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Chemometric Models and Electrochemical Techniques for Studying the Health of Li-Ion Batteries: A Review

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This study presents a thorough analysis of machine learning techniques utilized for monitoring the health and predicting the remaining useful life (RUL) of lithium-ion batteries, which is essential for optimizing the performance of electric vehicles (EVs). Given the challenges faced by lithium-ion batteries, such as capacity fading and environmental factors, key indicators like State of Health (SOH) and RUL become vital. The paper reviews several adaptive machine learning methodologies, including Support Vector Regression (SVR), Gaussian Process Regression (GPR), and hybrid neural networks that integrate convolutional neural networks (CNNs) with long short-term memory (LSTM) algorithms. Special emphasis is placed on these models' effectiveness in addressing the complex nonlinear behaviors associated with battery aging. Moreover, innovative approaches like fuzzy logic systems are examined, showcasing their potential to enhance SOH estimation via adaptable rule-based techniques. The manuscript stresses the necessity of integrating multiple methodologies to enhance predictive accuracy and reliability. By compiling empirical studies, the work aims to elucidate the capabilities of these algorithms, thereby enriching the knowledge base within battery management systems. Ultimately, this research aims to drive advancements in efficient energy storage solutions, which are crucial for the sustainable development of electric mobility.
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The rapid widespread of the electric transportation market is dependent on driving range of electric vehicles (EVs), their reliability and safety as well as the driving power management systems. Energy storage/supply systems (ESS) are key constituent elements for both electric vehicles and hybrid electric vehicles (HEVs).[1] Among ESS for EVs and HEVs, rechargeable battery systems are marginalizing any competitive technology thanks to their ability to easily supply energy in a wide variety of power regimes.[2] Lithium-ion batteries (LIBs) have been widely used in electronic devices, electric vehicles and power devices thanks to their excellent functional properties such as high energy density, long cycle life (3000 cycles at 80% depth of discharge), lack of environmental fingerprint under use (e.g. no CO_2 emissions), no memory effect, small specific weight, good safety and small internal resistance.[3–5] LIBs are currently the dominating technology used in ESS for EVCs and HEVs.

It is a matter of fact that extended, frequent or abuse use of battery-powered devices inevitably shorten the battery calendar life.[6] In fact, as the number of charge/discharge cycles of a LIB increases, the capacity of the device gradually decreases, ending to its expiration driven by the settings of the battery management system (BMS).[7] In this respect the design of an appropriate BMS is crucial to optimise the battery performance, extend their useful life thus reducing costs and increasing vehicle utilization efficiency and security.[8,9] One of the major tasks of the BMS is to evaluate the so-called health state of the battery as it degrades over time. This degradation is due to irreversible electrochemical and chemical processes occurring inside each cell as well as at pack level.[10] Advanced sensing and monitoring technologies are needed to predict and control battery functionality, as well as to identify, and further avoid, detrimental phenomena that can damage the battery health state.

Battery health issues can be categorized at two different levels: system level and cell level. System level health issues affect the entire ESS and are mainly originated by the variable dynamic operation conditions as these reverberates on all the pack constituents. Cell level health issues target one or few electrochemical cells and originates from abuse utilization of the EES or by manufacture inhomogeneities within the battery pack.

Battery health diagnosis is not a novel field of research and addresses two critical issues:

- Prognostic estimation of the battery behaviour and internal characteristics, all strongly interplayed with the dynamic environmental conditions.
- Safety and hazard monitoring upon utilization, both strongly interplayed with the dynamic battery utilization conditions.[11]

The so-called battery prognostic and health management (PHM) is an advanced solution that has emerged to optimize battery maintenance and ensure that the device can satisfy its application's power and energy demand. PHM aims to determine the present and to forecast the future health state of the EES based on real-time analysis of significant functional parameters of the device as well as environmental ones. Developing a PHM methodology reduces the critical failure and maintenance cost and increases the reliability of the battery systems.[12] Its efficacy requires the integration and processing in a suitable analytical prognostic model of a variety of stress factors (temperature, depth of discharge, current rate, state of charge,…) affecting the battery upon utilization.[13,14]

Generally speaking, battery PHM includes three critical components: (i) condition monitoring and data acquisition (CMDA), (ii) health diagnosis (state-of-health, SOH) and (iii) health prognosis.[15] CMDA implies the observation of battery states through the record of critical device parameters. Typically, voltage, current, temperature and resistance are the most common parameters used by most researchers in battery PHM.[16–20] On the other hand the battery health diagnosis cannot be easily and directly evaluated: typically, it is inferred from a quantitative parameter,i.e. the battery SOH, that is estimated from a variety of battery health indicators (HIs). Overall, the accurate monitoring of SOH as well as the prediction of the remaining useful life (RUL, related to the health prognosis) of the battery is a key point of the PHM model to ensure EVs' safe and reliable operations.[6,21] HIs are the quantitative and measurable quantities related to the utilization of a battery that display a predictable degradation trend through the device calendar life:[22]

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these can be direct or indirect and are all extracted from the battery performance variables.[23]

As already mentioned SOH and RUL are the most vital parameters of Li-ion batteries to evaluate the battery health conditions and predict its future performance.[24] In fact both parameters can be implemented in a battery degradation model embedded in the PHM protocol that is able to (a) trace the present (and past) performance, (b) estimate the current energy storage capacity, and (c) describe the extent of degradation and aging.[25] Recent summaries about SOH and RUL estimation models can be found in refs[4,19,26] and in refs,[27,28] respectively.

Going beyond the classical integration of battery functional parameters to estimate SOH and RUL,[4,19,29–31] recently machine learning (ML) algorithms have been proposed for battery health estimation.[12,32–34]

ML concerns learning patterns from data to build a model or to generate a set of rules that could be used to understand the characteristics of a system or applicable to new data, e.g., in order to predict one or more properties of interest.[35–37] For any ML approach, it is crucial to clearly define what the inputs and output(s) to the algorithms are.[38] Several review papers have been published in recent years that have discussed the influence of ML on the determination of energy storage devices‘ (ESDs) characteristics.[39–42] For instance, Zhang et al.[42] presented the advancements in prognostics and health management techniques by employing deep learning (DL). They introduced various models of DL and reviewed the applications of DL to detect dominant challenges in this field. Chen et al.[41] evaluated the application of ML to ESDs, such as batteries, thermoelectric, etc., and presented a ML framework for these devices.

This review aims to analyse the current state-of-the-art ML-based battery degradation models and the most common experimental methods used for an accurate estimate of the battery SOH and RUL using ML. This review article is divided into 5 Sections: the first section is a general introduction whereas in the second one the fundamental parameters and models are discussed. The third section describes the experimental techniques to estimate SOH and in the fourth one the model-based techniques are discussed. The final section lays out the conclusions of this review.

SOH and RUL as Meters of Battery Degradation

The degradation of a battery health quantitatively reflects in a deterioration of the battery performance, especially the capacity, energy and power. SOH and RUL are the most important and crucial synthetic descriptors to model and follow the Li-ion battery degradation.[24] Generally, SOH and RUL are biunivocally related to the usable capacity, available energy and power, which degrades with the battery aging.[43] With the increasing demand for Li-ion batteries, the SOH estimation plays an vital part in battery RUL prognostics as a capacity indicator.[34] Figure 1 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 are the prerequisite to predict 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 therefore the RUL.[19]

Estimation of SOH.—The commercialization of electric and hybrid vehicles leads to an increasing demand for long lifetime batteries. Knowing the SOH can be used to recognize an ongoing or a sudden degradation of the battery cells and to prevent a possible failure of the electric system and, accordingly, the vehicle. Even though the importance of the SOH is high, still does not exist a consensus in the industry or in the scientific community on what SOH is and how should be determined. It is a parameter that reflects the present condition of the battery cell described in percentage, being the 100% a fresh cell.

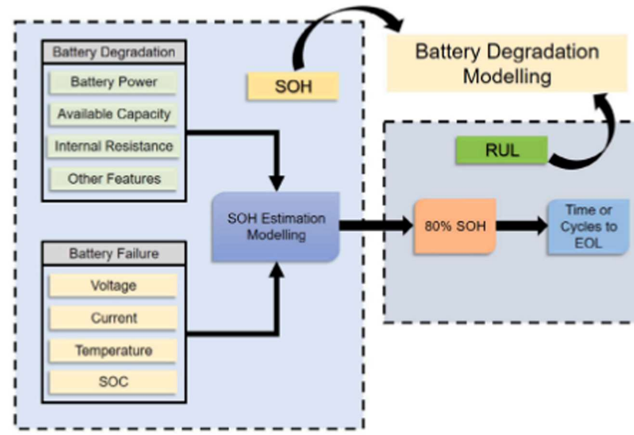

Figure 1. Relationship between SOH, RUL and battery degradation modelling. Reproduced with permission from Ref. 19.

Qualitatively when the capacity of a battery is decreased until 80% of the initial value, it is considered not usable for an electric vehicle and requires a replacement.[44–46] However, Li-ion batteries are complex systems to understand, and the processes of their ageing are even more complicated. Capacity decrease and power fading do not originate from one single cause, but from several various processes and their interactions. Moreover, most of these processes cannot be studied independently and occur at similar timescales, complicating the investigation of ageing mechanisms. Ageing mechanisms occurring at anodes and cathodes differ significantly. It is studied that dominant ageing mechanisms on anodes are caused by Solid Electrolyte Interface (SEI) formation which causes a significant increase of the impedance. This effect occurs mainly in the beginning of cycle life.[4,47]

SOH can be defined as the status of battery health to supply specific power and energy compared with its ability to deliver power when it was in an initial state.

One possible mathematical evaluator for SOH is the ratio between the capacity at the general cycle k (Q_k) and nominal capacity (Q_n), as shown in the following equation:[17,19,48]

$$SOH = \frac{Q_k}{Q_n} \tag{1}$$

In general, charge capacity fading of positive active material can be originated from these three basic principles: structural changes during cycling, chemical decomposition or dissolution reaction and surface modifications. Other effects that occur in batteries can also cause an increment in the impedance, like: loss of contact between the inactive components, metal dissolution or electrolyte decomposition.[49]

It important to recall that any battery degradation mode includes an internal resistance parameter, which also used to define the SOH for battery cells and packs. An internal resistance increase may directly lead to the battery power fade and decreases with capacity. As the Li-ion batteries start degrading due to the degradation of the active material, the internal resistance starts increasing and the capacity starts decreasing with time.[50] 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, another possible quantitative evaluator of SOH is given by the following equation:[51]

$$SOH = \frac{R_{eol} - R}{R_{eol} - R_{new}} \quad [2]$$

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.

These two equations (i.e. capacity and internal resistance) are both used to quantify the battery SOH and identify the process of battery degradation.[52]

The determination of the SOH can be done by two mainly different approaches: experimental and adaptive methods.[53,54] Another method that it is used to estimate the SOH is the data-driven approach's family.[24] Experimental methods store the cycling data history of the battery. With it and a previously gained knowledge about the influence of the main parameters affecting the battery lifetime, an estimation of the SOH can be performed. This approach requires a good insight in the interrelation of operation and degradation of the battery cell, either gained by physical analysis or the evaluation of large data sets of operation history in connection with SOH tests of the battery cell. Adaptive methods determine the SOH through calculation from parameters that are sensitive to the degradation of the battery cell. This necessary data must be measurable or should be examined throughout the operation of the battery. This possibility gives the advantage of not needing many tests and simulations of the battery behaviour. It will ensure a better adaptability on different battery types and chemistries, but they also play with the drawback of having a high computational load, which complicates the online running of the model on a real application.[4] To have a clear view of the principal differences between the experimental and adaptive methods was developed Table I.

Therefore, methods for the determination of the state of health of the battery cells are investigated through the determining of the available capacity and the internal resistance of the battery cells. To understand the performance of each method in a better way, following the just mentioned classification some methods will be explained in a deeper way. These lists of methods, which can be found in literature, are classified in Fig. 2.

Relationship of RUL with device degradation.—RUL predicts the remaining time or number of cycles of battery until the SOH of the battery reaches to end of life (EOL).[55] The EOL is the time and the number of charge–discharge cycles when the battery holds out the failure limit. RUL is indicated by the following formula:

$$RUL_N = C_N - C_{EOL} \quad [3]$$

Where C_N is the present cycle, and C_{EOL} is the cycle at the end of life. The mechanism of degradation and RUL estimation correlate closely to the operating state and reliability of the Li-ion battery. 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. However, there is no universal model which is known as the best model to estimate RUL due to data unavailability, model complexity, and system restrictions.[28] The study of Lipu et al.[24] splits the RUL methodologies into four categories such as adaptive filter techniques, intelligent techniques, stochastic techniques and others, as shown in Fig. 3.

There is a strong relatedness between RUL and battery degradation, since the distinctive features required to model the battery degradation are like that can be used for RUL prediction. Liu et al.[56] devised the battery degradation model and estimated the RUL simultaneously using operating parameters of Li-ion batteries. 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.[57,58]

Experimental Techniques to Estimate SOH

The most useful and simplest method to monitoring battery life is through the measurements of battery voltage, current, capacity and temperature. The incremental capacity (IC) curves are another important feature which have a strong correlation to the battery SOH.[59] Weng et al.[60] predicted the battery SOH from the changes of the IC peaks. The applicability of the knowledge to different chemistries, cell designs, or operating conditions is limited since that experimental are empirical results.

Voltage profiles.—The charging process of LIBs includes two proceedings: constant-current (CC) charging and constant voltage (CV) charging. The terminal voltage curves with different cycles in constant current charging mode are shown in Fig. 4. For example, before 400 s, the voltage curve of a battery with more cycle cycles has a greater slope than a battery with fewer cycle cycles. In addition, the slope of the terminal voltage curve changes more rapidly when the battery health deteriorates. In summary, the battery terminal voltage curve of the constant-current charging process can reflect the SOH of the battery. Due to the long duration of the constantcurrent charging cycle, the voltage sampling interval is divided into 200s–500 s of charging time considering the time cost of data acquisition. Thousands of voltage points can be measured in the sampling interval, which means that it is impractical to use all these voltage data to estimate the SOH in practice. Therefore, typical features need to be extracted from a certain number of terminal voltage samples as the input to the machine learning algorithm Lin et al.[17] paper. The authors of Ref. 17 for his study have used a benchmark dataset from Ref. 61.

Impedance measurements.—Other way of determining the SOH is by estimating the actual value of the impedance. For reaching this purpose Electrochemical Impedance Spectroscopy (EIS) is used. For example, in several documents like in Refs. 62, 63 they focus on the non-destructive measurement of a battery's internal impedance as a function of frequency. Since battery impedance increases with ageing and different battery dynamics tend to affect different frequency ranges on the EIS measurement, impedance spectroscopy can be used as a diagnostic tool. At high frequencies, inductive effects in the battery wiring and porous structure are prominent. In

Table I. Differences between experimental techniques and adaptive methods.[4,49,54] Reproduced with permission from Ref. 4.

	SOH estimation	
	Experimental techniques	Adaptive methods
Based on	Storing the lifetime data and the use of the previous knowledge of the operation performance of the cell/battery.	Calculation of the parameters, which are sensitive to the degradation in a cell//battery.
Advantages	1. Low computational effort	1. High accuracy
	2. Possible implementation in a BMS	2. Possible to be used as in situ estimation
Drawbacks	1. Low accuracy	1. High computational effort
	2. Not suited for situ estimation	2. Difficult in BMS implementation

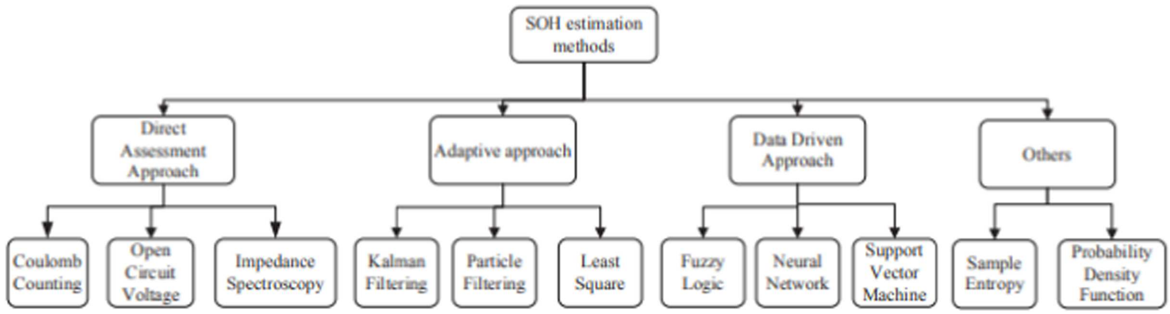

Figure 2. Classification of SOH estimation methods. Reproduced with permission from Ref. 24.

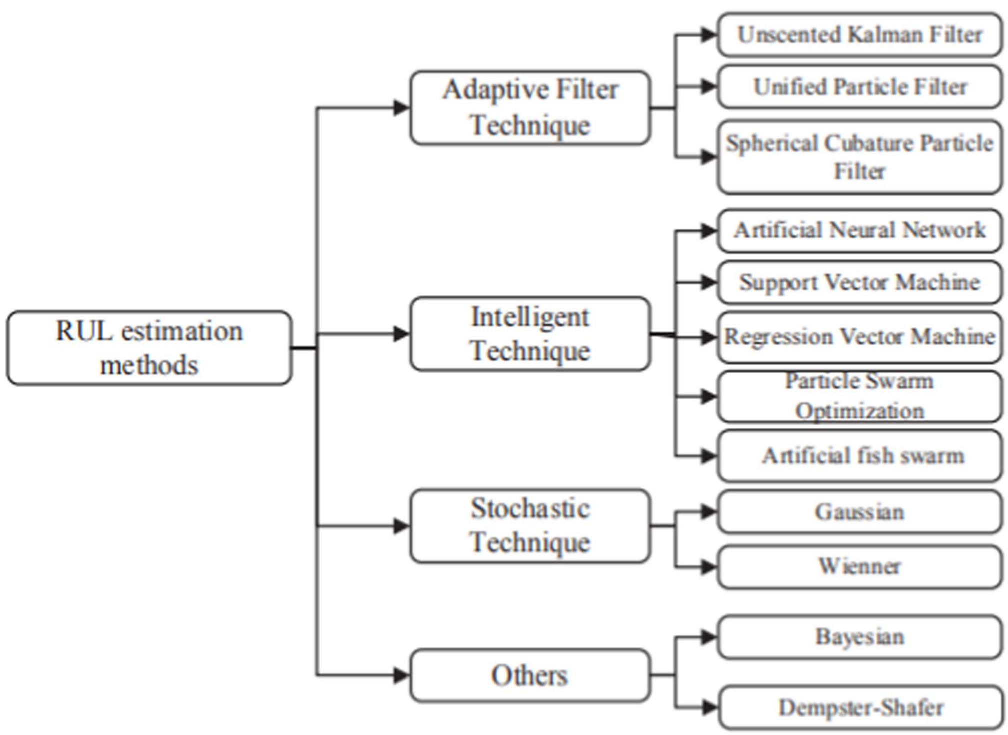

Figure 3. The RUL estimation methods for lithium-ion battery. Reproduced with permission from Ref. 24.

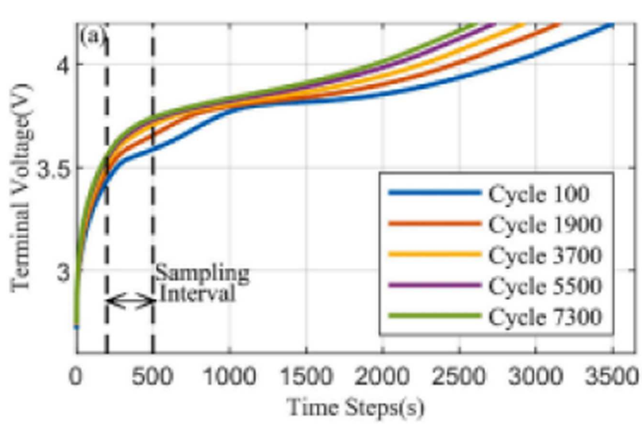

Figure 4. The terminal voltage curves of a single cell in constant-current charging mode. Reproduced with permission from Ref. 17.

addition, impedance becomes purely ohmic as frequency decreases. At lower frequencies, capacitive effects become important.[64] Due to this highly valuable information and to base the SOH estimation on this EIS measurement, equivalent circuit models have been developed to estimate the SOH of a battery in the most simple and accurate way. The fact that the large battery currents used in applications such as electrified vehicles, tend to excite complex dynamics that equivalent circuit models typically do not capture, makes this estimation method stronger.[65] The type of experimental Li-ion battery that was used from Chen et al.[64] is LR1865SK (Tianjin Lishen, China), and its nominal capacity is 2600 mAh. In Fig. 5 is shown the schedules of the cycling aging test that Chen et al. have performed.

The EIS test is performed after the characteristic test and 4 h' rest, and the frequency range is 0.01 Hz–1 kHz. Eight of the EIS curves of each battery are selected. During the aging process, the EIS curves generally showed a tendency to move to the upper right of the Nyquist plane, except for SK14. The radius of the small circle hardly changed while the radius of large circle increased. The intersection of the EIS curve and the *x*-axis of the Nyquist plot indicates the ohmic resistance of the cell. The results show that the ohmic resistance of the four cells increases during aging. The small arc in the EIS curve indicates the resistance of the solid electrolyte interphase (SEI) film on the electrode surface. The radius of the small arc remains constant, indicating that the SEI film is stable. The large arc is related to charge transfer, and the increase in arc radius indicates that the charge transfer resistance may be greater.

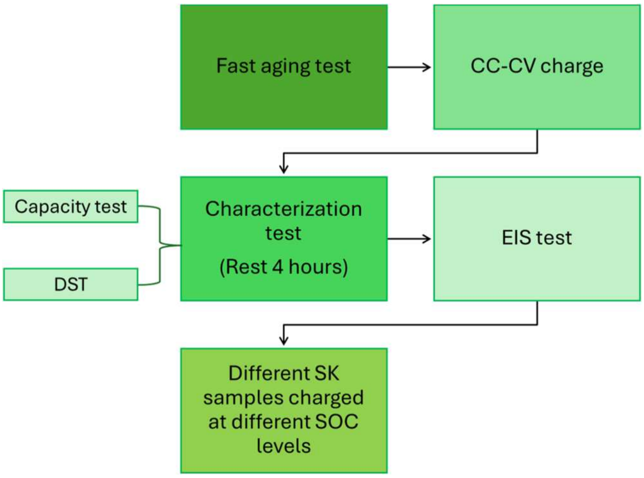

Figure 5. Schedules of the cycling test and EIS test proposed by Ref. 64.

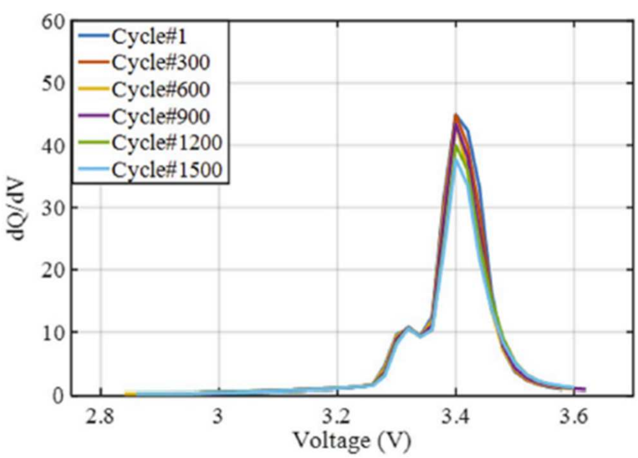

Figure 6. The complete IC curves. Reproduced with permission from Ref. 66.

Incremental capacity analysis (ICA).—In recent years, Incremental Capacity (IC) features are widely used to describe the battery aging process as shown in the Fig. 6. The voltage plateaus on the voltage curves can be transformed into easily recognizable peaks on the IC curves through differentiating the charged capacity relative to its terminal voltage under the CC protocol. The charged capacity and corresponding voltage should be precisely acquired beforehand, which can be calculated from

$$Q = I \ * \ t \tag{4}$$

where C is the capacity, I and t are the charging current and time respectively.[66] IC can describe the phase change characteristics of the battery during the lithium-ion active material insertion and delamination. Due to these advantages, IC analysis is considered as one of the critical techniques with great potential for studying the aging mechanism of batteries.[67] In constant current charging mode, the IC is calculated as:

$$IC = \frac{dQ}{dV} = I\frac{dt}{dV} \tag{5}$$

where Q is the capacity, V is the voltage, t is the sampling time, and I is the charging current.[17]

As the number of cycles increases, the IC peaks' curve both moves by lower potential values and the area underneath decreases, that is shown in Fig. 7.[66]

The peak of the IC curve (PICC) gradually decreases with a clear trend. The peak in the IC curve has a unique shape, height, and location, which reflects the electrochemical reactions during the charging and discharging of batteries. The decrease in PICC may be related to the loss of active materials in lithium-ion batteries. With the cycling number increasing, the active material can no longer be embedded in the lithium and these internal changes have a significant impact on the PICC. Therefore, PICC is a valuable feature to describe the degradation of battery capacity.[68–70]

Improved ICA.—ICA is a preferred method for estimating the SOH of lithium-ion batteries. IC curves contain abundant features that can characterize essential information about the aging mechanism and SOH of the battery.[71] However, the standard ICA is limited by the sampling mechanism and storage capacity of the devices; hence, it has low resolution and accuracy in the initial and termination stages of discharge, where the voltage changes sharply, and it is vulnerable to noise perturbations in the measurement data. To bridled these problems, Li et al.[68] proposed an improved version of ICA by adopting interpolation and smoothing.

The original IC curve, i.e., dQ/dV–V, can be obtained by differentiating the Q–V curve. This operation can be approximated as follows:

$$\left.\frac{dQ}{dV}\right|_k \approx \frac{\Delta Q_k}{\Delta V_k} = \frac{Q_k - Q_{k-1}}{V_k - V_{k-1}} \tag{6}$$

where Q is the instantaneous discharge capacity and V is the instantaneous discharge voltage. According to the definition of the formula, the voltage and capacity data should be strictly monotonic. Before performing differentiation, the raw voltage and capacity data must be interpolated to increase the data points for high calculation accuracy. Moreover, after performing differentiation, the generated IC curves must be further denoised using the filtering method to achieve smoothness. In the study of Li et al.,[72] a new interpolation algorithm and the Savitzky–Golay filter were employed to interpolate the raw data and smooth the IC curves, respectively. The discharge capacity Q can be calculated using the Ah counting method:

$$Q(k) = \sum_{j=0}^{k} I(j) * \Delta T \tag{7}$$

where I is the instantaneous discharge current and ΔT is the sampling time interval. The IC curve represents the rate of change of the capacity with the voltage during the charge and discharge process. Consequently, the internal health state of the battery can be determined by extracting the features of the curve for modelling.[73]

Internal resistance measurements.—The life evolution of a battery is determined by its capacity loss and the increment of its internal resistance. Due to this reason several authors have made their research in order to measure the internal resistance of a battery cell.[74] When measuring the resistance, current pulses are applied. The resistance is described in[75] and shown in Eq. 7 following the Ohm's law:

$$R = \frac{\Delta I}{\Delta V} \tag{8}$$

where corresponds to the voltage drop and refers to the applied current pulse at 1 C. This way, the current/voltage changes is evaluated, and the internal resistance is calculated depending on the state of charge (SOC) and temperature (T). In the work of Xiong et al.,[75] there is also explained a way to calculate the polarization resistance of electrical vehicles using discharge curves. Making a comparison between the discharge curves at different currents, and the same curves but recalculated to the 1 C discharge curve, an

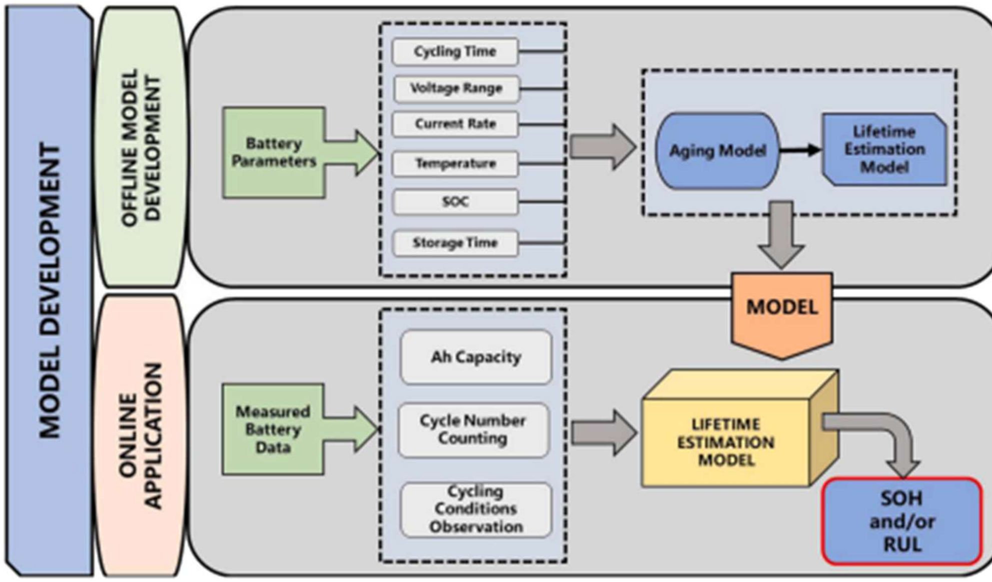

Figure 7. Conceptual diagram for ML based battery lifetime estimation, and degradation model. Reproduced with permission from Ref. 19.

additional voltage drop appears which determines the polarization resistance. A significant number of curves are needed previously to be able to calculate the resistance on board. The author in Ref. 76 uses the same pulses methodology to estimate the internal resistance, but by applying different timing pulses: 10 ms, 2 s and 30 s of the current pulse. The degradation is also studied when taking into consideration different parameters like Depth of Discharge (DOD), temperature or SOC. It is concluded that the SOC seems to be completely independent from the growth of the resistance. Several works uses the current pulses in order to check the evolution of the resistance, applying different timing or current rate pulses.[77,78] Another technique to measure the internal resistance is the Joule effect. The losses produced by this effect makes changes in the temperature of the cell. In order to follow this evolution a calorimeter needs to be used.[79] In Ref. 80 an evaluation of large-capacity 40 Ah and 80 Ah Li-ion cells developed for industrial use is done. Their performances show that the cells exhibit reduced voltage characteristics and increased IR in degraded conditions.

Destructive methods.—Classical methods used to study the SOH may require the destruction of the cell, disabling any further use of the cell.

- Raman Spectroscopy.[81–83]
- X-ray Diffraction.[84]
- Scanning Electron Microscope (SEM).[85,86]
- X-ray Photoelectron Spectroscopy (XPS).[87–90]
- Scanning Transmission Electron Microscope (STEM).[91]
- Cyclic Voltammetry.[92]
- Auger Electron Spectroscopy (AES).[93,94]
- Atomic Force Microscopy (AFM)[95,96]

Machine Learning Approaches for Lithium-Ion Batteries

Characterizing and simulating battery degradation mechanisms is a complex and challenging task. Estimating the State of Health (SOH) and Remaining Useful Life (RUL) of a battery typically spans multiple charge/discharge cycles, introducing two critical timeframes that make accurate prediction particularly difficult. From a data processing perspective, assessing a battery's health status involves defining a mathematical model that links input variables—representing the battery's current state—to one or more output variables that serve as indicators of future performance. In this context, data-driven modeling[97] using flexible machine learning techniques offers a promising approach. These methods enable predictions without the need to assume any predefined statistical or probabilistic distributions, or specific chemical or physical laws. Instead, the functional relationship between input and output variables is learned directly from available data by adjusting the model parameters.

In the remainder of this section, the machine learning algorithms which have been most frequently used so far for the estimation of the state of health of lithium-ion batteries will be described, not only in terms of their theory, but also in terms of the accuracy, generalizability, speed, reliability, and completeness of the corresponding models.[97–101]

- Accuracy: The accuracy of a model indicates its ability to correctly predict the SOH of a battery. Models with higher accuracy provide accurate and reliable results which can be used to make informed decisions. The use of feature selection and a proper hyperparameter tuning are possible ways of improving accuracy.
- Generalizability: Generalizability measures the ability of a model to accurately predict the SOH of a battery in a real-world application environment. A model with high generalizability can be used in different environments without its accuracy being compromised.
- Speed: The speed of a model indicates the time taken for it to predict the SOH of a battery. The faster the model, the easier it is to deploy in real-world applications.
- Reliability: The reliability of a model indicates its ability to consistently provide accurate results. Models with higher reliability can be trusted to provide accurate results which can be used to make decisions.
- Completeness: The completeness of a model indicates its ability to include all relevant information for predicting the SOH of a battery. Models with higher completeness can provide richer information which can be used to make better decisions.

With the rapid development of technology, machine learning has made breakthrough progress in many fields.

Machine learning for studying the SOH and RUL.—Data-driven approaches for the evaluation of the degradation state of Li-ion batteries and for the estimation of their SOH have recently gained a lot of attention. These methods are advantageous as they do not explicitly rely on the knowledge of the underlying chemistry of the battery, instead being capable of learning the behaviour of the battery from historical or monitored data. Machine learning algorithms such as artificial neural networks (ANNs), support vector machines (SVMs), and relevance vector machines (RVMs), as well as other intelligent algorithms, have been used to extrapolate the estimated SOH and map the relationship between battery degradation, health indicators, and battery SOH by learning from a historical database. SOH and RUL are calculated by ML methods through the collection and analysis of data throughout battery operation. This has the benefit of not needing extensive battery behaviour tests and simulations and it is able to be adapted to various features and battery types. However, ML techniques have a downside of requiring high-end computation, making online model operation on real-world applications like electric vehicles (EVs) more complex. Despite this drawback, machine learning has emerged as a powerful tool for investigating battery degradation, and many studies have been conducted to estimate SOH using various machine learning methods such as non-linear regressions, SVM, Bayesian methods, neural networks, Gaussian processes and fuzzy logic.[102–134] In particular, Long et al.[124] developed an autoregressive model based on capacity degradation trend. Liu et al.[125] proposed an incremental learning optimized relevance vector machine (RVM) algorithm for RUL estimation. Ma et al.[126] utilized the false nearest neighbours (FNN) to calculate the sliding window sizes required for prediction and integrated the advantages of convolutional neural network and long short-term memory (LSTM) to design a hybrid neural network (HNN) for model training and prediction. Richardson et al.[127] adopted a Gaussian Process Regression (GPR), which was applied to make predictions on short-term and long-term cycle data sets of batteries for predicting SOH. Ma et al.[128] introduced the idea of broad learning (BL) and developed BL-Extreme Learning Machine (BL-ELM). Furthermore, these techniques have been used in a variety of applications such as predicting battery lifetime,[129] identifying potential causes of degradation, and providing insights into the health of the battery.[130] Machine learning has been used to identify patterns in battery data, allowing researchers to gain a better understanding of the degradation process.[131] Machine Learning algorithms have been used to identify signs of imminent failure and to detect degradation trends. In addition, machine learning can be used to develop predictive models to forecast battery performance and to detect anomalies in the data.[132] Overall, machine learning can be a valuable tool for battery degradation studies and can provide researchers with valuable insights into the behaviour of batteries over time.[133]

Based on these considerations, the following sub-sections describe, in detail, the most commonly used machine learning techniques for the estimation of the SOH through the development of battery degradation models.

Support vector machines (SVM).—Support Vector Machines are a supervised learning (SL) technique that has proved to be particularly effective for addressing large-scale data classification challenges.[135] The popularity of SVM is largely due to the fact that, although originally developed as a linear binary classification tool, through a suitable data transformation (projection onto a higher-dimensional feature space, where the problem becomes linearly separable), they are capable of handling complex nonlinear patterns.[136] In particular, the non-linear transformation is implemented through the choice of a suitable kernel, which represents an inner product in the resulting higher-dimensional feature space. (see the Figure 8) The possibility of formulating the model in terms of inner products between (a part of) the training data and the input vector of the individual to be predicted constitutes the basis of the so-called "kernel trick": rather than defining what the optimal non-linear transformation of the data to the feature space could be, one directly hypothesizes the inner product in the transformed space and this is accomplished through a non-linear function (the kernel) with adjustable meta-parameters, which enhance the model's adaptability. Examples of commonly used kernels include the polynomial one:

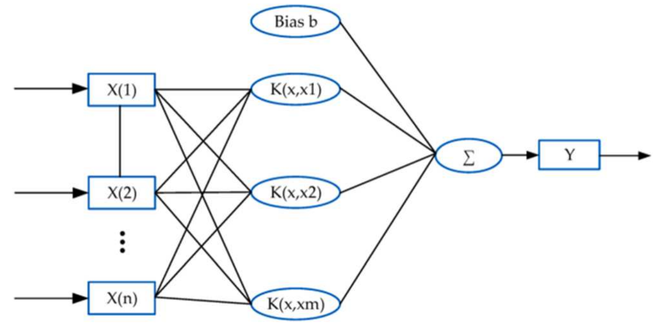

Figure 8. Schematic structure of SVM. Reproduced with permission from Ref. 110.

$$K(\boldsymbol{x}_i, \boldsymbol{x}_j) = (1 + \boldsymbol{x}_i^T \boldsymbol{x}_j)^p \quad [9]$$

and the Gaussian one:

$$K(\boldsymbol{x}_i, \boldsymbol{x}_j) = \exp\left(-\frac{\|\boldsymbol{x}_i - \boldsymbol{x}_j\|^2}{2\sigma^2}\right) \quad [10]$$

where $\boldsymbol{x}_i$ and $\boldsymbol{x}_j$ are two generic input vectors and the polynomial order p and the Gaussian width σ represent the meta-parameters which can be tuned to achieve the desired degree of non-linearity. Accordingly, by calling y the response to be predicted, the SVM classification model can be defined as:[134]

$$y(\boldsymbol{x}) = \sum_{j=1}^{N} \omega_j K(\boldsymbol{x}, \boldsymbol{x}_j) \quad [11]$$

where $\boldsymbol{x}_j$ and $\boldsymbol{x}$ are the input vectors of the jth training sample and of the individual to be predicted, respectively, N is the number of training samples and ω_j is the weight determining the contribution of the jth training sample to the classification output. Moreover, another desirable property is that, even with very huge data sets, the model relies only on a limited subset of training data (the so-called support vectors) which are the ones closest to the decision boundary, and are the only ones having a weight different from zero in Eq. 11.[135]

In order to ensure the flatness of the function, a small ω is required, and this can be discovered by minimizing the norm $\|\omega^2\|$. In addition, slack variables are introduced in case the optimization problem cannot be solved. When Support Vector Machines (SVM) are applied to regression tasks such as battery State of Health (SOH) and Remaining Useful Life (RUL) estimation, the method is referred to as Support Vector Regression (SVR).[137] SVR is particularly well-suited for nonlinear regression problems. It operates in high-dimensional feature spaces using linear quadratic programming techniques, enabling it to deliver optimal regression performance.[138] In addition to traditional SVM methods, numerous studies have sought to enhance SVM performance through hybrid approaches. For instance, Dong et al.[139] developed a novel technique by integrating SVM with the adaptive Particle Filter (PF) algorithm. Similarly, Chen et al.[140] proposed a fixed-size Least Squares SVM (LS-SVM) model based on arbitrary entropy for SOH estimation. The logic structure of the SVM model, as illustrated in Fig. 9, outlines the workflow beginning with data collection—where training data must include both input and output variables—and progressing to model training and prediction.

SVM-based methods have been extensively applied to RUL prediction. Wang et al.[141] proposed an iterative multi-step SVR model for improved RUL forecasting. Klass et al. validated an RUL estimation approach using SVM models and virtual standard performance tests, incorporating battery data and EV current profiles

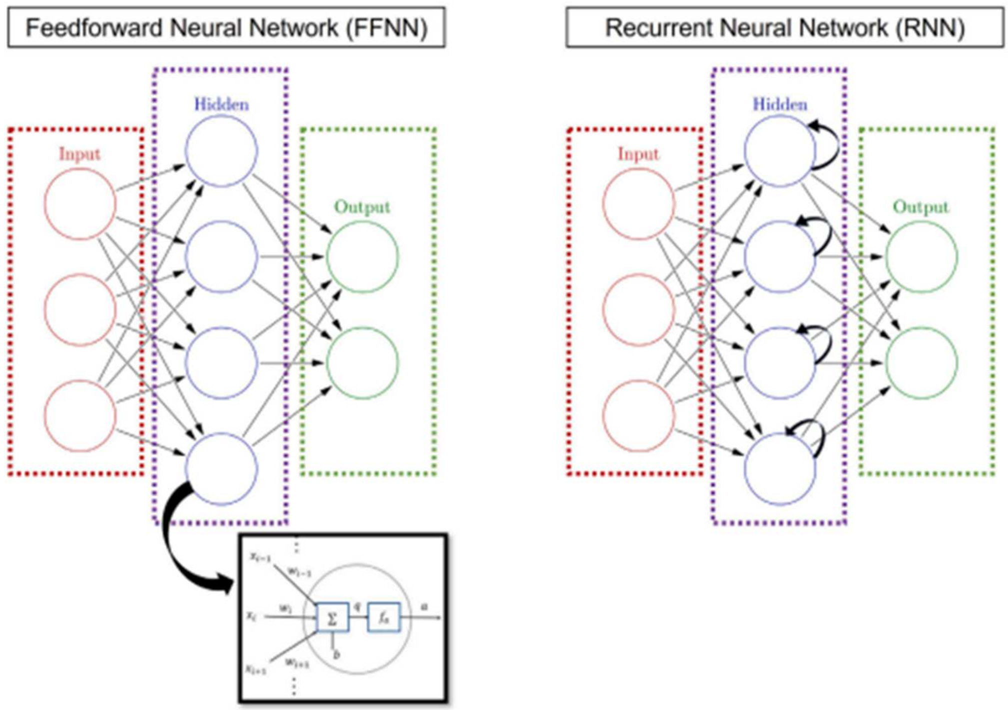

Figure 9. Visual representation of FNN and RNN, each circle is a neuron. Reproduced with permission from.[19]

from experimental setups.[142] Patil et al. introduced an innovative approach that combines both classification and regression capabilities of SVM for real-time RUL prediction in lithium-ion batteries. Their model analyzes voltage and temperature profiles from Li-ion battery cycling under various operating conditions, extracting key features. The approach successfully provides accurate RUL estimations, especially as the battery nears its end of life (EOL).[143] Other hybrid methods also exist. Pattipati et al.[144] advanced the capabilities of Support Vector Machines (SVM) by integrating them with a Hidden Markov Model (HMM), which significantly improved the predictions of Remaining Useful Life (RUL) for batteries. This hybrid model capitalizes on the established linear relationship between a battery's resistance and its remaining capacity, enabling the SVM to deliver more accurate forecasts regarding capacity degradation over time. Such enhancements demonstrate the utility of combining traditional predictive models with probabilistic frameworks to refine battery health assessments. Gao et al. proposed a particle swarm optimization-enhanced multi-kernel SVM (MSVM) model, combining polynomial and radial basis kernel functions for accurate RUL estimation.[145] Their method proved effective in identifying health indicators with minimal input parameters. While SVM-based approaches demonstrate strong performance in battery RUL estimation, a crucial aspect of prognostics remains not only predicting future values accurately but also quantifying the uncertainty associated with those predictions.

Gaussian process regression (GPR).—Regression techniques are commonly applied in battery health estimation, as they can enhance existing mathematical models and offer strong potential for developing accurate battery degradation predictions. Among them, Gaussian Process Regression (GPR) is particularly effective for tackling complex battery aging problems. Its non-parametric nature allows it to flexibly model nonlinear relationships while also providing direct estimates of uncertainty in the predictions.[146]

GPR predicts system behavior by modeling it through a combination of Gaussian processes, where any finite set of variables follows a joint Gaussian distribution.[147] The predicted SOH distribution is given by the following equations:

$$m(x) = E(f(x)) \quad [10a]$$

$$k_f(x_i, x_j) = E[(f(x_i) - m(x_i))(f(x_j) - m(x_j))] \quad [11a]$$

Here, $f(x)$ represents a random variable corresponding to the value at input x, with $m(x)$ as the mean function and $k_f(x_i, x_j)$ as the covariance or kernel function. The kernel captures the similarity between input points, which significantly affects GPR performance.[148,149] Zhang et al.[150] applied GPR with optimized covariance functions to estimate battery capacity across later cycles, using hyperparameters learned from training data. Deng et al.[151] compared several data-driven techniques—Linear Regression (LR), Support Vector Machines (SVM), Relevance Vector Machines (RVM), and GPR—for battery SOH estimation. They introduced a novel health indicator (HI) extraction method and evaluated the approaches across different battery types and operating conditions. Liu et al.[152] developed a GPR-based SOH prediction model trained on aging data collected under various storage temperatures. The effectiveness of the model was assessed by examining its accuracy, ability to generalize across different scenarios, and the quantification of uncertainty in its predictions. For instance, Richardson et al.[105] employed Gaussian Process Regression (GPR) to create a robust model for predicting the degradation of lithium-ion batteries. This approach not only utilized the inherent strengths of GPR but also incorporated specific knowledge about the mechanisms leading to battery degradation, thereby allowing the model to more accurately reflect the intricate patterns associated with the aging process of batteries. Many studies have since integrated GPR with other methods to improve prediction. Liu et al.[43] combined Linear Gaussian Process Functional Regression (LGPFR) with multi-step-ahead forecasting to track SOH, including both capacity fading and local regeneration. They further enhanced predictions with a Quadratic GPR model (QGPFR). Yu et al.[153] introduced a hybrid approach that integrates Multiscale Logic Regression (MLR) and GPR for SOH estimation. Qiao et al.[154] similarly proposed a multiscale GPR strategy to address SOH prediction with high precision. More advanced models, such as GPR with Neural Networks (GPRNN), have shown superior real-time prediction capability. Zhou et al.[155] employed

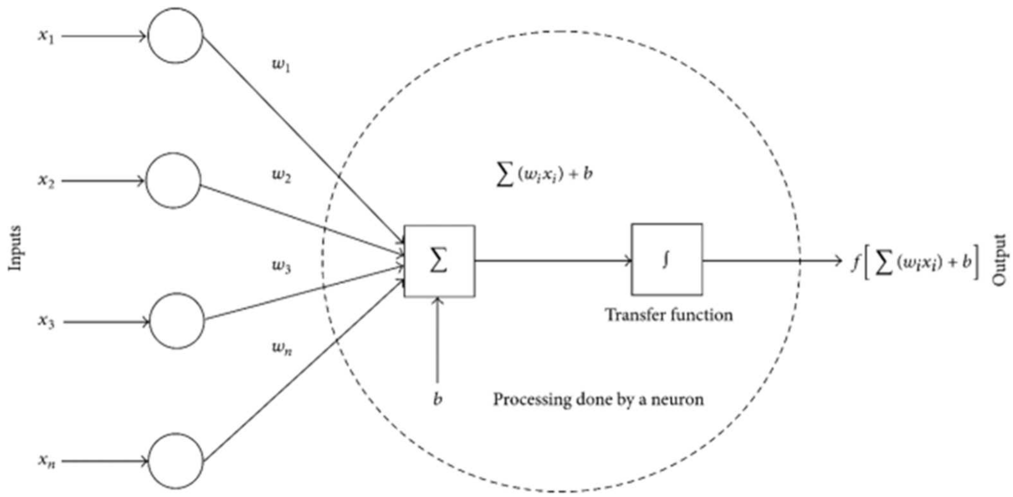

Figure 10. Mathematical model of a single neuron in ANNs. Reproduced with permission from Ref. 110.

GPRNN—where the variance function is modeled via a neural network—for SOH forecasting, demonstrating its effectiveness compared to basic GPR, LGPFR, QGPFR, and multiscale GPR techniques. As a flexible, probabilistic, and non-parametric Bayesian method, GPR offers several distinct advantages for RUL prediction.[156] Richardson et al.[105] highlighted its strength in both short- and long-term predictions of RUL using capacity datasets from Li-ion cells. Liu et al.[157] validated GPR's ability to monitor and forecast battery health through experimental studies. Li et al.[158] developed a novel RUL prediction method using a Gaussian Process Mixture (GPM), which models various degradation trajectories with separate GPRs. Experimental results on two commercial Li-ion batteries confirmed the method's accuracy, showing that GPM outperforms both standard GPR and SVM in RUL estimation.

Neural networks (NN).—Neural networks are often used to analyze complex nonlinear systems that cannot be fully or accurately described using conventional mathematical models. These networks are generally categorized into two main types: feedforward networks and recurrent networks. As illustrated in Fig. 10, the architecture of an Artificial Neural Network (ANN) consists of input, hidden, and output layers composed of artificial neurons. The input layer receives pre-processed data and passes it to the hidden layers. Each neuron in the hidden layer acts as a mathematical unit, producing outputs based on a weighted linear combination of its inputs. A layer comprises neurons that simultaneously receive input from, and send output to, connected nodes in adjacent layers. This structure allows signals to propagate from the input layer through the hidden layers to the output layer. In contrast, recurrent networks introduce feedback connections, enabling outputs from later layers to be looped back into earlier ones. This interconnected design allows the network to retain memory of previous states, making it suitable for dynamic and time-dependent modelling tasks.[159,160]

Neural Networks (NNs) are widely employed for self-learning and adaptability, and their effectiveness does not depend on modelling the internal electrochemical processes of the battery. Instead, they are used to model the relationship between key battery parameters and the degradation of lithium-ion batteries over time. NNs have proven to be powerful tools for reliably predicting the State of Health (SOH) across various battery conditions, dynamic loads, and temperature environments.[161] Battery degradation typically occurs over multiple charge-discharge cycles, and the degradation patterns between these cycles are often highly dependent and correlated. Capturing these interdependencies is essential for accurate SOH estimation. Several studies have explored the application of Artificial Neural Networks (ANNs) in modeling battery degradation and estimating SOH. For example, Wu et al. proposed a structured approach using ANN for SOH estimation.[162] Pan et al. developed a method for real-time SOH estimation using a Feedforward Neural Network (FNN), based on data collected over one year from Li-ion battery cells subjected to ten different driving cycle profiles. Their FNN-based technique utilizes inputs such as voltage, time, voltage inflection points, and degradation curve data across varying cycle counts, with SOH as the output variable.[163] Chaoui et al. introduced an Input Time-Delayed Neural Network (ITDNN), a variant of FNN, which incorporates time-delayed input data such as terminal voltage, current, temperature, and historical signals. This method effectively captured the battery's memory effects and dynamic behavior to improve SOH prediction.[164] Yang et al. proposed a straightforward approach using a three-layer Backpropagation (BP) neural network to estimate SOH. In this study, the maximum available capacity was predicted using a BP neural network. Parameters for a first-order equivalent circuit model (ECM) were extracted through a direct identification method and used as inputs to the BP network, with the current SOH value as the output.[165] Recurrent Neural Networks (RNNs), which are especially suited to processing sequential data, are increasingly used in artificial intelligence applications and have shown great promise in predicting battery health. Because battery degradation is a time-dependent process, RNNs are a natural fit for SOH estimation. Their inputs typically include time-series data such as temperature, voltage, current, and delayed versions of voltage and current. RNNs have been widely reported to outperform FNNs in SOH estimation. For instance, Chaoui et al. proposed an RNN-based model for predicting both the State of Charge (SOC) and SOH of lithium-ion batteries.[166] Another study presented a practical RNN-based approach that leverages real-world EV driving data—such as current and voltage—to track SOH. This RNN-based degradation model effectively handles sequential input and has been validated for its adaptability and reliability across varying EV driving scenarios.[167] To address the limitations of RNNs in handling long-term dependencies, Long Short-Term Memory (LSTM) networks—a specialized form of RNN—were introduced. Unlike traditional RNNs or FNNs, LSTM networks include input, forget, and output gates that allow them to better capture long-range temporal dependencies. Several studies have applied LSTM networks to SOH estimation tasks. Qu et al., for example, developed a predictive LSTM model using a sliding window approach, where the estimated SOH at the next time step depends on a series of past observed SOH values:[168]

$$SOH^{e}_{t+1} = f\left([SOH^{o}_{t},\ SOH^{o}_{t-1},\ ..,\ SOH^{o}_{t-s+1}]\right) \qquad [12]$$

where SOH^{e}_{t+1} is the estimated SOH at time $t + 1$, while SOH^{o}_{τ} is the observed SOH at time $\tau = t,\ t - 1,\ \ldots, t - s + 1$, s being the length of the sliding window. SOH forecasting based on LSTM is also

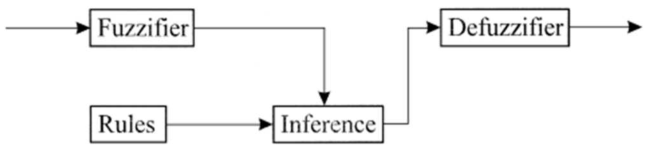

Figure 11. Scheme of a Fuzzy logic system. Reproduced with permission from Ref. 180.

applied in actual settings and applications. For instance, Chen et al. offered a SOH estimation strategy for EV battery life prediction using LSTM. The number of charging and discharging cycles, the discharge time under constant current, and the charging capacity are used to construct the prediction model with LSTM.[159] While it is not necessary for them to model the battery in its entirety, all Neural Network approaches have the advantage of being able to adapt to the nonlinear battery data relatively rapidly. However, they need to be taught through a lot of cycles.

Since NNs have accurate generalization ability and can learn about nonlinear relationships between data and output, they are also the most often used approach for calculating battery RUL.

In recent years, numerous studies have explored the use of various neural network architectures for estimating the Remaining Useful Life (RUL) of batteries. Several types of Artificial Neural Networks (ANNs), including Feedforward Neural Networks (FNN), Recurrent Neural Networks (RNN), and Convolutional Neural Networks (CNN), have been successfully applied to predict battery RUL.[169] Wu et al. proposed a method for estimating the RUL of lithium-ion batteries using a FNN, aligning with the standard definition of RUL. The FFNN effectively models the relationship between RUL and the battery's charge curve due to its simplicity and computational efficiency. Their results led to the development of an online RUL prediction technique based on FNNs.[170] In contrast, RNNs have been shown to accurately simulate the aging behavior of Li-ion cells by accounting for specific operational conditions, providing valuable insights into RUL. These networks are widely used in high-performance energy storage systems, particularly in hybrid and electric vehicles, where RNN-based models serve as primary predictors.[171] Another study proposed the use of RNNs to monitor the RUL of EV batteries using real-world data, where the batteries undergo dynamic cycling according to diverse driving patterns.[166,167] Additionally, an adaptive RNN model has been introduced to forecast unknown impedance fluctuations in new batteries by leveraging historical impedance data from various cells. This approach enhances prediction accuracy through adaptive recurrent feedback mechanisms.[172] CNNs have also been investigated for their suitability in predicting Li-ion battery RUL. Lin et al. employed a CNN model to achieve high prediction accuracy and used an orthogonal strategy for optimizing model parameters.[173] Furthermore, Deep Neural Networks (DNNs), which are multilayer ANNs capable of handling complex nonlinear relationships, have emerged as an effective solution for more intricate prediction tasks, such as estimating the RUL of multiple batteries simultaneously.[174]

Fuzzy logic system (FLS).—Fuzzy logic serves as a reasoning framework that mimics human decision-making processes and is particularly effective in addressing complex issues characterized by uncertainty and imprecision.[175] Its adaptability makes fuzzy logic an advantageous approach for estimating the State of Health (SOH) of batteries, as it can effectively process and interpret data from highly nonlinear, dynamic environments typical in battery management systems. By employing a rule-based system, fuzzy logic enhances the accuracy of health assessments, confirming its utility in real-world applications of battery monitoring and evaluation. Fuzzy logic employs a rule-based system to process data from complex, nonlinear systems and offers the ability to generalize data—an advantage when assessing battery aging and SOH.[176,177] For example, Zenati et al. improved SOH estimation accuracy by incorporating two measured parameters into a fuzzy logic system, which operated effectively across a wide range of temperatures and currents. Their approach emphasized the need for a system that selects the most suitable coefficients based on the battery's operating conditions, thereby enhancing SOH reliability.[178] To deliver more precise SOH evaluations, a fuzzy logic system (FLS) was developed to calculate coefficients applied to ohmic resistance and capacity measurements in a linear combination. Since lithium-ion batteries are complex and nonlinear in nature, fuzzy logic is particularly well-suited for this task as it does not require a precise mathematical model to determine appropriate coefficients.[179] A typical fuzzy logic system consists of four main components: a rule base, a fuzzifier, an inference engine, and a defuzzifier. Input data are usually discrete values. The fuzzifier converts these crisp inputs into fuzzy sets (although fuzzy inputs defined by membership functions are also used in some cases). Fuzzy logic models are typically built using "If-Then" rules, as illustrated in Fig. 11.[180]

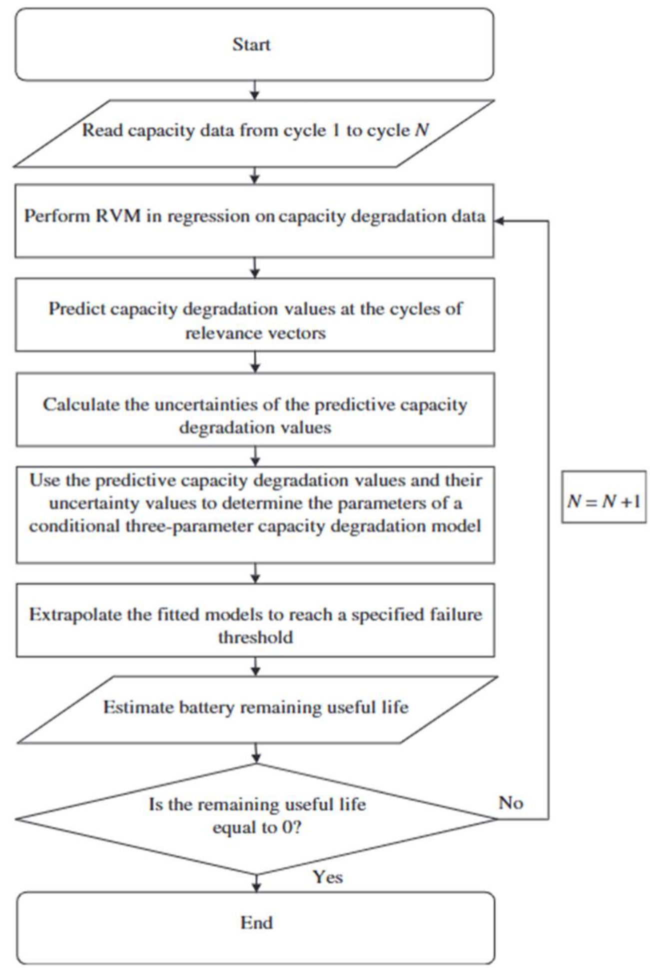

Figure 12. Flow-chart describing the procedure for estimating RUL based on RVM. Reproduced with permission from Ref. 184.

A study also proposes the use of a neuro-fuzzy (NF) system to develop an online machine health prognosis model. The findings indicate that the NF approach offers greater accuracy and reliability in predicting the State of Health (SOH) compared to Recurrent Neural Networks (RNN), as it can quickly and effectively capture the system's dynamic behaviour.[181]

Relevance vector machine (RVM).—The Relevance Vector Machine (RVM) is a sparse Bayesian method for kernel regression that performs regression in a probabilistic framework. RVM is known for its high accuracy, learning capability, sparsity, ease of training, and ability to produce probabilistic output predictions. However, a major limitation is its reliance on large training datasets, which increases computational complexity, processing time, and

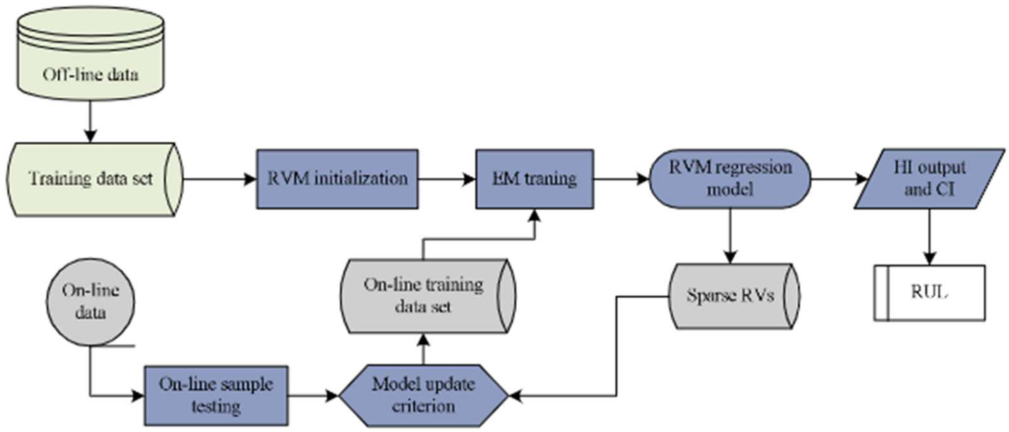

Figure 13. Flow-chart of the incremental RVM algorithm for the estimation of RUL. Reproduced with permission from Ref. 185.

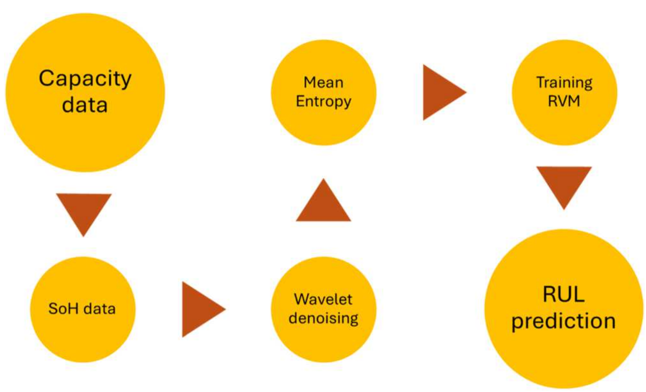

Figure 14. Schematic diagram of the RVM-based approach proposed by Ref. 186.

memory requirements.[182] Despite this, due to its sparse nature, the RVM model is capable of making efficient predictions for new data points.[183] The functional form of RVM is similar to that of the Support Vector Machine (SVM), as described in Eq. 9, but unlike SVM, RVM provides probabilistic classification capabilities.[182] RVM has been increasingly applied in the degradation prediction stage and is often integrated with other techniques to estimate the Remaining Useful Life (RUL) of batteries. For example, Wang et al. developed a lithium-ion battery prognostic model using the RVM algorithm in combination with a capacity degradation model to predict RUL, as illustrated in Fig. 12. Their approach leverages RVM's ability to select the most relevant training vectors, thereby enhancing prediction accuracy.[184]

Liu et al. proposed an incremental online learning strategy for the Relevance Vector Machine (RVM) to enhance the accuracy of Remaining Useful Life (RUL) predictions as shown in the Fig. 13.[185]

Similarly, Li et al. utilized the RVM algorithm in conjunction with mean entropy to predict the RUL of lithium-ion batteries. In their study, mean entropy was employed to determine the optimal dimension for accurate time series reconstruction (see Fig. 14).[186] In efforts to improve prediction performance and robustness, researchers have increasingly explored hybrid approaches that integrate multiple methodologies. For instance, Roman et al. developed a machine learning-based battery health management framework that

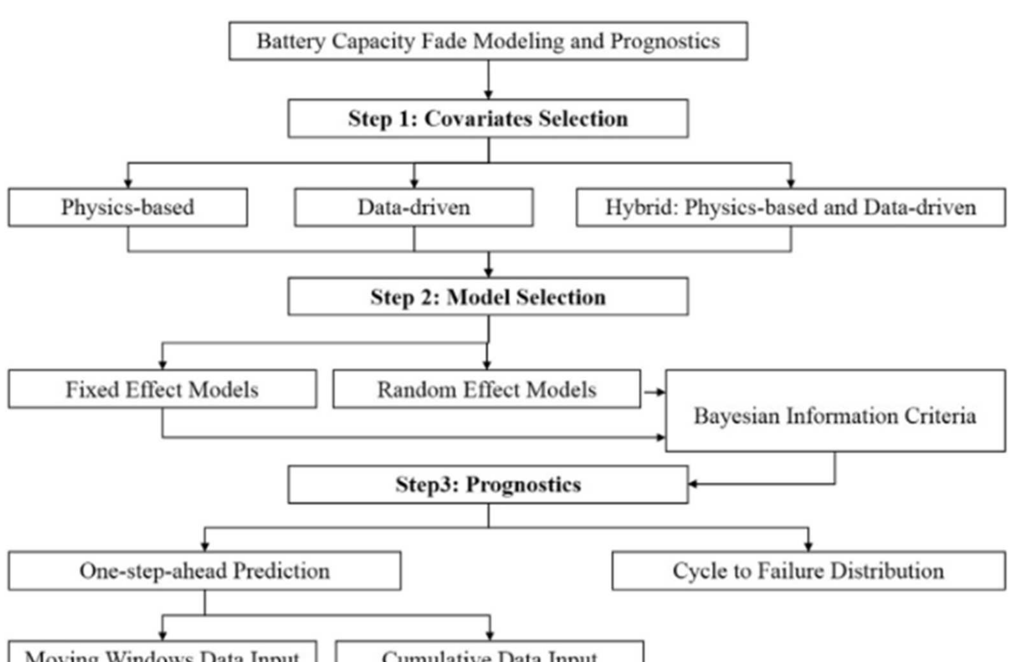

Figure 15. Flow-chart of the Bayesian-based approach for battery fade modelling and prognostic proposed in Ref. 189. Reproduced with permission from Ref. 189.

combines experimental battery data with predictive modelling to estimate the State of Health (SOH). The study evaluated four algorithms—Bayesian Ridge Regression (BRR), Gaussian Process Regression (GPR), Random Forest (RF), and a deep neural network ensemble (DNNe). Each method was assessed based on its prediction error and uncertainty. While RF and BRR achieved the lowest error rates, the DNNe model delivered the highest calibration score, reflecting improved uncertainty estimation.[187]

Bayesian methods.—Bayesian techniques play a crucial role in informed decision-making by offering a structured approach to managing uncertainty. They provide credible intervals with probable upper and lower bounds, enhancing the reliability of predictions.[188] In one study, researchers developed a systematic methodology to simulate battery capacity degradation over repeated cycles. This approach included steps for system identification, model selection, and prognostic data filtering. The proposed Bayesian framework, whose flow-chart is schematized in Fig. 15, effectively quantifies uncertainty in estimating battery capacity and Remaining Useful Life (RUL) under varying operational conditions.[189]

Another study explored battery degradation and introduced a Naive Bayes (NB) model for predicting the Remaining Useful Life (RUL) of batteries under diverse usage conditions and ambient temperatures. The research showed that the NB method could effectively predict the RUL of lithium-ion batteries during continuous discharge scenarios, regardless of specific operational parameter values. Compared to Support Vector Machines (SVM), the proposed NB model demonstrated superior predictive performance.[190] Naive Bayes is a widely used data mining algorithm recognized for its strong empirical performance. It represents the simplest form of a Bayesian network.[191] Based on Bayes' theorem, NB operates under the assumption that all predictors are conditionally independent. Using this assumption, it calculates the probability that an observation belongs to a particular class.[192] While NB typically classifies observations into the class with the highest probability, it has also been successfully applied to regression tasks, where class probabilities are combined in different ways. Despite the fact that the conditional independence assumption rarely holds true in practice, NB is known for its simplicity, robustness, and resilience to noise and missing data, making it effective in many real-world applications.[193,194] To further enhance RUL prediction, He et al. developed an online method based on Dynamic Bayesian Networks (DBNs). This approach uses a forward inference process to predict RUL in real time, with DBN parameters learned from battery aging datasets. Experimental results confirm the effectiveness of this method in accurately estimating the RUL of lithium-ion batteries.[195]

Conclusions

In conclusion, the assessment and prediction of the state of health (SOH) and remaining useful life (RUL) of lithium-ion batteries is an area of active research harnessing the capabilities of various machine learning techniques. Among these, Gaussian Process Regression (GPR) has demonstrated notable effectiveness in modelling battery degradation due to its non-parametric nature, which accounts for the complexities associated with battery aging while providing quantifiable uncertainty in predictions. The flexibility of GPR allows it to model various degradation trajectories, showcasing promising results in comparison to traditional models like Support Vector Machines (SVM).

The advent of deep learning methods has further advanced the state of the art in RUL prediction. Convolutional Neural Networks (CNN) and Deep Neural Networks (DNN) represent significant strides in using multilayer architectures to handle complex data patterns. These networks have been tailored to not only improve prediction accuracy but also to enhance the ability to estimate SOH from dynamic operational data. The integration of these advanced neural architectures with ensemble methods, such as combining GPR with DNNs, has shown potential for elevating real-time prediction capabilities beyond traditional independent approaches.

Another important aspect is the evolution of hybrid models, which merge the strengths of different algorithms, such as combining SVM with Hidden Markov Models or particle swarm optimization. This synergy allows for improved handling of non-linear relationships and uncertainty estimation, thus enriching the overall prediction performance. Fuzzy logic systems also offer an innovative approach by processing complicated data within an adaptive framework, which can enhance SOH estimation accuracy.

Overall, the diverse array of methodologies reveals an increasing trend towards adopting complex machine learning frameworks that integrate theoretical robustness with empirical practicality, fuelling advancements in battery health monitoring systems. Enhanced prediction capabilities will not only contribute to the operational efficiency of energy storage systems but also aid in the development of sustainable practices within the electric vehicle industry and beyond.

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