2021 IEEE 5th Advanced Information Technology, Electronic and Automation Control Conference (IAEAC) | 978-1-7281-8028-1/20/$31.00 ©2021 IEEE | DOI: 10.1109/IAEAC50856.2021.9390929

State of Charge Estimation for Lithium-Ion Battery based on Artificial Neural Network

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Abstract—**State of charge (SOC) estimation for lithium-ion battery is an important part of battery management system (BMS). Accurate SOC estimation can extend lifespan of the batteries and ensure safety of the batteries operated in electric vehicles. In this paper, a data-driven SOC estimation method is presented. Various artificial neural networks (ANNs) with different hidden layers are trained by a data set which consists of a series of the battery voltage, current and SOC variables obtained from a dynamic discharge test. The battery SOC is then estimated by the trained ANNs. Comparisons of the SOC estimated by the ANNs and model-based method combining with extended Kalman filter (EKF) are implemented. Root mean squared error (RMSE) and mean absolute error (MAE) of the SOC estimated by the data-driven method are very close to those estimated by the model-based method. The results prove that data-driven methods can accurately estimate the SOC of lithium-ion batteries.**

Keywords—neural network; SOC; estimation; battery

I. INTRODUCTION

Electric vehicles (EVs) become more and more popular even the substitute for internal combustion engine vehicle owing to environmental friendly [1]. The main cost of EVs lies in the battery. A series of problems about the battery, such as short life, long charge time, low energy density and high price, have not been well solved so far. These problems have become the bottleneck restricting the development of electric vehicles. It is very important to extend the battery life and improve the working efficiency of the battery for EVs. In EVs, a battery management system (BMS) is essential to ensure the safety of the battery. One of the most important functions of BMS is to monitor the states of the battery, especially the state of charge (SOC). Accurate SOC estimation can extend lifespan of the battery and ensure safety of the battery operated in EVs.

Conventional methods for estimating the battery SOC include open circuit voltage (OCV) method and coulomb counting (CC). Using OCV method, the SOC is estimated by the relation between the SOC and OCV. Despite the simplicity of OCV method, it is cannot be employed to on-line estimation because the OCV is only obtained after the battery gets enough resting [2]. CC method is based on the integration of battery current with respect to time. The SOC estimation accuracy of CC method mainly depends on the precision of current sensors and the initial value error of SOC. Hence a periodic SOC calibration is required in order to reduce cumulative error [3]. In addition, model-based techniques have been widely used to estimate the battery SOC. For the model-based estimation method, in general the battery must be first modelled, and then the battery SOC is estimated by adaptive filter algorithms. Among various battery models, electrical equivalent circuit model (EECM) is most popular and has been investigated by researchers [4]. EECM uses basic electronic components, for example resistors, capacitors and voltage source, to describe the internal dynamic behavior of the battery. There is a good balance between the complexity and accuracy for EECM. Adaptive filter algorithms for SOC estimation mainly include particle filter (PF) [5], nonlinear observers, and Kalman filter and its variants, such as extended Kalman filter (EKF) [6], dual extended Kalman filter (DEKF) [7], adaptive extended Kalman filter (AEKF) [8], unscented Kalman filter (UKF) [9], and adaptive unscented Kalman filter (AUKF) [10].

The accuracy of the battery SOC estimation using model-based method is dependent on the accuracy of the battery model. However, any exact mathematical or circuit model cannot completely describe the highly nonlinear behavior of the battery. As we all know, neural network has the ability to construct arbitrary nonlinear relationship between input and output vectors. In this paper, the battery is regarded as a “black-box”, which indicates that it is no need to know the knowledge of the battery model. We use artificial neural network, namely back propagation neural network (BPNN), to construct this “black-box”, which is then trained by a large number of data include the battery current, terminal voltage and SOC. The battery SOC can be estimated by the trained BPNN when the battery current and terminal voltage is entered into the network. This SOC estimation method is so called as data-driven method. The structure is organized as follows: Section 2 presents BPNN-based SOC estimation method, and reviews the SOC estimation method based on a second order RC model and EKF algorithm. Section 3 shows the experiments and results of the battery SOC estimation. Finally, Section 4 concludes the paper and points out further work.

II. SOC ESTIMATION METHODS

A. Neural Network-Based Method

It is difficult to establish the precise battery model, for example electrochemical model, electrical equivalent circuit model and electrochemical impedance model, due to the complex dynamic characteristics of the battery when it is operated in charge or discharge process. Here various BPNN networks are designed to formulate the relationship between the battery SOC and directly measurable variables, namely the battery current and terminal voltage. These neural networks have three or four layers, i.e. one input layer, one or two hidden layers consisting of various number of neurons, and one output layer. The structure of one of BPNN networks for the battery SOC estimation is shown in Fig. 1.

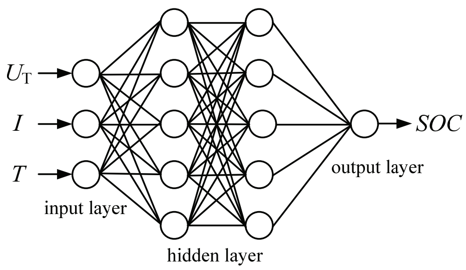

Fig. 1. The structuct of one of BPNNs for the battery SOC estimation.

The BPNN network shown in Fig.1 has four layers. The input layer has three neurons connecting three input variables, i.e. the battery current, the terminal voltage and the battery temperature. There is only one neuron in the output layer, which corresponds to the battery SOC. The neural network has two hidden layers, every which has five neurons. The hidden layer operation is executed using hidden neurons, activation functions, and network hyper parameters. The output layer estimates the battery SOC using the information of the hidden layers and activation function. The BPNN network must be trained to get appropriate connection weights and biases before using it to estimate the battery SOC. The training data set should cover the data in the situations that need to be estimated in the future as much as possible.

B. Model-Based and EKF Method

In this paper, we establish a second order RC model and identify the parameters in the model. Based on the model, EKF algorithm is employed to estimate the battery SOC. The main aim of doing the job is to evaluate the performance of the neural network-based method by comparing it with the model-based method. The second order RC model is shown in Fig. 2. The model consists of one voltage source, U_{ocv}, one equivalent internal resistance, R_0, and two RC branches. One of RC branches, i.e. R_1 and C_1, describes the electrochemical polarization, and another branch describes the concentration difference polarization in the battery. The U_{ocv} is the open circuit voltage of the battery, U_T is the battery terminal voltage, and I is the battery charge or discharge current.

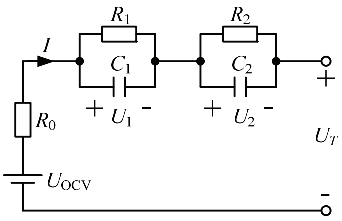

Fig. 2. Second order RC model of a lithium-ion battery.

Based on the second order RC model, the state vector, x_k, can be expressed by $x_k = \left[\mathrm{SOC}_k, U_{1,k}, U_{2,k}\right]^{\mathrm{T}}$, when using EKF algorithm to estimate the battery SOC. The state equation and output equation of the battery model can be expressed as the following:

State equation:

$$\begin{pmatrix} \mathrm{SOC}_{k+1} \\ U_{1,k+1} \\ U_{2,k+1} \end{pmatrix} = \begin{pmatrix} 1 & 0 & 0 \\ 0 & \mathrm{e}^{\frac{-\Delta t}{R_1 C_1}} & 0 \\ 0 & 0 & \mathrm{e}^{\frac{-\Delta t}{R_2 C_2}} \end{pmatrix} \begin{pmatrix} \mathrm{SOC}_k \\ U_{1,k} \\ U_{2,k} \end{pmatrix} + \begin{pmatrix} \frac{-\Delta t \eta}{C_{\mathrm{N}}} \\ R_1\left(1-\mathrm{e}^{\frac{-\Delta t}{R_1 C_1}}\right) \\ R_2\left(1-\mathrm{e}^{\frac{-\Delta t}{R_2 C_2}}\right) \end{pmatrix} I_k \quad (1)$$

Output equation:

$$U_{T,k} = \begin{pmatrix} 0 & -1 & -1 \end{pmatrix} \begin{pmatrix} \mathrm{SOC}_k \\ U_{1,k} \\ U_{2,k} \end{pmatrix} - R_0 I_k + U_{\mathrm{OCV},k} \quad (2)$$

where Δt is the sample time, $U_{1,k}$ and $U_{2,k}$ are the voltage of the two RC branches, and k is the current time step.

The state and output equations of extended Kalman filter are expressed as the following:

$$\begin{cases} x_{k+1} = A_k x_k + B_k u_k + w_k \\ y_k = C_k x_k + D_k u_k + v_k \end{cases} \quad (3)$$

where u_k is input, w_k and v_k are the process noise and measurement noise with zero mean. A_k, B_k, C_k and D_k are the state transition matrix, input matrix, output matrix and output value transmission matrix, respectively. Compare equation (1) and (2) with equation (3), we can get:

$$\begin{cases} A_{k=} \begin{bmatrix} 1 & 0 & 0 \\ 0 & \mathrm{e}^{\frac{-\Delta t}{R_1 C_1}} & 0 \\ 0 & 0 & \mathrm{e}^{\frac{-\Delta t}{R_2 C_2}} \end{bmatrix} \\ B_k = \left[-\frac{\eta \Delta t}{C_{\mathrm{N}}}, R_1\left(1-\mathrm{e}^{\frac{-\Delta t}{R_1 C_1}}\right), R_2\left(1-\mathrm{e}^{\frac{-\Delta t}{R_2 C_2}}\right)\right]^{\mathrm{T}} \\ C_{k=} \left[\left.\frac{\mathrm{d}U_{\mathrm{OCV}}(\mathrm{soc}_k)}{\mathrm{dsoc}_k}\right|_{\mathrm{SOC}_k=\mathrm{SOC}_k^{\wedge}}, -1, -1\right] \\ D_k = -R_0 \\ y_k = U_{T,k} \\ u_k = I_k \end{cases} \quad (4)$$

As can be seen from equation (4), state estimation using EKF can be only implemented after the parameters in the battery model are identified. This is just the essential difference between model-based and data-driven methods.

III. Results and Discussion

A. Test Bench and Lithium-Ion Battery

A test bench, which consists of an electronic load, a thermal chamber, a DC power source, an A/D converter and a computer, is built to get train data as well as to identify the model parameters. A lithium-ion battery with a rated capacity of 3 Ah and a rated voltage of 3.7 V is used for the tests. In the experiments, the battery is placed in the thermal chamber at the temperature of 25 °C, and hence the influence of temperature on SOC estimation and parameter identification is ignored for the model-based method.

B. Training and Test Data

We use the test bench to discharge the battery in order to get training and test data. Discharge current ranges from 0.1A to 6 A with the interval of 0.1 A. There are some relaxation stages, i.e. the discharge current is zero, in the discharge process. Based on coulomb counting method, the battery SOC is calculated by the following equation:

$$SOC_k = SOC_{k-1} - \frac{\Delta t}{C_N} I_k \tag{5}$$

where the sample time of Δt is 0.1 s, and the rated capacity of C_N is 3 Ah. The initial SOC, namely SOC_0, is one and the last SOC is about 0.06. The whole number of training and test data is 40 362. Fig. 3 shows the training and test data.

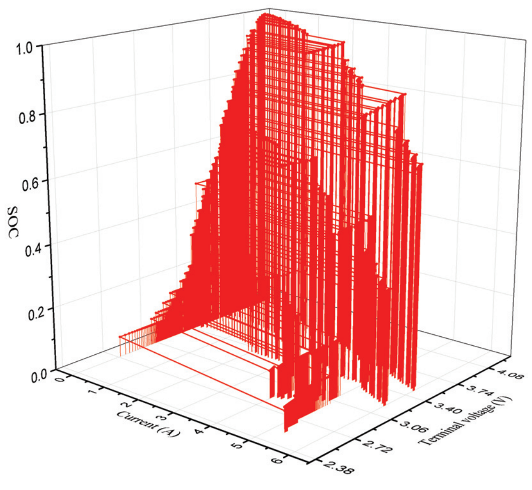

Fig. 3. The data for training and testing BPNNs for the battery SOC estimation.

C. Parameter Identification

The parameters of OCV, R_0, R_1, R_2, C_1, and C_2 need to be identified using the second order RC model to estimate the battery SOC. Fully charge the battery, i.e. SOC is one, and record the open circuit voltage after resting for 2 hours. Then discharge the battery with 0.5 C current for 12 minutes, and after resting for 2 hours again record the open circuit voltage while SOC is 0.9. Repeat the discharge process until the SOC is 0.1. The OCV and SOC discrete point data are obtained. the functional relationship between OCV and SOC can be obtained by 8-order polynomial fitting, as shown in Fig.4.

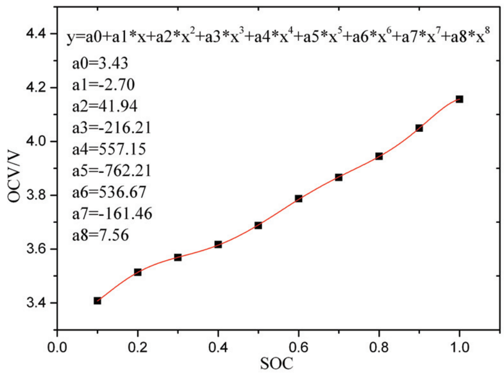

Fig. 4. The relationship between OCV and SOC

One 1C current pulsed discharge test is implemented for identifying other parameters. Detail identification procedure refers to the reference [11]. The identification results are shown as Table 1.

TABLE I. The Identified Parameters Regarding to SOC

SOC	$R_0/m\Omega$	$R_1/m\Omega$	$R_2/m\Omega$	C_1/kF	C_2/kF
1	45.1	10.2	8.5	10.1	22.91
0.9	42.5	15.5	8.3	2.12	31.32
0.8	43.7	14.2	9.3	1.85	34.33
0.7	35.8	15.5	13.2	2.24	111.23
0.6	39.6	15.8	7.6	2.62	163.45
0.5	41.5	14.3	6.5	2.44	121.75
0.4	41.8	14.4	6.1	2.56	63.34
0.3	42.7	15.5	9.9	2.78	33.45
0.2	43.4	14.3	15.4	2.23	25.56
0.1	44.7	19.4	11.3	1.34	47.45

D. BPNN Training and Test

We used two-thirds of the whole data for training and one-third for testing the network with a constant temperature rate, a variable current and terminal voltage as input and the SOC as output. Except the SOC, the variable of the current and terminal voltage are both normalized before entering the network. Hyperbolic tangent S-type function is used as the transfer function of hidden layer, while output layer employs linear function as its transfer function. The BPNN is trained based on Levenberg-Marquardt method, which means the training function chooses *trainlm* in MATLAB. Here, we set the maximum iteration epoch 1000, and the training goal MSE (Mean Squared Error) 4×10^{-5}. Fig. 4 shows the training result of a BPNN with two hidden layers of which have both 15 neurons. As we can see, the training procedure stops after 946 epochs and the MSE drops to about 5.45×10^{-5}, which is very close to the goal value.

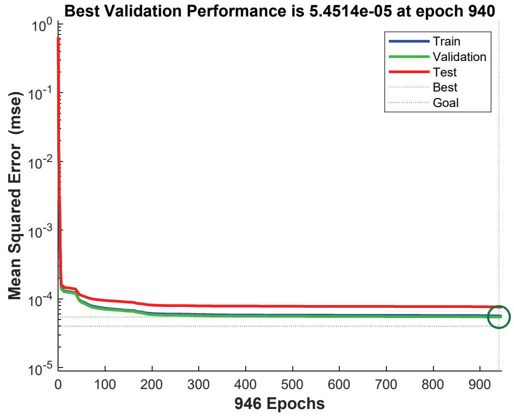

Fig. 5. The training result of a BPNN with two hidden layers of which have both 15 neurons.

The trained BPNN network is tested using the test data set consisting of 13 454 data vectors. The test result is shown in Fig. 6. The SOC estimated by the BPNN can track the real SOC well, although there are some variations. The SOC error seems to be higher when the SOC is below 0.4, which indicates the non-linear behavior of the battery becomes more complex at low SOC resulting in more difficulty to estimate SOC.

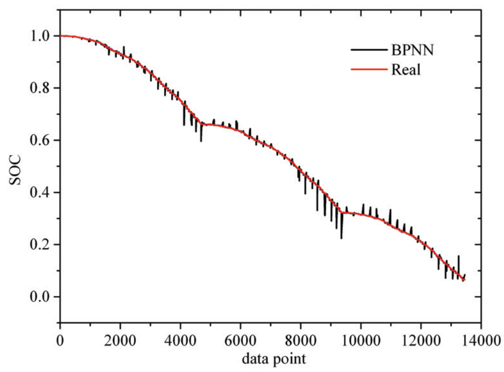

Fig. 6. The SOC estimated by a BPNN with two hidden layers of which have both 15 neurons.

In general, the performance of a method for estimating the battery SOC is evaluated in the light of the root-mean squared error (RMSE) and the mean absolute error (MAE), respectively, which are calculated as the following equations:

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{k=1}^{n}\left(SOC_k - \overline{SOC}_k\right)^2} \tag{6}$$

$$\mathrm{MAE} = \frac{1}{n}\sum_{k=1}^{n}\left|SOC_k - \overline{SOC}_k\right| \tag{7}$$

where n is the number of SOC data, SOC_k denotes the real SOC at the time of k, and $\overline{SOC}_k$ denotes the SOC estimated by the estimation method at the time of k. We calculate the RMSE and MAE of the BPNN method as shown in Table 2. Taking the SOC of 0.4 as the dividing point, the whole SOC is divided into two different ranges. We also calculate the RMSE and MAE of the SOC within the two different ranges. For the SOC range from 0.4 to 1, the RMSE and MAE are 0.66% and 0.23%, respectively, and for the SOC range from 0.06 to 0.4, the RMSE and MAE are 0.92% and 0.34%, respectively. The RMSE and MAE for the range with high SOC are both less than those for the range with low SOC, thus the calculated results agree with the SOC shown in Fig. 6.

TABLE II. RMSE AND MAE OF SOC ESTIMATED BY A BPNN WITH TWO HIDDEN LAYERS OF WHICH HAVE BOTH 15 NEURONS.

SOC estimation method	RMSE	MAE
BPNN	0.78%	0.29%

E. *Effect of BPNN Structure on SOC Estimation*

The SOC estimation results using BPNNs with different network structure are maybe different. In order to analyze the effect of BPNN structure on SOC estimation, we construct two kinds of BPNNs. One has only one hidden layer. The number of neurons of the hidden layer ranges from 5 to 20, in other words, the first kind includes 16 different BPNNs. Another has two hidden layers, both which have same number of neurons. The number of neurons of every hidden layer also ranges from 5 to 20, thus the second kind also includes 16 different BPNNs. We use the same data set to train then test these BPNNs to evaluate their performance.

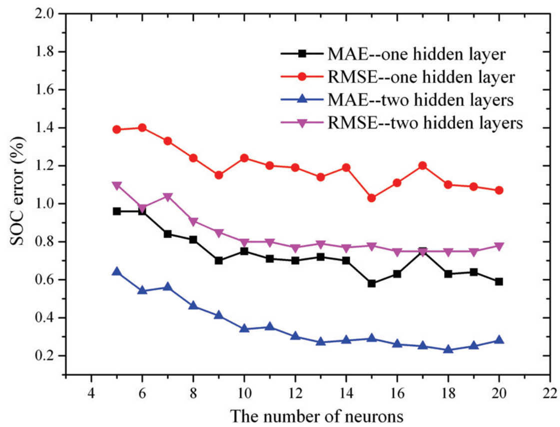

Fig. 7. RMSE and MAE of SOC estimated by different BPNNs

The RMSE and MAE of the battery SOC estimated by these 32 BPNNs are calculated respectively, and the results are shown in Fig. 7. It can be seen that the RMSE and MAE of the SOC estimated by the BPNNs with two hidden layers are both less than those of the SOC estimated by the BPNNs with only one hidden layer. This shows that the BPNN with two hidden layers has more ability to describe nonlinear behavior of the battery than that with only one hidden layer. We also construct the BPNN with three hidden layers to estimate the battery SOC. However, the performance of the three-hidden-layer BPNN is similar with that of the two-hidden-layer BPNN, which indicates that it is enough to use a two-hidden-layer BPNN to describe the relationship between the battery current, terminal voltage, temperature and the SOC. Using BPNN with more than two hidden layers not only cannot improve the performance for estimating the battery SOC, but also increase the computational burden. In addition, as the number of neurons increases, the RMSE and MAE will reduce, but there are almost no changes when the number is more than 18. This is due to so-called "saturation characteristics", namely the performance of the network has reached highest level when it has 18 neurons.

F. Comparisons of SOC Estimation

In order to further evaluate the performance of BPNN, we compare the SOC estimated by the BPNNs with that estimated by EKF algorithm based on the second order RC model. Comparisons of the SOC estimated by EKF and the BPNN with two hidden layers of which have both 15 neurons are shown in Fig. 8. The SOC estimated by EKF algorithm cannot track the real SOC well, and there is a considerable divergence between them. In order to quantitatively analyze the difference between the performances of two methods, we calculate the RMSE and MAE of the estimated SOC as shown in Table 3. It can be seen that the BPNN has lower estimation error, which demonstrates the ability of BPNN to estimate the battery SOC.

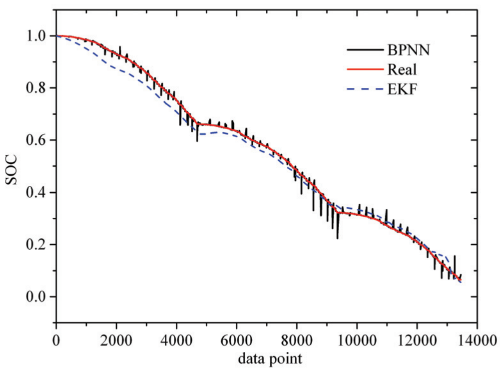

Fig. 8. Comparisons of the SOC estimated by BPNN and EKF

TABLE III. RMSE AND MAE OF SOC ESTIMATED BY BPNN AND EKF ALGORITHM

SOC estimation method	RMSE	MAE
PNN	0.78%	0.29%
EKF	3.08%	2.69%

IV. CONCLUSIONS

In this paper, we construct 32 different BPNN networks to estimate a lithium-ion battery SOC. These neural networks have one or two hidden layers and every hidden layer has 5-20 neurons. The 32 BPNNs are trained and then tested by a data set including 40 362 data vectors. The test results show the BPNN has a good ability to describe nonlinear behavior of the battery. Compared with the EKF method based on the second order RC model, BPNN has better performance for estimating the battery SOC. Moreover, we find that a BPNN with two hidden layers has enough ability to describe the nonlinear behavior of the battery and estimate the SOC, and the number of neurons of every hidden layer is better not to be more than 18. The effect of temperature on the SOC estimation is ignored in this paper. In real application, this is a challenge, which will be solved in our future work.

ACKNOWLEDGMENT

This work was supported by the Natural Science Foundation of the Anhui Higher Education Insititutions of China under Grant No. KJ2019A0898 and KJ2019A0890.

REFERENCES

[1] F. Herrmann, F. Rothfuss, "Introduction to hybrid electric vehicles, batteryelectric vehicles, and off-road electric vehicles," Advances in Battery Technologies for Electric Vehicles, vol.15, issue 1, pp. 3–16, 2015.

[2] 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," Journal of Power Sources, vol. 159, issue 2, pp. 1484-1487, 2006.

[3] Y. H. Zhang, W. J. Song, S. L. Lin, and Z. P. Feng, "A novel model of the initial state of charge estimation for LiFePO 4 batteries," Journal of Power Sources, vol. 248, issue 2, pp. 1028-1033, 2014.

[4] J. H. Meng, G. Z. Luo, M. Ricco, and M. Swierczynski, "Overview of lithium-ion battery modeling methods for state-of-charge estimation in electrical vehicles," Applied Sciences, vol. 8, issue 5, pp. 659-675, 2018.

[5] A. Tulsyan, Y. Tsai, R. B. Gopaluni, and R. D. Braatz, "State-of-charge estimation in lithium-ion batteries: a particle filter approach," Journal of Power Sources, vol. 331, issue 11, pp. 208-223, 2016.

[6] F. Liu, J. Ma, W. X. Su, H. N. Chen, and M. W. He, "Research on parameter self-learning unscented Kalman filtering algorithm and its application in battery charge of state estimation," Energies, vol. 13, issue 7, pp. 1679, 2020.

[7] L. M. Wang, D. Lu, Q. Liu, L. Liu, and X L. Zhao, "State of charge estimation for LiFePO4 battery via dual extended kalman filter and charging voltage curve," Electrochimica Acta, vol. 296, issue 2, pp. 1009-1017, 2019.

[8] Y. Q. Shen, "Adaptive extended Kalman filter based state of charge determination for lithium-ion batteries," Electrochimica Acta, vol. 283, issue 9, pp. 1432-1440, 2018.

[9] Y. Tian, B. Z. Xia, W. Sun, Z. H. Xu, and W. W. Zheng, "A modified model based state of charge estimation of power lithium-ion batteries using unscented Kalman filter," Journal of Power Sources, vol. 270, issue 12, pp. 619-626, 2014.

[10] J. C. Lv, B. C. Jiang, X. L. Wang, Y. R. Liu, and Y. C. Fu, "Estimation of the state of charge of lithium batteries based on adaptive unscented Kalman filter algorithm," Electronics, vol. 9, issue 9, pp. 1425, 2020.

[11] L. Y. Ling, Y. L. He, B. Gong, and L. K. Xing, "State-of-charge estimation of lithium battery using adaptive extended Kalman filter," Journal of Anhui University of Science and Technology (Natural Science), vol. 40, issue 4, pp. 19-25, 2020.