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Observer for Lithium-Ion Battery State of Charge Estimation in Electric Vehicles

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Abstract:*This paper recommends a new method for SOC estimation. In this technique, a new equivalent circuit battery model with one RC block is designed considering self-discharge. Associated with theconventional methods, some improvements have been chieved. Firstly, a Sliding Mode Observer (SMO) is adopted to estimatethe SOC. Secondly, the new method divides the SOC estimation into two stages which include charging stage and dischargingstage according to the battery status. The series resistance and parallel resistance of RC block in the battery model are taken intoaccount to estimate the SOC in discharging of battery. It enhances the SOC estimation accuracy especially for large dischargecurrent. Finally, a simulation is conducted to verify the performance of the method.*

Keywords: Lithium-ion Batteries, SOC Estimation, Sliding Mode Observer, Battery Status

I. INTRODUCTION

Increasingly along with the fossil energy depletion, air pollution and more and more seriousglobal climate changes, people have begun to realize the great importance of the utilization anddevelopment of non-fossil energy [1]. Governments all over the world have introduced a variety ofincentives to reduce pollutant emissions and greenhouse gas emissions [2–6]. Since transportationconsumes a large amount of energy, it is necessary to develop and utilize electric vehicles (EVs) torealize green mobility. Lithium-ion batteries (LIBs) have many advantages, such as high power densityand durability, and therefore they have been widely used in EVs. However, when overchargingoccurs, the LIBs are more likely to burn and explode than other batteries, necessitating higherrequirements for battery management system (BMS) [7–10]. A few parameters, such as maximumdischarge current, specific energy of weight, specific energy of volume, and power density, determinean EV's performance [11–15]. The most important index for a BMS is state of charge (SOC). Because ofthe inherently time-varying and non-linearity characteristics of LIB under working conditions, accurateestimation of SOC remains a challenge [16–19].

In general, many SOC estimating methods do notconsider battery status (including charging, discharging andrest) and parasitic parameters. In this paper, a new SOCestimation based on SMO method and battery status isproposed. The proposed method uses equivalent circuitmodel with one RC block to model the battery. It requireslittle computation and memory resources and can be appliedto real application with lower hardware configuration. Themethod divides the SOC estimation into two stages, ie,charging and discharging. When the battery is discharging,

II. BACKGROUND WORKS

The aforementioned methods can enhance the robustness andaccuracy of the SOC estimation. However, they may engender a significant number of calculationsfor implementation because an error covariance matrix must be propagated at each samplinginstance [20]. Other model-based approaches with constant gains, such as Luenberger observer [21,22],sliding mode observer [23,24], and nonlinear observer [25], have also been adopted to estimate theSOC. These methods depend on the exhaustive understanding of battery dynamics for the appropriateselection of the gains, which affect the estimation accuracy and convergence rate of the

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observer.Nevertheless, the significant nonlinearity of SOC-OCV function means the sensitivity of the outputwith respect to the state varies greatly and constant gain is not suitable [26]. More recently, the SOCestimation methods based on sliding mode observer with gains adaption has been proposed toovercome the limitation [4,27]. They are able to reduce the chattering magnitudes and improve theSOC estimation accuracy by dynamically adjusting the switching gains of the observer. In addition,nonlinear observers with gains adaption proposed in [28,29] have been used to balance the estimationaccuracy and convergence rate of the SOC. However, the methods proposed in [28,29] need additionalcalculation to obtain the Jacobian of the output with respect to currently estimated states, which isused to weight the gain at each sampling instance. It is worth noting that the computational cost ofSOC estimation algorithm is important for its implementation on embedded hardware.

III. SYSTEM CONFIGURATION

The Equivalent circuit model of the Li-ion battery used inthis paper is shown in Fig.1. The model can mimic theprecise dynamic behavior of the lithium-ion battery. In thismodel, the open circuit voltage (OCV) is represented by acontrolled voltage source, $V_{oc}(V_{soc})$. It is a function ofbattery's SOC, which is denoted by Vsoc. Furthermore, aninstantaneous terminal voltage variation due to the batterycurrent I_b is given by inserting a series resistance denoted byR_s. R_s is also called ohmic resistance. It can expend theenergy and reduce SOC when the battery is discharging.Nevertheless, the RC block (C_f, R_f) shows the dynamicsresponse of battery voltage when a step load current isapplied. The whole charge capacitor Rsd is denoted by C_n(C_n=3600C_Q, C_Q is norm capacity (A*h)) and theself-discharge energy loss due to long time storage.Although the Li-ion has low self-discharge, It still influencethe accuracy of SOC especially for large current Ib. Sincethere are modeling errors, uncertainties and time-varyingelements in the model, 'IS , 'IRF and 'IVRF stand for theseerrors and uncertainties.

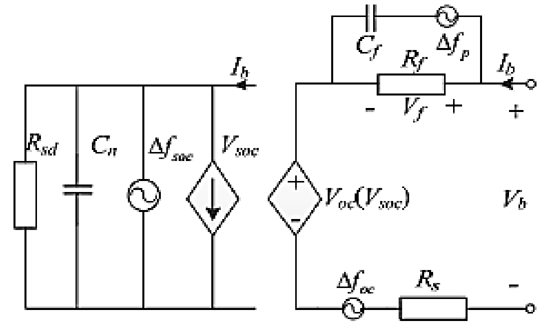

Fig.1. Equivalent circuit model of the Li-ion battery

Since the battery is a highly nonlinear device, SMO iswell suited for solving the nonlinear problem. It needs fairlyaccurate battery model to eliminate the model uncertaintiesand requires little time for implementing and this solves theproblems of coulomb counting method. The SOC can be estimated by the SMO designed. However, itworths noting that the SOC estimation is different betweenbattery charging and discharging.The new SOC estimation method in this paper makessome improvements to the common SOC algorithm. Firstly,the new SOC estimation method takes into account theeffect of self-discharge resistor when charging anddischarging the battery. It's still necessary for the Li-ionbattery with low self-discharge. Secondly, the new SOCestimation method calculates the energy consumption of Rsand Rf on the basis of SMO when the battery is discharging.So the proposed SOC estimation in this paper is divided into two parts. When the battery is charging, the SOC estimation uses the SMO.

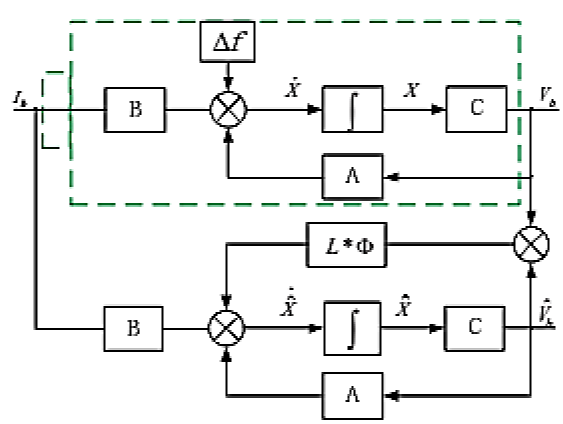

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Fig.2. The structure of sliding-mode observer

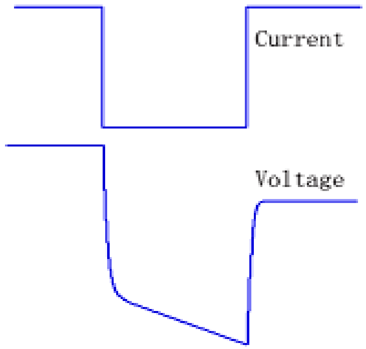

Fig.3. The experiment of battery discharge

The discharge experiments are conducted to get theparameters of the battery model in Fig.1. The experimentprocess is shown in Fig.3. Firstly, charging the battery up to100% and leave the battery for two hours. Secondly,discharging the battery for ten minutes at 1C (6A) ratecurrent and then leaving it unused for one hour. The SOC ofthe battery declines by 10%. Repeating the second steps sixtimes until the SOC of the battery reaches zero. By thesesteps, the parameters of battery model can be recognized.The relationship between SOC and OCV can also beobtained.

IV. SIMULATION RESULTS

To verify the performance of the proposed SOCestimation in this paper, a digital simulation for 6000mAhLi-ion battery based on MATLAB/Simulink R2013A isconducted.

To simulate the noises in the real applications, thepseudorandom noise is added to the Li-ion battery(6000mAh). The frequency of the pseudorandom noise is100Hz. The maximum value is 0.1V and the minimum valueis -0.05V. The value of discharge current is 6A. The batterydischarges for 4 seconds and stop discharging for 1 second.Repeat this process till the voltage of battery drops to 2.75V.The part of the discharging current is shown in Fig.4. The initial value of battery voltage is 4.2V and the SOC is 1.

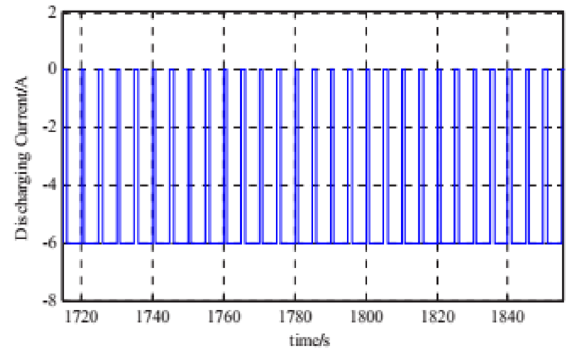

Fig.4 The part of the discharing current in simulation.

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The simulation result of ˆVbis shown in Fig.5. And theerror between estimated value and real value is shown in Fig.6. As we can see from Fig.5 and Fig.6, the accuracy of Vˆbmestimation using sat function can be higher than sgnfunction.

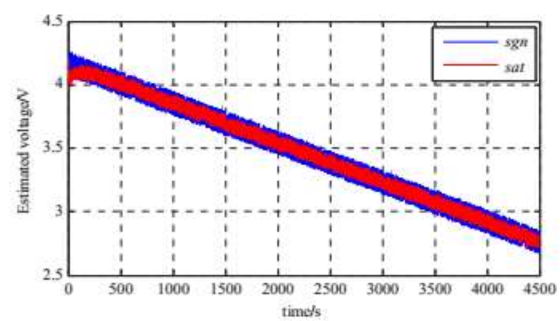

Fig.5. The estimated voltage of battery using sat and sgn

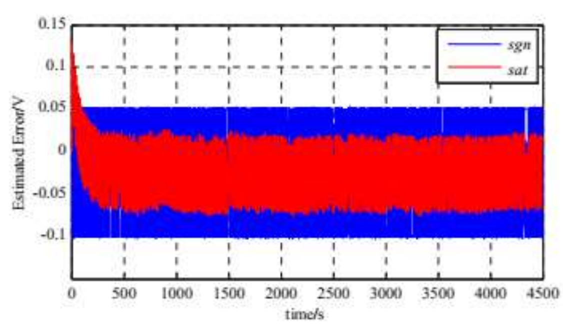

Fig.6. The estimated error of battery voltage using sat and sgn

V. CONCLUSION

This paper put forward a new SOC estimation method forLi-ion battery. A new equivalent circuit battery modelconsidering self-discharge is adopted in this method.Besides, the use of SMO can compensate the model errorsand solves the problems of coulomb counting method. Inaddition, the SOC estimation method in this paper considersthe influence of inner resistance of battery according to thebattery status. The saturation function is designed to reducethe chattering phenomena. Finally, the simulation resultsshow that it's better than the traditional method. In a word,the proposed SOC estimation method is valuable inengineering practice since a lower hardware configurationand software design

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