Analysis on the Influence of Measurement Error on State of Charge Estimation of LiFePO4 Power Battery

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***Abstract*—The error sources of state of charge(SOC) estimation of li-ion battery based on Kalman filter is analyzed in this paper. To LiFePO4 power battery, the extremely flat part during the normal SOC range of SOC-OCV curve will require strong restriction to the voltage detection especially. This paper aims at the influence of the measuring precision of the voltage and current signal of battery management system (BMS) to SOC estimation of the li-ion battery including LiFePO4 battery. 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 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 analysis result, in addition, a high-precision data acquisition system is developed as a precise calibration benchmark device for BMS.**

Keywords- SOC estimation, LiFePO4 power battery, measuring precision, BMS

I. INTRODUCTION

As the main component of Hybrid Electric Vehicle (HEV), power battery is essential to the performance of the whole power system. Compared to other traditional technologies (e.g. Lead-acid or Ni-MH batteries), Li-ion battery is undoubtedly more advanced for its higher power and energy density, higher efficiency and faster recharge. Especially to LiFePO4, its long cycle life, low cost of raw materials, superior safety characteristics together with the recent advances in their electrochemical performances made it very attractive cathode materials for lithium secondary batteries especially for EV and HEV applications.

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. Besides, the SOC-OCV curve of LiFePO4 power battery exists an extremely flat part during the normal SOC 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 for Li-ion battery including LiFePO4 power battery.

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 of Li-ion battey as shown in Figure. 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 Figure. 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].

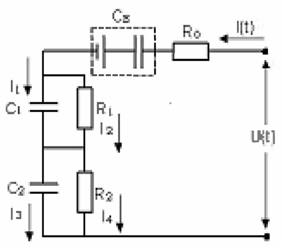

Figure 1. Equivalent physical model of li-ion battery pack

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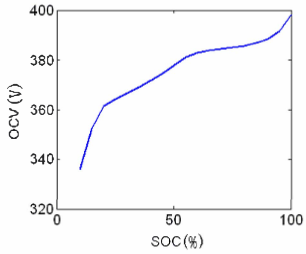


Figure 2. Relationship between SOC and OCV

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

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

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

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 Σ_w and Σ_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 - Error Sources of SOC Estimation.

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.

$$\hat{\boldsymbol{A}}_k = \left.\frac{\partial f(\boldsymbol{x}_k, \boldsymbol{u}_k)}{\partial \boldsymbol{x}_k}\right|_{\boldsymbol{x}_k = \hat{\boldsymbol{x}}_k} = \begin{pmatrix} 1 & 0 & 0 \\ 0 & \exp(-\Delta t/\tau_1) & 0 \\ 0 & 0 & \exp(-\Delta t/\tau_2) \end{pmatrix} \quad (6)$$

$$\hat{\boldsymbol{C}}_k = \left.\frac{\partial g(\boldsymbol{x}_k, \boldsymbol{u}_k)}{\partial \boldsymbol{x}_k}\right|_{\boldsymbol{x}_k = \hat{\boldsymbol{x}}_k} = \left(\mathrm{d}OCV / \mathrm{d}SOC\big|_{\hat{s}oc_k} \;\; -1 \;\; -1 \right) \quad (7)$$

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:

$$k = 0 \qquad \hat{\boldsymbol{x}}_0^+ = \mathrm{E}(\boldsymbol{x}_0) \quad (8)$$

$$\boldsymbol{\Sigma}_{x_0}^+ = \mathrm{E}[(\boldsymbol{x}_0 - \hat{\boldsymbol{x}}_0^+)(\boldsymbol{x}_0 - \hat{\boldsymbol{x}}_0^+)^T] \quad (9)$$

$$\boldsymbol{\Sigma}_w = \mathrm{E}(\boldsymbol{w} \times \boldsymbol{w}^T) \qquad \boldsymbol{\Sigma}_v = \mathrm{E}(\boldsymbol{v} \times \boldsymbol{v}^T) \quad (10)$$

Recursive calculation:

$$\hat{\boldsymbol{x}}_k^- = f(\hat{\boldsymbol{x}}_{k-1}^+, \boldsymbol{u}_{k-1}) \quad (11)$$

$$\boldsymbol{\Sigma}_{x_k}^- = \hat{\boldsymbol{A}}_{k-1} \boldsymbol{\Sigma}_{x_k}^+ \hat{\boldsymbol{A}}_{k-1}^T + \boldsymbol{\Sigma}_w \quad (12)$$

$$\boldsymbol{L}_k = \boldsymbol{\Sigma}_{x_k}^- \hat{\boldsymbol{C}}_k^T (\hat{\boldsymbol{C}}_k \boldsymbol{\Sigma}_{x_k}^- \hat{\boldsymbol{C}}_k^T + \boldsymbol{\Sigma}_v)^{-1} \quad (13)$$

$$\hat{\boldsymbol{x}}_k^+ = \hat{\boldsymbol{x}}_k^- + \boldsymbol{L}_k[\boldsymbol{y}_k - g(\hat{\boldsymbol{x}}_k^-, \boldsymbol{u}_k)] \quad (14)$$

$$\boldsymbol{\Sigma}_{x_k}^+ = (\boldsymbol{I} - \boldsymbol{L}_k \hat{\boldsymbol{C}}_k) \boldsymbol{\Sigma}_{x_k}^- \quad (15)$$

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 $\hat{\boldsymbol{x}}_k^-$ and $\boldsymbol{L}_k$ in the recursive calculation. When the measurement error of voltage increases (that is $\boldsymbol{\Sigma}_v$ 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.

In order to get the general character and different trend of how the measurement precision of BMS influences SOC estimation to Li-ion battery especially to LiFePO4, for comparison, the measuring precision of BMS of LiMn2O4 is taken into account firstly and followed by the simulation of LiFePO4 in the following simulation process.

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 parameter identification result basing on the measuring data of the battery [2]. The SOC estimation procedure is shown in Figure. 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.

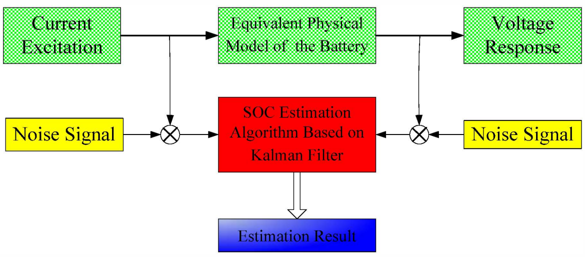


Figure 3. SOC estimation procedure

1) 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 this and the following parts. The initial setting current excitation and the corresponding voltage response are shown in Figure. 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.

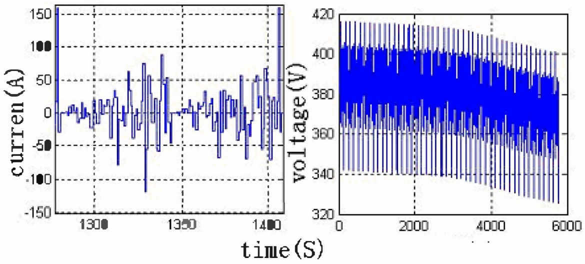


Figure 4. Current and voltage signals

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 Figure. 5, 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.

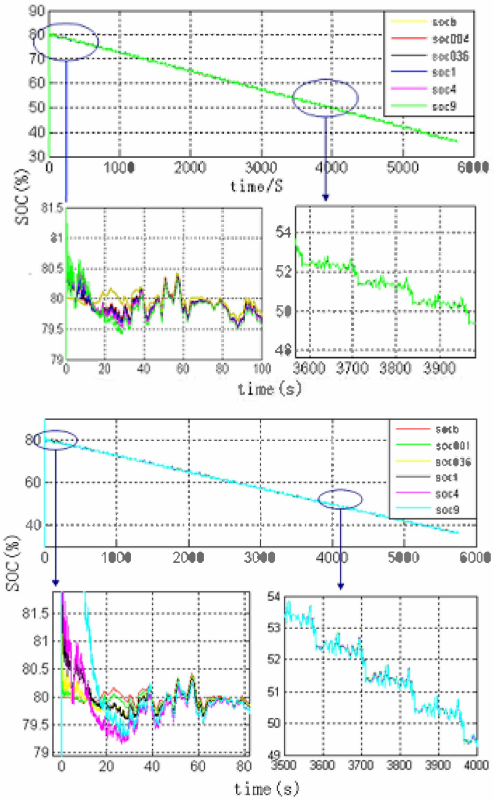


Figure 5. SOC curves of different current(upper) and voltage(nether) noise variance

From Figure 5 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 Figure. 6. 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.

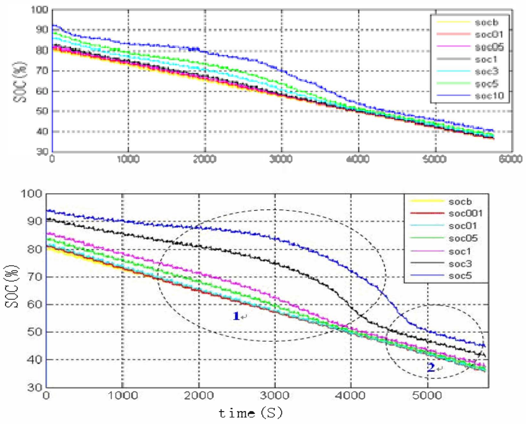


Figure 6. SOC curves of different current(upper) and voltage(nether) offset error

As shown in Fig. 6, 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 Figure. 6. According to Figure. 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 Figure. 6）. Comparatively, the SOC changes little with voltage error because of the steep SOC-OCV curve under 50% of SOC (circle 2 in Figure. 6).

2) 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 the section above and the current curve under China city driving cycle is shown in Figure. 7. Similar to the section above, the variance of the current is changed in sequence when fixing the variance of the voltage, and then exchanges the order. The results are shown respectively in sub-figures in Figure. 8.

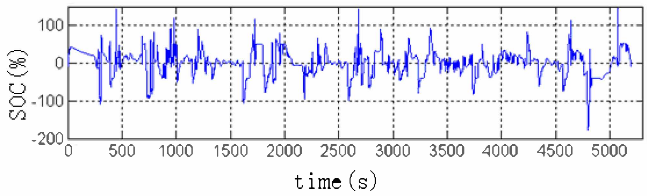


Figure 7. Current excitation of China drivng cycle

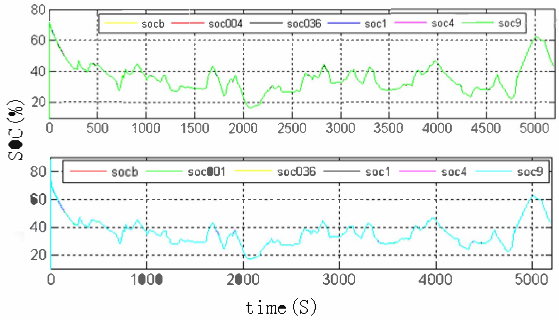


Figure 8. SOC curves of different current and voltage noise variance

The impacts of offset error of the current and voltage measurement under real conditions are simulated and the results are respectively shown in Figure 9.

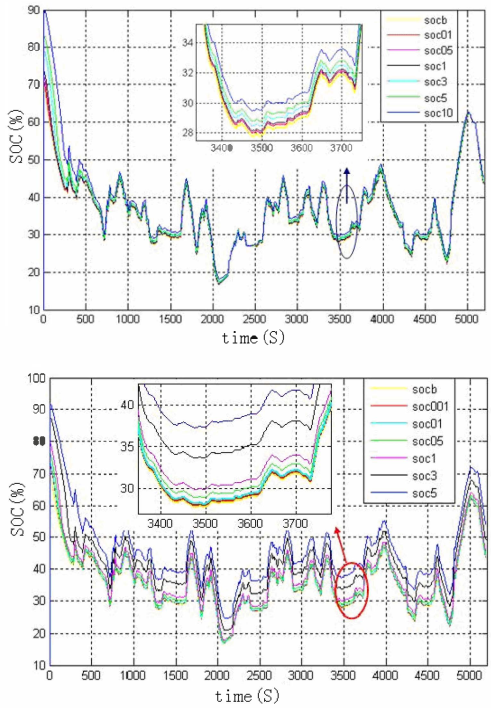


Figure 9. SOC curves of different current(left) and voltage(right) offset error

The results in Figure 9 are similar to the result in the section above. 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.

B. Simulation of $LiMn_2O_4$ Power Battery Pack

As concluded from the previous simulation, the precision of the voltage signal plays a more important role in the estimation of SOC and the voltage measurement error has different effect on the result during different SOC range. In the whole range of the SOC, it will raise an extremely strict demand to the precision of voltage if there exists a very flat part in the SOC-OCV curve. From another point of understanding, useful information obtained from the voltage signal that is the signal to noise ratio of voltage will decrease with increment in voltage measurement error. This will have a great influence on SOC estimation of LiFePO4, whose SOC-OCV curve is flat as shown in Figure. 10. It is obvious that OCV varies slightly versus SOC, thus the voltage measurement error will be possible to hide out the information entirely provided by OCV change.

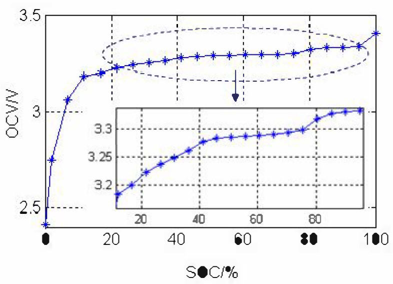


Figure 10. SOC-OCV curve of single cell LiFePO4 battery

Here we take the same simulation process as the simulation of LiMn2O4 battery previously and replace the SOC-OCV curve with the corresponding curve of serial 80 LiFePO4 battery cells. Considering of the Gaussian white noise with mean of zero and offset error of the voltage and current signal, the simulation result are shown in Figure.11 and Figure.12.

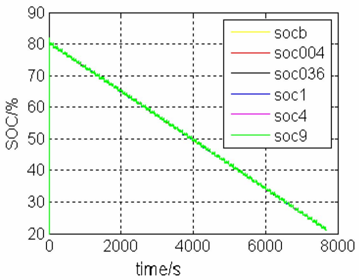
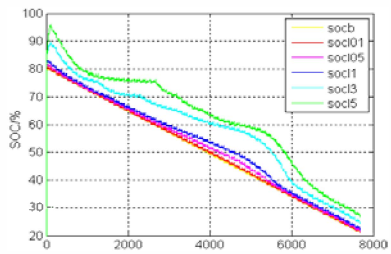


Figure 11. SOC curves of different current noise variance



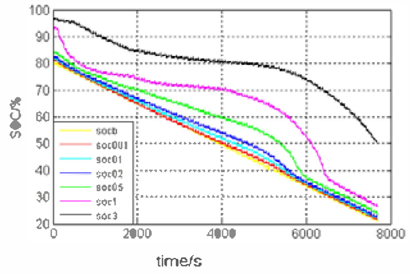


Figure 12. SOC curves of different current(left) and voltage(right) offset error

According to Figure.11, To the BMS of LiFePO4 power battery, the Gaussian white noise with mean of zero has little effect on the SOC estimation result, thus the algorithm has a relatively low requirement to the conversion resolution of A/D and the noise of circuit of current and voltage channels. However, in order to get smaller error of the initial value and convergence speed of SOC during the whole SOC range 0-100%, the conversion resolution of A/D and the noise of circuit of voltage channel must be kept as small as possible.

From Figure.12, we advance that the offset error of the current measurement is less than 0.5A while voltage 0.2V and this will ensure the precision of the SOC result (5%). The influence of the measuring error in real vehicle condition is less than that in setting condition to SOC estimation is also applicable here.

V. CONCLUSIONS

From the comparative simulation result of the LiMn2O4 and LiFePO4 Power Battery Pack in the sections above, we can see that it requires stronger restriction to the voltage detection to BMS of LiFePO4 Power Battery. To the current 380V LiPePO4 power battery system, it is proposed that the offset error of the current detection is less than 0.5A, there is no special requirement to its noise and the conversion resolution of A/D, while to the voltage detection, the offset error is less than 0.2V, and it is necessary to increase the conversion resolution of its A/D and reduce the circuit noise according to this paper. The analysis above provides a principle to the hardware index design of BMS.

We also draw conclusions in general condition to the BMS of Li-ion batteries 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.

VI. CALIBRATION SYSTEM

According to the simulation result above and in order to correct the measuring error of BMS, a high-precision data acquisition system is developed as shown in Figure. 14. 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].

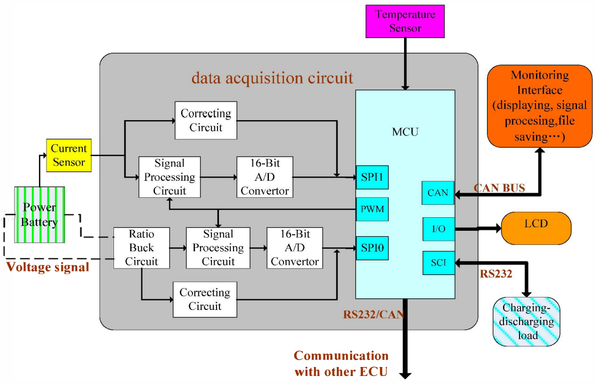


Figure 13. Diagram of calibration system structure

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