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Comparative Analysis of Active and Passive Cell Balancing Strategies in Battery Management Systems

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Abstract: *Battery management systems (BMS) play a crucial role in ensuring the performance, reliability, and longevity of modern battery systems by employing cell balancing techniques. This paper presents a comparative study of active and passive cell balancing strategies, focusing on balancing speed, energy dissipation, thermal effects, and State of Health (SoH). Passive balancing methods, utilizing resistive dissipation, are simple and cost-effective but suffer from low efficiency and significant energy loss as heat. Active balancing, on the other hand, redistributes energy between cells using converters, offering superior performance and energy efficiency but at a higher cost and complexity.*

Simulation models were developed in MATLAB/Simulink to evaluate both strategies under various conditions. For passive balancing, resistances of 1 Ω, 0.5 Ω, and 0.1 Ω were used, while active balancing employed a buck-boost converter with MOSFETs. The results demonstrated that active balancing achieved faster SOC (State of Charge) equilibrium with minimal energy dissipation. However, low-resistance passive balancing (e.g., 0.1 Ω) offered comparable balancing speed at the expense of increased thermal impact. A thermal analysis was conducted to evaluate dynamic temperature changes during operation, incorporating aging and environmental factors, which revealed their significant influence on battery performance and SoH degradation.

Additionally, a mathematical scaling approach was applied to extrapolate the findings from a two-cell model to larger systems, providing insights into the scalability of both techniques. The study concluded that active balancing is ideal for high-performance applications requiring efficiency and speed, while passive balancing remains viable for cost-sensitive systems with lower performance requirements. This research highlights the trade-offs between energy efficiency, thermal stability, and complexity in cell balancing, offering valuable guidance for the design and optimization of BMS across various applications..

Keywords: Cell Balancing Techniques, Active vs. Passive Balancing, Battery Management Systems (BMS),Energy Dissipation and Thermal Effects

I. INTRODUCTION

A battery management system is a crucial component of any electric vehicle (EV). It integrates various electrical and electronic circuits, including converter and inverter circuits, to effectively monitor and optimize the performance of the battery system [1]. Its primary functions include monitoring the battery's status, enhancing its efficiency and reliability, preventing overcharging and over-discharging, and extending the overall lifespan of the battery [2]. The health of each battery cell within the pack is assessed by measuring its state of charge (SOC), which represents the ratio of the remaining charge to the cell's total capacity. The SOC is determined using various battery parameters, including voltage, integrated charge and discharge currents, and temperature measurements [3]

A Battery Balancing System (BBS) includes two types of balancing methods: **passive** and **active**. Passive balancing dissipates excess energy from higher-charge cells as heat through resistors, offering simplicity and low cost but with lower efficiency and more heat generation. Active balancing transfers energy between cells using capacitor-based, DC-DC converter-based, or transformer-based circuits, providing higher efficiency [4]

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Battery systems in electric vehicles (EVs) face significant challenges due to cell imbalance, which can lead to reduced capacity, accelerated degradation, and eventual system failure. Over time, individual cell voltages within a pack diverge, resulting in uneven energy distribution and reduced operational efficiency. Proper cell balancing is crucial to maintaining the performance and lifespan of the battery pack, as it ensures that all cells remain within a safe operating range. Among the available techniques, **passive balancing** is widely adopted in industrial applications due to its simplicity, low cost, and ease of implementation. However, passive balancing suffers from inefficiencies, such as energy loss as heat and prolonged balancing times, which limit its effectiveness for high-performance applications like EVs [5, 6].

Conversely, **active balancing techniques** address these limitations by redistributing energy between cells instead of dissipating it as heat. This approach improves energy efficiency and reduces thermal impacts, making it particularly suitable for high-capacity battery packs. Despite these advantages, active balancing systems are generally restricted to research and experimental setups due to their higher complexity, cost, and design requirements [6, 7]. The trade-offs between active and passive balancing—particularly in terms of balancing speed, energy dissipation, and thermal stability—remain a critical area of investigation. Furthermore, factors such as **aging effects**, **environmental variations**, and their influence on long-term battery health and **State of Health (SoH)** have not been adequately explored in comparative studies [7, 8].

While several studies have proposed and evaluated balancing methods, many focus on small-scale setups or qualitative comparisons. Quantitative analyses that consider real-world conditions, such as varying resistance, high-capacity cells, and operational constraints, are limited. Additionally, the energy dissipation trade-offs in passive balancing and the thermal impacts of active balancing are often addressed in isolation, lacking a holistic view of their combined effects on battery performance [6, 8].

This study seeks to bridge these gaps by providing a detailed evaluation of active and passive balancing strategies under varying conditions. The objectives include comparing **balancing speed**, quantifying **energy dissipation**, analyzing**thermal effects**, and assessing **State of Health (SoH)** trends over time. By incorporating factors such as aging and environmental variations, this research aims to identify the trade-offs between speed, energy efficiency, and thermal stability. Ultimately, the findings will contribute to the optimization of battery management systems for EV applications, ensuring enhanced performance, reliability, and longevity [5, 6, 7, 8].

II. BLOCK DIAGRAM OF BATTERY MANAGEMENT SYSTEM (BMS)

The architecture of a Battery Management System (BMS) can vary depending on the employed system and the specific algorithms implemented [9], [10]. A basic BMS structure consists of several functional blocks that work together to ensure battery health, performance, and safety. The primary blocks of the system are detailed below:

Measurement Block

The primary role of the measurement block is to monitor vital parameters such as cell voltages, currents, temperatures, and ambient temperature. These physical measurements are converted into digital signals, enabling efficient processing by thesystem. Although using sensors at the individual cell level incurs high costs, their integration offers the advantage of enabling fine-grained cell balancing, enhancing system reliability and accuracy.

Battery Algorithm Block

This block calculates the **State of Charge (SOC)** and **State of Health (SOH)** by utilizing the data from the measurement block. SOC represents the current capacity of the battery as a percentage of its total rated capacity and functions similarly to a fuel gauge, indicating how much charge remains and predicting the vehicle's remaining range [11], [12]. Factors such as temperature fluctuations and charge/discharge cycles can alter SOC values, requiring the BMS to incorporate these variables into the estimation process. A commonly used method for SOC estimation is through open-circuit voltage (OCV) measurement, referencing pre-stored discharge characteristics. However, this method does not account for temperature effects, highlighting the importance of employing more comprehensive estimation algorithms that include such factors. Accurate SOC calculations are essential to prevent overcharging or undercharging, particularly when regenerative braking introduces charge imbalances.

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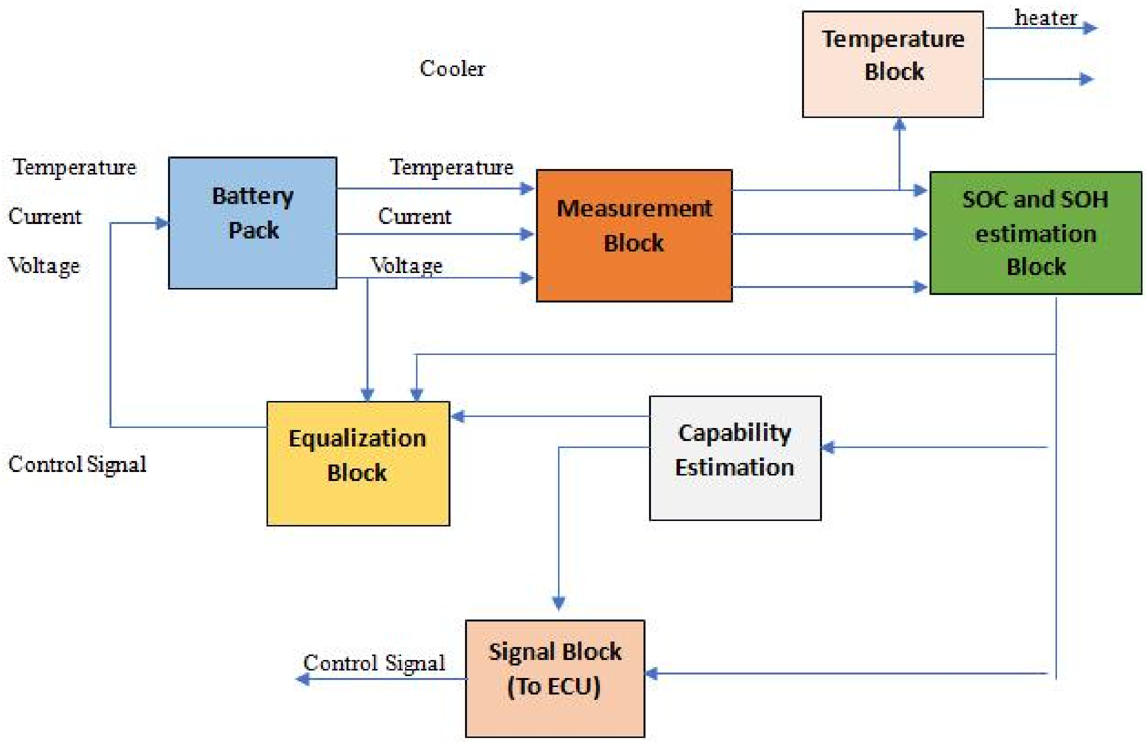

Fig 1 Block Diagram of Battery Management System

Capability Estimation Block

The capability estimation block calculates the maximum allowable charge and discharge currents at any given moment based on the SOC and SOH values. This information is then sent to the **Electronic Control Unit (ECU)**, enabling the BMS to regulate charging and discharging while taking necessary safety precautions. This ensures optimal performance and protection of the battery from potential operational risks.

Cell Equalization Block

Cell variations are inevitable, as individual cells within a battery pack exhibit differing characteristics. The primary role of this block is to ensure that all cells operate at similar SOC and voltage levels to prevent system malfunctions.[15] It identifies variations between cells' voltages or SOC values, and if the difference exceeds a predefined threshold, it initiates equalization. Two methods are employed:

1. **Dissipative Equalization**: Excess energy from cells with higher SOC is discharged until the SOC levels are balanced. While this method is simple, it leads to energy waste.
2. **Active Equalization**: Cells with higher SOC are charged using external circuits or high-voltage connections to balance the system. Although this technique is more efficient, it is cost-intensive. Additionally, active balancing reduces energy wastage by utilizing algorithms that allow under-voltage cells to draw charge from other cells rather than wasting excess energy.

Thermal Management Block

The thermal management block monitors battery cell temperatures to ensure they operate within safe limits, preventing overheating that could lead to permanent damage.[14] It communicates with a cooling system or heating system to maintain optimal temperature ranges. Additionally, this block sends a control signal to the ECU in the event of an abnormal temperature increase, which could harm the battery or the user [13]. This ensures the thermal stability of the system during operation and safeguards against catastrophic failures.

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III. SIMULATION ENVIRONMENT

The simulations and analyses were conducted using MATLAB/Simulink 2021a, a widely recognized platform for modeling and simulating dynamic systems. This version provided robust tools and specialized libraries to create accurate representations of battery balancing systems.

The majority of components, including battery models, resistances, and switching elements, were sourced from the Specialized Power Systems library within Simulink, enabling precise simulation of electrical and thermal behaviors. Custom MATLAB scripts were employed for post-processing and data visualization.

The primary objective of the simulation environment was to evaluate the effectiveness of active and passive balancing strategies under various operational conditions. The framework allowed for detailed comparisons of key performance metrics, including balancing speed, energy dissipation, thermal effects, and State of Health (SoH), to assess the trade-offs inherent to each method.

This setup provided the flexibility to simulate real-world scenarios while maintaining computational efficiency and high-fidelity results.

Passive Balancing

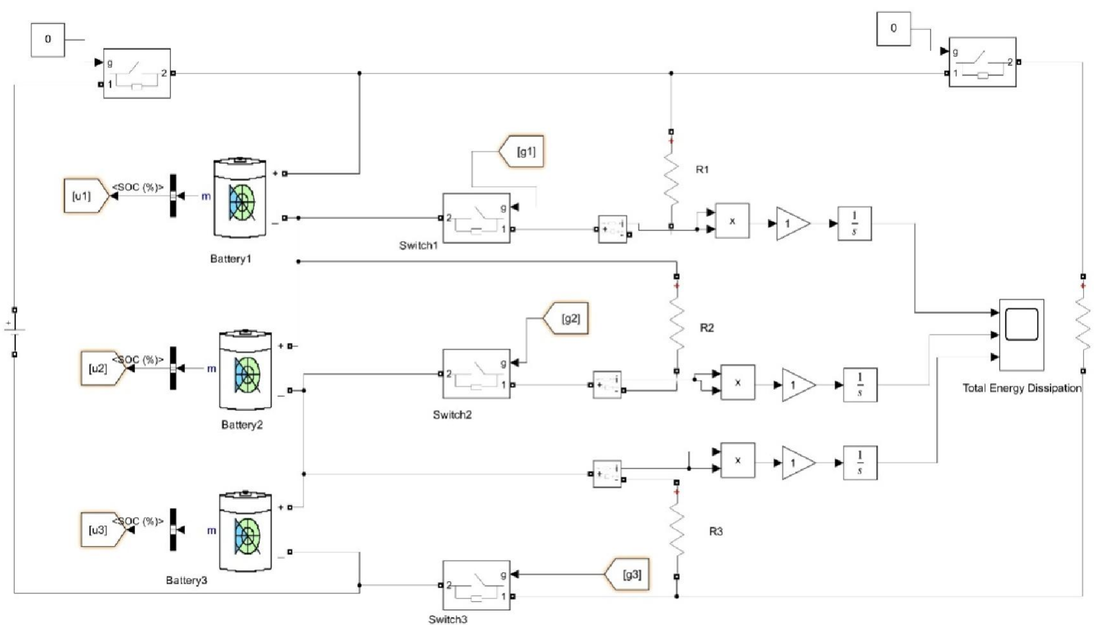

Fig 2 Passive Balancing Simulation Circuit

In the passive balancing simulation, three batteries connected in series were used to model the balancing system. A simple resistive approach was adopted to facilitate balancing. A resistor was placed across the battery with higher state-of-charge (SOC) to dissipate excess energy until balance was achieved among the series-connected batteries. A **current sensor** was connected in series with the resistor to monitor the current flowing through the circuit. This allowed for accurate measurement of energy dissipation using the standard energy dissipation formula $E = \int_0^T I^2 R \, dt$, where III is the current and RRR is the resistance.

after running the simulation, the data from the current sensor was extracted to the MATLAB workspace for further analysis. This approach allowed for a detailed analysis of the total energy dissipation during the passive balancing process, including observing trends in balancing speed, energy consumption, and SOC convergence.

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Active Balancing

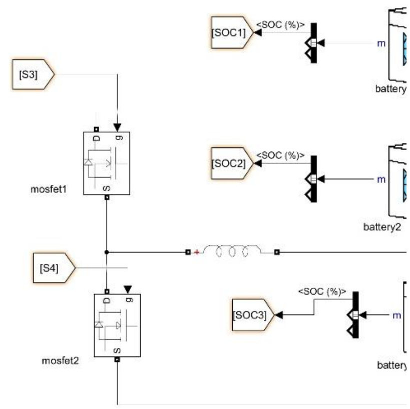

Fig 3 Active Balancing Simulation Circuit

For the active balancing simulation, three batteries connected in series were also employed to evaluate the active balancing mechanism. In this approach, a **buck-boost converter** was used to facilitate the redistribution of energy among the cells. The converter's functionality was controlled by a combination of **MOSFETs** and inductors, ensuring efficient energy transfer while maintaining system stability.

A **current sensor** was connected in series with the MOSFETs and inductors to measure the current during the balancing operation. This allowed the calculation of energy dissipation using the same standard formula $E = \int_0^T I^2 R\, dt$, considering the contributions of both the inductor and the active switching circuits. Similar to the passive balancing simulation, the extracted data from the current sensors was sent to the MATLAB workspace for comprehensive post-simulation analysis. This analysis provided insights into the comparative performance of the active balancing strategy, focusing on metrics such as energy dissipation, balancing speed, and efficiency.

IV. METHODOLOGY

This section provides a detailed description of the models, scenarios, and metrics used to compare active and passive balancing strategies.

Battery and Circuit Models

The simulations employed detailed battery and circuit models to represent the characteristics and behavior of balancing systems accurately. These models were designed to replicate real-world scenarios, incorporating key electrical, thermal, and physical properties of lithium-ion battery cells commonly used in electric vehicles and stationary energy storage systems.

Battery Specifications

The battery cells used in this study were parameterized with realistic specifications to ensure accuracy in evaluating balancing strategies. The key parameters included:

- **Nominal Voltage**: 3.7 V per cell, representing standard lithium-ion chemistry,
- **Capacity**: 2 Ah per cell, ensuring consistency across balancing strategies,
- **Mass**: 0.05 kgper cell, reflecting typical lithium-ion cell mass,
- **Specific Heat Capacity**: $1200 J/(kg \cdot °C)$,representing the thermal properties of lithium-ion materials,
- **Thermal Resistance**: 0.01 $°C/W$., modeling the heat dissipation capability of the cells under operational conditions.

These specifications enabled the accurate simulation of electrical performance, energy dissipation, and temperature rise, which are critical for assessing balancing strategies.

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Active Balancing Circuit

The active balancing circuit employed a **MOSFET-based design** to redistribute charge dynamically between cells. The circuit featured:

- **Fixed Internal Resistance (R_f)**: 0.01 Ω, representing the on-state resistance of the MOSFETs,
- **Buck-Boost Converter**: Incorporated to enable precise and efficient charge redistribution, minimizing voltage imbalances across cells,
- **Switching Logic**: Controlled by pulse-width modulation (PWM), ensuring optimal balancing and energy transfer.

This design prioritized efficiency, reducing energy dissipation and limiting temperature rise, making it suitable for high-performance applications like electric vehicles.

Passive Balancing Circuit

The passive balancing circuit employed a simpler approach using a **resistive network** to equalize cell voltages. The network configurations included:

- **Resistances**: R=1 Ω,0.5 Ω, and 0.1 Ω, chosen to study the trade-offs between balancing speed and energy dissipation,
- **Heat Dissipation**: Modeled through resistors, representing the energy lost during balancing as heat.

Lower resistances offered faster balancing speeds but increased energy losses, while higher resistances were more energy-efficient but slower in achieving equilibrium.

Scenarios Simulated

The study explored multiple balancing scenarios to evaluate and compare the performance of active and passive balancing mechanisms. These simulations were designed to capture key metrics such as balancing speed, energy dissipation, thermal behavior, and long-term battery health under varying conditions.

- **Balancing Mechanisms**

Two distinct balancing strategies were simulated:

1. **Passive Balancing**:
    - Resistive networks were used to dissipate excess energy as heat to equalize cell voltages,
    - Three resistance configurations were tested to study their impact on performance:

      $R = 1\,\Omega$

      $R = 0.5\,\Omega$

      $R = 0.1\,\Omega$
    - These configurations demonstrated the trade-offs between faster balancing speeds (lower resistance) and increased energy dissipation.
2. **Active Balancing**:
    - A MOSFET-based circuit with a fixed internal resistance $R_f = 0.01\,\Omega$was employed to dynamically redistribute charge between cells,
    - A buck-boost converter facilitated controlled charge transfer, minimizing voltage imbalances across the battery cells while limiting energy dissipation,
    - This method prioritized efficiency and lower thermal impact compared to passive balancing.

- **Simulation Period**

Each simulation was run for a duration sufficient to achieve **SOC balancing**, defined as the time required for the deviation in SOC among cells to drop below a set threshold ($\Delta SOC < 0.01$).

The simulation times varied based on the balancing strategy and resistance values:

- Lower resistances in passive balancing achieved faster balancing but resulted in higher energy losses and thermal effects,

Active balancing, with its efficient charge redistribution, achieved the target SOC threshold within shorter timeframes

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- **Evaluation Metrics**

To comprehensively evaluate and compare active and passive balancing strategies, several performance metrics were analyzed. These metrics provided insights into balancing speed, energy dissipation, thermal effects, and the long-term impact on battery health.

- **Balancing Speed**

The speed of balancing was evaluated by measuring the time required for the **State of Charge (SOC) deviation** between battery cells to drop below a defined threshold:
$\Delta SOC<0.01$

SOC Deviation: The difference between the highest and lowest SOC values in the battery pack.

Measurement: The time to achieve this threshold was recorded for:

- **Active balancing** with MOSFET-based charge redistribution ($Rf = 0.01\,\Omega$),
- **Passive balancing** with resistances of $R = 1\,\Omega, 0.5\,\Omega,\ and\ 0.1\,\Omega$.

This metric directly reflects the efficiency of each balancing strategy in achieving equilibrium among battery cells.

- **Energy Dissipation**

The total energy dissipated during balancing was calculated using the formula:

$$E = \int_0^T I^2 R\ dt$$

Where:

E: Total energy dissipation (in Joules),
I: Current through the balancing circuit,
R: Resistance of the balancing circuit element (MOSFET or resistor),
T: Total simulation time.

Key considerations:

Passive Balancing: Energy was dissipated as heat through resistors, with higher dissipation observed at lower resistance values,

Active Balancing: Minimal energy dissipation occurred due to efficient charge transfer via MOSFETs.

The total energy dissipated for each method and resistance scenario was compared to identify trade-offs between speed and efficiency.

- **Thermal Effects**

Temperature rise in the battery cells was analyzed to evaluate the thermal impact of balancing strategies. The temperature change was calculated based on energy dissipation and thermal properties:

$$\Delta T(t) = \frac{EnergyDissipated(J)}{Mass\ (kg)\}\ \times Specific\ Heat\ (J/(kg \cdot {}^\circ C))}$$

Where:

Mass: $0.05\ kg$

Specific Heat Capacity: $1200\ J/(kg \cdot {}^\circ C)$

The simulations incorporated:

1. **Time-Dependent Thermal Effects**:
   - Instantaneous temperature changes were computed dynamically over time.
2. **Environmental Temperature Variations**:
   - Ambient temperature was modeled as a sinusoidal function to simulate seasonal fluctuations.

These analyses provided insights into the thermal efficiency and stability of active and passive balancing methods.

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- **State of Health (SoH)**

The **State of Health (SoH)** was modeled to assess the long-term impact of balancing strategies on battery capacity. SoH was defined as:

$$\mathrm{SoH}(t) = \frac{\text{Current Capacity}}{\text{Initial Capacity}}$$

Where:

Initial Capacity: Nominal capacity of 2 Ah

Current Capacity: Remaining capacity at time t, adjusted for degradation due to cumulative energy dissipation and thermal effects.

The following were incorporated into the SoH model:

1. **Aging Effects**:
   - Capacity degradation was linked to:
     - Cumulative energy dissipation,
     - Exposure to elevated temperatures over time.
   - Nonlinear aging dynamics were modeled as:

     $$\text{Aging Factor} = \exp\left(\alpha \cdot T(t) + \beta \cdot \text{Cumulative Dissipation}(t)\right)$$

     Where α and β are sensitivity factors.
2. **Degradation Trends**:
   - SoH trends were analyzed for both active and passive balancing strategies to identify their impact on battery longevity.

V. RESULTS

This section presents the simulation outcomes, emphasizing the trade-offs between active and passive balancing strategies under different conditions. Key performance metrics, including balancing speed, energy dissipation, and long-term impacts, are discussed in detail.

Balancing Speed

The speed of balancing was evaluated by measuring the time required for the **State of Charge (SOC) deviation** among cells to drop below a threshold ($\Delta SOC < 0.01$). The results provide insights into how quickly each strategy equalizes the SOC levels across the battery cells.

- **SOC Balancing Speed**

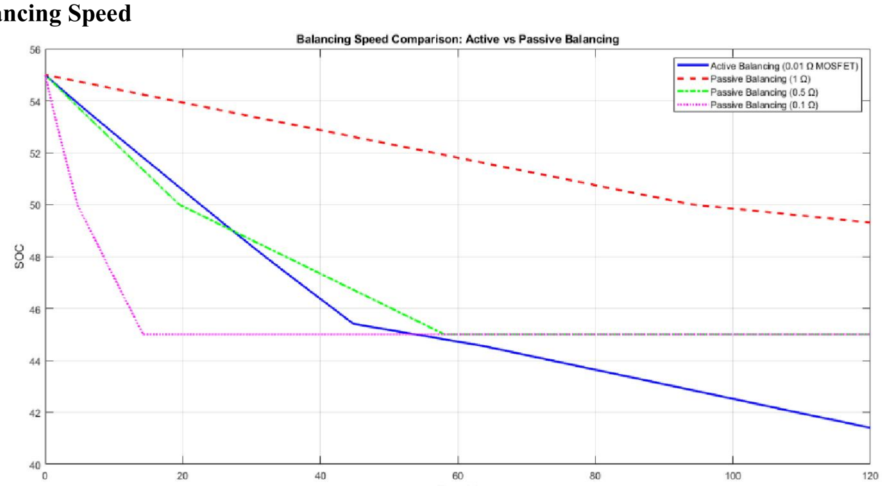

Fig 4 Balancing Speed in each Method

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A comparative analysis was conducted using the **SOC Progression Comparison** graph. Key observations include:

1. **Active Balancing**:
   - Achieved equilibrium significantly faster than passive methods across all scenarios.
   - The MOSFET-based active balancing circuit, $R_f = 0.01$, efficiently redistributed charge without introducing delays or significant energy losses.
2. **Passive Balancing**:
   - Faster balancing was observed with lower resistances ($R = 0.1\,\Omega$), as lower resistance allowed higher current flow, reducing the balancing time.
   - Higher resistances ($R = 1\,\Omega$and $R = 0.5\,\Omega$) exhibited slower convergence due to the limited current flow and heat dissipation constraints.

- **Key Observations**

1. **Passive Balancing with $R = 0.1\,\Omega$**:
   - This configuration achieved the fastest balancing among the passive methods.
   - However, the high current flow resulted in increased energy dissipation, making it less efficient overall.
2. **Active Balancing**:
   - Outperformed all passive configurations in terms of balancing speed.
   - The MOSFET-based design ensured minimal energy loss, making it a more efficient and thermally stable option.
3. **Supporting Data**

The following data from Table I highlights the differences in balancing speed:

TABLE I SOC PROGRESSION FOR ACTIVE AND PASSIVE BALANCING METHODS

Time (s)	Active Balancing (0.01 Ω)	Passive (1 Ω)	Passive (0.5 Ω)	Passive (0.1 Ω)
0	55.0000	55.0000	55.0000	55.0000
60	44.7226	51.8067	45.0117	45.0116
120	41.4041	49.3079	45.0133	45.0132

- At 60 seconds, the SOC of active balancing is already significantly lower (44.7226%) compared to all passive configurations.
- At 120 seconds, active balancing continues to progress toward equilibrium faster than any passive strategy.

The analysis confirms that **active balancing** is the superior method for achieving rapid SOC equalization with minimal energy dissipation. While **passive balancing with $R = 0.1\,\Omega$**offers comparable speed, it comes at the expense of higher energy loss, making it less suitable for applications requiring efficiency and thermal stability.

SOC Progression Comparison

The progression of State of Charge (SOC) over time was analyzed to illustrate how active and passive balancing methods achieve equilibrium. The analysis focused on the speed and behavior of each method during the balancing process..

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- **SOC Over Time**

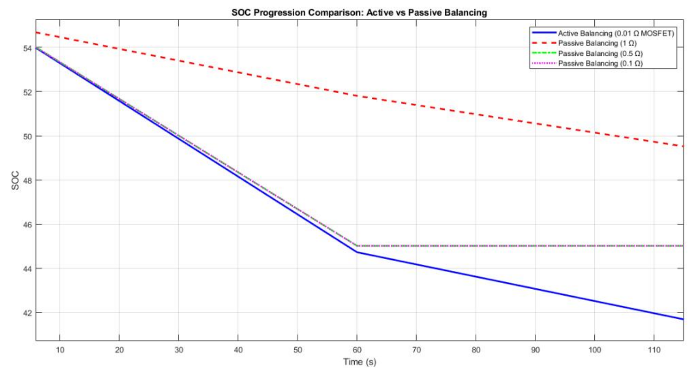

Fig 5 SOC Over time

Graphs comparing SOC progression for active and passive balancing highlight significant differences in convergence rates:

1. **Active Balancing:**
   - The MOSFET-based circuit demonstrated rapid convergence, achieving SOC equilibrium faster than passive methods across all scenarios.
   - This efficiency was consistent regardless of initial SOC imbalances, emphasizing the method's suitability for high-speed applications.
2. **Passive Balancing:**
   - The balancing speed depended heavily on resistance values:
     - Higher resistance ($R = 1\,\Omega$): Exhibited delayed convergence due to limited current flow,
     - Moderate resistance ($R = 0.5\,\Omega$): Improved speed but still lagged behind active balancing,
     - Lower resistance ($R = 0.1\,\Omega$): Approached the speed of active balancing but at the expense of higher energy dissipation.

The SOC progression data from Table 1 illustrates this behavior, showing faster SOC reductions in active balancing and delayed convergence in passive balancing, particularly at higher resistances.

Energy Dissipation

Energy dissipation during balancing is a critical metric for evaluating the efficiency and thermal impact of each strategy. The results demonstrate a clear trade-off between balancing speed and energy efficiency, particularly for passive methods.

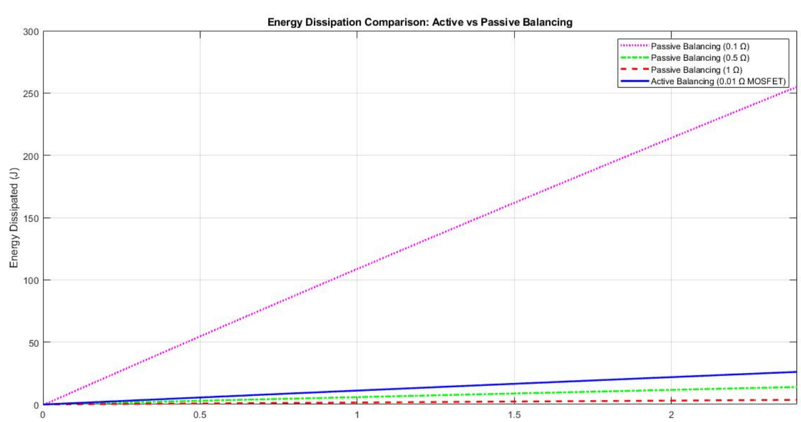

Fig 6 Energy Dissipation in each Scheme

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- **Total Energy Dissipation**

TABLE II THE CUMULATIVE ENERGY DISSIPATION FOR EACH SCENARIO

Scenario	Total Energy Dissipation (J)
Active (0.01 Ω MOSFET)	31.666
Passive Balancing (1 Ω)	34,810
Passive Balancing (0.5 Ω)	73,232
Passive Balancing (0.1 Ω)	324,210

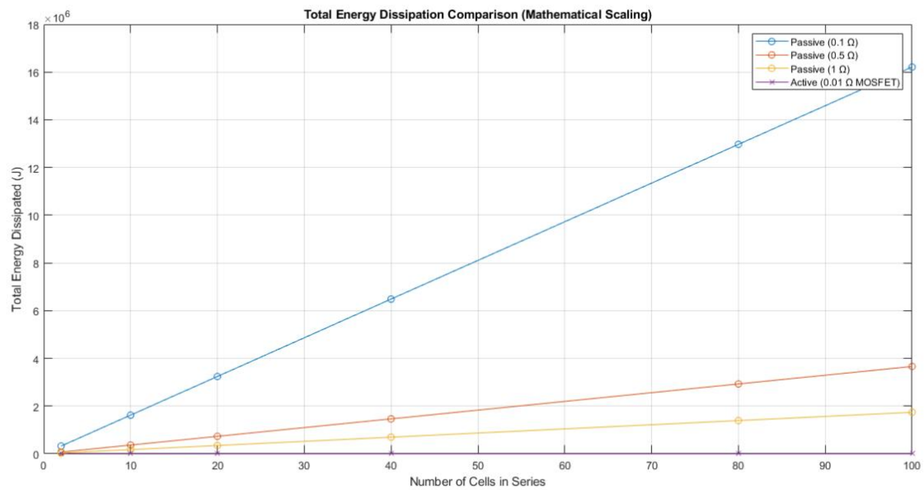


Fig 7Total Energy Dissipation Comparision

- **Key Observations:**
    - Active balancing resulted in the lowest energy dissipation due to efficient charge redistribution with minimal resistive losses,
    - Passive balancing with lower resistances ($R = 0.1\ \Omega$) dissipated significantly more energy due to increased current flow, while higher resistances ($R = 1\ \Omega$)offered better energy efficiency but slower balancing speeds.

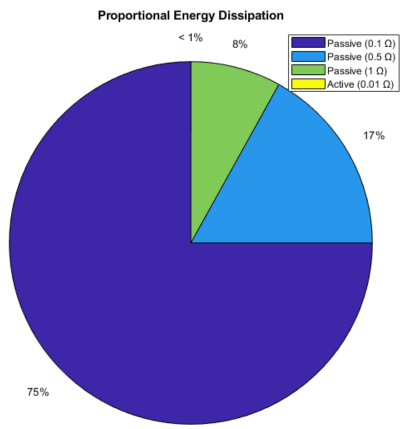
- **Proportion of Energy Dissipated**

A pie chart was generated to illustrate the proportion of energy dissipation among key components for active and passive methods.

The chart highlights:

- **Active Balancing:**
    - Majority of energy dissipated in the MOSFET and negligible thermal impact on other components.
- **Passive Balancing:**
    - Dominant energy loss through resistors, with lower resistances exacerbating dissipation.

The pie chart reinforces the efficiency of active balancing, which minimizes energy loss while maintaining faster balancing speeds compared to passive methods.



Thermal Analysis

- **Static Thermal Effects:**

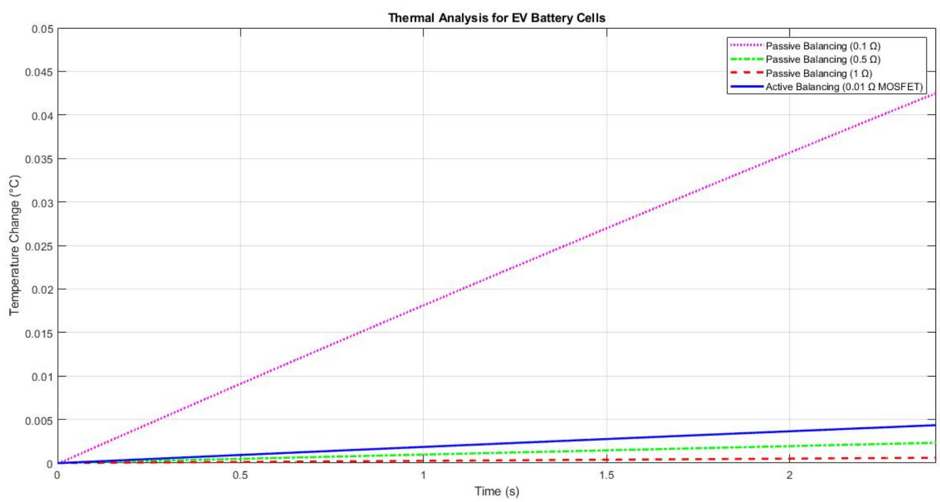


Fig 9 Thermal Analysis battery Cells

Graph Analysis: The maximum temperature rise for each balancing strategy is depicted in the thermal comparison graphs.

Key Observations:

- **Active Balancing (0.01 Ω MOSFET):** Produced negligible heat, maintaining temperature stability across all scenarios.
- **Passive Balancing:**
  - $R = 0.1\,\Omega$: Exhibited the highest temperature rise due to greater current flow.
  - $R = 0.5\,\Omega$ and $R = 1\,\Omega$: Demonstrated progressively lower heat generation, but at the expense of balancing speed.

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- **Dynamic Thermal Effects:**

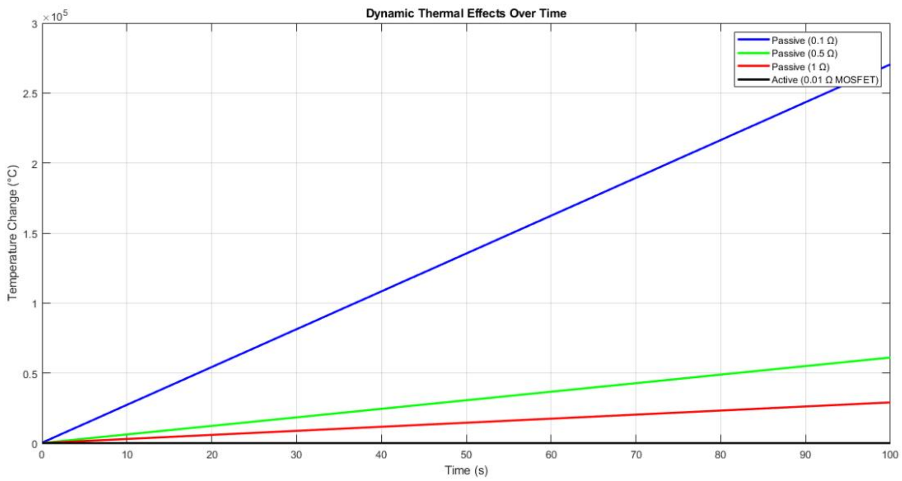

Fig 10 Dynamic Thermal Effect Over Time

Graph Analysis: The temperature variation over time was studied, including the effects of aging and environmental conditions.

Key Observations:

- **Active Balancing:** Maintained better thermal stability with minimal fluctuation over time, even under adverse conditions.
- **Passive Balancing:**
  - Lower resistance ($R = 0.1\,\Omega$) caused significant dynamic thermal variations.
  - Higher resistance configurations ($R = 0.5\,\Omega$ and $R = 1\,\Omega$) reduced temperature fluctuations but delayed the balancing process.

State of Health (SoH)

- **SoH Over Time:**

  Graph Analysis: State of Health degradation was compared for different balancing strategies.

  Results:
  - **Active Balancing:** Preserved battery health better over time, maintaining higher SoH.
  - **Passive Balancing:**
    - $\boldsymbol{R = 0.1\,\Omega}$: Exhibited accelerated degradation due to increased current and heat.
    - $\boldsymbol{R = 0.5\,\Omega}$ **and** $\boldsymbol{R = 1\,\Omega}$: Slower SoH deterioration but showed trade-offs in balancing speed and energy efficiency.

- **Key Observations:**

  Active Balancing: Minimizes capacity loss even under harsh conditions, proving to be more effective in maintaining battery longevity.

  Passive Balancing: Lower resistance sacrifices SoH for faster balancing, highlighting the trade-off between efficiency and longevity.

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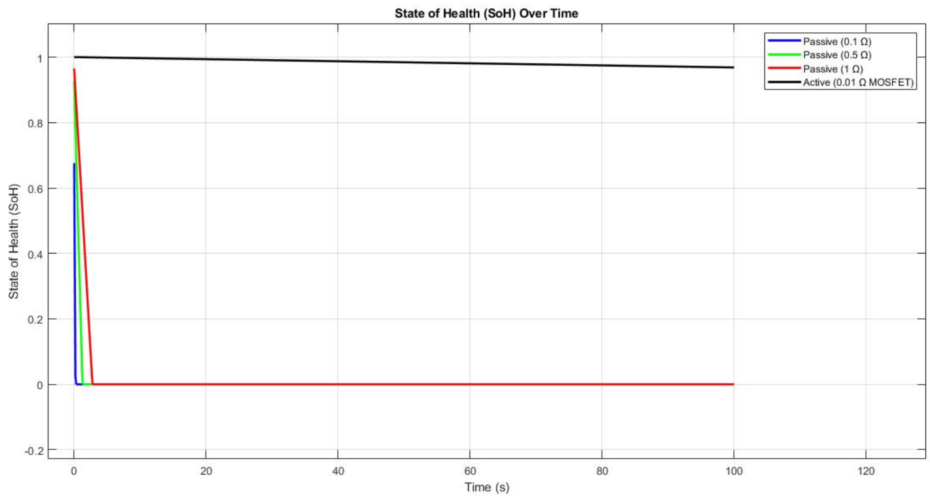

Fig 11 State Of Health Over Time

Trade-Offs

- **Balancing Speed vs Energy Dissipation:**
  Active Balancing (0.01 Ω MOSFET): Demonstrates rapid SOC equalization with minimal energy dissipation.
  Passive Balancing:
    - $R = 0.1\,\Omega$**:** Comparable speed to active balancing but at the cost of increased heat and energy loss.
    - $R = 0.5\,\Omega$ *and* $R = 1\,\Omega$: Slower speeds with better thermal and energy efficiency.
- **Thermal Effects vs SoH:**
  Active Balancing: More thermally efficient and maintains better SoH, ensuring longer battery lifespan.
  Passive Balancing: While faster balancing can be achieved with lower resistance, it results in significant thermal and SoH trade-offs.

VI. CONCLUSION

This study provided a comprehensive comparative analysis of **active and passive cell balancing strategies** within battery management systems (BMS). The analysis explored the performance trade-offs, thermal effects, energy dissipation, and the influence of environmental factors and aging on **State of Health (SoH)** over time. The findings offer key insights into the advantages and limitations of these two balancing strategies.

The **balancing speed comparison** demonstrated that **active balancing** achieves faster SOC (State of Charge) equilibrium across all tested scenarios, while **passive balancing** exhibited delayed convergence, particularly at higher resistances. These results indicate that active balancing is superior in terms of speed, while passive balancing offers simplicity and cost advantages but with longer balancing times.

Regarding **energy dissipation**, the analysis revealed that active balancing dissipates significantly less energy compared to passive balancing. Passive balancing, depending on the resistance values employed (0.1 Ω, 0.5 Ω, and 1 Ω), showed varying levels of energy dissipation, with lower resistances achieving faster balancing at the cost of higher losses. A mathematical scaling approach was used to further assess dissipation trends, supported by simulation data and analysis.

The study also included **thermal analysis**, examining the effects of temperature on balancing performance and system health. It was found that dynamic thermal effects, combined with environmental variations and aging, affect battery performance and **State of Health (SoH)** over time. These findings emphasize the importance of accounting for thermal stress and environmental factors when evaluating the long-term effects on battery life and performance.

The simulation environment was developed using MATLAB/Simulink, incorporating **passive and active balancing mechanisms**. Passive balancing relied on resistive networks, while active balancing utilized buck-boost converters with

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MOSFETs and inductors. Data was extracted to the MATLAB workspace for further analysis, allowing a comprehensive comparison of performance metrics across both balancing strategies.

In conclusion, this study highlighted that **active balancing** offers advantages such as faster speed and reduced energy dissipation, but it involves higher complexity and cost. On the other hand, **passive balancing** remains a cost-effective and straightforward choice, albeit with inherent inefficiencies such as increased energy dissipation and heat generation. The insights from this research contribute to the understanding of energy management strategies, thermal effects, and aging trends, offering guidance for future design and optimization of battery management systems across various applications.

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