An Overview and Comparison of Online Implementable SOC Estimation Methods for Lithium-Ion Battery

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***Abstract*—With the popularity of electrical vehicles, the lithium-ion battery industry is developing rapidly. To ensure battery safe usage and to reduce its average lifecycle cost, accurate state of charge (SOC) tracking algorithms for real-time implementation are required for different applications. Many SOC estimation methods have been proposed in the literature. However, only a few of them consider the real-time applicability. This paper classifies the recently proposed online SOC estimation methods into five categories. Their principal features are illustrated, and the main pros and cons are provided. The SOC estimation methods are compared and discussed in terms of accuracy, robustness, and computation burden. Afterward, as the most popular type of model-based SOC estimation algorithms, seven nonlinear filters existing in literature are compared in terms of their accuracy and execution time as a reference for online implementation.**

***Index Terms*—Comparison, lithium-ion battery, nonlinear filter, online implementation, state of charge (SOC) estimation.**

I. Introduction

Environmental pollution is a severe problem all around the world in these years, especially, global warming has attracted a lot of attentions from both academic and industry sectors. Through the guidance of Paris Agreement, countries and governments have made their efforts to save energy and reduce emission. Consequently, electrification of transportation is becoming an inevitable trend in the future [1]. The electrical vehicle (EV) industry is developing fast to meet people's urgent demand for transportation with low carbon emissions.

High specific energy, long cycle life, and low self-discharge rate make lithium-ion battery one of the most promising energy storage components for EV applications [2]–[6]. Just as the fuel gauge in traditional vehicles, the amount of capacity left in the battery is undoubtedly an important index related to the driving experience. Accurate state of charge (SOC) can help drivers to make wise decisions on when to charge the battery and also help the battery management system (BMS) to avoid overcharging and over discharging which may cause safety issues [7], [8]. SOC cannot be directly measured, and it has to be estimated from the estimation of other battery quantities.

In order to fulfill the energy requirement of EV, large numbers of batteries are connected in series or parallel. Due to the cost limitation, the platform where BMS is implemented has limited computational ability. An accurate online SOC estimation method in a real-time platform is not easy. Thus, it is necessary to analyze the features of the online implementable SOC estimation methods.

Besides the accuracy, efficiency and robustness are the other two factors to be considered for SOC estimation in real-time applications [9]. Measuring battery current and voltage inevitably yields errors from sensors. Moreover, the established battery models are not perfect and do not take into account all factors affecting the modeling accuracy. The inner battery characteristics also vary with different operating conditions (e.g., temperature, load current) and battery aging. Hence, the estimation algorithm must be robust to both the measurement errors and the modeling errors. As previously described, the computation ability of BMS is limited. The SOC estimation algorithm should be less time-consuming in order to satisfy the computing power of the low-cost microcontrollers.

Because of the good performance in SOC estimation, nonlinear filters (such as, extended Kalman filter (EKF) [10], [11], unscented Kalman filter (UKF) [6], [12], [13], central difference Kalman filter (CDKF) [14]–[16], square root unscented Kalman filter (SR-UKF) [17], [18], square root central differ-

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ence Kalman filter (SR-CDKF) [19], particle filter (PF) [20], [21], H-infinity filter [22]–[24], etc.) are widely investigated in the literature on the basis of a model-based structure.

Many approaches for an accurate prediction of the battery SOC have been presented in the literature, but a relatively limited number of them consider BMS limitations and the real-time requirement and validate proposed methods online in a test bench. Therefore, this paper aims to summarize the features of SOC estimation methods that are suitable for online implementation and compare their advantages and disadvantages. The goal is to contribute to bridging the academic achievements of SOC estimation research into industrial application.

In contrast to the previous overview works on SOC estimation methods, this paper is mainly focused on the recent publications of online implementable SOC estimation methods. In this paper, the online SOC estimation methods are divided into five categories based on their characteristics. A detailed discussion on their pros and cons is given in this paper. Moreover, the previously mentioned seven nonlinear filters are compared in terms of accuracy and execution time in this work, which is different from [25].

The structure of this paper is as follows: Section II details the online feasible estimation methods and their characteristics presented in the literature. Section III discusses the suitability of those methods for online implementation and presents their pros and cons. The comparison of seven nonlinear filters in accuracy and execution time are shown in Section IV. Conclusions are drawn in Section V.

II. Battery Model and Error Analysis

A large number of SOC estimation methods have recently been proposed in the literature. Depending on their governing principles, the online SOC estimation algorithms are divided into five categories: Coulomb counting methods (CCMs); open circuit voltage methods (OCVMs); impedance spectroscopy based methods (ISBMs); model-based methods (MBMs) and artificial neural networks based methods (ANNBMs). This section details their features and reviews some recently published papers for each category.

A. Coulomb Counting Method

The definition of SOC is as follows:

$$Z(t) = Z(0) - \int_0^t \frac{\eta_i \cdot i(t)}{C_n} dt \qquad (1)$$

where $Z(t)$ is the SOC at time t and $Z(0)$ is the initial SOC; η_i is the Coulombic efficiency. C_n is the battery capacity, $i(t)$ is the current and the discharging current is considered as positive in (1).

From (1), it easy to note that SOC is defined as the integration of the current. Therefore, Coulomb counting is a direct and efficient method for calculating SOC. The self-discharge, temperature, and current rate (see Fig. 1) have an impact on the capacity of battery. Moreover, the inaccuracy of current sensor and the batteries' discontinuous usage in reality also make an accurate initial SOC hardly to be known. Errors from current sensors also accumulate in the calculation process. To overcome these drawbacks, measures for enhancing the CCM are proposed in [26]–[31]. Since Coulombic efficiency effects the accuracy of CCM, updating the Coulombic efficiency online during the estimation process helps to improve the SOC accuracy [27], [28]. However, it is not easy to calculate the true value of Coulombic efficiency, and the battery must be tested under different current rates in advance.

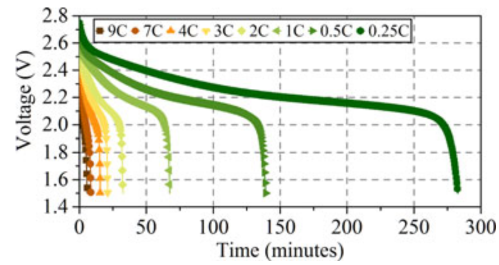

Fig. 1. Voltage changes with discharging rate.

Combining with the OCV-SOC lookup table is also a good way to compensate the shortages of CCM. In [10], the authors reset the initial SOC of CCM by predicting OCV in very short interruption time, which automatically decreases the SOC estimating error. Compared with the conventional CCM, the proposed method increases the SOC estimation accuracy by 2.07% when UDDS profile is used. Considering the OCV, resting time and temperature effect, battery's initial SOC is predicted for CCM in [30] and the error of SOC estimation is further reduced by adding the energy efficiency.

Removing errors (including measurement dc bias, self-discharge current, and leakage current) [8] from the current measurement also decreases the accumulated errors in CCM. If the initial SOC is known in advance and high precision current sensors are included in the BMS, CCM is very effective and suitable for real-time SOC estimation.

B. Open Circuit Voltage

In order to reach the internal equilibrium, the battery has to be disconnected from any load and rest for enough longer relaxation time. OCV is then measured under this condition. The OCV–SOC lookup table is the most efficient method if an accurate OCV is known. However, the relaxation time of Li-ion battery can be generally as long as 10 h or even more, which affects the practicality of the OCVM. Furthermore, the relationship between OCV and SOC has proven to change with temperature and age [32]–[35]. Hence, extensive works focusing on improving its accuracy by considering temperature and aging effects are proposed in [33]–[36]. Additionally, the characteristics of OCV–SOC curve are closely related to the battery chemistry. For example, the OCV–SOC curve is quite flat for lithium iron phosphate batteries (see Fig. 2), which means that a small error in OCV measurement causes a large error in SOC estimation. In Fig. 2, the difference of OCV is merely 72 mV in the SOC range of 30–80%. Moreover, the voltage hysteresis problem also affects the accuracy of OCV measurement [37]. Thus, classical OCVM is not quite acceptable for most online conditions. In

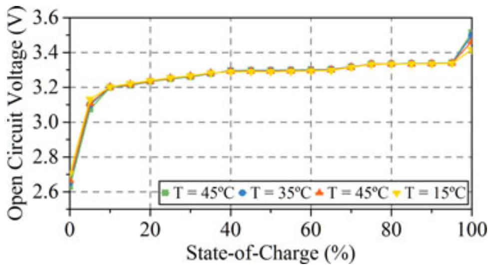

Fig. 2. Flat OCV–SOC relationship of $LiFePO_4$ battery.

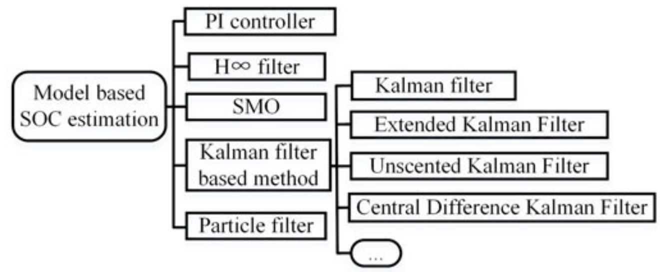

Fig. 3. Model-based SOC estimation methods.

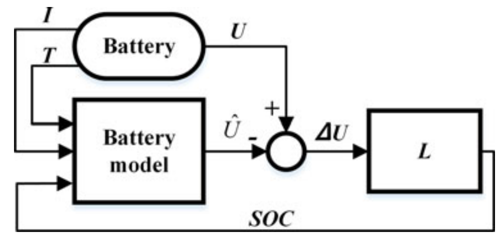

Fig. 4. Structure of MBMs.

order to improve its utility, researchers are also working on fast OCV prediction in short relaxation time [38]–[40].

A new OCV relaxation model is proposed in [41]. The OCV is able to be estimated in just a few minutes after the current interruption. After parameter identification and curve fitting, the proposed model is validated on a 16 bit Infineon microcontroller at the 66 MHz clock frequency. Combining with the low-cost voltage sensor, Kalman filter is also applied to OCV prediction in short battery disconnected period in [42]. In this way, OCVM has higher computational efficiency and is suitable for online estimation. Although OCVM confronts many drawbacks, it is still worth improving its applicability for online applications.

C. Impedance Spectroscopy Based Method

An electrochemical impedance spectroscopy (EIS) is based on injecting small amplitude ac signals to a battery at different frequencies. The battery impedance at different frequencies is expressed as follows:

$$R_{\mathrm{EIS}}(w) = \frac{U_{\mathrm{AC}}}{I_{\mathrm{AC}}} \cdot e^{j\cdot\varphi} \tag{2}$$

where U_{AC} and I_{AC} are the peak amplitudes of voltage and current, respectively; φ is the phase shift between current and voltage. The magnitudes of R_{EIS} are expressed by Bode plot and Nyquist diagram.

Several parameters (ohmic resistance, charge transfer resistance, and double layer capacitance) are analyzed from the measured EIS data. Those parameters are functions of SOC, which can be further used as indicators of SOC [41]. It is proven in [42] that the battery impedance is SOC dependent at low frequency.

However, EIS is not easy to measure online and also varies with battery types and experimental conditions [43]. The EIS measurement equipment is usually designed for laboratory use and is very expensive. But EIS is still a powerful tool for analyzing battery internal characteristics and estimating SOC. Many efforts have been made to implement the online EIS measurement [44]–[48], which greatly enhances the possibility of EIS for online applications. An onboard EIS measurement system is proposed in [45], which consists of class A power amplifier, low pass filter, and digital-to-analog converter (DAC) for generating sinusoidal signals. The battery charger is applied to generate current for EIS measurement in [46]. In [47], the authors propose a low cost and practical solution for online measurement of ac impedance by controlling the dc–dc converter. Although EIS is sensitive to SOC and is a nondestructive method, the exact relationship of EIS and SOC, as well as the repeatability of EIS for online measurement, still need further research.

D. Model-Based Methods

Among all the SOC estimation methods, the model based ones seem to be the most practical choice for online SOC estimation at present. Most recent works are related with MBM, and a classification is proposed in Fig. 3.

Deduced from Fig. 4, the expression of MBMs is typically demonstrated as follows [49]:

$$\begin{cases} \dot{Z} = \frac{\eta_i}{C_n} \cdot i_t - L \cdot (\hat{u}_t - u_t) \\ \hat{u}_t = h(Z, i_t, \ldots) \end{cases} \tag{3}$$

where u_t is the terminal voltage at time t measured by voltage sensors, $\hat{u}_t$ is the output from the established battery model, $h(.)$ represents the battery model.

Note that the feedback for correcting the SOC is based on the difference between the terminal voltage measured by the sensor and the output of the battery model. Due to the closed-loop structure, MBMs are able to deal with unknown initial SOC. In (3), L is the gain for compensating the SOC from CCM. The methods presented in Fig. 4 use a different algorithm to calculate the gain L, such as proportional integral (PI) [50], [51], H-infinity filter [22]–[24], Kalman filter [10], [12], [13], [17], PF [20], [21], etc. Based on two RC equivalent circuit model, authors in [50] propose a simple structure and highly effective SOC estimation method using two independent PI observers. One PI observer improves the modeling accuracy, and the other one estimates the OCV for SOC estimation simultaneously. H-infinity filter is also used for decreasing the effect of noise and parameter uncertainty on the estimation accuracy. An adaptive H-infinity filter is proposed in [22] for improving the accuracy of SOC estimation results against the noise from sensors and the inaccuracy from battery model. With recursive least square (RLS) updates parameters, the proposed method achieves accurate SOC in a hardware-in-the-loop experiment. Kalman filter is definitely the most popular MBMs due to its robustness to noise in the stochastic process. EKF estimates battery internal temperature and SOC at the same time on the basis of a novel thermoelectric model presented in [52]. In [12], authors validate UKF implemented in a Freescale MC9S12XF512 for SOC estimation. In order to improve the accuracy of battery modeling, electrochemical model-based SOC estimation methods are also proposed in [11], [53], [54].

As previously described in this paper, MBMs rely on precise battery model for accurate SOC estimation. However, battery internal parameters are changed during charging and discharging process. It is difficult to build an accurate enough model to describe all the battery external characteristics. Especially, the computational complexity of the battery model should be restricted to a reasonable range for online applications. Being insensitive to initial SOC and robust to measurement noise, MBMs are very popular for different kinds of online SOC estimation applications.

E. Artificial Neural Network Based Method

Different kinds of artificial neural network (ANN) and some similar methods are very popular in mapping the nonlinear relationship between inputs and outputs of a system. ANN is capable of directly establishing the relationship between battery SOC and the related factors (such as current, voltage, and temperature). Then, engineers are able to create the SOC estimator without any prior knowledge of the battery.

Methods, such as ANN [52], [55]–[57], support vector machine (SVM) [58], extreme learning machine (ELM) [59], multivariate adaptive regression splines (MARS) [9], [60], etc., have the ability to deal with the nonlinear mapping problem. Fuzzy logic has a similar characteristic as ANN, thus it is also used for SOC estimation [61]. ANNBMs must be trained offline in order to establish the nonlinear relationship. Afterwards, they can run efficiently in a real-time application. Two different structures of ANN are applied to estimate SOC in [52]. Considering the battery capacity fade, accurate SOC is obtained from ANN estimator during the entire battery lifespan. SVM and MARS are used in [58], [60] to immediately establish the nonlinear map of SOC and other measured input variables, respectively.

If appropriate samples are selected and optimized parameters are chosen in the training process, the ANNBMs are able to present accurate SOC estimation. However, it can be easily found that the practicability of these methods is closely related to both the data samples and the training process. Since the practical conditions are various, the generalization of ANNBMs under different driving cycles should be considered for online application. Generally, ANNBMs are easily transplanted to hardware for online implementation after having been trained offline.

III. Discussion

After introducing the features of the SOC estimation methods, their suitability for online usage is discussed in this section. According to the analysis in the previous section, their suitability for online implementation is listed in Table I.

TABLE I
Advantages and Disadvantages of Different SOC Estimation Methods for Online Implementation

Categories of Methods	*Advantages*	*Disadvantages*
Coulomb counting method	• Computational effectively; • Direct SOC calculation; • Easy to understand	• Accurate initial SOC is needed; • Current sensor error accumulated.
Open circuit voltage method	• One to one relationship between OCV and SOC; • Small computation burden.	• Long relaxation time for OCV measurement; • Temperature, age, and battery types affect the OCV.
Impedance Spectroscopy based method	• Sensitive to SOC variation; • Diverse parameters indicate SOC	• Difficult for online measurement; • Different with battery type, experimental condition, etc.
Model-based method	• Insensitive to initial SOC; • Good robust; • High accuracy	• Rely on modeling accuracy; • High computing cost
ANN-based method	• Do not need previous knowledge of battery; • Easy transplant to hardware after offline training	• Large amount of training samples is needed; • Hard to generalize to different working conditions.

From Table I, it can be seen that all these methods have their own advantages and disadvantages. However, accuracy, robustness, and computational cost are three most important factors to be taken into account in BMS. EV is considered as an example to analyze and compare different methods in this paper.

From an accuracy point of view, each method is capable of achieving good results under specific situations. Since CCM is an open loop structure, initial SOC, and current measurement are undoubtedly extremely important for its accuracy. Normally, accurate initial SOC and high precision current sensors are almost unrealistic because of the limited cost in EV. OCVM relies on a precise OCV value for estimating SOC. The OCV can be obtained after the car is parked for a long time without use. During the driving process, the current interruption may also happen when the car is stopped at the traffic light or meet traffic jams. However, the current interruption under these circumstances is usually too short for battery relaxation. Thus, fast OCV estimation is urgent for the application of OCVM in real time. OCV–SOC curve should be steep for guaranteeing the estimation accuracy. Small errors from voltage sensors may cause large SOC estimation errors because of the flat OCV curve and OCV hysteresis of the $LiFePO_4$-based battery. ISBM is hardly measured online and varies with measurement conditions. Thus, it is important to establish the clear relationship between EIS and SOC. The accuracy of MBM relies on a precise battery model. Selecting the appropriate model structure for a specific battery enhances the estimation accuracy. However, it is difficult to simulate the complex electrochemical process of the battery. Equivalent circuit model is widely used in MBM. Moreover, the performance and convergence of the corrected algorithm are closely related to an accurate estimated SOC. The accuracy of MBMs is expected to be acceptable for EV applications if the right battery model and the suitable estimation algorithm are chosen. ANNBMs are extremely accurate if the current profile of the EV driving cycle is similar to the training samples.

The practical application always encounters a variety of operating conditions, which means robustness is an important factor. In EV applications, the battery pack should fulfill different power requirements. The battery current, temperature, and age keep changing all the time. Including feedback process for correction, a closed-loop system is usually more robust than open-loop system. Thus, MBMs have a superior robustness compared with the others. However, a better robustness can also be achieved by the other methods by taking some measures. The robustness of CCM under different driving cycles can be enhanced by considering the temperature and aging effects. Similarly, adding those effects to OCV–SOC lookup table helps to adjust the OCVM under various conditions. For ISBM, measuring EIS at different working conditions prior to usage also improves its robustness in real-time applications. MBMs have a better robustness because of the feedback correction mechanism. Since the accuracy of battery model may be reduced during battery usage, online updating parameters are critical for ensuring its robustness. The estimation algorithms should also be insensitive to modeling and sensor errors. A large amount of training data should be collected in advance for the robustness of ANNBMs. Moreover, the parameters in the training process must be optimized, and various validation processes should be performed in order to avoid the local optimization.

The computational overload must be considered for hardware implementation. CCM and OCVM are computationally efficient, as they involve a simple calculation process. ISBM needs a powerful processor, since the necessity of measuring EIS online and dealing with a large amount of data. MBMs are time-consuming, especially Kalman filter containing matrix operation in the estimation process. Low-cost applications can choose PI observer or sliding mode observer because of their lower computation burden. ANNBM is less time consuming if ANN is trained offline before transplanting to an embedded system.

Measures can be taken to guarantee the accuracy, robustness, and computational efficiency of online SOC estimation methods. For a real-time application, the most suitable method is application dependent and should be a good tradeoff of all influencing factors (e.g., the requirement of accuracy, robustness, and computational effort, etc.). This is also the reason why we choose to compare seven nonlinear filters in Section IV.

IV. Performance of the Different Nonlinear Filters on Online SOC Estimation

As described in Part D of Section II, nonlinear filters are very popular for online SOC estimation. Therefore, the most common nonlinear filters proposed in the literature are compared in terms of accuracy and execution time in this Section including: EKF [10], [11], UKF [6], [12], [13], CDKF [14]–[16], SR-UKF [17], [18], SR-CDKF [19], PF [20], [21], H-infinity filter [22]–[24].

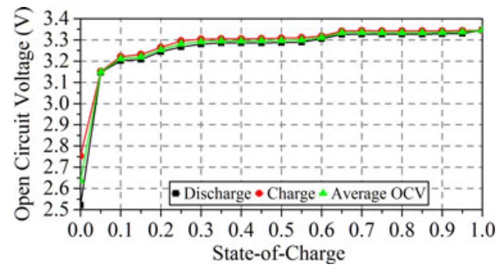

Fig. 5. OCV–SOC measurement.

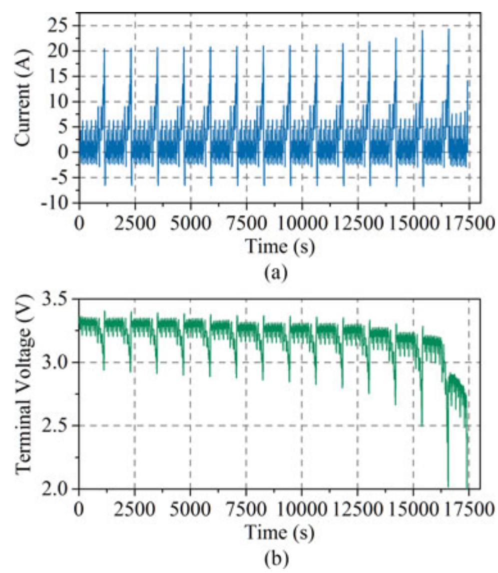

Fig. 6. Current and voltage measurement during the NEDC driving cycles. (a) Current. (b) Terminal voltage.

For the purpose of comparing different nonlinear filters in an identical condition, we take the following measures.

1) The same two RC battery model is applied to each method.
2) The code of each method is written by the same person to avoid differences in coding effectiveness.
3) The same battery and driving cycle are used to validate the nonlinear filters.

A $LiFePO_{4/c}$ battery cell is tested in the MACCOR 4000 series, and the measurement data is collected for validating the seven nonlinear filters. The accuracy of MACCOR is $\pm 0.01\% + 1$ digit for voltage measurement and $\pm 0.02\% + 1$ digit for current measurement. The nominal capacity of the battery is 10 Ah, and the nominal voltage is 3.2 V. The temperature in the chamber is set to 25 °C and the sample time is 1 s. The OCV–SOC relationship is measured every 5% SOC interval from the test bench as shown in Fig. 5.

Multi-NEDC driving cycles are applied to test the battery, and the following measurements in Fig. 6 are collected. On the basis of the two RC battery model (in Fig. 7) and the measurement data from MACCOR, seven different kinds of nonlinear filters are used to estimate SOC. The reference SOC is also obtained from MACCOR. In order to eliminate the parameter uncertainty, RLS is applied to update the parameters of the battery model online. The comparison of the nonlinear filters is shown in Fig. 8.

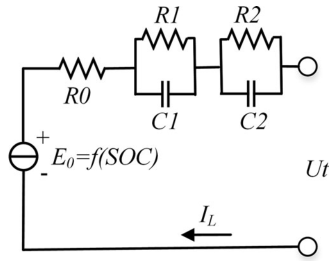

Fig. 7. Structure of two RC battery model.

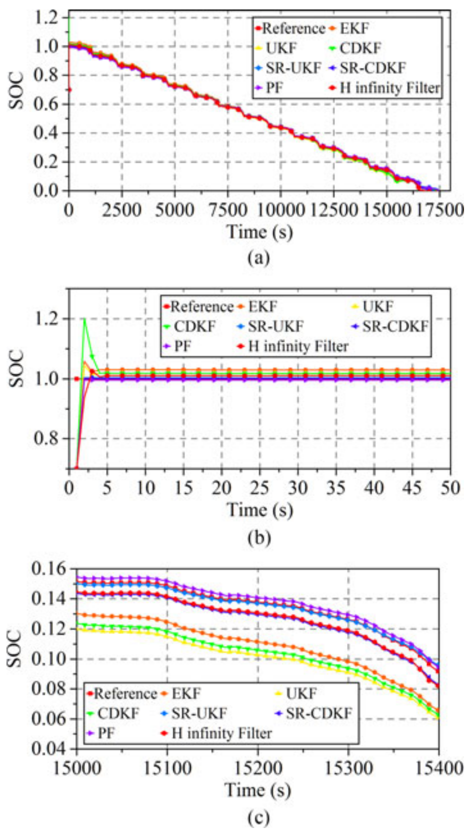

Fig. 8. Estimation results of different nonlinear filters. (a) SOC estimation results. (b) SOC value at the beginning of the estimation (0–50 s). (c) SOC estimation in lower SOC area.

The initial SOC is arbitrarily set to 0.7, and the number of the particulars in PF is 100.

The OCV–SOC relationship is established by the curve fitting of the average OCV (see Fig. 5) as shown in (4).

$$\begin{aligned}\mathrm{OCV} = &-330.2741 \cdot \mathrm{SOC}^8 + 1507.8350 \cdot \mathrm{SOC}^7 \\ &- 2869.7023 \cdot \mathrm{SOC}^6 \\ &+ 2949.8632 \cdot \mathrm{SOC}^5 - 1773.9467 \cdot \mathrm{SOC}^4 \\ &+ 632.0383 \cdot \mathrm{SOC}^3 \\ &- 128.9882 \cdot \mathrm{SOC}^2 + 13.8940 \cdot \mathrm{SOC} + 2.6371 \quad (4)\end{aligned}$$

All methods are able to converge to the reference SOC within a limited time as shown in Fig. 8(a). In Fig. 8(b), a zoom of the SOC estimation results is shown. It is possible to note that SR-CDKF, SR-UKF, PF, and H-infinity filter achieve better results than the other nonlinear filters. That is because the square root filter is developed to increase the numerical accuracy of Kalman filter. PF is proposed for the severe nonlinear system, and it is able to work with arbitrary nonlinear noise distribution [62]. Due to the high nonlinearity of battery model in the lower SOC area, these four filters are able to obtain better results also in the lower SOC area in Fig. 8(c).

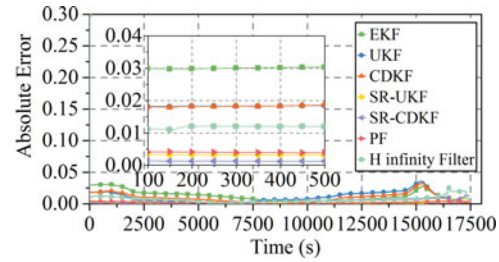

Fig. 9. Absolute error of different nonlinear filters.

TABLE II
COMPARISON OF MAE AND EXECUTION TIME

Method	MAE	Execution time (ms)
EKF	0.0121	0.023177
UKF	0.0105	0.093621
CDKF	0.0096	0.093438
SR-UKF	0.0022	0.132310
SR-CDKF	0.0039	0.142347
PF	0.0020	1.454133
H infinity filter	0.0065	0.034674

The absolute error in Fig. 9 indicates that EKF, UKF, and CDKF have a larger SOC estimation error. This is particularly true in the higher and lower SOC ranges, where the nonlinear characteristic of the battery is more evident. The absolute error in Fig. 9 also proves that SR-UKF, SR-CDKF, PF, and H-infinity filter are more suitable for strongly nonlinear system compared with the other three nonlinear filters. The mean absolute error (MAE) and the execution time of each nonlinear filter are listed in Table II.

The execution time is measured through a Processor-in-the-Loop way. The nonlinear filters are downloaded to a MicroZed development board (Xilinx Zynq XC7Z020) by the model-based design approach in Simulink. In Table II, PF obtains the best results in terms of MAE (0.0020), while the execution time is much longer than the others methods. The MAE of H-infinity filter is 0.0065 which is 50% of EKF. But its execution time is 0. 034674 ms, which is 150% of EKF. Therefore, H-infinity filter is a better tradeoff between accuracy and execution time for online SOC estimation.

V. Conclusion

SOC estimation is crucial for many applications of Li-ion batteries. This paper reviews the SOC estimation methods that are suitable for online usage and classify them into five categories: CCMs, OCVMs, ISBMs, MBMs, and ANNBMs. The principles and features of each method are recalled in this work. The CCM directly estimates SOC from the integration of current, which is computationally effective. The initial SOC and the accumulation of sensor errors decrease the practicality of the CCM. The OCVM makes full use of the monotonous relationship of OCV and SOC. However, the long relaxation time of the batteries affects its use in real-time applications. ISBM can directly reflect the internal parameters changes inside the battery. The ISBMs are sensitive to SOC variations, but the difficulty in online EIS measurement limits its online usage.

Different types of MBMs have been proposed in the literature, however, the Kalman filter is the most popular one. MBMs are more accurate and robust than other methods, but they are also more computationally demanding. Moreover, their performance is closely related to the established battery model. ANNBMs are easy to implement online after offline data training. However, the complicated data collecting process and the applicability of the method on the new coming data not having been trained limits its online usage.

The suitable online SOC estimation method in real applications should be a good tradeoff of the accuracy, robustness, and computational effort on the foundation of the specific condition. The comparison of seven different nonlinear filters for SOC estimation proves the accuracy of the MBMs. The experimental results have shown that the H-infinity filter gives a good compromise in terms of accuracy and execution time. Then, it is a good choice for online SOC estimation.

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