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Optimizing BMS operating strategy based on precise SOH determination of lithium ion battery cells

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Abstract

Today's challenge of integrating highly variable and less predictable components in electric drive trains requires new approaches of interactive vehicle control strategies derived by controlling SOH-parameters actively. The paper describes which measurement methods extract physical parameters and why these parameters are used as input variables for an additional SOH-management algorithm. Additionally, the authors report from practical experience of integrating different parameter extraction methods and SOH-models.

Keywords: SOH, performance prediction, Kalman filter, ageing model

1 Introduction

Safety and lifetime issues are the dominant properties of a battery management system (BMS) in automotive applications. To ensure an always safe behaviour of the battery in an overall lifetime of 10-15 years a different operating strategy must be applied in comparison to typical consumer or industrial applications. A good knowledge of the current state of the battery cells is required to adapt the operating mode to achieve specified lifetime goals. While the state of charge (SOC) information is used mainly for the dynamic operation strategy, the SOH information should be used for the long-term coverage of the performance of the cell. The automotive requirement of the increase of the internal resistance must be less than 50 percent above specification and the battery capacity loss must be less than 20 percent at end of the lifetime. Thus, the battery must be operated in its optimum conditions at every time and even adopt to specific driver profiles. In parallel, the BMS has to protect the cells from any long-term defects by not overestimating the cell performance also at the last, often unknown period of lifetime. Therefore two steps in the control strategy have to be implemented:

- Precise determination of the current cell state
- Deriving the optimum operating strategy from the detected states

By intention, the additionally processed SOH parameters will work in coexistence to SOC parameters which are also processed at common BMS control strategies. The main focus on this paper is on the determination of the required values and the adaptation of the operation strategy according to the actual health state. In turn, as drivers of today expect so called "range" and "performance" modes, SOH management will even effect SOC management and vice versa.

2 Determination of the current cell state

2.1 SOH Definition

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The SOH represents the synthesized health state of the traction battery. The range of this purely synthetic parameter "SOH" is determined by 0 to 100 percent. At Begin of life (BOL) the SOH is 100%, at End of life (EOL) the SOH is 0%, that means the battery can no longer be used for the application specified in the vehicle requirements specification. We define that the battery reaches its EOL state if battery-capacity decreases to 80% of its initial value, or the internal resistance doubles, or the required maximum power of a cell can no longer be provided. Therefore, the main measures for the SOH value are capacity and internal resistance of the lowest performing cell. This is true, as there is no major active balancing circuit directly supporting under load conditions. Depending on the type of vehicle, the relevance of the particular parameter is different. The achievable electrical range, defined by the battery capacity is more important for an electric vehicle. On the other side the maximum available power is important for hybrid electric vehicles (HEV), a constantly small internal resistance is preferable. Summarized, there are different requirements the SOH in EV and HEV/PHEV applications. This can be considered with weighting factors.[3]

We propose the SOH as:

$$SOH = f(C_{act}, R_{i,act}) = \alpha \cdot \left(\frac{C_{EOL} - C_{act}}{C_{EOL} - C_N} \right) + \beta \cdot \left(\frac{R_{i,EOL} - R_{i,act}}{R_{i,EOL} - R_{i,N}} \right)$$

in wich

C_{act}	actual capacity
C_N	nominal capacity
C_{EOL}	capacity at end of life
$R_{i,act}$	actual internal resistance
$R_{i,N}$	nominal internal resistance
$R_{i,EOL}$	internal resistance at end of life
α	weighting factor capacity
β	weighting factor internal resistance

2.2 SOH Modelling

There are two options to estimate the SOH parameters. One possibility is an approach that uses the electro-impedance spectroscopy (EIS). This method operates in laboratory environment, which is – stand alone - due to the big complexity not suitable for in-vehicle use. Due to the fact that a battery is a strong non-linear system (at high current levels) with distinctive time dependability, a measurement procedure, which does not need a high stimulation or change the state of the cell, is preferable. An approach to describe the complex behaviour is to model the complex impedance of the battery system by superposition of the single cell impedances.
By the help of system theory methods, the non-linear transfer function of the system can be found and used for parameter identification. The aim is to make EIS available for automotive applications to determine the SOH parameters very accurate. Impedance spectra gained from EIS include physically linked information for parameterization of an advanced battery model and can give information on failure states. These information are sometimes further processed in safety models which generate additional information on cell-level failure modes.

In contrast, the use of Kalman filters for the estimation of the SOH parameters capacity and internal resistance is a second possibility for SOH estimation. The equivalent circuit diagram of the battery model is transferred into a state space model and the state matrices and vectors have to be identified. The filters are designed and adjusted for the targeted state space. [3] The schematic of the Kalman Filter is shown in figure 1. The algorithm consists of a set of equations and works in two steps. In the first step called “Time update” the Kalman Filter predicts the state of the system given the past state estimation and the system input. It also computes the uncertainty of the prediction.

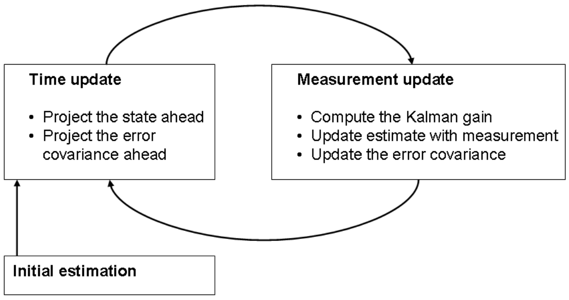

Figure 1: Schematic of Kalman Filter

In a second step called “Measurement update” the algorithm compares the predicted values with the measured values. Based on the prediction error, the state estimation is updated. In reference to the prediction error the uncertainty is also updated.
It should be made clear, the calibration of robust Kalman Filter arrangements require very extensive measurement work. Current benchmarking shows, these Kalman Filter algorithms sometimes can not deliver true values, if cells fade to internal defects the algorithm can not differentiate the cause. Therefore, a clear analysis for robustness is required to prevent misleading functionality.

2.3 Measurement methods

The described method of EIS application to battery cells measures the currents and voltages in the time domain for a full frequency sweep or step response. Afterwards the collected data will be digital signal processed. By a fourier transformation the spectra I(jω) and U(jω) are generated. By divisions of I(jω) and U(jω) the impedance is calculated. The quality of impedance spectra depends to the hardware in use. To choose the appropriated hardware it needs to take into account different requirements for sampling time and precision. For the application of EIS on board of a car a low cost and low space consuming solution is required. The challenges of an automotive application are the high number of cells inside of a battery which have to be checked and the strong EMC disturbances generated by high currents inside and outside the battery enclosure. Innovative solutions for the on board application of EIS can be thought of using cell controller slaves with integrated signal processing. This reduces the amount of measurement data transferred to the master unit. Currently promoted solutions that make use of on board passive balancing circuits to excite cells only generate a very low voltage response. The authors believe in higher modulation currents to get clear impedance results with high signal to noise ratio. As no commercial solution is currently available, the authors initiated an internal project to develop a research hardware platform to investigate in future solutions for EIS on board measurement.

2.4 Battery modelling

For the diagnosis of batteries different models are used. Empirical models describe the behaviour of the cell voltage for a given current in the time domain.
To model the impedance behaviour of a battery cell two Randles circuits in series were used which will lead to ambiguities in the parameter extraction process. Another problem is the assumption of a flat electrode surface which is not the case for modern large porous electrodes. Based on the work of DeLevie and others, models for porous electrodes were developed using different approaches like transmission line theory or fractional electrodes. These models can describe the high frequency behavior of the impedance which often employs a flat slope towards higher frequencies.
With an infinite number of RC-elements with distributed time constants it would be possible to represent the Randles model in the frequency as well as in the time domain. For the simulation the number of RC elements is most often limited. All these models describe the information that’s in the impedance spectra or in the time behavior of a cell by a limited number of parameters and are therefore highly suitable for defining more complex measures of the battery like SOC or SOH. One of the main problems is therefore the extraction of these parameters from measurements.[1,4] Solutions for innovative parameter extraction have been presented in a dedicated paper last year.

2.5 On-line battery modelling

Due to the preconditioning criteria for the impedance spectroscopy (Causality, Time Invariance, Stationarity and Linearity) it is limited

to applications in the laboratory. By using intelligent algorithms the criteria causality and linearity can be neglected, i.e. the excitation signal could be a multi frequency signal. Before calculating the impedance, a correction of non-linearities has to be carried out. If the impedance spectrum is found, the parameter of a suitable cell model can be evaluated by using optimization algorithms. The measured spectrums were used to evaluate the parameters of two different cell models; one is considering solid electrodes the other one is considering porous electrodes. Different cell chemistries were used for verification.
For on-line applications the total battery current as excitation signal was also considered. The current signals in the car will be dominated by the drive train current. Therefore, the signal is high dynamically during the different driving cycles and high current values can be observed. Also, the frequency spectrum over time is much limited, however, relevant spectral components can be determined.[1,4] To overcome these limitation, pre-calibrated impedance models are required. This helps to find parameters even if the spectral bandwidth is limited and the values are noisy.

2.6 Test results

The developed parameter extraction routines successfully set up the Randles and DeLevie models. The obtained values can be used in parallel for quality assessment. Tests of a stressed and a factory new battery cell showed the drift of almost all parameters. Therefore the used parameters give information of the degrading of cell internal mechanisms, i.e. the charge transfer to the collector foils, the ion transport ability or the double layer behaviour. Also the harmonization of anode and cathode can be observed by evaluating the time constants of each electrode. Having analyzed the results, the authors believe that EIS also can support failure models.

Hardware limitations and not optimal measurement conditions of standard automotive electronics make the EIS still difficult. Higher specification of voltage and current measurement is required i.e. increase of sampling frequency and synchrony. This could add extra cost to cost-sensitive electronic parts. One solution is to identify the parameters with pre-calibrated models that estimate the parameter values in the time domain. The authors believe more tests with advanced parameter estimation algorithms need to be carried out to prove the concept for different conditions.[1]
In turn, first results of Kalman Filters show the possibility to make use for SOH optimization features if standard hardware electronic devices are used.

3 Optimizing BMS operating strategy

To find optimal operating strategies, the problem needs to be defined generally. An always valid optimization function and constraints need to be defined. The general optimization problem is defined by

$$F(x_1, x_2, ..., x_n) \rightarrow \min \qquad (1)$$

and the constraints

$$G_i(x_1, x_2, ..., x_n) \leq d_i \qquad (2)$$

There are several optimization strategies with different characteristics and implementations. A common classification is noted below:

a) Global optimization
b) Local optimization
c) Heuristic optimization

Global optimization methods can be numerical or analytical. Information about the constraints are given at each time step. In Local optimization the global problem is separated in a set of local problems. In this case information about past and present conditions is necessary. Heuristic approaches have no explicit optimization.

Derived from energy management of hybrid electric vehicles, that is also supposed to find the optimal solution to use a combustion engine in combination with an electric motor, the SOH Management needs to solve the problem to find the optimal performance limits against the drive mode and the estimated parameters of the SOH, shown in figure 2. The Input values for the SOH estimation are the actual current, voltage and temperature. A special configuration of Kalman-Filters was used to estimate the SOH parameters capacity and internal resistance. The driving mode can accept the values “sport” and “range”. In the sports-mode the major aim is the allocation of the maximum power, the electrical range would be disregarded. On the other side the range-mode stands for preserve driving. The developed SOH-Management consists of an aging model and an optimization block.

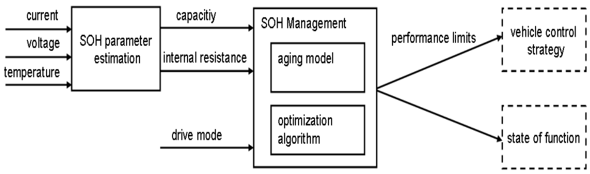

Figure 2: Schematic of SOH-Management and processing for different EE-Architectures

With the information about the current estimated SOH parameters, the aging model for SOH-prediction and the optimization block finds the optimal values for the performance limits to achieve the specified driving mode.
The performance values are the state of charge limits, the maximum current, the time limits for the maximum current, and the temperature limits. Finally, these values are processed differently in different EE-architectures. Some architectures process performance prediction decentralized, others integrate drive control strategies on vehicle-control-unit level.
For demonstration purpose, Figure 3 shows an exemplary history of the synthetic SOH parameter for a traction battery in use for some years. Section I describes a moderate driver. The estimated SOH is higher than the Reference-SOH-line (broken line). Section II shows the SOH in a critical area below specification. The SOH falls under the Reference line due to an aggressive driving style. Without an optimizing strategy it can not be assured, that the battery will reach the predefined EOL target, shown in area III. By using the proposed optimization strategy the performance values will be limited to assure the lifetime goal.

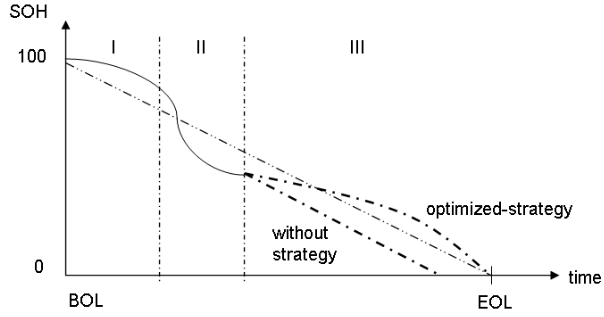

Figure 3: SOH-Management with optimized and without optimized strategy

This method also can be helpful if the vehicle changes its place of application. Different ambient storage and operation temperatures have a major influence of the SOH even if the car has been never driven in this period. So the adaption of the performance values guarantees the achievement of the predefined EOL targets in different sales regions. It also helps to keep the vehicles economic value predictable for a long time period which in many sales regions is important to attract customers.
As the traction battery still is a very expensive service component, the reliability of the health state over long-term becomes extremely relevant. It also needs to be mentioned, the life-time expectations differ much from customer specific drive cycles, the propose method for SOH management minimizes the engineering and validation efforts to assure EOL specifications for all occurring cycles. The validation efforts can be concentrated on standard ageing modelling that are required to set up reliable aging models. Interactive calibration of the performance values help to control the highly varying aging behaviour of battery cells.

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