Enhancing Battery Pack Capacity Utilization in Electric Vehicle Fleets via SoC-Preconditioning

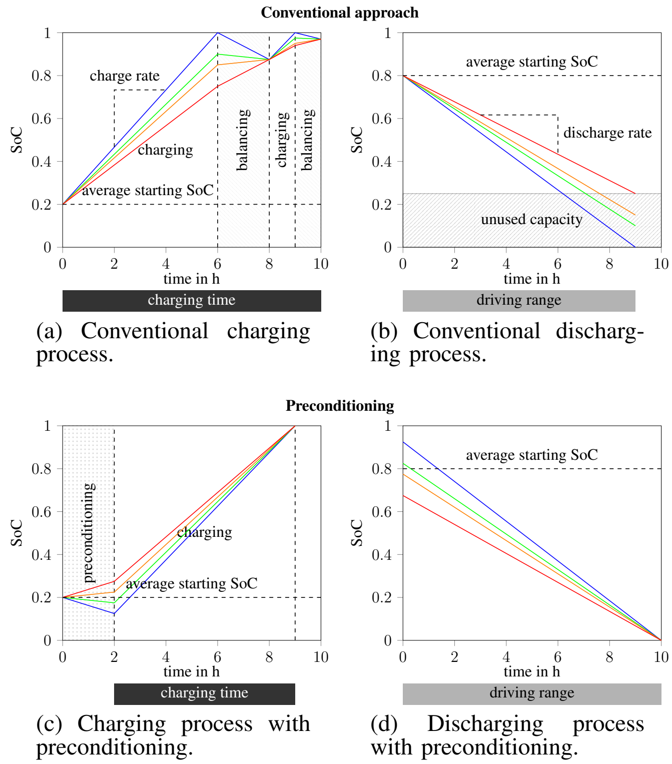
Alexander Lamprecht[1], Ananth Garikapati[2], Swaminathan Narayanaswamy[1], Sebastian Steinhorst[2]
[1]TUMCREATE, Singapore, alexander.lamprecht@tum-create.edu.sg
[2]Technical University of Munich, Germany

***Abstract*—Modern public transport solutions based on autonomous electric vehicles are on the rise. Public transportation as a service on demand is becoming a reality. Therefore, vehicles suitable for these kinds of applications need to be developed. One critical factor for such vehicles is a short turnaround time at the charging spot. Maximizing the utilization of a given battery pack capacity and minimizing the time spent charging are therefore of central importance. 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' charging rate to precondition them for achieving an equal time to full charge. Applying the same approach for discharging, we also extend the driving range of an EV, which otherwise is limited by the cell with the lowest SoC in the pack. Case studies show that our proposed preconditioning algorithm increases the usable energy of the battery pack by up to 3 % compared to conventional balancing algorithms all while effectively halving the time connected to a charging station, all without requiring any additional hardware components.**

I. Introduction and Related Work

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. The profitability of Battery Electric Vehicles (BEVs) thus 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 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 [1]. Moreover, due to variances in manufacturing and rate of aging, Li-Ion cells charge and discharge at different rates [2]. This effect accumulates charge in stronger cells over time and renders the pack unusable due to the diminishing overall usable capacity if not addressed.

This work was financially supported in part by the Singapore National Research Foundation under its Campus for Research Excellence And Technological Enterprise (CREATE) programme. With the support of the Technische Universität München - Institute for Advanced Study, funded by the German Excellence Initiative and the European Union Seventh Framework Programme under grant agreement n° 291763.



(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.

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 [3], [4]. However, this method necessitates additional circuitry containing temporary energy storage elements such as inductors, capacitors or transformers accompanied by MOSFETs.

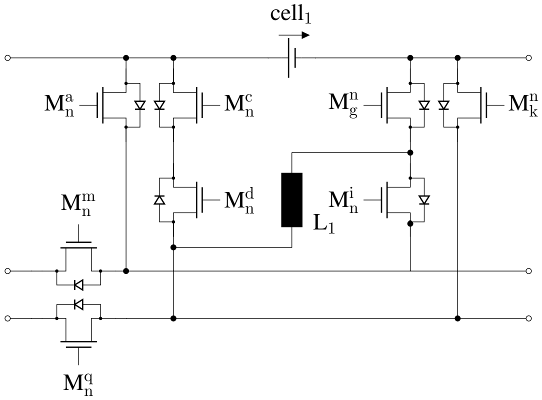


Fig. 2: The underlying non-neighbor ACB architecture of our evaluation framework consists of eight switches and one inductor.

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 [5]. 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 [6]. 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 Figure 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 Figure 1b) due to the different SoH values of the cells.

In this paper, we propose a novel ACB approach called *proactive SoC-preconditioning*. 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 all cells in the pack reach the minimum or maximum thresholds at the same time after discharging or charging. This is achieved by shifting the value that needs to be equalized from SoC to the time to fully charged t_{FC} or discharged t_{FD} for each cell in the pack by taking their SoH into account. Figure 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 Figure 1a is interrupted multiple times 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 during the usage of the vehicle, 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 [7]. 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).
- Based on the preconditioning algorithm, we implement a framework using the ACB architecture displayed in Fig. 2 to evaluate the performance of our proposed approach (Section III).
- Case studies performed with a synthetic usage scenario of a minibus like vehicle on a fixed route with 30 stops. We show that our proposed preconditioning algorithm increases the usable battery pack capacity by up to 4 % while reducing the time the EV needs to be connected to a charger by 17 % (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 know the future battery pack behavior, since the upcoming usage determines to what level the SoC of each cell should be set. Fortunately fixed routes in a public transport system have very consistent and repeating usage patterns which serve as the foundation for the decision making in the preconditioning process. Preconditiong yields these two options:
A) The provided range of the battery pack is sufficient to complete the trip and it therefore gets preconditioned so that at the end of the charging process after the trip all cells reach 100 % SoC simultaneously.
B) The provided range of the battery pack is not or barely sufficient and it therefore can be preconditioned so that all cells reach 0 % SoC simultaneously slightly increasing the range. The following section will detail the differences between these two options which we call preconditioning for charging and preconditioning for discharging.

We assume that the BMS is aware of the cell voltage, the cell current, the temperature, the SoC and the SoH of each cell in the pack, as this information is used to calculate the charging or discharging rate of the individual cells [8].

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].

[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 %.

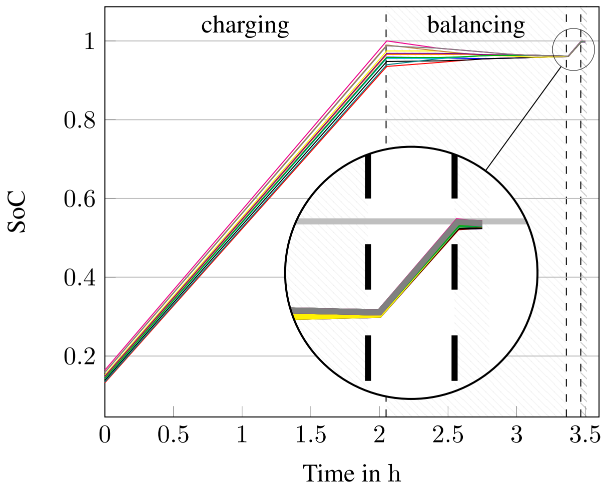


Fig. 3: Conventional charging process. Alternating charging and balancing phases to achieve full charge will extend the time the vehicles is connected to the charging station.

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.

Figure 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 SoH to predict the rate a particular cell charges at and, therefore, the time t_{FC} after which this cell would be fully charged with a given charging current. t_{FC} is calculated according to Equation 1 for all cells using the knowledge of their current SoC (represented by the remaining charge Q_{Batt}), the charging current i_{charge}, and the charge factor α_{charge} which represents the cells' internal resistance and overall capacity adjusted for aging (cyclic and calendaric) and temperature. All $t_{\mathrm{FC,j}}$, where j is the index of the respective cell, are stored in a list $\mathcal{T}$.

$$t_{\mathrm{FC,j}} = \frac{Q_{\mathrm{MAX}} - Q_{\mathrm{Batt}}}{i_{\mathrm{charge,j}} \cdot \alpha_{\mathrm{charge,j}}} \tag{1}$$

Instead of the cell's SoC we now use t_{FC} as the base of the preconditioning procedure. The preconditioning charge transfer strategy for charging, visualized in Figure 4, comprises the following steps:

1) Initialize the parameters of the battery pack and the single cells such as number of cells in series and parallel N_{s} and N_{p} as well as the SoC and SoH distribution.
2) Define pair List ($\mathcal{P}$), the set of pairs $p = (\sigma, \delta)$ where σ is the source and δ the destination cell for a charge transfer.
3) Determine source σ: The cell with the lowest t_{FC}.

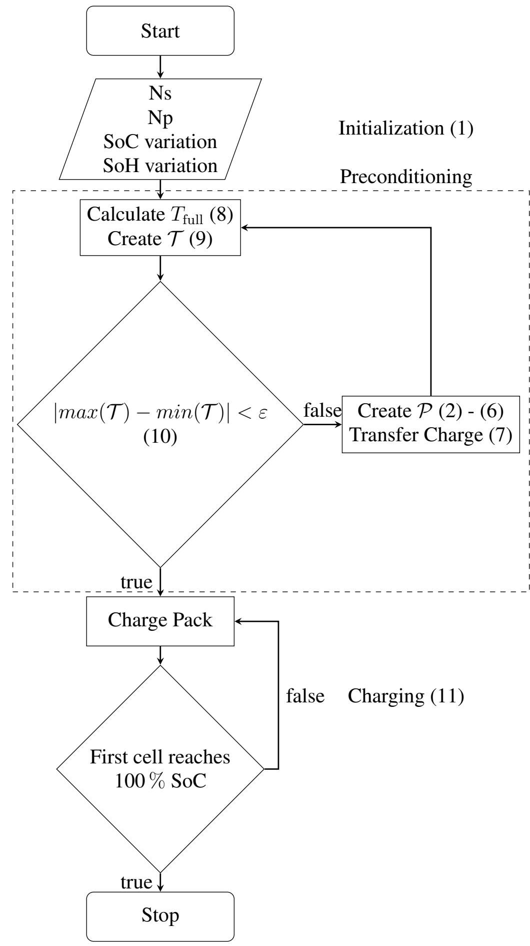
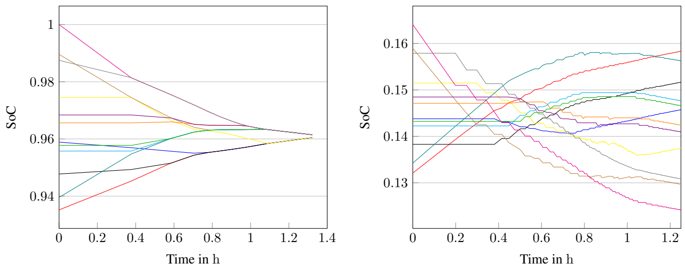


Fig. 4: The preconditioning algorithm highlighting the relevant steps in a charge cycle with preconditioning.

4) Pick destination δ: The range γ for picking the destination cell is limited by the architecture, charge transfer time and losses. Hence within the given γ on either side of the σ, the cell with the highest t_{FC} is picked as the destination.
5) The determined pair $p = (\sigma, \delta)$ is added to $\mathcal{P}$ and all cells in the closed interval $[\sigma, \delta]$ are removed from the time list $\mathcal{T}$.
6) The above steps are repeated till $\mathcal{P}$ can no longer be populated further.
7) Once $\mathcal{P}$ is populated, charge transfers between all pairs are executed.
8) Resulting SoC values are estimated and the other parameters such as t_{FC} are updated.
9) The time list $\mathcal{T}$ is then updated.
10) The maximum and minimum values are checked against a predefined threshold ε. Should the value be higher than ε, the process is repeated till the t_{FC} of all batteries are equalized.
11) Charge the battery pack until full, which is now possible in one run, maintaining a low variation due to the preconditioning.

After the preconditioning process, the time to full (t_{FC}) charge for all cells are equalized, though their respective SoC may vary widely. Figure 5b displays the SoC development of the cells during this preconditioning process, compared to a



(a) Conventional Balancing (b) Preconditioning

Fig. 5: SoC development during a) conventional balancing and b) preconditioning.

conventional ACB shown in Figure 5a. 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 (CC) charging phase and omit the Constant Voltage (CV) phase considering the current trend to fast charging. Figure 6 shows the preconditioning phase with subsequent 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. In our example it results in a reduction from 3.5 h to slightly more than 2 h or 40 %.

B. Preconditioning for Discharging

Similar to the charging process, the battery pack can be preconditioned for discharging. Therefore, we define a parameter t_{FD}, which is calculated according to Equation 2 that depends on the current SoC, the predicted average discharging current $i_{\mathrm{discharge,j}}$, and the discharge factor $\alpha_{\mathrm{discharge,j}}$.

$$t_{\mathrm{FD,j}} = \frac{Q_{\mathrm{Batt}}}{i_{\mathrm{discharge,j}} \cdot \alpha_{\mathrm{discharge,j}}} \tag{2}$$

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' t_{FD} are equalized. This ensures that the discharging of the battery pack results in all cells reaching 0 % SoC at the same time.

III. Analysis and Evaluation Framework

This section introduces the evaluation model which was implemented to test the proposed preconditioning algorithm and to compare it with conventional methods. The simulation itself is implemented in Python as a discrete-event based simulation. Therefore, rather than simulating all parameters of the system behavior for each time step, discrete events are recorded and the time lapsed is calculated and added to the entire simulation time. This allows dealing with multi-timescale simulations and speeds up simulation times considerably. The simulation is considered multi-timescale because the interactions at the balancing architecture level are in the micro- to milliseconds range, while the charging or discharging processes can be in the range of hours.

Our simulation model consists of four layers. The first layer a) comprises of the battery cell model. The overlying layer b) groups multiple cells in series to form a battery pack. The individual cells are connected to the ACB architecture, which forms the third layer c). The fourth layer d) consists of the

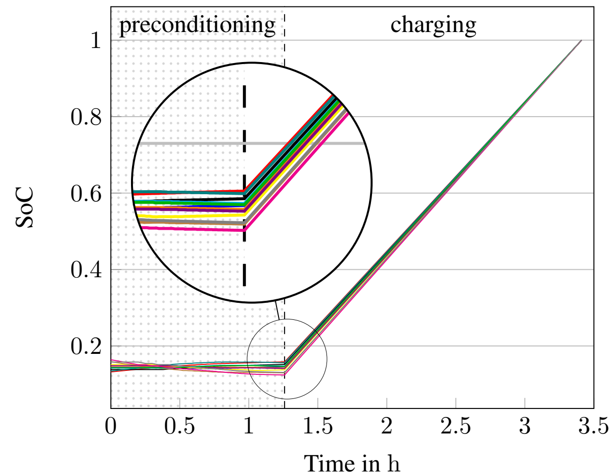


Fig. 6: Preconditioning process. The preconditioning phase (dotted) is followed by only one charging phase resulting in all cells of the battery pack to be fully charged at once.

charge transfer strategy which manages the charge transfer between the battery modules.

a) Cell Model: To model the cells in our framework, a Samsung INR18650-25R Li-Ion cell with a nominal voltage of 3.6 V, nominal capacity of 2.5 Ah and an internal resistance of 22.15 mΩ [9] was chosen. In order to provide the necessary current to drive an electric vehicle, multiple of these cells need to be connected in parallel to form a battery module. The model of these battery modules contains the values for the SoC of the cells, their respective SoH, which we assume can be computed with adequate precision [10], as well as the number of cells in parallel N_{P}.

b) Battery Pack: Connecting multiple battery modules in series results in a battery pack. This is necessary to obtain the voltage required to operate the electric drive of an BEV. In this paper, we use the specifications of the BMW i3's 2106 battery pack as our models parameters. We therefore define a battery pack in 96S24P configuration with a module capacity of 60 Ah, a voltage of 351.4 V, and a total pack capacity of 21.1 kWh.

Besides these parameters, the battery pack model is able to calculate the overall capacity, the remaining t_{FC} and t_{FD} as well as the remaining range based on the WLTC Class 3 drive cycle [11].

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

Based on this architecture, for each charge transfer, equivalent circuit models for the sending cell σ and the receiving cell δ are derived. This allows us to calculate the equivalent ohmic resistances R_σ and R_δ of the sending and the receiving circuit consisting of the inner resistance R_{Batt}, the resistance of the inductor R_{ind} and the resistance of the MOSFETs R_{MOSFET}.

$$\begin{aligned} R_\sigma &= R_{\text{Batt}} + R_{\text{ind}} + 3 \cdot R_{\text{MOSFET}} \\ R_\delta &= R_{\text{Batt}} + R_{\text{ind}} + (3 + 2 \cdot d) \cdot R_{\text{MOSFET}} \end{aligned} \tag{3}$$

The variable d describes the distance between the sending and the receiving cells. Besides the ohmic losses generated during the charge transfer process, the switching losses generated by the MOSFETs are calculated. The value for the desired balancing current directly dictates the duty cycle. The number of necessary cycles is given by the amount of charge that needs to transferred and the amount of charge that can be transferred in a given cycle. For active cell balancing it is implemented by calculating the difference between the charge content in the source Q_σ and the destination Q_δ, and the effective charge that is transferred in a cycle.

$$n_{\text{cycles}} = \frac{(Q_\sigma - Q_\delta)}{(Q_{\text{efftx}} + Q_{\text{efftrx}})} \tag{4}$$

Q_{efftx} is the effective charge transferred and received after subtracting switching losses.

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 facilitates 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 [12]. A typical example of such a charge balancing process is displayed in Fig. 5a.

IV. Case Study

In this section the effectiveness of the preconditioning algorithm in a real world scenario is evaluated. Therefore, a round trip of a minibus-like vehicle with a 21.6 kWh battery pack with a 96S24P configuration with synthetic drive cycle is simulated, and the performance of the preconditioning algorithm is analyzed. The framework is able to use arbitrary drive cycles as the underlying basis of the trip simulation. It's therefore possible to compare different use case scenarios.

The simulated round trip consists of 30 stations with 1 km between each stop. At each station, the vehicle stops for 1 minute. During discharging the battery pack can either perform preconditioning, conventionally balance, or be idle. At the beginning of the trip the battery pack is at 100 %. The cells of the battery pack are set to have an SoH of 80 % with a random spread of 0.5 %. All simulations use the same random seed to guarantee reproducibility. After completion of the round trip the vehicle returns to the charging station and the battery pack gets charged with an ultra-fast charger and, if necessary, balanced. The time it takes to complete the charging/balancing procedure is then compared for the three scenarios. Therefore we set the parameters for the usage pattern to be:

- round trip distance: 31 km
- stationary time at stops: 1 min
- charging after each completed round trip

Fig. 7 displays the resulting SoC distribution of the battery pack for the three scenarios discharging (Fig. 7 top), discharging with ACB (Fig. 7 center), and discharging with preconditioning for charging (Fig. 7 bottom) during the entire round trip. It is visible that the duration of the charging and

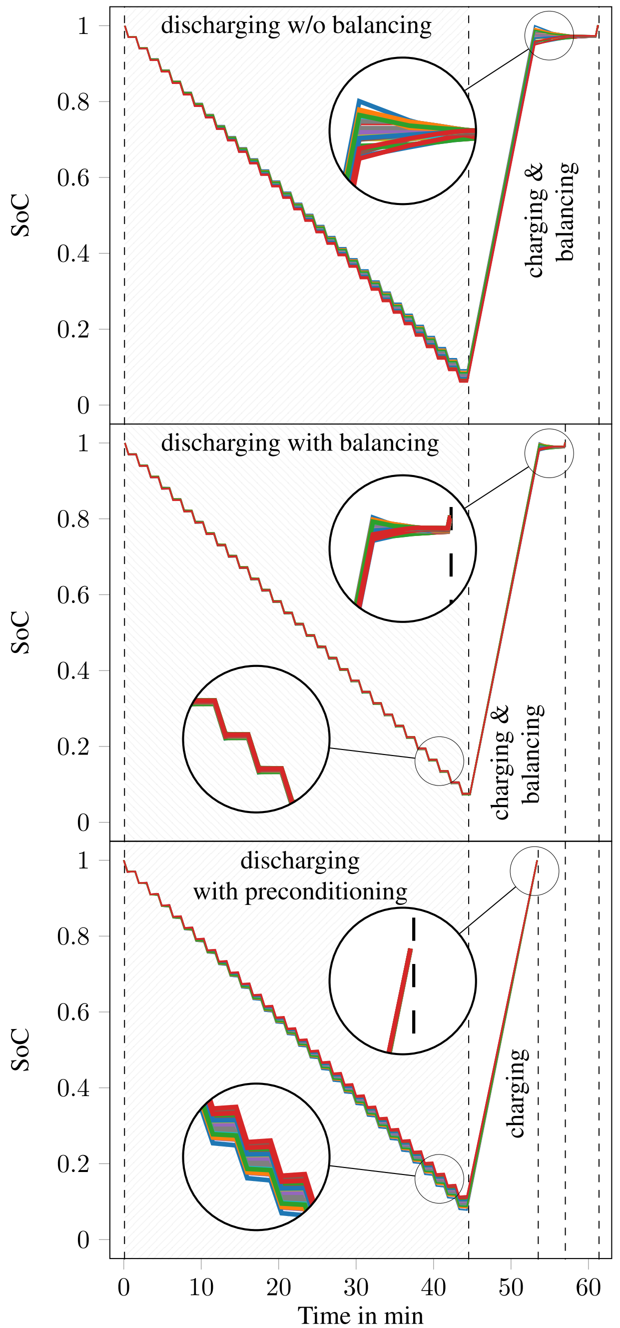


Fig. 7: Development of the cell's SoC during a round trip with 31 stops and subsequent charging phase. **Top**: discharging with subsequent charging and balancing phase. **Center**: discharging with balancing and subsequent charging and balancing phase. **Bottom**: discharging with preconditioning for minimized charging time and subsequent charging phase. No balancing required while charging.

balancing phase at the end of the trip depends on the scenario. Balancing during discharging reduces the total time connected to a charging station by 25.7 % compared to just discharging. The bottom part of Figure 7 shows that our proposed preconditioning approach, however, removes the balancing phase entirely, resulting in a reduction of the time spent at the charging station by 48.6 %. These results mainly arise from the fact that

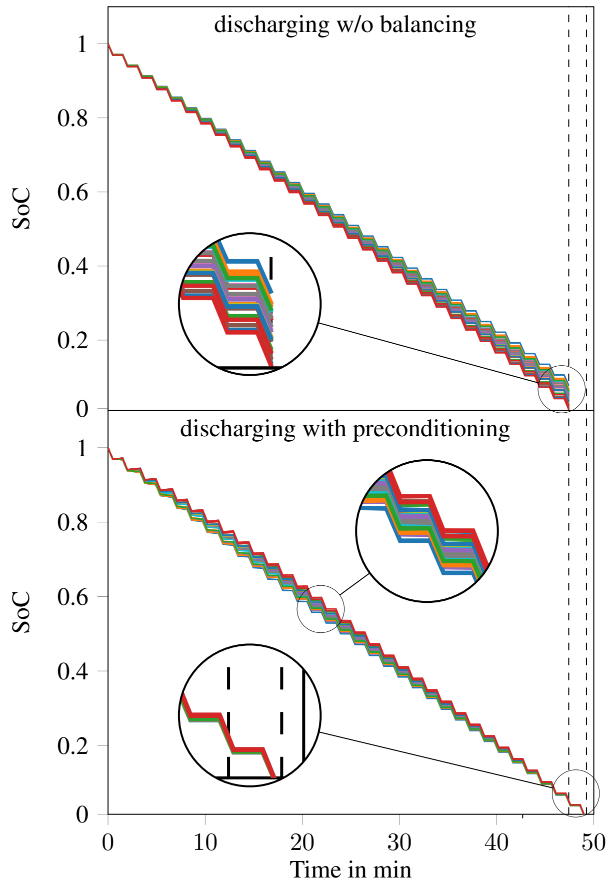


Fig. 8: Development of the cell's SoC during discharging. **Top**: discharging conventionally. **Bottom**: discharging with preconditioning for maximized capacity.

the charging current is magnitudes higher than the balancing current. This results in the inability to mitigate the spreading of the cells SoCs by reactive balancing alone and gives a substantial advantage to the preconditioning approach due to utilizing the time before charging to proactively counteract the spreading effect.

Besides the simulation for an entire round trip, another simulation is performed to evaluate the impact of preconditioning for discharging. This time, the focus is on maximizing the overall energy output of the battery pack. Therefore, the same discharge profile as the previous simulation is used but altered to keep discharging until the first cell reaches 0 % SoC. The resulting difference in discharge time and, therefore, range between conventional discharging and discharging with preconditioning for discharging are compared. Fig. 8 shows the results of these calculations. It is visible that the preconditioning approach allows to use the entire energy of the battery pack by draining all cells to 0 % SoC whereas the conventional discharging results in unused energy remaining in the pack, that cannot be used without overdischarging cells. In this example the preconditioning approach increases the range by 1 km or 3 %.

V. Conclusion

In this paper we propose a novel approach to battery pack management for systems with ACB architectures. ACB enables the transfer of charge from one cell to another. Conventionally, it is used to balance SoCs in a battery pack. We propose a proactive preconditioning algorithm that uses the remaining time until fully charged or discharged as the balancing target instead of the cell's 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. A modular simulation framework was designed and implemented to test and validate the concept. We chose the state-of-the-art architecture from [5] for our evaluation. The framework is designed modularly, which allows us to easily compare different configurations and architectures. With the results from this simulation framework and a realistic use case, we are able to 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 48.6 %. Further, it is established that, using preconditioning, the usable capacity drawn from the pack can be increased by 3 % when compared to conventional discharging. Even though these results are just representing this specific use case, it has been shown that the preconditioning approach is generally beneficial for charging time and usable capacity and is superior to conventional balancing.

Future work could encompass evaluation of the influence of the preconditiong algorithm in different driving conditions, namely a comparison between different driving cycles. A long term evaluation including battery deterioration could yield insight on the benefits for battery life and economic viability. Furthermore, the viability for application in private BEV can be investigated, as they have lower usage hours and present challenges in predicting their usage in general.

References

[1] M. A. Hannan, M. M. Hoque, A. Hussain, Y. Yusof, and P. J. Ker, "State-of-the-Art and Energy Management System of Lithium-Ion Batteries in Electric Vehicle Applications: Issues and Recommendations," *IEEE Access*, vol. 6, pp. 19362–19378, 2018.

[2] G. Lacey, T. Jiang, G. Putrus, and R. Kotter, "The effect of cycling on the state of health of the electric vehicle battery," in *Proc. of UPEC*, pp. 1–7, Sept 2013.

[3] M. Einhorn, W. Roessler, and J. Fleig, "Improved Performance of Serially Connected Li-Ion Batteries With Active Cell Balancing in Electric Vehicles," *IEEE Transactions on Vehicular Technology*, vol. 60, pp. 2448–2457, jul 2011.

[4] S. Narayanaswamy, S. Park, S. Steinhorst, and S. Chakraborty, "Multi-pattern active cell balancing architecture and equalization strategy for battery packs," in *Proc. of ISLPED*, pp. 43:1–43:6, 2018.

[5] M. Lukasiewycz, M. Kauer, and S. Steinhorst, "Synthesis of Active Cell Balancing Architectures for Battery Packs," *IEEE Transactions on Computer-Aided Design of Integrated Circuits and Systems*, vol. 35, no. 11, pp. 1876–1889, 2016.

[6] S. Narayanaswamy, M. Kauer, S. Member, S. Steinhorst, M. Lukasiewycz, S. Chakraborty, and S. Member, "Modular Active Charge Balancing for Scalable Battery Packs," *IEEE Transactions on Very Large Scale Integration (VLSI) Systems*, pp. 1–14, 2016.

[7] W. Li, L. Kang, X. Guo, and Y. Yao, "Multi-Objective Predictive Balancing Control of Battery Packs Based on Predictive Current," *Energies*, vol. 9, p. 298, apr 2016.

[8] C. Zhang, F. Yan, C. Du, J. Kang, and R. Turkson, "Evaluating the Degradation Mechanism and State of Health of LiFePO4 Lithium-Ion Batteries in Real-World Plug-in Hybrid Electric Vehicles Application for Different Ageing Paths," *Energies*, vol. 10, no. 1, p. 110, 2017.

[9] Samsung SDI, "INR18650-25R Datasheet," 2013.

[10] L. W. Juang, P. J. Kollmeyer, T. M. Jahns, and R. D. Lorenz, "Improved modeling of lithium-based batteries using temperature-dependent resistance and overpotential," *2014 IEEE Transportation Electrification Conference and Expo (ITEC)*, pp. 1–8, 2014.

[11] E. A. Grunditz and T. Thiringer, "Characterizing BEV powertrain energy consumption, efficiency, and range during official and drive cycles from Gothenburg, Sweden," *IEEE Transactions on Vehicular Technology*, vol. 65, no. 6, pp. 3964–3980, 2016.

[12] M. Kauer, S. Naranayaswami, S. Steinhorst, M. Lukasiewycz, S. Chakraborty, and L. Hedrich, "Modular system-level architecture for concurrent cell balancing," in *Proc. of DAC*, pp. 1–10, 2013.