POLITECNICO
MILANO 1863

SCUOLA DI INGEGNERIA INDUSTRIALE
E DELL'INFORMAZIONE

A review of estimation methods related to the definition of the state of charge and state of health for the battery

TESI DI LAUREA MAGISTRALE IN
XXXXX ENGINEERING-INGEGNERIA XXXXX

Author: **Mohsen Janbozorgi**

Student ID:	10694676 (Mat: 941260)
Advisor:	Prof: Loredana Cristaldi
Academic Year:	2021-22

Abstract

One of mankind's greatest concerns today is global warming due to greenhouse gas emissions from the burning of fossil fuels. In addition to the depletion of non-renewable resources, the use of renewable energy has become the government's top priority. Generally speaking, in the generation of renewable energy by different means of production like PVs, wind, etc., having capable battery systems and energy storage systems is a must. Above and beyond, electric vehicles (EVs) show great performance in terms of efficiency and CO2 emissions reduction and are widely used in the automotive industry, which are powered by rechargeable batteries. There is a diversity of energy storage technologies, ranging from lead acid to NiMH to lithium-ion batteries, which are being employed. Lithium-ion (Li-ion) batteries take the lead and are commonly used in energy storage systems for renewable energy systems such as EVs and power plants due to their high power and energy density and long service life. These advantages lead to more focus and investment on this technology to increase its robustness and stability.

In order to protect battery systems and have a reliable control and supply system, a battery management system (BMS) is employed, which protects the battery from being overcharged or discharged and delivers cell balancing. As a result, BMS must be able to anticipate the state of charge (SOC) and state of health (SOC) with reasonable accuracy. There are various methods for estimating SOC and SOH that can be analyzed, classified, and weighed in terms of pros and cons.

The purpose of this article is to offer an overview of the SOC and SOH approaches now available in the literature, along with the advantages and disadvantages of generally used methods, as well as a comparison of the most often used methods.

Key-words: Battery, SOC, SOH, State of charge, State of health

Abstract in lingua italiana

Una delle più grandi preoccupazioni dell'umanità oggi è il riscaldamento globale dovuto alle emissioni di gas serra dovute alla combustione di combustibili fossili. Oltre all'esaurimento delle risorse non rinnovabili, l'uso dell'energia rinnovabile è diventato la massima priorità dei governi. In generale, nella generazione di energia rinnovabile con diversi mezzi di produzione come il fotovoltaico, il vento, ecc, è essenziale avere l'immagazzinamento di energia e batterie idonee. Inoltre, i veicoli elettrici (EV), alimentati da batterie ricaricabili, mostrano grandi prestazioni in termini di efficienza e riduzione delle emissioni di CO2 e sono ampiamente utilizzati nell'industria automobilistica. Esiste una varietà di tecnologie di immagazzinamento dell'energia, che va dall'acido di piombo ,al NiMH, alle batterie agli ioni di litio. Le batterie agli ioni di litio (Li-ion) assumono un ruolo grazie alla loro alta potenza, densità energetica e alla lunga durata e sono comunemente usate nei sistemi di immagazzinamento dell'energia per i sistemi di energia rinnovabile come i veicoli elettrici e le centrali elettriche. Questi vantaggi portano a una maggiore attenzione e investimenti su questa tecnologia per aumentarne la robustezza e la stabilità.

Per proteggere i sistemi a batteria e avere un sistema di controllo e alimentazione affidabile, viene impiegato un sistema di gestione della batteria (BMS), che protegge la batteria dal sovraccarico o dallo scaricamento e fornisce il bilanciamento delle celle. Di conseguenza, il BMS deve essere in grado di anticipare lo stato di carica (SOC) e lo stato di salute (SOC) con una precisione ragionevole. Ci sono vari metodi che possono essere analizzati, classificati e pesati in termini di pro e contro usati per stimare SOC e SOH.

Lo scopo di questo articolo è quello di offrire una panoramica degli approcci SOC e SOH attualmente disponibili in letteratura, così come i vantaggi e gli svantaggi dei metodi generalmente utilizzati, nonché un confronto tra i metodi più spesso utilizzati.

Parole chiave: Battery, SOC, SOH, State of charge, State of health.

Contents

Introduction

One of humanity's most pressing worries today is global warming, which is caused by greenhouse gas emissions from the use of fossil fuels. The replacement of fossil fuels is a major source of concern for civilization. Global warming, the depletion of fossil fuels, and the growing prices of traditional energy sources have all driven the development and widespread usage of renewable energy sources. Clean, renewable energy is now being used in a variety of industrial sectors. Due to the nature of renewable energy sources such as solar energy and wind energy, which are not accessible continuously during the day and night, they cannot be used in situations where a continual supply of energy is needed. As a result, batteries are used in order to maintain power continuity [1]. Above and beyond, electric vehicles (EVs) have excellent performance in terms of efficiency and CO2 emissions reduction, and they are extensively employed in the automotive sector, where they are powered by rechargeable batteries. From lead acid to nickel-metal-hydride (NiMH) to lithium-ion batteries, there are many different types of energy storage systems available. With its unique and beneficial characteristics, lithium-ion batteries take the lead. Because of their high power and energy density, lithium-ion batteries have a long shelf life [2] Lithium-ion batteries are also an excellent choice for electric cars in the transportation system business because of their minimal weight.

It is necessary to use a battery management system (BMS) in order to control battery systems and eliminate any potential explosion dangers associated with the batteries. A battery management system (BMS) is an electronic component that manages a battery pack of rechargeable batteries. When BMS is used, the major purpose is to keep the batteries in a safe, dependable, and efficient state while also preventing the battery pack from being used for a shorter amount of time than intended. In order to do so, the BMS must accurately predict the various characteristics of the battery pack [3]. State of charge (SOC) and state of health (SOH) are two of the most important characteristics to consider. The presence of these states cannot be observed directly by sensors, but they may be inferred by measuring associated measurable factors such as the voltage and current of the batteries as well as their temperature.

SOC is a one of the primary parameters of battery pack which is related to accessible capacity of the batteries. By knowing this factor, BMS retrains from overcharging or discharging of batteries. SOC can be estimated by using battery model system and algorithm. There are several definitions of SOC.

SOH is another key parameter which provides information about aging status of the battery pack. Due characteristics and working condition of the battery pack, internal residence grows gradually over time, as well as the capacity decreases. Hence battery aging leads to an incremental drop in the power and energy. By tracking of internal resistance and power of the battery, SOH can be estimated [4].

This essay is regarded an overview on methodologies of SOC and SOH estimations, comparison most common methods as well as advantages and drawbacks.

1 Chapter one

State of Charge (SOC) definition

Generally speaking, SOC is defined as the ratio between its current Capacity ($Q(t)$) to the nominal capacity (Qn). The nominal capacity of a battery is defined as the greatest amount of charge that can be held in it, and it is normally stated by the manufacturer in the specifications. The following is an illustration of the SOC definition in practice (1-1) [5]:

$$SOC(t) = \frac{Q(t)}{Qn} \tag{1-1}$$

A more technical definition is the ratio between the amount of energy that can be stored in the battery and its maximum storage capacity [2]. The state of charge defines as a function of rated available capacity of the battery and varies from 0 (completely discharged) to 100% (fully charged). In practice, SOC must keep over 50% and the battery pack start getting re-charged at SOC 50%. Moreover, SoCmax of battery get decreased over the time due to aging effect.

Numerous approaches to SOC estimation are in the literature. The following categories may, nevertheless, be recognized in some literary works:

Among the first are those classified as "Direct measurement," which are cost-effective but not precise in terms of measurement accuracy [5]. Since batteries have electrochemical characteristics; therefore, the influence of temperature and aging cannot be completely eliminated.

The next category is book-keeping systems, which are based on current monitoring and charge counting of the battery as well as other factors [6]. When using this approach, the discharging current is used as an input and the SOC is calculated by integrating the discharging current over a period of time [5].

Regarding SOC estimations, adaptive systems, as the next best option, are critical. Because of the unpredictability of both battery and user behavior, building an accurate SOC indicator system that is capable of integrating direct and indirect measurements is the most difficult component of producing an accurate SOC indicator system [6]. A variety of unique adaptive approaches for SOC estimates have been developed in recent years, thanks to advances in artificial intelligence (AI).

When it comes to the functioning of lithium-ion batteries in electric vehicles, there are many difficulties to overcome. Predicting the state of charge (SOC) of the battery is challenging because of the Nonlinear uncertainty in the battery [7]. Hence, nonlinear observer methods are developed. Furthermore, the development of learning and data-driven algorithms have taken a significant stride forward in recent years, resulting in an improvement in the accuracy of state of charge estimate [8].

Finally, but definitely not least, hybrid methodologies are discussed in order to make advantage of the many methods of estimating SOC that are accessible to the user.

State of Health (SOH) definition

The state of health (SOH) is often characterized from the viewpoints of capacity loss and impedance growth, which are both important considerations. In situations where the power capability of batteries is of importance, the impedance-based SOH assessment is critical to success. This condition allows for the calculation of impedance to be done immediately by referring to the relationship between current and voltage response [9]. A large number of SOH estimates have been discussed in the literature. The internal resistance, impedance, and capacity of the battery are the three basic indications used to estimate SOH. In addition to the battery capacity, internal resistance and impedance indicate the battery's power capabilities. In hybrid applications, battery power is important, unlike in EVs where battery energy is critical [10].

Some literature, on the other hand, permits classification into the three groups listed below: model-based methods, experimental methods, and data-driven (machine learning) methods. Model based methods necessitate the development of a mathematical or physical model that accurately captures the many capabilities. Experimental methods are based on measurements and data that have been gathered in order to analyze the battery's aging behavior. Following that, Data driven methods are a hybrid of the two approaches discussed above and are based on features which are taken from partial or full Lithium-ion battery charging/discharging data which further can be divided into two categories -non-probabilistic and probabilistic [11]. Moreover, in photovoltaic systems, in terms of health indicators, the methods for estimating SOH may be classified into two broad categories: terminal voltage and other signals. The majority of HIs are derived from terminal voltage, which may be classified into four categories based on how the signals are subsequently utilized [12].

Statement of overall purpose

To properly categorize SOC and SOH estimate approaches, this study will evaluate existing research on the subject in order to classify them properly. Additionally, the various SOC and SOH estimate processes are discussed in depth so that the reader may select the one that is most appropriate for his or her particular situation. In this article, you will find up-to-date information on approaches that will be beneficial in the design and analysis of a project from a technical and financial standpoint, which includes the battery system. Furthermore, it will be beneficial to students and professionals working in the fields of renewable energy systems and electric vehicles.

2 Chapter two

As mentioned in pervious section, SOC is one of the most important parameters of the battery. In this chapter information about deep review of SOC will be provided.

SOC definition

For a better understanding of SOC, additional analytical tasks such as predicting useful life and capacity estimates are required, both of which have been presented for the last 40 years or so, but have yet to get a formal description [13]. Due to the fact that SOC is a good indicator of battery performance, SOC estimation is an important component of battery management systems. A SOC estimate with high accuracy tells us how much energy remains in batteries, as well as evaluating their reliability. It is difficult to determine the SOC of batteries because they contain chemical energy that cannot be quickly accessible [14].

There are various ways to define SOC. As indicated in Eq (2-1), the current integration technique is the most conventional way for estimating SOC. Current integration represents the ratio of the available current capacity to the theoretical capacity [13]:

$$SOC = 1 - \frac{\int idt}{Cn} \tag{2-1}$$

Cn= theoretical(nominal) capacity

t=time

In another definition SOC is Calculated by dividing the battery's current capacity(Q(t)) by its nominal capacity (Qn). The nominal capacity is the battery's maximum charge as the following equation [5]. The quantity of ampere-hours that the cell is capable of delivering at normal operating temperature. Battery activity is not adequately described by static descriptions. . [15]

$$SOC(t) = \frac{Q(t)}{Qn} \tag{2-2}$$

The battery's charge (in [Ah]). On a bar graph, 100 percent represents a fully charged battery, whereas 0 percent represents an empty battery. [16] When it comes to the definition of SoCs, the following parameters might be specified: Depth of discharge (DoD) is defined as the ratio of the discharged capacity of a fully charged battery to the maximum capacity of the battery which is illustrated in **Error! Reference source not found.**.

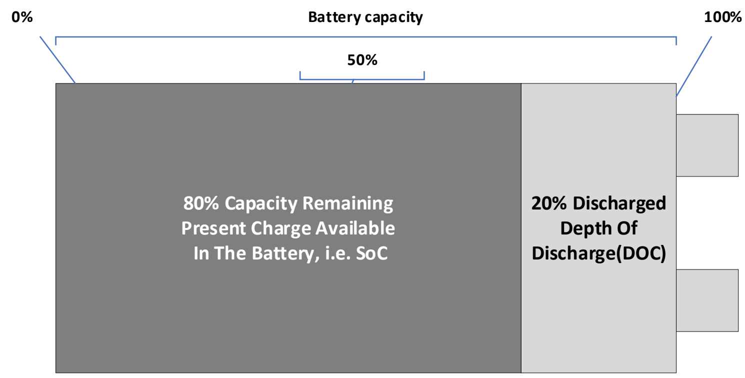

Figure 1: SOC, Available Capacity Remaining [17]

For the battery to operate safely and securely, it is necessary to have accurate and strong SOC information available. In case of not anticipated precisely SOC, many negative repercussions will occur in the Battery Management System (BMS) as a result of this situation, including battery degradation and shortened battery life cycles. [7] As a result, this demonstrates the need of precise estimation of SOC approaches for BMS.

SOC Classification

In terms of SOC classification, in the literature, a large number of methods have been presented. This study categorizes the SOC estimate methodologies into six categories. The very first methods are Direct measurements which are so called Conventional methods and employs the physical features of the battery such as voltage, resistance, Impedance and etc. Next category is book keeping systems which are based on current measurement and integration. In the technical world, this is referred to as coulomb counting, that basically means as "counting the charge going to or from the battery [16]. A variety of models and techniques are used to compute the SOC via the Adaptive Systems. In order to characterize the nonlinear features of batteries and estimate the SOC, the machine learning method need a vast quantity of training data and extensive computation. In case of extremely non-linear systems, the nonlinear observer methods are used. Furthermore, hybrid approaches are offered in order to take benefit of more than one way at the same time[18] which improves the estimation accuracy.

The categorization of SOC estimate methodologies is represented in the Figure 2.

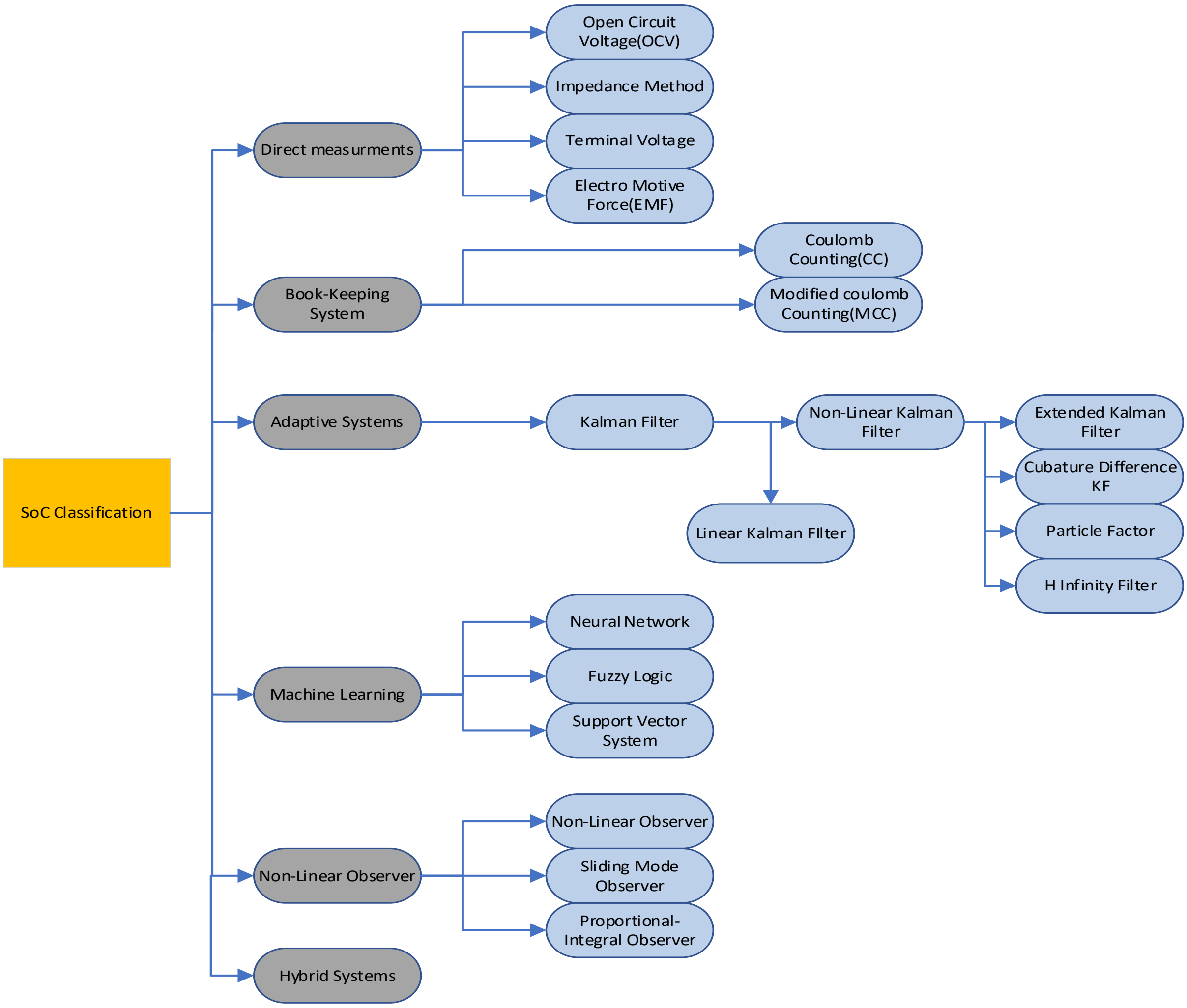

Figure 2-SOC classification

2.1 Direct measurement methods

In direct measurement techniques, the state of charge of the battery is often determined by the connection between various physical properties of the battery. The main parameters are Voltage (V), Impedance (Z) and voltage relation time (τ). In a realistic setup, this battery variable should be observable electrically. It is also necessary to monitor the temperature because it has a significant impact on these physical quantities. (Equation (2-3)). It is shown in Figure 3 how the SOC idea is applied to direct measurements.

$$SOC(t) = f_T(V.Z.\tau.T) \tag{2-3}$$

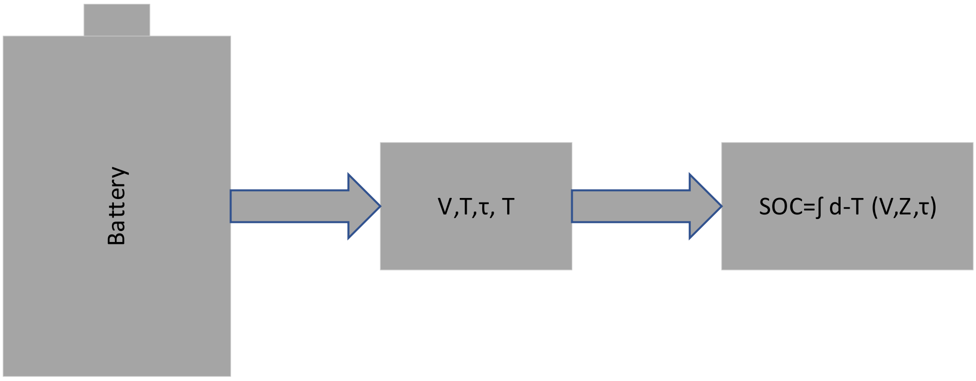

Figure 3: SOC concept in direct measurement [16]

Direct measurement systems offer the primary benefit of not requiring constant connection to the battery, which is a significant advantage in some applications. The measurements may be carried out as soon as the battery is connected. This is in contrast to the fact that changes in temperature have a considerable influence on the accuracy of the measurement. [16].

In the following, the direct measurement methods are presented.

2.1.1 Open Circuit Voltage (OCV)

The very first usage of OCV method developed in 1975 [19]. The OCV may be determined using the following equation(2-4), which is proportional to the battery SOC:

$$OCV = V_{terminal} + IR \tag{2-4}$$

$V_{terminal}$ refers to the voltage of the battery terminal, I is the actual current and R is the resistance. In case of I=0, the amount of OCV=$V_{terminal}$ .The SOC estimation equals the OCV estimation. Nonetheless, this takes time after a current interruption due to the many relaxation processes operating within a battery [20]. It is thus feasible to estimate the SOC of a battery using an open circuit voltage after the battery has gone through the relaxation process in order for the battery to attain equilibriums. This is one of the disadvantages of this strategy since it takes a long time to attain a condition of equilibrium in most cases [21]. This is due to a number of factors, including aging, oxidation-reduction potential (ORP), and electrode system performance [22]. OCV is generally determined via offline testing at a certain temperature, which is not ideal for online SOC calculation of batteries.

Not all batteries have the same connection between OCV and SOC. Because the OCV-SOC relationship varies among batteries, it is difficult to predict the SOC precisely [5]. A linear approximate relationship is between SOC and OCV in most batteries but some other factors such as battery size and technology have effect on this relationship [23]. But when it comes to Li-ion batteries, this relationship not linear anymore [24]. Eq(2-5) demonestare the relationship between SOC and Voc [25] and Figure 4 demonestrates the relationship between SOC and OCV[26].

$$Voc(t) = a1 + SoC(t) + \mathrm{a0} \tag{2-5}$$

a0= $V_{terminal}$ at SOC=0

a1 is obtained, at SOC=100%, by being aware of a0 and Voc

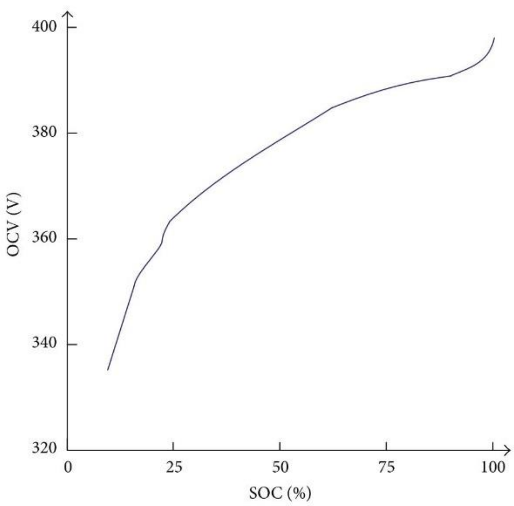

Figure 4-Relationship of SOC and OCV

This approach is not ideal for continuous operation of the battery, it is unsuitable for flat OCV-SOC curves, and it is also only applicable to open-loop and offline systems, among other limitations. [28]

2.1.2 Model-based SOC estimation:

As previously stated, OCV is regarded as an offline approach. Electrochemical models and analogous circuit models, which are the two most often used battery models, are used in order to apply a SOC estimation technique in online applications such as EVs. Battery performance is widely investigated using the battery electrochemical model, which takes into consideration the effects of electrodynamics and chemical thermodynamics on a wide range of internal materials and components. The electrochemical model can be expressed in the form of the following equation. When the battery model characteristics are known, it is straightforward to monitor the battery's SOC using the OCV-SOC look-up table [29]`.

$$U = Uoc - UR - Up \tag{2-6}$$

U= battery terminal voltage

Uoc= Ocv

UR=Voltage across the resistance

Up=electrical potential caused by polarization process

Ref [30]. Took a similar method, in which they employed an equivalent circuit model on the basis of nRC networks and took into account the polarization and dynamic properties of the lithium-ion battery. Using the recursive least squares (RLS) approach with an optimal forgetting factor, an online OCV was built and the results were compared to experimental results obtained for various RC networks in the next phase. The results of the experiment were used to develop a lookup table for OCV-SOC. The proposed approach has the potential to reach an online SOC estimation accuracy of less than 5 percent. Other models are presented in refs [31, 32].

2.1.3 Impedance Method.

Due to the battery's electrochemical processes, in order to improve the measurement accuracy and resilience, in this methodology impedance measurement across a broad range of frequencies are implemented at different charge and discharge currents which sometimes referred to as electrochemical impedance spectroscopy (EIS).

To apply EIS, an electrochemical model is required, which predicts battery impedance utilizing inductances and capacitances across a large frequency range. An equivalent circuit was developed by [33] which consisted of an inductive arc operating at a high frequency and two capacitive arcs operating at a low frequency, respectively. To determine the model impedances, a non-linear least-squares fitting approach is employed under a variety of various SOC values. Another almost accurate and economical approach is using terminal voltage and discharge current to estimate EMF voltage which may work online if the impedance value is normalized. However, battery age and temperature variations may cause predicted findings to be inaccurate [18].To construct the EIS models, the authors employed a variety of techniques to determine the SOC of the battery in refs [34–37] .

2.1.4 Terminal Voltage

Despite the fact that voltage measuring has become increasingly widespread, particularly for mobile phone applications, it does not provide the most reliable data. While determining a cell's remaining capacity by detecting its voltage level is less costly and requires less computational effort than other methods, in practice voltage measurements may be quite deceptive. That said, the voltage loss during discharge varies substantially with cell temperature and discharge rate [38]. This graph (Figure 5) illustrates the voltage curve of Li-Ion batteries discharged at various rates.

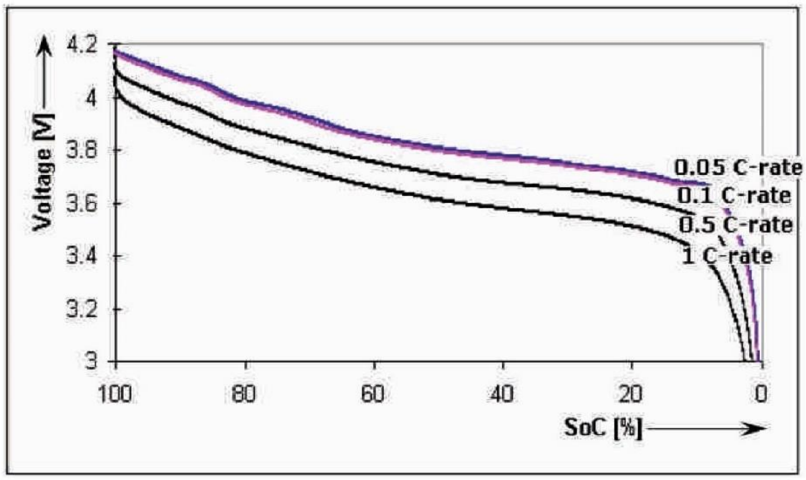

Figure 5: Li-ion battery voltage curves at different discharge rates. [39]

Figure 5 depicts the link between cell voltage and discharged capacity. As shown, the voltage discharge curve is heavily dependent on discharge rate. As long as the system knows how the battery voltage is related to the cell temperature and discharge rate, it can minimize the estimate inaccuracy. When such observed curves are taken into consideration, the procedure becomes more involved and costly than a Coulomb counting technique. . [39]

2.1.5 Electromotive Force (EMF)

Electromotive force (EMF) is the internal driving force of a battery that is responsible for supplying energy to a load which generally calculated through thermodynamic data and the Nernst equation. Using a technique known as linear interpolation, the EMF may be calculated in another way as well, in which the average battery voltage, calculated at the same SOC, is inferred from the battery voltages during two consecutive discharge and charge cycles using the same currents and at the same temperature. [20] Voltage relaxation may be also used to determine the EMF. After an interruption in current the voltage will return to EMF value. When a battery is almost discharged this process If the battery is nearly completely depleted, the process may take a lengthy time, particularly in cold conditions or with an excessive discharge current rate [40]. Li-ion battery EMF is an excellent indicator of SOC. If

SOC is stated in relative capacity, the connection between EMF and SOC remains constant throughout battery cycling. Look-up table, Piecewise linear function and Mathematical function, according to the literature, these are the three most prevalent EMF solutions in look- up table [6].

Table 1 illustrates a comparison of direct measuring methods:

Methods	**Advantages**	**Disadvantages**	**Errors (and ref)**	
OCV	Easy to set up and use with good precision	Offline methods, achieving equilibrium takes a long time.	The error varies with respect to OCV/SOC curves	[41]
Model-based	Online method with good accuracy	Depends greatly on how accurate the model is.	≤ ±5%	[30]
EIS	Online low-cost technique with accurate result (In case of normalized impedance value)	Inaccurate results might be caused by battery aging and temperature fluctuations.	The error Varies with respect to V/SOC curves	[42]
Terminal Voltage	Cheap and fast	Result is affected by temperature	The error Varies with respect to V/SOC curve	[39]
EMF	Conveniently priced and ease to use	Achieving equilibrium takes a long time.	≤ ±2%	[43]

Table 1-Direct measurement method comparison

2.2 book-keeping systems

The battery discharge current data are used as input in the book-keeping estimate technique and that is on the basis of current measurement and integration[20]. It is possible to add certain internal battery effects such as self-discharge, capacity loss, and discharging efficiency using this technique. For the purposes of this study, two types of bookkeeping estimating approaches were used: Both the conventional and modified Coulomb counting methods are used. The counting technique based on Coulomb's coefficients. [5]

A bookkeeping system for a smartphone app depicted in Figure 6. An in-built bookkeeping module constantly examines the battery and provides voltage, temperature, current and integration to the CPU in order to calculate SOC. In order to establish the battery's capacity, the battery identifying data are utilized. The CPU regularly refreshes the data in the electrically erasable ROM (EEPROM). Battery power, ground and one-wire interface are the only three output connectors necessary. [20]

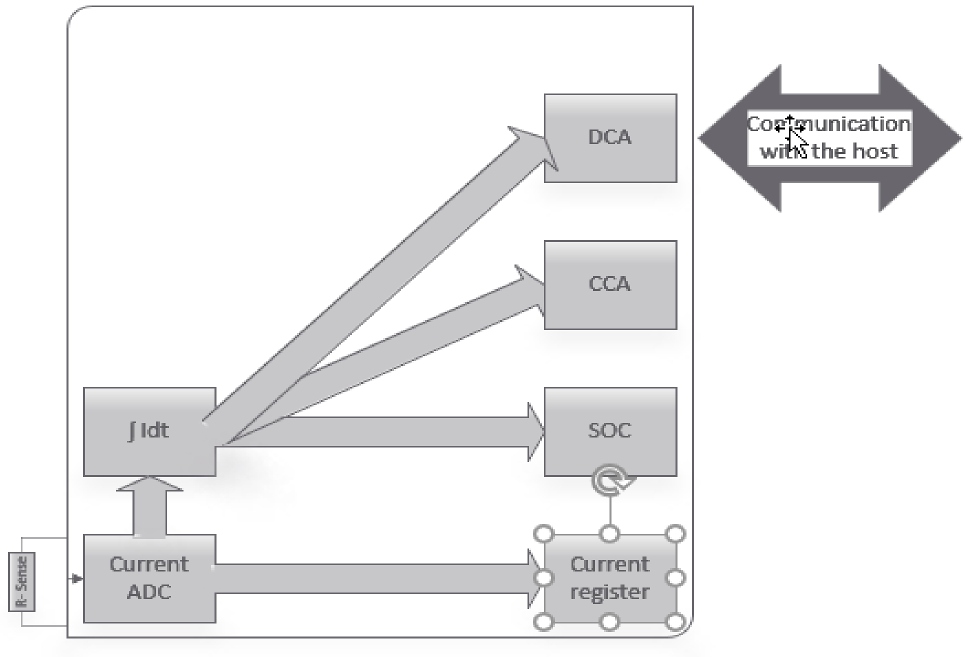

Figure 6: Block diagram of the book-keeping support module[20]

Generally, in the literature two primary book-keeping approaches are presented: Coulomb counting method and modified Coulomb counting method. [14]

2.2.1 Coulomb counting (CC)

It is the most straightforward and natural manner technique of determining battery state-of-charge (SOC). It implies counting the charge entering or leaving the battery which is based on the integration of current with respect to time while the battery is charging/discharging. SOC is expressed theoretically in equation(2-7) [44]:

$$SOC_t = SOC_{(t-1)} + \frac{I_t(t)}{Q_n}\Delta t \tag{2-7}$$

I(t)= Discharging current

$SOC_{(t-1)}$= Previously estimated value

A long-term monitoring and memory need to makee this approach unsuitable for real-time SOC estimates, but essential for evaluating other methods' correctness [45].

Several drawbacks can be pointed out in this method:

1- As an open-loop method, it is subject to errors as a result of unknown disturbances and factors like as noise, temperature, current, and so on [45]. 2-
2- There are challenges in identifying the beginning value of SOC, which results in a cumulative impact [46].
3- Measurement error of sensor has a sharp cumulative effect on accuracy of the estimation.
4- Last but not the least, complete discharge of the cell and frequent capacity calibration are required for maximum capacity to be achieved, which reduces the battery's useful life. [18]

The results of the laboratory trials show that correcting SOC may reduce estimation error to around 4% and that energy efficiency can further reduce estimation error [46].

2.2.2 Modified Coulomb Counting

A methodology, referred to as the modified Coulomb counting method, is suggested in order to enhance the Coulomb counting method. The corrected current (as a function of discharging current) is used in conjunction with the modified Coulomb counting technique to increase the accuracy of measurement. Corrected current is computed using experimental data as (2-8). [26] :

$$I_c(t) = K_2 I(t)^2 + K_1 I(t) + \ K_0 \tag{2-8}$$

K_1, K_2, K_0= Constant value of exprimental data

SOC is determined using the modified Coulomb counting technique, which is represented by the following equation:

$$SOC_t = SOC(t-1) + \frac{I_c(t)}{Q_n}\Delta t \tag{2-9}$$

The modified Coulomb counting approach outperforms the regular Coulomb counting method in terms of accuracy. [1]. [14]

By extending the Peukert equation for discharging to include battery capacity rate and temperature dependency, Xie Jiale *et al.* were able to produce an improved coulomb counting strategy which is so called ampere-hours (Ah) counting. It is intended to strike a balance between sampling frequency and accumulation accuracy with a frequency-adjustable current sampling system. The findings support the effectiveness and generalizability of the proposed technique. [47]

Another Method was enhanced by Ng *et al.*, who combined simultaneous estimation of SOH and SOC with dynamic re-calibration on the maximum releasable capacity of a working battery, resulting in a more exact SOC estimation and higher accuracy[45].

Improved Coulomb counting technique is proposed by He and Guo with real-time error correction, which in the unsteady state CC estimation of SOC leads to a substantially higher estimation rate. By eliminating the cumulative SOC error of CC, numerical iteration technique achieves substantially greater accuracy than the standard CC approach, also uses a compensation coefficient to decrease error buildup. The experimental findings show that this method has a SOC error of less than 1% and a computation cost 94% less than EKF. So it helps to real-time SOC estimate in EVs [48]. Although the coulomb counting approach is quite complicated, it remains heavily dependent on the accuracy of the current probe; as a result, the integration of repeated mistakes results in a rising disparity between the real and estimated SOC values [49]. This implies that the SOC estimate should be revised on a regular basis using an OCV measurement.

Table 2illustrates a comparison of book- keeping methods:

Methods	Advantages	Disadvantages	Errors (and ref)	
CC	Easy to set up and use, Consumption of less energy	Open loop approach, Inaccurate results from unknown disruptions, SOC starting value is difficult to determine cause cumulative impact	≤ ±4%	[46]
ICC	As same as CC, more accurate	Complicated, Accuracy depends on the current probe.	≤ ±1%	[[30]

Table 2- Book- keeping method comparison

2.3 Adaptive systems

Due to Battery and user unpredictable behavior, it is difficult to develop an accurate SOC indicator. In this instance, an adaptive system based on direct measurement, bookkeeping, or a mix of both is required [16]. As artificial intelligence has progressed, numerous innovative adaptive algorithms for SOC estimates have been shaped in recent years. Back propagation (BP) neural networks, radial basis function (RBF) neural networks, fuzzy logic approaches, support vector machines, fuzzy neural networks, and the Kalman filter are among the newly developed methods. Adaptive systems are self-designing systems that can be autonomously altered to accommodate changing conditions. Besides, adaptive systems provide excellent results for SOC estimation due to non-linearity of SOC in chemical batteries[50]. This section will discuss many adaptive SOC systems that are currently available.

Kalman Filter

A clever instrument for estimating the battery's SOC, the Kalman filter, which filters parameters from unclear, erroneous data. Despite its high computing cost, KF has recently become a highly popular method for estimating the battery condition in batteries. The self-correcting characteristic of KF makes it ideal for high current variations. It is widely utilized in vehicles, radar tracking, aircraft, and navigation tracking applications. Using KF has several advantages, the most important of which is that it reliably estimates states that are impacted by external disturbances such as noise that follows a Gaussian distribution. Despite this, KF cannot be used to forecast the state of a nonlinear system in its natural state. Furthermore, it necessitates the use of extremely complicated mathematical computations. The KF family algorithm's self-correcting feature makes it ideal for model-based online SOC estimation which are divided into two categories: linear and nonlinear. [18]

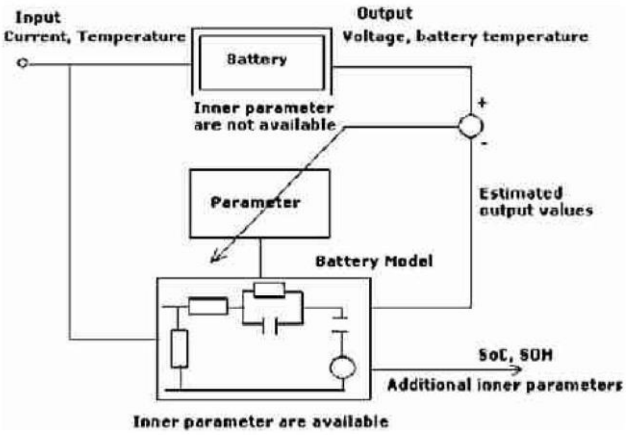

Figure 7: Method for SOC and SOH determination using a Kalman filter [6]

2.3.1 Linear Kalman Filter

Linear Kalman filter (LKF) utilizes a linear filtering for estimation of state variables and employ discrete mathematical equations of the time domain linear dynamic system. In addition to providing optimum state estimation, this recursive approach has the main benefit of limiting the minimum mean square error [51].

Specifically, the KF linear model is composed of two parts: a process Eq.(2-10), which predicts the current state x_k from the prior state x_{k-1}, and a measurement Eq(2-11), which brings the present state closer to its genuine value by updating it [18].

$$x_{K+1} = A_K x_K + B_K + w_k \tag{2-10}$$

$$y_K = C_K x_K + D_K u_K + v_k \tag{2-11}$$

x_{K+1}=State equatiuon

y_K=Measurementequation

x= Presents the system state

u=Control input

w=Process noise

y=measurement input

v=measurement noise

A, B, C and D= the covariance matrix, dynamics of the system

SOC estimation for lithium-ion batteries using a Kalman filter have been proposed by Yatsui and Bai. Experiments show that the Kalman filter works well when used in an online environment [26]. In order to characterize KF, an RC battery model employed in BMS, which is translated to a state spare model to explain dynamic features of the battery. The calculated RMS error of SOC using KF is quite tiny compared to measurement error [52]. With the same method, An electrical equivalent model of a lithium-ion battery, with a voltage supply and a resistance, was developed which demonstrated less than 5% error in SOC estimation [53]. Using KF has the benefit of properly estimating states impacted by external disturbances like Gaussian noise. A nonlinear system, however, cannot be predicted using KF directly. It also necessitates complicated math [18].

2.3.2 Non-linear Kalman Filter

When dealing with linear systems, the linear Kalman filter is the best option. For OCV-based estimates, Kalman filters cannot be employed directly because of the nonlinearity of the battery system. So, several Kalman Filters have been designed to include non-linear signals by using local linearization and optimizing Kalman filters for SOC estimate which led to the OCV function be linearized, and the resulting SOC estimation can be improved. [54] Among the nonlinear KF algorithms, there are three main types: extended KF (EKF), sigma-point KF (SPKF), and cubature KF (CKF), which may be further split into central difference KF (CDKF), and unscented KF (UKF) [55].

2.3.2.1 Extended Kalman Filter (EKF)

Commonly used for the battery parameter is the Extended Kalman Filter (EKF), which is a nonlinear variant of the Linear KF. EKF works by linearizing nonlinear functions using partial derivatives and first-order Taylor series expansion[56]. The algorithm of EKF is demonstrated as Figure 8:

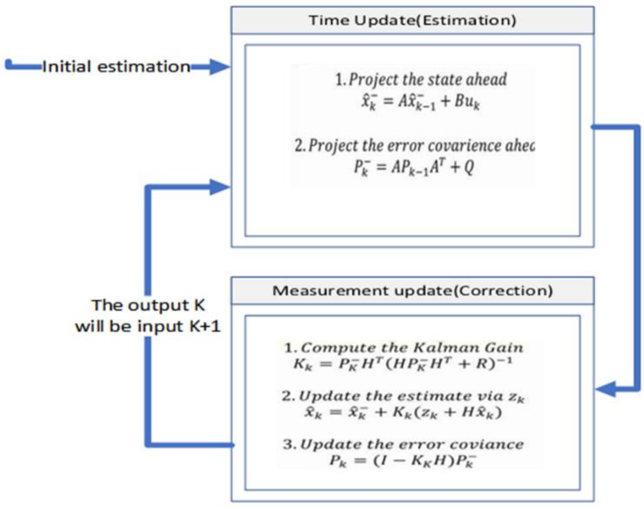

Figure 8- algorithm of EKF [18]

Through the use of terminal current and voltage data, an extended Kalman filter (EKF) was utilized to estimate concentrations of major chemical species averaged throughout a thickness of the active material in order to calculate the state-of-charge (SOC) of a lithium-ion battery [57]. This approach is substantially more accurate than Coulomb Counting. SOC/SOH, as well as any other battery metrics that may be described by a battery model, can be monitored using this device. The Extended Kalman Filter had an average SOC estimating error of less than 1 percent [58].

EKF was utilized in [59] to identify battery model parameters and state estimation which requires the Jacobian matrix to be computed, and impacts the projected SOC accuracy. Due to the first-order Taylor expansion in linearization, the EKF method is limited to first-order accuracy. The EKF algorithm's accuracy is dependent on battery model parameters and previous knowledge of system noise signals. In case of incorrect previous information may cause estimate process inaccuracy and divergence, leading of improvement in the EKF algorithm [60].

To deal with system noise unpredictability and over-reliance on outdated data, Zhao *et al.*[61] projected the adaptive fading extended Kalman filter (AFEKF) which combines adaptive extended Kalman with fading extended Kalman by using equivalent circuit model and the procedure is validated via an experimental platform. The approach improves the speed and accuracy of SOC estimate, and the SOC error is smaller than 2%.

When the amount of observed data are inadequate to forecast the SOC (or SOH), another research recommends an integrated model that combines the dual extended Kalman filter (DEKF) and autoregressive (AR) models. Derived from the DEKF, the AR model performs better in predicting battery state using past data. A health indicator is utilized to improve the performance of the prediction model since the DEKF has restricted capacity estimate capability. In comparison to outcomes achieved using a single variable, the multivariate AR model produces much superior results.[62]

Another improvement in EKF (IEKF) proposed by Sepasi *et al.* [56] which is an online method of SOC estimation by considering aging factor and can be used for the higher accuracy of SOC estimation in EV. He *et al.* [63] developed an estimation of SOC by using EKF which was composed of five RC models. The estimate algorithm's sensitivity to beginning values was tested. The findings showed that robust EKF-based SOC estimate may effectively minimize initial SOC inaccuracy.

To deal with system noise unpredictability and over-reliance on outdated data, Zhao *et al.*[61] projected the adaptive fading extended Kalman filter (AFEKF) which combines adaptive extended a further alternate approach for determining the states of a nonlinear system is the Sigma point Kalman Filter (SPKF) method. When employing only a small number of functions, SPKF produces more accurate results than EKF in terms of mean and variance. A set of sigma points is selected by the procedure that is identical in value to both the mean and covariance of the model that is being constructed. Using this model has the benefit of having the same computation complexity as EKF without the need to take into account Jacobian matrices. The model does not have to compute the derivatives or the original function, which is another benefit. Kalman with fading extended Kalman by using the equivalent circuit model and the procedure is validated via an experimental platform. The approach improves the speed and accuracy of SOC estimate, and the SOC error is smaller than 2%. Adopting an adaptive covariance matrix update strategy helps avoid error divergence and biased solution in the adaptive extended Kalman filter estimation technique (AEKF) [55].

2.3.2.2 Cubature Kalman Filter

The divergence and dimensionality of the EKF and SPKF were enhanced by using this strategy. Using the third-degree spherical radial cubature rule, it is possible to compute Gaussian weighted noise signals as well as multivariate moment integrals using this method. This algorithm is based on the third-order radial volume criteria and addresses the issue of nonlinear state estimation by utilizing a volume coordinate sequence as its input. CKF was shown to have the highest accuracy while requiring more calculation time than EKF, according to the findings. [55]

In [64], the EKF, UKF, CKF, and PF as four non-linear battery internal state estimate approaches that are being compared in terms of their efficiency and complexity. Because it strikes a compromise between complicity and accuracy, the CKF-based SOC estimation technique is highly recommended. An innovative adaptive CKF method (ACKF) has been presented by Xia et al., which is an adaptation of CKF based on the model employing the second (RC) equivalent circuit SOC estimation of LI-ion battery. The ACKF method outperforms the EKF and CKF algorithms in terms of SOC estimate accuracy, convergence to diverse starting SOC errors, and resilience to voltage measurement noise. [65]

2.3.2.3 Particle Filter (PF)

Another methodology of SOC estimation in a nonlinear system which is indifferent to the system's size, is Particle Filter. This method utilizes a collection of random particles (weighted random samples) and a non-Gaussian distribution to apply the Monte Carlo simulation approach in order to calculate the system's post priority density. Eq (2-12) shows the process model of PF [66]:

$$SoC(t) = SoC(0) - \int_0^t \frac{\eta i(\tau)}{Qn} d\tau \tag{2-12}$$

$SoC(t)$=SOC in time t

$SoC(0)$=Initial SOC

η= Proportion Coeff(effect of discharging)

Qn= Nominal Capacity of Cell

i(τ)= instantaneous discharging current at time (τ)

Outcomes of the comparison between PF and EKF reveal that the PF and EKF have equal performance in estimating accuracy, although the PF method can converge to the actual SOC six times quicker than the EKF, making it more appropriate for embedded applications (Figure 9) [67].

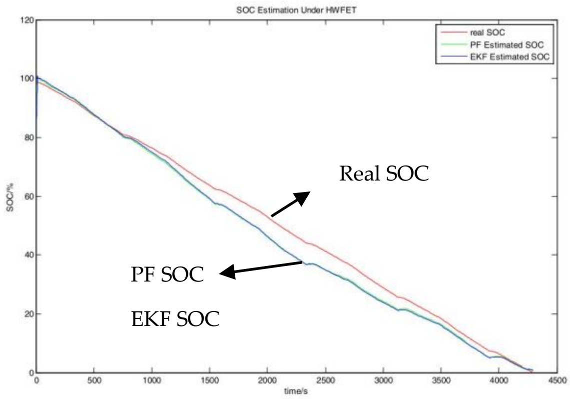

Figure 9: SOC using PF and EKF methods [67]

For a OCV-based SOC estimation, Chen *et al.* present a particle filter approach. The program predicts remaining dischargeable time depending on voltage. The prognostics architecture uses two states of charge definitions. Prognostics using voltage-based SOC has reduced relative error under various current and temperature circumstances. In this case, the voltage-based SOC has better projection of remaining dischargeable time [68].

The unscented particle filter and the extended Kalman filter were compared and examined in a series of dynamic driving cycles at different temperatures. Fast convergence and good accuracy have been demonstrated by using the suggested unscented particle filter approach for dynamic driving schedules [69].

Zhengxin et al. suggested an accurate and rapid approach that is a mixture of EKF and PF as Extended Particle Filter that estimates lithium-ion battery SOC in the situation of nonlinear and time-variant lithium-ion battery systems. The results of trials on the test bench confirm that the Immune Genetic Extended Kalman Particle Filter approach is a potential choice for estimating the SOC of lithium-ion batteries [70].

To address the uncertain open circuit voltage behavior of lithium iron phosphate batteries, a stochastic model-based SOC is computed using PF In this case, the hysteresis effect is omitted in the Monte Carlo simulation. On EVs and off-grid power supplies, model validation is accomplished with great precision [71].

2.3.2.4 H infinity filter

When using the H Filter, the data about the process noise or measurement noise characteristics of the battery is not required. Despite its simple appearance, this model is capable of coping with specific situations. However, age, hysteresis, and temperature influences might alter the model's accuracy[18]. When it comes to the characteristics of the H infinite model, it is very efficient in decreasing the effect of external interference on the output. Accordingly, the battery SOC may be determined without needing exact statistical features of system and measurement errors. In contrast to Kalman filter techniques, the H infinity filter method ensures secure SOC estimation error is less than a set attenuation threshold in the worst-case scenario [72].

Lin *et al.* proposed a method with the Linear matrix inequality (LMI) - based H-infinity state observer, the model-based SOC estimators are developed, and their usefulness is proven by experimental data acquired from two types of lithium-ion batteries running at two EV deriving cycles. The comparison of three single-model SOC estimation approaches shows that some local estimation errors have been corrected and statistical errors have decreased, indicating that the SOC estimation accuracy and reliability has improved against battery materials, driving cycles, and inaccurate initial SOC values [73]. Another SOC estimation experiment is done to identify the parameters online, proposed a SOC joint estimation technique using H infinity filter (HF) and unscented Kalman filter (UKF) algorithms. Different temperatures have verified the HF-UKF SOC combined estimate approach. However, the approach is adaptable to incorrect beginning SOC values and varying operating temperatures [74].

Table 3 illustrates a comparison of adaptive system methods comparison:

Methods	Advantages	Disadvantages	Errors (and ref)	
Linear Kalman Filter	Estimates accurately states impacted by external disturbances like noises with a Gaussian distribution.	It necessitates intricate math. A nonlinear system's state cannot be estimated directly with KF.	≤ ± 5% ≤ ± 1.76%	[53] .[75]
Extended Kalman Filter (EKF)	Accurately predicts the state of a nonlinear dynamic system.	If the system is significantly non-linear, it may have limited robustness, and Linearization error may arise.	≤ ±1%	[58]
SPKF	Without the use of Jacobian matrices, EKF has the same computational complexity as EKF.	There are a lot of Complex computations involved.	≤ ±2%	[76]
UKF	Compute without Jacobian matrix or Gaussian noise. Up to third order non-linear system states accurately estimated.	a lack of robustness	≤ ±4%	[77]
Cubature Difference Kalman Filter	Enhanced divergence and dimensionality, more accurate compare to EKF	High complexity	≤ ±1.5%	[65]
Particle Filter (PF)	High accuracy with less processing time.	Mathematical complexity is required to tackle the issue.	≤ ±3.1%	[67]
H infinity filter	Precision, low computing cost, and quick response time.	Accuracy may be influenced by factors like as aging, hysteresis, and temperature variation.	≤ ± 2.49%	[78]

Table 3-Adaptive system methods comparison

2.4 Machine learning

Machine learning methods (also known as Data Driven methods [79]) are a hybrid of experimental and model-based approaches. SOC estimate using machine learning is becoming an appealing field for scholars to examine as a computer technologies progress. To be precise, they employ training data, measurements, and models during the learning process in order to predict the battery SOC value (as well as SOH). Data training and learning are two steps of machine learning-based SOC estimation [80]. To obtain a collection of training data, certain experiments are conducted on the Li-Ion batteries in a supervised environment. Many data sets may be generated using CCM based on the connection between input voltage, current, temperature, SOH and impedance to output voltage, current, temperature, SOH and impedance (SOC). During the learning phase, SOC estimate is carried out with the aid of these data sets. . [55]

There are a number of machine learning techniques that can be used for battery SOC prediction in the literature. Support vector machine (SVM) and neural network (NN) approaches, among others, are becoming increasingly significant in the online estimation of SOC[81]. All of these techniques assume the Li-ion batteries is a black box model, with internal dynamics discovered by massive amounts of collected data[54].

Historical data are used to evaluate the relationship between SOC and other observed variables, such as terminal voltage and current. Temperature is also included in these algorithms [82, 83]. When dealing with nonlinear issues, data-driven tactics are beneficial; nevertheless, the datasets and training methods that are used might have an impact on how well they function. Furthermore, the requirement for a large amount of data gathering in order to cover all of the possible operational scenarios leads in a high overall processing challenge. [84],[7]

2.4.1 Neural Network (NN):

The Neural Network (NN) approach may be used to provide a complicated non-linear model due to its flexibility and self-learning capabilities. Without knowing the battery's data or starting charge state, NN estimates SOC using training data. As with the human brain, a NN is composed of interconnected fundamental processing units called neurons. When given enough neurons and layers, NNs can approximate any nonlinear function, making them excellent for simulating complex systems. NNs may learn and modify their internal structure in order to adapt to a changing environment. Parallel computation enables neural networks to be incredibly efficient at data processing. Due to the data-driven nature of neural networks, it is feasible to construct a system model without having a thorough understanding of the system's physical characteristics[81]. As seen in the Figure 10, The network is composed of three major layers: the input layer, the hidden layer, and the output layer[85].

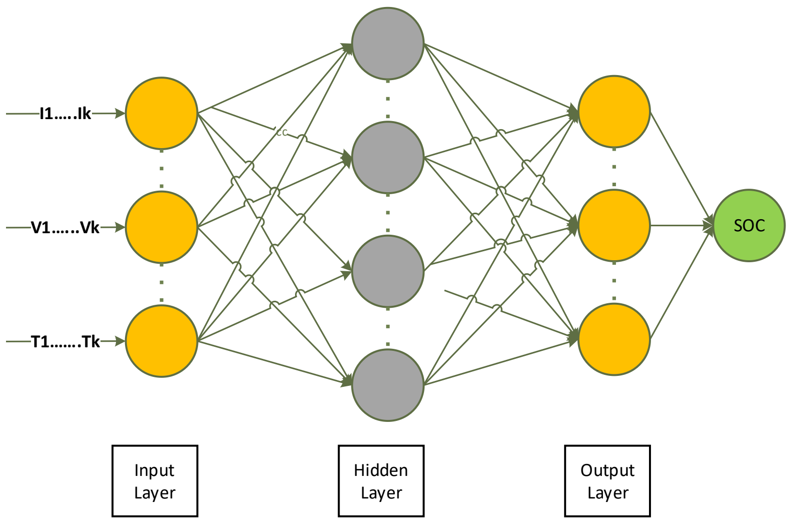

Figure 10: multi-layer feed-forward neural network's architecture

In order to estimate SOC, data such as current, terminal voltage and temperature are required. Because this method copes with nonlinear conditions, a large amount of data and memory is required for training, overloading the system [18]. Equation (2-13) illustrates the empirical equation for NNs [86].

$$y_i = s(\sum_{j=1}^{N}(W_{ij}x_j + b_i)) \tag{2-13}$$

W_{ij}=Weight to neuron i from neuron j $\quad$ b_i= bias

y_K=Measurement equation $\quad$ x_i=input verctors

This technique's effectiveness has been proven in Li-ion battery testing utilizing a neural network-based thermal-electric coupled model [87] . The kinetic model may be used to determine the properties of a battery over a longer period of time[7]. Kuchly *et al.* developed a neural network model that is capable of correcting initial SOC estimate mistakes and handling current measurement bias, while also attaining superior estimation performance than a traditional neural network model that takes just instantaneous information as an input [88]. Data estimation can also be accomplished by combining the neural network with particle filtering techniques [89]. The lithium iron phosphate battery's SOC prediction error may be greatly reduced thanks to an Improved neural network method developed by Guo [90]. The algorithm's efficiency is tested by comparing the lithium batteries SOC value to the neural network's estimated SOC value. As a result of this research, the algorithm can efficiently anticipate the SOC of lithium batteries for electric vehicles [90]. An EKF-based battery model was proposed by Chen et al., which took into account the influence of hysteresis open circuit voltage. For the estimate of SOC, NN was combined with EKF and used. The suggested combination model outperforms all others in terms of accuracy estimation, with an error of less than one percent in the estimation of accuracy [91].

There are several uses for fuzzy neural networks, notably in the detection of unknown systems. By computing the optimal coefficients of the learning mechanism, FNN can successfully match the nonlinear system in nonlinear system assessment. [30]. Li *et al.* proposes an improved Fuzzy Neural Network (FNN) to predict SOC of a lithium-ion battery using a reduced form genetic method (RGA). A continuous nonlinear function was approximated using twelve inputs and one output. The validation findings show that the approach can accurately anticipate any degree of precision[92].

2.4.2 Fuzzy Logic (FL)

By utilizing adequate training datasets, Fuzzy Logic (FL) is another method that can present complex, non-linear models. There are four parts in FL employment as follows, which is demonstrated in Figure 11 [50]:

- Output variables are linked to input variables by a set of rules
- A database providing input and output variable membership functions
- An inference mechanism,
- To convert the fuzzy output sets to real-valued.

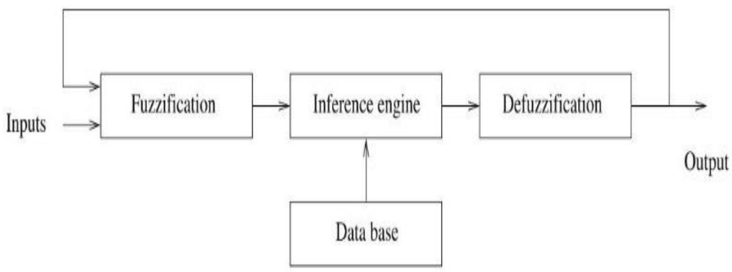

Figure 11: The Logic of Fuzzy [50]

With FL's powerful function, a nonlinear model may be predicted with ease; nevertheless, this demands a big memory unit, extensive computations, and a high-end computer system [18].

In ref [93] a SOC and SOH estimation method by utilizing Fuzzy logic to analyzing date come from coulomb counting and Impedance spectroscopy are proposed. Using the presented model, it is possible to forecast SOC with a maximum error of 5%.

In ref [94] a fuzzy logic model employing to estimation of SOC/SOH of Li-ion battery at all temperatures was developed. This model estimates two quantities: the cycle number and remaining pulse number for the battery by processing the data. Testing for ac impedance and voltage recovery was performed at room temperature and 0°C. The results reveal an inaccuracy of one pulse to estimate the remaining pulses and a 2.5 error to anticipate the cycle number.

Malkhandi developed a model for SOC estimation for by utilizing a learning system and coulomb counting. This model ensures that time- dependent variables are error-free. By employing Fuzzy Logic system

In [92], FL algorithm is presented for the estimation of SOC model by using the coulomb metric method. A learning system is used which adjusts the coulomb metric method so that time-dependent variable does not contain any error. The suggested system's efficacy is then tested using a microcontroller-based FL system.

2.4.3 Support Vector Machine (SVM)

An SVM is an information processing technique that has been employed in a number of different applications throughout the past decade. The SVM has been used to the problem of regression analysis. A stronger nonlinear estimating approach than a Least Squares estimation system, because the SVM is less sensitive to small changes than the Least Squares estimation system [96]. SVM is based on the notion of structural risk reduction, can outperform traditional neural networks in terms of performance since they minimize structural risk. Although this approach has several advantages, it also has some drawbacks, including a rising modeling size and a single output structure[52]. Because the cost function for developing the model rejects any training data that is near (within a threshold e) to the model prediction, the model built by SVR is only dependent on a portion of the training data [26]. Eq (2-14) illustrates the empirical eq of support vector machine:

$$Y_i = \sum_{i}^{N} W, K(x_i . x) + B \tag{2-14}$$

Y_i=Estimated output

$(x_i . x)$=Support vectors

W=Weight

B= bias

K= Kernel

Using the correct training data, this approach can predict SOC rapidly and accurately in non-linear and high-dimensional models. But the model has a lot of complicated calculations in it. Moreover, adjusting a model's parameters requires a lot of trial and error, which might take ages [18].

In ref [96] a support vector machine (SVM) was used to estimate the SOC on a larger scale for Li-P batteries. A study has shown that an EKF SOC estimator can be made more accurate by using this method, because it costs less than a coulomb counter. Because of the use of unscented Kalman filters as well as least-square support vector machines.

In ref[97] an estimation of SOC using SVM is on Li-Ion batteries was implemented. Employing this model by increasing the likelihood reveals even with fewer training samples results in more accurate estimation.

In another experiment of SOC estimation of large-scale batteries, parameters (V, I, T) are employed in model building. On working condition of battery, this model demonstrated accurate SOC estimation with the coefficient of determination of 0.97. [98] .By using an enhanced support vector machine (SVM) method, Hu *et al.* found that regression-based SOC estimate was easier and more accurate than using artificial neural networks [78]. SOC is calculated using the weighted least squares support vector machine (WLS-SVM) algorithm, according to the approach described by Chen *et al.* in his paper. A number of tests have been conducted to verify the approach, and the results have revealed that less sophisticated computing results in an improvement in resilience[100].

Table 4 illustrated Machine learning method comparison:

Methods	**Advantages**	**Disadvantages**	**Errors (and ref)**	
NN	It is feasible to implement a non-linear system.	The training data require a considerable amount of storage space.	≤ ± 4.6%	[101]
FL	A non-linear dynamic system may be modelled with this software.	The training data require a considerable amount of storage space.	≤ ±5%	[93]
SVM	Exhibits excellent performance in non-linear and high-dimensional models and can estimate SOC fast and accurately.	High-complexity computations and iterative process of trial and error is required to fine tune the model's parameters.	≤ ±6%	[98]

Table 4-Machine learning method comparison

2.5 Nonlinear observer- based

The next sections address the three most prevalent non-linear observer-based approaches that are currently available:

2.5.1 Non-linear Observers (NLO)

Due to the non- linear features of batteries, using linear methods increase the estimation error of measurements. A reliable and robust technique for estimating SOC is required due to the fact that the SOC is immeasurable and nonlinearly fluctuates with different parameters such as battery degradation, current rate ambient temperature. Hence, the other methods so called non-linear observer is employed, in this approach non-linear observation equation is applied in linear systems [54]. The equivalent circuit model is used to develop the state-space equations in Non-Linear observer (NLO) approaches. This technique does not necessitate the use of sophisticated matrix operations, and it demonstrates robustness in the face of measurement failures and parameter uncertainty. When compared to the EK technique, the provided method has lowered the calculation cost while maintaining performance comparable and convergence performance in SOC estimation. This strategy can both enhance SOC estimate accuracy and speed up convergence compare to SMO [102].

A SOC estimation of Li-ion batteries is proposed using a NLO based on ISS (input-to-state stability). In this method by implementing two RC networks in the equivalent circuit, the SOC is estimated through ISS based estimator. ISS-based estimator for SOC estimation provides excellent accuracy and enhanced resilience, according to simulation findings, which are consistent with the literature. [103]

2.5.2 Sliding Mode Observer (SMO)

Next robust technique for estimating SOC is the sliding motor observer (SMO). The discontinuous feedback signal is a distinguishing characteristic of this method. Aside from that, enabling one or more state-space manifolds. There are no substantial uncertainties regarding the outcome of this finite time convergent controller since it is a finite time controller. In spite of this, the chatter problem cannot be overlooked [104]. In this system with variables $s(x) \in R$, by using it switching input, it controls the output to be $s(x)=0$. As seen in the following equation(2-15), the sliding variables of the r th order sliding mode in a dynamic system are defined as follows [105]:

$$S = S' = S'' = S''' = \cdots S^{r-1} = 0 \tag{2-15}$$

Researchers propose an equivalent circuit model identified during experimentation to estimate SOC of EV Li-ion batteries by using a non-singular terminal sliding mode observer. This non-singular terminal sliding mode, which is second-order quick embossing, uses linear and non-singular sliding modes. SMO performs poorly compared to the suggested approach for SOC estimation, and this approach can cover the slow convergence and chattering inherent to the SMO. Moreover, due to model uncertainty, the KF-based approach cannot converge, whereas the suggested technique can [106].

Skrylnyk *et al.* proposed SOC estimation based on the sliding mode observer on Lead-Acid Batteries. In this method due to the robustness of the model, possibility of external uncertainty and disturbance are removed. On the hand, due to the application of high-frequency switching control, it is necessary to investigate the chattering in these systems[107].

Another method is proposed for SOC and SOH estimation using adaptive sliding observer. By using the equivalent circuit model, the experimental result of this approach shows the improvement in the SOC and SOH estimation and performance under uncertainties. Moreover, this robust method prevents the chattering effect from occurring [108].

2.5.3 Proportional-integral observer (PIO)

PIO, as next non-linear observer- based strategy for SOC estimation, provides an efficient and robust control method which as an alternative to feedback control systems, it is frequently employed. According to this controller's primary purpose, it is able to quickly and precisely converge the estimated voltage to the observed voltage [18]. Accuracy, robustness and easy implementation can be named as primary features of this strategy. In this method the precision of the battery model's characteristics has a significant impact. When the effects of aging, hysteresis, and thermal impact are taken into account, the parameters of the battery model will be time-varying [109].The structure of PI observer is illustrated in Figure 12 [109].

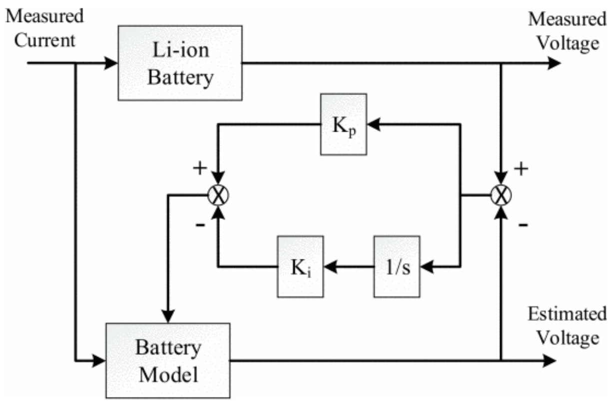

Figure 12- Structure of a PI observer

A SOC estimate technique based on the PI observer is proposed in ref [104], which avoids the need for sophisticated calculation and makes use of an RC model as a substitute for the Li-Ion battery model. The results demonstrate that the predicted SOC approaches the reference in a short period of time. Comparing estimate errors to coulomb counting, errors are limited to a tiny range of 2% (small band) when. However, the model parameters are fixed, making it difficult to construct an effective gain matrix to reduce the error to the smallest possible amount.

An adaptive PI observer designed by P. Li *et al.* to estimate SOC more accurately with the updating the parameters at the same time. Moreover, the stability of the observer is ensured by the use of Lyapunov stability analyses. The findings reveal that the suggested estimation using this adaptive PI observer is much more precise and resilient than the estimation using EKF or a non-adaptive PI observer, which is consistent with the literature [109].

Table 5 illustrated Nonlinear observer method comparison:

Methods	**Advantages**	**Disadvantages**	**Errors (and ref)**	
NLO	Accuracy convergence speed and calculation cost have been improved.	To decrease the error, it is difficult to design a suitable gain matrix.	≤ ± 4.5%	[102]
SMO	Stability and robustness are guaranteed through improved tracking control.	To manage the sliding regime, it is difficult to alter the switching gain.	≤ ±3%	[110]
PIO	Robust method SOC estimation with accurately and quickly.	Could deliver inaccurate results if the controller is not properly designed.	≤ ±1%	[104]

Table 5-Nonlinear observer method comparison

2.6 Hybrid Systems

This category is concerned with techniques that make use of the structure of the previously described state estimate of two or more distinct approaches in order to obtain an optimal model with more merits. Additionally, the cost of the battery management system is decreased. Moreover, A hybrid estimating approach can optimize the information accessible because the information provided in the individual estimating method is restricted. More data and information combinations lead to more accurate estimation result. Nevertheless, the process involves immensely challenging mathematical computations that necessitate the use of a big memory device. There are a number of hybrid techniques to estimate SOC that may be discovered in the literature.

Zhou *et al.* proposed a hybrid SOC estimation method based on utilizing EKF and PF and recursive least square approach is used to identify the equivalent circuit. Due to its capacity to accurately approximate the posterior probability density, the suggested technique is a preferable choice for generating proposal distributions in particle filter frameworks. The suggested technique outperforms the EKF and PF methods in terms of accuracy and in in the longer average discharge phase [111].

According to another study, a combined SOC estimation method based on Ampher-hour Counting and multiple OCVs was developed. The available capacity is impacted by temperature and current, resulting in inaccurate SOC estimates. The suggested improved Ah counting system, which adjusts available capacity and coulombic efficiency according to temperature, resolves this problem. When used for calibration and as a supplement to compensate for mounting mistakes in Ah counting caused by the limited precision of current sensors and the lack of a suitable starting SOC, the OCV technique is beneficial to all parties involved. In order to estimate beginning SoCs, rated and non-rated OCV–SoCs are computed based on the available capacities at different temperatures. The data demonstrate that the approach can properly estimate SOC at a variety of ambient temperatures. [112].

Li and Wang proposes a hybrid method in order to increase SOC estimation speed and accuracy of Adaptive Extended Kalman Filter (AEKF) in a nonlinear condition, since it is unable to track SOC fast. In order to find working status, an EV operating condition estimator is used to determine station and non-stationary situation. The AEKF approach is used to estimate SOC when EVs are stable, while the look-up table method is utilized when they are not. The experimental findings reveal that the suggested hybrid estimation approach has greater SOC estimation accuracy and improved convergence rate [113].

In ref [114], the EKF technique is used to develop an adaptive method for estimating SOC that incorporates both coulomb-accumulation and open-circuit voltage method. As the NiMH battery system in an EV is highly dynamic, the coulomb-accumulation factor is vital for estimating SOC. Because of the limitations of coulomb-accumulation, the open-circuit voltage can be employed as an adjunct approach to get the SOC closer to its real value in the steady state. A robust, noise-immunity, and accuracy feature of the proposed adaptive approach makes it particularly suitable for EV applications.

Using two separate methodologies, a new SOC estimating method may be employed in real-time: EMF method during equilibrium and coulomb counting method in discharge state. SOC and remaining run-time RRT may be accurately calculated using a basic Qmax adoption approach, which also increases the SOC estimate system's capacity to deal with the aging impact. The charge state's stability is used to modify Qmax for aging in this technique. The Qmax adaptation approach can increase the accuracy of the SOC and RRT estimates for a new battery. The finding shows that the Qmax adoption approach will improve SOC and RRT estimate accuracy by a significant amount [115].

In ref [49] a SOC estimation technique based on the use of a mix of feedforward neural networks to generate an enhanced battery model and the EKF algorithm is suggested. The findings indicate that the SOC estimate can converge to the reference value even when the starting SOC error and initial capacity error are set incorrectly, and after convergence, the SOC estimation errors are within 2% of the reference value.

3 Chapter 3

High-performance and dependable battery health management systems are necessary to meet the new battery application challenges, which range from energy storage systems, PV systems to transportation, as well as to assure the safety and longevity of electric cars and hybrid electric vehicles [116]. SOH of a battery offers crucial information on the battery's performance and lifespan, as well as allowing for improved energy management in hybrid vehicles. The SOH of a battery has been estimated using a variety of methodologies developed via various research investigations. This is a factor that reflects the amount of deterioration of the battery [117]. However, determining battery SOC and SOH may be very difficult owing to the battery's nonlinear complicated behavior. Battery SOH estimation becomes difficult due to the presence of several unknown and unexpected elements that influence battery health.

They are responsible for the unexpected battery ageing process, and several studies have been conducted to better understand this process in the literature [118]. When it comes to some application such as EVs Real-time estimation of battery SOH is critical since enables the detection of battery malfunctions and the prevention of potentially harmful incidents. It allows battery fault diagnosis and help prevent hazardous accidents. Electric vehicle batteries are also more difficult to charge since they take longer to recharge, therefore charging happens at random when the battery isn't fully charged. According to driving habits, traffic circumstances, and other external variables, EV batteries deplete dynamically [119].

The primary goal of this study is to introduce the most recent and most widely used battery SOH estimation methods and identify the advantages and disadvantages.

SOH definition:

Several indications or conceptions are produced to assess lithium-ion battery aging by researchers. The most often utilized indication is SOH. SOH is defined as the current condition of an aged battery's ability to offer a specified performance when contrasted to its ability to give specific performance when it was in its original state. As a result, the relative capacity of batteries is utilized as a measure of their SOH and capacity loss. The following formula eq (3-1) can be used to determine the cell's relative capacity. For most batteries, "end of life" (EOL) occurs when their capacity drops to 80% of what it was when new [120].

$$SOH = C_{Reletive} = \frac{C_{Present}}{C_{Initial}} * 100\% \quad (3\text{-}1)$$

$C_{Reletive}$=relative capacity of current cells
C_present=capacity of current cells
C_initial=InitialCapacity

In terms of internal resistance, some literatures [121, 122] defined SOH as following eq (3-2) :

$$SOH = \frac{R_e - R}{R_e - R_n} * 100\% \quad (3\text{-}2)$$

R_e=internal resistance in end of life the battery
R =Internal resistance
R_n=internal resistance of the new battery

The SOH of a battery may be computed by dividing the actual indicator value (capacity, impedance, or resistance) by the original indicator value. To determine the battery's SOH, it is important to monitor its changes since Berecibar *et al.* state battery capacity declines as much as 20% and internal resistance increases by up to 160% when the battery is at its end of life (EoL) in vehicle applications [123] which is an extremely difficult process, as both battery resistance and capacity fluctuate due to numerous distinct factors, also in terms of their relations with one another.

SOH estimation challengers:

There are several difficulties in estimating SOH in the batteries because of the way the batteries are designed. For starters, the SOH of a Lithium-ion cell is an internal feature of the battery that cannot be measured directly. For correct acquisition of SOH characteristics, it is important to have voltage, current, and temperature as inputs to the system. Furthermore, the SOH of a lithium-ion cell is influenced by internal multi-parameter coupling as well as external stressors such as temperature, current, and loading mode, among others. Furthermore, in order to foresee, many prediction algorithms currently rely on irreversible off-line state data, which is influenced by monomer changes and has little repeatability. The online identification method has also been plagued by difficulties; finally, the degradation curve of lithium-ion batteries is nonlinear, making it difficult to properly and reliably determine the SOH of these batteries in real-world working conditions.

SOH classification:

There are many ways to classify SOH estimation methods. These classification criteria inevitably differ slightly from each other, and may even overlap in some perspectives. For example, in two distinct articles, the same procedure is classified into two different categories. As a result, it may be confusing due to the overlap of certain attributes of the naming rules and is not conducive for researchers to have an in-depth understanding. Furthermore, the categorization techniques of the relevant reviews that have already been published are often insufficient, and there are only a few different types of review methodologies to choose from. A deeper comparison and description of typical methods might be included, but there is still potential for development.

As we did for SOC classification, Venugopal and T. classified SOH methods into 4 primary groups, Direct measurement, Adaptive Filter, Data Driven and Model based methods [124]. In ref [120] multiple methodologies were used to describe and analyze the aging processes and SOH estimating methods, ranging from microscope observations to statistical analysis, each having its own pros and cons features. In another research by Yang *et al.*, the factors used to describe SOH, such as capacity, impedance, and aging-mechanism parameters, are utilized to categorize SOH estimating techniques. According to [126] , they categorized SOH estimation techniques based on their distinctive factors and described them from two perspectives: short-term and long-term. Lithium batteries' SOH management systems were analyzed and compared in ref [12] using various techniques of extracting health state information. In the context of embedded application environments, a new set of metrics in [4] developed for evaluating the operational efficiency of various SOH estimation and prediction methods. The majority of existing techniques for measuring SOH rely on a capacity fading and electrochemical (EC) model, since as battery age increases, the capacity declines and the EC parameters change. All of these techniques, on the other hand, estimate SOH under solid assumptions and static cycle conditions. Due to the fact that real-world EV batteries require real-time SOH calculation and that charging and discharging occur in a dynamic way, these conditions are not ideal for testing [127]. In ref [116] the battery internal resistance, impedance, and capacity are the three key indications that determine this condition. As Noura *et al.* proposed, SOH in EV application is divided into three primary categories: experimental approaches, model-based methods, and Machine Learning methods. Machine learning approaches are a hybrid of experimental and model-based techniques [116]. Photovoltaic systems were the primary topic of a study of lithium-ion battery SOH estimate methods conducted by Tian et al. In terms of the signals utilized to extract health indicators (HIs), they divide existing approaches into two primary categories: terminal voltage and other signals[119].

In this paper, SOH estimation methods categorized into 4 main groups: Experimental based, model-based, adaptive filters and data-based estimation that can be further categorized into different groups.

Figure 13 demonstrates SOH classification:

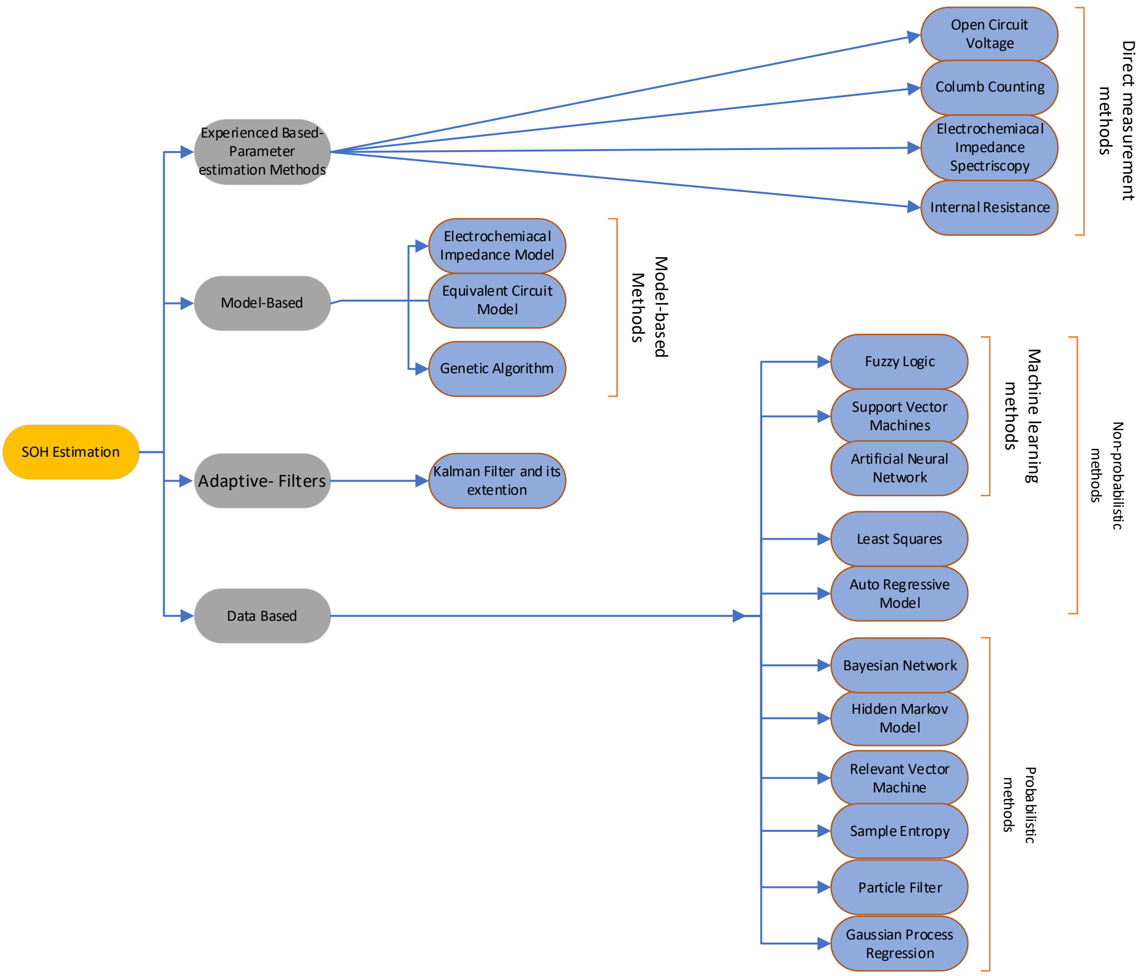

Figure 13- SOH classification

Experimental methods are almost carried out in labs since they need the use of specialized equipment and take a long time to complete. They are based on the collection of data and measurements that may be utilized to better understand and analyze the aging behavior of the battery over time. In this part, we will discuss the most important experimental approaches for estimating the battery SOH. Moreover, these methods are expensive to implement and making them unsuitable for real-time applications [128].

3.1 Experimental methods:

3.1.1 Direct measurement methods:

Battery's Internal Resistance Measurement:

Battery internal resistance is a key SOH indication that determines how much voltage drops when current is delivered to the battery. Aging and deterioration has a significant effect on this value, (the value SOH decrease over time). As a result, it is frequently employed as a reliable indication for estimating the battery SOH. The current pulse approach is the most often utilized method. On the basis of Ohm's Law, it works Battery internal resistance is determined by measuring the voltage drop that occurs when a specific current is applied [129]. The eq (3-3) Shows the formula [130]:

$$Rb(SOC.T) = \frac{OCV(SOC.T) - Vbat(SOC.T)}{Ipulse} \tag{3-3}$$

Rb=Battery internal resistance

OCV= Open Cicuit Voltage

Vbat= Applied voltages

Ipulse= Applied current

Using Electrochemical Impedance Spectroscopy (EIS), Piatowicz et al. present a method for measuring the internal resistance of a battery, which is accurate yet challenging to apply [11].

When it comes to hybrid applications, the internal resistance of the battery is a significant signal of interest. This indication indicates how much the battery has degraded in terms of its capacity to provide electricity [10].

Electrochemical Impedance Spectroscopy (EIS):

This method measures a battery's internal impedance over a wide range of frequencies and currents [131]. In addition, various battery dynamics effect different frequency ranges on the EIS measurement, hence impedance spectroscopy may monitor the battery's SOH. With impedance spectroscopy, calculating ECM parameters is the simplest technique to determine SOH. To employ impedance spectroscopy as a diagnostic technique, a battery's electrochemical model is required, which is often unique. The ECM is built using 16 parameters in ref [132] ten parameters are determined using Particle swarm optimization (PSO) while the rest of the parameters remain unaltered. Between 0.025Hz and 4kHz, the experiment is carried out with 100% and 50% charged lithium-ion batteries. Randle's model was determined to be 8 times less accurate than the suggested model.

Due to the high cost and complexity of on-board installation, EIS cannot be used to SOH estimate. This approach works well in the lab [133].

Based on the equivalent-circuit technique and EIS data, Eddahech et al. have developed a model of lithium-ion polymer cells that uses this approach. It was possible to accurately predict lithium-ion cell aging behavior using the battery SOH indicator built using RNN, which took into account the unique operational settings and offered useful data on the predicted battery life. Simulated battery behavior and SOH monitoring findings are a promising step toward developing a real-time, automated battery monitoring system [134].

Open Circuit Voltage (OCV)

Depending on whether a battery is being charged or discharged, the voltage of the battery will rise or fall. During comparing higher-capacity batteries to lower-capacity batteries, higher-capacity batteries have less voltage variation when charging and discharging. Using the link between ampere hours charged or drained and the voltage differential experienced during the respective charging or discharging, it is feasible to determine battery capacity. Laboratory trials, on the other hand, are necessary in order to anticipate the relationship between SOH and CV. Moreover, for efficient OCV estimation, an extremely precise battery model with characteristics that can be adapted to the battery's ageing condition is necessary [135]. The SOH estimate technique based on open circuit voltage (OCV) can be used online or offline. In spite of this, rigorous laboratory studies are carried out in order to establish a link between SOH and OCV. A battery's capacity deterioration and model parameters are analyzed based on the charging curve during various battery cycles in order to correctly predict battery SOH.

SOH was estimated using the OCV model in ref [136]. Battery aging characteristics are predicted using incremental capacity analysis (ICA) at various operating temps. The model reliably measures the SOH of the battery with an estimation error of only 1%. Some additional researchers studied battery capacity fading and model parameters to properly evaluate SOH by monitoring charging curves at various battery lifespans. SOH is estimated with the use of a transformation function and a non-linear least square technique utilizing an electrochemical model (ECM) and the Constant Current-Constant Voltage charging method. SOH's estimating error is less than 3% at all ages [137].

Coulomb Counting (CC)

This approach counts the charge transported through the battery during complete charge-discharge by continually measuring the input and output current. With this information, the remaining capacity is calculated This takes a long time and necessitates a large amount of storage space and in the case of defective initial ampere-hour values, inaccurate estimations occur. Hence calibration is required often to prevent charge integration problems and the basic approach of Coulomb counting frequently requires extra ways to update the value and avoid any mistakes [135]. In the CC technique, SOH is determined by dividing the discharge value by the rated capacity [138]. In another research [45], depth of discharge (DOD) is used to determine the SOH. When comparing the DOD and the battery's capacity, you can obtain an idea of how much charge has been released. Because of the efficiency of charging and discharging, each charge and discharge cycle is balanced out. It is also necessary to recalibrate the battery in order to eliminate the cumulative impact that happens when the battery is completely charged and discharged on successive occasions. The fact that CC consumes very little electricity is a significant advantage. In spite of this, there is a significant estimate inaccuracy of less than 10%, which is unacceptable. Accuracy might be improved by 3 percent by including a Kalman filter (KF).

In [139] for lithium-ion batteries, a new improved coulomb counting approach has been presented to estimate SOH. Correcting operational efficiency and evaluating SOH were both evaluated to increase estimate accuracy. The estimation error may be decreased below 1% throughout the operational cycle by re-evaluating the SOH. Because of the straightforward computation and basic hardware requirements, the suggested approach may be simply implemented in all portable devices, as well as electric automobiles, without difficulty.

In the following Table 6-Experimental methods comparisons, are illustrated:

Methods	Advantages	Disadvantages	Errors (and ref)	
Internal Resistance	-Simple -Accurate	An offline and time-consumed method		
EIS	-Allows for a simple computation when used as a stand-alone technique	-Offline method -Current pattern is distinct -Restricted to specific battery	2%	[134]
OCV	-Easy to use	-Offline method	<1%	[140]
CC	-Calculation of data is simple -Consume less power	-Calibration requirement	<1% after 28th cycle when correction is applied	[139]

Table 6-Experimental methods comparisons

3.1.2 Model-based method

Lithium-ion batteries' deterioration and failure mechanisms are used as a model to estimate SOH. The model's essential parameters, which indicate the internal aging degree, have decay laws whose correctness is dependent on them for estimation. [141, 142]. EIS (electrochemical impedance spectroscopy) is a pretty well-established approach that may be used in a variety of ways [143]. It may be classified into two groups based on the distinction between model construction theory and the algorithmic basis of state prediction: electrochemical models and equivalent circuit models:

Electrochemical Model Method

In the electrochemical model, the lithium-ion battery's electrochemical reaction process is a key component. The porous electrode theory and kinetic knowledge are utilized to create a physical model by extracting internal characteristics that describe the battery's dynamic aging and failure process, which may be used for SOH estimate and prediction [144]. There is substantial theoretical backing for the electrochemical model technique in order to accurately describe the battery's internal electrochemical reaction and intensity as it ages. Lithium-ion movement law and the changing trend of active chemicals in positive and negative electrodes at various SOH sites may be correctly described by this technique. As a result of its complexity, the lithium-ion battery electrochemistry system has a wide range of side effects. Because the model's aging condition is complex and includes various characteristics linked together, utilizing a single range has limited generality, dynamic forecast accuracy, and does not provide online real-time SOH estimate and prediction when working conditions change.

A more accurate modeling of the chemical behavior of a battery, including electrolyte volume and concentration, density of active components, corrosion and porosity of active components, may be achieved using the EChM model[145]. However, because of its complexity and high computing cost, it is unlikely that this model would be implemented in a real EV's BMS.

Equivalent Circuit Model:

A significant amount of electrotechnics is used in the equivalent circuit model; the battery is treated as a black box, and its input-output working system is based on the construction of electrical components, so it is essentially a mathematical model of the lithium-ion battery that has evolved into a circuit model to describe the capacity decline characteristics of the lithium-ion battery over time. In order to arrive at a solution, the Kirchhoff current and Kirchhoff voltage equations were employed. In order to achieve the aim of estimating SOH, the extrapolation of features associated with SOH estimation was paired with known values that could be measured [146].

Many different algorithms [63, 147] have been devised to determine model parameters such as V, I, T, and impedance from basic electrical elements such as resistors, capacitors, and voltage sources using basic electrical elements. Although the ECM technique is simple to apply in BMS, it necessitates the use of time-consuming experimental experiments to obtain a wide group of datasets.

In ref [148] It was discovered that SOH had a considerable influence on the Thevenin ECM parameters, as well as SOC and temperature, in addition to other factors. As SOH decreases, the ohmic and polarization resistances decrease as well, although the polarization capacitance decreases as well.

Genetic Algorithm (GA)

Non-linear model parameters may be estimated using this approach in any field of physics. It is possible to utilize GA as a decent prediction algorithm by using raw data from BMS, such as voltage. Nonetheless, it requires a large volume of data to discover values and is challenging to execute online due to the high processing power required to do so [135].

In ref [149], Using real-time measurements of current and voltage, a genetic algorithm (GA) is used to predict the battery model parameters including the diffusion capacitance. Once the diffusion capacitance has been known, the battery SOH may then be calculated. It is also important to take into account the effect of temperatures on SOH estimate findings. The proposed approach was further validated by testing on a variety of batteries.

In the Table 7 the main advantages and disadvantages of Model-based SOH method are illustrated:

Methods	Advantages	Disadvantages	Errors (and ref)	
Electrochemical Model Method	-Good accuracy -Online	-Low adaptation	-	[120]
Equivalent Circuit Model	-Online -Operate without data -Can be used for different kind of LIB	-Low adaptation -Fair predication and accuracy -Time Consuming approach. -In a continual discharge situation, the battery is allowed to cycle.	Proprietary dataset: 0.12% NASA dataset –0.57% to 0.19	[120] [146]
GA	-Can be implemented in non- linear systems.	-High processing power is required -Difficult to be used as Online.	5.11%	[149]

Table 7-Model-based methods comparison

Adaptive Filters

Kalman filter and its extensions (KF)

With the Kalman filter, you may estimate the output variable by taking measurements in a series over a period of time. The zero-mean distribution of the measurement noise and the zero-mean distribution of the process noise are among the assumptions that underpin Kalman filtering. There are two phases involved in the procedure. In the prediction phase, the Kalman filter predicts the current output variable, and in the updating phase, it forecasts the current output variable. After that, Kalman filters are used to reduce the discrepancy between estimated and observed state variables, which helps to enhance estimates even more. The system degradation model, on the other hand, must be present in order to make use of the Kalman filter. Originally, the Kalman filter was intended to be utilized in linear systems, and this was the case. [150]. As previously stated, the degradation model for batteries is complex and non-linear, as seen in the preceding section. If you have a nonlinear system, such as those used for SOH estimation, an improved version of the Kalman filter can be employed. Examples of such systems are Extended Kalman Filter (EKF), Unscented Kalman Filter (UKF), and DKF. Although KF on linear systems produces a stable state estimator, the stability of the estimator cannot be evaluated because of the heuristic nature of EKF. It is standard practice to use EKF for model building since it is a non-linear model internal state that may be changed. [151]

The estimation of SOC and SOH is carried out with the help of UKF and support vector regression techniques. This model has been evaluated on a number of cycles and aging tests and has been shown to have an estimation error of less than one percent. [59]. In ref [152] for estimating SOH, DEKF is used, capacity and voltage patterns are utilized to derive the first-order Randle circuit characteristics, respectively. The Hamming neural network is used to identify typical patterns in order to enhance the SOH forecast. There was a 5% discrepancy in the findings. In the Table 8 you can see the details regarding adaptive filter methods:

Methods	Advantages	Disadvantages	Errors (and ref)
Adaptive Filters (KF)	-Accurate and capable to remove noise -Online	-The calculation is complicated.	5% [152]

Table 8- Adaptive filters comparison

3.2 Data-Based Methods

Lithium-ion battery properties such as incremental capacity, differential voltage (DV), or internal resistance (IR) may be determined analytically from the partial or entire charging/discharging cycle data acquired. These methods reduce the need for physical models to capture some of the physics connected to deterioration, which is a major problem in the context of this research. Many probabilistic and non-probabilistic methods may be used to link the patient's general health condition to these variables (SOH). Because of these qualities, the online implementation of SOH is greatly aided by the trade-off between the effectiveness of an algorithm and the complexity of a computer system. Probabilistic and non-probabilistic methods for the estimation of SOH based on analytically generated characteristics. Non-probabilistic models may provide a definitive answer, whereas probabilistic models provide a measure of prediction uncertainty.

3.2.1 Non-probabilistic methods

3.2.1.1 Machine learning methods

Fuzzy Logic Method

In order to deal with data obtained from non-linear, complicated systems, fuzzy logic employs a set of fuzzy rules. When this is done, the data may be broken down into fuzzy subsets. Uncertainty levels are assigned to each of the subgroups. SOH estimation accuracy is determined by the accuracy of the fuzzy sets' members, which belong to a member function (MF). Selecting the right MF for SOH prediction is critical. In case of employing this approach, there is no need to know anything about how the system works. This enables for a greater degree of abstraction, which comes from real-world testing and applications, to define a complicated system. Although this approach has a better level of precision, the quantity of computing required is more.

The index of SOH is calculated using two exponential functions, as indicated in the following equation (3-4) [153]:

$$Y_{fit} = a_0 + a_1 e^{-(\frac{x}{\alpha_1})^{\beta_1}} + a_2 e^{-(\frac{x}{\alpha_2})^{\beta_2}} \tag{3-4}$$

x=No of Cycle

Y= Normalized Capacity Value

The fit function is estimated using the fuzzy technique. FL first calculates the health index using a fitting curve with an inaccuracy between 5% and 10%. When assessing health index, a neural network is employed to minimize the inaccuracy by 5% in step 2.

Support Vector Machine

Non-linear systems may benefit from the use of Support Vector Machines, which analyze data and identify patterns. SVMs have been extensively utilized in pattern recognition to solve classification difficulties. In addition, regression issues may be solved using the SVM. As a non-linear estimator, the SVM is often more robust than a least squares estimator since it is intolerant to tiny changes. As a result of its capacity to handle minimal training datasets, SVM is commonly employed. In contrast, as the training data set grows, the number of support vectors grows as well, which raises the computational cost [135].

Researchers [154, 155] have devised an SVM in order to overcome the aforementioned difficulties and acquire a precise SOH estimation. Batteries may be predicted during various periods of life using an SVM classification and regression model[155]. The technique claims to deliver desired outcomes. It's not possible to get input vectors for on-board SOH estimation when discharging because of the random nature of discharge current. Nuhic *et al.* use an SVM method to estimate SOH in a wide range of environments and load circumstances by getting the enormous quantity of information on the lithium-ion cell through performing several measurements in time. Battery health may be accurately assessed utilizing a variety of driving cycles at varying temperatures, according to the validation process [156].

As part of [154], the SVM algorithm is used in conjunction with rain flow theory to forecast the SOH under difficult operational circumstances. However, certain feature vectors are challenging to measure and quantify in practice. Hence, real-time estimate requires that feature vectors be selected with care. Because SVM relies on huge amounts of data to develop and train models, it can put a strain on the BMS's ability to store vast amounts of data. The SVM-based SOH estimation technique should therefore be carefully built to assess fewer data points with high accuracy.

In ref [157] a new approach for determining a patient's SOH has been developed based on partial charge voltage and current data. Discussion and analysis are given to extracting feature variables such as energy signal, Ah-throughput and charging time. With the SVM kernel function being RBF, the support vector machine is used to estimate the SOH value. Full and partial charging data are used to test the SVM's ability to predict SOH performance. SOH may be correctly estimated for practical use using the mentioned technique, as shown by experiment results.

Artificial Neural Network

As it discussed in chapter 2, There are several layers of an Artificial Neural Network (ANN). The ANN, like the human brain, must grow. It employs each neuron's weights and biases to learn. This means that ANNs cannot be used on real-life models. Any nonlinear mapping may be approached using ANN by extending the hidden layers and neurons in the network [158]. It may take many cycles to train an ANN. Because of this, the trained ANN can only be utilized for one task. To anticipate SOH of batteries with dynamic deterioration, which makes it challenging to employ [135]. A broad variety of improved methods are employed in the estimation SOC and SOH in lithium battery. Nonlinear self-learning is a key feature of ANNs. An accurate estimate and prediction model is built using a large number of training data samples and then fine-tuned using these data samples. When it comes to battery chemistry and SOH monitoring, in [159] researchers applied the NN technique and pattern recognition. High accuracy may be achieved using the NN approach, which has shown to be quite promising. More training data, such as current and temperature, may help to increase the performance of NN even more.

Real-time estimation of remaining service life was enhanced in ref [160] by immediately adopting 10 sets of real car road test data and selecting the current, voltage, temperature, SOC, and SOH factors as the key parameters of the neural network at the same time. SOH and SOC fusion estimation was used by [161] to develop and propose a new neural network prediction technique. Recursive closed loop behavior was used to estimate a SOH estimate, according to researchers. In this way, the estimation results were considerably improved by combining the SOH and SOC predictions.

.

3.2.1.2 Least Square

With the Least Squares approach (LS), a collection of data points is fitted to the displayed curve by reducing the total of the offsets or residuals of the points from the curve. Normally, it is represented as regression. Lithium-ion batteries have been studied using the Least Square Method (LSM). It is also used to determine battery electrical model parameters. It may be used to anticipate capacity deterioration without learning the model parameters [135].

As a statistical methodology, the LS regression analysis is known as the LS regression method. The approach is used to determine the line of best fit for a dataset in which each point reflects the connection between unknown dependent variables and known dependent variables [162].

Lithium-ion cell degradation characteristics may be identified using an offline linear LS technique provided in [163]. In order to test the deterioration hypothesis and estimate SOH, battery resistance and solid phase diffusion time are employed as important factors. The data for new and old lithium-ion batteries is updated using an on-line adaptive gradient and an offline linear least squares approach. Solid electrolyte interference layer (SEI) layer development is predicted by the suggested model [163].

3.2.1.3 Auto Regression Model

Time-series data may be utilized to study the underlying pattern of a system and make predictions for the near future using the Autoregressive Model. Training an AR Model depends on the completeness of previous data. Recursive model training and updating is essential in most practical applications since the historical data are often missing. Easy parameterization and minimal computing cost are two of the AR model's main features. As a result, an underfitting model is generated since the battery capacity fading process is generally nonlinear. Moving averages may be used in conjunction with the AR model to create an Autoregressive Integrated Moving Average (ARIMA) framework to address this issue. Moving averages instead of regressions employ the previous prediction mistakes in a regression-like model instead of utilizing past predicted values[135].

SOH and battery cycle life may be calculated using an approach in ref [164] It is their goal to enhance the battery capacity for forklift operations by using autoregressive integrated modeling averages (ARIMA) and supervised learning (bagging with decision trees as the base estimator; BAG).

Increased rain flow counting was combined with the autoregressive integrated moving average modeling estimation method to assess the battery's SOH based on the cycle methodology and machine learning notion on lithium-ion batteries by [165] A confidence interval approach was developed to accommodate the error range after studies with a dynamic testing time and process conditions were completed. The proposed strategy has an ideal error of 5.3 percent when using dynamic stress testing, and an inaccuracy of 0.8 percent when using the SOH during cycling settings as a sample.

Elman neural network (NN) and autoregressive moving average (ARMA) models may be used together to forecast lithium-ion battery SOH, according to ref [166]. As a first step, the battery's voltage and capacity deterioration are evaluated over time, and the battery's aging health factor is decided based on the voltage profile variation. In the second stage, data on capacity deterioration is processed using empirical mode decomposition (EMD), which eliminates the problem of modest capacity recovery and allows the retrieval of multiple data sequences and related residues. The ARMA and Elman NN models are then constructed using these models. Each estimate is then combined to get the final SOH sequence estimates. Addressed fusion techniques outperform single ARMA and Elman-NN models in SOH estimation.

3.2.1 Probabilistic methods

Analytical characteristics and SOH are linked using probabilistic models in this part. Probabilistic models should be used for determining the health of lithium-ion batteries in order to take uncertainty into account.

3.2.1.1 Bayesian Network (BN)

The Bayesian model assumes that each indicator is interrelated from the other predictors, so by utilizing it, a probability for an observation to be categorized as belonging to a certain class is calculated. For its competitiveness in practical applications, it is well-known sophisticated and resilient to disturbance plus incomplete information, it has a number of advantages, including its simplicity and efficiency. It also allows for the usage of many classes at once. The Relevance Vector Machine and the Particle Filter are used to control the ambiguity of classification or regression [135].

In ref [167], Stochastic battery deterioration processes are shown using a BN-based SOH estimate framework, which is verified using real-world data from EV operations. SOH dispersion increases with battery age, and results demonstrate that the model can accurately predict this tendency. At certain aging stages, the calibrated SOH range can be entirely covered by the estimated SOH range.

SOH estimate and RUL prediction were merged by Dong and colleagues using the dynamic Bayesian-PF (DBN-PF) based data-driven technique. In case certain feature data are lacking, CC and CV charge periods were merged. They could give an accurate and robust assessment of battery SOH and reliable prediction of RUL notably for old batteries, the terms of two experimental battery datasets collected through various aging trajectories. The self-learning capacity of the suggested technique was credited with good estimation accuracy and resilience. Furthermore, the proposed approach could be used in a wide range of real-world situations when battery operating information was insufficient. [168].

3.2.1.2 Hidden Markov Model

Relying on the Markov Chain, Baum developed the Hidden Markov Model (HMM), the foundation of which was built in the 1970s.

The Hidden Markov Model comprises two stochastic models as follows:

- Observable sequence (derived from monitored signals)
- Invisible states of health of the object (Hidden)

Furthermore, because it is a resource strategy, it is a critical approach for real-world application. Based on the complexity of battery simulation models and the accuracy of HMM in estimating outcomes, a variety of previous studies have examined ways to assess battery life states using an HMM. In reference [170], a technique for evaluating battery health statuses is presented that is based on HMM. When evaluating the lifespan of a battery, it is important to take into consideration the internal resistance of the battery. The HMM technique is used to determine the battery's life phases. Piao et al. propose a strategy for obtaining characteristic values from HMMs, which is described in detail below. HMMs have the potential to produce forward log-likelihood probabilities. In addition, by relying on only two factors, the recommended strategy saves time. This is the foundation upon which online battery life prediction is based.

Based on neural networks (NNs) with feature and weight restrictions, in ref[171] researchers employed a Markov chain to correct for estimation errors. SOH estimate was shown to be quite accurate, with an error margin of just 1.7% based on the test findings.

3.2.1.3 Sample Entropy

In 2000, Richman and Moorman [172] presented the use of SampEn to measure the complexity of time series, which was an advance on the prior approach, approximate entropy (ApEn), developed by Pincus [173]. When it comes to monitoring the capacity of a battery, sample entropy is a useful diagnostic tool for assessing the battery's variance and complication in voltage behavior. Using this technique, the SampEn feature and battery capacity estimates are generated by acquiring data on discharge voltage and time. In accordance with IEEE Std. 1188-2005 [174], the time capacity of a battery is used to estimate its expected capacity. Hence, SOH is calculated using the capacity approach, which is the ratio of the current capacity to the capacity of the starting time period [175].

In addition to analyzing the probability of time series, it may be used to forecast battery health performance while assessing the uniformity of a data sequence. Sample entropy should be used in conjunction with a machine learning technique that uses it as an incoming data characteristic and SOH (usually capacity) as the target vector of the learning process [135].

Widodo *et al.* suggested SampEn as a key feature for input training of learning systems, notably support vector machines (SVM) and relevance vector machines (RVM). Battery health may be predicted using the SOH determined by temporal capacity determination in the suggested approach. Using SVM and RVM in SOH prediction, findings demonstrates that the proposed strategy is a viable one. RVM surpasses SVM-based battery health prognostics in our investigation[176].

A novel approach based on empirical mode decomposition sample entropy (EMDSE) and support vector machine (SVM) is presented in ref [177] in order to increase the accuracy in calculating the SOH of a battery. In contrast to the traditional SE-based approach, EMD is used to filter out the noise from the original signal. Afterwards, the EMDSE is utilized for SVM training, and the possibility of a correlation between the SOH and EMDSE is established. The EMD technique reduces noise in the original voltage signal, and the suggested algorithm based on EMDSE improves estimate accuracy.

3.2.1.4 Particle Factor

Particle Filters are classified under non-linear filters which combine Bayesian learning techniques and sampling to provide good state tracking performance while keeping the computational load under control. It is classified as a sequential Monte Carlo method, which estimates the state Probability Distribution Function (PDF) from a set of particles and the associated weights. The use of weight, helps in adjusting the state PDF to its most likely form. However, for particle filter, the number of defined samples imposes and important effect on calculation speed and accuracy. So, huge number of samples are required for practical application. Also, accuracy of particle filter-based model could be easily affected by variable current and temperature.

Battery SOC and maximum usable power are estimated in [178] using PF's non-linear dynamic model based on SOC. The battery power is computed using an optimization approach in this new algorithm. Charge and discharge data are used to test the suggested theory. According to [132], a new mutation particle filter (MPF) may identify low-weighted particles for SOH estimate. The model's performance is benchmarked. The studies show that the MPF can successfully monitor system dynamics and characteristics while lowering RMSE and standard deviation (SD).

State space models based on PF have been proposed by [179]. Prediction accuracy was greatly improved after the use of updated Kalman filtering settings. A significant amount of math is required, though.

More samples led to steadily rising accuracy for SOH prediction as seen by these findings. Due to this, a huge number of factors are required to produce the PF prediction results more accurate, which considerably increases the complexity and quantity of calculation required by the online proposed method, leads to poor timely.

3.2.1.5 Gaussian Process Regression (GPR)

In several disciplines, the non-parametric and probabilistic nature GPR approach has been used. High dimension, tiny sample, and non-linearity are all examples of complicated regression issues that may be handled by this method. In comparison to NN and SVM, GPR is easier to implement. Additionally, it may describe the uncertainty of estimated findings in the form of a confidence interval with upper and lower limits. Thereby helping to make decisions. GPR may be used to estimate the state-of-health (SOH) of lithium-ion batteries since the aging process is nonlinear and complicated [135].

For SOH estimate, Yang *et al.* has developed an enhanced GPR model . In this study, the GRA approach is used to examine the correlation between choosing characteristics and SOH. Improvements in the fundamental GPR model are made in the areas of similarity measurement and covariance function design so that SOH estimates can be more accurately predicted. Batteries in cyclic aging tests have minimal SOH estimation errors, according to SOH estimation data. The GPR model suggested in this study has the following advantages: high precision, resilience, output probabilism, etc. And a well-built GPR model may be used in a real-world application[180].

Using a multiscale GPR model, lithium-ion batteries' SOH may be predicted in ref [181]. Using a wavelet analysis approach, it is possible to isolate the global deterioration, local regeneration, and fluctuations in the SOH time series. Because the results show that a unified framework for accurate and speedy SOH prediction is provided by multiscale GPR modeling, it is useful for SOC estimate and RUL prognosis. There are several health management systems with multiscale features that the suggested technique might be applied to. A you can see, Table 9 shows the comparing between data-based methods:

Methods	**Advantages**	**Disadvantages**	**Errors (and ref)**	
FL	-High precise online with simple model, without any intermediary processing, measure SOH directly. -Useful for non-linear system, robust and accurate method.	Temperature and current are the only elements considered. -Highly dependent on the training data's quality, variety, and amount and powerful controller is needed	<2% 1,4-9.2%	[182] [183]
SVM	- Accurate - Nonparametric - Robust -Fast response.	- Depend heavily on the quality, the diversity and the quantity of the training data used - Require a high-performance controller	2%	[184]
NN	- Accurate & online - Requires least amount of data than Fuzzy Log	- Depend heavily on the quality, the diversity and the quantity of the training data used - Require a high-performance controller	<0.5%	[59]
LS	- Precise - Robust - Simple structure and fast response	- Relies in terms of accuracy on the selected model - Require a high performance controller -It will take some time to refine the controller.	±5%	[185]

ARM	-Easy parameterization -Minimal computing cost	The association between battery aging aspects cannot be analyzed in detail, hence the estimate findings may not be complete.	0.7-5/3%	[166]
BN	-Accurate -Robust, -Can be used when some battery information was lacking.	-Charging time has the effect on this method. -Temp effect is not considered.	<1.6%	[168]
HMM	-It just requires two inputs -Time-saving method -Strong base for online estimation	-Complexity of mathematical equations	<10%	[170]
Sample Entropy	-Good accuracy	-High degree of difficulty in computing	2%	[186]
PF	-Good accuracy -Fast response	-High degree of difficulty in computing, -Lots of data are required.	<2%	[187]
GPR	-High accuracy, -Low computational time.	-High degree of difficulty in computing	0.49-0.98%	[181]

Table 9- Data-Based Methods

4 Chapter 4

Conclusion

It is prudent to estimate the SOH and SOC values when developing a battery management system because they provide a snapshot of the battery's long- and short-term health. In order to classify the existing SOC and SOH estimation approaches, this study reviewed existing research. We also discuss in detail the various estimation processes for SOC and SOH, thereby assisting with the development of advanced BMS for applications ranging from electric vehicles, solar cells, and large-scale power systems. According to the study, there is no one right way to estimate battery states. Rather, the most appropriate approach will depend on the application and the requirements of the system.

A variety of SOC approaches and algorithms are examined in this report. A full description, including the advantages and disadvantages of the model. The review classified SOC estimation techniques into 6 major groups.

It is said in this article that while direct measuring methods are simple to use, their accuracy is greatly compromised by factors like as age, temperature, and external disruptions. The OCV method is the most widely used direct measuring technique. The OCV/SOC battery connection is the basis for this technique. The Battery is separated from the circuit during OCV measurement, and SOC is computed using the OCV as a reference point for the battery. The flat OCV-SOC curves and this method's applicability exclusively to open-loop systems exclude its use in continuous battery operation.

Bookkeeping approach was then used to get a more accurate estimate of the battery's SOC. The battery charging/discharging current is used as an input in this approach. Counting coulombs method is a simple way to use under this accounting system. Time-integrated battery charge and discharge currents. This approach is more commonly employed in the BMS for SOC estimation because of its simplicity and lack of complexity. As a result, this technology has a number of drawbacks, including inaccuracies in sensors and a lack of accuracy in open-loop systems.

Also observed is that an adaptive filter method may anticipate a non-linear dynamic state with high precision, while using little computer resources and operating at a high level of performance. Only linear systems can be solved using the traditional KF approach. EKF and UKF are presented in order to broaden their applications to nonlinear systems, which are nonlinear in nature. SOC information based on battery state-space analysis is delivered using these approaches, which successfully removed process and measurement noise. It is, however, difficult to construct the method for the matrix's mass because of the complexity of the implementation. Moreover, due to the high computational cost and weak robustness of the approach, it is not recommended.

Using machine learning approaches, it is possible to simulate a nonlinear dynamic system while taking into account factors like as age, temperature, and noise. The SVM and ANN algorithms are complex approaches for predicting the battery's precise SOC statistics. Moreover, the approach involves sophisticated calculation and necessitates the use of a big storage device to keep the training data. Fuzzy logic algorithms are the greatest way to get an accurate assessment of the battery's SOC. On the other side, they are similar to ANNs in that they are extremely sensitive to the training data they are fed.

It has been shown that the nonlinear observer has increased its resilience against perturbations and increased its precision, convergent speed, and computing expense.

In the presence of disturbances and uncertainties, SMO is one of the most reliable approaches for estimating the SOC. The system's switching gains are difficult to calculate. The model can still generate incorrect results, though, if the controller is not built appropriately.

In terms of SOH estimation methods, four major categories of approaches for are discussed in depth. The accuracy of experimental procedures is high, and the computational approach is easy to understand. Specific equipment, on the other hand, is necessary in order to carry out the experimentation. Aside from that, they are time-consuming approaches that are best suited for lab and testing environments. For model-based techniques, their advantages are that they have a simple structure and that they provide accurate and robust estimations. Furthermore, they provide quick processing and simple method implementation, but they have certain drawbacks, such as the demand for pre-validation during the development phase of the process. Additionally, in terms of accuracy and computing time, these strategies rely greatly on the model. Adaptive filters are capable of removing noise and providing precise estimate in real time. Using the upgraded version of KF, it is possible to work with nonlinear systems. The computing procedure, on the other hand, is time-consuming. The last category consists of data-based approaches, which provide very exact results while being simple to apply. Furthermore, they are often known for their quick response times. On the other hand, the vast majority of them require a strong controller, which is expensive. Furthermore, some approaches involve a lengthy and complicated computing procedure.

The findings of this article might lead to the reader selects the one that is most appropriate for his or her particular situation. In this paper, you find up-to-date information on approaches that will be beneficial in the design and analysis of a project from a technical and financial standpoint, which includes the battery system. Furthermore, it will be beneficial to students and professionals working in the fields of renewable energy systems and electric vehicles.

5 Bibliography

[1] M. Z. Daud, A. Mohamed, and M. A. Hannan, “An improved control method of battery energy storage system for hourly dispatch of photovoltaic power sources,” *Energy Conversion and Management*, pp. 256–270, 2013. [Online]. Available: http://inis.iaea.org/search/search.aspx?orig_q=RN:46001088

[2] S. C. Chen, C. C. Wan, and Y. Y. Wang, “Thermal analysis of lithium-ion batteries,” *Journal of Power Sources*, vol. 140, no. 1, pp. 111–124, 2005, doi: 10.1016/j.jpowsour.2004.05.064.

[3] C. Campestrini, M. F. Horsche, I. Zilberman, T. Heil, T. Zimmermann, and A. Jossen, “Validation and benchmark methods for battery management system functionalities: State of charge estimation algorithms,” *Journal of Energy Storage*, vol. 7, pp. 38–51, 2016, doi: 10.1016/j.est.2016.05.007.

[4] L. Ungurean, G. Cârstoiu, M. V. Micea, and V. Groza, “Battery state of health estimation: a structured review of models, methods and commercial devices,” *Int J Energy Res*, vol. 41, no. 2, pp. 151–181, 2017, doi: 10.1002/er.3598.

[5] Jiale XieJiale XieJiale XieChang, Wen-Yeau, “The State of Charge Estimating Methods for Battery: A Review,” *ISRN Applied Mathematics*, vol. 2013, pp. 1–7, 2013, doi: 10.1155/2013/953792.

[6] V. Pop, H. J. Bergveld, P. H. L. Notten, and P. P. L. Regtien, “State-of-the-art of battery state-of-charge determination,” *Meas. Sci. Technol.*, vol. 16, no. 12, R93-R110, 2005, doi: 10.1088/0957-0233/16/12/R01.

[7] S.-L. Wang *et al.*, “An improved coulomb counting method based on dual open-circuit voltage and real-time evaluation of battery dischargeable capacity considering temperature and battery aging,” *Int J Energy Res*, vol. 45, no. 12, pp. 17609–17621, 2021.

[8] K. Liu, Y. Shang, Q. Ouyang, and W. D. Widanage, “A Data-Driven Approach With Uncertainty Quantification for Predicting Future Capacities and Remaining Useful Life of Lithium-ion Battery,” *IEEE Trans. Ind. Electron.*, vol. 68, no. 4, pp. 3170–3180, 2021, doi: 10.1109/TIE.2020.2973876.

[9] A. Basia, Z. Simeu-Abazi, E. Gascard, and P. Zwolinski, “Review on State of Health estimation methodologies for lithium-ion batteries in the context of circular economy,” *CIRP Journal of Manufacturing Science and Technology*, vol. 32, pp. 517–528, 2021, doi: 10.1016/j.cirpj.2021.02.004.

[10] N. Noura, L. Boulon, and S. Jemeï, “A Review of Battery State of Health Estimation Methods: Hybrid Electric Vehicle Challenges,” *WEVJ*, vol. 11, no. 4, p. 66, 2020, doi: 10.3390/wevj11040066.

[11] G. Piłatowicz, A. Marongiu, J. Drillkens, P. Sinhuber, and D. U. Sauer, "A critical overview of definitions and determination techniques of the internal resistance using lithium-ion, lead-acid, nickel metal-hydride batteries and electrochemical double-layer capacitors as examples," *Journal of Power Sources*, vol. 296, pp. 365–376, 2015, doi: 10.1016/j.jpowsour.2015.07.073.

[12] J. Tian, R. Xiong, and W. Shen, "A review on state of health estimation for lithium ion batteries in photovoltaic systems," *eTransportation*, vol. 2, p. 100028, 2019, doi: 10.1016/j.etran.2019.100028.

[13] *Proceedings of the Power Conversion Conference-Osaka 2002 (Cat. No.02TH8579)*: IEEE, 2002.

[14] M. Danko, J. Adamec, M. Taraba, and P. Drgona, "Overview of batteries State of Charge estimation methods," *Transportation Research Procedia*, vol. 40, pp. 186–192, 2019, doi: 10.1016/j.trpro.2019.07.029.

[15] N. K. M'Sirdi, A. Belhani, and A. Naamane, "Battery Models for Estimation of State of Charge by Sliding Mode Observer," in *Smart Innovation, Systems and Technologies*, vol. 12, *Sustainability in Energy and Buildings*, R. J. Howlett, L. C. Jain, N. M'Sirdi, and A. Namaane, Eds., Berlin, Heidelberg: Springer Berlin Heidelberg, 2012, pp. 133–149.

[16] H. J. Bergveld, W. S. Kruijt, and P. H. L. Notten, *Battery management systems: Design by modelling*. Dordrecht, Netherlands: Springer-Science+Business Media B.V, 2002.

[17] R. Sakile and U. K. Sinha, "Estimation of lithium-ion battery state of charge for electric vehicles using a nonlinear state observer," *Energy Storage*, 2021.

[18] M. A. Hannan, M. Lipu, A. Hussain, and A. Mohamed, "A review of lithium-ion battery state of charge estimation and management system in electric vehicle applications: Challenges and recommendations," *Renewable and Sustainable Energy Reviews*, vol. 78, pp. 834–854, 2017.

[19] Christianson C C and Bourke R F: *Battery state of charge*, 1975.

[20] V. Pop, H. J. Bergveld, P. H. L. Notten, and P. P. L. Regtien, "State-of-the-art of battery state-of-charge determination," *Meas. Sci. Technol.*, vol. 16, no. 12, R93-R110, 2005, doi: 10.1088/0957-0233/16/12/R01.

[21] L. Zheng, L. Zhang, J. Zhu, G. Wang, and J. Jiang, "Co-estimation of state-of-charge, capacity and resistance for lithium-ion batteries based on a high-fidelity electrochemical model," *Applied Energy*, vol. 180, pp. 424–434, 2016, doi: 10.1016/j.apenergy.2016.08.016.

[22] Y. Xing, W. He, M. Pecht, and K. L. Tsui, "State of charge estimation of lithium-ion batteries using the open-circuit voltage at various ambient temperatures," *Applied Energy*, vol. 113, pp. 106–115, 2014, doi: 10.1016/j.apenergy.2013.07.008.

[23] I. Snihir, W. Rey, E. Verbitskiy, A. Belfadhel-Ayeb, and P. H. Notten, "Battery open-circuit voltage estimation by a method of statistical analysis," *Journal of Power Sources*, vol. 159, no. 2, pp. 1484–1487, 2006, doi: 10.1016/j.jpowsour.2005.11.090.

[24] M. Coleman, C. K. Lee, C. Zhu, and W. G. Hurley, "State-of-Charge Determination From EMF Voltage Estimation: Using Impedance, Terminal Voltage, and Current for Lead-Acid and Lithium-Ion Batteries," *IEEE Trans. Ind. Electron.*, vol. 54, no. 5, pp. 2550–2557, 2007.

[25] Z. Rao, S. Wang, and G. Zhang, "Simulation and experiment of thermal energy management with phase change material for ageing LiFePO4 power battery," *Energy Conversion and Management*, vol. 52, no. 12, pp. 3408–3414, 2011, doi: 10.1016/j.enconman.2011.07.009.

[26] W.-Y. Chang, "The State of Charge Estimating Methods for Battery: A Review," *ISRN Applied Mathematics*, vol. 2013, pp. 1–7, 2013, doi: 10.1155/2013/953792.

[27] D. Tingting, L. Jun, Z. Fuquan, Y. Yi, and J. Qiqian, "Analysis on the influence of measurement error on state of charge estimation of LiFePO4 power Battery," in *2011 International Conference on Materials for Renewable Energy & Environment*, Shanghai, China, May. 2011 - May. 2011, pp. 644–649.

[28] R. Sakile and U. K. Sinha, "Estimation of lithium-ion battery state of charge for electric vehicles using a nonlinear state observer," *Energy Storage*, 2021, doi: 10.1002/est2.290.

[29] M. A. Hannan, M. Lipu, A. Hussain, and A. Mohamed, "A review of lithium-ion battery state of charge estimation and management system in electric vehicle applications: Challenges and recommendations," *Renewable and Sustainable Energy Reviews*, vol. 78, pp. 834–854, 2017, doi: 10.1016/j.rser.2017.05.001.

[30] H. He, X. Zhang, R. Xiong, Y. Xu, and H. Guo, "Online model-based estimation of state-of-charge and open-circuit voltage of lithium-ion batteries in electric vehicles," *Energy*, vol. 39, no. 1, pp. 310–318, 2012, doi: 10.1016/j.energy.2012.01.009.

[31] D. Di Domenico, G. Fiengo, and A. Stefanopoulou, "Lithium-ion battery state of charge estimation with a Kalman Filter based on a electrochemical model," in *2008 IEEE International Conference on Control Applications*, San Antonio, TX, USA, Sep. 2008 - Sep. 2008, pp. 702–707.

[32] X. Hu, S. Li, and H. Peng, "A comparative study of equivalent circuit models for Li-ion batteries," *Journal of Power Sources*, vol. 198, pp. 359–367, 2012, doi: 10.1016/j.jpowsour.2011.10.013.

[33] Li Ran, Wu Junfeng, Wang Haiying, and Li Gechen, "Prediction of state of charge of Lithium-ion rechargeable battery with electrochemical impedance

spectroscopy theory," in *2010 5th IEEE Conference on Industrial Electronics and Applications*, 2010, pp. 684–688.

[34] *2007 IEEE Vehicle Power and Propulsion Conference*, 2008.

[35] S. Buller, M. Thele, R. W. de Doncker, and E. Karden, "Impedance-based simulation models of supercapacitors and Li-ion batteries for power electronic applications," in *Crossroads to innovation*, Salt Lake City, UT, USA, 2003, pp. 1596–1600.

[36] H.-G. Schweiger *et al.*, "Comparison of several methods for determining the internal resistance of lithium ion cells," *Sensors (Basel, Switzerland)*, vol. 10, no. 6, pp. 5604–5625, 2010, doi: 10.3390/s100605604.

[37] A. Zenati, P. Desprez, and H. Razik, "Estimation of the SOC and the SOH of li-ion batteries, by combining impedance measurements with the fuzzy logic inference," in *IECON 2010 - 36th Annual Conference on IEEE Industrial Electronics Society*, Glendale, AZ, USA, Nov. 2010 - Nov. 2010, pp. 1773–1778.

[38] V. Pop, *Battery management systems: Accurate state-of-charge indication for battery powered applications / by Valer Pop … [et al.]*. Dordrecht: Springer, 2008. [Online]. Available: http://www.springer.com/gb/ BLDSS

[39] L. Climent Soto and M. García Nart, *10 años de planeamiento urbanistico en España, 1979-1989: 10 anni di pianificazione urbanisistica in Spagna, 1979-1989*. Spain, Venezia: Ministerio de Obras Públicas y Urbanismo Instituto del Territorio y Urbanismo; Istituto universitario di architettura di Venezia Dipartimento di analisi economica e sociale del territorio, 2008.

[40] H. J. Bergveld, W. S. Kruijt, and P. H. L. Notten, "Battery State-of-Charge indication," in *Battery Management Systems*, H. J. Bergveld, W. S. Kruijt, and P. H. L. Notten, Eds., Dordrecht: Springer Netherlands, 2002, pp. 193–240.

[41] C. Truchot, M. Dubarry, and B. Y. Liaw, "State-of-charge estimation and uncertainty for lithium-ion battery strings," *Applied Energy*, vol. 119, pp. 218–227, 2014, doi: 10.1016/j.apenergy.2013.12.046.

[42] M. Coleman, C. K. Lee, C. Zhu, and W. G. Hurley, "State-of-Charge Determination From EMF Voltage Estimation: Using Impedance, Terminal Voltage, and Current for Lead-Acid and Lithium-Ion Batteries," *IEEE Trans. Ind. Electron.*, vol. 54, no. 5, pp. 2550–2557, 2007, doi: 10.1109/TIE.2007.899926.

[43] W. Waag and D. U. Sauer, "Adaptive estimation of the electromotive force of the lithium-ion battery after current interruption for an accurate state-of-charge and capacity determination," *Applied Energy*, vol. 111, pp. 416–427, 2013, doi: 10.1016/j.apenergy.2013.05.001.

[44] H. He, R. Xiong, and H. Guo, "Online estimation of model parameters and state-of-charge of LiFePO4 batteries in electric vehicles," *Applied Energy*, vol. 89, no. 1, pp. 413–420, 2012, doi: 10.1016/j.apenergy.2011.08.005.

[45] K. S. Ng, C.-S. Moo, Y.-P. Chen, and Y.-C. Hsieh, “Enhanced coulomb counting method for estimating state-of-charge and state-of-health of lithium-ion batteries,” *Applied Energy*, vol. 86, no. 9, pp. 1506–1511, 2009, doi: 10.1016/j.apenergy.2008.11.021.

[46] Y. Zhang, W. Song, S. Lin, and Z. Feng, “A novel model of the initial state of charge estimation for LiFePO4 batteries,” *Journal of Power Sources*, vol. 248, pp. 1028–1033, 2014, doi: 10.1016/j.jpowsour.2013.09.135.

[47] Xie Jiale, Ma Jiachen, and Bai Kun, “Enhanced Coulomb Counting Method for State-of-Charge Estimation of Lithium-ion Batteries based on Peukert's Law and Coulombic Efficiency,” *Journal of Power Electronics*, vol. 18, no. 3, pp. 910–922, 2018, doi: 10.6113/JPE.2018.18.3.910.

[48] L. He and D. Guo, “An Improved Coulomb Counting Approach Based on Numerical Iteration for SOC Estimation With Real-Time Error Correction Ability,” *IEEE Access*, vol. 7, pp. 74274–74282, 2019, doi: 10.1109/ACCESS.2019.2921105.

[49] C. Chen, R. Xiong, R. Yang, W. Shen, and F. Sun, “State-of-charge estimation of lithium-ion battery using an improved neural network model and extended Kalman filter,” *Journal of Cleaner Production*, vol. 234, pp. 1153–1164, 2019, doi: 10.1016/j.jclepro.2019.06.273.

[50] N. Watrin, B. Blunier, and A. Miraoui, “Review of adaptive systems for lithium batteries State-of-Charge and State-of-Health estimation,” in *2012 IEEE Transportation Electrification Conference and Expo (ITEC)*, Dearborn, MI, USA, 2012, pp. 1–6.

[51] Z. Yu, R. Huai, and L. Xiao, “State-of-Charge Estimation for Lithium-Ion Batteries Using a Kalman Filter Based on Local Linearization,” *Energies*, vol. 8, no. 8, pp. 7854–7873, 2015, doi: 10.3390/en8087854.

[52] T. O. Ting, K. L. Man, E. G. Lim, and M. Leach, “Tuning of Kalman filter parameters via genetic algorithm for state-of-charge estimation in battery management system,” *TheScientificWorldJournal*, vol. 2014, p. 176052, 2014, doi: 10.1155/2014/176052.

[53] M. Urbain, S. Rael, B. Davat, and P. Desprez, “State Estimation of a Lithium-Ion Battery Through Kalman Filter,” in *2007 IEEE Power Electronics Specialists Conference*, Orlando, FL, USA, Jun. 2007 - Jun. 2007, pp. 2804–2810.

[54] I. B. Espedal, A. Jinasena, O. S. Burheim, and J. J. Lamb, “Current Trends for State-of-Charge (SOC) Estimation in Lithium-Ion Battery Electric Vehicles,” *Energies*, vol. 14, no. 11, p. 3284, 2021, doi: 10.3390/en14113284.

[55] P. Shrivastava, T. K. Soon, M. Y. I. B. Idris, and S. Mekhilef, “Overview of model-based online state-of-charge estimation using Kalman filter family for lithium-ion batteries,” *Renewable and Sustainable Energy Reviews*, vol. 113, p. 109233, 2019.

[56] S. Sepasi, R. Ghorbani, and B. Y. Liaw, “Improved extended Kalman filter for state of charge estimation of battery pack,” *Journal of Power Sources*, vol. 255, pp. 368–376, 2014, doi: 10.1016/j.jpowsour.2013.12.093.

[57] O. Barbarisi, F. Vasca, and L. Glielmo, “State of charge Kalman filter estimator for automotive batteries,” *Control Engineering Practice*, vol. 14, no. 3, pp. 267–275, 2006, doi: 10.1016/j.conengprac.2005.03.027.

[58] W.-Y. Chang, “The State of Charge Estimating Methods for Battery: A Review,” *ISRN Applied Mathematics*, vol. 2013, pp. 1–7, 2013, doi: 10.1155/2013/953792.

[59] D. Andre, C. Appel, T. Soczka-Guth, and D. U. Sauer, “Advanced mathematical methods of SOC and SOH estimation for lithium-ion batteries,” *Journal of Power Sources*, vol. 224, pp. 20–27, 2013, doi: 10.1016/j.jpowsour.2012.10.001.

[60] R. Xiong, J. Cao, Q. Yu, H. He, and F. Sun, “Critical Review on the Battery State of Charge Estimation Methods for Electric Vehicles,” *IEEE Access*, vol. 6, pp. 1832–1843, 2018, doi: 10.1109/ACCESS.2017.2780258.

[61] Y. Zhao, J. Xu, X. Wang, and X. Mei, “The Adaptive Fading Extended Kalman Filter SOC Estimation Method for Lithium-ion Batteries,” *Energy Procedia*, vol. 145, pp. 357–362, 2018, doi: 10.1016/j.egypro.2018.04.064.

[62] J. Park, M. Lee, G. Kim, S. Park, and J. Kim, “Integrated Approach Based on Dual Extended Kalman Filter and Multivariate Autoregressive Model for Predicting Battery Capacity Using Health Indicator and SOC/SOH,” *Energies*, vol. 13, no. 9, p. 2138, 2020, doi: 10.3390/en13092138.

[63] H. He, R. Xiong, and J. Fan, “Evaluation of Lithium-Ion Battery Equivalent Circuit Models for State of Charge Estimation by an Experimental Approach,” *Energies*, vol. 4, no. 4, pp. 582–598, 2011, doi: 10.3390/en4040582.

[64] V. Pathuri Bhuvana, C. Unterrieder, and M. Huemer, “Battery Internal State Estimation: A Comparative Study of Non-Linear State Estimation Algorithms,” in *2013 IEEE Vehicle Power and Propulsion Conference (VPPC)*, Beijing, China, 2013, pp. 1–6.

[65] B. Xia, H. Wang, Y. Tian, M. Wang, W. Sun, and Z. Xu, “State of Charge Estimation of Lithium-Ion Batteries Using an Adaptive Cubature Kalman Filter,” *Energies*, vol. 8, no. 6, pp. 5916–5936, 2015, doi: 10.3390/en8065916.

[66] B. S. Bhangu, P. Bentley, D. A. Stone, and C. M. Bingham, “Nonlinear Observers for Predicting State-of-Charge and State-of-Health of Lead-Acid Batteries for Hybrid-Electric Vehicles,” *IEEE Trans. Veh. Technol.*, vol. 54, no. 3, pp. 783–794, 2005, doi: 10.1109/TVT.2004.842461.

[67] M. Gao, Y. Liu, and Z. He, "Battery state of charge online estimation based on particle filter," in *2011 4th International Congress on Image and Signal Processing*, Shanghai, 2011, pp. 2233–2236.

[68] Z. Chen, H. Sun, G. Dong, J. Wei, and J. Wu, "Particle filter-based state-of-charge estimation and remaining-dischargeable-time prediction method for lithium-ion batteries," *Journal of Power Sources*, vol. 414, pp. 158–166, 2019a, doi: 10.1016/j.jpowsour.2019.01.012.

[69] Y. Wang and Z. Chen, "A framework for state-of-charge and remaining discharge time prediction using unscented particle filter," *Applied Energy*, vol. 260, p. 114324, 2020, doi: 10.1016/j.apenergy.2019.114324.

[70] J. Zhengxin, S. Qin, W. Yujiang, W. Hanlin, G. Bingzhao, and H. Lin, "An Immune Genetic Extended Kalman Particle Filter approach on state of charge estimation for lithium-ion battery," *Energy*, vol. 230, p. 120805, 2021, doi: 10.1016/j.energy.2021.120805.

[71] S. Schwunk, N. Armbruster, S. Straub, J. Kehl, and M. Vetter, "Particle filter for state of charge and state of health estimation for lithium–iron phosphate batteries," *Journal of Power Sources*, vol. 239, pp. 705–710, 2013, doi: 10.1016/j.jpowsour.2012.10.058.

[72] Z. Chen, J. Zhou, F. Zhou, and S. Xu, "State-of-charge estimation of lithium-ion batteries based on improved H infinity filter algorithm and its novel equalization method," *Journal of Cleaner Production*, vol. 290, p. 125180, 2021, doi: 10.1016/j.jclepro.2020.125180.

[73] C. Lin, H. Mu, R. Xiong, and W. Shen, "A novel multi-model probability battery state of charge estimation approach for electric vehicles using H-infinity algorithm," *Applied Energy*, vol. 166, pp. 76–83, 2016, doi: 10.1016/j.apenergy.2016.01.010.

[74] Q. Yu, R. Xiong, and C. Lin, "Online Estimation of State-of-charge Based on the H infinity and Unscented Kalman Filters for Lithium Ion Batteries," *Energy Procedia*, vol. 105, pp. 2791–2796, 2017, doi: 10.1016/j.egypro.2017.03.600.

[75] M. W. Yatsui and H. Bai, "Kalman filter based state-of-charge estimation for lithium-ion batteries in hybrid electric vehicles using pulse charging," in *2011 IEEE Vehicle Power and Propulsion Conference*, Chicago, IL, USA, 2011, pp. 1–5.

[76] G. L. Plett, "Sigma-point Kalman filtering for battery management systems of LiPB-based HEV battery packs," *Journal of Power Sources*, vol. 161, no. 2, pp. 1356–1368, 2006, doi: 10.1016/j.jpowsour.2006.06.003.

[77] Y. Tian, B. Xia, W. Sun, Z. Xu, and W. Zheng, "A modified model based state of charge estimation of power lithium-ion batteries using unscented Kalman filter,"

Journal of Power Sources, vol. 270, pp. 619–626, 2014, doi: 10.1016/j.jpowsour.2014.07.143.

[78] Y. Zhang, C. Zhang, and X. Zhang, “State-of-charge estimation of the lithium-ion battery system with time-varying parameter for hybrid electric vehicles,” *IET Control Theory & Applications*, vol. 8, no. 3, pp. 160–167, 2014, doi: 10.1049/iet-cta.2013.0082.

[79] K. Liu, Y. Shang, Q. Ouyang, and W. D. Widanage, “A Data-Driven Approach With Uncertainty Quantification for Predicting Future Capacities and Remaining Useful Life of Lithium-ion Battery,” *IEEE Trans. Ind. Electron.*, vol. 68, no. 4, pp. 3170–3180, 2021, doi: 10.1109/TIE.2020.2973876.

[80] Z. Li, J. Huang, B. Y. Liaw, and J. Zhang, “On state-of-charge determination for lithium-ion batteries,” *Journal of Power Sources*, vol. 348, pp. 281–301, 2017, doi: 10.1016/j.jpowsour.2017.03.001.

[81] W. He, N. Williard, C. Chen, and M. Pecht, “State of charge estimation for Li-ion batteries using neural network modeling and unscented Kalman filter-based error cancellation,” *International Journal of Electrical Power & Energy Systems*, vol. 62, pp. 783–791, 2014, doi: 10.1016/j.ijepes.2014.04.059.

[82] H. Chaoui and C. C. Ibe-Ekeocha, “State of Charge and State of Health Estimation for Lithium Batteries Using Recurrent Neural Networks,” *IEEE Trans. Veh. Technol.*, vol. 66, no. 10, pp. 8773–8783, 2017, doi: 10.1109/TVT.2017.2715333.

[83] S. G. Li, S. M. Sharkh, F. C. Walsh, and C. N. Zhang, “Energy and Battery Management of a Plug-In Series Hybrid Electric Vehicle Using Fuzzy Logic,” *IEEE Trans. Veh. Technol.*, vol. 60, no. 8, pp. 3571–3585, 2011, doi: 10.1109/TVT.2011.2165571.

[84] V. Thangavel, O. X. Guerrero, M. Quiroga, A. M. Mikala, A. Rucci, and A. A. Franco, “A three dimensional kinetic Monte Carlo model for simulating the carbon/sulfur mesostructural evolutions of discharging lithium sulfur batteries,” *Energy Storage Materials*, vol. 24, pp. 472–485, 2020, doi: 10.1016/j.ensm.2019.07.011.

[85] *State of charge estimation for Li-ion batteries using neural network modeling and unscented Kalman filter-based error cancellation.* [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0142061514002646 (accessed: Nov. 17 2021).

[86] V. Chandran, C. K. Patil, A. Karthick, D. Ganeshaperumal, R. Rahim, and A. Ghosh, “State of Charge Estimation of Lithium-Ion Battery for Electric Vehicles Using Machine Learning Algorithms,” *WEVJ*, vol. 12, no. 1, p. 38, 2021, doi: 10.3390/wevj12010038.

[87] Q.-K. Wang, Y.-J. He, J.-N. Shen, Z.-F. Ma, and G.-B. Zhong, “A unified modeling framework for lithium-ion batteries: An artificial neural network based thermal

coupled equivalent circuit model approach," *Energy*, vol. 138, pp. 118–132, 2017, doi: 10.1016/j.energy.2017.07.035.

[88] J. Kuchly *et al.*, "Li-ion battery SOC estimation method using a Neural Network trained with data generated by a P2D model," *IFAC-PapersOnLine*, vol. 54, no. 10, pp. 336–343, 2021, doi: 10.1016/j.ifacol.2021.10.185.

[89] C. Zhang, Y. Zhu, G. Dong, and J. Wei, "Data-driven lithium-ion battery states estimation using neural networks and particle filtering," *Int J Energy Res*, 2019, doi: 10.1002/er.4820.

[90] Y. Guo, Z. Zhao, and L. Huang, "SOC Estimation of Lithium Battery Based on Improved BP Neural Network," *Energy Procedia*, vol. 105, pp. 4153–4158, 2017.

[91] Z. Chen, S. Qiu, M. Masrur, and Y. L. Murphey, "Battery state of charge estimation based on a combined model of Extended Kalman Filter and neural networks," in *The 2011 International Joint Conference on Neural Networks*, San Jose, CA, USA, Jul. 2011 - Aug. 2011, pp. 2156–2163.

[92] I.-H. Li, W.-Y. Wang, S.-F. Su, and Y.-S. Lee, "A Merged Fuzzy Neural Network and Its Applications in Battery State-of-Charge Estimation," *IEEE Transactions on Energy Conversion*, vol. 22, no. 3, pp. 697–708, 2007, doi: 10.1109/TEC.2007.895457.

[93] A. J. Salkind, C. Fennie, P. Singh, T. Atwater, and D. E. Reisner, "Determination of state-of-charge and state-of-health of batteries by fuzzy logic methodology," *Journal of Power Sources*, vol. 80, 1-2, pp. 293–300, 1999, doi: 10.1016/S0378-7753(99)00079-8.

[94] P. Singh, R. Vinjamuri, X. Wang, and D. Reisner, "Design and implementation of a fuzzy logic-based state-of-charge meter for Li-ion batteries used in portable defibrillators," *Journal of Power Sources*, vol. 162, no. 2, pp. 829–836, 2006, doi: 10.1016/j.jpowsour.2005.04.039.

[95] S. Malkhandi, "Fuzzy logic-based learning system and estimation of state-of-charge of lead-acid battery," *Engineering Applications of Artificial Intelligence*, vol. 19, no. 5, pp. 479–485, 2006, doi: 10.1016/j.engappai.2005.12.005.

[96] T. Hansen and C.-J. Wang, "Support vector based battery state of charge estimator," *Journal of Power Sources*, vol. 141, no. 2, pp. 351–358, 2005, doi: 10.1016/j.jpowsour.2004.09.020.

[97] J. Meng, G. Luo, and F. Gao, "Lithium Polymer Battery State-of-Charge Estimation Based on Adaptive Unscented Kalman Filter and Support Vector Machine," *IEEE Trans. Power Electron.*, vol. 31, no. 3, pp. 2226–2238, 2016, doi: 10.1109/TPEL.2015.2439578.

[98] J. C. Álvarez Antón, P. J. García Nieto, F. J. de Cos Juez, F. Sánchez Lasheras, M. González Vega, and M. N. Roqueñí Gutiérrez, "Battery state-of-charge estimator

using the SVM technique," *Applied Mathematical Modelling*, vol. 37, no. 9, pp. 6244–6253, 2013, doi: 10.1016/j.apm.2013.01.024.

[99] J. N. Hu *et al.*, "State-of-charge estimation for battery management system using optimized support vector machine for regression," *Journal of Power Sources*, vol. 269, pp. 682–693, 2014, doi: 10.1016/j.jpowsour.2014.07.016.

[100] Y. Chen, W. Liu, J. Yao, and J. Zhang, "Separation Mechanism and Design Principles of the Teetered Bed Separator for Cleaning Fine Coal," in *2011 Asia-Pacific Power and Energy Engineering Conference*, Wuhan, China, Mar. 2011 - Mar. 2011b, pp. 1–4.

[101] A. Affanni, A. Bellini, C. Concari, G. Franceschini, E. Lorenzani, and C. Tassoni, "EV battery state of charge: neural network based estimation," in *IEMDC 2003: IEEE international electric machines and drives conference*, Madison, WI, USA, 2003, pp. 684–688.

[102] B. Xia, C. Chen, Y. Tian, W. Sun, Z. Xu, and W. Zheng, "A novel method for state of charge estimation of lithium-ion batteries using a nonlinear observer," *Journal of Power Sources*, vol. 270, pp. 359–366, 2014, doi: 10.1016/j.jpowsour.2014.07.103.

[103] Y. Ma, B. Li, G. Li, J. Zhang, and H. Chen, "A nonlinear observer approach of SOC estimation based on hysteresis model for lithium-ion battery," *IEEE/CAA J. Autom. Sinica*, vol. 4, no. 2, pp. 195–204, 2017, doi: 10.1109/JAS.2017.7510502.

[104] J. Xu, C. C. Mi, B. Cao, J. Deng, Z. Chen, and S. Li, "The State of Charge Estimation of Lithium-Ion Batteries Based on a Proportional-Integral Observer," *IEEE Trans. Veh. Technol.*, vol. 63, no. 4, pp. 1614–1621, 2014, doi: 10.1109/TVT.2013.2287375.

[105] A. Belhani, N. K. M'Sirdi, and A. Naamane, "Adaptive Sliding Mode Observer for Estimation of State of Charge," *Energy Procedia*, vol. 42, pp. 377–386, 2013, doi: 10.1016/j.egypro.2013.11.038.

[106] O. Rezaei, H. A. Moghaddam, and B. Papari, "A fast sliding-mode-based estimation of state-of-charge for Lithium-ion batteries for electric vehicle applications," *Journal of Energy Storage*, p. 103484, 2021, doi: 10.1016/j.est.2021.103484.

[107] O. Skrylnyk, R. Lepore, C. S. Ioakimidis, M. Remy, and M. Frère, "State-of-charge observers for lead-acid storage units used in autonomous solar applications," *Journal of Energy Storage*, vol. 14, pp. 1–7, 2017, doi: 10.1016/j.est.2017.09.006.

[108] J. Du, Z. Liu, Y. Wang, and C. Wen, "An adaptive sliding mode observer for lithium-ion battery state of charge and state of health estimation in electric vehicles," *Control Engineering Practice*, vol. 54, pp. 81–90, 2016, doi: 10.1016/j.conengprac.2016.05.014.

[109] P. Li, N. Chen, J. Chen, and N. Zhang, “A State-of-Charge Estimation Method Based on an Adaptive Proportional-Integral Observer,” in *2016 IEEE Vehicle Power and Propulsion Conference (VPPC)*, 2016, pp. 1–6.

[110] I.-S. Kim, “Nonlinear State of Charge Estimator for Hybrid Electric Vehicle Battery,” *IEEE Trans. Power Electron.*, vol. 23, no. 4, pp. 2027–2034, 2008, doi: 10.1109/TPEL.2008.924629.

[111] D. Zhou, A. Ravey, F. Gao, D. Paire, A. Miraoui, and K. Zhang, “Online estimation of state of charge of Li-ion battery using an iterated extended Kalman particle filter,” in *2015 IEEE Transportation Electrification Conference and Expo (ITEC)*, Dearborn, MI, USA, Jun. 2015 - Jun. 2015, pp. 1–5.

[112] W. Junping, G. Jingang, and D. Lei, “An adaptive Kalman filtering based State of Charge combined estimator for electric vehicle battery pack,” *Energy Conversion and Management*, vol. 50, no. 12, pp. 3182–3186, 2009, doi: 10.1016/j.enconman.2009.08.015.

[113] Y. Li and C. Wang, “A Hybrid Estimation Method for SOC of Lithium Batteries in Electrical Vehicles Considering Vehicle Operating Condition Recognition,” in *2017 4th International Conference on Information Science and Control Engineering (ICISCE)*, Changsha, Jul. 2017 - Jul. 2017, pp. 797–801.

[114] Jiaxi Qiang, Guoqiang Ao, Jianhui He, Ziqiang Chen, and Lin Yang, “An adaptive algorithm of NiMH battery state of charge estimation for hybrid electric vehicle,” in *2008 IEEE International Symposium on Industrial Electronics*, 2008, pp. 1556–1561.

[115] M. Danko, J. Adamec, M. Taraba, and P. Drgona, “Overview of batteries State of Charge estimation methods,” *Transportation Research Procedia*, vol. 40, pp. 186–192, 2019, doi: 10.1016/j.trpro.2019.07.029.

[116] N. Noura, L. Boulon, and S. Jemeï, “A Review of Battery State of Health Estimation Methods: Hybrid Electric Vehicle Challenges,” *WEVJ*, vol. 11, no. 4, p. 66, 2020, doi: 10.3390/wevj11040066.

[117] X. Hu, F. Feng, K. Liu, L. Zhang, J. Xie, and B. Liu, “State estimation for advanced battery management: Key challenges and future trends,” *Renewable and Sustainable Energy Reviews*, vol. 114, p. 109334, 2019, doi: 10.1016/j.rser.2019.109334.

[118] A. Barré, B. Deguilhem, S. Grolleau, M. Gérard, F. Suard, and D. Riu, “A review on lithium-ion battery ageing mechanisms and estimations for automotive applications,” *Journal of Power Sources*, vol. 241, pp. 680–689, 2013, doi: 10.1016/j.jpowsour.2013.05.040.

[119] J. Tian, R. Xiong, and W. Shen, "A review on state of health estimation for lithium ion batteries in photovoltaic systems," *eTransportation*, vol. 2, p. 100028, 2019, doi: 10.1016/j.etran.2019.100028.

[120] C. Lin, A. Tang, and W. Wang, "A Review of SOH Estimation Methods in Lithium-ion Batteries for Electric Vehicle Applications," *Energy Procedia*, vol. 75, pp. 1920–1925, 2015, doi: 10.1016/j.egypro.2015.07.199.

[121] D. Andre, A. Nuhic, T. Soczka-Guth, and D. U. Sauer, "Comparative study of a structured neural network and an extended Kalman filter for state of health determination of lithium-ion batteries in hybrid electricvehicles," *Engineering Applications of Artificial Intelligence*, vol. 26, no. 3, pp. 951–961, 2013, doi: 10.1016/j.engappai.2012.09.013.

[122] Y. Bao, W. Dong, and D. Wang, "Online Internal Resistance Measurement Application in Lithium Ion Battery Capacity and State of Charge Estimation," *Energies*, vol. 11, no. 5, p. 1073, 2018, doi: 10.3390/en11051073.

[123] M. Berecibar, I. Gandiaga, I. Villarreal, N. Omar, J. van Mierlo, and P. van den Bossche, "Critical review of state of health estimation methods of Li-ion batteries for real applications," *Renewable and Sustainable Energy Reviews*, vol. 56, pp. 572–587, 2016, doi: 10.1016/j.rser.2015.11.042.

[124] P. Venugopal and V. T., "State-of-Health Estimation of Li-ion Batteries in Electric Vehicle Using IndRNN under Variable Load Condition," *Energies*, vol. 12, no. 22, p. 4338, 2019, doi: 10.3390/en12224338.

[125] S. Yang, C. Zhang, J. Jiang, W. Zhang, L. Zhang, and Y. Wang, "Review on state-of-health of lithium-ion batteries: Characterizations, estimations and applications," *Journal of Cleaner Production*, vol. 314, p. 128015, 2021a, doi: 10.1016/j.jclepro.2021.128015.

[126] S. Yang, C. Zhang, J. Jiang, W. Zhang, L. Zhang, and Y. Wang, "Review on state-of-health of lithium-ion batteries: Characterizations, estimations and applications," *Journal of Cleaner Production*, vol. 314, p. 128015, 2021, doi: 10.1016/j.jclepro.2021.128015.

[127] G. You, S. Park, and D. Oh, "Real-time state-of-health estimation for electric vehicle batteries: A data-driven approach," *Applied Energy*, vol. 176, pp. 92–103, 2016, doi: 10.1016/j.apenergy.2016.05.051.

[128] H. Meng and Y.-F. Li, "A review on prognostics and health management (PHM) methods of lithium-ion batteries," *Renewable and Sustainable Energy Reviews*, vol. 116, p. 109405, 2019, doi: 10.1016/j.rser.2019.109405.

[129] K. Wang *et al.*, "Internal resistance and heat generation of soft package Li4Ti5O12 battery during charge and discharge," *Energy*, vol. 149, pp. 364–374, 2018, doi: 10.1016/j.energy.2018.02.052.

[130] H. Chaoui and H. Gualous, "Online parameter and state estimation of lithium-ion batteries under temperature effects," *Electric Power Systems Research*, vol. 145, pp. 73–82, 2017, doi: 10.1016/j.epsr.2016.12.029.

[131] K. B. Hatzell, A. Sharma, and H. K. Fathy, "A survey of long-term health modeling, estimation, and control of Lithium-ion batteries: Challenges and opportunities," in *2012 American Control Conference (ACC)*, Montreal, QC, Jun. 2012 - Jun. 2012, pp. 584–591.

[132] D. Z. Li, W. Wang, and F. Ismail, "A Mutated Particle Filter Technique for System State Estimation and Battery Life Prediction," *IEEE Trans. Instrum. Meas.*, vol. 63, no. 8, pp. 2034–2043, 2014, doi: 10.1109/TIM.2014.2303534.

[133] L. Yao *et al.*, "A Review of Lithium-Ion Battery State of Health Estimation and Prediction Methods," *WEVJ*, vol. 12, no. 3, p. 113, 2021, doi: 10.3390/wevj12030113.

[134] A. Eddahech, O. Briat, N. Bertrand, J.-Y. Delétage, and J.-M. Vinassa, "Behavior and state-of-health monitoring of Li-ion batteries using impedance spectroscopy and recurrent neural networks," *International Journal of Electrical Power & Energy Systems*, vol. 42, no. 1, pp. 487–494, 2012, doi: 10.1016/j.ijepes.2012.04.050.

[135] A. Basia, Z. Simeu-Abazi, E. Gascard, and P. Zwolinski, "Review on State of Health estimation methodologies for lithium-ion batteries in the context of circular economy," *CIRP Journal of Manufacturing Science and Technology*, vol. 32, pp. 517–528, 2021, doi: 10.1016/j.cirpj.2021.02.004.

[136] C. Weng, J. Sun, and H. Peng, "A unified open-circuit-voltage model of lithium-ion batteries for state-of-charge estimation and state-of-health monitoring," *Journal of Power Sources*, vol. 258, pp. 228–237, 2014, doi: 10.1016/j.jpowsour.2014.02.026.

[137] Z. Guo, X. Qiu, G. Hou, B. Y. Liaw, and C. Zhang, "State of health estimation for lithium ion batteries based on charging curves," *Journal of Power Sources*, vol. 249, pp. 457–462, 2014, doi: 10.1016/j.jpowsour.2013.10.114.

[138] L. Ungurean, G. Cârstoiu, M. V. Micea, and V. Groza, "Battery state of health estimation: a structured review of models, methods and commercial devices," *Int J Energy Res*, vol. 41, no. 2, pp. 151–181, 2017, doi: 10.1002/er.3598.

[139] K. S. Ng, C.-S. Moo, Y.-P. Chen, and Y.-C. Hsieh, "Enhanced coulomb counting method for estimating state-of-charge and state-of-health of lithium-ion batteries," *Applied Energy*, vol. 86, no. 9, pp. 1506–1511, 2009, doi: 10.1016/j.apenergy.2008.11.021.

[140] D. Wang, F. Yang, K.-L. Tsui, Q. Zhou, and S. J. Bae, "Remaining Useful Life Prediction of Lithium-Ion Batteries Based on Spherical Cubature Particle Filter,"

IEEE Trans. Instrum. Meas., vol. 65, no. 6, pp. 1282–1291, 2016, doi: 10.1109/TIM.2016.2534258.

[141] M. Cacciato, G. Nobile, G. Scarcella, and G. Scelba, "Real-Time Model-Based Estimation of SOC and SOH for Energy Storage Systems," *IEEE Trans. Power Electron.*, vol. 32, no. 1, pp. 794–803, 2017, doi: 10.1109/TPEL.2016.2535321.

[142] A. Guha and A. Patra, "State of Health Estimation of Lithium-Ion Batteries Using Capacity Fade and Internal Resistance Growth Models," *IEEE Trans. Transp. Electrific.*, vol. 4, no. 1, pp. 135–146, 2018, doi: 10.1109/TTE.2017.2776558.

[143] C. Pastor-Fernández, K. Uddin, G. H. Chouchelamane, W. D. Widanage, and J. Marco, "A Comparison between Electrochemical Impedance Spectroscopy and Incremental Capacity-Differential Voltage as Li-ion Diagnostic Techniques to Identify and Quantify the Effects of Degradation Modes within Battery Management Systems," *Journal of Power Sources*, vol. 360, pp. 301–318, 2017, doi: 10.1016/j.jpowsour.2017.03.042.

[144] Y. Wang *et al.*, "A comprehensive review of battery modeling and state estimation approaches for advanced battery management systems," *Renewable and Sustainable Energy Reviews*, vol. 131, p. 110015, 2020, doi: 10.1016/j.rser.2020.110015.

[145] M. Huang and M. Kumar, "Electrochemical Model-Based Aging Characterization of Lithium-Ion Battery Cell in Electrified Vehicles," in *Proceedings of the ASME 11th Annual Dynamic Systems and Control Conference - 2018-: Presented at ASME 2018 11th Annual Dynamic Systems and Control Conference, September 30 - October 3, 2018, Atlanta, Georgia, USA / sponsored by the Dynamic Systems and Control Division, ASME*, Atlanta, Georgia, USA, 2018.

[146] X. Bian, L. Liu, and J. Yan, "A model for state-of-health estimation of lithium ion batteries based on charging profiles," *Energy*, vol. 177, pp. 57–65, 2019, doi: 10.1016/j.energy.2019.04.070.

[147] T. Grandjean, A. McGordon, and P. Jennings, "Structural Identifiability of Equivalent Circuit Models for Li-Ion Batteries," *Energies*, vol. 10, no. 1, p. 90, 2017, doi: 10.3390/en10010090.

[148] M.-K. Tran *et al.*, "A comprehensive equivalent circuit model for lithium-ion batteries, incorporating the effects of state of health, state of charge, and temperature on model parameters," *Journal of Energy Storage*, vol. 43, p. 103252, 2021, doi: 10.1016/j.est.2021.103252.

[149] Z. Chen, C. C. Mi, Y. Fu, J. Xu, and X. Gong, "Online battery state of health estimation based on Genetic Algorithm for electric and hybrid vehicle applications," *Journal of Power Sources*, vol. 240, pp. 184–192, 2013, doi: 10.1016/j.jpowsour.2013.03.158.

[150] N. A. Azis, E. Joelianto, and A. Widyotriatmo, “State of Charge (SOC) and State of Health (SoH) Estimation of Lithium-Ion Battery Using Dual Extended Kalman Filter Based on Polynomial Battery Model,” in *2019 6th International Conference on Instrumentation, Control, and Automation (ICA)*, Bandung, Indonesia, 2019, pp. 88–93.

[151] D. Pavkovic, V. Smetko, M. Hrgetic, and A. Komljenovic, “Dual Kalman filter-based SOC/SoH estimator for an ultracapacitor module,” in *2014 IEEE Conference on Control Applications (CCA)*, Juan Les Antibes, France, Oct. 2014 - Oct. 2014, pp. 1783–1788.

[152] J. Kim, S. Lee, and B. H. Cho, “Complementary Cooperation Algorithm Based on DEKF Combined With Pattern Recognition for SOC/Capacity Estimation and SOH Prediction,” *IEEE Trans. Power Electron.*, vol. 27, no. 1, pp. 436–451, 2012, doi: 10.1109/TPEL.2011.2158554.

[153] M. Landi and G. Gross, “Measurement Techniques for Online Battery State of Health Estimation in Vehicle-to-Grid Applications,” *IEEE Trans. Instrum. Meas.*, vol. 63, no. 5, pp. 1224–1234, 2014, doi: 10.1109/TIM.2013.2292318.

[154] M. A. Patil *et al.*, “A novel multistage Support Vector Machine based approach for Li ion battery remaining useful life estimation,” *Applied Energy*, vol. 159, pp. 285–297, 2015, doi: 10.1016/j.apenergy.2015.08.119.

[155] V. Klass, M. Behm, and G. Lindbergh, “A support vector machine-based state-of-health estimation method for lithium-ion batteries under electric vehicle operation,” *Journal of Power Sources*, vol. 270, pp. 262–272, 2014, doi: 10.1016/j.jpowsour.2014.07.116.

[156] A. Nuhic, T. Terzimehic, T. Soczka-Guth, M. Buchholz, and K. Dietmayer, “Health diagnosis and remaining useful life prognostics of lithium-ion batteries using data-driven methods,” *Journal of Power Sources*, vol. 239, pp. 680–688, 2013, doi: 10.1016/j.jpowsour.2012.11.146.

[157] X. Feng *et al.*, “Online State-of-Health Estimation for Li-Ion Battery Using Partial Charging Segment Based on Support Vector Machine,” *IEEE Trans. Veh. Technol.*, vol. 68, no. 9, pp. 8583–8592, 2019, doi: 10.1109/TVT.2019.2927120.

[158] J. Zhang, X. Liu, C. Chen, and A. Simeone, “An Intelligent Deformation-Based Approach to the State of Health Estimation of Collided Lithium-Ion Batteries for Facilitating Battery Module Safety Evaluation,” *Energy Technol.*, vol. 8, no. 11, p. 2000624, 2020, doi: 10.1002/ente.202000624.

[159] M. Ragsdale, J. Brunet, and B. Fahimi, “A novel battery identification method based on pattern recognition,” in *2008 IEEE Vehicle Power and Propulsion Conference*, Harbin, Hei Longjiang, China, Sep. 2008 - Sep. 2008, pp. 1–6.

[160] E. Hou, X. Qiao, and G. Liu, "Remaining Useful Life Prediction of Power Lithium-Ion Battery based on Artificial Neural Network Model," in *Proceedings of the 2017 International Conference on Mechanical, Electronic, Control and Automation Engineering (MECAE 2017)*, Beijing, China, Mar. 2017 - Mar. 2017.

[161] A. Bonfitto, "A Method for the Combined Estimation of Battery State of Charge and State of Health Based on Artificial Neural Networks," *Energies*, vol. 13, no. 10, p. 2548, 2020, doi: 10.3390/en13102548.

[162] M. H. Lipu *et al.*, "A review of state of health and remaining useful life estimation methods for lithium-ion battery in electric vehicles: Challenges and recommendations," *Journal of Cleaner Production*, vol. 205, pp. 115–133, 2018, doi: 10.1016/j.jclepro.2018.09.065.

[163] G. K. Prasad and C. D. Rahn, "Model based identification of aging parameters in lithium ion batteries," *Journal of Power Sources*, vol. 232, pp. 79–85, 2013, doi: 10.1016/j.jpowsour.2013.01.041.

[164] M. Huotari, S. Arora, A. Malhi, and K. Främling, "A Dynamic Battery State-of-Health Forecasting Model for Electric Trucks: Li-Ion Batteries Case-Study," in *Proceedings of the ASME International Mechanical Engineering Congress and Exposition (IMECE2020)*, Virtual, Online, 2020.

[165] J. Huang, S. Wang, W. Xu, W. Shi, and C. Fernandez, "A Novel Autoregressive Rainflow—Integrated Moving Average Modeling Method for the Accurate State of Health Prediction of Lithium-Ion Batteries," *Processes*, vol. 9, no. 5, p. 795, 2021, doi: 10.3390/pr9050795.

[166] Z. Chen, Q. Xue, R. Xiao, Y. Liu, and J. Shen, "State of Health Estimation for Lithium-ion Batteries Based on Fusion of Autoregressive Moving Average Model and Elman Neural Network," *IEEE Access*, vol. 7, pp. 102662–102678, 2019, doi: 10.1109/ACCESS.2019.2930680.

[167] Q. Huo, Z. Ma, X. Zhao, T. Zhang, and Y. Zhang, "Bayesian Network Based State-of-Health Estimation for Battery on Electric Vehicle Application and its Validation Through Real-World Data," *IEEE Access*, vol. 9, pp. 11328–11341, 2021, doi: 10.1109/ACCESS.2021.3050557.

[168] G. Dong, W. Han, and Y. Wang, "Dynamic Bayesian Network-Based Lithium-Ion Battery Health Prognosis for Electric Vehicles," *IEEE Trans. Ind. Electron.*, vol. 68, no. 11, pp. 10949–10958, 2021, doi: 10.1109/TIE.2020.3034855.

[169] Y. Lin, M. Hu, X. Yin, J. Guo, and Z. Li, "Evaluation of Lithium Batteries Based on Continuous Hidden Markov Model," in *2017 IEEE International Conference on Software Quality, Reliability and Security Companion (QRS-C)*, Prague, Czech Republic, Jul. 2017 - Jul. 2017, pp. 221–225.

[170] C. Piao, Z. Li, S. Lu, Z. Jin, and C. Cho, "Analysis of Real-Time Estimation Method Based on Hidden Markov Models for Battery System States of Health,"

Journal of Power Electronics, vol. 16, no. 1, pp. 217–226, 2016, doi: 10.6113/JPE.2016.16.1.217.

[171] H. Dai, G. Zhao, M. Lin, J. Wu, and G. Zheng, "A Novel Estimation Method for the State of Health of Lithium-Ion Battery Using Prior Knowledge-Based Neural Network and Markov Chain," *IEEE Trans. Ind. Electron.*, vol. 66, no. 10, pp. 7706–7716, 2019, doi: 10.1109/TIE.2018.2880703.

[172] J. S. Richman and J. R. Moorman, "Physiological time-series analysis using approximate entropy and sample entropy," *American journal of physiology. Heart and circulatory physiology*, vol. 278, no. 6, H2039-49, 2000, doi: 10.1152/ajpheart.2000.278.6.H2039.

[173] S. M. Pincus, "Approximate entropy as a measure of system complexity," *Proceedings of the National Academy of Sciences of the United States of America*, vol. 88, no. 6, pp. 2297–2301, 1991, doi: 10.1073/pnas.88.6.2297.

[174] *Recommended practice for maintenance, testing, and replacement of valve-regulated Lead-Acid (VRLA) batteries for stationary applications: 1188-1996 …*, 1996.

[175] T. Okoshi, K. Yamada, T. Hirasawa, and A. Emori, "Battery condition monitoring (BCM) technologies about lead–acid batteries," *Journal of Power Sources*, vol. 158, no. 2, pp. 874–878, 2006, doi: 10.1016/j.jpowsour.2005.11.008.

[176] A. Widodo, M.-C. Shim, W. Caesarendra, and B.-S. Yang, "Intelligent prognostics for battery health monitoring based on sample entropy," *Expert Systems with Applications*, vol. 38, no. 9, pp. 11763–11769, 2011, doi: 10.1016/j.eswa.2011.03.063.

[177] X. Sui, S. He, D.-I. Stroe, and R. Teodorescu, "Lithium-ion Battery State of Health Estimation Using Empirical Mode Decomposition Sample Entropy and Support Vector Machine," in *2020 IEEE Applied Power Electronics Conference and Exposition (APEC)*, New Orleans, LA, USA, Mar. 2020 - Mar. 2020, pp. 3424–3429.

[178] C. Burgos-Mellado, M. E. Orchard, M. Kazerani, R. Cárdenas, and D. Sáez, "Particle-filtering-based estimation of maximum available power state in Lithium-Ion batteries," *Applied Energy*, vol. 161, pp. 349–363, 2016, doi: 10.1016/j.apenergy.2015.09.092.

[179] D. Wang and K.-L. Tsui, "State Space Models Based Prognostic Methods for Remaining Useful Life Prediction of Rechargeable Batteries," in *ICSA book series in statistics, 2199-0980, Statistical modeling for degradation data*, D.-G. Chen, Y. Lio, H. K. T. Ng, and T.-R. Tsai, Eds., Singapore: Springer, 2017, pp. 307–334.

[180] D. Yang, X. Zhang, R. Pan, Y. Wang, and Z. Chen, "A novel Gaussian process regression model for state-of-health estimation of lithium-ion battery using charging curve," *Journal of Power Sources*, vol. 384, pp. 387–395, 2018b, doi: 10.1016/j.jpowsour.2018.03.015.

[181] Y.-J. He, J.-N. Shen, J.-F. Shen, and Z.-F. Ma, “State of health estimation of lithium-ion batteries: A multiscale Gaussian process regression modeling approach,” *AIChE J.*, vol. 61, no. 5, pp. 1589–1600, 2015, doi: 10.1002/aic.14760.

[182] D. A. Martinez, J. D. Poveda, and D. Montenegro, “Li-Ion battery management system based in fuzzy logic for improving electric vehicle autonomy,” in *2017 IEEE Workshop on Power Electronics and Power Quality Applications (PEPQA)*, Bogota, Colombia, May. 2017 - Jun. 2017, pp. 1–6.

[183] H.-T. Lin, T.-J. Liang, and S.-M. Chen, “The state-of-health diagnosis of Li-Co batteries with fuzzy identification,” *Conference Proceedings - 2012 IEEE 7th International Power Electronics and Motion Control Conference - ECCE Asia, IPEMC 2012*, pp. 2678–2682, 2012, doi: 10.1109/IPEMC.2012.6259285.

[184] B. Pattipati, C. Sankavaram, and K. Pattipati, “System Identification and Estimation Framework for Pivotal Automotive Battery Management System Characteristics,” *IEEE Trans. Syst., Man, Cybern. C*, vol. 41, no. 6, pp. 869–884, 2011, doi: 10.1109/TSMCC.2010.2089979.

[185] M. V. Micea, L. Ungurean, G. N. Cârstoiu, and V. Groza, “Online State-of-Health Assessment for Battery Management Systems,” *IEEE Trans. Instrum. Meas.*, vol. 60, no. 6, pp. 1997–2006, 2011, doi: 10.1109/TIM.2011.2115630.

[186] X. Hu, S. E. Li, Z. Jia, and B. Egardt, “Enhanced sample entropy-based health management of Li-ion battery for electrified vehicles,” *Energy*, vol. 64, pp. 953–960, 2014, doi: 10.1016/j.energy.2013.11.061.

[187] S. Schwunk, N. Armbruster, S. Straub, J. Kehl, and M. Vetter, “Particle filter for state of charge and state of health estimation for lithium–iron phosphate batteries,” *Journal of Power Sources*, vol. 239, pp. 705–710, 2013, doi: 10.1016/j.jpowsour.2012.10.058.

6 List of figures

7 List of tables