EVERLASTING

Electric Vehicle Enhanced Range, Lifetime And Safety Through INGenious battery management

D8.6 – White Paper 03

February 2018

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Public

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DELIVERABLE SHEET

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DISCLAIMER

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LIST OF ABBREVIATIONS AND ACRONYMS

ACRONYM	DEFINITION
Ah	Ampere-hour
BMS	Battery Management System
CC	Constant Current
CV	Constant Voltage
kWh	kiloWatt-hour
OCV	Open Circuit Voltage
SOC	State Of Charge
SOH	State Of Health
SOF	State Of Function
DOD	Depth Of Discharge
RMS	Root Mean Square
RMSE	Root Mean Squared Error
MAE	Mean Absolute Error

1 WHITE PAPER: INTRODUCTION

The EVERLASTING project (http://everlasting-project.eu/) will develop innovative technologies to improve the reliability, lifetime and safety of Lithium-ion batteries by developing more accurate, and standardized, battery monitoring and management systems. This allows predicting the battery behaviour in all circumstances and over its full lifetime and enables pro-active and effective management of the batteries. This leads to more reliability and safety by preventing issues rather than mitigating them.

To raise the awareness of the vital and positive role of battery management systems (BMS), a three-monthly white paper will be written on different BMS topics, aimed at a general technical public. These white papers are a few pages long and will be distributed via the EVERLASTING website and through the partners.

The first white papers focused on “BMS Functions” and on the “State of Charge (SOC) definition”. This new white paper will go more in detail on the “evaluation of SOC accuracy”.

2 WHITE PAPER 03: EVALUATION OF SOC ACCURACY

2.1 INTRODUCTION

In this white paper we will discuss how to evaluate the accuracy of a SoC estimation algorithm. We first have to agree on a reference measurement that we trust to be correct. It is often claimed that an algorithm is x% accurate but what does that mean? Is this the average error or the maximum error? Under which circumstances was this measured? What charge or discharge cycle was used ? In order to be able to compare the accuracy of several algorithms, a standard definition and measuring procedure is preferred. We will highlight in this white paper the specific problems in determining the accuracy of the SOC.

2.2 REFERENCE

To evaluate the accuracy of a SOC algorithm, a reliable reference is needed. Of course, obtaining a reference is faced with the same hurdles as explained in the second white-paper. There the SOC was defined as the ratio between the actual stored charge $Q_{\mathrm{actual},t}$ and the nominal capacity $Q_{\max,t}$.

$$SOC_t = \frac{Q_{\mathrm{actual},t}}{Q_{\max,t}}$$

It was explained that $Q_{\max,t}$ refers to the maximum capacity under nominal test conditions. Thus, logically, the SOC algorithm should be validated under the same conditions. However, such stable test conditions are rarely representative of practical applications. In electric vehicles for example, current draw is very dynamic, temperatures can change throughout a trip, … One approach is to base the nominal capacity on the theoretical maximum capacity that can be extracted from the battery cells.
Note that $Q_{\max,t}$ can be updated during the life of the cell, reflecting the fact that an SOC level of 100% represents a different amount of stored charge for a new versus an aged cell.

2.2.1 DETERMINING MAXIMUM NOMINAL CAPACITY

Physically, the full-charged state is reached when all active convertible material in the cell is in its charged state. The corresponding electrical charge that is stored inside the cell then defines the maximum nominal capacity. However, since it is impossible to ‘measure’ the state of the convertible material, the maximum capacity has to be measured using a charge and/or discharge test that is terminated when reaching predefined cut-off voltages and currents. A so-called constant-current followed by a constant-voltage (CC-CV) test will approach the theoretical limit. This procedure is graphically represented in Figure 1.

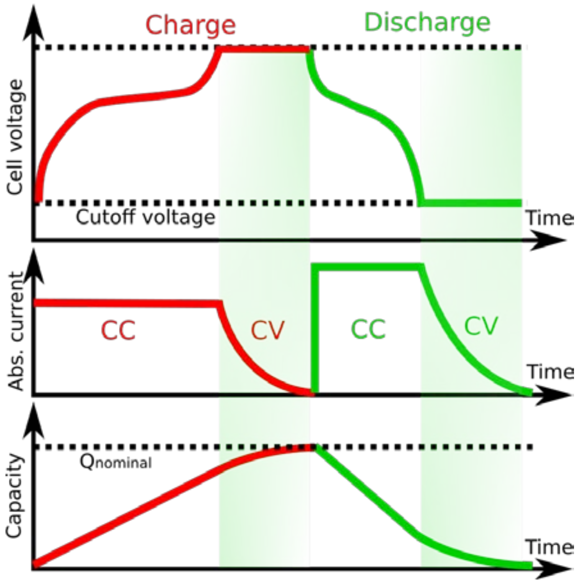

Figure 1: CC-CV charging principle

The cells are first charged at a constant current, until the voltage reaches the maximum allowed cell voltage. Charging then continues at this voltage while the current decreases. Eventually, the current will drop to a fraction of the original charge current (e.g. C/100). At this point the cell is considered fully charged. The discharging happens in a similar fashion. Initially discharging starts at a constant current, until the lower cut-off voltage is reached, followed by a constant-voltage discharge until the current becomes negligible.

As long as the losses in the battery are small, this will result in a reproducible capacity figure, regardless of the charge- or discharging current. Manufacturer datasheets usually do not mention cell discharge capacity based on CC-CV but only on CC.

It should be noted that a CC-CV test is usually repeated multiple times, since the measured capacity depends also on the short-term history of the cells. Cells that were unused for some time or used within a limited DOD range could exhibit a (slightly) increasing capacity during repeated CC-CV tests.

2.2.2 ACTUAL CHARGE LEVEL

As discussed in section 2.2.4 of the second white paper, several methods exist to keep track of the actual charge level, referred to as SOC algorithms. For a benchmark that is limited in time (e.g. up to a few days), the SOC can be based on the integrated current logged by the battery tester, as they are often equipped with an accurate current sensor. This method is commonly referred to as Coulomb Counting.

$$SOC_t = SOC_{t=t0} + \frac{1}{Q_{\text{nominal},t}} \int_{t=t0}^{t} I_{\text{battery},t}(t)\, dt$$

However, for longer tests, even a small integration error (due to sensor accuracy and a finite sampling interval) and a charge efficiency < 1 will accumulate and slowly render the reference charge level and SOC useless. Basic algorithms calibrate the SOC when the battery is clearly charged or depleted, but such situations do not necessarily occur sufficiently often.

Eventually, the measured nominal charge will also depend on external factors such as temperature, internal factors such as losses and ageing and as mentioned to some degree also the short-term history of the cell.

2.2.3 EVALUATION OF SOC ALGORITHM ACCURACY

Summarized, to allow a qualitative evaluation of the accuracy of an SOC algorithm, the following is required:

- A reference SOC level, a reliable initial state and the nominal capacity, usually based on an accurate current-integration. For example, a properly calibrated battery tester can achieve a current error less than ±1.5mA in the range of 0.5-5A [1], or ±0.03% error on the full scale. Current sensors for commercial applications are usually in the 1-2% error level.
  Alternatively, instead of a complete SOC reference profile, reference points can be used. The test profile would be interrupted at fixed intervals, during which the cell is CC-CV discharged under controlled conditions. The measured extracted charge can then be compared to the SOC level when the test was interrupted.
- A test profile
  - that is short enough to limit the unavoidable drift of the reference SOC. After a continuous test of one week, for example, the integration error with aforementioned battery tester could have accumulated to 0.25Ah. For small cells this represents a significant SOC range.
  - that is long enough to show the algorithm’s convergence behaviour.
  - with enough current/power variation to show the algorithm’s performance under dynamic conditions.
- Stable environmental conditions, to avoid a mismatch of the nominal capacity between the reference and the test.
- An error indicator or evaluation method by which the SOCs will be compared.

Fortunately, there is no shortage of standard test profiles for batteries that are equally well suited for SOC benchmarking, such as driving profiles or application independent test-profiles [2]. Tests with long pauses can give the algorithm more time to compensate for modelling errors.

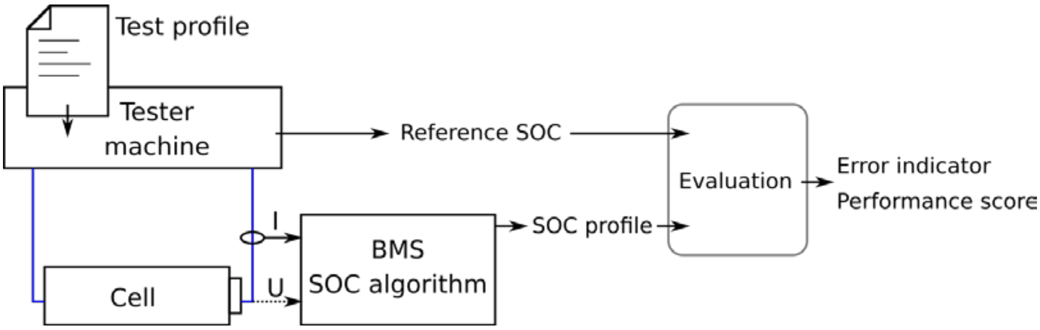

Figure 2: Evaluation setup for SOC algorithm accuracy evaluation

2.3 ERROR INDICATORS AND EVALUATORS

Once a test profile has been chosen and carried out, the task remains to compare the reference SOC with the SOC obtained from the algorithm under test.

2.3.1 SINGLE INDICATOR

For simplicity a single error indicator could be used. A few possibilities are:

1. Maximum error
   The largest deviation from the reference profile is taken:
   Absolute difference $x = SOC_{\mathrm{estim}} - SOC_{\mathrm{real}}$

   $$\mathrm{MAXERR} = \max(x) - \min(x)$$

   Since outliers define the result, this indicator alone is obviously unreliable to compare SOC estimation performance. However, it is often used since it provides a worst-case view on the SOC error [3].

2. Root Mean squared error (RMSE) or sample standard deviation

   $$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=0}^{n}\left(SOC_{\mathrm{estim},i} - SOC_{\mathrm{real},i}\right)^2}$$

   Outliers will have a disproportionate effect on the RMSE, thus this measure is sensitive to outliers. The RMS and RMSE are not unit free, but for comparing SOC values (which have no unit and are always in the range [0-1]) on a single test profile this is not a problem.

3. Mean Absolute Error (MAE)

   $$\mathrm{MAE} = \frac{1}{n}\sum_{i=0}^{n}\left|SOC_{\mathrm{estim},i} - SOC_{\mathrm{real},i}\right|$$

   As the name suggests, this is the mean of the absolute error. Or, it represents the average magnitude of the errors in the predicted SOC, without considering their direction. It is more easy to interpret than the RMSE and is less sensitive to outliers than the RMSE. Used in [4] and [5].

The sensitivity to outliers for the evaluation is important. On one hand, we do not want the indicator to hide large but short-term deviations, but on the other hand, these deviations do not always tell the whole picture. Often we will also want to show the error sensitivity to e.g. voltage or current measurement error [3].

2.3.2 EVALUATION SYSTEM

An alternative to using a single statistic on a single test profile is to define an evaluation system, such as in [2], including several categories. The SOC error is classified using error boundaries, to allow for a nonlinear 'penalty' when deviating from the reference.
For example, the estimation accuracy K_{est} in [2] is based on the absolute difference with the reference SOC (δ) and multiplied by the percentage part of the total time $\Delta t_{\delta\epsilon\varepsilon_i}$ and the corresponding error boundary value $P(\varepsilon_i)$:

$$\sum_{i=1}^{6}\left(P(\varepsilon_i) * \sum \frac{\Delta t_{\delta\epsilon\varepsilon_i}}{t_{\text{end}}}\right)$$

with

$$P(\varepsilon) = \begin{cases} 5 \text{ for } 0\% \leq |\varepsilon| \leq 0.5\% \\ 4 \text{ for } 0.5\% \leq |\varepsilon| \leq 1\% \\ 3 \text{ for } 1\% \leq |\varepsilon| \leq 2\% \\ 2 \text{ for } 2\% \leq |\varepsilon| \leq 4\% \\ 1 \text{ for } 4\% \leq |\varepsilon| \leq 8\% \\ 0 \text{ for} |\varepsilon| \leq 8\% \end{cases}$$

Eventually the set of final scores can be plotted on a net diagram and includes e.g. estimation accuracy, drift, temperature stability and transient behaviour to give a more balanced picture of the SOC algorithm's performance.

This approach also highlights the importance of tests with a relatively short duration in time. Each test is focused on evaluating specific features of the SOC algorithm, instead of a using single long-duration test that averages the error out.

2.4 SUMMARY

In this white paper we discussed the difficulties in defining the SOC of a battery or cell, such as finding the nominal capacity and establishing a reference for comparison. The need for a good comparison was also highlighted, preferably using an evaluation system that takes various aspects into account, versus using a single error statistic.

2.5 REFERENCES

[1] PEC, “Technical Reference Manual ACT0550,” 2016.
[2] C. Campestrini, M. F. Horsche, I. Zilberman, T. Heil, T. Zimmermann, and A. Jossen, “Validation and benchmark methods for battery management system functionalities: State of charge estimation algorithms,” *J. Energy Storage*, vol. 7, pp. 38–51, Aug. 2016.
[3] J. Klee Barillas, J. Li, C. Günther, and M. A. Danzer, “A comparative study and validation of state estimation algorithms for Li-ion batteries in battery management systems,” *Appl. Energy*, vol. 155, pp. 455–462, Oct. 2015.
[4] H. Guo, J. Jiang, and Z. Wang, “Estimating the State of Charge for Ni-MH Battery in HEV by RBF Neural Network,” in *2009 International Workshop on Intelligent Systems and Applications*, 2009, pp. 1–4.
[5] H. Lee, J. Park, and J. Kim, “Comparative evaluation of LiFePO4 cell SOC estimation performance with ECM structure and noise model/data rejection in the EKF for transportation application,” in *2016 IEEE Applied Power Electronics Conference and Exposition (APEC)*, 2016, vol. 2016–May, pp. 1690–1694.