Journal of Informatics
Electrical and Electronics Engineering, 2022,
Vol. 03, Iss. 01, S. No. 001, pp. 1-11
ISSN (Online): 2582-7006

SOC Estimation for Electrical Vehicle lithium Batteries base on Simplified-spherical Un-scented Kalman Filtering

Yibo Wang

School of Advanced Technology, Xi'an Jiaotong-liverpool University (XJTLU), Suzhou, China
suw773126@gmail.com

How to cite this paper: Y.Wang, "SOC Estimation for Electrical Vehicle lithium Batteries base on Simplified-spherical Un-scented Kalman Filtering," *Journal of Informatics Electrical and Electronics Engineering* (*JIEEE*), Vol. 03, Iss. 01, S No. 001, pp. 1–11, 2022.

http://doi.org/10.54060/JIEEE/003.01.001

Received: 05/04/2022
Accepted: 24/04/2022
Published: 25/04/2022

Abstract

In order to develop electric vehicles, it is vital to be able to accurately estimate the state charge (SOC) of a lithium battery. To address the problem that the Extended Kalman Filter (EKF) algorithm leads to the Taylor expansion truncation of the higher-order system. In this paper, a system of state-space equations is established based on the second-order equivalent circuit model, and a simplified-sphere sample approach is used to improve the Unscented Kalman Filter (UKF) algorithm. The SOC estimation performance of the three algorithms is tested under constant current discharge, pulse dis-charge conditions, and UDC conditions, respectively. The simulation results show that Simplified-spherical Unscented Kalman Filtering (SUKF) has smaller errors between SOC estimation and theoretical reference values than EKF and UKF. The SUKF is less computationally intensive than UKF and has better timeliness in the onboard battery management system.

Keywords

Electrical Vehicle, State of Charge estimation, Extended Kalman Filter, Unscented Kalman Filter, Urban Driving Cycle

1. Introduction

Electric vehicles are powered by power batteries and the performance of those batteries directly determines the safety of those vehicles during operation. Currently, for the monitoring and control of batteries in electric vehicles, the most common method is to select a suitable Battery Management System (BMS) [1-2]. The main functions of the BMS can be divided into battery cell balancing system, State of Charge (SOC) estimation, State of Power (SOP) estimation and State of Health (SOH) estimation, etc [3]. Among them, the battery charge status will change rapidly with the change of vehicle running speed, and the inaccurate SOC value will affect the user experience and the future range estimation [4]. Therefore, how to obtain accurate battery SOC value by algorithm is the key problem that needs to be solved [5].

According to the principle of SOC estimation algorithms, the algorithms can be divided into four categories: the open-circuit voltage method as the representative of the table-checking method, the mathematical theory-based Ampere-time Integration (AHI) method, the model-based Kalman Filtering (KF) algorithm and Robust Filtering (RF) algorithm, and the data-driven algorithm like Artificial Neural Network (ANN) and Support Vector Machine (SVM) [6-8]. At present, the industry commonly uses the open-circuit voltage method and the AHI method to realize the online monitoring of battery SOC. However, in the process of battery use, due to the polarization effect in the process of battery charging and discharging, and considering the sensor accuracy and error, the implementation of lithium battery SOC estimation by the open-circuit voltage method will produce large errors [9]. The AHI method requires the accurate initial SOC value in the algorithm, cause inaccurate initial SOC value will lead to a large error in the subsequent estimation of the whole algorithm. Although the data-driven-based method is more effective and accurate, it requires a large amount of experimental data as training samples and has higher requirements for processors and larger computational effort. Therefore, the current research focuses on Kalman Filtering algorithms [10].

For the nonlinear system with higher-order terms, the Extended Kalman Filter (EKF) algorithm uses Taylor expansion, which will lead to truncation error and filter divergence [11-13]; at the same time, the Jacobian matrix needs to be calculated at each cycle estimate, increasing the computational complexity of the system [14]. Therefore, the literature [15] proposes to implement lithium battery SOC estimation by the Unscented Kalman Filter (UKF) algorithm. In the UKF algorithm, no linearization of the nonlinear system is necessary [16-17]. Instead, the unscented transformation is combined with a Kalman Filter algorithm, and a suitable sampling strategy is applied to approximate the state variables, which is able to avoid the error induced by the EKF hair due to its disregard for higher-order terms [18]. However, the UKF algorithm needs to recalculate the sigma point set at the end of each cycle, which will lead to a large computational effort for the whole algorithm and high requirements for the central processing chip of real-time SOC estimation [19-20]. Therefore, this paper uses a Simplified-sphere Unscented Kalman Filter (SUKF) algorithm to implement SOC estimation, which simplifies the hypersphere monomorphic sampling strategy, thus reducing the computational effort of the whole algorithm.

2. Model building and parameter identification

2.1. Battery Equivalent Circuit Modeling

In order to more accurately characterize the electrical properties of LiFePO4 battery, an equivalent circuit model is generally established to reflect the external characteristics of the lithium battery. Currently, Rint, Thevenin, PHGV, S-ECM, RC and second-order models are all common equivalent circuit models [21]. Since the second-order RC equivalent model has no significant difference in accuracy compared to the third-order or higher-order models, and the constructed matrix is of lower order and less computationally intensive and can describe the different polarization characteristics of the battery more accurately than the Thevenin model, the second-order RC model is used in this experiment [22]. Its corresponding circuit model is shown in Fig 1.

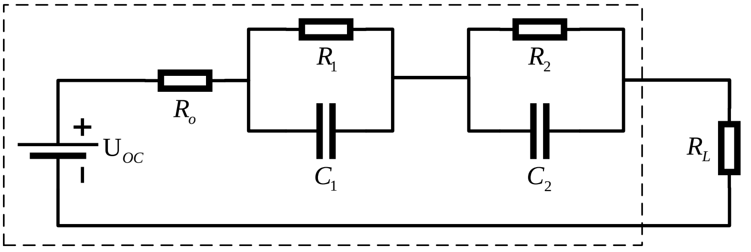

Figure 1. Second-order RC equivalent circuit model

Where U_{oc} is the open circuit voltage of the battery, R_o is the ohmic internal resistance, which is mainly used to respond to the sudden change of terminal voltage during the charging and discharging process of the battery. C_1 and R_1 denote the electrochemical polarization capacitance and resistance, respectively, and the RC link composed of C_1 and R_1 simulates the electrochemical polarization effect of the battery, C_2 and R_2 denote the concentration difference polarization capacitance and resistance, respectively, and the RC link composed of C_2 and R_2 simulates the concentration difference polarization effect [23-25]. The parameters of the circuit components in the second-order RC model change when SOC changes. The mathematical model of the circuit according to Kirchhoff's law is:

$$U_{out} = U_{oc} - U_1 - U_2 - R_o I \tag{1}$$

$$U_1 = -\frac{1}{R_1 C_1} U_1 + \frac{1}{C_1} I(t) \tag{2}$$

$$U_2 = -\frac{1}{R_2 C_2} U_2 + \frac{1}{C_2} I(t) \tag{3}$$

Where U_1 is the voltage across the polarization circuit R_1C_1, U_2 is the voltage across the polarization circuit R_2C_2, and t is the charge/discharge time.

By discretizing the battery model, the discrete state equation and output equation are obtained as

$$x_{k+1} = Ax_k + BI_{L,k} + w_k \tag{4}$$

$$U_{o,k+1} = U_{oc}SOC_k - U_{1,k} - U_{2,k} - I_k R_o \tag{5}$$

$$x_k = \begin{bmatrix} SOC_k \\ U_{1,k} \\ U_{2,k} \end{bmatrix} \tag{6}$$

$$A = \begin{bmatrix} 1 & 0 & 0 \\ 0 & e^{-\frac{T_s}{R_{1,k}C_{1,k}}} & 0 \\ 0 & 0 & e^{-\frac{T_s}{R_{2,k}C_{2,k}}} \end{bmatrix} \tag{7}$$

$$B = \begin{bmatrix} -\dfrac{T_s}{\eta_k Q_N} \\ (1 - e^{-\frac{T_s}{R_{1,k-1}C_{1,k-1}}})R_{1,k-1} \\ (1 - e^{-\frac{T_s}{R_{2,k-1}C_{2,k-1}}})R_{2,k-1} \end{bmatrix} \tag{8}$$

where T_s is the sampling time, w_k is the process noise, and v_k is the observation noise.

2.2. Second-order equivalent model identification

To accurately determine the individual electrical primary parameters in the second-order equivalent RC circuit model, the data corresponding to each SOC state must be obtained and fit using the least squares method [26-28]. The SOC value of a lithium battery can be expressed by Eq 9.

$$SOC_t = SOC_0 - \frac{\int_0^t \eta I_L(\tau) d\tau}{Q_N} \tag{9}$$

Where SOC_t is the SOC value at moment t, SOC_0 is the SOC value in the initial state, is the rated capacity of the lithium battery in Ah, n is the charge/discharge Coulomb efficiency, and I_L is the current of the lithium battery at moment t.

In order to be able to accurately obtain the individual component parameters in the second-order equivalent circuit model of the Li-ion battery, it is necessary to perform tests by the static method and the HPPC method, followed by fitting based on the curves. The data obtained by the static method and HPPC experiments are summarized in Table 1

Table 1. Second-order equivalent model parameters at different SOC value

$SOC(\%)$	$OCV(V)$	$R_b(\Omega)$	$R_1(\Omega)$	$C_1(F)$	$R_2(\Omega)$	$C_2(F)$
100.00	3.4458	0.0294	0.0314	254.1	0.0234	12217.8
90.02	3.2843	0.0295	0.0054	662.8	0.0234	12217.8
80.04	3.2772	0.0295	0.0051	664.3	0.0293	8269.2
70.07	3.2552	0.0292	0.0052	673.4	0.0321	9573
60.09	3.2428	0.0346	0.0053	0.599.9	0.0188	19124.6
50.11	3.2372	0.0331	0.0053	0.587.1	0.0337	8636.7
40.13	3.2285	0.0332	0.0050	0.597.0	0.0402	6999.0
30.16	3.2025	0.0339	0.0054	0.584.4	0.0391	8976.4
20.18	3.1674	0.0351	0.0057	0.547.9	0.0451	7130.4
10.20	3.1094	0.0340	0.0051	0.590.6	0.0637	4855.9
0.22	2.2051	0.0333	0.0085	0.526.1	0.1703	2562.8

By fitting the SOC-OCV curve by the least squares method, the electrical characteristics curve of this battery can be obtained as shown in Fig 2.

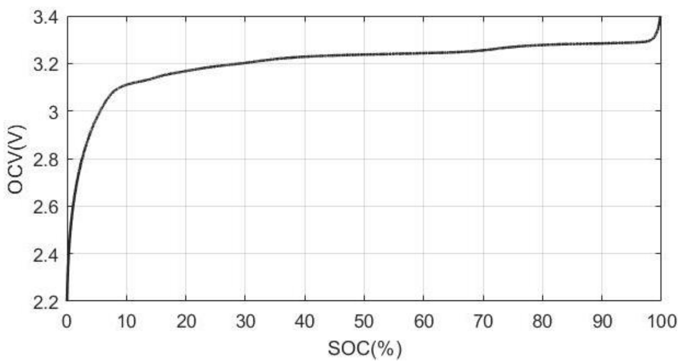

Figure 2. OCV-SOC curve during constant current discharge

The ninth-order expression for fitting the OCV-SOC curve by the least squares method will be

$$OCV = -581.459SOC^9 + 2589.76SOC^8 - 4705.02SOC^7 - 32935.14SOC^6 + 26781.84SOC^5 \\ -11641SOC^4 + 2482.852SOC^3 - 148.7085SOC^2 - 25.3186SOC + 3.26412 \tag{10}$$

In the process of building the mathematical model, in order to reduce the computational effort, the other parameter values inside are generally divided linearly according to the interval where the SOC value is currently located.

3. Simplified-sphere Unscented Kalman Filtering Algorithm

3.1. Extended Kalman filtering algorithm

The Kalman Filter algorithm is suitable for linear systems but is not applicable to the battery SOC estimation process due to the strong nonlinear nature of the external battery characteristics [29-30]. Therefore, the EKF algorithm is generally used after linearizing the nonlinear system. The discrete equations of the nonlinear system can be transformed into

$$x_{k+1} = f(x_k, u_k) + w_k \tag{11}$$

$$y_k = g(x_k, u_k) + v_k \tag{12}$$

where y_k is the output value at time k, x_k is the state variable at time k, u_k is the control input variable of the system, v_k is the system observation noise, $f(x_k, u_k)$ is the nonlinear state transfer function of the system, and $g(x_k, u_k)$ is the nonlinear observation function of the system.

To find an estimate of the state vector in the discrete system described in Eq, we can use the EKF algorithm. The whole process is outlined in Eq.13 to Eq.17.

Status Forecast:
$$\hat{X}_{k+1|k} = F(\hat{X}_k, U_{k+1}) \tag{13}$$

Error covariance prediction:
$$P_{k+1|k} = A_k P_k A_k^T + Q_{k+1} \tag{14}$$

Kalman filter gain:
$$K_{k+1} = P_{k+1|k} C_{k+1}^T (C_{k+1} P_{k+1|k} C_{k+1}^T + R_{k+1})^{-1} \tag{15}$$

Update status estimates:
$$\hat{X}_{k+1} = \hat{X}_{k+1|k} + K_{k+1}\left[Y_{k+1} - \hat{Y}_{k+1|k}\right] \tag{16}$$

Update error covariance:
$$P_{k+1} = (I - K_{k+1}C_{k+1})P_{k+1|k}(I - K_{k+1}C_{k+1})^T + K_k R_k K_k^T \tag{17}$$

Where, A_k is the state transfer matrix, C_k is the measurement matrix, Q_k is the process noise, R_k is the variance matrix of the measurement noise W_k, and K_k is the Kalman filter gain coefficient.

3.2. Unscented Kalman Filtering algorithm

The main idea of the EKF algorithm is to linearize the nonlinear system by Taylor expansion. However, such a forced transformation will cause Taylor truncation errors, the higher-order terms are neglected, which may cause the filtering system to diverge, and the EKF algorithm linearizes the nonlinear equations and obtains a locally optimal solution [31]. Only when both the state and observation equations are continuous and the degree of nonlinearity is low, it can converge to the global optimum better [32-33]. In order to overcome the higher order truncation error of the EKF algorithm at the second order and above, the unscented transform is introduced into the Kalman filter algorithm to construct the UKF algorithm.

Before performing the UKF algorithm, it is necessary to first construct the sigma point by Eq.18 and Eq.19.

$$x^i\begin{cases}\hat{x}(i=0)\\ \hat{x}+\sqrt{(n+\lambda)P_x}(i=1,\cdots,n)\\ \hat{x}-\sqrt{(n+\lambda)P_x}(i=n+1,\cdots,2n)\end{cases} \tag{18}$$

$$\begin{cases}\omega_m^0=\dfrac{\lambda}{n+\lambda}\\ \omega_c^0=\dfrac{\lambda}{n+\lambda}+1-\alpha^2+\beta\\ \omega_m^i=\omega_c^i=\dfrac{1}{2(n+\lambda)},i=1\ldots 2n\end{cases} \tag{19}$$

After that, the sigma point set is passed nonlinearly according to the following equation:

$$y^i=f(x^i),i=0,\ldots,2n \tag{20}$$

Calculate the mean and covariance of y according to the following two equations:

$$\hat{y}=\sum_{i=0}^{2n}\omega_m^i y^i \tag{21}$$

$$P_y=\sum_{i=0}^{2n}\omega_c^i(y^i-\hat{y})(y^i-\hat{y})^T \tag{22}$$

By contrast to the EKF algorithm, which must linearize the nonlinear function, the UKF algorithm can be directly applied to the battery model for SOC estimation, thereby reducing system estimation errors and improving algorithm accuracy.

3.3. Simplified-sphere Unscented Kalman Filtering algorithm

In the UKF algorithm, each recalculation of the sigma point set generates a large amount of computation; therefore, it can be achieved by a smaller computation by Simplified-sphere Unscented Kalman Filter (SUKF) algorithm. The Simplified-sphere sampling strategy is used to perform the square root UKF operation, and the prediction equation and update equation are modified accordingly to form the SUKF algorithm. The steps of the SUKF algorithm to implement SOC estimation are as follows.

First, select $0\le W_0\le 1$.

Determine sigma weights based on W_0 by Eq.23:

$$W_i=\frac{1-W_0}{n+1},i=1,2,\ldots,n+1 \tag{23}$$

With this sampling method, the distance from the sigma point to the center $\hat{x}$ will gradually become farther and farther as the dimension of x increases, resulting in a non-local sampling effect. Therefore, the problem of non-local effects needs to be solved by the proportional sampling correction algorithm shown in the following equation:

$$\omega_i=\begin{cases}1+(W_0-1)/\alpha^2,i=0\\ W_i/\alpha^2,i\neq 0\end{cases} \tag{24}$$

where α is a scaling factor that controls the Cartesian distance between the sampling points and the mean value.

When the dimension of the input state equation is 1, the sequence of initialized vectors is

$$\chi_0^1 = [0], \chi_1^1 = \left[-\frac{1}{\sqrt{2\omega_1}} \right], \chi_2^1 = \left[\frac{1}{\sqrt{2\omega_1}} \right] \tag{25}$$

When the dimension of the input state equation is greater than 1, the sequence of initialized vectors is

$$\chi_i^j = \begin{cases} \begin{bmatrix} \chi_0^j \\ 0 \end{bmatrix}, i = 0 \\ \begin{bmatrix} \chi_i^j \\ -\dfrac{1}{\sqrt{j(j=1)\omega_1}} \end{bmatrix}, i = 1, \dots, j \\ \begin{bmatrix} 0_{j-1} \\ \dfrac{j}{\sqrt{j(j+1)\omega_1}} \end{bmatrix}, i = j+1 \end{cases} \tag{26}$$

where j is the dimension of the vector and i is the order of the sampled points.
Based on the above equation, the sigma weights can be defined as

$$\omega_i^m = \begin{cases} \omega_0, i = 0 \\ \omega_i, i \neq 0 \end{cases}$$
$$\omega_i^c = \begin{cases} \omega_0 + (1 + \beta - \alpha^2), i = 0 \\ \omega_i, i \neq 0 \end{cases} \tag{27}$$

Where ω_i^m and ω_i^c are the predicted weights of the corrected mean and variance, respectively, and the α and β are the factors that mediate the sigma point distance and higher order information.
After that, the system state mean, and covariance are added to generate sigma points as

$$\chi_i = \hat{x} + \sqrt{P_{xx}\chi_i^j} \tag{28}$$

Compared with the UKF algorithm, the SUKF algorithm reduces the number of sigma points from $2n+1$ to $n+2$, which results in better filtering in real time and better overall filtering performance.

4. Experimental testing

4.1. Constant current discharge test

As a test method to do the common SOC estimation algorithm, constant current discharge test uses a constant current discharge, and the product of discharge current and time is the remaining power, which can mainly simulate the working environment of lithium battery in the process of electric vehicle overhaul. In this designed constant current discharge experiment, the battery discharge current is set to be constant at 0.8 A. Fig 3 shows the test results of lithium battery constant current discharge in a noisy environment, and the SUKF algorithm used in this paper can keep the maximum error amplitude within 0.01%, and the result filtering performance is stronger compared to EKF and UKF algorithms.

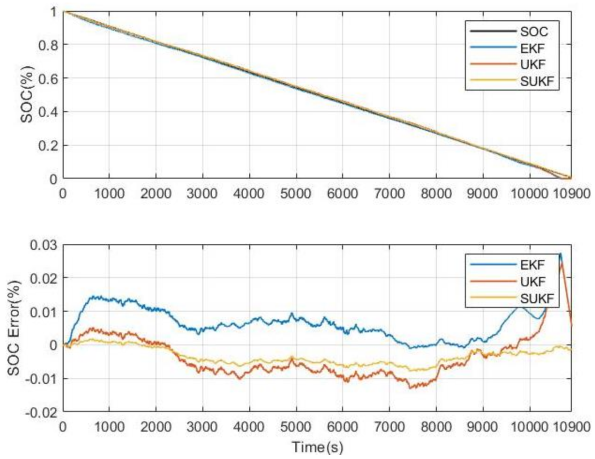

Figure 3. SOC estimation and error curve of three algorithms under constant current discharge

4.2. Pulse discharge test

The pulse discharge test can simulate the change process of SOC during the fast start of electric vehicle. Setting that Li-ion battery has a 100% charge at the beginning, 3000~4000s, 5000~6000, and 7000~8000s are operated upon in order to control output current of Li-ion battery. The SOC value is then estimated using three algorithms. Fig 4 shows the simulation result. Throughout the process, the difference between the SOC estimation curve obtained by SUKF and the real SOC curve is smaller and the algorithm yields better results.

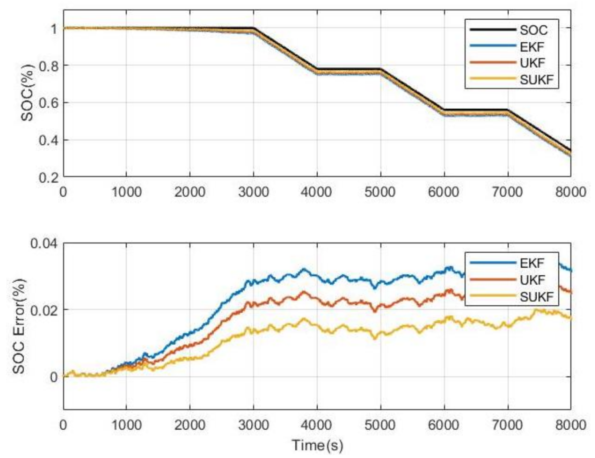

Figure 4. SOC estimation and error curve of three algorithms under pulse discharge test

4.3. UDC working condition

The UDC technique is used to test the performance of the three algorithms under the actual, complex driving conditions of the road. Fig.5 shows the change in current during the entire process, allowing the accuracy of the model to be verified. Fig. 6 shows SOC estimation and corresponding error values in this case. In this simulated real-working environment, the SUKF algorithm achieves a higher level of accuracy than the other two algorithms due to its greater robustness.

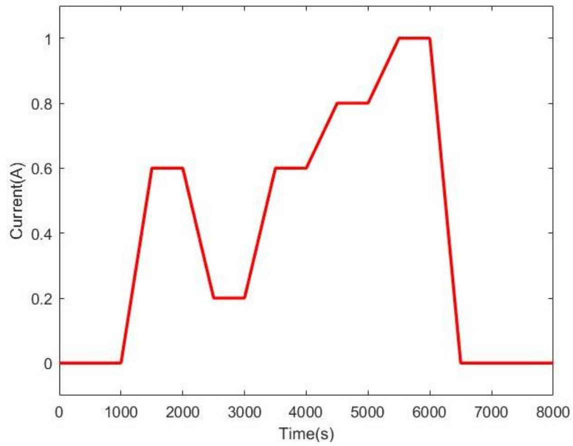

Figure 5 Current variation curve under UDC conditions

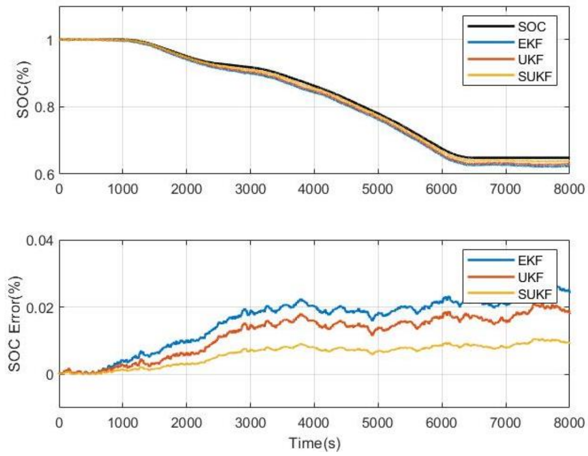

Figure 6. SOC estimation and error curves of three algorithms under UDC operating conditions

5. Conclusion

Simulation tests were conducted under different working conditions to observe the error size of the three algorithms to implement the Li-ion battery SOC algorithm. Compared with the EKF and the UKF, the error between the SOC value and the real value obtained by the SUKF algorithm used in this paper under different working conditions is smaller and the robustness performance is better.

References

[1]. W. Qiu and Z. Qiu, "Design for symmetrical management of storage battery expert system based on single battery," 2006 International Conference on Mechatronics and Automation, 2006, pp. 1141-1146, doi: 10.1109/ICMA.2006.257786.

[2]. S. Maitreya, H. Jain and P. Paliwal, "Scalable and De-centralized Battery Management System for Parallel Operation of Multiple Battery Packs," 2021 Innovations in Energy Management and Renewable Resources(52042), 2021, pp. 1-7, doi: 10.1109/IEMRE52042.2021.9386861.

[3]. X. Li, R. Ma, L. Wang, S. Wang and D. Hui, "Energy Management Strategy for Hybrid Energy Storage Systems with Echelon-use Power Battery," *2020 IEEE International Conference on Applied Superconductivity and Electromagnetic Devices (ASEMD)*, 2020, pp. 1-2, doi: 10.1109/ASEMD49065.2020.9276135.

[4]. M. T. Lawder *et al.*, "Battery Energy Storage System (BESS) and Battery Management System (BMS) for Grid-Scale Applications," in *Proceedings of the IEEE*, vol. 102, no. 6, pp. 1014-1030, 2014. doi: 10.1109/JPROC.2014.2317451.

[5]. F. Helling, S. Götz and T. Weyh, "A battery modular multilevel management system (BM3) for electric vehicles and stationary energy storage systems," *2014 16th European Conference on Power Electronics and Applications*, 2014, pp. 1-10, doi: 10.1109/EPE.2014.6910821.

[6]. D. N. T. How, M. A. Hannan, M. S. Hossain Lipu and P. J. Ker, "State of Charge Estimation for Lithium-Ion Batteries Using Model-Based and Data-Driven Methods: A Review," in *IEEE Access*, vol. 7, pp. 136116-136136, 2019, doi: 10.1109/ACCESS.2019.2942213.

[7]. R. Xiong, J. Cao, Q. Yu, H. He and F. Sun, "Critical Review on the Battery State of Charge Estimation Methods for Electric Vehicles," in *IEEE Access*, vol. 6, pp. 1832-1843, 2018, doi: 10.1109/ACCESS.2017.2780258.

[8]. E. Aslan and Y. Yasa, "A Review on The Battery State of Charge Estimation Methods For Electric Vehicle Battery Management Systems," *2019 11th International Conference on Electrical and Electronics Engineering (ELECO)*, 2019, pp. 281-285, doi: 10.23919/ELECO47770.2019.8990463.

[9]. M. Naguib, P. Kollmeyer and A. Emadi, "Lithium-Ion Battery Pack Robust State of Charge Estimation, Cell Inconsistency, and Balancing: Review," in *IEEE Access*, vol. 9, pp. 50570-50582, 2021, doi: 10.1109/ACCESS.2021.3068776.

[10]. S. Shete, P. Jog, R. K. Kumawat and D. K. Palwalia, "Battery Management System for SOC Estimation of Lithium-Ion Battery in Electric Vehicle: A Review," *2021 6th IEEE International Conference on Recent Advances and Innovations in Engineering (ICRAIE)*, 2021, pp. 1-4, doi: 10.1109/ICRAIE52900.2021.9703752.

[11]. Y. Zhang, X. Cheng, Y. Fang and Y. Yin, "On SOC estimation of lithium-ion battery packs based EKF," *Proceedings of the 32nd Chinese Control Conference*, 2013, pp. 7668-7673.

[12]. L. Bo, Y. Xueqing and Z. Lin, "Li-ion battery SOC estimation based on EKF algorithm," *2015 IEEE International Conference on Cyber Technology in Automation, Control, and Intelligent Systems (CYBER)*, 2015, pp. 1584-1588, doi: 10.1109/CYBER.2015.7288182.

[13]. S. Gang, Z. Wei, H. Zhonghua and L. Shanshan, "Estimation of battery SOC based on improved EKF algorithm," *2016 IEEE Information Technology, Networking, Electronic and Automation Control Conference*, 2016, pp. 151-154, doi: 10.1109/ITNEC.2016.7560338.

[14]. W. Zhang and W. Du, "SoC estimation based on adaptive EKF with colored noise," *2017 Chinese Automation Congress (CAC)*, 2017, pp. 1373-1377, doi: 10.1109/CAC.2017.8242981.

[15]. H. Du, G. Liu, J. Zhang, G. Tian and S. Wang, "SOC Estimation of Lithium-ion Batteries Based on Adaptive UKF," *2021 IEEE 4th International Conference on Renewable Energy and Power Engineering (REPE)*, 2021, pp. 137-140, doi: 10.1109/REPE52765.2021.9617029.

[16]. X. Zhang, J. Wu and G. Kang, "SOC estimation of Lithium battery by UKF algorithm based on dynamic parameter model," *2016 13th International Conference on Ubiquitous Robots and Ambient Intelligence (URAI)*, 2016, pp. 945-950, doi: 10.1109/URAI.2016.7734116.

[17]. M. Shehab El Din, A. A. Hussein and M. F. Abdel-Hafez, "Improved Battery SOC Estimation Accuracy Using a Modified UKF With an Adaptive Cell Model Under Real EV Operating Conditions," in *IEEE Transactions on Transportation Electrification*, vol. 4, no. 2, pp. 408-417, June 2018, doi: 10.1109/TTE.2018.2802043.

[18]. Y. Liu, Z. He, M. Gao, Y. Li and G. Liu, "Dual estimation of lithium-ion battery internal resistance and SOC based on the UKF," *2012 5th International Congress on Image and Signal Processing*, 2012, pp. 1639-1643, doi: 10.1109/CISP.2012.6469649.

[19]. D. Mitra and S. Mukhopadhyay, "UKF Based Estimation of SOC and Core Temperature of a Lithium Ion Cell Using an Electrical Cell Model," *2018 15th IEEE India Council International Conference (INDICON)*, 2018, pp. 1-6, doi: 10.1109/INDICON45594.2018.8987074.

[20]. Q. Zheng, J. Yang, Q. Luo and K. Shi, "Estimation of state of charge of lithium battery based on BCRLS-UKF algorithm," *2021 IEEE International Conference on Computer Science, Electronic Information Engineering and Intelligent Control Technology (CEI)*, 2021, pp. 22-26, doi: 10.1109/CEI52496.2021.9574593.

[21]. S. Zhang, H. Sun and C. Lyu, "A method of SOC estimation for power Li-ion batteries based on equivalent circuit model and extended Kalman filter," 2018 13th IEEE Conference on Industrial Electronics and Applications (ICIEA), 2018, pp. 2683-2687, doi: 10.1109/ICIEA.2018.8398164.

[22]. Y. Song, M. Park, M. Seo and S. W. Kim, "Improved SOC estimation of lithium-ion batteries with novel SOC-OCV curve estimation method using equivalent circuit model," 2019 4th International Conference on Smart and Sustainable Technologies (SpliTech), 2019, pp. 1-6, doi: 10.23919/SpliTech.2019.8783149.

[23]. J. Wehbe and N. Karami, "Battery equivalent circuits and brief summary of components value determination of lithium ion: A review," 2015 Third International Conference on Technological Advances in Electrical, Electronics and Computer Engineering (TAEECE), 2015, pp. 45-49, doi: 10.1109/TAEECE.2015.7113598.

[24]. S. Zhang, H. Sun and C. Lyu, "A method of SOC estimation for power Li-ion batteries based on equivalent circuit model and extended Kalman filter," 2018 13th IEEE Conference on Industrial Electronics and Applications (ICIEA), 2018, pp. 2683-2687, doi: 10.1109/ICIEA.2018.8398164.

[25]. C. Kamrueng, S. Kittiratsatcha and S. Polmai, "A Number of RC Pairs Consideration of Electrical Equivalent Circuit Model of Li-ion Battery," 2020 6th International Conference on Engineering, Applied Sciences and Technology (ICEAST), 2020, pp. 1-4, doi: 10.1109/ICEAST50382.2020.9165523.

[26]. M. J. Malatji and S. P. D. Chowdhury, "Comparative study on Improvement in Battery Management System of Hybrid Batteries," 2019 IEEE PES/IAS PowerAfrica, 2019, pp. 307-312, doi: 10.1109/PowerAfrica.2019.8928868.

[27]. X. Sui, S. He, D. -I. Stroe, X. Huang, J. Meng and R. Teodorescu, "A review of sliding mode observers based on equivalent circuit model for battery SoC estimation," 2019 IEEE 28th International Symposium on Industrial Elec-tronics (ISIE), 2019, pp. 1965-1970, doi: 10.1109/ISIE.2019.8781412.

[28]. Z. Chang et al., "Review of SOC estimation methods for lithium battery based on EKF," 2021 IEEE 4th Advanced Information Management, Communicates, Electronic and Automation Control Conference (IMCEC), 2021, pp. 1319-1326, doi: 10.1109/IMCEC51613.2021.9482085.

[29]. F. Si, Z. Li, X. Long, F. Jiang and W. Hua, "Research on Estimation of Battery State of Electric Vehicle Battery Management System," 2020 IEEE 5th Information Technology and Mechatronics Engineering Conference (ITOEC), 2020, pp. 465-469, doi: 10.1109/ITOEC49072.2020.9141648.

[30]. C. Wang, X. Fan, L. Gao and X. Zhang, "Estimation of SOC of Battery Based on RVM-EKF Algorithm," 2018 11th International Symposium on Computational Intelligence and Design (ISCID), 2018, pp. 173-176, doi: 10.1109/ISCID.2018.10141.

[31]. X. Zhang and R. Zhang, "Estimation of Lithium Battery SOC Based on Fuzzy Unscented Kalman Filter Algo-rithm," 2021 IEEE/IAS Industrial and Commercial Power System Asia (I&CPS Asia), 2021, pp. 200-204, doi: 10.1109/ICPSAsia52756.2021.9621532.

[32]. M. Liu, N. Cui, S. Liu, C. Wang, C. Zhang and S. Gong, "Adaptive strong tracking unscented Kalman filter based SOC estimation for lithium-ion battery," 2017 Chinese Automation Congress (CAC), 2017, pp. 1437-1441, doi: 10.1109/CAC.2017.8242993.

[33]. J. Hu, S. Wu, Y. Wang, F. Lu and D. Liu, "Lithium Battery SOC Estimation Based on Improved Unscented Kalman Filter," 2020 15th IEEE Conference on Industrial Electronics and Applications (ICIEA), 2020, pp. 511-515, doi: 10.1109/ICIEA48937.2020.9248230.