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Defining Power Ability Curves for a Heterogeneous Multi Pack Battery System

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Executive Summary

This study aims to investigate the power reduction phenomena in heterogeneous battery pack configurations that arise due to an uneven current split, focusing on defining the power ability curves for the mixed system. Multiphysics based system model has been developed to investigate the factors contributing to power loss when the aged packs are mixed with fresh packs. Different methods are proposed to estimate the power retention curves for one and two fresh packs mixing into the homogeneous system. Having power ability curves for a heterogeneous multi pack system helps in defining the decision-making strategies for refurbishment of ESS during replacement and maintenance activities. Some strategies are introduced at the end to conduct the most conservative estimations while pack mixing.

Keywords: Energy storage systems, Modelling & Simulation, Retrofitting EVs, Recycle & re-use, Energy Management

1 Introduction

The escalating demand for electric vehicles (EVs) has resulted in considerable advancements in battery technologies, with a focus on improving performance, energy utilization, and overall efficiency [2]. With the introduction of electrified heavy commercial vehicles and Battery Energy Storage Systems (BESS) for the grid, there is an increased need for scalable ESS with multiple battery packs in one system [3] [4]. Due to different user demands, for instance, higher energy, greater power, or longer cycle life, the optimal number of packs installed in an ESS may vary between users. In addition to adaptable performance, a scalable system also provides advantages such as redundancy and simplified serviceability.

In some instances, one or a few packs in a system could be replaced if they become damaged in a traffic accident or if an increase in usable energy is needed due to the capacity fading of the installed packs. Capacity fade is still a significant challenge in energy storage systems, and it is common for cells to lose 20 - 30 % of their nominal capacity over their useful life [5]. Hence, unless heterogeneous system performance is evaluated correctly, all packs might need replacement, even though only one is damaged. Hence, unless heterogeneous system performance can be properly evaluated, there might be a need to replace all packs even though only one is damaged.

Installing battery packs to the BESS at different time span enables systems to grow in capacity gradually. This would result in a heterogeneous system with packs at multiple different SOHs, and the power performance of such a system needs to be easily communicated and understood. It also supports circular design principles, helping achieve sustainability targets [6]. Battery packs that are not fit for the high energy density applications can still be useful where volumetric constraints are less strict [7]. Scalable and flexible multi-pack systems, therefore, offer significant benefits and enable very efficient resource utilization. However, these mixed configurations introduce new engineering complexities, such as uneven current distribution among packs [8], misalignment in OCV-SOC curves, thermal management challenges [9], and varying degradation rates among the different cells.

The performance of heterogeneous multi-pack systems is influenced by multiple factors, including power losses, capacity utilization, and thermal effects, all of which can reduce overall system efficiency [10]. Understanding the power reduction mechanisms within these configurations is essential to optimize their performance and ensure the longevity of the battery system. Power drop due to mismatched internal resistances, capacities or OCV's leading to unequal current distribution, which can significantly impact the overall power output of the system [11] [12].

This study aims to investigate the power reduction phenomena in mixed battery pack configurations, focusing on key performance attributes such as resistance, capacity, and OCV. By analyzing the factors that contribute to power unavailability, the research seeks to identify a high-level metric to efficiently communicate power capability of a mixed battery systems. The findings will provide valuable insights into the design and management of battery systems in electric vehicles, contributing to the development of more efficient and sustainable energy storage solutions. Conventional power curves or tables for batteries usually assume static preconditioning. Since a heterogeneous multi-pack system can experience varying power drops across its SOC window, depending on how the current SOC was reached, our new method is needed to properly illustrate the power capability of the full system.

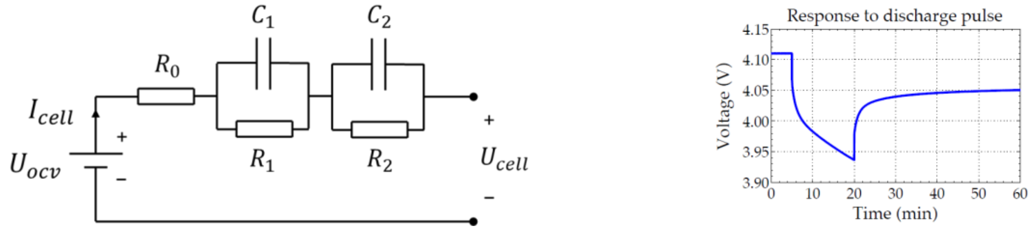
2 Methodology

In this section, the detailed methodology is discussed. The mathematical model is included to describe the coupled electrothermal model of the battery. In model overview, the MATLAB model for multipack battery system is discussed. Afterwards, simulation overview is explained with focus on process flow of the study, simulation use cases and load profiles considered in the analysis.

2.1 Mathematical Modelling and Model Overview

This study presents a coupled battery electrothermal model, where a 2RC Equivalent Circuit Model (ECM) is integrated with the thermal model to accurately predict battery behavior under varying conditions.

The ECM model has been used to simulate the dynamic electric behavior of the battery. The model incorporates two resistor-capacitor (RC) networks to capture the transient response and predict battery performance under various dynamic conditions. The 2RC model consists of open-circuit voltage U_{ocv} with charge/discharge hysteresis. It is the steady state voltage across the battery terminals when no load is connected. Instantaneous resistance R_0 causes an instant voltage drop when the load is connected. The two RC Networks as shown in Fig 1: R_1 represent the first polarization resistance accounts for the activation overpotential from the chemical reaction at the interface of the electrodes and C_1 models the short-term energy storage capability of the battery due to double layer formation at the electrode interface.



(a) (b)

Figure 1: (a) 2RC Equivalent Circuit Model (ECM), (b) voltage polarization during discharge pulse [1]

For second RC Network (R_2 and C_2), where R_2 represents the second polarization resistance due to concentration overpotential in the battery. The time constant $\tau_1 = R_1C_1$ and $\tau_2 = R_2C_2$ defines the time required to charge/discharge the capacitor through resistance. The $\tau_1$is smaller than τ_2, as the concentration overpotential evolves slower than activation overpotential.

The current across the RC circuit can be written as,

$$I_{cell}(t) = I_{R1}(t) + I_{C1}(t) \tag{1}$$

Where current across capacitor C_1 can be written,

$$I_{C1}(t) = C_1 \frac{dV_{C1}(t)}{dt} \text{ , } also\ V_{C1}(t) = V_{R1}(t) = R_1 I_{R1}(t) \tag{2}$$

From equations 1 and 2,

$$I(t) = I_{R1}(t) + C_1 R_1 \frac{dI_{R1}(t)}{dt} \tag{3}$$

Also rewriting the equation 3 to solve for $I_{R_{1,2}}(t)$

$$\frac{dI_{R_{1,2}}(t)}{dt} = -\frac{1}{R_{1,2}C_{1,2}} I_{R1,2}(t) + \frac{1}{R_{1,2}C_{1,2}} I(t) \tag{4}$$

The terminal voltage is estimated using,

$$U_{cell}(t) = U_{ocv} - I(t)R_0 - R_1 I_{R_1}(t) - R_2 I_{R_2}(t) \tag{5}$$

Initially, the model is calibrated using parameter estimation techniques by optimizing the RC parameters $R_{0,1,2}(SOC), C_{1,2}(SOC)$. Such that the model output matches closely with the experimental data such as terminal voltage, SOC and OCV.

The battery SOC is estimated by coulomb counting method, which integrates the current over time to estimate the charge transfer.

$$Q(t) = Q(0) + \int_0^t I(t)dt \tag{6}$$

Where, $Q(t)$ is the charge at time (t), and $Q(0)$ is the initial charge.

SOC is estimated using the relationship between charge and capacity such that

$$SOC(t) = \frac{Q(t)}{Q_{max}} \times 100 \tag{7}$$

Where, Q_{max} is the maximum charge/discharge capacity of the battery.

The system voltage U_{sys} for N_p parallel strings and N_s series battery packs is estimated from cell voltage,

$$\frac{I_{sys}}{N_p} = I_{cell} \xRightarrow{Cell\ model} U_{cell} \text{ , } U_{cell}N_s = U_{sys} \tag{8}$$

Battery performance and its characteristics such as internal resistance and capacity are significantly influenced by the temperature. So, by integrating a thermal model with the battery electrical model is a sophisticated approach that allows for a more comprehensive understanding of battery behavior under various conditions. As the Thevenin 2RC model simulates the battery's voltage and current behavior, incorporating resistive and capacitive elements. The thermal model calculates the battery's temperature based on heat generation and dissipation, using the energy equation:

$$\rho C_p \frac{\partial T}{\partial t} = \nabla.(K.\nabla T) + Q_{gen} \tag{9}$$

Where ρ is the density, C_p is the specific heat capacity, K is the thermal conductivity, T is the temperature of the battery. The rate of irreversible heat generation Q_{gen} during charging/discharging can be calculated using,

$$Q_{gen} = I^2(R_0) + abs(IdV_{R1}) + abs(IdV_{R2}) \tag{10}$$

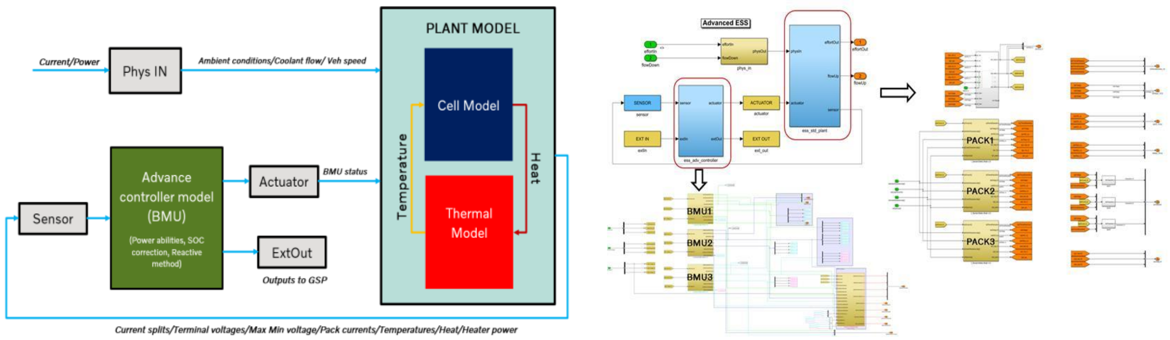
The battery temperature influences the electrical model parameters R_0, R_1, C_1, R_2 & C_2 defined as functions of SOC and temperature in a 2D lookup table:

$$R_{0,1,2} = f_n(SOC, T) \tag{11}$$

$$C_{1,2} = f_m(SOC, T) \tag{12}$$

The simulation study is conducted using MATLAB Simulink, where the energy storage system (ESS) model comprises a plant model and an advanced controller model (BMU) as shown in Fig.2. The plant model includes a cell model coupled with a thermal model. The cell model is developed using ECM 2RC method [1], while the thermal model is a reduced-order representation of the battery pack, capturing thermal dissipation and heat generation to study temperature evolution in the cell and pack under varying conditions.

The plant model is connected to an advanced controller model, commonly referred to as the BMU, for each battery pack in a multi-pack system as shown in Fig.2(b). This controller implements strategies such as voltage-current balancing and lookup-based SOC-temperature-current dependent power abilities, which defines the performance based on the demanded c-rate. Additionally, the system SOC is estimated by weighted average based sliding SOC method. Such that it equals the highest packs SOC at high SOC, the lowest pack SOC at low SOC. The system operates in a closed loop, where key parameters such as pack voltage, temperature, cell resistance, pack current and power abilities are interdependent.



2(a) 2(b)

Figure 2: (a) Model overview, (b) Multipack Battery Model in MATLAB

Each pack configuration differs with certain parameters like state of health (SOH), available cell capacity (SOQ), cell resistance (SOR), open circuit voltage (OCV) and corresponding performance abilities. The total system current is split into individual pack current based on voltage current balancing algorithm which works on voltage equalization principle as the packs are connected in parallel.

The multipack controller fuses the multiple power abilities into one ability for the whole system. Actual current split will decide how much power can be withdrawn from the system without violating any single pack's power ability. The system current limit during operation can be defined as (Eq. 13).

$$I_{ESS}^{lim} = \frac{I_{ESS}}{\max\left(\frac{I_{BP_{1-6}}}{I_{BP_{1-6}}^{lim}}\right)} \tag{13}$$

Two different methods are used to calculate the current split among the different packs with indistinguishable results. The first method utilizes analytically derived equations to calculate the current split from each packs R_0 and "$OCV_{instant}$", where the instant OCV is the sum of both the traditional steady state OCV term and the potential across the R_1 and R_2 resistances. The pack current I_j for the j^{th} pack in parallel system is the summation of individual pack current based on Kirchhoff's law [1].

ESS system current can be expressed as in (Eq. 14).

$$I_{ESS} = \sum_{j=0}^{N_p-1} I_j = U_{ess} \sum_{j=0}^{N_p-1} \frac{1}{R_j} - \sum_{j=0}^{N_p-1} \frac{U_{ocvInst,j}}{R_j} \tag{14}$$

The pack current is defined from Ohms law and (Eq. 14) can be described as in (Eq. 15).

$$I_j = \frac{\frac{\sum_{j=0}^{N_p-1} \frac{U_{ocvInst,j}}{R_j} + I_{ESS}}{\sum_{j=0}^{N_p-1} \frac{1}{R_j}} - U_{ocvInst,j}}{R_j} \tag{15}$$

The current distribution between the battery packs depends on their capacity, resistance and OCV. Capacity dependence is represented indirectly in terms of OCV change.

The other method is used to calculate the current split by numerically finding the current that gives voltage balance in accordance with Kirchoff's Voltage Law defined in Eq (16). Where a current split is calculated such that the limit of $f(z)$ tends to zero. This method allows for direct application on any battery model without extraction of R_0 and $OCV_{instant}$ and is accurate, but slightly slower than the first approach.

$$V_1 - V_2 = f(z) \text{ such as } \lim_{V1-V2} f(z) \rightarrow 0 \text{ and } \Delta V = 0 \tag{16}$$

The percentage power retention of heterogeneous mixed battery system is estimated using,

$$Power\ Retention\ \% = \left(\frac{P_{avg,heterogeneous}}{P_{avg,baseline}}\right)_{SOH} \tag{17}$$

2.2 Simulation overview and ways of estimating aged pack characteristics

The study adheres to the process flow chart outlined in Fig. 3. It commences with the definition of requirements, including use cases, pack State of Health (SOH), State of Charge (SOC) window, and system current. Based on these requirements, an appropriate modeling method is selected, such as the scaled, aged, or interpolation method. In the scaled method, the State of Resistance (SOR) of the pack is adjusted using a multiplication factor defined at the pack SOH. The aged method utilizes data from aged cells to model cell behavior. The interpolation method involves interpolating aging data between available aging test data. Subsequently, power attributes are collected and processed to eliminate system noise. Thereafter, the maximum, minimum, and average capabilities are extracted to assess power retention. From the power retention curve, a replacement matrix is formulated for all simulation use cases, facilitating decision-making. If the method satisfies the decision-making criteria, the process flow concludes; otherwise, feedback is provided to the requirements to continue the process for other simulation cases.

Simulations are conducted on both homogeneous and heterogeneous multi-battery pack systems to facilitate systematic study. A homogeneous system consists of a multipack configuration where all packs maintain the same State of Health (SOH) level, serving as the baseline cases for comparison with the heterogeneous system. In contrast, heterogeneous systems comprise a mixed pack configuration, featuring one or two packs fresh pack mixed with different baseline SOH levels.

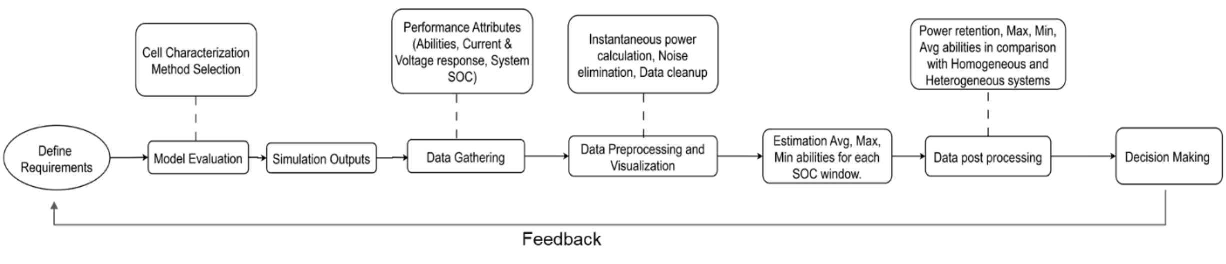


Figure 3: Simulation process flow chart

Various combinations of simulation use cases are presented, including one or two packs mixed with pack SOH at End of Life (EOL), Beginning of Life (BOL), and Middle of Life (MOL). The simulation methods employed include scaled, aged, and interpolation models, with load cycles categorized as 1. pulse discharge, 2. pulse charge, 3. cyclic discharge, and 4. cyclic charge, as detailed in Tables 1 and 2 below.

Table 1: Homogeneous system simulation cases

<table>
<tr><td colspan="36">Homogeneous system</td></tr>
<tr><td colspan="4">EOL</td><td colspan="4">BOL</td><td colspan="4">MOL</td><td colspan="4">EOL</td><td colspan="4">BOL</td><td colspan="4">MOL</td><td colspan="4">EOL</td><td colspan="4">BOL</td><td colspan="4">MOL</td></tr>
<tr><td colspan="12">Scaled Model</td><td colspan="12">Aged Model</td><td colspan="12">Interpolation Model</td></tr>
<tr><td>1</td><td>2</td><td>3</td><td>4</td><td>1</td><td>2</td><td>3</td><td>4</td><td>1</td><td>2</td><td>3</td><td>4</td><td>1</td><td>2</td><td>3</td><td>4</td><td>1</td><td>2</td><td>3</td><td>4</td><td>1</td><td>2</td><td>3</td><td>4</td><td>1</td><td>2</td><td>3</td><td>4</td><td>1</td><td>2</td><td>3</td><td>4</td><td>1</td><td>2</td><td>3</td><td>4</td></tr>
</table>

1----> Pulse Discharge
2----> Pulse Charge
3-----> Cyclic Charge
4-----> Cyclic Discharge

Table 2: Heterogeneous system simulation cases

<table>
<tr><td colspan="72">Heterogeneous System</td></tr>
<tr><td colspan="36">1 Pack</td><td colspan="36">2 Packs</td></tr>
<tr><td colspan="4">EOL</td><td colspan="4">BOL</td><td colspan="4">MOL</td><td colspan="4">EOL</td><td colspan="4">BOL</td><td colspan="4">MOL</td><td colspan="4">EOL</td><td colspan="4">BOL</td><td colspan="4">MOL</td><td colspan="4">EOL</td><td colspan="4">BOL</td><td colspan="4">MOL</td><td colspan="4">EOL</td><td colspan="4">BOL</td><td colspan="4">MOL</td><td colspan="4">EOL</td><td colspan="4">BOL</td><td colspan="4">MOL</td></tr>
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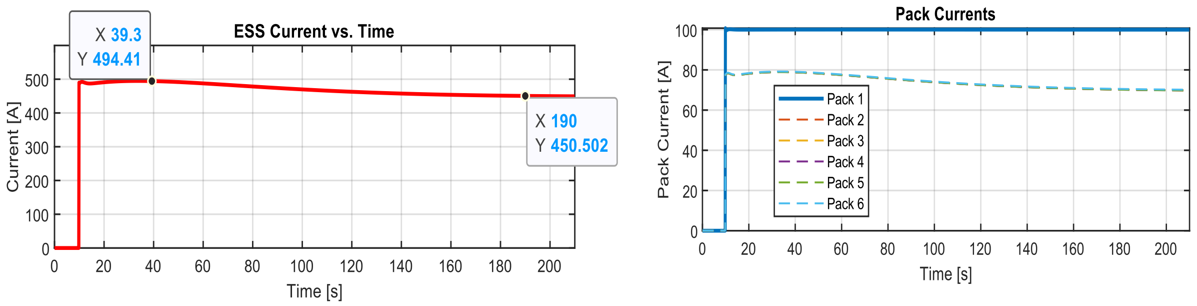
3 Results & Discussion

In this study, approximately 108 simulation scenarios were assessed to examine the performance degradation caused by different combinations, including the number of incoming packs, cell characterization methods, State of Health (SOH) metrics, and current profiles.

3.1 Pre-study: Dynamic Behavior of a Heterogeneous ESS

A single pack with a simple cell configuration such as 200s1p still usually shows a very dynamic power ability which is strongly dependent on cell temperatures, SOC and charge/discharge history. Traditionally, the power ability for a system is communicated by a certain available pulse length power at a given SOC and temperature. A continuous power ability is usually given for each SOC and temperature that corresponds to the power ability at that temp and SOC, regardless of how the battery reached that state. In a heterogeneous multi-pack system, the concept of continuous power ability doesn't transfer to the fused multi-pack power ability. Even when the multi-pack controller relies solely on the continuous abilities communicated by each pack, there will still be significant dynamics of the full ESS power ability, and the system will be sensitive to how it reached the state defined by temp and SOC.

Fig. 4, shows the pack and system current at 50 % SOC for a heterogeneous system of 6 battery pack of 200s1p configuration, where 1 pack at SOH=100% and SOR=100% is mixed with 5 packs at SOH=80% and SOR=150%. With a pack limit of 100 A, a homogeneous 6 pack system would be able to deliver 600A. However, the heterogeneous system can deliver close to 500A initially, but within 3 minutes this current ability has dropped to ~450 A, since the fresh pack is hitting its peak current. This even though each pack allows 100A each for the whole charge pulse. This is evidence that the uneven current splits can limit the system to operate at its full abilities. Hence, the sum of the continuous abilities isn't enough, but a new metric is needed for communicating the power ability for a heterogeneous multi-pack system at different SOCs and temperatures. A battery model could always be used together with a use case to accurately predict the power ability, but to facilitate communication of the system performance something similar to traditional power ability curves is needed.

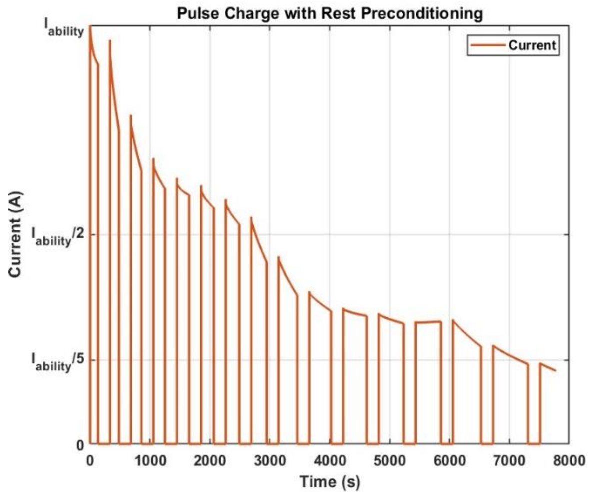


4(a) 4(b)

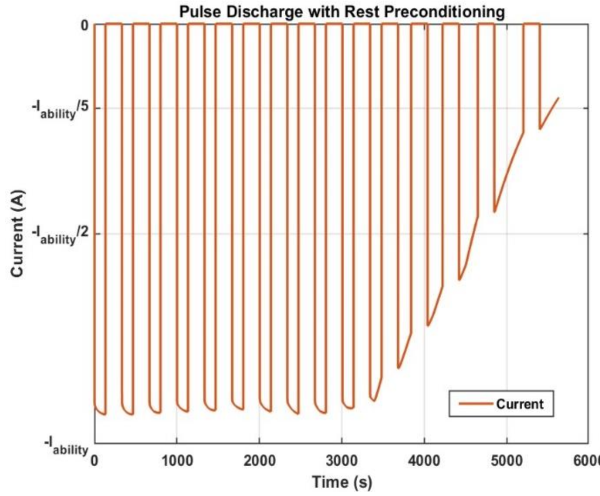
Figure 4: (a) Multi-pack system current (b) Individual pack current at ~50% SOC.

3.2 Power Retention Analysis

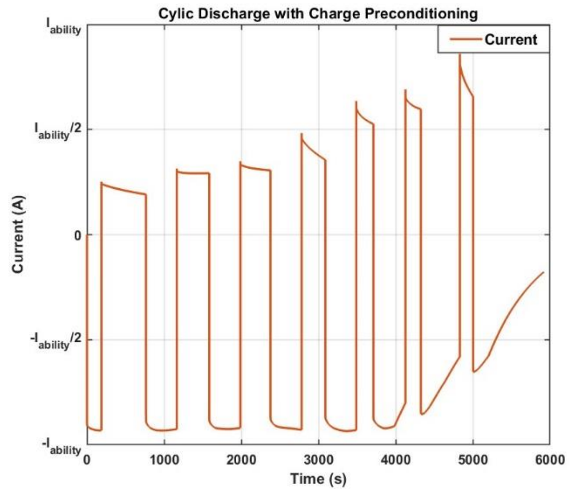
Power retention is the ratio of the average actual power from the heterogeneous mixed battery system to that of a defined homogeneous baseline system at certain SOH. Analysis has been performed by operating the system at different load profiles such as pulse charge Fig. 5(a), pulse discharge Fig. 5(b), cyclic discharge Fig. 5(c) and cyclic charge Fig. 5(d). The key attributes such as SOC, temperature, pack voltage and actual currents were monitored to estimate the instantaneous power delivered. To define the power abilities at each pulse, the maximum, minimum and average powers are extracted from the instantaneous power. This process was applied across various use cases mentioned in Table 1 and Table 2, where scenarios such as one or two incoming fresh packs in the homogenous multi-pack battery system are evaluated using scaled, aged and interpolated cell characterization methods. In the study below, MOL packs mixed with 1 or 2 fresh packs are shown.



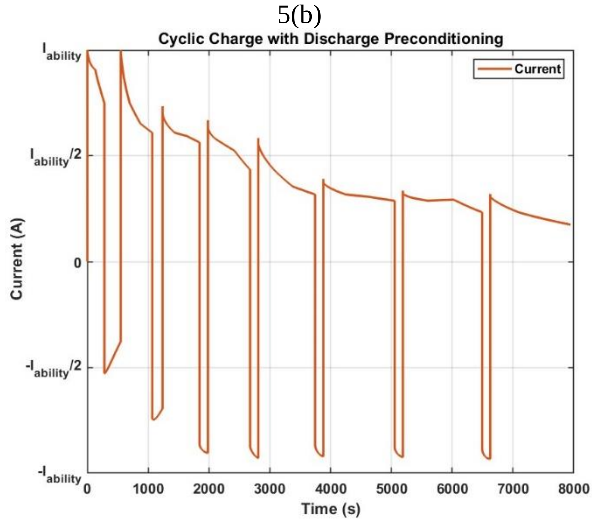
5(a)



5(b)



5(c)



5(d)

Figure 5: (a) Pulse charge profile with rest preconditioning, (b) Pulse discharge profile with rest preconditioning, (c) Cyclic discharge profile with charge preconditioning, (d) Cyclic charge profile with discharge preconditioning.

3.2.1 Pulse Charge with Rest Preconditioning

The pulse charge profile operates the ESS at its maximum defined current abilities on a 5% change in SOC with a dedicated preconditioning rest period between pulses. For instance, as shown in Fig 5(a), if the system's depth-of-discharge (DOD) window ranges from 10% to 90%, the ESS is allowed to charge between 10% to 15% SOC, followed by a rest period before the next pulse begins. The cycle repeats in successive 5% SOC increments throughout the entire operating range.

As illustrated in Fig. 6(a), the power retention analysis reveals notable performance variations across different pack configurations and cell characterization methods.

The two fresh pack system demonstrate an average power loss of approximately 7-8% within the SOC window of 20-90%. In contrast, the single pack system experiences a higher average loss of 10-12% over the same range. However, within SOC window of 50-70%, the single pack system exhibits better power retention compared to other pack configuration for aged and interpolation methods.

In the higher SOC window of 75-80%, the interpolation method tends to overpredict power retention with values exceeding 100%, indicating an unrealistic estimation and overutilization. In contrast, the aged method provides a more conservative and accurate estimation of power retention between 85-90% for both the configurations. A significant drop in performance up to 77% is observed in the lower SOC region, primarily due to open circuit voltage (OCV) shift arises due to SOH difference between heterogeneous and homogeneous packs. This results in a non-linear trend in power retention curves.

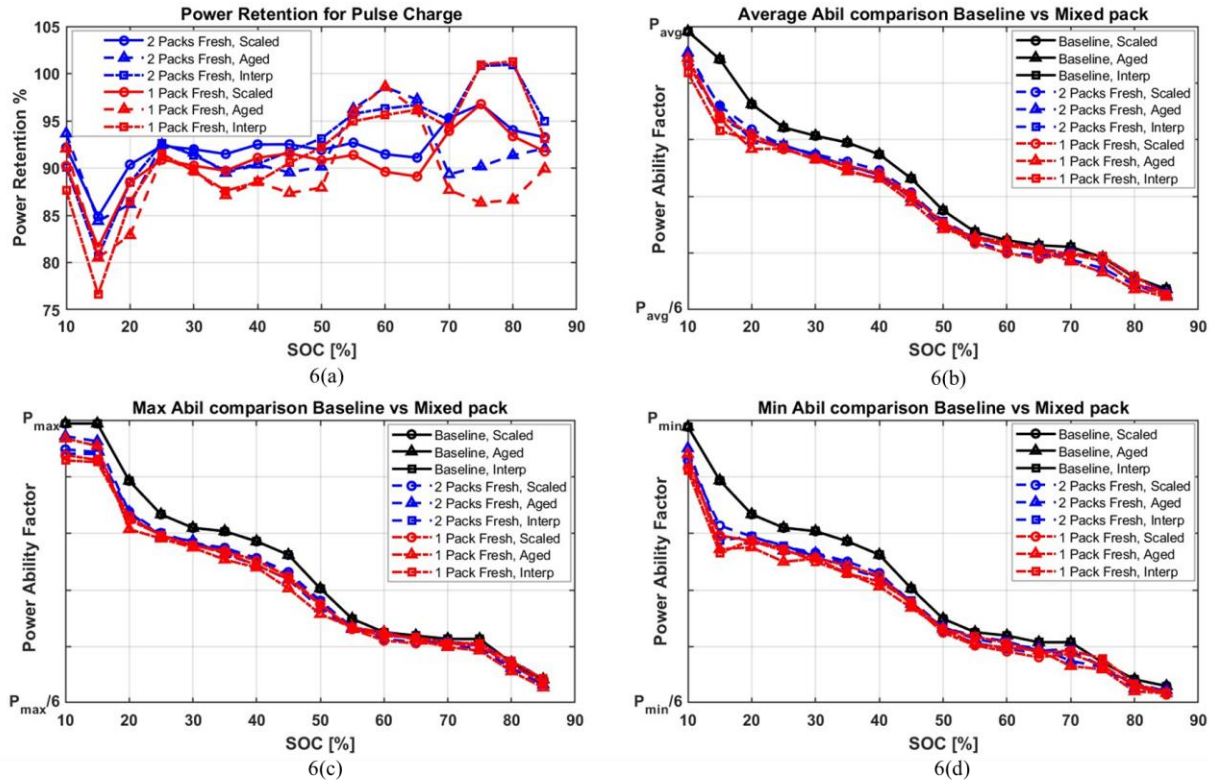


Figure 6: (a) Power retention curves, (b) Average power ability factor, (c) Max power ability factor, (d) Min power ability factor for pulse charge scenario.

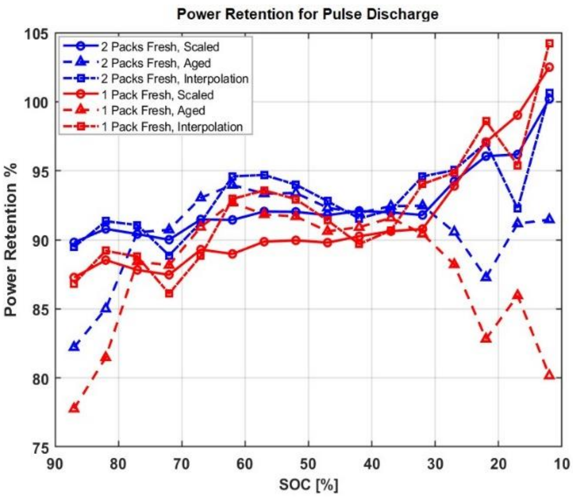
As shown in Fig. 6(b), 6(c) and 6(d), all methods exhibit similar baseline power curves due to the identical OCV curves in the baseline homogeneous system. A greater deviation in power between the baseline and heterogeneous systems is observed in the early SOC range of 10-50% SOC, indicating higher initial degradation. Afterwards, the power curves converge and closely follow the baseline. Around 75-80% SOC, the interpolation method results in overestimating the power which leads to exceeding power retention more than 100%.

3.2.2 Pulse Discharge with Rest Preconditioning

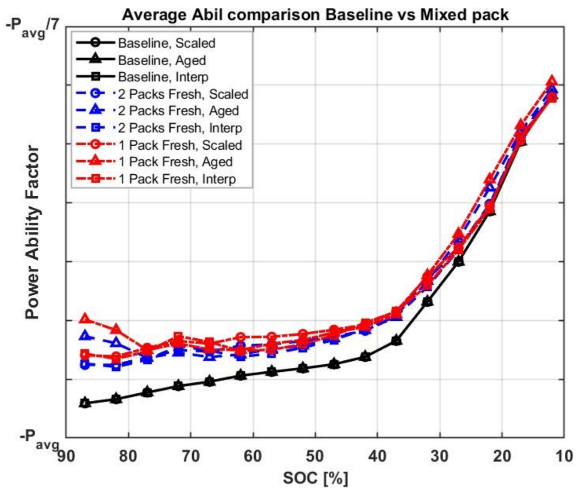
A similar methodology was applied for pulse discharge as shown in Fig. 5(b), where the ESS is discharged over 5% SOC intervals with intermittent rest preconditioning. As shown in Fig. 7, the performance degradation trend observed during pulse discharge are same as that of the pulse charge profile. In the 90% to 30% SOC region, the two fresh pack configurations show an average power drop of approximately 5-8%, while the single fresh pack configuration exhibits a more pronounced degradation of about 10-12%.

At the lower end of the SOC spectrum (around 12%), the scaled and interpolation methods tend to overpredict performance, with estimated power retention exceeding 100%, indicating unrealistic utilization. For example, higher discharge power at low SOC can be explained by one pack being at the lower SOC than the rest of the packs. Hence, most of the packs are at a lower SOC having higher power ability than the compared baseline and the system SOC is defined from the high SOC outlier based on sliding SOC method.

In contrast, the aged method offers more conservative and accurate estimates, predicting power retention between 93% and 80% across both pack configurations. Similarly, at the higher SOC range (80-90%), the aged method estimates a power retention approximately 83% for the two-pack scenario and 77% for the one pack scenario primarily attributed due to OCV shifts and SOH differences among the pack.



7(a)

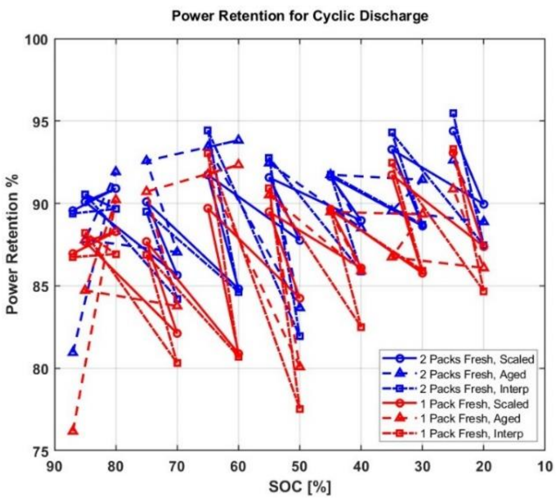


7(b)

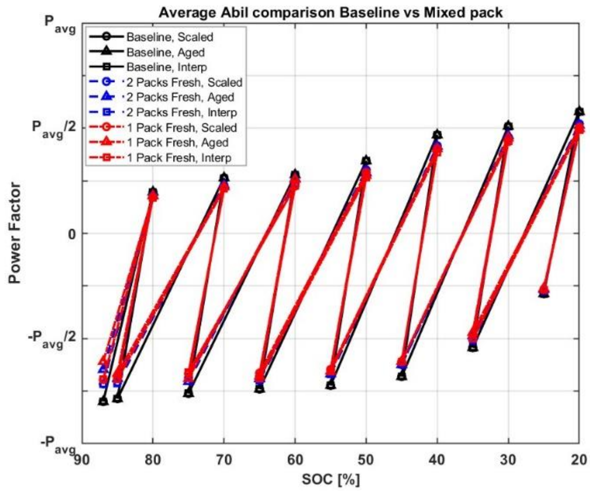
Figure 7: (a) Power retention curves, (b) Average power ability factor for pulse discharge scenario.

3.2.3 Cyclic Discharge with Charge Preconditioning

In this case, as shown in Fig. 5(c), the ESS undergoes cyclic discharge, where each cycle begins with a 15% SOC increment followed by a 5% charge. For example, if the SOC window spans from 10% to 90%, the system first discharges from 90% to 75% SOC, then charges from 75% to 80% SOC for preconditioning. This discharge-charge sequence is repeated in successive 15% discharging and 5% charging steps across the entire SOC range. This helps in simulating realistic cyclic discharge conditions for the system.



8(a)



8(b)

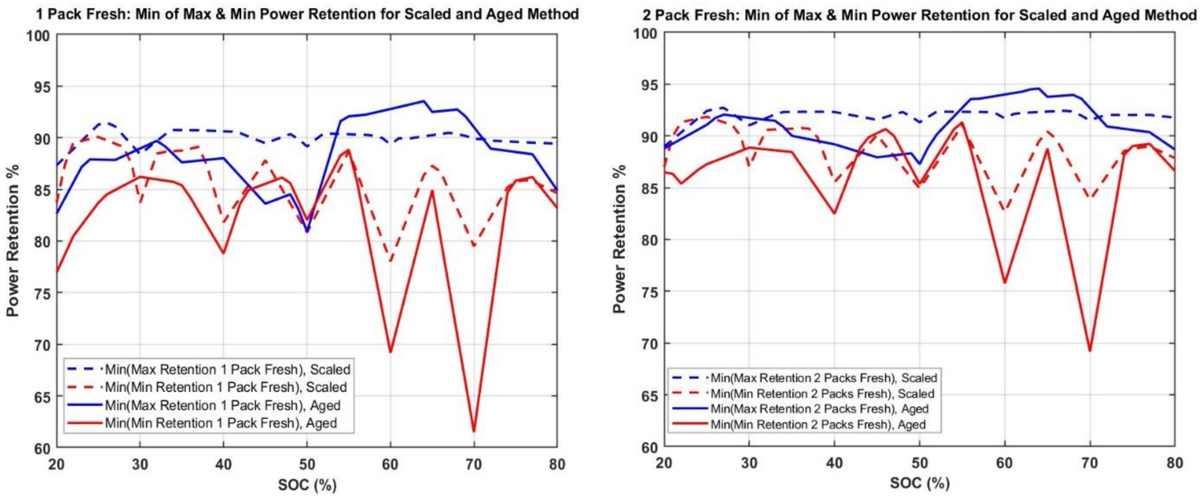
Figure 8: (a) Power retention curves, (b) Average power ability factor for cyclic charge scenario.

As shown in Fig. 8, the cyclic discharge profile exhibits power degradation trends like those observed in the previous pulse-based profiles, with both charging and discharging preconditioning effects presented in single plot. Consistent with earlier observations, the single fresh pack combination demonstrates a more significant power drop compared to the two fresh pack configurations. In the two fresh pack scenarios, average power degradation during discharging ranges from 11.5-12.5% in the (10-50%) SOC window, with charge preconditioning showing slightly lower drop of 7-7.5%. In the higher SOC region (60-90%) the degradation remains same for discharge as of (10-50%) and 8-9% during charge. In contrast, the single fresh pack scenario exhibits more pronounced losses, with discharging degradation of 15-16% and charge preconditioning dropping by 9-10% in the lower SOC range. At higher SOCs, the power drop remains same as of lower SOC range for discharge and increases to 11-12% for discharge.

3.3 Max-Min Power Comparison for Aged and Scaled Method

Based on our analysis using various load profiles, we examined different methods along with their characteristics. The maximum power within any state of charge (SoC) window represents the highest retained power, while the minimum power reflects the lowest retained power. When deciding whether to swap one or two battery packs, the maximum and minimum power values serve as key performance indicators. These values help define the essential ESS power requirements needed to meet our objectives.
The aged method offers the highest accuracy and reliability compared to other methods studied so far. However, it requires a substantial amount of testing data to make accurate predictions. In contrast, the scaled method is quick and simple to implement, making it beneficial for those in the early stages of development.

In the figure below, we analyze the minimum power retention derived from the maximum and minimum power retention curves across all load profiles. Fig. 9(a) illustrates the minimum power retention achievable with one fresh pack swap, using both the aged and scaled methods. It demonstrates that the minimum of the maximum power retention values for both methods provides a reasonably close approximation, with an average difference of 3% across the entire SOC range of 20-80%. However, the minimum of the minimum power retention curve reveals a greater deviation between the aged and scaled methods in the SOC range above 55%. This suggests that the aged method offers valuable insights into more precise estimations, aiding in decision-making. If one must adopt a conservative approach, the minimum of the minimum power retention should be examined, as it defines the least power achievable from a heterogeneous system when engaging with stakeholders. Furthermore, the scaled method has shown good performance in accurately estimating power trends compared to the aged methods for majority of the SOC window.



9(a) 9(b)

Figure 9: Minimum Power retention curves for a) 1 fresh pack mixing, (b) 2 fresh pack mixing for all load profiles using aged and scaled method

In fig 9(b), The two pack swapping system is analysed for making the decision, the power retention seems approximately 5% higher than the 1 pack swap, this indicates the less performance degradation compared to 1 pack. Also, the power retention drops below 80% for the SOC above 55% like 1 pack swap. So, if the requirement is of min 60 % power retention, then 1 pack is capable to fulfil the demand. However, if the minimum power retention requirement is 70% then 2 pack swap is required to fulfil the requirement. This decision is made based on minimum of minimum power retention with the aged methods. And it seems to be the most conservative prediction possible. However, if we go with the scaled method then both 60% and 70% minimum power retention requirements can be fulfilled with 1 pack swap only. So, it is important to select the better method for the analysis based on requirements and available resources.

4 Conclusion

This study investigated and compared the power ability curves for heterogeneous multi-battery pack system with the homogeneous system. Different methods viz. scaled, aged and interpolation, are compared to estimate the power retention for single and two pack mixing in the homogeneous system. The following conclusions are drawn from the study:

1. Power retention analysis helps us define conservative power abilities of heterogenous system instead of directly scaling the individual pack abilities which would give too high abilities.
2. Among the three characterization methods evaluated, the aged method demonstrates the highest accuracy in estimating power retention, owing to its reliance on actual test data. Provided such data is available, this method is preferred.
3. The interpolation method used to estimate power retention based on test data of certain SOH, sometimes leads to overestimations, resulting in values greater than 100% at both low and high SOC levels. This method performs better within the mid SOC range. Thus, it is important to choose the appropriate method based on specific requirements and the availability of data.
4. Estimating the minimum of minimum power retention enables us to determine the most conservative power abilities for heterogeneous systems. This estimation can allow us to make decisions regarding the number of battery packs to be swapped based on the power requirements of stakeholders.
5. By creating these power ability curves for heterogeneous multi pack systems, quick and easy comparisons between heterogeneous systems and homogeneous replacement systems is possible without the need for running detailed use case dependent multipack simulations.

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Presenter Biography

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