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Kalman filter for adaptive learning of look-up tables with application to automotive battery resistance estimation

Björn Fridholm [a,c,*], Torsten Wik [b], Magnus Nilsson [c]

[a] Volvo Car Corporation, Göteborg, Sweden
[b] Automatic Control, Department of Signals and Systems, Chalmers University of Technology, Göteborg, Sweden
[c] Viktoria Swedish ICT, Göteborg, Sweden

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A B S T R A C T

In online automotive applications, look-up tables are often used to model nonlinearities in component models that are to be valid over large operating ranges. If the component characteristics change with ageing or wear, these look-up tables must be updated online. Here, a method is presented where a Kalman filter is used to update the entire look-up table based on local estimation at the current operating conditions. The method is based on the idea that the parameter changes observed as a component ages are caused by physical phenomena having effect over a larger part of the operating range that may have been excited. This means that ageing patterns at different operating points are correlated, and these correlations are used to drive a random walk process that models the parameter changes. To demonstrate properties of the method, it is applied to estimate the ohmic resistance of a lithium–ion battery. In simulations the complete look-up table is successfully updated without problems of drift, even in parts of the operating range that are almost never excited. The method is also robust to uncertainties, both in the ageing model and in initial parameter estimates.

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1. Introduction

The characteristics of many physical systems vary with both operating conditions and age. These variations typically occur on very different time-scales and can thus be treated separately in parameter estimators. Parameter variations due to operating conditions are often modelled explicitly, e.g. using look-up tables, while ageing is typically handled by robust design or by an adaptive scheme acting on a slower time scale.

An example of such a system is automotive lithium–ion batteries, where the ohmic resistance changes considerably both with temperature, State-of-Charge, and age (Broussely et al., 2005; Remmlinger, Buchholz, Meiler, Bernreuter, & Dietmayer, 2011; Vetter et al., 2005). Variations with age are much slower than changes with operating conditions (Jossen, 2006), which motivates handling these two types of variations separately. In the literature, there are several articles focusing on building models valid over the operating range, using look-up tables (Debert, Colin, Bloch, & Chamaillard, 2013; Do, Forgez, el Kadri Benkara, & Friedrich, 2009; Hu, Yurkovich, Guezennec, & Yurkovich, 2009; Jaguemont, Boulon, & Dubé, 2015) and elementary functions (Chen & Rincón-Mora, 2006; Hu, Li, Peng, & Sun, 2012; Lam, 2011; Zou, Hu, Ma, & Li, 2015). To handle variations due to ageing, recursive algorithms such as recursive least squares (RLS) (Hu, Sun, Zou, & Peng, 2011; Zou et al., 2015) or Kalman filters (Do et al., 2009; Plett, 2004) are commonly used for online estimation of parameters at the current operating conditions.

Within the battery community, there appears to be no published methods for updating look-up tables. Some previous work on updating look-up tables can, however, be found in other fields using Kalman filters (Höckerdal, Frisk, & Eriksson, 2011; Guardiola, Pla, Blanco-Rodriguez, & Cabrera, 2013) and recursive least squares (Peyton Jones & Muske, 2009), though the focus is then on an update of the look-up table only at the operating points closest to the current operating conditions. This means that the parameter estimate in operating points that have not been visited for a long time may be far from the true value. For vehicle batteries, this can cause a problem, for instance when cold cranking in operating conditions that have not been updated for a long time (Anderson & Moore, 1979).

In this work, we present a novel method for updating an entire look-up table based on information only at the current operating conditions. This is made possible by modelling correlations between changes in parameter values at different operating points over ageing and include them in a Kalman filter that handles the update of the look-up table.

* Corresponding author at: Volvo Car Corporation, Göteborg, Sweden.
E-mail address: bjorn.fridholm@volvocars.com (B. Fridholm).

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This paper is structured such that Section 2 introduces some notation used in the paper. Section 3 presents look-up tables and Section 4 the ageing model. In Section 5, the proposed algorithm is presented and in Section 6, it is tested in a simulation study. Eventually, Section 7 summarises the results.

2. Notation

Some terms used in the paper have specific meaning that are important to keep in mind and are therefore listed in Table 1 with a short description. Some other important non-standard notations are listed in Table 2. Note that subscripts k always is a time index, i.e. $\Theta_k = \Theta(k)$, while indices i and j always refers to an element of the vector containing the operating points. More standardised notation are described when introduced.

3. Look-up tables

In Fig. 1, a one-dimensional look-up table is depicted. Denote by x_i, $i = 1, \ldots, n$, the operating points defining the look-up table break-points. Let $\Theta \in \mathbb{R}^n$ be the corresponding vector of look-up table values, and define the time varying index, $i(k)$, as:

$$i(k) = \max\{j = 1, \ldots, n \mid x_j \le x(k)\},$$

where $x(k)$ is the current operating condition, which in general is between the break-points of the look-up table. Define the scalar value $\eta \in [0, 1]$ as:

$$\eta(k) = \frac{x(k) - x_{i(k)}}{x_{i(k)+1}(k) - x_{i(k)}}, \quad x_1 \le x(k) \le x_n,$$

where η is limited to be 0 if $x(k) < x_1$ and 1 if $x(k) > x_n$. With linear interpolation, the current parameter value is given by (cf. Fig. 1):

$$\theta^x(k) = (1 - \eta(k))\theta_{i(k)}(k) + \eta(k)\theta_{i(k)+1}(k).$$

In the following, the vector $C_k = [c_1(k), \ldots, c_n(k)]$ will be defined by the elements:

$$c_j(k) = \begin{cases} 1 - \eta(k), & j = i(k) \\ \eta(k), & j = i(k) + 1 \\ 0, & \text{otherwise} \end{cases}$$

which means that the look-up table output can be written in matrix notation as:

$$\theta^x(k) = C_k \Theta(k). \tag{1}$$

4. Ageing model

The ageing model proposed here builds on the idea that the changes observed due to ageing has an underlying physical cause and will thus affect the parameter values at all operating points. This leads to a long-term trend in the changes that can be utilised to improve estimation at parts of the look-up table where data have not been collected for a long time. In Swierczynski (2012), several reasons for an increase in battery impedance as the battery ages are presented, such as conductor corrosion and loss of active electrode surface. It is reasonable to assume that these effects are visible across the entire operating range. Such a correlation is also observed in the data presented in Waag, Käbitz, and Sauer (2013), where data from three different cells at two stages of ageing are shown for five different temperatures and two SoC levels. The data are reproduced in Fig. 2, where cell A is new, cell B was aged 200 cycles and cell C was aged 1900 cycles.

In Fig. 2, the resistance for all three batteries at two different operating points, −10 °C and 25 °C, are shown in an x–y plot. It indicates strong correlation between changes in parameter values at different operating points over ageing, where an increase in resistance at one temperature correlates well with an increase at other temperatures.

Table 2
Notation.

Θ	Look-up table parameter vector with elements corresponding to the operating points. Note that it is always the same physical parameter, e.g. ohmic resistance, but at different operating points, e.g. different temperatures
θ_i	Parameter value at operating point i
Θ_k	Parameter vector at current time step, i.e. short notation for $\Theta(k)$
θ^x	Parameter value at current operating condition
x	Operating condition
x_i	Operating point i
i, j	Index of operating point
k	Time index in discrete time
η	Interpolation variable
w, v, e	Realisations of Gaussian random variables
Σ	Covariance matrix used to model ageing
μ_i	Expected value for parameter θ_i
σ_i	Standard deviation for parameter θ_i
$\rho_{i,j}$	Correlation coefficient between parameter θ_i and θ_j

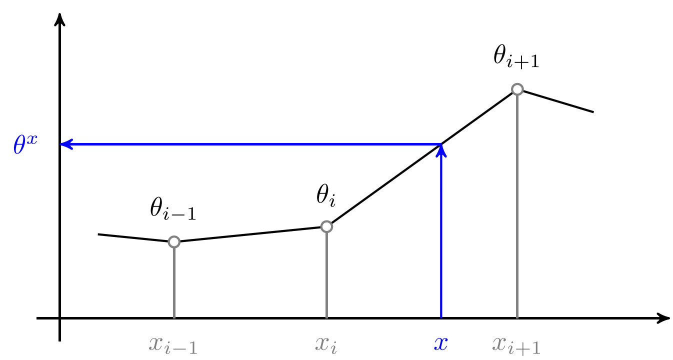

Fig. 1. Example of 1-D look-up table. Here $\eta = 0.6$.

Table 1
Abbreviations and nomenclature.

BoL	Beginning-of-Life, i.e. a new battery where SoH = 100%
EoL	End-of-Life, i.e. when a battery is considered useless for the application, SoH = 0%
MoL	Middle-of-Life, not always well defined in literature, but here we mean SoH around 50%
Operating condition	Currently active conditions. In this document, the operating condition is always temperature
Operating points	Discretisation of the operating range into a vector
Operating range	The expected range that must be handled by the model, e.g. highest to lowest temperature
SoC	State-of-Charge
SoH	State-of-Health, in this work only defined by number of charge/discharge cycles the battery has been exposed to
Spilling effect	Refers to when information from one operating condition is used to update operating points related to other operating conditions

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