to integrate the learning outcomes in order to generate a better learning effect than a single method [160]. Many researchers have sought to integrate multiple methods at the same time in order to improve the results and prediction accuracy. For example, Roman et al. introduced a machine learning-based battery health management pipeline which combines experimental battery data with machine learning modelling to estimate SOH. The study explores four algorithms: Bayesian ridge regression (BRR), GPR, random forest (RF), and a deep ensemble of neural networks (dNNe). All algorithms are assessed on error values and uncertainty. The lowest error was achieved by RF and BRR while considering uncertainty assessment metrics, dNNe achieves a better calibration score, with an average increase in MAPE of 0.43% and RMSPE of 0.97%. The dNNe model achieved a RMSPE of 0.45% with a calibration score of 91.02% [161]. In addition, other machine learning ensemble methods like RF, gradient boost and Ada-Boost are also employed in literature for robust and accurate SOH estimation [162–164].

Table 7
Summary of the hybrid methods based SOH/RUL estimation and degradation modelling studies.

Method	Refs	Battery	SOH/RUL estimation	Operation mode	Evaluation index	Evaluation error
RVM - GM	Zhao et al. [168]	LIBs	RUL	Online	RMSE	<5%
LSSVR - PSO	Yang et al. [168]	$LiFePO_4$	SOH	Online	RMSE	0.0192
AR - PF	Liu et al. [42]	LIBs	RUL	Online	RMSE	<2%
AR - EMD	Chen et al. [166]	$Li(NiCoMn)O_2$	SOH	N/A	MSE	$<1\times10^{-4}$
RVM - UKF	Zheng et al. [169]	LIBs	RUL	Online	RMSE	<3%
NN - PF	Wu et al. [170]	LIBs	RUL	N/A	Error	10%
RVM - Mean Entropy	Li et al. [171]	LFP	SOH	Offline	Standard error	<4%
Polynomial regression - PF	Xing et al. [109]	LIBs	RUL	Offline	Error	1%
Brownian Motion - PF	Dong et al. [172]	Li-ion IFP18650	SOH and RUL	Online	RMSE	<4%
GPR - PF	Li et al. [86]	Li-ion IFP18650	SOH	Offline	MAPE	<0.0102
MLP - PF	Cadini et al. [173]	LIBs	RUL	Online	Relative error	10%
RBF - PF	Sbarufatti et al. [136]	Li-ion IFP18650	RUL	Online	Average error	<10%
RVM - KF	Chang et al. [174]	LIBs	RUL	Online	Error	<5%
Logistic Regression - GPR	Yu et al. [45]	Li-ion IFP18650	RUL	Online	Average Error	<10%
SVR - PF	Dong et al. [95]	Li-ion IFP18650	SOH and RUL	Online	RMSE	<0.024
FFNN - KF	Bai et al. [175]	Li-ion IFP18650	SOH	Online	MSE	<0.067
BSA - SVM	Li et al. [176]	Li-ion IFP18650	RUL	Offline	RMSE	<0.06

5.1.5. Hybrid techniques

Hybrid methods are a integration of multiple approaches, with the same or distinct types of methods being used. Furthermore, by adjusting the model parameters, there are combinations of optimization algorithms and other methods that provide better results. The most commonly used hybrid approaches are those that combine data-driven and SOH prediction methods of the same type [26]. A fusion or hybrid approach enables effective use of information from the ML approaches to achieve dynamic SOH estimation outcomes.

Several studies have been carried out using hybrid techniques which use regression, SVMs, and neural networks in combination with different adaptive model techniques [165]. A summary of the hybrid methods based SOH estimation and degradation modelling studies is given in Table 7. Li et al. used the fusion operation of RVM and mean entropy to accurately predict the SOH of the Lithium Phosphate (LFP) battery. The authors used the online mode of operation and results of the study indicate that the proposed hybrid has a standard SOH prediction error less than 4% [98]. Xu et al. implemented a hybrid method based on GPR and particle filter (PF) hybrid method, which is used to estimate the SOH of standard Li-ion IFP18650 battery in an offline operation mode. The study indicates a high accuracy of the GPR-PF hybrid method, which shows a mean absolute percentage error (MAPE) of less than 0.01 [86]. Chen et al. proposed an auto-regressive (AR) approach combined with empirical mode decomposition which is used to estimate the SOH of Li(NiCoMn)O_2 battery with mean square error (MSE) less than 1×10^{-4} [166]. Yang et al. used a particle swarm optimization (PSO)-least square support vector regression (LS-SVR) strategy to provide an effective SOH estimation result with high accuracy and good generalization ability, with the PSO algorithm being used to increase the global optimization algorithm's capacity. The results of the study indicate that proposed technique is able to estimate SOH with high accuracy [167]. Zhao et al. presented a hybrid technique based on the grey model and the RVM (GM). From the SOH sequence, the approach predicts the SOH values of the regeneration cycle, the regeneration cycle number, and normal degradation. The method uses a multi-step SOH prediction based on the time series for the typical degradation modelling phase. The results indicate the estimation result with high accuracy and RMSE of less than 5% [168].

5.2. RUL estimation using machine learning approach

The ability to accurately forecast the RUL of a faulty component is critical for system prognosis and health management. Operators can use RUL to find out when a component needs to be replaced. A Li-ion battery is considered to have failed when its capacity drops by 20%–30% of its rated value. The remaining time or number of cycles before the battery's SOH approaches 0% is referred to as RUL [177,178]. The RUL is typically predicted based on a capacity degradation pattern reaching a preset failure threshold, and it is obtained by subtracting the current health of the battery from the estimated life of the battery. Battery health estimation tools are developed to forecast the SOH as a function of the historical usage data. The relationship between the battery RUL predictors and SOH estimator for an EV vehicle battery is illustrated in Fig. 13, which represents the stages of data collection and data processing for battery health management. It also describes the process to establish the model for RUL prognostics using SOH estimation and diagnostics. In addition to the SOH estimation, RUL prediction of Li-ion batteries plays an important role in practical applications of battery health management, and provides meaningful insights in terms of battery echelon utilization and safety management [30]. The steadily fading battery capacity is often employed as an effective health indicator for Li-ion battery RUL prediction to track the battery's degradation process.

Considerable research efforts have been devoted to RUL estimation. Recent research has focused on data-driven approaches that leverage statistical machine learning to relate real-time, non-invasive RUL measurements of the battery to battery health without modelling a physical mechanism [17,179]. According to Hu et al. current RUL prediction methods can be divided into model-based, data-driven, and hybrid methods. These methods vary in terms of computational complexity, model accuracy, and requirements. The data-driven model incorporating machine learning mechanism is considered to be a promising RUL prognosis technology [180]. Data-driven machine learning algorithms extract valuable features from acquired data in order to characterize the current state, and, as a result, to model the degradation trend [181]. The utilization and applications of ML methods for SOH estimation and RUL prediction are quite distinct. The input features for SOH estimation are collected from the BMS during operation, and the outputs are the estimated capacity at a given moment. In order to predict RUL, ML techniques often require estimated or measured SOH information, such as capacity values, as inputs [29]. To create the degradation model, ML approaches effectively extract feature information from RUL prediction, and based on this information, they describe intrinsic degradation correlations and patterns [93]. Therefore, machine learning methods have become the focus of RUL prediction and battery degradation modelling.

A reliable ML based approach for precise battery degradation modelling and RUL estimation is of extreme importance for advanced battery management [89]. Predicting a battery's RUL and detecting possible unpredictable scenarios induced by battery aging are the ultimate goals of battery health management. The battery health monitoring data is typically used to fit the degradation model and calculate the RUL by extrapolating the variables to the failure threshold in ML-based methodologies [17]. By using ML approaches, it is not necessary to

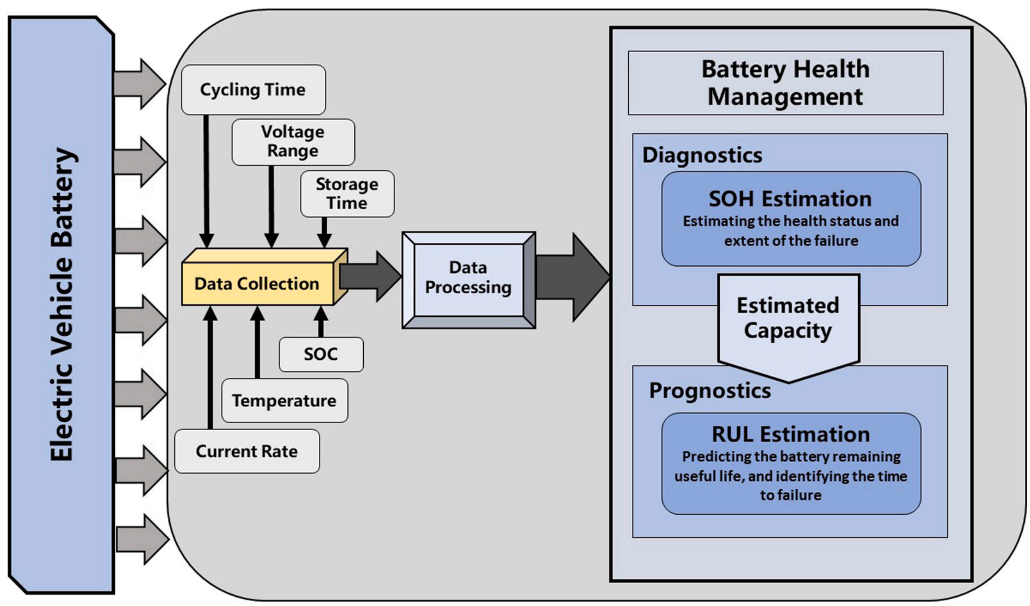

Fig. 13. Battery SOH estimation and RUL prediction algorithm framework.

simulate various degradation mechanisms in detail; rather, the acquired data is used to predict RUL. The requirement of large amount of training datasets that are quite relevant to the degradation, is a fundamental drawback of ML techniques. To further understand the prognostics of RUL reported in the literature, various studies developed a data-driven based ML prediction model to exhibit RUL. Prognostics ensure that complex systems, such as battery RUL prediction, are understood and developed by integrating data generation and data-driven modelling.

5.2.1. Support vector machine

SVM is a powerful method for handling large amounts of battery data, which include sets of current, voltage, SOC, Ah and temperature data. These datasets are be widely used to devise battery models [182]. Numerous studies have used SVM technique for RUL estimation [183]. For instance, Wang et al. proposed an SVM-based iterative multi-step prediction model in order to accomplish accurate RUL prediction [184]. Klass et al. developed and evaluated RUL estimation method based on SVM models and virtual standard performance tests. The study carried out the validation of the RUL estimation method based on battery data from experimental work, while standard performance tests and EV current profiles served as input data to the SVM modelling [117]. Patil et al. suggested a novel method for estimating Li-ion battery RUL in real-time that incorporates the classification and regression properties of the SVM algorithm. The researchers evaluated Li-ion battery cycling data under various operating settings and extracted crucial elements from the voltage and temperature profiles. When the battery is nearing its EOL, the proposed model provides an approximate estimation and predicts the accurate RUL as shown in Fig. 14 [185].

Some studies focused on different SVM based hybrid DDMs for RUL estimation. Pattipati et al. obtained battery RUL prediction after incorporating the Hidden Markov model (HMM) into SVM. The nonlinear SVM models are utilized to forecast capacity decline due to a high degree linear correlation between battery resistance and capacity [186]. Gao et al. proposed a multi-kernel SVM (MSVM) based on polynomial kernel and radial basis kernel function, in combination with particle swarm optimization, to predict RUL of the battery [187]. Experiments show that the model has a good accuracy in detecting health characteristics with few parameters. The application of SVM depicts a reasonable performance on the battery RUL estimation. However, forecasting future values of the variable of interest, as well as describing the uncertainty associated with these values, is a crucial component of RUL prognostics. There are other machine learning algorithms that presents a more stable and competitive prediction and provide a principled approach to dealing with uncertainty as compared to SVM [188].

5.2.2. Bayesian methods

Bayesian approaches offer a logical approach to dealing with uncertainty, as well as a plausible interval with probabilistic upper and lower bounds, which is critical for making informed decisions [189]. In a study, the authors developed a systematic technique based on identification, model selection, and a strategy for prognostics data selection to simulate battery capacity fading across recurrent cycles. Under diverse operating situations, the suggested Bayesian technique is capable of quantifying the uncertainty in predicting battery capacity and RUL [190]. Another study characterized battery degradation and a Naive Bayes (NB) model is developed for RUL prediction of batteries under various usage scenarios and ambient temperatures. Furthermore, the analysis shows that the RUL of Li-ion batteries is predicted using the NB technique in constant discharge situations, regardless of the exact values of the operating parameters. The proposed model has an improved prediction performance as compared to SVM [107]. He et al. developed a unique online technique based on Dynamic Bayesian Networks (DBNs) for estimating the RUL of Li-ion batteries. The parameters of the DBN model are learned using training data obtained from battery aging studies, and the DBN model is inferred using a forward approach to predict the RUL in real-time. Experimental results represent the effectiveness of the proposed method in estimating the RUL of Li-ion batteries [106].

5.2.3. Gaussian process regression

Gaussian process regression (GPR) is a flexible, probabilistic, non-parametric Bayesian approach that offers a number of unique advantages for RUL prediction. It represents variance around its mean predictions to describe related uncertainty in the evaluation and prediction [191]. These advantages of GPR have been exploited in a number of studies for battery RUL prognostics, and it is applied in different batteries and situations theoretically. Richardson et al. demonstrated that GPRs are used to estimate battery conditions and outlined many important advantages over other data-driven and mechanical techniques. On chosen capacity datasets from Li-ion cells, the study used Gaussian processes for short- and long-term RUL prediction [100].

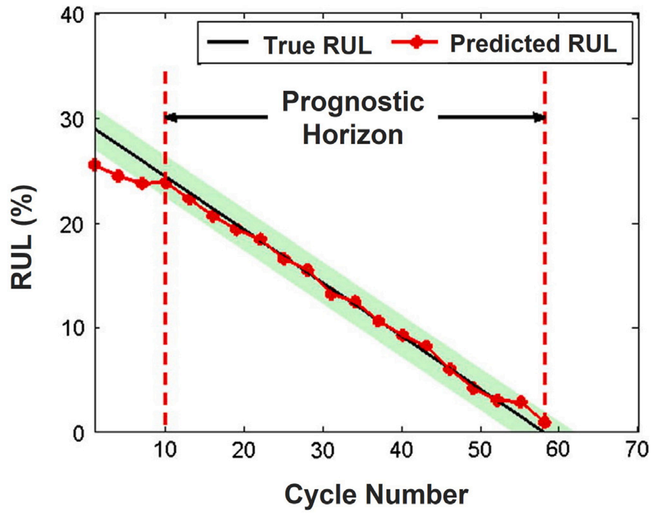

Fig. 14. RUL prediction of the SVM based approach [185].

Liu et al. evaluated the GPR model to realize the battery SOH and proposed RUL prediction approach. Experimental results prove the effectiveness and confirm that the algorithm is effectively applied to the battery monitoring and prognostics [192]. Li et al. introduced a new RUL prediction approach based on the Gaussian Process Mixture (GPM), which fits distinct segments of trajectories with different GPR models. Due to the outstanding testing results of two commercial Li-ion batteries, the method is proved to be effective for RUL prediction. When the models' performance is compared, it is clear that the GPM is more accurate than the GPR and SVM [133].

5.2.4. Neural networks

Neural networks (NN) is another industry-leading machine learning technique as it can attain high levels of accuracy. Furthermore, NNs are the most typically used method for estimating battery RUL as they have accurate generalization and learning of nonlinear relation between data and output. Many of the recent studies have considered different types of neural networks for RUL estimation. A summary of the neural networks based RUL prediction and degradation modelling studies is given in Table 6. Different types of ANNs have been successfully applied for battery RUL prediction in various studies, including FFNN, RNN, CNN, ARIMA [104,179]. FFNN is used as a machine learning method for RUL estimation due to its ability for nonlinear simulation. Based on the historical distribution of observed battery data, You et al. built a real-time RUL estimation method utilizing a FFNN [21]. On the basis of RUL definition, Wu et al. proposed a Li-ion battery RUL estimation method using FFNN. For its simplicity and effectiveness, FFNN simulates the link between RUL and charge curve. Based on these findings, an online method for estimating Li-ion battery RUL using FFNN is presented [193]. The experimental findings show that the proposed strategy performs in an effective way in terms of RUL estimation for online applications.

On the other hand, RNN provides an accurate simulation of Li-ion cell aging behavior as explored in a study, taking specific operational conditions into account and providing practical information on the battery RUL [142]. RNN-based predictors are used in a wide range of high-performance energy storage systems for hybrid and electric vehicles [194]. An application of dynamically driven RNN is presented in a study for online EV battery analysis. A nonlinear auto-regressive architecture of RNN is designed for SOC, SOH and RUL estimation [195]. In another study related to EV battery analysis, RNN is proposed to trace the EV battery RUL, using measurable data from an EV where batteries are cycled dynamically according to various driving patterns [196]. An adaptive RNN is also presented in a study for predicting the RUL of Li-ion cells, based on a history of cell impedance data from numerous batteries as a starting point for predicting the unknown impedance variation of a new battery. Adaptive recurrent feedback is used in the suggested strategy to improve prediction accuracy [197]. A study by Che et al. proposed a novel RNN based method to predict RUL using health indicators (HIs) and online model correction. A combination of transfer learning and gated recurrent neural network (TL-GRNNs) is used to improve the RUL prediction accuracy, which uses the most relevant battery to train the pre-model and fine-tune the model using early cycling data of the test battery. GPR is used to optimize the threshold for HIs to determine the EOL. Experimental results show that the proposed method provides more accurate RUL prediction than the conventional method. The proposed method predicts RUL with an error of fewer than 5 cycles [198].

Some studies used RNN based LSTM approach to estimate RUL. For instance, to forecast RUL, Zhang et al. suggested an RNN-based LSTM. The data was gathered using a variety of Li-ion cells at varied current rates and temperatures. The model obtains satisfactory results in predicting RUL independent of offline training data [199]. Chinomona et al. considered the aging characteristics extracted from the voltage, current, and temperature to analyze the degradation of the battery and determine the battery RUL using RNN-LSTM [200]. Chen et al. used LSTM networks to develop a prediction model that properly calculated RUL with an RMSE of less than 4% [166]. A study by Li et al. improves RUL prediction, and proposed a prognostic framework shared by multiple batteries. A variant LSTM neural network, called AST-LSTM NN, is designed for the promising performance of RUL prediction. AST-LSTM NNs have mapping structures of many-to-one and one-to-one, and are independently well-trained for the prediction of SOH and RUL. The experiments carried out on NASA dataset results in lower average RMSE (A-RMSE) of 0.0216 for SOH prediction and conjunct error (CE) of 0.0831 for RUL estimation. A comparison of the RUL estimation results of the proposed AST-LSTM NNs, with the estimation results of other methods including RNN, and LSTM is depicted in Fig. 15 [201].

Convolutional neural network (CNN) is also studied in the previous studies as it is suitable for predicting RUL of Li-ion battery. Li et al. constructed a CNN model to achieve high accuracy for RUL prediction of Li-ion battery and applied orthogonal method for optimizing model parameters [146]. Deep Neural Network (DNN), which acts as multi-layer ANN, is another suitable technique that achieves better accuracy for complex prediction problems such as multi-battery RUL estimation due to its ability of high complex non-linear fitting [202,203]. Ren et al. devised a similar DNN integrated deep learning approach in a study for multiple Li-ion battery RUL prediction. The study used a multi-dimensional feature extraction method with an auto-encoder model to

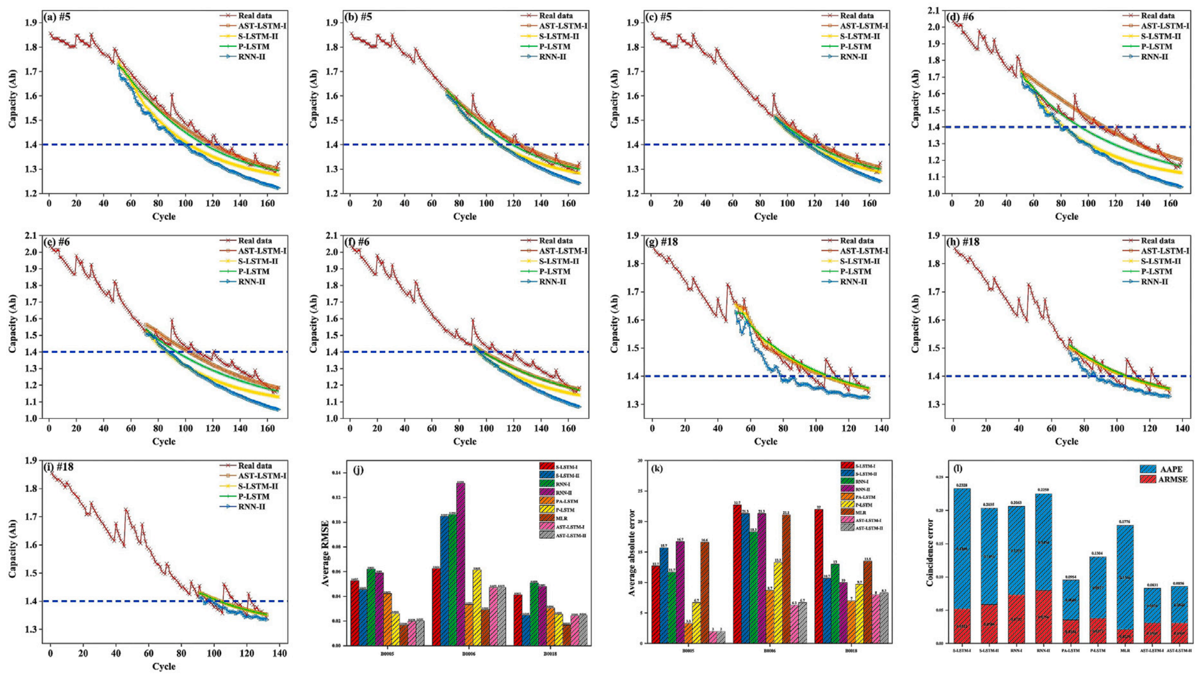

Fig. 15. The RUL prediction results of different methods [201].

depict battery health decline, and an RUL prediction model based on DNN is trained to estimate multi-battery remaining cycle life [204].

5.2.5. Relevance vector machine

Relevance vector machine (RVM) is a sparse Bayesian approach for the kernel regression which undertakes regression in a probabilistic way. RVM has a high level of accuracy, learning ability, sparsity, a simple training process, and a probability distribution prediction output. However, one clear disadvantage is that training requires enormous datasets, resulting in significant computational complexity, time, and memory needs [205]. Due to RVM model's sparsity, it is possible to make efficient predictions for new observations [206]. RVM has the identical function form of SVM as mentioned in Eq. (4). However, unlike SVM, it has the ability to provide probabilistic classification [205]. The residual capacity and battery health of Li-ion batteries have been evaluated using RVM based on the characterization data derived by the charging behaviour [97]. The RVM model has been gradually used for the degradation prediction phase, and it is integrated with other methods for battery RUL estimation. In a study, Wang et al. created a Li-ion battery prognostic model that included an RVM algorithm and a capacity degradation model to predict RUL. To increase prediction performance, the suggested RVM picks the significant training vector [183]. To improve the RUL prediction precision, Liu et al. presented an incremental on-line learning technique for RVM [99]. Li et al. used the RVM algorithm, and mean entropy to develop the RUL prediction of Li-ion batteries. The mean entropy is used in the study to determine the ideal dimension for proper time series regeneration [98]. A summary of the RVM based RUL prediction and degradation modelling studies is given in Table 8.

5.2.6. Hybrid techniques

ML methods and physical-model methods are potentially complementary to each other; therefore, it is desired to develop a hybrid model-combining the two approaches — to achieve an accurate RUL prediction. With such combined model, the battery working in field can be better described and simulated, which will eventually provide a solid foundation for the battery health estimation and prediction [31]. Numerous studies have been carried out using ML methods in combination with different adaptive model techniques. SVM, RVM, neural networks, GPR and other ML methods are widely used in combination with other adaptive and empirical methods for accurate RUL prediction. A summary of recent work based on the hybrid techniques for RUL prediction and degradation modelling studies is given in Table 6.

(i) *SVR Based*
Wang et al. suggested a hybrid SVR and differential evolution (DE) model to improve RUL prediction accuracy for Li-ion batteries. DE has been used to obtain the kernel parameters of SVR [213]. Furthermore, a number of studies made use of SVR and combined it with PF for RUL prediction of batteries [95,214,215]. A hybrid technique called the improved bird swarm algorithm optimization least squares support vector machine (IBSA-LSSVM) has been presented in a study to estimate the RUL. The LSSVM model's optimum parameters are determined using IBSA. The goal of the method is to improve prediction accuracy and stability [176].

(ii) *Neural Network Based*
Qu et al. proposed a neural-network-based method that achieved a high accuracy by combining LSTM network with PSO and attention mechanism for RUL prediction [216]. Cadini et al. suggested a hybrid strategy for RUL prediction that included PF and multilayer perception (MLP) neural networks. The posterior probability density function (PDF) of the MLP parameters is determined recursively using PF [173]. To represent the battery system dynamics, Bai et al. used FFNN and Kalman filtering (KF). The authors used a collection of battery trial data to back up the proposed strategy [175]. Sbarufatti et al. demonstrated a method that combined PF and radial basis function (RBF) neural networks to predict RUL, with PF being able to dynamically determine RBF parameters. The algorithm adjusts to the changing dynamics caused by battery aging [136]. Pang et al. developed a new approach for forecasting the RUL of a Li-ion battery that combines wavelet decomposition technology (WDT) with the Nonlinear Auto Regressive Neural Network (NARNN) model [217].

(iii) *GPR Based*
Joint estimation GPR models are also proposed to accurately estimate the capacity and predict the RUL. A high RUL prediction

Table 8
Summary of the RVM based SOH/RUL estimation and degradation modelling studies.

Refs	Battery	SOH/RUL estimation	Operation mode	Stress factors considered	Evaluation index	Evaluation error
Hu et al. [206]	LIBs prismatic cells	SOH	Online	Temperature, DOD, C-rate, SOC	RMS	0.92%
Saha et al. [182]	Li-ion IFP18650	RUL	Offline	Temperature, SOC	Accuracy	Minimum error
Zhou et al. [207]	Li-ion IFP18650	RUL	Online	Charging/Discharging voltage, current and temperature	RMSE	0.0117
Wang et al. [183]	LIBs	RUL	Offline	Temperature, Current, Voltage	RMSE	<0.0116
Qin et al. [208]	Li-ion IFP18650	RUL	Online	Current, Voltage	RMSE	<5%
Li et al. [98]	LIBs	SOH	Offline	Temperature, Voltage, Current	RMSE	<0.004
Song et al. [209]	Li-ion IFP18650	RUL	Online	Temperature, Voltage, Current	MAE & RMSE	<0.01
Zhang et al. [210]	Li-ion IFP18650	RUL	Online	Temperature, Voltage, Current	MSE	<0.0002
Widodo et al. [211]	Li-ion IFP18650	SOH	Offline	Temperature, Voltage, Current	RMSE	5.96×10^{-5}
Liu et al. [47]	Li-ion IFP18650	RUL	Online	Temperature, C-rate, Current, and Voltage	RMSE	<0.054
Zhang et al. [212]	Li-ion IFP18650	RUL	Offline	Temperature, C-rate	MSE	<0.0007

accuracy is achieved in a study by combining the GPR method with probability predictions [43]. Another study proposes a mechanism for forecasting the RUL of Li-ion batteries by combining GPR and logistic regression (LR) [45]. Wavelet de-noising (WD) method and the GPR model are also fused in a research study to evaluate the performance of RUL prognostics and obtain a higher accuracy for RUL prediction of Li-ion battery [101].

(iv) *AR Based*
Liu et al. explored an improved nonlinear degradation auto regressive (ND–AR) model for Li-ion battery RUL estimation. A battery RUL prognostic joint framework of ND–AR model and RPF algorithm is proposed to realize various Li-ion batteries RUL estimation [42]. In another study, Saha et al. presented a comparative study of ARIMA, extended KF, RVM, SVM and PF approaches on experimental data collected from Li-ion batteries in the RUL prediction [218]. Zhou and Huang suggested an approach based on empirical mode decomposition (EMD) and ARIMA To estimate the RUL of Li-ion batteries. An aging test dataset of Li-ion batteries is used to validate the methodology [103]. In one study, researchers used a novel and optimised AR model in which the model order is modified adaptively using the particle swarm technique for battery RUL prediction [219].

(v) *RVM Based*
Various studies also applied RVM in combination with different techniques to forecast RUL. For instance, Saha et al. explored the battery prognostic problem in a study through Bayesian learning based RVM–PF framework to encapsulate the randomness of RUL and improve its prediction with extensive measurements [220]. The advantages of this model-based approach over other techniques capable of handling uncertainties like NN and GPR, are also demonstrated in [221]. RVM and grey relation analysis (GRA) are utilized by Qin et al. to forecast RUL. The duration of the charging and discharging voltage difference is chosen as the model's input first, followed by feature selection to eliminate redundant points in the data [208]. Li et al. employed used mean entropy and RVM to calculate the RUL. The authors used mean entropy to determine the best dimension for time series regeneration, and then used RVM to anticipate Li-ion battery SOH and RUL [98]. Song et al. estimated Li-ion battery RUL with an iterative updated RVM fused with the KF algorithm [85], whereas Zhao et al. implemented a hybrid method for RUL estimation by using the RVM and the grey model (GM) alternately [168]. To estimate the RUL of the Li-ion battery, Zhang et al. suggested an approach based on the EMD denoising method and the multiple kernel relevance vector machine (MKRVM). By using the EMD denoising technique to the measured capacity data, noise-free capacity data can be obtained. Its capacity forecasting model is developed using MKRVM based on the noise-free capacity data. [212]. Chang et al. developed a hybrid method to obtain the RUL of Li-ion batteries By integrating UKF, EMD and RVM [174].

A few studies also conducted research on RUL prognosis using novel data-driven techniques including Dempster–Shafer theory and the Bayesian Monte Carlo method, sample entropy and sparse Bayesian predictive modelling, Box–Cox transformation and Monte Carlo simulation [222,223].

6. Discussion

With the ever-increasing complexity and dynamics of battery storage systems, battery degradation modelling has become more complex. Qualitative changes are apparent in Li-ion battery degradation process. However, it is challenging to identify quantitative features that are linked to degradation. The data-driven based prognostics approach resolves this by performing real-time, non-invasive measurements on the battery without modelling a physical process and utilizing statistical machine learning to link SOH and RUL to the battery degradation. Different ML methods have been proposed in literature for modelling the battery degradation using health SOH diagnostics and RUL prognostics of Li-ion battery. All of the presented ML-based SOH and RUL prediction algorithms have their own set of applications, and in some cases, superior results can be obtained. Each method's complexity and style of operation differ, which can have an impact on practical applications. There is no single accurate method to model all current issues related to the battery degradation. The characteristics of each ML method comprise of the accuracy, computational effort and generalization ability which are usually required to assess their performance and applicability. This section discusses the characteristics of the existing ML methods in order to recommend the most suitable models for Li-ion battery SOH estimation and RUL prediction. Furthermore, some considerations are discussed concerning approach selection, and performance evaluation for the particular ML method application of Li-ion battery aging prediction. This is crucial to comprehend the methods' scope of applicability and complexity, as well as to serve as a reference for actual implementation and future study. In addition, this section also discusses about the aspects related to applicability of ML methods in EV applications for battery safety, reliability and its life improvement through battery degradation modelling.

6.1. SOH, RUL and battery degradation modelling

Lithium-ion batteries face a core difficulty associated with environmental degradation factors, capacity fade, aging-induced degradation, and end-of-life repurposing. The performance and capacity of Li-ion batteries gradually deteriorates over time due to the aging process and impacts from the operating conditions. The SOH and RUL are main benchmarks to analyze battery health conditions, and provide helpful technical information that outline the efficacy of the batteries as well as facilitate in the identification, development and testing of numerous parameters that will enhance and further improve the efficiency of BESS. The SOH indicates the battery aging level and reflects the reduction in the total useful capacity and increment in internal resistance of the battery. RUL denotes the period from the present time to the end of the battery useful life. Both these measurement indices provide an accurate and effective framework of battery degradation model. Various studies have proposed to capture the relationship between battery SOH estimation, RUL estimation and battery degradation trend. The characteristic parameters associated with Li-ion battery aging are capacity fade, and internal resistance which have a strong correlation with the battery SOH. These parameters act as the health indicators to estimate the battery SOH whereas the accurate SOH estimation is the foundation and prerequisite for the RUL prediction. The SOH estimation and RUL prediction, in combination, devise the model to predict the battery degradation trend by quantitatively utilizing battery aging parameters of capacity fade and internal resistance. Thus, establishing the model of degradation behaviour of Li-ion batteries hence requires accurate estimation of SOH, and RUL. Appropriate and robust algorithms of SOH estimation and RUL prediction are necessary in addressing the battery degradation challenges, improve the battery operation and performance, allowing them to be used to their maximum potential and attaining extended life before replacement or disposal.

6.2. Machine learning and battery aging prediction

Machine learning methods are the evolutionary methods, which require less pre-test work, and carry out precise estimation of the slowly changing parameters critical to battery degradation modelling such as battery life (RUL) and health (SOH). The drawbacks of these methods include high requirements on the efficiency and portability of the algorithm and high dependence on the transmitted data [25]. These methods have great potential for battery health management and battery degradation modelling. ML models are the viable choice when there is no functional dependence information from a Physics-based model. ML functions as a black box, where battery datasets are fed and SOH and RUL predictions are generated.

ML techniques provides better estimation accuracy than other adaptive methods as analyzed in a study by comparing the IC analysis with GPR and RF [162]. Dynamic conditions involving drastic variations in the usage of current and voltage, and temperature stresses make it difficult to accurately model the battery degradation. ML can be employed in a dynamic setting, such as a driving cycle of an electric vehicle, due to its flexible properties. Temperature changes can be used as input variables for model training and linked to aging. However, these methods require a greater computational effort, which is a major hurdle in their online application. Based on the battery's usage pattern, a suitable SOH estimation method should be chosen. Because of its capacity to adapt to non-linear battery state behaviour, ML is a potential solution for batteries under more complex operating situations, such as those found in EV.

6.3. Comparison of different ML methods

The ML methods and their usage in different studies is described in two parts; one for the SOH estimation, and the other for the RUL prediction. The methods explored for SOH estimation and RUL prediction include SVM, ANN, RNN, RVM, GPR, fuzzy logic, Bayesian methods, ensemble learning, and hybrid methods. The basic workflow required for online SOH/RUL estimation using feature input prediction algorithms is depicted in Fig. 6. Feature extraction is a critical phase and a difficult problem in battery deterioration modelling, because it has a direct impact on performance. In the domain related to battery degradation modelling, there is no established optimum model for estimating SOH and RUL due to system complexities, data availability, and application constraints. In some cases, though, one strategy may outperform another. In this part of the discussion, the comparison of different ML methods have been made in terms of the approach selection, non-linear data handling capability, complexity, robustness and then an conclusive interpretation of this comparison is given.

6.3.1. Approach selection

For the particular ML method application for Li-ion battery aging prediction, the structure of the selected model is important. Users' requirements and criteria, such as the testing environment, accuracy, and forecast time, needs to be addressed when selecting effective methodologies for battery degradation modelling. The model's capacity to fit future aging data is constrained in an online learning setting. ARIMA models are susceptible to similar problems. ANN models, assuming a constant architecture, have a fixed number of weights and are theoretically capable of approximating any battery degradation function within a desired accuracy range, as long as the model specification is properly established. Methods involving filtering techniques to update aging models can be exposed to limitations, and hence the ability to perform accurate predictions strongly depends on the reliability of the initial model.

SVR, GPR, and RVM have an associated parameter, providing the model more flexibility to react to new data acquired during online operation. When a reliable ML model is already available, filtering-based hybrid approaches can be a good way to update it and make it more adaptable to future battery data. In contrast, in a circumstance where the model must be devised from the scratch, a method like GPR or RVM is more appropriate. This strategy can provide the model more adaptability when it comes to new data points while also minimizing the amount of battery testing hours needed to train it.

6.3.2. Non-linear data handling capability

The ability to model nonlinear relations like the battery degradation behaviour is crucial when modelling Li-ion battery aging because the relationship between some battery stress factors and battery health is substantially nonlinear. The outcomes of the studies described in above sections which are based on SVR, GPR, RVM and ANN techniques depict that these methods allow performing regressions on nonlinear data, and they can only provide an estimated point in regression, but ARIMA can only provide a linear auto-regression, hence it might not be suited for predicting Li-ion battery aging.

6.3.3. Robustness

The review of different ML studies used for SOH and RUL estimation shows that the most resilient mechanisms for dealing with tiny data fluctuations and outliers include SVR, RVM, and GPR. SVR and RVM have inherent sparse behaviour and robust mechanisms, allowing them to deal with small data fluctuations and aberration, ignore tiny data variations and discard immaterial data. GPR provide robustness when facing minor deviations. However, some studies raise questions about GPR's robustness in practical applications, as actual operating conditions may vary widely. There is no comparable mechanism in ARIMA and ANNs to improve the robustness of the forecasts.

6.3.4. Complexity

The computation complexity is evaluated as the resources required by a ML model. In particular, it focuses on the time and memory requirements. The determination of a model computational complexity is useful because by this way, one can suggest modifications that would improve the computation results. Since the computation complexity is generally difficult to quantify in the ML model, one common practice is to characterize functions according to the correlation between run time or space requirements and the input size. It is clarified here that based ML approaches reduces the inherent complexity involved with the battery degradation modelling as they attempt to learn by examples and are capable to capture complex degradation mechanisms and relationships among collected battery data that are complex to describe [29]. ML is a potential solution for batteries to deal with the operational and degradation modelling complexities of EVs due its capacity to adapt to non-linear battery state behaviour. It is noted that there is a trade-off in balancing the model complexity and computational burdens for ML methods-based SOH and RUL estimation.

6.3.5. Interpretation of comparison

ML-based SOH and RUL prediction algorithms presented in the review study have their own set of applications, and in some cases, superior results can be obtained. Complexity and operation style of each method differs, which can have an impact on practical applications. There is no single accurate method to model all current issues related to the battery degradation. Hence, none of the aforementioned methods can be considered an absolutely superior method, and a trade-off among the desired accuracy, the output confidence interval, the ability to deal with non-linearity, robustness, computation complexity, the ability to deal with data sparsity, and generalization should be considered for each particular situation.

6.4. Battery degradation models for EV applications

Li-ion batteries are increasingly being employed in a variety of applications to deliver a variety of services, owing to their technological and market maturity. Li-ion batteries have a high energy density, a high power density, a long life, and are environmentally friendly, hence they have a wide range of applications. However, their performance degrades with aging and usage, resulting in a loss in both energy and power capacity. The models used for algorithm development needs to capture the impact of battery capacity degradation on various real-world applications like EVs. ML is one of the progressive method which is being studied as a new approach to improve the battery degradation models. It is important to use ML methods to minimize the computational burden of models, so that they can be used on-board vehicles in real time. The ML based SOH and RUL estimation presents very interesting results with quite high accuracy. Yet, unless a significant amount of data from real EVs under different operating conditions and for different battery types are available, this estimation technique is hard to conduct. Besides, ML models are only as good as the experimental data on which they are used, so minimizing errors in battery data collection is critical. Due to a paucity of data on deterioration mechanisms mixed with the need for quick computation, battery degradation models are frequently oversimplified, and thus not allowing the users to observe the real impact of it on the EV applications. Li-ion battery degradation can be estimated through the development of aging models. The model development is typically necessary in order to optimise the operation and performance of the battery particularly for EV application. An assessment of the state-of-the-art ML based Li-ion battery degradation models, including accuracy, computational complexity, and amenability to algorithm development is already presented in the above sections. This section discusses the utilization and implications of battery degradation models for EV related aspects. The aspects which are discussed incorporate existing degradation models with EV batteries through BMS and energy management, V2G services, optimization strategies for accurate modelling, and optimized operation and performance of the EV battery.

6.4.1. Utilization of battery degradation models in EVs

Safety and reliability of Li-ion batteries is critical for the large-scale penetration of EVs. The main limitation of the Li-ion based EV batteries resides in the aging as battery undergoes a sophisticated degradation process during EV operations. Degradation occurs over time under specific driving conditions, and it results in decreased driving range due to reduced capacity, decreased charging/discharging efficiency due to increased resistance, and the critical need for battery replacement when capacity falls below the degradation limit [84]. The charging strategy of EVs is one of the most significant contributor to battery aging. Excessive charging time reduces the practicality of EVs, negatively impacting the user experience and reducing user confidence, while an excessive charging current causes the battery temperature to increase rapidly, resulting in capacity degradation and a significant reduction in the service life. The potential influential factors affecting the EV usage and energy consumption are mostly related to battery states, battery aging, driving behaviour, and environmental conditions [224,225]. There are two concerns in the Li-ion battery application, including the expensive energy capacity as the battery cost accounts for a large portion of the total cost of an EV, and the limited driving environment, which limits the performance and adoption of EV. Therefore, mitigating the battery capacity degradation through proper modelling, prolonging the battery life and optimizing battery capacity and energy management are the main goals of maximizing the overall lifetime value of EVs.

One of the most challenging task in modelling the degradation trend of the EV battery is to identify factors that are causing it. Many factors from the environment interact to produce diverse degradation effects on EV batteries, which makes it difficult to establish a degradation model through existing methods. Degradation comprehension is a difficult task, and throughout the years, numerous studies explored the battery degradation models [226]. The diversity and the multitude of existing studies dealing with battery degradation provide a reasonable information, which investigate EV battery aging factors, effects, and characteristics. Based on the explored aspects, many studies further investigated the methods applied to model the degradation mechanisms in EV battery [227].

6.4.2. Integration of degradation models with BMS

Failure of a Li-ion battery in EV can result in hazardous conditions such as fires and explosions, as well as increased maintenance or replacement expenses. Li-ion battery health in EV needs to be examined on a frequent basis in order to discover flaws, and addressing safety concerns [46]. The BMS features battery faults detection system and provides early alerts and reports regarding battery aging information to ensure battery safety [112]. The BMS in an EV ensures the safe and reliable operation of the battery pack by continuously monitoring the states of the battery and making the battery operate within the appropriate voltage and temperature windows [25]. As a result, the irreversible damage to the battery is avoided, thus effectively prolonging battery lifetime [228].

The integration of accurate degradation models with BMS enhances its ability to extend battery life of EV by ensuring that operations are optimized for battery longevity. BMS enables model-based estimation of battery states such as SOC, SOH and RUL. It measures and quantify the evolution of the electrical performances of EV batteries and predict accurately their RUL in real use [229]. The implementation of robust and accurate ML techniques in BMS can protect cells and battery packs by assuring proper operational voltage and temperature ranges, ensuring safe operation, extending battery service life, and keeping batteries in a healthy state [123]. Current, voltage, and temperature sensors, as well as vehicle control, are all BMS inputs that can serve as crucial input features for ML algorithms while SOH and RUL can act output features. This represents that the BMS can very well oversee the battery safety and reliability, and improve battery life when integrated with ML algorithms. Furthermore, accurate ML based degradation models once integrated with BMS allows EV batteries to be used to their greatest capability and life expectancy before being replaced. To ensure the safe operation of battery packs, further improvements in the BMS and degradation models are necessary so that batteries in EVs are capable of delivering the required power and energy for an extended driving range.

6.4.3. Energy management, optimization strategies, and battery degradation modelling

The degradation models are used to examine and optimize the energy management strategy, with an emphasis on increasing battery lifespan, in addition to application design utility. The combination of accurate degradation models and optimized energy management strategies in EVs has the ability to improve the battery life. Various studies proposed different optimization techniques which considers the battery degradation models for the optimal battery size, DOD and energy management in EVs [230]. Since charging behaviour affects battery life, optimized EV charging frameworks including energy management and battery degradation models are significant for EV application prospects Some studies also consider battery degradation model as a key aspect to assess the operational costs of the EV battery, and to achieve economy-conscious battery charging management by coupling the battery degradation model indicators which include battery SOC, charging current, terminal voltage, and temperature, and are then applied to capture the nonlinear electrical, thermal, and degradation dynamics of a Li-ion battery [231,232]. The analysis of these studies demonstrates that an optimized EV power management strategy which concurrently accounts for battery degradation model and capacity loss, can effectively deals with the dynamic EV operations and extend its battery lifetime.

6.4.4. V2G services and EV battery degradation

The dynamics of EV have a different impact on the predictive behaviour of the battery degradation models when compared to controlled charging events or the V2G interactions. The impact on battery degradation from delivering V2G services is investigated in a study and found that the battery degradation is most dependent on energy throughput, and is most sensitive to DOD when providing ancillary services [233]. The study also evaluated that the provision of V2G services requires multiple battery pack replacements over EV lifetime. Conversely, a study investigated the impacts of EV battery degradation and the battery life cycle on V2G system [234]. The analysis of various studies shows that the battery degradation models reviewed in this articles, along with several other challenges, has an additional challenge to deal with the V2G aspect of the EVs. However, the combination of battery degradation models and optimal strategies like EV charge/discharge optimization model, frequency regulation, and power peak load levelling helps in enhancing the battery reliability and extending its lifetime.

6.5. Challenges and future directions

Battery degradation model development is vital from a research viewpoint in order to find routes for improvement in battery performance and extending the life of the batteries that are to be used for various applications. Significant improvement has been made in the ML techniques for battery degradation modelling, and SOH and RUL estimation over the last decade. However, the current ML research in SOH/RUL estimation domain has gaps and faces several challenges, in terms of accurate modelling and application to battery health and safety management The challenges and future directions are summarized from the perspective of ML techniques for battery degradation modelling and SOH/RUL estimation and application.

6.5.1. Challenges

Following are the challenges related to ML algorithms in modelling battery degradation and in determining SOH and RUL for a battery:

- ML techniques used in SOH and RUL estimation lack the information of battery aging mechanism.
- ML algorithms lack useful battery pack data for accurate prediction which most real-life applications generate whereas experiments are being done at a cell level.
- The diversity of degradation paths create challenges for accurate ML estimation and prediction. Different aging conditions can present the same capacity at a certain stage and vary significantly in the next stage, which substantiate the necessity to develop a robust model.
- The common parameters of BMS output include voltage, current, and temperature, can be manifested as the input features for ML algorithms. The extraction and estimation of these measured parameters is a significant challenge in comprehensively modelling the battery degradation based on the collected data.
- Prediction capability of algorithms largely varies due to difference in testing conditions and real-life practical conditions of training and testing of algorithms.
- RUL has an explicit threshold, which can be defined with the help of the capacity of the battery. However, the RUL threshold for the battery degradation based parameters is vague, and requires extensive experiments accurate prediction.
- Balancing the model complexity and computational burdens for ML methods based SOH and RUL estimation is another challenge.
- Many of the studies carried out experiments on cells cycling under constant current with fixed ambient temperature [26,223,235]. A few battery degradation are carried out under dynamics driving profiles [21,140,236], which shows the validation of the reviewed ML based SOH and RUL estimation methods for real-world application is insufficient, which is another challenge in this area.

6.5.2. Prospects and future directions

Based on the previous sub-section, there are still wide range of challenges in the ML based research and industrial implementation for battery degradation. To better conduct future studies, we discuss the following critical tasks and potential research directions.

- Detailed degradation mechanism studies at different levels are necessary to comprehensively estimate battery SOH and RUL. Most of the degradation tests are based on single stress factor and are performed at cell-level, which is not favourable for a thorough understanding of the battery degradation involving inconsistency. Therefore, degradation tests at the cell level as well as pack level which include multiple stress factors such as dynamically changing current and temperature need to be conducted.
- Offline development of DDMs which update dynamically to become self-improving models can be used to improve the accuracy and precision. Deep learning ANN methods have been proved to have strong self-learning capability. Use of such self-learning algorithms is recommended for accurate SOH and RUL prediction.
- The estimation of the SOH and RUL and their features extraction under dynamic discharging and controllable charging process is a critical task. Therefore, the ML based estimation method should take all the battery operation features into account. It is quite necessary to conduct further research from the perspective of the effect of data quality and quantity on battery SOH and RUL estimation.
- The development of an appropriate ML-based hybrid model for estimating SOH and RUL while taking into account various model disturbances and uncertainties needs to be studied further.
- BMS should include a platform based on big data, cloud computing, cloud storage and other emerging technologies which can solve the difficulty of data acquisition and improve the accuracy and robustness of onboard algorithms in real-time applications.
- Current battery health management activities may face additional obstacles as a result of the potential of battery failure. As a result, efforts must be made to offer appropriate machine learning-based solutions that take into account the uncertainties in estimation findings and system operations.
- Development of the battery model which is more suitable for parameter characterization of degradation process for which ML based hybrid methods can be new research direction to improve the model performance and accuracy.
- SOH values are frequently used as training data in the construction of degradation models. Such SOH values are regarded accurate in the literature. In a real-world scenario where degradation models are applied onboard and updated online, training data is typically estimated using estimation methods, which can result in some inaccuracy in the estimations, affecting the overall effectiveness of the ML-based degradation model. Therefore, a

good degradation model should be developed with a precise estimation algorithm which is robust when dealing with input data uncertainty.

These recommendations will make a big difference in terms of accurate battery degradation modelling, as well as SOH and RUL estimation. This assessment will give researchers and manufacturers a concrete understanding of how to progress Li-ion battery development in the future, particularly for EV applications.

7. Conclusion

This review article systematically presents state-of-the-art machine learning methods and technologies for battery degradation modelling associated with both SOH and RUL estimation. We present a comprehensive classification and sub-classification of several machine learning algorithms described in the literature, and we investigate these strategies in light of the growing interest in applying them to develop more accurate Li-ion battery degradation models. Specifically, we have classified and summarized all those machine learning approaches based on technical merits, which are directly or indirectly used for battery degradation modelling and accuracy improvement. In particular, the major performance aspects of machine learning approaches such as approach selection, non-linear data handling capability, robustness, and complexity are elaborated in relation with the corresponding battery degradation modelling.

In this study, a comprehensive introduction to battery degradation is given along with the factors and potential causes of model inaccuracy. A clear link between SOH and RUL is established corresponding to battery degradation modelling. A technical framework for SOH and RUL estimation and prediction to model the battery degradation is then developed. Battery degradation modelling and analysis is also described using machine learning methods as they are gaining increased attention for both health estimation and lifetime prediction problems. The need and importance to use machine learning methods for battery degradation modelling are then demonstrated. A separate classification of the several machine learning based Li-ion battery degradation models for SOH estimation and RUL prediction proposed in the literature is then presented along with their corresponding evaluation outcomes. Finally, the article summarizes and compares the characteristics of the existing ML methods in order to find the most suitable adaptive models for Li-ion battery SOH and RUL estimation. It also discusses about the aspects, challenges and future directions related to applicability of ML methods for battery safety, reliability and its life improvement through battery degradation modelling.

In summary, the identification and development of the self-adaptive modelling approaches in the field of battery aging modelling is still in its early stages, and their use for industrial use may be limited, so additional research and development is needed before these models gain true commercial acceptance. In the perspective of machine learning, this article only introduces the SOH and RUL prediction research status. The SOH and RUL prediction methods can also be discussed in further depth, as well as the contrasts between them. More study may be done utilizing real-world applications to evaluate current battery degradation modelling methodologies. Reduced laboratory battery testing labours, improved forecast accuracy, and model adaptability can all be enhanced by battery degradation modelling methodologies combined with more extensive validation. Certain recommendations are made with the goal of advancing the state-of-the-art by suggesting practical techniques to construct self-adaptive Li-ion battery aging models.

The battery health management system has the potential to be revolutionised by machine learning techniques, which are supported by a platform of open-source tools and data sharing. Further study into enhancing these SOH and RUL estimation approaches for Li-ion batteries would aid in achieving sustainability, particularly in the EV sector. The rise of the electric vehicle market, which uses Li-ion batteries, as well as improved production and recycling methods, would benefit the global environment by lowering GHG emissions. Through this paper, the authors hope that anyone interested in ML based battery degradation modelling can benefit from this work. Engineers can choose appropriate ML methods to estimate the better SOH and RUL according to the certain requirements. Researchers can get inspirations to further improve these methods. We also hope that this review will be a beneficial source to aid the design and operation of battery health estimation, and remaining life prediction systems, whilst apprising about the aspects related to battery reliability and life improvement to research community, simultaneously.

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.

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