On the Efficacy of SoC-Preconditioning on the Utilization of Battery Packs in Electric Vehicles

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Abstract*—During the last decade Electric Vehicles (EVs) surged in popularity. However, their mass adoption is slowed by the limited capacity of their Energy Storage System (ESS). Lithium Ion (Li-Ion) technology has established itself as the de-facto standard for mobile applications, though its energy density and cost put a hard limit on the maximum size of viable EV battery packs. Maximizing its utilization therefore becomes of central importance. To efficiently use a battery pack over its entire lifetime, the State of Health (SoH) of the cells needs to be taken into account. In this paper, we propose a novel *preconditioning* algorithm to minimize the time an EV is connected to the charging station. Our proposed approach uses existing Active Cell Balancing (ACB) hardware of the battery pack to precondition the State of Charge (SoC) of cells such that all cells reach the top SoC threshold at the same time without requiring an additional balancing phase during charging. This is done by considering the individual cells' SoH to precondition them for achieving an equal time to charge fully. Applying the same approach for discharging, we can extend the driving range of an EV, which otherwise is limited by the cell with the lowest SoC in the pack. Our analysis of various usage scenarios shows that our proposed preconditioning algorithm increases the usable energy of the battery pack by up to 1.8 % compared to conventional balancing algorithms while effectively halving the time connected to a charging station, all without requiring any additional hardware components.

I. Introduction and Related Work

This paper builds on the concept originally presented in [1] during the 22nd Euromicro Conference on Digital System Design (DSD). In the pursuit of sustainable mobility and reduced CO_2 emissions, the electrification of the transport sector is playing an important role. It enables efficient, and therefore potentially more cost effective, silent transport without emitting exhaust gases locally. However, the electrification of vehicles is impeded by factors such as long charging times, limited range and cost of the battery pack. Due to the last point, investment in Battery Electric Vehicles (BEVs) is most profitable where the initial cost of the battery pack can be offset by savings in fuel. Therefore, he profitability of BEVs increases with rising usage hours. Because of this, the predestined use case for BEVs is in public transport. For this, however, minimizing the charging time is of crucial importance to reduce the turnaround time and, hence, increase

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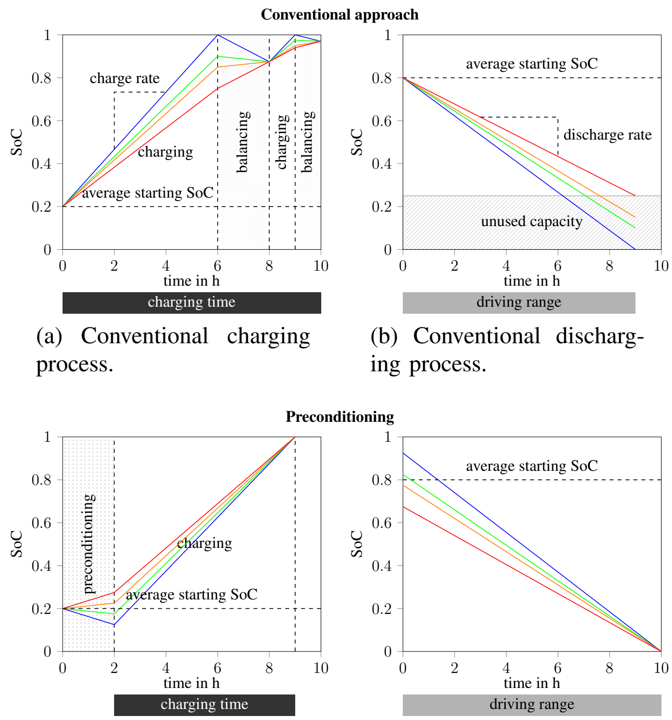


(a) Conventional charging process.

(b) Conventional discharging process.

(c) Charging process with preconditioning.

(d) Discharging process with preconditioning.

Fig. 1: Illustration of the proposed preconditioning algorithm with an exemplary battery pack with four cells. (a) and (b) show the development of the cells' State of Charge (SoC) over time for conventional charging and discharging respectively. In (c) and (d) the proposed preconditioning algorithm for charging and discharging is displayed. Instead of balancing all cells to the same SoC level after charging or discharging, they are individually balanced to a certain SoC so that they reach a uniform SoC level after charging or discharging, thus significantly shortening the charging time while increasing the usable capacity.

profitability. To facilitate this, methods need to be developed to optimally utilize the given limited capacity of the battery pack and reduce the charging time. The technology currently used in most battery packs for BEVs is Lithium Ion (Li-Ion) cells.

Since these cells can potentially be dangerous, a Battery Management System (BMS) is required to monitor the cell parameters such as voltage and temperature and to guarantee a safe and reliable operation [2]. Moreover, due to variances in manufacturing and rate of aging, Li-Ion cells charge and discharge at different rates [3]. This effect accumulates charge in stronger cells over time and renders the pack unusable due to the diminishing overall usable capacity if not addressed. Cell balancing is typically performed to minimize the variations in SoC of individual cells in the pack. The conventional approach is passive charge balancing, where excess charge is dissipated as heat over a resistor that is attached to each cell. Naturally, this leads to a reduction in efficiency. To counter this drawback, a different method is gaining traction: Active Cell Balancing (ACB), where the SoC of all cells is equalized by transferring energy instead of dissipating it [4], [5]. However, this method necessitates additional circuitry containing temporary energy storage elements such as inductors, capacitors or transformers accompanied by MOSFETs.

Problem motivation: Existing ACB techniques focus on equalizing the SoC of all cells in a battery pack. However, the rate at which the ACB architectures can equalize the pack depends on the variations in the charge levels and the balancing current value, which is typically limited by the hardware components in the ACB architecture. We focus on the ACB architecture in Fig. 2 since it has been shown to be highly efficient with a reasonable number of switches [6]. This architecture furthermore allows non-neighbor balancing, which makes direct charge transfers between non-adjacent cells possible. In comparison to the high magnitude of charging or discharging currents, which can be in hundreds of Amperes for Electric Vehicle (EV) applications, the balancing current is small, typically between 1 A to 10 A [7]. It, therefore, may not be possible to counteract the spread in the cells SoC resulting from charging or discharging in real-time. The charging process, even when started with an equalized pack, might need more than one balancing phase in between (as shown in Fig. 1a), since each cell charges at a different rate, due to their variations in the State of Health (SoH). As a result the overall charging time, i.e., the total time the vehicle is plugged in the charging port, is increased. A similar phenomenon is also observed during the discharging process, where the driving range is reduced (as shown in Fig. 1b) due to the different SoH values of the cells.

In this paper, we present further analysis of the ACB approach, called *proactive SoC-preconditioning*, introduced in

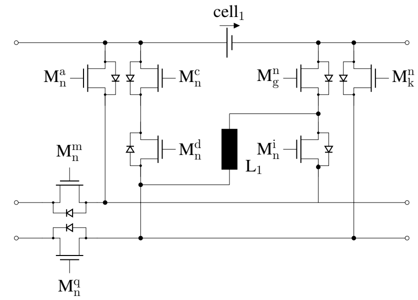


Fig. 2: The underlying non-neighbor ACB architecture of our evaluation framework consists of eight switches and one inductor.

[1]. In comparison to existing ACB techniques, which mainly focus on maintaining an equal SoC of all cells, our proposed preconditioning algorithm deliberately sets the SoC value of the cells, so that, after discharging or charging, all cells in the pack reach their minimum or maximum cut-off voltages at the same time. This is achieved by shifting the value that needs to be equalized from SoC to Residual Missing Energy (RME) or Residual Available Energy (RAE), as detailed in Section II, for each cell in the pack by taking their SoH into account [8]. Fig. 1 visualizes the differences between the conventional charging and discharging approaches and our proposed preconditioning method, exemplary for a battery pack consisting of four cells. Each line in the graphs stands for the development of the SoC of one cell over time. It is visible that the actual charging phase for the conventional ACB method shown in Fig. 1a is interrupted in order to perform the balancing phase, thus prolonging the time the BEV needs to be plugged in to the charging port.

On the contrary, the charging phase of our proposed preconditioning process is consolidated into one single phase by preconditioning the SoC of the cells to different values depending on their charging or discharging rate and SoH. Since this preconditioning process can be performed without being connected to a charger, the overall time the BEV is connected to the charging station can be significantly reduced.

Related work regarding proactive balancing can be found in literature, however the impact on battery pack efficiency and specifically charging times has not been examined sufficiently [9]. Our specific **contributions** in this paper are:

- We propose a proactive *preconditioning* algorithm in order to prepare a battery pack for upcoming usage (Section II).
- We implemented the algorithm in the open source balancing Cyber-Physical Co-Simulation Framework (CPCSF) from [10]. This framework features an empirical battery aging model based on [11] and support for vehicle, drive cycle and climate models to generate different usage scenarios.
- We performed a case study with synthetic usage scenarios, simulating a Tesla Model S and its battery pack over

its entire lifetime (Section III).

- We show that our proposed preconditioning algorithm increases the total energy throughput by up to 1.8 %, while reducing the overall combined balancing and charging time by up to 70 % (Section IV).

II. Preconditioning Algorithm

Conventional charge balancing algorithms use the cell's SoC as the underlying balancing parameter. Since the balancing process happens after the charging or discharging, in order to counteract the resulting SoC variation, it is of reactive nature. Our proposed preconditioning algorithm, however, uses the ACB architecture proactively. This fundamental shift makes it necessary to anticipate the future battery pack behavior, since the upcoming usage determines the target SoC level for each cell. Preconditioning yields these two options:
A) The battery pack gets preconditioned, so that at the end of the charging process all cells reach 100 % SoC simultaneously, therefore reducing the overall charging time.
B) The battery pack gets preconditioned, so that all cells reach the SoC threshold at which charging becomes necessary simultaneously, therefore increasing the range. The following section will detail the differences between these two options which we call preconditioning for charging and preconditioning for discharging.

A. Preconditioning for Charging

A conventional charging operation consists of multiple phases:

1) Charge the battery pack until the first cell reaches 100 % SoC[1].
2) Balance the battery pack until all cells have a uniform SoC.
3) Charge the battery pack again until the first cell reaches 100 % SoC.
4) Repeat the process until a defined threshold of SoC variance is met and all cells are close to 100 % SoC.

Fig. 3 displays this process for an exemplary battery pack consisting of 12 cells. First, the battery pack is charged until one cell reaches 100 % SoC. It can be observed that the SoCs of the cells diverge during this phase due to their difference in charging rate determined by their SoH values. This spread is then counteracted with a subsequent balancing phase and the process is repeated. The battery pack needs to be plugged in during the entire charging process because it is unknown if after each charging phase another balancing phase is necessary.

Our preconditioning approach, on the other hand, incorporates knowledge of the battery aging status to predict the rate a particular cell charges at. To quantify this aging status, the SoH is introduced. As there is no consensus on the definition of the SoH yet, many different definitions can be found in literature [12]. In this paper we define the SoH as a weighted combination of two values, one for the loss in capacity (SoH_{C}) and one for the increase in internal resistance (SoH_{R}) with $SoH, SoH_{\mathrm{C}}, SoH_{\mathrm{R}} \in [0,1]$. This separation allows to optimize the impact of the algorithm in terms of the expected usage scenario. In a scenario where available energy (e.g. range of a car) is more important, the weights can be shifted towards SoH_{C}, whereas the weights can be shifted towards SoH_{R} for a scenario that emphasizes power output. An SoH of 1 represents nominal capacity or nominal internal resistance. End-of-life (EOL) criterions are chosen for the remaining capacity and the internal resistance, upon which the respective SoHs are defined to be 0. The criterion EoL_{C} is defined as the remaining capacity C_{m} reaching 75 % of the nominal capacity C_{n}. The criterion EoL_{R} is defined as the internal resistance $R_{\mathrm{i,m}}$ doubling, compared to the nominal internal resistance $R_{\mathrm{i,n}}$. SoH_{C} and SoH_{R} are therefore defined according to Equations 1 & 2.

$$SoH_{\mathrm{C}} = \left(\frac{C_{\mathrm{m}}}{C_{\mathrm{n}}} - EoL_{\mathrm{C}}\right) \cdot \frac{1}{1 - EoL_{\mathrm{C}}} \tag{1}$$

$$SoH_{\mathrm{R}} = \left(EoL_{\mathrm{R}} - \frac{R_{\mathrm{i,m}}}{R_{\mathrm{i,n}}}\right) \cdot \frac{1}{EoL_{\mathrm{R}} - 1} \tag{2}$$

As the SoH reflects the aging induced battery degradation, it can be used to define a metric to quantify missing and available energy in a given cell. This metric can serve as the basis upon which the balancing algorithm converges to instead of the SoC. In the previous work in [1] we used a time based metric that used knowledge about the charging or discharging currents to estimate its values. We however have since learned that the current cancels out if the SoH is used instead. The resulting metric RME, is defined according to Equation 3 and incorporates the cells' nominal capacity C_{n}, its SoC and SoH,

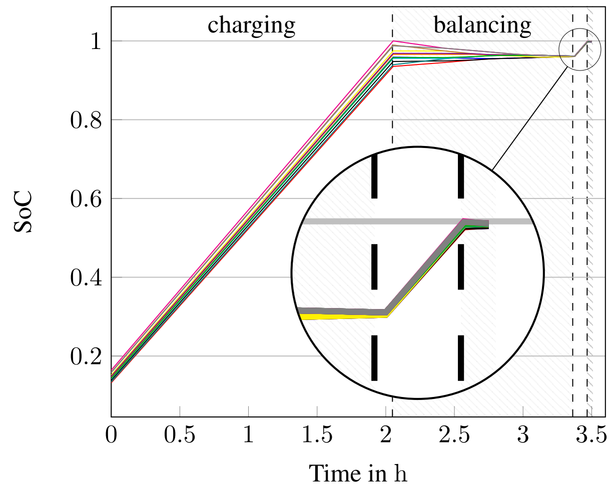


Fig. 3: Conventional charging process. Alternating charging and balancing phases to achieve full charge will extend the time the vehicles is connected to the charging station.

[1]We denote with 100 % SoC the SoC chosen by the manufacturer which guarantees a suitable lifetime of the pack. The effective "physical" SoC at 100 % might be lower (e.g. 80 %). This also applies to 0 % SoC where the physical SoC might be chosen around 20 %.

its EOL criterion, as well as the target SoC_{t} for the operation after the balancing procedure [8]. j denotes the index of the respective cell.

$$RME_{\mathrm{j}} = -C_{\mathrm{n}} \cdot (SoC_{\mathrm{t}} - SoC_{\mathrm{j}}) \cdot (SoH_{\mathrm{C,j}} \cdot (1 - EoL_{\mathrm{C}}) + EoL_{\mathrm{C}}) \tag{3}$$

All RME_{j} are stored in the list $\mathcal{T}_{RME}$.

Instead of the cell's SoC we now use RME as the base of the preconditioning procedure. The preconditioning charge transfer strategy for charging, visualized in Fig. 6, comprises the following steps:

After the preconditioning process for charging, the RME values of all cells are equalized, though their respective SoC may vary widely. Fig. 4b displays the SoC development of the cells during this preconditioning process, compared to a conventional ACB shown in Fig. 4a. After preconditioning the battery pack the actual charging phase is initiated, which leads to all cells in the pack reaching 100 % SoC at the same time. We assume a Constant Current Constant Voltage (CCCV) charging strategy with a charging rate of 0.5 c Fig. 5 exemplary shows the preconditioning phase with subsequent Constant Current (CC) charging phase for a battery pack with 12 cells. The BEV doesn't need to be plugged in to the charging port during the preconditioning phase, which significantly reduces the length of the charging time.

B. *Preconditioning for Discharging*

Similar to the charging process, the battery pack can be preconditioned for discharging. Therefore, we define a parameter Residual missing energy RAE, which is calculated according to Equation 4 that depends on the SoH_{C}, the EoL_{C}, and the current SoC [8].

$$RAE_{\mathrm{j}} = C_{\mathrm{n}} \cdot (SoC_{\mathrm{j}} - SoC_{\mathrm{t}}) \cdot (SoH_{\mathrm{C,j}} \cdot (1 - EoL_{\mathrm{C}}) + EoL_{\mathrm{C}}) \tag{4}$$

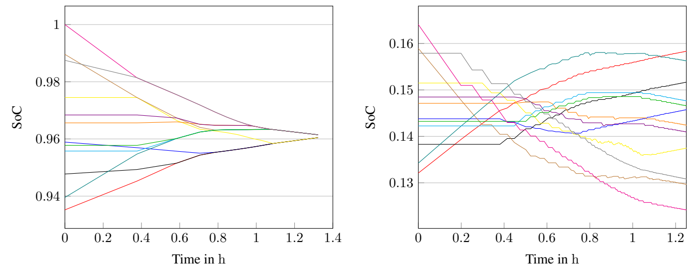
This value is calculated for all cells in the pack and becomes our new underlying balancing parameter. Similar to the preconditioning for charging, we follow the aforementioned steps until all cells' RAE_{j} are equalized. This ensures that the discharging of the battery pack results in all cells reaching their target SoC at the same time, and therefore maximizing the utilization of the battery pack.

III. Analysis and Evaluation Framework

In extension of the work presented in [1], we implemented the preconditioning algorithm in the battery cycling, aging and balancing simulation framework from [13] which in turn is based on the CPCSF from [10].

This framework allows to model the behavior of individual cells in a battery pack for realistic use cases of a vehicle over it's entire lifetime. The details of this framework are presented in this section.

The framework is set up in layers around models of battery cells, which form the fundamental core and hold all the information about the cells physical parameters as well as aging status. Each layer consecutively adds functionality to the framework, such as a battery pack model, consisting of a BMS wrapping the cells, and a ACB system. The battery pack model is embedded in a larger vehicle model, that provides discharging functionality, by generating a vehicle specific energy demand over a drive cycle, and charging functionality, by emulating a CCCV charging system. This vehicle model is controlled by scenarios, that provide instructions about the usage pattern of the vehicle as well as a climate model of the environment.



(a) Conventional Balancing (b) Preconditioning

Fig. 4: SoC development during a) conventional balancing and b) preconditioning.

a) Cell Model: To model the cells in our framework, a Panasonic NCR18650B Li-Ion cell with a nominal voltage of 3.6 V, nominal capacity of 2.5 Ah was chosen. The cell model contains information about its current SoC, SoH and internal resistance R_{i} and provides an interface to apply current as well as measure its current voltage.

It furthermore features a method to simulated the cell aging, based on the cycle count, the calendric age, the Depth of Discharge (DoD), the ambient temperature, the SoC at which a cell is stored and other cell inherent parameters detailed in [11].

b) Battery Pack: Multiple battery cells are connected to form the battery pack. The battery pack is modeled after a Tesla Model S battery pack with 18650 cells in 96S74P configuration and 85 kWh capacity [14].

Besides these parameters, the battery pack model provides a BMS, that monitors the state of the individual cells and maintains the pack in a safe operating range, as well as ACB functionality to equalize the cells charge levels.

c) Active Cell Balancing Architecture: To enable ACB, a charge transfer circuit is modeled in our framework. In this paper we focus on an inductor based architecture displayed in Fig. 2. This architecture has been derived from an automatic circuit synthesis as the optimal solution. It furthermore allows for non-neighbor charge transfer, meaning it is not limited to charge transfer between adjacent cells. However, it has the limitation that a cell cannot participate in any charge transfer if it is situated between two cells that are currently exchanging charge. Therefore, charge transfers over long distances result

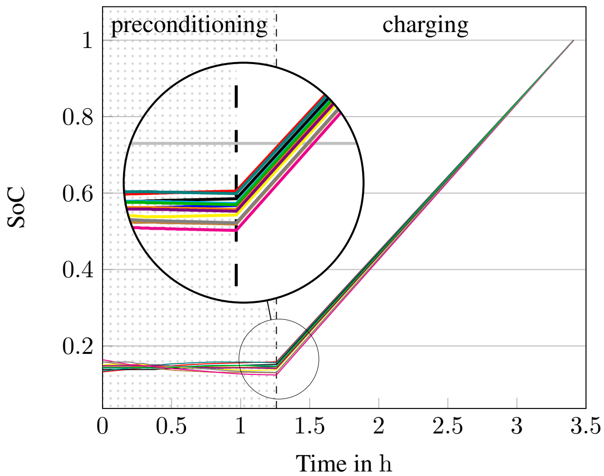


Fig. 5: Preconditioning process. The preconditioning phase (dotted) is followed by only one charging phase resulting in all cells of the battery pack to be fully charged at once.

in lower losses but also reduce the number of concurrent charge transfers.

d) Charge Balancing Strategy: The fundamental problem, that is addressed by charge balancing strategies, is to pick a set of pairs $p = (\sigma, \delta)$ of sending (σ) and receiving (δ) cells, to facilitate charge transfers that transmit charge as quick as possible while minimizing losses at the same time. This results in an optimization problem between balancing time and balancing losses. There are many balancing strategies discussed in literature. We chose one that has proven to be efficient on our chosen balancing architecture [15]. A typical example of such a charge balancing process is displayed in Fig. 4a.

e) Vehicle model: The battery pack is part of a vehicle model, that provides it with information about the environment, such as temperature, and applies a charging or discharging current. The charging current is provided by a CCCV charger and is set to a charging rate of 0.5 C. The discharging current is derived from the energy demand of a Tesla Model S that is driven according to the WLTP class 3 drive cycle [16]. The vehicle models' energy demand estimation uses open source measurements for the ABC coefficients done by the EPA [17].

f) Scenarios: To generate a realistic usage pattern for the vehicle model, scenarios are defined. These scenarios determine the daily utilization and control the SoC at which the charging process is initiated. They furthermore provide a climate model to simulate the effect of ambient temperature on the aging process. In this example a temperature climate model with temperature data from the city of Munich was chosen to replicate seasonal variations. The model, however, does not take into account the heating that occurs during usage and, therefore, mainly models the effect of the temperature during storage.

Four scenarios were generated where the two parameters

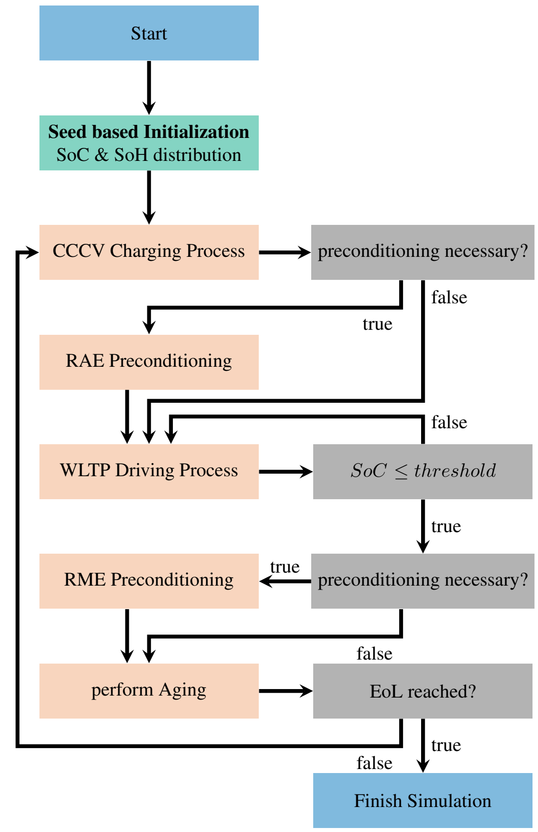


Fig. 6: Overview of the structure and interdependencies of the elements of the simulation scenarios.

daily driving time t_{dd} and SoC threshold at which the charging is initiated SOC_{T} were varied. We chose the daily driving time to either be 1 h or 2 h which results in $\approx$ 46 km or $\approx$ 92 km respectively. For each of the four scenarios simulations with preconditioning and with regular SoC balancing were conducted for comparison. We chose these driving distances, as on the one hand, a representation of the average daily driving behavior in the USA and, on the other hand, an intensive use case [18]. The second varied parameter was the threshold at which the charging is initiated SOC_{T}. We chose this value to either be 10 % or 40 % to cover one use case where the battery gets depleted regularly and one scenario where it is recharged at intermediate SoC values. These parameter variations allow us to evaluate the efficacy of the preconditioning algorithm over a broader range of usage scenarios. Fig. 6 displays a flow chart of the processes and decisions controlled by the scenario. After initialization of the model and the cells' SoC and SoH distribution, based on a seed for reproducibility, a cycle is entered. In this cycle the battery pack is repeatedly charged and discharged, following the scenario parameters, and the cells are aged according to the implemented aging model from [11]. After every charging and discharging operation a check is performed whether the criteria for preconditioning are met. The criteria are met, if the RME deviation or the RAE deviation respectively surpass a threshold of 5 %. The cycle is repeated until the battery back has reached its EOL. The results from these simulations are presented in the following section.

IV. Results

The case study, that has been conducted in the original version of this paper, has shown, that SoC preconditioning can have positive impact on the capacity utilization of battery backs, while reducing the combined charging and balancing time [1]. However, a certain aging state was presupposed and therefore, the SoH development over time was not taken into account. The simulation framework, detailed in Section III, on the other hand, allows for a more in-depth analysis of the efficacy of the preconditioning method, over a wide range of aging conditions. In the following, the simulation results for the four scenarios are laid out. Table I lists the scenario parameters.

Over the lifetime of a Li-Ion cell, its remaining capacity continuously decreases. Various factors, amongst which are cycling frequency, charging and discharging currents, temperature and time in general, influence the aging behavior. As detailed in Section III, the aging status is quantified by the SoH. Fig. 7 displays the simulated SoH development of all scenarios over their battery pack's lifetime.

The SoH deterioration is simulated according to the model presented in Section III.

The solid line graphs the pack's average SoH, while the transparent areas represent the band between minimum and maximum SoH. The figure shows, that the utilization, both in terms of driving frequency as well as DoD, has a significant influence on the aging behavior. It can be seen, that the weakest cell in scenario $SOC_{\mathrm{T}}10\_t_{\mathrm{dd}}2$ reaches its EOL after $\approx$ 9 years while the other scenarios are able to last until the end of the simulation after 10 years. Besides that also the influence of the seasonal climate conditions is visible. Most importantly however, is the increasing gap between minimum and maximum SoH. This gap results in an expanding disparity in the usable capacity between the cells, which is counteracted by the preconditioning algorithm.

In the following the results of the preconditioning algorithm are directly compared to results from a simulation with identical initial configuration, with the only difference being,

Identifier	Driving Cycle	Climate Model	Charging Threshold SOC_{T}	Daily Driving Time t_{dd}
$SOC_{\mathrm{T}}40\_t_{\mathrm{dd}}1$	WLTP3	Munich	40 %	1 h
$SOC_{\mathrm{T}}40\_t_{\mathrm{dd}}2$	WLTP3	Munich	40 %	2 h
$SOC_{\mathrm{T}}10\_t_{\mathrm{dd}}1$	WLTP3	Munich	10 %	1 h
$SOC_{\mathrm{T}}10\_t_{\mathrm{dd}}2$	WLTP3	Munich	10 %	2 h

TABLE I: Overview of the simulation parameters of the different scenarios.

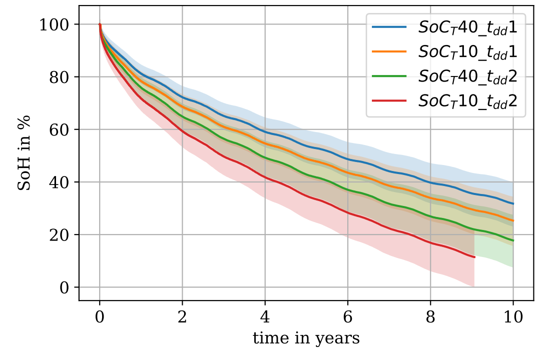


Fig. 7: Development of the battery pack's SoH over time. The solid line graphs the average SoH for each pack, while the transparent band covers the spectrum between minimum and maximum SoH.

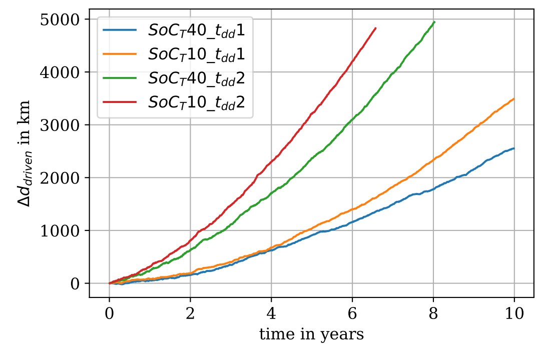


Fig. 8: Difference in total driving distance between the results from the preconditioning scenario and the reference scenario with SoC balancing, integrated over time.

that conventional SoC balancing was applied. This serves as a baseline to quantify the efficacy of the preconditioning method. Two metrics are of key interest. Firstly the amount of energy that can additionally be extracted from the battery pack during discharging, and subsequently the gained absolute driving range. Secondly the combined charging and balancing time as this represents the time during which the vehicle needs to remain plugged in to a charger.

Fig. 8 displays the difference in total driven distance between the scenarios with preconditioning and those without. The plots show that the preconditioning algorithm increases the total driven distance compared to the conventional balancing.

This increase in performance stems from the ability of the preconditioning algorithm to make the residual energy in all cells accessible, which would otherwise have been inaccessible with the conventional SoC balancing method, as discharging would have to be stopped as soon as one cell has reached its discharge cut-off voltage. The preconditioning algorithm, on the other hand conditions the cells before discharging, so that all cells reach their discharging cut-off voltage at the same time.

Moreover, the gradients of the graphs increase over time, which indicates that the benefits from preconditioning intensify with progressing aging. It is furthermore visible that higher vehicle utilization results in higher gains from the preconditioning. For the highest load scenario $SOC_{\mathrm{T}}10\_t_{\mathrm{dd}}2$ a total driving distance benefit of 3500 km after 5 years can be observed.

Fig. 9 charts the ratio of the total energy throughput of the scenarios with preconditioning and those without. It again is visible that the scenarios with high utilization exhibit a larger gain from the precondition due to the increased aging disparity. For the scenario $SOC_{\mathrm{T}}10\_t_{\mathrm{dd}}1$ a relative performance gain in energy throughput of 1.18 % after 10 years is visible.

Lastly, the ratio of the combined balancing and charging times between the scenarios with preconditioning and the reference scenarios is plotted in Fig. 10. For all scenarios a beneficial trend for the preconditioning method can be seen. This stems from the fact that the methods all but eliminates the balancing phase after the charging process, potentially cutting the charging time in half. It again is visible, that higher utilization yields higher gains from the preconditioning method. The reduction in time required for a full charge can be reduced by between 30 % and 70 % depending on the level of utilization.

We have shown that our proposed preconditioning method has beneficial impact for both charging time as well as usable capacity of a battery pack for all presented scenarios.

V. Conclusion

In this paper we proposed a novel approach to battery pack management for systems with Active Cell Balancing (ACB) architectures. ACB enables the transfer of charge from one cell to another. Conventionally, it is used to reactively balance State of Charges (SoCs) in a battery pack. We propose a proactive preconditioning algorithm that uses knowledge about the cells' State of Health (SoH) to derive a metric that can be used as the balancing target instead of the SoC. We are able to show that this shift increases the battery pack's total usable capacity while, at the same time, significantly reducing the time the pack needs to be connected to a power source. The concept was first introduced in [1] during the 22nd Euromicro Conference on Digital System Design (DSD). This paper conducts further investigation into the viability of the concept by simulating a variety of different usage scenarios in our combined battery aging and balancing framework. The scenarios vary the Depth of Discharge (DoD) as well as the daily driving distance during a charging/discharging cycle. The results from these simulations show, that preconditioning of the battery pack is effective in reducing the total time the pack must be connected to the grid during charging by up to 70 %. Further, it is established that, using preconditioning, the usable capacity drawn from the pack can be increased by 1.8 % when compared to conventional discharging. The remaining question now is the integration of the preconditioning algorithm in real world use case scenarios. And specifically the decision, whether to use the RME or RAE optimization target. However, this issue can be solved by observing the user's behavior, or it even becomes trivial for predetermined routes, such as in public transport applications. Overall, our findings confirm the results of the previous paper for the entire range of aging conditions of the battery pack.

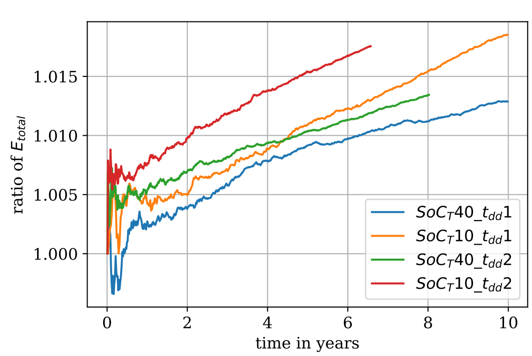


Fig. 9: Total energy throughput ratio of the preconditioning results and the reference scenario with SoC balancing, integrated over time.

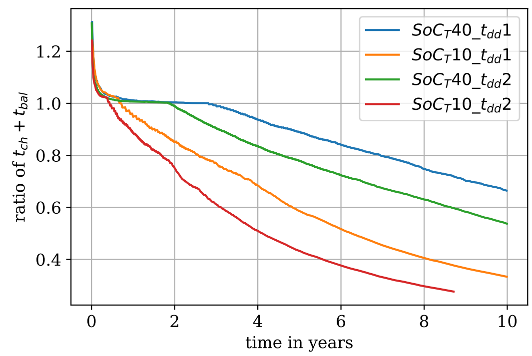


Fig. 10: Combined charging and balancing time ratio of the preconditioning results and the reference scenario with SoC balancing, integrated over time.

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