OPTIMIZED SOC EQUALIZATION AND PREDICTION IN LITHIUM-ION BATTERIES: A PI-CONTROLLED BUCK-BOOST APPROACH WITH BAYESIAN-KALMAN FORECASTING

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Abstract: *This study introduces an intelligent approach for lithium-ion battery state-of-charge (SOC) equalization, utilizing a Buck-Boost converter regulated by a Proportional-Integral-Derivative (PID) controller. The developed hardware model facilitates active cell balancing, ensuring optimal energy distribution across battery cells. To enhance prediction accuracy, a hybrid machine learning model Bayesian Linear Regression integrated with a Kalman Filter is implemented for day-ahead SOC forecasting. Input values for the SOC prediction model are sourced from the hardware setup, enabling a real-time, data-driven approach to battery management. Experimental results validate the effectiveness of the Buck-Boost converter with PID control in achieving precise SOC equalization, while the hybrid model reliably forecasts SOC trends. This research advances battery management systems (BMS) by integrating hardware-based cell balancing with predictive machine learning, enhancing the efficiency and reliability of electric vehicles and renewable energy storage solutions. This combined approach underscores the potential for intelligent BMS designs to extend battery lifespan and optimize energy usage in clean energy applications.*

Keywords: state-of-charge (SOC), Proportional-Integral-Derivative (PID) controller, Machine Learning, Bayesian Linear Regression (BLR), Kalman Filter.

1. INTRODUCTION

In electric vehicles, battery storage systems often comprise cells with differing capacities, internal resistances, and charge/discharge characteristics. This can cause an uneven state of charge (SOC) and temperature distribution among the cells, leading to reduced performance and lifespan. Battery Management Systems (BMS) are increasingly essential to mitigate this, as they help balance the cells and ensure optimal performance, thereby extending the battery's lifespan [1]. Battery balancing systems typically operate by monitoring and comparing the status of individual battery cells, such as open-circuit voltage or state of charge (SOC). In general, there are three common types of balancing topologies: passive balancing topology, and active balancing topology. Excess energy from cells with higher voltage or SOC is dissipated in passive balancing systems, usually as heat. While this method is straightforward, it is inefficient and introduces additional strain on the battery's thermal management system [2]. Active cell balancing in lithium-ion batteries transfers energy between cells to ensure a uniform state of charge (SOC), improving efficiency, extending battery life, and reducing thermal strain. Techniques have evolved from traditional capacitor and inductor-based methods to more advanced solutions like switched capacitors, flyback transformers, and buck-boost converters, offering greater precision and scalability for modern applications [3].

Accurate prediction of SOC is essential for optimizing battery usage, preventing overcharging or deep discharging, and prolonging battery life. Traditional methods for estimating SOC, such as the Coulomb counting method or open-circuit voltage measurement, have limitations regarding accuracy and real-time applicability. With the implementation of a hardware model for active balancing, a vast amount of real-time data regarding the behaviour of individual cells becomes available. This data can be utilized to improve SOC prediction through machine learning algorithms. Machine learning models can be trained using data from the hardware system, including voltage, current, temperature, and historical SOC values, to predict SOC with greater precision. This paper discusses the process of predicting SOC using Bayesian Linear Regression. This model offers several advantages in the context of SOC prediction: it handles uncertainty and provides probabilistic predictions, making it well-suited for scenarios where sensor noise, battery aging, and variations in operating conditions contribute to the uncertainty in SOC estimation.

2. Literature Review

In recent years, the need for efficient and intelligent Battery Management Systems (BMS) for lithium-ion batteries has grown significantly due to their critical role in electric vehicles (EVs) and renewable energy storage systems. SOC equalization and prediction models play an essential part in optimizing battery performance and longevity. Existing literature reveals various approaches for SOC estimation, including extended Kalman Filters, model-based methods, and machine learning (ML) models, each contributing distinct benefits and limitations. Machine learning approaches have emerged as powerful tools for SOC prediction due to their ability to handle complex, non-linear data patterns that conventional methods struggle to capture. Models such as Artificial Neural Networks (ANNs), Support Vector Machines (SVMs), and Long Short-Term Memory (LSTM) networks have shown success in SOC prediction. However, these methods often require large datasets for training, making them less effective in environments with limited data. Bayesian Linear Regression (BLR) is particularly relevant in this context, offering probabilistic predictions that can account for uncertainties in data, which is beneficial in dynamic conditions.

Furthermore, Kalman Filters, widely used for linear and time-varying applications, provide a robust framework for improving prediction accuracy through recursive updates. Combining BLR with a Kalman Filter offers a hybrid model that harnesses the strengths of both methods, accommodating uncertainty and providing accurate, updated SOC forecasts. The integration of hardware-based systems with ML models, such as the PID-controlled Buck-Boost converter for active balancing, has shown promising results in enhancing real-time SOC accuracy and efficient energy use. This review highlights the potential of hybrid ML models in advancing SOC prediction, supporting the practical implementation of intelligent BMS for EVs and renewable energy solutions.

3. Cell Balancing Techniques

Cell balancing is a critical process in managing lithium-ion (Li-ion) battery packs, particularly for ensuring longevity, performance, and safety. Large battery packs consist of multiple cells connected in series or parallel. Due to variations in manufacturing, aging, or operating conditions, cells can exhibit different capacities, internal resistance, and voltage behaviour, leading to imbalance. This imbalance, if not managed, can degrade battery performance, increase safety risks, and reduce the overall lifespan of the battery pack. Additionally, charging and discharging the cells at different cycle rates result in a state of charge (SoC) imbalance between them. In recent years, numerous cell-balancing topologies have been proposed, which can be broadly classified into two main categories: active and passive

topologies. This classification is based on the type of energy storage elements used and the methods employed for balancing energy between the cells.
Energy transfer between battery cells can be achieved using various methods. In a single capacitor setup, energy is transferred from a higher-energy cell to a lower-energy cell via one capacitor. Switched capacitors allow energy equalization between two neighbouring cells, while double-tiered switched capacitors enable energy transfer between both adjacent and nonadjacent cells using two rows of capacitors. A single inductor transfers energy from one cell to another, and several inductors are used for equalization between two adjacent cells. A single transformer facilitates energy transfer between the entire battery pack and individual cells, while a single-core transformer with multiple secondary windings achieves pack-to-cell equalization. Finally, multiple magnetic core transformers ensure energy balancing for each cell through individual multi-winding transformers.

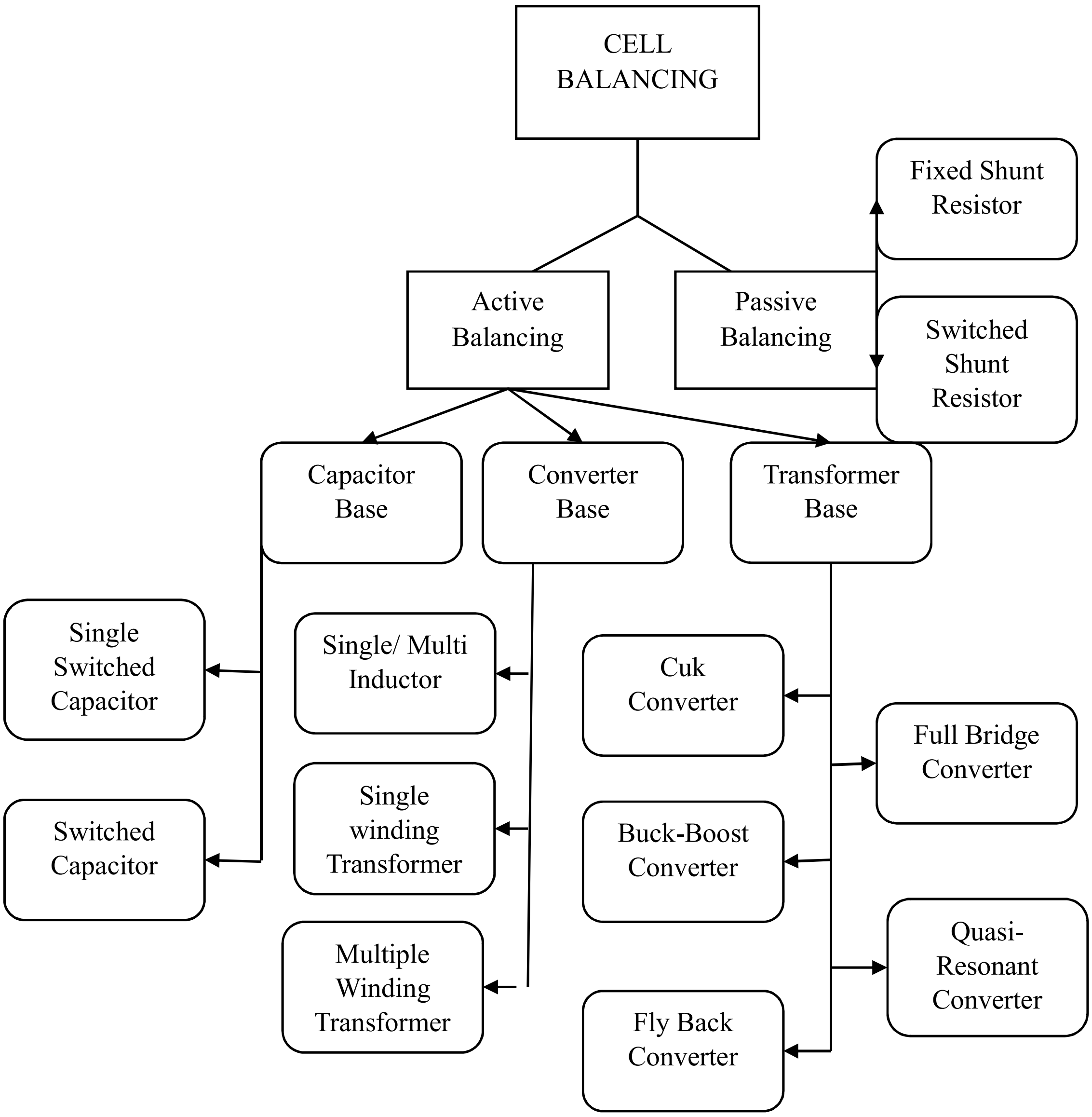

Figure 1. Classification of cell balancing techniques

4. Methodology

This study presents an intelligent lithium-ion battery management approach, combining a Buck-Boost converter with PID control for SOC equalization and a hybrid Bayesian Linear Regression-Kalman Filter model for day-ahead SOC forecasting, tested with real-time data from the hardware setup, ultimately enhancing accuracy, reliability, and efficiency for electric vehicle and renewable energy applications by merging hardware-based balancing and predictive machine learning for optimized energy distribution. The buck-boost converter is outlined in Fig.1. capacity to exchange vitality from a Energy storage system source or battery pack to weaker cells, a concept already inspected [4]. The system redistributes excess vitality from each of the cells to the pack and from higher cells to the DC association. These converters require a cell voltage- detecting framework and a modern controller.

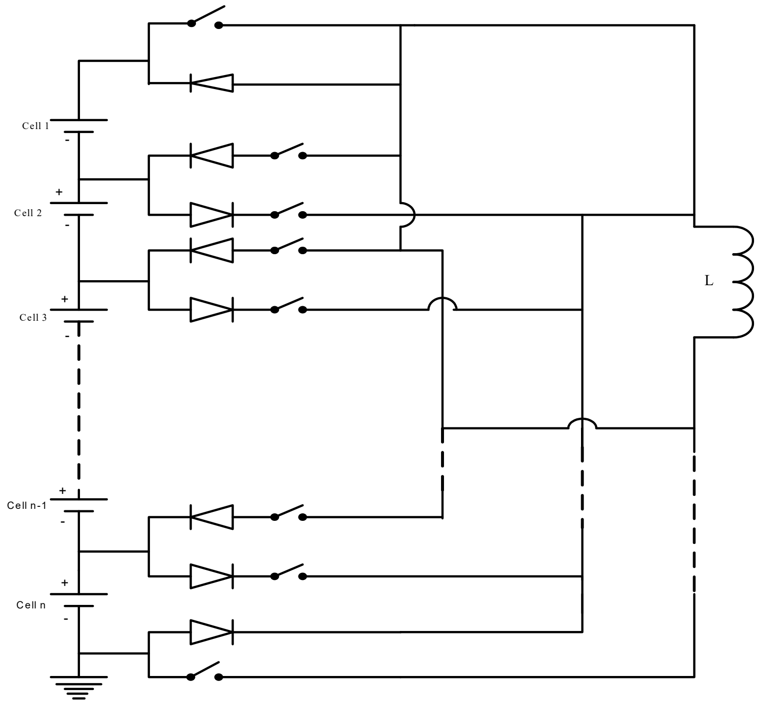

Figure 2. Simplified circuit representation of the Buck-Boost balancing Technique

The voltage of each battery cell and the difference between adjacent cells are continuously monitored. Managing energy flow through each converter and adjusting the duty cycle based on voltage differentials ensures balance, requiring precise voltage detection and control. This approach involves more components than switched-capacitor methods. Although balancing converters is complex and costly, their modular design enhances efficiency, as discussed by the authors [5]. Energy is stored in capacitors and inductors, and cell balancing is achieved through either state-of-charge (SOC) or voltage balancing during charge and discharge cycles. In this study, cell balancing is achieved by maintaining each cell at a consistent SOC.

4.1 Experimental analysis

4.1.1 Passive Cell Balancing

In passive balancing, each battery cell is connected in parallel with a resistor. When a cell reaches a higher voltage compared to others in the series, the resistor allows excess energy to dissipate as heat, reducing the cell's voltage. This process helps equalize the voltage across all cells but wastes energy in the form of heat, making it less efficient compared to active balancing. Passive balancing typically occurs when the battery is idle or in specific balancing intervals, as it doesn't require additional complex circuitry but relies on resistive elements to balance cell voltages.

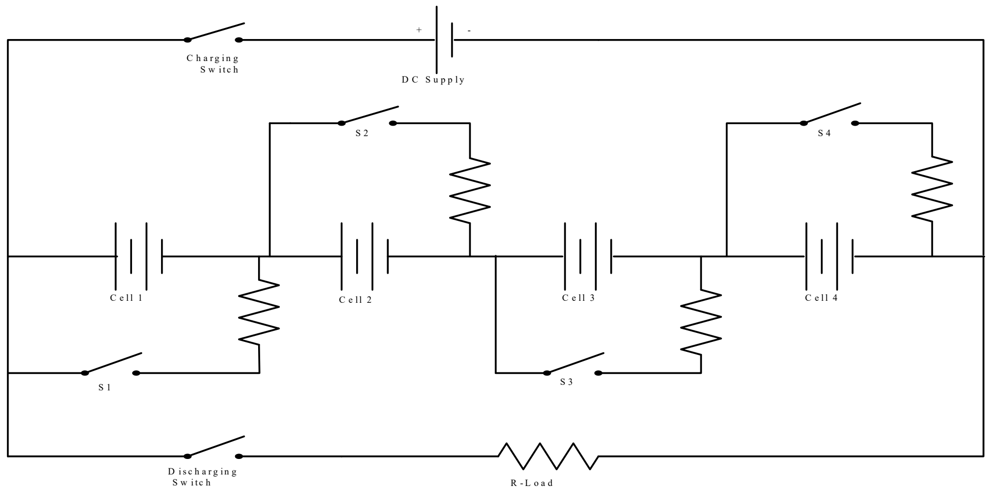

Figure 3. A passive balancer model

The cell balancing process is enabled through the implementation of a buck-boost converter, comprising two diodes, switches, and an inductor. The inductor functions as a temporary energy storage medium, facilitating the transfer of energy from cells of a higher state of charge to those with a lower state of charge. The activation of IGBT switches is determined by sensors attached to each cell. In the event of a discrepancy in the state of charge between cells, these switches are engaged to establish a conduit for the transfer of charge from the cell with the highest state of charge to the cell with the lowest state of charge within the entire unit. Capacitors are utilized as filters to mitigate undesired anomalies within the system.

4.1.2 Passive Cell Balancing

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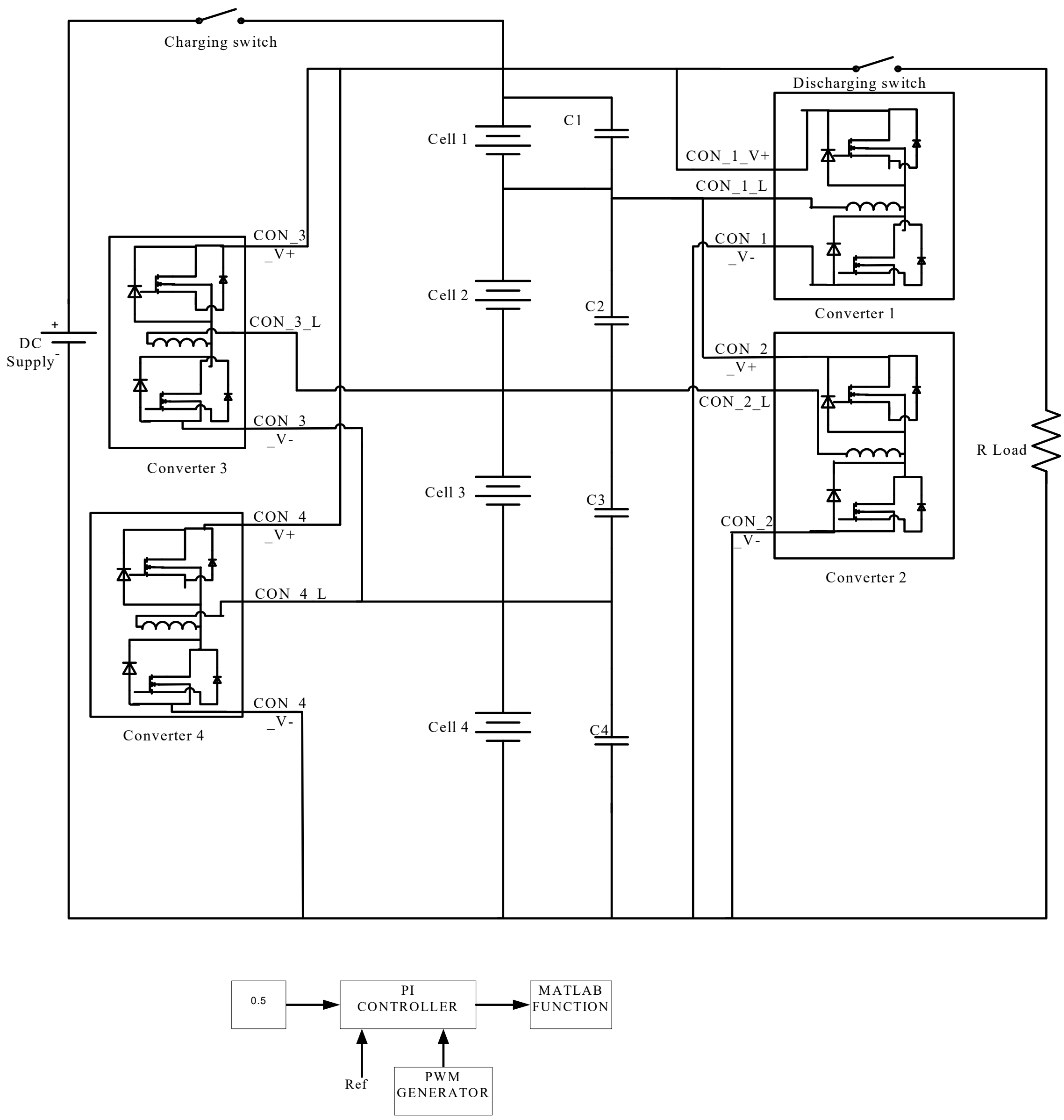

Figure 4. Active cell balancing of the Buck-Boost converter using PI controller balancer model

For active balancing, a four-cell lithium-ion battery pack is connected in series. The MATLAB simulation model includes components such as a capacitor, diodes, an inductor, an idealized switch, a charging/discharging switch, along with MATLAB control for SOC calculation, a scope for monitoring, and PWM control for switch operation. The simulation targets a scenario where cell 3 is overcharged and cell 1 is undercharged. By adjusting the duty ratio of the PWM signal, the switch (switch-1) alternates on for T1 seconds and off for T2 seconds, facilitating charge transfer to achieve balance. This study investigates both the active buck-boost converter and passive shunt resistor balancer for cell balancing applications.

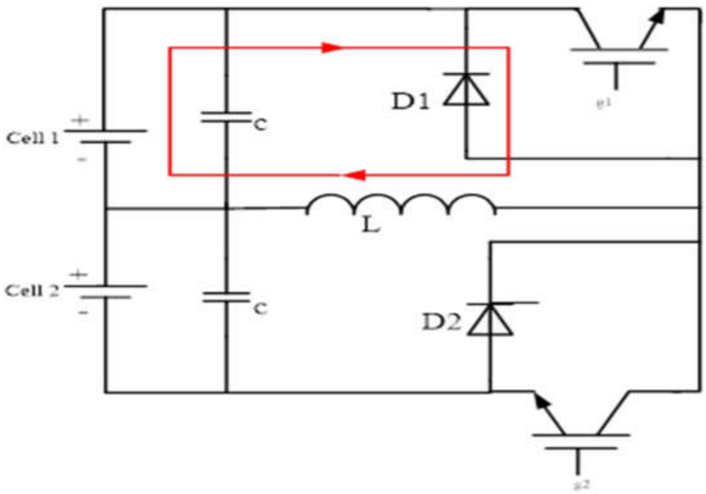

Figure 5. Cell 1 discharge energy and store energy in inductor L

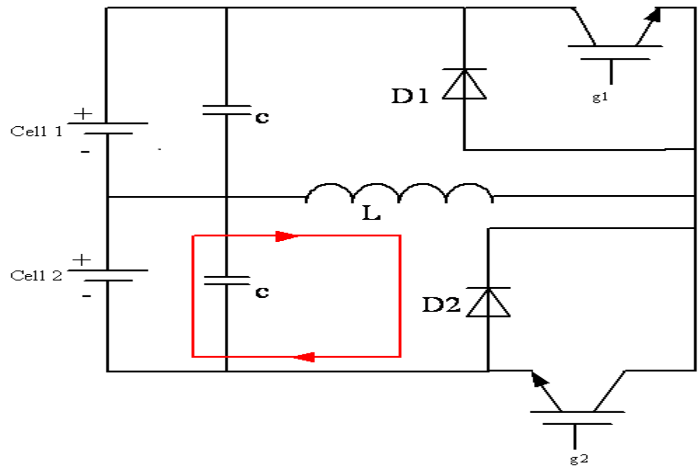

Figure 6. Energy stored in inductor L flows to cell-2 to active balancing

A PI controller compares the target setpoint with the actual value to calculate an error and adjusts the control signal based on this. The proportional part minimizes immediate errors, while the integral part continuously corrects any lasting discrepancies. This combined output is sent to the PWM module, which converts it into pulse widths to control system operations. By modulating the PWM duty cycle, the PI controller enables precise energy transfer between cells, promoting balance by adjusting charging for lower-SOC cells and discharging for higher-SOC cells. This method prevents overcharging or over-discharging, enhances battery health, and improves overall efficiency.

5. Data Preprocessing and Model Training

Before applying the Bayesian Linear Regression (BLR) integrated with the Kalman Filter, it is essential to preprocess the collected data. This preprocessing includes several steps to ensure high data quality and optimal model performance. First, data cleaning is performed to address missing values, outliers, and noise, which could otherwise impair the model's accuracy. Next, normalization or standardization is applied to scale the features, placing them on a similar scale and facilitating smoother model convergence. Finally, the data is split into training, validation, and test sets, enabling robust model training, validation, and evaluation. This thorough preprocessing enhances the predictive accuracy and stability of the BLR-Kalman Filter integration, optimizing it for dynamic and real-time applications.

5.1 Feature selection

For feature selection in predicting the state of charge (SOC) for a lithium-ion battery system, the primary inputs include B1-B4 voltage measurements and pack voltage to capture individual cell and overall battery levels, current to assess energy discharge/charge rates, and temperature to account for efficiency and longevity impacts. Additionally, safety and cell relay statuses provide insights into system protection and balancing. Humidity may also be included as an environmental factor under specific conditions. Together, these features support accurate, data-driven SOC modelling and safety analysis.

6. Structural Framework of a Bayesian Linear Regression Model Combined with A Kalman Filter

For a Bayesian Linear Regression model combined with a Kalman Filter for SOC (State of Charge) estimation, the approach leverages Bayesian principles for probabilistic predictions with uncertainty estimation, while the Kalman Filter adjusts and refines these predictions dynamically as new data arrives. Below is a structural framework along with the primary formula for SOC estimation.

6.1. Structural Framework for SOC Estimation:

In Bayesian Linear Regression, define an initial prior distribution for model parameters to predict SOC based on features (voltage, current, temperature), and for Kalman Filter initialization, set initial state estimates and covariance matrices using prior information on SOC. Using training data, estimate SOC by modelling the linear relationship between input features X (e.g., battery characteristics like voltage, current) and the target variable Y (SOC).

$$y = X\beta + \epsilon \tag{1}$$

where β represents the weights (parameters) of the model, and ϵ is the error term with a Gaussian distribution.

After the Bayesian Linear Regression model generates an initial SOC prediction, the Kalman Filter refines this estimate by adjusting for deviations using observed measurements, accounting for real-time uncertainty and noise.

2. Mathematical Formulation for SOC Estimation:

The Bayesian Linear Regression produces an initial SOC estimate, and then the Kalman Filter refines it. The key steps in SOC estimation with this combined model are as follows:

Kalman Filter Update:

Prediction Step:

- Predict the next SOC state based on the previous state and model dynamics.

$$\widehat{SOC}_{t|t-1} = \widehat{SOC}_{t-1} + \Delta SOC \tag{2}$$

where ΔSOC can be estimated based on a battery model that accounts for current flow and internal resistance.

Update Step:

- Kalman Gain Calculation:

$$K_t = \frac{P_{t|t-1}H_t^T}{H_t P_{t|t-1} H_t^T + R} \tag{3}$$

Where $P_{t|t-1}$ is the error covariance, H_t is the measurement matrix, and R is the measurement noise.

- Corrected SOC:

$$\widehat{SOC}_{t|t} = \widehat{SOC}_{t|t-1} + K_t(Z_t - H_t\widehat{SOC}_{t|t-1}) \tag{4}$$

where Z_t is the observed SOC.

Update Error Covariance:

$$P_{t|t} = (I - K_t H_t)P_{t|t-1}$$

This model estimates the SOC using Bayesian Linear Regression and continuously refines the estimation with the Kalman Filter. The Bayesian approach accounts for model uncertainty, while the Kalman Filter addresses real-time measurement noise, improving the robustness and reliability of SOC predictions.

6.2. Model Evaluation

For model evaluation in Bayesian Linear Regression, various metrics are used to assess the model's predictive performance. Common evaluation metrics include Mean Absolute Error (MAE), which measures the average magnitude of the errors in predictions, and Root Mean Squared Error (RMSE), which provides a measure of the average magnitude of the errors, giving more weight to larger errors. Additionally, R-squared (R2R^2R2) is used to quantify the proportion of variance in the dependent variable that can be explained by the independent variables, indicating the model's explanatory power. These metrics collectively help in determining the model's accuracy and effectiveness in predicting the State of Charge (SOC) of lithium-ion batteries.

Mean Squared Error (MSE):

$$\mathrm{MSE} = \frac{1}{\mathrm{n}}\sum_{\mathrm{i}=1}^{\mathrm{n}} \mathrm{n}\,(\mathrm{y_i} - \widehat{y_\imath})^2 \tag{5}$$

Where:

n is Number of data points,

y_i = Actual Values

$\hat{y}_i$= Predicted Values

Mean Absolute Error (MAE):

$$MAE = \frac{1}{n}\sum_{i=1}^{n} | y_i - \hat{y}_i | \tag{6}$$

Root Mean Squared Error (RMSE):

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n} n\,(y_i - \hat{y}_i)^2} \tag{7}$$

R-Squared (R^2):

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y}_i)^2} \tag{8}$$

Where:

$\bar{y}_i$= Mean of the actual values

6.3. Statistical analysis

In evaluating the robustness and reliability of the State of Charge (SOC) prediction model, statistical methods such as the Durbin-Watson test and Multivariate Analysis of Variance (MANOVA) are essential. These tests help ensure that the model's predictions are unbiased, consistent, and free from issues like autocorrelation, which can affect its accuracy. Durbin-Watson helps us check if the model's prediction errors are random. If they are, the model is reliable. MANOVA tells us if different input factors (like voltage, current, and temperature) are affecting the model's predictions in a significant way. If they do, the model is robust across different conditions. Together, these methods ensure that our SOC prediction model is both reliable (making consistent predictions) and robust (working well under different battery conditions).

$$DW = \frac{\sum_{t=2}^{n}(e_t - e_{t-1})^2}{\sum_{t=1}^{n} e_t^2} \tag{9}$$

Where:

e_t = residual (error) at time t

e_{t-1}= Residual (error) at time t-1

N=Number of Observation

Formula for MANOVA: One of the key statistics used in MANOVA is Wilks' Lambda.

$$\Lambda = \frac{det(W)}{\det(T)} \tag{10}$$

Where:

- W is the within-group covariance matrix,
- T is the total covariance matrix (which includes both within-group and between-group variances),
- Det(.) represents the determinant of the matrix.

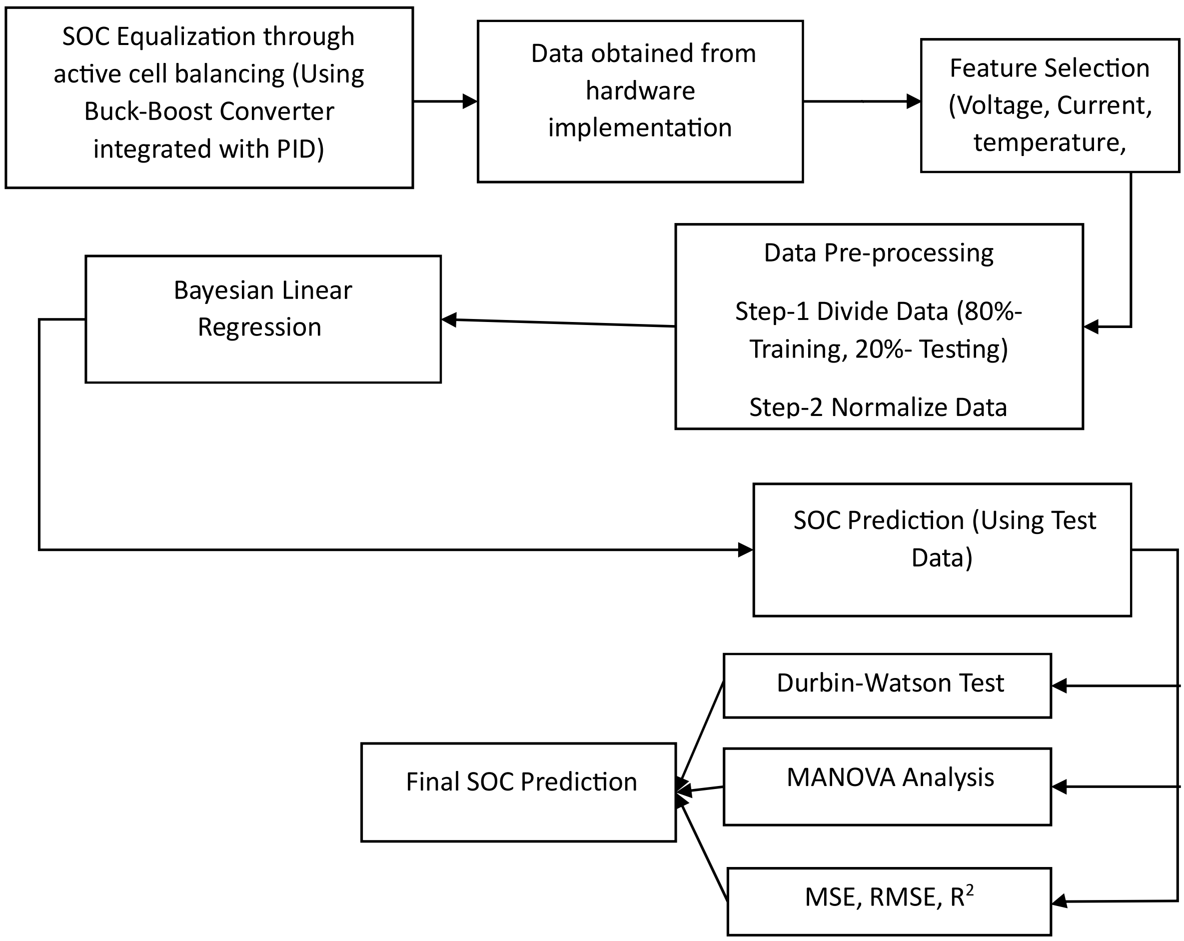

Figure 7. Flowchart of SOC Forecasting

7. Results and Discussion

All four batteries maintain identical capacity and nominal voltage, yet vary in state of charge (SOC). These SOC discrepancies and capabilities were deliberately chosen to expedite the simulation duration. While various methods exist for estimating SOC.

Table 1. Simulation Parameters

Lithium-Ion Battery Parameter	Range Selected for simulation
SOC of Battery (1)	46.50%
SOC of Battery (2)	48.20%
SOC of Battery (3)	49.80%
SOC of Battery (4)	48%
Nominal Voltage	3.7v

Rated Capacity	0.54Ah
Inductor	1mH
Load	1kΩ
PWM Converter	2 Level
Frequency	100Hz
Generator type	Single Phase Half-Bridge (2 Pulse)
Balancing Capacitor	1mF

The duty ratio method contributes to fluctuating balancing rates along each SOC line, as evident in Figures 6 and 7.The captured waveforms were derived during the ACB charging process, with Cell1 at 46.5%, Cell2 at 48.2%, Cell3 at 49.8%, and Cell4 at 48% of their respective capacities. The observations stem from the proposed model, encompassing a range of parameters relating to both active and passive balancing. Figures 11, 12, and 13 illustrate Simulink waveforms portraying the equalization phase of a four-cell battery system across three distinct passive cell balancing modes. Notably, at 262.5 seconds, all four batteries undergo simultaneous charging to reach 3.9 volts. Pre-passive balancing cells exhibit transitional phases, while the employment of IGBTs supplants switches in the passive cell balancing process. The outcomes of the simulation are subject to the influence of various variables. Control algorithms effectively manage diverse cell disparities, module variations, balancing interconnect topology adjustments, and the characteristics of the balancing circuit, duly impacting both the battery efficiency and the speed of the balancing mechanism.

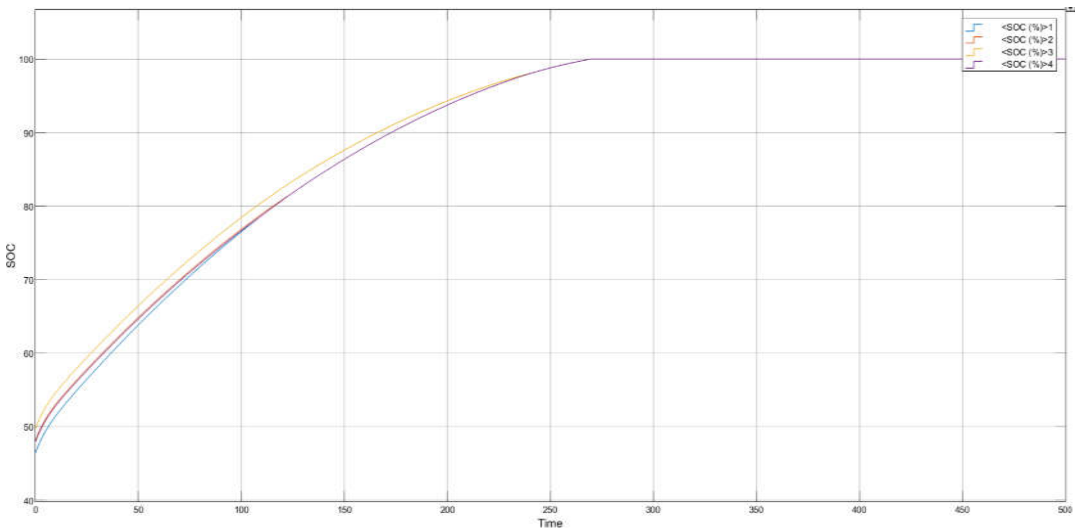

Figure 8. Passive cell balancing during charging mode

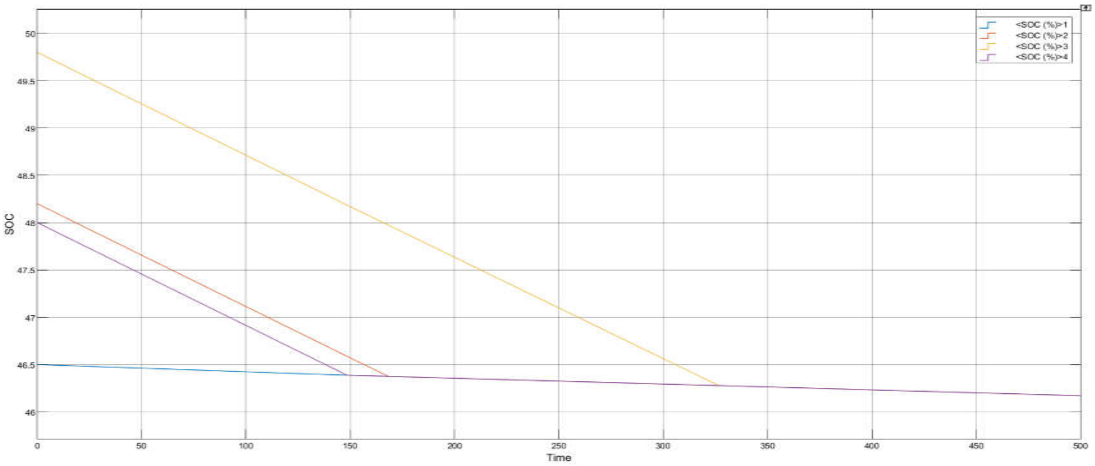

Figure 9. Passive cell balancing during discharging mode

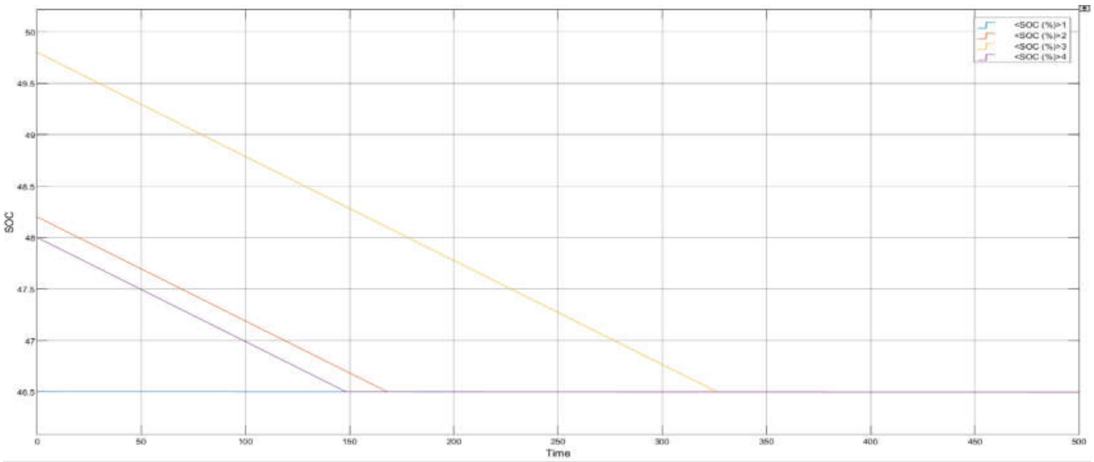

Figure 10. Passive cell balancing during Static mode

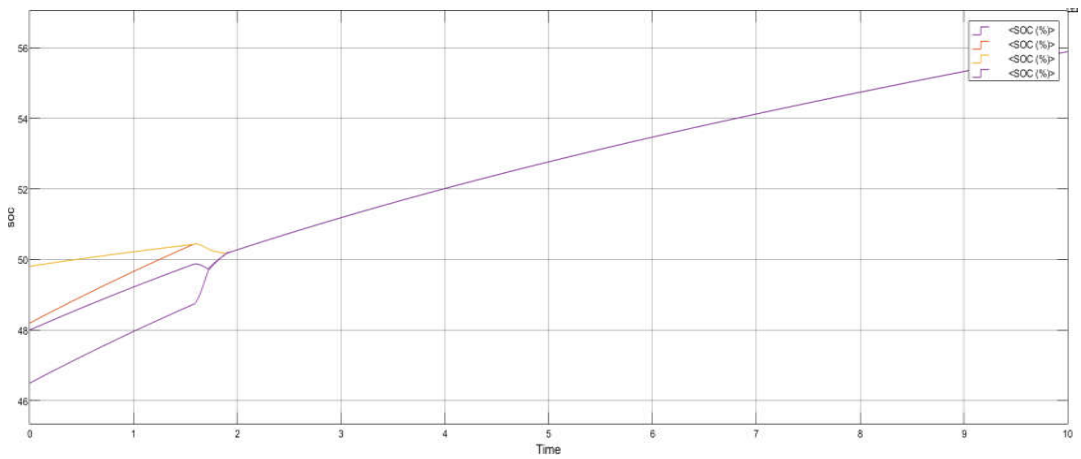

Figure 11. Active cell balancing during charging mode.

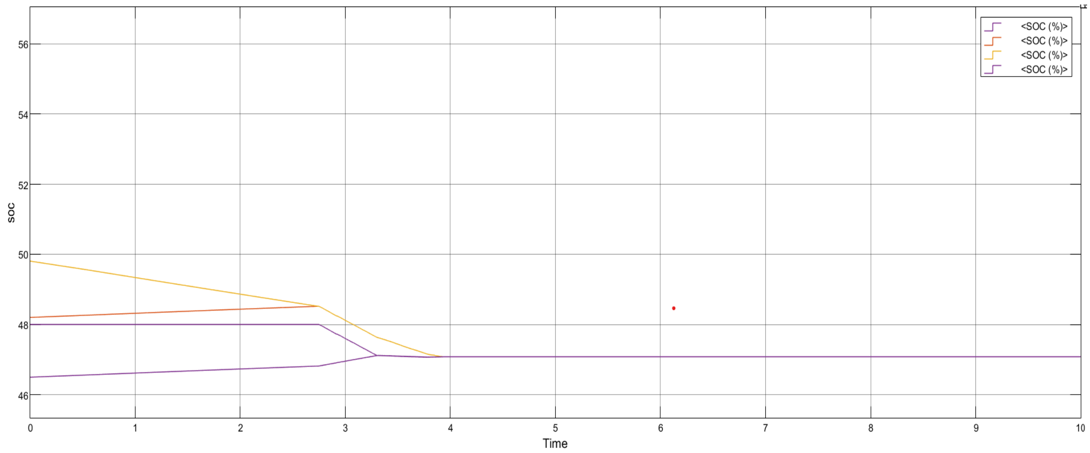

Figure 12. Active cell balancing during discharging mode.

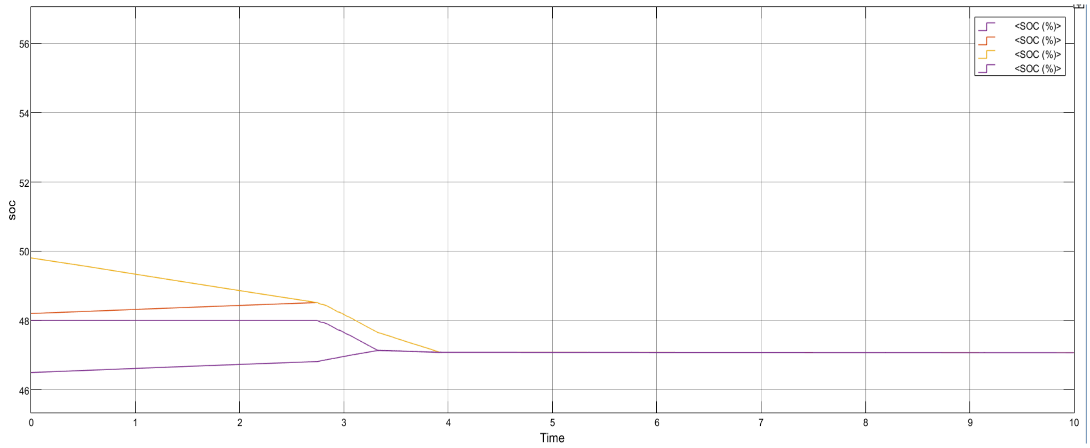

Figure 13. Active cell balancing during static mode.

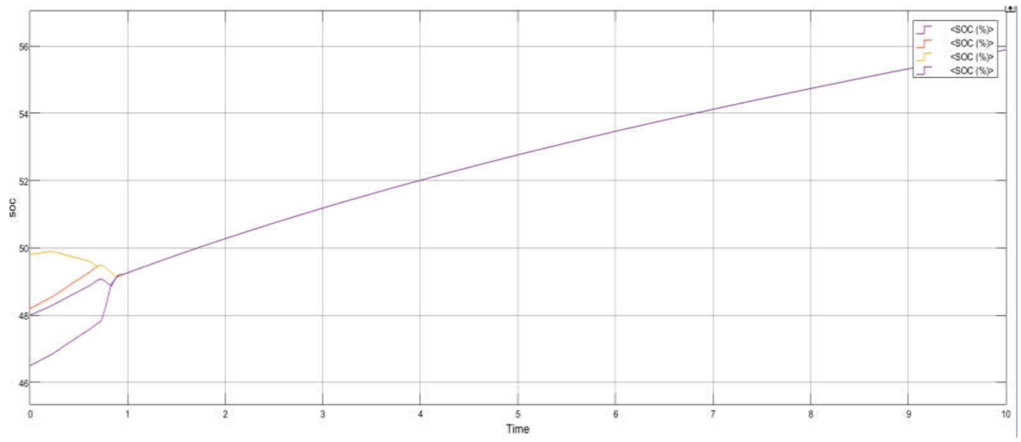

Figure 14. Active cell balancing during charging mode with PI controller

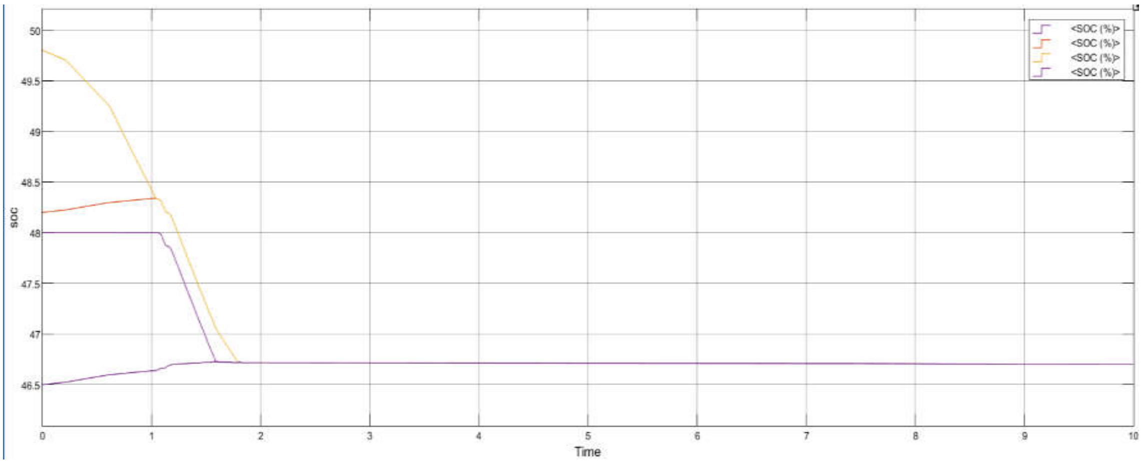

Figure 15. Active cell balancing during discharging mode with PI controller

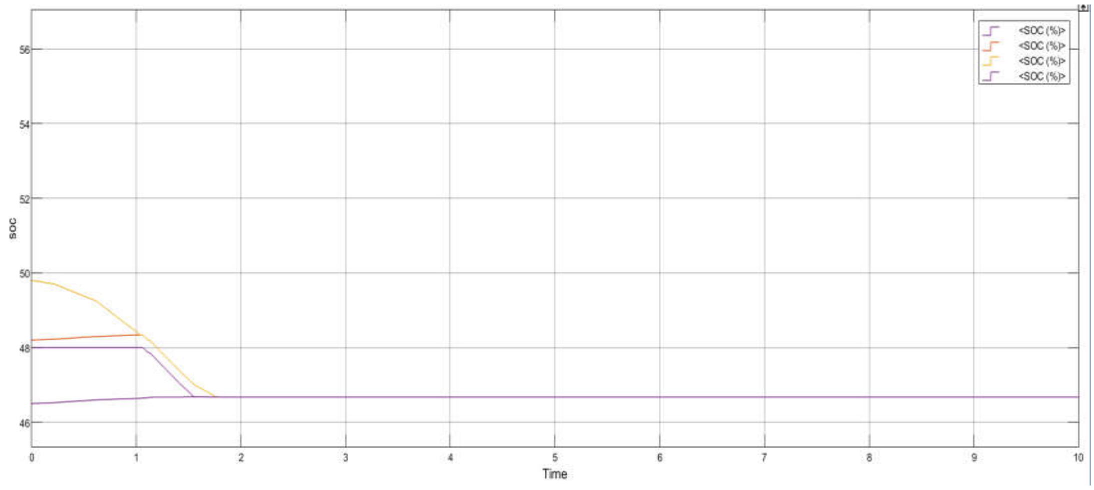

Figure 16. Active cell balancing during static mode with PI controller

8. Conclusion

This research investigated active cell balancing for lithium-ion battery packs using a buck-boost converter. The proposed approach leverages a single circuit with a PI controller for efficient cell balancing, simplifying the design and reducing component count. A MATLAB/Simulink model incorporating both active and passive balancing confirmed the superiority of active balancing in achieving faster equalization times (1.79s static, 0.89s charging, 1.89s discharging) and extending battery life. Future work can focus on improving model accuracy by minimizing switching power losses. This could involve strategies like prioritizing balancing between cell groups using dedicated circuits and optimizing control algorithms that consider cell voltages, currents, and power efficiency.

In conclusion, this study demonstrates the effectiveness of a single-circuit active cell balancing approach using a buck-boost converter and a PI controller for lithium-ion batteries. This innovative design simplifies the system and achieves efficient energy transfer between cells. Simulations confirmed the superiority of active balancing in achieving faster equalization times (e.g., 1.79s static, 0.89s charging) and extending battery life compared to passive methods. Beyond the technical advancements, this approach offers significant real-world benefits. Implementing active cell balancing with buck-boost converters has the potential to optimize battery performance and lifespan in various applications, including electric vehicles, renewable energy storage systems, and portable electronics. Overall, this research contributes to the development of robust and efficient battery management systems, paving the way for improved performance and longevity in lithium-ion battery technology.

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