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Review Article

Hybrid Methods Using Neural Network and Kalman Filter for the State of Charge Estimation of Lithium-Ion Battery

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With the increasing carbon emissions worldwide, lithium-ion batteries have become the main component of energy storage systems for clean energy due to their unique advantages. Accurate and reliable state-of-charge (SOC) estimation is a central factor in the widespread use of lithium-ion batteries. This review, therefore, examines the recent literature on estimating the SOC of lithium-ion batteries using the hybrid methods of neural networks combined with Kalman filtering (NN-KF), classifying the methods into Kalman filter-first and neural network-first methods. Then the hybrid methods are studied and discussed in terms of battery model, parameter identification, algorithm structure, implementation process, appropriate environment, advantages, disadvantages, and estimation errors. In addition, this review also gives corresponding recommendations for researchers in the battery field considering the existing problems.

1. Introduction

With the worldwide reduction of nonrenewable energy sources and carbon dioxide emissions, clean energy development has become an important theme [1–3]. Lithium-ion batteries are gradually regarded as the most natural green alternative to traditional fossil fuels for their high energy density, no memory effect [4], long life, and environmental protection [5]. Lithium-ion batteries are now widely used in electric vehicles, ships, and distributed energy storage systems. With the continuous development of the smart grid, the hybrid energy storage system consisting of lithium-ion batteries and supercapacitors has become an attractive option [6]. The continuous development of lithium-ion batteries also achieves emission peak and carbon neutrality goals.

In contrast to conventional fossil fuels, lithium-ion batteries also need a state parameter indicating the current remaining energy. Therefore, the state of charge (SOC) is proposed [7–9]. SOC is defined as the ratio of the current available capacity of the battery to the maximum available capacity. Consequently, accurate battery capacity estimation is crucial to estimate the SOC [10–12]. By clarifying the change in SOC, the abnormal charging capacity of the battery can be determined, ensuring the safe operation of the electric vehicle [13]. Meanwhile, the accurate estimation of the battery SOC is also the basis for managing lithium-ion batteries and understanding the battery status. However, SOC cannot be measured directly and can only be estimated based on the relationship between SOC and measurable variables [14, 15]. Consequently, it is essential to establish a reliable and accurate SOC estimation method [16].

More and more researchers are enthusiastic about estimating SOC using hybrid methods to improve the precision of SOC estimation. Achieving accurate SOC estimation in natural application environments remains a challenge due to the inconsistency of batteries in the pack [17]. The hybrid method combining neural network with Kalman filter (NN-KF) can solve the nonlinear relationship between battery SOC and other variables by using the self-learning ability and strong self-adaptability of neural

network (NN) [18–20] on the one hand. On the other hand, it is the ability to combine the fast convergence property of the Kalman filter to achieve a real-time estimation of SOC [21–23] and reduce the influence of noise on the results. This review classifies this hybrid method into Kalman filter-first method and the neural network-first method. It is promising to apply the NN-KF hybrid method into practice as an efficient method to obtain SOC estimates for lithium-ion batteries.

The remainder of this review is organized as follows: Section 2 describes the types and characteristics of lithium-ion battery models, the methodological flow of the Thevenin model parameter identification, and a detailed evaluation of all methods. A detailed and comprehensive introduction to the current framework and remarks of Kalman filter-first methods and neural network-first methods is presented in Section 3. Section 4 discusses the future direction from the perspective of the current situation. Conclusion is drawn in Section 5.

2. Modeling and Parameter Identification

SOC estimation of lithium-ion batteries requires high accuracy and reliability of the model, so it is essential to use a reasonable model and a suitable parameter identification method to simulate the battery characteristics.

2.1. Battery Model. Establishing a battery state-space model plays an essential role in the accurate estimation of SOC and directly affects the accuracy of the SOC estimation. To make the state model closer to the actual usage environment and meet the needs of combining neural network and Kalman filter, the battery model must be simple and compatible with the actual situation [24]. The standard battery models used in the research are the Thevenin and the neural network-based models. The following is a brief description of their characteristics.

Thevenin model has a simple structure, high accuracy, and strong robustness even in unknown cell environments. Figure 1(a) shows that it consists of an ideal voltage source U_{OC}, a series resistor R_0, and a capacitor-resistor (RC) network, where R_0 represents the battery's internal resistance, and R_1 and C_1 are the polarization resistance and polarization capacitance, respectively.

The number of RC networks is changeable, and its number represents the order of the Thevenin model. Figure 1(b) is the structural diagram of the second-order Thevenin model.

The complex dynamic characteristics and uncertain operating conditions make building a suitable battery model difficult. The results of SOC estimation under cold conditions were reported to be inadequate [25–29]. Accordingly, the Thevenin model is not perfect [30]. Other suitable battery models, such as the electrochemical-thermal degradation model [31], are still needed to describe the complex battery behavior at different ambient temperatures.

Neural network, a branch of artificial intelligence, has been widely used for predicting outcomes based on input data [32–35]. Compared with the Thevenin model, the neural network-based modeling method does not need to consider the electrochemical state inside the battery. However, it only needs to use the measurable parameters as inputs and establish a nonlinear relationship between the input data and the output data to construct the estimated battery SOC model through the self-learning capability [36].

2.2. Model Parameter Identification. Thevenin model parameters are susceptible to operating conditions such as SOC levels and ambient temperature. During the use of lithium-ion batteries, it is helpful to describe the electrochemical characteristics and improve the accuracy if the model parameters can be effectively identified. Meanwhile, the accurate identification of model parameters can facilitate the combination of Kalman filter and neural network to improve the accuracy of battery SOC estimation. The schematic diagram of the recognition process is depicted in Figure 2.

A large number of algorithms, including genetic algorithms (GA) [37], least squares (LA) [38], and hybrid pulse power characteristic (HPPC) test [39], have been used in recent years for parameter identification of Thevenin models.

Taking the first-order Thevenin model as an example, the unknown parameters are R_0, R_1, and C_1. According to Kirchhoff's law and analyzing the model, the following equations can be obtained:

$$\begin{cases} U_{OC} = U_L - U_R - U_1, \\ I_L = C_1 \dfrac{\mathrm{d}U_1}{\mathrm{d}t} + \dfrac{U_1}{R_1}. \end{cases} \tag{1}$$

The discrete equation is obtained according to equation (1), as shown in the following equation:

$$\begin{cases} \begin{bmatrix} \mathrm{SOC}_{k+1} \\ U_{1,k+1} \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ 0 & e^{-(\triangle t/\tau)} \end{bmatrix} \begin{bmatrix} \mathrm{SOC}_k \\ U_{L,k+1} \end{bmatrix} + \begin{bmatrix} -\dfrac{\triangle t}{Q_N} \\ R_1\left(1 - e^{-(T/\tau)}\right) \end{bmatrix} I_{L,k}, \\ U_{L,k} = U_{OC,k} - R_{0,k} I_{L,k} + \begin{bmatrix} 0 \\ -1 \end{bmatrix}^T \begin{bmatrix} \mathrm{SOC}_k \\ U_{1,k} \end{bmatrix}. \end{cases} \tag{2}$$

In the above two equations, U_1 is the RC network voltage and U_L is the terminal voltage. Q_N is the rated capacity of the battery and I_L is the circuit current. $\triangle t$ is the sampling time interval, and τ is the time constant, $\tau = R_1 C_1$. k is the time parameter.

Yang et al. use GA for the first-order Thevenin model to identify the parameters [37]. GA is a global search method formed by simulating the genetics and evolution of organisms in their natural environment. However, it cannot use the feedback information in time, so the search speed is slow, and it is not good enough to solve the large-scale computation problem. In response to these problems, the
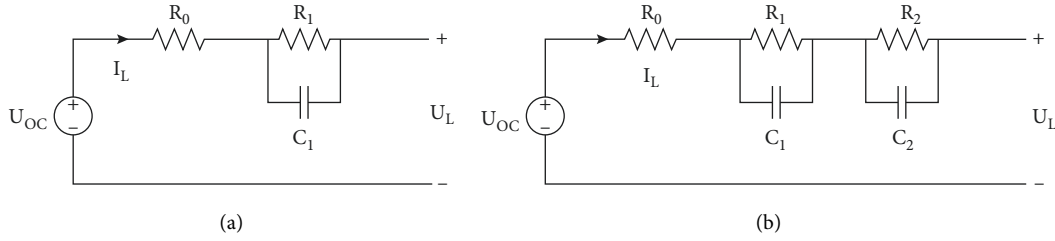
Figure 1: The structure of Thevenin models. (a) Thevenin equivalent circuit model. (b) Second-order Thevenin equivalent circuit model.
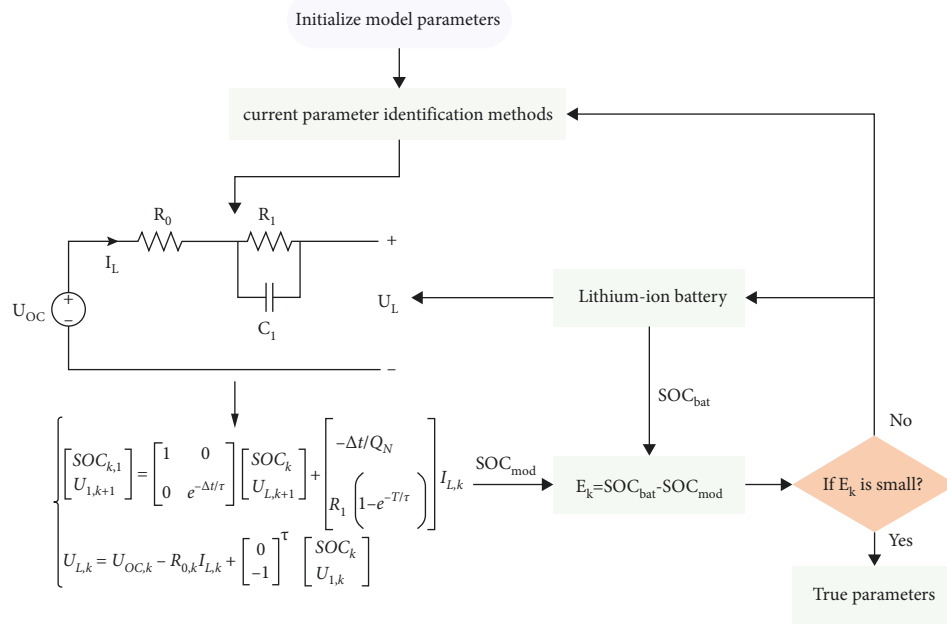

Figure 2: The process of battery parameter identification.

particle swarm optimization (PSO) algorithm is favored by many researchers because it is easier to implement and has lower computational complexity [40].

LA is also a standard method for the identification of battery model parameters. Thevenin battery model can be considered a linear system, identified by the parameter identification toolbox in Matlab/Simulink [41]. According to the parameter fitting function in the toolbox, parameter identification can be achieved using LA. The recursive least squares (RLS) method is proposed to make the algorithm relevant to the practical use environment. Compared to LS, it can extract model parameters in real time using new measurement data [42], significantly reducing the computational and storage effort. Recently, Li et al. performed discharge experiments on lithium-ion batteries and combined RLS to identify R_0, R_1, and C_1 in the battery model. The data from the voltage recovery stage makes it easier to obtain the model parameters to be identified with a high degree of accuracy [43].

The battery model is also affected by noise in the natural application environment. The RLS method is susceptible to noise, resulting in inaccurate identification of model parameters. The recursive total least squares (RTLS) [44], adaptive forgetting recursive total least squares (AF-RTLS) [45], and the Frisch scheme-based bias compensating recursive least squares (FBCRLS) [46] have been proposed to effectively suppress the model identification errors caused by noise, which provides more reliable SOC estimation.

A recursive least squares method with forgetting factors (FFRLS) is also applied to the parameter identification of the Thevenin model. FFRLS has faster convergence and better tracking performance with an increased forgetting factor λ [47]. In general, the smaller λ, the better the computational fit of the system, but the more significant the fluctuation. So, determining the λ value quickly is also an urgent problem to be solved.

HPPC tests can be used to determine the model parameters at different temperatures and different discharge rates. Li et al. (2021) conducted several experiments and finally created a table of battery parameters concerning temperature and discharge rate [39]. Experimental data from another part also verified the validity of the HPPC method. The appropriate methods for identifying battery parameters are summarized in Table 1.

TABLE 1: Methods for identifying battery model parameters.

Years	Methods	Advantages	Disadvantages
2019	GA [37]	Parallel and global search	Slow search speed
	LA [41]	Calculate the coefficients at one time	Offline
	RLS [42]	Process data in real-time	Taking up a lot of storage space
2020	FFRLS [47]	Better performance	Difficult to decide the value of λ
2021	RLS [43]	Conduct discharge experiments	Time-consuming
	HPPC [39]	Consider temperature and discharge rate	Tedious
	PSO [40]	Lower computational complexity	Easily fall into the local optimum

3. State-of-Charge Estimation

3.1. Kalman Filter-First Method. The basic idea of the Kalman filter-first method is that when the sensor obtains voltage, current, and temperature measurements from the battery, it can be iterated directly since various methods have previously determined the battery model parameters. The values needed by the neural network are then computed, and the final SOC estimation results are output by the neural network. The structure diagram is shown in Figure 3.

The Kalman filtering-first method is highly resistant to interference and suitable for SOC estimation in complex environments, while having high robustness. However, the method relies on an accurate battery model, and different battery models also require reasonable methods for parameter identification.

The traditional KF algorithm is proposed to solve the linear problem [48–50], while the lithium-ion battery can be considered a nonlinear system. Therefore, it is hardly used in the battery SOC estimation process. Several algorithms that can handle nonlinear systems, such as extended Kalman filter (EKF) and Unscented Kalman filter (UKF), are proposed.

The EKF linearizes nonlinear systems with Taylor series expansions, essentially a recursive algorithm. Xu et al. used EKF for the initial estimation of battery SOC and then used the estimated SOC value along with voltage and current as of the input to the long short-term memory (LSTM) network [47]. The model's performance was verified at −15°C, 0°C, and 25°C, respectively, and the mean absolute error (MAE) was less than 1%. The EKF-LSTM maintains high estimation accuracy even at very low ambient temperatures. Similarly, EKF can be combined with the back propagation neural network (BPNN) to estimate the battery SOC [51]. The EKF-BP algorithm is verified by dynamic stress test (DST), Beijing Bus Dynamic Stress Test (BBDST), and other complex working conditions. The estimated error is less than 1.10%.

Both the above algorithms are for individual lithium-ion batteries, while in practical applications, such as electric vehicles, the application of lithium-ion battery packs is much more. When estimating the battery pack SOC, it is not appropriate to consider it as a simple battery. The method discussed previously cannot be directly applied to a battery pack consisting of many batteries. Developing a simple, reliable, and effective SOC estimation method for battery packs is essential.

Dao et al. developed a smart battery management system (BMS) based on KF and NN to estimate the SOC of a lithium-ion battery pack, as shown in Figure 4. The battery pack temperature range is 19–42°C. The performance is better than ANN and KF alone by experimental evaluation on real battery packs with an error of less than 1% [52]. However, there are still some problems with this method. For example, the capacity balance between each battery in the pack is not considered in the application. The capacity decay of each battery varies during use, and the impact of capacity balance on BMS and battery pack SOC estimation needs to be considered.

EKF suffers from computational overload for complex nonlinear problems and generates linearity errors. UKF, proposed by Julier and Uhlmann in 1997 [53], uses lossless transformations to obtain the mean and covariance of individual probabilities, avoiding solving Jacobi matrices. By constructing an adaptive unscented Kalman filter (AUKF) algorithm based on the Thevenin model, Hosseininasab et al. presented a combined NN and AUKF method for SOC estimation [54]. Considering the initial offset, capacity error, and current sensor drift considering shunt thermal effects, the root-mean-square Error (RMSE) still reaches 0.954% at 25°C. The results of SOC estimation based on the Kalman filter-first method are summarized in Table 2.

3.2. Neural Network-First Method. The Kalman filter-first method can accommodate the initial error of the SOC and estimate the SOC effectively online. However, the high computational requirements and effective model parameterization need to be effectively addressed before practical application, which has limited the application of the method to some extent. In contrast, the neural network modeling approach can avoid the detailed study of lithium-ion battery models and parameter identification. A good battery SOC estimation algorithm can be built using only previous reliable data.

For the neural network method alone [55], the SOC estimation results highly depend on the dataset used. Once the data set differs significantly from the applied battery operating conditions, the error in the estimation results of the lithium-ion battery SOC can be substantial. The neural network-first method avoids this problem. Even if a less than perfect data set is used, the output of the NN can be corrected using the KF, and finally, an accurate battery SOC can be obtained.
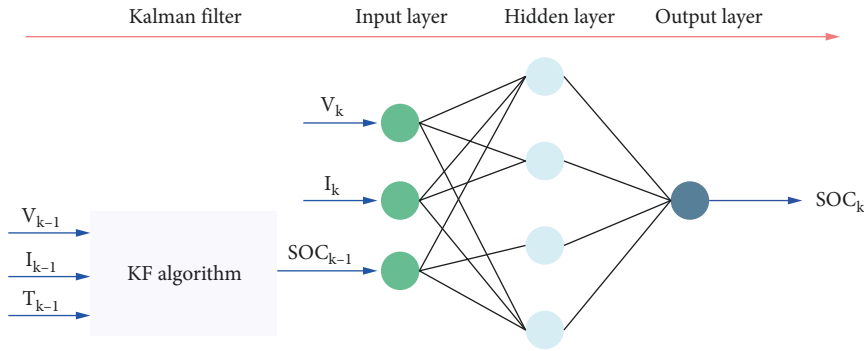
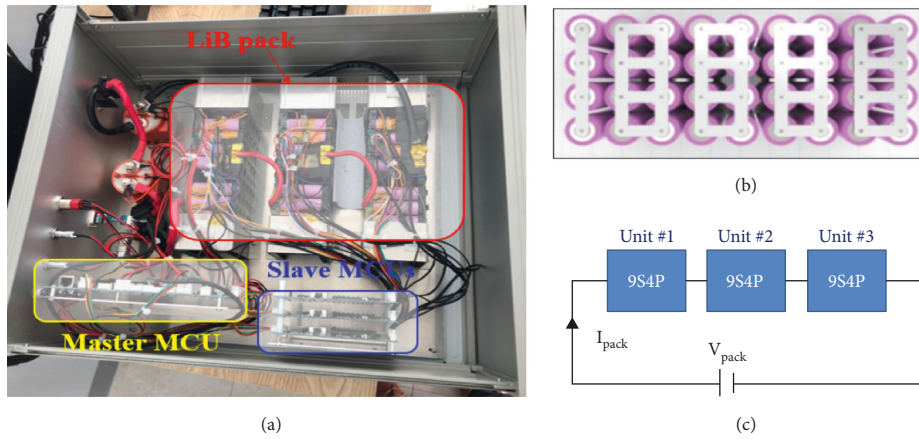FIGURE 3: The structure diagram of the KF priority method.

FIGURE 4: Configurations of the smart BMS and lithium-ion battery pack. Reproduced with permission from reference [23]. Copyright 2021, energies. (a) Smart BMS for experiment. (b) LiB unit configuration (9S4P). (c) LiB pack configuration with units.

TABLE 2: Kalman filter priority methods used for SOC estimation.

Years	Methods	Remarks	Temperature	SOC errors
2019	EKF-LSTM [47]	High accuracy at low temperatures	−15°C, 0°C, 25°C	MAE < 1%
2020	UKF-NN [54]	Easy to implement	25°C	RMSE = 0.954%
2021	EKF-BPNN [51]	Real-time estimation	Unspecified	<1.10%
	EKF-ANN [52]	Estimate SOC of the battery pack	19–42°C	<1%

The central idea of the neural network-first method is first to use the neural network to reveal the nonlinear relationship between SOC and measurable variables such as current, voltage, and temperature. The output of the NN is then smoothed using a KF algorithm to achieve accurate and stable SOC estimates.

3.2.1. Feed-Forward Neural Network. Feedforward neural network (FNN) is simple in structure and easy to train, which has become the most common method for SOC estimation of lithium-ion batteries [56–58].

Qin et al. used a nonlinear autoregressive neural network (NARXNN) to estimate the SOC of lithium-ion batteries and then applied UKF to reduce the error [59]. Compared with the battery SOC estimation results based on NARXNN alone, the error is reduced by about 1% at 0°C. Since each estimate uses data from a single sampling point and does not consider the dynamic chemistry of the battery, the estimation accuracy of this method is usually not very high.

The polarization characteristics of the battery can be used as a new input to the FNN to describe the dynamic chemistry of the battery accurately. One way to consider polarization is to increase the NN input data from a single sample point to multiple sample points [60], which requires selecting a suitable time constant. The method for selecting the time constant is designed as shown in Figure 5, where τ represents the time constant and $r(x, y)$ represents the correlation coefficient. Chen et al. (2019) designed a neural network-first battery SOC estimation method based on an improved FNN model and EKF algorithm [61]. The SOC estimation error can be kept to less than 2% even with inaccurate initial SOC value, inaccurate initial capacity, and low temperature (−10°C, 0°C, and 10°C). This method is more suitable for complex electric vehicle application environments.
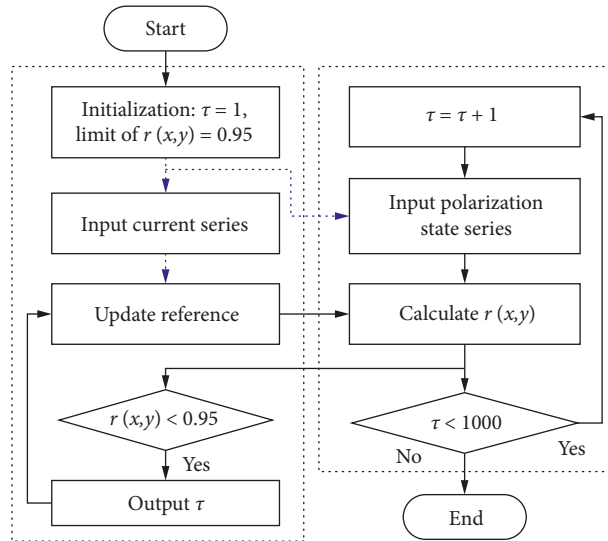
FIGURE 5: The selection process of time constants. Reproduced with permission from reference [29]. Copyright 2019, Elsevier.

The terminal voltage can be used as the output of the neural network. Meanwhile, the SOC is considered as an internal state, which is indirectly estimated through the feedback error of the voltage [62]. This indirect method has the advantage of uncertainty enhancement and feedback compensation. The effect of temperature on SOC, however, is not considered. Table 3 lists the above studies.

3.2.2. Deep Learning. In recent years, deep learning algorithms have attracted the attention of researchers in the field of battery state estimation because of their ability to automatically extract features and their good generalization performance [63]. Deep learning algorithms are also increasingly introduced into the SOC estimation of lithium-ion batteries.

Deep belief network (DBN) can be combined with KF. The DBN can extract the relationship between battery SOC and input parameters with its strong nonlinear fitting ability. The KF eliminates measurement noise and improves SOC estimation accuracy [64]. The framework of the proposed model is shown in Figure 6. The RMSE of the SOC estimation by DST is lower than 0.7%. This hybrid is suitable for estimating the SOC of lithium-ion batteries under dynamic conditions.

LSTM network can handle time-series data considering the time dependence of SOC estimation. Yang et al. (2020) used a stepwise search algorithm to determine the hyperparameters of the LSTM network and further reduce the estimation error by UKF [65]. The results show that the RMSE of the LSTM-UKF method is 1.1%, which is better than other FNN methods. In addition, the method has excellent generalization ability to the temperature at 0–50°C, and more reliable SOC estimation results can be obtained at temperatures without training data.

The commonly used LSTM network is a "many-to-many" structure, as shown in Figure 7. The output at moment $t + 1$ is related to the input information at moment $t + 1$

and moment t. The results in earlier information have little to no impact on the current output, making it impossible to take full advantage of the past information.

To address this problem, Tian et al. (2020) proposed a "many-to-one" structure of the LSTM network [66]. This framework introduced an adaptive cubature Kalman filter (ACKF) algorithm that maximizes the impact of the above measurements on current SOC estimates and further extended the applicability of the neural network-first method. High estimation accuracy was achieved in the temperature range of 10 to 50°C. This LSTM-ACKF method avoids finding the optimal hyperparameters in the training phase of the LSTM network, which is very difficult. Only a rough selection in the training phase is needed, and then a more accurate SOC estimation result can be obtained using ACKF.

To accurately estimate the SOC for lithium-ion battery packs, a combination of LSTM and improved square root cubature Kalman filter (SRCKF) is proposed [67]. To address the inconsistency of batteries among packs, Shu et al. designed an iterative rule for LSTM-SRCKF using the smoothing method with the maximum and minimum SOC values in the packs as features. The method could converge quickly to the reference value even at sub-zero temperatures, with RMSE less than 0.4%. This method still has not considered aging problems such as battery capacity decay.

By combining different neural networks, the advantages of each can be retained, which improves the estimation efficiency and applicability. One-dimensional convolutional units can be combined with the gated recurrent unit (GRU) to form a new deep neural network (DNN), as shown in Figure 8. The DNN used 10 minutes of data as input for fast and accurate SOC estimation across the entire battery SOC range [68].

The KF algorithm is introduced to enhance the robustness of the neural network. The DNN-KF method can quickly adapt to batteries with different aging states, and the RMSE can be less than 3.146%. The deep learning-based SOC estimation methods are summarized in Table 4.

TABLE 3: SOC errors of those estimation methods.

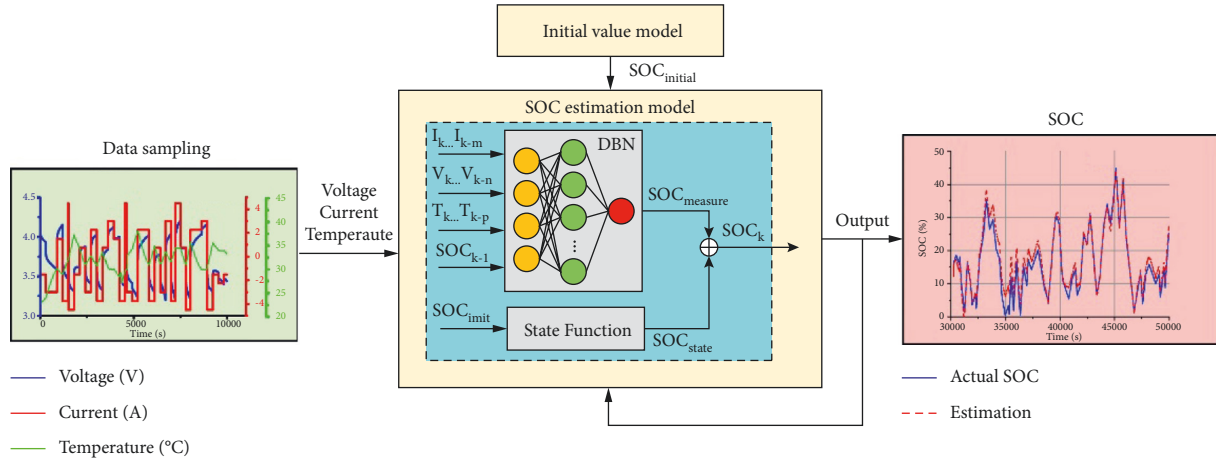| Years	Methods	Remarks	Temperature	SOC errors
2019	NARXNN-UKF [59]	Ignoring dynamic properties	0°C, 25°C, 45°C	<3.55%
	FNN-EKF [61]	Introducing the new input	−10°C, 0°C, 10°C	<2%
2020	RBFNN-UKF [62]	Indirect method to estimate SOC	Unspecified	Unspecified

FIGURE 6: The framework of the proposed model based on DBN-KF. Reproduced with permission from Ref 32. Copyright 2019, Elsevier.
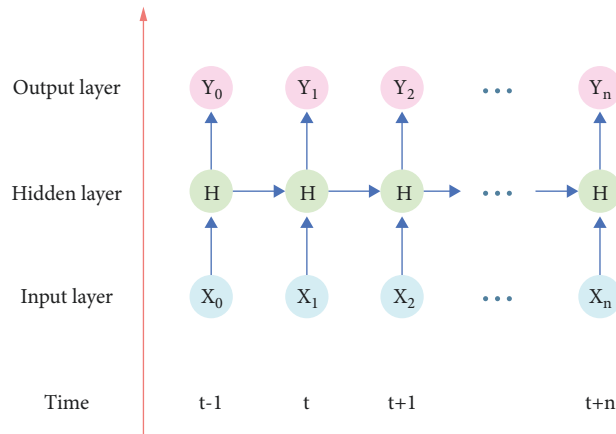

FIGURE 7: Basic LSTM architecture.

4. Discussion

From the above experimental results, the NN-KF hybrid method to estimate the SOC of lithium-ion battery is accurate. However, there are still some problems that need to be investigated.

(1) The problem of SOC estimation for lithium-ion battery packs has still not been effectively addressed. Battery capacity and SOC imbalance in packs are widespread problems [69]. As a result, developing an NN-KF hybrid method considering the capacity balance of lithium-ion batteries is necessary to improve battery safety and extend the applicability of SOC estimation methods.

(2) In subsequent studies, the use of transfer learning to improve the generalization ability of the hybrid method can be considered so that the method can be generalized to SOC estimation of other types of lithium batteries. After transfer learning, the hybrid method can be quickly adapted to various situations.

(3) Expand the types of the NN-KF hybrid methods through the mutual hybrid of different neural networks and Kalman filters. Analyzing the effects of different combinations on the SOC estimation and finding a more suitable hybrid method might be the following research priorities.

(4) Noise disturbance is still a pressing problem for the Kalman filter-first method. Therefore, an effective method is needed to improve the accuracy of model parameter identification and SOC estimation in the whole life cycle of the battery under noise disturbance.
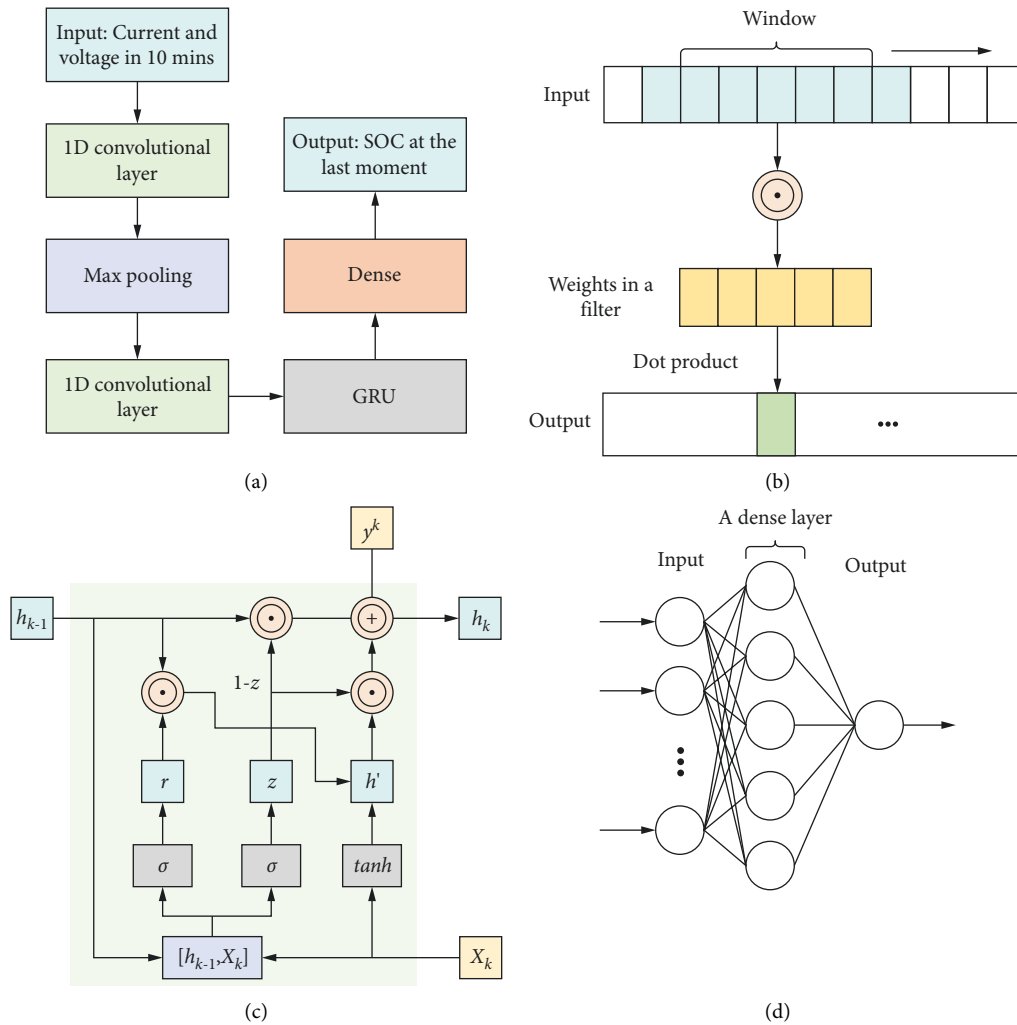
FIGURE 8: Schematic diagrams of (a) the developed DNN, (b) a 1D convolutional unit, (c) a GRU, and (d) dense layers. Reproduced with permission from reference [36]. Copyright 2021, Elsevier.

TABLE 4: Deep learning frameworks used for SOC estimation.

Years	Methods	Remarks	Temperature	SOC errors
2019	DBN-KF [64]	Better for dynamic conditions	22°C to 45°C	RMSE <0.7%
2020	LSTM-UKF [65]	Excellent generalization to temperature	0°C to 50°C	RMSE <1.1%
	LSTM-ACKF [66]	Making the most of past information	10°C to 50°C	RMSE <2.2%
2021	LSTM-SRCKF [67]	New iteration rules designed	−20°C to 0°C	RMSE <0.4%
	DNN-KF [68]	Short input time required	Unspecified	RMSE <3.15%

(5) The SOC estimation results are sensitive to temperature changes. In the future, it is essential to improve the stability of SOC estimation methods in more extreme environments. Furthermore, the ambient temperature does not directly reflect the chemical properties inside the battery. The surface temperature of the battery can be used as an input variable for the hybrid method.

(6) SOC needs to be predicted without interruption during the battery life. Therefore, it is essential to ensure that the SOC is accurately estimated even during the continuous aging of the battery. Few hybrid methods consider this problem. Future work is to integrate state of health (SOH) and remaining useful life (RUL) as aging parameters into the NN-KF hybrid method, adapting to different degrees of dynamic characteristics and aging states of the battery.

5. Conclusion

This review analyzes the SOC estimation of lithium-ion batteries based on the NN-KF hybrid method. First, the battery model is introduced, and the parameter

identification methods and procedures are discussed to prepare for SOC estimation. Then, the Kalman filter-first method and the neural network-first method are introduced, and the remarks of each method. Finally, the future development direction is proposed with the actual existing problems.

Lithium-ion batteries' chemical reactions and aging mechanisms are very complex, making it challenging to describe them with a specific model. The existing model parameter identification methods all have their advantages and disadvantages. None of them perfectly matches the natural application environment, which means that most Kalman filter-first methods can only achieve good estimation performance in simulated environments. Of course, the advantages of small computation and short estimation time of Kalman filter-first methods are challenging to be possessed by neural network-first methods. Future research focuses on making the SOC estimation results of NN-KF hybrid methods more accurate, applying these methods to practical application environments, and achieving real-time estimation.

In conclusion, this review makes a significant contribution to the accurate estimation of the SOC and help to expand the use of lithium-ion batteries. The widespread use of lithium-ion batteries can promote energy conservation, carbon dioxide emission reduction, and environmental protection, contributing to emission peak and carbon neutrality goals. This review can also provide a valuable overview and recommendations for researchers in the battery field.

Conflicts of Interest

The authors declare no conflicts of interest.

Acknowledgments

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