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State Of Charge estimation based on Extended Kalman Filter in Electric Vehicles

Azizeh Lotfivand
Engineering and Tech. Dept.
Liverpool John Moors University
Liverpool, Britain
nazlylotfy@yahoo.com

Dingli Yu
Engineering and Tech. Dept.
Liverpool John Moors University
Liverpool, Britain
D.Yu@ljmu.ac.uk

Barry Gomm
Engineering and Tech. Dept.
Liverpool John Moors university
Liverpool, Britain
J.B.Gomm@ljmu.ac.uk

***Abstract*—Because of their inherent safety, fast charging capacity, and extended cycle life, lithium-ion batteries are preferred over other types of batteries in electric vehicle applications. It's critical to be able to determine state factors like state of charge and state of health in order to generate an accurate battery model. The state of charge estimation algorithms for generic Lithium-ion batteries was enhanced using LA92 drive cycle experiment data. To begin, a mathematical model for an analogous circuit battery was created with the goal of accurately imitating the behavior of a lithium-ion battery. The Thevenin model is created by 2 RC branches and identifies the model parameters with the Extended Kalman Filter. The Hybrid Pulse Power Characterization (HPPC) test data obtained at 40°C, 25°C, 10°C, 0°C, and -10°C are used to calculate the SOC 3-dimensional curve as a function of SOC and T. A comparison of the two methods is shown, indicating that the EKF method of battery SOC evaluation is more accurate than the coulomb counting method. The error observed from the EKF results is less than 1% and it shows EKF is reliable for estimating the battery's states.**

Keywords; Electric Vehicles (EV); Lithium-ion batteries (Li-Ion); State of Charge (SOC); Extended Kalman Filter (EKF)

I. *INTRODUCTION*

Recently, environmental concerns like carbon emissions and global warming issues and the depletion of energy resources lead to use electrical vehicles (EV). Among several types of batteries, Lithium-ion batteries are more preferable for some characteristics like their small size, high energy density, light weight, high output power, high safety and low self-discharge rates [2]. Nevertheless, lithium batteries are sensitive to temperature and aging. Therefore, special attention must be paid to their working environment to avoid physical damage, aging, and thermal runaway.

For better performance of lithium-ion batteries, their Safety and longevity Battery management System (BMS) is crucial. An efficient BMS has the following key responsibilities: (i) estimates and evaluates the battery states accurately including state of charge (SOC), state of energy (SOE), state of health (SOH) and remaining useful life (RUL), (ii) controls the battery temperatures within the safe limit, (iii) operates fault diagnosis, fault prognosis, and fault handling and (iv) balances the voltage, charge, and capacity among battery cells [2]. Estimate the battery status of charge is one of the key functions of BMS. However, accurate SOC estimation is difficult and cannot be measured directly and multiple factors affect the value, so it is difficult to measure SOC when battery is working; Therefore, the SOC must be estimated. The SOC is the ratio of a battery's available capacity Q(t) to the maximum charge that can be stored and ranges it from 0% to 100%, with intervals of 10%; however, it can be changed as desired. There are several ways for determining SoC, the most simple and common of which is Coulomb counting (CC). Its precision, however, is dependent on the initial SOC and sensor accuracy [2] [3]. It is an open loop control to method in which the sensor errors are compounded together.

Another technique is the OCV-SOC curve method, where OCV represents the battery's open circuit voltage. This method converts open circuit voltage to equivalent SOC. For Li-ion batteries, however, the curve will be flat in the middle, making accurate estimation impossible.

Closed loop control methods such as Extended Kalman Filter (EKF) is proposed in this study to solve the shortcomings of CC and OCV-SOC curve methods.

The electrical equivalent two RC model [4] is used in this study to estimate state of charge (SOC) using the EKF and UKF methods. Simulation data are used to compare the EKF method the CC method. The battery electrical equivalent model and its state space analysis are discussed in Section II. In section III, multiple estimation approaches for state of charge estimation are presented and compared results and conclusion are discussed in Section IV.

II. BATTERY ELECTRICAL EQUIVALENT MODEL AND ITS STATE SPACE ANALYSIS

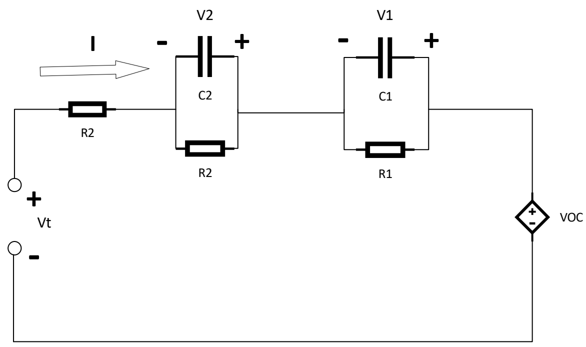

Figure 1. Battery Thevenin Model.

$$\dot{V_1}(t)=\frac{-V_1(t)}{R_1C_1}+\frac{I(t)}{C_1} \quad (1)$$

$$\dot{V_2}(t)=\frac{-V_2(t)}{R_2C_2}+\frac{I(t)}{C_2} \quad (2)$$

$$\dot{SoC}=\frac{\eta I(t)}{Q} \quad (3)$$

$$V_t(t) = V_{OC}(SoC(t)) + V_1(t) + V_2(t) + I(t)R_0 \quad (4)$$

The state and measurement equations are as followings:

$$\dot{x}(t)=Ax(t)+Bu(t) \quad (5)$$

$$\dot{Y}(t)=Cx(t)+Du(t) \quad (6)$$

$$A=\begin{bmatrix} \frac{-1}{R_1C_1} & 0 & 0 \\ 0 & \frac{-1}{R_2C_2} & 0 \\ 0 & 0 & 0 \end{bmatrix} \quad B=\begin{bmatrix} \frac{1}{C_1} \\ \frac{1}{C_2} \\ \frac{\eta}{Q} \end{bmatrix} \quad (7)$$

$$C=\begin{bmatrix} 1 & 1 & \frac{dV_{OC}}{dSOC} \end{bmatrix} \quad D=[R_0]$$

$$\text{State Vector}=x(t)=\begin{bmatrix} V_1(t) \\ V_2(t) \\ SoC(t) \end{bmatrix} \quad (8)$$

The state matrix is A, the input matrix is B, the output matrix is C, and the feedthrough matrix is D.
EKF approach uses a discrete state space model. This is due to the fact that data will be updated after each time step. The following is the discrete state space model:

$$V_1(k+1)= e^{\frac{-\Delta T}{R_1C_1}}V_1(k)+R_1(1-e^{\frac{-\Delta T}{R_1C_1}}) \quad (9)$$

$$V_2(k+1)= e^{\frac{-\Delta T}{R_2C_2}}V_2(k)+R_2(1-e^{\frac{-\Delta T}{R_2C_2}}) \quad (10)$$

$$A=\begin{bmatrix} e^{\frac{-\Delta T}{R_1C_1}} & 0 & 0 \\ 0 & e^{\frac{-\Delta T}{R_2C_2}} & 0 \\ 0 & 0 & 0 \end{bmatrix} \quad B=\begin{bmatrix} R_1(1-e^{\frac{-\Delta T}{R_1C_1}}) \\ R_2(1-e^{\frac{-\Delta T}{R_2C_2}}) \\ \frac{\eta\Delta T}{Q} \end{bmatrix}$$

$$C=\begin{bmatrix} 1 & 1 & \frac{dV_{OC}}{dSOC} \end{bmatrix} \quad D=[R_0] \quad (11)$$

The most popular and straightforward method for estimating SOC is the Coulomb counting method [7]. However, there are two major issues with this method: the initial SoC and sensor noise [8]. SoC estimation will be erroneous if the starting SoC is incorrect. Because the CC method is an open loop control method, sensor noise accumulates at each time step. Closed loop approaches such as EKF is employed to solve these shortcomings. The suggested methodology employs the EKF method to estimate SOC and Terminal voltage.
The Hybrid Pulse Power Characterization (HPPC) test data obtained at 40°C, 25°C, 10°C, 0°C, and -10°C are used to calculate the SOC 3-dimensional curve as a function of SOC and T. In the proposed methodology, figure 2 is resulted by fitting a four-order polynomial to the entirety of the SOC-OCV data with thermal effects on Open Circuit Voltage.

OCV=f (SOC, Temperature) (10)

It can be written as following:

$$OCV_{fit}=p00+p10*SOC+p11*SOC*T+ p20*SOC^2+p11*SOC*T+p02*T^2 +P30*SOC^3+p21*SOC^2*T +p12*SOC*T^2+p03*T^3+p40*SOC^4 +P31*SOC^3*T+p22*SOC^2*T^2 +P13*SOC*T^3+p04*T^4 \quad (11)$$

Derivative of OCV with respect to SOC is:

$$df\_OCV\_SOC=4*p40*SOC^3+3*p31*SOC^2*T+ 3*p30*SOC^2+2*p22*SOC* T^2+2*p21*SOC*T+2*p20*SOC+p13*T^3 + p12 * T^2 + p11 * T + p10 \quad (12)$$

Derivative of OCV with respect to SOC is:

$$df\_OCV\_T=p31*SOC^3+2*p22*SOC^2*T+p21*SOC^2+ 3*p13*SOC*T^2+2*p12*SOC*T+p11*SOC+4*p04*T^3+ 3*p03*T^2+2*p02*T+p01 \quad (13)$$

These derivatives are required for C matrix to linearization and achieving Jacobians.

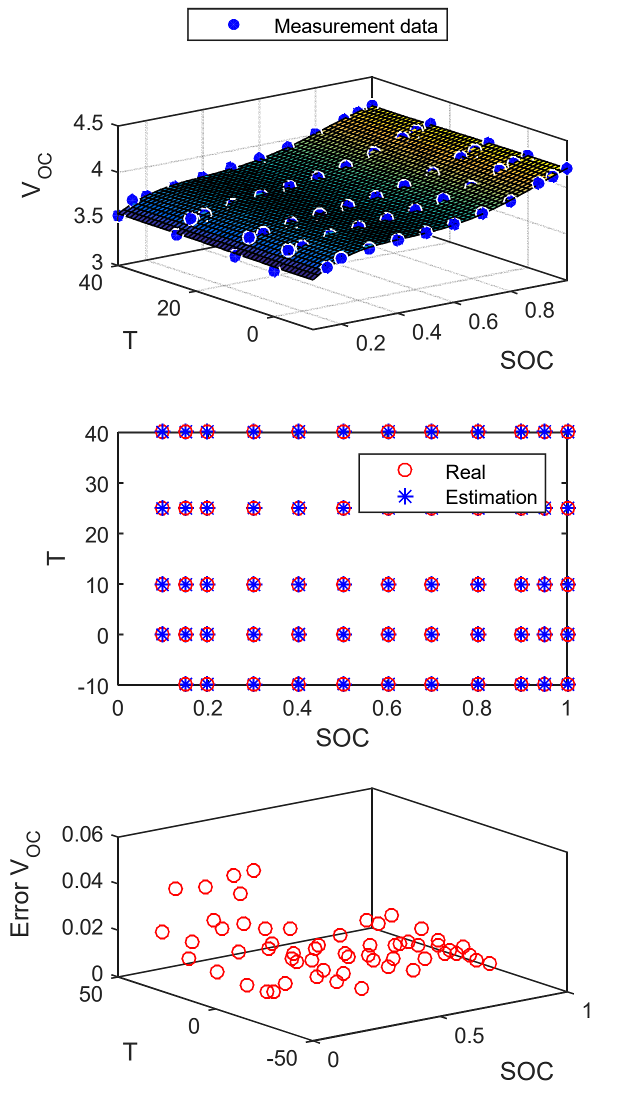

Figure 2. a. dimensional Open Circuit voltage curve as a function of State of Charge and temperature b. real points and fitted curve c. Error between real points and fitted curve

According to figure 2 it can be seen than 3-dimentional curve has acceptable error less than 0.05% .

III. ESTIMATION APPROACHES FOR STATE OF CHARGE

A. Coulomb Counting

The measured current is integrated with regard to time in this method.

$$SOC(t) = SOC_0+\frac{1}{Q}\int_0^t Idt \tag{14}$$

The beginning state of charge is SOC_0, and the total state of charge is SOC. I is the charging/discharging current and Q is nominal capacity of the battery.

B. EKF(Extended Kalman Filter) algorithm

The Li-ion battery has extremely nonlinear and dynamic properties. The battery's OCV-SoC characteristic curve, for example, is nonlinear. Furthermore, due to changing operating conditions, some essential EECM (Equivalent electrical circuit model) metrics, such as polarization resistance and capacitance, show time-varying characteristics. As a result, the Linear Kalman Filter cannot be used directly to estimate the SOC of a Li-ion battery. OCV-SoC characteristics and other parameters must be linearized around their operation point [9]. However, because the OCV of most Li-ion batteries does not settle to its ultimate value instantly, a large amount of rest time is required for proper mapping of the OCV-SoC relationship, which is not possible in many applications.[10] The Extended Kalman Filter (EKF) is based on the transition and measurement equations being linearized. As long as the linear approximations are accurate enough, it can be employed for nonlinear circumstances. The EKF uses a first order Taylor approximation of nonlinear functions via Jacobians. Gaussians are used to model both the process and the observation noises [11]. The transition equation's distribution of propagating states is approximated as a Gaussian PDF. Similarly, the Gaussian PDF is used to approximate the distribution of measurements acquired with the measurement equation.

The nonlinear system's equations are as follow:

$$x(n+1)=f(x(n), u(n), w(n)) \tag{15}$$

$$y(n)=h(x(n), v(n)) \tag{16}$$

(a) Prediction stage:

$$x_a(n+1)=f(x_e(n), u(n)) \tag{17}$$

$$M(n+1)=F(n)\, P(n)F(n)^T+W(n)\sum_w W(n)^T \tag{18}$$

(b) Correction stage:

$$K(n+1)=M(n+1)H(n)^T.[H(n)M(n+1)H(n)^T+ V(n)\textstyle\sum_v V(n)^T]^{-1} \tag{19}$$

$$P(n+1)=M(n+1)-K(n+1)H\,(n)M(n+1) \tag{20}$$

$$x_e(n+1)= x_a(n+1)+K(n+1)[y(n+1)-h(x_a(n+1,0)] \tag{21}$$

To anticipate the future state, the transition equation is employed directly. The related covariance matrix M is constructed according to using the Jacobians assessed at $x_e(n)$, w(n):

$$H(n)=\frac{dh(x,v)}{dx} \qquad F(n) = \frac{df(x,w)}{dx} \tag{22}$$

Covariance matrix P is updating by the following Jacobians that is evaluated at x$a\,(n+1),\,\mathbf{v}(n)$:

$$V(n)=\frac{dh(x,v)}{dv} \qquad W(n)=\frac{df(x,w)}{dw} \tag{23}$$

The estimation error is directly computed using the measurement. Comparing the prediction and update step equations in Standard Kalman Filter with these steps in EKF, we can say that the Jacobian F(n) is said to serve the role of the A matrix, while the C matrix is the Jacobian H(n).
The state estimate covariance matrix is P, the process noise covariance matrix is W, and the measurement noise covariance matrix is V. While, y is the measurement taken from the sensor. The Kalman filter will be based on the Kalman gain and determine whether to rely on an estimate or a measurement. Based on using the Kalman filter, the state estimate and state will be updated.

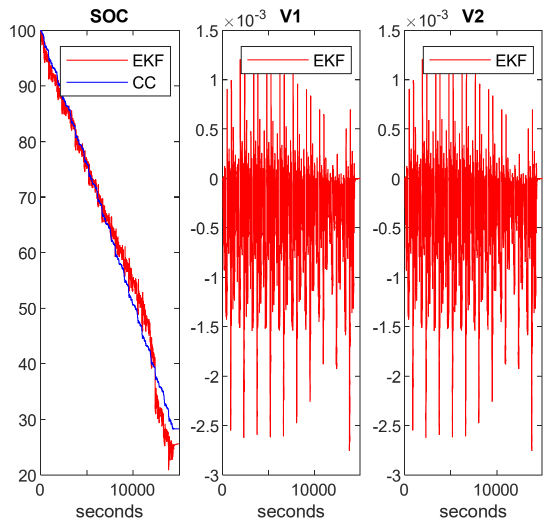

Figure 3. a. SOC estimation by EKF and formal Coulomb Counting method b. V1 estimation by EKF c. V2 estimation by EKF

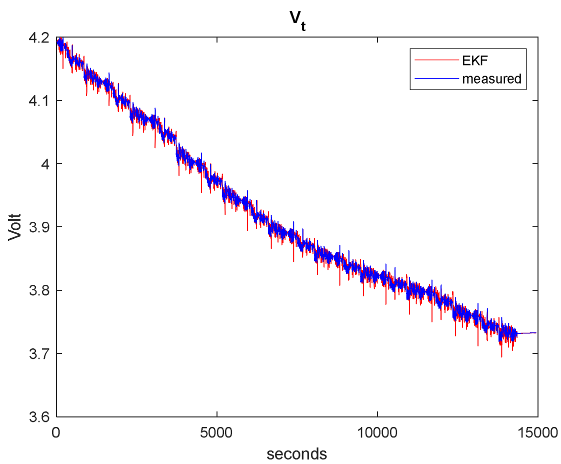

Figure 4. Measured and estimated battery terminal voltage

Observation noise and process noise directly affect errors and RMSE. Therefore, by tuning the values the best amount for them set as follows:

$$Sw=\begin{bmatrix} 1.0e^{-6} & 0 & 0 \\ 0 & 1.0e^{-5} & 0 \\ 0 & 0 & 1.0e^{-5} \end{bmatrix} \qquad Sv=10^{-5} \tag{23}$$

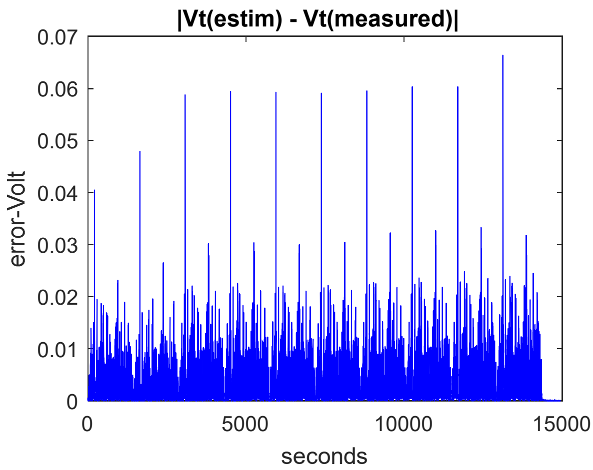

Figure 5. Estimation error of terminal voltage

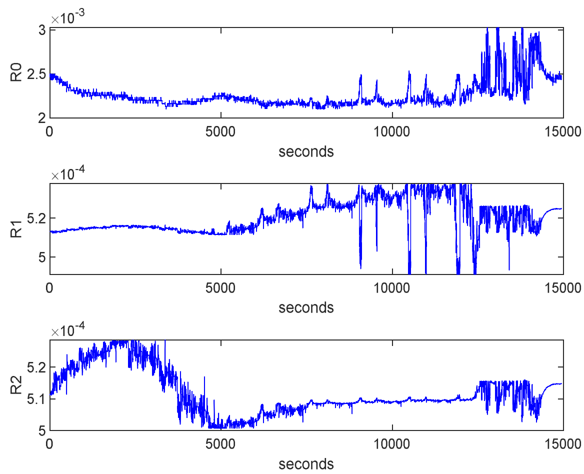

Figure 6. Battery internal Resistances

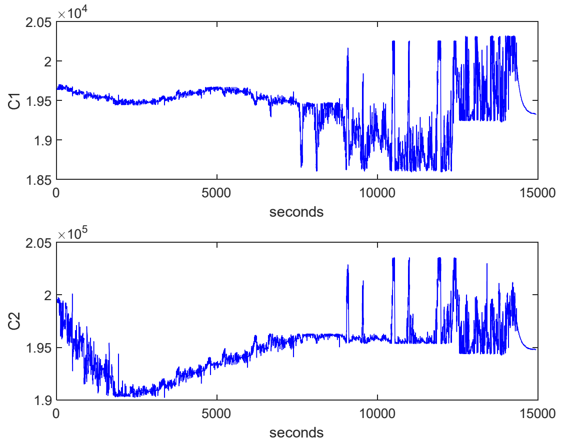

Figure 7. Battery internal Capacities

IV. CONCLUSION

In this study, the EKF methods is used to estimate the SOC and terminal voltage of a Lithium ion battery. The state space analysis is calculated using the 2 RC Lithium ion electrical equivalent model. The Open Circuit Voltage (OCV) 3-dimensional curve as a function of SOC and T is calculated using the Hybrid Pulse Power Characterization (HPPC) test data acquired at 40°C, 25°C, 10°C, 0°C, and -10°C. It can be seen that the EKF method of battery SOC estimation is more accurate than the coulomb counting approach, according to a comparison of the two methods. The inaccuracy in the EKF results is less than 1%, indicating that EKF is a trustworthy method for estimating battery states. Moreover, The Root Mean Square Error (RMSE) is utilized as the assessment index to quantify the estimation error of techniques. RMSE values for Terminal Voltage and SOC are 5% and 1.7% respectively.

REFERENCES

[1] Kollmeyer, Phillip; Skells, Michael (2020), “Turnigy Graphene 5000mAh 65C Li-ion Battery Data”, Mendeley Data, V1, doi: 10.17632/4fx8cjprxm.1

[2] Nikolian, A., Firouz, Y., Gopalakrishnan, R., Timmermans, J.-M., Omar, N., Van den Bossche, P. and Van Mierlo, J. (2016) Lithium ion batteries—Development of advanced electrical equivalent circuit models for nickel manganese cobalt lithium-ion. Energies, 9 (5), 360

[3] Hussain, S., Nengroo, S.H., Zafar, A., Kim, H.-J., Alvi, M.J., Ali, M.U., 2019. Towards a smarter battery management system for electric vehicle applications:a critical review of lithium-ion battery state of charge estimation. Energies 12, 446.

[4] H. Aung, K. S. Low and S. T. Goh, "Modeling and state of charge estimation of a lithium ion battery using unscented Kalman filter in nanosatellite," 2014

[5] C. Vidal, O. Gross, R. Gu, P. Kollmeyer and A. Emadi, ”xEV Li-Ion Battery Low-Temperature Effects—Review,” in IEEE Transactions Vehicular Technology, vol. 68, no. 5, pp. 4560-4572, May 2019.

[6] C. Chang, Y. Zheng, and Y. Yu, “Estimation for Battery State of Based on Temperature Effect and Fractional

[7] Z. Zou, J. Xu, B. Cao, Z.Chen, “Evaluation of Model Based State of Charge Estimation Methods for Lithium-Ion Batteries,” 2014

[8] T Huria, M Ceraolo, J Gazzarri, R Jackey, “Simplified Extended Filter Observer for SOC Estimation of Comercial Power-Oriented LFP Lithium Battery Cells” , 2013 SAE World Congress

[9] B.L. Kumari, K.P. Raju, V.Y.V. Chandan, R.S. Krishna, V.M.J. Rao, Application of extended Kalman filter for a free falling body towards Earth. Int. J. Adv. Comput. Sci. Appl. **2**(4), 134–140 (2011)

[10] H. Chaoui, S. Mandalapu, Comparative study of online open circuit voltage estimation techniques for state of estimation of lithium-ion batteries, Batteries 3 (2) (2017) 12.

[11] M. Hossain, M. Haque, S. Saha, M. Arif, A. Oo, State of estimation li-ion batteries based on adaptive extended Kalman filter, in: 2020 IEEE Power & Energy Society General Meeting, PESGM, IEEE, 2020, pp. 1–5.

[12]