

Guide for the Focused Utilization of Aging Models for Lithium-Ion Batteries - An Automotive Perspective

Claudia Meis, Stefan Mueller, Stephan Rohr, Matthias Kerler, and Markus Lienkamp
Technische Universitaet Muenchen

ABSTRACT

Battery aging in electric and hybrid vehicles is a major issue, and one which has to be taken into consideration during all stages of the vehicle lifecycle. It depends on many factors, such as the cell chemistry, the cell design and stress factors as well as the current rate, Δ DOD and temperature. The stress factors have been identified as being crucial due to their influence on two important battery parameters: capacity and inner resistance. Battery aging models are essential to describing the interacting influences that stress factors have on battery parameters. They provide insights about battery aging without the need for extensive measurements. Various battery aging models with widely varying capabilities are described in the literature.

The aim of this paper is to provide a decision guide for utilizing the most appropriate aging model for the major stages of the vehicle lifecycle: vehicle development, operation (onboard and offboard) and post-operation.

First, this paper summarizes the correlation of many known stress factors on battery parameters, considering all factors separately. Second, evaluation criteria for aging models and vehicle lifecycle stages are established. Third, the importance of the obtained evaluation with regard to the vehicle lifecycle stages is analyzed. Using the same criteria, the different kinds of battery aging models are evaluated in the fourth step. In the final section, a guide for the focused utilization is established.

In conclusion, the information obtained about requirements for aging models in major stages of the vehicle lifecycle and the evaluated aging models reduce the need for further research and development work for selecting the most beneficial cluster of aging models.

CITATION: Meis, C., Mueller, S., Rohr, S., Kerler, M. et al., "Guide for the Focused Utilization of Aging Models for Lithium-Ion Batteries - An Automotive Perspective," *SAE Int. J. Passeng. Cars – Electron. Electr. Syst.* 8(1):2015, doi:10.4271/2015-01-0255.

INTRODUCTION

Over the past few years, lithium-ion batteries have been used in various applications, especially for consumer electronics. However lithium-ion batteries are growing in popularity for automotive applications because they are lightweight and powerful compared to other electrical energy storages [1]. Battery degradation has a significant consequence on the reliability and safety of a battery system's function, which determines its feasibility and acceptance in the electric drive vehicle and in electrical energy storage applications [2]. Therefore, it is essential to generate an in-depth understanding and knowledge about battery aging for all of the vehicle lifecycle stages. Aging occurs in different applications at each stage of the lifecycle and has different requirements that have to be considered. For the efficient operation and management of lithium-ion batteries during vehicle operation, determining the state of health (SOH) is critical [3]. According to [4], predicting the lifetime for lithium-ion batteries is a key issue with respect to reliable integration of the battery not only into the vehicle, but also for stationary applications and warranty reasons.

The SOH can be quantified by key performance parameters of cells: the capacity and the internal resistance [5]. If batteries are unable to meet the vehicle requirements after underrunning a defined capacity and performance, which depend on the internal resistance, they will be replaced.

The crucial point about battery aging is that various stress factors, such as current, temperature, state of charge (SOC), and Δ SOC have a nonlinear impact on battery parameters and thus the SOH. Additionally, the influences interact with each other.

The most accurate method of SOH measurement is a controlled discharge test in a laboratory setting. However, this test cannot be implemented in the vehicle as a real time measurement technique [3], and it certainly cannot be used to predict aging, for example during the development of a battery or while determining the most appropriate second life application. Therefore, battery aging simulation is complex, but essential. In the current literature, various battery aging models with widely varying capabilities are described. They basically model the correlation between stress factors and battery parameters (Fig.1).



Figure 1. Inputs and Outputs of Aging Models

The focused utilization of aging models is necessary in order to benefit from different capabilities. This paper comprises five steps to developing a decision guide for selecting and using the most appropriate aging model for the major stages of the vehicle lifecycle: vehicle development, operation (onboard and offboard) and post-operation.

1. **Investigation of stress factors for battery aging:** To model the effect of aging, the impact of each stress factor on battery parameters has to be investigated. Generally, every kind of aging model can consider all stress factors, but not all aging models in the literature include all stress factors. After using the guide to find a type of aging model, it is crucial to determine precisely which stress factors are required and to accordingly select a specific aging model for the recommended cluster.
2. **Definition of evaluation criteria:** The criteria are based on [6]. They are redefined and expanded in order to reflect the different requirements of the major stages of the vehicle lifecycle and to identify the important capabilities of aging models. The criteria enable an evaluation of the fit of aging models to the major vehicle lifecycle stages.
3. **Analyzing the battery aging in automotive applications:** To be able to make statements regarding the requirements for aging models, it is crucial to identify the roles that aging plays in the major stages. Therefore, the role of battery aging models in the stages of the vehicle lifecycle is analyzed first. Next, the stages are evaluated according to the proposed criteria.
4. **Research and evaluation of battery aging models:** Similar to the vehicle lifecycle stages, different types of aging models are described, analyzed and evaluated according to the same evaluation criteria.
5. **Developing a decision guide for aging models for the vehicle lifecycle stages:** As a final step, the results are consolidated and illustrated in a dual matrix and evaluated using flexible electrical energy management (FEEM) as the example application.

STRESS FACTORS FOR BATTERY AGING

In the literature, stress factors are defined as conditions, unexpected interfaces and interactions of components which can result in failure or degradation of the system [7]. With regard to battery aging, it describes the operating conditions of the battery, e.g. temperature, current, etc., which lead to aging errors [8]. Basically battery aging can be divided into calendar aging and cycle aging. Calendar aging only takes storage with a specific SOC and temperature into account. Cycle aging also includes the charging and discharging processes [9].

Aging failures are changes inside the battery, such as increased solid-electrolyte interphase (SEI) layer growth, which result in a change in the battery parameters. Essentially, these changed battery parameters lead to degradation of the customer functions, e.g. performance, which becomes evident during acceleration and in a decreasing vehicle range [8]. Numerous studies show the dependency

between stress factors and battery parameters. In the following, the current, temperature, SOC, and Δ SOC stress factors as well as their impact on the battery parameters are examined based on the literature and summarized in Table 1.

In [8], the impact of various C-rates on internal resistance is investigated for LiFePO₄ cells. The results at 5C and 14C and 10% DOD showed that higher current leads to accelerated increase of internal resistance. In addition, the capacity is reduced with high charging rates, thus high currents. The cause is lithium plating [10]. According to [11], the current rate for charging and discharging has an exponential influence on the capacity fade.

In [12], the impact of charge throughput on battery parameters is examined. The author discusses charge throughput models (CTM). The basic assumption is that with the amount of charge that is transferred from anode to cathode, the SOH continuously decreases. According to this model, after transferring a defined charge throughput, the cells reach their end of life (EOL) [12]. Charge throughput is current over time and due to that, it will be considered with regard to the current stress factor.

Furthermore, studies with NMC cells in [4] show an exponential capacity decrease as temperature rises and SOC increases. Moreover, temperature has a stronger impact on internal resistance than current load and cycling of the battery. This is due to the fact that increasing temperature accelerates SEI growth [8]. Nevertheless, a test at 65°C indicates a different behavior at high temperatures. The assumption is that chemical reactions occur, which can, for example, lead to gassing processes and cell failure. These results are in discrepancy with the exponential trend [4]. One cause of capacity decrease in correlation with temperature is the Mn dissolution reaction [13]. But low temperatures can shorten the battery lifetime as well, due to lithium plating [14].

To consider the influence of SOC, [4] compared SOC ranges from 60% to 80% with 30% to 50% at 40°C. Faster degradation at a higher state of charge was measured, and it can also be observed that the resistance increases much faster than the capacity decreases. In [4], it is also stated that capacity fade depends on rising voltage and rising temperature in an exponential way. In addition, [15] comes to the conclusion that the capacity decreases and the inner resistance increases exponentially with a higher storage state of charge. According to [16], the decrease in capacity and increase in inner resistance correlates linearly to the storage SOC. It is also shown that cycling around a middle voltage (45% and 55% SOC) leads to the lowest capacity loss and resistance increase. A U-shaped function can be found with a minimum at around 50% SOC. In conclusion, from a calendar aging perspective, a lower SOC is beneficial and from a cycling aging standpoint, the optimum is around 50% SOC [16]. In this context, it has to be considered that deep discharge and overcharge can result in dendrite formation [8]. This should be avoided through the battery management system and will not be a topic of this paper.

According to [11], the capacity of battery cells decreases exponentially and the inner resistance increases exponentially with deeper cycles. For example, the author states that a battery cell is able to perform 3221 deep cycles (until 80% DOD) as compared to 34957 shallow cycles (until 20% DOD).

Table 1. Dependencies between the most important stress factors and battery parameters

Increasing Stress factors	Capacity	Inner Resistance
Current	Decrease ^{1,4} to exponential decrease ⁶	Increase ¹
Temperature	Exponential decrease ^{2,3,5,7,8,9,10,11} , polynomial equation of 3rd order ⁶	Exponential increase ^{2,7,8,9,10}
SOC	Linear decrease ¹⁰ , exponential decrease ^{2,8,9} , U-shaped function ¹⁰	Exponential increase ^{2,9} , linear increase ¹⁰ , polynomial equation of 2nd order ⁸
ΔSOC	Exponential decrease ⁶ , linear decrease ¹⁰	Exponential increase ⁶ , linear increase ¹⁰

¹ for LFP cells [8]

² for NMC cells at high temperatures [4]

³ for LFP cells at high temperatures [17]

⁴ for LFP cells [10]

⁵ for LiMn2O4 cells at high temperatures [13]

⁶ for LFP cells [11]

⁷ for NMC cells [12]

⁸ for LFP cells [15]

⁹ for NMC cells [15]

¹⁰ for NMC cells [16]

¹¹ for NMC cells [18]

EVALUATION CRITERIA

To evaluate the fit of aging models to the major stages of the vehicle lifecycle, a new definition of the five criteria mentioned in [6] was needed in order to reflect the different requirements of the stages and identify the important capabilities of aging models. These criteria are: adaption, precision, operating without data, performing in real time context, and prediction capacities. In this approach, simulation steps have to be calculated in a given time, which is mainly dependent on the computational effort required for the aging model. Therefore, we redefined the “real time” evaluation criteria as “computational effort”. The “operating without data” criteria is included in the new “parameterization” evaluation criteria.

In conclusion, this paper reuses three criteria and extends three further criteria, yielding the following six evaluation criteria:

1. **Parameterization:** This criterion provides an indication about the effort needed for reliable data collection in order to use the aging model properly. Required test procedures and test equipment were therefore considered, as well as the training process, for example for learning algorithms.

2. **Adaption:** The additional effort required to fit the aging models to other cell chemistries is taken into account. The focus is on the necessary structural change of the model and the effort needed for building the model again.
3. **Computational effort:** Computational effort evaluates the required calculation operations and loops needed to generate acceptable results.
4. **Precision:** The precision criterion provides information about the discrepancy between simulation results and real measurements.
5. **Prediction:** Prediction is a black and white evaluation. Models which are only able to estimate the current state of the battery are not predictive. Models which can provide information about EOL or the aging of the battery for the next time step are predictive.
6. **Robustness:** This evaluation criterion examines the influence that measurement inaccuracies have on the accuracy of the calculated output of the aging model. Structural errors such as offsets are not considered.

BATTERY AGING IN AUTOMOTIVE APPLICATIONS

Vehicle lifecycle can be divided into three main stages: development, operation and post-operation. All stages can be supported by different types of aging models. Within the development process, a rough design of the battery is first conceived, followed by the detailed development. During vehicle operation, aging models can either be used onboard or offboard the vehicle. During post-operation, the battery conditions must be analyzed and the decision regarding second life, remanufacturing or recycling has to be made.

Vehicle (Battery) Lifecycle

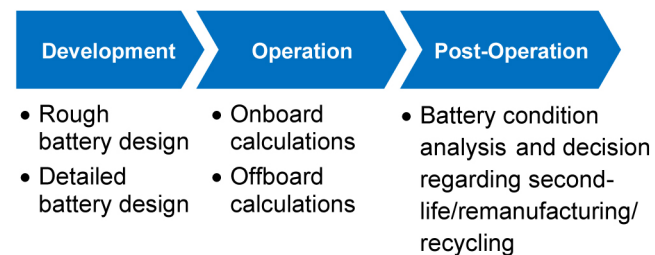


Figure 2. Stages of Vehicle Lifecycle

Vehicle Development - Rough Battery Design

To create an initial battery concept during the vehicle development process, the battery cells have to be selected. In this step, many criteria are considered, such as cell design (cylindrical, prismatic, pouch), cell size, cell chemistry (NMC, LFP, etc.), cell capacity, cell voltage, cell lifetime, availability of cells and cell price. To compare different cells with regard to cell lifetime, aging models can be used. At this stage, it is important to estimate the possible vehicle range and battery lifecycle until the battery's EOL is reached according to automotive standards. Therefore, in this stage, aging models must be predictive.

To select a suitable cell out of a broad variety, from a lifetime standpoint, an aging model that can be easily parameterized is beneficial for comparing results in a feasible period of time. By selecting an adaptive aging model, the same model can be used for all calculations with different cells and it is easier to compare the results.

As high-performance computers can be used during vehicle development versus cost-effective control devices inside the vehicle, computational effort does not play a decisive role in this stage. The computational effort should not be too high, because many different cells need to be investigated.

On the one side, there are many estimations, especially with respect to vehicle operation, in the early stage of the battery design. Consequently, the results of the aging simulations do not have to be more precise than the vehicle operation assumptions. On the other side, wrong decisions concerning cell selection in the early stage of development have a strong impact on battery performance during operation and therefore at least an acceptable degree of precision is necessary. Furthermore, the aging models need to be robust, since expensive measurement equipment for a broad variety of cells would add up quickly.

Vehicle Development - Detailed Battery Design

When developing the detailed battery design based on a specific cell, the electric interconnection of the battery cells has to be decided on in particular. The number of parallel cell strings determines the current and temperature at each cell, which are two of the main stress factors for cycle aging. Besides the design of the battery, the operating strategy, which is also developed at this stage of the vehicle life, controls the current and state of charge of the battery in a hybrid electric vehicle and at least the limits of current, temperature and state of charge in an electric vehicle. Furthermore, the cooling concept of the battery and the thermal management have a major effect on the battery's temperature. In conclusion, many decisions made during the detailed development of the battery should be addressed from a cell lifetime perspective by using the support of aging models. Predictability of these aging models is a key requirement in the detailed development of the battery.

In this stage, the effort needed for parameterizing aging models can be greater than for a first rough estimation, as only one or a few battery variants will be considered. In this case, the aging models do not have to be adaptive as well. However, if it must be possible to consider more stress factors at a later point, for example because it turns out that they also play an important role in the specific vehicle application, then the aging models should be adaptive. Additionally, adaptability is also important if several vehicles with different cells are considered at the same time. For example, the holistic FEEM in [19] uses one electrical management for various vehicles with different batteries.

The computational effort needed for the detailed battery design phase can be high, but it is not irrelevant, since development time is limited. Precision of aging models is much more important at this stage of the vehicle lifecycle. However, the maximum precision of an aging model for vehicle battery development is not as essential as it is for

cell research, for instance. In general, more sophisticated measurements can be used at this stage, since a limited cell variety is investigated. Therefore, the robustness of the aging model becomes less important. But measured cells can be prototypes and the assumptions about vehicle operations still do not necessarily match the real operation conditions completely, so robustness cannot be totally disregarded.

Vehicle Operation - Onboard

During vehicle operation, an aging model can be used onboard to estimate the current SOH of the battery. In this case, the model used does not need to be predictive. However, for controlling the power distribution in a hybrid vehicle, for example, predictive aging models can be used to determine the battery's optimal degree of utilization. Within the scope of thermal management, a predictive aging model can also be used, for example to precondition the battery. Furthermore, the charging strategy, e.g. for smart grid applications, can rely on the aging model, which can be predictive.

The acceptable effort needed for parameterization depends on the time of parameterization. If the aging model for the onboard application is parameterized before it is used in the vehicle, the effort can be high, since a vehicle manufacturer usually only uses a few variants of different cells. If the aging model is parameterized onboard during operation, the effort should be lower, because it minimizes the time the aging model can be used. The onboard aging model does not have to be adaptive, if the same model is used for the entire operation time. But if a software update should be possible, adaptability has to be considered. In addition, if the described FEEM of the development stage is used during operation, the aging model needs to be adaptive as well.

The computational effort onboard should be quite low, as only control devices that are as cost-effective as possible should be used. To avoid the high cost of sensors, the aging model has to be robust. Nevertheless, the quality of the results should be acceptable, since aging estimations have a great impact on vehicle performance parameters, such as driving range, maximum speed and acceleration. Consequently, the precision of the calculated results has to be good.

Vehicle Operation - Offboard

The aging of batteries inside vehicles can also be calculated offboard, for example on servers. The advantage of this approach is to reduce computational effort and memory for historical data onboard. Furthermore and even more important is to use information from more vehicles in order to improve individual SOH estimation and predict aging of vehicle fleets. This enables conclusions for the battery development for next vehicle generations as well as calculations concerning warranties. Furthermore, offboard aging modeling can be used to predict the EOL of the battery.

The acceptable parameterization effort and adaptability depends on the variety of vehicle batteries being considered. If the aging for one type of battery is modeled, for example to predict the EOL of batteries, the effort can be high and the aging model does not need to be adaptive. But if a vehicle fleet with totally different batteries inside