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# A comparative study and review of different Kalman filters by applying an enhanced validation method

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ABSTRACT

The Kalman filter is a common state of charge estimation algorithm for lithium-ion cells. Since its first introduction in the application of lithium-ion cells, different implementations of Kalman filters were presented in literature.

However, due to non-uniform validation methods and filter tuning parameters, the performance of different Kalman filters is difficult to quantify. On this account, we compare 18 different implementations of Kalman filters with an enhanced validation method developed in our previous work. The algorithms are tested during a low-dynamic, high-dynamic and a long-term current load profile at −10 °C, 0 °C, 10 °C, 25 °C and 40 °C with a fixed set of filter tuning values. To ensure comparability, a quantitative rating technique is used for estimation accuracy, transient behaviour, drift, failure stability, temperature stability and residual charge estimation.

The benchmark shows a similar estimation accuracy of all filters with an one and two RC term equivalent circuit model. Furthermore, a strong dependency on temperature during high-dynamic loads is observed. To evaluate the importance of the tuning parameters, the temperature dependency is reduced with an individual filter tuning. It is reasoned, that not only the filter type is significant for the estimation performance, but the filter tuning.



## 1. Introduction

For lithium-ion cells several state of charge (SOC) estimation algorithms are presented in literature. One of the most common algorithms is the Kalman filter (KF). The KF was invented by Rudolph Kalman [1] in 1960 and originally used to estimate trajectories for manned and unmanned spacecrafts. In 2004, Plett [2–4] introduced a method to use the KF for SOC estimation of lithium-ion cells. This method was commonly adapted in later works, resulting in various implementations of state estimation based on KF. In consequence due to different validation methods, filter tunings, equivalent circuit models (ECMs) and environmental conditions, filter algorithms are often not comparable.

In the paper, we present a comparative study of the most commonly used filter algorithms. Based on the validation method developed in [5]. The focus of this work is to show the influence of the temperature, ECM and the filter tuning on the estimation behaviour and accuracy of the investigated KF.

To give an overview of the different filter algorithms, the current state of the art of single Kalman filter (SKF) and dual Kalman filter (DKF) is presented. In Section 2 the ECMs used in this paper are derived and the parametrisation of the models is presented. In Section 3 the general KF equations are described and the differences between the filter variations are identified. After that, Section 4 summarises the validation and benchmark method from our previous work [5]. The measurement set-up and filter tuning is shown in Section 5, followed by the comparison of different filters in Section 6. To summarise our work, a conclusion is given in Section 7.

### 1.1. Equivalent circuit models

In the field of battery modelling, the charge and discharge behaviour of batteries is mainly described by three different modelling approaches. The most accurate, but, in consequence, most complex method is the electrochemical model. Here, mass and charge transfer reactions in the battery are described on a fundamental level with numerous partial differential equations. With this approach an accurate prediction of the terminal voltage can be achieved. However, the high complexity of the model comes with the price of high parametrisation and computational effort. In

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**Acronyms**

| | |
|---|---|
| AEKF | adaptive extended Kalman filter |
| AKF | adaptive Kalman filter |
| BMS | battery management system |
| CC | constant-current |
| CCCV | constant-current constant-voltage |
| CDKF | central difference Kalman filter |
| CV | constant-voltage |
| DAEKF | dual adaptive extended Kalman filter |
| DC | direct current |
| DEKF | dual extended Kalman filter |
| DKF | dual Kalman filter |
| ECM | equivalent circuit model |
| EKF | extended Kalman filter |
| KF | Kalman filter |
| LKF | linear Kalman filter |
| LUT | look-up table |
| NCA | nickel-cobalt-aluminium |
| NN | neuronal network |
| OCV | open circuit voltage |
| RMS | root mean square |
| SAEKF | single adaptive extended Kalman filter |
| SEKF | single extended Kalman filter |
| SKF | single Kalman filter |
| SLC | synthetic load cycle |
| SLKF | single linear Kalman filter |
| SOC | state of charge |
| SPKF | sigma point Kalman filter |
| SRCDKF | single central difference Kalman filter |
| SSRCDKF | single square root central difference Kalman filter |
| SSRUKF | single square root unscented Kalman filter |
| SUKF | single unscented Kalman filter |
| UKF | unscented Kalman filter |

[6–9] a KF-based SOC estimation with an electrochemical model is introduced. Here the state vector of the filter includes more than five states variables.

An additional modelling method is the black box model. Here, no physical knowledge about internal cell processes is required. Examples for black box models are stochastic models [10], fuzzy logic models [11] or neuronal network (NN) models [12]. To the authors knowledge, for the application with a Kalman Filter, in literature only NN models are interesting [13,14].

The most common approach is based on an ECM. Here the electrochemical behaviour of the cell is approximated by electrical elements such as resistors or capacities. Here, common implementations, like the Shepherd, Unnewehr and Nernst models, approximate the cell behaviour with a voltage source and additional resistors [3]. In [3,15–22] this three models are combined and used in a KF. [19] achieved higher estimation accuracy by using a combined approach of the Shepard, Unnewehr, Nernst model and the combination of these models by selecting the model in dependency on the voltage level.

By extending the ECM with additional capacitor and resistor networks (RC terms), model accuracy can be significantly enhanced. However, an increasing amount of RC terms results in higher model complexity and parametrisation effort. In [23,2,3,24–29,13,30–45] different KFs are implemented with one RC term. To achieve a higher accuracy of the voltage calculation, [46–60] implemented different KFs with two RC terms.

Further enhancements of model accuracy can be achieved by implementing a charge and discharge dependency of the ECM elements [25,34,3,17] and/or hysteresis effects of the open circuit voltage (OCV) [3,61,16,29].

Hu et al. [62] compared the above mentioned models and their influence on the filter accuracy and comes to the conclusion that the ECM battery model with one RC term provides the best compromise between accuracy and complexity.

### 1.2. Kalman filter

The KF is based on a set of differential equations to predict the state of a physical process. Therefore, it minimises the error of the states variables related to the measured and predicted output of a linear system. A common use of the filter in the battery field is to calculate the predicted output based on an ECM and a coulomb counter. Therefore, the relationship between the SOC and the OCV is considered. For linear systems a linear Kalman filter (LKF) can be used for state estimation [50,44].

Due to the non-linear cell behaviour, the LKF is rarely used in literature. By linearising the system and measurement matrices in the actual state by first-order Taylor approximation of the differential equations, the KF can be applied to batteries. This approach is called extended Kalman filter (EKF) [17,27,25,26,4,63,64,47,49,31,51]. However, filter estimation can result in insufficient errors and divergence of the filter, due to the linearisation error and the neglect of the higher-order derivatives of the Taylor approximation [64]. For this reason the sigma point Kalman filter (SPKF) is developed. Here no derivatives are required, the linearisation is approximated by a set of sigma points [65,24,64]. Two common types of the SPKF are the unscented Kalman filter (UKF) and the central difference Kalman filter (CDKF). In [50,17,40,66–69] a UKF based on the unscented transformation is presented. This transformation is a method to approximate the expected value and the covariance of a non-linear transformed random variable by omitting the derivation of system and measurement matrices [64].

The CDKF is based on the interpolation according to Sterling [64,70,23]. As in the case of the UKF, the derivation is omitted. The difference between both filters is connected to the implementation of scaling and gain factors. While the CDKF uses only one scaling factor, the UKF uses three. The disadvantage of both filters is the required square root calculation of the covariance matrix with the Cholesky factorisation in each time step. Thereby rounding errors can occur and the positive definition of the covariance matrix cannot be guaranteed [71]. To reduce the calculation error, Wan et al. [67] and Rudolph Van der Merwe et al. [64] introduced the square root forms of the UKF and CDKF. Here the Cholesky factorisation is only updated and not calculated in each time step.

### 1.3. Dual Kalman filter

The state of charge estimation with a KF highly dependent on the correctness of the ECM parameters. If parameters are not exact or changing over time the estimation error of the filter increases. A joint or dual estimation can compensate this by adapting the ECM parameters. In case of the joint estimation, the states and parameters are in the same state-space [72,73]. Due to the higher order of the resulting system, the computational effort increases with the third order ($n^3$) of the state vector $n$ [24]. To keep the systems order low, a separate state-space model can be used. Here, both filters work in parallel [26,2–4,70,64,74], but, in consequence, the correlation between the states and parameters may get lost. This could arise in higher estimation errors [24].