State Of Charge estimation using Extended Kalman Filter in Electric Vehicles

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2022 27th International Conference on Automation and Computing (ICAC) | 978-1-6654-9807-4/22/$31.00 ©2022 IEEE | DOI: 10.1109/ICAC55051.2022.9911137

***Abstract*— Lithium-ion batteries are in the top priority among other batteries because of being safe, quick charging, and long-life cycle and are widely used in electric vehicles for having precise battery model, it is essential to decide factors like state of health and state of charge. In this paper using LA92 drive cycle experiment data is used for the state of charge estimation algorithm Firstly, for imitating the lithium-ion batterie's behavior in accurate way, a mathematical model of analogous battery is required. The 2RC branches are included in Thevenin model and Hybrid Pulse Power Characterization (HPPC) test data achieved at 40°C, 25°C, 10°C, 0°C, and -10°C is used to calculate the SOC 3-dimensional curve as a function of SOC and T. Coulomb counting (CC) and extended Kalman Filter method were observed for estimating the state of charge. The results show that EKF is more precise than CC (Coulomb Counting). The mistake of estimation with EKF is less than 1% that shows the reliability of the algorithm. and**

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

I. INTRODUCTION

Recently, environmental concerns like greenhouse gas removal global climate change 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]. Nonetheless, aging and temperature are two factors that could influence on their operation. Therefore, emphasize on environment temperature will prevent aging, thermal runaway, and physical injury.

Better performance of lithium-ion batteries, their Safety and longevity we require Battery management System (BMS). An effective BMS has 4 main characteristics as following: (a) keeping the battery temperatures between the certain limits (b) precisely estimating batteries' state of charge (SOC), state of energy (SOE), state of health (SOH), remaining useful life (RUL), (c) equalizes the voltage, charge, and capacity among battery cells (d) operates fault detection, fault forecasting, and fault overcoming and [2]. Estimate the battery state of charge is allied to main duties 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 proportion of a battery's usable 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 them is Coulomb counting (CC). Its precision, however, is dependent on the first SOC and sensor precision [2] [3]. In this method all the sensor errors are compounded together and reflected to the results.
Another technique is the OCV-SOC curve method, where OCV represents the battery's open circuit voltage. This method converts open circuit voltage to corresponding SOC. For Li-ion batteries, however, the curve will be plain in the midway, making accurate estimation impossible.
Closed loop control methods such as Extended Kalman Filter (EKF) is proposed in this study for solving the shortcomings of CC and OCV-SOC algorithm.
The equivalent electrical circuit consists of two RC model [4] is used in this paper to estimate state of charge (SOC) with the EKF and UKF algorithms. Simulation data are used to compare the EKF method with the CC method. In the following section the equivalent electrical model of battery and its corresponding equations are discussed in detail. In the next section, multiple estimation approaches for state of charge estimation are presented and compared results and conclusion are discussed in the last part.

II. SELECTED BATTERY MODEL AND CORRESPONDING EQUATIONS :

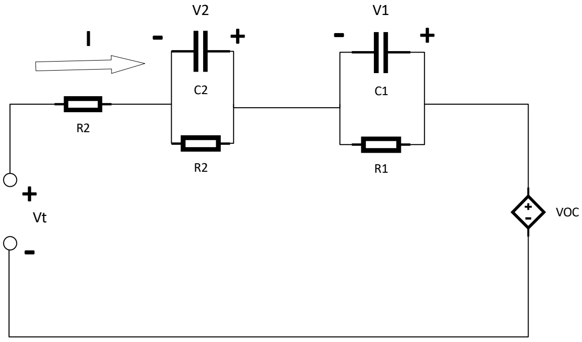

Figure 1. Battery Thevenin Model.

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

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

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

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

The state and measurement equations are as followings:

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

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

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

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

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

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 prominent and forthright method for estimating SOC is the Coulomb counting method [7]. However, there are two problems using these algorithms: the first amount of SoC and sensor noise [8]. SoC estimation will be erroneous if the starting SoC is incorrect. Because the CC method is not a close loop control method, so sensor noise will be added 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 achieved in 4 temperature from 40°C to -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.

$$OCV=f\,(SOC, Temperature) \quad (10)$$

It can be written as following:

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

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.

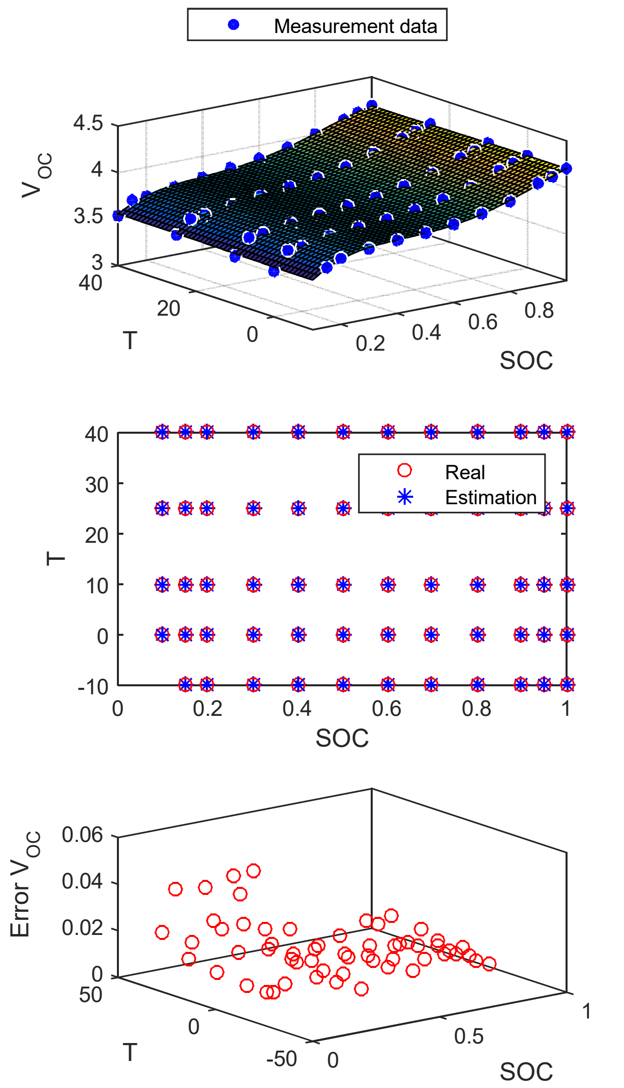

Figure 2. a. dimensional OCV curve in line with State of Charge and temperature b. real points and fitted curve c. Error between real points and fitted curve

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 current is accomulated regarding the time in this algorithm.

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

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 batteries are completely nonlinear, and their characteristics are changed all the time. For example, dimensional OCV curve in line with State of Charge is completely nonlinear. Furthermore, due to changing operating conditions, some essential EECM (Equivalent electrical circuit model) metrics, such as polarization resistance and capacitance, change by time. Therefore, Linear Kalman Filter is useless to estimate the SOC of these kinds of batteries. It is required to linearize all parameters including OCV-SoC around their functioning spot [9]. Nevertheless, the OCV in most Li-ion batteries needs a long time to settle in the correct value and we should take it time before measuring and having precise SOC-OCV curve and in some cases, there is not enough time to put.[10] The Extended Kalman Filter (EKF) has two main transition and measurement equations that should be linearize. If the linear approximations are accurate enough, it can be employed for nonlinear circumstances. First order Taylor approach is applied for linearizing transition and measurement equation by Jacobians. Process noise and observation noise assume being Gaussian [11]. The transition equation's distribution of propagating states is estimated as a Gaussian PDF. Measurement equations are estimated to be Gaussian as well.

The nonlinear system's equations are as follow:

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

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

(a) Prediction stage:

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

$$\mathrm{M(n+1)=W(n)\sum\nolimits_w W(n)^T + F(n)\ P(n)F(n)^T} \tag{18}$$

(b) Correction stage:

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

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

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

To predict the future state, the transition equation is used straightforwardly. The related covariance matrix M is constructed by Jacobians with x_e(n), w(n) assessment:

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

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).

P is the state covariance, W is the process noise covariance matrix, and V assumed as the measurement noise covariance matrix. Using data taken from sensor (y) and Kalman gain, the Kalman filter will decide to rely on estimation or measurement. As a result, Kalman filter will update the estimation While, y is the measurement taken from the sensor.

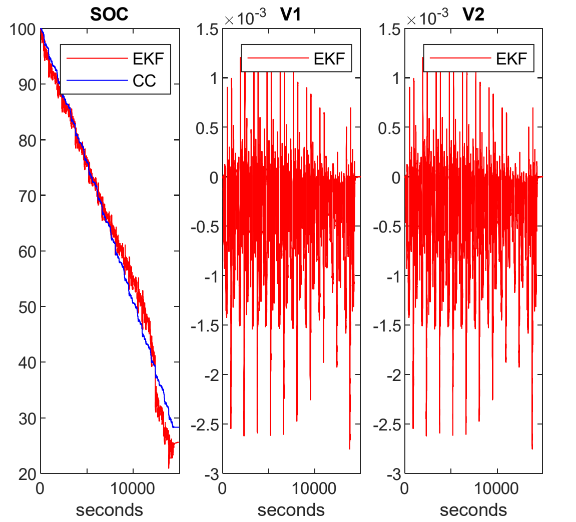

Figure 3. a. SOC estimation by EKF and formal Coulomb Counting method b. V1 estimation by EKF c. V2 estimation by EKF

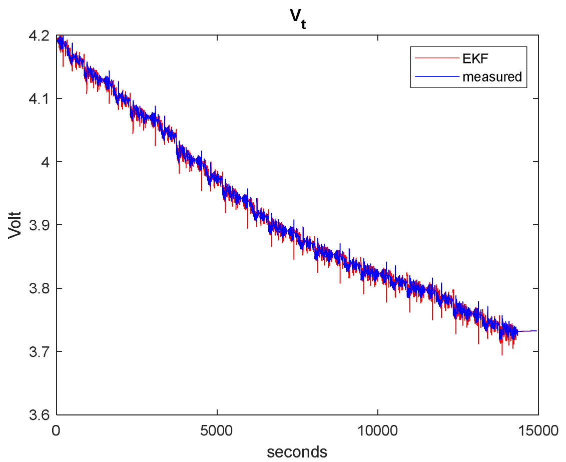

Figure 4. Measured and estimated battery terminal voltage

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

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

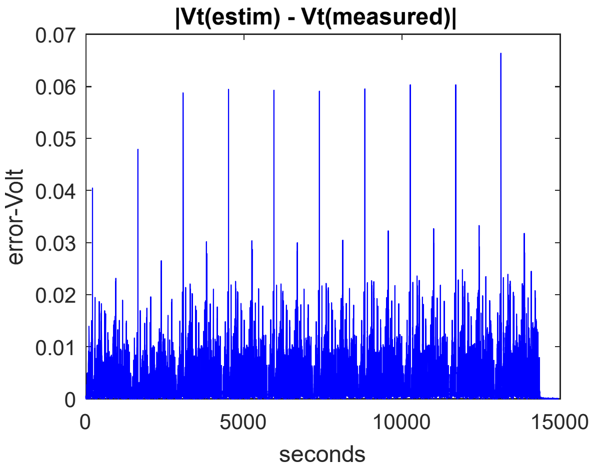

Figure 5. Estimation error of terminal voltage

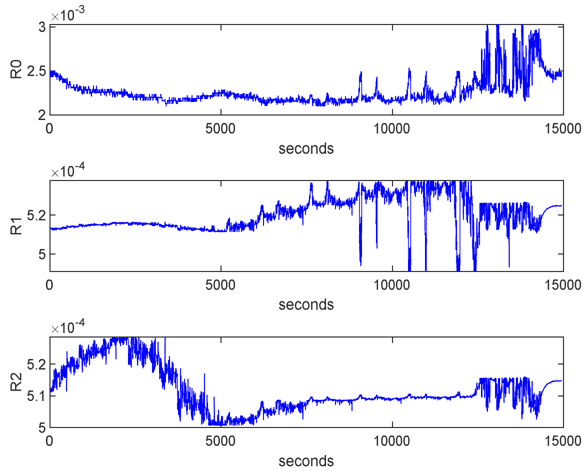

Figure 6. Battery internal Resistances

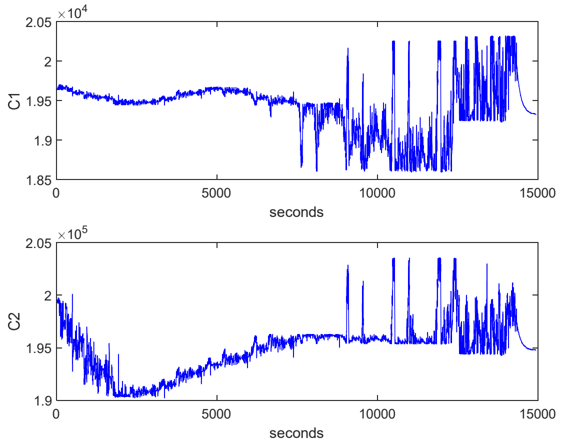

Figure 7. Battery internal Capacities

IV. CONCLUSION

In this study, SOC and terminal voltage estimation done with the EKF algorithm Li-ion batteries. The state space analysis is done by applying related equations on the 2 RC branch battery model. The Hybrid Pulse Power Characterization (HPPC) test data obtained at several temperature from 40°C to -10°C are used to calculate the SOC 3-dimensional curve as a function of SOC and T. The simulation results show that the EKF is more productive and precise than C_C (Coulomb Counting). As a result, this method is more reliable method. The inaccuracy in the EKF results is less than 1%, indicating that EKF is a trustworthy method for estimating battery states. Moreover, RMSE is utilized for assessment index to quantify the estimation error of techniques. RMSE values for Terminal Voltage and SOC are 5% and 1.7% respectively.

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