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Review

Critical review of the methods for monitoring of lithium-ion batteries in electric and hybrid vehicles

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HIGHLIGHTS

- Most comprehensive and extensive review of methods for battery monitoring.
- More than 350 sources including scientific and technical literature are studied.
- Consideration of requirements on battery monitoring algorithms is included.
- Strengths and weaknesses of the methods are elaborated based on requirements.

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ABSTRACT

Lithium-ion battery packs in hybrid and pure electric vehicles are always equipped with a battery management system (BMS). The BMS consists of hardware and software for battery management including, among others, algorithms determining battery states. The continuous determination of battery states during operation is called battery monitoring. In this paper, the methods for monitoring of the battery state of charge, capacity, impedance parameters, available power, state of health, and remaining useful life are reviewed with the focus on elaboration of their strengths and weaknesses for the use in on-line BMS applications. To this end, more than 350 sources including scientific and technical literature are studied and the respective approaches are classified in various groups.

1. Introduction

Hybridization and electrification of vehicle propulsion systems have become key trends in the automotive industry in recent years. These trends are considered as primary instruments for increasing the total efficiency and decreasing or even eliminating carbon dioxide (CO_2) emissions and other pollutants from vehicles. Batteries form key components not only for pure battery electric vehicles (BEVs) but also for intermediate storage of electrical energy in fuel cell electric vehicles (FCEVs) and other hybrid EVs (HEVs). Currently only lithium-ion batteries (LIBs) are considered as a highly prospective technology for automotive applications because of its good

Abbreviations: AEKF, adaptive extended Kalman filter; ANFIS, adaptive neuro-fuzzy inference system; ANN, artificial neuronal networks; ASPKF, adaptive sigma-point Kalman filter; BEV, battery electric vehicle; BMS, battery management system; CDKF, central-difference Kalman filter; CPE, constant phase element; DCVP, discharging–charging voltage patterns; ECM, equivalent circuit model; EKF, extended Kalman filter; EMF, electromotive force; EMS, energy management system; FCEV, fuel cell electric vehicle; FPU, floating-point unit; GHQF, Gauss–Hermite quadrature filter; HEV, hybrid electric vehicles; KF, Kalman filter; LIB, lithium-ion battery; LMS, least mean squares (filter); LOLIMOT, local linear model tree; NCA, nickel–cobalt–aluminum-oxide (cathode material); NiMH, nickel–metal hydride (battery); NMC, nickel–manganese–cobalt (cathode material); OCV, open-circuit voltage; PDE, partial differential equation; PF, particle filter; PHEV, plug-in hybrid electric vehicle; RCP, rapid control prototyping (hardware, system); RLS, recursive least squares (filter, method); RUL, remaining useful life; RVM, relevance vector machine; SAVP, statistical analysis of voltage pattern; SOA, safe operating area; SoC, state of charge; SoF, state of function; SoH, state of health; SPKF, sigma-point Kalman filter; SVM, support vector machine; UKF, unscented Kalman filter; WRLS, weighted recursive least squares (filter, method).

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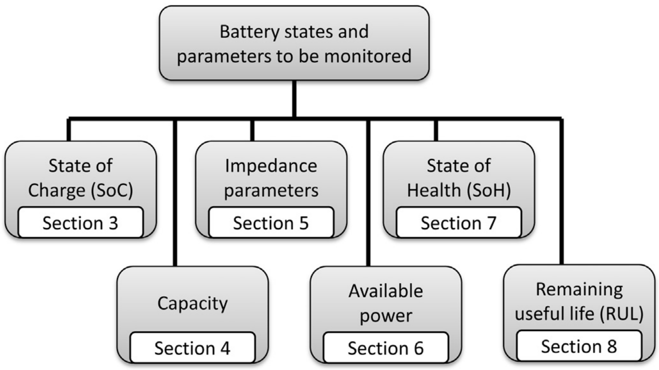

Fig. 1. Battery states and parameters to be monitored in electric and hybrid vehicles.

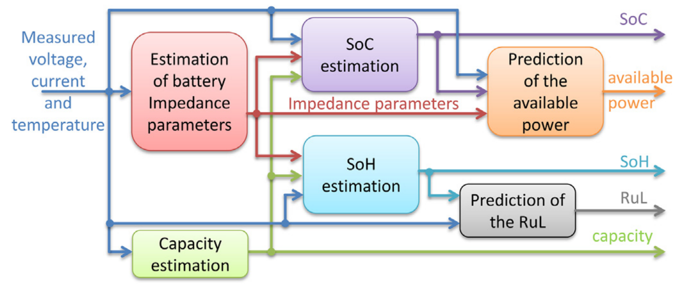

Fig. 2. A typical interaction and information flow between individual methods within of the battery monitoring system.

performance characteristics and promising potential for cost reduction [1,2].

LIB packs are always equipped with a battery management system (BMS). The BMS consists of hardware and software for battery management including, among others, algorithms determining battery states. The continuous determination of battery states during operation is called battery monitoring.

Since batteries are complex electrochemical devices with a distinct nonlinear behavior depending on various internal and external conditions, their monitoring is a challenging task. This task is additionally hindered by considerable changes in battery characteristics over its lifetime due to aging. On the other hand, very precise and especially reliable battery monitoring is a key function of the BMS. This function enables safe and reliable operation of the battery pack and, hence, of the total application where the battery pack is used. Therefore, special algorithms for battery monitoring are required. The requirements on battery monitoring algorithms are summarized in Section 2.

In next sections, the methods for the monitoring of battery states and parameters (Fig. 1) presented in scientific and technical literatures are reviewed.[1] The focus is to elaborate their strengths and weaknesses rather than to describe their respective approaches in detail. For detailed descriptions of the methods, the reader is advised to refer to the respective original sources referenced in this work or to the reviews that can be found in Refs. [3–22]. In the following sections, only methods that are applied or can be potentially applied for monitoring LIBs in BEVs and HEVs are considered. Some other methods specific for other battery technologies exist, e.g., lead-acid batteries or other applications, but their consideration lies beyond the scope of this paper.

The battery SoC can be employed in the figurative sense as a replacement for a fuel gauge used in conventional vehicles. The SoC is basically the relationship between the residual battery capacity in its present state (C_r) and total capacity C_{bat} after completely charging the battery, expressed in a percentage: $SoC = C_r / C_{bat} \cdot 100\%$. Methods for the SoC monitoring are considered in Section 3 and methods for the estimation of the total battery capacity in Section 4.

For EV applications, batteries must not only deliver a certain amount of energy to the drive train during operation but also provide a certain power in various situations. The battery's capability to fulfill certain tasks is often referred to as the state of function (SoF). For the energy management system (EMS) operating in EVs, knowing the maximum power that can be applied to and from the battery by charging or discharging, respectively, is essential. This power depends, among others, on the present battery impedance characteristics. The methods for the estimation of the battery impedance and for the prediction of the available power are considered in Sections 5 and 6, respectively.

The capability of the battery to store energy and provide a certain power decreases over the battery lifetime because of aging. As an indicator for this deterioration, the additional battery state—state of health (SoH)—is defined. The methods for its determination are considered in Section 7.

The final battery state of interest is the remaining useful life (RUL). As RUL usually the remaining time or number of load cycles until the battery reaches its end of life (EoL) is understood. The methods for the RUL estimation are considered in Section 8.

A typical interaction and information flow among individual methods within of the battery monitoring system is shown in Fig. 2.

2. Requirements on battery monitoring algorithms

In this section the requirements on battery monitoring algorithms are given (Fig. 3). First, the battery monitoring algorithms have to consider battery characteristics. One challenge is that battery characteristics depend significantly on the battery internal and external conditions (for example, SoC, temperature, current). The other challenge is that almost all battery characteristics, including, for example, battery capacity and impedance parameters, changes significantly over the battery lifetime due to aging [23].

Second, the battery monitoring algorithms have to consider strong limitations regarding the operating conditions of LIBs. The

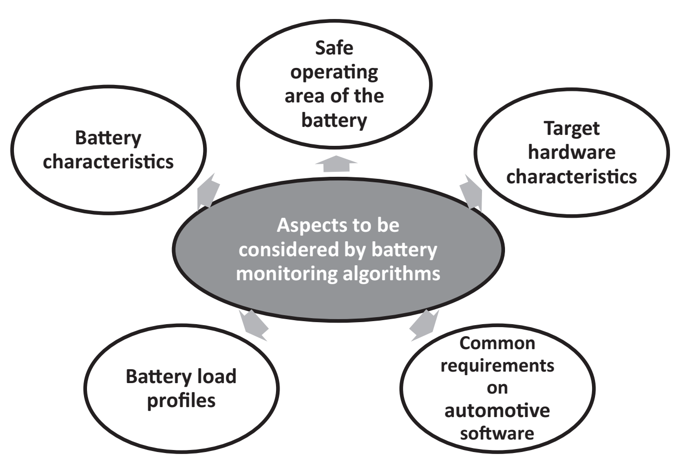

Fig. 3. Requirements on battery monitoring algorithms.

[1] This review is based on the Ph.D. thesis of Wladislaw Waag submitted to Faculty of Electrical Engineering and Information Technology at RWTH Aachen University in October 2013.