

Active Cell Balancing of Series Connected Battery Cells with Alpha Zero Algorithm

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Abstract

To operate safely and efficiently, lithium-ion storage units rely heavily on Battery Management Systems (BMS). Small variations during production ensure every cell ages differently, gradually causes changes in internal resistance, capacity and self-discharge speed. Correcting this imbalance is essential, as mismatched cells limit overall pack performance, accelerate breakdown and increase safety risks. Without balancing, the weakest cell in the string dictates the performance of the entire pack. An active buck-boost converter topology is utilized to enable efficient bidirectional energy transfer between individual cells. The dynamic performance of the balancing system is governed by a Proportional-Integral (PI) controller, whose parameters are optimized using the Alpha Zero algorithm. By treating controller tuning as a policy-search problem guided by the Alpha Zero algorithm systematically explores non-linear system dynamics to determine optimal gain values under fluctuating loads. The proposed balancing framework is evaluated through extensive MATLAB simulation and experimental validation under diverse operating conditions. Performance metrics such as balancing speed, energy efficiency, overshoot, and settling time are benchmarked against traditional tuning technique of Ziegler-Nichols method. Results demonstrate that the Alpha Zero tuned PI controller significantly reduces cell balancing duration.

Keywords - Active cell balancing, buck-boost converter, alpha zero, state of charge

I. Introduction

The rising demand for electric vehicles and renewable storage has accelerated the need for robust lithium-ion battery packs. Operating high-voltage EV platforms requires connecting individual 3.7V cells in series [1]. This design creates cell imbalance due to inherent manufacturing tolerances, localized heat variations, and unequal self-discharge rates [2, 3]. Consequently, the total pack capacity becomes restricted by the lowest-performing cell, which

hits charge or discharge limits first. Traditional passive balancing dissipates this extra charge through resistive heating, which operates at only 60–70% efficiency and adds thermal stress [4, 5]. Active balancing architectures utilizing capacitors, transformers, or DC/DC converters, resolve these constraints by dynamically shifting energy between cells instead of dumping it as heat [6].

DC-DC converters are deployed for active cell balancing in battery management systems for series connected Li-ion packs for electric vehicles and renewable energy storage applications [6]. Unlike passive balancing, which dissipates excess energy from high-state-of-charge (SoC) cells as heat through resistors, active balancing uses bidirectional DC-DC converters to transfer energy from cells with higher SoC to those with lower SoC or to the entire pack. This approach significantly improves balancing speed and overall system efficiency while reducing thermal stress and extending battery life. In series connected battery, manufacturing tolerances and varying operating conditions inevitably cause SoC imbalances that reduce usable capacity and increase the risk of overcharging or over discharging, making active balancing essential for reliable operation [8, 9].

Amongst the DC-DC converters, buck-boost converter-based balancing offers flexible voltage conversion, bidirectional energy flow and compact design. The comparative analysis of Buck-Boost, SEPIC and Zeta converters shows that the buck –boost converter give 95% efficiency as compared to 91% of SEPIC and 87% of zeta converter [10, 11].

Control strategies for active balancing with DC-DC converters typically employ closed-loop voltage or SoC control to drive all cells toward a common target, ensuring convergence without overshoot [12]. More advanced approaches include current-mode sliding mode control for bidirectional DC-DC converters, which provides robustness against parameter variations and disturbances. Comparative studies of various topologies and control techniques highlight trade-offs in convergence speed, stability margins, and implementation complexity, guiding designers in selecting the most appropriate architecture for their specific application. These control strategies are integral to realizing the theoretical benefits of active balancing in practical battery management systems [11, 13, 14]. The HIL approach [15] is also adopted for digital twin implementation for BMS and cell balancing operations.

Energy routing architectures for Buck-Boost equalizers range from adjacent Cell-to-Cell topologies to Cell-to-Pack, Pack-to-Cell, and multi-tier hierarchical systems [16, 17]. Adjacent Cell-to-Cell conversion simplifies switch driving logic and provides high localized efficiency,

but suffers from cumulative conduction losses and slow convergence speed across large battery stacks [18]. Cell-to-Pack and Pack-to-Cell topologies mitigate long transfer paths by stepping up cell voltage to supply the full pack bus or stepping down pack voltage to charge lower-SOC cells [19]. To optimize efficiency across massive battery arrays, hierarchical architectures combine bidirectional Buck-Boost converters for intra-module balancing with secondary isolated flyback or switched-capacitor units for inter-module energy transfer, dramatically accelerating total equalization time [20].

To address the non-linear dynamics of Lithium-ion cells under dynamic driving profiles, recent research increasingly replaces static rule-based switches with Machine Learning (ML) and data-driven optimization strategies [21]. Traditional PWM and fixed-threshold logic struggle to adjust duty cycles optimally under varying temperature and degradation states. Supervised learning architectures are deployed alongside Buck-Boost equalizers to perform continuous online SOC, State of Health (SOH), and Remaining Useful Life (RUL) estimations, passing high-accuracy state feedback directly into the switching controller [22].

The Deep Reinforcement Learning algorithms, such as Deep Q-Networks and Proximal Policy Optimization, treat active cell balancing as a dynamic optimization game [23]. In these setups, DRL agents monitor real-time cell parameters and continuously learn optimal switching sequences and pulse widths. Event-triggered DRL controllers activate Buck-Boost balancing cycles only when beneficial, preventing unnecessary switching actions, reducing inductor conduction losses, mitigating Electromagnetic Interference and minimizing thermal stress on power MOSFETs [24]. Advanced Model Predictive Control and dynamic programming frameworks are similarly integrated with ML models to achieve predictive online current adjustments, accelerating global pack convergence while extending battery longevity [25].

This paper focuses on active cell balancing of series connected battery cells with SOC balancing control based approach with buck boost converter. The buck-boost converter configuration is selected as it can be extended to large no. of battery cells connected in series topology. A cell balancing algorithm is developed for SOC balancing of the battery cells. A PI controller is used for controlling the buck boost converter operation. This controller is later tuned with alpha zero tuning algorithm that dynamically adjusts the controller proportional and integral gains. The MATLAB Simulation results are presented to demonstrate the performance.

II. Converter Topology and Control Technique

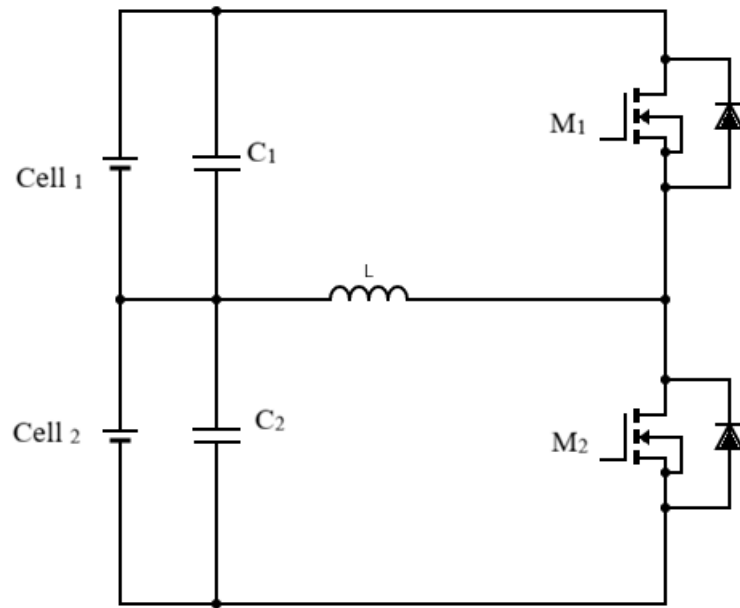


Figure 1: Circuit Topology of Active Cell Balancing with Buck-Boost Converter

The figure 1 shows active cell balancing topology based on bidirectional buck-boost converter. This topology is derived from cuk converter and is designed to transfer energy directly between two adjacent battery cells (Cell 1 and Cell 2) to ensure they maintain the same State of Charge (SoC). The circuit operation is controlled in two modes of energy transfer between the cells.

Cell1 to Cell2 Energy Transfer

This energy transfer mode is active when the SOC of cell1 is greater than cell2. When MOSFET M1 is turned ON and M2 is OFF, current flows from Cell 1 through M1 and into the inductor. The inductor stores energy in its magnetic field and the current increases linearly. The voltage across inductor is,

$$V_L = L \frac{di}{dt} \quad \dots (1)$$

When M1 is turned OFF. The inductor resists the change in current and reverses its polarity. The energy stored in the inductor now discharges into Cell2 through freewheeling diode of M2. Thus the energy transfer takes place from Cell1 to Cell2

Cell2 to Cell1 Energy Transfer

This energy transfer mode is active when the SOC of Cell2 is greater than Cell1. When MOSFET M2 is turned ON (S2 high), and M1 is OFF, current flows from Cell 2 through the inductor and M2. The inductor stores energy.

The inductor current equation becomes,

$$\Delta i_{L(+)} = \frac{V_{Cell1}}{L} DT \quad \dots (2)$$

Where, D = duty cycle and T = time period

When M2 is turned OFF, the inductor voltage boosts and discharges its stored energy into Cell 1 through the freewheeling diode of M1.

$$\Delta i_{L(-)} = \frac{V_{Cell2}}{L} (1 - D)T \quad \dots (3)$$

Thus the energy transfer takes place from cell 2 to cell 1.

By applying volt second balance principle, the voltage equation of the circuit is written as,

$$V_{Cell2}D = V_{Cell1}(1 - D) \quad \dots (4)$$

$$\frac{V_{Cell1}}{V_{Cell2}} = \frac{D}{1-D} \quad \dots (5)$$

From equation (5), the output voltage of the buck boost converter is proportional to the duty cycle of the converter. Hence the charge to cell at lower SOC from the one at higher SOC can be accomplished by regulating the corresponding duty cycle of the switching device.

Managing charge flow across series-connected cells requires complex decision-making regarding when to trigger transfers, how much energy to move, and which paths yield the least power loss. Machine learning serves as the necessary intelligence layer to govern these power electronics, turning simple switching hardware into an adaptive, highly efficient energy distribution system. Alpha Zero intelligent active-balancing strategy is developed in which the measured cell voltages constitute the system state, Alpha Zero with Monte Carlo Tree Search determines the optimal source–destination cell pair, and a bidirectional buck–boost converter transfers energy between the selected cells. The objective is to minimize the maximum cell-voltage deviation while reducing balancing losses and balancing time. The flowchart for alpha zero tuning algorithm is seen in figure 2 and that for the cell balancing algorithm is shown in figure 3.

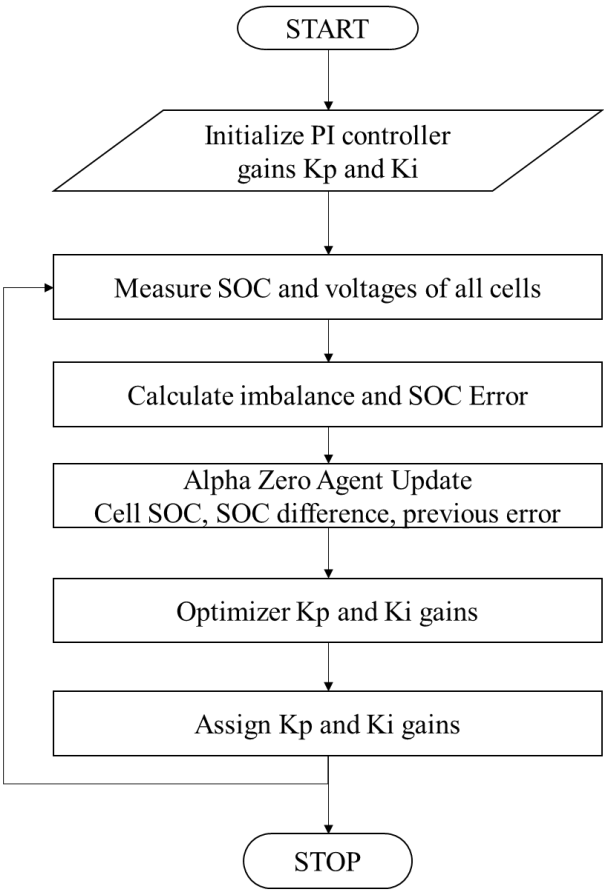


Figure 2: Alpha Zero PI controller tuning flowchart

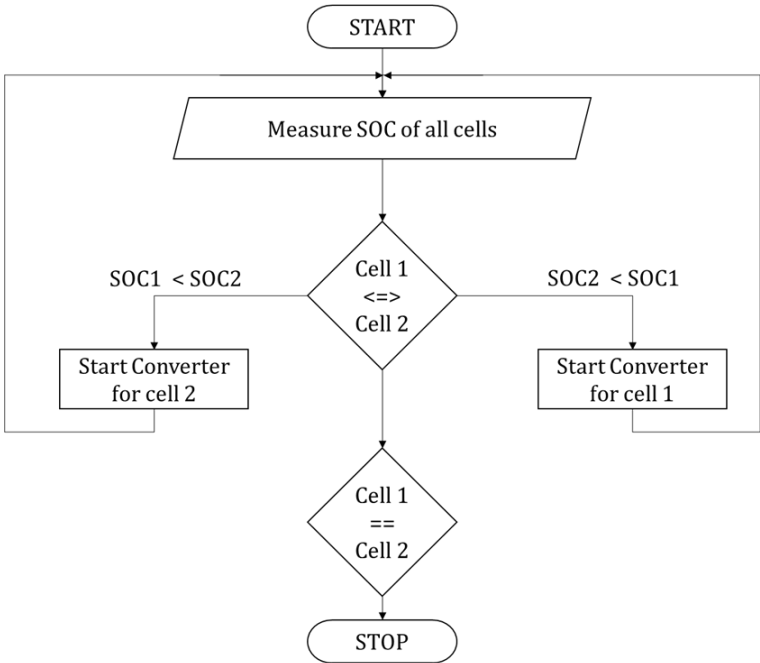


Figure 3: Active cell balancing work flow

III. Results and Discussion

Table 1: System Specifications

Battery Cells	3.7 V 5.40 Ah
DC-DC Converter	Buck – boost converter
Switching Frequency	10 kHz
Inductor	1.3 mH
Capacitor (C1, C2)	1 μ F
SoC Estimation	Coulomb Counting
Balancing algorithm	SOC based
PI controller tuning algorithm	Alpha Zero
PI controller Gains (Ziegler Nichol)	$K_p = 1$, $K_i = 0.1$

The specifications of the system considered for experimentation are mentioned in table 1. The system is designed for balancing of two cells of 3.7V and 3000mAh rating. The switching frequency of the converter is selected to be 10 kHz. The SOC estimation is done with coulomb counting method. The cell balancing algorithm continuously monitors the SOC levels of battery cells and thereby controls the triggering of MOSFETs. The MATLAB simulation model of the system is shown in figure 4. The simulation model is executed in two cases of SOC unbalance and results are noted for MOSFET gate pulses and SOC curves.

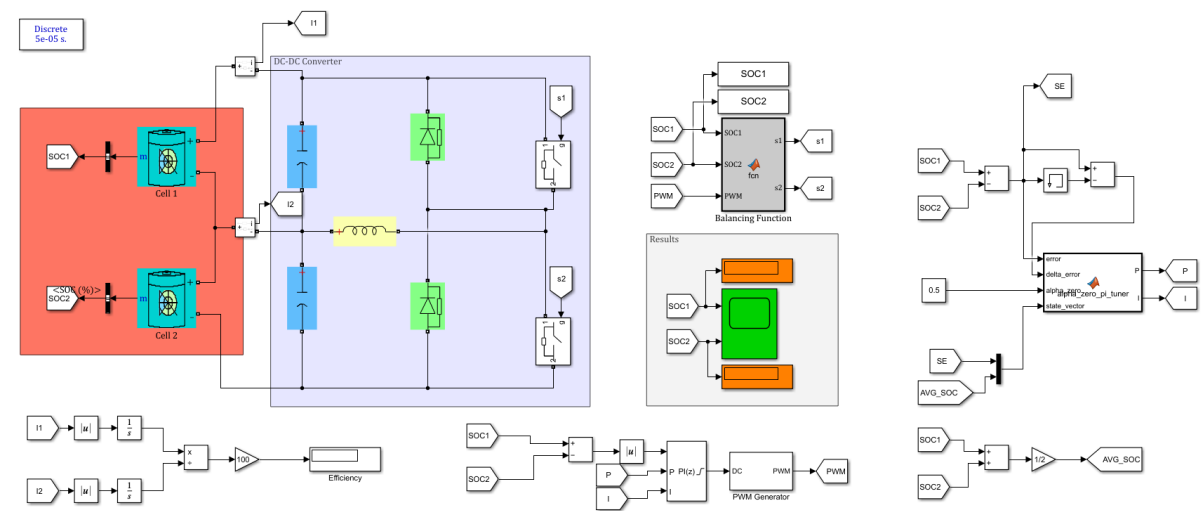


Figure 4: MATLAB Model of Active Cell Balancing

The simulation results are taken with PI controller tuned with classical Ziegler Nichol method at first and then the same controller is tuned with alpha zero algorithm and results are noted. The simulation results are compared on the basis of balancing time with these two tuning techniques

a. Results with PI Controller (Ziegler Nichol Tuned)

Case 1: $SOC_{cell1} = 90\%$ and $SOC_{cell2} = 80\%$

In this case the SOC of Cell1 is considered to be greater than that of the Cell2. The SOC curves during the balancing is seen in figure 5 where, the SOC of Cell1 is observed to be falling and that of Cell2 to be increasing. This indicates the energy transfer from Cell1 to Cell2. The PWM triggering signals of MOSFET are shown in figure 6. Once the cell balancing is achieved, the energy transfer stops and the gate pulses of the MOSFET M1 are turned OFF. The balancing time for 10% SOC difference is recorded to be 11 seconds.

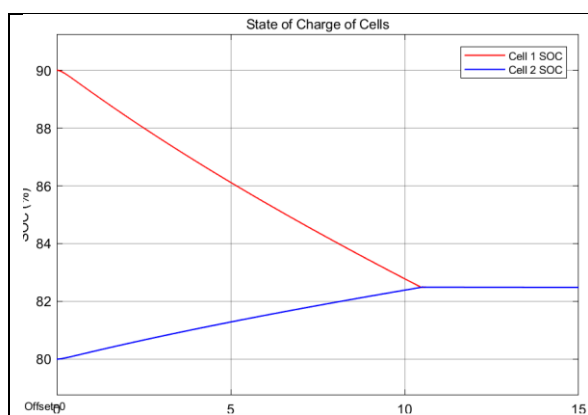


Figure 5: SOC Curve during cell balancing

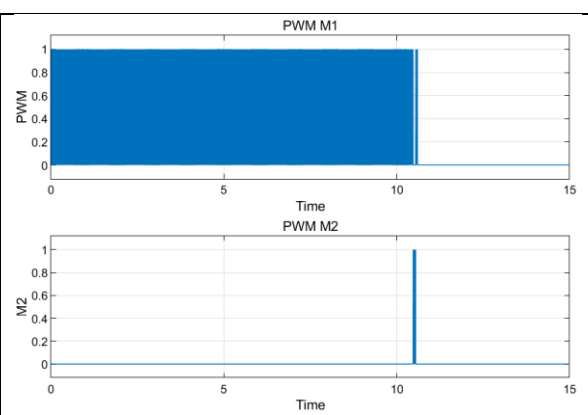
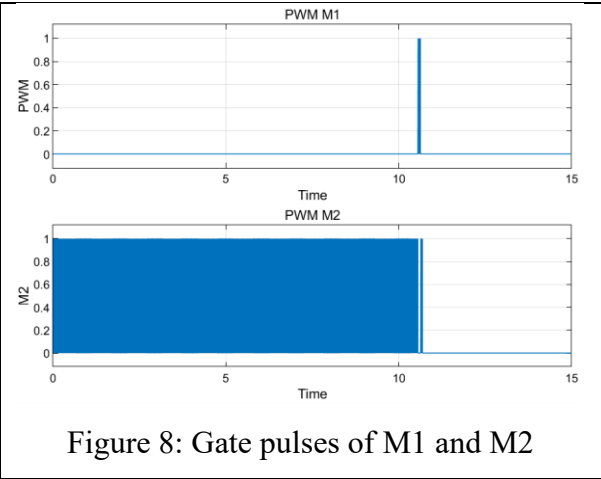
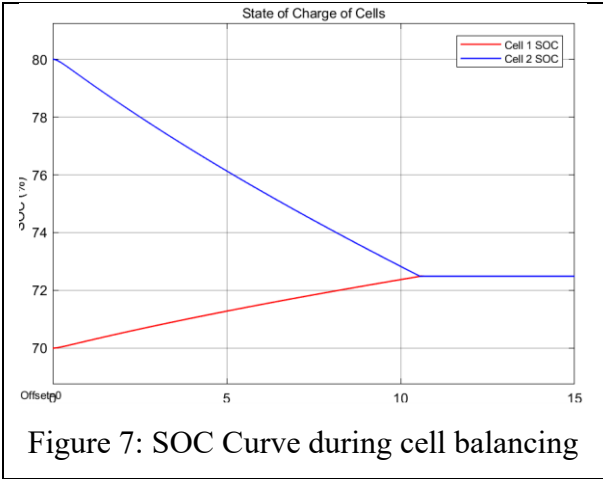


Figure 6: Gate pulses of M1 and M2

Case 2: $SOC_{cell2} = 80\%$ and $SOC_{cell1} = 70\%$

In this case the SOC of Cell2 is considered to be greater than that of the Cell1. The SOC curves during the balancing is seen in figure 7 where, the SOC of Cell2 is observed to be falling and that of Cell1 to be increasing. This indicates the energy transfer from Cell2 to Cell1. The PWM triggering signals of MOSFET are shown in figure 8. Once the cell balancing is achieved, the energy transfer stops and the gate pulses of the MOSFET M2 are turned OFF. The waveforms also shows that the imbalance of 10% in SOC of the cells is balanced within 11 seconds.

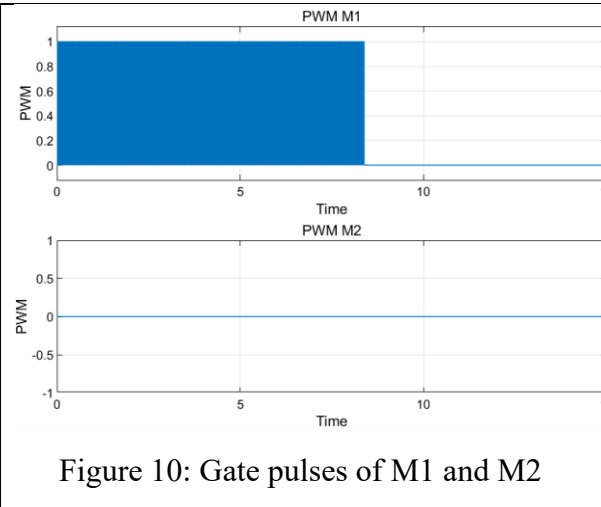
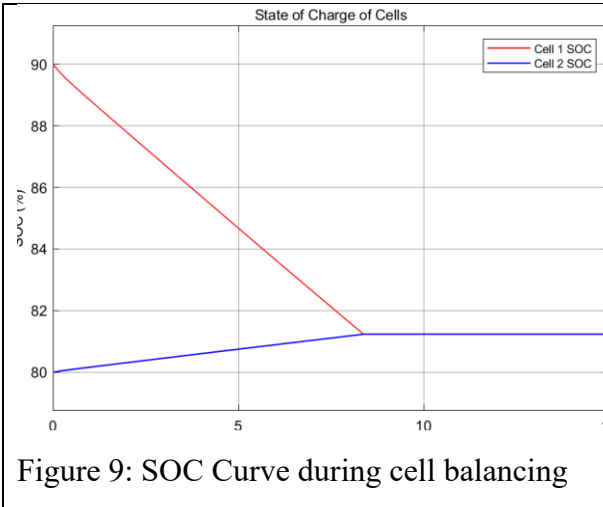


From figure 6 and figure 8, it is also noted that, as the balance state reaches, a small glitch is observed in triggering of MOSFETs M1 and M2 before turning OFF the switching signals.

b. Results with PI Controller (Alpha Zero Tuned)

Case 1: $SOC_{cell1} = 90\%$ and $SOC_{cell2} = 80\%$

In this case the SOC of Cell1 is considered to be greater than that of the Cell2. The SOC curves during the balancing is seen in figure 9 where, the SOC of Cell1 is observed to be falling and that of Cell2 to be increasing. This indicates the energy transfer from Cell1 to Cell2. The PWM triggering signals of MOSFET are shown in figure 10. Once the cell balancing is achieved, the energy transfer stops and the gate pulses of the MOSFET M1 are turned OFF. The charge transfer efficiency in this case is recorded to be 87.65%. The balancing time for 10% SOC difference is recorded to be 8 seconds.



Case 2: $SOC_{cell2} = 80\%$ and $SOC_{cell1} = 70\%$

In this case the SOC of Cell2 is considered to be greater than that of the Cell1. The SOC curves during the balancing is seen in figure 11 where, the SOC of Cell2 is observed to be falling and that of Cell1 to be increasing. This indicates the energy transfer from Cell2 to Cell1. The PWM triggering signals of MOSFET are shown in figure 12. Once the cell balancing is achieved, the energy transfer stops and the gate pulses of the MOSFET M2 are turned OFF. The charge transfer efficiency in this case is recorded to be 87.65%. The waveforms also shows that the imbalance of 10% in SOC of the cells is balanced within 8 seconds.

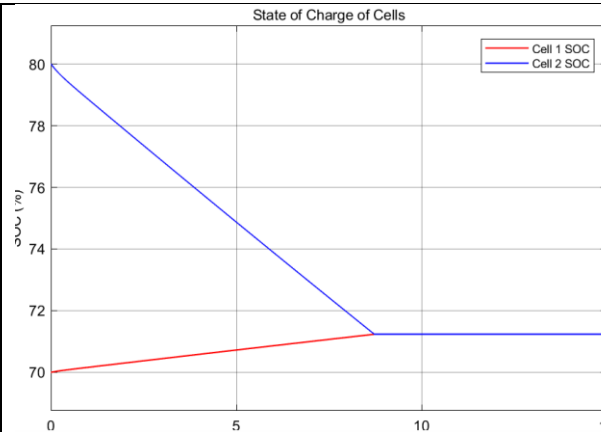


Figure 11: SOC Curve during cell balancing

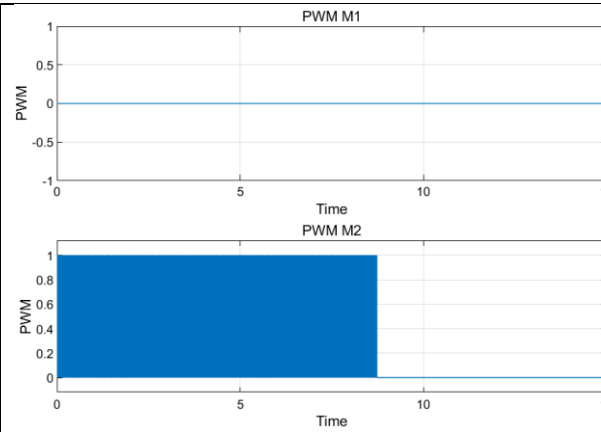


Figure 12: Gate pulses of M1 and M2

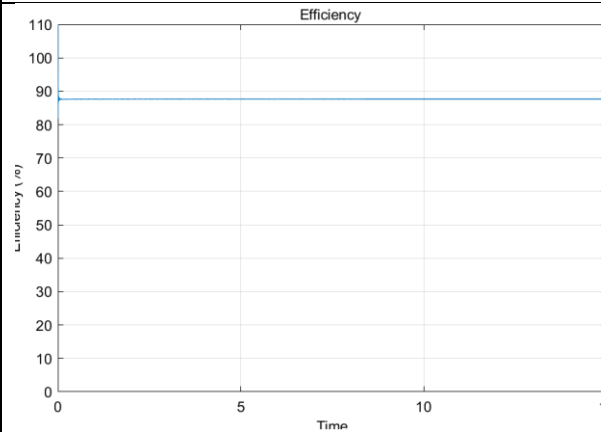


Figure 13: Efficiency (Cell 1 to Cell 2)

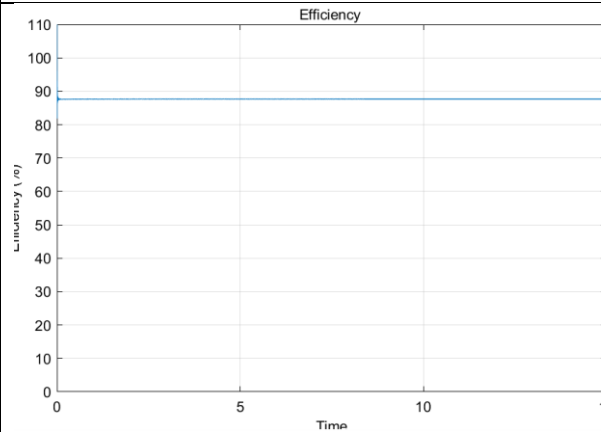


Figure 14: Efficiency (Cell 2 to Cell 1)

From figure 3 and figure 5, it is seen that the time taken for cell balancing in either of the energy transfer modes is same i.e. 105 seconds for 20% difference in SOC of the cells. The efficiency curves of figure 13 and figure 14 show that the charge transfer efficiency is recorded as 87.65%.

The buck boost converter can handle higher balancing current and hence makes it suitable to achieve rapid balancing of the battery bank enabling the direct cell to cell energy transfer. Also charging of a battery cell requires a slightly higher voltage to be applied across it. A buck boost converter is capable of handling distinct voltage levels in moving energy between any two potential levels. The topology architecture is also suitable for scaling to a higher no. of series connected cells. The alpha zero algorithm tunes the PI controller and sets the proportional and integral gain to speed up the balancing operation. The alpha zero tuned PI controller achieved faster balancing as compared to conventional technique of Ziegler Nichol tuning.

IV. Experimental Results

Applying Alpha Zero to active cell balancing in Battery Management Systems transforms standard rule-based energy transfer into an AI-guided control architecture. The physical setup integrates an active balancing topology of buck boost converter with a hybrid execution unit. In hardware test beds, a microcontroller handles high-speed analog-to-digital conversion and pulse-width modulation. By treating battery equalization as a finite willing where state inputs consist of individual cell state-of-charge and voltage, the system selects optimal switch pairings and duty cycles to equalize energy distribution. The photographs of the hardware model is seen in figure 15. The experimental results of active cell balancing with conventional PI controller and Alpha Zero tuned PI Controller are mentioned in table 2.

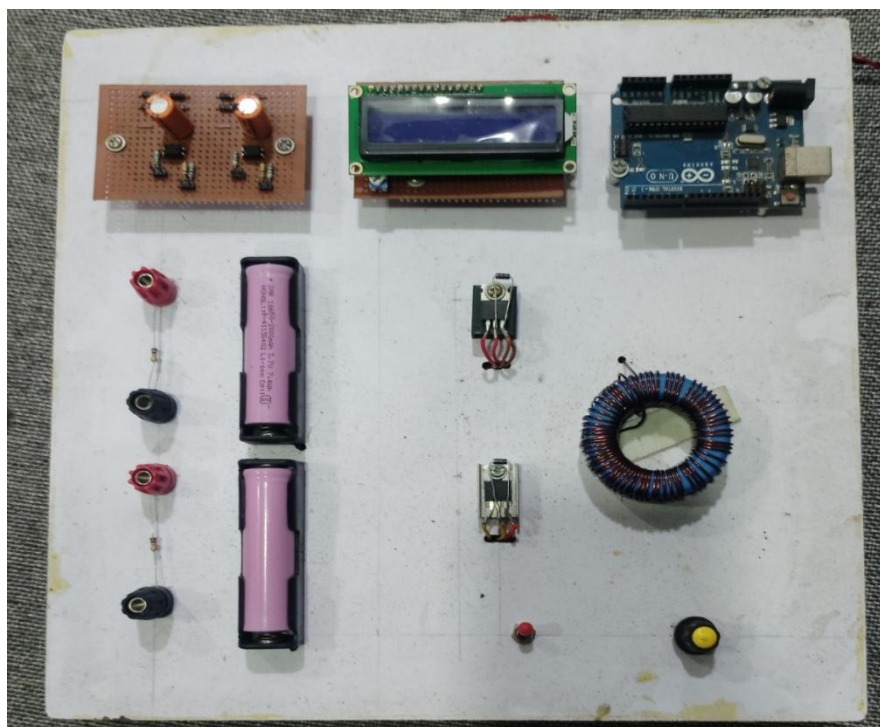


Figure 15: Photograph of hardware model

Table 2: Observations of active cell balancing

Controller	Initial SOC	Converter mode	Final SOC	Time (Seconds)
Conventional PI Controller	Cell 1: 85% Cell 2: 60%	Buck	Cell 1: 70% Cell 2: 70%	480
	Cell 1: 70% Cell 2: 85%	Boost	Cell 1: 75% Cell 2: 75%	290
Alpha Zero Tuned PI Controller	Cell 1: 85% Cell 2: 60%	Buck	Cell 1: 70% Cell 2: 70%	455
	Cell 1: 70% Cell 2: 85%	Boost	Cell 1: 75% Cell 2: 75%	275

The table 2 shows that the alpha zero tuned controller achieves faster balancing as compared to the conventional PI controller.

V. Conclusion

Active cell balancing reshapes battery management by replacing passive heat dissipation with efficient energy transfer. Rather than bleeding off surplus charge as wasted heat, active balancing reroutes energy between cells and preserving pack capacity. The simulation results are presented in idle state of operation. The cell balancing results indicates that the balancing action with PI controller tuned system takes 11 seconds for 10% unbalance in the SOC. When the same topology is tuned with Alpha Zero algorithm, the same unbalance is compensated in 8 seconds. The circuit topology takes same amount of time of charge transfer in either direction and hence the balancing time can be dictated for balancing act with 87.65% efficiency.

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