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A review of lithium-ion battery state of charge estimation and management system in electric vehicle applications: Challenges and recommendations

M.A. Hannan[a,*], M.S.H. Lipu[b], A. Hussain[b], A. Mohamed[b]

[a] Department of Electrical Power Engineering, Universiti Tenaga Nasional, Malaysia
[b] Department of Electrical, Electronic and Systems Engineering, Universiti Kebangsaan Malaysia, Kajang

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ABSTRACT

Due to increasing concerns about global warming, greenhouse gas emissions, and the depletion of fossil fuels, the electric vehicles (EVs) receive massive popularity due to their performances and efficiencies in recent decades. EVs have already been widely accepted in the automotive industries considering the most promising replacements in reducing CO_2 emissions and global environmental issues. Lithium-ion batteries have attained huge attention in EVs application due to their lucrative features such as lightweight, fast charging, high energy density, low self-discharge and long lifespan. This paper comprehensively reviews the lithium-ion battery state of charge (SOC) estimation and its management system towards the sustainable future EV applications. The significance of battery management system (BMS) employing lithium-ion batteries is presented, which can guarantee a reliable and safe operation and assess the battery SOC. The review identifies that the SOC is a crucial parameter as it signifies the remaining available energy in a battery that provides an idea about charging/discharging strategies and protect the battery from overcharging/over discharging. It is also observed that the SOC of the existing lithium-ion batteries have a good contribution to run the EVs safely and efficiently with their charging/discharging capabilities. However, they still have some challenges due to their complex electro-chemical reactions, performance degradation and lack of accuracy towards the enhancement of battery performance and life. The classification of the estimation methodologies to estimate SOC focusing with the estimation model/algorithm, benefits, drawbacks and estimation error are extensively reviewed. The review highlights many factors and challenges with possible recommendations for the development of BMS and estimation of SOC in next-generation EV applications. All the highlighted insights of this review will widen the increasing efforts towards the development of the advanced SOC estimation method and energy management system of lithium-ion battery for the future high-tech EV applications.

1. Introduction

The world is moving towards some serious consequences such as global warming, greenhouse gas (GHG) emission caused by extensive use of diesel, petrol in vehicle operation, which emits tons of CO_2 every year [1–3]. Besides, the rising crude oil price also causes serious setback of the automobile industry and urges the necessity to develop alternative fuel-driven vehicles. To address the problems, the implementation of EV has gained huge attention and become attractive choices for academic researchers and automobile specialists due to their promising features in reducing GHG [4–7].

Implementation of rechargeable battery in EV application has become very popular in recent years [8–10] since renewable energy sources such as solar energy, wind energy, are intermittent in nature and could not be applicable where continuous and reliable supply is required [11]. Various energy storages, such as lead acid, NiMH, lithium-ion batteries have been used in an EV [12]. Among them, lithium-ion battery is widely accepted due to its high energy density, long lifespan and high efficiency [13,14]. Because of its lucrative features, a lot of investments have already been made to enhance the stability and robustness of lithium-ion battery [15]. Even though of high primary cost, market growth of lithium-ion battery has been increasing steadily and is expected to continue its growth [16].

An effective BMS using the lithium-ion battery is compulsory so that battery can operate safely and reliably, prevent any physical damages, and handle thermal degradation and cell unbalancing [17,18]. Moreover, different states of the battery such as the SOC, state of health (SOH) can be assessed through an efficient battery management system, which can sense temperature, measure voltage and current, regulate safety alarm to avoid any overcharging/over discharging. Furthermore, a BMS is essential for controlling and updating data, detecting faults, equalizing battery voltage that are the important factors for achieving a good accuracy of SOC and SOH.

* Corresponding author at: Department of Electrical Power Engineering, Universiti Tenaga Nasional.

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Nomenclature

ANFIS	Adaptive Neural Fuzzy Interface System
ANN	Artificial Neural Network
ASGSMO	Adaptive Switching Gain Sliding Mode Observer
BI	Bi-linear Interpolation
CC	Coulomb Counting
EIS	Electrochemical Impedance Spectroscopy
EKF	Extended Kalman Filter
EMF	Electro-Motive Force
FL	Fuzzy Logic
FNN	Fuzzy Neural Network
GA	Genetic Algorithm
IR	Impulse Response
KF	Kalman Filter
MARS	Multivibrate Adaptive Regression Splines
NLO	Nonlinear Observer
NN	Neural Network
OCV	Open Circuit Voltage
PF	Particle Filter
PIO	Proportional-integral Observer
RBFNN	Radial Basis Function Neural Network
RLS	Recursive Least Square
SMO	Sliding Mode Observer
SPKF	Sigma Point Kalman Filter
SVM	Support Vector Machine
UKF	Unscented Kalman Filter
UPF	Unscented Particle Filter

SOC in battery management system is considered as one of the critical and important factors, which have been researched in recent decades. Battery SOC does the similar operation of the fuel gauge in a gasoline-driven vehicle which indicates how much energy is left inside a battery to power a vehicle [19]. Accurate estimation of battery states not only helps to provide information about the current and remaining performance of the battery but also gives assurance of a reliable and safe operation of the EV. However, battery SOC estimation is one of the main challenges for the successful operation of EVs. Due to non-linear, time-varying characteristics and electrochemical reactions, battery SOC cannot be observed directly [20]. Furthermore, the performance of the battery is highly affected by aging, temperature variation, charge-discharge cycles which make the task of estimating an accurate SOC very challenging [21].

Very few literature have been found which provide a detailed explanation of all the methods to estimate SOC of EV [22–25]. The literature has demonstrated some common methods to estimate SOC; however, each method has shortcomings in terms of accuracy and lack of data. In addition, complex calculation and high computation cost are the others concerns which make the estimation process very difficult. Hence, the academics, researchers, scientists have performed an extensive research to enhance the accuracy of battery SOC. Nevertheless, the issues in estimating an accurate SOC have not resolved yet. Besides, the challenges in estimating the SOC have not been identified. Thus, this research paper fills up the gap by exploring different existing methodologies and addressing the key issues and challenges for the estimation of SOC. This research will be very helpful for the automobile manufacturers and engineers in terms of deciding the appropriate method and identifying challenges.

This paper briefly discusses the lithium-ion battery state of charge estimation and management system in EV applications. The main concern is to develop an efficient SOC estimation method/algorithm of lithium-ion batteries. In addition, there are some issues and challenges regarding its estimation methodologies. This paper reviews the published articles to gain knowledge on SOC estimation methods in order to propose the most efficient model/algorithm. A detailed SOC estimation methods with its benefits and drawbacks is briefly elaborated. The issues and challenges of implementing various SOC methods along with possible solutions are also addressed to provide information and knowledge to the vehicle manufacturer. This knowledge will be important for future development of implementing new SOC methods or upgradation of earlier SOC methods.

2. Status of lithium-ion battery

There are many energy storages, such as lead acid, NiMH, lithium-ion batteries, which have been used widely for EV application. However, among them, lithium-ion batteries have been an attractive choice among automobile engineers in spite of its high capital cost [26]. Due it its promising performance in the application of automobile, cellular phone, notebook computers [27], a significant research and development have been performed to enhance the performance of lithium-ion batteries in terms of safety, reliability, and durability [28]. Conte et al. [29] made a comparative study of various energy storage devices, as reported in Table 1. It is clearly visible that, lithium-ion battery has better power and energy density compared to other energy storage devices. In addition, it has some attractive features such high efficiency, long cycle life, low discharge rate and high voltage.

Table 2 presents the main components of lithium-ion batteries and their characteristics. The table shows which electrode (particularly positive electrode) made the lithium-ion battery is suitable for specific application in terms of power, safety, cost, and lifespan.

A schematic of a lithium-ion battery is presented in Fig. 1 [31]. The cell has five regions, including composite negative electrode (anode), the composite positive electrode (cathode), a separator and two electrode current collectors; made of copper and aluminum respectively. The composite negative electrode (anode) and the positive (cathode) electrode are divided by an electrolyte separator such as $LiPF_6$. Lithium metal oxides (e.g., $LiCoO_2$, $LiNiO_2$, $LiMn_2O_4$) is used to build a positive electrode while graphite or petroleum coke is used to make a negative electrode. The composite electrodes are held together with carbon black. When the discharge process initiates, lithium ions are readily available to be accepted by positive electrode while a complete lithiation occurs in the negative electrode. During discharge, there is deintercalation between negative electrode particles and solution phase. During the same time, there is an intercalation between

Table 1
Performance comparison among various energy storage devices [29].

	Temperature [°C]	η (%)	Energy		Power [W/kg]	Voltage [V]	Self-discharge [%/Month]	Cycle life @80%DOD	Cost estimation	
			[Wh/l]	[Wh/kg]					[$/kWh]	[$/kW]
Lead Acid	−30–60	85	50–70	20–40	300	2,1	4–8	200	150	10
NiMH	−20–50	80	200	40–60	1300–500	1,2	20	> 2500	500	20
Li-ion	−20–55	93	150–200	100–200	3000–800	~3,6	1–5	< 2500	800	50–75
EDLC	−30–65	97	5	5–20	1500	~2,5	30	Not applicable	2000	50

Table 2
Major components of lithium-ion batteries and their properties [30].

Abbrev	LCO	NLO	NCA	NMC	LMO	LFP	LTO
Name	Lithium Cobalt Oxide	Lithium nickel oxide	Lithium nickel cobalt aluminum oxide	Lithium nickel, manganese cobalt oxide	Lithium manganese spinel	Lithium iron phosphate	Lithium titanate
Positive electrode	$LiCoO_2$	$LiNiO_2$	Li(Ni0,85Co0,1Al0,05)O2	Li(Ni0,33Mn0,33Co0,33)O2	$LiMn_2O_4$	$LiFePO_4$	LMO, NCA
Negative electrode	Graphite	Graphite	Graphite	Graphite	Graphite	Graphite	$Li4Ti_5O_{12}$
Cell voltage (V)	3.7–3.9	3.6	3.65	3.8–4.0	4	3.3	2.3–2.5
Energy density (Wh/kg)	150 mA h/g	150	130	170	120	130	85
Power	+	o	+	o	+	+	++
Safety	–	o	o	o	+	++	++
Lifetime	–	o	+	o	o	+	+++
Cost	–	+	o	o	+	+	o

positive electrode lithium-ions and $LiCoO_2$ particles. Therefore, a concentration gradient is formed which shifts the electrode from positive side to the negative side. Since the concentration of lithium particles is strongly related to the equilibrium potential of the two electrodes, thus cell voltage reduces during the discharge process until it reaches to 3 V. It is very crucial to measure the voltage of lithium-ion batteries within the safe region since batteries may subject to over-charge/over-discharge which may cause serious damage such as fire, explosion.

3. Overview of battery management systems (BMS)

Since the lithium-ion battery is effective and efficient in achieving better performance during their long lifespan, special attention must be paid to their operating conditions to avoid any physical damage, aging and thermal runaways. Therefore, there is an urgent need to build an efficient BMS, which can precisely measure, estimate and regulate the battery SOC.

Presently, BMS has been widely used by various automobile companies, colleges and universities. BMS products have been developed by a few companies such as American Elithion Corporation, Australian EV power, British REAPSystem, Beijing Key Power Technology, Harbin Guantuo Power Equipment Co. Ltd, Huizhou Epower Electronic Co. Ltd, etc [32]. A developed and comprehensive BMS has been used in portable electronic modules such as cellular phone, notebook. However, implementation of BMS in EVs is still in early stage. The reason is that the number of batteries in an EV is hundred times higher than that of portable devices. In addition, EVs are designed to provide high power, high voltage and high current, which makes BMS more complex than portable electronics.

BMS in the vehicle may consist of many components such as sensors, controller, actuators which are controlled by many models, algorithms, and signals. Various researchers have proposed the battery model in different ways. Xing et al. [33] categorized the component of BMS into the hardware and software structure perspective, as shown in Fig. 2.

3.1. Hardware

In order to monitor and measure the battery parameters such as battery voltage, current and temperature, various sensor systems are included in BMS. Electrochemical Impedance Spectroscopy (EIS) theory has been proposed by some researcher to monitor battery cell impedance [34]. However, high device cost and space constraints are the complications to get high accuracy data outside the laboratory environment. There are many safety circuits, which have been used in BMS long ago. However, an improvement in safety circuitry is required to accurately control the alarms to prevent over-heating, overcharge, and over-discharge. Charge control is necessary to govern the charge-discharge protocol. As the batteries are charged by constant voltage/constant current method (CV/CC), a galvanostat and potentiostat are required to balance battery cells. Since the temperature difference among cells has an effect on cell performance, reliability, cell imbalance, and a thermal management module are placed inside the BMS. Pesaran [35] stated the importance of monitoring and operating cell within the proper temperature interval and highlighted the necessity to decrease the temperature difference among cells. Data transfer throughout the BMS is required since BMS module operates in stand-alone mode. In order to communicate data within the BMS, a controlled transceiver is required. With the recent advancement of smart batteries and wireless telecommunication, a vast amount of data can be communicated between a battery and a charger.

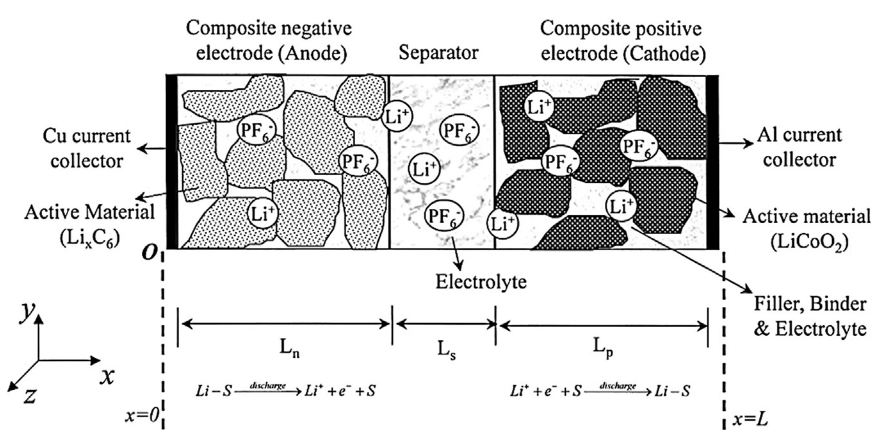

Fig. 1. A schematic presentation of typical lithium-ion battery [31].

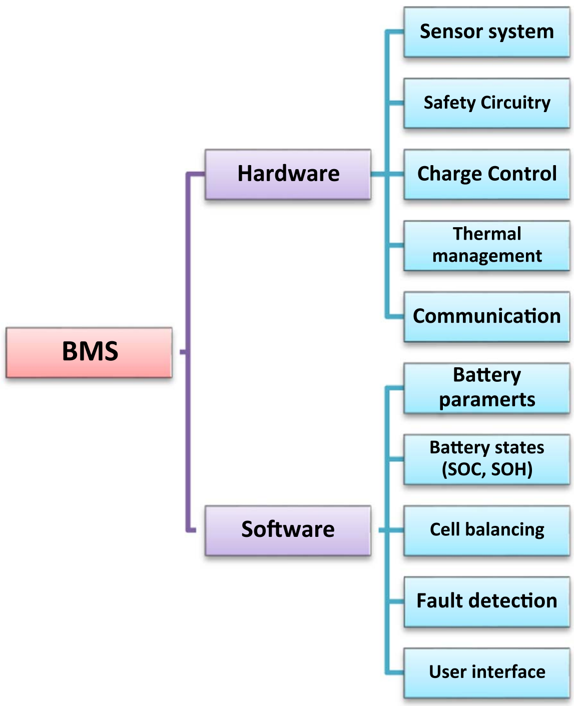

Fig. 2. Basic framework of BMS in EV.

3.2. *Software*

The software is considered as the center of BMS as it controls the operation of hardware, makes decisions and estimates states for all sensors. Cell balancing control, switch control, safety circuit design is controlled by the software of a BMS. The software also performs the online data analysis for continuously controlling and updating battery functions, which are a key factor for successful operation of battery since it determines fault identification and state estimation. The user will get the information from the battery through a user interface with required suggestions.

Detection of Battery parameters includes individual cell voltage measurement (to prevent over discharge and overcharge), total cell voltage, total current, impedance detection, temperature detection, smoke detection and so on. Battery state estimation contains SOC and SOH which sets the working conditions based on various models and algorithms such as state space models, neural networks, fuzzy logic and so on [36]. SOC is estimated using voltage, current and temperature. SOH is estimated according to performance degradation in battery which is related to capacity fade and power fade [37]. Battery cell balancing is needed to get the better performance without causing any overcharging or over-discharging. The objective of cell balancing is to make the value of SOC among cells as close as possible. In order to identify the abnormalities in battery and fault analysis, an intelligent data control system is required where historical data to be stored and an alarm signal to be provided before any fault occurs. The user will get all the necessary information through a user interface, which will show on the display of BMS. Depending on the value of the SOC, the available driving range will be displayed on the dashboard. In addition, battery replacement and abnormal alarming are required to protect the battery from being damaged.

A comprehensive block diagram of BMS is shown in Fig. 3. The operational detail is described in various blocks. A measurement block converts the voltage, current and temperature at each point of the battery into a digital signal. These parameters are used to estimate the states (SOC, SOH) of battery in the next stage. A battery capability estimation block controls the maximum charge/discharge current with the help of a suitable algorithm. The outcomes of this block are delivered to the cell equalizer in order to limit the battery over-charge/over discharge abnormalities. A ground fault detection block is added to enhance the security of the system. Thermal management block monitors the temperature to ensure that a battery performs in safe and reliable condition. This unit controls a fan and a heater in such a way that a battery operates in the optimal temperature range. A controlled transceiver block is used to control input and output data. An efficient and high speed controlled transceiver device is needed to transmit and receive a vast amount of data.

4. State of charge (SOC)

There has always been a big concern to estimate the SOC for all

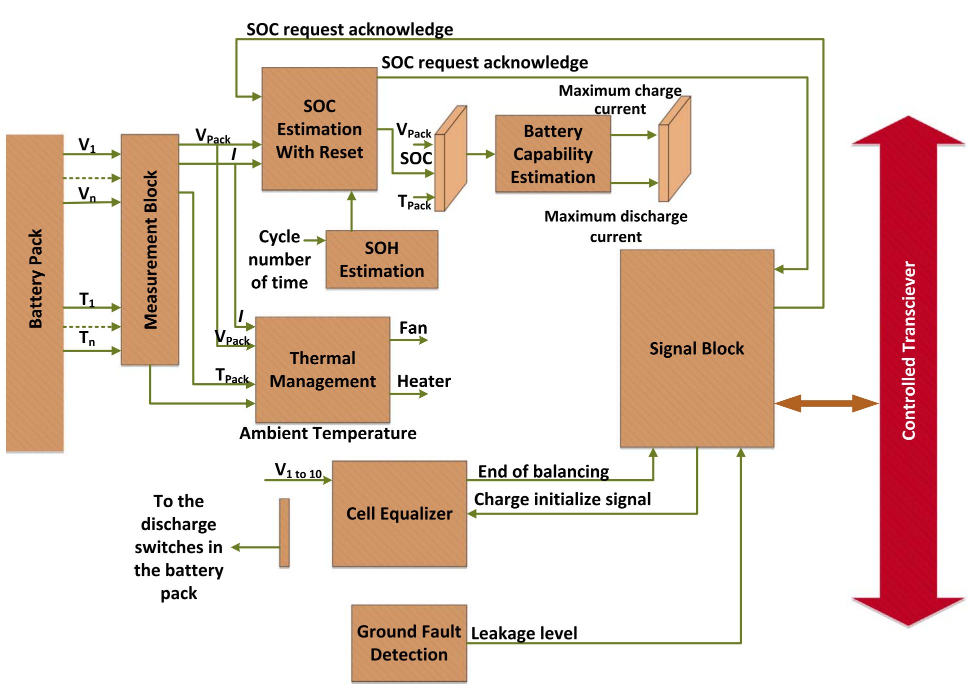

Fig. 3. Block diagram of BMS.

energy storage devices. SOC estimation with high accuracy not only gives us information about remaining useful energy, but also it evaluates the reliability of batteries. In addition, an accurate and efficient SOC estimation gives an idea about charging/discharging strategies, which have a significant impact on battery application where each cell may have different capacities due to aging, temperature, self-discharge and manufacture difference.

Several methods to estimate SOC have been introduced since the 1980s, however, a proper definition has yet to explain as the understanding of SOC needs further analytical tasks, such as prediction of remaining useful life and estimation of capacity. The most classical method to estimate SOC is current integration, which expresses the ratio of the available current capacity to the nominal capacity [38] is shown in Eq. (1).

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

where i is the battery current; C_n is the nominal capacity; t is time. Due to variation in external load and the internal chemical reaction of the battery, the nominal capacity decreases gradually over time, which leads to non-stationary, non-linear battery degradation characteristics. In addition, large SOC errors may occur due to accumulation in terminal measurements, thus need to recalibrate the value from time to time [39]. Another way to define SOC with the effect of coulombic efficiency is expressed as follows.

$$SOC = 1 - \frac{\int i.\ \eta dt}{C_n} \tag{2}$$

where η is the coulombic efficiency defined as the ratio of energy require for charging to the discharging energy needed to regain the original capacity.

A general SOC system is shown in Fig. 4. Battery cells are connected either in series or parallel, having at least two terminals. An analog to digital converter (ADC) is added into the SOC system for converting voltage, temperature as well as current in sense resistance into digital signals. Based on the measured signals, a microcontroller/microprocessor estimates the SOC of the system. There are different models/algorithms for determining SOC, which is stored in microcontroller/microprocessor. Two memory units are used in SOC system; one is read only memory (ROM) and the other is random access memory (RAM). The basic data is stored in ROM such as the amount of discharge and charge/discharge efficiency. ROM also stores algorithms for SOC when the SOC is estimated using EMF. The historical data is stored in RAM such as the number of charge/discharge cycles. Each parameter have an impact on the accuracy of SOC. Calibration of SOC is also needed if SOC estimation is based on measurement and integration of current because the current measurement inaccuracy causes errors which accumulates over time.

5. SOC estimation methods

Different kinds of literature have presented the classification of SOC in a different manner. This paper divides the SOC estimation methods into the five categories, which are shown in Fig. 5. The conventional method uses the physical properties of the battery, which includes voltage, discharge current, resistance, and impedance. The adaptive filter algorithm uses various models and algorithms to calculate the SOC. The learning algorithm requires a large amount of training data and heavy computation to describe the nonlinear characteristics of lithium-ion to estimate the SOC. The nonlinear observer is designed to handle with the highly nonlinear system. The other methods include MARS, BI, IR and hybrid method. MARS, BI, and IR use extended linear model, two linear interpolations, and linear time invariant system respectively. The hybrid method combines two or three SOC algorithms to estimate SOC. It takes the advantage of each method to obtain optimal performance, which improves the estimation accuracy.

5.1. Conventional method

5.1.1. Open Circuit Voltage (OCV) method

Since SOC in a lithium-ion battery is connected to embedding quantity in the active material, an open circuit voltage can be considered to estimate SOC after the battery gets sufficient resting to reach balance [40]. Usually, an approximate linear relationship exists between SOC and OCV. However, the relationship between SOC and OCV is not exactly same for all types of batteries. The relationship depends on capacity and material of the battery [41]. For instance, a lead-acid battery has a linear relationship between SOC and OCV while a lithium-ion battery does not hold that relationship [42].

It is a simple method and has high precision. However, the main drawback of OCV method is that it takes long rest time to reach equilibrium condition [43]. The duration of time to reach from operating state to stable state depends on SOC states, temperature and so on. For instance, at low temperature, $C/LiFePO_4$ takes more than two hours to reach equilibrium. Thus, the method is applicable only when the vehicles are placed in parking rather than operated at driving mode. Furthermore, careful observations are required to

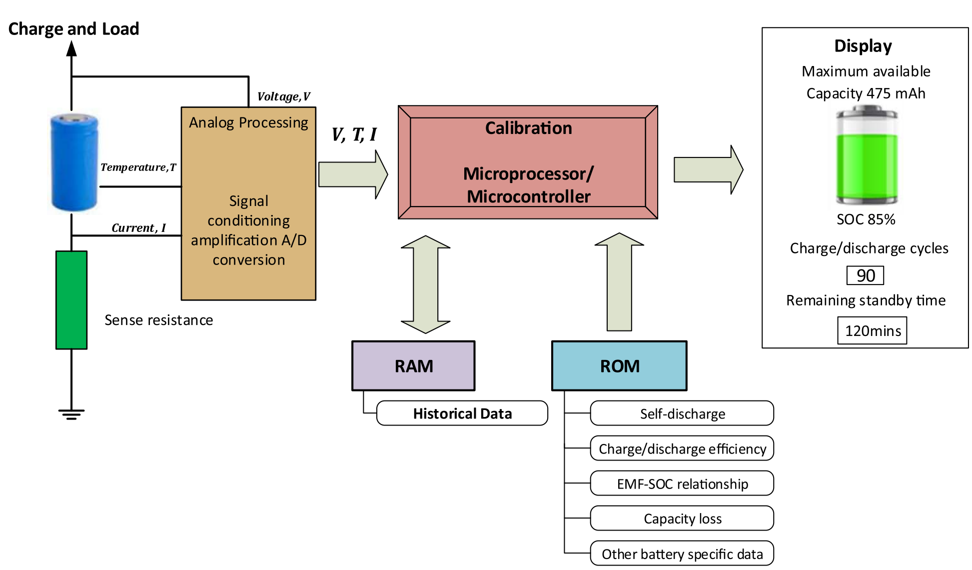

Fig. 4. General SOC system architecture.

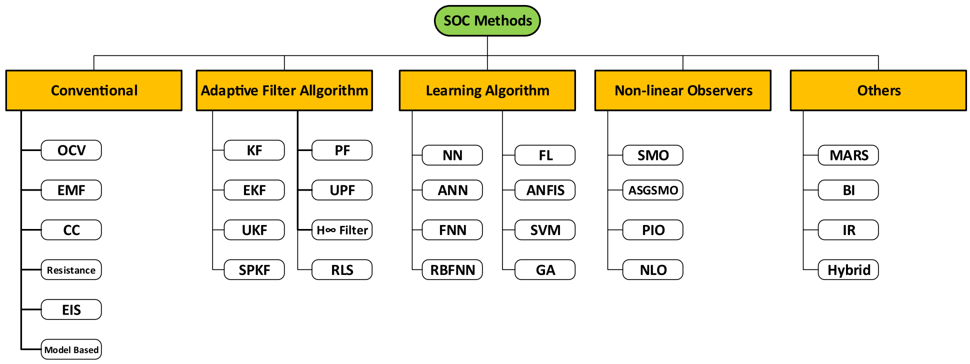

Fig. 5. Classification of SOC estimation methodologies.

measure the charge and discharge voltage since batteries have hysteresis characteristics which result in high OCV when the battery is charged and low OCV when the battery is discharged [44], as shown in Fig. 6.

5.1.2. Electromotive Force (EMF) method

The relationship between battery EMF and SOC is widely used for determination of battery capacity as shown in Fig. 7. Battery EMF can be measured as an equivalent to OCV in equilibrium condition when the substantial time has passed after the current interruption takes place. Several researchers have used OCV relaxation to observe and predict EMF. OCV relaxation process occurs when the battery gets charged and discharged with frequent current disruption, as shown in Fig. 8. The OCV relaxation may need several hours to reduce the effect of diffusion overvoltages.

In [46], adaptive methods were developed to model OCV relaxation process using EMF and exponential functions. The aim is to observe the OCV relaxation when the current is interrupted each time. The benefit of this model is its simplicity to determine parameters; nevertheless, it predicts the relaxation process inaccurately. Waag and Sauer [47] proposed an advanced adaptive approach to compare the online fitting of an OCV relaxation model with the measured OCV relaxation curve. This model has an equivalent circuit consisting of a voltage source (represents the EMF) in series with the resistances connected in parallel and a constant phase element (CPE). EMF is estimated depending on the fitting model parameters. The new values of the voltage and current of a battery are measured at each time. Once battery current reaches to zero, the algorithm to measure EMF is started. The data for battery open circuit voltage is stored as long as the battery current remains zero. When OCV samples get sufficient number, it is fitted to the measured EMF. As a result, all four model parameters (EMF, ΔOCV, impedance, weighting factor) are determined.

5.1.3. Coulomb counting method

Coulomb counting method is the easiest method to estimate the battery SOC. The method is easy to implement with low power computation. It is based on the integration of battery current with respect to time while the battery is charging/discharging. The mathematical expression to measure SOC is denoted in Eq. (2). Nevertheless, it is an open-loop algorithm and could result in significant inaccuracies due to uncertain disturbances and variables such as noise, temperature, current, etc. Also, there are difficulties in determining the initial value of SOC which causes a cumulative effect [48]. In addition, the estimation accuracy depends highly on the current sensors used which may be affected by measurement error, which also result in cumulative effect [38]. Furthermore, the method needs complete discharge of the cell and periodic capacity calibration to obtain maximum capacity, which shorten the battery lifespan [49].

5.1.4. Internal resistance method

The method uses battery voltage and current to measure the internal resistance of the battery. Voltage is measured with the variation of current change during small duration (< 10 ms). The ratio of voltage and current variation results in DC resistance, which represents the capacity of the battery in DC. A small interval less than 10 ms is needed not only to capture the ohmic effect, but also to reduce the effect of transfer reaction and acid diffusion [50]. However, the value of estimated resistance contains an error if the time is longer. In addition, the method has good adaptability as well as the high accuracy of SOC estimation only during the end period of discharging. Furthermore, due to its low value (in milliohm range), the accuracy to get internal resistance is very hard to obtain. The internal resistance changes slightly with a wide range of SOC which is difficult to observe [32], as indicated in Fig. 9. Due to this shortcoming, the DC internal resistance is hardly used to estimate SOC.

5.1.5. Electrochemical Impedance Spectroscopy (EIS)

EIS has been extensively used in order to obtain an understanding of the electrochemical reactions occurred inside the batteries and for determination of SOC. A proper electrochemical model is necessary to implement EIS. Then, EIS estimates the battery impedance using inductances and capacitances over a wide range of frequencies [51]. Ran et al. [52] established an equivalent circuit which included an inductive arc operated at high-frequency and two capacitive arcs operated at low-frequency. A non-linear least-squares fitting method is used under a different state of charging values to calculate the model impedances. However, EIS results are difficult to reproduce if the system is not operated in a steady state condition. Coleman et al. [53] estimated battery EMF voltage using impedance, terminal voltage and discharge current under load. The approach has low cost, achieves good

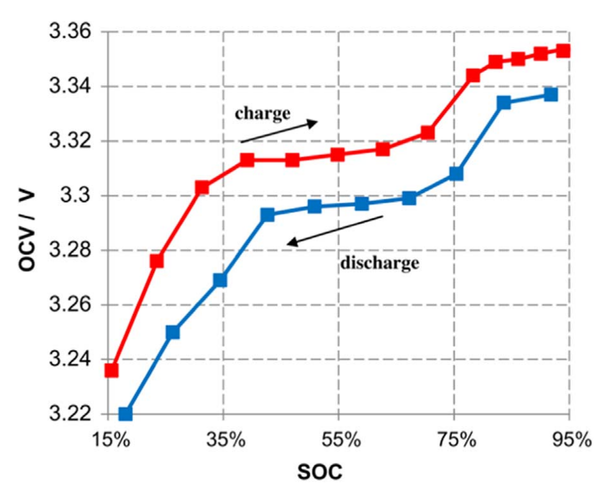

Fig. 6. OCV/V vs SOC charge and discharge profile of C/$LiFePO_4$ battery tested under 25 °C, for 3 h [44].

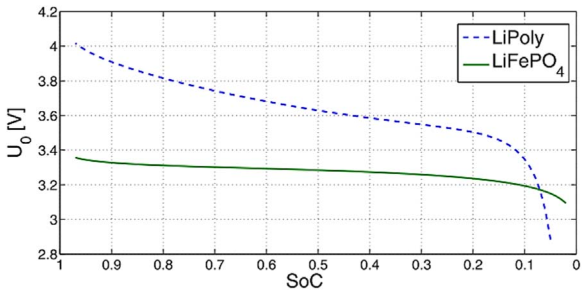

Fig. 7. EMF voltage U_0 as function of SOC [45].

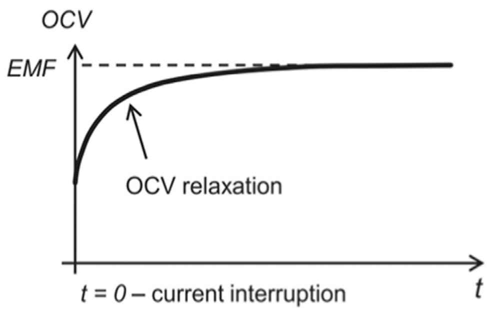

Fig. 8. Voltage relaxation after the battery is discharged and the current is switched off [47].

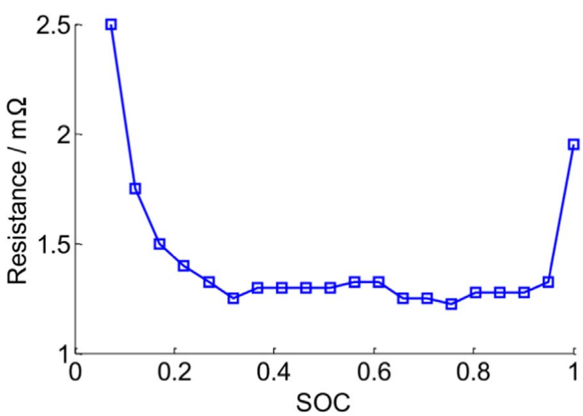

Fig. 9. Variation of internal resistance with respect to SOC in lithium ion batteries (tested under 25 °C, using the Hybrid Pulse Power Characterization (HPPC) test procedure) [32].

accuracy and can operate online if the value of impedance is updated with a normalized value. However, the influence of battery aging and temperature variation could differ the estimated results from the real values, which result in a lack of accuracy.

5.1.6. Model-based SOC estimation

Since OCV method cannot perform online and needs sufficient rest time to monitor SOC, therefore, the method cannot be implemented while the vehicle is moving. In order to have online SOC, the development of battery model is required. The most frequent usage of battery models contains electrochemical model [54–57] and equivalent circuit model [58,59]. The battery electrochemical model is used often for analysis of battery performance as it relates to many internal materials and considers the effect of electrodynamics and chemical thermodynamics. The electrochemical model can be represented as

$$U = U_{OC} - U_R - U_P \tag{3}$$

where, U is battery terminal voltage, U_{OC} is the battery OCV, U_R is the potential difference across the resistance, U_P is the electric potential caused by polarization process. By knowing the battery model parameters, it is easy to monitor the battery SOC through OCV-SOC look-up table. The similar approach is used by He et al. [60] where an equivalent circuit model consisting of nRC networks was used and the polarization and dynamic characteristics of the lithium-ion battery were considered. After, online OCV was implemented by using recursive least squares (RLS) algorithm with an optimal forgetting factor and then compared with experimental outcomes for different RC networks. Finally, the OCV-SOC lookup table was derived based on experimental results. The proposed method could provide acceptable accuracy of online SOC estimation with the error being less than 5%.

A comparative research was conducted by Hu et al. [59] on twelve commonly used equivalent circuit models of lithium-ion batteries. Two types of lithium-ion cells are used at three different temperatures to obtain data sheets. The multi-swarm particle swarm optimization (MPSO) algorithm is applied for finding the optimal model parameters. The effectiveness of these twelve models is then thoroughly investigated by applying models to both training and validation data sets to assess the model accuracy and complexity. The comparative study shows that the first order RC model with one-state hysteresis is ideal for $LiFePO_4$ battery due to its high precision. Domenico et al. [57] proposed an approximate electrochemical model to estimate SOC of lithium-ion batteries by considering several factors such as electrolyte concentration, material concentration, and microscopic current density. The main drawback of this model is that it lacks a detailed explanation on the electrochemical reactions for a specific battery. The process is very complex and cannot be implemented for all types of battery.

5.2. Adaptive filter algorithm

5.2.1. Kalman filter (KF)

Kalman filter (KF) is an intelligent tool to estimate the dynamic state of the battery. It is a well-designed method, which filters parameters from uncertain, inaccurate observations. It is commonly used in many applications such as automobiles, radar tracking, aerospace technologies and navigator tracking. In recent years, the usage of KF in battery state estimation has become very successful regardless of its high computational cost. The most attractive features of KF are that it has self-correcting nature, which helps to tolerate a high variation of current.

The KF is sets of mathematical equations, which predicts and corrects a new state repeatedly as the system operates. The algorithm provides a recursive solution through a linear optimal filtering for estimating state variables. The equations are operated in state-space form and consider a discrete-time version of the cell dynamics. The method compares the measured input data and output data to calculate the minimum mean squared deviation of the true state. The process noise and measurement noise are assumed to be zero, Gaussian and independent of each other. The KF linear model consists of a process Eq. (4) which predicts the current state x_k from the earlier state x_{k-1} and a measurement Eq. (5) which updates the current state to converge it to the real value [61].

$$Stateequatiuon : x_{k+1} = A_k x_k + B_k u_k + w_k \tag{4}$$

$$Measurementequation : y_k = C_k x_k + D_k u_k + v_k \tag{5}$$

where x presents the system state, u is the control input, w is process noise, y is measurement input, v is measurement noise, A, B, C and D are the covariance matrixes which are time varying and describe the dynamics of the system.

Ting et al. [62] used a battery management system (BMS) which includes a RC battery model for modeling a KF. The mathematical equations are derived from RC model, which are converted to state space model to explain the dynamic characteristics of a battery. The result indicates that the estimated root-mean-squared (RMS) error (1.92×10^{-4} V) of SOC using KF is very small compared to measured error (1.0013 V). Urbain and Rael [63] used the same technique on a simple electrical equivalent model of the lithium-ion battery which contains a voltage source connected in series with a resistance. With the help of Matlab-Simulink software and dSPACE real-time card, SOC is estimated with an error being less than 5%. Yatsui and Bai [64] combined the outcomes of KF with open-circuit voltage and coulomb counting to compensate the non-ideal factors which play a role as long as the batteries are in operation. The implementation of KF improves the accuracy of SOC coulomb counting method in lithium-ion batteries with an error of ± 1.76%.

The advantages of using KF are that it accurately estimates states affected by external disturbances such as noises governed by Gaussian distribution. Nonetheless, KF cannot be used directly for state prediction of a nonlinear system. Also, it requires highly complex mathematical calculations.

5.2.2. Extended Kalman Filter (EKF)

Since KF is unable to deal with non-linear characteristics of battery models, therefore, EKF has been used frequently to operate in non-linear applications. EKF uses partial derivatives and first order Taylor series expansion to linearize the battery model. The state-space model is linearized at each time instance, which compares the predicted value with its measured terminal voltage of batteries to correct the estimation parameters for SOC. However, linearization error could occur if the system is highly non-linear since first order Taylor series suffers from a lack of accuracy in a highly non-linear condition. [65]. The detailed operation of EKF is illustrated in Fig. 10 [66].

Lee et al. [67] implemented dual EKF in an electrochemical model to estimate battery SOC and capacity on the basis of the proposed OCV-SOC. In order to find the relationship of OCV-SOC, a cut-off voltage of 3.6 V is selected arbitrary and the conventional OCV-SOC data is constructed based on the reference voltage. The simulated result shows that the model achieved better accuracy than the real value with a smaller initial error of ± 5%. In [68], a nonlinear battery model along with EKF is used for the estimation of SOC of lithium-ion battery. The nonlinear model is constructed using a nonlinear, open circuit voltage and second order RC model connected in series. EKF is implemented to reduce the effect of the process and measurement noise. The proposed model achieves more precise results for estimating SOC with unknown initial SOC. In [69], EKF and dual EKF are used in $LiFePO_4$ cells to estimate the battery SOC in two different models, namely, zero state hysteresis and hysteresis state respectively. The results show that the proposed method can accurately predict SOC in dynamic environments with a maximum error of 4%. In [70], an improved second-order battery model is established and battery SOC is estimated based on EKF under Hybrid Pulse Power Characterization (HPPC) state and constant discharge condition. The proposed model has better performance than coulomb counting method in terms of effectiveness and dynamic adaptability.

An Adaptive Extended Kalman filter (AEKF) is offered in [71] for obtaining correct and robust SOC of the lithium-ion batteries by using an improved Thevenin battery model. EKF method is used for estimating the parameters of the proposed model. The performance is investigated through federal urban driving schedules. The simulation results indicate that AEKF is better than EKF in terms of accuracy and reliability. The comparison study shows that the estimated SOC error is reduced to 1.06% from 3.16%. In [72], AEKF algorithm is implemented in an online Thevenin model to monitor SOC through SOC-OCV look-up table. The performance of the model is validated through an Urban Dynamometer Driving Schedule (UDDS) test in which AEKF shows satisfactory performance with an error being less than 2%. In [73], AEKF algorithm is applied to obtain the online parameters of $LiFePO_4$ battery model and to estimate SOC based on OCV. A comparison study between offline and online terminal voltage is performed under HPPC and UDDS tests. The experimental outcomes show that online SOC estimation can reduce the error by 4%.

5.2.3. Unscented Kalman Filter (UKF)

Since EKF operates only in the first and second order of a non-linear model and results in a significant error in a highly non-linear state-space model, thus UKF algorithm is used to address the problems. UKF is an updated version of KF that applies discrete-time filtering algorithm and unscented transform to solve filtering problems. A set of points called sigma points is used to represent the mean and the covariance of the state distribution. The posterior mean and covariance of the third order Taylor series are also accurately captured by UKF. The attractive feature of this algorithm is that Jacobian matrix is not required to calculate and noise is not needed to be Gaussian because batteries are operated in the highly nonlinear state and the properties of noise are usually unknown. Also, the accuracy of UKF is better than EKF as it accurately predicts system states up to the third order of any non-linear system. However, the method suffers from poor robustness due to uncertainty in modeling and disturbances in the system.

He et al. [74] considered battery voltage and coulomb counting for UKF based SOC estimation. UKF is used to automatically adjust the model parameters to reduce SOC error caused by changing environmental situations and self-discharge of the battery. The effectiveness of the method was evaluated through collecting data from $LiFePO_4$ batteries operated in different tests. Sun et al. [75] proposed a zero state hysteresis model for the online estimation of SOC in lithium-ion batteries based on Adaptive Unscented Kalman filter (AUKF). The benefit of this model is that it adaptively corrects the noise covariances in the process and measurement state. In addition, the implementation of this method is easy and requires fewer resources because of the simple structure of the zero-state hysteresis battery model. A comparison is studied among EKF, AEKF and UKF-based algorithm where AUKF is demonstrated as a better model in terms of performance and accuracy. In [76], AUKF based SOC for a lithium-ion battery is established by using an extreme learning machine (ELM). The ELM algorithm requires less computation load to tune the parameters of the models based on experimental data. Four algorithms, including EKF, AEKF, UKF and AUKF are used to compare the estimation results of SOC. The comparison reports show that AEKF and AUKF are good in converging data while AUKF achieves the best output in terms of accuracy.

5.2.4. Sigma Point Kalman Filter (SPKF)

SPKF is another alternative method for the assessment of states in the non-linear system. SPKF achieves more accurate results than EKF in terms of mean and covariance using a limited number of functions. The algorithm selects sets of sigma points, which is exactly similar to the value of mean and covariance of the model being developed. The advantages of using this model are that it has identical calculation complexity as EKF without considering Jacobian matrices. In addition, the model does not need to compute the derivatives and original function.

In [77], the estimation of SOC for $LiFePO_4$ batteries is compared among three models based algorithms such as SPKF, EKF, and

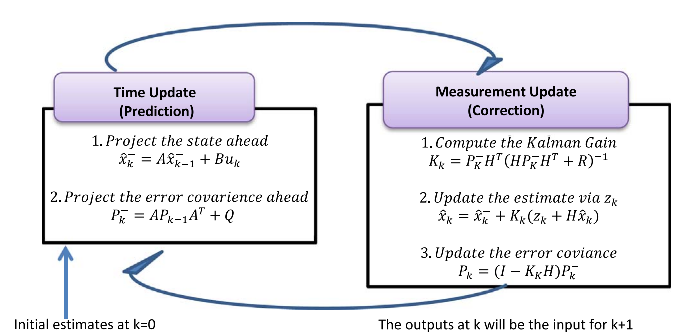

Fig. 10. Operation of EKF [66].

Luenberger observer. The experimental results denote that SPKF improves the accuracy of the SOC estimation considering the effect of battery tracking accuracy and robustness. SPKF also delivers stability in numerical calculations since it does not need to compute Jacobian matrices. In [78], SPKF based SOC estimation using joint battery model is presented. Battery SOC is assessed by taking into account the relationship between SOC and OCV. The reports indicate that the proposed combined method requires little computational load and less memory storage for achieving effective results.

5.2.5. Particle Filter (PF)

The PF algorithm is used for the estimation of states, which approximates the probability density function of a non-linear system by applying the Monte Carlo simulation technique with a set of random particles and a non-Gaussian distribution. Gao et al. [79] established two models for the estimation of SOC employing PF. The process model describes how the value of SOC related to variable discharge current while measurement model reflects how the battery terminal voltage varies with SOC, temperature and discharge current. The simulation reports demonstrate that the proposed algorithm is efficient as its computation time is six times faster in comparison with EKF. In [80], a stochastic model based SOC is estimated by using PF to overcome the ambiguous behavior of open circuit voltage of lithium iron phosphate batteries. The Monte Carlo simulation tool is applied to develop a stochastic model which correctly tracks the SOC with hysteresis effect can be ignored. The model validation is performed on EVs and off-grid power supply during different aging states and the results denote high accuracy. An unscented particle filter (UPF) algorithm is introduced by He et al. [81] for the estimation of SOC of high-power lithium-ion batteries. A new model is built by considering the effect of drift noise, temperature, charge/discharge rate and running mileage. The robustness of the model is evaluated by making a comparison with EKF, UKF, and PF algorithm. The numerical calculations show an improvement in UPF over UKF in minimizing Root Mean Squared Error (RMSE) and Maximum absolute error (MaxAE) by 30.2% and 12.6% respectively.

5.2.6. H∞ Filter

H∞ Filter considers time-varying battery parameter and does not need to know any specifications of process noise and the measurement noise characteristics. It is a simply designed model, which has the strong robustness to perform under certain conditions. However, aging, hysteresis and temperature effects could deviate the accuracy of the model. In [82], H∞ based algorithm is introduced to estimate SOC of lithium-ion battery. Time-varying parameters (temperature, current, state of health) are considered to model a second order RC filter circuit. A HPPC experiment is carried out to extract the parameter (voltage, current and resistance) of the model. The proposed model is validated by using six UDDS cycles and achieves a better accuracy with an acceptable SOC estimation error of 2.49%. In [83], a universal linear model employing adaptive H∞ filter (AHF) is presented to estimate SOC of a lithium-ion battery. Some free parameters of the model are considered as a function of SOC since both free parameters and SOC are related to charge/discharge process in each cycle. Polynomial function together with the least square method is applied to approximate the functions. The performance of the method is investigated by using defined tests and then compared with AEKF and square-root UKF. The AHF performs better than other methods in terms of accuracy, computational cost and time efficiency.

5.2.7. Recursive Least Square (RLS)

Recursive Least Square (RLS) is another effective tool which is used in the time-varying system. The algorithm calibrates parameters of the adaptive dynamic model with forgetting factor. In [84], an adaptive model based SOC estimation is proposed employing recurrent neural network (RNN). RLS algorithm is used to estimate the model parameters with the help of forgetting factor. The proposed model helps to reduce the predicted SOC error and noise in the measured voltage. Finally, the estimated SOC value is compared to the real value and results show that the model achieves good accuracy with a maximum error of 1.032%. In [85], RLS algorithm is used to predict the dynamic behaviors of a lithium-ion battery using the parallel RC network. The relationship between OCV and SOC is expressed by Nernst equation. The model also considers the impact of hysteresis considering a zero state hysteresis model. The model parameters are found by using the RLS algorithm. Two experiments, including HPPC and constant discharge, are performed to evaluate the performance of the proposed model. High accuracy of SOC estimation is achieved with a maximum relative error of 2.121%.

5.3. Learning algorithm

5.3.1. Neural Network (NN)

Neural network (NN) is an intelligent mathematical tool, which has the adaptability and self-learning skills to demonstrate a complex nonlinear model. NN uses the trained data to estimate SOC without knowing the information about internal structure of the battery and initial SOC. Three layers are used for the formation of a NN network, including an input layer, an output layer and one or more hidden layers, as shown in Fig. 11 [86]. The NN takes discharge current, terminal voltage and temperature as input and SOC as output to build the structure of the NN network of $LiFePO_4$ batteries. The advantage of this method is that it is capable of working in battery non-linear conditions while the battery is charging/discharging. Nevertheless, the algorithm needs to store a large amount of data for training which not only requires large memory storage but also overloads the entire system.

Chen et al. [87] suggested an EKF based battery model considering the effect of hysteresis open circuit voltage. Then, NN was integrated with EKF for the estimation SOC. The proposed combined model delivers the best performance in estimating accuracy which error being less than 1%. In [88], the voltage at previous state, SOC and current at present state are used as inputs and voltage at present state is considered as output to find an appropriate model trained by NN. The trained model is transformed to a state-space equations and then SOC is estimated by using EKF. In [89], back-propagation neural network (BPNN) is introduced to predict the remaining capacity of lithium-ion batteries by applying charge-discharge tests. The model uses discharge current and discharge voltage as an input and capacity

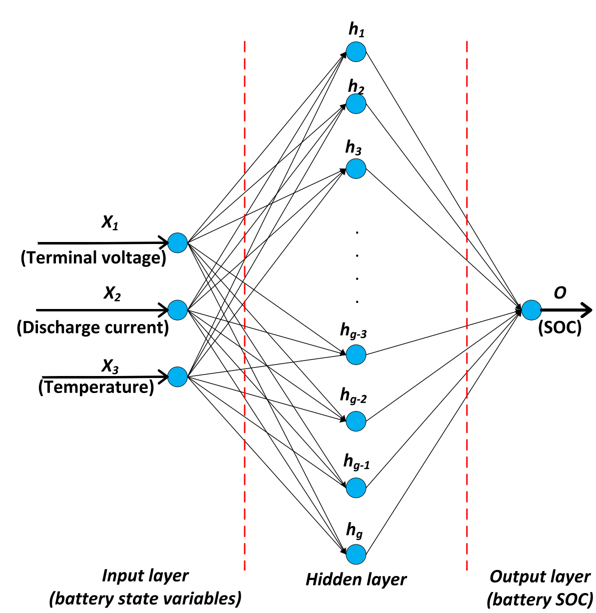

Fig. 11. The complete structure of NN for estimating SOC [86].

as output. The model compares the error between predicted and actual capacity, which is under 5%. Moreover, radial basis function neural network (RBFNN) is suggested in [90] which is a useful mathematical algorithm for estimating SOC if the system has the incomplete data information. The method is very effective in developing a battery model in terms of process speed and accuracy.

5.3.2. Fuzzy logic (FL)

Fuzzy logic (FL) is another powerful algorithm to present a complex, non-linear model with the help of the appropriate training dataset. The implementation of FL is divided into four parts, which include a relationship in rule-based input-output, the membership function for both input and output, reasoning and defuzzification of outputs. Though FL has a powerful function to predict a non-linear model, it requires large memory unit and complex computations as well as a costly processing unit.

Salkind et al. [36] applied fuzzy logic to estimate SOC of Li/SO_2 battery by using data from EIS/ coulomb counting method. The model uses three inputs including impedances monitored at different frequencies and SOC as output. The proposed model predicts SOC with a maximum error of ±5%. Singh et al. [91] used FL to estimate SOC of lithium-ion batteries for the application of a portable defibrillator. FL model is developed by using ac impedance and voltage recovery measurements as input and SOC as output. First, an accurate model is established by estimating the number of pulses operated at three different temperatures (0, 20 and 40 °C). Then, FL model is built at room temperature with a collection of sufficient data. 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. Then, a microcontroller based FL algorithm is applied to validate the effectiveness of the proposed system. A Merged Fuzzy Neural Network (FNN), which is superior than other traditional neural networks, is offered in [93] to estimate SOC of a lithium-ion battery employing a reduced form genetic algorithm (RGA). The algorithm used twelve inputs and one output to approximate a continuous non-linear function. The validation results demonstrate that the method is effective in predicting any suitable degree of accuracy.

A more advanced algorithm named adaptive neuro-fuzzy inference system (ANFIS), which is more efficient in estimating SOC, is also reviewed in [94]. Chau et al. [95] used ANFIS algorithm to estimate SOC of lithium-ion battery. The proposed model uses discharged/ regenerative capacity distributions and temperature distributions as the inputs and the state of available capacity (SOAC) as the output. The performance of the model is evaluated through a battery discharge process which results in high accuracy with an average error being less than 1%. In [96], ANFIS algorithm based SOC is developed to estimate SOC by using five inputs and one output. Least squares estimate (LSE) along with gradient method is applied to train the ANFIS model. The results are compared with BP neural network, which shows that ANFIS has better performance in modeling a non-linear dynamic system. In [97], the application of ANFIS is proposed to assess the battery residual capacity of lithium-ion battery while the battery is discharging in constant and random manner. The comparison between actual and predicted results denote that the proposed model is effective in estimating accuracy and has an average error under 1%.

5.3.3. Support Vector Machine (SVM)

SVM is based on kernel function and uses regression algorithm to transform a non-linear model in the lower dimension to a linear model in high dimension. With the help of non-linear mapping β, the model maps the input data x into a high dimensional feature space. For instance, Wu et al. [98] expressed the equations of SVM with a sample of N points $\{x_k, y_k\}$ where input vector denotes $x_k \in R^n$ and output vector denotes $y_k \in R^n$

$$y = \alpha^T . \beta(x) + s \tag{6}$$

where α is the weight vector whose dimension is equal to the kernel space, $\beta(x)$ is a mapping to dimensional feature space; s is the expression of biasness. The advantage of this method is that it performs well in non-linear and high dimension models with an ability to predict the SOC quickly and accurately by using the right training data. However, the model is loaded with highly complex computation. In addition, trial and error process is needed to adjust the parameters of a model, is also likely to need a long time.

In [99], SVR algorithm is used for the estimation of SOC of high capacity lithium-ion battery. Some independent variables, including voltage, current and temperature are used to extract the parameters of the model while the battery is charging/discharging. The model is validated and confirms the high accuracy of SOC with an estimated coefficient of determination of 0.97. In [100], least square support vector machines (LS-SVM) based SOC is established by considering the relationship of voltage, current and temperature to assess SOC. The assessment tests show that the model has high accuracy in predicting SOC very quickly with the ability to tolerate noise. The similar relationship of SOC to voltage, current and the temperature is suggested in [101] where SOC is estimated based on weighted least squares support vector machine (WLS-SVM) algorithm. The method is verified by experiments and the reports show that there is an improvement in robustness with less complex computation.

5.3.4. Genetic Algorithm (GA)

Genetic Algorithm (GA) has been applied successfully in engineering, physics, mathematics field to identify the optimal model parameters of a nonlinear system. The basic function is to transform the parameters in the most effective way to enhance the efficiency of the system. Zheng et al. [102] proposed a charging cell voltage curves (CCVC) hypothesis to estimate the capacity of the $LiFePO_4$ battery pack using a simplified equivalent model with voltage-capacity rate curve (VCRC). The GA is used to find the optimum parameter. The model is evaluated by using four $LiFePO_4$ cells connected in series and reports show that the estimated error is under 1%. Xu et al. [103] used the first order RC battery model based SOC estimation of a lithium-ion battery using a combined method including coulomb counting method and model based SOC estimation method. The battery parameters are optimized by using the GA. The proposed model is validated by using different drive cycles and reports demonstrate a better prediction in assessing the accuracy with an error below 1%.

5.4. Non-linear observer

5.4.1. Sliding Mode Observer (SMO)

Sliding Mode Observer (SMO) has enhanced tracking control to guarantee stability and robustness of the system against environmental disturbances and model uncertainties. The model is established by using the state equation as output state, which is decomposed to the observer equations in the next stage. A feedback switching gain is designed to control sliding regime to guarantee the robustness characteristics. Kim et al. [104] developed a Sliding Mode Observer (SMO) based SOC estimation method to compensate the non-linear dynamic characteristics of the battery using a simple RC circuit. The proposed method was able to control the convergence time at a high value of charge/discharge value. The robustness of the model is enhanced significantly and the model operated effectively in uncertainties and disturbances. UDDS is used to validate the methods and reports show that SOC error is under 3%. Chen et al. [105] used adaptive gain SMO (AGSMO) algorithm on a combined equivalent circuit model to estimate SOC of lithium polymer battery. The battery pulse charge is used to extract the model parameters and state equations are derived by using terminal voltage and circuit model. Experiments are conducted to evaluate the proposed model and results demonstrate the model superiority in controlling the robustness without causing any chattering ripples. In [106], SOC is estimated based on AGSMO using battery equivalent circuit model. The proposed model performs well in reducing the chattering level with the help of adjustable switching gain. Lyapunov stability theory is applied for verifying the error convergence. Validation tests are performed in both city and suburban areas and the results are promising in terms of SOC error, which is lower than other conventional method based on SMO.

5.4.2. Proportional-integral Observer (PIO)

PIO is an efficient control method, which has been applied widely as a replacement of feedback control system. The function of this controller is to converge the estimated voltage to the measured voltage in a precise and quick manner. Xu et al. [107] developed a RC battery model of the lithium-ion battery for the estimation of SOC using PIO. Then the observability matrix of battery model is established to reconstruct the state variables. The battery model is identified from SOC-OCV relationship using a test workbench. Furthermore, the UDDS driving cycle is carried out to validate the proposed model and results indicate that the error is limited to 2% in comparison with both known and unknown SOC cases. The advantage of this model is that it accurately estimates SOC with less computation time. Also, the robustness of the model is improved against the model uncertainty.

5.4.3. Non-linear Observers (NLO)

Many observers have been used to estimate the state, including both linear [108,109] and non-linear observer [110]. Linear observer is used in common; nevertheless, it increases the error of the SOC estimation. Therefore, the non-linear observer is used which is implemented in a linear system with non-linear observation equations. Xia et al. [111] proposed NLO based SOC estimation method of lithium-ion batteries by using a first order RC equivalent circuit. SOC is estimated from OCV using the state space equations and ninth order polynomial. The model validation is performed by using discharge test and urban driving cycle test. The results report that the performance of the proposed method is better than EKF and SMO in terms of accuracy, converge speed and computation cost. Also, it has enhanced robustness against the disturbances. However, finding a proper gain matrix to reduce the error is a difficult task.

5.5. Others

5.5.1. Multivibrate Adaptive Regression Splines (MARS)

MARS can be used for the extension of a linear model, which can build a non-linear model automatically and interact with the variables with the help of a nonparametric regression algorithm. The model consists of a dependent variable $\vec{y}$ and M basis functions [112].

$$\hat{\vec{y}} = \hat{f}_M(\vec{x}) = c_0 + \sum_{m=1}^{M} c_m B_m(\vec{x}) \tag{7}$$

where $\vec{y}$ is the dependent variables, c_0 is constant, $B_m(\vec{x})$ presents the mth basis function, c_m presents the coefficient of mth basis function. The proposed model has two phases: forward selection and backward deletion. At the beginning of the forward phase, the MARS adds the basis function continuously to find a pair of basis function to achieve the maximum decline in the sum of-squares residual error. At the end of this stage, a large model is established which over fits the data. At the beginning of the backward deletion phase, the algorithm eliminates the terms of the model one by one until it finds the best effective model. At the conclusion of this stage, one model is selected based on the lowest generalized cross-validation (GCV) value.

A MARS based SOC estimation method is presented in [113] for high capacity $LiFePO_4$ battery. Battery model parameters, coefficient and basic function are extracted from current, voltage, temperature and charge/discharge cycles. The model is assessed by experiments with a coefficient of determination of 0.98. An accuracy of 1% is achieved when the SOC is estimated between 25% and 90% using dynamic data profile [constant current constant voltage (CCCV) charge and constant current (CC) discharge].

5.5.2. Bi-linear interpolation (BI)

Linear interpolation based SOC estimation can be performed using battery charging and discharging characteristics. The algorithm is valid until charge and discharge currents remain unchanged with the known value of SOC. Nevertheless, charging and discharging currents do not remain stable since the battery currents are strongly related to battery capacity and external factors. Therefore, SOC estimation using linear interpolation for constant current is not conducive for online EV application. To address the challenges, a bi-linear interpolation can be used to estimate SOC under the different value of currents. Bi-linear interpolation algorithm presents the extension of two linear interpolations. Liye et al. [114] proposed bi-linear interpolation algorithm for the estimation of SOC using a 3D look-up table. At first, the linear interpolation of charging and discharging current in constant condition was investigated. Then, a 3D SOC look-up table was established by using the value of voltage and current, which helped to form the algorithm of bi-linear Interpolation. The model validation is performed through simulation and real experiments, data and the results indicate that the model provides stability in performance and obtains high accuracy. The proposed model is universally accepted for vehicle application driven in the real-word operating condition.

5.5.3. Impulse Response (IR)

IR is applied to determine the output of a linear time-invariant (LTI) system with a random output. The convolution of the input with impulse response defines the output of the system, which is expressed mathematically in Eq. (8).

$$y[k] = x[k] * h[k] \tag{8}$$

where $y[k]$,$x[k]$,$h[k]$ represents output, input and impulse response respectively. In order achieve precise results, a narrow current pulse is selected in such way so that pulse width should be sufficiently small in comparison with the shortest time constant of the system. A compromise is made between the timing of impulse response and highest waveform magnitude because of high duration in time constant of the batteries. Ranjbar et al. [114] presented online based SOC estimation method using IR. A convolution theory is adopted to calculate the terminal voltage of the battery by convolving the input current with a suitable set of impulse responses. The simulation results are compared with the real SOC value and reports show that estimated value demonstrates the best fit to the real value of SOC.

5.5.4. Hybrid method

A hybrid method consists of two to three algorithms, which enhance the efficiency and accuracy of the battery model. The method not only achieves effective and reliable results but also decreases the cost of battery management system. However, the method has very complex mathematical calculations, which require a large memory device.

Estimation of SOC including coulomb counting, OCV and KF method is studied in [115]. First, SOC is estimated using coulomb counting and OCV method, which reduce the estimated error of standalone coulomb counting method. After, KF method is applied to enhance the accuracy of SOC estimation. In [116], a combination of EKF and multi-state method is proposed using an equivalent circuit model. The model is transferred to discrete state space model, which is further linearized using Jacobin matrix. Some improvements have been made regarding parameter initialization and error covariance. The simulation results show that the model delivers good accuracy with an estimated average error being less than 2.7%. In [117], a hybrid model is established employing EKF and coulomb counting method to estimate the time-varying dynamic system. First, OCV based SOC estimation is applied. Each time, the value of SOC is corrected using EKF. The process continues until the battery gets fully discharged. The reports show that the model accuracy is below 6.5%. In [118], SOC is estimated based on AUKF employing radial basis function (RBF). RBF is used to adjust the parameters of the model and AUKF is applied to assess the SOC. The combined method is compared with AEK and outcomes show that AUKF performs better than AEK in reducing error. In [119], A mixture of discrete-time Kalman and H∞ filters are applied to the nonlinear model of a lithium-ion battery. The proposed model is compared with the discrete-time sliding mode observer (SMO) and the adaptive Luenberger based estimation schemes. The accuracy of the proposed method is improved significantly with an estimated error being less than 1%.

Comparison of different methods with a focus on advantages and disadvantages is shown in Table 3. Summary of SOC estimation error is presented in Table 4.

6. Issues and challenges

Developing and deploying lithium-ion battery management with SOC estimation in EV application has become major challenges due to its complicated electro-chemical reactions and performance degradation over time caused by various internal and external factors. Furthermore, most of the defined experiments of the battery are conducted in a laboratory environment with standard voltage, current limits, and low-temperature variation. However, very few research have

Table 3
Advantages and disadvantages of SOC methods.

Method	Advantages	Disadvantages
OCV	• Easy to implement • High precision	• Takes long rest time to reach an equilibrium condition. • Only applicable only when the vehicles are not moving.
EMF	• Simple method • Low cost	• Significant time is required for current interruption to model OCV relaxation process
CC	• Easy to implement • Less power consumption	• Has inaccurate results due to uncertain disturbances • Difficulties in determining the initial value of SOC which causes cumulative effect
Resistance	• Simple and easy	• Has a high accuracy of SOC estimation only during the end period of discharging. • Resistance changes slightly with wide range of SOC which is difficult to observe
EIS	• Online, low cost • Achieve good accuracy if impedance value is normalized	• Results have an impact on aging and temperature
Model-based	• Online • High precision	• Highly depends on model accuracy • Lacks a detailed explanation on the electrochemical reactions for a specific battery.
KF	• Accurately estimates states affected by external disturbances such as noises governed by a Gaussian distribution.	• KF cannot be used directly for state prediction of a nonlinear system. • It requires highly complex mathematical calculations. • Possibilities of divergence due to an inaccurate model and complex calculation.
EKF	• Predicts a non-linear dynamic state with good precision.	• Limited robustness. • Linearization error could occur if the system is highly non-linear.
UKF	• Jacobian matrix and Gaussian noise are not required to calculate. • Accurately predicts system states up to the third order of any non-linear system.	• Suffers from poor robustness due to uncertainty in modeling and disturbances in the system.
SPKF	• Has identical calculation complexity as EKF without considering Jacobian matrices. • Has an improvement in accuracy and robustness.	• Complicated. • Heavy calculations.
PF	• Less computation time. • High accuracy.	• Need a complex mathematical tool to solve the problem.
H∞ Filter	• Satisfactory performance in terms of accuracy, computational cost and time efficiency.	• Aging, hysteresis and temperature effects could deviate the accuracy of the model.
RLS	• High accuracy • Eliminates noise in the measured voltage	• Heavy computation • Unstable operation if the value of forgetting factor is not appropriate
NN	• Capable of working in battery non-linear conditions	• Need large memory storage to store the trained data
FL	• Performs well in modeling a non-linear dynamic system. • Effective in predicting any suitable degree of accuracy considering charging state, aging and temperature	• Requires large memory unit. • Has a complex computation. • Needs costly processing unit.
SVM	• Performs well in non-linear and high dimension models • Predict the SOC quickly and accurately by using the right training data.	• Has high complex computation. • Trial and error process is needed to adjust the parameters of the model which is time-consuming.
GA	• High accuracy • Robust against noisy function	• Heavy computation • Fine tuning of parameters is required to get effective results. • Delay in optimization response time.
SMO	• Has enhanced tracking control to guarantee stability and robustness	• Difficult to adjust switching gain to control sliding regime
PIO	• Accurately estimates SOC with less computation time. • Robustness of the model is improved against the model uncertainty.	• Could deliver inaccurate results if the controller is not properly designed.
NLO	• Improved performance in terms of accuracy converge speed and computation cost. • Enhanced robustness against the disturbances.	• Difficult to find a proper gain matrix to reduce the error.
MARS	• High accuracy	• Accuracy disperses at the beginning and end of SOC period.
BI	• Provides stability in performance • High accuracy	• Formation of 3D SOC look-up is a challenging task.
IR	• Estimated value demonstrates best fit to the real value of SOC.	• Could provide poor precision if the width of the narrow current pulse is not sufficiently smaller than the shortest time constant.
Hybrid	• The hybrid system not only reduces the cost of the system but also makes the estimation results more effective and reliable.	• Combining two or three methods is a laborious task • Has high complex computation.

Table 4
Average error of different SOC methods.

Method	Author	Ref.	Avg. error
OCV	Truchot et al.	[120]	Unspecified
EMF	Waag and Sauer	[47]	≤ ±2%
CC	Zhang et al.	[121]	≤ ±4%
Resistance	Wang and Liu	[50]	Unspecified
EIS	Coleman et al.	[53]	Unspecified
Model-based	He et al.	[60]	≤ ±5%
KF	Yatsui and Bai	[64]	≤ ±1.76%
EKF	Jiang et al.	[122]	≤ ±1%
UKF	Tiang et al.	[123]	≤ ±4%
SPKF	Plett	[124]	≤ ±2%
PF	Gao et al.	[79]	Unspecified
H∞ Filter	Zhang et al.	[82]	≤ ±2.49%
RLS	Eddahech et al.	[84]	≤ ±1.03%
NN	Affanni	[125]	≤ ±4.6%
FL	Salkind	[36]	≤ ±5%
SVM	Alvarez	[126]	≤ ±6%
GA	Zheng	[102]	≤ ±2%
SMO	Kim	[104]	≤ ±3%
PIO	Xu et al.	[107]	≤ ±1%
NLO	Xia et al.	[111]	≤ ±4.5%
MARS	Álvarez Antón et al.	[113]	≤ ±1%
BI	Liye et al.	[114]	≤ ±5%
IR	Ranjbar	[127]	Unspecified
Hybrid	Li et al.	[116]	≤ ±2.7%
	Xu et al.	[117]	≤ ±6.5%
	He et al.	[74]	≤ ±3.5%
	Hu et al.	[128]	≤ ±3%

been found on battery operating in different conditions such as heavy rain, hot and humid climate, cold weather as well as vibration from uneven roads. In addition, the variation in external loads makes an impact on the available capacity of a battery. Therefore, some un-modeled effect adds in the existing models and algorithms, which have not been taken into account yet. Moreover, cell unbalancing, battery aging process, temperature, dynamic hysteresis characteristics, self-discharge, charge-discharge rate are the other factors, which are responsible for declining performance of the battery. The researchers have proposed various battery models to estimate SOC; however, each model suffers from limited information for real EV applications. Furthermore, lack of accuracy, complex calculation, and high computation cost have become a major concern to accurately estimate battery states.

6.1. Cell unbalancing

Cell imbalance could result in the imprecision of SOC estimation. Cells in EVs are wired in series to supply high voltage while they are connected in parallel to provide high capacity. Each cell has its own chemical and manufacturing characteristics, which may differ while charging and discharging. During charging, a cell could easily reach to full capacity charge due to capacity fading which might cause danger. Overcharging may happen in a cell after other cells in the battery have already been fully charged. Likewise, a cell may suffer from over-discharging if it has continual discharge action while the rest of the cells have already reached to full discharge. Overcharge in Lithium-ion battery causes distortion, leakage, rise in pressure, which results in an explosion of cells. On the other hand, over-discharge may shorten the life cycle, due to high current and frequent over-discharge [129]. Moreover, a charge imbalance may happen due to repeated charging and discharging that reduces the capacity and lifetime of battery cells [130,131].

An effective cell monitoring and cell balancing method are necessary to protect and prolong the battery life so that batteries can deliver energy for long periods without having any abnormalities. The cell balancing mechanism can be divided into two ways: active and passive [132]. A passive method is simple, cost-effective which transfers an excess amount of current and energy through battery cell resistance; however, it has heart problems and low efficiency [133]. The active method uses switched capacitor, inductor or transformer, which is cost-effective and efficient in design; nevertheless, exchange of energy or charge among cells not only needs time but also makes complications in the charge-discharge profile [134].

6.2. Battery modeling

Battery modeling has a significant impact on achieving an accurate value of SOC. Due to the complicated electrochemical and dynamic environment, establishing a battery model is subject to a challenge. Various models have proposed for estimating SOC, such as Thevenin model, runtime-based electrical model, combined electric model; however, each model suffers from a lack of accuracy and lack of adaptability to operate in different operating conditions.

6.2.1. Thevenin model

Thevenin model consists of one or two RC networks to predict the battery response at a particular state of charge and open circuit voltage, which is assumed to be constant. Thevenin model is capable of forecasting the transient response of the battery voltage with a variation of current load, and thus it can be applied to different dynamic conditions [135]. The disadvantages of this model are its lack of working capability in real applications since the units of all parameters are considered constant in all conditions, which may not hold true as parameters may vary in different working conditions. In addition, the model is unable to simulate capacity fading or the battery runtime due to thermal impacts [136]. Due to its limitation of having constant parameters in charge and discharge process, Thevenin model has been improved from time to time by adding ideal diodes, Zener diodes to measure open circuit voltage and internal resistance, as shown in Fig. 12 [137].

6.2.2. Runtime-based electrical model

A runtime based model is proposed to create battery runtime, as shown in Fig. 13. The simulation of the runtime complex circuit network is performed by PSPICE to get voltage response while the discharge current is constant [138]. The benefit of this model is that it has the capability to work under aging and various thermal effects. Hageman [139] conducted an experiment to observe the battery capacity in a different type of batteries under different temperatures where the capacity at 25 °C was set as the internal capacity. Nonetheless, the model cannot work accurately in dynamic load conditions to predict voltage and runtime response.

6.2.3. Combined electric model

Chen and Rincon [140] proposed a combined electric model which is a combination of RC networks (same as Thevenin model) and runtime model, as shown Fig. 14. The combined model considered the thermal impact and battery degradation to simulate the battery runtime and voltage response. The battery terminal voltage is simulated by an RC network under different dynamic load conditions while capacitor and the current controlled current source are capable of estimating SOC, capacity, and runtime of the battery. The model considers the battery capacity as a function of temperature, self-discharge and number of cycles rather than

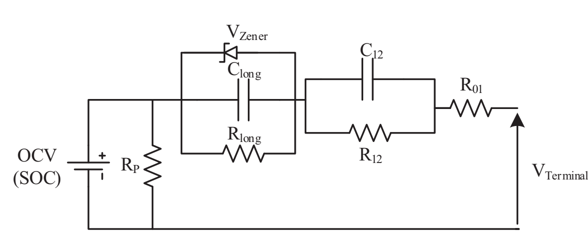

Fig. 12. Improved Thevenin model [137].

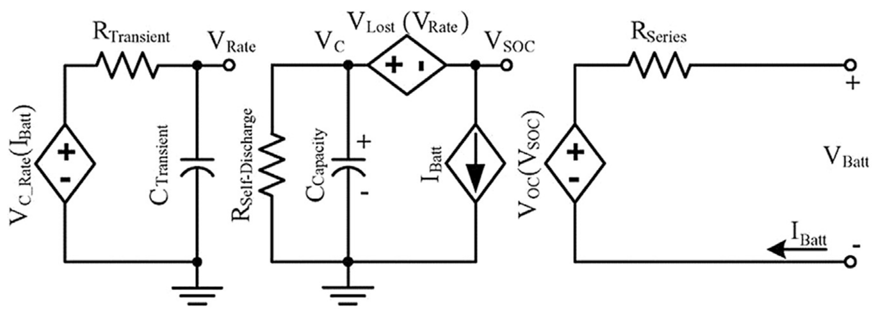

Fig. 13. Runtime-based electrical base model [140].

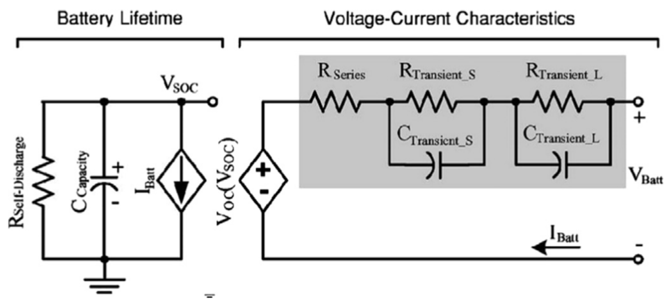

Fig. 14. Combined electrical model [140].

assuming capacity as constant or infinite [141]. A voltage controlled voltage source is used to work in different SOC values since battery open circuit voltage is a function of SOC. In addition, the model uses two RC networks to explain the transient response of voltage in two different time constants. Although the model provides high accuracy with its ability to work in a dynamic condition, it does not estimate battery state of health (SOH) and can update model parameters automatically. Therefore, the prediction results inaccurate as the cell ages. Comparison of different model with their advantages and drawbacks is shown in Table 5.

There is need of developing an appropriate battery model, which can operate precisely in varying load condition. The enhanced self-correcting (ESC) model, the higher order of RC model with one-state hysteresis can be proposed to address the drawbacks.

6.3. Aging

Accurate estimation of SOC could not be performed due to aging. Internal resistance and capacitance degradation are the main two factors for causing aging of the battery. There are two types of aging process, which may occur in a battery. The first aging process is possible to monitor as it degrades gradually over time, and the second process is difficult to observe until any sudden transformation in battery performance occurs [142]. The researchers have found that the aging occurs due to anode/cathode materials; however, the attention is focused on the material structure. The structural changes and phase transitions are the main concerns for battery aging in the cathode [143]. In addition, the temperature has an impact on the aging process where high temperature accelerated the degree of aging. Nevertheless, the low temperature could have a negative impact on aging, specifically when the charging process takes place [144]. The rise of internal resistance is caused by the structural changes in anode and cathode and an increase in the thickness of SEI (Solid Electrolyte Interphase). The rate SEI formation depends on the changes in temperature. The degree of SEI formation does not depend on the carbon material at low temperatures, whereas at high temperature, the SEI development in graphite is higher than other carbon materials [145]. Wu et al. [146] explained the effects of various factors of battery aging taking place at anode including overcharge, over-discharge, high and low temperature, high rate of cycling and high storage of SOC as indicated in Fig. 15.

In order to overcome the challenges of aging, an appropriate model with a specific algorithm/formula which particularly control the parameters of cell aging must be developed. Lavigne et al. [147] proposed a lithium-ion open circuit voltage (OCV) curve model to estimate battery health indicator with the optimization of only one parameter as batteries aging. Such a result has been achieved through an investigation of electrodes stoichiometries differences as aging. The model adjustment is divided into two steps algorithms. At the first step, an OCV curve is identified as an initial stage. In the next stage, two OCV measures in normal operation or in specific operation (charge phase for instance) are used to characterize the aging of a parameter of the cell. The error of the model remains small in spite of variation in aging and temperature. In [148], a nonlinear, electrolyte enhanced, single particle cell model (NESPM) is built including aging due to the growth of solid electrolyte interphase (SEI) layer. An analytic aging formula is derived from aging model to identify the controlling parameters of cell aging. A comparison of NESPM aging and aging formula is made between two different hybrid EV current profiles predicts. The experimental results validate the aging predictions.

6.4. Degradation factors

Degradation factors could deviate the result of SOC from the real value. There are some degradation factors, which play a role to perform unsatisfactorily in estimating SOC. This paper has considered temperature, hysteresis effect, self-discharge and charging/discharging rate as the degradation factors.

6.4.1. Temperature

Battery thermal energy management plays an important role to thermal characteristics and behavior of lithium batteries. The capacity of battery reflects on SOC estimation with an effect of temperature

Table 5
Comparison of different models.

Model	Advantages	Drawbacks
Thevenin model	Easy and simple to implement	Units of resistance and capacitance are considered constant, cannot work to predict capacity fading
Runtime-based electrical model	Capable of working under aging and various thermal effects.	Cannot work accurately under dynamic load conditions
Combined electrical model	High accuracy in dynamic load condition	Not good at self-updating model parameters

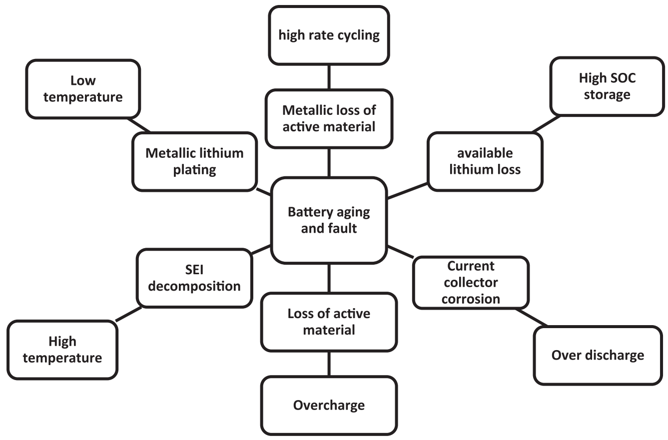

Fig. 15. Reasons for battery aging at anode [146].

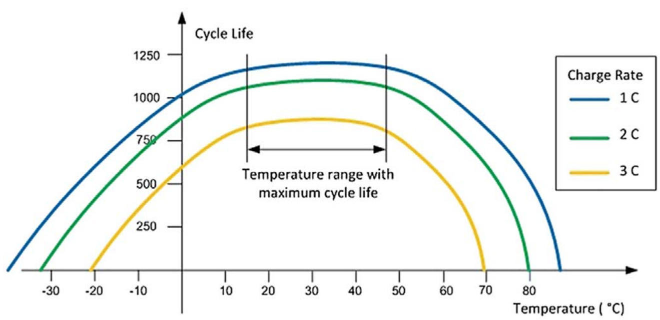

Fig. 16. Battery life vs. temperature at different charging rate of lithium-ion battery [154].

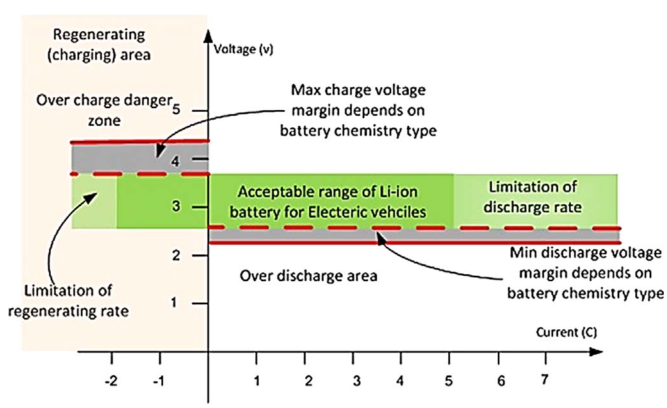

Fig. 17. Charge and discharge rate factors of Li-ion batteries [165].

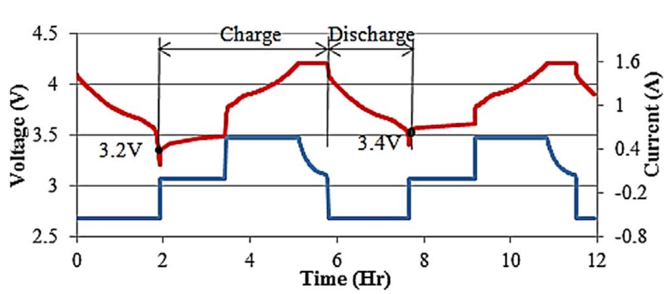

Fig. 18. Battery discharge curve [168].

variation. The ambient temperature is proportional to the capacity of the battery [149]. The increasing of temperature results in a decrease in viscosity and an increase in activity of the electrolyte which may strengthen the migration effect and ion diffusion [150]. Li et al. [151] conducted an experiment to find the capacity of lithium-ion batteries with the variation of temperature. The results show that the capacity of $LiPF_6$ and $LiBF_4$ batteries decreases dramatically when the temperature reaches below −20 °C, whereas there is only less than 10% reduction of capacities at 25 °C. Qian et al. [152] monitored the impact of temperature variation on lithium-ion battery cycle and found that the ambient temperature controls the film development of the cathode on battery life cycle. High temperature not only hampers the battery life but also increases the danger of catastrophic failure, one the contrary, low temperature also curtails the battery life due to an increase in internal resistance. Dubarry et al. [153] observed the changes in resistance of two $LiFePO_4$ batteries at 25 °C and 60 °C. The result shows that the resistance of battery tested at 60 °C is five times greater than a battery operated at 25 °C.

In order to improve the performance of the lithium-ion battery, the battery should be operated in the safe region. Fig. 16 shows the best operating region of the temperature of lithium-ion batteries for different charging rate. The figure denotes that the best range of temperature for charging a lithium-ion battery lies in between 15 °C and 50 °C.

6.4.2. The hysteresis characteristics

The battery SOC has the higher value during charging than discharging due to the fact that the polarization resistance has a significant impact on open circuit voltage. This phenomenon causes the SOC deviating from its accuracy what is known as the dynamic hysteresis characteristics (DHC) [155]. The characteristics have a serious concern in estimating SOC. The concentration polarization, electrochemical polarization, and ohmic resistance are the main factors for causing this effect. The effect of hysteresis may also happen due to the dissipation of energy in the crystal structure of the electrode during the two-phase transition [156]. The interaction among lithium ions and active material particles due to the intercalation and deintercalation processes take place in the cathode's active material namely the $FePO_4$, also represent fundamental factors of the hysteresis behavior of the OCV [157].

Addressing the phenomena of hysteresis of lithium-ion batteries requires the development of suitable model/algorithm. Zu et al. [158] proposed adaptive discrete Preisach model (ADPM) to estimate SOC using OCV–SOC hysteretic relationship of $LiFePO_4$ batteries. The accuracy of the model is significantly improved with an error being less 1%. Dong et al. [159] used dual IIM (invariant-imbedding-method) algorithm to enhance the estimation accuracy against the effect of hysteresis. The robustness of the model is simulated using OCV hysteresis phenomena and the model achieves high accuracy with an error of $\pm 2\%$.

6.4.3. Self-discharge

Battery self-discharge is common phenomena, which have an impact on SOC estimation. Self-discharge is expressed as a loss of charge with storage time, which depends on various factors consisting of ambient temperature, cycle times and storage time. Takashi et al. [160] investigated the characteristics of self-discharge in graphite electrodes with different sizes of particles. The results show that the self-discharge rate depends not only on the specific surface area but also on the particle size. The SEI formation and loss of the lithium species are the other responsible causes to occur self-discharge in lithium-ion batteries. The effect of diffusion process has also made an account for occurring self-discharge, which controls the reaction of self-discharge at graphite electrode in lithium-ion batteries.

A development of a battery model or tuning of battery model structure, which could reduce the effect of self-discharge is necessary. In [161], an equivalent circuit network (ECN) model for a lithium-sulphur cell under discharge is proposed to estimate SOC using the prediction-error minimization technique. A mixed-size discharge current pulse profile is used at four temperatures from 10 °C to 50 °C, which linearizes the ECN parameters for a range of states-of-charge, currents, and temperatures. A nonlinear polynomial-based battery

Table 6
Challenges to monitor battery SOC and corresponding causes, impacts, and remedies.

No	Challenges	Causes	Impacts	Remedy
1	Cell unbalancing	● Battery cell has its own chemical and manufacturing characteristics, which may differ while charging and discharging.	● Overcharge in lithium-ion battery causes distortion, leakage, rise in pressure. ● Over-discharge will shorten the life cycle.	● An effective cell balancing mechanism can be proposed which is divided into two ways: active and passive [135].
2	Battery modeling	● Establishing a battery model is difficult due to the complicated electrochemical and dynamic environment.	● Cannot operate under dynamic load conditions. ● Cannot update model parameters automatically.	● Enhanced self-correcting (ESC) model, the higher order of RC model with one-state hysteresis can be proposed [172].
3	Aging	● Caused by internal resistance and capacitance degradation. ● Other factors include irreversible changes in the structure of the components, characteristics of electrolyte, anode, and cathode.	● Dendrite is formed which causes battery fire. ● Temperature is raised suddenly, which causes catastrophic failure.	● An OCV curve model to estimate battery health indicator is proposed with the optimization of only one parameter as batteries aging [147]. ● A nonlinear, electrolyte enhanced, single particle cell model (NESPM) is built including aging due to the growth of solid electrolyte interphase (SEI) layer [148]
4	Temperature	● Caused by a decrease in viscosity and an increase in activity of the electrolyte, which may strengthen the migration effect and ion diffusion.	● Temperature rises results in an increase in resistance of battery cell. ● Battery capacity decreases as the temperature decreases.	● The best range of temperature and charging rate of lithium-ion battery cycle is identified [154].
5	Hysteresis Characteristics	● Concentration polarization, electrochemical polarization, and ohmic resistance are the main causing factors. ● Also caused by dissipation of energy in the crystal structure of the electrode during the two-phase transition and interaction among lithium ions and active material particles.	● SOC has the higher value during charging than discharging	● Adaptive Discrete Preisach model (ADPM) to estimate SOC using OCV–SOC hysteretic relationship of LiFePO4 batteries is proposed 161]. ● Dual IIM (invariant-imbedding-method) algorithm is developed to enhance the estimation accuracy against the effect of hysteresis [159].
6	Self-discharge	● SEI formation and loss of the lithium species are responsible for occurring self-discharge in lithium-ion batteries.	● There is a gradual loss of charge with storage time, ambient temperature, and cycle times.	● An equivalent circuit network (ECN) model for a lithium-sulphur cell under discharge to estimate SOC using the prediction-error minimization technique is proposed [161].
7	Rate of charge and discharge	● Phase diffusion is one of the main limiting factors for causing high discharge current in plastic lithium-ion batteries.	● Has an influence on charge transport and density of electrode and electrolyte.	● The acceptable range of charging and discharging current of the lithium-ion battery is identified [165].
8	Challenges of monitoring battery health	● The complicated electrochemical process of the battery. ● Measurement is influenced by disturbance, signal noise.	● Direct measurements of battery parameters (voltage, current and temperature) are a difficult job.	● An established prognostic model with a goal to collect the variables continuously from a defined experiment cycle under stable conditions is developed [173].
9	Estimation of maximum capacity	● Discharge process will not occur at same discharge current and will not be always discharged at the constant cut-off voltage	● Error in the measurement of maximum capacity could result in a poor accuracy of SOC.	● Electrochemical-polarization (EP) battery model is proposed to estimate SOC using RLS algorithm and a hardware-in-the-loop (HIL) validation test [169].
10	Communication method	● Charging mechanism is not uniform which makes it difficult to develop a uniform charger.	● Could have a problem to charge a battery due to the absence of uniform charger.	● Wireless technology may be implemented to transfer information between a battery and a charger [171].

model is built using these parameters, which are suitable for use in a battery management system. The model validation is performed using New European Driving Cycle (NEDC) driving cycle and the terminal voltage is judged accurately with a root mean square error of 32 mV.

6.4.4. Rate of charge and discharge

It is expected to operate battery within acceptable boundaries of voltage and current to prevent overcharge/over-discharge. Nevertheless, the battery is not always performed in same charge/discharge rate, which results in significant effects on SOC estimation. Due to the limited interaction of internal active material inside the battery along the electrode thickness direction, there is a decrease in capacity with an increment of discharge rate. The higher the rate of discharge, the more we will get the depth of interaction. The rate of charge and discharge has an influence on charge transport and density of electrode and electrolyte. The rate of capacity is raised to 0.9 g/cm^3 with the increased value of electrode density [162]. Chuangfeng et al. [163] examined the performance of charge-discharge rate in different batteries and found that lithium polymer battery is more effective than $LiFePO_4$ when the discharge current is in constant mode. Arora et al. [164] found that the phase diffusion is one of the main limiting factors for causing high discharge current in plastic lithium-ion batteries.

Since over charge/discharge could shorten battery life and speed up battery degradation, the batteries should be designed in a manner so that it can work in the acceptable range. Nevertheless, the battery degradation rate does not remain same in the acceptable range and it depends on how charging or discharging rate takes place. Usually, the degree of discharge is determined by the speed or acceleration of the car, the weight of the vehicle and the slope of the route. In order to perform a lithium-ion battery safely, a threshold value to control the discharge current needs to be operated at fixed value. Also, the charging rate needs to remain constant throughout the charging process, nevertheless, high charging rate could happen, which reduces the battery life. Yuan and Liu [165] identified the acceptable range of charging and discharging current of the lithium-ion battery where the x-axis denotes the current depending on battery nominal capacity (C-rate) and the y-axis represents the voltage (V), as shown in Fig. 17. The discharging and charging current value is presented by positive and negative values. The overcharge occurs when the voltage increases above the maximum defined charging voltage, on the other hand, if voltage reduces below the defined cutoff voltage, over discharge takes place. Based on the type of lithium-ion battery, two critical thresholds (gray zones) have been identified (for example, the maximum threshold voltage for $LiFePO_4$ and $LiCoO_2$ are defined as 3.7 V and 4.35 V respectively).

6.5. Challenges of monitoring battery health

Battery SOC estimation needs to assess voltage, current directly from the battery at a frequent basis. However, it is physically hard to measure any direct measurements in batteries due to the complicated electrochemical process. The solutions to monitor battery health are based on conventional method observing the critical variables during operation which can provide practical and accurate information about internal chemical reactions of battery [166]. These variables consist of current (I), voltage (V), battery temperature (T_b), ambient temperature (T_a) and battery internal resistance (R). Nevertheless, assessing these variables online would be a difficult task. some methods have been proposed which can measure parameters online during battery operation without causing any disturbance to the main functionality. However, disturbance, signal noise could result in poor accuracy. Moreover, the approach considers the accuracy and precision of various sensors, which has an impact on prediction results. For example, a voltage sensor with an accuracy of ± 0.1 V, cannot measure any voltage within 0.01 V, which causes errors in impedance calculation [167].

An established prognostic model with a goal to collect the variables continuously from a defined experiment cycle under stable conditions should be developed. This approach should deliver an accurate estimation of battery health status by eliminating noise and uncertainty in the measurements from the sudden change in battery characteristics. Besides, the battery pack should respond within milliseconds or seconds during power outages to avoid significant loss of data. In order to tackle these cases, a data acquisition system is required to record raw data at high frequency. Otherwise, accumulation of error will continue over time, causing negative impacts on the accuracy of results, specifically in the estimating state of charge. Furthermore, a standard and reference are required based on the recorded data since the implementation of battery in vehicle application have not yet matured. More weight factors may be added to capacity and energy such as the number of charge/discharge cycles, a rise in resistance and decline in actual capacity.

6.6. Estimation of maximum capacity

Battery SOC has a strong relationship with a maximum capacity, which determines the battery performance and available lifetime. The maximum capacity is estimated by integrating discharge current with respect to time. The capacity increases as long as the integration time exists and the capacity maximizes when the battery is completely discharged at the current remains unchanged. Nevertheless, the battery discharge process will not occur at constant discharge current every time and will not be always discharged at the same cut-off voltage [168]. Lithium-ion battery discharge profile with respect to the different depth of discharge is shown in Fig. 18. The battery is charged to a maximum value at 4.2 V while it is discharged at different cutoff voltages. Thus, there is a challenge to estimate maximum capacity with a variation of current loads and different depth of discharge.

Xiong et al. [169] estimated peak power of lithium-ion battery using an electrochemical-polarization (EP) battery model. EP model's parameters are identified by using RLS algorithm. A hardware-in-the-loop (HIL) test is applied to validate the results. Compared to HPPC test, the proposed model delivers more reliable performance when there is a sudden change in load current. More importantly, the method can achieve precise results when SOC is high or low by avoiding overcharging or over-discharging.

6.7. Communication method

Battery SOC requires a communication mechanism, which is used for charging a battery from battery charging station to the storage device. A BMS enables a battery to communicate with the charger, internal modules, and external environment. At present, most of the manufacturers of EV use a controlled transceiver to communicate with internal modules. A communication between a charger and a battery is developed through a system management bus (SMBus) which is able to transfer battery data, such charging-discharging current, voltage and SOC [170]. However, different manufacturers have different charging mechanism, which makes it difficult to develop a uniform charger. Also, difficulties arise with the charger when it applies to different applications.

To address the problem, a uniform communication method should be developed. Wireless technology may be implemented in an EV not only to transfer information between a battery and a charger but also to record external data such as ambient temperature, humidity, vibration [171].

The various challenges for SOC estimation methods along with possible remedies are presented in Table 6.

7. Conclusion and recommendations

The lithium-ion battery management system with a focus on various methods to estimate SOC and highlight related challenges in EV applications are critically reviewed in this paper. The lithium-ion battery is highly recommended for vehicle operation because of its high voltage generating capability, long life cycle, and high energy density. The paper also describes lithium-ion battery mechanism and configuration. The importance of battery management system (BMS) is explained for achieving safe and reliable operation of the lithium-ion battery. The functions of each element in hardware and software group of BMS system are briefly discussed.

This review investigates the various methods and algorithms for SOC estimation. A comprehensive explanation, including model benefits, drawbacks, and error estimation from different literature is extensively studied. The review identifies that the conventional methods are easy to implement, however, they are highly affected by aging, temperature and external disturbances. It is also noticed that an adaptive filter algorithm can predict a non-linear dynamic state with a good precision, less computational cost and high efficiency. However, the method suffers from heavy computation burden and poor robustness. The learning algorithm performs well in modeling a nonlinear dynamic system considering aging, temperature, and noises. Nonetheless, the method has complex computation and needs a large memory unit to store the trained data. The nonlinear observer has enhanced robustness against the disturbances and improved performance in terms of accuracy, converge speed and computation cost. Nevertheless, the model could deliver inaccurate results if the controller is not properly designed. The grouping of various SOC methodologies with an explanation of the advantages and disadvantages will assist the automotive manufacturers to gain brief outlines and directions that will help them to identify appropriate estimation methodology for the application.

Estimating an accurate SOC has become major challenges due to the high sensitivity of lithium-ion battery including various internal and external factors and complicated electro-chemical reactions. This paper identifies several challenges which are responsible for achieving a low accuracy of SOC, such as battery aging process, temperature, self-discharge, charge-discharge rate, dynamic hysteresis characteristics, and cell unbalancing. The possible solutions are also suggested related to each challenge. The researchers will find an overview of various challenges from this review which could encourage them to do further studies on how to overcome these challenges.

There are some significant and selective suggestions for the further technological development on SOC estimation of lithium-ion batteries, which have been coming out through this review, such as:

i. In achieving proper system functionality and market acceptance, safety, mobility, and durability issues of lithium-ion battery needs to be addressed.
ii. An efficient battery management system in terms of charge equalization, thermal control, fault detection, battery charging/overcharging in obtaining SOC with high accuracy needs to be established.
iii. Further research on SOC estimation methods need to be investigated over conventional methods under the effect of aging, hysteresis, different discharge rate and temperature.
iv. An appropriate model needs to be developing for the estimation of SOC using an adaptive filter algorithm under various model uncertainties and disturbances in the system.
v. An optimal number of neurons selections in the hidden layer of the intelligent network and parameters optimization model with less computational time using learning algorithm needs to be further researched.
vi. Designing an appropriate controller to enhance the robustness of nonlinear system and predictive analytical model to achieve a good accuracy of SOC estimation need to be investigated.
vii. A generalized validation and benchmark method for SOC estimation method is necessary.
viii. Further studies need to be conducting to improve the performance of wireless power transfer to charge a battery in terms of data security, reliability, and interference.

These suggestions would be a remarkable contribution towards the accurate estimation of SOC. Thus, it is concluded that the further development of methodologies for estimating SOC of lithium-ion batteries will dominate the market of the EV in the future.

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