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On-line remaining energy prediction: A case study in embedded battery management system ☆

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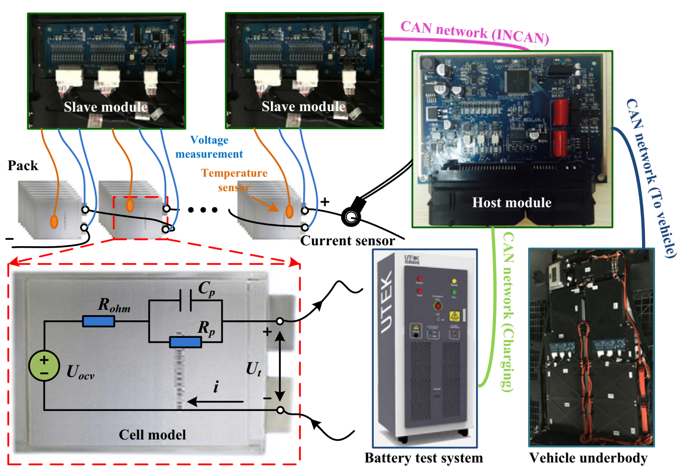
HIGHLIGHTS

- The remaining energy prediction based on the μC/OS-II RTOS is proposed.
- The first-order RC equivalent circuit model is employed for SoE estimation.
- The Bayesian learning technique is used for SoE estimation.
- The real road test in Wuhui city, China is performed to verify the proposed method.

GRAPHICAL ABSTRACT



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ABSTRACT

Modern electric vehicles (EVs) and hybrid electric vehicles (HEVs) require a reliable battery management system (BMS). The remaining energy and the state-of-energy (SoE) are very important indexes for the embedded BMS used in both EV and HEV applications. As a case study in the embedded BMS, this paper presents the implementation of remaining energy prediction based on the μC/OS-II real time operating system (RTOS). In considering that there are accumulated errors caused by inevitable drift noise of the current or voltage sensors, a model based SoE estimator is developed based on a first-order RC equivalent circuit model. Moreover, the Bayesian learning technique is used for SoE estimation to get accurate and robustness estimation results. Lastly, two different kinds of batteries are carried out under laboratory experiments and real road test to verify the robustness of the proposed SoE estimation approach. The results indicate that the maximum absolute estimation error (MAEE) and the root-mean square error (RMSE) are within 2% and 1% for both $LiFePO_4$ and $Li(Ni_{1/3}Co_{1/3}Mn_{1/3})O_2$ batteries.

1. Introduction

Electric vehicles (EVs) and hybrid electric vehicles (HEVs) always work in a complex operating environment. Therefore, factors such as temperature, humidity and load capacity pose great challenges to the battery security, effective use and cycle life. The

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battery management systems (BMS) are developed to reduce the abuse of the battery, improve energy efficiency and extend battery cycle life [1–5].

The battery remaining mileage prediction (RMP) in battery management system is critical to improve battery anti-abuse ability including over-charging and over-discharging. The state-of-charge (SoC) serves a similar function to the petrol gauge in the traditional oil-fueled vehicles and has been wildly used for RMP in EVs and HEVs [6–21]. However, the voltage levels of different types of batteries are quite different. Even with the same capacity, the stored energy of the battery is bound to be very different, which causes a corresponding difference in the useful life or mileage of EVs. In addition, in different SoC intervals, when the battery is charged or released the same capacity, there are differences between the charging and discharging energy. The released or stored energy of the battery is related to not only the open-circuit voltage (OCV), but also the current SoC of the cell. At the low-end of the SoC, the energy corresponding to the same capacity change is less than the high-end of the SoC. From the aspect of the capacity, it cannot effectively reflect these problems. The state-of-energy (SoE) which describes the remaining energy as a percentage of the maximum available energy, analyzes the battery remaining mileage from the viewpoint of energy [22]. In fact, the main function of the battery is to store and release energy. The running distance and endurance time of the EVs or HEVs are directly related to the quantity of energy released by the battery. Hence, describing the state of the battery from the viewpoint of energy is of more practical significance.

In recent years, many methods have been reported in literatures for battery remaining energy or SoE estimation. The definition of SoE is proposed in Ref. [22] as a new indicator of the energetic reserve. Ref. [23] presented a new criterion for direct evaluation of the remaining energy which allows a direct determination of battery's power and energetic performances from a power solicitation profile. Based on a combination of electrochemical impedance spectroscopy (EIS) method and charge/discharge curves analysis. Ref. [24] presented a new parameterization method for a typical equivalent electrical circuit model, in which the model parameters are determined as the function of power and SoE instead of current and SoC. Ref. [25] investigated the energy efficiency of Li-ion battery and the direct energy counting algorithm is used for charging and discharging energy calculation. Ref. [26] proposed a back propagation neural network (BPNN) method to estimate the SoE. The battery terminal voltage, current and temperature are taken as the inputs, and the output layer is the estimated SoE. Furthermore, the proposed BPNN method has been validated under dynamic temperature and current conditions. In Ref. [27], the wavelet neural network (WNN) based battery model is developed for the SoE estimation. The robustness of the proposed method is validated under dynamic experimental conditions. Ref. [28] proposed a Gaussian model for SoE estimation. The genetic algorithm (GA) and Akaike information criterion (AIC) method are used for model parameter identification and determination of model order. The central difference Kalman filter (CDKF) is employed for SoE estimation and the algorithm is verified on two kinds of lithium-ion batteries. Ref. [29] proposed a joint estimator for both SoE and state-of-power (SoP) based on an adaptive unscented Kalman filter (UKF). The robustness of the joint estimator against uncertain operating temperatures and aging levels is systematically analyzed. Ref. [30] proposed a remaining energy prediction method through coupled prediction of future states, parameters, and output. The predictive–adaptive energy prediction method is compared with the direct calculation method and other energy prediction methods.

The above methods for battery SoE estimation can achieve good results from characterization tests under different operating conditions, mainly the temperature, the battery current and other battery states. However, for real applications, the estimation algorithms should be developed depending on the acceptable complexity of calculation and the ability of being embeddable. Therefore the real-time performance and reproducibility should be fully concerned. In this paper, we provide the implementation of remaining energy prediction on μC/OS-II real time operating system (RTOS) based on Matlab/Simulink software platform, Codewarrior integrated development environment (IDE) and FreescaleXS12 micro control unit (MCU). Considering that the energy counting algorithm has accumulated error and it is hard to calibrate the initial error, a model based SoE estimator is developed based on a first-order RC equivalent circuit model. Moreover, the Bayesian learning algorithm is used for SoE estimation to get accurate and robustness estimation result. To verify the robustness of the proposed SoE estimation approach, two different kinds of lithium-ion batteries are carried out under laboratory experiments and real road test.

This paper is organized as follows: In Section 2, the implementation of remaining energy prediction based on the embedded system is introduced. In Section 3, a model based SoE estimator is proposed by a first-order RC equivalent circuit model and the Bayesian learning algorithm. In Section 4, we first introduce the test bench, and then the loading profile dynamic stress tests (DST) and a real road test of Wuhui City in China are carried out on different kinds of batteries. Finally, the conclusions of this work are given in Section 5.

2. Remaining energy prediction based on embedded system

2.1. Design of embedded system

Modern EVs and HEVs require a real-time and reliable battery management system. The software of the embedded battery management system is developed based on practicality with the characteristics of universality, intelligent, individuation and friendly interaction. It is an evolution of modular software programming and distributed design of embedded software. Based on the advantages of clear structure and stable capability, the μC/OS-II RTOS has been a new focus in the embedded systems which can manage up to 64 tasks with priorities from 0 to 63, including: create tasks, delete tasks, change the priority of the tasks, tasks suspend and resume, etc. The multi-mission characteristic of the μC/OS-II RTOS makes the battery management and control excellent, solving the problem of complication and real-time.

The battery management systems in modern EVs and HEVs are always constructed distributed, which usually consist of one host module and several slave modules. A typical topological structure of the battery management system is shown in Fig. 1. The functions of the host module mainly include: communication and processing information from the slave modules, battery states estimation, fault diagnosis, control of power releasing & charging, key data recording, etc. The slave modules are mainly used to measure cell voltage, temperature, as well as to carry out the control order of the host module. The three isolated CAN networks are used for internal communication, charging control and vehicular control. In this work, the host module and the slave module are developed based on MC9S12XEP100 and MC9S08DZ60, respectively. Meanwhile, the μC/OS-II RTOS is adopted as the embedded operating system.

2.2. Energy counting method

Based on the hardware platform shown in Fig. 1, the energy counting algorithm is carried out on the host module. Fig. 2 shows