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# Reliable state of charge and state of health estimation using the smooth variable structure filter

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ABSTRACT

This paper introduces a reliable strategy for the state of charge (SOC) and the state of health (SOH) estimation of healthy and aged Lithium polymer cells. Dynamics of the cell are modeled using some equivalent circuit models and parameters of each model are calculated by adaptive particle swarm optimization. The modeling process involves modeling and parametric uncertainties as well as measurement and instrumentation noise. They may degrade the performance of an optimal filter for SOC and SOH estimation. To alleviate effects of such uncertain factors, the smooth variable structure filter (SVSF) is implemented. The SVSF is a novel robust state estimation method that benefits from the robustness property of variable structure systems. The performance of the SVSF is compared with the extended Kalman filter (EKF) for real-time SOC estimation of a healthy and an aged Lithium polymer cell. The paper moreover presents a novel method for SOH estimation using the SVSF's chattering signal and without the need for modeling the cell undergoes aging. Experiments show performance benefits of the SVSF for reliable SOC and SOH estimation of healthy and aged Lithium polymer cells.

## 1. Introduction

Li-Ion batteries are increasingly used in energy storage devices for applications such as electric vehicles, cell phones, laptops, medical devices, etc. This is due to their high energy density, durability, safety, lack of hysteresis, and slow loss of charge when not in use. In order to improve the performance of Li-Ion batteries and increase their safety and efficiency, accurate management, monitoring, and control are required (Afshari, Attari, Ahmed, Farag, & Habibi, 2016). Battery management systems are designed to estimate quantities representing battery's operating conditions (e.g. state of charge (SOC), state of health (SOH), etc.) and at the same time to prevent the battery from working under dangerous situations. They accurately estimate the battery's SOC as a function of the operating time. In this context, state and parameter estimation methods are used to estimate values of the SOC and the SOH based on indirect, inaccurate and uncertain sensor measurements. Note that the accuracy of the SOC and the SOH estimation may decrease due to factors such as inaccuracies in modeling batteries, parametric variations due to aging, sensor noise, unpredictable temperature variations, hysteresis effects, unknown initial SOC, etc.

### 1.1. The state estimation task

State estimation is referred to as the task of calculating numeric values of hidden state variables from indirect, inaccurate and partial measurements of a system. The main objective of state estimation is to minimize the state estimation error as well as to preserve robustness versus noise, and uncertainties. The Kalman filter is the most popular method for state estimation that applies to linear systems restricted to white noise with a Gaussian distribution. The Kalman filter is a model-based estimator and provides optimal state estimates by minimizing the state error covariance matrix given a known model. For the generic case of systems with nonlinear state and/or measurement models, several numerical solutions were proposed. These solutions are generally based on linearization of the state and measurement model (e.g., the Extended Kalman filter (Afshari, Gadsden, & Habibi, 2017)) or PDF approximation (e.g., the Unscented Kalman filter (Ristic, Arulampalam, & Gordon, 2004), or the Cubature Kalman filter (Arasaratnam & Haykin, 2009)). In the extended Kalman filter (EKF), the gain is obtained by locally linearizing the state or measurement model at the operating point. The main concern with the Kalman-type filtering is the assumption of having a perfect model with known parameters. In real applications, however,

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**Nomenclature**

| | |
|---|---|
| C | Capacitance element, C-rate |
| $C_n$ | Nominal capacity of the cell |
| EKF | Extended Kalman filter |
| H | Linear measurement matrix |
| K | Filter's gain |
| OCV | Open circuit voltage |
| PSO | Particle swarm optimization |
| $\mathbf{Q}^{EKF}$ | State error covariance for EKF |
| R | Resistance element |
| $R_0$ | Internal resistance element |
| $\mathbf{R}^{EKF}$ | Measurement error covariance for EKF |
| SOC, Z | State of charge |
| SOH | State of health |
| SVSF | Smooth variable structure filter |
| V | Voltage |
| $V_t$ | Terminal voltage |
| sat() | Saturation function |
| sgn() | Sign function |
| $e_x$ | State estimation error |
| $e_z$ | Measurement error |
| $e_{z,k\|k}$ | a priori (updated) measurement error |
| $e_{z,k+1\|k}$ | a posteriori (predicted) measurement error |
| $f$ | Nonlinear state model |
| $i$ | Current |
| $k$ | Discrete-time index |
| $u$ | Control variable |
| $v$ | Measurement noise |
| $w$ | Process noise |
| $x$ | State vector |
| $x_{k\|k}$ | The *a priori* (updated) state value |
| $x_{k+1\|k}$ | The *a posteriori* (predicted) state value |
| z | Measurement vector |
| $\Xi$ | Chattering indicator |
| $\Delta t$ | Sampling time |
| $\alpha$ | Scaling factor for chattering indicator |
| $\gamma$ | Convergence rate |
| $\eta$ | Coulombic efficiency of the cell |
| $\beta$ | Existence boundary layer |
| $\psi$ | Smoothing boundary layer |
| $\hat{\square}$ | Estimated quantity |
| $\square^+$ | Pseudo-inverse operator |

there may be considerable uncertainties about the model structure, physical parameters, noise, and initial conditions. These factors may significantly degrade the Kalman filter's performance from its optimal solution.

To overcome or at least decrease effects of such factors on the estimator's performance, robust state estimation is proposed in which the filter is insensitive to a wider range of noise and uncertainties. There is a large number of publications in the literature devoted to design of robust state estimators for systems with norm-bounded noise and uncertainties, such as minimax estimators (Krener, 1980), considering the worst case scenario for state estimation, e.g. the $H_\infty$ filter (Zames, 1981), or set-membership estimators (Milanese & Tempo, 1985). There are some robust estimation methods mainly based on applying a technique to robustify the Kalman filter (Gandhi & Mili, 2010). Robust Kalman filters (Gandhi & Mili, 2010) are applied to systems with norm-bounded modeling uncertainties in which an upper bound of the mean square estimation error is minimized. Robust state estimation may be achieved by means of the variable structure filtering (Gadsden & Habibi, 2013; Habibi, 2007). The smooth variable structure filter (SVSF) (Habibi, 2007) is a relatively new robust state estimation that benefits from the robustness property of variable structure systems. It guarantees the stability of state estimates by applying a discontinuous gain and pushing the measurement error to zero (Habibi, 2007). Afshari, Al-Ani, and Habibi (2015) and Afshari, Gadsden, and Habibi (2018) have introduced a second-order state estimation method that works similar to the SVSF method, but instead of using a smoothing boundary layer for chattering removal, it applies a second-order time-difference condition. They also overviewed main Gaussian filters applied for state and parameter estimation (Afshari et al., 2017).

### *1.2. Modeling Lithium-Ion batteries*

In order to apply a model-based filter (e.g. Kalman filter, SVSF, etc.) for the SOC and SOH estimation, dynamics of the battery need to be modeled. Several methods have been reported in the literature for modeling Li-Ion batteries. These methods may be categorized into three main approaches that include: 1- empirical modeling, 2- equivalent circuit modeling, and 3- electrochemical modeling. Empirical models or black-box models simulate the terminal voltage behavior of Li-Ion batteries without the need for considering the underlying physics or any electrochemical reactions that may happen within the cells. These models are mainly based on a series of math functions with unknown parameters. Values of these parameters can be calculated using a set of input–output data and an optimization method. The optimization method calculates the unknown parameters by minimizing the output error that is the difference between the simulated and the measured output (terminal voltage).

Equivalent circuit models use lumped-element components such as resistors and capacitors to simulate dynamics of a cell. Based on the different levels of modeling complexity, they may include first-order, second-order, or third-order resistor–capacitor elements in addition to an element that represents the hysteresis effect. They do not model the cell's underlying chemistry. In contrast, the electrochemical modeling approach considers the electrochemical reactions happening inside a cell. They simulate the internal electrochemical dynamics of the cell using a set of partial differential equations. Electrochemical modeling is the most accurate approach, while it is computationally more expensive. Several techniques have been reported in the literature in order to simplify electrochemical models and apply them to real-time implementations. Note that however, the choice among these three modeling approaches is a compromise between modeling complexity, accuracy, and computational cost (Afshari, Attari et al., 2016).

The equivalent circuit approach is one of the most popular approaches for modeling Li-Ion batteries. It is because a circuit model may be rather simple, e.g. only has a voltage source and a variable resistance, or maybe complex given local conditions in a spatially-resolved model (Plett, 2004b). This approach uses a group of resistors and capacitors, where their magnitudes are obtained using an optimization method. The optimization method employs a random search at each time step to extract the parametric values such that the error between the measured terminal voltage and the simulated one is minimized. The main advantage of the equivalent circuit approach for modeling is its capability for real-time applications with an acceptable performance. The main disadvantage of this approach is its limitation for modeling the electrochemical reactions that take place internally inside the cell. This limitation prevents it from modeling some physical behaviors including the power fading, the capacity fading and more importantly the aging effect (Plett, 2004b). Ferrari-Trecate, Muselli, Liberati, and Morari (2003) have proposed a new method for the identification of hybrid systems formulated in the piecewise affine form. This method is based on the use of clustering for the classification of data points, followed by constructing a model for each cluster and linear identification of its parameters (Ferrari-Trecate et al., 2003).