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Estimating power capability of aged lithium-ion batteries in presence of communication delays

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HIGHLIGHTS

- An adaptive power limit algorithm is developed.
- Stability analysis of the adaptive algorithm in presence of communication delays.
- Extensive lab validation in temperatures between −20 and + 25 °C.
- 5 s power estimation accuracy is within ± 2%.

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ABSTRACT

Efficient control of electrified powertrains requires accurate estimation of the power capability of the battery for the next few seconds into the future. When implemented in a vehicle, the power estimation is part of a control loop that may contain several networked controllers which introduces time delays that may jeopardize stability. In this article, we present and evaluate an adaptive power estimation method that robustly can handle uncertain health status and time delays. A theoretical analysis shows that stability of the closed loop system can be lost if the resistance of the model is under-estimated. Stability can, however, be restored by filtering the estimated power at the expense of slightly reduced bandwidth of the signal.

The adaptive algorithm is experimentally validated in lab tests using an aged lithium-ion cell subject to a high power load profile in temperatures from −20 to +25 °C. The upper voltage limit was set to 4.15 V and the lower voltage limit to 2.6 V, where significant non-linearities are occurring and the validity of the model is limited. After an initial transient when the model parameters are adapted, the prediction accuracy is within ± 2% of the actually available power.

1. Introduction

The energy management system (EMS) of a plug-in hybrid electric vehicle (PHEV) uses information about the power available from the electric system to optimize efficiency, performance, and driving experience [1–3]. To avoid premature ageing, the battery power must be limited by specifying regions of safe use in terms of limits on voltage, current, and temperature. Power capability of the battery cannot be measured directly and the battery management system (BMS) must therefore estimate the power available for the next few seconds into the future [4]. This can be achieved using model-based techniques where the current–voltage characteristics are used to predict the voltage response to a given constant current. A major difficulty in this task is that the characteristics of the battery changes considerably with both operating conditions and age [5–7]. However, on-line parameter estimation techniques such as recursive least squares or Kalman filter can be used to maintain accuracy in the power estimation, by keeping the battery model updated over time.

State-of-power (SoP) can be divided into two separate parts; (i) predicting the maximum charge and discharge power that is available without violating constraints on voltage, current, etc., and (ii) limiting the power if the request of the vehicle exceeds the available power. A typical set-up in a vehicle application is shown if Fig. 1. The BMS measures current, voltage and temperature of the battery cells and estimates the maximum power that the battery pack can deliver. This is sent over the controller area network (CAN) to the EMS. The EMS collects power requests from all subsystems connected to the battery and communicates how much power each component may use. The

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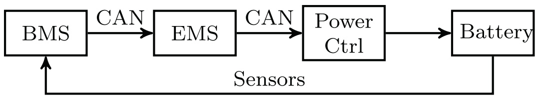

Fig. 1. Typical controller configuration in vehicle application.

consumers (here represented by the power controller) then actuates the power out-take from the battery. In the limiting case, closed-loop control of the power containing several networked controllers is formed. As will be shown later in this article, a combination of communication delays and uncertain model parameters may impact stability of the system. Similar observations are also presented in Ref. [8].

Adaptive power estimation has been analysed before, see for instance [9,10] for two recent review articles on the subject of power prediction. In summary, different approaches have been considered, such as:

- Analytic expressions based on an equivalent circuit model (see e.g. Refs. [11,12])
- Kalman filter based estimation (see Refs. [13–15])
- Particle filter based estimation (see Ref. [16])
- Neural networks (see Ref. [17])

This article extends the work in Ref. [11], where an analytical calculation of the battery SoP was presented. The method was analysed for stability and performance in simulations, and the main contributions in this article are (i) stability analysis of adaptive maximum (minimum) current estimation in the presence of parametric uncertainty and communication delays; and (ii) experimental validation in battery lab using an aged cell in cold temperatures.

The article is structured as follows; in Section 3 the models and algorithms are introduced. Section 4 presents a robustness analysis together with an extension to the power limit algorithm that handles parameter uncertainty. In Section 5, a laboratory validation of the adaptive system is presented. Section 6 summarizes the results.

2. Nomenclature

In Table 1, the notation used in this article is listed.

Table 1
Nomenclature.

Symbol	Description
v	Cell voltage
i	Current
p	Power
v_1	Voltage over RC pair in equivalent circuit model
T	Time constant of RC pair in equivalent circuit model
C	Capacitance in equivalent circuit model
R_0, R_1	Resistances in equivalent circuit model
z_{soc}	State of charge
v_{oc}	Open circuit voltage function
y	Output in linear regression model
φ	Regression vector in linear regression model
θ	Parameter vector in linear regression model
e	Noise term
Δt	Prediction horizon of SoP algorithm
v_{lim}	Voltage limit used in SoP algorithm, either v_{max} or v_{min}
v_{max}	Upper voltage limit
v_{min}	Lower voltage limit
i_{lim}	Current limit used in SoP algorithm, either i_{max} or i_{min}
$i_{lim,v}$	Current limit based on voltage
$i_{lim,c}$	Fixed current limit
i_{max}	Maximum current
i_{min}	Minimum current (i.e. maximum discharge current)
Δv	Voltage margin from v to v_{lim}
I, V	Laplace transform of i and v respectively
K	Gain of SoP algorithm
G	Transfer function representation of equivalent circuit model
F, F_0	Transfer functions describing the SoP algorithm
τ	Time delay from CAN communication
SoC	State of charge
SoP	State of power
PHEV	Plug-in hybrid electric vehicle
BMS	Battery management system
EMS	Energy management system
CAN	Controller area network
OCV	Open circuit voltage

3. Adaptive state-of-power algorithm

An adaptive state-of-power algorithm consists of three major parts, (i) a battery model, (ii) parameter estimator, and (iii) a prediction of the power that can be delivered or absorbed without violating battery constraints. This section presents these parts by reviewing some previous results.

3.1. Battery model

In battery estimation applications, equivalent circuit models are often used to predict voltage as a function of current (see e.g. Refs. [5,18,19]). The prediction horizons of interest for the SoP considered here are in the range of 1–5 s, which means that slower dynamics of the cell can be discarded. Here, a first-order equivalent circuit model, where the voltage v_1 models diffusion effects (see Fig. 2), is considered suitable for the purpose.

In continuous time, the equivalent circuit model is described by

$$\dot{v}_1(t) = -\frac{1}{T}v_1(t) + \frac{1}{C}i(t) \tag{1}$$

$$v(t) = v_{oc}(z_{soc}(t)) + v_1(t) + R_0 i(t), \tag{2}$$

where z_{soc} is the state-of-charge, v_{oc} is the open circuit voltage, $T = R_1 C$ is the time constant, and $\dot{v}_1 = dv_1/dt$. The parameters R_0, R_1, $C \in \mathbb{R}^+$ and variables v, v_1, $i \in \mathbb{R}$ are defined in Fig. 2. The sign convention is such that a positive current (power) charges the battery.

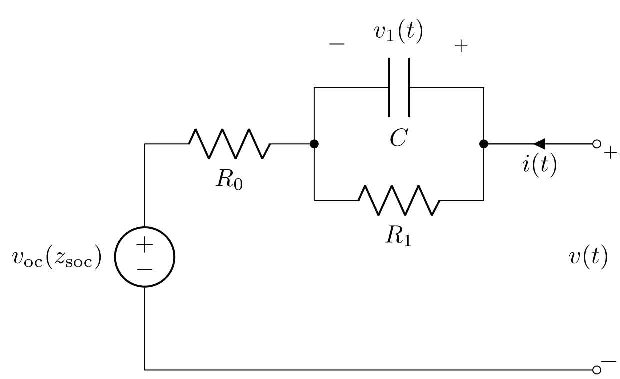

Fig. 2. Equivalent circuit battery model.

3.2. Recursive parameter estimation

Since the battery characteristics change significantly with both operating conditions and age, it is common to include some kind of parameter adaptation in the algorithms of the BMS. There are several alternatives to this, both in continuous time [12,20], and in discrete time [21–23].

For parameter estimation, models are often formulated in regressor form, i.e.

$$y(t) = \varphi^T(t)\theta(t) + e(t),$$

where $y \in \mathbb{R}$ is the output, $\varphi \in \mathbb{R}^n$ is the regression vector, $\theta \in \mathbb{R}^n$ is the parameter vector, $e \in \mathbb{R}$ is a noise term, and n is the number of