Analysis on the Influence of Measurement Precision of the Battery Management System on the State of Charge Estimation

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***Abstract*—The error sources of state of charge (SOC) estimation algorithm on the basis of Kalman filter is analyzed in this paper. Aiming at the influence of the measuring precision of voltage and current in battery management system (BMS) to SOC estimation, a simulation analysis is performed independently in Simulink on the assumption that other factors are under ideal conditions, in which the effects of Gaussian white noise and the offset error of measurement of BMS are discussed respectively to simulate the actual vehicle condition. The principle to the precision index design of BMS is proposed according to the simulation result. At last, a high-precision data acquisition system is developed as a precise calibration benchmark device for BMS.**

Keywords-state of charge estimation; battery management system; precision simulation;

I. INTRODUCTION

As the main component of Hybrid Electric Vehicle (HEV), power battery is essential to the performance of the whole power system. In order to understand the battery performance and ensure the implementation of control strategy, battery management system (BMS) is introduced to supervise the battery package, and to BMS, its ability to accurately estimate and report the state of charge (SOC) is the key technology.

Batteries in HEV work in diversified driving cycle, being subjected to both large dynamic transients in current and power demand over a wide temperature range. In order to forecast SOC accurately under such arduous conditions, the estimation algorithm based on Kalman filter is used and proved to be effective from the testing results.

Error of the estimation algorithm above is influenced by several aspects, including the time-variance of the battery, the non-linear characteristics of the battery model, some assumption of the noise and the measurement error of BMS. The error problem cased by the former three aspects can be solved by improvement of the algorithm [1]. This paper focuses on how the measurement precision of BMS influences SOC estimation and the analysis result provides a principle to the hardware index design of BMS.

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II. SOC ESTIMATION ALGORITHM

A. Equivalent Physical Model

Battery states monitoring is realized through an integrated solution which recruits the Kalman filter to estimate SOC and is based on an equivalent circuit model as shown in Fig. 1, where R_0 represents the internal ohmic resistance and C_E represents the open circuit voltage of the battery pack. The R_1C_1 and R_2C_2 circuits simulate the delay of the battery terminal voltage caused by the polarization and other factors. C_E here is not a pure capacitor, instead, it is to decide the OCV of the pack according to the relationship between SOC and open circuit voltage (OCV) as shown in Fig. 2, which also shows that this relationship is nonlinear. I(t) and U(t) are the current and the terminal voltage of the battery pack at time t respectively[2].

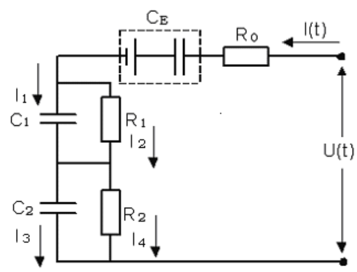

Figure 1. Equivalent physical model of battery pack

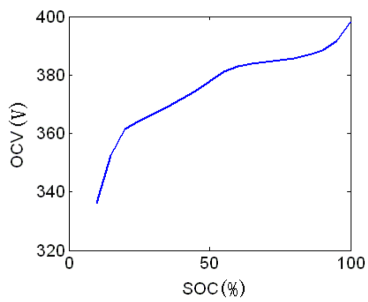

Figure 2. Relationship between SOC and OCV

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The state equation and output equation of the model above in discrete space could be described as:

$$\begin{pmatrix} SOC_{k+1} \\ U_{k+1}^{R_1C_1} \\ U_{k+1}^{R_2C_2} \end{pmatrix} = \begin{pmatrix} 1 & 0 & 0 \\ 0 & \exp(-\Delta t/\tau_1) & 0 \\ 0 & 0 & \exp(-\Delta t/\tau_2) \end{pmatrix} \times \begin{pmatrix} SOC_k \\ U_k^{R_1C_1} \\ U_k^{R_2C_2} \end{pmatrix} + \begin{pmatrix} -\frac{\eta_i \Delta t}{C} \\ R_1(1-\exp(-\Delta t/\tau_1)) \\ R_2(1-\exp(-\Delta t/\tau_2)) \end{pmatrix} i_k + w_k \quad (1)$$

$$U_k = OCV(SOC_k) - i_k R_0 - U_k^{R_1C_1} - U_k^{R_2C_2} + v_k \quad (2)$$

Here $U_{k+1}^{R_1C_1}$ and $U_{k+1}^{R_2C_2}$ denote respectively the voltage of the R_1C_1 and R_2C_2 circuits. Δt is the sample period of BMS. τ_1 and τ_2 are the time constants of the R_1C_1 and R_2C_2 circuits respectively. i_k is the current of the time step k while C the capacity of the battery. η_i means the coulomb coefficient. $OCV(SOC_k)$ represents the one to one correspondence between SOC and OCV.

In the above two formulas, w_k and v_k are system noise which is not related with each other. In general, they come from the error caused by sensor, system modeling and inaccurate system parameters, let $\sum_w$ and $\sum_v$ be their variance respectively. The two parameters in the algorithm are closely related to the noise of hardware and environment, which will be discussed in part III.

B. Algorithm Principle

Here we define the parameters x_k as:

$$x_k = [SOC_k \; U_k^{R_1C_1} \; U_k^{R_2C_2}]^T \quad (3)$$

The discrete non-linear system model is described as below:

$$x_{k+1} = f(x_k, u_k) + w_k \quad (4)$$

$$y_k = g(x_k, u_k) + v_k \quad (5)$$

Combining the equations (1) to (5), we define A_k and C_k in the following formulas when estimating SOC.

$$A_k = \left.\frac{\partial f}{\partial x}\right|_{x_k = \hat{x}_k^+} = \begin{pmatrix} 1 & 0 & 0 \\ 0 & e^{-\Delta t/\tau_1} & 0 \\ 0 & 0 & e^{-\Delta t/\tau_2} \end{pmatrix} \quad (6)$$

$$C_k = \left.\frac{\partial g}{\partial x}\right|_{x_k = \hat{x}_k^-} = \begin{pmatrix} \left.\frac{\mathrm{d}(OCV)}{\mathrm{d}(SOC)}\right|_{soc = soc_k^-} & -1 & -1 \end{pmatrix} \quad (7)$$

As a internal state of the system model, SOC could be estimated directly from the algorithm process based on kalman filter which is listed in the following formulas, here I and E() denote Unit Matrix and Mathematical Expectation respectively.

Initialization:

$$k = 0 \quad \hat{x}_0^+ = \mathrm{E}(x_0) \quad \Sigma_{x_0}^+ = \mathrm{E}[(x_0 - \hat{x}_0^+)(x_0 - \hat{x}_0^+)^T]$$

$$\Sigma_w = \mathrm{E}(w \times w^T) \quad \Sigma_v = \mathrm{E}(v \times v^T)$$

Recursive calculation:

$$\hat{x}_k^- = f(\hat{x}_{k-1}^+, u_{k-1})$$

$$\Sigma_{x_k}^- = \hat{A}_{k-1} \Sigma_{x_k}^+ \hat{A}_{k-1}^T + \Sigma_w$$

$$L_k = \Sigma_{x_k}^- \hat{C}_k^T (\hat{C}_k \Sigma_{x_k}^- \hat{C}_k^T + \Sigma_v)^{-1}$$

$$\hat{x}_k^+ = \hat{x}_k^- + L_k[y_k - g(\hat{x}_k^-, u_k)]$$

$$\Sigma_{x_k}^+ = (I - L_k \hat{C}_k)\Sigma_{x_k}^-$$

III. ERROR SOURCES OF SOC ESTIMATION

The SOC estimation algorithm basing on Kalman filter is validated to be effective and could reach high estimation accuracy from the theory analysis and testing results [3]. However, the inherent shortcomings (assumption) of its realization foundation result in some error to SOC, which include the time-variance and the non-linear characteristics of the battery model, some assumption of the noise and the measurement error of BMS.

Time-variance of the battery refers to the variation during its using process while non-linear characteristic of the battery model is mainly due to the non-linear relationship between SOC and OCV. The improvement of the algorithm aiming to solve the two problems above are the algorithms respectively called dual extened Kalman filter (DEKF), which has the functions of online parameter identification and unscented Kalman filter (UKF)[4]. The model noise and measuring noise are assumed to be Gaussian white noise with independent identical distribution in the Kalman filter algorithm, while the actual situation of these assumptions may be difficult to set up, this could be improved by Particle Filter Algorithm according to [5].

As the data source of the algorithm, the current and voltage measuring result greatly contribute to the accuracy of SOC estimation. The impact of current accuracy is reflected in the state prediction step while the voltage accuracy in state updating step, which are shown respectively in the expressions of $\hat{x}_k^-$ and L_k in the recursive calculation. When the measurement error of voltage increases (that is Σ_v increases), its regulative action to SOC prediction in state updating step will decreases because of the decline of regulative weight of voltage signal, and then, SOC estimation will depends on current integration to a great extent, obviously its accuracy will decrease with the time.

IV. SIMULATION ANALYSIS ON THE INFLUENCE OF MEASURING PRICISION TO SOC

Though the measuring precision of BMS is not the problem of the estimation algorithm itself, it is a non-negligible realistic factor which has great influence to SOC result. Therefore, here we focus on this circumstance and simulate it independently on the assumption that other factors are under ideal condition, and then, the reasonable precision index of BMS is proposed according to the simulation.

A. Simulation Process

The mathematical model is established in Simulink on the basis of the transfer function drawn through the equivalent physical model of the battery pack in Fig. 1 and the relative parameters used in the model are obtained from the identification result basing on the measuring data of the battery [2]. The SOC estimation procedure is shown in Fig. 3, in which the voltage response is the output signal by inputting the typical exciting current into the model. The corresponding current and voltage signal are the initial data to the algorithm and the current integration result is considered as the true value of SOC-SOCreal. Superimposing the random noise of different grades on the input current and voltage signals gotten above respectively to simulate the real measuring situations of BMS and taking the two signals with noise as input of SOC estimation algorithm embedded into S-function in Simulink, we can obtain the estimated SOC result SOCesti. Thus, the influence of measuring precision of BMS on SOC estimation is analyzed basing on simulation method by comparing SOCesti with SOCreal.

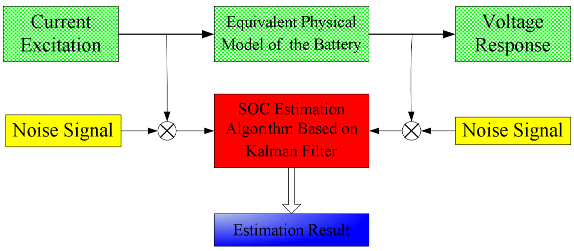

Figure 3. SOC estimation procedure

B. Simulation of Setting Current Excitation

In order to propose the measuring index of BMS in general condition, the simulation is taken under both the setting and real vehicle current excitation in the following B and C parts. The initial setting current excitation and the corresponding voltage response are shown in Fig. 4, and then, they are added respectively by the Gaussian white noise with mean of zero and variance of different grades. Here the variance sequence is obtained from the empirical Data.

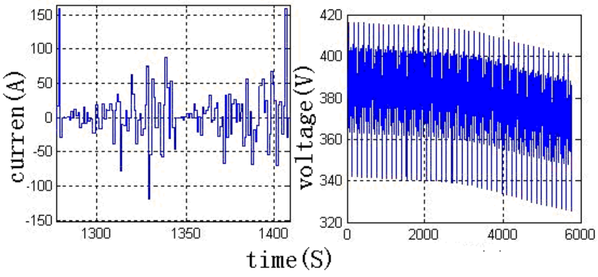

Figure 4. Current and voltage signals

Firstly, we fix the variance of the voltage and change the variance of the current in sequence, and then exchange the order. The results are shown respectively in Fig. 5 and Fig. 6, here socb is the real SOC through the current integration while soc004 to soc9 mean SOC results in the current variance sequence of 0.04 to 9. It is similar to the definition of the latter parameters.

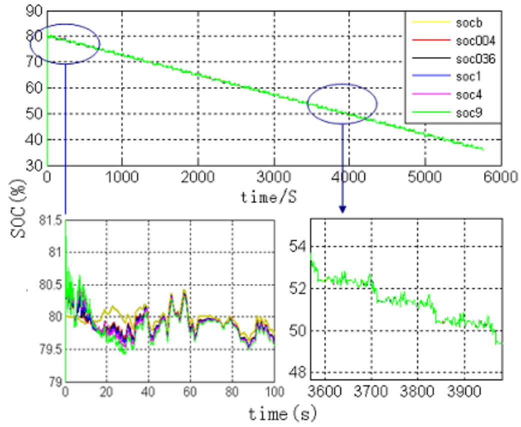

Figure 5. SOC curves of different current noise variance

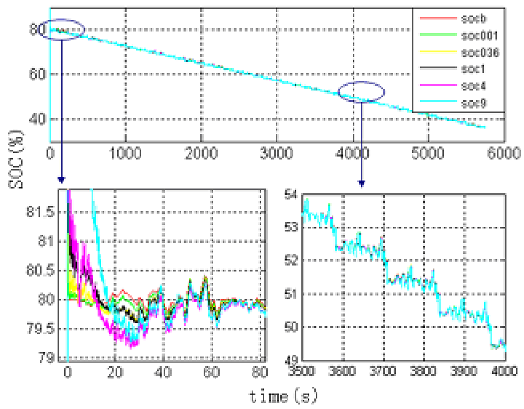

Figure 6. SOC curves of different voltage noise variance

From the two figures above we can see that the current and voltage noises which are presented as the Gaussian white noise with mean of zero and variance of different grades only affect the initial value and convergence speed of SOC. They do not influence the whole SOC estimation result and do not bring additional error.

The input noise is assumed to be white noise with mean of zero, but in practical situations, the measuring results also include certain offset error. The impacts of offset error of the current and voltage are simulated and the results are respectively shown in Fig. 7 and Fig. 8. Here socb is the real SOC through the current integration while soc-x means SOC result with the corresponding current or voltage offset error x.

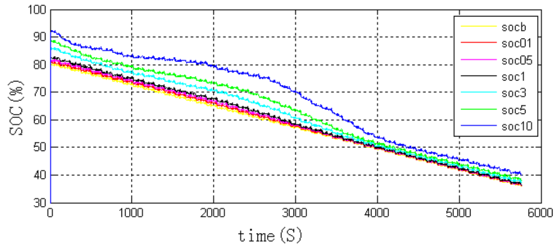

Figure 7. SOC curves of different current offset error

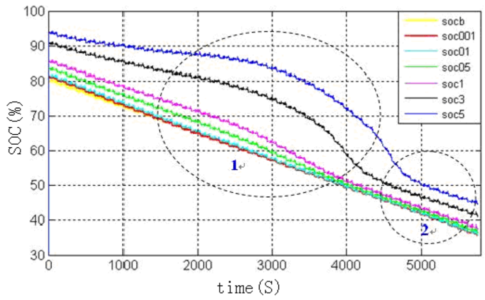

Figure 8. SOC curves of different voltage offset error

As shown in Fig. 7, the accuracy of SOC decreases with the increase of the current offset error. When the SOC error reaches to a certain degree by error accumulation of current integration along with time, it tends to converge because of the regulative effect of voltage.

Just due to this regulative effect of voltage in state prediction step, the offset error of the voltage will bring an error to the whole range of SOC but affect differently in different SOC range as shown in Fig. 8. According to Fig. 2, SOC-OCV curve is flat during SOC range of 60% to 80%, thus the little voltage error may result in significant fluctuation to SOC（circle 1 in Fig. 8）. Comparatively, the SOC changes little with voltage error because of the steep SOC-OCV curve under 50% of SOC (circle 2 in Fig. 8).

C. Simulation of real Current Excitation

In order to investigate the effectiveness of the simulation result in real vehicle condition, here we select the typical China city driving cycle as input of the model of HEV, and then, the output current signal of the battery system is taken as the current excitation in the simulation experiment. The simulation process is similar to part B and the current curve under China city driving cycle is shown in Fig. 9. Similar to part B, the variance of the current is changed in sequence when fixing the variance of the voltage, and then exchange the order. The results are shown respectively in sub-figures in Fig. 10.

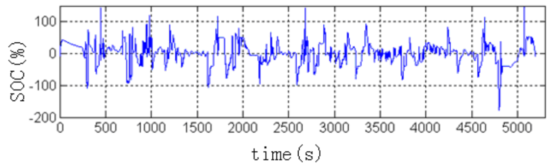

Figure 9. Current excitation of China drivng cycle

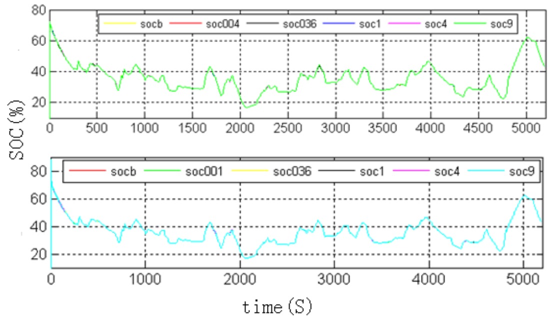

Figure 10. SOC curves of different current and voltage noise variance

The impacts of offset error of the current and voltage measurement under real conditions are simulated and the results are respectively shown in Fig.11 and Fig. 12.

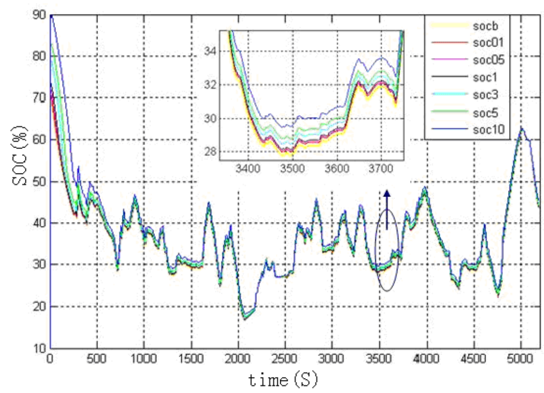

Figure 11. SOC curves of different current offset error

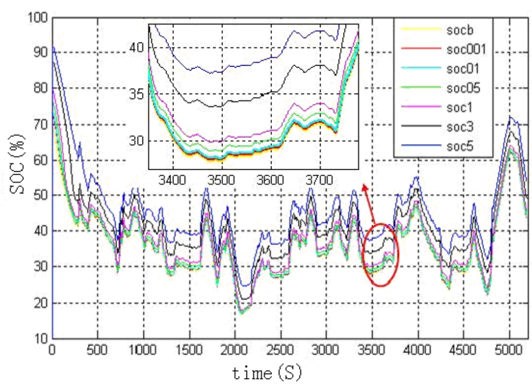

Figure 12. SOC curves of different voltage offset error

The results in Fig. 10 to Fig. 12 are similar to which in part B. It also can be seen that the influence of the measuring error in real vehicle condition is less than that in setting condition to SOC estimation.

D. Conclusion

From the simulation result of the setting and actual driving cycles in part B and C above, we could draw conclusions in general condition as below:

- Gaussian white noise with mean of zero, which is determined by the conversion resolution of A/D in BMS, only affect the initial value and convergence speed of SOC. They do not influence the whole SOC estimation result and do not bring additional error.
- Offset error of the voltage and current, caused by the offset error of measuring channels in BMS will bring an error to the whole range of SOC estimation result.
- Comparing with the precision of the current signal, the SOC result is more easily affected by the measuring error of voltage, thus, it has more necessity to increase the measuring accuracy of the voltage signal, especially during the flat part of SOC-OCV curve.

V. CALIBRATION SYSTEM

According to the simulation result above and in order to

correcting the measuring error of BMS, a high-precision data acquisition system is developed as shown in Fig. 13. Its current dc precision of the whole measuring range can reach 0.05A, while voltage 0.01V and temperature 0.0625℃. Testing result shows that it satisfies the specifications of being a precise calibration benchmark device for BMS [6].

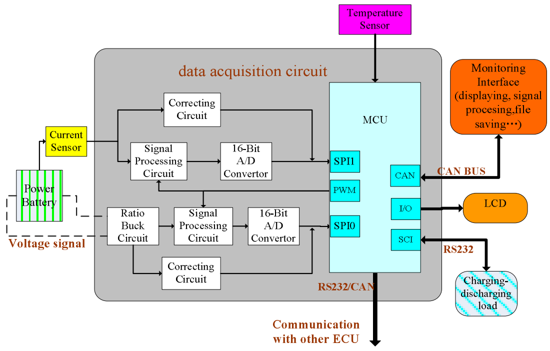

Figure 13. Diagram of system structure

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