Received November 11, 2017, accepted December 2, 2017, date of publication December 6, 2017,
date of current version February 14, 2018.

Digital Object Identifier 10.1109/ACCESS.2017.2780258

Critical Review on the Battery State of Charge Estimation Methods for Electric Vehicles

RUI XIONG, (Senior Member, IEEE), JIAYI CAO, QUANQING YU, (Student Member, IEEE), HONGWEN HE, (Senior Member, IEEE), AND FENGCHUN SUN

National Engineering Laboratory for Electric Vehicles, School of Mechanical Engineering, Beijing Institute of Technology, Beijing 100081, China

Corresponding authors: Hongwen He (hwhebit@bit.edu.cn) and Fengchun Sun (sunfch@bit.edu.cn)

This work was supported in part by the National Natural Science Foundation of China under Grant 51507012 and in part by the Beijing Nova Program under Grant Z171100001117063.

ABSTRACT Battery technology is the bottleneck of the electric vehicles (EVs). It is important, both in theory and practical application, to do research on the modeling and state estimation of batteries, which is essential to optimizing energy management, extending the life cycle, reducing cost, and safeguarding the safe application of batteries in EVs. However, the batteries, with strong time-variables and nonlinear characteristics, are further influenced by such random factors such as driving loads, operational conditions, in the application of EVs. The real-time, accurate estimation of their state is challenging. The classification of the estimation methodologies for estimating state-of-charge (SoC) of battery focusing with the estimation method/algorithm, advantages, drawbacks, and estimation error are systematically and separately discussed. Especially for the battery packs existing of the inevitable inconsistency in cell capacity, resistance and voltage, the advanced characterizing monomer selection, and bias correction-based method has been described and discussed. The review also presents the key feedback factors that are indispensable for accurate estimation of battery SoC, it will be helpful for ensuring the SoC estimation accuracy. It will be very helpful for choosing an appropriate method to develop a reliable and safe battery management system and energy management strategy of the EVs. Finally, the paper also highlights a number of key factors and challenges, and presents the possible recommendations for the development of next generation of smart SoC estimation and battery management systems for electric vehicles and battery energy storage system.

INDEX TERMS Batteries, data-driven estimation, electric vehicles, model based estimation, multi-scale, state of charge.

I. INTRODUCTION

Battery technology is a major technical bottleneck with electric vehicles (EVs). To develop a battery system that can satisfy the requirements of EVs, many countries, such as America, Japan and Germany, have launched their own special projects to improve the performance of batteries [1], [2]. Through the Tenth Five-Year Plan, Eleventh Five-Year Plan, and Twelfth Five-Year Plan, performance of battery cells has achieved significant improvement. The Ni−MH battery and lithium-ion battery have been widely used in a variety of EVs.

To ensure the safe application, improve the driving range, optimize the power management strategy, prolong the service life and decrease the cost of the batteries, efficient management for batteries is very necessary [3]–[10]. A general block diagram of a battery management system (BMS) is shown in Fig.1.

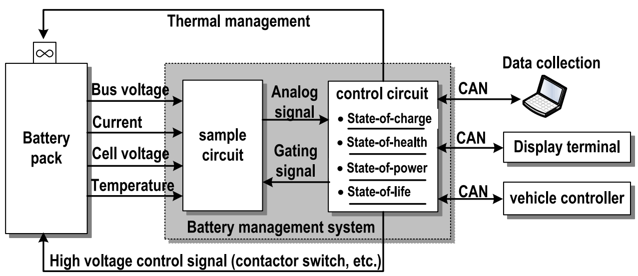

FIGURE 1. General function of a battery management system.

A BMS consists of many kinds of sensors, actuators, controllers and signal line. The basic task of a BMS is to ensure safe and optimal use of the energy inside the battery and to provide accurate battery state information for the vehicular energy management system. What's more, it should have the capability to give appropriate interventions for the battery system if it is operated in an abnormal condition. This is achieved by monitoring and controlling the charging and discharging process of batteries. The main task of the sample circuit is to measure the current, voltage and temperature according to the gating signal obtained from the control circuit. The basic task of the control circuit is to estimate the state of charge (SoC), state of health (SoH), state of available power capability (SoP) and state of life (SoL) of batteries through advanced algorithms with measurements of battery current, voltage and temperature converted from the analog signal. And then this information will be transmitted to the vehicular controller and provide key decision factors for vehicular energy management and power distribution [11]–[13].

The SoC of a battery is defined as the percentage of the remaining capacity in its maximum available capacity. Battery SoC does the similar operation of the fuel gauge in a gasoline-driven vehicle which indicates how much energy is left inside a battery to power an EVs. Accurate estimation of battery SoC not only helps to provide information about the real-time remaining capacity and energy of the battery, but also gives assurance of a reliable and safe vehicular operation. However, since batteries are complex electrochemical devices with a distinct nonlinear behavior depending on various internal and external conditions, their accurate SoC estimation is a challenging task. On the other hand, because the voltage and energy of one cell are low, ten to thousands of cells have to be connected in corresponding series and parallel to satisfy the requirements of EVs. Considering the inconsistent cell characteristics of the performance and operating conditions inside every battery pack, SoC estimations for solving their inner inhabited states remain very challenging. Furthermore, the performance of the battery is highly affected by aging, temperature variation, charge- discharge cycles which make the task of estimating an accurate SoC very challenging [11]–[13].

In considering the indispensable function of battery SoC in battery management, lots of methods have been proposed for determining the SoC accurately. Early from the year of 1960s, the academics, researchers, scientists have performed an extensive research to carry out the battery SoC estimation [14], [15]. However, very few literatures have been found which provide a detailed description of the key difficulties to estimate battery SoC although more than half a century of efforts have been paid, the accurate estimation problem of battery SoC has not been solved efficiently [16]–[18]. Reference [2], [10], [16], [17] have presented a detailed SOC estimation in terms of overall research progress, future development trends and the origin of SOC estimation. However, there is no systematic exposition of the SOC calculation process and algorithm selection and how to deal with the uncertain environment conditions and grouping of battery system in the electric vehicles. Thus, this paper hopes to fill up the gap by exploring different existing methodologies and addressing the key issues and challenges for the SoC estimation of battery pack, not only focus on the battery cells. It will be very helpful for the researcher, scientist and vehicle manufacturer to choose an appropriate method for battery management and energy management.

This paper presents a classification for the existing SoC estimation methods. It systematically reviews the battery SoC estimation methods in EV applications with the completely operation process for each type. In order to provide detailed information and knowledge to the vehicle manufacturer and BMS developers, the benefits and drawbacks of the existing SoC estimation methods have been briefly elaborated in Section 2. The issues and challenges of implementing various SoC methods for battery pack are illustrated in Section 3. The conclusion and recommendation are presented in Section 4.

II. SoC ESTIMATION METHODS

As mentioned in the introduction, the determination of battery SoC is always an essential part of a BMS. The accurate and reliable estimation of battery SoC can provide a necessary assessment factor for vehicle energy management and optimal design of the control system. Therefore, a larger number of methods have been proposed for estimating battery SoC in real-time. For comparing these methods in more detail, we have classified them into four groups and the classification is illustrated in Fig.2.

A. LOOKING-UP TABLE BASED METHODS

SoC of batteries has a direct mapping relationship with their external (static) characteristic parameters, such as the open circuit voltage (OCV), impedance et al. Thus, by measuring their parameters and then using the method of the looking−up table which was built with the relationships between SoC and one or more parameters, we can infer the SoC [19]–[22].

Let us take battery OCV as an example. Fig.3 shows battery OCV versus SoC for a lithium−ion polymer battery (LiPB).

It indicates that the OCV of a LiPB cell shows a monotonically increasing trend with its SoC. Thus, if we know the OCV, we can infer battery SoC through looking-up the table between OCV and SoC. This relationship is exploited for the estimation of SoC for most battery management technologies. It can be efficiently used for calibrating the erroneous SoC. However, it is hard to measure the precise OCV in real-time because the measurement of battery OCV requires cutting off the power and having the battery rest for an extended period. On the other hand, the measurement of battery impedance relies on the measurement device, thus, it cannot be implemented for running EVs.

This type of SoC estimation method is more suitable for being applied to the laboratory environment.

B. AMPERE-HOUR INTEGRAL METHOD

When the maximum available capacity of a battery is known and its current can be measured precisely, the ampere-hour integral method can permit the accurate calculation of the variation of the SoC. If we know the initial SoC, we can obtain the accurate SoC. The calculation equation for the

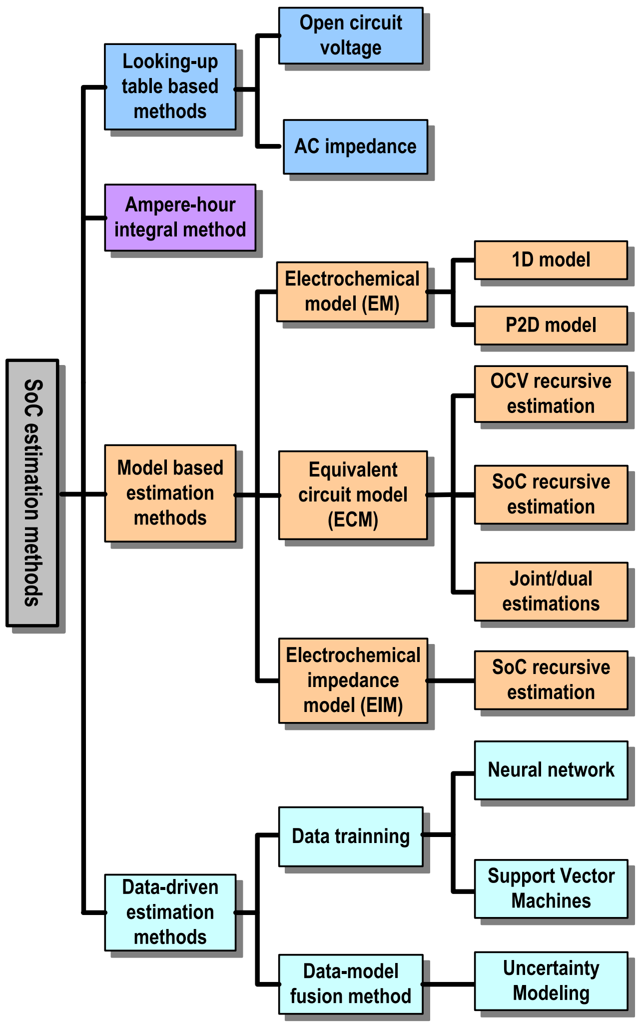

FIGURE 2. Classification of the SoC estimation methods.

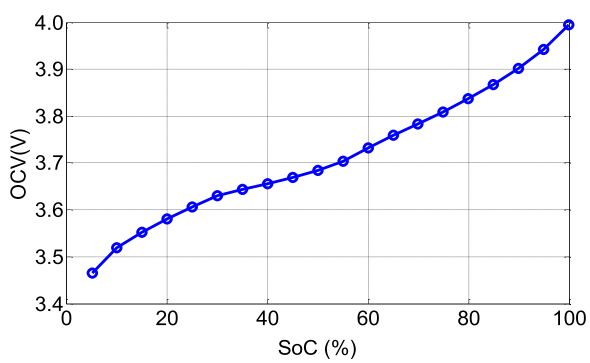

FIGURE 3. OCV curve of a LiPB cell.

ampere-hour integral method is presented in Eq. (1).

$$z_k = z_0 - \int_{t_0}^{t_k} \eta I_{\mathrm{L}}(t)dt \Big/ Q \tag{1}$$

where z denotes battery SoC, z_{k} and z_0 denote the SoC at discrete-time t_{k} and t_0 respectively. t_0 denotes the initial value, $t_{\mathrm{k}} = t_0 + k \times \Delta t$, Δt denotes the sampling interval. η denotes the coulomb efficiency, $I_{\mathrm{L}}(t)$ denotes the load current of battery, Q denotes the maximum available capacity. It should be emphasized that Q has been defined as the nominal/rates capacity in some studies. Since battery capacity is affected by the operating conditions and aging status, it should not be constant in SoC calculation. Thus, we use the maximum available capacity.

This method works very accurately for batteries because there are no significant side effects during normal operation. However, for the estimation of the SoC by this method, there are three drawbacks that need to be dealt with first. First, the initial SoC must be known. Second, the measurement errors of battery current from random disturbances, such as noise and temperature drift, are inevitable. Lastly, the Q is required to be recalibrated as the variation of the operating conditions and aging levels of the battery. The combination of the above-mentioned factors would further decrease the reliability of this method. Therefore, the ampere-hour integral method is more apt to work with other supporting techniques, for example, model-based methods.

C. MODEL-BASED ESTIMATION METHODS

With the development of battery technologies, a large number of battery models have been put forward for the purpose of vehicle power management and BMS [2]. The most commonly used models can be roughly summarized as three types: electrochemical model (EM), equivalent circuit model (ECM) and electrochemical impedance model (EIM). In the model-based SoC estimation methods, battery models are expressed as state equations. A lot of nonlinear state estimation algorithms and adaptive filters are employed to estimate or infer the internal state of batteries. The typical algorithms are Kalman filter [23]–[25], Luenberger observe [26], PI (proportion integration) observer [27], H∞ observer [28], sliding−mode observer [29], [30], et al. The Kalman filter has become a general technique for nonlinear estimation and machine learning applications.

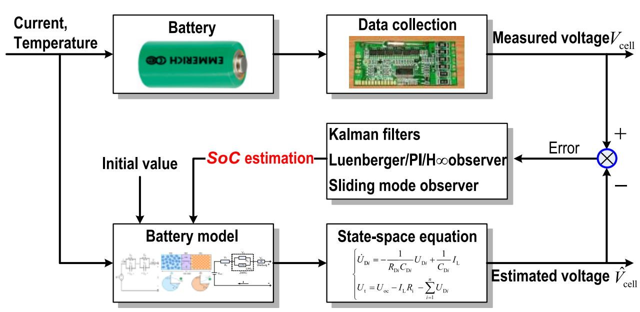

FIGURE 4. A general flowchart of the model-based SoC estimation method.

Fig.4 shows a general flowchart of model-based SoC estimation methods. Actually, these methods are a type of fusion method. It combines the ampere-hour integral method and battery OCV parameters table based looking-up method through state equation of batteries. It is noted that the SoC of batteries acts as a bridge between the ampere-hour integral method and the looking-up table based methods. An inaccurate SoC estimate calculated by the ampere-hour integral method brings an erroneous battery OCV, and then it increases the prediction error of the terminal voltage. In this way, the minimum prediction error of battery terminal voltage can be achieved only when the best SoC has been obtained. In other words, the OCV can be used to correct the estimation error.

1) ELECTROCHEMICAL MODEL (EM)

The EM, as proposed by Prof. Newman, has been employed to lots of applications with the development of the battery technologies. In general, the EM describes the mass, energy, and momentum transport of each specie for each phase and component of a battery cell. More specifically, the electrochemical model has capability to describe the macroscopic quantities such as cell current and voltage and local distribution on a microscopic scale for cell concentration, potential, current, and temperature [31], [32]. Its strengths are the better prediction of the inward spatial and temporal states of the battery, such as the concentration of the solid/electrolyte phase and the current/potential distribution of the two electrodes. The widely used electrochemical models for battery SoC estimation are the one-dimension (1D) model [32]–[34], the pseudo two-dimensional (P2D) model [35], the quasi-three dimensional full order physical model [36] and the first principle model [31], among which the simplification of the P2D model, single particle model [31], [37]–[44] is most popular.

Chao-Yang Wang proposed a simplification model of 1D electrochemical model though the transfer function method [33], [34]. The order and complexity of the original 1D model have been greatly reduced. Then an extended Kalman filter (EKF) has been employed to build a model-based SoC estimator with this simplified model [45]. To improve the prediction performance of the EM with regard to voltage, degradation and temperature behaviors of battery, Doyle et al. proposed a P2D electrochemical model on the basis of its physical process [46], [47]. A common disadvantage of the P2D model is the long simulation time due to the large number of nonlinear equations, thus this model becomes computationally inefficient for simulating conditions such as cycling behavior and series/parallel configuration of stacked cells in battery packs. To solve the problem of low computational efficiency of the P2D model which is unsuitable for BMS application, the single particle model has been proposed and the schematic of the model is presented in Fig.5.

The single particle model ignores the detailed distribution of local concentration and potential in the solution phase and instead accounts for a lumped solution resistance term. Furthermore, the local reaction currents across the porous electrode are assumed to be uniform, which allows treating a porous electrode as a large number of single particles, all of which are subjected to the same conditions. These assumptions are reasonable for low applied current densities, thin electrodes, and highly conductive electrodes [48]. Based on the single particle model, the EKF and unscented Kalman filter (UKF) are respectively used to build the SoC estimator by Santhanagopalan and White [43], [49].

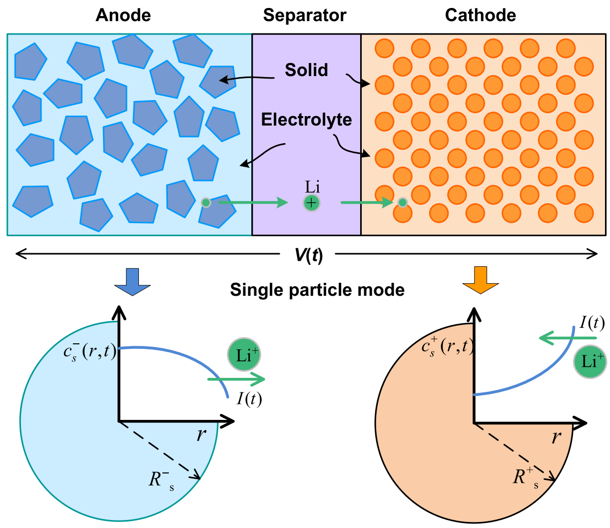

FIGURE 5. Schematic of the single particle model [41].

Estimation methods based on the EM can reflect the effect of kinetic process and charge transfer process in the battery. The estimations can not only satisfy the required accuracy of the BMS, but also provide some rules for the optimal design of the battery. However, though several simplifications have been made, it is difficult to identify all parameters. Additionally, it requires high professional background, thus it hardly can be applied to the BMS directly.

2) EQUIVALENT CIRCUIT MODEL (ECM)

The ECM is widely applied to BMS and vehicular energy management system [50]–[77]. It uses electrical circuit components, such as resistors, capacitors, and voltage source to build circuit networks to describe the terminal voltage of batteries. It can describe various dynamic behaviors of the battery accurately. It has good applicability and expansibility, and can be used to develop the model-based SoC estimation approach precisely. Fig.6 presents an ECM with n RC networks, named the NRC model hereafter. The model contains three parts: (i) Voltage source: it uses OCV (open circuit voltage) to denote battery voltage source. (ii) Ohmic voltage cross the equivalent ohmic resistance R_{i}, which represents the electrical resistance from various battery components or with the accumulation and dissipation of charge in the electrical double layer. (iii) Dynamic voltage behavior and the mass transport effects: the elements of R_{D} and C_{D} are used to describe the diffusion resistance and diffusion capacitance. $C_{\mathrm{D}i}$ denotes the ith equivalent diffusion capacitance and $R_{\mathrm{D}i}$ denotes the ith equivalent diffusion resistance, $U_{\mathrm{D}i}$ is the voltage across $C_{\mathrm{D}i}$, $i = 1, 2, 3, 4, \ldots n$ [60]. In Fig. 6, i_{L} denotes battery load current, U_{t} denotes battery terminal voltage. Electrical behavior of the NRC battery model can

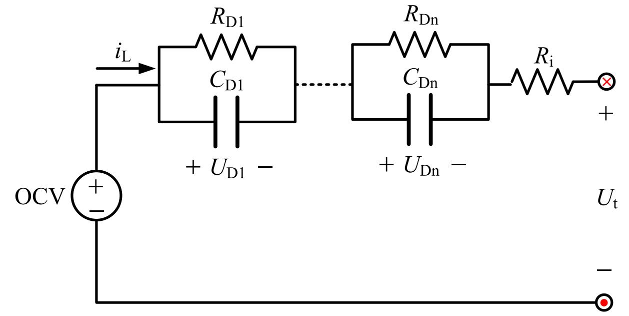

FIGURE 6. Schematic diagram of the NRC ECM [60].

be expressed by Eq. (2).

$$\begin{cases} \dot{U}_{Di} = -\dfrac{1}{R_{Di}C_{Di}}U_{Di} + \dfrac{1}{C_{Di}}I_L \\ U_t = U_{oc} - I_L R_i - \displaystyle\sum_{i=1}^{n} U_{Di} \end{cases} \tag{2}$$

It is noted that the symbol of battery current is positive during the discharging process and the symbol is negative for charging process.

Following are three typical realizations of the model-based SoC estimation with the ECM.

a: OCV RECURSIVE ESTIMATION

Since battery OCV shows a monotonically increasing trend with SoC, the SoC can be predicted in real-time through the online identified OCV. The commonly used algorithms for battery system identification are recursive least squares (RLS) and the Kalman filter. The RLS method gets the optimal matching results for battery parameters by minimizing the sum of squares of the terminal voltage prediction error based on the ARX (auto regressive exogenous) model [61]. The Kalman filter achieves the accurate real-time parameters by minimizing the root mean square error between the desired output value and actual output value based on its state equation.

Based on the presented NRC equivalent circuit model, References [60]–[62] have proposed a RLS-based online parameter identification method with an incremental analysis based ARX model, and the trade-offs between model complexity and prediction precision have been systematically analyzed and evaluated. It can provide a reference for selecting the structure of battery model. With the online identified battery OCV, the authors have implemented the SoC estimation with the looking-up table based method. The results indicate that the SoC estimation errors are less than 5%. What's more, when the order of the NRC model is more than three, it is hard to obtain all parameters of the ARX model with the RLS based methods. To overcome these problems, an adaptive extended Kalman filter (AEKF) has been employed to develop an online parameter identification model and a recursive SoC estimation method. Results suggest that the SoC estimation with the mapping relationship

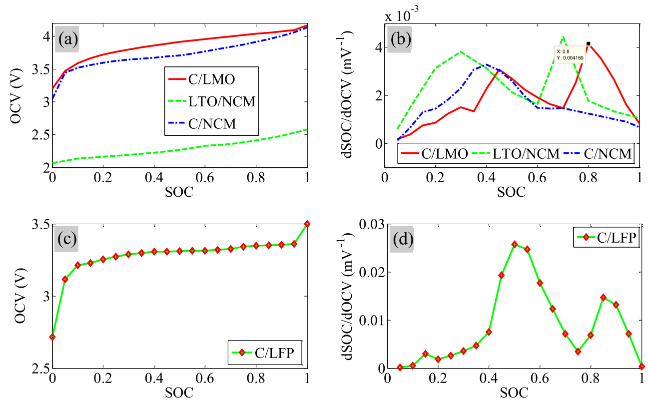

FIGURE 7. OCV curves and SoC variation per mV OCV: (a) OCV maps; (b) SoC variation per mV OCV; (c) OCV map; (d) SoC variation per mV voltage [64].

also can ensure an acceptable accuracy for the $LiMn_2O_4$ lithium battery [63].

It is worth noting that the mapping relationship between battery SoC and OCV is very sensitive to the material characteristic and aging status of battery cell. Fig.7 shows the OCVs of the four types of lithium-ion battery cells as well as corresponding SoC variation per mV voltage. The first one is $LiMn_2O_4$ cell which uses carbon (C) as its negative electrode and lithium manganese oxide (LMO) as its positive electrode (abbreviated as C/LMO). The second one is $Li_4Ti_5O_{12}$ lithium-ion cell which uses lithium titanate ($Li_4Ti_5O_{12}$) as its negative electrode and $Li[NiCoMn]O_2$ as its positive electrode (abbreviated as LTO/NCM). The third one is $Li[NiCoMn]O_2$ lithium-ion cell (abbreviated as C/NCM) and the last one is lithium iron phosphate $LiFePO_4$ cell (abbreviated as C/LFP).

Fig.7 shows that the OCV behaviors of the four kinds of lithium-ion battery cells are different, the slope of OCV curve of C/NCM is relatively steep and C/LFP is very flat. Thus, the corresponding SoC rates of change per mV OCV are very different. Considering that the voltage measurement inaccuracy of 5 mV, the interpolation error of battery SoC for C/LFP lithium-ion battery cell will be more than 10% while the errors for the other three kinds of lithium-ion batteries are less than 2.5%. On the other hand, the uncertain operating temperatures and aging levels also affect the mapping relationships between battery SoC and OCV, and maybe reduce the inference accuracy. Therefore, the OCV recursive estimation based SoC prediction method is not sufficiently accurate for main kinds of lithium-ion batteries.

b: SoC RECURSIVE ESTIMATION

Let us take the EKF for an example. The EKF remains the most preferred state estimator for solving both unconstrained and constrained state estimation problems in the field of battery modeling and state estimation. In state estimation, the EKF is the standard method of choice to achieve a recursive (approximate) maximum likelihood estimation of the

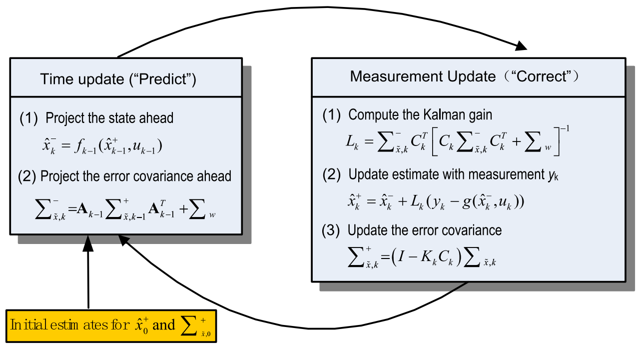

FIGURE 8. A general diagram of the time-discrete EKF.

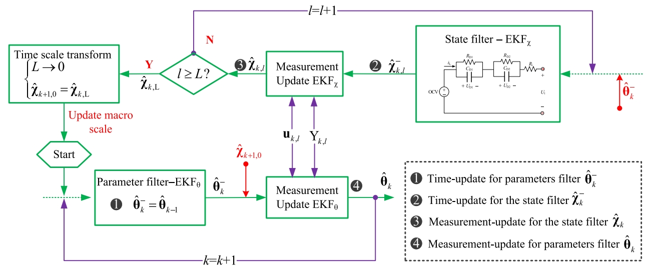

FIGURE 9. Implement flowchart of multi–scale EKF.

inhabited state. It provides optimal state estimation with minimum mean square error based on the information obtained from the system model and assumptions on uncertainties (noise) [65].

In 2004, G. L. Plett applied EKF to identify the parameters of the ECM and estimate the SoC of the batteries [23]–[25]. Taking the simple model as an example, the detailed implement processes of the SoC estimation with the EKF are described as follows. The model equation can be expressed by Eq.(3).

$$\begin{cases} z_{k+1} = z_k - \eta_i I_{\mathrm{L},k} \Delta t / Q \\ g_k = \mathrm{OCV}(z_k) - R I_{\mathrm{L},k} \end{cases} \tag{3}$$

where OCV(z) denotes the function for battery OCV, Q denotes battery nominal capacity of battery, R denotes ohmic resistance of battery. Then the Jacobi matrices of the EKF can be provided by:

$$\begin{cases} A_{k-1} = 1 \\ C_k = \partial \mathrm{OCV}(z_k) / \partial z_k \end{cases} \tag{4}$$

A general flow diagram of the EKF is presented in Fig.8, where L denotes Kalman gain matrix.

Corrections for the residual error of the model-based estimation process presented in Fig.4 are executed by updating the state estimation with the measurements in the EKF algorithm. Since the characteristics of state and measurement noise are considered in EKF, these SoC estimation methods achieve strong noise immunity. It is worth noting that battery OCV can affect the state estimation through the Kalman gain matrix since the Kalman gain matrix K is updated by the Jacobi matrix C, which is updated by the OCV of battery from Eq.(4). Thus, the relationship between battery OCV and SoC plays a significant role in EKF based SoC estimation.

In Fig. 8, x_{k} is the vector of dynamic states, u_{k} is the control input, w_{k} represents process noise which is assumed to be discrete-time Gaussian zero-mean white noise with covariance of $\sum_{\mathrm{x,k}}$. It should be noted that $\hat{\mathbf{x}}_{\mathrm{k}}^-$ and $\hat{\mathbf{x}}_{\mathrm{k}}^+$ both are estimates of the same quantity; and both are estimates of x_k. However, $\hat{\mathbf{x}}_{\mathrm{k}}^-$ is the estimate of $\mathbf{x}_{\mathrm{k}}$ *before* the measurement $\mathbf{y}_{\mathrm{k}}$ is taken into account, which is called *priori* estimate, and $\hat{\mathbf{x}}_{\mathrm{k}}^+$ is the estimate of *after* the measurement $\mathbf{y}_{\mathrm{k}}$ is taken into account, which is called *posterior* estimate.

However, the estimation accuracy of battery SoC with the above recursive estimation methods relies on the prediction accuracy of the model. As a result, an inaccurate or inappropriate battery model will lead to unrealistic estimates. Ref. [74] provided a detailed analysis of the SoC estimation results considering the uncertain model parameters of the battery. It shows that the dual/joint estimation for battery parameters and states is an effective solution.

c: JOINT/DUAL ESTIMATIONS

Considering that the battery parameters tend to change slowly over time while system states are prone to rapid fluctuation over time, it is not an optimal choice to use the same time scale for battery parameter and state estimation; on the contrary, the approach with the same scale barely can achieve accurate and reliable system estimates, and largely increases the computational cost of the control system. On the other hand, accurate and real-time estimation of battery capacity is an indispensable prerequisite for battery SoC estimation. The SoC estimation algorithm with the known battery capacity is difficult to apply to the BMS. So the multi-scale EKF is developed which uses the macro scale to estimate the battery parameters and uses the micro scale to estimate the system state, and the parameters of battery include model parameters and capacity, the state is the SoC. The implement flowchart of the proposed multi-scale EKF is presented in Fig.9.

Verification results of the multi-scale EKF show that maximum estimation errors of the capacity and SoC of batteries are less than 2% against uncertainty operating conditions and degradation status [77]. Where the macro-scale'' and micro-scale mean the estimation under big and small calculated time intervals. Based on the above analysis, the joint/dual estimation methods for battery parameters and states are more suitable for EVs application.

3) ELECTROCHEMICAL IMPEDANCE MODEL (EIM)

The electrochemical impedance spectroscopy (EIS) provides a unique tool for the analysis of the dynamic behavior of batteries. Compared with step-response methods, which are widely used for building ECMs, harmonic small-signal excitation allows for direct measurement of system response in any operating point. What's more, the parameters in EIMs

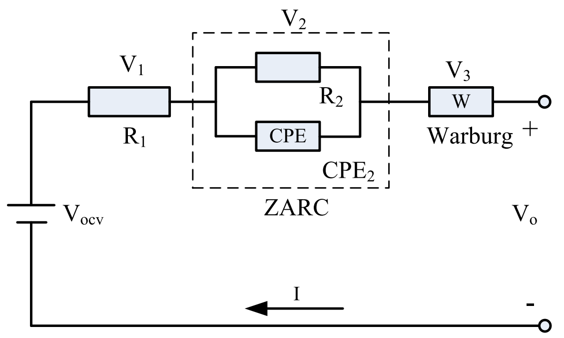

FIGURE 10. Equivalent circuit of the impedance model.

have a more substantial meaning than those presented in ECMs. In addition to the resistance, capacitor and voltage sources, the porous electrode theory based EIMs further comprise Warburg element, constant phase element (CPE), ZARC element et al. Based on the analysis with the measurements of EIS, [78] proposed an equivalent circuit of the EIM which is presented in Fig. 10.

In Fig.10, V_{ocv} denotes the OCV of the battery; V_1, V_2 and V_3 denote the voltage for R_1, ZARC and Warburg respectively; V_{o} is the terminal voltage of the battery which can be measured directly; I denotes the load current.

Based on the measurements of EIS at different SoC points, we can identify the parameters of EIM. Then with the state-equation of the EIM, we can use the calculation processes of the model-based estimation method presented in Fig.4 to estimate the SoC of battery in real-time [51], [78]–[80]. The estimation results of the battery SoC with the above described method shows that the maximum errors are less than $\pm 1\%$ [78].

D. DATA-DRIVEN ESTIMATION METHODS

Data-driven control methods merely use the input-output data of the system to develop a controller. Since these methods do not require an accurate plant model, the estimations and assumptions introduced in the plant modeling step are omitted. In particular, the data driven control approach can show great advantages in the following cases [81]:

(1) The global mathematical model of the controlled system is completely unknown;

(2) The uncertainties of the controlled system model are great;

(3) The mathematical model cannot be built for defining the controlled system with uncertain structure in its operating process;

(4) The mechanism model of the controlled system is too complicated or the number of the order is too prohibitive or it is impractical to analyze and design.

The black-box model is a typical data-driven method and the intelligent system is a classic approach. Due to the internal complex chemical reaction process and uncertain external operating conditions of batteries, it is challenging to model batteries accurately by ECM and EIM. However, the black-box model which uses the nonlinear relationship of the input data to train the model has several potential benefits such as parallel distributed processing, high computation rates, fault tolerance and adaptive capability to deal with this complicated problem. The typical algorithms that can be used for the black-box model includes the fuzzy controller [82], [83], the neural network [84]–[86], the support vector machine [87], [88] and a combination of these algorithms [89]–[91].

Nonlinear statistical data modeling tools are more practical. They can be used to model complex relationships between inputs and outputs or to find patterns in data. Ref. [85] used the neural network to develop the SoC estimator, where the input layer contains the current, temperature, SoC of the battery, and the voltage is the output layer. Results show high computation accuracy with this method.

The black-box model method can effectively solve nonlinear problems of modeling and state estimation, and realize high prediction accuracy. However, these algorithms are very sensitive to their parameters and they may not even be convergent with bad parameters selection when the train data cannot completely cover the present operating conditions.

E. RECOMMENDATION FOR THE ENGINEERING APPLICATIONS

The data-model fusion method is a type of online data driven estimation approach. It merges the online data-driven method and the model-based method, where the data-driven method can identify the system parameter in real-time with the online measurements. The model with real-time behavior can greatly improve the performance of the controlled system. The relationship between the online measurement data and the offline data is relative but interdependent. The online data-driven method merely uses the real-time measurements of the controlled system and the knowledge obtained from data processing to design the controller. It can ensure the convergence, stability and the robustness of the controlled system. Commonly used algorithms for the online data-driven methods are the RLS based method [75], the support vector machine [92], [93], the bias-correction based methods [60].

Sun and Xiong [94] proposed a data-model fusion method to estimate the SoC of a multi-cell series connected battery pack. Through the detailed analysis of the terminal voltage behavior of the battery, a model bias function between the ‘‘average pack model’’ and each single cell involved in the battery current, SoC and the current rate has been developed. Then the RLS and AEKF have respectively been used to update the model bias and estimate the SoC for all cells in the battery pack. Results indicate that both the voltage prediction error and SoC estimation error are less than 1% for all cells. They also indicate that the data-driven method does not repel the model-based method. In contrast, they are able to penetrate and complement each other and achieve a novel data model fusion method. It is worth noting that the data-driven method uses the experiment data in different levels and time scales, which is different from the model-based method that uses the offline data once.

Based on the above analysis for four types of SoC estimation methods for battery cell, we can find that each type has its own advantages. Taken as a whole, the joint/dual estimation methods for battery parameters and states and the data-model fusion method are two progressing method for achieving the accurate battery SoC estimation in real practical application. However, the prediction performance of battery models will degrade as the variation of battery aging, and operating condition and environment, different SoC operating ranges also will affect the model and method performance. Reference [95] discussed the predicted accuracy of the same battery models and different battery models under different SoC operating ranges, respectively. It found that the performance of the battery model is very sensitive to the above factors and then a new battery model merged by different models through the Bayes theorem has been proposed. Results show the fusion model has better overall performance under different battery operating conditions, aging levels and working ranges. Therefore, we can merge different types of battery models, i.e., EM and ECM, to form a multi-model fusion based data driven SoC estimation model/methodologies for ensuring the overall performance of battery SoC estimation. In this methodology, the joint/dual method can be employed as one part.

III. SoC ESTIMATION FOR BATTERY PACKS

Considering that the voltage and capacity/energy levels of battery cell cannot meet the requirements of EVs, the battery packs are usually composed of up to hundreds of cells connected in series or parallel. As we know, the more numbers of the cells connected in battery packs, the greater of the difference happens in each battery cell. What's worse, the inconsistencies in cells performance caused by the manufacturing chain coupling with the operation conditions of the battery system will lead to different degradation rate in their performance, and in turn spread the differences in individual cells [96]. As a result, it is difficult to fully guarantee the conformity of the initial performance parameters as well as the intrinsic or extrinsic operation condition of battery packs, and this non-uniform characteristic would lead to a difference in battery state. Consequently, the differences in battery performance degradation would be aggravated by those differences in battery state in turn.

On the other hand, for one battery cell, we can measure its capacity and SoC through discharging it from fully charged status to fully discharged status. Different from battery cell, the capacity and SoC of battery pack are not the basic natures. It is because the inconsistent characteristics of battery capacity, resistance, voltage et al, exist in battery pack unavoidably, which makes the accurate capacity and SoC measurements of battery pack are very hard. Battery pack shows strong time-varying, nonlinear, non-uniform and other complex characteristics. In this way, the SoC estimation of the battery pack can be equivalent to an estimation problem for the inner inhabited state of a strong time-varying, nonlinear, non-uniform and other complex hybrid connection battery system. However, so far there is no systematic theory to solve this problem.

To achieve accurate SoC estimations for battery packs, several efforts have been made and they can be classified into three types.

A. CELL CALCULATION BASED METHODS

Generally, it has three kinds of realizations.

(i) **"Big cell" method**, which regards the battery pack as a big cell, the battery pack's voltage and current are used to calculate the SoC of battery pack [26], [97]. However, the inconsistent characteristics in cells performance have been ignored. Obviously, it cannot ensure the safety application of the battery pack although it has less amount of calculation.

(ii) **"Short board effect" method**, which uses the extreme cell to calculate the SoC of battery pack. Namely, during discharging process the cell with lowest voltage is used for indicating the SoC of battery pack and during charging process the cell with highest voltage is used for indicating the SoC of battery pack. Obviously, it can improve the safety of the battery pack, but for battery pack commonly used of 30∼80% SoC operating range, this method will reduce the energy utilization of the battery pack.

(iii) **One by one calculation method**, which estimates the SoC for all cells in battery pack and then calculates the SoC of battery pack. As expect, this kind of method can obtain the desired estimation accuracy. However, the computational cost is big and it is not suitable for BMS in EVs.

B. SCREENING PROCESS BASED METHODS

It selects the battery cells which have similar battery capacity, resistance, et al, to construct a battery pack and then use the SoC of one cell from the battery pack to represent the SoC of battery pack due to the fact that all cells have good consistency. Reference [96] proposed a second level screening process to select the battery cells for packaging a battery pack, as shown in Fig.11. The results showed that the SoC estimation errors are less than 2% for all the cells in the battery pack. However, as aging process goes on, the performance of this method will degrade to the "big cell" method. The greater difference of the cells will make the estimation error bigger and bigger.

C. BIAS CORRECTION METHODS

Fig. 12 presents a bias correction based SoC estimation methods for cells series connected battery pack.

It firstly builds a nominal model for battery pack and then uses the bias-correction method to online identify the difference between the nominal model and the battery cell, the SoC estimation is carried out with the corrected model. With the SoC of each cell, the SoC of battery pack can be calculated lastly [94].

$$U_{\mathrm{t}}^{j} = U_{\mathrm{oc}} - U_{\mathrm{D1}} - \ldots - U_{\mathrm{Dn}} - i_{\mathrm{L}}R_{\mathrm{i}} + \delta(C_{rate}^{j}, z^{j}, \Delta Q^{j}) \tag{5}$$

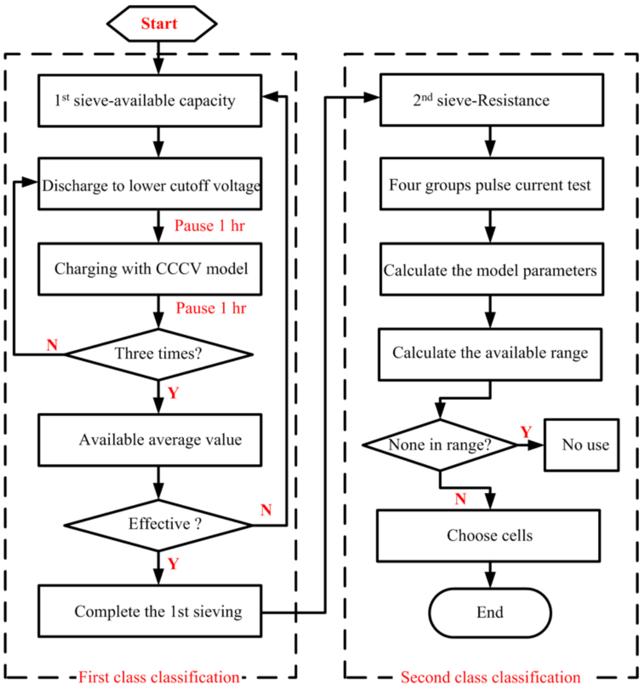

FIGURE 11. Detail operation procedure of cells filtering approach (the CCCV model means constant charge and constant voltage model).

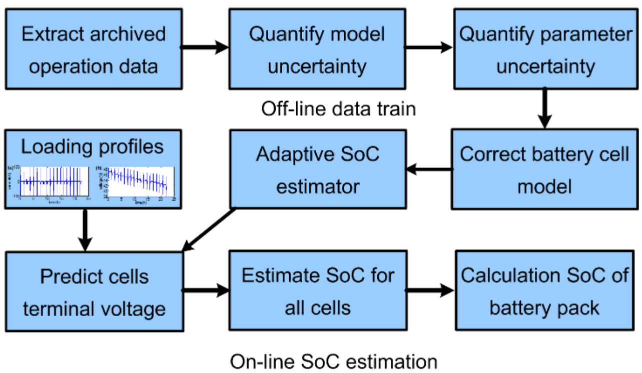

FIGURE 12. Flowchart of the proposed framework for battery SoC estimation [94].

where uncertainty δ is the function of cell discharge/charge rate$-C^j_{rate}$, cell SoC$-z^j$, maximum available capacity difference ΔQ^j between cell j and average value of battery pack. It is noted that the superscript j is used to denote the cell number in battery pack. The determination of model and parameter uncertainties is a recognized problem. In this study a Radial Basis Function (RBF) neural network was used to develop a response surface approximate method for the determination of the bias function. Results indicate that this method shows has good performance. It is noted that the nominal model can be built from the average pack model or special cell model. This method can reduce the computational cost and improve the real-time performance of the battery model. It is a promising method for solving the SoC of battery packs against their strong time-varying, nonlinear and non-uniform characteristics. However, if the number for battery cells in an electric vehicle is too big, the computational cost is required to be greatly reduced.

IV. CONCLUSION AND RECOMMENDATION

Battery SoC estimation is an essential function of a BMS used in electric vehicles. This paper reviews and compares typical SoC estimation methods, with a focus on their use in electric vehicles. Four types of battery cell SoC estimation methods and three kinds of SoC estimation methods for battery pack have been systematically evaluated and summarized. Although a large number of estimation methods have been proposed and corresponding progress and applications have been obtained, the systematic theories and methods for the reasonable management of battery packs cannot be determined. Both the theoretical research and technological application of the SoC estimation are remaining challenges.

(1) Multi-constraint, multi-scale and multi-state joint/ dual estimation. Estimation of battery SoC involves the accuracy of initial values and the measurement, and also involves the identification for path of capacity degradation and the thermal behavior of batteries. The existing methods mainly work for correcting the initial error of SoC or achieving the joint/dual estimation for battery capacity and SoC, but they seldom consider the mechanical properties (fatigue damage), electrical properties (degradation path of capacity) and thermal properties (thermal failure track) of batteries. The fusion method by combining of data-driven control strategy, multi-scale multi-dimension optimization theory and optimal estimation theory may provide an effective solution for the multi-constrain multi-scale state joint estimation.

(2) Multi models fusion modeling method for batteries. Commonly used battery models for EVs comprise of EMs, ECMs and EIMs. EMs can model the complex chemical reaction process of batteries but they cannot provide a comprehensive description of capacity degradation, thermal failure and the mechanical fatigue process of batteries. The strength of the ECMs and EIMs is that the structure and order of the models are relatively simple, and the limitations are that they cannot illustrate the inner reaction kinetics as well as the capacity degradation and aging path of batteries. Each types of battery models have its strengths and drawbacks, so a fusion model by combing different types of battery models with a well-designed fusion rule can achieve good predictive performance under uncertain battery aging levels, operating conditions and battery materials.

(3) SoC estimation for a hybrid connection battery system with strong time-varying, nonlinear and non-uniform characteristics. The battery pack used in the EVs consists of hundreds of battery cells. It is difficult to ensure the consistency of the parameter and state for all cells. What's worse, due to the disturbance of uncertain operating conditions, aging levels and the balancing strategies, SoC estimation methods designed for battery cell cannot ensure the SoC estimation accuracy of the multi-cell battery pack. As a result, this will finally lead to inefficient energy use. Thus, the SoC

estimation of the battery pack can be equivalent to a kind of state estimation problem for a hybrid system with strong time-varying, nonlinear and non-uniform characteristics. Thus, we can seek solutions from the uncertainty modeling theory, the system identification theory and the data-driven control theory.

REFERENCES

[1] M. O. Ramoni and H. C. Zhang, "End-of-life (EOL) issues and options for electric vehicle batteries," *Clean Technol. Environ. Policy*, vol. 15, no. 6, pp. 881–891, 2013.

[2] X. Hu, C. Zou, C. Zhang, and Y. Li, "Technological developments in batteries: A survey of principal roles, types, and management needs," *IEEE Power Energy Mag.*, vol. 15, no. 5, pp. 20–31, Oct. 2017.

[3] R. Xiong, H. He, F. Sun, and K. Zhao, "Online estimation of peak power capability of Li-Ion batteries in electric vehicles by a hardware-in-loop approach," *Energies*, vol. 5, no. 5, pp. 1455–1469, 2012.

[4] 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.

[5] C. Zhang, L. Y. Wang, X. Li, W. Chen, G. G. Yin, and J. Jiang, "Robust and adaptive estimation of state of charge for lithium-ion batteries," *IEEE Trans. Ind. Electron.*, vol. 62, no. 8, pp. 4948–4957, Aug. 2015.

[6] 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.

[7] R. Xiong, Y. Zhang, H. He, X. Zhou, and M. G. Pecht, "A double-scale, particle-filtering, energy state prediction algorithm for lithium-ion batteries," *IEEE Trans. Ind. Electron.*, vol. 65, no. 2, pp. 1526–1538, Feb. 2018.

[8] R. Xiong, Q. Yu, L. Y. Wang, and C. Lin, "A novel method to obtain the open circuit voltage for the state of charge of lithium ion batteries in electric vehicles by using H infinity filter," *Appl. Energy*, vol. 207, pp. 341–348, Dec. 2017.

[9] A. Scacchioli, G. Rizzoni, M. A. Salman, W. Li, S. Onori, and X. Zhang, "Model-based diagnosis of an automotive electric power generation and storage system," *IEEE Trans. Syst., Man, Cybern., Syst.*, vol. 44, no. 1, pp. 72–85, Jan. 2014.

[10] 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 Sour.*, vol. 226, pp. 272–288, Mar. 2013.

[11] 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. 331–340, Dec. 2017.

[12] 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.

[13] X. Hu, R. Xiong, and B. Egardt, "Model-based dynamic power assessment of lithium-ion batteries considering different operating conditions," *IEEE Trans. Ind. Informat.*, vol. 10, no. 3, pp. 1948–1959, Aug. 2014.

[14] M. Lurie, H. N. Seier, and R. C. Shair, "State of charge indicators for nickel cadmium batteries," *State Charg. Indic Nickel Cadmium Batter.*, 1963.

[15] C. W. Lillehei, A. B. Cruz, Jr., I. Johnsrude, and R. D. Sellers, "A new method of assessing the state of charge of implanted cardiac pacemaker batteries," *Amer. J. Cardiol.*, vol. 16, no. 5, p. 717, 1965.

[16] 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.

[17] Z. Li, J. Huang, B. Y. Liaw, and J. Zhang, "On state-of-charge determination for lithium-ion batteries," *J. Power Sour.*, vol. 348, pp. 281–301, Apr. 2017.

[18] J. Kalawoun, K. Biletska, F. Suard, and M. Montaru, "From a novel classification of the battery state of charge estimators toward a conception of an ideal one," *J. Power Sour.*, vol. 279, pp. 694–706, Apr. 2015.

[19] R. Xiong, J. Tian, H. Mu, and C. Wang, "A systematic model-based degradation behavior recognition and health monitoring method for lithium-ion batteries," *Appl. Energy*, vol. 207, pp. 367–378, Dec. 2017.

[20] V. Pop, H. J. Bergveld, D. Danilov, P. P. L. Regtien, and P. H. L. Notten, *Battery Management Systems: Accurate State-of-Charge Indication for Battery-Powered Applications*, vol. 9. Springer, 2008.

[21] S. Rodrigues, N. Munichandraiah, and A. K. Shukla, "Review of state-of-charge indication of batteries by means of a.c. impedance measurements," *J. Power Sour.*, vol. 87, nos. 1–12, pp. 12–20, 2000.

[22] X. Hu, F. Sun, and Y. Zou, "Comparison between two model-based algorithms for Li-ion battery SoC estimation in electric vehicles," *Simul. Model. Pract. Theory*, vol. 34, pp. 1–11, May 2013.

[23] G. L. Plett, "Extended Kalman filtering for battery management systems of LiPB-based HEV battery packs: Part 3. State and parameter estimation," *J. Power Sour.*, vol. 134, no. 2, pp. 252–261, 2004.

[24] G. L. Plett, "Extended Kalman filtering for battery management systems of LiPB-based HEV battery packs: Part 2. Modeling and identification," *J. Power Sour.*, vol. 134, no. 2, pp. 262–276, 2004.

[25] G. L. Plett, "Extended Kalman filtering for battery management systems of LiPB-based HEV battery packs: Part 3. State and parameter estimation," *J. Power Sour.*, vol. 134, no. 2, pp. 277–292, 2004.

[26] 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, 2010.

[27] 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.

[28] F. Zhang, G. Liu, L. Fang, and H. Wang, "Estimation of battery state of charge with H_∞ observer: Applied to a robot for inspecting power transmission lines," *IEEE Trans. Ind. Electron.*, vol. 59, no. 2, pp. 1086–1095, Feb. 2012.

[29] I.-S. Kim, "The novel state of charge estimation method for lithium battery using sliding mode observer," *J. Power Sour.*, vol. 163, no. 1, pp. 584–590, 2006.

[30] I. S. Kim, "Nonlinear state of charge estimator for hybrid electric vehicle battery," *IEEE Trans. Power Electron.*, vol. 23, no. 4, pp. 2027–2034, Jul. 2008.

[31] A. P. Schmidt, M. Bitzer, Á. W. Imre, and L. Guzzella, "Experiment-driven electrochemical modeling and systematic parameterization for a lithium-ion battery cell," *J. Power Sour.*, vol. 195, no. 15, pp. 5071–5080, 2010.

[32] S. K. Rahimian, S. Rayman, and R. E. White, "State of charge and loss of active material estimation of a lithium ion cell under low earth orbit condition using Kalman filtering approaches," *J. Electrochem. Soc.*, vol. 159, no. 6, p. A860, 2012.

[33] K. A. Smith, C. D. Rahn, and C.-Y. Wang, "Model-based electrochemical estimation of lithium-ion batteries," *Control Syst. Technol.*, vol. 18, no. 1, pp. 714–719, 2008.

[34] K. A. Smith, C. D. Rahn, and C. Y. Wang, "Control oriented 1D electrochemical model of lithium ion battery," *Energy Convers. Manag.*, vol. 48, no. 9, pp. 2565–2578, 2007.

[35] 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 Sour.*, vol. 278, pp. 814–825, Mar. 2015.

[36] X. Li and S. Choe, "State-of-charge (SoC) estimation based on a reduced order electrochemical thermal model and extended Kalman filter," in *Proc. Amer. Control Conf.*, 2013, pp. 1100–1105.

[37] H. Fang, Y. Wang, Z. Sahinoglu, T. Wada, and S. Hara, "Adaptive estimation of state of charge for lithium-ion batteries," in *Proc. Amer. Control Conf. (ACC)*, 2013, pp. 3485–3491.

[38] S. J. Moura, N. A. Chaturvedi, and M. Krstic, "PDE estimation techniques for advanced battery management systems—Part I: SoC estimation," in *Proc. Amer. Control Conf.*, 2012, pp. 566–571.

[39] S. J. Moura, N. A. Chaturvedi, and M. Krstic, "PDE estimation techniques for advanced battery management systems—Part II: SOH identification," in *Proc. Amer. Control Conf.*, 2012, pp. 566–571.

[40] S. J. Moura, N. A. Chaturvedi, and M. Krstić, "Adaptive partial differential equation observer for battery state-of-charge/state-of-health estimation via an electrochemical model," *J. Dyn. Syst. Meas. Control*, vol. 136, no. 1, p. 11015, 2013.

[41] J. Scott Moura, M. Krstic, and N. A. Chaturvedi, "Adaptive PDE observer for battery SoC/SOH estimation," in *Proc. 5th Annu. Dyn. Syst. Control Conf. Joint JSME 11th Motion Vibrat. Conf.*, 2012, pp. 101–110.

[42] J. Lee, O. Nam, and B. H. Cho, "Li-ion battery SoC estimation method based on the reduced order extended Kalman filtering," *J. Power Sour.*, vol. 174, no. 1, pp. 9–15, 2007.

[43] S. Santhanagopalan and R. E. White, "State of charge estimation using an unscented filter for high power lithium ion cells," *Int. J. Energy Res.*, vol. 34, no. 2, pp. 152–163, 2009.

[44] 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, p. 61302, 2010.
[45] K. A. Smith, C. D. Rahn, and C.-Y. Wang, "Model-based electrochemical estimation and constraint management for pulse operation of lithium ion batteries," *IEEE Trans. Control Syst. Technol.*, vol. 18, no. 3, pp. 654–663, May 2010.
[46] M. Doyle, "Comparison of modeling predictions with experimental data from plastic lithium ion cells," *J. Electrochem. Soc.*, vol. 143, no. 6, p. 1890, 1996.
[47] 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, p. 1526, 1993.
[48] S. Santhanagopalan, Q. Guo, P. Ramadass, and R. E. White, "Review of models for predicting the cycling performance of lithium ion batteries," *J. Power Sour.*, vol. 156, no. 2, pp. 620–628, 2006.
[49] S. Santhanagopalan and R. E. White, "Online estimation of the state of charge of a lithium ion cell," *J. Power Sour.*, vol. 161, no. 2, pp. 1346–1355, 2006.
[50] S. Lee, J. Kim, J. Lee, and B. H. Cho, "State-of-charge and capacity estimation of lithium-ion battery using a new open-circuit voltage versus state-of-charge," *J. Power Sour.*, vol. 185, no. 2, pp. 1367–1373, 2008.
[51] M. Thele, O. Bohlen, D. U. Sauer, and E. Karden, "Development of a voltage-behavior model for NiMH batteries using an impedance-based modeling concept," *J. Power Sour.*, vol. 175, no. 1, pp. 635–643, 2008.
[52] S. Wang, M. Verbrugge, J. S. Wang, and P. Liu, "Multi-parameter battery state estimator based on the adaptive and direct solution of the governing differential equations," *J. Power Sour.*, vol. 196, no. 20, pp. 8735–8741, 2011.
[53] Y. He, W. Liu, and B. J. Koch, "Battery algorithm verification and development using hardware-in-the-loop testing," *J. Power Sour.*, vol. 195, no. 9, pp. 2969–2974, 2010.
[54] M. Verbrugge, "Adaptive, multi-parameter battery state estimator with optimized time-weighting factors," *J. Appl. Electrochem.*, vol. 37, no. 5, pp. 605–616, 2007.
[55] M. Verbrugge, D. Frisch, and B. Koch, "Adaptive energy management of electric and hybrid electric vehicles," *J. Electrochem. Soc.*, vol. 152, no. 2, p. A333, 2005.
[56] 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.
[57] I. Snihir, W. Rey, E. Verbitskiy, A. Belfadhel-Ayeb, and P. H. L. Notten, "Battery open-circuit voltage estimation by a method of statistical analysis," *J. Power Sour.*, vol. 159, no. 2, pp. 1484–1487, Sep. 2006.
[58] C. Piao, W.-L. Fu, G.-H. Lei, and C.-D. Cho, "Online parameter estimation of the Ni-MH batteries based on statistical methods," *Energies*, vol. 3, no. 2, pp. 206–215, 2010.
[59] Y.-H. Chiang, W.-Y. Sean, and J.-C. Ke, "Online estimation of internal resistance and open-circuit voltage of lithium-ion batteries in electric vehicles," *J. Power Sour.*, vol. 196, no. 8, pp. 3921–3932, 2011.
[60] F. Sun, R. Xiong, and H. He, "A systematic state-of-charge estimation framework for multi-cell battery pack in electric vehicles using bias correction technique," *Appl. Energy*, vol. 162, pp. 1399–1409, 2016.
[61] R. Xiong, H. He, and K. Zhao, "Research on an online identification algorithm for a thevenin battery model by an experimental approach," *Int. J. Green Energy*, vol. 12, no. 3, pp. 272–278, 2015.
[62] H. He, R. Xiong, and J. Fan, "Evaluation of lithium-ion battery equivalent circuit models for state of charge estimation by an experimental approach," *Energies*, vol. 4, no. 4, pp. 582–598, 2011.
[63] 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.
[64] R. Xiong, X. Gong, C. C. Mi, and F. Sun, "A robust state-of-charge estimator for multiple types of lithium-ion batteries using adaptive extended Kalman filter," *J. Power Sour.*, vol. 243, pp. 805–816, Dec. 2013.
[65] R. E. Kalman, "A new approach to linear filtering and prediction problems," *J. Basic Eng.*, vol. 82, no. 1, p. 35, 1960.
[66] B. S. Bhangu, P. Bentley, D. A. Stone, and C. M. Bingham, "Nonlinear observers for predicting state-of-charge and state-of-health of lead-acid batteries for hybrid-electric vehicles," *IEEE Trans. Veh. Technol.*, vol. 54, no. 3, pp. 783–794, May 2005.
[67] J. Han, D. Kim, and M. Sunwoo, "State-of-charge estimation of lead-acid batteries using an adaptive extended Kalman filter," *J. Power Sour.*, vol. 188, no. 2, pp. 606–612, 2009.
[68] F. Sun, X. Hu, Y. Zou, and S. Li, "Adaptive unscented Kalman filtering for state of charge estimation of a lithium-ion battery for electric vehicles," *Energy*, vol. 36, no. 5, pp. 3531–3540, 2011.
[69] S. Sepasi, R. Ghorbani, and B. Y. Liaw, "Improved extended Kalman filter for state of charge estimation of battery pack," *J. Power Sour.*, vol. 255, pp. 368–376, Jun. 2014.
[70] Y. Shen, "Hybrid unscented particle filter based state-of-charge determination for lead-acid batteries," *Energy*, vol. 74, pp. 795–803, Sep. 2014.
[71] R. Xiong, F.-C. Sun, and H.-W. He, "Data-driven state-of-charge estimator for electric vehicles battery using robust extended Kalman filter," *Int. J. Automotive Technol.*, vol. 15, no. 1, pp. 89–96, 2014.
[72] Z. Cheng, J. Lv, Y. Liu, and Z. Yan, "Estimation of state of charge for lithium-ion battery based on finite difference extended Kalman filter," *J. Appl. Math.*, vol. 2014, Apr. 2014, Art. no. 348537.
[73] A. Baba and S. Adachi, "SoC estimation of HEV/EV battery using series Kalman filter," *Elect. Eng. Jpn.*, vol. 187, no. 2, pp. 53–62, 2014.
[74] F. Sun, R. Xiong, and H. He, "Estimation of state-of-charge and state-of-power capability of lithium-ion battery considering varying health conditions," *J. Power Sour.*, vol. 259, pp. 166–176, Aug. 2014.
[75] R. Xiong, F. Sun, H. He, and T. D. Nguyen, "A data-driven adaptive state of charge and power capability joint estimator of lithium-ion polymer battery used in electric vehicles," *Energy*, vol. 63, pp. 295–308, Dec. 2013.
[76] D. Andre, C. Appel, T. Soczka-Guth, and D. U. Sauer, "Advanced mathematical methods of SoC and SOH estimation for lithium-ion batteries," *J. Power Sour.*, vol. 224, pp. 20–27, Feb. 2013.
[77] R. Xiong, F. Sun, Z. Chen, and H. He, "A data-driven multi-scale extended Kalman filtering based parameter and state estimation approach of lithium-ion olymer battery in electric vehicles," *Appl. Energy*, vol. 113, no. 1, pp. 463–476, Jan. 2014.
[78] 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 Sour.*, vol. 233, pp. 277–284, Jul. 2013.
[79] J. Kowal, D. Hente, and D. U. Sauer, "Model parameterization of nonlinear devices using impedance spectroscopy," *IEEE Trans. Instrum. Meas.*, vol. 58, no. 7, pp. 2343–2350, Jul. 2009.
[80] W. Waag, S. Käbitz, and D. U. Sauer, "Experimental investigation of the lithium-ion battery impedance characteristic at various conditions and aging states and its influence on the application," *Appl. Energy*, vol. 102, pp. 885–897, Feb. 2013.
[81] Z.-S. Hou and J.-X. Xu, "On data-driven control theory: The state of the art and perspective," *Acta Autom. Sinica*, vol. 35, no. 6, pp. 650–667, Jun. 2009.
[82] 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 Sour.*, vol. 80, no. 1, pp. 293–300, 1999.
[83] 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 Sour.*, vol. 162, no. 2, pp. 829–836, 2006.
[84] W. X. Shen, C. C. Chan, E. W. C. Lo, and K. T. Chau, "A new battery available capacity indicator for electric vehicles using neural network," *Energy Convers. Manag.*, vol. 43, no. 6, pp. 817–826, 2002.
[85] Y. Shen, "Adaptive online state-of-charge determination based on neuro-controller and neural network," *Energy Convers. Manag.*, vol. 51, no. 5, pp. 1093–1098, 2010.
[86] C. Chan, E. W. Lo, and S. Weixiang, "The available capacity computation model based on artificial neural network for lead-acid batteries in electric vehicles," *J. Power Sour.*, vol. 87, nos. 1–2, pp. 201–204, 2000.
[87] T. Hansen and C.-J. Wang, "Support vector based battery state of charge estimator," *J. Power Sour.*, vol. 141, no. 2, pp. 351–358, Mar. 2005.
[88] W. Junping, C. Quanshi, and C. Binggang, "Support vector machine based battery model for electric vehicles," *Energy Convers. Manag.*, vol. 47, nos. 7–8, pp. 858–864, 2006.
[89] H. Cao, J. Yu, L. Kang, H. Yang, and X. Ai, "Modeling and prediction for discharge lifetime of battery systems using hybrid evolutionary algorithms," *Comput. Chem.*, vol. 25, no. 3, pp. 251–259, 2001.
[90] 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.

[91] T. Weigert, Q. Tian, and K. Lian, "State-of-charge prediction of batteries and batteryŰsupercapacitor hybrids using artificial neural networks," *J. Power Sour.*, vol. 196, no. 8, pp. 4061–4066, 2011.
[92] V. Klass, M. Behm, and G. Lindbergh, "A support vector machine-based state-of-health estimation method for lithium-ion batteries under electric vehicle operation," *J. Power Sour.*, vol. 270, pp. 262–272, Dec. 2014.
[93] J. Zhou, D. Liu, Y. Peng, and X. Peng, "Dynamic battery remaining useful life estimation: An on-line data-driven approach," in *Proc. IEEE IMTC-Int. Instrum. Meas. Technol. Conf.*, May 2012, pp. 2196–2199.
[94] F. Sun and R. Xiong, "A novel dual-scale cell state-of-charge estimation approach for series-connected battery pack used in electric vehicles," *J. Power Sour.*, vol. 274, pp. 582–594, Jan. 2015.
[95] C. Lin, H. Mu, R. Xiong, and J. Y. Cao, "Multi-model probabilities based state fusion estimation method of Lithium-ion battery for electric vehicles: State-of-energy," *Appl Energy*, vol. 194, pp. 560–568, May 2017.
[96] 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 Sour.*, vol. 242, pp. 699–713, Nov. 2013.
[97] 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.

RUI XIONG (S'12–M'14–SM'16) received the M.Sc. degree in vehicle engineering and the Ph.D. degree in mechanical engineering from Beijing Institute of Technology, Beijing, China, in 2010 and 2014, respectively. He conducted scientific research as a joint Ph.D. student in the DOE GATE Center for Electric Drive Transportation at the University of Michigan, Dearborn, MI, USA, between 2012 and 2014.

Since 2014, he has been an Associate Professor in the Department of Vehicle Engineering, School of Mechanical Engineering, Beijing Institute of Technology, Beijing, China. Since 2017, he has been an Adjunct Professor in the Faculty of Science, Engineering and Technology, Swinburne University of Technology, Melbourne, Australia. He has conducted extensive research and authored more than 100 peer-reviewed articles. He holds eight patents. His research interests mainly include electrical/hybrid vehicles, energy storage, and battery management system.

Dr. Xiong received the Excellent Doctoral Dissertation from Beijing Institute of Technology in 2014, the first prize of Chinese Automobile Industry Science and Technology Progress Award in October 2015 and the second prize of National Defense Technology Invention Award in December 2016. He received Best Paper Awards from the journal *Energies* and several International conferences by four times. He is serving as the Associate Editors of IEEE ACCESS and *Energy, Ecology and Environment*, Editorial Board of the Energies, subject assistant editor of *Applied Energy*, and Guest editor of the *Journal of Cleaner Production*. He was the conference chair of the 2017 International Symposium on Electric Vehicles (ISEV2017) hold in Stockholm, Sweden.

JIAYI CAO received the B.S. degree in vehicle engineering from the Jilin University, Changchun, China, in 2015. She is currently pursuing the M.Sc. degree in mechanical engineering with the School of Mechanical Engineering, Beijing Institute of Technology, Beijing.

Her research interests include modeling, optimization, and control of hybrid energy storage systems.

QUANQING YU (S'15) received his M.Sc. degree in mechanics from Beijing Institute of Technology, Beijing, China, in 2012. He is currently working toward the Ph.D. degree in mechanical engineering with Beijing Institute of Technology, Beijing, China. He conducted scientific research as a joint Ph.D. student in the Department of Electrical and Computer Engineering, Wayne State University, Detroit, MI, USA between 2016 and 2017.

Since 2017, he has been a visiting scholar in the Center for Advanced Life Cycle Engineering (CALCE), University of Maryland, College Park. He has published several papers related to lithium ion battery state estimation and battery health management. His research interests mainly include battery state estimation, reliability, fault diagnosis and prognosis.

Mr. Yu was a recipient of the Best Paper Award from the International conference on Energy, Ecology and Environment hold in Stockholm, Sweden.

HONGWEN HE (M'03–SM'12) received the Ms.E. degree in vehicle engineering from the Jilin University of Technology, Changchun, China, in 2000 and the Ph.D. degree in vehicle engineering from the Beijing Institute of Technology, Beijing, China, in 2003.

He is currently a Professor with the National Engineering Laboratory for Electric Vehicles, School of Mechanical Engineering, Beijing Institute of Technology. He has published over 100 papers and holds 20 patents. His research interests include power battery modeling and simulation on electric vehicles, design, and control theory of the hybrid power trains.

Dr. He was a recipients of the second prize of the Chinese National Science and Technology Award for the work on the development of new-energy electric bus powertrains in 2015, the first prize of Henan Science and Technology Award for the work on the development of hybrid bus powertrain in 2013, the first prize of Henan Science and Technology Award for the work on the development of battery electric bus powertrain in 2014 and the second prize of MIIT Technology Innovation Award for the research on the development of hybrid powertrains in off road vehicles in 2016.

FENGCHUN SUN received the Ms.E. and Ph.D. degrees in vehicle engineering from the Beijing Institute of Technology, Beijing, China, in 1984 and 1989, respectively, the joint Ph.D. degree from the Technical University of Berlin, Berlin, Germany, in 1989.

He is currently an Academician with the Chinese Academy of Engineering, a Professor and the Director of the National Engineering Laboratory for Electric Vehicles. He has been conferred the title Cheung Kong Scholar by the Ministry of Education, China. He has published over 200 papers and is the holder of 19 patents. His research interests include electric vehicles, electric drive systems, electric vehicle demonstration, and infrastructure.

Dr. Sun received the second prize from the Chinese National Science and Technology Progress Awards in 2008, the second prize from the Chinese National Technological Innovation Awards in 2004 and 2009, and the award for industrial innovation from the Ho Leung Ho Lee Foundation in 2007.