Comparison of UKF and EKF based State of Charge Estimation for Lithium ion Battery

Yusuf Muratoğlu
Mersin Üniveristesi
Elektrik-Elektronik Mühendisliği
Mersin/Turkey
muratogluyusuf@gmail.com

Alkan Alkaya
Mersin Üniveristesi
Elektrik-Elektronik Mühendisliği
Mersin/Turkey
alkanalkaya@mersin.edu.tr

***Abstract* — The battery state of charge (SoC) is a crucial function in battery management system (BMS) of electric vehicles (EVs). However SoC cannot be directly measured from the battery. Therefore, SoC should be estimated by using the measured signals, such as voltage and current via accurate model of the li-ion battery. In this paper, Unscented Kalman filter (UKF) is proposed to estimate the SoC of the lithium-ion (Li-ion) battery. The Li-ion battery is modelled with second order Thevenin model. The equivalent circuit parameters of the Thevenin model are identified and promoted by experimental data. The experimental test bench is developed for SoC estimation based on extended Kalman filter (EKF) and UKF. UKF based SoC estimation results are compared with EKF based SoC estimation results aspect of SoC performance. Experimental results show that EKF and UKF both are applicable and UKF is better than EKF with SoC accuracy and computational time.**

Keywords—state of charge (SoC); battery management system (BMS); unscented kalman filter (UKF); extended kalman filter (EKF); lithium-ion battery

I. INTRODUCTION

Recently, rechargeable battery technology has gained more and more attentions worldwide with the development of electric vehicles due to energy crisis and environmental issues [1]. Lithium-ion batteries are widely used in EVs in view of their high energy and power density, high nominal cell voltage, long life cycle, low self-discharge rate and not having a memory effect [2]. A battery pack is usually including battery cells connected in series and parallel. Hence, lithium-ion batteries need to be used with battery management system (BMS) to improve battery safety, reliability and performance [3]. As one of the most important function for BMS, state of charge (SoC) directly affects battery performance. Therefore, the estimation of battery SoC is a key parameter for BMS. Unfortunately, in practical applications the SoC cannot be directly measured, but it can be estimated by using a battery model based on the measured signals such as the voltage, current and temperature [4].

In the literature, various methods for SOC estimation have been proposed [5]. Common methods are the Coulomb counting method and open circuit voltage (OCV) method use for SoC estimation. Coulomb counting method only requires to measurement of the battery current and accurate knowledge of the initial SoC value. However this method has accumulated error problem from the integration process due to current drift [6,7]. Open circuit method estimate the SoC with relationship the OCV and the SoC, but this method needs to long resting time to reach the battery's steady-state. Hence, it is not suitable for online estimation [8,9]. To estimate SoC, computational algorithms such as neural networks and fuzzy logic have also developed. These methods which do not require battery model and detailed knowledge of battery systems define the battery as a black-box system and can achieve accurate SoC results. These methods are required a large amount and quality of the training data set, but collecting this data set is time consuming and nearly impossible [10,11].

Recently, researchers have been focused on model-based and close-loop estimation methods, among which the famous three methods are Kalman filter, extended Kalman filter and unscented Kalman filter [12,13]. Kalman filter which can solve initial SoC and cumulative error problems is widely used as accurate SoC estimator, but this method is only suitable for linear systems [14]. The Extended Kalman Filter (EKF) method which is used in non-linear systems linearizes the battery model using partial derivatives (Jacobian matrix) and first order Taylor series expansion. EKF provides accurate prediction of SoC of the battery, but linearization causes more computational running time and more estimation errors [15-20]. UKF uses an unscented transformation with a set of sample points called as sigma points to estimate SoC without any linearization. UKF has a higher accuracy in estimating posterior mean and covariance of the state distribution than EKF owing to this transformation [21-26].

In this study, lithium-ion battery is modelled using second order Thevenin equivalent circuit model and the experimental test bench is setup to SoC estimation. UKF and EKF are applied to estimate SoC of lithium-ion battery used in EVs. Error signals, mean square errors (MSE) and computational times were calculated to compare the performances of both algorithms. Experimental results show that both UKF and EKF perform SoC estimation with high accuracy, but UKF is better than EKF with SoC accuracy and computational time.

II. MODELING OF LITHIUM-ION BATTERY

In order to employ unscented Kalman filter and extended Kalman filter for state of charge estimation, an accurate model of the li-ion battery is required. Thevenin model (RC model), Randles model, NREL (National Renewable Energy Laboratory) model, PNGV (Partnership for a New Generation of Vehicles) model are widely used in equivalent circuit modeling equivalent circuit modeling techniques. Thevenin model has less computational complexity and more model accuracy than the other equivalent circuit models.

A. *Thevenin Equivalent Circuit Model of Lithium-ion Battery*

Second order Thevenin model is chosen shown in *Fig. 1* as the cell model of the li-ion battery.

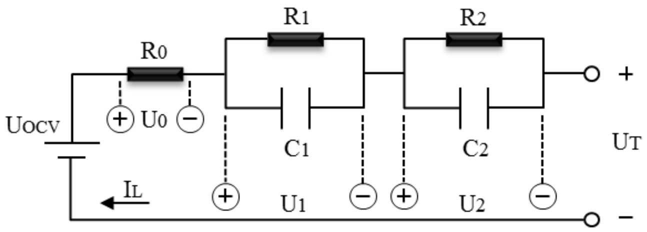

Fig. 1. Equivalent circuit model.

This model is a dynamic model of the battery that consists of a ohmic resistance R_0, polarization resistances R_1 and R_2, polarization capacitances C_1 and C_2, polarization voltages U_1 and U_2, open circuit voltage U_{OCV}, load current I_L.

The electrical behavior of the second order Thevenin model can be expressed as following equations:

$$\dot{U}_1 = -\frac{1}{C_1 R_1} U_1 + \frac{1}{C_1} I_L \tag{1}$$

$$\dot{U}_2 = -\frac{1}{C_2 R_2} U_2 + \frac{1}{C_2} I_L \tag{2}$$

$$U_T = U_{OCV} - U_1 - U_2 - I_L R_0 \tag{3}$$

B. *State of Charge Description*

SoC is defined as a ratio of the remaining capacity to the maximum available capacity of a battery; it is given by

$$SoC_t = SoC_0 - \frac{1}{C_b}\int_0^t \eta I_{L,\tau} d\tau \tag{4}$$

where SoC_t is the present state of charge, SoC_0 is the initial state of charge, C_b is the maximum available capacity, η is the charge-discharge efficiency, $I_{L,t}$ is the load current.

The discretization of (4) is,

$$SoC_k = SoC_{k-1} - \frac{\eta I_{L,k} \Delta_\tau}{C_b} \tag{5}$$

where SoC_k is the state of charge kth sampling time, SoC_{k-1} is the state of charge $(k-1)th$ sampling time, Δ_t is the sampling period.

C. *State-Space Model of Lithium-ion Battery*

The continuous state-space equation of a linear system can be expressed as,

$$\dot{x} = Ax + Bu \tag{6}$$

$$y = Cx + Du \tag{7}$$

where x is the state variables, u is the input vector, y is the output vector, A is the system matrix, B is the control matrix, C is the output matrix and D is the transmission matrix. For further analysis, state of charge and polarization voltages are chosen as the state variables in (6) and (7).

$$x = \begin{bmatrix} SoC & U_1 & U_2 \end{bmatrix}^T \tag{8}$$

In order to apply EKF method for SoC estimation, the state-space equation can be defined as,

$$\dot{x} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & -1/C_1R_1 & 0 \\ 0 & 0 & -1/C_2R_2 \end{bmatrix} x + \begin{bmatrix} -\eta/C_b \\ 1/C_1 \\ 1/C_2 \end{bmatrix} I_L \tag{9}$$

$$y = U_T = \begin{bmatrix} f(U_{OCV}, SoC) & -1 & -1 \end{bmatrix} x + \begin{bmatrix} -R_0 \end{bmatrix} I_L \tag{10}$$

III. STATE OF CHARGE ESTIMATION METHODS

In this section state of charge estimation techniques will be given.

A. *Extended Kalman Filter*

Extended Kalman filter is the nonlinear version of the Kalman filter which linearizes with first order Taylor series expansion. To estimate SoC based on EKF, the second order Thevenin model should be transformed to discrete-time state-space model. Discrete-time state-space model of nonlinear system can be described as:

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

$$y_k = h\left(x_k, u_k\right) + v_k \tag{12}$$

$$w_k \cong N\left(0, Q(t)\right) \tag{13}$$

$$v_k \cong N\left(0, R(t)\right) \tag{14}$$

x_k : System state vector

y_k : System output vector

u_k : System input vector

v_k : Measurement noise vector

w_k : Process noise vector

$Q(t)$ and $R(t)$: Weight matrices

$f(.)$ and $h(.)$: Nonlinear process and measurement function, respectively

The functions $f(.)$ and $h(.)$ are linearized using the Jacobian matrix and first-order Taylor-series expansion. The state- space model can be rewritten as:

$$x_{k+1} = A_k x_k + B_k u_k + w_k \tag{15}$$

$$y_k = C_k x_k + D_k u_k + v_k \tag{16}$$

Where,

$$A_k = \left.\frac{d\left[f\left(x_k, u_k\right)\right]}{d\left[x_k\right]}\right|_{x_k, u_k} \tag{17}$$

$$B_k = \left.\frac{d\left[f\left(x_k, u_k\right)\right]}{d\left[u_k\right]}\right|_{x_k, u_k} \tag{18}$$

$$C_k = \left.\frac{d\left[g\left(x_k, u_k\right)\right]}{d\left[x_k\right]}\right|_{x_k, u_k} \tag{19}$$

$$D_k = \left.\frac{d\left[g\left(x_k, u_k\right)\right]}{d\left[u_k\right]}\right|_{x_k, u_k} \tag{20}$$

The EKF consist of three major parts of initialization, prediction and correction as follows,

- Initialization (for $k = 0$)

At the beginning of EKF, initial value of state (x_0) and covariance (p_0) should be selected.

$$\hat{x}_0 = E\left[x_0\right] = x_0 \tag{21}$$

$$p_0 = E\left[(x_0 - \hat{x}_0)(x_0 - \hat{x}_0)^T\right] = p_{x0} \tag{22}$$

- Prediction (for $k = 1, 2, ..., \infty$)

In this stage, priori state estimate $\hat{x}_{k+1}^-$ and priori error covariance matrix P_k^- are calculated by using the following equations:

$$\hat{x}_{k+1}^- = A_k \hat{x}_k^+ + B_k u_k \tag{23}$$

$$P_k^- = A_k P_k A_k^T + Q_k \tag{24}$$

- Correction (for $k = 1, 2, ..., \infty$)

In this stage, first Kalman gain K_k and measurement of system output vector $\hat{y}_k$ are calculated by using (25) and (26). Then state estimation and covariance matrix estimation are updated.

$$K_k = P_k^- C_k^T / \left(C_k P_k^- C_k^T + R_k\right) \tag{25}$$

$$\hat{y}_k = C_k x_k^- + D_k u_k \tag{26}$$

$$\hat{x}_k^+ = \hat{x}_k^- + K_k (y_k - \hat{y}_k) \tag{27}$$

$$P_k = \left(I - K_k C_k\right) P_k^- \tag{28}$$

B. Unscented Kalman Filter

Unscented Kalman filter is a widely used state estimator for nonlinear systems using unscented transformation principle. In unscented transformation principle, a set of sigma points are selected and transform each sigma point through the non-linear function $f(.)$. Then the statistics of the transformed points are calculated to form the mean and covariance estimate. The UKF consists of four major parts of initialization, sigma point calculation, state prediction and measurement update as follows,

- Initialization (for $k = 0$)

$$\hat{x}_0^a = E\left[x_0^a\right] \tag{29}$$

$$P_0^a = E\left[(x_0^a - \hat{x}_0^a)(x_0^a - \hat{x}_0^a)^T\right] \tag{30}$$

- Sigma point calculation (for $k = 1, 2, ..., \infty$)

$$X_{i,k-1}^a = \begin{cases} \hat{x}_{k-1}^a & i = 0, \\ \hat{x}_{k-1}^a + \sqrt{(N+\lambda)P_{k-1}^a} & i = 1, ..., N, \\ \hat{x}_{k-1}^a - \sqrt{(N+\lambda)P_{k-1}^a} & i = N+1, ..., 2N, \end{cases} \tag{31}$$

where λ is a scale

$$\lambda = a^2(N+\kappa) - N \tag{32}$$

where a is a scale parameter in the range $0 \le a \le 1$ and κ is the other tuning parameter. In order to guarantee that the covariance matrix is a positive semidefinite, the condition $\kappa \ge 0$ must be satisfied.

- State prediction (for $k = 1, 2, ..., \infty$)

Each sigma point through the non-linear function $f(.)$,

$$X_{i,k-1}^x = f\left(X_{k-1}^x, X_{k-1}^v, u_{k-1}\right), \quad i = 0, ..., 2N \tag{33}$$

Then priori state estimate and priori error covariance matrix are calculated as:

$$\hat{x}_{k|k-1} = \sum_{i=0}^{2N}\left(w_m^{(i)} X_{i,k|k-1}^x\right) \tag{34}$$

$$P_{k|k-1} = \sum_{i=0}^{2N} w_c^{(i)}\left(X_{i,k|k-1}^x - \hat{x}_{k-1}\right)\left(X_{i,k|k-1}^x - \hat{x}_{k-1}\right)^T \tag{35}$$

where $w_m^{(i)}$ and $w_c^{(i)}$ are weights defined as:

$$w_m^{(i)} = \frac{\lambda}{N+\lambda}, \quad i = 0 \tag{36}$$

$$w_c^{(i)} = \frac{\lambda}{N+\lambda} + (1 - a^2 + \beta), \quad i = 0 \tag{37}$$

$$w_m^{(i)} = w_c^{(i)} = \frac{1}{2\left(N+\lambda\right)} \quad i = 1, ..., 2N \tag{38}$$

Each sigma point through the non-linear function $h(.)$,

$$Y_{k|k-1} = h\left(X_{k|k-1}^x, X_{k-1}^w, u_k\right), \quad i = 0, 1, ..., 2N \tag{39}$$

Then measurement of system output vector $\hat{y}_{k-1}$ is calculated as:

$$\hat{y}_{k-1} = \sum_{i=0}^{2N} w_m^i Y_{i,k|k-1} \tag{40}$$

- Measurement update (for $k = 1, 2, ..., \infty$)

The measurement covariance P_{y_k} and the cross-correlation covariance P_{x_k, y_k} are calculated as,

$$P_{y_k} = \sum_{i=0}^{2N} w_c^{(i)}\left(Y_{i,k|k-1} - \hat{y}_{k-1}\right)\left(Y_{i,k|k-1} - \hat{y}_{k-1}\right)^T \tag{41}$$

$$P_{x_k, y_k} = \sum_{i=0}^{2N} w_c^{(i)}\left(X_{i,k|k-1}^x - \hat{x}_{k-1}\right)\left(Y_{i,k|k-1} - \hat{y}_{k-1}\right)^T \tag{42}$$

Then Kalman gain is calculated based on measurement covariance and cross-correlation covariance

$$K_k = P_{x_k, y_k} P_{y_k}^{-1} \tag{43}$$

Finally, posteriori state estimate and posteriori error covariance matrix are calculated as:

$$\hat{x}_{k|k} = \hat{x}_{k|k-1} + K_k \left(y_k - \hat{y}_k \right) \tag{44}$$

$$P_{k|k} = P_{k|k-1} - K_k P_{y_k} K_k^T \tag{45}$$

IV. EXPERIMENTAL VALIDATION

In order to validate the estimation of SoC based on UKF and EKF, the experimental test bench is developed as shown in *Fig. 2*. The test bench consists of a Panasonic NCR18650B lithium-ion battery whose nominal voltage and nominal capacity are 3.6 V and 3200 mAh respectively, a Gwinstek PEL-2002/2040 programmable dc load, a Gwinstek PSH-3620A programmable dc power supply, a real-time controller DS1104 and a host computer.

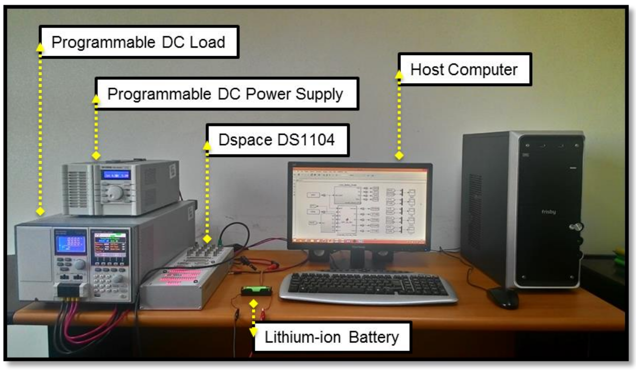

Fig. 2. Experimental setup.

For UKF and EKF, the initial parameters are given in *Table I.* and discrete state-space equations are specified the same as follows:

$$A_{k+1} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & \exp\left(-\Delta t / C_1 R_1\right) & 0 \\ 0 & 0 & \exp\left(-\Delta t / C_2 R_2\right) \end{bmatrix} \tag{46}$$

$$B_{k+1} = \begin{bmatrix} -\eta \Delta t / C_b \\ R_1 \left(1 - \exp\left(-\Delta t / C_1 R_1\right)\right) \\ R_2 \left(1 - \exp\left(-\Delta t / C_2 R_2\right)\right) \end{bmatrix} \tag{47}$$

$$C_{k+1} = \left[f\left(U_{OCV}, SoC_k\right) \quad -1 \quad -1 \right] \tag{48}$$

$$D_{k+1} = \left[-R_0 \right] \tag{49}$$

TABLE I. INITIAL PARAMETERS FOR UKF AND EKF

	UKF	EKF
Initial state	$x_0 = [1 \quad 0 \quad 0]$	$x_0 = [1 \quad 0 \quad 0]$
Initial covariance	$p_0 = diag([1 \quad 1 \quad 1])$	$p_0 = diag([0 \quad 0 \quad 0])$
Weight matrix	$Q = \begin{bmatrix} 1e\text{-}10 & 0 & 0 \\ 0 & 1e\text{-}10 & 0 \\ 0 & 0 & 1e\text{-}10 \end{bmatrix}$	$Q = \begin{bmatrix} 1e\text{-}8 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}$
Weight matrix	$R = 1e10$	$R = 1$

Q and R weight matrices are randomly determined after several attempts. UKF and EKF are developed on the proposed battery model. To estimate SoC of the lithium-ion battery, UKF and EKF are implemented with determined initial conditions. The experimental results of both algorithms are compared according to the SoC estimation results, error signals, mean square error and computational time criteria. SoC estimation results are given in *Fig.3* (extended figure is given in *Fig.4*), error signals are given in *Fig.5* and estimation performance with mean square error and computational time are given in *Table II*.

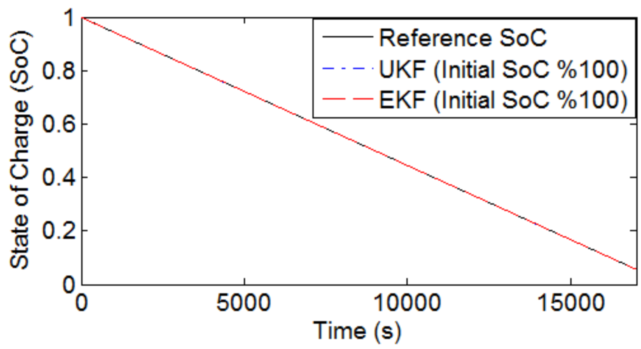

Fig. 3. Comparison of SoC estimation results of UKF and EKF.

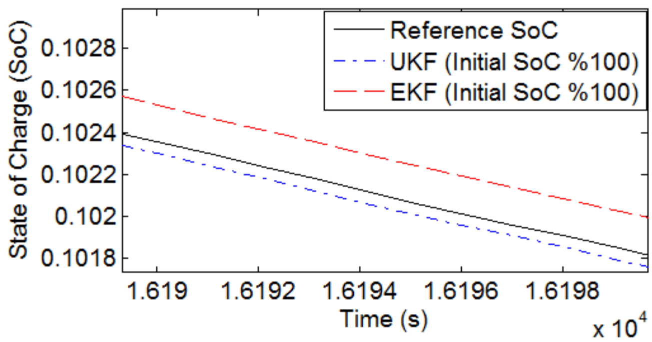

Fig. 4. Comparison of SoC estimation results of UKF and EKF (extended).

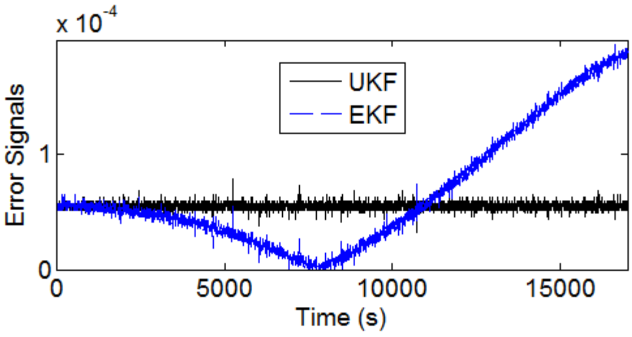

Fig. 5. Error signals.

TABLE II. ESTIMATION PERFORMANCE

Estimation Algorithm	Mean Square Error (10^{-9})	Computational Time (10^{-4} sec.)
Unscented Kalman Filter	3.0788	5.6932
Extended Kalman Filter	7.2494	150

V. CONCLUSION

In this paper, EKF and UKF methods have been carried out to estimate the state of charge of the lithium ion battery. Then, the performances have been compared experimentally in terms of mean square error and computational time. Experimental results show that UKF and EKF both are applicable. However, UKF estimated SoC almost two times accurate than EKF and also had almost thirty times less computational volume.

Possible future work is taking the ambient temperature effect in the account. Other possible future work includes developing battery management system to achieve the balancing the cells of the battery package by using the estimated SoC values based on EKF and UKF.

ACKNOWLEDGMENT

This work was supported by the Scientific and Technological Research Council of Turkey (TÜBİTAK-Project number: 114E515).

REFERENCES

[1] T.D. Atmaja, " Energy storage system using battery and ultracapacitor on mobile charging station for electric vehicle," Energy Procedia, vol. 68, pp. 429-437, 2015.

[2] L. Lu, X. Han, J. Li, J. Hua and M. Ouyang, "A review on the key issues for lithium-ion battery management in electric vehicles," Journal of power sources,vol. 226, pp. 272-288, 2013.

[3] M.T. Lawder, B. Suthar, P.W. Northrop, S. De, C.M. Hoff, O. Leitermann, ... and V.R. Subramania, "Battery energy storage system (BESS) and battery management system (BMS) for grid-scale applications," Proceedings of the IEEE, vol. 102(6), pp. 1014-1030, 2014.

[4] Y. He, X. Liu, C. Zhang and Z. Chen, "A new model for State-of-Charge (SOC) estimation for high-power Li-ion batteries," Applied Energy, vol. 101, pp. 808-814, 2013.

[5] C. Fleischer, W. Waag, H.M. Heyn and D.U. Sauer, "On-line adaptive battery impedance parameter and state estimation considering physical principles in reduced order equivalent circuit battery models: Part 1. Requirements, critical review of methods and modeling," Journal of Power Sources, vol. 260, pp. 276-291, 2014.

[6] X. Guo, L. Kang, Y. Yao, Z. Huang and W. Li, "Joint Estimation of the Electric Vehicle Power Battery State of Charge Based on the Least Squares Method and the Kalman Filter Algorithm," Energies, vol. 9(2), pp. 100, 2016.

[7] R. Xiong, F. Sun, X. Gong and C. Gao, "A data-driven based adaptive state of charge estimator of lithium-ion polymer battery used in electric vehicles," Applied Energy, vol. 113, pp. 1421-1433, 2014.

[8] M.A. Roscher and D.U. Sauer, "Dynamic electric behavior and open-circuit-voltage modeling of LiFePO 4-based lithium ion secondary batteries," Journal of Power Sources, vol. 196(1), pp. 331-336, 2011.

[9] S. Lee, J. Kim, J. Lee and B.H. Cho, "State-of-charge and capacity estimation of lithium-ion battery using a new open-circuit voltage versus state-of-charge," Journal of power sources, vol. 185(2), pp. 1367-1373, 2008.

[10] G. Dong, X. Zhang, C. Zhang and Z. Chen, "A method for state of energy estimation of lithium-ion batteries based on neural network model," Energy, vol. 90, pp. 879-888, 2015.

[11] P. Singh, R. Vinjamuri, X. Wang, and D. Reisner, "Design and implementation of a fuzzy logic-based state-of-charge meter for Li-ion batteries used in portable defibrillators," J. Power Sources, vol. 162, no. 2, pp. 829–836, 2006.

[12] S. Shao, J. Bi, F. Yang and W. Guan, "On-line estimation of state-of-charge of Li-ion batteries in electric vehicle using the resampling particle filter," Transportation Research Part D: Transport and Environment, vol. 32, pp. 207-217, 2014.

[13] H. He, H. Qin, X. Sun and Y. Shui, "Comparison study on the battery SoC estimation with EKF and UKF algorithms," Energies, vol. 6(10), pp. 5088-5100, 2013.

[14] Cheng, Z., Lv, J., Liu, Y. and Yan, Z., "Estimation of state of charge for lithium-ion battery based on finite difference extended Kalman filter," Journal of Applied Mathematics, vol. 2014, pp. 1-10, 2014.

[15] M. Li, "Li-ion dynamics and state of charge estimation," Renewable Energy, vol. 100, pp. 44-52, 2016.

[16] Z. Deng, L. Yang, Y. Cai and H. Deng, "Online Identification with Reliability Criterion and State of Charge Estimation Based on a Fuzzy Adaptive Extended Kalman Filter for Lithium-Ion Batteries," Energies, vol. 9(6), pp. 472, 2016.

[17] Z. Chen, X. Li, J. Shen, W. Yan and R. Xiao, "A Novel State of Charge Estimation Algorithm for Lithium-Ion Battery Packs of Electric Vehicles," Energies, vol. 9(9), pp. 710, 2016.

[18] L.W. Yao, J.A. Aziz, N.R.N. Idris and I.M. Alsofyani, "Online battery modeling for state-of-charge estimation using extended Kalman filter with Busse's adaptive rule," In Industrial Electronics Society, IECON 2015-41st Annual Conference of the IEEE, pp. 4742-4747, 2015.

[19] E. Kamal, A. El Hajjaji and A.M. Mabwe, "State of charge estimation based on extened Kalman filter algorithm for Lithium-Ion battery," In Control and Automation (MED), 2015 23th Mediterranean Conference on, pp. 734-739, 2015.

[20] P.E. Hartz, L. Liu and G. Zhu, "State of Charge Estimation for Lion-Lithium Batteries Using Extended Kalman Theorem," In Industrial Informatics-Computing Technology, Intelligent Technology, Industrial Information Integration (ICIICII), 2015 International Conference on, pp. 295-298, 2015.

[21] H. Zhigang, C. Dong, P. Chaofeng, C. Long and W. Shaohua, "State of charge estimation of power Li-ion batteries using a hybrid estimation algorithm based on UKF," Electrochimica Acta, vol. 211, pp. 101–109, 2016.

[22] M. Partovibakhsh and G. Liu, "An adaptive unscented Kalman filtering approach for online estimation of model parameters and state-of-charge of Lithium-ion batteries for autonomous mobile robots," IEEE Transactions on Control Systems Technology, vol. 23(1), pp. 357-363, 2015.

[23] Y. Tian, B. Xia, W. Sun, Z. Xu and 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, pp. 619-626, 2014.

[24] Y. Tian, C. Chen, B. Xia, W. Sun, Z. Xu and W. Zheng, “An adaptive gain nonlinear observer for state of charge estimation of lithium-ion batteries in electric vehicles,” Energies, vol. 7(9), pp. 5995-6012, 2014.

[25] W. He, N. Williard, C. Chen and M. Pecht, “State of charge estimation for electric vehicle batteries using unscented Kalman filtering,” Microelectronics Reliability, vol. 53(6), pp. 840-847, 2013.

[26] Y. Li, C. Wang and J. Gong, “A combination Kalman filter approach for State of Charge estimation of lithium-ion battery considering model uncertainty,” Energy, vol. 109, pp. 933-946, 2016.