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Comparative study of reduced order equivalent circuit models for on-board state-of-available-power prediction of lithium-ion batteries in electric vehicles

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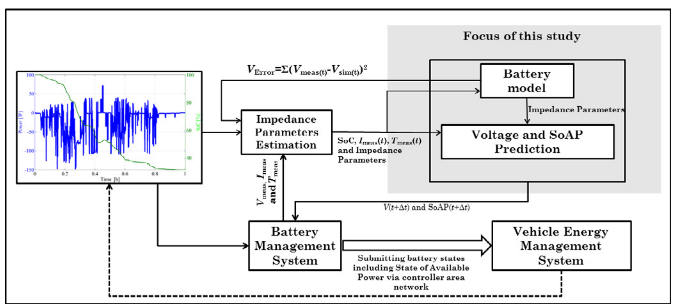
HIGHLIGHTS

- Seven impedance-based ECMs are investigated in MiL environment.
- The model using 3 ZARC-elements indicates highest impedance determination accuracy.
- $\overline{V}_{\mathrm{RMS}}$ increases by a factor of 5 with decreasing temperature from 40 °C to 0 °C.
- Error in power doubled when prediction time horizon increases from 10 s to 20 s.

GRAPHICAL ABSTRACT



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ABSTRACT

Battery management systems (BMS) are responsible for the reliable and safe operation of lithium-ion battery packs in electric vehicles (EVs). State-of-Charge (SoC), State-of-Health (SoH) and State-of-Available-Power (SoAP) are the major battery states that must be determined by means of so-called monitoring algorithms. In this study, a comparative study of a wide range of impedance-based equivalent circuit models (ECMs) for on-board SoAP prediction is carried out. In total, seven dynamic ECMs including ohmic resistance, RC-elements, ZARC-elements connected in series with a voltage source are implemented. The investigated ECMs are verified under varying conditions (different temperatures and wide SoC range) in a model-in-the-loop (MiL) environment using real vehicle data obtained in an EV prototype and current pulse tests. In this context, LIBs at different aging states using various active materials (NMC/C, NMC/LTO, LFP/C) are investigated. Furthermore, the current dependence of the charge transfer resistance is considered by applying the Butler-Volmer equation. The dependence of voltage estimation and SoAP prediction accuracy for different prediction time horizons on SoC, temperature and applied current rate is examined comprehensively.

1. Introduction

Lithium-ion batteries (LIBs) definitely belong to the most promising commercially available energy storage systems for use in electric vehicles (EVs). Partial or full electrification of the vehicle powertrain is one of the certainly unfailing measures to reach particular targets such

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as reducing a vehicle's local emission and providing the possibility to implement more consumer-friendly and security-relevant functions [1]. The higher specific volumetric and gravimetric energy and power density, lower weight, higher cycle lifetime and lower self-discharge rate of LIBs in comparison to settled energy storage systems (ESS) [2,3], e.g., lead-acid batteries, nickel-cadmium or nickel-metal hydride, have gained the attention of many vehicle manufacturers, suppliers and research institutions in recent years in order to explore and improve different LIB technologies. In large lithium-ion battery packs several hundred LIBs are connected in series and/or in parallel to fulfill specific electrical and thermal requirements. The performance of large lithium-ion battery packs used in EVs and their operation are controlled by means of so-called battery management systems (BMS) that consist of both software and hardware [4]. In other words, among the main tasks of BMS are battery state estimation, protection against battery over/under-voltage, over-current, over/under-temperature etc. A schematic overview of a lithium-ion battery pack consisting of electric and electronic components can be found in our previous study [5].

In spite of recent progresses in the development of battery monitoring algorithms development, an accurate and robust performance of the applied algorithms is still a challenging issue, keeping in mind that the algorithms have to work precisely under varying conditions over years. The main battery states of interests are often State-of-Charge (SoC), State-of-Health (SoH) and State-of-Available-Power (SoAP).

Various internal and external factors such as temperature distribution inside battery pack, change of battery impedance characteristics (i.e., mainly because of battery aging or temperature change etc.), cell-to-cell variations either in an initial state or over the battery lifetime resulting from different cell impedances or capacities, influence the battery behavior with regard to energy content and/or power capability. It is therefore necessary to use monitoring algorithms that work accurately over the battery lifetime. Furthermore, a precise estimation of battery states should be ensured in order to satisfy end consumers with regard to e.g., power and/or energy management strategy or safety aspects etc. During the early stages of monitoring algorithms development, especial emphasis should be put on low computational effort, low model parameterization effort, high model fidelity over a wide SoC and temperature range; furthermore, the physical equivalence should be taken into consideration as far as possible.

Up to now, different approaches for SoC and SoH estimation of LIBs have been shown and reviewed in the literature by many authors in the past [6–8]. However, the topic of SoAP prediction has not been explored sufficiently yet and there are still a lot of researches required to optimize, improve and understand this challenging task. By knowing the available battery power in addition to the actual battery SoC and SoH, a reasonable EMS strategy can be applied and specified vehicle functions, such as vehicle acceleration, deceleration or gradient climbing can be performed without exiting the battery's safe operating area (SOA) and affecting the lifetime of the battery or causing safety damage [9,10]. The SoAP is mainly referred to as the amount of power which the battery can deliver to or accept from the vehicle powertrain over a certain time horizon (Δt). As a general rule, the Δt for SoAP prediction lies between 1 s and 20 s in EVs [4]. As one of the state-of-the-art techniques for determining the static power capability of the battery, the hybrid pulse power characterization (HPPC) method presented by the partnership for new generation vehicles (PNGV) battery test manual, published by the Idaho National Engineering & Environmental Laboratory of the U.S. Department of Energy, can be addressed [11]. In fact, accurate results may be achieved by applying this technique in laboratory environments. But under real conditions, such as in vehicles where the available peak current or voltage for a specified time horizon need to be known, accurate power values are not provided and the results are mostly over or underestimated since only the operational design limits of battery voltage are considered [12,13].

In general, it can be stated that a battery's power fade occurring over the battery lifetime is mainly related to an impedance increase of the battery over its lifetime [14]. The power fade occurring over the battery lifetime directly influences the driving performance of the vehicle in terms of acceleration or battery charging during recuperation or charging periods [15]. The available battery power is mainly limited by temperature, SoC, voltage and current, i.e., parameters that are actually defined by SOA predefined by LIB manufacturers [5]. However, during a single applied current over a time horizon of several seconds ($\Delta t \leq 10$ s), the battery's temperature and SoC do not change significantly. Thus, it can be assumed that in practice battery voltage and current are the major limiting factors for SoAP prediction [16]. Because of safety reasons, the battery must be operated in a specific voltage window ($V_{\min} \leqslant V_{\text{operating}} \leqslant V_{\max}$) often predefined by LIB manufacturers. This limitation has an impact on the maximum current which can be drawn from or fed into the battery and is therefore often used as an indicator for power capability of the battery. Consequently, the maximum power that is allowed to be applied to the battery can be determined when the predefined SOA limit of battery current or individual cell or battery system voltage is reached.

The available methodologies for on-board SoAP prediction of LIBs in EVs can be classified into following two groups [5,17]:

- Methods based on (adaptive) characteristic maps,
- Methods based on equivalent circuit models (ECMs).

A detailed description of the techniques mentioned above can be found in our previous study [5] and will therefore not be further discussed here. The algorithms presented in the literature were often validated under nominal conditions or when the battery was in a new state. Moreover, in most of the cases the proposed algorithms are verified on cell level whereby additional challenges such as LIB inconsistencies and mechanical integrity issues occurring on system level are often neglected. However, as discussed in Refs. [5,17], the SoAP prediction becomes more challenging at low temperatures or when the battery is aged, as the LIB reaches the predefined SOA and power limits, readily [18,19]. Unfortunately, in almost all the research articles presented in the past, the authors investigated simple ECMs. The simplest ECM for an accurate dynamic battery modeling consists of an ohmic resistance (R_0) connected in series with an ideal voltage source (V_{OCV}) [20,21]. At the same time, enhanced ECMs consisting of a finite number of RC-elements connected in series to R_0 and V_{OCV} yield higher voltage estimation accuracy as the battery's transient behavior can be captured more precisely [22].

In Ref. [23], a comparative study of twelve various ECMs is performed. The employed ECMs are compared considering their robustness, model complexity and accuracy of the estimated battery voltage. The Multi-swarm particle swarm optimization (MPSO) algorithm is applied for on-board estimation of the ECM parameters. On the one hand, using a complex ECM yields a higher degree of voltage estimation accuracy, but on the other hand the parameter identification of such ECMs requires high computing power which is rarely given on low-cost embedded systems. According to the authors, the ECM using R_0 connected in series with one RC-element yields most accurate results with regard to the above mentioned criteria for voltage estimation.

In Ref. [24], a recursive joint estimator based on a dual extended Kalman filter (dual EKF) is applied for ECM parameters estimation. The authors give a systematic overview of ten different ECMs. Within the aforementioned study, LIBs in new state using lithium nickel cobalt manganese oxide, $Li(Ni_{1-x-y},Mn_x,Co_y)O_2$ (NMC) and lithium iron phosphate, $LiFePO_4$ (LFP) cathodes are investigated. Within the scope of the presented study, the impact of the employed ECMs on the estimation accuracy of SoC and SoAP is examined. According to the results, the ECM using R_0 and two RC-elements connected in series to V_{OCV} indicates the most precise result. However, the applied SoAP algorithm acts more as a Boolean signal (i.e., whether the required power can be applied/obtained to/from the battery or not) using HPPC technique rather than providing the amount of power that can be applied to the