CHEMICAL ENGINEERING TRANSACTIONS
VOL. 71, 2018
A publication of AIDIC
The Italian Association of Chemical Engineering
Online at www.aidic.it/cet
Guest Editors: Xiantang Zhang, Songrong Qian, Jianmin Xu

ISBN 978-88-95608-68-6; **ISSN** 2283-9216
DOI: 10.3303/CET1871213

Application of Kalman Filter Algorithm in Battery State-of-Charge Detection

Tuo Zheng

Wuhan Business University, Hubei 430056, China
tuozheng9112@163.com

This paper throws light on the State-Of-Charge (SOC) and the detection technology of vehicle battery based on the Kalman filter algorithm. To fill the gaps of the Ampere-hour integration estimation algorithm and the extended Kalman filter estimation algorithm based on Thevenin model, a dual Kalman filter algorithm is proposed based on the two algorithms to estimate the battery SOC. At last, the battery is tested on a special platform under constant-current and custom discharge conditions. A comparison runs for the estimated SOCs from these three algorithms against the value actually measured on vehicle battery. In this way, we bear out that the dual Kalman filter algorithm has a faster convergence speed and higher estimation accuracy than the ampere-hour integration and the extended Kalman filter algorithms alone.

1. Introduction

In the context that modern society and economy are enjoying the prosperity for development, the vehicles have become a common means of transportation in people's daily life and works. As vehicles consume energy first, now it comes to the energy conservation problem. Traditional vehicles manage the energy consumption roughly. Vehicle driving needs to consume huge mass of energy. With continuous rise of the vehicle popularity, this figure has reached a terrible level. Next, in life, we can often see that too many emissions will be caused when the vehicles are driving, and directly enter the atmosphere, causing a series of pollution issues, such as, smog, etc. As shrouded with the above two phenomena, people come to realize the importance of managing and controlling the energy consumption of vehicles. Relevant studies should be made to analyze this from the SOC and detection of vehicle battery.

2. Literature review

The main power of electric vehicles is provided by lithium batteries. The use conditions of power lithium batteries are relatively harsh. If it cannot be effectively managed, the battery life will be greatly reduced. Improper use can cause serious accidents such as an explosion. Therefore, it is very important to ensure that the automotive power lithium battery works under safe and efficient conditions. Battery management system (BMS) is a key device for energy management in electric vehicles and one of the key technologies for vehicle manufacturing (Bizeray et al., 2015). The battery management system mainly includes: real-time monitoring of battery state parameters, battery protection, fault diagnosis, energy management, thermal management, and state of charge estimation. Among them, the state of charge of the lithium battery is one of the key parameters provided by the battery management system. Its accuracy directly determines the quality of the battery management system, which in turn affects the performance of electric vehicles (Guo et al., 2016). Unlike the battery open circuit voltage, operating current, battery temperature and other parameters that can be directly measured, the state of charge of the battery cannot be directly measured. The state of charge is a description of the remaining battery capacity, but it does not currently have a uniform and standard definition. More commonly used is the definition given by the American Advanced Battery Association: under a given discharge rate, the state of charge is the ratio of the remaining capacity of the battery to the rated capacity under the same conditions.

Please cite this article as: Zheng T., 2018, Application of kalman filter algorithm in battery state-of-charge detection, Chemical Engineering Transactions, 71, 1273-1278 DOI:10.3303/CET1871213

The working process of lithium batteries is very complicated. Accurate estimates of battery state of charge have been the focus and difficulty of the industry. The state of charge of the battery cannot be directly measured, so it needs to be estimated. Many researchers at home and abroad have carried out research on battery charge state estimation methods for many years, and many effective estimation algorithms have been proposed. Some of them are offline estimation of battery state of charge, and some are online estimation of battery state of charge (Sheng et al., 2016). Electric vehicle battery workload conditions are complex. Therefore, accurate online estimation of the state of charge of electric vehicle power batteries is still challenging. At present, commonly used battery Soc estimation methods are: discharge experiment method, ampere-time integration method, open circuit voltage method, neural network method, Kalman filter method, weighted fusion method and various combination estimation algorithms (He et al., 2016). The Kalman filter algorithm is an optimal estimation algorithm. Its core idea is to use the observation to correct the estimated observations. The principle of correction is to minimize the posterior estimation error of the dynamic system state quantity. If the initial value is estimated to be inaccurate, the estimated value will approach the true value with the iterative operation. The Kalman filter algorithm is a model-based estimation algorithm (Li et al., 2015). In addition, when the Kalman filter algorithm is used to estimate the state of charge of the battery, the initial value of the state of charge of the battery is not high, which makes the Kalman filter algorithm suitable for electric vehicles. However, the Kalman filter algorithm has a strong dependence on the accuracy of the model. If the model is accurate, the Kalman filter algorithm can quickly converge to the true value and achieve good estimation accuracy. Conversely, if the accuracy of the battery model is not high, the estimation error of the state of charge will become larger or even divergent (Partovibakhsh and Liu, 2015). When using the Kalman filter estimation algorithm, the battery model is complex enough and the accuracy must be high enough, so that the estimated results are highly accurate. However, a model that is too complicated will increase the amount of calculation. In a typical electric vehicle battery state estimation scenario, it is not suitable to use a particularly complicated model. Xiong et al. elaborated on the application of Kalman filtering in the estimation of state of charge (Xiong et al., 2014). Yang et al. studied the Kalman filter estimation algorithm based on the An-time integral and first-order circuit model, and pointed out that the extended Kalman filter plays the role of an observer (Yang et al., 2017). Zou et al. studied the Kalman filtering algorithm based on the An-time integral and neural network model (Zou et al., 2015). Zheng et al. averaged the weighted fusion of the output state of the current-time integral method and the output state of the first-order RC model. This method has been applied to the GM hybrid system and achieved good results (Zheng et al., 2018).
In summary, the innovation of this research is that the Anshi integral method and the extended Kalman filter algorithm are optimized for the defects of the An-time integral estimation algorithm and the extended Kalman filter estimation algorithm based on Thevenin model. A dual Kalman filter algorithm is proposed to estimate the state of charge of the battery. Finally, through the battery test platform, the battery is tested under constant current discharge conditions and custom discharge conditions. Estimated result of state of charge of Ampere integral estimation algorithm, extended Kalman filter estimation algorithm and double Karl filter estimation algorithm was compared with real battery state of charge. Therefore, the estimation effect of the dual Kalman filter algorithm is verified. Compared with the estimation results using the singular integral method and the extended Kalman filter alone, the convergence speed is faster and the estimation accuracy is higher.

3. Method

3.1 Analysis of equivalent model of lithium battery

In the study of the SOC estimation for lithium batteries, the equivalent circuit models commonly used in the projects include the Thevenin, Rint and RC models. As shown in Figure 1, 2, and 3, there are circuits of the Thevenin, Rint, and RC models, respectively.
The Thevenin model is a classic one in the battery equivalent circuit model. E represents the electromotive forcein the battery, usually equivalent to the battery open circuit voltage Uoc; Ro is the battery's DC resistance, simulating the ohmic resistance in the battery; Rs is the battery polarization resistance; Cs is the battery polarization capacitance, analogous to the diffusion phenomenon in the battery chemistry reaction; I represents the load current when the battery works; UL represents the voltage at the battery terminals when the battery works.
The Rint model was originally designed by the Idaho National Laboratory, USA, where E is the electromotive force of the battery, numerically equal to the open circuit voltage Uoc; Ro represents the internal resistance of the battery; Iis the charge and discharge current when the battery works; UL is the terminal voltage when the battery works. This model ignores the dynamic characteristics of the battery and the nonlinear characteristics of the physicochemical reaction in the battery. It, as an ideal model, features the simple structure, easy to determine parameters, but it generally only serves as the basis of the complex equivalent model.

Rc and Cc in series represent the battery energy storage; Rb and Cbin series represent the battery polarization characteristics; Ro is the DC internal resistance; I is the load current when the battery works; UL is the voltage at the battery terminals when the battery works. In this model, the voltage across the capacitors Cc, Cb cannot be directly measured, and it is also relatively difficult to make an identification, so that the model has not been widely used in project practice.

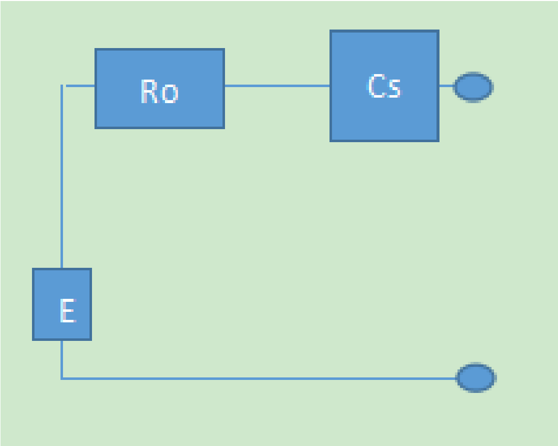

Figure 1: Thevenin equivalent circuit model

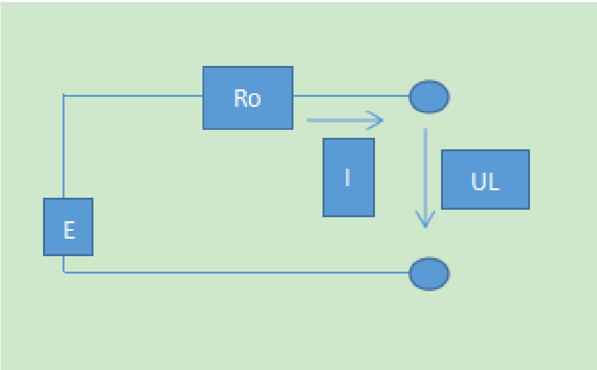

Figure 2: Rint equivalent circuit model

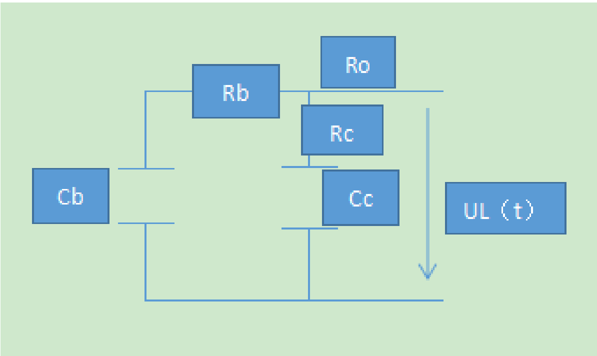

Figure 3: RC equivalent circuit model

3.2 Selection of lithium battery equivalent models

As analyzed above, this paper considers that the Thevenin model has some features, for example, it includes a definite physical meaning; it is easy to identify the model parameters in the project, and can simulate the dynamic characteristics of the battery; the model structure is relatively simple, and the computation amount falls within the capacity of the microcontroller; it can satisfy the demand of EVs for the SOC of the lithium battery. Therefore, the Thevenin model is chosen as the equivalent model for estimating the SOC of the power lithium battery.

3.3 Detection method for the SOC

The parameters that the Thevenin equivalent circuit model needs to identify include: E, Ro, Rs, Cs, where E represents the electromotive force of the battery. In the actual identification process, the common trick for identification is to test the open circuit voltage Uoc of battery after standing. Ro represents the DC internal resistance of the battery; Rs, Cs represent the battery polarization resistance and capacitance, respectively, used to simulate the polarization phenomenon of the battery; Ro, Rs, and Cs are identified by the hybrid pulse power characteristics (HPPC) test method for lithium batteries.

2.3.1 Uoc identification. The electromotive force E of the battery cannot be directly measured. After standing for a long time, the physicochemical changes in the battery tend to balance, and the electromotive force is numerically equivalent to the open circuit voltage Uoc. There is a one-to-one mapping relationship between the electromotive force and the SOC of the battery. The precise acquisition of the electromotive force E can improve the estimation accuracy of the SOC. In this paper, the relationship between Uoc and Soc can be available by measuring the open circuit voltage of the battery in a different SOCs.

2.3.2 HPPC test. In order to identify the remaining parameters Ro, Rs, Cs, in accordance with the Freedom CAR Power-Assisted Battery Test Manual, a series of HPPC tests are conducted on the bench, in order to fully reflecting the dynamic characteristics of the battery itself. The procedure for HPPC tests on the battery is given as follows.

2.3.2.1 Fully charge the battery at room temperature 25 ° C. At this time, Soc=1.

2.3.2.2) Discharge the battery at standard discharge current 1C (20A) for 2 minutes, then let it stand for 8 minutes, charge it for 2 minutes at the same current.

2.3.2.3) Discharge it at 0.5C (10A) for 0.1 h. At this time, the battery Soc is 0.95. After standing for 1 hour, conduct an HPPC teston it once.

2.3.2.4) Repeat steps 2 and 3, and perform the HPPC test on the battery once when Soc is 0.9, 0.85, 0.8, 0.75, 0.7, 0.65, 0.6, 0.55, 0.5, 0.45, 0.4, 0.35, 0.3, 0.25, 0.2, 0.15, 0.1, 0.05, respectively.

1.4 Design of SOC estimation algorithm based on Dual Kalman Filter

In order to fill the gaps of the ampere-hour integration and the Kalman filter algorithms, this paper proposes the dual Kalman filter algorithm based on the ampere-hour integration and extended Kalman filter algorithms for SOC estimation. It has such a core idea that the SOC of battery is first estimated by the former two algorithms in parallel, and then the Kalman fusion works on the results from the two algorithms. Fusional result is the final value. In doing so, error accumulation as the ampere-hour integration algorithm does can be avoided, and high model accuracy as the extended Kalman filter algorithm requires can also be reduced. The framework of the dual Kalman filter algorithm is shown in Figure 4, where, the system input I(k) is the load current at time k; UL(k) is the battery terminal voltage at time k; EKF_Soc(k+1) is the posterior SOC estimation when EKF output k+1;Ah_Soc(k+1) is the SOC at k+1when the ampere-hour integration algorithm outputs; Soc(k+1)is the final result of the SOC after the fusion.

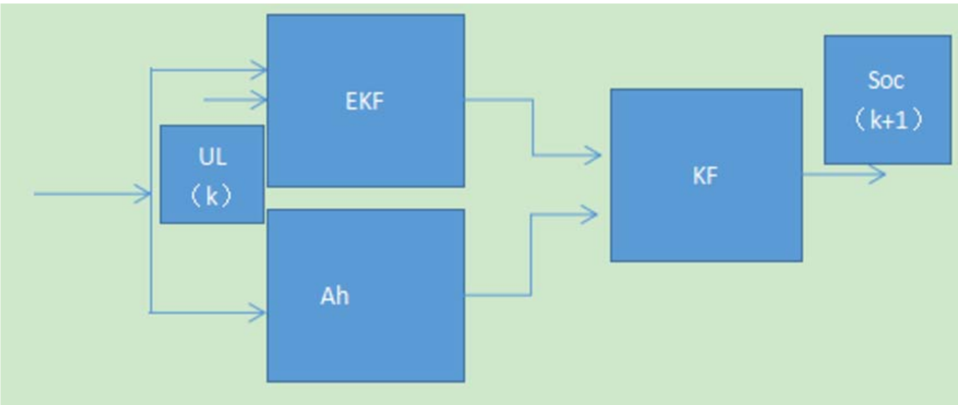

Figure 4: block diagram of algorithm for estimating the state of charge by double Calman filtering

4. Results

The measured values of SOC under constant current conditions and the estimated values from three algorithms are shown in Figure 5, and their errors are shown in Figure 6. It is thus clear that, at the 10A constant current discharge, the estimation error of the ampere-hour integration algorithm increases with time due to the accumulation of current measurement errors; the Kalman filter algorithm fast converges to true value when the initial SOC of the battery is inaccurate. After maintaining the stability, the maximum error is controlled within 2%; the output result of the dual Kalman filter algorithm is the Kalman fusion of the above two results, which has a faster convergence and less estimation error.

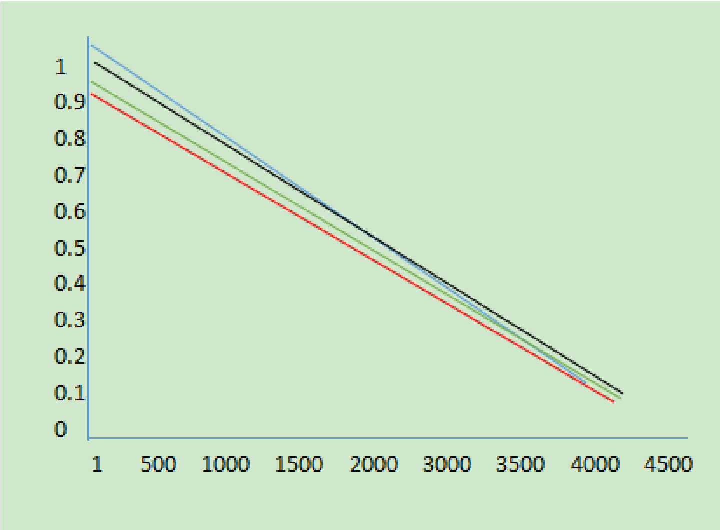

Figure 5: Comparison of different charge state estimation algorithms under constant current discharge conditions

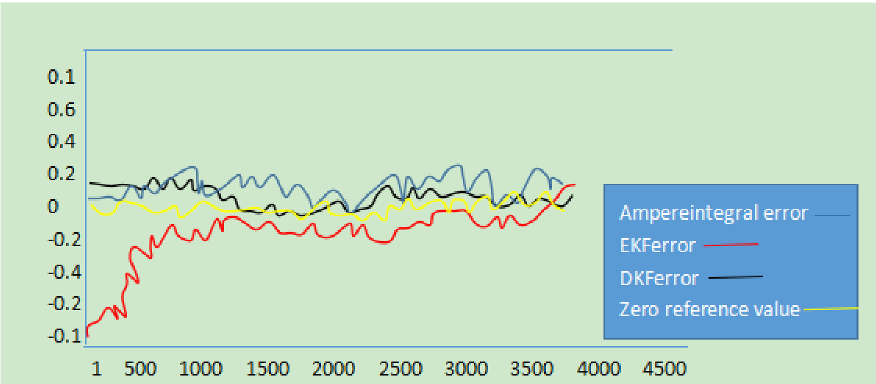

Figure 6: Comparison of estimation error of different charge state estimation algorithms under constant current discharge conditions

5. Conclusion

To make up for the gaps of two traditional algorithms, that is, the ampere-hour integration algorithm in which the initial value cannot be determined easily, and the error accumulation occurs due to the current integral, and the extended Kalman filter algorithm which requires a high accuracy for the model, based on the two, a dual Kalman filter algorithm is hereby proposed. It performs a linear Kalman fusion with the estimated results from the ampere-hour integration and Kalman filter algorithms. These algorithms are validated with estimation SOCs against the actual measuremen tsunder different conditions. It turns out that the dual Kalman filter algorithm has a better convergence speed and less error than the other two alone. Going forward, the battery Thevenin model in this topic is unilateral, not considering the effects of factors such as discharge rate, self-discharge, and temperature. In the future, we need consider more factors affecting the SOC.

Reference

Bizeray A.M., Zhao S., Duncan S.R., Howey D.A., 2015, Lithium-ion battery thermal-electrochemical model-based state estimation using orthogonal collocation and a modified extended Kalman filter, Journal of Power Sources, 296, 400-412, DOI: 10.1016/j.jpowsour.2015.07.019

Guo X., Kang L., Yao Y., Huang Z., Li W., 2016, Joint estimation of the electric vehicle power battery state of charge based on the least squares method and the Kalman filter algorithm, Energies, 9(2), 100, DOI: 10.3390/en9020100

He H., Xiong R., Peng J., 2016, Real-time estimation of battery state-of-charge with unscented Kalman filter and RTOS μCOS-II platform, Applied energy, 162, 1410-1418, DOI: 10.1016/j.apenergy.2015.01.120

Li D., Ouyang J., Li H., Wan J., 2015, State of charge estimation for LiMn2O4 power battery based on strong tracking sigma point Kalman filter, Journal of Power Sources, 279, 439-449, DOI: 10.1016/j.jpowsour.2015.01.002

Partovibakhsh M., Liu G., 2015, An adaptive unscented Kalman filtering approach for online estimation of model parameters and state-of-charge of lithium-ion batteries for autonomous mobile robots, IEEE Transactions on Control Systems Technology, 23(1), 357-363, DOI: 10.1109/TCST.2014.2317781

Sheng H., Xiao J., Wang P., 2016, Lithium iron phosphate battery electric vehicle state-of-charge estimation based on evolutionary gaussian mixture regression, IEEE Transactions on Industrial Electronics, 64(1), 544-551, DOI: 10.1109/tie.2016.2606588

Xiong R., Sun F., Chen Z., He H., 2014, A data-driven multi-scale extended Kalman filtering based parameter and state estimation approach of lithium-ion olymer battery in electric vehicles, Applied Energy, 113, 463-476, DOI: 10.1016/j.apenergy.2013.07.061

Yang R., Xiong R., He H., Mu H., Wang C., 2017, A novel method on estimating the degradation and state of charge of lithium-ion batteries used for electrical vehicles, Applied Energy, 207, DOI: 10.1016/j.apenergy.2017.05.183

Zheng Y., Ouyang M., Han X., Lu L., Li J., 2018, Investigating the error sources of the online state of charge estimation methods for lithium-ion batteries in electric vehicles, Journal of Power Sources, 377, 161-188, DOI: 10.1016/j.jpowsour.2017.11.094

Zou Y., Hu X., Ma H., Li S.E., 2015, Combined state of charge and state of health estimation over lithium-ion battery cell cycle lifespan for electric vehicles, Journal of Power Sources, 273, 793-803, DOI: 10.1016/j.jpowsour.2014.09.146