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AN0026
This document summarizes different ways to estimate the State of Charge of batteries

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Battery State of Charge calculation with EPC Converters

Introduction

Batteries in industrial markets are widely used to store energy, reduce peak consumption, operate non-mains connected machines and save braking energy. With the development of new chemical combinations and renewable technology, the expansion of the battery has grown rapidly leading to new demands and applications.

Since all the renewable energies and batteries usually generate and store energy in direct current, the use of DC/DC converters, instead of previously used DC/AC and AC/DC, is gaining uptakers as they achieve much higher efficiencies.

The company epic power designs and manufactures high efficiency bidirectional isolated and non-isolated DC/DC converters that serve the purpose of connecting different DC levels. These converters are especially used in moving applications such as lifts and AGVs to connect batteries and variable frequency (VVVF) drives to feed motors as can be seen in Fig. 1.

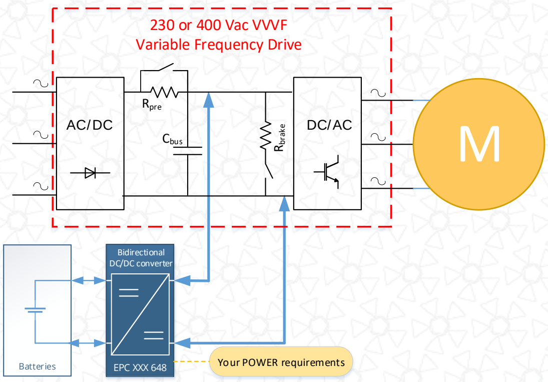

Fig. 1: Bidirectional DC/DC Converter to feed an AC VVVF drive directly from batteries

In most applications, epic power converters are the only connection to the battery as they can charge (directly or through an external charger connected to the converter) and discharge them. This requires a full knowledge of the energy going in and out, the status of the battery, the power, and the use it is having.

With this data it is possible to obtain more information about the state of the battery. With an external device that processes voltage, current, usage data (shared by the DC/DC converter via CAN bus) and knowing the type of battery connected, the State of Charge (SoC), the State of Health (SoH) and the State of Power (SoP) can be estimated accurately. This device is called "CAN - Battery Management System Interface" and can be used in any type of battery.

Fig. 2: CAN - Battery Management System Interface for EPC family converters

The "CAN - Battery Management System Interface" or "CAN - BMS Interface" ensures the correct operation of the battery, its safety and reliability and with the DC/DC converter it will establish communication to extend the life expectancy of the battery as much as possible by defining limits of operation.

In the following sections, the algorithms' running, their accuracy and inputs/outputs of the battery management system are explained.

State of Charge Calculation

The state of charge (SoC) can be described as the level of charge of a battery relative to its capacity. The units of SoC are percentage points and it is calculated as the ratio between the remaining energy in the battery at a given time and the maximum possible energy with the same state of health conditions.

$$SoC(t) = \frac{Q_{remaining}(t)}{Q_{max}(t)} * 100\ [\%] \qquad (1)$$

The obtention of the SoC is key for every application and sets base for other states' estimation although it may not be easy to obtain with every chemistry. Lithium-based batteries, and LFP particularly, show a highly non-linear relation between the SoC and the voltage measured in the batteries which require the use of prediction and estimation algorithms to obtain it.

There are many algorithms to obtain the SoC but the most widely used are the open circuit voltage (OCV) measurement, the Coulomb Counting method, and model-based methods such as Kalman Filters. Each one of these has its benefits and limitations depending on the application, type of battery, computation availability and required precision.

Method description

OCV measurement: This method is simple as it relates the internal voltage of the battery correlated with SoC and a lookup table of predefined values. Being so simple, it is not applicable to online applications as the internal voltage of the battery can only be obtained by disconnecting it and waiting for its stabilization.

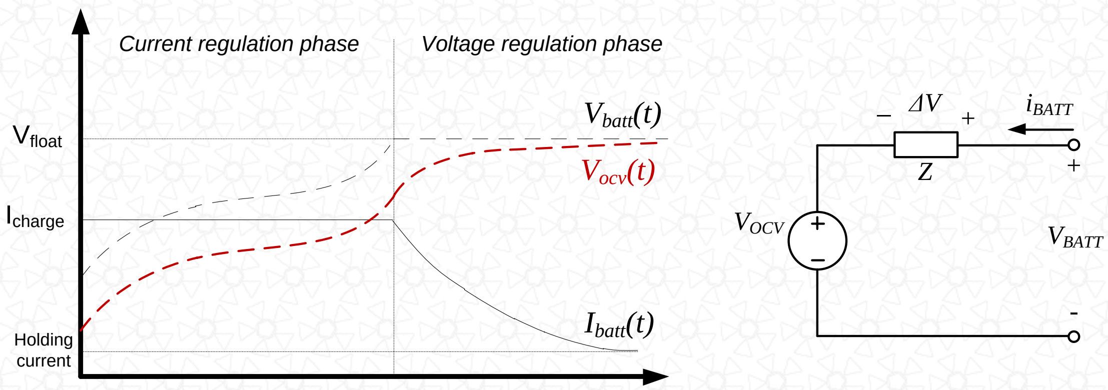

Fig. 3: Equivalent circuit of a battery and OCV evolution

For this reason, this method cannot be used in standard applications and it is not currently integrated in the estimation of the "CAN - BMS Interface".

Coulomb counting (CC) method: This method is one of the most common for estimating the SoC due to its simplicity. It relies on measuring the input and output current and the estimation of an initial state.

$$SoC(t) = SoC_0 - \frac{1}{C_{nom}} * \int_{t_0}^{t} i_{batt}(t)dt * 100 \qquad (2)$$

In this estimation method it is key to know the initial state of charge of the battery (this value is normally updated when the battery is completely charged) and to measure the current accurately. Even when this is done properly, the CC method continues integrating errors caused by inaccurate measurements and other factors which can potentially generate a serious lack of reliability in the method.

In Fig. 4 an SoC estimation with a CC method in an environment of low noise (measurement and stable battery conditions) and severe noise (inaccurate measurement and variation of battery conditions) is shown.

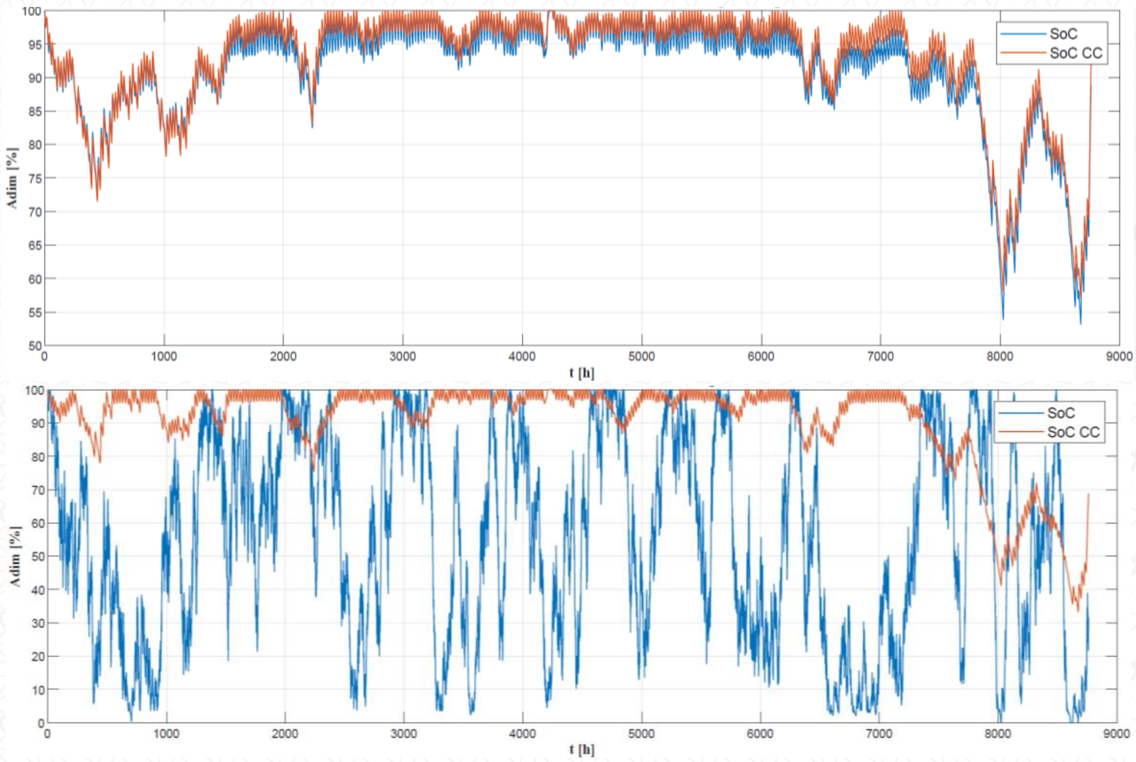

Fig. 4: SoC estimations by CC method for low and severe measuring errors

The first case in Fig. 4, with the estimation of CC in low error conditions, shows an average difference between the real and the estimated value of 2 %. That difference becomes much greater when non linearities such as temperature or depth of discharge (DoD) in the battery are included in the simulation.

To overcome such measurement problems and integrated errors over the time, this method can be used in combination with other model-based estimations.

Model-based methods: These methods are based on different algorithms that compare the actual response of the battery with the response of a simplified model of the battery or equivalent circuit. In general, these algorithms always use some degree of previous knowledge of the system (in this case, a circuital model), which makes a-priori estimations of the State of Charge. This estimation is then corrected with real time observations from the actual system, to obtain an a-posteriori estimation of SoC.

One of the most used algorithms is the Kalman filter, which takes into account the noise in the measurement and the noise (or confidence) in our model to obtain better predictions. In the case of highly non-linear batteries, such as lithium-based, the algorithm is modified into the Extended Kalman Filter (EKF) due to its capabilities of handling non-linear systems.

Although there are many different model of batteries, the most commonly used are those shown in Fig. 5 and Fig. 6 that describe the evolution of a battery voltage according to different electrical ideal elements.

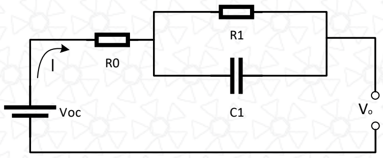

Fig. 5: First order RC Model

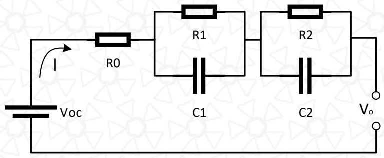

Fig. 6. Second-order RC Model

These models can be described as equations. The following example develops the model in Fig. 5, were V_{oc} depends on the current State of Charge. This non-linear relation can be stored in a Look-up table as well.

$$State\ equations\ := \begin{cases} \dfrac{d\ SoC(t)}{dt} = -\dfrac{i(t)}{C_{nom}} * 100 \\ \dfrac{dv_{c1}(t)}{dt} = -\dfrac{1}{C_1}\left(i(t) - \dfrac{v_{c1}(t)}{R_1}\right) \end{cases} \quad (3)$$

$$Measurement\ equation\ := \{V_o = V_{oc}\big(SoC(t)\big) - i(t)R_o - v_{c1}$$

These equations can be incorporated into the EKF framework by obtaining the jacobian of each term. Based on the previous SoC and the current measurement, the algorithm makes a prediction of the current SoC. Then, it proceeds with the Kalman gain computation and uses the voltage measurement to obtain the a-posteriori, corrected estimation for SoC by combining the initial SoC estimation and the information provided by the voltage measurement. This feedback makes the algorithm more robust to measurement errors and noise than the Coulomb Counting, since here a drift in the sensor is corrected. Note that in this case, current and voltage measurements are required.

Actual values of SoC vs estimations of EKF have been simulated and tested obtaining varying accuracy results depending on different scenarios of external noise (measurement and model inaccuracies) for a defined battery model as can be seen in Fig. 7 for low, medium and severe presence of noise.

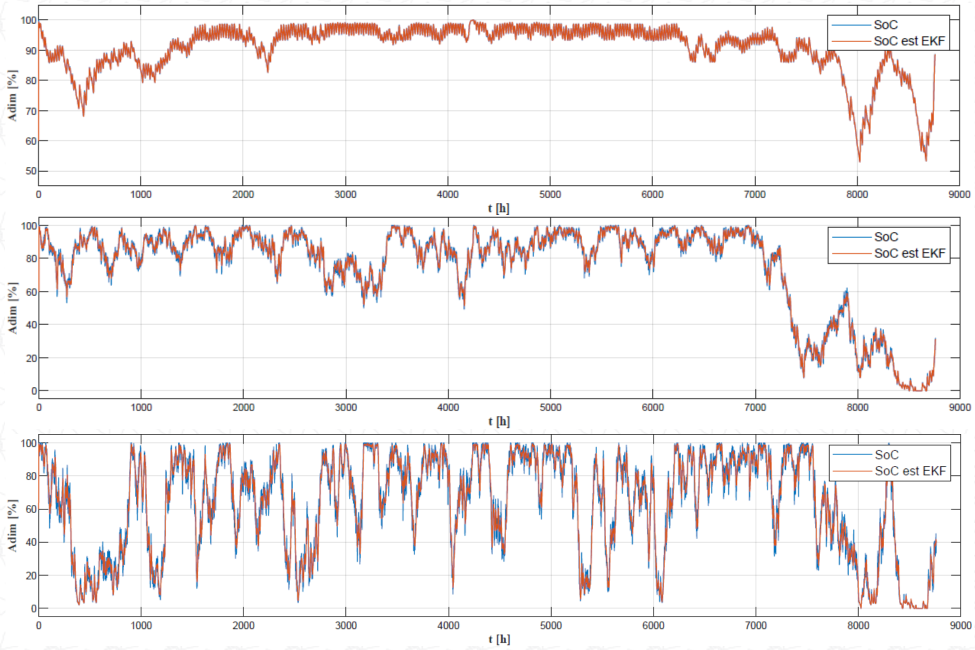

Fig. 7: SoC estimations by EKF method for low, medium, and severe noise

The results show that the average error between the real SoC and the estimated one is 0.13 % for low, 1.21 % for medium and 2.86 % for severe external noise.

The conclusion is that EKF is reliable against measurement error and an unknown initial state, the opposite of the CC, but the model must be well defined to obtain accurate results.

Model changes and battery aging:

It is important to note that both the Coulomb Counting and the EKF are basic SoC estimation algorithms, and they share a problem. They rely on parameters such as C_{nom}, R_1, C_1 and the look-up table, which are assumed constant along the life of the cell. However, there are external effects such as ambient temperature or battery aging which may change these parameters, so the predictions become less and less accurate. To solve this problem, more complex algorithms can be implemented. These algorithms are usually divided in two parts, one specialized in tracking the parameters and their evolution, and other which performs the SoC estimation.

Examples of these algorithms can be the Dual Kalman filtering, the Extremum Seeking algorithm or other methods based in machine learning.

Dual Kalman filtering uses two nested Kalman filters: One to track the parameters and their aging process and another one which uses these parameters for SoC estimation as seen before. Both work at the same time and interchange variables and states. The changes in the parameters of the battery are modelled as an external noise.

Extremum seeking introduces small signal variations into the initial parameters, and predicts the voltage evolution with said parameters. Then, compares the prediction with the real measurements, and changes these small variations. The small signal components keep on being adjusted until the parameter values converge to the real ones.

On the other side, machine learning techniques use data from real-life experiments to learn the behavior of the battery. They are able to estimate different parameters from the battery features or waveforms if they are provided from the database, as well as battery aging. There are multiple machine learning techniques that can be of use here, from simpler Multi-Layer Perceptrons to more advanced networks such as Convolutional Neural Networks, Self-Organizing Maps or Long-Short Term Memory networks.

SoC estimation in epic power "CAN - BMS Interface":

Coulomb counting and extended Kalman filter methods are used together to estimate the state of charge of a specific battery. Depending on the type of battery the model will differ and one of the methods will gain more influence than the other.

Comparing the battery voltage of a standard 12 Vdc lithium-ion and lead-acid battery in Fig. 8 it is easy to appreciate that the lithium battery voltage response to a continuous discharge is very flat. The voltage only changes rapidly when the battery is fully charged or when it is fully discharged.

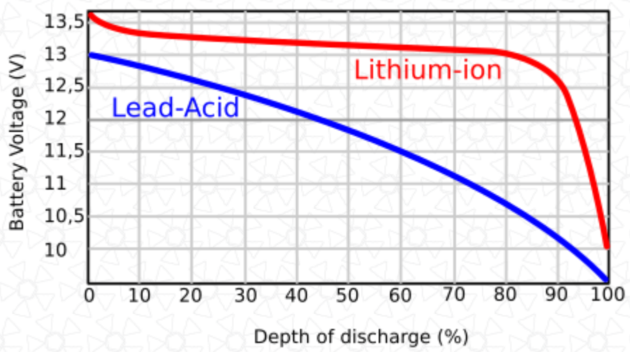

Fig. 8: Voltage evolution with Depth of Discharge

As the Kalman filter is fed from current, voltage and temperature measurements it will work especially well in the flat region of the battery. The coulomb counting (CC) is fed from a known SoC and the current measured and then can be applied appropriately to the side regions of the charging/discharging curve.

The inputs that each method requires are listed below:

- Extended Kalman filter
  - Current transferred: Must be measured with the highest accuracy possible. It is provided by the CAN communication of the DC/DC converter.
  - Battery Voltage measured: Must be measured with the highest accuracy possible. It is provided by the CAN communication of the DC/DC converter.
  - Battery Temperature: Needed only in certain cases. It will be measured directly on the battery by the EPC CAN BMS through a thermocouple or PTC.
  - Battery electrical model: The battery will need to be tested and studied to obtain an accurate model. Once done it will be included in the battery model library.

- Coulomb Counting:
    - Current transferred: Must be measured with the highest accuracy possible. It is provided by the CAN communication of the DC/DC converter.
    - Initial state of charge: It can be set by the algorithm or obtained by either the battery estimator or EKF estimator.

The outputs of both algorithms and the SoC obtained from the battery BMS will be weighted according to the battery performance, conditions, and previous estimations to obtain the SoC. As a second stage, models that consider the aging of the battery can be included to adapt the SoC calculation to the most accurate scenario.

Considering the above-mentioned SoC calculation methods, the definition of inputs/outputs and algorithms interaction is described in Fig. 9 with 5 inputs and 1 output, the state of charge. The output will be sent through CAN to epic power DC/DC converter.

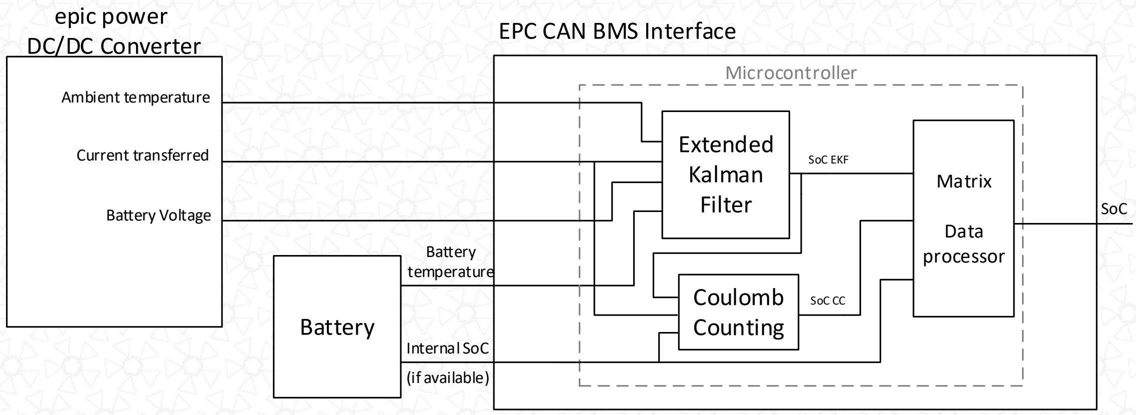

Fig. 9: EPC CAN BMS Interface inputs and outputs for SoC

As a conclusion, it is possible to obtain a good estimation of the SoC in a linear but especially in a non-linear (SoC related to Voltage) battery even under high levels of measuring inaccuracy. The algorithms and processing required for the calculations can be included in the “CAN BMS Interface” device that receive inputs from the CAN communication with epic power EPC converters.

To configure the “CAN BMS Interface” and its algorithms for a specific battery some tests must be performed with several units of them. In a different document, the definition of the first-time configuration procedure and the material needed is described.