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Real-time estimation of battery state-of-charge with unscented Kalman filter and RTOS μCOS-II platform ☆

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HIGHLIGHTS

- A novel RTOS μCOS-II Platform based BMS was developed.
- UKF algorithm was employed to estimate battery SoC in real environment.
- The robustness of the proposed approach against dynamic profiles is evaluated.
- The developed BMS can estimate battery SoC accurately against complex conditions.

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ABSTRACT

To develop an advanced battery estimation unit for electric vehicles application, the state-of-charge (SoC) estimation is proposed with an unscented Kalman filter (UKF) and realized with the RTOS μCOS-II platform. Kalman filters are broadly used to deploy various battery SoC estimators recently. Herein, an UKF algorithm has been employed to develop a systematic adaptive SoC estimation framework. Compared with traditional used extended Kalman filter, it uses an unscented transform to deal with the state estimation problem, thus it has the potential to achieve third order accuracy of the Taylor expansion for tracking posterior estimate of the inner inhabited state. Beneficial from it, the SoC estimation accuracy has been improved with higher tracking accuracy and faster convergence ability. To further evaluate and verify the performance of the proposed online SoC estimation approach, a battery-in-loop platform is built and the SoC estimation is calculated with a RTOS μCOS-II platform. The analog acquisition, communication system and SoC estimation algorithms were programmed, the performance of the proposed SoC estimation with UKF algorithm was finally investigated. The battery management system with UKF algorithm and RTOS μCOS-II platform has good performance and it can apply for electric vehicles.

1. Introduction

Nowadays, many governments and companies are forced to pay more attentions to the development of battery powered electric vehicles (EVs) for reducing greenhouse gas and PM2.5 emissions [1]. In order to fulfill the requirements of vehicle traction, battery packs usually contain large numbers of cells connected in series and in parallel. Battery management systems (BMS) consisting of cell measurement circuits and the corresponding monitoring software are used to provide the necessary knowledge for battery state-of-charge (SoC) and available peak power [2–5]. In this condition, to ensure the high efficient and safety operation of batteries in EVs, an accurate and practical battery SoC estimation approach is necessary [6–9].

1.1. Review of the estimation approach

A variety of approaches has been proposed for battery SoC estimation and the advantages/disadvantages of each of these approaches has been compared in Ref. [9]. Most of approaches can be categorized into direct measurement method (discharge test), current-based SoC estimation method (ampere hour

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integral), electrochemical impedance spectroscopy (EIS) based SoC inferring method, model-based method with nonlinear state estimation algorithms or fusion algorithm based on multiple algorithms [5–25].

Direct measurement method discharges battery to quantify its remaining amount of charge. It is relatively time-consuming for measurement. Therefore it is commonly used in laboratory for calibrating the SoC estimation approach. However, in considering that the measure of remaining amount of charge requires to cutoff the power, as a result, it cannot be used in EVs directly [9].

The performance of ampere hour integral method is highly reliant on the measuring accuracy and accurate initial SoC estimation. Although being a most commonly used open-loop method its calculation performance is easily affected and degraded by the inaccurate initial SoC estimation and accumulated calculation errors. [5,22]. Voltage or EIS-based SoC estimation method which uses measured voltage or measured EIS of battery to infer its SoC or capacity. It cannot be applied to EVs due to its measurement is relatively time-consuming [20,21].

Nowadays, large number of attempts has been made on developing model-based SoC estimation approaches aimed at realizing accurate and reliable battery SoC estimation through a variety of state estimation algorithms and filters. In this type of SoC estimation methods, an accurate battery model is the essential prerequisite of SoC estimation. With the high field battery model, the state estimation algorithm can be employed to track the SoC trajectory through comparing and reducing the voltage error between predicted value and measured value. Refs. [10–13] used extended Kalman filter (EKF) to identify battery model parameter and estimate battery SoC. It has obtained desired prediction precision. However, in deal with the nonlinear problem, the EKF algorithm intercepts the first order for the linearization process. As a result, it may bring huge cut-error when battery model is nonlinear. On the other hand, most of calculation approaches described above are verified under an off-line manner and Matlab soft environment. That is to say, the robust performance and practicality of these SoC estimation methods were not fully evaluated. For instance, many EKF-based SoC estimation methods discussed above were validated by off-line driving profiles. As a result, these methods hardly can apply to real environment directly. Most of estimation approaches realized their estimation accuracy in laboratory with archived loading profiles. Consequently, they cannot achieve accurate SoC estimations because of various unmeasured noises.

1.2. Contribution of the paper

A key contribution is that this study employs an unscented Kalman filter (UKF) to develop a real-time SoC estimation approach with RTOS μCOS-II Platform. It deals with the problem arising from system noise in practical engineering problems. Three contributions can be found when comparing with existing methods. (1) UKF algorithm is different from EKF algorithm in that an unscented transform technique has been used in UKF and which uses the statistics to approximate a nonlinear system. (2) μCOS-II, which is famous for its robust and open source, is applied in the realization of the hardware. (3) Related tasks including analog acquisition, communication system and SoC estimation algorithms have been programmed and the performance of the proposed UKF algorithms in SoC estimation is finally studied.

1.3. Organization of the paper

Section 2 describes battery modeling process. An UKF algorithm – based SoC estimator is depicted in Section 3. The battery control board design is illustrated in Section 4. The validation is presented in Section 5. Section 6 gives the conclusion.

2. Battery model

2.1. Lumped parameters battery model

An accurate and reliable battery model is the precondition of battery SoC estimation when using model-based method, Ref. [3] proposed an integrated battery system identification method for model order determination and parameter identification, the result indicated that the one RC and double RC network based lumped parameters battery model have better performance considering the model complexity and prediction precision. The one RC network based lumped parameters battery model (*Thevenin* model) is selected, as shown in Fig. 1, where R_o denotes the ohmic resistance; a RC (resistance R_p–capacitor C_p) network is used to describe the dynamic voltage behavior during charging and discharging. U_L is denotes the terminal voltage and U_p denotes the voltage across C_p. I_p is the outflow current of C_p.

From presented structure of *Thevenin* model in Fig. 1, we easily have the electrical equation for its working behavior:

$$\begin{cases} \dot{U}_p = -\frac{1}{C_pR_p}U_p + \frac{1}{C_p}I_L \\ U_L = U_{oc} - U_p - I_LR_o \end{cases} \tag{1}$$

where U_{oc} and I_L denote open circuit voltage (OCV) and load current (assumed positive for discharging process, negative for charging process). Its discrete format can be rewritten by:

$$\begin{cases} U_L = U_{oc} - U_P - I_LR_o \\ U_{p,k} = \exp(-\Delta t/\tau) \times U_{P,k-1} + (1 - \exp(-\Delta t/\tau)) \times I_{L,i-1}R_P \end{cases} \tag{2}$$

where $\tau = R_PC_P$, Δt denotes the sampling interval. $U_{p,k-1}$ is the value of U_p at kth step. $I_{l,k}$ is the value of I_L at kth step.

The definition of battery SoC is a rate which calculated by the remaining capacity to its maximum value. It can be calculated by the following equation:

$$SoC_t = SoC_0 - \frac{1}{C_a}\int_0^t \eta I_{L,\tau} d\tau \tag{3}$$

where SoC_t denotes battery SoC, SoC_0 denotes initial SoC, C_a denotes the maximum capacity. η is the current efficiency during the charge–discharge process.

Combining the battery model and the Ah counting method, a comprehensive battery model could easily be established. Here, U_p, SoC are chosen as state variable while U_L is the observable variable, and the state equation can be expressed as:

$$\begin{cases} x_{k+1} = \mathbf{A}x_k + \mathbf{B}u_k + w_k \\ y_{k+1} = \mathbf{C}x_k + \mathbf{D}u_k + v_k \end{cases} \tag{4}$$

where the input u_k is the load current I_L, and terminal voltage U_L of battery represents the output of the state-space equation. In considering that battery polarization voltage is a hidden state, namely it can hardly be measured directly. Thus, it serves as the system state vector combining with battery SoC. $\boldsymbol{w}$ represents model noise and $\boldsymbol{v}$

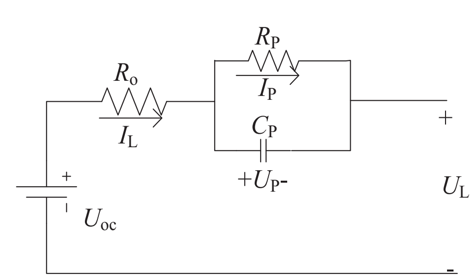

Fig. 1. Schematic of the *Thevenin* battery model.