IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

Received August 27, 2019, accepted September 13, 2019, date of publication September 18, 2019, date of current version October 1, 2019.

Digital Object Identifier 10.1109/ACCESS.2019.2942213

State of Charge Estimation for Lithium-Ion Batteries Using Model-Based and Data-Driven Methods: A Review

DICKSON N. T. HOW[1], (Member, IEEE), M. A. HANNAN[1], (Senior Member, IEEE), M. S. HOSSAIN LIPU[2], AND PIN JERN KER[1], (Member, IEEE)

[1]Department of Electrical Power Engineering, College of Engineering, Institute of Sustainable Energy, Universiti Tenaga Nasional, Kajang 43000, Malaysia
[2]Centre for Integrated Systems Engineering and Advanced Technologies (Integra), Faculty of Engineering and Built Environment, Universiti Kebangsaan Malaysia, Bangi 43600, Malaysia

Corresponding author: M. A. Hannan (hannan@uniten.edu.my)

This work was supported in part by the Ministry of Higher Education, Malaysia, under Project 20190101LRGS, and in part by Universiti Tenaga Nasional, Malaysia, in 2019, under Grant J510050797

ABSTRACT Lithium-ion battery is an appropriate choice for electric vehicle (EV) due to its promising features of high voltage, high energy density, low self-discharge and long lifecycles. The successful operation of EV is highly dependent on the operation of battery management system (BMS). State of charge (SOC) is one of the vital paraments of BMS which signifies the amount of charge left in a battery. A good estimation of SOC leads to long battery life and prevention of catastrophe from battery failure. Besides, an accurate and robust SOC estimation has great significance towards an efficient EV operation. However, SOC estimation is a complex process due to its dependency on various factors such as battery age, ambient temperature, and many unknown factors. This review presents the recent SOC estimation methods highlighting the model-based and data-driven approaches. Model-based methods attempt to model the battery behavior incorporating various factors into complex mathematical equations in order to accurately estimate the SOC while the data-driven methods adopt an approach of learning the battery's behavior by running complex algorithms with a large amount of measured battery data. The classifications of model-based and data-driven based SOC estimation are explained in terms of estimation model/algorithm, benefits, drawbacks, and estimation error. In addition, the review highlights many factors and challenges and delivers potential recommendations for the development of SOC estimation methods in EV applications. All the highlighted insights of this review will hopefully lead to increased efforts toward the enhancement of SOC estimation method of lithium-ion battery for the future high-tech EV applications.

INDEX TERMS State of charge, lithium-ion battery, electric vehicle, model-based approaches, data-driven approaches.

I. INTRODUCTION

The battery energy storage system (BESS) has been progressing speedily for the last decades due to the rapid growth of renewable energy-based power generation, development of smart grid technology, expansion of electric vehicle (EV) production and reduction of CO_2 emission [1], [2]. EVs are the growing technologies with the progress of BESS to substitute fossil fuels and mitigate carbon emissions [3]. Nevertheless, EV is facing challenges due to the short lifespan and slow charging process of BESS. Hence, the studies have been performed to develop a fast charging method of BESS based on advanced control theory [4], hierarchical navigation approach [5] and linear-quadratic strategies [6]. Furthermore, the researches are conducting extensively to enhance the energy capacity and extend the life cycles of BESS. The BESS systems are classified into various types according to their formations and composition materials [7]. The lithium-ion batteries (LIBs) are superior to other BESS with respect to power and energy, hence they are commonly used in EVs [8], [9]. Nevertheless, LIBs are costly, and they need proper safety mechanism to avoid an explosion. Presently, the investigations on LIB technology are progressing to fulfill the demand for future EVs [10]. Besides, the extensive

The associate editor coordinating the review of this manuscript and approving it for publication was Xiaosong Hu.

researches and developments are going on to decrease the production cost and enhance the longevity of LIBs [11].

The state-of-charge (SOC) describes the amount of energy left in BESS [12], [13]. SOC is not a physical quantity that can be measured directly. The SOC can only be estimated by measuring strongly correlated proxy quantities such as voltage, current, and temperature [14] and is usually expressed in a percentage in relation to the rated capacity. In the literature, SOC is defined as the ratio of the available amount of charge to the maximum amount of charge of the battery [15]. Equation (1) shows the mathematical definition of SOC.

$$SOC = \frac{Q_{available}}{Q_{rated}} \tag{1}$$

Despite the straightforward SOC definition expressed in (1), the accurate estimation of SOC for LIB is extremely non-trivial. The reason behind this is because of the rated capacity, Q_{rated} which does not reflect the true capacity of the battery as suggested by battery manufacturers [8]. To further complicate the situation, Q_{rated} is not constant throughout the battery lifespan as it changes depending on various factors such as the age of the battery, ambient temperature and the complex chemical reactions of the battery [16]. Furthermore, there are limited sensors such as amperometric sensor, potentiometric sensor and conductometric sensor that can directly measure the electrochemical phenomena in the battery [17]. Beyond that, mechanical factors such as manufacturing defects and physical damage in the assembly line are also notorious contributors [18]. Due to these various incalculable factors, high-accuracy SOC estimation remains a challenging problem to solve. Various solutions have been proposed to address the problem which will be fully discussed in the upcoming section.

A quintessential example of illustrating the benefits of an accurate SOC estimation can be seen in any battery management system (BMS). A BMS is an electronic system that manages a rechargeable battery pack by monitoring the states and parameters of the battery pack [19]. The example of battery states includes cell voltage, current, temperature, SOC, state of health (SOH), state of power (SOP) and so forth. Monitoring these states allow the BMS to make decisions such as when to charge the battery and when to trigger a cutoff to the battery usage to avoid hazardous operating conditions [20]. In this way, the BMS ensures that the battery and the end user is well protected from any harms. Figure 1 shows the block diagram of a typical BMS. Figure 2 illustrates the role of SOC estimation in a BMS.

SOC estimation is a fundamental component in a BMS that influences a host of other functions. The SOC value acts as an input for other calculations such as SOH, cell balancing and power calculations. In essence, accurate estimation of battery SOC would provide a concrete idea to the researchers and manufacturers on the advancement for the future development of EV such as [21].

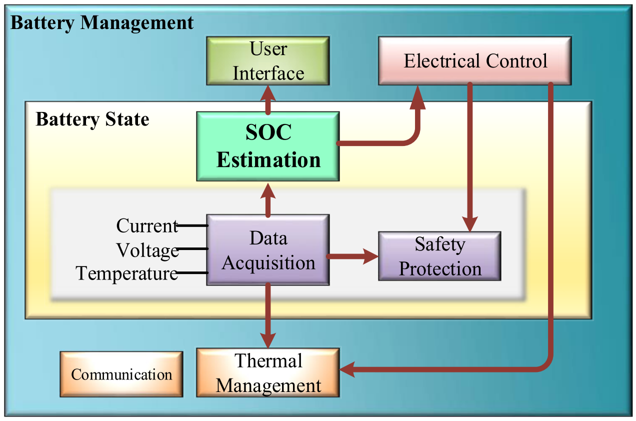


FIGURE 1. Block diagram of a battery management system [22].

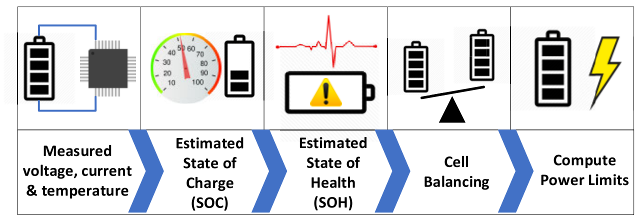


FIGURE 2. SOC estimation in BMS [21].

- Enhances the longevity of the battery pack. A BMS with an accurate SOC estimate can prevent damage to the battery pack by triggering cutoff under precise conditions.
- Increases the performance of the battery pack. A BMS with an accurate SOC estimate can maximize the full potential of the battery pack capacity.
- Ensures the greater power system reliability of any battery-operated device.
- Improves the battery power density in battery packs. The accurate SOC estimation allows battery packs to be designed accurately without being over-engineered which can result in smaller and denser battery packs.
- Achieves cost savings in smaller battery packs.

Many past studies have been performed to shed light on improving SOC estimation accuracy. Various models such as electrochemical model (EM) [23], equivalent circuit model (ECM) [24], electrochemical impedance model (EIM) [25] have been proposed to improve estimation accuracy. These methods attempt to model the behaviors of batteries by considering the stated factors in hopes of obtaining a precise SOC estimation. Despite that, the problem remains unresolved. Modeling a battery considering all possible factors may be infeasible due to the complex non- linearity, and time-variability of the system. Authors in [26] even suggested that the internal complex electrochemical processes in batteries are physically difficult to monitor by any direct measurement. Therefore, a prognostic battery model is developed by examining the critical variables including current (I), voltage (V), battery temperature (T), and operation time (t) from a designated experiment cycle. This approach can deliver accurate information on battery health status; however, has drawbacks on online execution. Furthermore, it is also possible that there are too many external uncertainties in the ambient environment (temperature, pressure, etc) that alter the internal electrochemical behaviors of the battery. Due to the aforementioned reasons, data-driven based SOC estimation approaches have received massive attraction since they have excellent computational capability to handle any complex nonlinear functions [27].

A small number of notable articles have been published to determine SOC of LIB in recent years. Authors in [28] suggested that there are four general methodologies in the literature used to estimate SOC for EV batteries. Each SOC method is explored with documented advantages and drawbacks. Although the authors presented a deep analysis of model-based approaches, data-driven based methods have not been reported extensively. Authors in [29] discussed the SOC estimation methods with merits, demerits, estimation error, issues, and challenges. However, the execution of the algorithms has not been explored in detail. A review by Zhang et al. [30] deals with the detail explanation of model-based SOC estimation methods to evaluate SOC of LIB. The review has highlighted a few common data-driven approaches with issues and challenges which have already been studied by Hannan et al. [29]. Authors in [31] presented an in-depth literature review of SOC estimation for LIB focusing on the estimation error, benefits, and weaknesses. However, the author did not provide any mathematical representation/flowchart/block diagram for the SOC algorithm implementation. Therefore, the main contribution of this study is the comprehensive explanation and implementation process of model-based SOC estimation approaches of LIB. In addition, this work proceeds to review the most recent and prominent data-driven methods for SOC evaluation. In line with that, this study dives deeper to explore the current issues and challenges. The information of this review will be valuable to the academic researcher and automotive engineers towards the selection of appropriate SOC estimation method which is significant for the enhancement of BMS for future EV applications.

II. LITHIUM-ION BATTERY CHARACTERISTIC

LIB has gained huge attention in research communities and automobile industries due to its high energy density, low self-discharge rate, high voltage, long lifespan, high reliability and fast recharging characteristics [32]. Figure 3 compares the different BESS where LIB is dominant with regard to specific power (W/kg) and specific energy (Wh/kg). Besides, the performance comparative analysis between LIB and other EV batteries in terms of nominal voltage, life cycle, depth of discharge and efficiency demonstrates that LIB appears to be a better choice for EV application, as shown in Fig. 4.

These lucrative properties of LIB have brought in many applications such as portable electronics, EVs, military, and even aerospace applications. Despite these attractive qualities, LIBs can prove hazardous since they contain

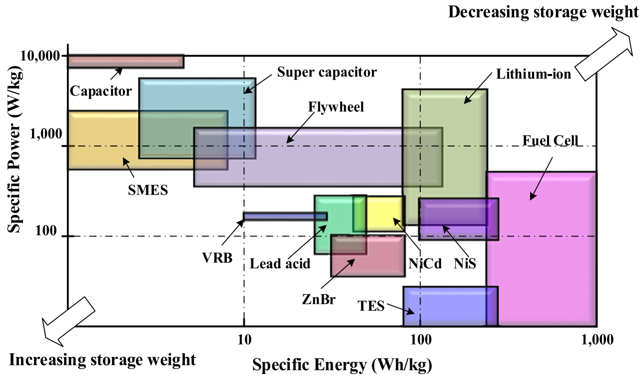


FIGURE 3. **Specific energy and power comparison among BESS [33] Acronyms: SMES (superconducting magnetic energy storage), VRB (vanadium redox battery), ZnBr (zinc-bromine battery), NaS (sodium sulphur), TES (thermal energy storage).**

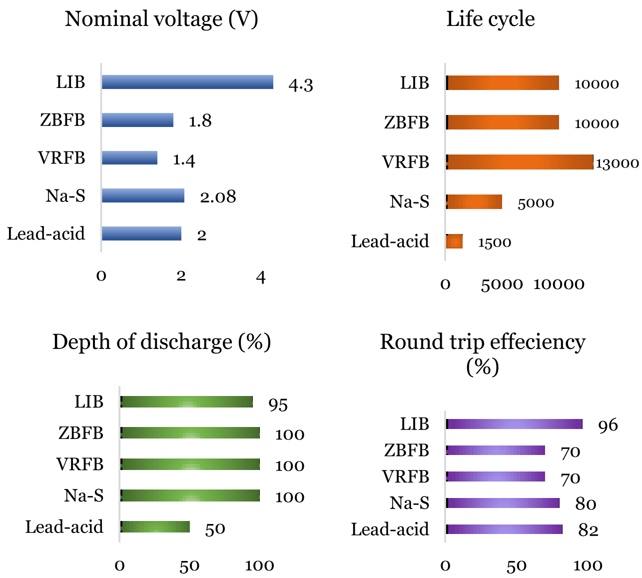


FIGURE 4. **Characteristics of different EV batteries [31].**

pressurized, flammable liquid electrolyte [34]. Under the right circumstances, LIB may cause explosions and fires even in a relatively small LIB package [35]. For instance, overcharging a LIB may lead to thermal runaways which could lead to leakage and explosions [16]. On the other hand, overdischarging a LIB may damage the battery beyond recovery and may induce premature aging [36]. In order to ensure the safe charging and discharging operation of LIBs, it is imperative that the SOC of the LIB is known at all times. An accurate SOC estimation enables the cut-off circuitry to disconnect LIB when it is out of the safe operating situation as well as triggers battery charging under optimal conditions. This confirms the fully utilization of the maximum potential of LIBs [37].

III. OVERVIEW OF MODEL-BASED AND DATA-DRIVEN METHOD

There exist two established decision-making paradigms to evaluate SOC; model-based and data-driven methods [30], [31], [38]. The model-based SOC estimation approaches (also known as the white-box models) are designed using the knowledge of the background processes. The model-based method is known as the conventional approach which can solve many problems especially in the engineering domain [39]. This approach often involves the practitioner to have a deep understanding of the system or process in order to construct the robust rules that can model the behavior of the system accurately [40]. The model-based SOC estimation approaches can be extremely powerful and accurate due to the reliance on a deep understanding of the system. Many problems in the domain of engineering and physics depend on a model-based approach. For example, modeling the gravitational force of the earth, modeling the trajectory of a projectile, etc. However, there are both practical and theoretical concerns towards obtaining the perfect model of any system [41]. On the practical side, the development of a robust SOC estimation model that could best describe a system typically requires a lengthy amount of time, laborious experiments and extensive research of the system by domain experts. On a theoretical point of view, the model-based SOC estimation methods need the extent of theoretical understanding of the system. For example, Li et al. [42] designed a simplified electrochemical model of LIB by integrating many physics including open-circuit voltage, solid-phase, liquid-phase diffusion, reaction polarization, and ohmic polarization. Each physics of the stated model is composed of many complex mathematical equations which make it hard to determine the battery parameters. Afterwards, a functional relationship is developed between stoichiometric numbers of electrodes and SOC. To conclude, a limited prior knowledge on the system inevitably leads to poor model design. Hence, it is imperative that domain experts understand multiple aspects of the system such as the mechanical, electrical, electronic, chemical and other details to develop a robust model.

On the other hand, the data-driven based SOC estimation are relatively new approaches enabled by the advent of big quantity of data and powerful computers. The data-driven methods (also known as black-box models) are built upon empirical observations with minimal or no knowledge of the background processes [43]. The data-driven approach relies extensively on analyzing data from the process; thus, it does not require practitioners to develop a deep, domain-specific understanding of the background process [44]. This approach may be useful to develop a SOC estimation model with limited prior information about battery internal characteristics and chemical reactions. In this light, the data-driven approach requires lesser time and knowledge to model a complex system compared to the model-based approach. For instance, long short term memory network (LSTM) has faster convergence to the true SOC in comparison to unscented Kalman filter (UKF) in case of inaccurate initial SOC, having root mean square error (RMSE) and mean absolute error (MAE) under 2% and 1%, respectively [45]. In addition, LSTM can examine SOC precisely by only monitoring battery measurements such as current, voltage and temperature, hence does not require information about battery internal chemistry, complex reactions, and model parameters estimation [46]. However, the heavy dependence of data-driven methods on the data implies that the quality of the data largely determines the accuracy and performance of the model. For example, the unbalanced data would cause a model to be subjected to bias in decision making (also known as overfitting and underfitting) [47]. These issues are well-addressed and the researchers have developed general guidelines to address the problem [48]. In essence, a data-driven approach would work effectively if a large number of appropriate data is readily available. However, the data-driven approach would not offer many benefits in the absence of these data. Table 1 highlights the main benefits and drawbacks of both model-based and data-driven method.

TABLE 1. The pros and cons of model-based and data-driven method.

Method	Advantages	Disadvantages
Model-based method	▪ Reliable and accurate ▪ Has universal validity.	▪ Requires extensive domain knowledge. ▪ Needs relatively longer development time.
Data-driven method	▪ Has shorter development time ▪ Does not require extensive domain knowledge	▪ Requires large amount of data. ▪ Unpredictable black box model.

The upcoming section reviews some of the most recent and prominent SOC estimation methods.

IV. SOC ESTIMATION METHODS

Based on recent published articles on SOC estimation, this review divides the SOC estimation methods into five groups namely; look-up table method, coulomb counting method, model-based estimation methods, data-driven estimation methods, and hybrid method, as shown in Fig. 5. Each category adopts different approaches to evaluate the performance of SOC. In this section, we provide a brief conceptual overview of each category.

A. LOOK-UP TABLE METHOD

The look-up table method exploits the direct mapping relationship between SOC and the external characteristics parameters such as the open-circuit voltage (OCV), impedance, etc. This method involves the tabulation of the relationship by running intensive experiments in the laboratory to characterize the behaviors of the battery [49]. The OCV look-up table method is simple in concept and is very accurate [50]. The flowchart of OCV based SOC estimation method is shown in Fig. 6 [31]. At first, LIB is completely charged for a fixed interval to reach depolarization phase. After, LIB is fully discharged using current pulses. Then, the battery is kept in rest for a fixed duration and corresponding OCV of LIB is measured. Following that, the relation between the OCV and the SOC is mapped. The similar process is followed to

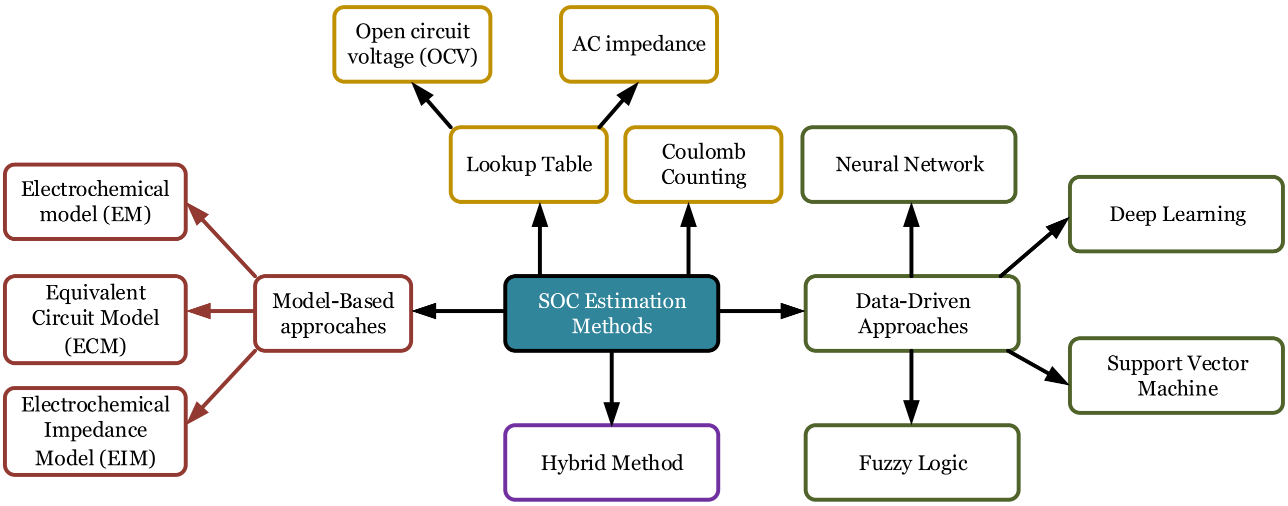


FIGURE 5. Classification of SOC estimation method.

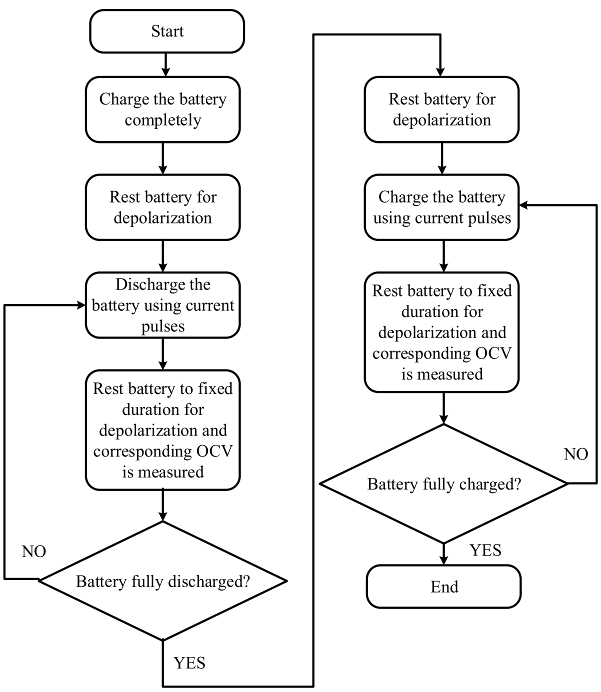


FIGURE 6. The flowchart of OCV-SOC estimation method [31].

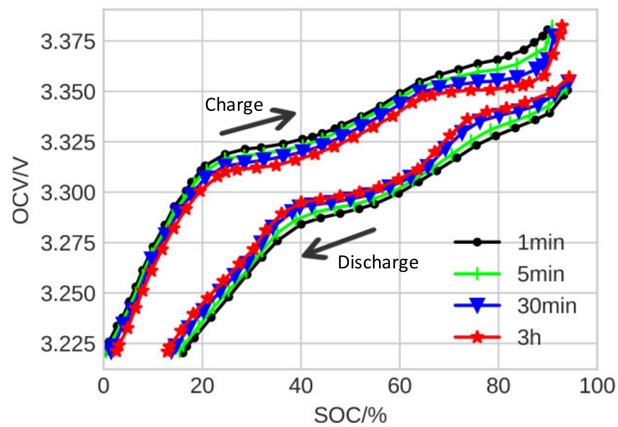


FIGURE 7. OCV- SOC curve for $LiFePO_4$ cell at different rest periods [52].

monitor OCV during the charging stage. Once the look-up table is established, measuring the instantaneous OCV of the LIB gives the SOC level.

Usually, higher voltage values are observed in LIB during charging compared to the values obtained during discharging, as shown in Fig. 7. The consequence is identified as hysteresis which is occurred due to ohmic resistance, polarization resistance, electrochemical polarization, and concentration polarization. Besides, the energy dissipation in the electrode during the phase transition may offer a hysteresis effect [51]. In $LiFePO_4$ cell, the developments of intercalation and deintercalation help the material particles to make interaction with lithium ions which in turn exhibits hysteresis characteristics [52]. While this method is fairly accurate, there is a major drawback. In order to accurately measure the OCV of LIB, it is imperative that the LIB is given a sufficient amount of rest time to reach an equilibrium condition. Measuring the OCV while the battery is in operation results in poor accuracy [29]. Apart from that, the OCV measurements are also influenced by other factors such as ambient temperature and aging of the battery [53].

The alternating current (AC) impedance methods is another technique under the look-up table category. The lithium-ion battery impedance look-up table is shown Table 2. The impedance parameters of LIBs are determined using the equivalent circuit along with the experimental impedance spectrum and non-linear least squares (NLLS) fitting procedure. The equivalent circuit is designed using the inductance (L) and a resistance (R_L) connected in parallel. The R_Ω stands for the ohmic resistance of the cell. A constant phase element (CPE) is characterized by Q_1 connected in parallel with a resistance R_1. Reaction resistance and

TABLE 2. Impedance parameters with regard to SOC for Lithium-Ion battery.

	SOC							
	0	**0.09**	**0.14**	**0.28**	**0.34**	**0.42**	**0.56**	**0.70**
Voltage (V)	6.09	6.38	6.73	7.25	7.39	7.57	7.81	7.94
R_L (Ω)	3.19	3.22	3.40	3.41	3.35	3.30	3.16	3.26
L (μH)	1.55	1.60	1.62	1.66	1.65	1.64	1.59	1.61
R_Ω (Ω)	0.27	0.27	0.26	0.26	0.25	0.25	0.25	0.25
R_1 (Ω)	0.13	0.14	0.14	0.22	0.26	0.24	0.21	0.21
Q_1 (Ω^{-1})	0.34	0.42	0.58	1.11	1.30	1.21	1.10	1.02
R_{ct} (Ω)	0.62	0.55	0.45	0.35	0.31	0.29	0.27	0.26
Q_2 (Ω^{-1})	0.62	0.62	0.61	0.65	0.65	0.66	0.65	0.65

capacitance contribution are denoted as R_{ct} and Q_2 respectively which may change with the electrode location, and thickness. In order to establish the impedance look-up table, the LIB is charged to a specified SOC value. Following that, the LIB is allowed 3 hours rest time before the AC impedance of the LIB is measured using an electrochemical impedance analyzer. The process is repeated at several SOC values to establish a look-up table [54].

The major drawback of look-up table methods is that they are only applicable when the battery is in the static state i.e. not subjected to any load and allowed sufficient rest time to achieve an equilibrium stage. Generally, the LIB is operated continuously in real-world applications outside of the laboratory environment. Hence, this approach may not be very feasible to estimate online SOC estimation.

B. COULOMB COUNTING METHOD

The coulomb counting method is by far the most extensively used method in SOC estimation [55], [56]. In this method, the SOC is estimated by measuring the discharging current of a battery and integrating them over time [57]. The SOC is calculated by the following equation,

$$SOC\,(t) = SOC_0\,(t_0) - \frac{\eta}{C_n}\int_{t_0}^{t} I\,(t)\,dt \qquad (2)$$

where, $SOC\,(t_0)$ is the initial state of charge, η denotes the coulombic efficiency, C_n represents rated capacity, $I\,(t)$ is the instantaneous discharge current of the battery.

The advantage of the coulomb counting method is its simplicity and stability [32]. This method is also fairly accurate under few circumstances, such as;

- The initial SOC of the battery must be known [28].
- The current sensors are accurately calibrated [29].
- The maximum available capacity of the battery must be properly re-calibrated under various operating conditions and aging levels of the battery [58].

Since this method is an open-loop algorithm, errors in the SOC estimation can be inevitable. A small error in measurement can be significant due to the cumulative effect as a result of the integration operation [59]. Thus, the initial value $SOC\,(t_0)$, and the current sensor also need to be accurate for the efficient operation of the algorithm [60]. Due to these shortcomings, the coulomb counting method is commonly used in combination with other methods such as model-based or data-driven methods to enhance the reliability.

C. MODEL-BASED SOC ESTIMATION METHODS

The model-based SOC estimation methods involve modeling of the electrical, chemical or a combination of both properties pertaining to a specific battery. The EM model based SOC estimation is based on the principles proposed in porous electrode theory [61]. The EM model relies on partial differential equations (PDE) to describe battery dynamics such as lithium diffusion and potential gradients. Figure 8 illustrates the schematic diagram of an EM model for LIB. EM method can be very accurate, nonetheless PDE computations can be expensive for real-time SOC estimation [62]. Hence, the researchers have reduced the PDE governing equations into lower order differential equations in order to facilitate the calculation complexity. The adaptive filtering algorithms have also been extensively used to estimate the lithium bulk and surface concentration [63].

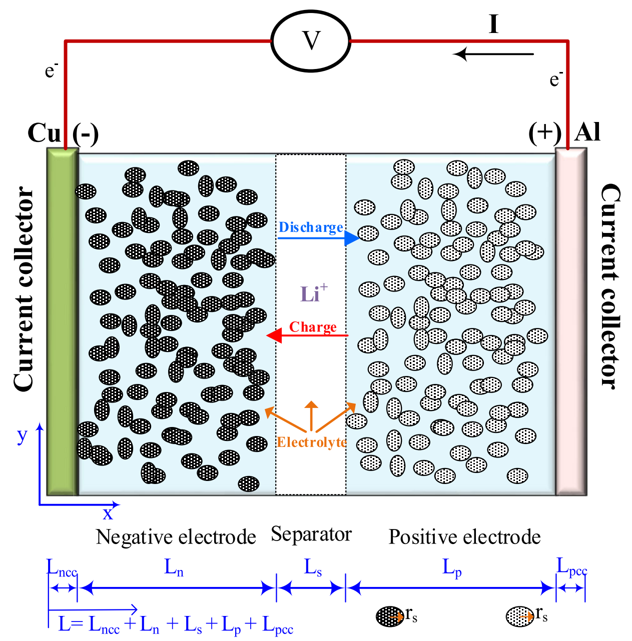


FIGURE 8. The schematic of an EM model of a LIB [64].

The ECM model based SOC evaluation requires the derivation of the circuit models consisting of various circuit elements arranged in series or parallel combination such that it replicates the dynamics of the battery. The various ECM models have been proposed including the Rint model, the RC model, and the Thevenin model [24]. The Thevenin model is used as typical ECM which is designed using one RC group, a resistance and voltage source, as depicted in Fig. 9 [65]. A considerable effort is often required to parameterize the ECM model in order to approximate the behavior of the battery [66]. ECM is computationally inexpensive and has

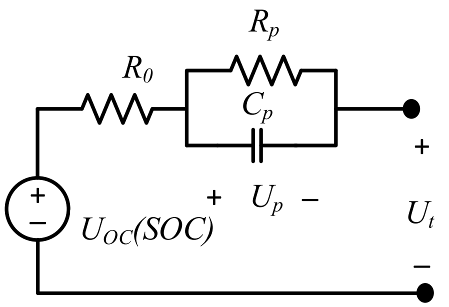


FIGURE 9. The schematic diagram of Thevenin equivalent circuit of LIB [68].

been used by researchers to estimate SOC in conjunction with adaptive filter algorithms such as the Kalman filter. [67].

The discrete form of equations can be formulated using the Thevenin equivalent circuit which can be expressed as,

$$\begin{cases} U_{P,k+1} = U_{P,k} exp\left(-\Delta T/\tau\right) + \left[1 - exp\left(-\Delta T/\tau\right) R_P I_k\right] \\ U_{t,k+1} = U_{OCV,k+1} + U_{P,k+1} + I_{k+1} R_0 \end{cases} \tag{3}$$

where U_{OCV}, U_t, and U_P denote the open circuit voltage, battery terminal voltage, and voltage drop across polarization resistance R_P, respectively. I represent the battery current. Accordingly, the state space function can be generated from the above equation,

$$\begin{cases} x\left(t\right) = \dot{A}x\left(t\right) + Du \\ y\left(t\right) = Cx\left(t\right) + Du + U_{OCV} \end{cases} \tag{4}$$

where, $A = \begin{bmatrix} \frac{1}{(R_P C_P)} & 0 \\ 0 & 0 \end{bmatrix}$, $B = \begin{bmatrix} \frac{1}{C_P} & \frac{1}{C_b} \end{bmatrix}^T$, $C = \begin{bmatrix} 1 & 0 \end{bmatrix}$, $D = R_0$ and $u = 1$

The constant discharge test is performed to effectively determine the battery model parameters through forgetting factor recursive least squares (FFRLS) algorithm [69]. By this way, the dynamic performance of the battery is captured and subsequently, the OCV response with respect to SOC can be quantified. Authors in [70] developed a fifth-order polynomial equation to characterize the relationship between OCV and SOC, as shown in the following equation,

$$\begin{aligned} U_{OC}\left(SOC\right) = {} & 3.083 + 4.859 \times SOC - 18.21 \times SOC^2 \\ & + 38.56 \times SOC^3 - 38.64 \times SOC^4 \\ & + 14.58 \times SOC^5 \end{aligned} \tag{5}$$

In many works, the model-based methods are used in conjunction with adaptive filters and state estimation algorithms. The most prominent algorithms include Kalman filters and its variants [15], [71]–[73], Particle filter [74]–[76], H∞ filter [67], [77], [78], Luenberger observer [79]–[81], proportion integration (PI) observer [82], [83], sliding-mode observer [84]–[87]. In [88], the adaptive extended Kalman filter (AEKF) is employed to improve the performance of Kalman filters in SoC estimation, as illustrated in Fig. 10. Firstly, the implementation process of the AEKF based SOC estimation model is established. Secondly, an online OCV estimation approach with the AEKF algorithm is developed to obtain the SOC by using OCV-SoC look-up table. Thirdly, a robust online model-based SOC estimation approach is proposed with the AEKF algorithm. Finally, the proposed model is validated by the experimental approach. The results indicate that the proposed online SOC estimation algorithm performs satisfactorily with the maximum SOC error under 2%. The parameter details shown in (6)-(14) can be found in [88].

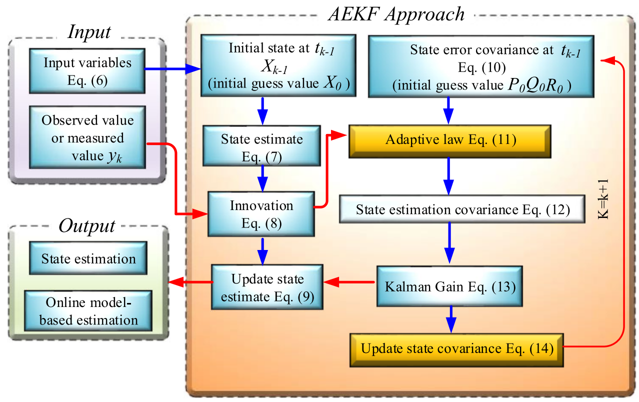


FIGURE 10. The flowchart of AEKF algorithm for SOC estimation [88].

$$\begin{cases} \dot{x} = f(x, u) + w \\ y = g(x, u) + v \end{cases} \tag{6}$$

$$\hat{x}_k^- = x_{k-1} + \dot{x}_{k-1} T_s \tag{7}$$

$$e_k = y_k - g(\hat{x}_k^-, u_k) \tag{8}$$

$$\hat{x}_k^+ = \hat{x}_k^- + K_k e_k \tag{9}$$

$$P_{k-1}, \quad Q_{k-1}, \ R_{k-1} \tag{10}$$

$$H_k = \frac{1}{M} \sum_{i=k-M+1}^{k} e_k e_k^T, \quad R_k = H_k - C_k P_k^- C_k^T \tag{11}$$

$$P_k^- = (I + A_k \Delta t) P_{k-1} (I + A_k \Delta t)^T + Q_k \tag{12}$$

$$K_k = P_k^- C_k^T (C_k P_k^- C_k^T + R_k)^{-1} \tag{13}$$

$$\begin{cases} Q_k = Q_k H_k K_k^T \\ P_k^+ = (I - K_k C_k) P_k^- (I - K_k C_k)^T + K_k R_k K_k^T \end{cases} \tag{14}$$

A double-scale dual adaptive particle filter (D-APF) based SOC estimation method is proposed in [89] to improve the accuracy of SOC and reduce the computational cost, as shown in Fig. 11. At first, the Thevenin circuit is utilized to design a battery model. Secondly, the battery parameters and SOC are assessed using the double-scale D-APF. The method is validated by different experiments under different battery types, and aging cycles. The results are excellent in achieving low SOC error being less than 1%. The parameters expressed in (15) and (16) are elaborated in [89].

$$\hat{x}_k = \sum_{i=1}^{N} m_{1,k}^i . x_k \tag{15}$$

$$\hat{\theta}_l = \sum_{j=1}^{M} m_{2,i}^j . \theta_l^j \tag{16}$$

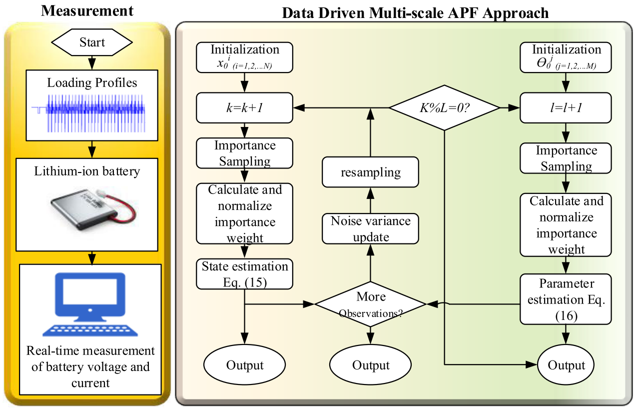


FIGURE 11. The implementation process of double-scale D-APF estimator [89].

In [90], H∞ filter based SOC estimation for LIB pack in EV applications is suggested, as shown in Fig. 12. Firstly, a commonly used ECM is used, and accordingly, the parameters of the model are determined. On this basis, the H∞ filter based on game theory is developed. The robustness of the proposed model is verified under random noise, bias noise, initial SOC error and EV drive cycles. The results are excellent in terms of mean absolute error (MAE), maximum SOC error and computational cost. The parameters characterization depicted in Fig. 12 can be found in [90].

Input	Current u_k, terminal voltage y_k, at each time, initial SOC x_0 $L=[1\ 0\ 0]$ Weighting matrices: S_k, P_0, W_k, V_k $k=0$
Estimation process	Step 1: Determine $\overline{S_k}$ $\overline{S_k} = L_k^T S_k L_k$ Step 2: Linearization of C_k $C_k = \left[\frac{\mathrm{d}U_{OC}(SOC)}{\mathrm{d}\,SOC}\right]_{SOC=S\hat{O}C} \quad -1 \quad -1$ Step 3: Find gain matrix K_k $K_K = AP_K[I - \theta\overline{S_k}P_K + C_k^T V_k^{-1} C_k P_k]^{-1} C_k^T V_k^{-1}$ Step 4: Calculate the estimation of y_k $\hat{y}_k = U_{OC}(\hat{x}_k, 1) - \hat{x}_{k,2} - \hat{x}_{k,3} - Du_k$ Step 5: State estimation at time $k+1$ $\hat{x}_{k+1} = A\hat{x}_k + Bu_k + K_k(y_k - \hat{y}_k)$ Step 6: Update covariance matrix $P_{k+1} = AP_K[I - \theta\overline{S_k}P_K + C_k^T V_k^{-1} C_k P_k]^{-1} A^T + BQ_k B^T$ Step 7: Output SOC estimation at time $k+1$ $S\hat{O}C_{k+1} = L_{k+1}x_{k+1}$ Step 8: Update time $k = k+1$
Output	$SOC(k) = S\hat{O}C(k)$

FIGURE 12. H∞ filter algorithm for SOC estimation [90].

A work in [91] proposes a novel observer-based SOC estimation method for LIB, as depicted in Fig. 13. The method is derived from second-order ECM and does not need any matrix calculation. The performance of the proposed method is evaluated under Federal Urban Driving Schedule (FUDS), and the New European Driving Cycle (NEDC). Furthermore, the noise effects and parameters disturbances are employed to check the method robustness. The experiment results

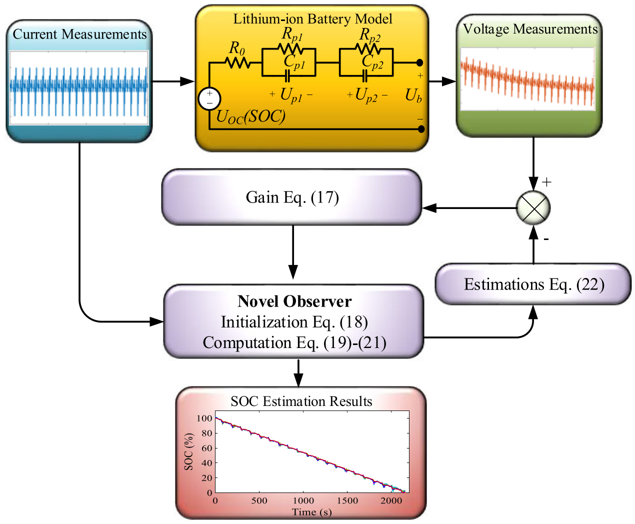


FIGURE 13. The schematic diagram of observer-based SOC estimation [91].

demonstrate the superiority of the proposed method with MAE below 1% and 2% in voltage noise and current noise, respectively. The parameter descriptions expressed in (17)-(22) can be found in [91].

$$c(k) = c_0 + \alpha\, exp(\beta U_L(k-1) - \hat{U}_L(k-1)) \quad (17)$$

$$\hat{U}_1(0) = 0, \quad \hat{U}_2(0) = 0, \; SoC(0) = SoC_{init} \quad (18)$$

$$\hat{U}_1(k+1) = (1 - \frac{T_s}{R_1C_1})\hat{U}_1(k) + \frac{T_s}{C_1}I_t(k) \quad (19)$$

$$\hat{U}_1(k+1) = (1 - \frac{T_s}{R_1C_1})\hat{U}_1(k) + \frac{T_s}{C_1}I_t(k) \quad (20)$$

$$\hat{S}oC(k+1) = \hat{S}oC(k+1) - \frac{T_s}{Q_N})I_t(k) + c(k)(U_l(k) - \hat{U}_l(k)) \quad (21)$$

$$\hat{U}_L(k) = g(\hat{S}oC(k)) - \hat{U}_1(k) - \hat{U}_2(k) - I_t(k)R_o \quad (22)$$

The EIM based SOC assessment includes more parameters on top of resistance, capacitor and voltage sources, and porous electrode theory by adding Warburg element, constant phase element, and Z_{arc} element into the model [92]. The EIM method consists of the EC model, incorporating the Z_{arc} and Warburg element. Figure 14 shows a basic schematic diagram of the EIM. The electrochemical impedance spectroscopy (EIS) allows researchers to peek deeper into the inner dynamics of the battery at different time scales. EIS allows for the estimation of the battery impedance using inductances and capacitances over a wide range of frequencies [93]. EIM has been shown to yield good results with low computational cost with a proper electrochemical model.

The advantage of model-based estimation is the precise SOC estimation provided that the battery is modeled accurately. This has been proven in [95] where EIM is combined with EKF to evaluate SOC for LIB. Some researchers also reported that model-based SOC estimation yields good real-time performance with robust closed-loop control and

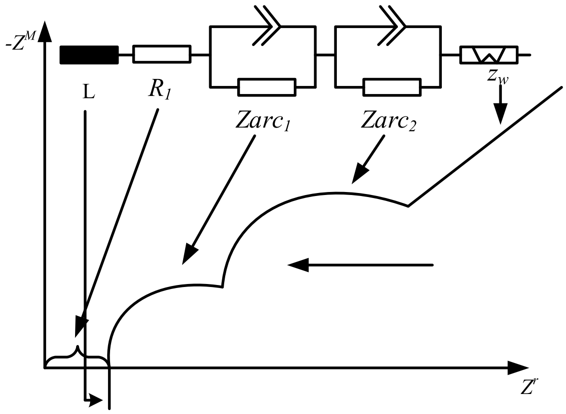


FIGURE 14. The schematic diagram of the EIM [94].

high adaptability [96]. A major drawback of the model-based SOC estimation is modeling complexity. In order to model a battery accurately, researchers often need to have a battery-specific, in-depth understanding of the electrochemical properties [97]. Secondly, model-based method may be very time consuming. For instance, the ECM method relies on the capacitance and resistance that are based on the SOC, current and/or temperature. This requires a large number of experiments to map the relationship of one parameter to another [28]. Finally, it is very challenging to identify all the significant parameters that constitute a good model. For instance, the additional elements such as resistor-capacitor pair or Warburg element may be added to improve the model accuracy for some batteries [98]. More often than not, the process of establishing a good model is laborious, time-consuming and requires in-depth priori knowledge. Therefore, the model-based approach is not always practical to implement on all types of battery.

D. DATA-DRIVEN SOC ESTIMATION METHODS

The data-driven SOC estimation techniques can estimate SOC accurately by measuring battery parameters including current, voltage and temperature, thus battery model, added filter used in the model-based approaches can be avoided [99]. Besides, the network parameters of data-driven methods are determined by the self-learning algorithm [100]. The process is completely different from model-based estimation techniques where human expertise and substantial time are needed for parameters estimation. The data-driven approaches often require the use of machine learning (ML) platform in order to obtain relationship and rules from the data [101]. Today, ML algorithms are being implemented in various fields from medical diagnosis [102], stock trading [103], robotics [104], psychology [105], mastering board games [106], law [107] and etc. achieving on-par or in some cases super-human performance. There is no exception to the field of battery research [101]. The idea of using ML algorithms to estimate battery states has been around since the past decade. This section describes in detail on some of the most prominent data-driven approaches for SOC estimation of LIBs. Throughout the literature, there exist a few established collections of the battery-related dataset published by different research groups. Table 3 tabulates the collection of available datasets for SOC estimation.

TABLE 3. Available dataset for SOC estimation.

Institution	Dataset Description
Center for Advanced Life Cycle Engineering (CALCE), University of Maryland	Low Current OCV Test, Incremental Current OCV and Dynamic Test Profiles (DST, FUDS, US06 and BJDST) at various temperatures [108]
Department of Automation, University of Science and Technology of China	Constant Current and DST at room temperature [109] Experimental data of LIB and ultracapacitor under DST and UDDS profiles at room temperature [110]
National Aeronautics and Space Administration (NASA)	Predicting Battery Life for Electric unmanned aerial vehicles (UAVs) [111]
SGT, Inc., NASA Ames Research Center, United States	Randomized Battery Usage Data Set [112]
McMaster Institute for Automotive Research and Technology	Panasonic 18650PF Li-ion Battery Data [46], [99]

This section elaborates some of the most recent data-driven models employed to estimate SOC for LIBs.

1) NEURAL NETWORK METHOD

The basic structure of a neural network (NN) consists of a three-layer formation as shown in Fig. 15. The input layer takes the vector of instantaneous current, voltage and temperature values. The output layer is the instantaneous SOC value. By training the NN with the input-output pairs, it is

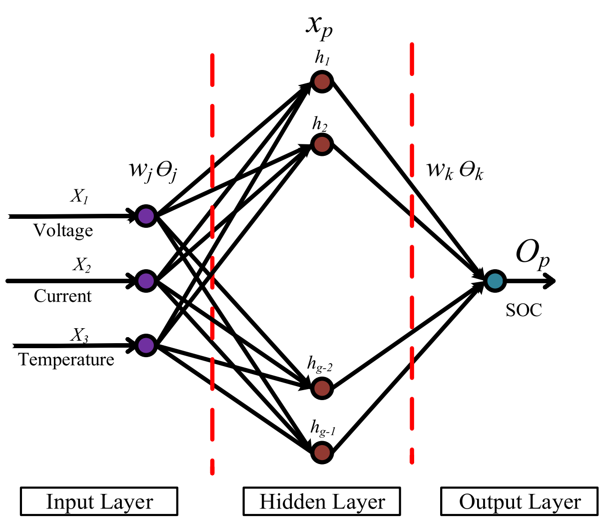


FIGURE 15. The general architecture of the 3-layer neural network for SOC estimation [113].

able to form a non-linear map that accurately models the input-output relationship without any prior knowledge of the internal structure of the battery [113]. The relationship between the input layer and the output layer is developed using suitable number hidden layers, hidden neurons, and activation function. SOC in the output layer can be expressed by,

$$SOC_i = f_i \left\{ \sum_k W_{j,k} O_j + \theta_{j,k} \right\} \tag{23}$$

where $W_{j,k}$, $\theta_{j,k}$ denote the weight and bias from the hidden layer to the output layer, respectively. O_j is the output of the hidden layer, and f_i represents the activation function.

According to the universal approximation theorem, a feed-forward NN with a single hidden layer is capable of approximating any continuous functions [114]. This property of NN has been exploited by researchers to solve many non-linear mapping problems in various fields that are too complex to model mathematically [115], [116]. Various configurations of NN are reported in the literature including back propagation neural network (BPNN), radial basis function neural network (RBFNN), Recurrent neural network (RNN), wavelet neural network (WNN). However, the fundamental working concept of these variations remains similar.

NN has been a popular method in many recent works. Tong et al. [117] proposed NN model for SOC estimation in three operation mood; idle, charge and discharge. US06 drive cycle is used for model training while the pulse test is used for model validation. The proposed model achieves average SOC error of 3.8% which outperforms other NN models. Kang et al. [118] suggested RBFNN model to estimate SOC under temperature, EV drive cycles and aging effects. The model is tested on 6 Ah LIB and reported mean absolute error (MAE) under 5%. In [119], RNN based SOC estimation model is evaluated for LIBs under pulse current loads and temperatures. The model obtains lower RMSE and high execution time compared to multilayer perceptron NN method. Cui et al. [120] developed an intelligent SOC estimation model using WNN for LIB. The model is proven effective in achieving MAE and maximum SOC error of 0.59% and 3.13%, respectively under NEDC.

2) DEEP LEARNING METHOD

Deep learning (DL) has been making great strides in many software disciplines including computer vision, speech processing, natural language processing, robotics, bioinformatics, chemistry, video games, search engines, online advertising, and finance to name a few [121]. The term deep lies in the number of computational layers in the neural network [83]. It is still an ongoing debate on the true definition of deep learning. However, it is a widely accepted notion that any neural network with more than two hidden layers is considered a deep network. Riding on this premise, this study proceeds to categorize neural networks with more than two hidden layers as DL methods.

At the present time, there exists a number of common DL network architectures. Among the notable ones are deep neural network (DNN), deep convolution neural network (DCNN), deep recurrent neural network (DRNN), LSTM and many more [121]. These architectures have distinct advantages and drawbacks depending on the application domain. For example, DCNN is extremely effective for image-related problems such as face recognition [122], traffic sign identification [123], cancer cells detection from medical scans [124]. On the other hand, DRNN and LSTM, are usually used in problems related to sequential data such as speech recognition [125], machine translation [126] or time series prediction [127].

To date, the use of DL methods in battery-related research is still very limited. To the best of the authors' knowledge, deep learning methods have been applied to battery prognostic and health management concerning SOH and remaining useful life (RUL) prediction [128]–[131] However, in the field of SOC estimation, there are very few established works. One study by Chemali et al. [46] has shed some light on the possibility of using DL in estimating SOC. In their work, the authors used a deep learning architecture known as the LSTM to estimate SOC of LIBs. The network can accurately predict SOC values with MAE 0.573% on fixed temperature. The authors go further by testing the network on a dataset that is different from the training set in ambient temperature. The LSTM network achieves MAE of 1.606%. In [45], LSTM algorithm based SOC estimation method is developed for LIB. The robustness of the proposed method is validated by different EV drive cycles. The results of SOC are compared with a model-based approach where LSTM shows better tracking performance with RMSE under 2% and SOC error within 1%. Another work by Chemali et al. [99] attempts to estimate the SOC of LIB using deep neural network (DNN). In this work [99], DNN model is established using an input layer, two or more hidden layers and one output layer, as shown in Fig. 16. The authors reported the lowest MAE of 1.10% validated over a variety of dataset. The input nodes consist of the instantaneous voltage and current as well as the average voltage and current over a time window. The output

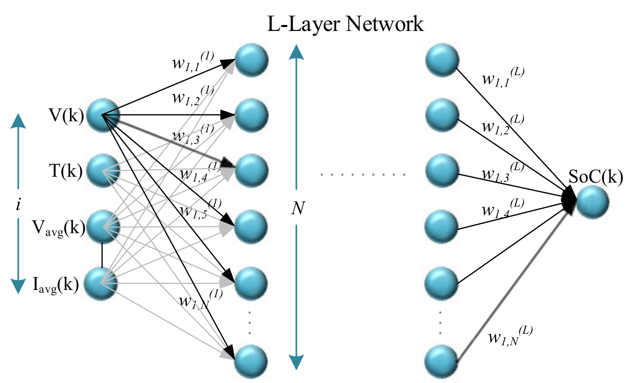


FIGURE 16. Deep learning network architecture for SOC estimation [99].

node is the estimated SOC at time k. L denotes the number of layers in the model. N denotes the number of neurons in a layer.

In [132], deep belief network (DBN) algorithm is proposed to examined SOC for LIB under dynamic load conditions. The proposed method achieves satisfactory results with average SOC error being less than 2.2%. In [133], a recurrent neural network with the gated recurrent unit (GRU) is established to evaluate SOC for LIB. The ensemble optimization method based on Nadam and AdaMAx optimizer is used to improve the training operation and determine the optimal parameters. The effectiveness of the proposed method is verified by different dynamic load profiles. The developed model shows superior performance in reducing data training duration and increasing accuracy. The summary of deep learning based SOC estimation results is shown in Table 4.

TABLE 4. Deep learning frameworks used for SOC estimation.

Method	Battery	Inputs	Configuration	Error
DNN [99]	2.9Ah Panasonic NCR18650PF	V(k), I(k), V_{avg}, I_{avg}	4 hidden layers 50 hidden neurons	MAE 0.61% RMSE 0.78%
LSTM [46]	2.9Ah Panasonic NCR18650PF	V(k), I(k), T(k)	500 hidden neurons	MAE 0.573%
GRU [133]	2.3 Ah 26650 $LiFePO_4$	V(k), I(k), T(k)	260 GRU unit 230 Batch size	RMSE 1.13% MAE 0.84%
DBN [132]	2.2 Ah NCM18650	V(k), I(k) T(k), SOC(k-1)	3 hidden layers	RMSE < 0.7% MAE < 0.57%

3) SUPPORT VECTOR MACHINE

Support vector machine (SVM) is a technique in ML often employed to solve tasks revolving classification and regression. An SVM attempts to construct hyperplanes in high dimensional space in order to separate data of one class from another. An optimal separation boundary is achieved when the distance from the hyperplane to the nearest data point of any class is maximized [134]. Figure 17 illustrates an example of hyperplane to separate distinct classes.

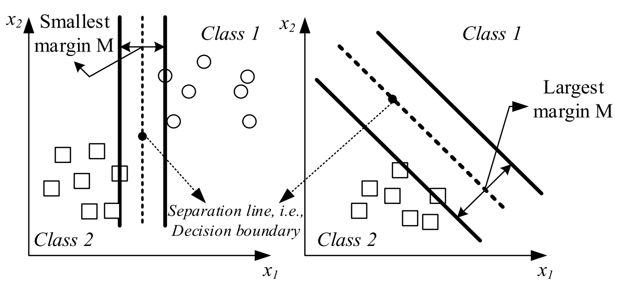


FIGURE 17. SVM algorithm attempts to construct hyperplane(s) that separates one class from another such that separation margin is the largest. The image on the right shows a large separation margin, M than the image on the left [139].

Anton et al. in [135], [136] explored support vector regression (SVR) to predict SOC of LIB as a function of cell current, voltage, and temperature. The authors derived static dataset and DST cycle from LIB. They trained the SVM with RBF kernel to predict SOC values with 10- fold cross-validation. They have reported RMSE of less than 0.71% on the same dataset. Hu et al. [137] examined SOC for BMS using SVR with RBF kernel. The authors used double-step search technique to expedite the training process and search for the optimal parameters of SVR. The method showed better accuracy than different NN models under diversified EV drive cycles. In [138], authors trained a weighted least squares support vector machine (WLS-SVM) to predict SOC from voltage, current, and temperature. The authors reported an improvement in robustness with less complex computation compared to other SVM models.

4) FUZZY LOGIC METHOD

Fuzzy Logic (FL) is a computing approach that offers flexibility in a statement. This approach facilitates the concept of partial truth, where the truth value may range from completely true, partially true, to completely false depending on the value it takes from 0 to 1 [140]. Instead of the conventional two-valued true or false logic, FL introduces the concept of many-valued logic. FL interface system is structured using fuzzification, fuzzy rule base, inference engine, and defuzzification [141]. There exist a few studies involving FL to estimate SOC. In [142], the authors proposed the use of FL with SVM to predict SOC of a LIB pack used in EV. Authors reported an improvement on SOC estimation accuracy and noise immunity compared to NN and common SVR models. Li et al. [143] developed fuzzy adaptive forgetting factor based strong tracking adaptive unscented Kalman filter (ST-AUKF) algorithm to estimate SOC. The fuzzy adaptive forgetting factor is employed to update battery model parameters. The proposed model shows superior performance against the unknown initial SOC and voltage sensor drift and can provide better results in comparison with tradition UKF method with respect to accuracy, robustness and convergence speed. Singh et al. [144] built a fuzzy logic based SOC estimation model by analyzing the data of impedance and voltage. The proposed model is implemented in a Motorola MC68HC12 microcontroller and achieves an average SOC error of 2 %. Salkind et al. [141] determined SOC using fuzzy logic with impedance spectroscopy data. The developed model is executed using Motorola 68HC11 microcontroller, LM35CZ temperature sensor, current sensor and analog-to-digital converter. The hardware is tested with LIBs and the error range is restricted under 5%.

Adaptive neuro-fuzzy inference system (ANFIS) is an improved algorithm with combines NN learning method and fuzzy inference system without the requirement of detail battery model. ANFIS is very powerful in mapping, modeling, decision making, signal processing and optimization [145]. Zahid et al. [146] developed ANFIS based SOC estimation model using six inputs including current, temperature, actual power loss, available and requested power, cooling air temperature and battery thermal factor. The training and testing results are evaluated under 10 different drive cycles.

The results demonstrate that the ANFIS model is dominant to BPNN and Elman neural network with SOC error below 1% in diversified drive cycles. In [147], ANFIS model is built with current, voltage, capacity and temperature to determine SOC for LIB. The average percentage error is reported to be only 0.53%. The ANFIS structure for SOC estimation using two inputs is illustrated in Fig. 18. The mathematical representations of the five stage ANFIS configuration are expressed in (24)-(28).

$$\mu_A = \frac{1}{1+\left|\frac{x-c_i}{a_i}\right|^{2b_i}} \tag{24}$$

$$\begin{cases} Q_{2,1} = w_1 = \mu_{A_2}(x)\mu_{B_1}(y) \\ Q_{2,2} = w_2 = \mu_{A_2}(x)\mu_{B2}(y) \end{cases} \tag{25}$$

$$\begin{cases} O_{3,1} = \vec{w}_1 = \frac{w_1}{w_1+w_2} \\ O_{3,2} = \vec{w}_2 = \frac{w_2}{w_1+w_2} \end{cases} \tag{26}$$

$$\begin{cases} O_{4,1} = \vec{w}_1 f_1 = \vec{w}_1 \left(p_1 x_1 + q_1 y_1 + r_1\right) \\ O_{4,2} = \vec{w}_2 f_2 = \vec{w}_2 \left(p_2 x_2 + q_2 y_2 + r_2\right) \end{cases} \tag{27}$$

$$O_5 = \sum_{i=1}^{2} \vec{w}_i f_i = \frac{\sum_{i=1}^{2} \vec{w}_i f_i}{\sum_{i=1}^{2} \vec{w}_i} \tag{28}$$

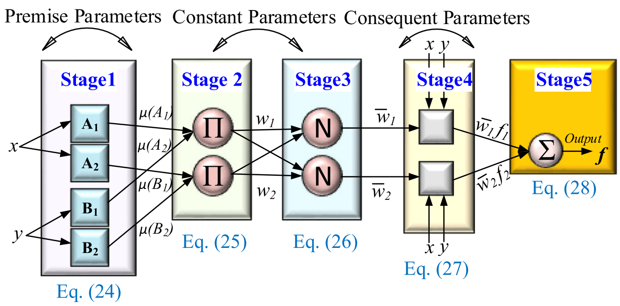


FIGURE 18. ANFIS structure for SOC estimation with five computation stages [147].

5) HYBRID METHOD

Hybrid methods are used to improve the accuracy and robustness of SOC estimation. Usually, two or three algorithms are combined together to develop a hybrid method. In most of the cases, optimization method is employed with model-based and data-driven methods to examine SOC which not only enhances the performance but also delivers accurate results. Few of the notable hybrid methods are explained in this section.

Genetic algorithm (GA) has seen many successful applications in engineering, physics, mathematics and so forth. Essentially, GA is a stochastic search algorithm capable of obtaining high-quality solutions in the search space [148]. The observations through the literature survey show that GA has been used as a search algorithm to obtain the optimal parameters of ECM model. Authors in [71] proposed GA to find the optimal battery parameters of ECM in order to estimate SOC using hybrid pulse power characterization (HPPC) experiment, as shown in Fig. 19. A series of actions including crossover, mutation, and selection are employed to identify the model parameters. The measured current and battery terminal voltage are assigned as the input and output of the model respectively during the process of parameters identification. The fitness value is determined by calculating the difference between measured voltage values and the model output. The proposed method can estimate SOC of LIB pack accurately and prevent the battery pack from overcharge and over-discharge with SOC error being less than 1%. The experiment results also confirm the suitability of the proposed algorithm in online BMS execution.

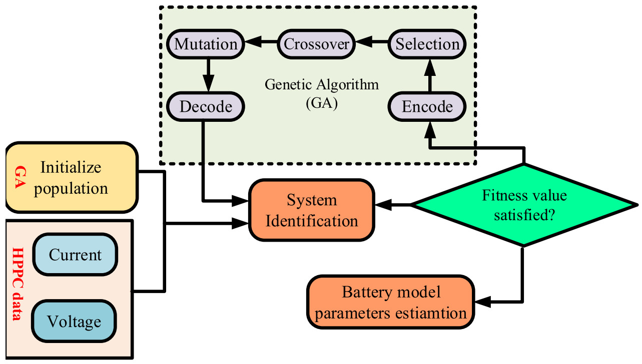


FIGURE 19. Battery model parameters determination using GA [71].

In [149], the authors proposed a charging cell voltage curves (CCCV) hypothesis to estimate the capacity of a LIB pack. GA is employed to search for optimal transformation parameters of the voltage-capacity rate curve (VCRC). The satisfactory outcomes with an error of less than 1% are achieved in both pack capacity and cell capacities. In [150], the authors used a first-order RC model in a combination with the coulomb counting method to estimate SOC of a LIB. The GA is used to optimize the battery parameters. The developed model is validated by experimental dataset obtained through battery test workbench. The results validate that the proposed model can examine SOC online under different drive cycles. Authors in [101] proposed a GA based fuzzy C-means clustering to estimate SOC of LIB in electric vehicles. The performance of the proposed method is verified by experiments and comparative analysis. The experimental results indicate that the model has a satisfactory SOC tracking precision with RMSE of 1.68%. In [151], RBFNN based adaptive GA method is proposed to estimate SOC for $LiFePO_4$ battery. GA is employed to determine the optimal value of centers, widths and connection weights of RBFNN. The effectiveness of the proposed method is tested under numerous discharging current profiles. The results prove the superiority of the proposed method over coulomb counting and BPNN methods in achieving a low error rate.

Particle Swarm Optimization (PSO) algorithm is used to explore a search space by iteratively trying to improve candidate with regards to a fitness function [152]. A search in the literature shows that PSO is often used in combination with the model-based method for SOC estimation of LIB. In [153] and [154], PSO is used as a search algorithm to optimize key parameters of the ECM such as voltage, capacity, resistance, and temperature. After, SOC is estimated by inserting the value of the optimized parameter into the ECM equation. In [155], The PSO algorithm is used to optimize only one parameter in the ECM model i.e. the lithium-ion concentration in the negative electrode, C_s. The proposed model is verified using the healthy and aged LIB experimental tests. The simulation and experimental results confirm the accurateness of SOC estimation under 1C charge and 1C discharge current profile. In another work [156], the authors used PSO to search for optimal SVM parameters to estimate SOC. The estimation results show that the proposed model outperforms the conventional SVM with regard to accuracy and convergence speed. The estimated SOC can track the actual SOC precisely with a small error limited to 1.3%. In [157], An optimal BPNN algorithm based SOC estimation model is built to evaluate SOC for LIB battery used in EV applications, as displayed in Fig. 20. PSO algorithm is utilized to search for the best values of network parameters including hidden layer neurons and learning rate. The results show that the proposed method is robust and has achieved promising outcomes in comparison with common BPNN and RBFNN methods with RMSE being less than 1% under diversified EV drive cycles.

Apart from GA and PSO, LIB SOC performance is enhanced by recent optimization techniques. In [114], BPNN is used in conjunction with backtracking search algorithm (BSA) to examine SOC of LIB. The proposed model is validated using DST and FUDS drive cycle. Furthermore, the results of BSA optimized BPNN method are compared with BSA optimized data-driven algorithms including RBFNN, general regression neural network (GRNN), and extreme learning machine (ELM). The authors reported RMS error of below 1.74% under various temperature and drive cycle profiles. In [117], a hybrid SOC intelligent algorithm is developed with recurrent nonlinear autoregressive with exogenous inputs (RNARX) based lighting search algorithm (LSA). The proposed model is validated by federal urban drive cycle (FUDS) and US06 drive cycles under different temperature conditions. The results of SOC are excellent in terms of accuracy, robustness and computational cost, having RMSE under 2%. In [118], extreme learning machine (ELM) based SOC estimation model is proposed for LIB. The gravitational search algorithm (GSA) is utilized to find the optimal hyperparameters of ELM algorithm. The developed model is excellent in terms of computation speed and accuracy, having SOC error under 4% in Beijing dynamic stress test (BJDST) cycle at 25°C.

Many of the data-driven methods are being used in combination with model-based methods. For instance, Charkhgard and Farrokhi [158] suggested using RBFNN in

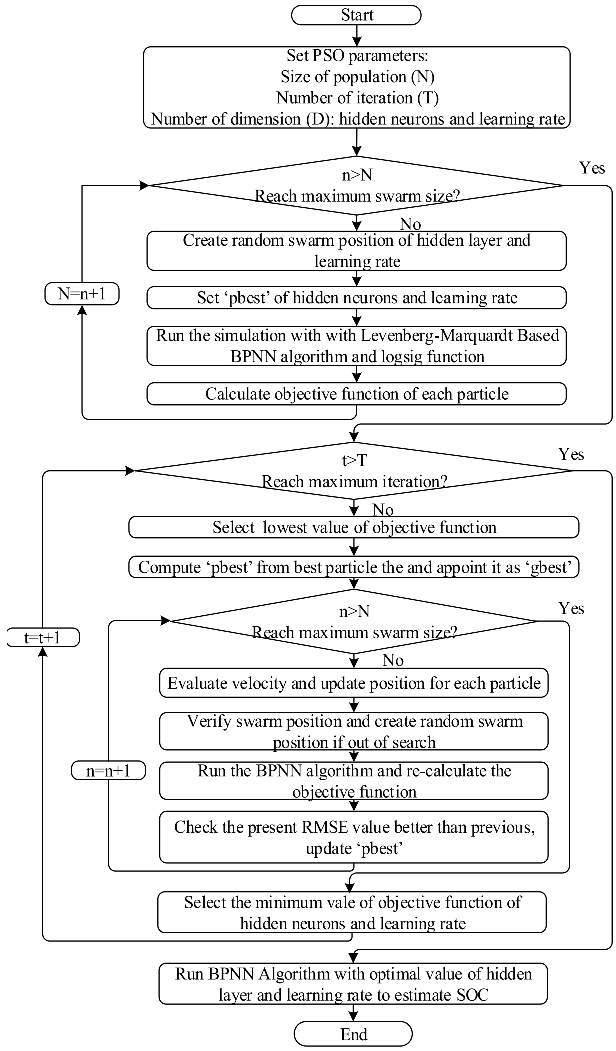


FIGURE 20. PSO based BPNN algorithm flowchart for SOC estimation [157].

conjunction with EKF to estimate SOC of LIB. The RBFNN is trained offline using self-collected LIB dataset. EKF is used to estimate SOC adaptively. The authors obtained RMSE of less than 3%. Huynh and Won [116] proposed BPNN based SOC estimation for electric vehicle batteries. Later, UKF algorithm is employed to reduce the noise and improve SOC accuracy. The results are reasonable with RMSE under 5% under various ambient temperatures and drive cycle profiles. Chen et al. [159] developed a feed-forward neural network (FFNN) based enhanced battery model. Then, EKF is used to evaluate SOC. The proposed model can track the true SOC quickly with SOC error below 2%.

V. KEY ISSUES AND CHALLENGES

The key challenge to SOC estimation of LIB is to improve accuracy, effectiveness, and robustness of algorithm with low computational complexity so that the method could be implemented in a low-cost BMS hardware. The target is to find an efficient SOC algorithm which could act a trade-off between accuracy and compactional complexity.

Usually, SOC error generates from many sources including current and voltage sensors, inaccurate battery model, initial SoC, inaccurate parameter selection during optimization [160]. Therefore, it is necessary to develop a technique with low SOC error sources. A few of the key issues and challenges are highlighted below.

A. SOC BALANCING PROBLEM

LIB pack in EV is configured using hundreds of cells connected in series or parallel in order to satisfy the requirement of high voltage and energy. SOC estimation of LIB pack is difficult to monitor and remains challenging. The inconsistency of SOC in each battery cell is observed in LIB pack due to the physical property change after repeated charging and discharging cycles [161], [162]. The difference in battery cell performance in terms of capacity and aging is caused by the limitations of manufacturing technology and tolerances, material defects with the different working conditions which in turn is reflected by the SOC divergence [163]. SOC imbalance among the LIB pack hardly delivers accurate information which affects power, energy computation and LIB safety system [164]. Several methods have been introduced in recent years to address the SOC balancing problem including cell calculation-based methods [165], screening process-based method [166] and bias correction method [167].

B. CHARGING STRATEGY

Charging approach of LIB has received wide attention in recent years in EV applications. Presently, EV does not have fast charging technology [168]. The slow charging operation of LIB could reduce the interest in the wide acceptance of EVs. On the contrary, quick charging strategies based on charging current acceleration generates heat which significantly affects the battery lifetime [168]. Hence, designing an effective charging strategy in order to achieve a good balance between charging efficiency, heat and lifespan, degradation is a challenging task. A state-of-the-art of fast charging methods are reported in [169] and various optimal charging strategies are highlighted in [170].

C. THERMAL RUNAWAY

SOC estimation under high temperature is a serious concern which needs further explorations in order to improve EV performance and obtain accurate SOC. The thermal runaway is commonly arisen by mechanical, electrical or heat abuses [171]. The mechanical abuse is induced in the form of penetration or collision, which results in an internal short circuit. The electrical abuse is caused by overcharge, lithium plating and exothermic reactions. The heat abuse is caused by high temperature and inefficient thermal management. Galushkin et al. [172] found that thermal runaway is occurred due to the increasing number of charge/discharge cycles and growth of SOC. The effects of thermal runaway of different types of LIB is depicted in Fig. 21 [173].

The SEI layer, negative electrode, and electrolyte start decomposing when the temperature lifts over 90°C [173].

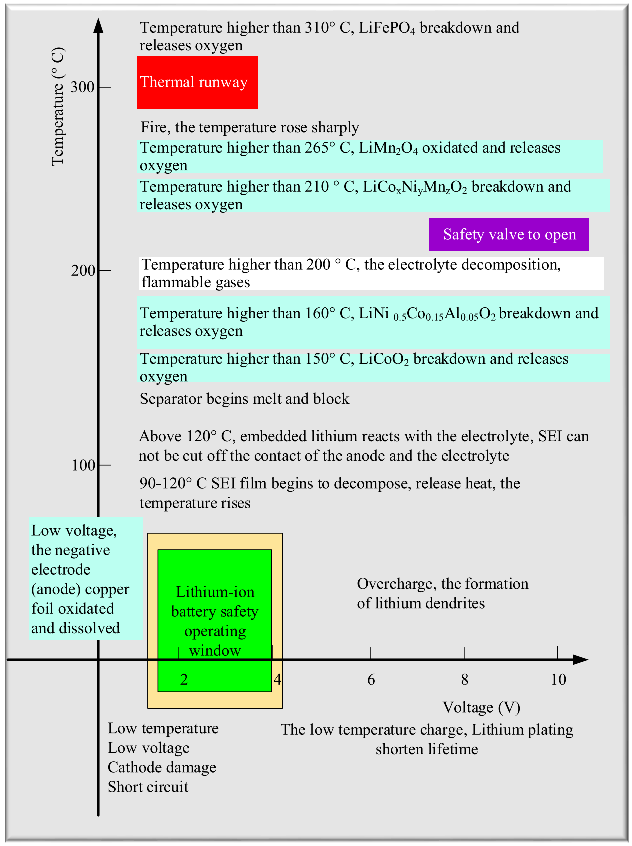
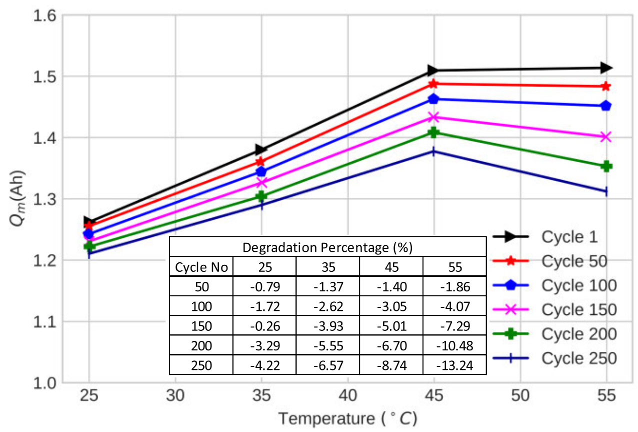


FIGURE 21. Lithium-ion cell operating window [173].

However, $LiFePO_4$ shows better thermal stability than other LIB materials due to the limited exothermic heat discharge. The existing research works highlight the heat generation mechanism of LIB towards enhancement of thermal modeling through thermodynamic energy balance [174], general energy-balance equation [175] entropy influence [176] and discharge performance [177].

D. CAPACITY FADING

At any discharge rate, the transformation of the battery active material initiates which results in capacity loss [178]. On the other hand, when the internal impedance of battery increases, the reduction in operating voltage, the power rate capability is observed [179]. The SOC error rates increases with the capacity fade and power fade [118], [119]. For instance, In [178], the relationship between capacity fade and temperature is illustrated, where the maximum charge storage capacity starts decreasing after reaching 45° C, as highlighted in Fig 22. Besides, it is also reported that, capacity reduces with the rise of aging cycle. Similar kind of outcomes are also is observed in [180], where a rise of capacity fade from 40% to 70% is noted as the temperature climbs up from 37° C to 55° C. The capacity loss is also monitored in $C/LiCoO_2$ cylindrical batteries when the voltage is increased beyond the threshold value, as recommended by the manufacturer [181].



Cycle No	25	35	45	55
50	-0.79	-1.37	-1.40	-1.86
100	-1.72	-2.62	-3.05	-4.07
150	-0.26	-3.93	-5.01	-7.29
200	-3.29	-5.55	-6.70	-10.48
250	-4.22	-6.57	-8.74	-13.24

FIGURE 22. The relationship between battery charge storage capacity and temperature [182].

E. LITHIUM-ION BATTERY MATERIAL ISSUE

Although lithium-ion batteries have excellent features, their performance is varied significantly by the positive and negative electrode, and subsequently has substantial impacts on SOC estimation. Lithium Cobalt Oxide (LiCO) batteries offer low capacity, good performance; however, their execution is constrained by high cost and the limited resource of cobalt. Lithium Nickel Manganese Cobalt Oxide (LiNMC) and Lithium Nickel Cobalt Aluminium Oxide (LiNCA) batteries have excellent performance, high capacity, and long lifespan; nevertheless, have insufficient resources of nickel, cobalt and hence results in high price. Lithium Manganese Oxide (LiMO) batteries have high voltage, moderate safety, good performance, enough resource of manganese and low price but have poor capacity and limited lifespan. Lithium Iron Phosphate (LiFP) batteries have low cost, low toxicity, enhanced life cycle, excellent safety, and abundant resource of iron but have drawbacks including low energy, capacity, and voltage. Lithium Titanate (LiTO) batteries have better life cycles and efficiency than other lithium-ion batteries; however, have weakness in capacity and voltage. LiTO is economically excellent and can deliver high performance. Graphite is widely used as negative electrodes due to adequate availability and long-life cycles. Nonetheless, Graphite has low energy density and is inefficient due to the solid electrolyte interface (SEI) formation [30], [183]. In [119], SOC is evaluated using two different chemistry of lithium-ion batteries namely lithium iron phosphate ($LiFePO_4$) and lithium titanate (LTO) under different aging profiles and temperatures. The results indicate that LTO battery has RMSE of 0.7012% while it is 0.5305% in $LiFePO_4$ battery at 25 °C. Moreover, the results prove that, $LiFePO_4$ is not suitable when the battery is highly cycled. For instance, LTO battery computes RMSE to be 0.00334 % after 1000 aging cycles, nevertheless RMSE in $LiFePO_4$ battery increases with aging cycles and is estimated to be 0.4547 % after 1000 aging cycles.

F. LITHIUM-ION BATTERY SAFETY CONCERN

Battery safety is another important issue which needs to be addressed appropriately while assessing SOC. Battery SOC estimation could be disturbed by over-current, over-voltage, overheating, low temperature, high temperature and material breakdown, as illustrated in Fig. 23.

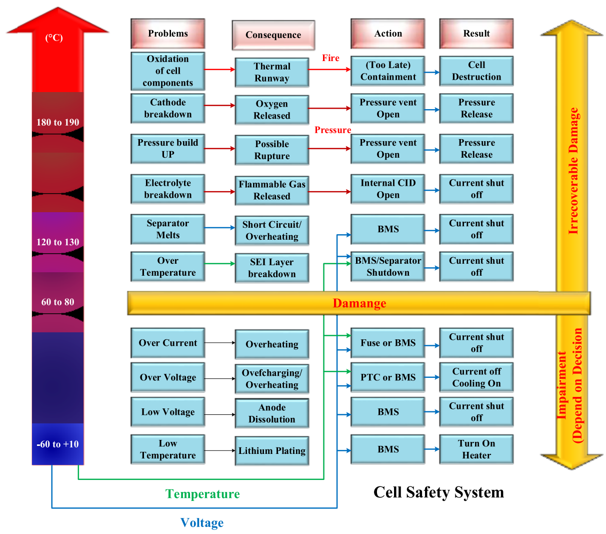


FIGURE 23. LIB fault diagnosis and protection [184].

The consequences of the mentioned effects result in short circuit, thermal runway, oxygen release, anode dissolution, lithium plating etc. Thus, an improved battery safety mechanism is needed which not only ensures safe and reliable operation of EV but also helps to determine accurate SOC estimation. Several actions can be employed to lessen these impacts. For instance, pressure vent control can be utilized to release pressure. Besides, current interrupt device (CID) can be used to provide protection against any extreme pressure rise. Moreover, the overheating and overcharge can be handled by fuse and pressure, temperature, current (PTC) switch [184].

G. DATA MEASUREMENT FROM TEST BENCH PLATFORM

A test bench platform is established to implement experimental validation of SOC estimation for LIB. The key issues concerning the battery test bench development are equipment precision, noise impact, and electromagnetic interference [185]. Generally, the battery testing platform comprises the battery charger, electronic load, sensor, controller and data acquisition module. If the separate equipment is used for battery load, supply and controlling battery charging and discharging, then the error in measurements would increase. Hence, a compact battery testing system (BTS) is needed which can sense the battery voltage, current as well as perform the control operation. Most of the previous works on SOC estimation were conducted using Digatron battery testing system [99], Arbin BT2000 battery testing system [186], and separate programmable load, supply, controller and data acquisition (DAQ) device [187]. Digatron and Arbin BT200 can deliver good results, however, the accuracy is not satisfactory when handling the highly non-linear battery data. Recently, an improved BTS, developed by NEWARE Electronic Company Ltd. has become popular due to high accuracy and negligible measurement noises. Hence, the development of a battery test bench with improved battery testing system for SOC estimation is significant that measures the current and voltage precisely and elevates the SOC estimation performance.

H. HARDWARE DEVELOPMENT CHALLENGES TO MONITOR REAL-TIME SOC

So far, the SOC estimation methods have been validated by experimental tests under different temperature conditions, noise effect and unknown initial SOC. However, the SOC estimation of LIB in realistic operating condition has not been explored comprehensively. The most challenging part is the execution of SOC estimation algorithm in a low-cost BMS with small memory storage and fast computation speed. Zhang et al. [188] established hardware-in-the Loop (HIL) experimental platform to validate adaptive H∞ filter based SOC estimation algorithm in real-time. Chen et al. [77] built a lithium-ion battery-in-loop test bench based on xPC target to simulate EV drive cycle and validate multiscale dual H∞ filter for SOC and capacity estimation in real-time. Tina et al. [189] developed field programmable gate array (FPGA) based BMS to evaluate SOC using system-in-the-loop platform. The proposed work has a quick execution time of 16.5μs and can run on low-cost hardware. Morello et al. [12] used HIL platform to test battery state estimators implemented on FPGA based BMS.

Apart from the issues and challenges mentioned above, SOC estimation can be affected by aging, battery model, hysteresis, cell unbalancing, self-discharge, charge-discharge current rate which have already been discussed by Zhang et al. [30] and Hannan et al. [29].

VI. CONCLUSION AND RECOMMENDATIONS

This review presents a critical examination of various SOC estimation strategies concerning their fundamental, accuracy, execution, benefits and drawbacks. In the domain of SOC estimation, a large pool of work has been explored in the application of model-based and data-driven estimation methods. Both the model-based and data-driven approaches have yielded significant results in SOC estimation. From the rigorous review, we noted that if the model of the system is known a priori, a model-based approach is theoretically the best approach from the viewpoint of statistical performance. On the contrary, if the system is not fully understood, the data-driven approach may outperform model-based solutions. Some researchers have been working to merge the two approaches to obtain the best of both. Nonetheless, due to the technology advancement, fast computing processor, high capacity storage device and big data availability, more research and development are advancing towards the data-driven algorithm based SOC estimation.

By analyzing both model-based and data-driven SOC estimation methods, it is found that coulomb counting method is an open-loop estimation system and suffers from cumulative error. In addition, discharge rate, battery aging, and sensor precision are other factors which affect its accuracy. OCV method is not appropriate for online EV operation since the battery needs substantial duration to reach a balance condition. Besides, OCV based SOC in $LiFePO_4$ battery has lack of accuracy due to the flat area existed in the middle SOC-OCV curve. EM model depends on PDE computation which is costly and has a limitation on online execution. ECM needs a substantial time for model parameter estimation and a balance is required between accuracy and computational complexity. The KF contains complex matrix operations which are difficult to execute on a low-cost microcontroller. The performance of KF is degraded with uncertainties in battery model configuration, noise level, physical parameter, and initial condition. NN is effective in estimating SOC accurately under EV drive cycles, temperatures, and aging effects and can capture battery non-linear characteristics without battery model, and added filter. Nonetheless, the performance of NN is constrained by the training duration and accurate value of hyperparameters. FL needs specific battery characteristic rules which are hard to obtain due to the varying characteristics of battery parameters under different load profiles. ANFIS involves a lot of calculations and a huge amount of training data which needs large storage device and costly processing unit. GA is composed of heavy computations, and has a slow optimization response time. PSO suffers from local optimum in high-dimensional space and has low convergence speed during the iterative process.

In light of these concerns, this review provides some recommendations for obtaining accurate and robust SOC estimation in solving the existing problems, such as,

- An in-depth investigation is required on the electrochemical battery model concerning capacity degradation, thermal failure, inner reaction kinetics and mechanical fatigue process.
- Further research works are required on fusion model with the improved fusion rule under different operating condition, battery cathode chemistry and battery aging cycles.
- The SOC estimation approaches in real time execution with embedded system prototyping of BMS needs further investigation.
- The explorations are required to develop an effective controller to balance SOC in LIB pack and control aging level.
- Careful attentions are needed to select the best value of battery model parameters and hyperparameters while designing a model-based and data-driven SOC estimation method, respectively.

- Further studies are required to reduce the computational complexity of data-driven approaches through different optimization techniques.
- LIB can be subject to more environment dynamics in a real-world application that can never be simulated in the laboratory. Hence, SOC estimation results should be further analyzed under various uncertainties including temperature, aging cycle, and noise effects.

The authors believe that these suggestions would make a remarkable contribution towards the improvement of SOC estimation algorithm in the future.

NOMENCLATURE

$a_i\ b_i\ c_i$	The parameters that change the shape of the membership function (MF)
$A,\ C$	Derivation matrices with respect to system state vector
$B,\ D$	Derivation matrices with respect to system input
C_1	The electrochemical polarization capacitance
C_2	The concentration polarization capacitance
$c(k)$	The observer gain
e_k	The difference between the observation y_k and the predicted observation $g(\hat{x}_k^-, u_k)$
$f_1 f_2$	The outputs within the fuzzy region specified by the fuzzy rule
H_k	The innovation covariance matrix
I	The unit matrix
I_t	The current following through the voltage source
K_k	The Kalman gain matrix
M	The moving estimation window size
$m_1 m_2$	The Gaussian system noise
P	Covariance matrix
$Q,\ R$	The process noise covariance
$p_i\ q_i\ r_i$	The design parameters to be determined during the training process in ANFIS model
Q_N	The discharge capacity of battery
R_o	The ohmic resistance of the LIB
R	The measurement noise covariance
R_1	The electrochemical polarization resistance
R_2	The concentration polarization resistance
Δt	The sampling period (in hours)
T_s	The sampling time
u	The system input
$\hat{U}_1 \hat{U}_2$	The estimation of the state variables $U_1 U_2$
$\hat{U}_L$	The estimation of the observation variable U_L
v	The measurement noise
w	The process noise
$w_1 w_2$	The firing strength
$\vec{w}_1 \vec{w}_2$	The normalized firing strength
x	The system state vector
$\hat{x}_k^-$	The priori estimate of x_k before the measurement y_k is taken into account
$\hat{x}_k^+$	The posteriori estimate of x_k after the measurement y_k is taken into account
$\hat{x}_k$	The guessed value at time k
y	The measurable system output
$\begin{cases} \dot{x} = f(x, u) + w \\ y = g(x, u) + v \end{cases}$	The functions specified by the particular used cell model.
$\alpha\beta$	The parameters used to adjust observer gain
$\mu_{A_1} \mu_{A_2}$	The fuzzy MF
$\hat{\theta}_l$	The guessed value at time l

REFERENCES

[1] L. A. Wong, V. K. Ramachandaramurthy, P. Taylor, J. B. Ekanayake, S. L. Walker, and S. Padmanaban, "Review on the optimal placement, sizing and control of an energy storage system in the distribution network," *J. Energy Storage*, vol. 21, pp. 489–504, Feb. 2019.

[2] M. A. Hannan, M. S. H. Lipu, P. J. Ker, R. A. Begum, V. G. Agelidis, and F. Blaabjerg, "Power electronics contribution to renewable energy conversion addressing emission reduction: Applications, issues, and recommendations," *Appl. Energy*, vol. 251, Oct. 2019, Art. no. 113404.

[3] P. Y. Kong and G. K. Karagiannidis, "Charging schemes for plug-in hybrid electric vehicles in smart grid: A survey," *IEEE Access*, vol. 4, pp. 6846–6875, 2016.

[4] C. Zou, X. Hu, Z. Wei, T. Wik, and B. Egardt, "Electrochemical estimation and control for lithium-ion battery health-aware fast charging," *IEEE Trans. Ind. Electron.*, vol. 65, no. 8, pp. 6635–6645, Aug. 2018.

[5] F. Xia, H. Chen, L. Chen, and X. Qin, "A hierarchical navigation strategy of EV fast charging based on dynamic scene," *IEEE Access*, vol. 7, pp. 29173–29184, 2019.

[6] H. Fang, Y. Wang, and J. Chen, "Health-aware and user-involved battery charging management for electric vehicles: Linear quadratic strategies," *IEEE Trans. Control Syst. Technol.*, vol. 25, no. 3, pp. 911–923, May 2017.

[7] M. Faisal, M. A. Hannan, P. J. Ker, A. Hussain, M. B. Mansor, and F. Blaabjerg, "Review of energy storage system technologies in microgrid applications: Issues and challenges," *IEEE Access*, vol. 6, pp. 35143–35164, 2018.

[8] J. Y. Yong, V. K. Ramachandaramurthy, K. M. Tan, and N. Mithulananthan, "A review on the state-of-the-art technologies of electric vehicle, its impacts and prospects," *Renew. Sustain. Energy Rev.*, vol. 49, pp. 365–385, Sep. 2015.

[9] V. Ruiz, A. Pfrang, A. Kriston, N. Omar, P. Van den Bossche, and L. Boon-Brett, "A review of international abuse testing standards and regulations for lithium ion batteries in electric and hybrid electric vehicles," *Renew. Sustain. Energy Rev.*, vol. 81, pp. 1427–1452, Jan. 2018.

[10] A. Opitza, P. Badamia, L. Shena, K. Vignaroobana, and A. M. Kannana, "Can Li-Ion batteries be the panacea for automotive applications?" *Renew. Sustain. Energy Rev.*, vol. 68, pp. 685–692, Feb. 2017.

[11] S. Ahmed, S. E. Trask, D. W. Dees, P. A. Nelson, W. Lu, A. R. Dunlop, B. J. Polzin, and A. N. Jansen, "Cost of automotive lithium-ion batteries operating at high upper cutoff voltages," *J. Power Sources*, vol. 403, pp. 56–65, Nov. 2018.

[12] R. Morello, R. Di Rienzo, R. Roncella, R. Saletti, and F. Baronti, "Hardware-in-the-loop platform for assessing battery state estimators in electric vehicles," *IEEE Access*, vol. 6, pp. 68210–68220, 2018.

[13] W. Wang, X. Wang, C. Xiang, C. Wei, and Y. Zhao, "Unscented Kalman filter-based battery SoC estimation and peak power prediction method for power distribution of hybrid electric vehicles," *IEEE Access*, vol. 6, pp. 35957–35965, 2018.

[14] M. S. H. Lipu, A. Hussain, M. H. M. Saad, A. Ayob, and M. A. Hannan, "Improved recurrent NARX neural network model for state of charge estimation of lithium-ion battery using pso algorithm," in *Proc. IEEE Symp. Comput. Appl. Ind. Electron. (ISCAIE)*, Penang, Malaysia, Apr. 2018, pp. 354–359.

[15] X. Wu, X. Li, and J. Du, "State of charge estimation of lithium-ion batteries over wide temperature range using unscented Kalman filter," *IEEE Access*, vol. 6, pp. 41993–42003, 2018.

[16] M. S. H. Lipu, M. A. Hannan, A. Ayob, M. H. M. Saad, and A. Hussain, "Review of lithium-ion battery state of charge estimation methodologies for electric vehicle application," *Int. J. Eng. Technol.*, vol. 7, no. 3.17, pp. 219–224, Aug. 2018.

[17] D. Grieshaber, R. MacKenzie, J. Vörös, and E. Reimhult, "Electrochemical biosensors—Sensor principles and architectures," *Sensors*, vol. 8, no. 3, pp. 1400–1458, Mar. 2008.

[18] A. J. Ilott, M. Mohammadi, C. M. Schauerman, M. J. Ganter, and A. Jerschow, "Rechargeable lithium-ion cell state of charge and defect detection by *in-situ* inside-out magnetic resonance imaging," *Nature Commun.*, vol. 9, no. 1, Dec. 2018, Art. no. 1776.

[19] G. Xu, X. Du, Z. Li, X. Zhang, M. Zheng, Y. Miao, Y. Gao, and Q. Liu, "Reliability design of battery management system for power battery," *Microelectron. Rel.*, vols. 88–90, pp. 1286–1292, Sep. 2018.

[20] K. W. E. Cheng, B. P. Divakar, H. Wu, D. Kai, and H. F. Ho, "Battery-management system (BMS) and SoC development for electrical vehicles," *IEEE Trans. Veh. Technol.*, vol. 60, no. 1, pp. 76–88, Jan. 2011.

[21] G. L. Plett, "Battery management systems," in *Battery Modeling*, vol. 1. Norwood, MA, USA: Artech House, 2015. [Online]. Available: https://us.artechhouse.com/Battery-Management-Systems-Volume-1-Battery-Modeling-P1753.aspx

[22] Y. Xing, E. W. M. Ma, K. L. Tsui, and M. Pecht, "Battery management systems in electric and hybrid vehicles," *Energies*, vol. 4, no. 11, pp. 1840–1857, 2011.

[23] M. Corno, N. Bhatt, S. M. Savaresi, and M. Verhaegen, "Electrochemical model-based state of charge estimation for Li-ion cells," *IEEE Trans. Control Syst. Technol.*, vol. 23, no. 1, pp. 117–127, Jan. 2015.

[24] H. He, R. Xiong, and J. Fan, "Evaluation of lithium-ion battery equivalent circuit models for state of charge estimation by an experimental approach," *Energies*, vol. 4, no. 4, pp. 582–598, Mar. 2011.

[25] U. Westerhoff, T. Kroker, K. Kurbach, and M. Kurrat, "Electrochemical impedance spectroscopy based estimation of the state of charge of lithium-ion batteries," *J. Energy Storage*, vol. 8, pp. 244–256, Nov. 2016.

[26] S. M. Rezvanizaniani, Z. Liu, Y. Chen, and J. Lee, "Review and recent advances in battery health monitoring and prognostics technologies for electric vehicle (EV) safety and mobility," *J. Power Sources*, vol. 256, pp. 110–124, Jun. 2014.

[27] L. Jin, S. Li, and B. Hu, "RNN models for dynamic matrix inversion: A control-theoretical perspective," *IEEE Trans. Ind. Informat.*, vol. 14, no. 1, pp. 189–199, Jan. 2018.

[28] R. Xiong, J. Cao, Q. Yu, H. He, and F. Sun, "Critical review on the battery state of charge estimation methods for electric vehicles," *IEEE Access*, vol. 6, pp. 1832–1843, 2018.

[29] M. A. Hannan, M. S. H. Lipu, A. Hussain, and A. Mohamed, "A review of lithium-ion battery state of charge estimation and management system in electric vehicle applications: Challenges and recommendations," *Renew. Sustain. Energy Rev.*, vol. 78, pp. 834–854, Oct. 2017.

[30] R. Zhang, B. Xia, B. Li, L. Cao, Y. Lai, W. Zheng, H. Wang, and W. Wang, "State of the art of lithium-ion battery SoC estimation for electrical vehicles," *Energies*, vol. 11, no. 7, p. 1820, Jul. 2018.

[31] M. U. Ali, A. Zafar, S. H. Nengroo, S. Hussain, M. J. Alvi, and H.-J. Kim, "Towards a smarter battery management system for electric vehicle applications: A critical review of lithium-ion battery state of charge estimation," *Energies*, vol. 12, no. 3, p. 446, Jan. 2019.

[32] Y. Zheng, M. Ouyang, X. Han, L. Lu, and J. Li, "Investigating the error sources of the online state of charge estimation methods for lithium-ion batteries in electric vehicles," *J. Power Sources*, vol. 377, pp. 161–188, Feb. 2018.

[33] G. Zubi, R. Dufo-López, M. Carvalho, and G. Pasaoglu, "The lithium-ion battery: State of the art and future perspectives," *Renew. Sustain. Energy Rev.*, vol. 89, pp. 292–308, Jun. 2018.

[34] Y. Sun, S. Saxena, and M. Pecht, "Derating guidelines for lithium-ion batteries," *Energies*, vol. 11, no. 12, p. 3295, Nov. 2018.

[35] Q. Wang, P. Ping, X. Zhao, G. Chu, J. Sun, and C. Chen, "Thermal runaway caused fire and explosion of lithium ion battery," *J. Power Sources*, vol. 208, pp. 210–224, Jun. 2012.

[36] A. Barré, B. Deguilhem, S. Grolleau, M. Gérard, F. Suard, and D. Riu, "A review on lithium-ion battery ageing mechanisms and estimations for automotive applications," *J. Power Sources*, vol. 241, pp. 680–689, Nov. 2013.

[37] A. Fotouhi, D. J. Auger, K. Propp, S. Longo, and M. Wild, "A review on electric vehicle battery modelling: From lithium-ion toward lithium–sulphur," *Renew. Sustain. Energy Rev.*, vol. 56, pp. 1008–1021, Apr. 2016.

[38] Z. Yanhui, S. Wenji, L. Shili, L. Jie, and F. Ziping, "A critical review on state of charge of batteries," *J. Renew. Sustain. Energy*, vol. 5, no. 2, pp. 1–11, Feb. 2013.

[39] S. Yin, X. Li, H. Gao, and O. Kaynak, "Data-based techniques focused on modern industry: An overview," *IEEE Trans. Ind. Electron.*, vol. 62, no. 1, pp. 657–667, Jan. 2015.

[40] S. Yin, S. X. Ding, X. Xie, and H. Luo, "A review on basic data-driven approaches for industrial process monitoring," *IEEE Trans. Ind. Electron.*, vol. 61, no. 11, pp. 6418–6428, Nov. 2014.

[41] Z.-S. Hou and Z. Wang, "From model-based control to data-driven control: Survey, classification and perspective," *Inf. Sci.*, vol. 235, pp. 3–35, Jun. 2013.

[42] J. Li, L. Wang, C. Lyu, and M. Pecht, "State of charge estimation based on a simplified electrochemical model for a single $LiCoO_2$ battery and battery pack," *Energy*, vol. 133, pp. 572–583, Aug. 2017.

[43] F. Yang, W. Li, C. Li, and Q. Miao, "State-of-charge estimation of lithium-ion batteries based on gated recurrent neural network," *Energy*, vol. 175, pp. 66–75, May 2019.

[44] F. Provost and T. Fawcett, "Data science and its relationship to big data and data-driven decision making," *Big Data*, vol. 1, no. 1, pp. 51–59, Mar. 2013.

[45] F. Yang, X. Song, F. Xu, and K.-L. Tsui, "State-of-charge estimation of lithium-ion batteries via long short-term memory network," *IEEE Access*, vol. 7, pp. 53792–53799, 2019.

[46] E. Chemali, P. J. Kollmeyer, M. Preindl, R. Ahmed, and A. Emadi, "Long short-term memory networks for accurate state-of-charge estimation of Li-ion batteries," *IEEE Trans. Ind. Electron.*, vol. 65, no. 8, pp. 6730–6739, Aug. 2018.

[47] P. Domingos, "A few useful things to know about machine learning," *Commun. ACM*, vol. 55, no. 10, pp. 78–87, Oct. 2012.

[48] C. M. Bishop, *Pattern Recognition and Machine Learning*. Springer, 2006. [Online]. Available: https://www.springer.com/gp/book/9780387310732

[49] J. Kim, G.-S. Seo, C. Chun, B.-H. Cho, and S. Lee, "OCV hysteresis effect-based SoC estimation in extended Kalman filter algorithm for a $LiFePO_4$/C cell," in *Proc. IEEE Int. Electr. Vehicle Conf.*, Greenville, SC, USA, Mar. 2012, pp. 1–5.

[50] P. Shen, M. Ouyang, L. Lu, J. Li, and X. Feng, "The co-estimation of state of charge, state of health, and state of function for lithium-ion batteries in electric vehicles," *IEEE Trans. Veh. Technol.*, vol. 67, no. 1, pp. 92–103, Jan. 2018.

[51] A. Barai, W. D. Widanage, J. Marco, A. McGordon, and P. Jennings, "A study of the open circuit voltage characterization technique and hysteresis assessment of lithium-ion cells," *J. Power Sources*, vol. 295, pp. 99–107, Nov. 2015.

[52] M. A. Roscher and D. U. Sauer, "Dynamic electric behavior and open-circuit-voltage modeling of $LiFePO_4$-based lithium ion secondary batteries," *J. Power Sources*, vol. 196, no. 1, pp. 331–336, Jan. 2011.

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

[54] S. Rodrigues, N. Munichandraiah, and A. K. Shukla, "AC impedance and state-of-charge analysis of a sealed lithium-ion rechargeable battery," *J. Solid State Electrochem.*, vol. 3, nos. 7–8, pp. 397–405, Sep. 1999.

[55] C. Truchot, M. Dubarry, and B. Y. Liaw, "State-of-charge estimation and uncertainty for lithium-ion battery strings," *Appl. Energy*, vol. 119, pp. 218–227, Apr. 2014.

[56] C. R. Lashway and O. A. Mohammed, "Adaptive battery management and parameter estimation through physics-based modeling and experimental verification," *IEEE Trans. Transport. Electrific.*, vol. 2, no. 4, pp. 454–464, Dec. 2016.

[57] K. S. Ng, C.-S. Moo, Y.-P. Chen, and Y.-C. Hsieh, "Enhanced Coulomb counting method for estimating state-of-charge and state-of-health of lithium-ion batteries," *Appl. Energy*, vol. 86, no. 9, pp. 1506–1511, Sep. 2009.

[58] W. Waag, C. Fleischer, and D. U. Sauer, "Critical review of the methods for monitoring of lithium-ion batteries in electric and hybrid vehicles," *J. Power Sources*, vol. 258, pp. 321–339, Jul. 2014.

[59] S. Sepasi, R. Ghorbani, and B. Y. Liaw, "A novel on-board state-of-charge estimation method for aged Li-ion batteries based on model adaptive extended Kalman filter," *J. Power Sources*, vol. 245, pp. 337–344, Jan. 2014.

[60] H. Rahimi-Eichi, U. Ojha, F. Baronti, and M.-Y. Chow, "Battery management system: An overview of its application in the smart grid and electric vehicles," *IEEE Ind. Electron. Mag.*, vol. 7, no. 2, pp. 4–16, Jun. 2013.

[61] M. Doyle, T. F. Fuller, and J. Newman, "Modeling of galvanostatic charge and discharge of the lithium/polymer/insertion cell," *J. Electrochem. Soc.*, vol. 140, no. 6, pp. 1526–1533, Jun. 1993.
[62] C. Lin, A. Tang, and J. Xing, "Evaluation of electrochemical models based battery state-of-charge estimation approaches for electric vehicles," *Appl. Energy*, vol. 207, pp. 394–404, Dec. 2017.
[63] A. Bartlett, J. Marcicki, S. Onori, G. Rizzoni, X. G. Yang, and T. Miller, "Electrochemical model-based state of charge and capacity estimation for a composite electrode lithium-ion battery," *IEEE Trans. Control Syst. Technol.*, vol. 24, no. 2, pp. 384–399, Mar. 2016.
[64] Y. Chen, W. Huo, M. Lin, and L. Zhao, "Simulation of electrochemical behavior in Lithium ion battery during discharge process," *PLoS ONE*, vol. 13, no. 1, Jan. 2018, Art. no. e0189757.
[65] H. W. You, J. I. Bae, S. J. Cho, J. M. Lee, and S.-H. Kim, "Analysis of equivalent circuit models in lithium-ion batteries," *AIP Adv.*, vol. 8, no. 12, Dec. 2018, Art. no. 125101.
[66] Y. Hu, S. Yurkovich, Y. Guezennec, and B. J. Yurkovich, "Electro-thermal battery model identification for automotive applications," *J. Power Sources*, vol. 196, no. 1, pp. 449–457, Jan. 2011.
[67] Q. Yu, R. Xiong, and C. Lin, "Online estimation of state-of-charge based on the H infinity and unscented Kalman filters for lithium ion batteries," *Energy Procedia*, vol. 105, pp. 2791–2796, May 2017.
[68] A. Hentunen, T. Lehmuspelto, and J. Suomela, "Time-domain parameter extraction method for Thévenin-equivalent circuit battery models," *IEEE Trans. Energy Convers.*, vol. 29, no. 3, pp. 558–566, Sep. 2014.
[69] Z. Zeng, J. Tian, D. Li, and Y. Tian, "An online state of charge estimation algorithm for lithium-ion batteries using an improved adaptive Cubature Kalman filter," *Energies*, vol. 11, no. 1, p. 59, Jan. 2018.
[70] J. Hou, H. He, Y. Yang, T. Gao, and Y. Zhang, "A variational Bayesian and Huber-based robust square root cubature Kalman filter for lithium-ion battery state of charge estimation," *Energies*, vol. 12, no. 9, p. 1717, May 2019.
[71] Z. Chen, X. Li, J. Shen, W. Yan, and R. Xiao, "A novel state of charge estimation algorithm for lithium-ion battery packs of electric vehicles," *Energies*, vol. 9, no. 9, p. 710, May 2016.
[72] W. Wang and J. Mu, "State of charge estimation for lithium-ion battery in electric vehicle based on Kalman filter considering model error," *IEEE Access*, vol. 7, pp. 29223–29235, 2019.
[73] S. Peng, C. Chen, H. Shi, and Z. Yao, "State of charge estimation of battery energy storage systems based on adaptive unscented Kalman filter with a noise statistics estimator," *IEEE Access*, vol. 5, pp. 13202–13212, 2017.
[74] J. Wang, L. Zhang, J. Mao, J. Zhou, and D. Xu, "Fractional order equivalent circuit model and SoC estimation of supercapacitors for use in HESS," *IEEE Access*, vol. 7, pp. 52565–52572, 2019.
[75] D. Zhou, K. Zhang, A. Ravey, F. Gao, and A. Miraoui, "Online estimation of lithium polymer batteries state-of-charge using particle filter-based data fusion with multimodels approach," *IEEE Trans. Ind. Appl.*, vol. 52, no. 3, pp. 2582–2595, May/Jun. 2016.
[76] S. Schwunk, N. Armbruster, S. Straub, J. Kehl, and M. Vetter, "Particle filter for state of charge and state of health estimation for lithium–iron phosphate batteries," *J. Power Sources*, vol. 239, pp. 705–710, Oct. 2013.
[77] C. Chen, R. Xiong, and W. Shen, "A lithium-ion battery-in-the-loop approach to test and validate multiscale dual H infinity filters for state-of-charge and capacity estimation," *IEEE Trans. Power Electron.*, vol. 33, no. 1, pp. 332–342, Jan. 2018.
[78] C. Lin, H. Mu, R. Xiong, and W. Shen, "A novel multi-model probability battery state of charge estimation approach for electric vehicles using H-infinity algorithm," *Appl. Energy*, vol. 166, pp. 76–83, Mar. 2016.
[79] B. Wang, Z. Liu, S. E. Li, S. J. Moura, and H. Peng, "State-of-charge estimation for lithium-ion batteries based on a nonlinear fractional model," *IEEE Trans. Control Syst. Technol.*, vol. 25, no. 1, pp. 3–11, Jan. 2017.
[80] S. Dey, B. Ayalew, and P. Pisu, "Nonlinear robust observers for state-of-charge estimation of lithium-ion cells based on a reduced electrochemical model," *IEEE Trans. Control Syst. Technol.*, vol. 23, no. 5, pp. 1935–1942, Sep. 2015.
[81] X. Han, M. Ouyang, L. Lu, and J. Li, "Simplification of physics-based electrochemical model for lithium ion battery on electric vehicle. Part II: Pseudo-two-dimensional model simplification and state of charge estimation," *J. Power Sources*, vol. 278, pp. 814–825, Mar. 2015.
[82] L. Zheng, L. Zhang, J. Zhu, G. Wang, and J. Jiang, "Co-estimation of state-of-charge, capacity and resistance for lithium-ion batteries based on a high-fidelity electrochemical model," *Appl. Energy*, vol. 180, pp. 424–434, Oct. 2016.
[83] J. Xu, C. C. Mi, B. Cao, J. Deng, Z. Chen, and S. Li, "The state of charge estimation of lithium-ion batteries based on a proportional-integral observer," *IEEE Trans. Veh. Technol.*, vol. 63, no. 4, pp. 1614–1621, May 2014.
[84] B. Ning, J. Xu, B. Cao, B. Wang, and G. Xu, "A sliding mode observer SoC estimation method based on parameter adaptive battery model," *Energy Procedia*, vol. 88, pp. 619–626, Jun. 2016.
[85] B. Xiong, J. Zhao, Y. Su, Z. Wei, and M. Skyllas-Kazacos, "State of charge estimation of vanadium redox flow battery based on sliding mode observer and dynamic model including capacity fading factor," *IEEE Trans. Sustain. Energy*, vol. 8, no. 4, pp. 1658–1667, Oct. 2017.
[86] X. Chen, W. Shen, Z. Cao, and A. Kapoor, "A novel approach for state of charge estimation based on adaptive switching gain sliding mode observer in electric vehicles," *J. Power Sources*, vol. 246, pp. 667–678, Jan. 2014.
[87] J. Du, Z. Liu, Y. Wang, and C. Wen, "An adaptive sliding mode observer for lithium-ion battery state of charge and state of health estimation in electric vehicles," *Control Eng. Pract.*, vol. 54, pp. 81–90, Sep. 2016.
[88] R. Xiong, H. He, F. Sun, and K. Zhao, "Evaluation on state of charge estimation of batteries with adaptive extended Kalman filter by experiment approach," *IEEE Trans. Veh. Technol.*, vol. 62, no. 1, pp. 108–117, Jan. 2013.
[89] M. Ye, H. Guo, R. Xiong, and Q. Yu, "A double-scale and adaptive particle filter-based online parameter and state of charge estimation method for lithium-ion batteries," *Energy*, vol. 144, pp. 789–799, Feb. 2018.
[90] B. Xia, Z. Zhang, Z. Lao, W. Wang, W. Sun, Y. Lai, and M. Wang, "Strong tracking of a h-infinity filter in lithium-ion battery state of charge estimation," *Energies*, vol. 11, no. 6, p. 1481, Jun. 2018.
[91] B. Xia, W. Zheng, R. Zhang, Z. Lao, and Z. Sun, "A novel observer for lithium-ion battery state of charge estimation in electric vehicles based on a second-order equivalent circuit model," *Energies*, vol. 10, no. 8, p. 1150, Aug. 2017.
[92] J. Xu, C. C. Mi, B. Cao, and J. Cao, "A new method to estimate the state of charge of lithium-ion batteries based on the battery impedance model," *J. Power Sources*, vol. 233, pp. 277–284, Jul. 2013.
[93] M. Li, "Li-ion dynamics and state of charge estimation," *Renew. Energy*, vol. 100, pp. 44–52, Jan. 2017.
[94] D. Andre, M. Meiler, K. Steiner, H. Walz, T. Soczka-Guth, and D. U. Sauer, "Characterization of high-power lithium-ion batteries by electrochemical impedance spectroscopy. II: Modelling," *J. Power Sources*, vol. 196, no. 12, pp. 5349–5356, Jun. 2011.
[95] D. Di Domenico, A. Stefanopoulou, and G. Fiengo, "Lithium-ion battery state of charge and critical surface charge estimation using an electrochemical model-based extended Kalman filter," *J. Dyn. Syst., Meas., Control*, vol. 132, no. 6, 2010, Art. no. 061302.
[96] M. Cacciato, G. Nobile, G. Scarcella, and G. Scelba, "Real-time model-based estimation of SoC and SOH for energy storage systems," *IEEE Trans. Power Electron.*, vol. 32, no. 1, pp. 794–803, Jan. 2017.
[97] M. Ye, H. Guo, R. Xiong, and R. Yang, "Model-based state-of-charge estimation approach of the lithium-ion battery using an improved adaptive particle filter," *Energy Procedia*, vol. 103, pp. 394–399, Dec. 2016.
[98] H. Dai, B. Jiang, and X. Wei, "Impedance characterization and modeling of lithium-ion batteries considering the internal temperature gradient," *Energies*, vol. 11, no. 1, p. 220, Jan. 2018.
[99] E. Chemali, P. J. Kollmeyer, M. Preindl, and A. Emadi, "State-of-charge estimation of Li-ion batteries using deep neural networks: A machine learning approach," *J. Power Sources*, vol. 400, pp. 242–255, Oct. 2018.
[100] M. S. H. Lipu, M. A. Hannan, A. Hussain, M. H. M. Saad, A. Ayob, and M. N. Uddin, "Extreme learning machine model for state-of-charge estimation of lithium-ion battery using gravitational search algorithm," *IEEE Trans. Ind. Appl.*, vol. 55, no. 4, pp. 4225–4234, Jul./Aug. 2019.
[101] X. Hu, S. E. Li, and Y. Yang, "Advanced machine learning approach for lithium-ion battery state estimation in electric vehicles," *IEEE Trans. Transport. Electrific.*, vol. 2, no. 2, pp. 140–149, Jun. 2016.
[102] M. L. Giger, "Machine learning in medical imaging," *J. Amer. College Radiol.*, vol. 15, no. 3, pp. 512–520, Mar. 2018.
[103] S. P. Chatzis, V. Siakoulis, A. Petropoulos, E. Stavroulakis, and N. Vlachogiannakis, "Forecasting stock market crisis events using deep and statistical machine learning techniques," *Expert Syst. Appl.*, vol. 112, pp. 353–371, Dec. 2018.

[104] Y. Xu, C. Yang, J. Zhong, N. Wang, and L. Zhao, "Robot teaching by teleoperation based on visual interaction and extreme learning machine," *Neurocomputing*, vol. 275, pp. 2093–2103, Jan. 2018.

[105] M. Walter, S. Alizadeh, H. Jamalabadi, U. Lueken, U. Dannlowski, H. Walter, S. Olbrich, L. Colic, J. Kambeitz, N. Koutsouleris, T. Hahn, and D. B. Dwyer, "Translational machine learning for psychiatric neuroimaging," *Prog. Neuro-Psychopharmacol. Biol. Psychiatry*, vol. 91, pp. 113–121, Apr. 2019.

[106] D. Silver, A. Huang, C. J. Maddison, A. Guez, L. Sifre, G. van den Driessche, J. Schrittwieser, I. Antonoglou, V. Panneershelvam, M. Lanctot, S. Dieleman, D. Grewe, J. Nham, N. Kalchbrenner, I. Sutskever, T. Lillicrap, M. Leach, K. Kavukcuoglu, T. Graepel, and D. Hassabis, "Mastering the game of Go with deep neural networks and tree search," *Nature*, vol. 529, no. 7587, pp. 484–489, Jan. 2016.

[107] E. Badal-Valero, J. A. Alvarez-Jareño, and J. M. Pavía, "Combining Benford's Law and machine learning to detect money laundering. An actual Spanish court case," *Forensic Sci. Int.*, vol. 282, pp. 24–34, Jan. 2018.

[108] CALCE. (2017). *Lithium-Ion Battery Experimental Data*. Accessed: Jan. 5, 2017. [Online]. Available: https://web.calce.umd.edu/batteries/data.htm

[109] X. Zhang, Y. Wang, D. Yang, and Z. Chen, "Behavior data of battery and battery pack SoC estimation under different working conditions," *Data Brief*, vol. 9, pp. 737–740, Dec. 2016.

[110] Y. Wang, C. Liu, R. Pan, and Z. Chen, "Experimental data of lithium-ion battery and ultracapacitor under DST and UDDS profiles at room temperature," *Data Brief*, vol. 12, pp. 161–163, Jun. 2017.

[111] *Predicting Battery Life for Electric UAVs—Data.gov*. Accessed: May 25, 2019. [Online]. Available: https://catalog.data.gov/dataset/predicting-battery-life-for-electric-uavs

[112] *Prognostics Center—Data Repository*. Accessed: May 25, 2019. [Online]. Available: https://ti.arc.nasa.gov/tech/dash/groups/pcoe/prognostic-data-repository/

[113] M. A. Hannan, M. S. H. Lipu, A. Hussain, M. H. Saad, and A. Ayob, "Neural network approach for estimating state of charge of lithium-ion battery using backtracking search algorithm," *IEEE Access*, vol. 6, pp. 10069–10079, 2018.

[114] T. D. Sanger, "Optimal unsupervised learning in a single-layer linear feedforward neural network," *Neural Netw.*, vol. 2, no. 6, pp. 459–473, Jan. 1989.

[115] G.-B. Huang, Y.-Q. Chen, and H. A. Babri, "Classification ability of single hidden layer feedforward neural networks," *IEEE Trans. Neural Netw.*, vol. 11, no. 3, pp. 799–801, May 2000.

[116] H. T. Huynh and Y. Won, "Regularized online sequential learning algorithm for single-hidden layer feedforward neural networks," *Pattern Recognit. Lett.*, vol. 32, no. 14, pp. 1930–1935, Oct. 2011.

[117] S. Tong, J. H. Lacap, and J. W. Park, "Battery state of charge estimation using a load-classifying neural network," *J. Energy Storage*, vol. 7, pp. 236–243, Aug. 2016.

[118] L. Kang, X. Zhao, and J. Ma, "A new neural network model for the state-of-charge estimation in the battery degradation process," *Appl. Energy*, vol. 121, pp. 20–27, May 2014.

[119] H. Chaoui and C. C. Ibe-Ekeocha, "State of charge and state of health estimation for lithium batteries using recurrent neural networks," *IEEE Trans. Veh. Technol.*, vol. 66, no. 10, pp. 8773–8783, Oct. 2017.

[120] D. Cui, B. Xia, R. Zhang, Z. Sun, Z. Lao, W. Wang, W. Sun, Y. Lai, and M. Wang, "A novel intelligent method for the state of charge estimation of lithium-ion batteries using a discrete wavelet transform-based wavelet neural network," *Energies*, vol. 11, no. 4, p. 995, Apr. 2018.

[121] Y. LeCun, Y. Bengio, and G. Hinton, "Deep learning," *Nature*, vol. 521, no. 7553, pp. 436–444, May 2015.

[122] C. Ding and D. Tao, "Trunk-branch ensemble convolutional neural networks for video-based face recognition," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 40, no. 4, pp. 1002–1014, Apr. 2017.

[123] H. Luo, Y. Yang, B. Tong, F. Wu, and B. Fan, "Traffic sign recognition using a multi-task convolutional neural network," *IEEE Trans. Intell. Transp. Syst.*, vol. 19, no. 4, pp. 1100–1111, Apr. 2018.

[124] T. Araújo, G. Aresta, E. Castro, J. Rouco, P. Aguiar, C. Eloy, A. Polónia, and A. Campilho, "Classification of breast cancer histology images using convolutional neural networks," *PLoS ONE*, vol. 12, no. 6, Jun. 2017, Art. no. e0177544.

[125] T. Afouras, J. S. Chung, A. Senior, O. Vinyals, and A. Zisserman, "Deep audio-visual speech recognition," in *Proc. IEEE Int. Conf. Acoust., Speech Signal Process. (ICASSP)*, Brisbane, QLD, Australia, Sep. 2018, pp. 20130–20134.

[126] L. Deng and Y. Liu, Eds., *Deep Learning in Natural Language Processing*. Singapore: Springer, 2018.

[127] Z. Che, S. Purushotham, K. Cho, D. Sontag, and Y. Liu, "Recurrent neural networks for multivariate time series with missing values," *Sci. Rep.*, vol. 8, no. 1, Apr. 2018, Art. no. 6085.

[128] P. Khumprom and N. Yodo, "A data-driven predictive prognostic model for lithium-ion batteries based on a deep learning algorithm," *Energies*, vol. 12, no. 4, p. 660, Feb. 2019.

[129] L. Li, Y. Peng, Y. Song, and D. Liu, "Lithium-ion battery remaining useful life prognostics using data-driven deep learning algorithm," in *Proc. Prognostics Syst. Health Manage. Conf.*, Chongqing, China, Oct. 2018, pp. 1094–1100.

[130] G. Zhao, G. Zhang, Y. Liu, B. Zhang, and C. Hu, "Lithium-ion battery remaining useful life prediction with deep belief network and relevance vector machine," in *Proc. IEEE Int. Conf. Prognostics Health Manage. (ICPHM)*, Dallas, TX, USA, Jun. 2017, pp. 7–13.

[131] S. Shen, M. Sadoughi, and C. Hu, "Online estimation of lithium-ion battery capacity using transfer learning," in *Proc. IEEE Transp. Electrific. Conf. Expo (ITEC)*, Detroit, MI, USA, Jun. 2019, pp. 1–4.

[132] D. Liu, L. Li, Y. Song, L. Wu, and Y. Peng, "Hybrid state of charge estimation for lithium-ion battery under dynamic operating conditions," *Int. J. Electr. Power Energy Syst.*, vol. 110, pp. 48–61, Sep. 2019.

[133] B. Xiao, Y. Liu, and B. Xiao, "Accurate state-of-charge estimation approach for lithium-ion batteries by gated recurrent unit with ensemble optimizer," *IEEE Access*, vol. 7, pp. 54192–54202, 2019.

[134] T. Hansen and C.-J. Wang, "Support vector based battery state of charge estimator," *J. Power Sources*, vol. 141, no. 2, pp. 351–358, Mar. 2005.

[135] J. C. A. Antón, P. J. G. Nieto, C. B. Viejo, and J. A. V. Vilán, "Support vector machines used to estimate the battery state of charge," *IEEE Trans. Power Electron.*, vol. 28, no. 12, pp. 5919–5926, Dec. 2013.

[136] J. C. Á. Antón, P. J. G. Nieto, F. J. de Cos Juez, F. S. Lasheras, M. G. Vega, and M. N. R. Gutiérrez, "Battery state-of-charge estimator using the SVM technique," *Appl. Math. Model.*, vol. 37, no. 9, pp. 6244–6253, May 2013.

[137] J. N. Hu, J. J. Hu, H. B. Lin, X. P. Li, C. L. Jiang, X. H. Qiu, and W. S. Li, "State-of-charge estimation for battery management system using optimized support vector machine for regression," *J. Power Sources*, vol. 269, pp. 682–693, Dec. 2014.

[138] Y. Chen, B. Long, and X. Lei, "The battery state of charge estimation based weighted least squares support vector machine," in *Proc. Asia–Pacific Power Energy Eng. Conf. (APPEEC)*, Wuhan, China, Mar. 2011, pp. 1–4.

[139] V. Kecman, *Support Vector Machines—An Introduction*. Springer, 2005, pp. 1–47.

[140] V. Novák, I. Perfilieva, and J. Močkoř, "Functional systems in fuzzy logic theories," in *Mathematical Principles of Fuzzy Logic*. Boston, MA, USA: Springer, 1999, pp. 179–222.

[141] A. J. Salkind, C. Fennie, P. Singh, T. Atwater, and D. E. Reisner, "Determination of state-of-charge and state-of-health of batteries by fuzzy logic methodology," *J. Power Sources*, vol. 80, nos. 1–2, pp. 293–300, Jul. 1999.

[142] H. Sheng and J. Xiao, "Electric vehicle state of charge estimation: Nonlinear correlation and fuzzy support vector machine," *J. Power Sources*, vol. 281, pp. 131–137, May 2015.

[143] Y. Li, C. Wang, and J. Gong, "A combination Kalman filter approach for state of charge estimation of lithium-ion battery considering model uncertainty," *Energy*, vol. 109, pp. 933–946, Aug. 2016.

[144] P. Singh, R. Vinjamuri, X. Wang, and D. Reisner, "Design and implementation of a fuzzy logic-based state-of-charge meter for Li-ion batteries used in portable defibrillators," *J. Power Sources*, vol. 162, no. 2, pp. 829–836, Nov. 2006.

[145] M. A. Awadallah and B. Venkatesh, "Accuracy improvement of SoC estimation in lithium-ion batteries," *J. Energy Storage*, vol. 6, pp. 95–104, May 2016.

[146] T. Zahid, K. Xu, W. Li, C. Li, and H. Li, "State of charge estimation for electric vehicle power battery using advanced machine learning algorithm under diversified drive cycles," *Energy*, vol. 162, pp. 871–882, Nov. 2018.

[147] W. X. Shen, C. C. Chan, E. W. C. Lo, and K. T. Chau, "Adaptive neuro-fuzzy modeling of battery residual capacity for electric vehicles," *IEEE Trans. Ind. Electron.*, vol. 49, no. 3, pp. 677–684, Jun. 2002.

[148] K. F. Man, K. S. Tang, and S. Kwong, "Genetic algorithms: Concepts and applications [in engineering design]," *IEEE Trans. Ind. Electron.*, vol. 43, no. 5, pp. 519–534, Oct. 1996.
[149] Y. Zheng, L. Lu, X. Han, J. Li, and M. Ouyang, "$LiFePO_4$ battery pack capacity estimation for electric vehicles based on charging cell voltage curve transformation," *J. Power Sources*, vol. 226, pp. 33–41, Mar. 2013.
[150] J. Xu, B. Cao, Z. Chen, and Z. Zou, "An online state of charge estimation method with reduced prior battery testing information," *Int. J. Elect. Power Energy Syst.*, vol. 63, pp. 178–184, Dec. 2014.
[151] W.-Y. Chang, "Estimation of the state of charge for a LFP battery using a hybrid method that combines a RBF neural network, an OLS algorithm and AGA," *Int. J. Elect. Power Energy Syst.*, vol. 53, pp. 603–611, May 2013.
[152] M.-H. Golbon-Haghighi, H. Saeidi-Manesh, G. Zhang, and Y. Zhang, "Pattern synthesis for the cylindrical polarimetric phased array radar (CPPAR)," *Prog. Electromagn. Res. M*, vol. 66, pp. 87–98, Mar. 2018.
[153] Q. Sun, H. Lv, S. Wang, S. Jing, J. Chen, and R. Fang, "HV battery SoC estimation algorithm based on PSO," in *Proc. 3rd Int. Conf. Electromech. Control Technol. Transp.*, 2018, pp. 667–670.
[154] L. Rozaqi, E. Rijanto, and S. Kanarachos, "Comparison between RLS-GA and RLS-PSO for Li-ion battery SoC and SOH estimation: A simulation study," *J. Mechatron., Elect. Power, Veh. Technol.*, vol. 8, no. 1, pp. 40–49, Jul. 2017.
[155] A. C. Shekar and S. Anwar, "Real-time state-of-charge estimation via particle swarm optimization on a lithium-ion electrochemical cell model," *Batteries*, vol. 5, no. 1, p. 4, Jan. 2019.
[156] G. F. Guo, L. Shui, X. L. Wu, and B. G. Cao, "SoC estimation for Li-ion battery using SVM based on particle swarm optimization," *Adv. Mater. Res.*, vol. 1051, pp. 1004–1008, Oct. 2014.
[157] M. S. H. Lipu, M. A. Hannan, A. Hussain, and M. H. M. Saad, "Optimal BP neural network algorithm for state of charge estimation of lithium-ion battery using PSO with PCA feature selection," *J. Renew. Sustain. Energy*, vol. 9, no. 6, Nov. 2017, Art. no. 064102.
[158] M. Charkhgard and M. Farrokhi, "State-of-charge estimation for lithium-ion batteries using neural networks and EKF," *IEEE Trans. Ind. Electron.*, vol. 57, no. 12, pp. 4178–4187, Dec. 2010.
[159] C. Chen, R. Xiong, R. Yang, W. Shen, and F. Sun, "State-of-charge estimation of Lithium-ion battery using an improved neural network model and extended Kalman filter," *J. Clean. Prod.*, vol. 234, pp. 1153–1164, Oct. 2019.
[160] J. Rivera-Barrera, N. Muñoz-Galeano, and H. O. Sarmiento-Maldonado, "SoC estimation for lithium-ion batteries: Review and future challenges," *Electronics*, vol. 6, no. 4, p. 102, 2017.
[161] M. Bragard, N. Soltau, S. Thomas, and R. W. De Doncker, "The balance of renewable sources and user demands in grids: Power electronics for modular battery energy storage systems," *IEEE Trans. Power Electron.*, vol. 25, no. 12, pp. 3049–3056, Dec. 2010.
[162] J. Cao and A. Emadi, "A new battery/ultracapacitor hybrid energy storage system for electric, hybrid, and plug-in hybrid electric vehicles," *IEEE Trans. Power Electron.*, vol. 27, no. 1, pp. 122–132, Jan. 2012.
[163] M. Dubarry, N. Vuillaume, and B. Y. Liaw, "Origins and accommodation of cell variations in Li-ion battery pack modeling," *Int. J. Energy Res.*, vol. 34, no. 2, pp. 216–231, Feb. 2010.
[164] H. Dai, X. Wei, Z. Sun, J. Wang, and W. Gu, "Online cell SoC estimation of Li-ion battery packs using a dual time-scale Kalman filtering for EV applications," *Appl. Energy*, vol. 95, pp. 227–237, Jul. 2012.
[165] X. Hu, F. Sun, and Y. Zou, "Estimation of state of charge of a lithium-ion battery pack for electric vehicles using an adaptive Luenberger observer," *Energies*, vol. 3, no. 9, pp. 1586–1603, Jul. 2010.
[166] R. Xiong, F. Sun, X. Gong, and H. He, "Adaptive state of charge estimator for lithium-ion cells series battery pack in electric vehicles," *J. Power Sources*, vol. 242, pp. 699–713, Nov. 2013.
[167] R. Yang, R. Xiong, H. He, H. Mu, and C. Wang, "A novel method on estimating the degradation and state of charge of lithium-ion batteries used for electrical vehicles," *Appl. Energy*, vol. 207, pp. 336–345, Dec. 2017.
[168] Y. Yin, Y. Hu, S.-Y. Choe, H. Cho, and W. T. Joe, "New fast charging method of lithium-ion batteries based on a reduced order electrochemical model considering side reaction," *J. Power Sources*, vol. 423, pp. 367–379, May 2019.
[169] Q. Lin, J. Wang, R. Xiong, W. Shen, and H. He, "Towards a smarter battery management system: A critical review on optimal charging methods of lithium ion batteries," *Energy*, vol. 183, pp. 220–234, Sep. 2019.
[170] R. Collin, Y. Miao, A. Yokochi, P. Enjeti, and A. von Jouanne, "Advanced electric vehicle fast-charging technologies," *Energies*, vol. 12, no. 10, p. 1839, May 2019.
[171] J. Zhang, L. Zhang, F. Sun, and Z. Wang, "An overview on thermal safety issues of lithium-ion batteries for electric vehicle application," *IEEE Access*, vol. 6, pp. 23848–23863, 2018.
[172] N. E. Galushkin, N. N. Yazvinskaya, and D. N. Galushkin, "Mechanism of thermal runaway in lithium-ion cells," *J. Electrochem. Soc.*, vol. 165, no. 7, pp. A1303–A1308, May 2018.
[173] L. Lu, X. Han, J. Li, J. Hua, and M. Ouyang, "A review on the key issues for lithium-ion battery management in electric vehicles," *J. Power Sources*, vol. 226, pp. 272–288, Mar. 2013.
[174] D. Bernardi, E. Pawlikowski, and J. Newman, "A general energy balance for battery systems," *J. Electrochem. Soc.*, vol. 132, no. 1, pp. 5–12, Jan. 1985.
[175] L. Rao and J. Newman, "Heat-generation rate and general energy balance for insertion battery systems," *J. Electrochem. Soc.*, vol. 144, no. 8, pp. 2697–2704, Aug. 1997.
[176] K. E. Thomas and J. Newman, "Thermal modeling of porous insertion electrodes," *J. Electrochem. Soc.*, vol. 150, no. 2, pp. A176–A192, Feb. 2003.
[177] K. Kumaresan, G. Sikha, and R. E. White, "Thermal model for a Li-ion cell," *J. Electrochem. Soc.*, vol. 155, no. 2, pp. A164–A171, Feb. 2008.
[178] P. Ramadass, B. Haran, R. White, and B. N. Popov, "Capacity fade of Sony 18650 cells cycled at elevated temperatures: Part I. Cycling performance," *J. Power Sources*, vol. 112, no. 2, pp. 606–613, Nov. 2002.
[179] S. Panchal, J. Mcgrory, J. Kong, R. Fraser, M. Fowler, I. Dincer, and M. Agelin-Chaab, "Cycling degradation testing and analysis of a $LiFePO_4$ battery at actual conditions," *Int. J. Energy Res.*, vol. 41, no. 15, pp. 2565–2575, Jul. 2017.
[180] K. Amine, J. Liu, and I. Belharouak, "High-temperature storage and cycling of C-$LiFePO_4$/graphite Li-ion cells," *Electrochem. Commun.*, vol. 7, no. 7, pp. 669–673, Jul. 2005.
[181] K. Takei, K. Kumai, Y. Kobayashi, H. Miyashiro, N. Terada, T. Iwahori, and T. Tanaka, "Cycle life estimation of lithium secondary battery by extrapolation method and accelerated aging test," *J. Power Sources*, vols. 97–98, pp. 697–701, Jul. 2001.
[182] F. Leng, C. M. Tan, and M. Pecht, "Effect of temperature on the aging rate of Li ion battery operating above room temperature," *Sci. Rep.*, vol. 5, no. 1, Oct. 2015, Art. no. 12967.
[183] M. A. Hannan, M. M. Hoque, A. Hussain, Y. Yusof, and P. J. Ker, "State-of-the-art and energy management system of lithium-ion batteries in electric vehicle applications: Issues and recommendations," *IEEE Access*, vol. 6, pp. 19362–19378, 2018.
[184] (2017). *Battery Management Systems (BMS)*. Accessed: Jul. 24, 2018. [Online]. Available: https://www.mpoweruk.com/bms.htm
[185] B. Xia, D. Cui, Z. Sun, Z. Lao, R. Zhang, W. Wang, W. Sun, Y. Lai, and M. Wang, "State of charge estimation of lithium-ion batteries using optimized Levenberg–Marquardt wavelet neural network," *Energy*, vol. 153, pp. 694–705, Jun. 2018.
[186] W. He, N. Williard, C. Chen, and M. Pecht, "State of charge estimation for Li-ion batteries using neural network modeling and unscented Kalman filter-based error cancellation," *Int. J. Elect. Power Energy Syst.*, vol. 62, pp. 783–791, Nov. 2014.
[187] H. Chaoui, C. C. Ibe-Ekeocha, and H. Gualous, "Aging prediction and state of charge estimation of a $LiFePO_4$ battery using input time-delayed neural networks," *Electr. Power Syst. Res.*, vol. 146, pp. 189–197, May 2017.
[188] Y. Zhang, R. Xiong, H. He, and W. Shen, "Lithium-ion battery pack state of charge and state of energy estimation algorithms using a hardware-in-the-loop validation," *IEEE Trans. Power Electron.*, vol. 32, no. 6, pp. 4421–4431, Jun. 2017.
[189] X. Tian, B. Jeppesen, T. Ikushima, F. Baronti, and R. Morello, "Accelerating state-of-charge estimation in FPGA-based battery management systems," in *Proc. 6th Hybrid Electr. Vehicles Conf. (HEVC)*, London, U.K., Nov. 2016, pp. 1–6.