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Robust recursive impedance estimation for automotive lithium-ion batteries

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HIGHLIGHTS

- Identifies potential problems encountered in recursive parameter estimation.
- Methods to improve performance and robustness of recursive parameter estimators.
- Robust algorithm for estimation of battery cell impedance parameters.

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ABSTRACT

Recursive algorithms, such as recursive least squares (RLS) or Kalman filters, are commonly used in battery management systems to estimate the electrical impedance of the battery cell. However, these algorithms can in some cases run into problems with bias and even divergence of the estimates. This article illuminates problems that can arise in the online estimation using recursive methods, and lists modifications to handle these issues. An algorithm is also proposed that estimates the impedance by separating the problem in two parts; one estimating the ohmic resistance with an RLS approach, and another one where the dynamic effects are estimated using an adaptive Kalman filter (AKF) that is novel in the battery field. The algorithm produces robust estimates of ohmic resistance and time constant of the battery cell in closed loop with SoC estimation, as demonstrated by both in simulations and with experimental data from a lithium-ion battery cell.

1. Introduction

The electrical impedance of the battery cell is used when estimating for instance State of Charge (SoC), State of Energy (SoE), State of Power (SoP) and State of Health (SoH). As the battery ages, its impedance increases due to e.g. loss of electrode surface area and conductor corrosion [3,25], and in order to maintain accuracy in all the estimations, it is vital to continuously monitor and update the impedance [6,8,21,29].

In the literature, several different approaches to impedance estimation have been presented. Most common are offline system identification methods using some type of lab tests. Two such approaches are frequency domain identification using electrochemical impedance spectroscopy (EIS), and time domain identification using pulse tests [19,27]. These methods rely on specialized equipment, test cycles and processing of large amounts of data, and are thus not suited for online implementation on low-cost processors used in automotive applications.

Focussing attention to methods suitable for online implementation, most of these rely on using an equivalent circuit model of the battery. The parameters are then estimated using primarily current and voltage information. Three conceptually different approaches are presented in the literature:

- *Recursive methods* store only data needed to perform one recalculation of the model (see e.g. Refs. [4,10,20,30]). The parameter estimates are then updated based on the new information in each time step. Low computational and storage costs have made this a popular choice for online parameter estimation.

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- *Non-recursive methods* estimates parameters based on batches of data and thus requires larger amounts of data to be stored. While often used in offline system identification methods, the storage requirements means that they are less suitable for online applications. There can, however, be cases when non-recursive methods are needed (see e.g. Refs. [7,17,24]).
- *Machine learning algorithms* such as structured neural networks (SNN) (see e.g. Ref. [2]) and support vector machines (SVM) (see e.g. Ref. [14]) are useful when the battery characteristics cannot be accurately described by a simple model. Using training data, the algorithms learn how the system works. Problems such as large storage requirements and risk of overfitting reduces their applicability in online automotive tasks.

A comprehensive review of methods used in the literature, can be found in Ref. [26].

The rest of this article will focus on recursive methods with three main contributions; (i) a set of examples illustrating when recursive algorithms can fail; (ii) modifications to handle these issues; and (iii) design and experimental evaluation of an algorithm for estimation of battery impedance.

The structure is such that in Section 2, the recursive methods in focus are presented. In Section 3, the test environment and battery model used for evaluation of the estimators are described. Section 4 highlights issues that can be encountered in recursive estimators and proposes solutions to these problems. An algorithm is proposed in Section 5 and then evaluated using both simulations and experimental data in Section 6. Finally, Section 7 summarizes the results.

2. Recursive parameter estimation

In the following sections, two frequently used recursive parameter estimators are presented; the recursive least squares (RLS) and the Kalman filter. These algorithms are related and both use a linear regression model of the system in generic form,

$$y(k) = \varphi^T(k)\theta(k) + e(k), \tag{1}$$

where y is the observed output, φ is the regressor, θ is the parameter vector to be estimated and e is a noise term.

2.1. Recursive least squares

The method of solving an over-determined set of equations using least squares is well known to most engineers. In mathematical terms, the method determines the parameter vector $\hat{\theta}$ that minimizes the squared error between the measured output and the output predicted by the model (1), i.e.

$$\hat{\theta}(k) = \arg\min_{\theta} \frac{1}{2}\sum_{i=1}^{k} \lambda^{k-i}\left(y(i) - \varphi^T(i)\theta\right)^2, \tag{2}$$

where $0 \ll \lambda \leq 1$ is a forgetting factor introduced to weigh recent data more than old. This minimization problem has an analytic solution that can be implemented as a recursive algorithm:

$$\hat{\theta}(k) = \hat{\theta}(k-1) + K(k)\varepsilon(k) \tag{3}$$

$$K(k) = P(k-1)\varphi(k)\left(\lambda + \varphi^T(k)P(k-1)\varphi(k)\right)^{-1} \tag{4}$$

$$P(k) = \left(I - K(k)\varphi^T(k)\right)P(k-1)\Big/\lambda, \tag{5}$$

where K is the estimator gain, P is the covariance estimate and $\varepsilon(k) = y(k) - \varphi^T(k)\hat{\theta}(k-1)$ is the residual between measured and estimated output.

In the literature, there are several versions of recursive least squares estimators [1,9,16]. By simplifications, reformulations of the cost function or avoiding estimation of the covariance estimate, they can be tailored to system requirements. In this work, the regular RLS algorithm with exponential forgetting factor (3)–(5) is used. In the battery estimation field, RLS has been used for parameter estimation in e.g. Refs. [10,30].

2.2. Kalman filter

The Kalman filter can be seen a special case of the RLS algorithm, where the parameter variations are modelled as random walks, i.e.

$$\theta(k+1) = \theta(k) + w(k),$$

where $w(k) \sim \mathcal{N}(0, R_w)$ is a Gaussian white noise. Like in (1), the measurement is distorted by additive noise,

$$y(k) = \varphi^T(k)\theta(k) + v(k), \tag{6}$$

but now it is assumed that $v(k) \sim \mathcal{N}(0, R_v)$ is a Gaussian white noise. The Kalman filter algorithm then becomes

$$\hat{\theta}(k) = \hat{\theta}(k-1) + K(k)\varepsilon(k) \tag{7}$$

$$K(k) = P(k-1)\varphi(k)\left(R_v(k) + \varphi^T(k)P(k-1)\varphi(k)\right)^{-1} \tag{8}$$

$$P(k) = P(k-1) - K(k)\varphi^T(k)P(k-1) + R_w(k), \tag{9}$$

where we note that the noise covariances, R_w and R_v, which represents the noise statistics, often are considered as tuning parameters. Derivation of the linear Kalman filter can be found in several sources, for instance the original paper [12] or more recent descriptions, such as [28]. In the battery estimation field, Kalman filters are used for parameter estimation in e.g. Refs. [4,20].

3. Test environment

In the upcoming discussions, a test environment is used to evaluate the algorithms and to highlight potential problems.

3.1. Equivalent circuit battery model

In online battery management systems, it is common to use a model of the current–voltage response in form of an equivalent circuit like the one in Fig. 1. Discretized with sampling time Δt and zero order hold, it is described by

$$u_{RC_1}(k+1) = e^{-\frac{\Delta t}{C_1R_1}}u_{RC_1}(k) + R_1\left(1 - e^{-\frac{\Delta t}{C_1R_1}}\right)i_{cell}(k) \tag{10}$$

$$u_{RC_2}(k+1) = e^{-\frac{\Delta t}{C_2R_2}}u_{RC_2}(k) + R_2\left(1 - e^{-\frac{\Delta t}{C_2R_2}}\right)i_{cell}(k) \tag{11}$$

$$u_{cell}(k) = u_{ocv}(z_{soc}(k)) + u_{RC_1}(k) + u_{RC_2}(k) + R_0 i_{cell}(k), \tag{12}$$

where z_{soc} is the SoC of the battery, and the rest of the parameters and signals are defined in Fig. 1. Note that the notation is slightly