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Probability based remaining capacity estimation using data-driven and neural network model

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HIGHLIGHTS

- The data-driven model is established for battery state-of-charge estimation.
- The neural network model is established for battery state-of-energy estimation.
- The probability based estimation method is employed for battery state estimation.
- The HPPC/DST/UDDS profiles are performed for experiment verification.

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ABSTRACT

Since large numbers of lithium-ion batteries are composed in pack and the batteries are complex electrochemical devices, their monitoring and safety concerns are key issues for the applications of battery technology. An accurate estimation of battery remaining capacity is crucial for optimization of the vehicle control, preventing battery from over-charging and over-discharging and ensuring the safety during its service life. The remaining capacity estimation of a battery includes the estimation of state-of-charge (SOC) and state-of-energy (SOE). In this work, a probability based adaptive estimator is presented to obtain accurate and reliable estimation results for both SOC and SOE. For the SOC estimation, an n ordered RC equivalent circuit model is employed by combining an electrochemical model to obtain more accurate voltage prediction results. For the SOE estimation, a sliding window neural network model is proposed to investigate the relationship between the terminal voltage and the model inputs. To verify the accuracy and robustness of the proposed model and estimation algorithm, experiments under different dynamic operation current profiles are performed on the commercial 1665130-type lithium-ion batteries. The results illustrate that accurate and robust estimation can be obtained by the proposed method.

1. Introduction

Energy and environmental crisis have long been challenges facing the world's automobile industry. The grim energy and environmental situation around the world has accelerated the strategic transformation of transportation and energy technology. Therefore, new energy vehicles such as the battery electric vehicles (BEV), hybrid electric vehicles (HEV), and fuel cell electric vehicles (FCEV) are generally considered as good candidates to replace conventional internal combustion engine vehicles. With the advantages of high energy density, environmentally benign features, wide operating temperature range, low self-discharge rate and long cycle life, the lithium-ion batteries have become widely used in electric vehicles in recent years. Since large numbers of lithium-ion batteries are composed in pack and the batteries are complex electrochemical devices with a distinct nonlinear behavior depending on various internal and external conditions, their monitoring and safety concerns are key issues for the application of battery technology [1].

As a key component to the battery power system, the battery management systems (BMS) are designed to provide monitoring, diagnosis, control and protecting functions to enhance the operation of the battery packs [2]. An intelligent BMS is always developed based on practicality with the characteristics of universality, intelligent, individuation, friendly interaction and has to be extensible in almost certain cases that more features can be added if

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necessary. Fig. 1 gives a block diagram of key technologies in BMS. As can be seen from the figure, the key technologies of the BMS can be summarized into three parts: (1) Battery state estimation. In an intelligent BMS, the battery performance is not only evaluated by the state-of-charge (SOC), but also evaluated from the state-of-energy (SOE) and other indicators to realize a comprehensive and accurate estimation. (2). Battery equalization. When a battery pack is first constructed, the capacities of each component cell can be well matched. However as time goes by, individual cells lose capacity at different degrees due to temperature variations and other factors. The weak cells effectively limit the run time of the battery pack. When the pack is charged, the weak cells reach the overcharge voltage limit before others, so other cells are not charged to their maximum available capacity. Likewise, when the pack is discharged, the weak cells reach their cut-off voltage sooner than the others and shorten the overall working time of the battery pack. Therefore the battery equalization circuits and algorithms are required to extend battery life, improve the cell consistency and efficiency. (3) Battery safe and efficient management. The battery management systems on modern electric vehicles are always distributed structured on high-speed Controller Area Network (CAN) bus. The battery parameters detection is expanded from voltage, current and temperature to connection, insulation, smoke, collision and so on. The fault diagnosis of BMS involves sensor fault, actuator fault, network fault, over charge, over discharge, over current, temperature anomaly, insulation fault, uniformity fault and so on. Battery safe and efficient management also involves safe charge/discharge control, battery thermal management, key data storage and analysis.

The SOC which reflects the residual capacity of the battery is not directly measurable and should be estimated by other approaches. Many methods have been proposed in the literature for battery states estimation [3–37]. The coulomb counting (ampere-hour integral) method is one of the most simple and general way [3]. Low-cost sensors for current measurement are available to achieve this method, and the required computing of this method is very low so that it can be generalized in different types of application scenarios. This approach is also possible and easy to be combined with other techniques such as the model based estimation approaches. However, it has accumulated error since there are inevitable sensor noise and measurement drift. This approach is also hard to calibrate the initial error and cannot get the precise initial SOC automatically. The open-circuit voltage (OCV) based method is another approach to obtain the battery SOC [4–5]. Through this method, batteries are required to have long time resting in order to reach balance. Therefore this method is appropriate only when the EVs are parking rather than driving. The artificial neural network (ANN) method has been employed for SOC estimation in Refs. [6–11]. A remarkable disadvantage of this method is a great number of data are needed to train the network and a lot of computations are required. Meanwhile, the prediction error can be greatly influenced by the training data and the training methods. To improve the performance of SOC estimation, model based estimation approaches such as the nonlinear observer [12–15], extended Kalman filter (EKF) [16–21], sigma-point Kalman filter (SPKF) [22–23], adaptive extended Kalman filter (AEKF) [24–26], unscented Kalman filter (UKF) [27–30], particle filter (PF) [31–32], unscented particle filter (UPF) [33], invariant imbedding method [34], sliding mode observer [35–37] were proposed. With low-complexity the nonlinear observer can be used when the system is observable. The Kalman filter series of algorithms can find the optimal solution provided by nonlinear observer. However these methods require accurate model parameters, and the system noise and observation noise must satisfy the Gaussian distribution; otherwise the filter performance will decrease or even diverge. In Ref. [34], Dong et al. proposed an online estimator for SOC and parameters estimation based on the invariant imbedding method. The accuracy and robustness of the proposed method have been validated under dynamic working conditions. The sliding mode observer can suppress the disturbance and modeling error, but the chatter cannot be ignored.

The voltage levels and working plateaus of different types of batteries are entirely different. Even with the same capacity the stored energy of the batteries are bound to be very different, which will cause a corresponding difference in the useful life or mileage of vehicles. Therefore the SOE is defined to indicate the remaining

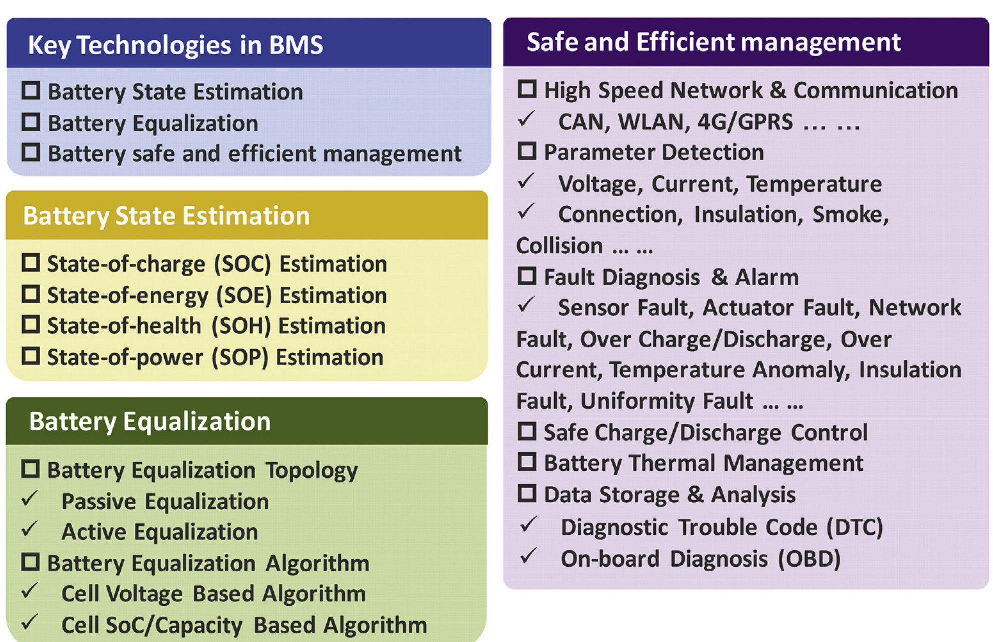

Fig. 1. Block diagram of key technologies in BMS.