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Supervisory long-term prediction of state of available power for lithium-ion batteries in electric vehicles

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HIGHLIGHTS

- A battery model incorporated with dynamic open circuit voltage is established.
- The adaptive two step filter is introduced into battery state estimation.
- A novel supervisory long-term battery SOAP prediction approach is put forward.
- The robustness of the proposed approaches is systematically evaluated.
- The experiment results verify the long-term SOAP prediction error reduced by 85.9%.

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ABSTRACT

The battery state of available power (SOAP) is crucial to improve the energy management of electric vehicles (EVs) and protect batteries from damage. This paper proposes a novel supervisory long-term prediction scheme of SOAP for lithium-ion batteries in electric vehicles. The supervisory long-term prediction denotes that the SOAP is online predicted under the supervision of the EV's future long-term driving conditions, instead of the traditional approaches under the constant working limitations. Firstly, to accurately capture the battery dynamics, a battery model incorporated with multi-parameters dynamic open circuit voltage is established, and the least square approach with an adaptive forgetting factor is applied to online identify the battery parameters. A new battery state estimation algorithm based on an adaptive two step filter is then proposed to improve the accuracy of the state estimation. A battery's long-term power demand (LTPD) prediction model is also established for EVs. Based on the improved battery model and predicted battery states, especially under the supervision of the predicted LTPD, the novel supervisory long-term battery SOAP prediction approach is finally put forward to make the prediction practical and accurate. The long-term state of charge (SOC) and SOAP of battery are online co-predicted by the derived algorithms. The robustness of the proposed approach against erroneous initial values, different battery aging levels and ambient temperatures is systematically evaluated by experiments. The experimental results verify the long-term battery SOAP prediction error reduced by 85.9% when compared with that by traditional approaches.

1. Introduction

To deal with the growing concern over oil shortage and environmental issues, electric vehicles (EVs) are becoming increasingly popular in the global market [1]. As the core power source of an EV, the lithium-ion battery needs to be well monitored by the battery management system (BMS). The accurate estimation and prediction of the battery states, including the state of charge (SOC) [2], state of health (SOH) [3] and state of available power (SOAP) [2] etc., is one of the most primary functions of the BMS.

Among these states, the battery SOAP represents the available charging or discharging power capability of the batteries [2]. For EV applications, it is used as a boundary by the vehicle control unit for limiting the battery operation. So it not only is essential in determining the performance of an EV such as the maximum acceleration, regenerating braking and gradient climbing [4], but also is the key to

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Nomenclature

AEKF	adaptive extended Kalman filter
AFFLS	least square approach with adaptive forgetting factor
ATSF	adaptive two step filter
AUKF	adaptive unscented Kalman filter
BMS	battery management system
DEKF	dual extended Kalman filter
ECM	equivalent circuit model
EKF	extended Kalman filter
EMS	energy management strategy
EV	electric vehicle
KF	Kalman filter
LS	least squares
LTPD	long-term power demand
MAE	mean absolute error
ME	maximum error
OCV	open circuit voltage
RBF-NN	radial basis function neural network
RC	resistance and capacitance
RELS	recursive extended least squares
RLS	recursive least squares
SOAP	state of available power
SOC	state of charge
UKF	unscented Kalman filter
UDDS	urban dynamometer driving schedule
WRLS	weighted recursive least squares
WVUSUB	west Virginia suburban driving schedule

protect the battery from damage for safety and service life [5]. Thus, an accurate prediction of battery SOAP is crucial for battery and vehicle management. Furthermore, many researchers have pointed out that the predictive energy management strategy (EMS) can remarkably reduce the energy consumption of various EVs (for example, of the pure electric vehicles [6], fuel cell hybrid electric vehicles [7] and hybrid electric vehicles [8]). To improve energy efficiency or to minimize energy consumption of an EV, the future available power of the battery is required. Accordingly, an accurate online long-term prediction of battery SOAP is becoming more and more essential to BMS.

1.1. Literature review

The SOAP prediction approaches used in BMS can be divided into characteristic-maps (CMs)-based approaches and equivalent-circuit-model (ECM)-based approaches [9]. The CMs-based approach uses the relationship between the battery parameters and the battery SOAP. The ECM-based approach uses the parameters of battery ECM to calculate the battery SOAP.

There are two significant challenges of battery SOAP prediction. The first one is how to accurately obtain the battery parameters and states online, since the accurate prediction of battery SOAP strongly depends on them [9]. However, the internal process of battery is time-variable, nonlinear and unmeasurable in field; and the values of battery parameters and states will vary with such random working conditions as driving loads and operating environment of battery [10]. Accordingly, an adaptive approach, which can identify the battery parameters and estimate the battery states adaptively in real-time operation, is useful in obtaining the battery parameters and states. And many approaches have been proposed in recent research.

The battery parameters and states can be estimated based on a model with certain filtering or data-driven algorithms. Exemplary approaches include the Kalman filter (KF)-based approaches, particle filter-based approaches [11], $H\infty$ filter-based approaches [12], sliding mode observer-based approaches [13], the least squares (LS)-based approaches, other adaptive filters and observer-based approaches [14], and the fuzzy logic [15] and machine-learning-based approaches [16], etc. C. Burgos-Mellado et al. [15] proposed a fuzzy battery model, and used the particle filtering algorithm to online estimate the battery SOC. E. Chemali et al. [16] used a recurrent neural network (RNN) with long short-term memory (LSTM) to estimate battery SOC. These data-driven approaches do not require a very in-depth understanding of the battery, but sufficient and rich data from prior tests must be collected to train the estimation model, which are the main weaknesses of these methods [17]. Therefore, many researchers have focused on the filter-based approaches. The ECM and / or electrochemical model [18] can be employed in these approaches. And the extended Kalman filter (EKF)-based approach is the most widely studied filter-based approach in literature. To improve the accuracy, it can be used in different variations. X. Zhao et al. [11] established a dual-polarization-resistance model to make the ECM robust under different current load, and then applied an extended Kalman particle filter to estimate the battery SOC. L. Pei et al. [19] proposed a dual EKF (DEKF) to directly estimate the ECM parameters and battery SOC. Z. Deng et al. [20] developed a dual adaptive EKF (AEKF) to estimate the battery parameters and SOC against varying degradations. The battery parameters and / or states can be estimated under different temperatures and aging conditions. However, the EKF algorithm or its variants perform a first-order Taylor expansion of the battery state-space model to approximate the nonlinear characteristic of lithium-ion battery. So the linearization errors in the EKF-based approaches are inevitable, which may harm the accuracy of battery parameters identification and states estimation. To solve this problem, the approaches based on unscented Kalman filter (UKF) [21] or adaptive UKF (AUKF) [22] were proposed. However, the robustness of UKF/AUKF might decrease with uncertain distribution [23]. Therefore, for accuracy improvement of battery parameters identification and states estimation in real applications, the contradiction between the linearization errors and robustness in these existing approaches needs to be settled.

Compared with KF-based approaches, the LS-based approach can avoid the complex matrix operations such as inversions. It can be implemented on a low cost microcontroller. Therefore, LS-based approaches are commonly used in BMS applications for battery parameter identification, especially the recursive least squares (RLS)-based approaches due to their no requirement of storage of a significant amount of data. S. Wang et al. [24] applied a weighted recursive least squares (WRLS)-based approach to regress the R-RC circuit ECM model parameters. T. Feng et al. [25] proposed a novel ECM by adding a moving average noise to the one RC circuit model, and applied the recursive extended least squares (RELS)-based approach to online identify the model parameters. The battery parameters can be efficiently identified online by RLS-based approaches. However, for accuracy improvement, two issues should be solved. Firstly, the dynamic characteristics of battery open circuit voltage (OCV) are not incorporated in these ECMs. So the hysteresis effects of battery are unable to be well reflected, which may harm the ECM accuracy in real applications. Moreover, the impedance characteristic of the battery depends significantly on the battery current rate [26]. But the RLS approach does not consider this current-dependence [27]. As a result, the accuracy of battery parameter identification might decrease in different current in the real working conditions.

The second significant challenge of battery SOAP prediction is how to realize the accurate long-term SOAP prediction. For safe and durable operation of battery and EMSs of EVs, researchers have studied on the long-term SOAP prediction. R. Xiong et al. [4] used AEKF-based approach to jointly estimate the battery SOC and SOAP, and realized a long-term SOAP prediction. S. Wang et al. [24] introduced a time-varying charge-transfer resistance to describe the diffusion effect,