

Review

# Towards a Smarter Battery Management System for Electric Vehicle Applications: A Critical Review of Lithium-Ion Battery State of Charge Estimation

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**Abstract:** Energy storage system (ESS) technology is still the logjam for the electric vehicle (EV) industry. Lithium-ion (Li-ion) batteries have attracted considerable attention in the EV industry owing to their high energy density, lifespan, nominal voltage, power density, and cost. In EVs, a smart battery management system (BMS) is one of the essential components; it not only measures the states of battery accurately, but also ensures safe operation and prolongs the battery life. The accurate estimation of the state of charge (SOC) of a Li-ion battery is a very challenging task because the Li-ion battery is a highly time variant, non-linear, and complex electrochemical system. This paper explains the workings of a Li-ion battery, provides the main features of a smart BMS, and comprehensively reviews its SOC estimation methods. These SOC estimation methods have been classified into four main categories depending on their nature. A critical explanation, including their merits, limitations, and their estimation errors from other studies, is provided. Some recommendations depending on the development of technology are suggested to improve the online estimation.

**Keywords:** battery management system; energy storage system; electric vehicle; lithium-ion battery; state of charge

## 1. Introduction

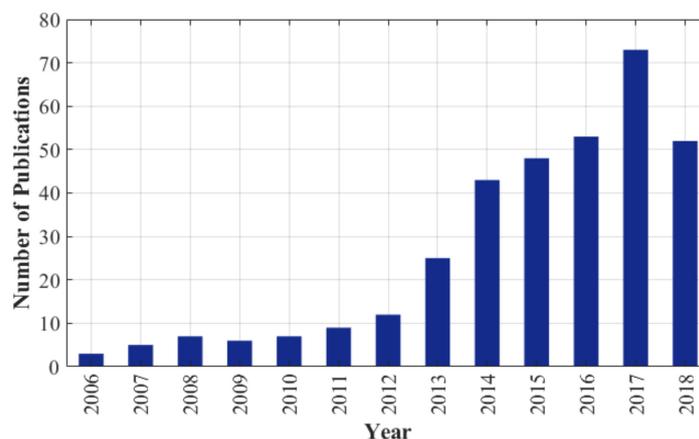
The global reserves of diesel, petrol, and other fossil fuels are decreasing rapidly due to their extensive use in transportation operation. The far-flung use of the traditional fuels produces tons of CO<sub>2</sub> yearly, which have harmful implications for the environment, such as greenhouse gas emissions (GHGE) and global warming [1]. In addition, the costs of these fuels are increasing exponentially, so there is a need for a secondary energy source for transportation, such as electric vehicles (EVs), new energy vehicles (NEVs), plug-in hybrid electric vehicle (PHEVs), battery electric vehicles (BEVs), and fuel cell electric vehicles (FCEVs) [2,3]. In recent years, rechargeable batteries (RBs) have attracted considerable attention owing to their high demand in EVs, HEVs, and PHEVs [4–7]. With the use of renewable energy, these transportation sources can reduce their GHGE by up to 40% [8]. The alternative energy sources, such as wave, wind, tidal, and solar, are episodic, so these energy resources also require an energy storage system (ESS) to maintain a smooth and reliable supply to the consumer [9].

In recent years, United States, Japan, China, and Germany have taken keen interest in the performance improvement of RBs and accomplished some significant results [10].

Different energy storage systems, such as lead-acid, lithium ion (Li-ion), sodium nickel chloride (NaNiCl), vanadium redox flow battery (VRFB), nickel cadmium (NiCd), zinc bromine flow battery (ZBFB), and sodium sulphur (NaS) batteries have been widely accepted for transportation in recent years [11]. Among them, the Li-ion battery offers high reliability, high power density, long lifespan, high energy density, low discharge rate, and high efficiency [3]. In addition, the cost of Li-ion batteries is declining, which enhances their use in the EV industry [12] and therefore, the Li-ion battery market is growing [13].

An efficient battery management system (BMS) is one of the primary components in EVs to guarantee the safe, reliable, efficient, and long-lasting operation of a Li-ion battery while dealing with the electric grid and challenging driving conditions [14–16]. Furthermore, an efficient BMS also provides information on the battery states, such as the state of available power (SOP), state of charge (SOC), state of life (SOL), and state of health (SOH). The BMS can sense the battery voltage, battery current, and temperature to avoid overcharge and over discharge conditions. These measured parameters can be utilized to estimate the states of the Li-ion battery [15,16].

Accurate SOC estimations have always been a critical and important concern in the design of BMS in EVs. Accurate and precise estimations can not only be used to evaluate the reliability of a battery, but also provide some important information, such as the remaining energy and/or remaining useable time [17]. In other words, the SOC shows the vehicle driving range or the remaining power of the battery in EVs. Furthermore, it prevents the Li-ion battery from over-charge/discharge. The Li-ion battery is a highly complex, time varying and nonlinear electrochemical system; its performance changes due to different factors, such as the charge-discharge current, aging, and temperature variations. Therefore, accurate SOC estimation of Li-ion battery is a tricky task because it cannot be directly assessed using any physical sensor [18]. Currently, the Li-ion battery SOC estimation is a hot topic for researchers. An assortment of SOC estimation techniques has been reported over the last decade. Figure 1 shows the trend of research articles published on SOC estimations for Li-ion batteries.



**Figure 1.** Number of publications on SOC estimation of Li-ion batteries per year.

These published research articles were found using the Web of Science database (<http://isiknowledge.com>). The search criterion was the “state of charge” then “lithium ion battery” from 2006 to August 2018. Figure 1 highlights the considerable interest in Li-ion battery SOC estimations in recent years.

This review paper discusses working and advantages of the Li-ion battery in EVs over other energy storage systems. The general working of an effective BMS is presented in detail. This review paper classifies the reported Li-ion battery SOC estimation techniques in different categories according to their nature. This review also discusses their respective advantages and limitations. Finally, future perspectives and recommendations are presented.

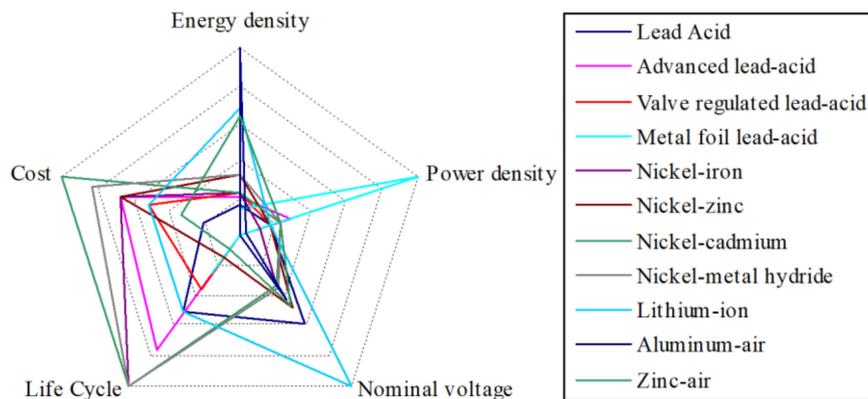
## 2. Energy Storage Systems for EVs

EVs consist of four main parts: an energy storage system (battery), mechanical transmission system, motor, and power converter [19]. Many energy storage systems are available, such as lead-acid, NaS, NaNiCl, NiCd, VRFB, ZBFB, and Li-ion. Table 1 lists the properties of the aforementioned batteries. Only ambient temperature batteries have been considered in EVs for safe and reliable operation.

**Table 1.** Properties of the different types of energy storage systems [20].

Battery Type	Energy Density (Wh/L)	Power Density (W/L)	Nominal Voltage (V)	Life Cycle	Depth of Discharge (%)	Round Trip Efficiency (%)	Estimated Cost (USD/kWh)
Lead-acid	50–80	10–400	2.0	1500	50	82	105–475
NaS	140–300	140–180	2.08	5000	100	80	263–735
NaNiCl	160–275	150–270	-	3000	100	84	315–488
NiCd	60–150	80–600	1.3	2500	85	83	-
VRFB	25–33	1–2	1.4	13,000	100	70	315–1050
ZBFB	55–65	1–25	1.8	10,000	100	70	525–1680
Li-ion	200–400	1500–10,000	4.3	10,000	95	96	200–1260

Table 1 shows that among all the storage devices, the VRFB has the highest life cycle. The Li-ion battery has the highest energy and power densities as compared to the others. In addition, the cost, life cycle, and nominal voltage of the battery are also critical factors. The nominal voltage of a cell is a critical point because it decides the quantity of single cells required in a battery pack for safe and reliable operation. The Li-ion battery appears to be a better option because of its energy density, lifespan, nominal voltage, power density, and cost. Figure 2 presents a spider chart of the different cell chemistries for a better understanding and comparison [6].

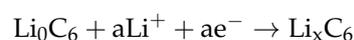


**Figure 2.** Spider chart for the different battery chemistries.

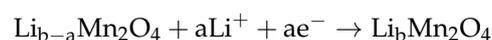
### Lithium Ion Battery

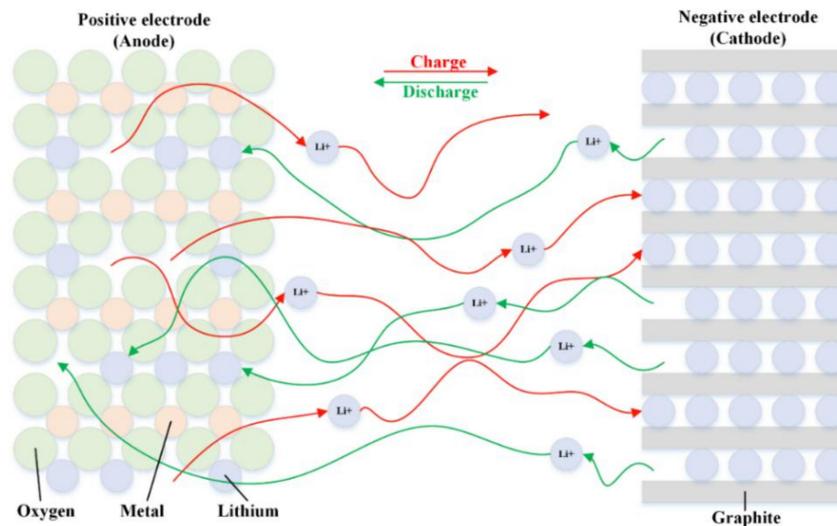
Figure 3 presents the simplified working diagram of a Li-ion battery. The Li-ion cell is made of a positive electrode (anode), negative electrode (cathode), a separator, and two current collectors.  $\text{Li}^+$  is transferred from the anode to the cathode through an electrolytic separator to complete the discharging cycle. The negative electrode is generally formulated from graphite and the anode general contains one of the following materials: Li-ion manganese oxide (LMO), Li-iron-phosphate (LFP), and Li-nickel-manganese-cobalt-oxide (LNMC). Diethyl carbonate or ethylene carbonate are used as the electrolyte. Aluminum and copper are used as positive and negative current collectors, respectively. The chemical reactions of LMO/graphite are reported as an example of both charging discharging.

For charging:



For discharging:





**Figure 3.** Schematic diagram of the Li-ion battery during the charging and discharging condition.

Different chemistries of Li-ion battery have been reported in the literature [21–24]. Table 2 compares the different types of Li-ion battery.

**Table 2.** Properties of the different types of Li-ion battery [10].

Type	Energy Density (Wh/kg)	Power Density (W/kg)	Life Cycle (100% DOD)	Estimated Cost (US\$/kWh)	Safety	Maturity
LMO	160	200	≥2000	~360	Good	Commercial
LFP	120	200	≥2500	~360	Good	Commercial
LNMC	200	200	≥2000	~360	Good	Commercial
Li-titanate oxide	70	1000	≥10,000	~860	Good	Demo
Li-sulfur	500	-	~100	-	Good	R&D stage

Although Li-ion battery is the best choice for EVs, it still needs a reduction in its capital cost along with improving performance and high life cycle. The reduction in its capital cost can be achieved in different ways, such as manufacturing and technology perspectives. A lot of efforts have been made to improve the round-trip efficiency and depth of discharge of Li-ion battery. According to a report, the reduction in the capital cost of Li-ion battery will be 77–574 USD/kWh from 200–1260 USD/kWh, the improvement in the energy density will be 200–735Wh/L, and the round-trip efficiency will increase 2% till 2030 [20].

### 3. Battery Management System (BMS) for EVs

After substantial progress in ESS, an effective and reliable BMS is needed. According to the most adopted definition, a BMS is a system that is capable of managing a battery [15]. The BMS in EVs consists of different types of sensors, actuators, and controllers. An efficient BMS performs the following main tasks: (i) protects the battery; (ii) operates the battery with a safe limit of current, voltage and temperature; and (iii) measures and estimates the battery states precisely. Figure 4 presents a schematic diagram of an efficient BMS.

The voltage and current measurement unit is installed to measure the voltages and currents of the entire string as well as that of a single cell. The temperature control unit is added to measure the temperature of the battery and coolant. The cooling and heating system can be controlled through this unit. This system also contains some analogue and digital inputs, such as an accelerating pedal sensor, brake pedal sensor, charging control, and engine ON/OFF switch. The balancing control unit consists of power dissipation resistors and capacitors. This is used to equalize the SOC of the cells in

battery packs. The safety unit is used to avoid physical damage to the battery packs. The system also protects the battery packs from overcharge and over-discharge conditions. The digital output of the BMS contains the SOC, SOH, balancing work indicator, and failure alarm. Considering the non-linear and inconsistent behavior of a battery, a precise and accurate SOC estimation is a difficult task. For a comprehensive diagram of an effective BMS, see Figure A1 of Appendix A.

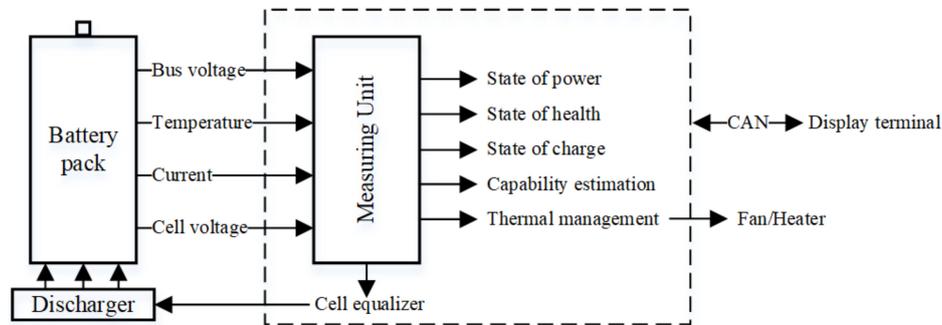


Figure 4. General diagram of a BMS.

#### 4. Methods to Estimate SOC

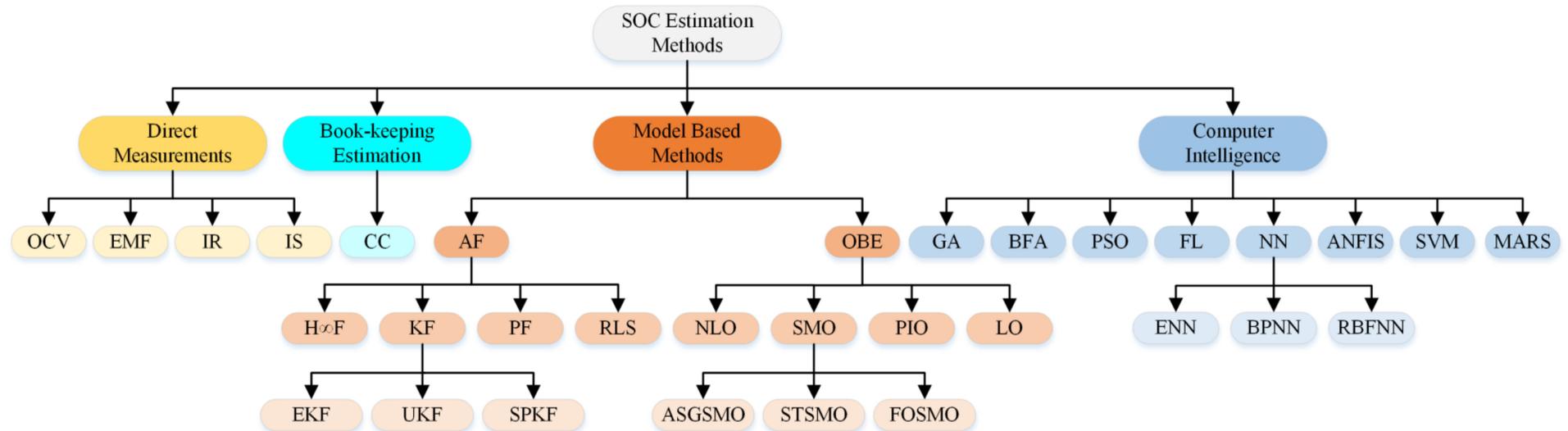
As discussed earlier, an accurate SOC estimation is the most crucial part of the BMS design in EVs. This not only provides information on the useful energy, but also prevents the battery from over charge/discharge condition. Therefore, the SOC estimation has attracted considerable interest, and different methods have been presented in the literature, to estimate the SOC accurately and precisely. In the present study, the estimation methods are classified into four main categories, as shown in Figure 5. The direct measurement method estimates the SOC using the physical properties. Book keeping estimation methods use the battery charge and discharge current as an input. In model-based methods, the battery parameters and SOC are estimated using adaptive filters and observers. The last methods are based purely on computer intelligence; they require high computational time and storage size.

The mean average error (MAE), maximum error (ME), and root mean square error (RMSE) can be utilized to quantitatively appraise the performance of different SOC estimation methods. The difference between the true and estimated value in continuous variables over the total number of samples is known as MAE. The RMSE can be calculated by taking square root of the average of squared difference between the true and estimated values in continuous variables. The mathematical forms of MAE and RMSE can be expressed as:

$$MAE = \frac{1}{n} \sum_{i=1}^n (true\ value - predicted\ value) \quad (1)$$

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (true\ value - predicted\ value)^2} \quad (2)$$

In Tables 3–21 the MAE and ME have been utilized to compare the results of different approaches. The computational complexity of all the methods cannot be compared because every operating system has different specs. The advantages and disadvantages of each method will be discussed in next section.



AF: Adaptive filters, ANFIS: Adaptive neuro fuzzy inference system, ASGSMO: Adaptive switching gain sliding mode observer, BFA: Bacterial foraging algorithm, BPNN: Back-propagation neural network, CC: Coulomb counting, EMF: Electromotive force, ENN: Elman neural network, EKF: Extended kalman Filter, FL: Fuzzy logic, FOSMO: Fractional order sliding mode observer, GA: Genetic algorithm,  $H_{\infty}F$ : H infinity filter, IR: Internal resistance, IS: Impedance spectroscopy, KF: Kalman filter, MARS: Multivariate adaptive regression splines, LO: Luenberger-based observer, NLO: Nonlinear observer, NN: Neural network, OBE: Observer based estimation, OCV: Open circuit voltage, PF: Particle filter, PIO: Proportional integral observer, PSO: Particle swarm optimization, RLS: Recursive least square filter, RBFNN: Radial basis function neural network, SPKF: Sigma point kalman filter, SVM: Support vector machine, SMO: Sliding mode observer, STSMO: Super twisting sliding mode observer, UKF: Unscented kalman filter.

**Figure 5.** Classification of the SOC estimation methods.

#### 4.1. Direct Measurements

A direct measurement SOC estimation method can be classified into the following four categories: electromotive force (EMF) method, impedance spectroscopy (IS) method, internal resistance (IR) method, and open circuit voltage (OCV) method. An explanation of each category is presented in their relative section. Table 3 provides the estimation errors summary of all direct SOC methods at the end of Section 4.1.

##### 4.1.1. Open Circuit Voltage (OCV)

The OCV method can be utilized to measure the SOC after an adequate pause to allow the battery to reach the equilibrium state. The Karhunen–Loeve expansion and linear regression method were used to predict the OCV curves at different charging currents [25]. The relationship between the SOC and OCV vary from battery to battery [26]. This method is very simple and highly accurate, but it needs long resting time to reach the equilibrium state. The resting time also depends on the environmental conditions. Moreover, careful measurements of the voltages are required due to the hysteresis characteristics of the battery [27]. This method is generally used in laboratories or as calibration auxiliary technology [28,29].

Figure 6 shows the working cycle of the OCV method. Initially, fully charge the Li-ion battery and then relax it for a fixed time to depolarize. After depolarization, discharge the Li-ion using current pulses until its full discharge, relax the battery for a fixed interval after each interval to depolarize and then measure the OCV of the Li-ion battery. The same process has to perform to measure OCV during charging mode.

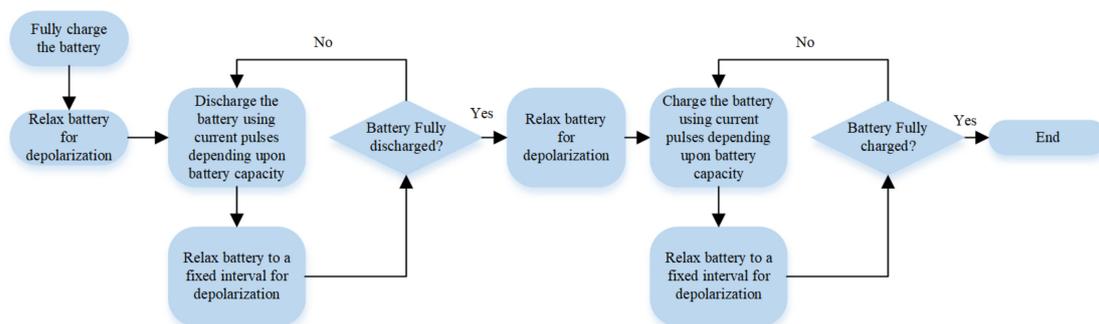


Figure 6. Working cycle of OCV-SOC estimation methods.

##### 4.1.2. Electromotive Force (EMF)

The SOC can also be measured using the EMF of the Li-ion battery. The EMF can be determined to be the OCV when the battery is in equilibrium. The EMF is associated with the battery SOC. The OCV using the EMF was modeled using different methods [30–32]. The SOC was then determined using the modeled OCV value. Coleman et al. [31] proposed a model to predict the EMF voltage for a SOC estimation. The authors divided the battery’s voltage curve into two parts. The first part contained the linear region (full to partial SOC) and other has a hyperbolic region (partial to low SOC) of the curve. In this method, the EMF was estimated using the load current and terminal voltage with some coefficients for the linear region, impedance, and the terminal voltage; the battery current was considered for the hyperbolic region. This model showed good results for a SOC estimation. Similarly, another study [32] presented an approach to estimate the EMF by considering the short OCV relaxation time after battery current stoppage. The proposed model has an EMF source with a parallel resistance and a constant phase element. The EMF was estimated using the battery current and terminal voltage. The algorithm took some time after interrupting the current to determine the EMF of the battery.

#### 4.1.3. Internal Resistance (IR)

This SOC estimation method used the battery charging/discharging current and terminal voltage to estimate the resistance of the Li-ion battery, which is also known as the DC resistance. The terminal voltage was measured with the change in current for a small interval of less than 10 milliseconds [33]. This small-time duration was always set to minimize the transfer reaction and acid diffusion effect; a large time duration is associated with some error. This method is highly accurate at the end points of the discharge. Recently, a direct current short pulse (DCSP) method has been proposed to determine the IR [34]. The value of the resistance is very low which is challenging to measure [15]. Therefore, this method is not a good choice for SOC estimation.

#### 4.1.4. Impedance Spectroscopy (IS)

The internal impedance can be utilized to characterize a Li-ion battery under different conditions. IS was applied to measure the SOC of a Li-ion battery. In the IS method, different current frequencies are applied across the Li-ion battery to determine the impedance [35–38]. Once the internal impedance is known, it can be plotted easily against the SOC. IS method can also be used for online SOC estimation [39]. Different studies that used IS method for the SOC estimation are shown in Table 3.

**Table 3.** MAE of the direct SOC estimation methods.

Method	Reference	MAE (%)
OCV	Truchot et al. 2014 [28]	Unspecified
	V. Pop et al. 2006 [29]	$\leq \pm 1.2\%$
EMF	Waag and Sauer. 2013 [32]	$\leq \pm 2\%$
IR	Wang and Liu. 2013 [33]	Unspecified
	Bao et al. 2018 [34]	$\leq \pm 1.4\%$
IS	Coleman et al. 2007 [31]	Unspecified
	Xu et al. 2013 [37]	$\leq \pm 1\%$
	Westerhoff et al. 2016 [36]	$\leq \pm 2.75\%$
	Wu et al. 2018 [38]	$\leq \pm 4\%$

#### 4.2. Book-Keeping Estimations

##### Coulomb Counting (CC)

The CC method is based purely on the battery charging or discharging current. This method integrates the battery charging or discharging current over time to find SOC [40]. The mathematical form of the CC method can be expressed as:

$$SOC(t) = SOC(t_o) - \frac{1}{Q} \int_{t_o}^t (\eta \cdot i_{bat}(t) - s_d) dt, \quad (3)$$

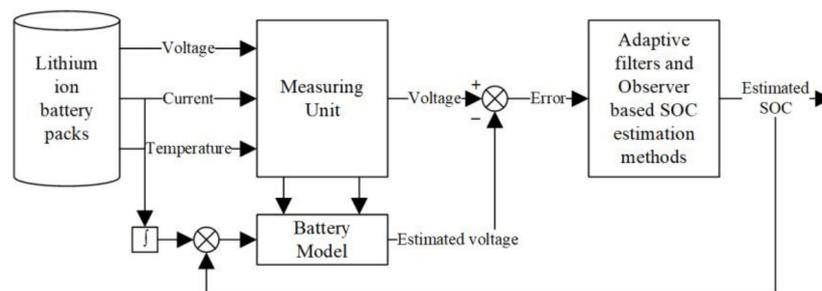
where  $SOC(t_o)$  and  $SOC(t)$  are the SOC at initial time and sampling time  $t$  respectively;  $\eta$  is the Coulombic efficiency;  $i_{bat}(t)$  is the instantaneous charging or discharging current (+ve for discharging and -ve for charging);  $s_d$  is the self-discharge rate, and  $Q$  is the nominal capacity. The implementation of this method is quite simple with very low computational complexity. The initial unknown SOC is the main concern in the CC. Moreover, the sensor error also has a negative effect on the accuracy of the SOC estimation. Therefore, this method works more efficiently, where the SOC needs to be estimated for the short period and the initial SOC is known [40]. Table 4 provides the estimation error summary of the bookkeeping estimation method [41–45].

**Table 4.** MAE/ME of the CC SOC estimation method.

Reference	MAE (%)
Zhang et al. 2014 [41]	$\leq \pm 4\%$
Wu et al. 2017 [42]	$\leq \pm 1.905\%$
Xie et al. 2018 [43]	$ME \leq \pm 2.69\%$
Xu et al. 2009 [44]	$ME \leq \pm 6.5\%$
Cheng et al. 2011 [45]	Unspecified

### 4.3. Model-Based Methods

The aforementioned conventional methods have some issues related to their efficiency and high estimation accuracy in real time. Model-based SOC estimation methods overcome the deficiencies of the conventional methods. Model-based methods use the Li-ion battery parameters to deploy the battery model and then estimate its SOC using some advanced algorithms. The electrochemical model (EChM) [46–50] and equivalent circuit model (ECM) [50–53] are the most commonly used model for the Li-ion battery. For further details on the type of battery models, merits, and demerits, see Rivera-Barrera et al. [40]. Figure 7 presents a general diagram of the model-based SOC estimation methods. The voltage, current and, the temperature has been measured to model the Li-ion battery. The difference between the estimated and true voltage value generated the error signal. The model-based methods utilized this error signal to estimate the SOC of the Li-ion battery. The model-based estimation methods are discussed herein separately in the subsequent sections.

**Figure 7.** General diagram of model-based SOC estimation methods.

#### 4.3.1. Adaptive Filters (AF)

The adaptive filtering (AF) algorithm has been used frequently in model-based SOC estimations of Li-ion batteries. The AF algorithm provides robustness and high accuracy to estimate the SOC of Li-ion batteries. Over the past few years, the use of the AF algorithm has increased owing to its high accuracy and self-correcting nature against varying input signals (current).

#### H Infinity Filter (H $\infty$ F)

The H infinity Filter (H $\infty$ F) is a popular methodology to solve the time-variant system like Li-ion battery [54]. H $\infty$ F is a simply designed and highly robust SOC estimation methodology. The method constructs a sub filter that can restrict the effects of uncertainty and perturbation of the system model. H $\infty$ F does not require any specification of the disturbances and model uncertainties, and it can also reduce the estimation error under the worst conditions; it is also known as a robust version of the Kalman filter [54]. The performance of H $\infty$ F is more sensitive to the design parameters. Zhang et al. [55] used the H $\infty$ F to address the issue of a battery SOC estimation in a 500kV transmission line inspection robot under unknown statistical properties and errors. Their proposed H $\infty$ F showed better result compared to the Kalman filter. In [56], a robust H $\infty$ F was presented to measure the SOC. Their proposed methodology considered the time varying parameters to model a Li-ion battery. The proposed algorithm was verified using six UDDS tests. The ME of their proposed algorithm was 2.49%. Different variants of H $\infty$ F have also been reported [57–61]. The researchers mostly used the ECM battery model

for SOC estimation. The H $\infty$ F method formulates the linear matrix inequalities (LMIs), which lessen the effects of a NG system and disturbances. The recursive least square method and its variants has been employed to identify the parameters [58,61]. The H $\infty$ F has also been merged with some other methods to improve the SOC estimation accuracy [62–67]. This has been combined with neural networks [62], genetic algorithms (GAs) [63], and unscented Kalman filters (UKFs) [64,66]. The accuracy of all the joint estimators was high but the system was relatively complex. Table 5 lists the previous studies.

**Table 5.** MAE/ME of the H $\infty$ F and its variant-based method to estimate the SOC.

Reference	MAE (%)
Zhang et al. 2012 [55]	Unspecified
Zhang et al. 2014 [56]	$\leq \pm 0.8436\%$
Zhu et al. 2017 [57]	$\leq \pm 3.96\%$
Zhang et al. 2017 [58]	$\leq \pm 0.02\%$
Xiong et al. 2017 [59]	$\leq \pm 1\%$
Xia et al. 2018 [60]	$\leq \pm 0.8\%$
Liu et al. 2018 [61]	$\leq \pm 0.6\%$
Alfi et al. 2014 [62]	ME $\leq \pm 1.1\%$
Lin et al. 2016 [63]	$\leq \pm 0.95\%$
Yu et al. 2017 [64]	$\leq \pm 0.5\%$
Lin et al. 2017 [66]	Unspecified

#### Kalman Filter (KF)

This is another method for the state estimation of a dynamic system. This method is most frequently used in the field of process control, surveying, transportation planning, biomedical field, and BMS design of EVs [68–70]. In recent years, in addition to its high computational complexity, the KF has attracted considerable interest to measure the SOC. The set of KF equations processes the measurements recursively [71]. The main feature of the KF is that it can filter out the disturbance (noise), high variations of measurements, and other inaccuracies of the system to estimate the states accurately. The KF tackles the uncertainty of the input values by taking the weighted average between the predicted and measured value [72]. To identify the system parameters, the KF can be used as a unit Jacobian transformation [68]. Urbain et al. [73] implemented the KF in real time to measure the SOC using simple ECM model. They showed that the maximum noted error was less than 5%. The KF has also been merged with other SOC estimation techniques, such as the CC, OCV [72], GA [74], and back-propagation neural network [75]. Some variants of KF, such as the square root cubature KF (SRCKF) [76] and dual square root cubature KF (DSRCKF) [77] have been also reported. Table 6 lists the previous studies.

**Table 6.** MAE/ME of KF based SOC estimation method.

Reference	MAE (%)
Urbain et al. 2007 [73]	ME $\leq \pm 5\%$
Yatsui et al. 2011 [72]	$\leq \pm 1.76\%$
Zhao et al. 2018 [75]	$\leq \pm 0.04\%$
Cui et al. 2018 [76]	$\leq \pm 0.71\%$
Chen et al. 2017 [77]	$\leq \pm 1.2\%$

#### Extended Kalman Filter (EKF)

Different variants of the KF, such as the extended Kalman filter (EKF), have been used to deal with nonlinearities of the system [54]. Recently, the EKF has attracted substantial interest as a method to measure the SOC [78]. In the EKF, nonlinear system dynamics and model measurements have been expanded through a linearization method, which linearize the battery model at each time step. The state space model compares the predicted and measured value to increase the SOC estimation accuracy

of a Li-ion battery [68]. The OCV-SOC estimator were designed using the EKF [79–82]. The EChM was also adopted [79]. The adaptive extended Kalman filter (AEKF) scheme was implemented on the ECM for SOC estimation [80,81]. The results highlighted the robustness and high accuracy of the proposed techniques. In the Thevenin ECM, an extra RC branch was added to improve the estimation accuracy using the EKF [83–85]. The hysteresis, Coulomb efficiency and polarization characteristics of Li-ion battery were also analyzed [83,86]. Mastali et al. [87] implemented the EKF and dual EKF to predict the SOC. They also discussed the battery geometry effects on the battery parameters. Some variants of the EKF have also been reported [88–90]. The robust EKF (REKF) addresses the uncertainty in the battery modelling and linearization error. The model also provides robustness against system noise. Xiong et al. [91] proposed a dual time scale EKF SOC estimator. They used a macro scale for battery parameter identification and a micro scale for the SOC prediction. Similarly, another study [92] used the temperature compensated model with the EKF to address the effects of temperature on the battery parameters. A grey predicted EKF was proposed to eliminate the effects of the truncation error [93]. The EKF in conjunction with a stochastic fuzzy neural network (SFNN) has been utilized for SOC estimation [94]. The SFNN modeled the nonlinear dynamic characteristics of the battery and the EKF estimated the SOC of a Li-ion battery. Table 7 lists the comparison of the previous studies.

**Table 7.** MAE/ME of the EKF, variants of the EKF and hybrid EKF-based SOC estimation method.

Reference	MAE (%)
He et al. 2011 [83]	$\leq \pm 1.06\%$
Zhu et al. 2012 [84]	ME $\leq \pm 4.2\%$
Xiong et al. 2012 [81]	$\leq \pm 2.0\%$
Jiang et al. 2013 [82]	$\leq \pm 1.0\%$
Hu et al. 2013 [88]	$\leq \pm 1.0\%$
Chen et al. 2013 [85]	$\leq \pm 3.0\%$
Xiong et al. 2014 [91]	$\leq \pm 1.5\%$
Sepasi et al. 2014 [89]	$\leq \pm 1.5\%$
Wang et al. 2017 [90]	Unspecified
Xie et al. 2018 [86]	ME $\leq \pm 2.0\%$
Yang et al. 2017 [92]	ME $\leq \pm 3.0\%$
Pan et al. 2017 [93]	$\leq \pm 1.3\%$
Huang et al. 2018 [78]	Unspecified
Xu et al. 2012 [94]	ME $\leq \pm 0.6\%$

### Unscented Kalman Filter (UKF)

When a system, such as a Li-ion battery, has severe non-linearities, tuning of the EKF becomes arduous and it provides uncertain estimates because the EKF depends mainly on linearization to disseminate the mean and covariance of the state [54]. Therefore, an UKF is used to minimize the linearization error of EKF. The basic concept of the UKF is that it is simpler to assess a probability distribution than a random non-linear function [68]. A deterministic “sigma point filter” approach is used to obtain the covariance and mean of the state with minimum sample points. The UKF carefully calculates the selected perturbations about the current state. The perturbed state propagates to calculate the samples for the estimated state and predicted measurement. In the UKF, there is no need to calculate the Jacobian matrix. The correctness of the UKF is better than EKF because it can predict the high order non-linear system states accurately. The UKF is more complex than EKF because of the modeling uncertainties and perturbations.

The UKF was implemented in several studies for the SOC estimation of the batteries [95–99]. The CC and simple model was considered with the UKF for a SOC estimation [95]. Tian et al. [96] used the UKF with a modified ECM to study the effects different temperatures and charge rates. Some variants of the UKF have also been reported [100–107]. In [100,102], an adaptive UKF (AUKF) adaptively adjusts the perturbation covariance of the state’s value; the zero-state battery hysteresis model was selected to reduce the complexity [100]. A machine learning algorithm was used to train the battery

model [101]. The comparison showed that the AUKF has a better accuracy and convergence rate than the EKF, AEKF, and UKF. Cai et al. [103] addressed the issue of the battery model accuracy. They proposed a fractional variable order model, which updates the value of the battery model adaptively. The UKF was implemented to estimate the SOC for a fractional system. Another variant of UKF method was used to calculate the noise directly [104]. This algorithm ensures symmetry in the matrices. The particle filter (PF) was also combined with the UKF to increase its robustness [108]. The PF helps to decrease the convergence time at the start because of the high initial error. Table 8 lists the performance of the UKF and its variants.

**Table 8.** MAE/ME of the UKF, variants of the UKF and hybrid UK-based SOC estimation method.

Reference	MAE (%)
He et al. 2013 [95]	ME $\leq \pm 4\%$
Tian et al. 2014 [96]	$\leq \pm 1.25\%$
Wang et al. 2018 [97]	Unspecified
Sun et al. 2011 [100]	$\leq \pm 1.0\%$
Du et al. 2014 [101]	$\leq \pm 1.5\%$
Partovibakhsh et al. 2015 [102]	$\leq \pm 0.028\%$
Cai et al. 2017 [103]	ME $\leq \pm 1.51\%$
Liu et al. 2017 [104]	$\leq \pm 0.5\%$
Peng et al. 2017 [105]	$\leq \pm 1.49\%$
Chen et al. 2017 [106]	$\leq \pm 2.88\%$
Li et al. 2018 [107]	$\leq \pm 1.5\%$
Li et al. 2018 [108]	$\leq \pm 0.31\%$

#### Sigma Point Kalman Filter (SPKF)

This method is another way to improve the efficiency and correctness of a SOC measurement of a nonlinear dynamic state space model, such as a Li-ion battery. The SPKF calculates the statistics of arbitrary variables that experience a nonlinear transformation, and then forms the Kalman time and measurement equations, which are the Gaussian assumption-based Bayesian estimation equations [109]. The variance of the error in the posterior covariance was considered to compensate for the linearization error. The posterior covariance and mean were calculated for limited values [16]. In the SPKF, there is no need to calculate the analytical derivatives (Jacobians and Hessians), as in the case of EKF. The SPKF depends only on a functional evaluation. The SPKF has better accuracy and robustness with same complexity as the EKF [71,109,110].

Plett [71] implemented the SPKF and EKF for SOC measurement. The results showed that the SPKF has high accuracy than the EKF. In his subsequent work, Plett [110] introduced a variant of the SPKF to increase its robustness. The UDDS test was performed to check the robustness of the proposed SOC estimation strategy for a Li-ion battery. The joint estimation of the inner resistance and SOC of a Li-ion battery by keeping other parameters constant was also proposed [111]. Another study compared the Luenberger observer, EKF and SPKF [112]. Another variant is strong tacking sigma point Kalman filter (STSPKF) [113], which used a strong tacking factor to adjust the process and measure the perturbation in real time. Table 9 summarizes the performance of the SPKF and its variants.

**Table 9.** MAE/ME of the SPKF and variants of the SPKF-based SOC estimation method.

Reference	MAE (%)
Plett. 2006 [71]	ME $\leq \pm 0.9\%$
He et al. 2012 [111]	Unspecified
Li et al. 2013 [112]	Unspecified
Li et al. 2015 [113]	$\leq \pm 0.83\%$

### Particle Filter (PF)

In the particle filter (PF), a Monte Carlo approximation approach is used to make a state estimation [54]. In the PF, some random large particles have been chosen to approximate the conditional probability density function [68]. This method has higher efficiency but at the cost of more complexity. Different researchers used the PF to SOC estimation [114–117]. The PF was merged with other techniques to improve its efficiency [118–120]. Fuzzy rules were used to model the battery and the PF was utilized to provide a co-estimation of the state of maximum power available (SoMPA) and SOC [118]. Furthermore, the forgetting factor RLS method was also used to determine the battery parameters with the PF as a SOC estimator [120]. Different variants of the PF have also been reported [121,122]. Recently, Ye et al. [123] proposed an online double scale and adaptive particle filter. They reduced the computational cost of the algorithm by considering that the battery parameters change more slowly than the SOC. They showed that the MAE of SOC estimation is less than 1% after the systems stability, and the convergence time of the proposed algorithm was only 136 second. Table 10 lists the performance of the UKF and its variants.

**Table 10.** MAE/ME of the PF, variants of the PF and hybrid PF-based SOC estimation method.

Reference	MAE (%)
Gao et al. 2011 [114]	Unspecified
Schwunk et al. 2013 [115]	Unspecified
He et al. 2013 [117]	$\leq \pm 3.5\%$
Burgos-Mellado et al. 2016 [118]	Unspecified
Zhou et al. 2016 [119]	$ME \leq \pm 1.61\%$
Xia et al. 2017 [121]	$\leq \pm 0.5\%$
Li et al. 2018 [122]	$\leq \pm 1\%$
Du et al. 2018 [120]	$ME \leq \pm 3.5\%$
Ye et al. 2018 [123]	$\leq \pm 1\%$

### Recursive Least Square (RLS)

This is a very useful method to identify the parameters of a time-varying system. The least square (LS) method identifies the system parameters by minimizing the least square error between the measured and estimated value [68]. The RLS is utilized in AF to determine the gain; it makes this process recursive and estimates the parameters of the system by amalgamating new information at each time step.

The RLS and its variants have been used widely to determine the parameters of Li-ion battery model [124–133]. The RLS has been applied to identify the characteristic of the battery for a 1<sup>st</sup> order ECM [124,129,132]. The OCV estimator was designed to determine the SOC. The results highlighted the robustness and high accuracy of the RLS. A recurrent neural network and RLS with a time dependent forgetting factor was utilized to SOC estimation [125]. The fading KF (FKF) was also implemented for SOC estimation [126]. The exponential and variable forgetting factor RLS methods were also used to estimate the SOC [127,128,130]. Table 11 lists the performance of the RLS SOC estimation method.

**Table 11.** MAE/ME of the RLS, variants of the RLS and hybrid RLS-based SOC estimation method.

Reference	MAE (%)
Hu et al. 2011 [124]	$ME \leq \pm 2.12\%$
Eddahech et al. 2012 [125]	$\leq \pm 1.03\%$
Safwat et al. 2017 [128]	$\leq \pm 3\%$
Duong et al. 2017 [129]	$\leq \pm 1.8\%$
Xia et al. 2017 [130]	$\leq \pm 1.41\%$
Ali et al. 2018 [132]	$\leq \pm 1.93\%$
Zhang et al. 2018 [133]	$\leq \pm 1\%$

### 4.3.2. Observer-Based estimation (OBE)

#### Non-Linear Observer (NLO)

Recently, the linear observer (LO) and NLO has been utilized for state estimation of batteries. The main drawback of the LO is the high estimation error compared to the NLO [134]. Xie et al. [135] introduced the NLO SOC estimator methodology. Their proposed methodology did not use a complex matrix operation for the estimation. The SOC was estimated using the OCV state space equations. The proposed methodology showed less complexity, higher precision, and better robustness than the EKF and sliding mode observer. An optimal adaptive gain nonlinear observer (OAGNO) was proposed in another study to state estimation of a battery [136]. Recently, the particle-swarm optimization algorithm was used to tune the observer. which showed high accuracy and robustness [137]. Other variants of NLO were also proposed for the improvement of estimation accuracy of SOC of a Li-ion battery [138,139]. For comparison of NLO-based SOC estimation methods, see Table 12.

**Table 12.** MAE/ME of the NLO-based SOC estimation method.

Reference	MAE (%)
Xia et al. 2014 [135]	ME $\leq \pm 2.89\%$
Tian et al. 2017 [136]	$\leq \pm 0.74\%$
Ma et al. 2017 [137]	$\leq \pm 2.0\%$
Li et al. 2017 [138]	$\leq \pm 0.35\%$
Chen et al. 2018 [139]	ME $\leq \pm 2.98\%$

#### Sliding Mode Observer (SMO)

This method enhances the control, robustness, and stability of a Li-ion battery system against perturbation [140–145]. The state equations are used to establish a battery model, and these equations are used for the observer. Feedback is taken to control the sliding regime to ensure robustness. The SMO can compensate for modelling errors. Du et al. [146] proposed an adaptive SMO to address the effect of chattering to during state estimation of a battery.

The 2nd order ECM was selected to compare the conventional and proposed SMO. The proposed SMO showed better accuracy with a high convergence rate. The chattering effect was also addressed using a second-order discrete-time SMO [147]. In [148], the dual SMO was proposed considering the capacity fading effect for SOC estimation. To improve the efficiency, accuracy, and robustness of the SMO, some variants, such as the adaptive gain SMO (AGSMO) [149], adaptive switching gain SMO (ASGSMO) [150], super-twisting SMO (STSMO) [151], fractional order SMO (FOSMO) [152], and Fuzzy SMO (FSMO) [153], have been reported in the literature. Table 13 shows the comparison of the SMO-based SOC estimation methods.

**Table 13.** MAE/ME of the SMO-based SOC estimation method.

Reference	MAE (%)
Kim et al. 2008 [140]	ME $\leq \pm 3\%$
Ning et al. 2016 [143]	ME $\leq \pm 2\%$
Ma et al. 2016 [144]	ME $\leq \pm 3\%$
Xia et al. 2017 [145]	$\leq \pm 0.86\%$
Chen et al. 2013 [150]	Unspecified
Zhong et al. 2017 [153]	$\leq \pm 1\%$
Huangfu et al. 2018 [151]	$\leq \pm 2\%$
Chen et al. 2018 [148]	$\leq \pm 1\%$

### Proportional Integral Observer (PIO)

The proportional integral observer (PIO) is a widely adopted, simple, and efficient method, because the feedback control system can be replaced easily using PIO. Xu et al. [154] adopted the 1st order ECM for SOC estimation of a battery through the use of a PIO. The UDDS cycle was used for validation. The robustness of their proposed methodology was quite high with acceptable accuracy. In their subsequent work, Xu et al. [155] jointly used the CC and model-based estimation method to improve the efficiency. They utilized a GA and PIO to determine the parameters and the SOC of a battery, respectively. The highpoint of their second work was that it could work easily without laboratory testing data. A comparison of the KF, SMO, Luenberger observer, and PIO was done in [156,157]. The results highlighted the superior performance of the PIO. The PIO is also used in combination with drifting corrector to address the issues of a flat OCV-SOC relation and current sensor error for a LiFePO<sub>4</sub> battery [26]. The issue of sensor error was addressed by dividing the measured current into a true value, current sensor drifting, and zero-mean noise of the sensor. Zheng et al. [158] merged the PIO and CC to estimate the SOC, capacity, and resistance of EChM. The influence of aging on the estimation was also addressed. Recently [159], the PIO was employed to enhance the linearization performance of the EKF. The RLS method was used to identify the 1st order ECM. The proposed methods show good robustness with a dynamic current at different temperatures. Also in another study [160], the two PIO were used to compensate for the inaccuracy of the SOC and current sensor error. Furthermore, they compared their proposed method with the EKF. They showed that their proposed method showed less complexity and higher accuracy than the EKF. For further comparison of the PIO-based SOC estimation methods, see Table 14.

**Table 14.** MAE/ME of the PIO-based SOC estimation method.

Reference	MAE (%)
Xu et al. 2014 [154,155]	ME $\leq \pm 2\%$
Tang et al. 2015 [26]	ME $\leq \pm 2.5\%$
Zheng et al. 2016 [158]	ME $\leq \pm 3.58\%$
Wei et al. 2017 [159]	ME $\leq \pm 5\%$
Meng et al. 2018 [160]	ME $\leq \pm 1.86\%$

### Luenberger Observer (LO)

The Luenberger observer (LO) has been also used to provide state estimations of non-linear and time varying systems [157,161]. Hu et al. [162] applied the LO for SOC estimation. They used a 1st order ECM for the estimation; the nonlinear least square method was utilized to identify the battery parameters and a stochastic gradient approach was used to set the observer gain. The proposed observer had low computational complexity. LO-based SOC estimator for EChM was also proposed by including the effects of variable temperature to improve the SOC estimation accuracy for Li-ion battery [163]. Recently, Tang et al. [164] presented another variant of the LO, a multi-gain Luenberger observer (MGLO). They showed that the proposed observer addressed the issues of modeling inaccuracy and sensor error for the SOC estimation. Their proposed method has higher robustness, better accuracy, and similar complexity to the LO. Table 15 provides the comparison of the LO-based SOC estimation methods.

**Table 15.** MAE/ME of the LO-based SOC estimation method.

Reference	MAE (%)
Hu et al. 2010 [162]	ME $\leq \pm 2.5\%$
Tanim et al. 2015 [163]	ME $\leq \pm 2.6\%$
Tang et al. 2017 [164]	Unspecified

#### 4.4. Computer Intelligence-Based Estimation Methods

##### 4.4.1. Genetic Algorithm (GA)

The genetic algorithm (GA) is a biologically inspired optimization method to find the unknown model parameters of a nonlinear system, such as a Li-ion battery. The GA generates a string of chromosomes randomly and uses biological operators, such as crossover, selection, and mutation, to find the optimal values. Zheng et al. [165] used the voltage-capacity rate curve and implemented a GA to model the battery pack. They used four cell series-connected Li-ion batteries and determined the capacities of the entire pack and individual cells. The maximum average SOC error of a cell in a string was 0.54%. The GA was also implemented to find the second order ECM parameters of a battery [166]. The formula using identified diffusion capacitance was derived to determine the SOH of a Li-ion battery. The GA fused with some other model-based estimation methods was used to estimate the SOC [155,167–171]. The GA was also utilized in tuning of the fading KF to further improve the estimation of the SOC for a Li-ion battery [126]. Recently, the 3D OCV-SOC method was proposed in which GA was utilized to find the SOC and SOH of a battery with high accuracy and good convergence rate [172]. Table 16 reports the MAE for the GA and its variants.

**Table 16.** MAE/ME of the GA, variants of the GA and hybrid GA-based SOC estimation method.

Reference	MAE (%)
Zheng et al. 2013 [165]	$\leq \pm 0.55\%$
Xu et al. 2014 [155]	$\leq \pm 2.0\%$
Khan et al. 2014 [168]	$ME \leq \pm 5.0\%$
Lim et al. 2016 [126]	$ME \leq \pm 2.0\%$ (in UDDS); $\leq \pm 3.0\%$ (in real driving EV)
Mu et al. 2017 [171]	$\leq \pm 2.98\%$
Yang et al. 2017 [172]	$ME \leq \pm 2.1\%$
Chen et al. 2018 [169]	$\leq \pm 1.0\%$

##### 4.4.2. Bacterial Foraging Algorithm (BFA)

The bacterial foraging algorithm (BFA) is a nature-inspired optimization technique that is established on the social foraging behavior of *Escherichia coli* bacteria. The BFA has been successfully used to solve many engineering and mathematical problems because of its simplicity and high efficiency [173,174]. The BFA was also used to estimate the unknown parameters of the single particle EChM of a Li-ion battery [175].

##### 4.4.3. Particle Swarm Optimization (PSO)

PSO is also a nature-inspired approach. The basic idea of this methodology is stimulated from the social behavior of different species, such as birds or fishes, interacting with each other or with the surroundings [176]. In this methodology, the main objective is information sharing in the group, where every individual bird in the flock does not know the precise location of the food, but they can track down the food site easily through information sharing [177]. PSO has been implemented successfully in many engineering problems to find optimal solutions [174,177–179]. PSO has been used to identify the model parameters of a Li-ion battery [180–186]. Recently, an improved EKF SOC estimator has been proposed in which PSO was utilized to identify the time varying parameters of the Li-ion battery [187]. Their proposed estimator produced a better result compared to the traditional EKF. Table 17 compares the MAE for PSO and its variants.

**Table 17.** MAE/ME of the PSO, variants of the PSO and hybrid PSO-based SOC estimation method.

Reference	MAE (%)
Sheikhan et al. 2012 [178]	$\leq \pm 1.9\%$
Aung et al. 2015 [185]	$ME \leq \pm 3.35\%$
Yu et al. 2017 [183]	Unspecified
Ye et al. 2017 [186]	$ME \leq \pm 1.0\%$
Lai et al. 2018 [187]	$ME \leq \pm 1.0\%$

#### 4.4.4. Fuzzy Logic (FL)

FL is another method to identify the unknown parameters of a highly complex and nonlinear system, such as a Li-ion battery. FL does not require a precise mathematical model of the system, as it only uses the input data and identifies the parameters using the fuzzy rule base. The working principle of FL can be divided easily into the following stages: fuzzification, fuzzy rule base, inference engine, and defuzzification [3]. FL requires however high storage and computational time to determine the parameters of a complex and nonlinear system. FL was also used to estimate the parameters of the SOC with improved accuracy [188–190]. Furthermore, the use of FL fused with other SOC estimation techniques has also been reported [118,191–193]. Li et al. [194] used RLS with a fuzzy adaptive forgetting factor to identify the time-varying parameters of a Li-ion battery; the adaptive UKF was used to estimate the SOC of the Li-ion battery [194]. For further comparison, see Table 18.

**Table 18.** MAE/ME of the FL-based SOC estimation method.

Reference	MAE (%)
Salkind et al. 1999 [188]	$ME \leq \pm 5.0\%$
Singh et al. 2006 [189]	Unspecified
Malkhandi 2006 [190]	$ME \leq \pm 5.0\%$
Li et al. 2016 [194]	$\leq \pm 0.59\%$

#### 4.4.5. Neural Network (NN)

The neural network (NN) is a computing system that is basically inspired by the human brain. The NN is a framework of many different machine learning algorithms to perform different tasks [195]. The NN has self-adaptability and learning abilities to establish a highly complicated and non-linear system, such as a Li-ion battery. The basic NN uses a three-layer formation, and input and output layer-containing neurons with system specifications. The relationship between the I/O layer is developed through neurons and hidden layers. The measurements of electric charge and the internal impedance were considered to form an NN [196,197]. The fused NN and EKF were applied to predict the SOC of a battery [198,199]. The NN was trained offline using the battery charge/discharge data [198]. The feed forward NN (FFNN) was introduced to SOC estimation [199]. The parameters of the battery were the inputs, and the UKF was used to decrease the prediction error. Dong et al. [200] proposed a wavelet NN-based battery model. They also considered temperature and current to further improve the modeling accuracy. Then, PF was employed to find the SOC. Another study compared the open and closed loop NN SOC estimators, in which they showed that the closed-loop NN estimator gives better performance than open loop NN [201]. Furthermore, the dual SOC and state of energy (SOE) estimator can be constructed using a NN [202]. Some variants of the NN were also used to SOC estimation [203–209]. Recently, Cui et al. [210] combined the discrete wavelet transform and wavelet NN methods to estimate the SOC. The wavelet NN was trained using the Levenberg Marquardt (L-M) technique. The inputs of the wavelet NN were managed by a discrete wavelet decomposition and reconstitution. Their proposed methodology produced better results than the BPNN, FFNN, L-M based BPNN, discrete wavelet transforms back propagation NN, and EKF. The backtracking search

algorithm (BSA) can be used to improve the performance of BPNN [211]. The comparison of MAE for NN-based SOC estimation methods is shown in Table 19.

**Table 19.** MAE/ME of the NN-based SOC estimation method.

Reference	MAE (%)
Affanni et al. 2003 [196]	ME $\leq \pm 4.6\%$
Rui-hao et al. 2011 [197]	ME $\leq \pm 4.91\%$
Chen et al. 2011 [212]	$\leq \pm 1.0\%$
He et al. 2014 [199]	ME $\leq \pm 2.5\%$
Dong et al. 2015 [200]	ME $\leq \pm 4.0\%$
Wang et al. 2016 [202]	ME $\leq \pm 2.5\%$
Hussein 2015 [203]	$\leq \pm 0.03\%$
Tong et al. 2016 [204]	$\leq \pm 3.8\%$
Dang et al. 2016 [205]	$\leq \pm 0.75\%$
Shi et al. 2010 [207]	$\leq \pm 1.25\%$
Kang et al. 2014 [208]	$\leq \pm 3.0\%$
Cui et al. 2018 [210]	$\leq \pm 0.93\%$
Hannan et al. 2018 [211]	$\leq \pm 0.87\%$

#### 4.4.6. Adaptive Neuro Fuzzy Inference System (ANFIS)

An ANFIS is an advanced form of the artificial NN, which is based mainly on the Takagi–Sugeno fuzzy inference system. The ANFIS has the benefits of FL and NN in a single framework. ANFIS is an extraordinary tool for modeling, optimization, and nonlinear mapping. Shen et al. [213] implemented the ANFIS-based SOC estimator using different discharge current profiles to validate the proposed technique. Five inputs and one output ANFIS model were also presented in [214]. The inputs were selected using linear correlation analysis, partial correlation analysis, and nonparametric correlation analysis. A gradient and least square algorithm were used to train the ANFIS. The comparison showed the better performance of ANFIS over BPNN. In another study [215], capacity and temperature distributions were taken into account to estimate the SOC. The experiments with different battery discharging current were carried out to validate their proposed technique. Furthermore, the performance of CC and ANFIS based Li-ion battery SOC estimator were also compared in [216]. Table 20 shows the studies using ANFIS method and their MAE.

**Table 20.** MAE/ME of the ANFIS-based SOC estimation method.

Reference	MAE (%)
Shen et al. 2002 [213]	$\leq \pm 0.92\%$
Cai et al. 2003 [214]	ME $\leq \pm 4.44\%$
Chau et al. 2004 [215]	$\leq \pm 1.0\%$
Fotouhi et al. 2015 [216]	$\leq \pm 2.0\%$
Dai et al. 2015 [217]	Unspecified
Awadallah and Venkatesh 2016 [218]	Unspecified

#### 4.4.7. Support Vector Machine (SVM)

In recent years, support vector machine (SVM) techniques have attracted considerable attention. The SVM is becoming a powerful tool to solve regression problems in nonlinear systems. The SVM uses different kernel functions and regression algorithms to transmute a nonlinear model into a linear model. On the other hand, the complexity of the SVM system is very high due to the complex quadratic programming. The voltage, current and temperature were considered to SOC estimation using the SVM [219–221]. The least square algorithm was used to improve the efficiency of the SVM [219]. Similar inputs were used to establish a relationship with the SOC using the weighted least squares SVM. A study used [222] extended Huber residual estimation algorithm in the objective function to achieve better robustness than the conventional SVM. Hu et al. [223] used a double step search to select

the parameters of support vector regression using a radial basis kernel function. Their proposed SVM showed better results compared to the NN. Another study [224] addressed the issue of sensor noise to reduce the errors. Their proposed strategy showed better results than the conventional SVM. Table 21 shows the study on the SVM-based SOC estimation method.

**Table 21.** MAE/ME of the SVM-based SOC estimation method.

Reference	MAE (%)
Chen et al. 2011 [222]	$\leq \pm 1.09\%$
Wu et al. 2011 [219]	$ME \leq \pm 5.0\%$
Anton et al. 2013 [221]	$ME \leq \pm 6.0\%$
Sheng et al. 2015 [224]	$\leq \pm 0.30\%$

#### 4.4.8. Multivariate Adaptive Regression Splines (MARS)

Friedman [225] introduced a new type of flexible regression analysis for high dimensional data called multivariate adaptive regression splines (MARS). The MARS model is an extension of product-spline-basis functions, where the parameters and basis function can be calculated automatically using the data. The main idea of MARS method is inspired basically by the recursive partitioning approach. The main advantage of the MARS method over the recursive partitioning approach is that it can generate continuous models using continuous derivatives. Antón et al. [226] used the MARS technique to SOC estimation. The parameters of the battery were used to extract the battery parameters, basis function, and coefficients. The model was evaluated with a determination coefficient of 0.98, and an accuracy of 1% was accomplished during the SOC level between 25% to 90%. The main advantage of their proposed technique is that it can be implemented easily on a low-cost microcontroller. In their subsequent work [227], a hybrid PSO optimized MARS technique to SOC estimation was proposed. They used a PSO algorithm to identify the optimal parameters of the MARS model, which further reduces the training time of the MARS model.

## 5. Discussion

The Li-ion battery is a highly complex electrochemical system and its performance degraded by different factors, such as hysteresis, aging and operating conditions. Therefore, it is very challenging task to estimate the SOC of a Li-ion battery accurately. Several discussed SOC estimation methods from easier to complicated are under investigation. The OCV method has a relatively high accuracy to estimate the SOC of Li-ion battery. The main shortcoming of the OCV method is its long relaxing time to reach equilibrium state to measure terminal voltage as OCV. So, the OCV method cannot be directly used to estimate the SOC of Li-ion battery in an EV application. The IR method use battery resistance to measure SOC, the main lapse is the low resistance value for wide SOC range. The CC method showed reliable results when the initial SOC of the Li-ion battery is known. The accuracy of the CC method mainly depends upon the initial SOC value and resolution of the sensor. The CC method fused with other methods like OCV and model-based is a good option to estimate the SOC in EVs. The accuracy of MB estimation methods mainly depends upon model exactness. So, battery models should guarantee not only to capture the complex chemical reaction of Li-ion battery, but they also consider the effects of capacity degradation, climate changes, and mechanical stress. Now a days, the KF family based SOC estimator is the most popular in online estimation applications. The advantages and limitation of KF and its variants-based methods has been listed in Table 22. The accuracy of the machine learning method is very high but it needs high training time and data storage size. The computational cost of these methods is also high. Table 22 summarizes the merits and limitations of each SOC estimation method discussed above.

**Table 22.** Summary of the classified SOC estimation methods for Li-ion batteries.

Method	Advantages	Limitations	Applicability in EVs
OCV	It is simple and easily implementable, and it has high accuracy.	This technique cannot be implemented for online estimations because it requires a long resting time to reach equilibrium, and precise measurements of the OCV are difficult due to the flat region in the middle of the OCV-SOC curve. Therefore, this method is only suitable to train and calibrate other methods.	No
EMF	This method is simple and inexpensive.	This technique requires significant time to model OCV relaxation after current disruption.	No
IR	It is simple and easily implementable.	It has low accuracy because large variations of the SOC have low impact on the change in resistance. Therefore, it is difficult to measure a small resistance.	No
IS	This method can measure the SOC online with reasonable accuracy.	This technique only has good results for identical charging and discharging currents. Therefore, it is unsuitable for EVs because of the large variations in charge/discharge current. It also has an effect on battery aging and temperature.	No
CC	It is simple and easily implementable with low computation cost.	Several factors, such as an unknown initial SOC, aging, temperature, self-discharging, coulomb efficiency and device precision, affect its accuracy.	Yes
H $\infty$ F	This method has reasonable accuracy, less computational cost, and good convergence rate.	The accuracy of the model can be affected by the aging, hysteresis and operating conditions (temperature) of the Li-ion battery.	Yes
KF	This method can estimate the states affected by external perturbations in real time and with high accuracy.	This method cannot be applied directly to estimate the states of a non-linear system. It depends strongly on the correctness of the model and measuring device precision, and the complexity of this technique is very high.	Yes
EKF	It can predict the states of a system accurately under noisy and inaccurate initial conditions.	The accuracy of this method depends mainly on the linearization. The linearization error could be significant for a highly nonlinear system. It also has low robustness.	Yes
UKF	This method can easily estimate states of any higher order (3rd order) nonlinear system. Unlike the EKF, it does not require to compute the Jacobian matrix and Gaussian noise.	Like the EKF, it has low robustness due to vagueness in modelling and perturbation.	Yes
SPKF	It has high accuracy and does not require to compute the Jacobian matrix.	It is complicated and requires lengthy calculations to estimate the SOC.	Yes
PF	This method has high accuracy, less computation cost, and good convergence rate.	It requires a very powerful mathematical tool to solve it.	Yes

Table 22. Cont.

Method	Advantages	Limitations	Applicability in EVs
RLS	This method has high accuracy and can eradicate the noise of the measured voltage.	The system and noise should satisfy the Gaussian distribution for better accuracy. It has high complexity and computational cost. Its accuracy mainly depends on the correctness of the battery model and selection of the forgetting factor.	Yes
NLO	This method has good convergence speed, reasonable computation cost, and high accuracy.	It is hard to determine a suitable gain for high accuracy.	Yes
SMO	This method enhances the tracking control to ensure stability and robustness.	It is hard to determine a suitable switching gain to control the sliding regime for high accuracy.	Yes
PIO	It can estimate the SOC accurately in the presence of an unknown initial SOC, imprecise battery capacity, and noisy current sensor.	The controller design has a significant effect on the estimation accuracy.	Yes
LO	This method is accurate and robust in the presence of modeling and sensor inaccuracy.	The selection of appropriate gain for the observer is a difficult task.	Yes
GA	This method has high accuracy and is robust in the presence of noisy environment.	It has high computational complexity, delays in response time, and requires fine-tuning of the parameters for high accuracy. The conversion of binary into a number is very important. This conversion increases the response time.	Yes
BFA	This method has reasonable accuracy for dynamic current profile.	It requires high computation time. More experiments are needed to validate this technique.	No
PSO	This method can measure the SOC online with reasonable accuracy.	It requires considerable effort to tune the parameters properly. The main issue of this technique to avoid local optima. This issue can be addressed by updating the objective function, which results in high computational cost.	Yes
FL	This method has good accuracy in different currents, aging, and temperature conditions.	It has high computation cost and requires high storage size and expensive data processing units.	Yes
NN	This method can provide SOC estimation under any condition. This is one of the most suitable methods for SOC estimations in EVs.	It also requires large data storage size to save the trained data.	Yes
ANFIS	This method has high accuracy.	The storage size should be very high to store trained data.	Yes
SVM	This method performs well in nonlinear and high dimensional models.	This method is time consuming.	Yes
MARS	It has reasonable accuracy.	It has good accuracy at the mid points of the SOC curve. More experiments are needed to validate this technique.	No

## 6. Future Perspectives of SOC Estimation

Some future perspectives and recommendations to achieve better performance of BMS of a Li-ion battery are the following:

- There should be some improvement in the round-trip efficiency, depth of discharge and energy density of Li-ion battery. The main concern of its capital cost should be addressed.
- The RC structured ECM model should be improve by adding some more mathematical components, which can more precisely characterize Li-ion battery properties.
- Fusion of different battery models can be a good option to achieve good results.
- Most of the research has been conducted in laboratory premises. So, there is a need of more research in the natural environment where the effects of different conditions such as hot, cold, snowy, rainy, and humid conditions can be checked.
- There are hundreds of cells in the battery pack of EVs. Very few researches have been reported on the estimation of battery packs. Further research is needed to estimate SOC of battery packs.
- The accuracy of the voltage and current sensor has been increased with the development of the technology that can increase the model accuracy. The rapid growth in the field of nanoelectronics has enabled the commercialization of a high-speed controller with a minimal physical size, which can easily tackle the complex mathematical modeling issues in the BMS of EVs. Therefore, the SOC estimation accuracy issue will be diminished soon due to the rapid advances in hardware resources. Owing to the rapid advances in machine learning algorithms, these methodologies are likely to be the future of SOC estimation technology in EVs.

## 7. Conclusions

This study compared the advantages and workings of a Li-ion battery with other ESS in detail. The Li-ion battery has been strongly recommended for EVs because of its high-power density, long lifespan, high energy density, nominal voltage, and relatively low cost. The important features and working cycle of an effective BMS to achieve safe and reliable battery operation in EVs were presented.

This review classified the Li-ion battery-based SOC estimation method into their respective categories according to their nature. A critical explanation, including their merits, limitations, and estimation errors from the literature, was studied in detail. This study concluded that the conventional (direct measurements and bookkeeping) methods are simple and easily implementable, but they suffer from the effect of aging, temperature, sensors drift, and external perturbations. The model-based estimation methods produce good results with high precision. The complexity of the adaptive filters-based method is very high, and it has poor robustness. The machine learning-based SOC estimation methods show the best results among all the methods assessed. The accuracy of these methods is very high under different aging and temperature conditions. These methods require high storage time and a rapid controller for computation. According to the authors, the machine learning algorithms will be the future of SOC estimation technology because of their high accuracy under different challenging conditions and rapid development in nanoelectronics technology. This review paper provides information to manufacturers and researchers developing new SOC methods or updating existing methods.

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## Appendix A

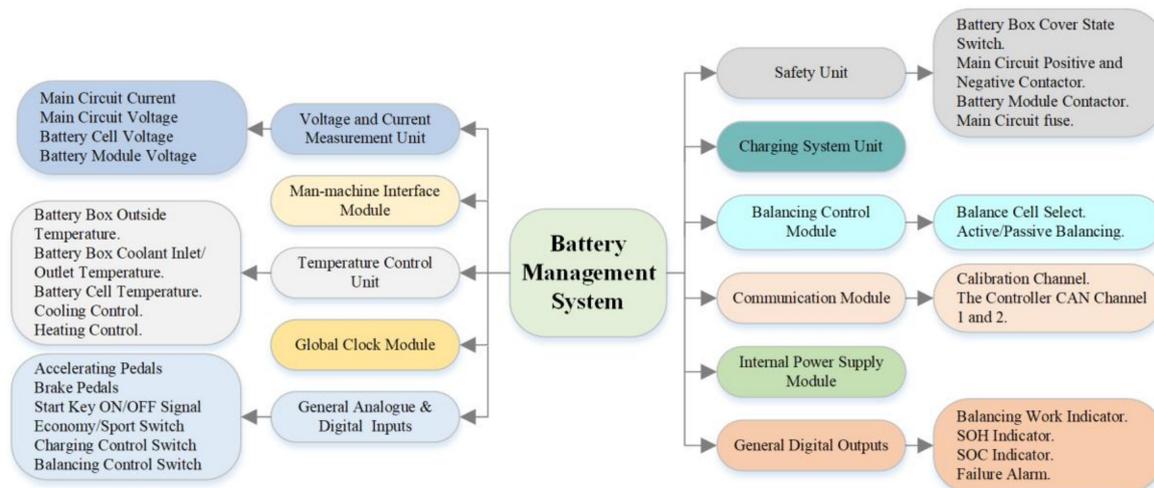


Figure A1. Comprehensive framework for an effective BMS.

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