Comparison of State-of-Charge Estimation Methods for Stationary Lithium-Ion Batteries

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***Abstract*—An accurate monitoring of the State of Charge (SoC) is mandatory for an efficient management of a Lithium-ion battery. Batteries of stationary systems barely have long resting periods when the cumulative errors can be reset. These special requirements make a robust and accurate SoC estimation algorithm necessary. A real stationary system including an experimental microgrid with renewable energy generation, home consumption and a 5.3 kWh Li-ion storage system is analyzed in this paper. Three representative SoC monitoring algorithms are applied and compared in terms of accuracy and robustness to battery aging and current measurement offset. A closed-loop method consisting of an adaptive filter and a state observer achieves best results while having a reasonable computational complexity.**

Keywords—Lithium-ion battery; monitoring; State of Charge; microgrid

I. Introduction

Efficient energy storage is a mayor challenge for the development of the electrical grid. Renewable energy is non-predictable and there is no assurance of power availability in the medium term. Nowadays, a fast decrease in the price of Lithium-ion batteries is being accomplished, mainly due to the mass production of batteries for electric cars [1]. This inviting price, together with the excellent electrical characteristics and long lifetime of Li-ion batteries, makes them a suitable choice for grid energy storage.

Battery state variables need to be accurately monitored in order to allow wise control decisions intended to optimize the performance of the storage system. If the monitoring of the battery is not rigorous, a bigger (and more expensive) battery is needed to meet the same operational requirements. Moreover, unexpected blackouts and battery lifespan shortening can be undesirable penalties of an improper monitoring algorithm. There are several variables to be monitored, such as battery impedance or capacity, State of Health, State of Function, etc. However, the most important one is the SoC, since it is a measure of the actual charge content of the storage system. A BMS is required for a safe operation of Li-ion batteries to control the voltage and temperature of each cell inside safe limits. An important function of the BMS is to provide an estimation of the battery SoC.

There is a wide variety of SoC-estimation algorithms, each of them with advantages and disadvantages. The used algorithm should depend on the particular application, the desired accuracy and the budget available. The most used algorithms can be classified into 3 main groups:

- Integrating methods: These methods predict the SoC of the battery based on an Ampere-hour counting. They are widely used because the required computational power is low, and their performance with Li-ion battery is better than with other types of batteries due to the lower magnitude of side reactions. Some authors take into account the coulombic efficiency [2], [3], or the capacity shift along the lifetime of the battery [4] to get a more accurate SoC value. The main disadvantage of the integrating models is the cumulative error in the current integration. A widely-used strategy to eliminate this cumulative error is to measure the open circuit voltage (OCV) of the battery and reset the SoC value. A long resting period is needed for the Lithium diffusion to stabilize and so to have a measurable OCV.
- Model-based methods: The battery behaviour is modelled and the observable variables (battery voltage v and current i) are related with the SoC through mathematical expressions. These estimators are not affected by cumulative error; however, they have a high sensitivity to model inaccuracies. Most of the models used to estimate the SoC represent the impedance of the battery through an electric circuit and adopt a polynomial expression for the OCV–SoC relationship [5]. The problem is that accurate models taking into account all the phenomena occurring in the battery have high computational requirements and therefore are not suitable for on-line SoC prediction. Additionally, the model-based prediction strategies are sensitive to variation in model parameters, which occurs with the battery aging and temperature changes.
- Closed-loop methods: The combination of Ampere-hour integration and model-based estimation is a good trade-off between computational simplicity, estimation accuracy and cumulative error mitigation. These methods get a SoC prediction through an Ampere-hour integration strategy, and use the voltage and current measurements to reduce the error through a battery model. The most typical algorithms used to combine these two information sources are the Kalman filters with some variations [2], [6], [7], adaptive filters [8],

[9] and Gauss–Hermite quadrature [10]. They have a good robustness against model parameters variation and measurement noise, but their computational requirements are sometimes too high.

Multiple research papers analyzing the performance of SoC estimators for electric vehicles (EVs) have been published [4], [6], [7]. SoC estimation is crucial for an EV, since estimation inaccuracy can result in unexpected fuel shortcoming. EVs have long resting periods where the battery is fully charged, which can be used to reset the SoC monitoring algorithm and remove the cumulative integration error. However, batteries used in stationary applications are usually maintained in medium SoC and may not have long resting periods or full charges. To the best of our knowledge there are no comprehensive studies aimed to analyze these particular requirements of stationary Li-ion batteries. This paper has the target of analyzing three SoC monitoring methods applied to a stationary battery installed in an experimental microgrid with renewable power generation and emulated home consumption.

To accomplish that, three methods for SoC estimation are chosen and explained in Section II. In Section III, the 5.3 kWh battery used for the experiments and the domestic microgrid are described. Subsequently, 8 hours of real performance of the battery in the microgrid are presented in Section IV and the three methods are compared in three different scenarios: (i) using the most accurate current measurement and impedance data, (ii) with an offset of 0.5 A in the measured current to simulate the sensor inaccuracy and (iii) using a model capacity 10% higher than the actual value and a model impedance 10% lower than the battery impedance to simulate a capacity loss and impedance raise indicative of battery aging. Finally, the main conclusions of this paper are summarized in Section V.

II. SoC ESTIMATION METHODS

A. Method based on Ampere-hour counting

This is an elementary method for SoC monitoring, whose accuracy is determined by the current sensor accuracy, test duration and capacity knowledge. The expression for SoC is:

$$SoC(t) = SoC_0 + \frac{1}{C} \cdot \int_0^t i(\tau) d\tau \quad (1)$$

Where C is the capacity of the battery, SoC_0 is the initial battery SoC, t stands for time and τ is the time integration variable. The assumption of unitary coulombic efficiency (η_c=1) is reasonable for Li-ion batteries in low-current and ambient temperature scenarios, since η_c>99.5% [11], [12]. This method requires the knowledge of the initial SoC. When this method is run over a long period of time, significant inaccuracy arises from accumulated current measurement errors. In this case, a full charge or full discharge is needed to reset the estimated SoC.

B. Method based on an electrical model

The battery voltage and current are monitored and the equivalent circuit shown in Fig. 1 is used to calculate the open-circuit voltage (OCV). The battery impedance consists of a resistance R_{ohm} which stands for ohmic losses and a parallel

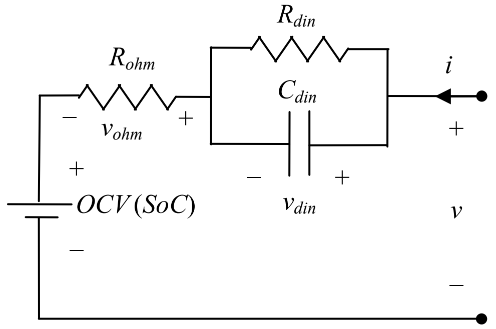

Fig. 1. Equivalent circuit used as battery model.

connection of R_{din} and C_{din} which represents other battery dynamic processes, being the diffusion of Lithium ions through the electrodes and membrane the most important one. This impedance is used to calculate the OCV from the measured voltage and current using (2):

$$OCV = v - \left(i - C_{din} \frac{dv_{din}}{dt} \right) \cdot R_{din} - i \cdot R_{ohm} \quad (2)$$

Once the OCV is known, a relationship between OCV and SoC is used to calculate SoC. This relationship is constant during the entire lifetime of the battery and a commonly used expression is an empirical polynomial. This model requires low computational effort and provides an adequate accuracy, being thus suitable for on-line SoC estimation.

C. Method based on an adaptive observer

This method is a variation of an idea presented by M. A. Roscher and D. U. Sauer [8] for SoC monitoring. These authors presented a model for lithium iron phosphate (LFP) batteries, whilst the battery analyzed herein has a lithium-niquel-manganese-cobalt oxide (NMC) cathode. The most notorious difference between both technologies is the hysteresis eye of the open-circuit voltage, which exists only in LFP batteries. The schematic of the estimation method is shown in Fig. 2.

Firstly, the algorithm uses a two-step adaptive filter. This adaptive filter calculates an *OCV'* based on the parameter vector (θ) from the previous iteration step. To do so, the actual cell voltage and current are measured. The first step of the adaptive filter predicts the voltage of the cell (v') based on the measured current. Then, the predicted cell voltage (v') is compared with the actual measured voltage (v) in the correction step in order to adapt the circuit parameters to be

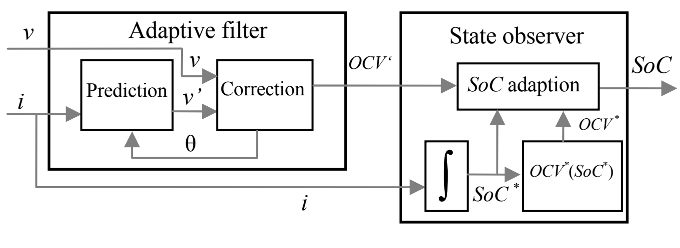

Fig. 2. Schematic diagram of the adaptive observer method.

used in the next iteration. By adapting the parameter vector θ, the prediction error (difference between v' and v) is recursively minimized. Since the OCV is one of the components of θ, the estimated OCV' is calculated.

In the state observer, an SoC^* is forecasted through (1) by current integration. From this forecasted SoC^*, an OCV^* is calculated using the OCV – SoC relationship. A comparison between OCV^* and OCV' leads to an SoC adaption using a scaling factor characteristic from this method called voltage feedback gain. Hence, this method provides an SoC taking into account the results from current integration and model parameters, therefore compensating possible offset errors in the current measurement. Moreover, as explained before, it is able to adapt the model parameters in the correction step to keep its good performance under different operating modes.

III. MICROGRID DESCRIPTION AND EXPERIMENTAL SETUP

A commercial 5.3 kWh NMC Li-ion battery is used to test the performance of the illustrative methods described above. This battery is the storage system of an experimental microgrid with renewable energy generation located at the Public University of Navarre (UPNA) [13]. A schematic diagram of the microgrid is shown in Fig. 3. The microgrid performance is handled by the Power Management System, which monitors the state of the microgrid and manages the power conditioning stage using the most suitable control strategy [14]. The PV and wind power generators are wired to the power conditioning stage. The rated power of the wind turbine is 6 kW and that of the PV generator is 4 kWp. The power consumption is emulated through a programmable electronic load, based on actual electricity consumption data measured in a five-member family home located in the vicinity of the UPNA. The energy storage system consists of the series connection of 36 Li-ion pouch battery cells with a rated capacity of 40 Ah. Each cell has a black-carbon anode, an NMC cathode, a liquid electrolyte and a polymer membrane. Likewise, the microgrid also allows for the energy exchange with the electrical grid, depending on the management strategy adopted.

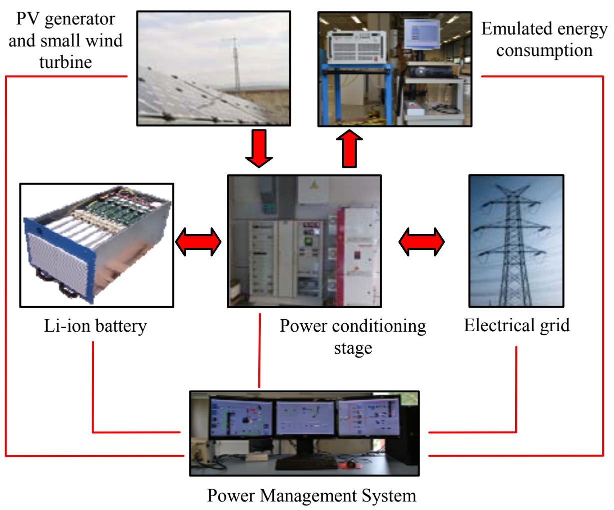

Fig. 3. Schematic diagram of the domestic microgrid used to test the SoC estimation methods.

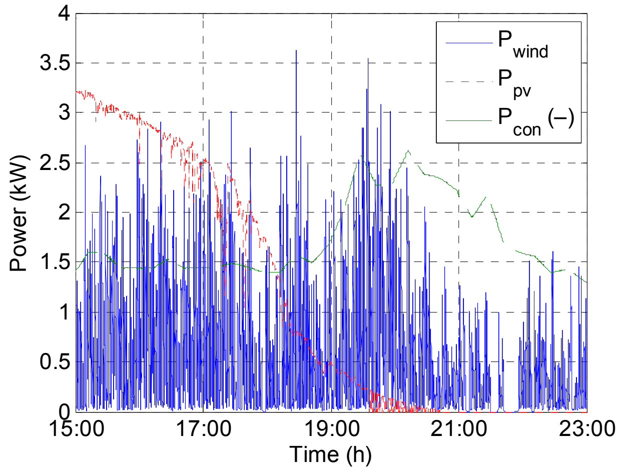

Fig. 4. Microgrid performance from 15:00 h. to 23:00 h of the 11th of April, 2013: Wind power generation (P_{wind}), photovoltaic power generation (P_{pv}) and inverted consummed power (P_{con}).

The afternoon and evening of the 11th of April, 2013 have been chosen to test the SoC monitoring algorithms. Fig. 4 shows generated and consumed power from 15:00 h to 23:00 h. It was a sunny day, as can be inferred from the PV generation, and the wind power has the usual gusty pattern. The control algorithm was programed to minimize the power exchange with the electrical grid, being the difference between generated and consumed power assumed by the Li-ion battery.

In a previous work, the Ampere-hour counting method has been used to estimate the SoC of this particular battery [15]. Since the battery is at an early stage of its lifetime, it was concluded that the actual capacity is the nominal capacity. Therefore, the only parameter required for the Ampere-hour counting method is $C = 40$ Ah.

The parameters of the equivalent battery circuit shown in Fig. 1 for the Li-ion battery used in this work were also calculated in a previous paper [16]. The resulting $OCV(SoC)$ relationship is expressed in (3) and the parameters are shown in Table 1.

$$OCV = 110 + 384 \cdot SoC + 3785 \cdot SoC^2 + 19976 \cdot SoC^3 + 59274 \cdot SoC^4 + \\ 1024800 SoC^5 + 102331 \cdot SoC^6 + 54734 \cdot SoC^7 + 12147 \cdot SoC^8 \tag{3}$$

In regard to the method based on the adaptive observer, the initial parameter vector ($\theta_{t=0}$) employed in the prediction step of the adaptive filter, uses the parameters shown in Table I. The correction of θ is accomplished through a correction gain diagonal matrix as explained in [8]. The current integration of the state observer is carried out as stated in (1) using $C = 40$ Ah, as previously explained. For the relationship

TABLE I. ELECTRICAL MODEL PARAMETERS

Parameter	Value	Unit
R_{ohm}	70.2	mΩ
R_{din}	35.7	mΩ
C_{din}	714.6	F

$OCV(SoC)$ we used (3). Finally, a voltage feedback gain is used for the SoC adaption.

IV. Model comparison

The power difference between renewable generation and home consumption (see Fig. 4) is mainly managed by the Li-ion battery, since the microgrid control algorithm minimizes the power exchange with the electrical grid. There is a power flow from the microgrid to the electrical grid only when the battery cannot assume more charge (17:45 h and 18:00 h).As shown in Fig. 5, the battery is charged during the afternoon, when the sun is shining and the domestic power consumption is low. The generated power decreases during the evening, and around 18:30 h the battery has to provide energy for the consumption. From this moment on, the battery SoC is reduced until the end of the test. The current shown in Fig. 5 has a high variability caused by the wind power generation.

The three methods explained in Section II with the parameters fitted to the real battery performance as shown in Section III are compared herein. Firstly, an ideal scenario with accurate knowledge of model parameters and current measurement is presented. However, a good monitoring method does not require a very precise (and expensive) current sensor and keeps its accuracy during the whole lifetime of the battery. Therefore, after the ideal scenario, the performances of the methods are compared in two scenarios: (i) an inaccurate current sensor and (ii) an aged battery. An inaccurate sensor is simulated in this paper by an offset in the measured current, which is the most harmful effect of a sensor inaccuracy for SoC monitoring. In the 8 hour microgrid experiment shown in Fig. 4, a measured current $i'=i+i_{offset}$, with $i_{offset}=0.5$ A will be considered. This offset represents around 10% of current measurement. The influence of this large offset in a short test is similar to that of a lower offset in a longer experiment. The battery aging is considered to induce a capacity fade and a resistive rise. Since the effect of aging is an actual battery resistance higher than the model parameters R_{ohm} and R_{din} and a battery capacitance lower than the parameter C, an aged battery is simulated by changing the algorithm input parameters to $C'=1.1\cdot C$, $R_{ohm}'=0.9\cdot R_{ohm}$ and $R_{din}'=0.9\cdot R_{din}$. Since an accurate current sensor is used during the test and the battery capacity

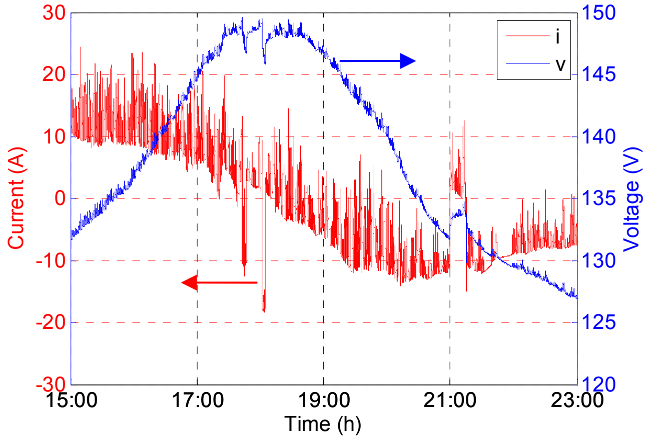

Fig.5. Battery current and voltage during the experiment.

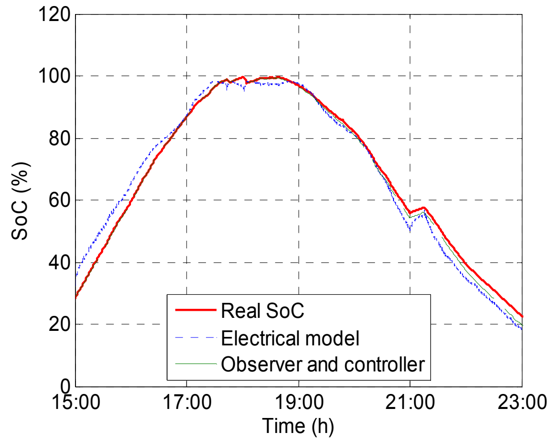

Fig. 6. State of charge estimation using accurate current measurement and circuit parameters through different estimation methods.

has been measured beforehand, the real SoC is assumed to be the value estimated by the Ampere-hour counting method using C=40 Ah. The RMSE and maximum error of the methods during the experiment are calculated and compared.

Fig. 6 shows a comparison between the performances of three SoC-estimation methods during the above-described experiment. The current measurement and equivalent circuit variables are accurate values. The RMSE and maximum error of each method are calculated and summarized in Table II. The electrical model accuracy is lower than the adaptive observer, since the battery model cannot take into account all the physical phenomena occurring in the battery.

The robustness of the three methods to current measurement offset is studied at this point and the results are shown in Fig. 7. The cumulative error of the Ampere-hour counting method is clearly seen in the red, solid line. This method is not suitable for the common scenario with an offset in the current measurement. As shown in Table II, the maximum error of the ampere-hour counting method in this scenario is the largest of the performed tests. The results of the electrical model method are similar to the scenario where the

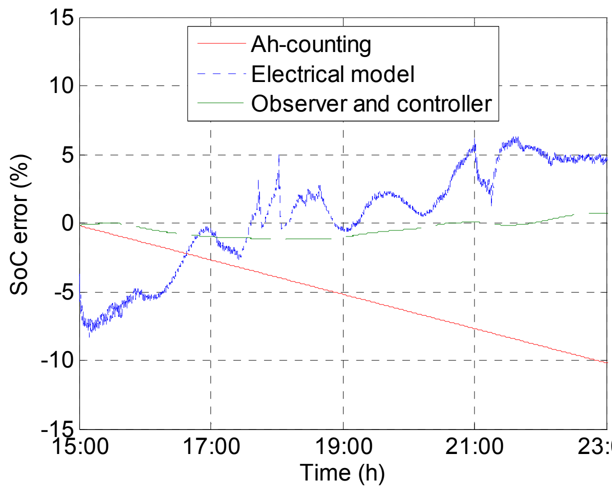

Fig. 7. SoC estimation errors of the three methods under current measurement offset.

current has not measurement offset, which proves that the electrical model method is robust to measurement offset. However, this method is not highly accurate, as shown in Fig. 7. The adaptive observer method keeps its high accuracy in this current offset scenario, as can be seen in Fig. 7 and Table II, with an SoC prediction RMSE=0.005% during the eight-hour experiment and a maximum error of 1.2%.

The performance of the methods for an aged battery is simulated as explained before, with different values of capacity and impedance. The results are shown in Fig. 8 and summarized in Table II. The Ampere-hour counting method does not have a cumulative effect, but the capacity fade triggers an error as high as 6.7% when the battery is charged. The accuracy of the electrical model is slightly lower than in the previous scenarios. This method keeps its robustness, but its accuracy is low for the three scenarios, nonetheless. The adaptive observer method keeps high accuracy and robustness under these conditions, with an error slightly higher than in the previous scenarios, as shown in Table II. In Fig. 8, the adaptive observer method is shown to behave in a similar manner to the Ampere-hour counting method at the beginning of the test. As the error increases, the adaptive observer algorithm corrects its

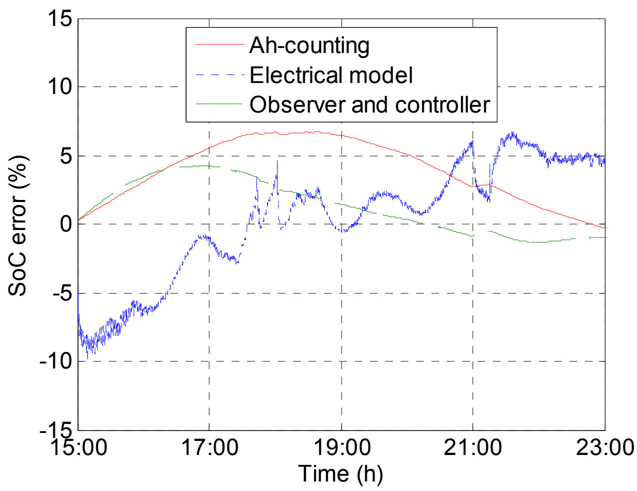

Fig. 8. SoC estimation errors of the three methods for an aged battery.

TABLE II. SoC ESTIMATION ERRORS OF THE THREE METHODS UNDER DIFFERENT OPERATIONAL CONDITIONS. AMPERE-HOUR COUNTING (AH-C), ELECTRICAL MODEL (EM) AND ADAPTIVE OBSERVER (AO) METHODS

	Ah-c	**EM**	**AO**
	Accurate variables		
RMSE (%)	---	$1.4 \cdot 10^{-1}$	$1.6 \cdot 10^{-2}$
Maximum error(%)	---	8.7	2.9
	Current measurement offset		
RMSE (%)	$3.6 \cdot 10^{-1}$	$1.5 \cdot 10^{-1}$	$5.0 \cdot 10^{-3}$
Maximum error(%)	10	8.3	1.2
	Aged battery		
RMSE (%)	$2.0 \cdot 10^{-1}$	$1.8 \cdot 10^{-1}$	$5.3 \cdot 10^{-2}$
Maximum error(%)	6.7	10	4.2

internal parameters and amends this miscalculation, achieving the most accurate results in the three scenarios.

V. CONCLUSION

A closed-loop SoC estimation method is needed for stationary applications, where the battery normally operates with an intermediate SoC and rarely has long resting period when the cumulative errors can be reset. The comparative experimental study presented herein reproduces an actual battery operating condition in a domestic microgrid with renewable energy generation and home consumption. From this comparative study, it can be concluded that the Ampere-hour counting method has a cumulative integrate error which makes it unacceptable for stationary applications. An electrical-model-based method can be appropriate for electronic devices where the current managed by the battery is low, but in a stationary application the high current values reduce the accuracy of the algorithm, especially for an aged battery with shifted circuit parameters. The closed-loop method analyzed herein achieves the lowest estimation error in the three situations. Therefore, the most suitable estimation algorithm for this application is a closed-loop algorithm which has the high accuracy distinctive of the Ampere-hour counting method, uses an electrical model to run an online correction of the cumulative error and is able to recalculate the model parameters, adjusting them to the actual battery parameters.

VI. ACKNOWLEDGMENT

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