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Analysing the Influence of Driver Behaviour and Tuning Measures on Battery Aging and Residual Value of Electric Vehicles

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Abstract

Lithium-ion cells are currently the dominant technology in the market for battery-powered electric vehicles. Their biggest downside is their degradation over lifetime and usage, limiting the main vehicle functions such as the driving power and range. Moreover, the battery aging state has a big influence on the expected residual value of electric vehicles. The speed of the degradation depends on specific operating conditions such as temperature, SOC level and current. These stress factors are influenced by the usage behaviour of the vehicle driver as well as possible tuning measures. The aim of this study is to investigate the impact of typical driver behaviour combined with tuning measures on battery aging and the resulting residual value. A fully configurable, longitudinal simulation model is presented for the analysis that covers the main components of an electric drivetrain and takes battery aging into account. The model allows us to simulate various possible driver characteristics and tuning measures. Furthermore, the affiliated regression model allows the establishment of a link between the battery aging induced by driver behaviour and the residual value. First results show that our approach is promising and indicate that driver behaviour has a big influence on battery aging and thus the residual value, this being further reinforced by tuning measures. In addition, there is no linear correlation between the aging induced by driver behaviour and the residual value.

Keywords: Battery Aging, Vehicle Operation, Driving Cycle, Residual Value, Tuning Measures, Electric Vehicles, Lithium-Ion Batteries

1 Introduction

Today, electric vehicles are becoming increasingly popular all over the world. Lithium-ion based cells are mainly used for energy storage and have many advantages over other types of batteries. However, they are also expensive, potentially safety critical and they show a pronounced aging behaviour. Battery aging is governed by many factors, which are greatly influenced by the driver's behaviour. Therefore, one can expect a correspondingly strong spread of the battery's State of Health (SOH) over its lifetime. Steinbuch supports this hypothesis with his battery degradation analysis [1]. Through the crowdsourcing of battery SOH over lifetime data from Tesla owners worldwide (Figure 1), he analysed the remaining driving range, which displays an almost linear correlation to the remaining capacity of the electric vehicle. His approach lacks accuracy but shows the trend and impact of the individual driver, vehicle and environment.

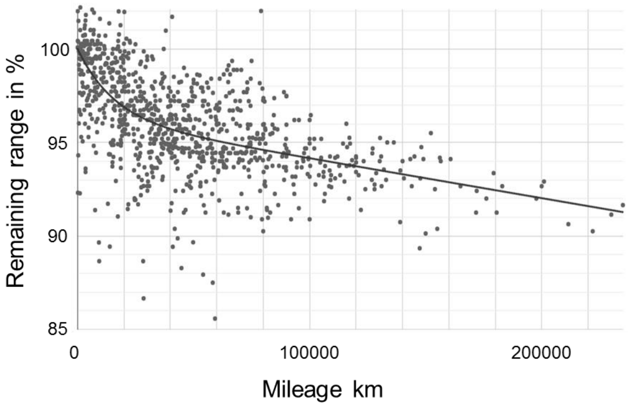

Figure 1: Crowdsourcing of remaining range of Tesla Model S

The expected SOH distribution of end of first life (EO1L) batteries is an important criterion for strategic decisions on the potential use of the EV-battery in Second Life applications. Furthermore, the distribution of aging states is an important parameter for the design of insurance products, which is not least reflected in the residual value. If tuning also becomes popular on electric vehicles, the driver behaviour is no longer limited by the restricted operating limits of non-manipulated vehicles. This leads to the risk of the aging spread becoming even wider. The influence on the residual value of tuning measures is also interesting for the field of security. The resulting damage can be taken into account in the security risk assessment [2] as well as the development of security concepts.

In this context, the question arises as to the extent to which the vehicle driver influences battery aging and thus the residual value of the vehicle and the battery?

1.1 Battery aging

The biggest downside of the market-dominating lithium-ion technology is the degradation over lifetime and usage, which limits main vehicle functions such as driving power, range and reliability [3]. Moreover, the battery aging state has a big influence on the expected residual value of electric vehicles. The speed of the degradation depends on specific stress factors. In [4], stress factors are defined as operating conditions of components and systems that can result in failure or degradation. With a focus on battery degradation, the operating conditions are temperature, State of Charge (SOC) level and current [3].

Due to the high complexity and interdependencies [5, 6], it is sensible to abstract and structure the aging of the lithium-ion cell. This can be separated into calendrical and cycle aging [6–8], whereby both effects have different major sources. Calendrical aging is typically influenced through stress factors such as temperature and SOC [6, 9]. Cycle aging covers the discharging and charging process [7]. This reflects the effect of current rates, temperature and depth of discharge on the battery parameters. In [10], we summarised the dependencies between the most important stress factors and battery parameters, summarising and evaluating the wide variety of existing battery aging models. Please refer to [11] for deeper insights into the degradation effects of the specific cell components.

In summary, the reduced vehicle functions such as driving power and range can be traced back to a reduced cell capacity and increase in its internal resistance. Therefore, to investigate the influence of the driver behaviour on battery aging, the SOH of EO1L batteries and the residual value of electric vehicles, it is essential to calculate the resulting stress factors within the longitudinal model and the effect on the drop in capacity and increase in internal resistance.

1.2 Possible driver parameters that may influence battery aging

In this section we explain how the driver influences the aforementioned stress factors. Basically, the stress factors are limited by the vehicle design, but can be influenced by vehicle drivers to a large extent. The entire vehicle system is utilised in such a way that no component is operated outside its specified operating range, mainly for safety reasons but also to minimise aging effect. For example, the battery management system monitors and limits the use of the electrical energy store. However, not all functions can be restricted because they are primary and important to the driver, for example the speed profile or the driving distance.

Grubwinkler [12] showed the high impact of driving profiles on energy consumption. According to Brundell-Freij et al. [13], the speed range of a road is an influencing factor for the power demand and is thus expected to be a relevant determinant for the stress on the battery through discharging at higher currents. Neudorfer et al. [14] analyses conventional driving cycles and categorises them as inner-city, overland and highway cycles. In the present paper, the shares of road types are considered as percentages of the daily driving distance. Furthermore, a factor for scaling maximum speed is employed since a real driver does not strictly adhere to speed limits and the power demand adjusts to velocity due to air resistance.

Further influencing factors can be derived from the driving resistance equations [15] because the power demand on the battery changes with the resulting resistance. This includes the acceleration behaviour, the additional load as well as changes in the rolling resistance coefficient, the frontal area or the drag coefficient. Apart from driving resistances, the driver is also able to influence the required power for auxiliaries such as lights or air-conditioning. The resulting power demand on the battery changes depending on frequency and intensity of use.

Table 1 summarises the possible driver influences and shows corresponding values. These are used for the parameterisation of the simulation. Finally, the driver determines where and in which ambient temperature range the vehicle is operated.

Table 1: Possible driver influences

Driver	**min**	**distribution peak**	**max**	**source**
Daily driving distance in km	5	20	50	[16]
Inner-city share in %	one cycle	33	100	assumption
Overland share in %	0	33	100	assumption
Highway share in %	0	33	100	assumption
Factor for max speed	0.8	1.0	1.2	[17]
Acceleration behaviour	slow	intermediate	fast	
Additional load in kg	70	108	425	[16, 18, 19]
Auxiliaries while driving (lights etc.) in W	300	425	550	[20]
Interior target temperature in °C	18	21	24	[21]
Charging behaviour		twice a day		
Vehicle				
Factor for air resistance (roof rack etc.)	1.0	1.0	1.2	[12]
Factor for rolling resistance	1.0	1.0	1.3	[12]
Environment				
Ambient temperature and irradiation profile		Nuremberg		[22]

Each parameter in Table 1 is shown in a specified range to represent as many different driver behaviours as possible. Figure 2 shows a few exemplary histograms of the distributions of driver-influenced parameters within a given range. In order to perform a Monte Carlo experiment in this work, we assumed each factor is normally distributed between a min and max value with a defined distribution peak to achieve realistic and transparent spreads of driver behaviour.

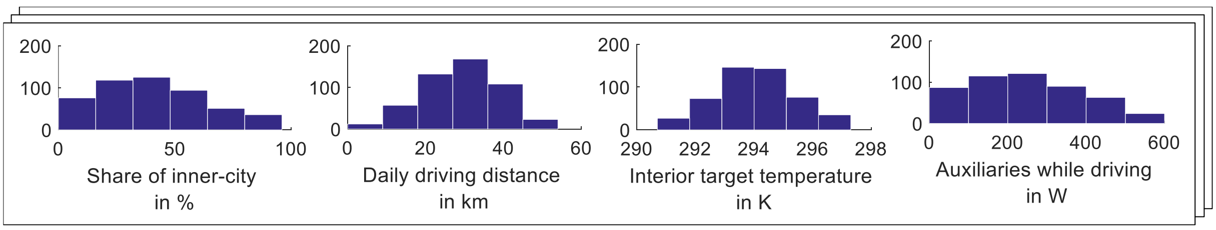

Figure 2: Distribution of influencing driver parameters

1.3 Objectives and approach

The objective of this paper is to answer the question of the extent to which drivers can influence the aging process of the vehicle battery and thus the aging or residual value distribution. In order to be able to make a quantitative statement about the influence of different driver profiles and tuning measures, an entire longitudinal model with an integrated aging model was developed and validated with real test data. The aging and residual value distributions were analysed along the service life as well as mileage using this model. For this purpose, a Monte Carlo experiment was carried out in which random driver profiles were selected from the influencing factors presented in chapter 1.2 and used to simulate the resulting cell capacity loss after four years as an indicator of battery aging. The specific aging-related residual value of the vehicle is derived from the respective aging state, the mileage and the vehicle age by means of a regression analysis. In order to assess the effects of selected tuning measures, the resulting influence on the aging distribution for a specific annual mileage is simulated and analysed.

2 Description of the EV Longitudinal Simulation Model

This chapter presents the key features of the Electric Vehicle Longitudinal Simulation Model that we used in the driver influence study. This model contains the main components of an electric drivetrain and enables an investigation of completely variable driver profiles and manipulations to all core components of the electric drivetrain. The model is built on basic physical equations and does not represent one specific vehicle but can be parameterised to various cases.

Chapter 2.1 begins by describing the overall model structure and providing general information about the model. This is followed by a detailed description of the modelling approach to important components. Since tuning measures are to be explicitly investigated, the behaviour at the system limits is also taken into account. Finally, the validation of the model is presented.

2.1 Overall model structure

The simulative analysis of the slow process of battery aging requires the consideration of a long time period. However, dynamic driver behaviour must also be taken into account. In order to achieve a compromise between dynamic driving situations, the slow process of aging and the resulting computation time, an efficient Simulink simulation model was developed that is operated with a step size of one second. The components of an EV, as shown in Matz et al. [23], are often bi-directionally interlinked within the main flow. If the logical dependencies (for example the distribution of the discharge current permitted by the battery) are also present, this results in a highly networked system structure. The danger here (particularly with a step size of 1s) is that time delays may occur in the main flow if not all of the loops have been correctly implemented. This can lead to incorrect model behaviour, especially in driving operations. We use a strictly linear model topology (Figure 3) that corresponds to the physical sequence, with a focus on the battery. The use of a purely linear topology and implementation with an intelligent bus structure allows the entire data bus to use only one "memory" element to also make the information generated from the previous time step available in the current time step. In this way, the arrangement of the components in the linear topology determines the primary flow of information.

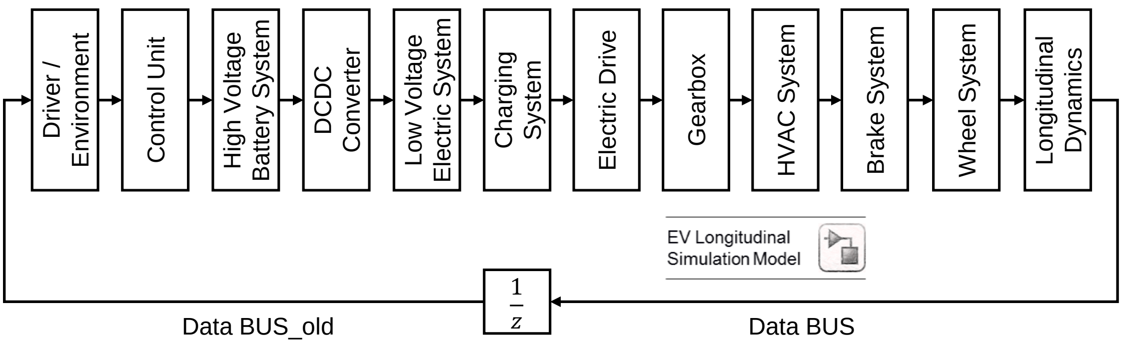

Figure 3: Overview of electric vehicle modelling

2.2 Modelling components including the behaviour at system limits

This section provides a brief overview of modelling the most important components and implementation of the corresponding system limits. Please refer to Matz et al. [23] and the detailed documentation that will follow in further works for the remaining components.

Driver model

Realistic driver behaviour has to be modelled to quantify the driver's influence on battery aging. The first aspect is to set up a realistic simulation environment for the vehicle, including the temperature of the environment as well as irradiation by the sun. The model presented here uses hourly data points for both parameters from Nuremberg available on [22]. Annual profiles were used to factor in seasonal effects. The simulation presented in this paper implements a time-based daily routine that models the driver's behaviour when the vehicle is parked, driven and charged. In each time slot for driving, the driver performs one predefined, position-based cycle and then parks. The results presented in this paper simulate four years, whereby each day contains two driving slots with subsequent charging. The simplifying assumption that all days are equal ignores weekends and vacations. Their influences may be examined in further works.

A position-based cycle is necessary to scale the acceleration behaviour and maximum speed without affecting the driven distance and to include stops at traffic lights with a specified stop interval at particular points. A driver controller is thus used that calculates accelerator and brake pedal actuations as function of current and desired velocity. The controller consists of a PI-controller for each pedal as well as a feed forward control for the acceleration pedal. The position-based cycle is a dynamically generated synthetic profile that is compiled from three basic cycles (inner-city, overland and highway). The NEDC was integrated over time for the inner-city and overland section to extract position and velocity data points. The first part of the NEDC (ECE-15) models a representative city-cycle, whereas the EUDC is a mix of overland and highway (speed range from 50 to 120 km/h). Consequently, the EUDC is used as overland cycle with a reduced maximum speed of 100 km/h. The highway cycle consists of three speed levels that are common on German highways (100, 120 and 140 km/h). Figure 4 shows an exemplary cycle with one part of each category respectively.

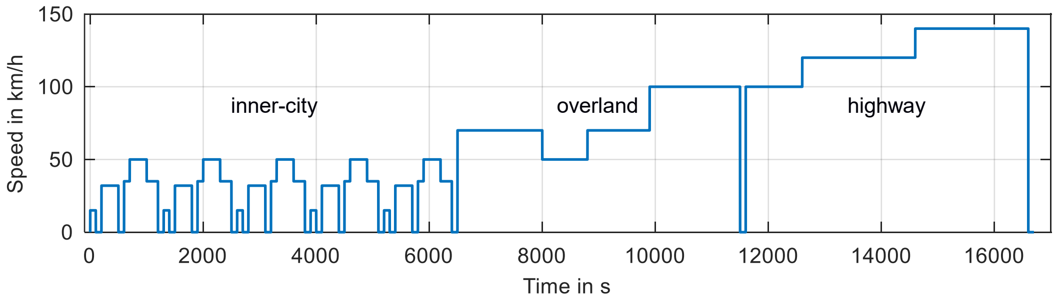

Figure 4: Exemplary synthetic driving cycle, assumption: free traffic flow, zero wind velocity, zero ground slope

Battery

We developed a thermal, electric and aging model of the 18650 2.05 Ah Sanyo UR18650E NMC cell in [24] as the battery model. We simplified the battery system by representing it with one cell to validate the longitudinal model. This assumption, did not consider the existing effects through parallel cell interconnection in the system, for example. The discrepancies in cell aging within the battery system are a consequence of the cell spread and different loading of the cells, caused by temperature and SOC inhomogeneities within the battery system [25].

While the thermal model provides the approximated cell temperature within the battery cell package for the other sub-models, the equivalent circuit model (ECM) of the cell calculates the terminal voltage and internal resistance according to the battery cell's load and temperature. These then influence the thermal development and aging within the cell. For long-term simulations, the impact of aging is also considered in the thermal model (increase of internal resistance) and the ECM (both increase of internal resistance and decrease of overall capacity). We performed several electrical and thermal characterisations of a Sanyo UR18650E cell when developing the model to determine the initial parameter set for the ECM and thermal model. The aging model is based on Schmalstieg et al. [6] from 2014, who performed accelerated aging tests to build the model.

This model contains the essential aging effects in NMC cells. Current NMC cells display a higher quality in terms of aging speed. In order to represent this further development, we took 80 % of the remaining capacity after 8 years under normal operating conditions as a reference and scaled the aging behaviour accordingly. The sub-models are described in [24] in detail and all parameters can be provided by the authors. The BMS monitors the system behaviour and stops the simulation in the event of a fault. In addition, it operates the battery within its performance specifications.

Powertrain including electric machine and power electronics

The powertrain model includes the electric machine and power electronic sub-models. A phenomenological modelling method is used. For this reason, the complex operating function is represented in a simplified manner using efficiency maps and taking torque and speed into account. The machine parameters are calculated according to Horlbeck [26] and the power electronics' parameters according to Pesce [27]. The power of the machine is limited when the inverter, the motor or the battery reaches its threshold. Therefore, the motor temperature is modelled separately and used to ultimately derate the performance of the power electronics.

HVAC

It is crucial to consider different energy sources and loads for the operation of electric vehicles. Cabin cooling and heating is an important load that accounts for a considerable percentage of the energy demand. We developed a simplified and dynamic thermal model for the cabin of a vehicle. This is why we applied a first-order cabin model that considers the cooling and heating convection through the car's surface according to Großmann [28] and the solar irradiation. The model is built on theoretical heat transfer, thermal inertia and solar radiation equations. The heat capacity of the car is represented by the air volume and interior according to [12]. We use the heat pump method represented by the COP to calculate the resulting electric power according to the heating power.

DC-DC converter and charger

The DC-DC converter is modelled with an efficiency map taking the voltage and current output into account. The charger is implemented with a PI-controller and considers the operating limits in terms of current and power set from the battery.

2.3 Validation of the EV model

We used data from the downloadable dynamometer database, which was generated at the Advanced Powertrain Research Facility (APRF) of Argonne National Laboratory under the funding and guidance of the U.S. Department of Energy (DOE), to validate the longitudinal model. This offers publicly available test data from independent laboratory tests of electric vehicles. For more information about the test facilities, test conditions and driving cycles please refer to [29]. The parameterisation of the model is based on the BMW i3 setup. We compared not only the battery voltage and SOC (Figure 5) but also the current and temperature over time.

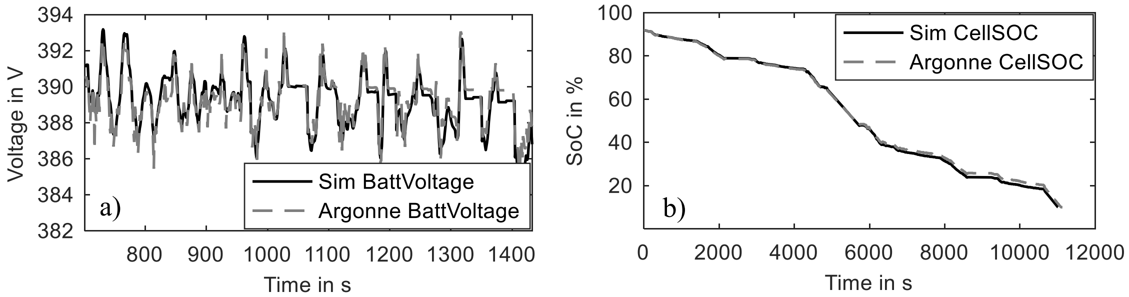

Figure 5: Comparison of Argonne data and simulation results, a) battery voltage, b) SOC

We performed the validation for four different Argonne test blocks: Test-ID 61505039 - 40 (~6 °C, very cold), Test-ID 61505028 - 30 (~0 °C, cold), Test-ID 61505019 - 22 (~23 °C, warm) and Test-ID 61505024 - 27 (~36 °C, very warm). The validation results in Table 2 show an average error below 5 % for all four different test scenarios and a good correlation between the simulation model and the Argonne data.

Table 2: Error simulation and Argonne data in %

Error simulation and Argonne data in %	very cold	cold	warm	very warm
Average SOC	1.8	1.5	0.8	0.5
Integrated current	2.2	0.1	5	4.9
Integrated power	4.1	2.3	1.9	2

3 Regression model for estimating the vehicle residual value

When it comes to estimating the residual value of vehicles, nearly all authors use statistical methods in their work to analyse the influencing factors of future residual values. For this purpose, large quantities of used cars need to be examined to identify the factors that have the greatest influence on the vehicle's value. The lack of corresponding data to parameterise the models is often a crucial problem. Historical data contains not only the price of the respective models but a lot of other important information such as the vehicle's age, mileage, power, etc. In the calculation or price, a vehicle is conceptually divided into quality properties and the effect of these quality characteristics on the price is then determined by means of a regression analysis. As a result, those price changes that are only based on qualitative changes in certain properties can be mathematically separated and eliminated from the pure price changes. The regression analysis is a statistical analysis to detect relationships between variables. Since vehicles are products that are subject to rapid technological changes, the differences in quality between vehicle models also has to be taken into account. New vehicle models will always be of a higher quality than the previous model. However, prices of products from two different periods can only be compared with each other if the quality remains constant [30]. This is why the hedonic approach is used, which equates quality-influencing factors.

The lack of long-term data for electric vehicles is the problem when transferring this conventional hedonic approach, based on regression models, for combustion engine-powered vehicles to electric vehicles. However, if the regression equation that represents the residual value function of an equivalent combustion vehicle were to be modified for a particular electric vehicle, the residual value of the electric vehicle could possibly be approximated. Trede of DAT (Deutsche Automobil Treuhand) employs such an approach when calculating the residual value of electric vehicles [31].

Equation (1) is the result of two different approaches. The first part, without the term $advantage_{TCO}$, is derived from Plötz et al. [30] and Dexheimer et al. [32]. It describes the residual value of an electric vehicle by adding the value of the traction battery to the original price of a comparable combustion vehicle. The latter should reflect the influence of taxation (e.g., the abolition of VAT). The term $advantage_{TCO}$ describes the (residual value) gains by lower fuel costs over the entire life cycle of the vehicle. Finally, to establish a link between the battery aging behaviour and residual value, we adjusted this linear regression model from Plötz et al. [30], Dexheimer et al. [32] as shown in equation (1) by taking the battery state of health into account and calculated the residual value distribution for the aging spread. We used the parameterisation from [30] for the Monte Carlo experiment.

$$residual\ \ value_{BEV} = e^{\alpha} \cdot e^{\beta_1 \cdot age} \cdot e^{\beta_2 \cdot \frac{km}{month}} \cdot \left(initial\ \ price + \kappa_R \cdot p_{battery}\right)^{\beta_3} + \cdots + \ advantage_{TCO} \quad (1)$$

where β_1: factor age, β_2: factor monthly km, β_3: factor original price, α: weighting factor, κ: battery capacity degraded kWh, $p_{battery}$: battery price €/kWh.

4 Results

4.1 Monte Carlo experiment

In order to receive the driver influence on battery aging we conducted a Monte Carlo experiment with the developed longitudinal vehicle model. For 10 000 samples, we randomly picked normal distributed driver profile parameters (Table 1) and simulated the vehicle usage for a duration of four years. The resulting cell capacity loss is used as indicator for battery aging. The normal distribution for the driver profile parameters is an assumption and does not necessarily fit reality but helps to gain transparency within the analysis. In this chapter, we provide first results.

Figure 6 a) shows capacity over time in three different mileage clusters for the 10 000 samples after the four simulated years of vehicle usage. The main outcome is the strong capacity spread induced by usage profiles, which is increasing with mileage. Aging and mileage are not correlative, making the mileage unsuitable as independent aging indicator. The increasing horizontal scattering is due to the accumulation of small errors of the driver controller. In future work it may be solved with a predictive controller. Figure 6 b) analyses the dependency of the remaining battery capacity from the accumulated energy throughput. To also show the evolution with time, three different time points are indicated (480 days, 960 days, 1440 days). The dependency shows a linear or even slightly quadratic shape, which tends to lower remaining capacity with higher energy throughput. Assumed a linear dependency for a specific point in time, the gradients of the shapes are decreasing for later time. This means that the correlation between energy throughput and aging is decreasing with ongoing time. Nevertheless, taking the effects of mileage and driver profile into account, the power throughput is the dominating indicator for the remaining capacity of the battery.

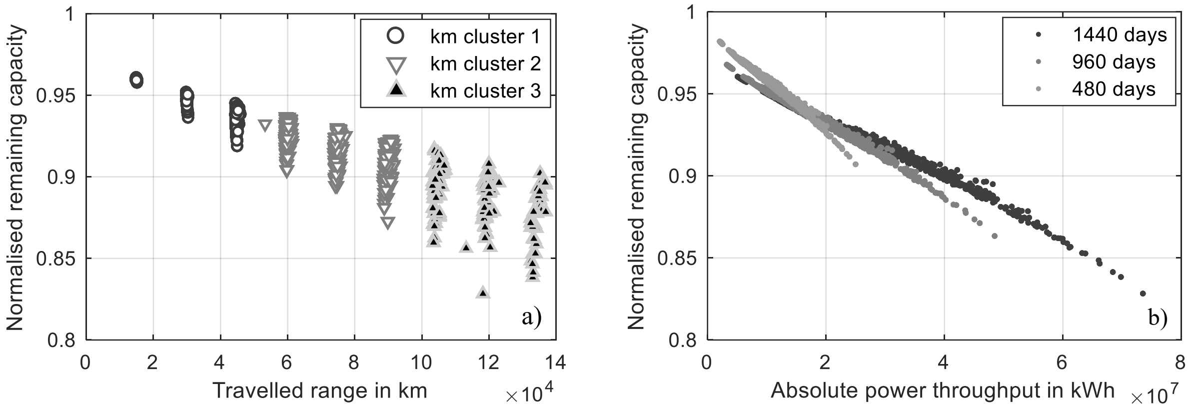

Figure 6: Dependency of battery aging on mileage a) and energy throughput b)

Figure 7 a) shows the development of capacity over the battery lifetime and its distribution after four years, clustered in the three mileage areas introduced in Figure 6 a). The distribution has a left shifted Weibull shape and is more left shifted with more driven kilometres and the spread is increasing. The impact of drivers becomes visible and stable. Furthermore, extreme drivers are increasingly drifting away from the bulk. Summarized, with increasing mileage, the driver impact even increases.

The residual value, shown in Figure 7 b), also reflects the decrease for the three different kilometre clusters. The residual value reaches 40 % in cluster 3 while cluster 1 is still above 50 %. The drop in the residual value is mainly dependent on the driven miles. Battery aging influence decreases with an increasing mileage.

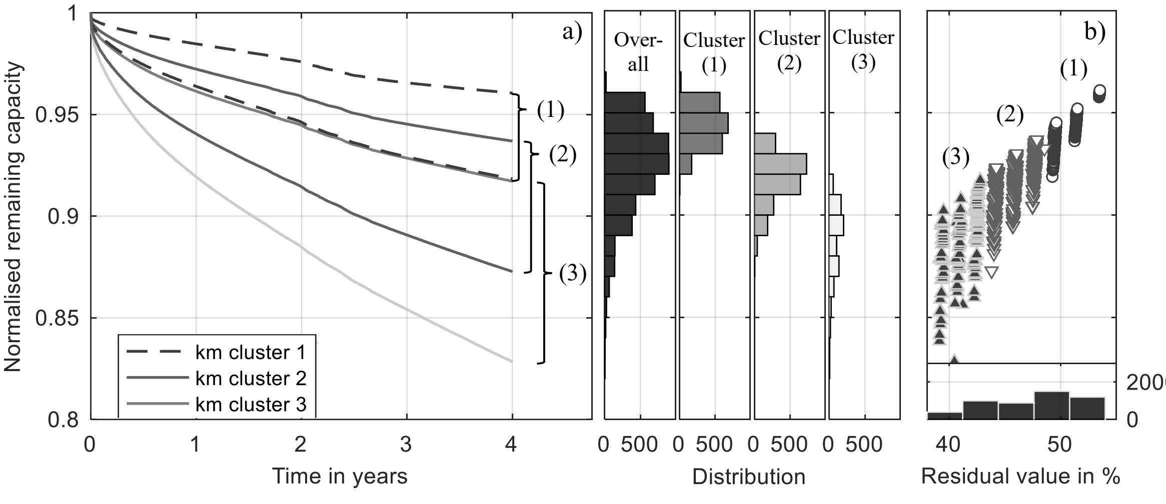

Figure 7: Driver-influenced aging distribution over time, aging spread, a) dependency of the remaining capacity on the energy throughput for three different time points, b) residual value after four years

4.2 Additional application of specific tuning measures

Potential tuning measures can be derived from the needs of electric vehicle drivers and the tuning market for conventional vehicles [2]. These range from purely optical measures or upgrading the vehicle right through to the classic performance enhancement. This results in a large number of possibilities for tuning measures, which can have different degrees of intensity and can also be combined. In order to demonstrate the fundamental effects on aging distribution, the following cases are considered:

a) A software-based power increase of 15 % (chip-tuning)
b) The use of newer cells (20 % more capacity, 10 % larger mass, 10 % lower internal resistance)
c) The additional use of powerful auxiliary equipment, such as a sound system (300 W additional load)

The tuning measures are simulated in combination with 500 samples of randomly selected driver profiles, though a fixed annual mileage of approximately 15 000 km. Figure 8 shows the resulting aging distributions for the three tuning measures considered after three simulated years.

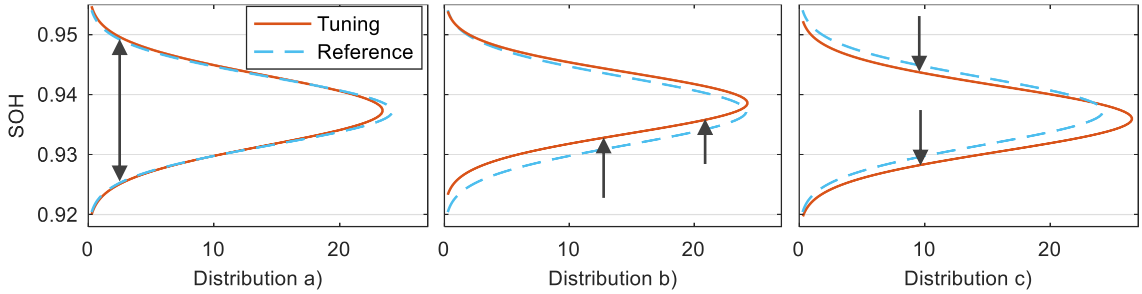

Figure 8: Aging distribution based on different tuning measures after three years

The increase in performance (case a) only relates to a small share of the daily driven distance and, in addition, to only a few drivers whose profiles demand additional performance. In individual cases, this results in significant effects on the aging behaviour. However, based on all drivers, the impact is negligible. Tuning measures that only affect specific individual drivers are therefore usually expressed in a broader distribution curve, the mean value hardly changes (Figure 8 b).

Case b), the use of more modern cells, affects all drivers but is expressed to different degrees in different driver profiles. There is a decline in aging, especially among drivers who have a high energy throughput. This is partly due to a lower depth of discharge (DOD) as well as a lower cell temperature. In the distribution curve, such tuning measures are expressed by a one-sided displacement (Figure 8 b).

An increased auxiliary load (case c) affects all driver profiles equally. The resulting aging distribution therefore shifts completely towards increased aging (Figure 8 c).

5 Discussion

The results of the analysis show a high sensitivity of the battery aging based on the driver behaviour. The dependency of the drop in capacity on the energy throughput shows a linear trend over time and various gradients dependent on the point in time. The capacity spread increases with the mileage.

It becomes obvious that mileage has a big impact on battery aging and that the driver impact increases with an increasing mileage. Therefore, the mileage of a vehicle cannot be the sole indicator for the remaining capacity of the battery, but according to our analysis it has a strong effect to the residual. During our analysis, we also investigated second-hand car prices on mobile.de and autoscout.de, and it became obvious that the residual values are currently high for electric vehicles. In our opinion, however, this is likely to be due to the low availability and under-developed second-hand electric car market. This will change when a second-hand car market becomes established. In addition, subsidies for new vehicles as well as the drop in the price of electric vehicles will lead to a decline in old models. Our analysis is based on a methodology for combustion-powered vehicles, which means we assumed an established second-hand car market. Because of this, our calculated development in value is pessimistic and will be more accurate in the future. Furthermore we didn't take future necessary battery replacement into account, because we just investigated four years of lifetime and replacement was not required.

There are many possible tuning measures that have a varying influence on battery aging. However, a large proportion of tuning measures do not affect all driver profiles, only selected ones, and of course, not all vehicles will be manipulated. This means that in a global perspective, the influence of the assessed tuning measures on the aging distribution is negligible compared to the driver profile, but should still be considered as an uncertainty. When it comes to the individual driver profiles, the situation changes and tuning measures may have a significant effect on aging. A systematic analysis of the numerous tuning measures and their characteristics in combination with selected driver profiles is necessary in this area. This comprehensive consideration will be the goal of future work.

6 Conclusion and future work

This article investigates the impact of statistically distributed driver behaviour in combination with tuning measures on battery aging and the resulting residual value. We therefore suggest a fully configurable longitudinal model that covers the main components of an electric drivetrain and considers battery aging.

Initial results show that our approach is promising and that driver behaviour has a big influence on battery aging and thus the residual value and being further reinforced by tuning measures. In addition, there is no linear correlation between driver-induced aging and the residual value and the impact of battery aging decreases with an increasing mileage.

Future work requires a detailed understanding of the impact of different driver behaviour profiles on battery aging. Hence, we will carry out sensitivity analyses for the different driver behaviour parameters and will discuss concrete profiles such as slow city driver with fast charging vs. fast highway drivers with home charging. In addition, we will vary the environmental profile and include several different vehicles.

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