State Of Charge estimation using Unscented Kalman Filter in Electric Vehicles

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***Abstract*— Lithium-ion batteries are preferred more than other types of batteries in electric vehicle applications due to their inherent safety, fast charge capacity, and long life. To create an accurate battery model, it is important to be able to identify health factors such as charge and health. Using LA92 drive cycle experimental data, the typical lithium-ion battery charge state estimation algorithm has been improved. First, we created a mathematical model of an analogue circuit battery to accurately mimic the behavior of a lithium-ion battery. The Thevenin model consists of two RC branches and uses an extended Kalman filter to identify model parameters. The three-dimensional curve of SOC as a function of SOC and T using hybrid pulsed power characteristic (HPPC) test data achieved at 5 degrees from 40°C to -10°. To calculate. A comparison of the two methods is shown, showing that the UKF method for battery SOC assessment is more reliable than the traditional method CC (Coulomb counting). The error observed in the UKF results is less than 1%, indicating that the UKF can reliably estimate battery condition.**

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

I. INTRODUCTION

The utilization of electric vehicles (EVs) has increased recently due to environmental challenges like carbon emissions, global warming, and the depletion of energy resources. Lithium-ion batteries are preferred over other types of batteries because of their small size, high energy density, lightweight, high output power, high level of safety, and low self-discharge rates [1]. However, temperature and aging are two factors that may affect how well they function.
hence placing a focus on ambient temperature

will shield against aging, thermal overheating, and physical harm.
The safety and endurance of lithium-ion batteries are important for improved performance. BMS, or battery management system, is essential. The qualities listed below are essential for a flawless BMS: (a) maintaining battery temperatures within defined ranges. (b) calculating the state of charge (SOC), state of energy (SOE), state of health (SOH), and remaining useful life of batteries with precision (RUL), (c) balancing the capacity, charge, and voltage of the battery cells. (d) carries out fault predicting, fault overcoming, and fault detecting [2]. Estimating the battery status of charge is one of the key functions of BMS. However, accurate SOC estimation is difficult and cannot be measured directly. Also, it is difficult to measure SOC while the battery is running, as several factors affect the value. Therefore, you need to estimate the SOC. SOC is the ratio of the battery's available capacity Q (t) to the maximum storable charge, ranging from 0% to 100% at 10% intervals. However, you can change it as needed. There are several ways to determine the SoC, but the simplest and most common is the Coulomb Count (CC). However, for having precise estimation its initial SOC and the accuracy of the sensor should be correct [2] [3]. This open-loop control technique makes sense of sensor failures. The OCV-SOC curve method is an additional approach. where OCV displays the battery's open circuit voltage. The open circuit voltage is converted to an equivalent SOC using this process. However, the curve is flat in the middle for lithium-ion batteries, making precise calculations impractical. The unscented Kalman filter (UKF), one of the closed-loop control methods proposed in this paper, aims to overcome the drawbacks of CC and OCV-SOC curve methods. In this study, the state of charge (SOC) is estimated using the UKF approach utilizing two electrically equivalent RC models [4]. The UKF and CC approaches are contrasted using the simulation data. Part II describes the battery's electrical equivalency model and state-space analysis. In part III, many estimation techniques for charge state estimation are described. Part IV compares the results and explains them.

2. CHOSEN BATTERY MODEL AND RELATED EQUATIONS

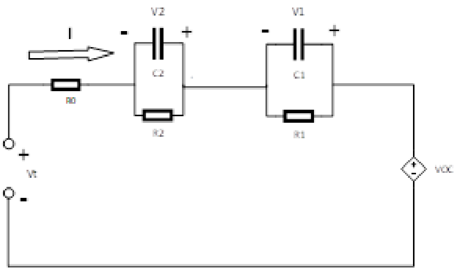

Figure 1. Battery Thevenin Model.

The Thevenin model in Figure 1 includes the open circuit voltage VOC, internal resistance, and equivalent capacitance. Ohm resistance Ro, electrochemical polarization resistance R1, and

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concentration polarisation resistance R2 are examples of internal resistances. The equivalent capacitance, which includes the electrochemical polarisation capacitance C1 and the concentration polarisation capacitance C2, represents the charge/discharge current and terminal voltage. The parameters of the battery are significantly influenced by temperature. It is an indirect proportion to temperature, for instance. [5] [6]. Vt stands for the output terminal voltage, whereas V1 and V2 indicate the first and second RC networks, respectively. Kirchhoff's voltage-current equation can be used to express the state-space equation, and the following relationship exists between the capacitance-voltage change and its current:

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

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

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

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

The state and measurement equations are as followings:

$$\frac{dx}{dt}=Bu(t)+Ax(t) \tag{5}$$

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

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

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

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

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 because data will be updated after each time step. The following is the discrete state space model:

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

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

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

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

The Coulomb counting method is the most common and simple technique for calculating SOC [7]. The first SoC value and sensor noise, however, are this algorithm's two fundamental flaws [8]. If the initial SoC is inaccurate, the SoC estimation will be flawed. As a result of the CC method's open-loop nature, sensor uncertainty increases with each passing time step. These flaws are addressed by using closed-loop methods like EKF. The EKF needs to linearize both equations consisting of state and measurement equations. It leads to lower-order nonlinear systems and is less precise at the same time. It assumes a drawback for the EKF method and so the UKF method is preferable. Using UKF Jacobians and Hessians is not required, and this method is 'derivative-free' among the Kalman filter family. EKF algorithm uses one spot that is called the mean, however, in UKF we have several points known as sigma points that consist of the mean. As in UKF, we need a few sigma points, it needs moderate computation. We use sigma points to find two main parameters consisting of the mean and covariance of the main data. There will be 2n+1 sigma points. Choosing sigma points is described as follows:

$$X_{k-1}^{[0]}=X_{k-1}^{+} \tag{12}$$

$$X_{k-1}^{[i]}=(\sqrt{(n+\lambda)P_{k-1}})+X_{k-1}^{+} \text{for i=1,2,...,n} \tag{13}$$

$$X_{k-1}^{[i]}=-(\sqrt{(n+\lambda)P_{k-1}})+X_{k-1}^{+} \text{ for i=n+1,..,2n} \tag{14}$$

Then these points go through equation 5 to7 and their weights are as follows:

$$w_m^{[0]}=\frac{\lambda}{n+\lambda} \tag{15}$$

$$w_c^{[0]}=(1-\alpha^2+\beta)+w_m^{[0]} \tag{16}$$

$$w_m^{[i]}=w_c^{[i]}=\frac{1}{2(n+\lambda)} \; for\; i=1,2,..,2n \tag{17}$$

$$\lambda=\alpha^2(n+k)-n \tag{18}$$

Since weights are normalized, the sum of them is one. X_{k-1}^{+} is supposed as the mean of the selected points, P_{k-1} is the covariance matrix of state variables, n is the number of state variables, k is another scaling factor and normally it is 3-n, α shows the stretch of sigma points [9], β shows prior knowledge of x distribution [9] and it is 2 for gaussian noises. [10]
The number of columns is i, the computing means the weight is $w_m^{[i]}$, computing covariance weight is $w_m^{[i]}$.
So, the Unscented Kalman Filter algorithm is as follows:
We can assume the nonlinear system as:

x(n+1)=f w(n) (,u(n), x(n)) (19)

Y(n)=h(v(n) ,x(n)) (20)

(a) prediction:

- By propagating sigma points via transition equation, we have:

$$x_k^i = f\left(X_{k-1}^{[i]}, u_k\right) \ for \ i = 0,1,..,2n \tag{21}$$

- Getting priori covariance matrix:

$$x_k^- = \sum_{i=0}^{2n} w_m^{[i]} \, x_k^i \tag{22}$$

$$P_k^- = \sum_{i=0}^{2n} w_c^{[i]} \left(x_k^i - x_k^-\right)\left(x_k^i - x_k^-\right)^T + Q \tag{23}$$

(b) Updating:

- Computing propagated sigma point measurements through measurement equations:

$$y_k^i = h\left(x_k^i, u_k\right) \ for \ i = 0,1,..,2n \tag{24}$$

- Computing measurement means:

$$y_k = \sum_{i=0}^{2n} w_m^{[i]} \, y_k^i \tag{25}$$

- Computing measurement covariance matrix:

$$P_k^y = \sum_{i=0}^{2n} w_c^{[i]} \left(y_k^i - y_k\right)\left(y_k^i - y_k\right)^T + R \tag{26}$$

- Computing cross-covariance matrix:

$$P_k^{xy} = \sum_{i=0}^{2n} w_c^{[i]} \left(x_k^i - x_k^-\right)\left(y_k^i - y_k\right)^T \tag{27}$$

- UKF Gain:

$$K_k = P_k^{xy}\left(P_k^y\right)^{-1} \tag{28}$$

- Updating the state variables:

$$x_k^+ = x_k^- + K_k(Y_k - y_k) \tag{29}$$

- Updating the state covariance:

$$P_k^+ = P_k^- + K_k P_k^y K_k^T \tag{30}$$

To estimate output, sigma points should be handed over measurement function. The results are used for obtaining cross-covariance P_k^{xy} between measurement and state estimation. The estimated measurement at the k^{th} iteration is y_k^i and y_k and P_k^y are its mean and covariance respectively. Y_k is the measurement signal from a sensor.

The SOC 3-dimensional curve as a function of SOC and T is calculated using the Hybrid Pulse Power Characterization (HPPC) test data obtained at 5 degrees from 40°C to -10°C. Figure 2 is the outcome of fitting a four-order polynomial to the whole set of SOC-OCV data with heat effects on Open Circuit Voltage according to the suggested methods.

OCV=f (SOC, Temperature) (31)

It can be written as follows:

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 (32)

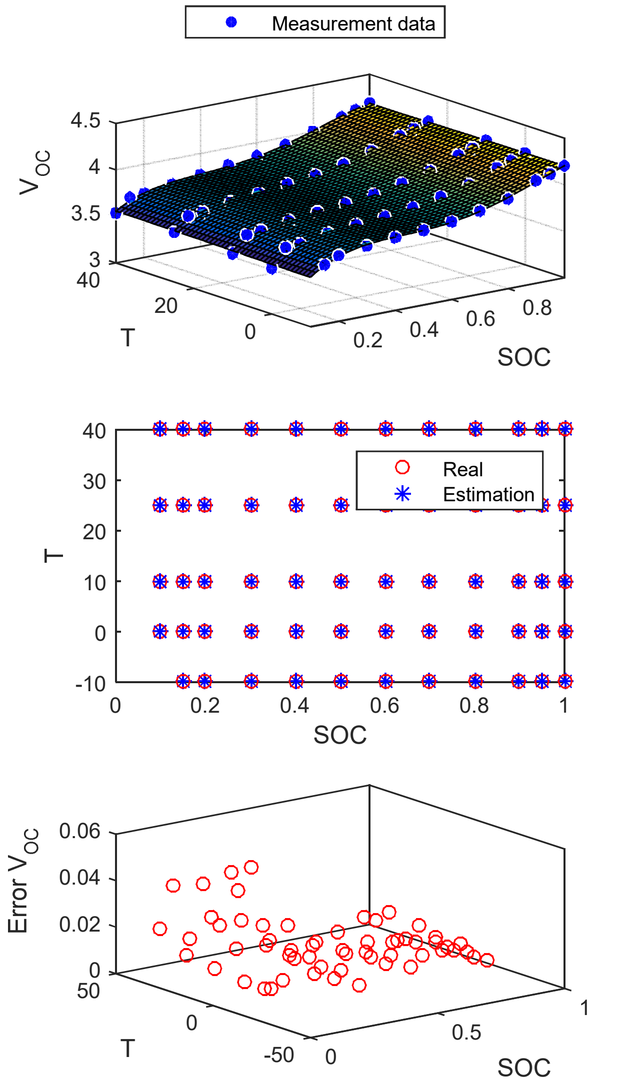


Figure 2. a. dimensional Open Circuit voltage curve as a function of State of Charge and temperature b. real points and fitted curve c. The error between real points and fitted curve

According to figure 2, it can be seen that the 3-dimensional curve has an acceptable error of less than 0.05%.

II. ESTIMATION APPROACHES FOR THE STATE OF CHARGE

A. Coulomb Counting

The measured current is integrated concerning time in this method.

$$\mathrm{SOC(t)} = \mathrm{SOC_0} + \frac{1}{Q}\int_0^t \mathrm{Idt} \tag{33}$$

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 the nominal capacity of the battery.

B. UKF(Unscented Kalman Filter) algorithm

The Li-ion battery has highly nonlinear and time-varying properties. The battery's OCV-SoC characteristic curve, for example, is not linear. Additionally, some crucial EECM (Equivalent Electrical Circuit Model) metrics, such resistance and capacitance, fluctuate over time and are not linear due to changing operating conditions. As a result, the Linear Kalman Filter is unable to calculate a Li-ion battery's SOC. At each application point, the OCV-SoC curve and other properties must be linearized [11]. However, because the OCV of the majority of Li-ion batteries does not reach its final value right away, it takes a while to achieve the right value in order to have the right OCV-SoC relationship, which is not feasible in many applications.[12]

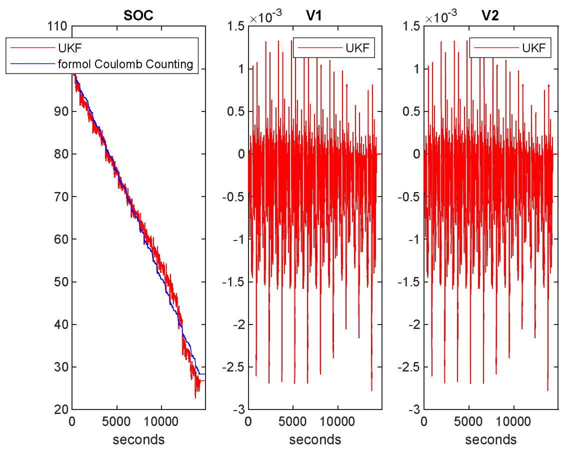


Figure 3. a. SOC estimation by UKF and formal Coulomb Counting method b. V1 estimation by EKF c. V2 estimation by EKF

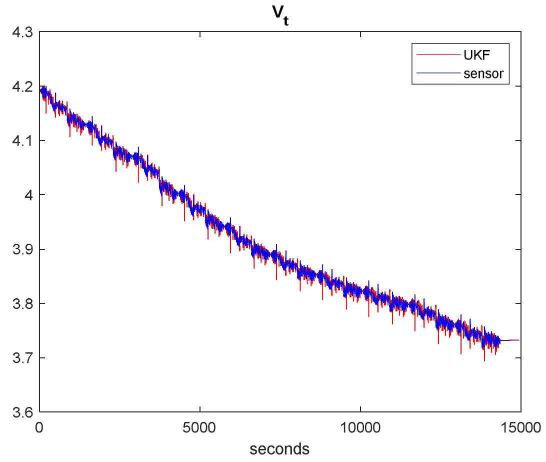
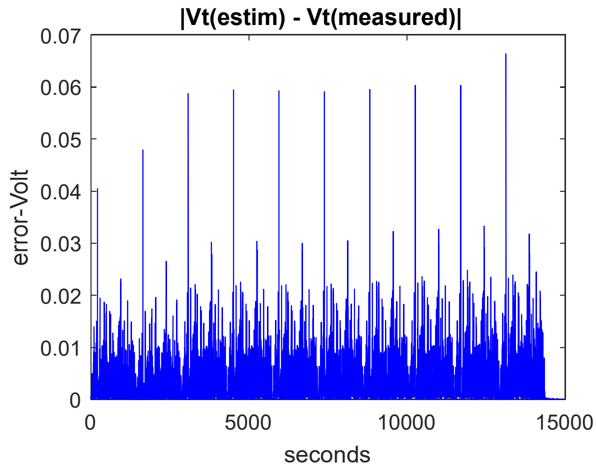


Figure 4. Measured and estimated battery terminal voltage

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

$$Q=\begin{bmatrix} 1.0e^{-4} & 0 & 0 \\ 0 & 1.0e^{-5} & 0 \\ 0 & 0 & 1.0e^{-5} \end{bmatrix} \qquad R=10^{-5} \tag{34}$$



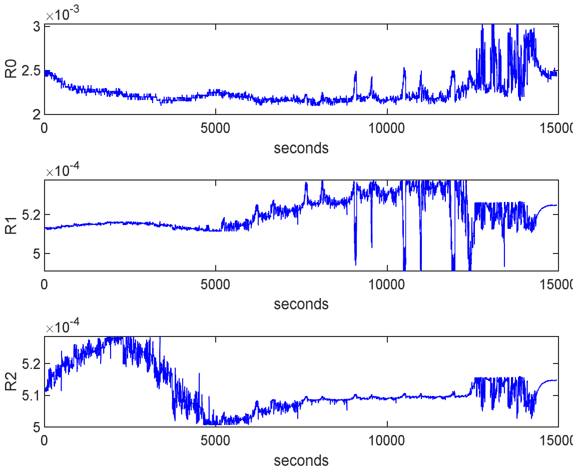


Figure 5. Battery internal Resistances

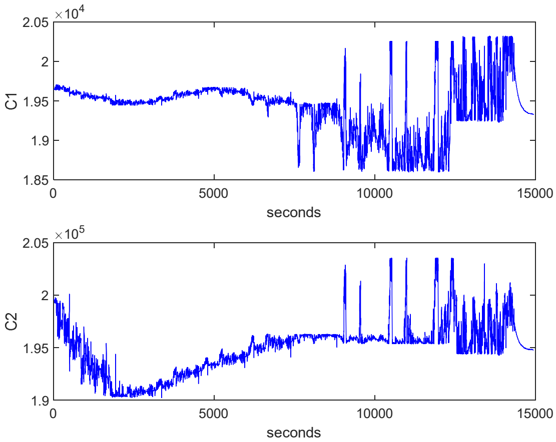


Figure 6. Battery internal Capacities

III. CONCLUSION

In this study, the UKF method 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 UKF method of battery SOC estimation is more accurate than the coulomb counting approach, according to a comparison of the two methods. UKF is a reliable approach for determining battery states because the error in the results is less than 1%. Additionally, The Root Mean Square Error (RMSE) is used as an evaluation metric to express the estimation error of methodologies. Terminal Voltage and SOC have RMSE values of 4% and 1.6%, respectively.References

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