Joint 48th IEEE Conference on Decision and Control and
28th Chinese Control Conference
Shanghai, P.R. China, December 16-18, 2009

The mix estimation algorithm for battery State-of-Charge estimator – Analysis of the sensitivity to measurement errors.

Fabio Codecà, Sergio M. Savaresi and Vincenzo Manzoni

Abstract — **The problem considered in this paper is the analysis of a battery State-of-Charge estimation algorithm: in particular the mix estimation algorithm. This algorithm provides the estimation mixing two estimation approaches: namely the Coulomb-Counting and the Model-Based. The mix algorithm is qualitatively able to provide a more robust and accurate estimation with respect to the estimation provided by the approaches the algorithm mixes together.**

The aim of this paper is to analyze the differences between the three algorithms and the advantages produced by the mixing procedure. In particular the paper presents the comparison of the mix algorithm behavior with the Coulomb-Counting and the Model-Based behaviors in case of measure errors.

I. Introduction

Technically, a unique battery State-of-Charge (SoC) definition does not exist. The State-of-Charge is usually intended as the ratio of the available capacity of a cell respect its maximum attainable capacity. It is an abstract energetic concept more than an actual physical variable; for this reason it is not directly measurable and it has to be estimated. Ever since rechargeable batteries have existed, many efforts have been invested in developing accurate SoC models. An accurate SoC estimation method is of paramount important in modern Electric Vehicles, Hybrid Electric Vehicles and Plug-in Hybrid Electric Vehicles (EVs, HEVs, PHEVs), since it improves the performances, reliability, and lifetime of the Battery-Pack, and allows the development of better algorithms for the energy management of the vehicle.

The State-of-Charge is mathematically defined as:

$$\mathrm{SoC}(t) = \frac{\mathrm{Ah_{nom}} - \int_0^t I(t)dt}{\mathrm{Ah_{nom}}}, \tag{1}$$

where $I(t)$ is the current extracted from the battery (which is assumed positive while discharging the battery), and Ah_{nom} is the nominal battery capacity. Definition (1) assumes that the current integration starts at $\mathrm{SoC}(t) = 100\%$ when $t = 0$.

Even if the problem seems relatively simple, actually it is not. Several algorithms are known in the art of determining the State-of-Charge of a cell or of a battery of several cells ([1][2][3][4][5][6]). Some of them are not feasible in a HEV application, because they require to disconnect the battery. Some others, like the one based on voltage measures, are more suitable in small-power electronic application, where the required power is usually near to be constant and small. Using Neural Networks, Fuzzy Logic and Kalman Filter it is usually possible to have a good SoC estimation, but they need an high computational power, which is not usually available in an embedded system. The Coulomb-Counting method (current integration) is still the most used method and the main information source, since it provides a simple way to estimate the variation of SoC. However it is impossible, with this method, to have an initial SoC estimate and any error on the current measure, most of all offset errors, can highly affect the estimation accuracy.

In [7] a new estimation algorithm has been proposed: it is called *mix estimation algorithm* since it is based on a mixing scheme which allows to combine two simple approaches, namely the Coulomb-Counting and the Model-Based. Its advantages are the low computation power requirements and the ability to provide an accurate estimation, combining the qualities of the approaches it mixes.

This paper presents an analytical analysis of the *mix estimation algorithm*. The analysis aims to compare the ability of the mix algorithm to deal with measure errors respect the Coulomb-Counting and the Model-Based approaches. All the results are based on the evaluation of the algorithm applied to a specific lithium-ion battery technology: a phosphate-based lithium-ion battery. However the same conclusions can be found using other battery technologies.

The paper is so organized. In Section II a reference test and the measurement errors we considered to perform the former analyses are described. In Section III the Coulomb-Counting approach, the Model-Based approach and the *mix estimation algorithm* are described: a qualitative analysis of their behavior applied to the reverence test is provided. In Section IV some analytical analysis of the algorithms are provided: analysis of their stability and their sensitivity to measurement errors are described.

II. Measurement Errors and Reference Test Description

In order to qualitatively analyze the algorithms' performances (provided in Section III), the reference test shown in Fig. 1 has been designed: the test current profile and its SoC are shown. Notice that the current has been measured with a high accuracy sensor ($I(t) = I_{TestBench}(t)$); the same sensor has been used to compute the State-of-Charge, evaluated through the definition (1.1).

Fabio Codecà, Sergio M. Savaresi and Vincenzo Manzoni are with the Dipartimento di Elettronica e Informazione, Politecnico di Milano, Piazza L. da Vinci 32, 20133 Milano, Italy (e-mail: codeca@elet.polimi.it).

978-1-4244-3872-3/09/$25.00

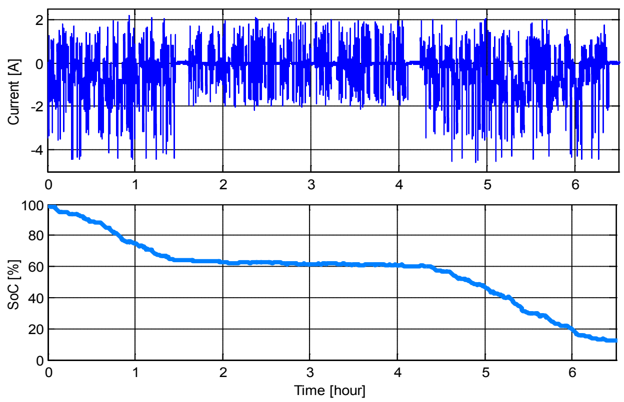

Fig. 1 - Reference test.

To analyze the algorithms' behaviors in case of current measurement errors, both for a qualitative performance analysis and the sensitivity analysis, we supposed the use of a less accurate current sensor. In particular we supposed to use an open-loop Hall current sensor, which provides a quite good measurement with low energy consumption (a key factor in EVs and HEVs). Usually the Hall current sensors measurements are characterized by an error constituted by high-frequency components, bursts and spikes, and a low-frequency offset trend [8]. Accordingly to some experimental analyses, we can define $I_{HallSens}$ as follows:

$$\mathrm{I_{HallSens}(t) = I_{TestBench}(t) + w_1(t) + \bar{I}_{err}}, \tag{2}$$

where $\bar{\mathrm{I}}_{\mathrm{err}}$ is a constant offset, which depends on the sensor accuracy and $w_1(t)$ is a white measurement noise.

A less accurate sensor is supposed also for the voltage measurement. In particular we supposed to use an ADC with a limited resolution. Its measure is defined as:

$$\mathrm{V_{ADC}(t) = V_{TestBench}(t) + w_2(t) + \bar{V}_{err}} \tag{3}$$

where $w_2(t)$ is a white measurement noise, $V_{TestBench}(t)$ is the true voltage and $\bar{V}_{err}$ is a constant offset, which depends on the ADC resolution.

III. Mix Coulomb-Counting and Model-Based Algorithms

The mix algorithm provides a robust SoC estimation with respect to noisy measures, wrong initializations and modeling errors, with a low computation complexity. It combines (in a closed-loop configuration) the Coulomb-counting and a Model-based method. The following paragraphs describe the three algorithms and show their behaviors when applied to the reference test previously described.

A. *Coulomb-Counting and model-based approach*

The *Coulomb-Counting* approach basically implements the definition (1.1) to evaluate the State-of-Charge. It uses a more general definition, defined as:

$$\mathrm{SoC(t) = SoC(0)} - \frac{1}{\mathrm{Ah_{nom}}}\int_0^t \mathrm{I_m(t)dt}, \tag{4}$$

where SoC(0) is the starting value of SoC and $I_m(t)$ is the measured current. This algorithm has the advantage of being the simplest and closest to the definition, but it also has the following drawbacks:

1. It needs the initial SoC value, which is often not available;
2. It is based on a simple integrator, which is an unstable system: if fed with a constant input, its output diverges with a ramp trend.

Considering the previous drawbacks, even if $\mathbf{SoC(0)}$ is known, the flaws characterizing the less accurate measure $\boldsymbol{I_{HallSens}(t)}$, in particular the offset $\boldsymbol{\bar{I}_{err}}$, would make the SoC estimation to diverge.

Fig. 2 shows how the Coulomb-Counting behaves when it is applied to the reference test. The picture shows the real SoC, the SoC estimated using $I_{HallSens}(t)$ and the right SoC(0), the SoC estimated using $I_{HallSens}(t)$ and the wrong SoC(0). The effects of the low accurate current measure are clearly visible, with high estimation errors.

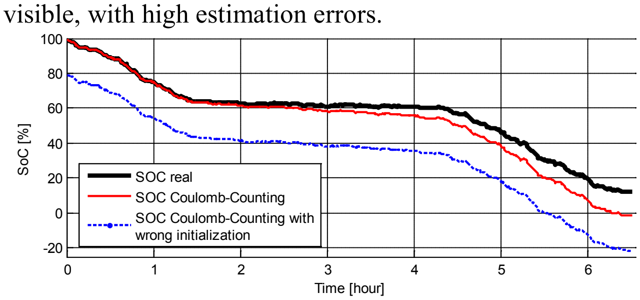

Fig. 2 - Coulomb-Counting estimation behavior (reference test).

The Model-Based method is an indirect methods because it uses the relationship between the battery voltage, usually the Open-Circuit-Voltage (OCV), and the battery State-of-Charge to provide the estimation. The Model-based method uses a battery model to compute the OCV: the model proposed in [7] has been used. Accordingly to that model, the OCV can be computed as:

$$\mathrm{V_{OCV}(SoC) = V_m(t) - G(s)I_m(t)}, \tag{5}$$

where $G(s) = \left(\mathrm{R_0} + \frac{\mathrm{R_1}}{1+s\mathrm{R_1C_1}} + \frac{\mathrm{R_2}}{1+s\mathrm{R_2C_2}}\right)$ and $\mathrm{I_m(t)}$ and $\mathrm{V_m(t)}$ are the measured current and voltage of the battery. Based on the Open-Circuit-Voltage, the SoC value is then estimated using the relationship between OCV and SoC shown in Fig. 3.

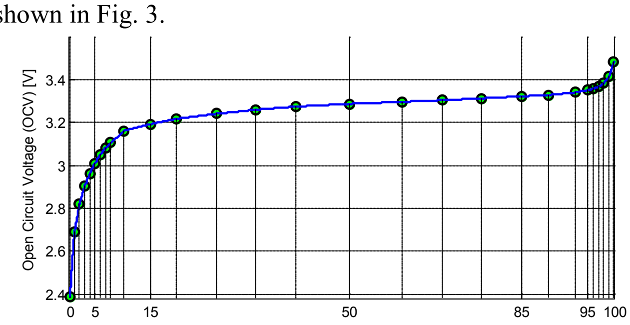

Fig. 3 - Lithium-ion phosphate OCV-SoC relationship.

The Model-Based algorithm is more complex than the Coulomb-Counting, because it performs an interpolation;

however it can theorically provide a more accurate estimation, because uses more information. Even though it still has some drawbacks:

1. It needs an accurate battery model to estimate the Open-Circuit-Voltage.
2. It uses the relationship between the Open-Circuit-Voltage and SoC, which usually in lithium-ion batteries is highly constant over the most part of their SoC range (which amplifies the impact of the noise on the estimated SoC).

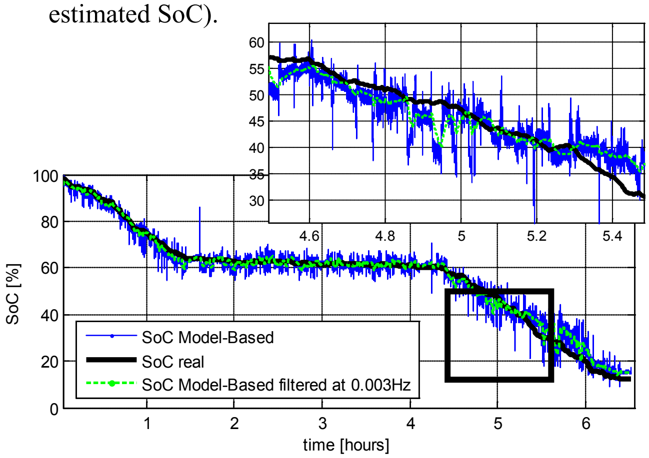

Fig. 4 - Voltage-Based estimation behavior (reference test).

For these reasons, even if we assume to have a highly accurate model, the estimated SoC will be affected by the measurements noise. This is clearly visible in Fig. 4, where the Model-Based algorithm is used to estimate the SoC with the reference test and $I_{HallSens}(t)$ and $V_{ADC}(t)$ are used. Notice how, even if the estimated SoC is close to the real one, it is highly noisy, even if it is filtered. This characteristic affects the algorithm capability to copy the real SoC behavior during short periods of time.

B. *Mix algorithm*

The complementary behavior of the two algorithms is exploited by "mixing" the two approaches in a more complex estimation architecture. The *mix estimation algorithm*[7] is based on a closed-loop rationale; its block-scheme representation is shown in Fig. 5.

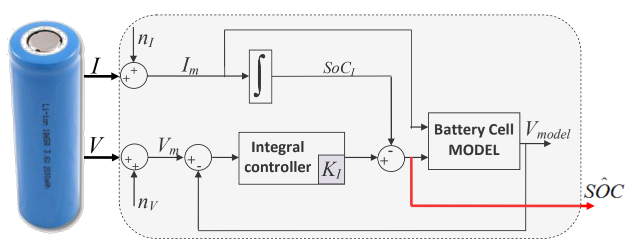

Fig. 5 - Pictorial representation of the mix estimation algorithm.

It is interesting to notice that the main idea of this method is to use the Coulomb-counting estimation for the basic SoC estimation, which is then corrected with a closed-loop control system, which tries to regulate the direct-model output voltage at the value of the actual measured voltage. The Coulomb-Counting estimation allows a fast reaction of the estimated SoC, while the closed-loop control system allows to slowly correct estimation problems due the Coulomb-Counting approach: by this way the algorithm is able to have good local and global performances. Accordingly to Fig. 5, the Coulomb-Counting part of the SoC estimation is a kind of feed-forward component of the control variable of the control system.

In Fig. 6 the way the algorithm performs when applied to the reference test is shown: the case in which $\mathrm{SoC}(0)$ is known and not known are shown. The algorithm uses $I_{HallSens}(t)$ and $V_{ADC}(t)$. The *mix estimation algorithm* clearly performs better than the Coulomb-Counting and the Model-Based method: the estimation is locally more accurate while the influences of the measurement noise remains low.

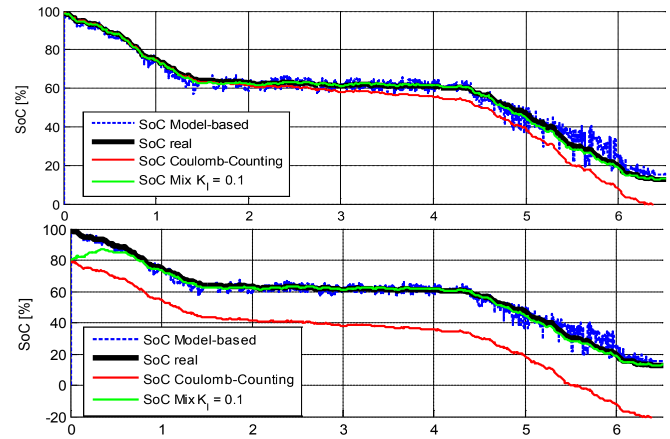

Fig. 6 - Mix algorithm behavior (reference test). In the top the case of right SoC(0); in the bottom the case of a wrong SoC(0).

IV. MIX ALGORITHM ANALYSIS

As shown in the previous Sections, the *mix estimation algorithm* provides better results than the Coulomb-Counting and the Model-Based algorithm. The previous Section only provided experimental/qualitative analysis. This Section is addressed to analyze some characteristics of the *mix estimation algorithm* in an analytical way: in particular its stability characteristics and its sensitivity to measurement errors. For all the characteristics, the comparisons with the Coulomb-Counting and the Model-Based algorithms are provided.

This Section is so structured. In Section A the linearization of the *mix estimation algorithm* is described: this step is necessary to perform the further analysis since the algorithm, and in particular the battery model, is a non-linear system (notice that the linearization results are necessary also for the analysis of the Model-Based algorithm). Section B is focused on the analysis of the algorithms stability. Sections C describes the sensitivity to measurement errors of the algorithms.

A. *Mix algorithm linearization*

The *mix estimation algorithm* characteristics are the following:

- It is a MISO system, since it has as input the current (I_m) and the voltage (V_m) of the battery and as output the estimated SoC ($\hat{SOC}$).
- It is a non-linear algorithm since the battery model is non-linear: in particular, the relationship defined by $V_{OCV}(\hat{SOC})$ is non-linear.

To perform the stability and the error sensitivity analysis the algorithm, and specifically $V_{OCV}(\hat{SOC})$, has been first linearized). The linearization is performed as:

$$\begin{aligned} V_{OCV}(\hat{SOC}) &= V_{OCV\_DC}(\hat{SOC}) \\ &= V_{OCV\_DC}(\overline{SOC}+\delta SOC) \\ &\approx \frac{\delta V_{OCV\_DC}}{\delta SOC}(\overline{SOC})\delta SOC \\ &= K_{SOC}\delta SOC, \end{aligned} \tag{6}$$

where $\delta SOC = \hat{SOC} - \overline{SOC}$.

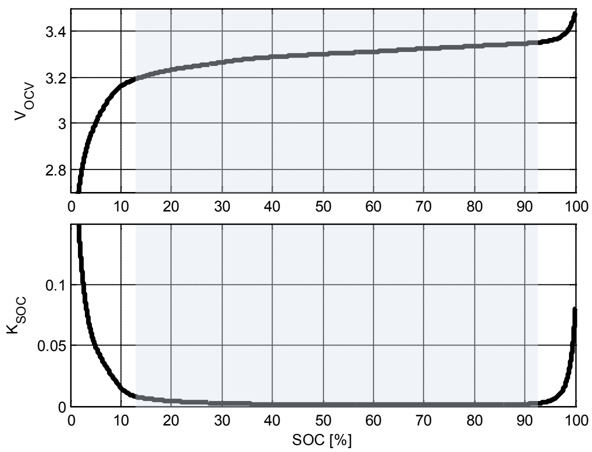

Fig. 7 - K_{SOC} for the phosphate-based battery.

The value of K_{SOC}, as well as the algorithm behavior, depends on the selected working point ($\overline{SOC}$). As shown in Fig. 7, different behavior zones can be defined: usually the low and high SoC values zones are characterized by high K_{SOC} values. Notice that the relationship between SoC and the Open-Circuit-Voltage is monotonically increasing, thus $K_{SOC} > 0$.

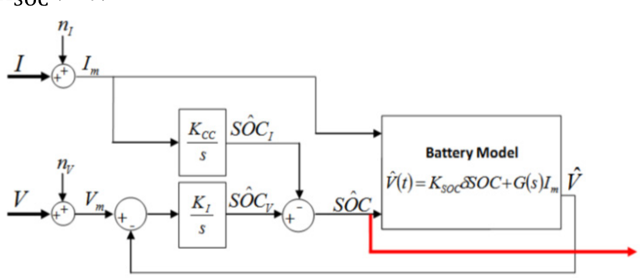

Fig. 8 - Mix algorithm schematic: linearized detailed scheme.

Using the linearization result, the algorithm scheme can be modified. It is shown in Fig. 8.

B. Mix algorithm behavior analysis: stability analysis

The stability analysis of the algorithm has been carried out in the frequency domain. Accordingly to the superposition principle, this analysis is performed evaluating the influence of each input on $\hat{SOC}$: if for each input the transfer function is asymptotically stable, the algorithm is asymptotically stable.

The *mix estimation algorithm* uses two inputs: the measured voltage V_m and the measured current I_m. The transfers function between V_m and $\hat{SOC}$ is:

$$\frac{\hat{SOC}}{V_m} = \frac{K_I}{s + K_I K_{SOC}}, \tag{7}$$

while the transfer function between I_m and $\hat{SOC}$ is:

$$\frac{\hat{SOC}}{I_m} = -\frac{K_I G(s) + K_{CC}}{s + K_I K_{SOC}}. \tag{8}$$

For both the inputs, the stability of the related transfer function is defined by the sign of $K_I K_{SOC}$. Since accordingly to the previous considerations $K_{SOC} > 0$, the stability depends on K_I value. Two different situations can be underlined:

- $K_I = 0$: in this situation the algorithm behaves exactly as the Coulomb-Counting algorithm, since the closed-loop around the battery model results to be *opened*. In this case the mix algorithm is just *simple stable* as the Coulomb-Counting algorithm.
- $K_I > 0$: in this situation, which describe the typical way of usage of the mix algorithm, both the transfer functions are asymptotically stable.

The case $K_I = 0$ is an extreme condition in which the mix estimation algorithm degenerates to a Coulomb-Counting algorithm, hence it is not considered. Then, accordingly to the superimposition principle, the mix algorithm is asymptotically stable.

The same stability analysis can be performed on the Coulomb-Counting and the Model-Based algorithms. Avoiding the details of this analysis, the conclusions are that the Coulomb-Counting algorithm is only simply stable while the Model-Based algorithm is asymptotically stable. This result underlines one of the advantages of the *mix estimation algorithm*, which provides the advantages of the Coulomb-Counting algorithm while increasing its stability characteristic.

C. Mix algorithm behavior analysis: measurement errors

This Section describes the sensitivity to measurement errors of the *mix estimation algorithm* compared to the Coulomb-Counting and the Model-Based algorithms. The analysis has been performed in two phases:

- In the first phase, the analysis has aimed to evaluate the static sensitivity to the measurement errors, both for the current and the voltage inputs: the effects have been evaluated separately and at different working conditions (identified by the $\overline{SOC}$ value). We call it a *static error analysis*.
- In the second phase, the analysis has aimed to evaluate the overall estimation errors on the reference test due to the measurement errors We call it a *dynamic error analysis*.

For both the analyses, the estimation error has been used as performance index. It is defined as:

$$e_{SOC}(t) = \left(SOC(t) - \widehat{SOC}(t)\right), \tag{9}$$

where $SOC(t)$ is the right State-of-Charge and $\widehat{SOC}(t)$ is the estimated one. The measurement errors characteristics previously defined have been used.

Measurement errors: static evaluation.

The *static error analysis* has been performed in the frequency domain, evaluating how each measurement error (in particular $\bar{I}_{err}$ and $\bar{V}_{err}$) affects the estimation error $e_{SOC}(t)$: the final value theorem has been used to perform this analysis. To analyze the impact of $\bar{V}_{err}$ on $e_{SOC}(t)$, the transfer function defined by (1.8) is used. The application of the final value theorem leads to the following equation:

$$\lim_{t\to\infty} e_{SOC}(t) = \lim_{s\to 0} \frac{\bar{V}_{err}}{s} s \frac{K_I}{s + K_I K_{SOC}} = \frac{\bar{V}_{err}}{K_{SOC}}. \tag{10}$$

The same result is obtained performing the analysis to the voltage-based algorithm. Notice that the effect of $\bar{V}_{err}$ on the estimated SoC does not depend on K_I: the *mix estimation algorithm* is not able to improve the estimation error with respect to the one produced by the voltage-based algorithm.

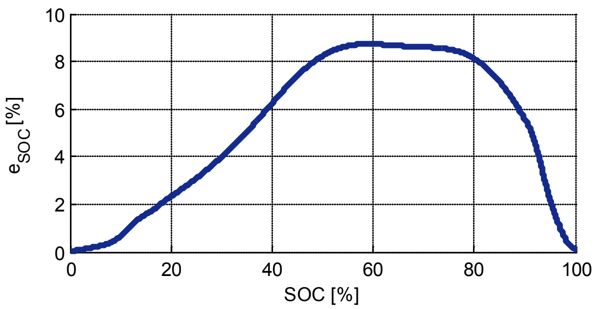

Fig. 9 - e_{SOC} in case of $\bar{V}_{err}(t) = 0.01V$.

Fig. 9 shows the values assumed by $e_{SOC}(t)$ accordingly to different working conditions (identified by the $\widehat{SOC}$ value). The effect of $\bar{V}_{err}$ is provided.

To analyze the impact of $\bar{I}_{err}$ on $e_{SOC}(t)$, the transfer function defined by (1.8) is used. The application of the final value theorem leads to the following result:

$$\lim_{t\to\infty} e_{SOC}(t) = \lim_{s\to 0} \frac{\bar{I}_{err}}{s} s \frac{-K_I G(s) - K_{CC}}{s + K_I K_{SOC}} = \bar{I}_{err} \frac{-K_I G(0) - K_{CC}}{K_I K_{SOC}}. \tag{11}$$

Notice that the effect of $\bar{I}_{err}$ on the estimated SoC depends on K_I. Two boundary conditions can be defined: $K_I = 0$ and $K_I = \infty$ which respectively identify the case in which the loop around the battery model is *opened* (the *mix estimation algorithm* behaves as the Coulomb-Counting algorithm) and the case in which the contribution of the Coulomb-Counting do not affect the estimation, since the gain of the closed-loop is the higher as possible (the *mix estimation algorithm* behaves as the Model-Based algorithm). In these two conditions, the effects of $\bar{I}_{err}$ are:

$$\lim_{K_I\to 0} \bar{I}_{err} \frac{-K_I G(0) - K_{CC}}{K_I K_{SOC}} = -\bar{I}_{err} \frac{G(0)}{K_{SOC}} - \infty = -\infty, \tag{12}$$

$$\lim_{K_I\to\infty} \bar{I}_{err} \frac{-K_I G(0) - K_{CC}}{K_I K_{SOC}} = -\bar{I}_{err} \frac{G(0)}{K_{SOC}}.$$

They correspond to $e_{SOC}(t)$ in case of $\bar{I}_{err}$ for the Coulomb-Counting algorithm (the top one) and for the Model-Based algorithm (the bottom one).

Fig. 10 shows the effects of $\bar{I}_{err}$ for different $\widehat{SOC}$ values: the effect for $K_I = \infty$ is underlined by a red line. Notice that there exists a value of K_I which neutralizes the effect of $\bar{I}_{err}$ on $e_{SOC}(t)$. It is then clear that the mix algorithm is able to improve the estimated SoC in case of a constant error on the current input with respect to the Coulomb-Counting and the Model-Based algorithms.

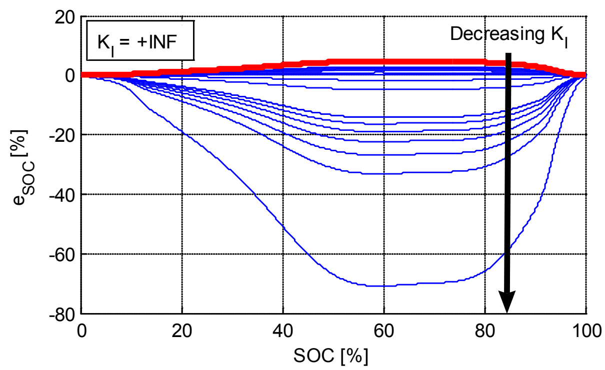

Fig. 10 - e_{SOC} in case of $\bar{I}_{err}(t) = 0.16A$.

Measurement errors: dynamic evaluation.

The *dynamic error analysis* aims to compare how the measure errors ($\bar{I}_{err}$, $\bar{V}_{err}$) affect the estimation provided by the mix algorithm with respect to the Coulomb-Counting and the Model-Based algorithms evaluating the estimation error on the reference test shown in Fig. 2. The *dynamic error analysis* aims to evaluate the overall performance of the algorithms in a real test, in which the SoC changes. The algorithms' performances have been evaluated using as the performance index $E[e_{SOC}(t)]$. Since the mix algorithm behavior depends on K_I, the mix algorithm performances have been evaluated with different K_I values.

The test we used is the reference test. It is a simulated test since it has been designed a priori, defining the current profile and then computing both the voltage and the SoC using the following reference battery models:

$$SOC = -\frac{K_{CC}}{s} I(t), \qquad V(t) = V_{OCV}(SOC) + G(s) I(t). \tag{13}$$

By construction, the SoCs computed by the Coulomb-Counting algorithm and the Model-Based algorithm on the simulated test provide $E[e_{SOC}(t)] = 0$.

The analysis has been performed in three different conditions:

- In the first condition an error ($\bar{V}_{err}$) on the voltage input has been considered. The test voltage input is defined as (1.3).

- In the second condition an error ($\bar{I}_{err}$) on the current input has been considered. The test current input is defined as (1.2).
- In the third condition both the errors have been considered.

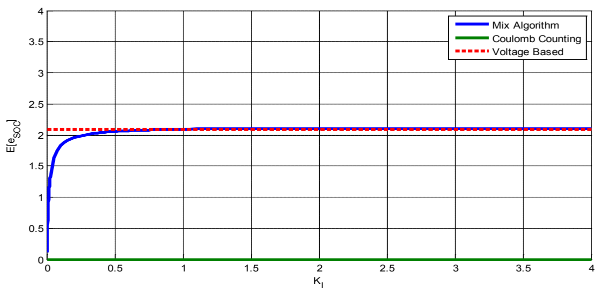

Fig. 11 - Dynamic test results: voltage error.

The results of the first testing condition are shown in

Fig. 11. As expected the Coulomb-Counting algorithm provides the exact SoC, while the Model-Based algorithm performs worst. Accordingly to the K_I value, the mix algorithm behaves in different ways. As expected, with $K_I = 0$ the performances are almost perfect: it behaves as the Coulomb-Counting since the closed-loop is *opened*. Increasing the value of K_I, the mix algorithm performances worsen, matching the performances of the voltage-based algorithm.

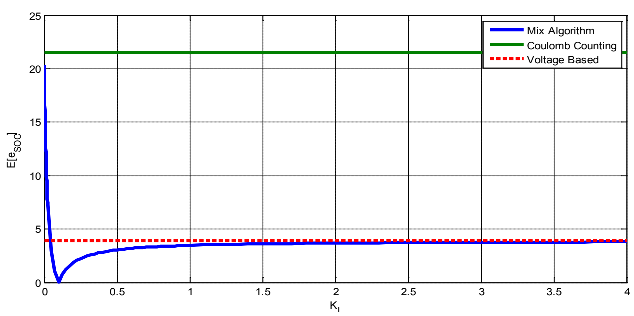

Fig. 12 - Dynamic test results: current error.

The results of the second testing condition are shown in Fig. 12. As expected by the *static error analysis* both the Coulomb-Counting algorithm and the Model-Based algorithm do not provide a perfect estimation. With $K_I = 0$ the performances of the mix algorithm are almost equal to the performances of the Coulomb-Counting algorithm while for high K_I values, the *mix estimation algorithm* performances match the performances of the Model-Based algorithm. As underlined by the *static error analysis*, there exists a K_I value which allow to neutralize the effect of $\bar{I}_{err}$ on $S\hat{O}C$.

The results of the third testing condition are shown in Fig. 13: in this test both the measure errors are considered. The results, even with different performances' values, confirm the results of the previous testing condition.

From the above results, it is clear that the *mix estimation algorithm* is able to improve the estimation performances in case of a constant current measurement error, while it cannot do anything on a constant voltage measurement error. From the knowledge of the battery model, it is possible to identify the value of K_I which allows to neutralize the impact of a constant current error on the estimated SoC.

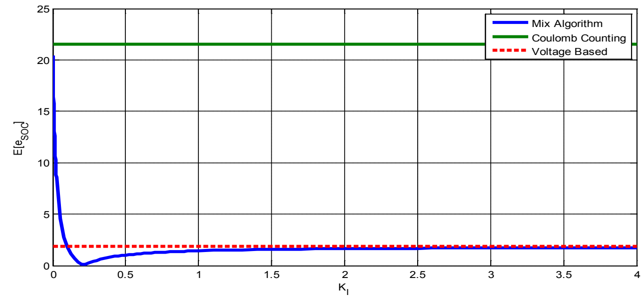

Fig. 13 - Dynamic test results: voltage and current error.

Acknowledgment

The authors would like to thanks Mattia Perego, for his help to the finalization of the results presented by this paper, and professor Giorgio Rizzoni, for the useful discussions about this topic.

References

[1] V. Pop, H. J. Bergveld, P. H. L. Notten, and P. P. L. Regtien, "State-of-the-art of battery state-of-charge determination," *Measurement Science and Technology*, vol. 16, no. 12, pp. R93-R110, 2005.

[2] J. H. Aylor, A. Thieme, and B. W. Johnson, " A battery state-of-charge indicator for electric wheelchairs," *IEEE Trans. Indust. Electron.*, vol. 39, p. 398–409, 1992.

[3] E. Peled, H. Yamin, I. Reshef, D. Kelrich, and S. Rozen, "Method and apparatus for determining the state-of-charge of batteries particularly lithium batteries," US Patent Patent 4,725,784, Sep. 10, 1984.

[4] A. Pop, et al., "Modeling Battery Behaviour for Accurate State-of-Charge Indication," *Journal of Electrochemical Society*, vol. 153, no. 11, pp. A2013-A2022, 2006.

[5] S. Rodrigues, N. Munichandraiah, and A. K. Shukla, "A review of state-of-charge indication of batteries by means of a.c. impedance measurements," *Journal of Power Sources*, vol. 87, pp. 12-20, 1999.

[6] A. J. Salkind, C. Fennie, P. Singh, T. Atwater, and D. E. Reisner, "Determination of state-of-charge and state-of-health of batteries by fuzzy logic methodology," *J. Power Sources*, vol. 80, p. 293–300, 1999.

[7] F. Codecà, S. M. Savaresi, and G. Rizzoni, "On battery State of Charge estimation: a new mixed algorithm.," *17th IEEE International Conference on Control Applications, Part of 2008 IEEE Multi-conference on Systems and Control, San Antonio, Texas, USA*, pp. 102-107, Sep. 2008.

[8] R. Portas and L. Colombel, "Accuracy of Hall-Effect Current Measurement Transducers in Automotive Battery Management Applications using Current Integration," *Automotive Power Electronics*, Sep. 2007.