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Review

# From a novel classification of the battery state of charge estimators toward a conception of an ideal one

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## HIGHLIGHTS

- Ideal model provides reliable *SoC* for any battery type and cycling condition, online.
- None of the existing estimation methods offer an ideal *SoC* model.
- Novel classification facilitates the identification of to-be improved aspects.
- Methods using closed loop processing are promising candidates for ideal *SoC* model.
- Machine learning online techniques adapt the model's parameters when a drift occurs.

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## ABSTRACT

An efficient estimation of the State of Charge (*SoC*) of an electrical battery in a real-time context is essential for the development of an intelligent management of the battery energy. The main performance limitations of a *SoC* estimator originate in limited Battery Management System hardware resources as well as in the battery behavior cross-dependence on the battery chemistry and its cycling conditions. This paper presents a review of methods and models used for *SoC* estimation and discusses their concept, adaptability and performances in real-time applications. It introduces a novel classification of *SoC* estimation methods to facilitate the identification of aspects to be improved to create an ideal *SoC* model. An ideal model is defined as the model that provides a reliable *SoC* for any battery type and cycling condition, online. The benefits of the machine learning methods in providing an online adaptive *SoC* estimator are thoroughly detailed. Remaining challenges are specified, through which the characteristics of an ideal model can emerge.



## 1. Introduction

At present time and in the foreseeable future, electrical batteries will continue to be used in real-time applications such as cell phones and laptops, hybrid and electrical vehicles, as well as in non real-time applications like energy storage systems.

The battery state of charge (*SoC*) is essential to calculate the autonomy and the available energy of the battery. An accurate *SoC* is fundamental to obtain an efficient control strategy to manage energy, as well as to guarantee a safe utilization of the battery by preventing under or over-charge that may lead to permanent damage. Energy management also plays a significant role in extending and optimizing the lifetime of the battery.

The battery being a complex electrochemical system, neither its remaining capacity nor its *SoC* can be directly measured. In addition, battery behavior depends on its utilization conditions like current profile, ambient temperature and state of health. Therefore one needs to develop a *SoC* estimation method, reliable and adaptable for real-time applications.

Two difficulties constrain the performances of a real-time *SoC* estimator. The first comes from the limited storage capacity and calculation resources of the Battery Management System (BMS). The second comes from the fact that the battery behavior depends on its technology and the cycling conditions.

Hence, we point out the need for an efficient model able to

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estimate the $SoC$ of any battery, regardless of its technology, under any cycling conditions in real-time contexts and applications. Such a model will be referred to hereafter as "ideal $SoC$ estimator".

By taking a closer look at the existing methods, it is clear that none possess the characteristics of this ideal $SoC$ estimator. In order to obtain it, a suitable approach must be identified among the large number of existing ones. Thus this identification can be achieved through a comprehensive classification of existing methods.

The $SoC$ estimation methods can be classified with respect to different criteria. The first one is the nature of the input variables, either measured or estimated. The second one is the type of the $SoC$ estimation model, which is a relationship between the input variables and $SoC$: physical, electrochemical or statistical regression model. The third criterion deals with the temporal dimension: static methods like those based on $SoC-OCV$ lookup tables and methods able to provide a real-time $SoC$ estimate. Also the methods can be classified according to the battery technology: Li-ion, Ni-MH, Lead-acid and so on. Finally, the classification can be made based on the mathematical tools used by the estimation method: Kalman filter, artificial neural network, fuzzy logic, etc. However it is important to distinguish between the tools applied to the $SoC$ estimation and those used to estimate the input variables like $OCV$ and electrical impedance. Indeed, the more the classification criteria are relevant, the more easily we can identify the methods that can be improved in order to provide an ideal $SoC$ estimator and flesh out new ways of developing it.

Several reviews of the existing $SoC$ estimation methods are available in the literature. The authors of [1–4] give an overview of the methods without classifying them. The drawbacks and advantages of each method are presented by the authors, but this is not sufficient to provide an exhaustive and well structured vision on the path to be followed to develop an ideal $SoC$ estimator. Pop et al. [5] give a chronological review of the estimation methods before classifying them under three categories: direct measurement methods, book-keeping systems that involve basic and modified Ah-counting, and adaptive systems which are supposed to be self-designed and to adjust automatically following the battery agingaging and online changes in battery and user's behavior. Kalman filter, artificial neural network and fuzzy logic approaches were allocated to this category, but the authors acknowledge that these methods have some important limits and cannot be considered as adaptive to all cycling conditions.

Chang [6] gives a similar classification while adding to it a fourth category of hybrid methods, each corresponding to a combination of the first three categories.

Hence the classification of Pop [5] and Chang [6] doesn't make a distinction between the nature of $SoC$ models and input variables, focusing the attention on the temporal and technological criteria.

Subsequently, the above classifications of the $SoC$ estimation methods does not strictly abide by all earlier mentioned criteria, thus rendering difficult the careful examination of the aspects to be improved.

In this paper we introduce a novel classification of the $SoC$ estimation methods based on their concept, their adaptability and their performances in real-time applications.

This novel classification shows the importance of machine learning methods in providing an ideal $SoC$ estimator. This estimator is capable of providing precise $SoC$ values in real-time configurations, and automatically adapts to the evolution of the battery behavior, all of this while being fully independent of the battery technology.

The rest of the paper is organized as follows. Section 2 recalls the definition of the battery state of charge and addresses the limitations of the classical definition. Section 3 introduces a novel classification of the existing $SoC$ estimation methods. Section 4 gives an analysis of the most important aspects of these existing methods and study their ability to become a generalized $SoC$ estimation method. Before concluding, a discussion of the characteristics of an ideal $SoC$ estimator and the benefits of a machine learning approach in providing this ideal $SoC$ estimator are conducted in Section 5. The conclusion sums up the findings of this paper and the challenges that remain to be addressed.

## 2. Battery state of charge

### 2.1. Definition of the state of charge

The state of charge of a battery is defined as the ratio between the available capacity and the reference capacity, which is the maximum capacity that can be withdrawn from the fully charged battery under reference conditions. The reference conditions are generally a constant current rate and a specific ambient temperature. A battery being a chemical energy storage system, there is no sensor that directly measures. These reference and available capacities must be calculated.

### 2.2. Challenges in estimating the battery capacity

One way to compute the battery capacity is the "discharge test". It consists of discharging the battery under reference conditions to reach the end of discharge criterion, i.e. the cutoff voltage.

However the discharge test cannot be applied in real-time application, as well as in off-line application as it leads to a loss of energy. The state of charge can be calculated based on the Ah-counting equation:

$$SoC_t = SoC_{t_0} + \frac{\int_{t_0}^{t} I_\tau \, d\tau}{C_{ref}} \tag{1}$$

where $SoC_{t_0}$ is the initial $SoC$, $I$ the algebraic current measurement: positive for a charge current and negative for a discharge current and $C_{ref}$ the reference capacity. A numerical implementation requires a temporal discretization, and then the $SoC$ is calculated using the following formula:

$$SoC_t = SoC_{t-\Delta t} + \frac{I_t \times \Delta t}{C_{ref}}, \tag{2}$$

where $\Delta t$ is the sampling interval, which can be constant or variable. It is clear that the precision of this method depends on the accuracy of the current sensor as well as on the sampling interval.

Nevertheless, the reference capacity is not constant during the battery charge/discharge; it depends on the state of health and the cycling conditions like the current profile and the ambient temperature. In a real-time context, the cycling conditions are uncontrolled as they depend on the user's behavior, weather conditions, road conditions, etc. Accordingly, in some situations, the state of charge can be lower than 0 or higher than 100. The establishment of a deterministic function to provide a reliable value of the reference capacity is a challenging problem.

## 3. Novel classification of the SoC estimation methods

From a global point of view every estimation method is characterized by its input variables, the $SoC$ estimation model and the type of the $SoC$ estimation processing, see Fig. 1.

The input variables can be either directly measured by a sensor, or estimated through a physical, electrochemical or statistical