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Proposal and Validation of a SOC Estimation Algorithm of $LiFePO_4$ Battery Packs for Traction Applications

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Abstract

An accurate onboard State-of-Charge (SOC) estimation is one of the key functions a Battery Management System (BMS) has to perform in order to provide the optimal performance management of the battery system under control.

In this framework, this paper presents a proposal of an Enhanced Coulomb Counting (CC) State-of-Charge estimation algorithm based on Constant Voltage Charge Detection (CVCD) and Open Circuit Voltage (OCV) model for $LiFePO_4$ batteries. Designed for onboard BMS implementation, it is characterized by its simplicity and operability in wide operating conditions (under diverse load profiles, temperatures, SOC ranges, etc.). The description of the algorithm at both, cell and battery-module level is detailed in the paper. Furthermore, its on-line experimental validation and scope determination is tested under three different traction applications and cell specimens in an own-developed real time validation platform: 2.5 Ah cells (Type A) in a residential elevator application, 8 Ah cells (Type B) in a pure electric on-road vehicle application and 100 Ah cells (Type C) in an electric railway vehicle application. According to the achieved results, the accuracy and versatility of the algorithm for different operating scenarios is certainly proven. In the worst case scenario the algorithm is capable of keeping the SOC estimation of the system under test stabilized around 5% of error.

Keywords: lithium battery, BMS (Battery Management System), diagnosis, state of charge, battery model

1 Introduction

As part of the diagnostic approach, Battery Management Systems perform the onboard SOC estimation. Coulomb Counting (CC) method, based on time integration of the battery current, is the simplest technique for it. However, it is very sensitive to measurement errors that are accumulated over time and lead to drifts between estimated and real state of charge of the battery. In order to improve them, open-loop recalibration algorithms (e.g., OCV measurements), closed-loop corrective ones (e.g., Kalman Filters [1], etc.) or estimation techniques based on artificial intelligence (e.g., Neural Networks [2], Fuzzy Logic [3], etc.) are used.

In general terms, the first ones are characterized by their simplicity for BMS implementation. The second and third ones are generally more sophisticated and complex than the prior ones. They provide precision at the expense of higher computational cost.

In this context, as a trade-off between accuracy and BMS implementability, this research work presents a proposal and full experimental validation of a simple, modular and scalable SOC estimation algorithm for $LiFePO_4$ batteries; cell technology that according to future outlooks will be spread in traction applications in the coming years [4]. The algorithm in question consists of an Enhanced Coulomb Counting technique based on Constant Voltage Charge Detector and OCV(SOC) precise model for dynamic recalibration.
Section 2 describes the main essence of the algorithm at cell and module level.
Section 3 demonstrates its scope at both levels through a deep experimental validation process where Type A, Type B and Type C cells are cycled at real operating conditions of different traction applications.

2 SOC estimation based on ECC with CVCD and OCV models

While the SOC estimation error caused by pure Coulomb Counting increases in time diverging its value from the real one, the hybrid algorithm proposed in this paper aims to reduce and stabilize it. Besides guaranteeing accuracy regardless of the battery cycling time, it is characterized by being simple (highly demanded for BMS implementation), flexible (scalable and modular), versatile (easily adaptable for different cells) and reliable. All these features make the algorithm suitable for its on-board BMS application.

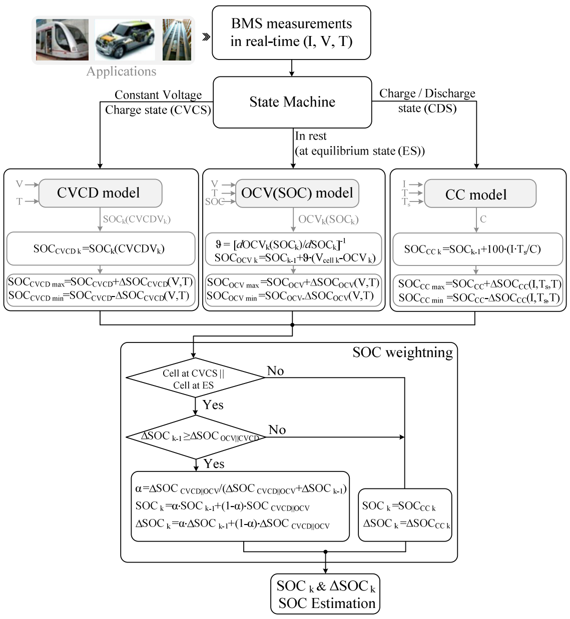

Figure 1: Proposed cell level SOC estimation algorithm based on ECC with CVCD and OCV model

The algorithm itself is designed for cell level diagnostics. Nevertheless, with some slight adaptations it is applied for battery-module level estimations as well.

2.1 Cell level SOC estimation

Cell level SOC diagnostic algorithm is depicted in Fig. 1. It is based on a system state detector (State Machine) which, depending on the real time measurements of the cell (current, voltage and temperature samples), detects its current state: if the cell is charging or discharging, if it is at rest or in equilibrium state. Moreover, during a constant current - constant voltage (CC-CV) charge process it can also detect if the cell is involved in the CV charge step. Depending on the identified state, the State Machine activates the appropriate SOC estimation approaches. When the system is charging or discharging CC technique. In case the State Machine identifies a Constant Voltage Charge process the CVCD estimation method. Finally, OCV(SOC) model in case the cell is at equilibrium state.
Each of the cited techniques is based on a singular model that having BMS acquisitions as input provide SOC estimation values as output. In this hybrid arrangement, all model-outputs (SOC_{CC}, SOC_{CVCD}, SOC_{OCV}) participate specifically in the overall SOC estimation.
In addition to performing the SOC estimation, the algorithm also considers the maximum errors that each estimation technique introduces ($\Delta SOC_{CC}(I,T_s,T)$,$\Delta SOC_{CVCD}(V,T)$,$\Delta SOC_{OCV}(V,T)$). They are due to modelling errors and current, voltage and temperature inaccuracies introduced by the deployed measurement hardware. Thus, the algorithm defines the instantaneous maximum error bands relative to each technique ([SOC_{CCmin}, SOC_{CCmax}], [$SOC_{CVCDmin}$, $SOC_{CVCDmax}$], [SOC_{OCVmin}, SOC_{OCVmax}]).
Once estimation and error bands are specified, with the aim at achieving the most reliable final estimation, SOC Weighting module weights the contribution of the CC, CVCD and OCV based estimation techniques. According to their instantaneous error bandwidth it gives higher priority to the most precise one at every instant.
The models of each estimation strategy are roughly discussed in the next subsections.

2.1.1 CC model

CC model consists of the already introduced Ah counting technique. It integrates the charge/discharge current of a cell in time and makes it relative to its capacity in order to provide the SOC estimation. Regarding this technique, the precision of the current measurement system and the sample time used for current integration are factors that have direct impact on the final estimation accuracy.

2.1.2 CVCD model

CVCD model relates the CV value of a CC-CV charge process of a cell with its final SOC state. In order to get this CVCDV(SOC) map, several CC-CV charge processes to different CV values (e.g., 3.6, 3.55, 3.5, 3.45, etc.) have to be performed to a cell at different temperatures. Fig. 2 and Fig. 3 show some of the results obtained from the cell-characterization process carried out for the modelling.
In the particular case of Fig. 2, it is observed that at 25 ºC, for example, charge processes with CV values superior to 3.4V mean that the final SOC of a Type C cell is higher than 98%. Below 3.4V in contrast, 50 mV differences turn into big SOC differences.
As it was expected, the SOC of the cell varies significantly with temperature. At lower temperature, lower the SOC at the same CV value.

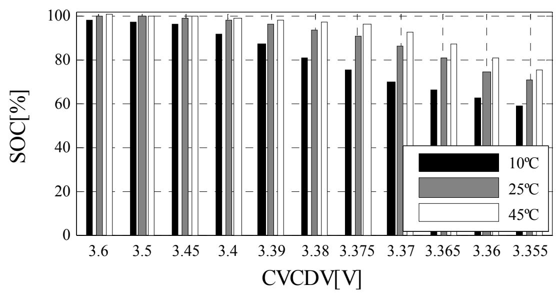

Figure 2: CVCDV(SOC) map of a Type C cell at 10 ºC, 25 ºC and 45 ºC

Furthermore, not all the cells have the same CVCDV(SOC) relation. The results illustrated in Fig. 3 show that in case of the compared Type A and Type C cells, while at high SOCs the relation is similar, as CV value decreases, these differences diverge notably.

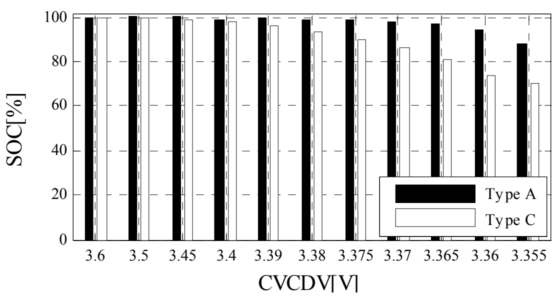

Figure 2: CVCDV(SOC) map of Type A and Type C cells at 25 ºC

The accuracy of the voltage measurement system used for the characterization of the model and for the final diagnosis system (BMS hardware) will determine the precision of the technique in question.

2.1.3 OCV(SOC) model

A measurement of voltage in terminals of a cell when it is at equilibrium state gives information about its SOC state.
For most Li-Ion chemistries, this relation between the SOC and OCV can be considered direct and is modelled by a monotonic function. For lithium iron phosphate ($LiFePO_4$) batteries nevertheless, it becomes a many-to-many mapping family of curves, determined by the cycling history of the cell. This fact becomes the SOC estimation of such batteries challenging. It is necessary, consequently, a high precision voltage measurement system and an accurate OCV model to consider the flat shape and pronounced hysteresis phenomena they present [5].
From the deep OCV sensitivity assessment performed with Type A Type B and Type C $LiFePO_4$ cells, it is concluded that the factors that mainly affect the variability of the OCV of such cells and therefore, can lead to estimation errors are: the time of the cell under relaxation, the hysteresis phenomena (Fig. 4 and Fig. 5) and temperature variations (Fig. 6). Current seems not to have a direct impact on it (Fig. 7).
Fig. 4 and Fig. 5 depict OCV major and minor loops of Type B and Type C cells. The first loops are formed when a fully charged cell is subsequently fully discharged, and vice-versa. The second ones, when partial consecutive charge discharge cycles are applied to a cell. The importance of considering the cycling history of a cell is patent. Otherwise, a 3.29 V in Fig. 4, for example, could represent any value between 30% and 70% of SOC.
Regarding temperature, OCV shows a big variability as well (Fig. 6). In this case, the same 3.29 OCV measurement at different temperatures could imply an estimation error of 30% of SOC.
Between all the different OCV(SOC) models identified in literature (e.g. [6]-[10]), the one presented in [11] was used as the basis for the design of an enhanced OCV model in this research work. The developed approach consists of an empirical model that improved in terms of precision considers all the quoted OCV influential factors. It is capable therefore to operate at a wide range of operating conditions with high accuracy. Appropriately parameterized, it is suitable for

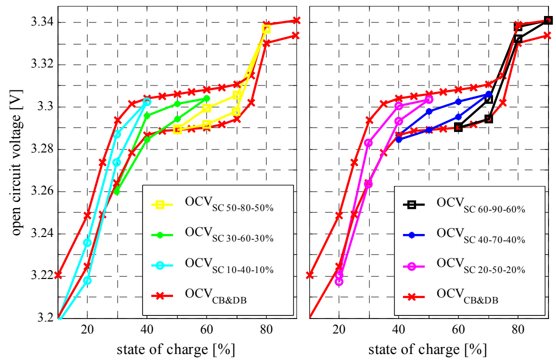

Figure 4: OCV major and minor hysteresis loops of Type B cell

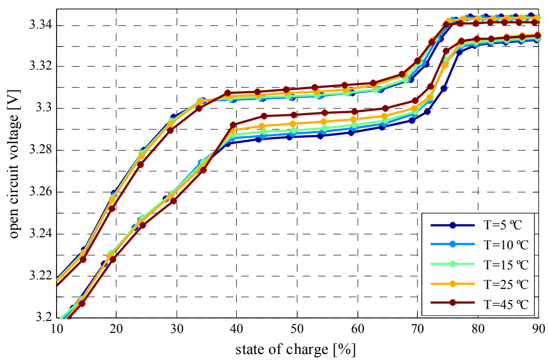

Figure 6: OCV major loops of Type A cell at different temperatures [T=5ºC, 10ºC, 15ºC, 25ºC and 45ºC]

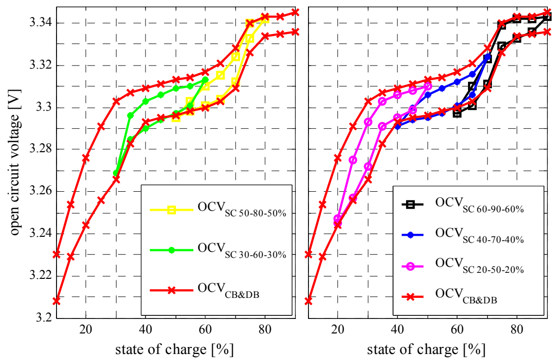

Figure 5: OCV major and minor hysteresis loops of Type C cell

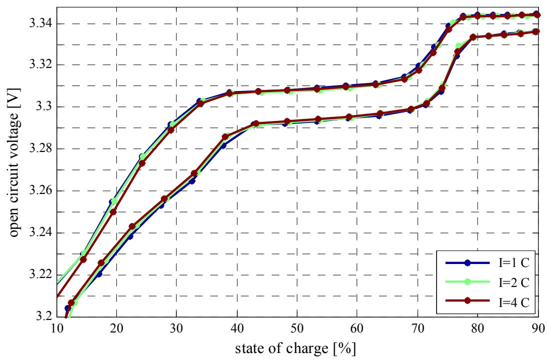

Figure 6: OCV major loops of Type A cell at different currents [I=1C, 2C and 4C]

$LiFePO_4$ cells from diverse manufacturers and formats with different energy and power characteristics.

2.2 Battery-module level SOC estimation

Before the complexity and computational cost that the direct cell-by-cell implementation of the algorithm introduced in Section 2.1 could imply, a more manageable method that keeps the trade-off between cost and performance is set out (Fig. 8).

Based on the proposed single cell ECC SOC estimation method, three SOC estimations are performed in parallel to achieve the module level one: (i) SOC_{MIN} with the lowest cell voltage, (ii) SOC_{MAX} with the highest cell voltage, and (iii) SOC_{AVG} with the average voltage of all cells in the battery-module. As a result of these three estimations, the SOC range where the battery pack operates can be calculated. Accordingly, SOC_{MAX} and SOC_{MIN} give information about the proximity of the system to the end of charge and discharge states, while SOC_{AVG} represents the average state of the battery-module.

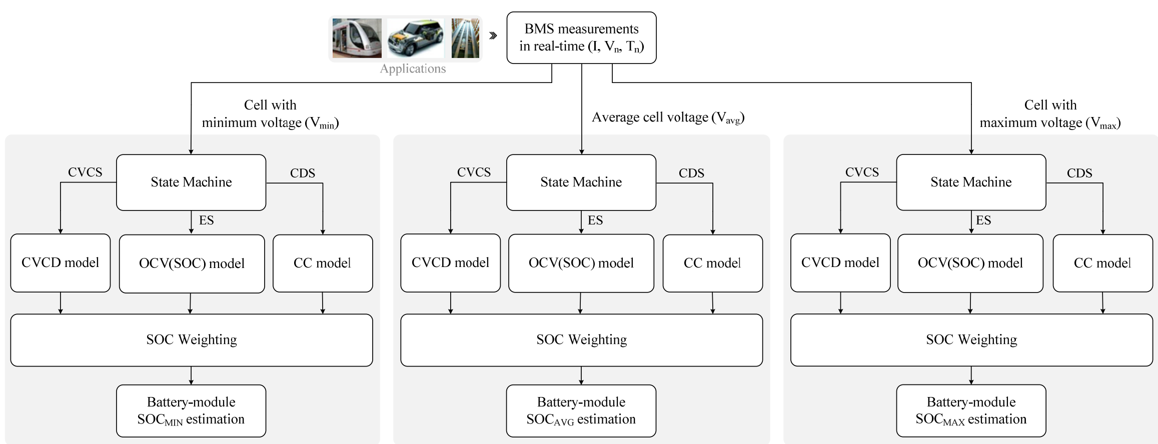

Figure 8: Proposed battery-module level SOC estimation algorithm

3 Applied experimental validation

For the experimental validation and scope determination of the proposed SOC estimation algorithm at both, cell and battery-module level, a set of three different traction scenarios are studied: (i) 2.5 Ah cylindrical cells (already known as Type A) in a residential elevator application, (ii) 8 Ah cylindrical cells (Type B) in an electric on-road vehicle application and (iii) 100 Ah prismatic cells (Type C) in an electric railway vehicle application.

The variety of these selected case studies aims at proving the versatility of the algorithm when applied to $LiFePO_4$ cells with different design features (energy and power characteristics, format and manufacturer) intended for working under diverse operating conditions (load profile, temperature, SOC operating range, etc.).

The setup of the validation framework as well as the estimation results at each validation scenario are reported in the next subsections.

3.1 Validation setup

The experimental validation platform consists of a rapid prototyping approach that enables running own developed diagnostic algorithms in real time. Its strength relies on the capacity of proving them under realistic application conditions time and cost-effectively. Therefore, it is used as a fast and easy tune-up and reliable evaluation tool before the implementation of a new developed algorithm in the final BMS product.

The setup comprises a Module Management System (MMS) prototype, a virtual prototyping system (dSPACE), a link module, a battery tester, a climatic test chamber and finally the cell or battery-module under test. Fig. 9 depicts the overall configuration by a block diagram.

The MMS (Fig. 10), fully developed by IK4-Ikerlan, is responsible for the monitoring, protection and balancing of the battery-module. It collects measurements of every cell voltage and several temperatures along the system. It then processes this data and extracts information for battery protection and diagnostic determination.

In order to provide the greatest validation reliability, the MMS is designed to have the necessary features the final BMS product approach is required. In general terms, it is composed by 3 monitoring and protection daisy-chained specific ICs (bq76PL536 from Texas Instruments) and a microcontroller (R5F21236DFP from Renesas Technology). Each of the ICs monitors 2 temperatures and between 3 to 6 cells with a ±3 mV typical accuracy at once and sends this information to the immediately below IC. The microcontroller is connected to the bottom IC through SPI (Serial Peripheral Interface) and in the present arrangement has the role of transmitting all the data acquired by the ICs to the dSPACE by a CAN (Controller Area Network) bus.

For the battery-module safety guarantee, the MMS provides hardware and software protection with programmable thresholds and delay times against over- and under-voltages and over-temperatures. In case of approaching any hazardous situation relative to these factors, it activates a fault alarm that opens the main contactors of the power circuitry.

Additionally, the MMS includes a dissipative balancing system and low-power sleep mode functionalities for the cases the battery-module is unbalanced and inoperative.

In the present framework, the dSPACE becomes the calculation core of the platform. It receives the battery-module information from the MMS and provides the on-line execution and monitoring of the proposed SOC estimation algorithm. It also performs the cell balancing management and the record of historics.

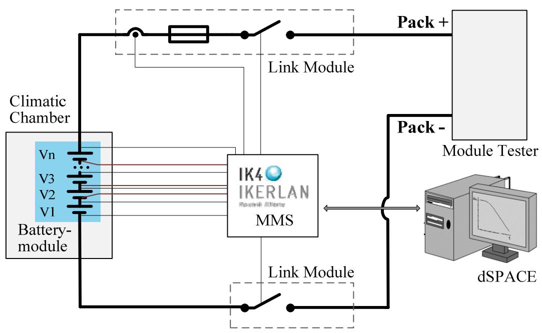

Figure 9: Experimental platform used by IK4-Ikerlan for the fast prototyping of diagnostic algorithms

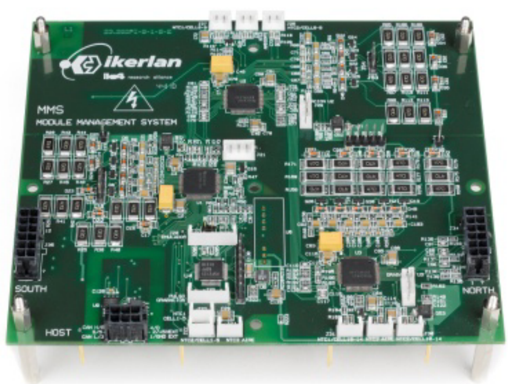

Figure 10: Module Management System (MMS) prototype fully developed by IK4-Ikerlan

The link module, in turn, includes a current sensor for diagnostic purposes and all the hardware related to the battery-module protection. It comprises main contactors and fuses to open both poles of the circuit in the event of a failure and even a residual current device to avoid current leakages though the user, in case of insulation absence.
Finally, the battery-module tester (Digatron BNT 100-100-2 BDBT) and the climatic test chamber (CTS T-40/600/Li) are used to emulate the real operating conditions (load profiles and temperature variations) of the battery-module under certain application tests.

3.2 Validation scenario 1: Residential Elevator application

The first validation scenario consists of reproducing the operation of a $LiFePO_4$ battery in a domestic elevator application.
The integration of batteries in such applications pursues mainly three objectives: cost saving by reducing the power peaks demanded from the electric grid, efficiency increase by saving regenerative breaking energy from the traction motor and automatic rescue functionality by providing stored energy to the system in case of a power outage. Fig. 11 block diagram represents a three-phase residential elevator with a Li-Ion storage system.

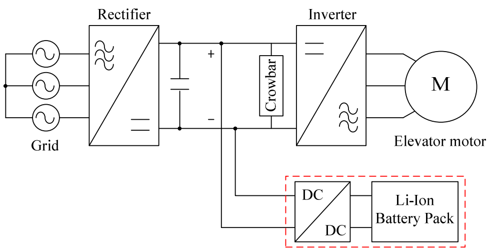

Figure 11: Block diagram of a three-phase residential elevator with a Li-Ion storage system

The cells selected for the validation of the proposed SOC estimation algorithm at this operation environment are ANR26650M1-B cells from the A123 systems manufacturer (Type A). They are characterized by a 2.5 Ah nominal capacity, 4C and 28C maximum continuous charge and discharge current rates and operating temperatures between -30 ºC and 50 ºC.
The validation test profile, in turn, consists of an elevator operating profile that simulates 30 days of use. In order to accelerate the time under test nevertheless, all trips that an elevator performs in a day are linked together without any pause in between. Only a pause of 2h is introduced at the end of each simulated day to simulate night periods.
Fig. 12 depicts a fraction of the quoted load profile and Fig. 13 and Fig. 14 show some of the acquired results of the algorithm once characterized for the cells and application under study.
The scope of the introduced ECC algorithm is calculated taking as a reference SOC estimations carried out by a high precision current measurement system (HPM) that the battery-module tester incorporates.
As Fig. 14 depicts, the irregular shape that $|SOC_{ECC}\text{-}SOC_{HPM}|$ term draws is due to the variable participation of CC, CVCD and OCV model in SOC estimation. After 30 days of use, the algorithm is capable of keeping the estimation error stable around a 5% of SOC.
For the validation of the algorithm at battery-module level, 12 of such cells are assembled to build up a 92 Wh module prototype. Table 1 gathers its main characteristics.

Table 1: Battery-module characteristics for a Residential Elevator application

Battery-module	
Nº cells	12s
Nominal Voltage (V)	38.4
Capacity (Ah)	2.4
Energy (Wh)	92.16
Max. Dch. Power (W)	675.84
Weight (kg)	1.2

Just as the procedure followed at cell level, the overall battery-module system is excited with a load profile relative to 30 days of operation of an elevator (Fig. 12). Fig. 15, Fig. 16 and Fig. 17 show the experimental results for this case.
Fig. 15 comprises the voltage in terminals of every cell in the battery-module. It can be distinguished that all of them follow a singular path in time. These results reflect the actual SOC dispersion that exists between them. Nevertheless, thanks to the proposed SOC estimation algorithm this dispersion can be quantified and the cells that are limiting the operation of the battery when reaching a full (dis)charge state can be identified. In case of having a balancing system [12], it will be possible to correct the dispersion. In opposite case, it will tend to increase. In the present capture (Fig. 16), the difference between the most and least charged cells is around 6% of SOC.
Regarding average SOC_{AVG} estimation, ECC diverges maximally 6% from the real SOC and keeps the error stable around 4% in an accelerated test that simulates 20 days of continuous operation.

3.3 Validation scenario 2: Electric On-Road Vehicle application

The second validation scenario consists of reproducing the operation of a $LiFePO_4$ battery in an electric road vehicle application. In this case, the replacement of the internal combustion engine of a traditional road vehicle by an electric motor (in combination to a storage system) aims at increasing the efficiency of the overall traction system and reducing CO_2 emissions to atmosphere. Fig. 18 describes the simplified integration of a Li-Ion battery in an on-road pure electric vehicle application.

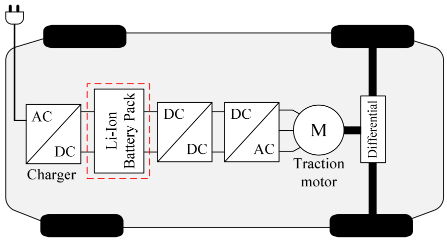

Figure 18: Block diagram of an on-road pure electric vehicle with a Li-Ion storage system

For the validation of the ECC algorithm in this environment, FTP-75 test procedure defined by the US Environmental Protection Agency (EPA) [13] is used in combination with constant 5 W charging processes to simulate a one-day cell level city driving profile of an electric road vehicle (Fig. 19). On this occasion, the cells selected for testing are several $LiFePO_4$ cells of type OMLIFE-8AH-HP manufactured by OMT (Type B). They are characterized by a 8 Ah nominal capacity, 10C and 25C maximum continuous charge and discharge current rates and operating temperatures of 0…45 ºC for charging and -20…60 ºC for discharging.
In this second validation framework, apart from the evaluation of the algorithm at 25 ºC, the target is to check its suitability for a wide range of operating temperatures. For this purpose, individual cells are excited with the cited validation profile pattern at different temperatures. Fig. 20 presents the voltage response of one of them together with the OCV estimation that the algorithm calculates. The voltage in terminals of the cell varies as much as around 400 mV depending on the temperature at it is excited. However, as the ECC algorithm considers the impact of this factor, the difference between estimation and measurements (in circles) does not exceed an average value of 3 mV in any of the three cases. The potential of the algorithm for carrying out a proper SOC estimation at different operating temperatures is demonstrated therefore, as Fig. 22 results illustrate. During a one day execution, the algorithm registers a maximum error of 2% and is capable of keeping the estimation error stable around this value at the end of the day. It provides a 48% less error than the simple Coulomb Counting technique.

3.4 Validation scenario 3: Electric Railway Vehicle application

The third and last validation scenario involves an energy storage system in an electric railway vehicle application. Alone or in combination with electric double layer capacitors it helps increasing the efficiency of the system by recovering the braking energy from the traction motor and reducing the power peaks consumed from the catenary. Moreover, its integration can provide an electric railway vehicle with the possibility of driving a certain distance without overhead power cable. Fig. 23 represents the integration of a Li-Ion battery pack in a railway vehicle application.

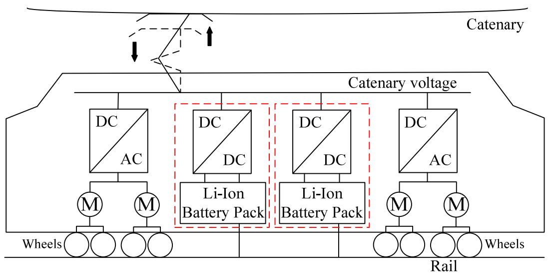

Figure 23: Block diagram of an electric railway vehicle with a Li-Ion storage system

For the performance assessment of the algorithm at cell level, 100 Ah cells from the CALB manufacturer (SE100AHA) are used (Type C). They can operate up to 0.3C between 0…45 ºC in charge and up to 3C between -20…55 ºC in discharge.
In this case, the current profile used for validation (Fig. 24) is composed by six different railway vehicle day patterns (nights have been reduced to 3h in order to reduce test duration). Fig. 25 shows the voltage response of the cell during the tested week and Fig. 26 reflects the scope of the algorithm, which results in a less than 2% of SOC estimation error.
Shifting from cell to battery-module level, a 5kWh battery prototype based on the described cells (Table 2) is built up for the algorithm validation.

As in the previous case, the battery-module is tested under the current profile introduced in Fig. 24.

Table 2: Battery-module characteristics for an Electric Railway Vehicle application

Battery-module	
Nº cells	16s
Nominal Voltage (V)	51.2
Capacity (Ah)	100
Energy (kWh)	5.12
Max. Dch. Power (kW)	15.36
Weight (kg)	59.6

Fig. 27 illustrates the voltage response of every cell to the excitation current in question. Little voltage divergences reflect the SOC differences among the cells. According to Fig. 28, the estimation error caused by the algorithm when calculating the average SOC of the system is 5%. Therefore, in this application passing from cell to module level estimation means incrementing the estimation error in 3%.

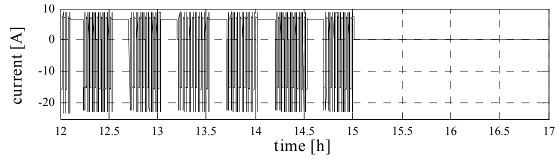

Figure 12: Accelerated one day current profile of a cell in a residential elevator application

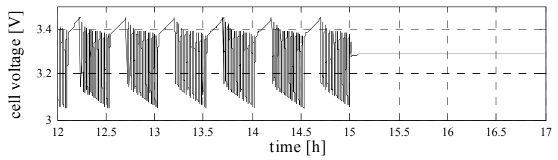

Figure 13: Voltage response of a cell in a residential elevator application to an accelerated one day current profile

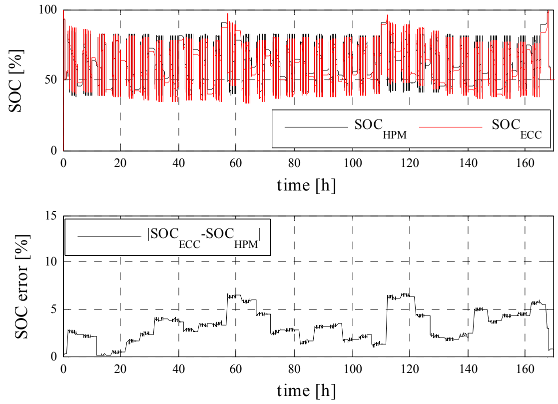

Figure 14: SOC estimation comparison between ECC and simple CC of a cell along 30 days in a residential elevator operation

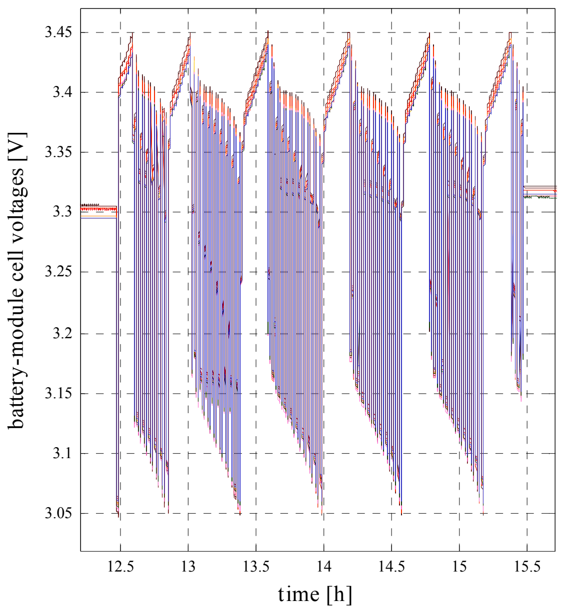

Figure 15: Voltage response of the cells of a battery-module during a one-day cycling in a residential elevator operation

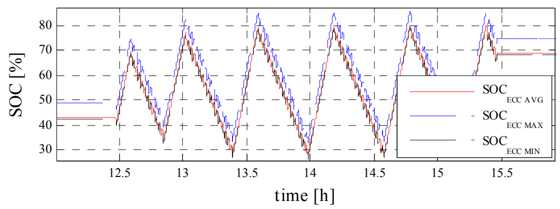

Figure 16: SOC_{MAX}, SOC_{MIN} and SOC_{AVG} of a battery-module during a one-day cycling in a residential elevator operation

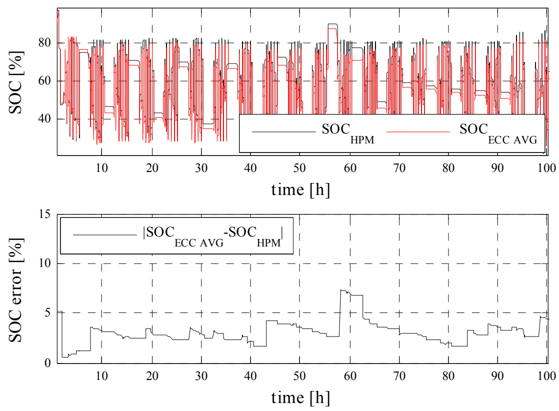

Figure 17: Average SOC estimation comparison between ECC and simple CC of a battery-module in a residential elevator operation

Experimental results of validation scenario 1

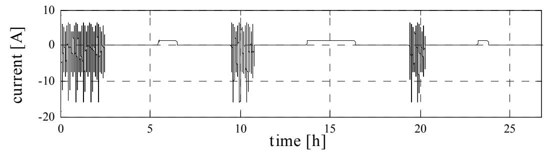

Figure 19: One day current profile of a cell in an on-road pure electric vehicle application

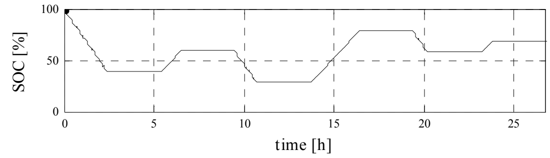

Figure 21: Ideal one day SOC profile of a cell in an on-road pure electric vehicle application

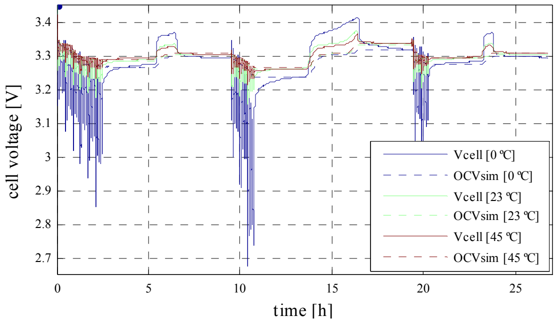

Figure 20: Voltage response of a cell in an on-road pure electric vehicle application to a one day current profile

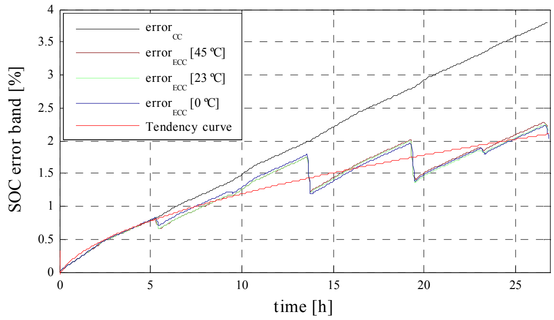

Figure 22: SOC estimation comparison between ECC and simple CC of a cell in a one day on-road pure electric vehicle operation

Experimental results of validation scenario 2

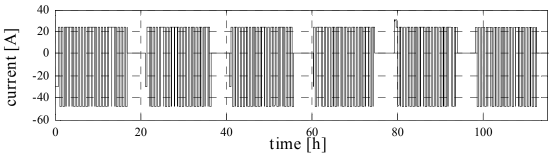

Figure 24: One week current profile of a cell in an electric railway vehicle application

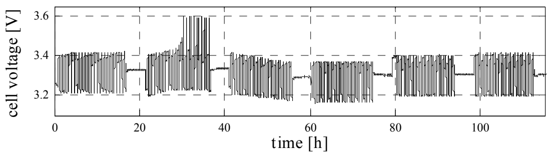

Figure 25: Voltage response of a cell in an electric railway vehicle application to a one week current profile

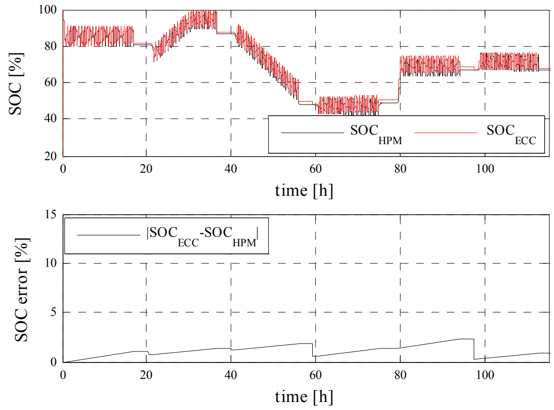

Figure 26: SOC estimation comparison between ECC and a simple CC of a cell in a one week electric railway vehicle operation

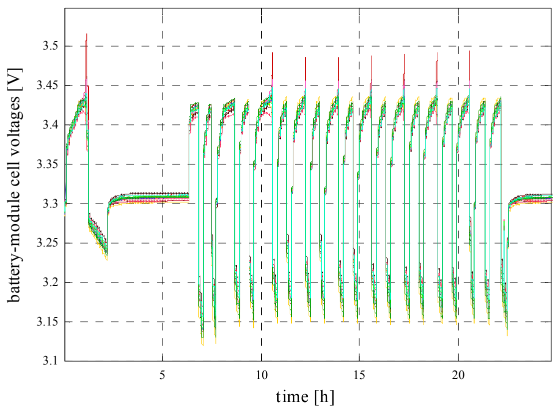

Figure 27: Voltage response of the cells of a battery-module during a set of cycles in an electric railway vehicle operation

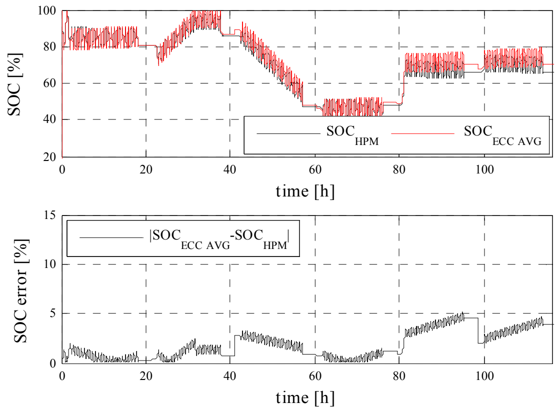

Figure 28: Average SOC estimation comparison between ECC and simple CC of a battery-module in a one week electric railway vehicle operation

Experimental results of validation scenario 3

4 Conclusions

An Enhanced Coulomb Counting State-of-Charge estimation technique based on Constant Voltage Charge Detector and Open Circuit Voltage model has been presented for the diagnosis of $LiFePO_4$ batteries. Based on the hybridization of three independent SOC estimation methods, its accuracy and implementability make the algorithm suitable for BMS application. When applied to cell level, the algorithm estimates the SOC of the cell under test. When applied to battery-module level, it provides the SOC range where it operates: SOC_{MAX} (relative to the most charged cell), SOC_{MIN} (relative to the least charged cell) and SOC_{AVG} (relative to the average). Thanks to this information, a balancing strategy can be performed to correct the SOC dispersion between the cells and prolong the operation of the battery.

As part of the diagnostic approach, an OCV(SOC) model has been designed and developed. It considers the hysteresis effect that characterizes $LiFePO_4$ cells as well as temperature and current factors. This ensures the validity of the model for a wide range of operating conditions. A CVCD model has also been developed. The description of both models has been supported by experimental data of different $LiFePO_4$ cells.

The full algorithm has been validated at cell and module level. For this purpose, a real-time validation platform based on an own developed MMS and a dSPACE has been used. The target has been to prove the scope of the algorithm at final application conditions. For versatility evaluation three different traction scenarios have been tested. In the worst case, the algorithm has kept the SOC estimation stabilized around 5% of error.

Acknowledgments

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