Light-weighted Battery State of Charge Estimation based on the Sigma-delta Technique [★]

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Abstract: In this paper, a light-weighted state-of-charge (SoC) estimator is proposed to ensure the estimation accuracy as well as significantly reduce the computational effort. Specifically, the sigma-delta ($\Sigma\Delta$) technique is employed to extract battery SoC under noisy measurements (up to $\pm$ 100mV and 100mA) and validated under different battery aging conditions. Illustrative results demonstrate that in this circumstance, the proposed estimator presents low sensitivity to model accuracy and is also suitable for the non-Gaussian noises. Besides, the second-order $\Sigma\Delta$ estimator is capable of achieving a satisfactory accuracy (RMSEs are all within 1.5% for different aging batteries), while its computational effort is just 15% of that of the extended Kalman filter. These features pave a solution to the design of a light-weighted SoC estimator based on general micro-controller unit, further making the proposed $\Sigma\Delta$ estimator become suitable for improving the reliability and practicability of battery management especially for electrical vehicle applications.

Keywords: Battery management; Electrical vehicle; State of charge estimation; Sigma-delta technique; Light-weighted design;

1. INTRODUCTION

Lithium-ion (Li-ion) batteries have been widely utilized in electrical vehicles (EVs), owing to their superiorities such as high energy density and low self-discharging rate. However, the driving distances of existed EVs are still shorter in comparison with the petrol energy vehicles. The batteries' available energy would gradually decrease during driving operations. All these elements increase the users' anxiety of driving distance, further hindering the wide popularity of EVs. Therefore, to effectively monitor battery remaining energy and available driving distance, a compact but reliable battery management system (BMS) is essential for real EV applications (Liu et al. (2019b)).

Battery state estimation is a preliminary but key function module to improve the practicability of a BMS (Feng et al. (2020b)). As a widely utilized factor to reflect the percentage of the remaining energy/capacity of battery, accurate state of charge (SoC) estimation is of extreme importance in advanced BMS (Dreef et al. (2018); Liu et al. (2019a); Liu et al. (2020)). For EV applications, such state information of battery could not only provide the priori information for driving distance, but also benefit the charging/heating design and energy management (Ouyang et al. (2019b,a); Shang et al. (2019a,b); Liu et al. (2018b, 2016b)), further help to relief the user's anxiety and guarantee EV could work under reliable condition (Fang et al. (2014)).

To date, extensive approaches have been proposed to obtain battery SoC (Hu et al. (2019)). One straightforward solution is the Coulomb counting approach to directly calculate SoC in cases that the battery capacity, initial SoC and current profiles could be precisely captured. However, due to the inevitable measurement noise and the variation of battery capacity under different aging cases, it is generally difficult to online measure these parameters accurately (Liu et al. (2017)). Therefore, the attempt has been made to obtain battery SoC information by other techniques such as battery model and estimator (Lin et al. (2019)).

With the help of developed observers such as extended Kalman filter (EKF) (Tang et al. (2016); Liu et al. (2016a)), unscented Kalman filter (UKF) (He et al. (2016)), particle fileter(PF) (Tang et al. (2019b)), and H-Infinity (Yu et al. (2017)), a large amount of estimators

have been designed to achieve reasonable SoC estimation of battery based on proper models. For these observer-based SoC estimation approaches, the computational effort and memory consuming are key issues to affect their popularity. In general, engineers tend to use the mature products that have been verified to be reliable for several years to implement their design. The general micro-controller unit (MCU) may not be always powerful to support the advanced algorithms such as UKF, PF, ..., for onboard SoC estimation (Hu et al. (2019)). In such case, it is also imperative to design a suitable light-weighted estimator for reducing the computation and memory burdens of MCU especially for real EV applications. However, the existed light-weighted estimators such as the Luenberger observer, proportional-integral (PI) observer, sliding model observer(SMO), V-min EKF (EKF using simple OCV-R models) still present some limitations. For instance, original Luenberger observer would be the most simple model-based observer but the SoC estimation performance is generally poor (Hu et al. (2020)). The improved gain-switching Luenberger observer and PI observer could present better performance but the switching rule and PI parameters are required to be carefully tuned. For the SMO, there would exist inherent chattering problem for real-time SoC estimation (Xu et al. (2014)). For the EKF, the estimation performance still highly relies on the model accuracy and requires the Gaussian noise assumption (Tang et al. (2016)). In light of this, how to design an effective estimator to not only achieve satisfactory estimation accuracy of battery SoC but also present low computational cost is still an open but challenging issue.

Based upon the above discussions, driven by the main purpose to achieve a good trade-off between the estimator's performance and the corresponding computational effort, a light-weighted SoC estimator through employing the sigma-delta ($\Sigma\Delta$) technique is designed in this study. Experimental results demonstrate that the proposed $\Sigma\Delta$-based estimator is able to provide satisfactory SoC estimation performance under different battery aging conditions. In compariosn with the typical EKF, several distinguishing features can be observed as: 1) Even using a simple battery OCV-R model, the proposed $\Sigma\Delta$ estimator could achieve better SoC estimation accuracy under different aging conditions (RMSEs are all within 1.5%), which is enough for general commercial BMS; 2) The computational effort of this $\Sigma\Delta$ estimator is just 15% of that of the EKF; 3) This $\Sigma\Delta$ estimator is an over-sampling based technique, which could be suitable for non-Gaussian cases; 4) The proposed estimator presents good robust and is less sensitive to the model accuracy. These features make the proposed $\Sigma\Delta$-based estimator become a promising candidate to achieve light-weighted battery SoC estimation and enhance the practicability of battery management for EV applications.

2. EXPERIMENTAL PLATFORM AND BATTERY MODELLING

2.1 Experimental Platform

In order to collect suitable experimental data for battery light-weighted SoC estimation test, the battery testing platform with a schematic diagram as shown in Fig. 1 is utilized in this study. This platform is composed of three main components including a thermal chamber to set test temperature, a battery test system to charge or discharge batteries, and a host PC to control and monitor the battery experimental process. More detailed information of this platform can be found in Tang et al. (2019c,a), which are not repeated here due to space limitations.
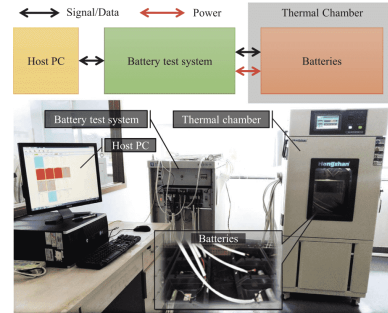

Fig. 1. Schematic diagram of battery experimental platform (Tang et al. (2019c)).

For this test, three SONYVTC5 batteries with a rated capacity of 2.5Ah are utilized. These batteries' capacity present a degradation of 15% after 800 cycles with a constant current-constant voltage (CCCV) charging and constant current (CC) discharging cyclic operation from Tang et al. (2020). To generate different aging states of these batteries, the selected cells are aged with 100, 500, and 800 cycles, respectively. Under the 25°C ambient temperature, the capacities of these three cells (labeled as #1, #2, and #3) are 2.392Ah, 2.168Ah and 2.056Ah, respectively.

After setting the experimental platform, the QC/T 897-2011 A.3 profile has been selected for parameter identification, while the FUDS profile has been adopted to test the SoC estimation performance of the three cells. The corresponding current and voltage profiles are shown in Fig. 2.

2.2 Battery modelling

There exists lots of equivalent circuit models with different levels of accuracy and complexity to capture battery electrical behaviours (Feng et al. (2020a)). To reflect the benefits of our proposed SoC estimator, a simple OCV-R battery model is utilized in this study to describe the battery dynamics as

$$OCV = g(x) = a_0 + a_1 \cdot x + a_2 \cdot x^2 + a_3 \cdot x^3 + a_4 \cdot x_4 \tag{1}$$

$$V_t = f(x, I) = g(x) + I \cdot R \tag{2}$$

where V_t is the battery terminal voltage, x stands for the SoC, R is the resistance, and I is the current, whose value is defined to be positive when charging the cell.

The battery referenced SoC at time k could be obtained by typical Coulomb-counting method as

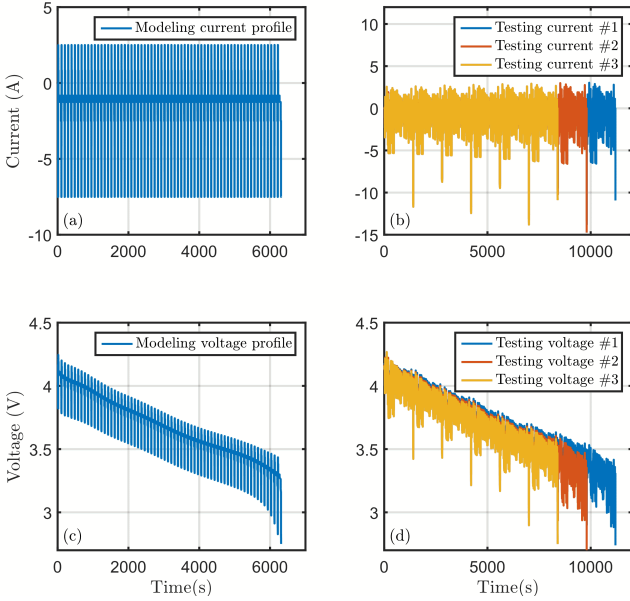$$x_k = x_0 + \sum_{\tau=0}^{\tau=k} \frac{\eta_\tau \cdot I_\tau \cdot \Delta T}{C_n} \tag{3}$$

Fig. 2. Modeling and testing profiles. (a): Modeling current profile of cell#1. (b): Testing current profile of the three cells; (c): Modeling voltage profile of cell#1; (d): Testing voltage profile of the three cells.

where x_0 is the battery initial SoC at time 0, ΔT stands for the sampling interval with the unit of 1 second, C_n represents the battery's actual capacity, and η means the Coulomb efficiency which is treated as 1 in this study.

To identify the parameters of Eq. (1), an offline nonlinear curve fitting tool provided by MATLAB is utilized (Jia-de (2008)). With the load profile suggested by Q/T 897-2011 standard, the identification result of cell #1 is shown in Fig. 3. It can be seen that this battery OCV-R model is able to describe the battery performance with a reasonable accuracy. However, the modeling error would become larger than 100mV when the cell gets close to its fully-discharged state.
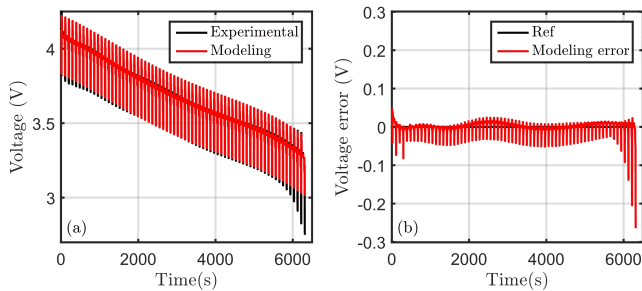

Fig. 3. Model identification result.

3. METHODOLOGY

In this section, the proposed $\Sigma\Delta$-based estimator is detailed, followed by a brief introduction of the benchmarking EKF algorithm. To improve the readability of the paper, the following subsection starts from the description of the first-order $\Sigma\Delta$ estimator.

3.1 Sigma-Delta estimator

$\Sigma\Delta$ technique is a powerful technique to suppress the measurement noise based on the oversampling technique (Dagher et al. (2019)). We first introduce a first-order $\Sigma\Delta$ estimator. The structure of this first-order $\Sigma\Delta$ estimator is illustrated in Fig. 4. It should be noted that the output of the comparator is a binary value (0/1). Consequently, the output of the battery OCV can only be binary. This process is inherently linear. To fully use the nonlinear battery model, a low-pass filter as described in (4) is integrated into the loop. As a result, the input of $f(\cdot, \cdot)$ is no longer binary values.

$$\hat{x}_k = \hat{x}_{k-1} \cdot (1 - \alpha) + x_k \cdot \alpha \qquad (4)$$
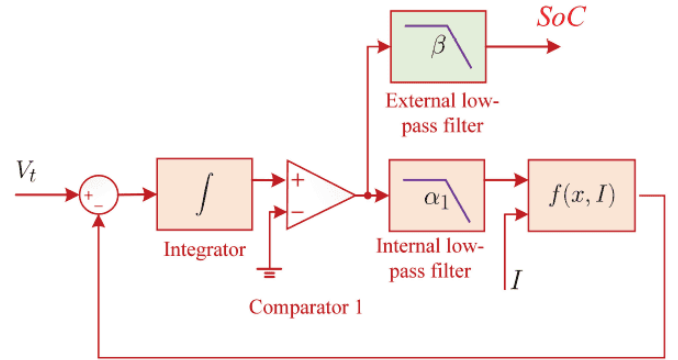

Fig. 4. Structure of the first-order $\Sigma\Delta$ estimator.

Detailed implementation of this first order $\Sigma\Delta$ estimator can be found in Algorithm 1.

Algorithm 1 First order $\Sigma\Delta$ estimator

1: **procedure** $\hat{z}_{1:L} = \text{FOSDE}(V_{t,1:L}, I_{1:L})$
2:     Initialize $\hat{x}_0^1, \hat{z}_0, \alpha_1, \beta, S_0^1$;
3:     **for** $k = 1 : L$ **do**
4:         $\hat{v}_k^1 = f(\hat{x}_{k-1}^1, I_k)$;
5:         $S_k^1 = S_{k-1}^1 + (V_{t,k} - \hat{v}_k^1)$;
6:         **if** $S_k^1 > 0$ **then**
7:             $CM_1 = 1$;
8:         **else**
9:             $CM_1 = 0$;
10:         **end if**
11:         $\hat{x}_k^1 = \hat{x}_{k-1}^1 \cdot (1 - \alpha_1) + CM_1 \cdot \alpha_1$;
12:         $\hat{z}_k = \hat{z}_{k-1} \cdot (1 - \beta) + CM_1 \cdot \beta$;
13:     **end for**
14: **end procedure**

Following the above process, the structure of the second-order $\Sigma\Delta$ estimator for battery SoC estimation can be then derived, which is shown in Fig. 5. Different from the first-order one, another $\Sigma\Delta$ part with an integrator, comparator and low-pass filter is integrated into the structure, further resulting in another feedback path for the voltage from model. Detailed implementation of this second order $\Sigma\Delta$ estimator are illustrated in Algorithm 2.

3.2 Benchmarking algorithm

To evaluate the estimation performance of proposed $\Sigma\Delta$ estimator, a standard EKF with the simple battery OCV-
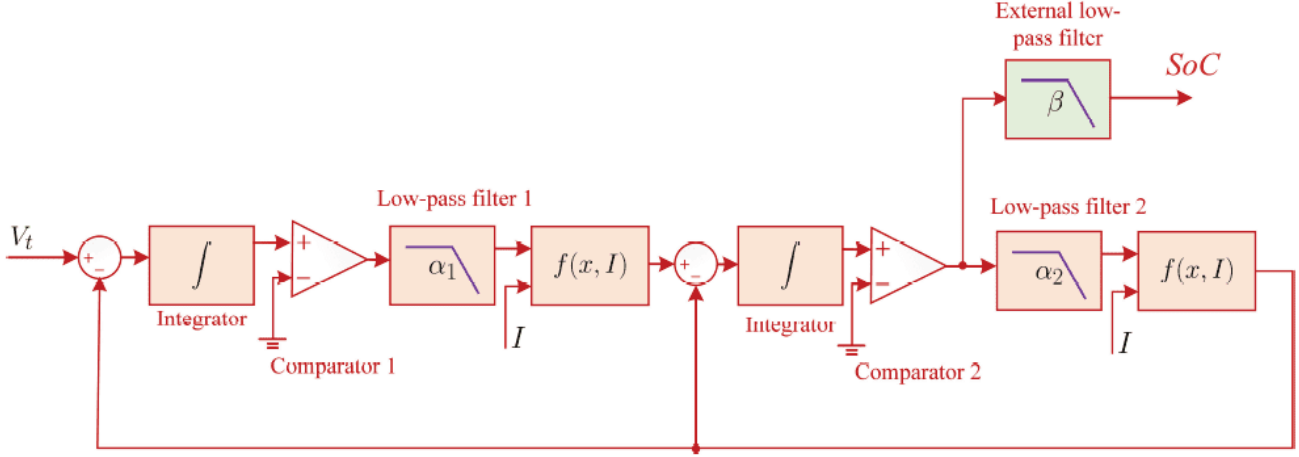
Fig. 5. Structure of the second-order $\Sigma\Delta$ estimator.

Algorithm 2 Second order $\Sigma\Delta$ estimator

1: **procedure** $\hat{z}_{1:L} = \text{SOSDE}(V_{t,1:L}, I_{1:L})$
2:     Initialize $\hat{x}_0^1, \hat{x}_0^2, \hat{z}_0, \alpha_1, \alpha_2, \beta, S_0^1, S_0^2$;
3:     **for** $k = 1 : L$ **do**
4:         $\hat{v}_k^1 = f(\hat{x}_{k-1}^2, I_k)$;
5:         $S_k^1 = S_{k-1}^1 + (V_{t,k} - \hat{v}_k^1)$;
6:         **if** $S_k^1 > 0$ **then**
7:             $CM_1 = 1$
8:         **else**
9:             $CM_1 = 0$
10:         **end if**
11:         $\hat{x}_k^1 = \hat{x}_{k-1}^1 \cdot (1 - \alpha_1) + CM_1 \cdot \alpha_1$;
12:         $\hat{v}_k^2 = f(\hat{x}_k^1, I_k)$;
13:         $S_k^2 = S_{k-1}^2 + (\hat{v}_k^2 - \hat{v}_k^1)$;
14:         **if** $S_k^2 > 0$ **then**
15:             $CM_2 = 1$;
16:         **else**
17:             $CM_2 = 0$;
18:         **end if**
19:         $\hat{x}_k^2 = \hat{x}_{k-1}^2 \cdot (1 - \alpha_2) + CM_2 \cdot \alpha_2$;
20:         $\hat{z}_k = \hat{z}_{k-1} \cdot (1 - \beta) + CM_2 \cdot \beta$;
21:     **end for**
22: **end procedure**

R model is also utilized as the benchmarking algorithm. For paper completenesss, a brief process of EKF is illustrated in Algorithm 3. We suggest the authors to refer to Liu et al. (2018a); Tang et al. (2016) for more details.

Algorithm 3 Extended Kalman filter

1: **procedure** $\hat{z}_{1:L} = \text{EKF}(V_{t,1:L}, I_{1:L})$
2:     Initialize $\mathbf{P}_0, \mathbf{Q}, \mathbf{R}, \mathbf{A}, \mathbf{B}, \mathbf{D}, \hat{z}_0$
3:     **for** $k = 1 : L$ **do**
4:         $z_k^- = \mathbf{A} \cdot \hat{z}_{k-1} + \mathbf{B} \cdot I_k$;
5:         $\mathbf{C}_k = \frac{\partial f}{\partial x}|_{x = z_k^-}$
6:         $\mathbf{P}_k^- = \mathbf{A} \cdot \mathbf{P} \cdot \mathbf{A}^T + \mathbf{Q}$;
7:         $\mathbf{K}_k = \mathbf{P}_k^- \cdot \mathbf{C}_k^T \cdot (\mathbf{C}_k \cdot \mathbf{P}_k^- \cdot \mathbf{C}_k^T + \mathbf{R})^{-1}$;
8:         $z_k = z_k^- + \mathbf{K} \cdot (V_{t,k} - f(z_K^-, I_k))$;
9:         $\mathbf{P}_k = (\mathbf{I} - \mathbf{K}_k \cdot \mathbf{C}) \cdot \mathbf{P}_k^-$;
10:     **end for**
11: **end procedure**

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4. EXPERIMENTAL RESULTS

This section verifies the performance of developed $\Sigma\Delta$ estimator under different battery aging conditions. With the model built on cell #1, the SoC estimators have been tested on all three batteries using an FUDS profile.

For the configurations of the first and second order $\Sigma\Delta$ estimator, the initial SoC is set as 60%, which means $\hat{x}_0^1 = \hat{x}_0^2 = \hat{z}_0 = 0.6$. The filtering factors are set as $\alpha_1 = 0.03$, $\alpha_2 = 0.3$, $\beta = 0.005$, respectively. The initial value of integrator is set as: $S_0^1 = S_0^2 = 0$. For the algorithm comparison purpose, the initial SoC of EKF is also set as 60%. Other key parameters of EKF are initialized as $\mathbf{P} = 0.25$, $\mathbf{Q} = 10^{-4}$, $\mathbf{R} = 25$, respectively. To quantitatively analyse estimators' performance, three common utilized indicators including the root-mean-square error (RMSE [%]), the maximum-absolute error (MAE [%]) and the operating time (OT [ms]) according to Liu et al. (2019) are utilized in our study. It should be known that the RMSE and MAE are calculated from 2000 second to the end of the test. OT is calculated by MATLAB in this study.

After using our developed estimators to estimate battery SOCs, all estimation results are shown in Fig. 6-8, while the corresponding performance indicators are illustrated in Table 1. According to these experimental results, some observations could be made.
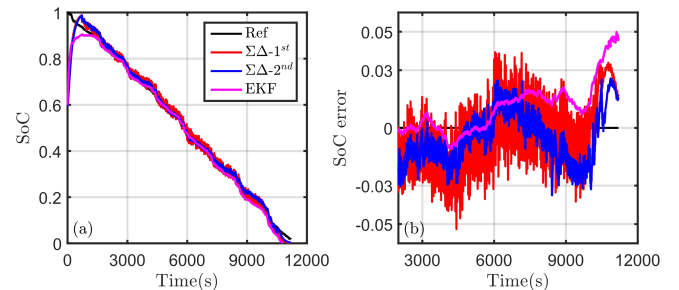

Fig. 6. SoC estimation result of cell #1.

First, although minor chattering problem (about $\pm 1\%$) exists, the RMSE and MAE indicators of the second order $\Sigma\Delta$ observer is competitive to that of the EKF.
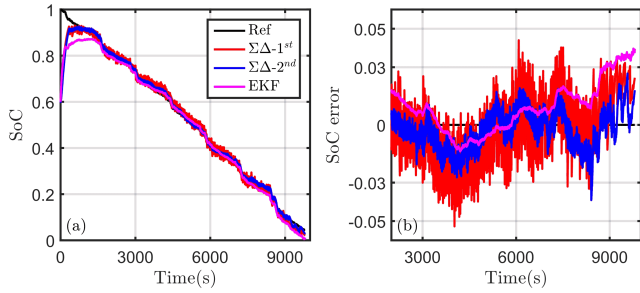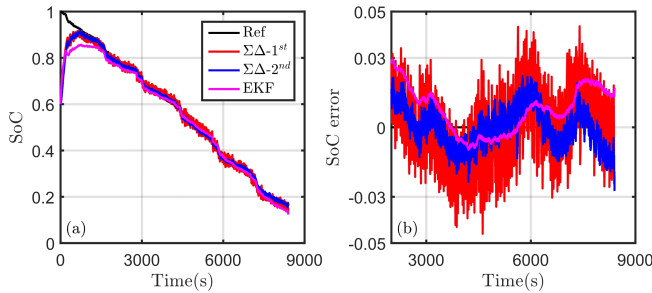
Fig. 7. SoC estimation result of cell #2.

Fig. 8. SoC estimation result of cell #3.

Table 1. Algorithm performance

	#1			#2			#3		
	RMSE	MAE	OT	RMSE	MAE	OT	RMSE	MAE	OT
EKF	1.71	4.99	534	1.57	3.97	486	1.22	2.92	393
$\Sigma\Delta$-1st	1.70	5.27	24	1.66	5.28	24	1.52	4.60	21
$\Sigma\Delta$-2nd	1.41	3.50	55	1.02	3.91	48	0.84	2.75	43

Quantitatively, the operating time of $\Sigma\Delta$ observer is only 15% of that of the EKF. After convergence process, the error of the second order $\Sigma\Delta$ observer could be generally limited to 3%. Here the convergence rates of the proposed $\Sigma\Delta$ observers are also similar to that of the EKF.

Second, by increasing the order of the $\Sigma\Delta$ observer, the noise rejection performance could be significantly improved. However, it should also be noted that the computational effort of second order $\Sigma\Delta$ observer is almost twice as that of the first order. In addition, stabilizing the higher-order $\Sigma\Delta$ observer would be difficult due to the effects of the series-connected integral part.

Third, although the battery model for the proposed $\Sigma\Delta$ observer is built through using the newest cell, it turns out to be that the proposed method can still work well at different battery aging conditions. From Fig. 3, the model accuracy at low SoC is low. However, the SoC error at the end of the test is not significantly increased through using the proposed observers. However, it can be seen from Fig. 6 and 7 that the errors of the EKF algorithm increase to 4% at the end of the test. This fact implies that the proposed $\Sigma\Delta$ observer is less sensitive on model accuracy, which, in turn, indicates the reasonability of using a simple OCV-R model.

5. FURTHER DISCUSSIONS

A light-weighted $\Sigma\Delta$ estimator framework is proposed in this study, which brings the benefits to significantly reduce the computatioanl effort of battery SoC estimation. According to our obtained observations, several further discussions can be made as:

First, the proposed estimator is an over-sampling based technique and does not require the noise to be Gaussian. The noise rejection performance of the proposed technique is highly related to the external low-pass filter. In this article, we only used a simple low-pass filter with the form of (4), leaving room to the further improvement of the algorithm performance.

Second, the $\Sigma\Delta$ technique can be improved to $PI - \Delta$ (Tang et al. (2018)) or other types of nonlinear PID controller, which can further improve the stability of the higher-order observers.

Third, the battery is a highly nonlinear system. However, when calculating the integration, the voltage error obtained at different SoC has the same weight in this study. By using some weighting factors obtained from the gradient of the OCV-SoC curve, the weighted integral of the voltage error is able to stand a chance for improving the algorithm performance.

6. CONCLUSION

Light-weighted SoC estimator is of extreme importance for enhancing the practicability and reliability of battery management. In this paper, a first-order sigma-delta and second-order sigma-delta estimators are proposed for effectively estimating battery SoC under different aging states. With up to $\pm$ 100mV and 100mA measurement noises, the proposed estimator presents low sensitivity to model accuracy. Illustrative results show that the second-order sigma-delta estimator could achieve satisfactory accuracy with no more than 1.5% of RMSE for various aging batteries. The most distinguishing feature is that the computational effort of this type of estimator is just 15% of that of the EKF. This competitive performance make the proposed sigma-delta estimator become a promising tool to provide satisfactory SoC estimation accuracy and significant reduced computational effort for general commercial BMS, further benefiting the reliability and practicability of battery management in real EV applications.

In the future, the proposed algorithm will be implemented by pure analog hardware with the redundant design concept for other battery state estimations, and some other elements such as the thermal behaviour will also be considered.

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