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A novel approach for state of charge estimation based on adaptive switching gain sliding mode observer in electric vehicles

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HIGHLIGHTS

- State equations are derived from the battery equivalent circuit model.
- An adaptive switching gain sliding mode observer for state of charge estimation is purposed.
- The new observer minimises the chattering and improves the estimation accuracy.
- The experimental results of a lithium-polymer battery verify the effectiveness of the purposed observer.

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ABSTRACT

In this paper, a novel approach for battery state of charge (*SOC*) estimation in electric vehicles (EVs) based on an adaptive switching gain sliding mode observer (ASGSMO) has been presented. To design the ASGSMO for the *SOC* estimation, the state equations based on a battery equivalent circuit model (BECM) are derived to represent dynamic behaviours of a battery. Comparing with a conventional sliding mode observer, the ASGSMO has a capability of minimising chattering levels in the *SOC* estimation by using the self-adjusted switching gain while maintaining the characteristics of being able to compensate modelling errors caused by the parameter variations of the BECM. Lyapunov stability theory is adopted to prove the error convergence of the ASGSMO for the SOC estimation. The lithium-polymer battery (LiPB) is utilised to conduct experiments for determining the parameters of the BECM and verifying the effectiveness of the proposed ASGSMO in various discharge current profiles including EV driving conditions in both city and suburban.

1. Introduction

Due to the progressive rise of petrol costs and environmental concerns on exhaust emission from petrol-driven vehicles, the eco-friendly electric vehicles (EVs) have greatly exhibited promising potential to revive as the leading means of transportation in upcoming decades. The EV performance is highly dependent on battery characteristics such as operation voltage, temperature, charge or discharge rate and aging. Among existing battery types applicable to EVs, lithium-polymer battery (LiPB) is widely recognised as the most capable candidate for the development and innovation of the new generation EVs. Compared with other types of EV batteries such as lead-acid batteries, nickel–cadmium batteries and nickel–metal hydride batteries, LiPBs are superior in terms of high energy and power density, broad operating temperature range, rapid charge capability, no memory effects, long cycle life and extremely low self-discharge rate [1,2].

The amount of battery available capacity is closely related to the state of charge (SOC), which is considered as one of the key factors in battery management system (BMS) for supporting optimal battery performance and safety in EVs. The accurate battery SOC indication is essential for predicting a reliable travelling range, maximising the efficiency of battery energy utilisation and preventing the batteries in EVs from over-charging or over-discharging. Unfortunately, the SOC involves in intrinsic electrochemical processes of a battery, and it cannot be directly measured by a sensor. It should be estimated by an advanced mathematical algorithm with the aids of measurable signals such as terminal voltage and current from the battery.

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A number of techniques have been proposed to estimate the SOC of a battery and each one has its own advantages in certain aspects [3–5]. The most straightforward approach is the ampere-hour (Ah) counting, which simply integrates the battery charge and discharge currents over time. The SOC can be calculated by referring to the calibration point at the fully charged battery. This method is inexpensive to be implemented in hardware, but the estimation accuracy is strongly dependent on the sampling frequency and the precision of the current sensor. Moreover, this non-model and open-loop-based estimator can easily accumulate errors caused by embedded noises and current measurement drift and it is also incapable of determining the initial SOC. An enhanced version of Ah counting has shown improved SOC estimation results by online evaluating Coulombic efficiency with recalibration of the battery capacity [6].

The impedance measurement has been declared as an effective technique for the SOC estimation [7–9]. It loads a series of small amplitude a.c. signals into a battery to detect the responses of the battery in the wide range of frequencies. The SOC can be obtained by analysing the battery impedance, but the measured impedances cannot completely represent the dynamics of batteries in the case of large discharge current in EVs. Another drawback of this approach is that a set of the bulky and costly auxiliary equipment such as the signal generator and the impedance spectroscope is required to carry out impedance measurement.

Another category of the SOC estimation methods is relied on computational and intelligence-based strategies, which encompass artificial neural networks (NNs), fuzzy neural networks, adaptive fuzzy neural networks and support vector machine [10–13]. These data-oriented approaches can accurately estimate the SOC for all kinds of batteries in the absence of the details of batteries, but they require a large number of training sample data to train the NNs. Therefore, they demand more powerful and costly data processing chips to handle the massive computation loads in the BMSs. Furthermore, the SOC would be unpredictable in case of discharge current profiles loaded in EV batteries deviated from those represented by the training data.

The Kalman filter (KF), as a classical state estimation method for dynamic systems, was also developed to estimate the SOC based on a linear model [14,15]. For the battery represented by a nonlinear model, some advanced KF techniques such as extended KF (EKF) [16,17], sigma-point KF (SPKF) [18,19] and unscented KF (UKF) [20,21] were proposed to achieve online SOC estimation. The essential idea of the EKF approach is to transform a nonlinear system into a linear system by linearising the nonlinear function based on the first order Taylor series expansion, such a process gives rise to large linearisation errors and complicated computation of the Jacobian matrix which may lead to the instability of the filter and inaccurate estimation for highly nonlinear battery systems in EVs. Instead of the local linearisation in the EKF, the SPKF and UKF approaches use an unscented transformation to approximate a Gaussian distribution of the state random variable with a set of sample points or sigma points and offer better SOC estimation results in terms of accuracy and robustness [18–21].

All these KF-based SOC estimation algorithms, however, require accurate battery model parameters with the assumption that constant values of the process and measurement noise covariance are priori known, which are hardly practical and error-prone due to the complex electrochemical reactions inside batteries for EV driving conditions. Furthermore, the constant values of noise covariance can result in remarkable errors and divergence in the battery SOC estimation. Later, both an adaptive EKF (AEKF) and an adaptive UKF (AUKF) have been developed to estimate the values of the process and measurement noise covariance during the online process [22,23]. They have demonstrated better precision in the SOC estimation and filter divergence restraint at the expense of higher complexity and computational cost.

More recently, the H_∞ observer-based method has been proposed to estimate the SOC without the requirement of the exact statistical properties of the battery. This method minimises the errors of system and measurement so that the SOC estimation error is less than a given attenuation level [24,25], where an alternative feedback gain is employed to tackle modelling errors and disturbances. Similarly, the sliding mode observer (SMO) based SOC estimation method has been adopted to overcome the uncertainties of battery model, external disturbances and measurement noises [26,27]. Nevertheless, this method relies on the exhaustive understanding of battery dynamics for the appropriate selection of the SMO parameters such as uncertainty boundaries and switching gains, leading to the trade-off between the chattering magnitude and the convergence speed in the SOC estimation.

In this paper, a novel approach for the SOC estimation based on an adaptive switching gain sliding mode observer (ASGSMO) has been proposed. Comparing with constant switching gains SMO, the ASGSMO is able to dynamically adjust the switching gains in response to the tracking errors, and guarantee the reachability of sliding mode surface and trigger the sliding mode. Once the sliding mode is activated, the switching gains are self-tuned to "adequate" levels to counteract the modelling errors and reduce the chattering magnitudes, thereby improving the SOC estimation accuracy.

The remaining part of this paper is organised as follows. In Section 2, a battery equivalent circuit model (BECM) is presented to characterise the discharge behaviours of the LiPB in the presence of parameter uncertainties. The detailed procedures to identify the BECM parameters are also explained in this section. In Section 3, the ASGSMO design methodology is elaborated for the SOC estimation. The proposed ASGSMO is validated for SOC estimation by experimental results in Section 4, followed by conclusions in Section 5.

2. Battery modelling

2.1. Battery equivalent circuit model

There have been numerous attempts to establish a precise battery model for achieving an accurate battery state estimation. The battery equivalent circuit models consisting of circuit components such as capacitors, resistors, diodes and voltage sources have been widely studied and developed to capture dynamic characteristics of a battery for reducing modelling errors [28–30]. These circuit-based models are also applied to the battery SOC estimation due to their state equations are intuitively derived from circuit analysis for mathematical computation. In this paper, without the

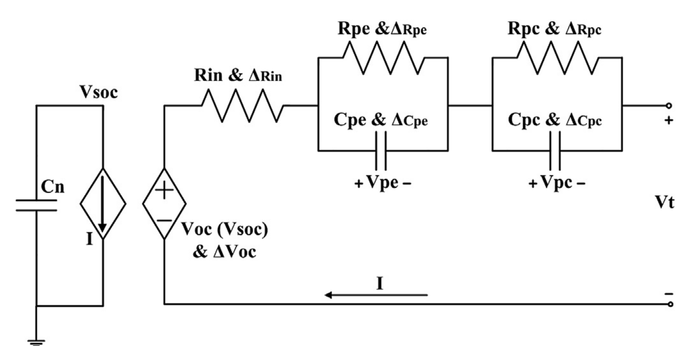

Fig. 1. Schematic diagram of BECM.