Proceedings of the 2022 6th CAA International Conference on Vehicular Control
and Intelligence (CVCI), Nanjing, China, October 28-30, 2022

State-of-charge estimation for lithium-ion battery pack based on Unscented Kalman Filter considering cell inconsistency

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2022 6th CAA International Conference on Vehicular Control and Intelligence (CVCI) | 978-1-6654-5374-5/22/$31.00 ©2022 IEEE | DOI: 10.1109/CVCI56766.2022.9964827

***Abstract*—The accuracy of battery state of charge (SOC) estimation has tremendous value in the safe use of battery. However, inconsistencies between batteries will affect the power and usable capacity. When vehicle battery pack contains hundreds of single cell, more efforts should be devoted to develop a high-precision and low-complexity method of SOC estimation. In the article, a mean-difference model (MDM) has been established to precisely characterize the battery characteristics, in which the thevenin model is chosen to be mean model (MM) to characterize the whole battery pack features, and the rint model is used to evaluate the inconsistency between batteries. The mean difference model parameters are identified by means of forgetting factor least square (FFRLS), and then the SOC were estimated by the unscented kalman filter (UKF). The validity of MDM and the UKF is verified on a small series battery pack at last.**

Index Terms*—Battery model, SOC inconsistency, SOC estimation

I. Introduction

With the intensification of worldwide environmental pollution and energy crisis, the use of clean renewable energy is becoming more widespread. The electric energy used by electric vehicles is cleaner and more renewable than the oil used in gasoline vehicles [1]. As an important part of electric vehicles, batteries attract the attention of many researchers. Lithium battery have been a research hotspot because of the high energy density, high power density and long life [2, 3]. In an electric vehicle, a battery pack is usually composed of hundreds of single batteries in parallel and series. However, because of the inconsistency between batteries, the power, safety, capacity and other battery characteristics are affected. SOC is the most important parameter of lithium battery. Unfortunately, SOC cannot be directly measured. The safety and use of electric vehicles requires an precise understanding of the Cdynamic of each single battery. As a consequence, it is essential to identify the battery inconsistency and exactly estimate the battery SOC.

Variations between batteries are pervasive. As the operating environment varies, this adds to the inconsistency between cells. In realistic situation, it is essential to build an exact model that can describe the inconsistency between batteries. Many scholars have studied how to accurately quantify the inconsistency of batteries. Equivalent circuit models have received significant attention because of their accuracy and ease of parameter identification [4, 5]. Zheng et al. [6] used the MDM to characterize the performance of the battery pack. The MM considers the whole battery features, and difference model (DM) mainly considers SOC difference and internal resistance difference between batteries. Hu et al. [7] also described the inconsistency between batteries founded on the MDM. This research is not to increase the accuracy of the model, but to introduce a fuzzy system to increase the adaptation and precision of SOC estimation in the case of inconsistency. Dong et al. [4] added the inconsistency of coulomb efficiency in the difference model part, on the basis of Zheng et al. [6] difference model.

In a battery pack with hundreds of series and parallel, it is impractical to calculate each battery SOC because of limited computing power used in electric vehicles. Therefore, many effort are taken to develop algorithms that take into account accuracy and low the complexity. Dong et al. [4] used an adaptive extended kalman filter (AEKF), meanwhile reduced the amount of computation through high-frequency average SOC estimation and low-frequency ΔSOC estimation. Dai et al. [8] studied a method for online determination of all monomer SOC in a series battery pack. The approach is founded on Extended Kalman Filter (EKF). The mean battery SOC is estimated first, then combined with the ”average cell” and the performance differences between each cell, an SOC estimate for all cells is generated. Zhou et al. [9] proposed the ”representative battery” method, three battery parameters of SOC_{max}, SOC_{min} and C_{min} are selected to characterize the overall battery performance.

In the paper, the inconsistency of SOC estimation is studied in the light of mean-difference model. Thevenin model is used to characterize the average battery pack characteristics, and rint model that takes the assumption of SOC and internal resistance difference into account, is used to simulate the difference nature between batteries. Then FFRLS and UKF are applied to parameter identification and SOC estimation of mean-difference model respectively. The battery packs containing different SOC single cells were constructed for experimental verification. The final results show that mean-different model and SOC estimation strategy are accurate enough.

The rest of the article is organized as follows. Section 2 elaborates thevenin model as MM and rint model as DM. Then, FFRLS is used to identify the parameters of mean difference model. The UKF is used to estimate the average battery SOC and characterize the inconsistency of the SOC of each single cell in Section 3. Section 4 introduces the experimental scheme and shows experimental results and discussion. Section 5 concludes with a conclusion in the end.

II. Battery pack model considering battery inconsistency

A. The mean-model

Accurate SOC estimation depend on that accurate battery model which is capable of representing battery dynamic characteristics. The equivalent circuit model of the battery contains rint model, thevenin model and dual polarization model. The rint model is simple and cannot reflect the charging and discharging characteristics of the battery, so the precision is low. The dual-polarization model is more precise, but more parameters and higher dimensional matrices increase the computational load. In the equivalent circuit model, blindly increasing the RC order is not proportional to the accuracy of the model, while the thevenin model has precision and low complexity Superiority [10]. Therefore, the thevenin model is used as mean model, as shown in Fig 1. In mean model, U_{oc} is the open circuit voltage (OCV). There is a Strict corresponding nonlinear properties between OCV and battery SOC in the equilibrium state, so OCV can represent the SOC state accurately. I represents the current that goes by these cells, positive means discharging, negative means charging. R_0 represents the average internal resistance of the Series battery pack. R_D and C_D are polarization resistance and polarization capacitance, represent the polarization behavior of mean model cell. U_{mean} represents the average terminal voltage of the cells of the batteries in series.

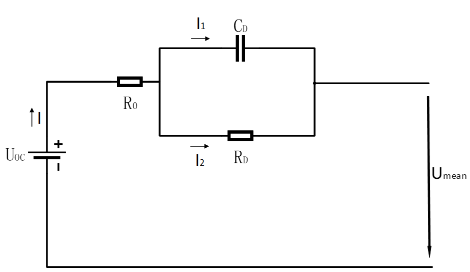

Fig. 1. Thevenin model for MM.

SOC is usually defined numerically as the rate of remaining capacity to battery capacity [11]. This most widely used

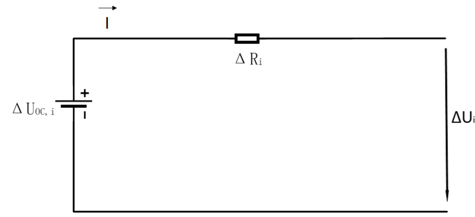

Fig. 2. Rint-model for DM.

algorithm is the ampere-hour integration method in SOC estimation, which is usually used as a reference SOC algorithm in a short time. The equation is as follows:

$$SOC = SOC_{initial} - \frac{\int \eta I dt}{C_n} \tag{1}$$

where $SOC_{initial}$ is the original value of the battery SOC, η is the flat Coulomb efficiency of the battery, and C_n represents the battery capacity.

In order to apply the above equation better, the equation (1) is discretized [12], and the following form is obtained:

$$SOC_{mean,k} = SOC_{mean,k-1} - \frac{\eta I_{k-1} \Delta t}{C_n} \tag{2}$$

where k represents the sampling point, $SOC_{mean,k}$ is the average SOC of the mean model, Δt is the sampling interval. I_{k-1} is the current at time $k-1$.

U_{mean} is expressed by the following formula:

$$U_{mean} = \frac{1}{N}\sum_{i=1}^{N} U_i \tag{3}$$

where i indicates the rank of the single battery, U_i represents the terminal voltage that is measured by the voltage sensor, and N represents the quantity of single battery.

The SOC of single cell and the battery pack have the following relationship:

$$SOC_i = SOC_{mean} + \Delta SOC_i \tag{4}$$

where SOC_i represents the SOC of battery i, ΔSOC_i represents the difference between SOC_i and SOC_{mean}. The calculation of ΔSOC_i will be described in detail by the difference model.

B. The difference-model

Due to the power requirements of electric vehicles and the level limits on battery manufacturing, it is currently necessary to connect plenty of simplicial batteries to satisfy the power and voltage demands for Electric Vehicles. However, because of differences between batteries, such as SOC, internal resistance, polarization capacitor resistance, coulomb efficiency, capacity, etc, the more detailed the difference model is considered, the more accurate the battery pack model is. In the cause of balancing the computational complexity and the precision of the battery pack model, this paper focuses on two factors when constructing the difference model, SOC and internal resistance.

As shown in Fig 2, it is the rint model that considers two factors namely SOC differences and internal resistance differences, which can effectively represent the inconsistency of battery SOC estimation on account of battery internal resistance. In Fig 2, ΔR_i is the internal resistance difference of battery i, $\Delta U_{OC,i}$ is the OCV difference of battery i, ΔU_i is the terminal voltage difference of battery i. ΔU_i can be defined as:

$$\Delta U_i = U_i - U_{mean} \tag{5}$$

The ohmic characteristic of the DM is indicated as:

$$\Delta U_i = \Delta U_{OC,i}(\Delta SOC_i) - I\Delta R_i \tag{6}$$

III. Parameters identification and Estimation algorithm

A. Parameters identification

To perform SOC estimation, the parameters of MM and DM must be identified first. FFRLS is widely used in parameter identification of models because of its simplicity and effectiveness, and has the reliability of practical tests, so it is used in the parameter identification of MM and DM in this paper. FFRLS is based on the principle of minimizing the sum of squares of errors to iteratively update the parameters. The introduction of the forgetting factor is capable of making RLS method reasonably forget the storico information and keep up with the parameter changes faster. For a normal battery, the variation of the internal resistance changes slowly and is capable of being identified.

1) MM parameters identification: In the identification of MM parameters, the current I and the average terminal voltage U_{mean} are used as input parameters. The status variables of the parameter identification are as follows:

$$\Phi_k = [y_{k-1}, I_k, I_{k-1}] \tag{7}$$

$$y_k = U_{oc,k} - U_{mean,k} \tag{8}$$

where $U_{mean,k}$ represents the average battery pack terminal voltage, I_k is the battery pack current, and $U_{oc,k}$ is the average battery pack OCV at time k.

The single-input single-output regression model can be described as follows:

$$y_k = \Phi_k \theta_k + e_k \tag{9}$$

where y_k represents the measurement system output at time k, θ_k and Φ_k represent the parameter matrix and information matrix at time k respectively, e_k represents zero-mean stochastic noise at time k.

The following FFRLS procedure is performed:

$$\begin{cases} K_k = \dfrac{P_{k-1}\Phi_k^T}{\Phi_k P_{k-1}\Phi_k^T + \mu} \\ \theta_k = \theta_{k-1} + K_k[y_k - \Phi_k\theta_{k-1}] \\ P_k = \dfrac{1}{\mu}[P_{k-1} - K_k\theta_k P_{k-1}] \end{cases} \tag{10}$$

where K_k is the algorithm gain, P_k represents the covariance matrix, μ represents the forgetting factor.

Then, the MM parameter identification results are presented in the Table I.

TABLE I
The identified results of FFRLS for MM.

Battery pack	***Paramete***	***Value***
	R_0	1.25e-02
	R_1	3.4e-03
	τ_1	3.586

TABLE II
The identified results of FFRLS for DM.

Battery number	***Paramete***	***Value***
1	$\triangle R_0$	-1.1037e-02
2	$\triangle R_0$	-1.1045e-02
3	$\triangle R_0$	-1.1060e-02
4	$\triangle R_0$	-1.0967e-02
5	$\triangle R_0$	-1.1062e-02
6	$\triangle R_0$	-1.1057e-02
7	$\triangle R_0$	-1.1046e-02
8	$\triangle R_0$	-1.0644e-02

2) DM parameters identification: Similar to MM, for the parameter identification of DM, the battery pack current I and SOC_{mean} obtained from the battery pack MM are used as input parameters. The state variables of parameter identification are as follows:

$$\Phi_{k,i} = [y_{k-1,i}, I_k] \tag{11}$$

$$y_{k,i} = \triangle U_{oc,k,i} - \triangle U_{k,i} \tag{12}$$

where $\triangle U_{oc,k,i}$ represents the OCV difference, $\triangle U_{k,i}$ is the terminal voltage difference, $\Phi_{k,i}$ is the information matrix.

Then, the DM model parameters are identified using (9) and (10).

Similarly, the Parameter identification results of DM are presented in the Table II.

B. Estimation algorithm

Under the condition of having an accurate and appropriate model, there should also be an effective algorithm to realize the exact battery SOC estimation, which could be applied to engineering. EKF transforms nonlinear problems into linear problems through Taylor formula, then applies the KF to solve them. UKF obtains the mean and variance by directly finding a Gaussian distribution that approximates the true distribution. Since lithium-ion battery belong to strong nonlinear systems, so using UKF to estimate the battery SOC will theoretically have better results. The specific process of UKF is presented in Fig 3.

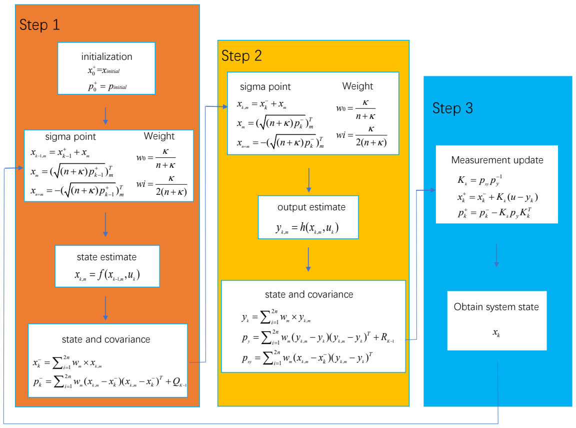

Fig. 3. The operation mechanism of the UKF algorithm.

1) SOC estimation algorithm based on MM: The I and U_{mean} are used as the system input and system output respectively, and this model formula is linearized. The state vector of the UKF and the system input are expressed as:

$$x = [SOC_{mean}, U_D] \tag{13}$$

$$u = I \tag{14}$$

The UKF state space equation is expressed as:

$$x_{k+1} = f(x_k, u_k) + w_k \tag{15}$$

$$y_k = g(x_k, u_k) + v_k \tag{16}$$

The system equations and measurement equations are expressed as follows:

$$\begin{aligned} f(x_k, u_k) = &\begin{bmatrix} 1 & 0 \\ 0 & exp(\frac{-\Delta t}{\tau_D}) \end{bmatrix} \times \begin{bmatrix} SOC_{mean} \\ U_{D,k} \end{bmatrix} \\ &+ \begin{bmatrix} \frac{-\eta \Delta t}{C_n} \\ R_D(1 - exp(\frac{-\Delta t}{\tau_D})) \end{bmatrix} \times I_k \end{aligned} \tag{17}$$

$$g(x_k, u_k) = U_{oc,k} - I_k R_0 - U_{D,k} \tag{18}$$

where w_k and v_k are the process and measurement white Gaussian noise of the time period t_k respectively.

Differentiating $f(x_k, u_k)$ and $g(x_k, u_k)$ respectively with respect to x_k, then leting $x_k = x_k^+$ and $x_k = x_k^-$ respectively, getting A_k and C_k as follows:

$$A_k = \frac{\partial f}{\partial x}|_{x_k = x_k^+} = \begin{bmatrix} 1 & 0 \\ 0 & exp(\frac{-\Delta t}{\tau_D}) \end{bmatrix} \tag{19}$$

$$C_k = \frac{\partial g}{\partial x}|_{x_k = x_k^-} = \begin{bmatrix} \frac{\partial U_{oc}(SOC)}{\partial SOC}|_{SOC = SOC_{mean,k}^-} & -1 \end{bmatrix} \tag{20}$$

2) SOC estimation algorithm based on DM: For DM, the input parameters contain the battery pack current I measured by the sensor and SOC_{mean} obtained by the MM. The output parameter is the battery cell terminal voltage difference $\triangle U_i$. So the DM state variables and state equations are defined as:

$$x_i = \triangle SOC_i \tag{21}$$

$$x_{i,j+1} = f(x_{i,j}, u_j) + w_{i,j} \tag{22}$$

$$y_{i,j} = g(x_{i,j}, u_j) + v_{i,j} \tag{23}$$

$$f(x_{i,j}, u_j) = \triangle SOC_{i,j} \tag{24}$$

$$g(x_{i,j}, u_j) = \triangle U_{OC,i,j}(\triangle SOC_{i,j}) - I_j \triangle R_i \tag{25}$$

where $\triangle SOC_{i,j}$ represents the OCV difference when the battery i is in a balanced state at point j, positive means $SOC_{i,j}$ is greater than SOC_{mean}, negative means $SOC_{i,j}$ is less than SOC_{mean}.

As MM, taking the derivative of $g(x_{i,j}, u_j)$ with respect to $x_{i,j}^-$, we get:

$$C_{i,j} = \frac{\partial g}{\partial x}|_{x_{i,j} = x_{i,j}^-} = \frac{\mathrm{d} \triangle U_{OC,i}(\triangle SOC_i)}{\mathrm{d} \triangle SOC_i}|_{\triangle SOC_i = \triangle SOC_{i,j}^-} \tag{26}$$

IV. Experimental validation and Discussion

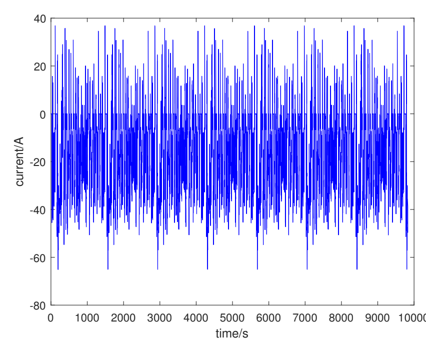

Fig. 4. UDDS current curve diagram.

For the sake of validating the effectiveness and feasibility of MDM and battery SOC estimation strategy, a rigorous experimental process is carried out in a series battery pack. The inconsistency between individual cells are constructed, and the effectiveness of UKF algorithm is validated under dynamic conditions.

In this paper, experiments are carried out on a battery pack consisting of eight individual cells in series. The capacity measurement and the Hybrid Pulse Power Characteristic (HPPC) measurement condition are performed on each cell prior to the experiment. The Rated capacity of each cell is 43Ah, the charge and discharge cut-off voltages are 4.2V and 3V respectively. Under normal internal and external conditions, the SOC inconsistency of the single battery selected for the same electric vehicle will not be too different. So the specific operation plan is to release the energy of 5% SOC of the fifth battery first, which constitutes the inconsistency of the SOC of the fifth battery and other batteries. At the same time, there are sensors for collecting voltage, current and temperature in the whole experiment process. Through the experimental set up, the performance of the proposed way is verified. For purpose of making the SOC estimation operating results more realistic, the Urban Dynamometer Driving Schedule (UDDS) working conditions are used for simulating vehicle operating environment. This UDDS operating current is shown in Fig 4.

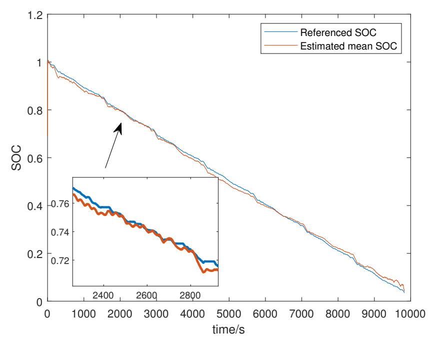

Fig. 5. Estimated average SOC and referenced SOC.

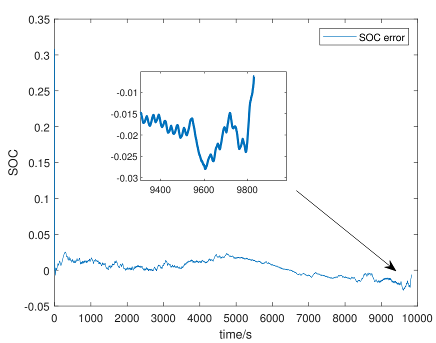

Fig. 6. Estimated mean SOC error.

In this experimental test, the ARBIN BT-MP tester can be applied, and its voltage and current sampling accuracy is about ±0.05%. This test is carried out under the control of a thermal chamber with a stationary temperature of 25 °C. On the other hand, if an exact original value can be provided, the SOC obtained by the ampere integration method is precise enough in a short period of time.

A. SOC estimation result based on mean model

The mean battery SOC is shown in the Fig 5. It is mainly composed of two parts, namely, the SOC of mean model and the reference to obtain average SOC through the ampere-hour integral way. The Fig 6 is the difference between the SOC reference and the SOC estimated value obtained by employing UKF. It is capable of being confirmed from the Fig 6 that SOC_{mean} maximum estimation error is within range of 2.76%. The consequences can indicate that SOC_{mean} estimation on the basis of the mean model and UKF algorithm can be precise enough.

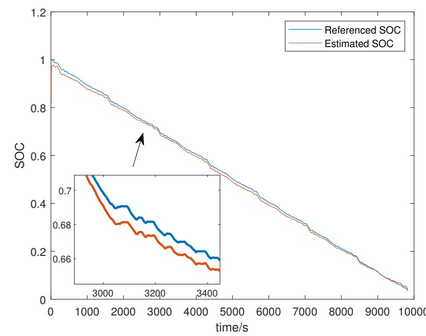

Fig. 7. Estimated SOC and referenced SOC.

B. SOC estimation result based on mean-different model

After using the DM and UKF to attain each single cell $\triangle SOC$, SOC_{mean} and $\triangle SOC$ of the battery are calculated as follows:

$$SOC = SOC_{mean} + (\frac{n-1}{n} \triangle SOC_{normal} - \frac{1}{n} \triangle SOC_{abnormal}) \tag{27}$$

where, SOC represents the SOC obtained by the mean difference model, SOC_{mean} is the battery SOC estimated in the MM, $\triangle SOC_{normal}$ is the $\triangle SOC$ of normal single cell, $\triangle SOC_{abnormal}$ is the $\triangle SOC$ of abnormal single cell discharged in advance, n represents the number of experimental batteries.

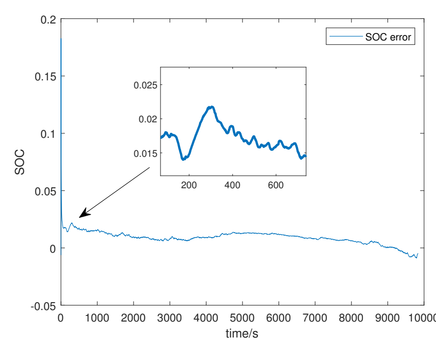

Fig. 8. Estimated SOC error.

As shown in the Fig 7, the curves represent the estimated the sum of mean SOC_{mean} and $\triangle SOC$ and the referenced SOC. In Fig 8, It is in a position to be confirmed that SOC maximum estimation error reaches 2.17% by employing UKF in the mean difference model. Compared with the SOC estimation result of only the mean model, the SOC maximum estimation error can be reduced by 0.59%. It shows that this SOC estimation strategy on account of the mean difference model can effectually decrease the maximum estimation error.

V. Conclusions

The inconsistency of SOC will seriously affect the safety, charge and discharge capacity and working life of the battery. The article adopts the mean-different model and UKF estimation method for battery pack inconsistency. An 8-string batteries is constructed to verify the battery inconsistency. The thevenin model that equilibrates model precision and computational complexity is chosen as the mean model, and the rint model can be chosen to characterize the inconsistency of battery pack. Then, the least squares method with forgetting factor is applied to recognising the parameters of MDM, in the meantime UKF is applied to estimating the SOC of battery pack. In this SOC estimation strategy, the estimated $\triangle SOC$ is divided into two categories: normal and abnormal, and weights are added according to the ratio of the number of normal or abnormal batteries to the total number of batteries. Then SOC_{mean} is added to obtain the final SOC estimation result. SOC estimation with the battery pack has a maximum error of 2.17%. The consequences indicate that this SOC estimation strategy is capable of evaluating the battery inconsistency well and estimating the SOC very accurately.

However, due to fewer batteries and less battery inconsistency classification in this experimental verification, how to more accurately characterize battery inconsistencies and how to reasonably add $\triangle SOC$ describing battery inconsistency to SOC_{mean} requires further research and experimental verification.

Acknowledgment

This work is supported by the National Natural Science Foundation of China (U1864205, 61633015), and the Key Technology Research and Development Program of Shandong Province (No.2019JZZY020814).

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