AI-BASED PASSIVE CELL BALANCING IN LITHIUM-ION BATTERY PACKS: A SIMULATION-BASED COMPARISON OF PSO AND GWO ALGORITHMS

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Abstract

With the rapid growth of electric vehicles, the efficiency and safety of Battery Management Systems (BMS) have become increasingly critical. One of the most common issues in battery packs is the voltage imbalance among series-connected lithium-ion cells, which can degrade system performance, reduce battery lifespan, and increase safety risks. This paper focuses on minimizing voltage discrepancies among three lithium-ion cells using a passive balancing method enhanced with intelligent optimization techniques.

A real-time monitoring and control model was developed in MATLAB/Simulink to observe and regulate cell voltages dynamically. Instead of relying on fixed threshold values, the proposed system employs Particle Swarm Optimization (PSO) and Grey Wolf Optimization (GWO) algorithms to identify cells requiring balancing adaptively. This adaptive control structure enables the system to respond flexibly to varying operating conditions.

Simulation results demonstrate that both algorithms effectively reduce inter-cell voltage differences while maintaining overall system stability. Moreover, findings indicate that the PSO-based controller provides slightly higher energy efficiency compared to the GWO-based approach. Nevertheless, both algorithms deliver reliable and robust performance under passive balancing scenarios, confirming their suitability for advanced BMS applications.

Keywords: Lithium-Ion Battery, Passive Balancing, PSO, GWO, Simulink, Battery Management System.

I. Introduction

Lithium-ion (Li-ion) batteries have become a cornerstone of modern energy storage systems, especially in electric vehicles (EVs), portable electronics, and renewable energy applications. Their high energy density, long operational life, and low maintenance requirements have made them the preferred choice for high-performance power solutions. These batteries are typically composed of multiple cells arranged in series and/or parallel. Over time, inconsistencies in cell behavior emerge due to differences in internal resistance, temperature exposure, and aging, resulting in voltage imbalances.

Such imbalances can compromise both system performance and safety by causing overcharging or premature discharge in individual cells. To address this, Battery Management Systems (BMS) incorporate balancing mechanisms, which are broadly categorized as active or passive. Passive balancing is widely adopted due to its structural simplicity and lower cost. It works by dissipating excess energy from higher-voltage cells as heat through resistive elements. However, conventional passive systems often use fixed thresholds, limiting their ability to adapt to varying cell conditions.

This study presents a MATLAB/Simulink-based model for passive balancing of a three-cell Li-ion battery pack. The control logic employs two heuristic algorithms—Particle Swarm Optimization (PSO) and Grey Wolf Optimization (GWO)—to dynamically manage the balancing process based on real-time voltage data. Unlike static threshold methods, these algorithms enable adaptive decision-making, improving efficiency and responsiveness.

Simulation results demonstrate that PSO achieves faster convergence, while GWO offers greater stability under varying initial conditions (Güven and Yörükeren, 2024). These findings underscore the importance of algorithm selection in enhancing the reliability and effectiveness of passive balancing strategies in Li-ion battery systems.

1.1. Literature Review

Extensive research on electric vehicles and BMS has demonstrated that effective BMS design is critical to ensuring battery safety, efficiency, and longevity. The literature highlights that a BMS performs essential functions such as voltage and temperature monitoring, State of charge (SOC) and State of Health (SoH) estimation, and cell balancing.

Aldoğan (2012) discussed the design of a BMS specifically for electric vehicles, emphasizing its role in reducing environmental impact while maintaining system reliability. The study detailed different BMS architectures—centralized, distributed, and modular—and compared passive and active balancing strategies for Li-ion batteries.

Similarly, Parameswari and Usha (2024) analyzed the design and performance of BMS in electric vehicles, comparing various battery chemistries (Li-ion, nickel, and lead-acid) and modeling approaches. Their work categorized battery modeling techniques into electrochemical, circuit-based, and artificial neural network-based models, emphasizing their importance for improving BMS efficiency.

In a related study, Janjua et al. (2018) evaluated SOC estimation accuracy for Li-ion batteries in electric vehicle applications using the Coulomb counting and Extended Kalman Filter (EKF) methods. Their results showed that EKF-based estimation produced approximately 1% less error than Coulomb counting, demonstrating its superior precision for BMS control.

Priyanka et al. (2023) developed a SystemC-based BMS simulation environment integrating a CAN communication interface. Their work enabled real-time testing of BMS algorithms under realistic driving conditions and provided valuable insights into optimizing energy efficiency and ensuring system safety.

Krishna et al. (2024) proposed an advanced BMS architecture integrating DC-DC converters for direct energy transfer between cells. Their design significantly reduced balancing time and cost by minimizing relay use while maintaining safety and performance, especially in conjunction with DC fast-charging systems.

Turgut (2018) designed a modular BMS using a distributed structure for Li-ion batteries. Each module monitored voltage and temperature and transmitted data to a central controller through a CAN-based communication protocol. Passive balancing was performed using a fuzzy logic controller, effectively increasing battery life and ensuring stable operation.

Similarly, Hisar (2023) developed a low-cost and user-friendly BMS for EV applications utilizing the LTC6804 IC and Arduino microcontroller. The proposed system provided protection against overcurrent, overvoltage, and overheating conditions, ensuring uniform cell charging and extended battery life.

Another contribution by Parameswari and Usha (2024) introduced a hybrid BMS design combining active and passive cell connection techniques using SEPIC DC-DC converters and microcontroller-based control. Simulation and experimental results confirmed improved voltage, current, and temperature measurement accuracy.

Hannan et al. (2017) reviewed SOC estimation and management systems for Li-ion batteries in EV applications, emphasizing challenges associated with electrochemical complexity and accuracy limitations in SOC prediction. The study also underscored the necessity of accurate estimation for improving overall sustainability.

Temperature effects in BMS were investigated by Karlsen et al. (2019), who examined the temperature dependence of Li-ion battery performance, especially under cold climates. Their study proposed model-based and data-driven approaches for thermal management to extend battery life and maintain safety.

Nembhard et al. (2022) analyzed industrial standards and safety protocols in BMS development. Their review covered safety structures, functionality, and test procedures, stressing the importance of standardization to ensure reliable and sustainable energy management.

Similarly, Güven and Akbaşak (2021a) examined the effects of direct current (DC) fast-charging units on power grid infrastructure by simulating electric vehicle connection points to identify and mitigate disturbances caused by charging operations [1]. Their research offered valuable insights into the challenges associated with integrating electric vehicles into existing electrical networks and proposed technical solutions to enhance grid stability.

Furthermore, Güven and Akbaşak (2021b) developed a MATLAB/Simulink-based model for DC fast-charging systems to facilitate the widespread adoption of electric vehicles. Their study analyzed the charging dynamics of EV batteries and the control strategies of AC/DC and DC/DC converters integrated within a multi-vehicle charging configuration. Simulation results revealed that the implementation of filtering and control system integrations significantly improved system stability and reduced power disturbances, thereby demonstrating the advantages of DC fast-charger integration in modern power systems.

Earlier work by Di Domenico et al. (2008) introduced the concept of a Smart BMS using Texas Instruments' BQ78PL114 IC. The proposed system featured real-time monitoring, cell protection, and PowerPump technology for optimized energy transfer and extended battery life.

Saxena and Kumar (2015) developed an intelligent BMS using the Atmel ATA6870 and ATmega32HVB microcontroller. Their architecture enabled real-time voltage and temperature monitoring while preventing critical faults such as overvoltage and overheating, ensuring improved energy efficiency and reliability.

Samaddar et al. (2020) presented a MATLAB/Simulink-based simulation of a resistor-based passive balancing circuit, demonstrating its simplicity and low-cost applicability. Similarly, İnan et al. (2023) proposed a dual-microcontroller BMS for real-time voltage monitoring and protection against thermal and overvoltage conditions, confirming the practicality of passive balancing in EVs.

Finally, Shukla and Patel (2022) designed and simulated a passive balancing system for Li-ion EV batteries. Their results showed that constant-current charging provided more stable and consistent SOC behavior compared to constant-voltage methods, completing the balancing process in approximately 3700 seconds.

Collectively, these studies underline the evolution of BMS design from traditional control-based systems to intelligent, algorithm-driven, and adaptive architectures. The integration of optimization algorithms such as PSO and GWO represents a major step forward in achieving faster balancing, enhanced safety, and improved energy utilization for Li-ion battery systems in electric vehicles and renewable energy applications.

1.2. Motivation

In lithium-ion battery packs, particularly those with series-connected cells, voltage imbalances are inevitable due to variations in manufacturing, internal resistance, and thermal exposure. These imbalances can lead to premature aging, reduced usable capacity, and potential safety issues such as thermal runaway or overcharging. Traditional passive balancing techniques—despite their simplicity and low cost—often operate based on fixed thresholds, making them insufficient for dynamically changing battery conditions.

There is a growing need for more adaptive balancing mechanisms that maintain system safety and efficiency without significantly increasing hardware complexity. Nature-inspired algorithms such as PSO and GWO provide promising alternatives by offering real-time decision-making capabilities based on instantaneous cell voltages. These algorithms can identify optimal energy dissipation paths and adjust the balancing process dynamically, even under fluctuating system behavior.

Implementing such intelligent control strategies enables passive systems to perform with higher precision and flexibility, addressing the limitations of static logic while preserving their practical and economic advantages.

2. Theoretical Background and Key Concepts

2.1. Structure and Characteristics of Lithium-Ion Batteries

Lithium-ion batteries are rechargeable energy storage devices widely used in applications ranging from portable electronics to electric vehicles, owing to their high energy density, low weight, long cycle life, and excellent efficiency. These features make them one of the most preferred battery types in modern energy storage systems.

A typical Li-ion battery consists of four main components: an anode, a cathode, a separator, and an electrolyte. The anode is usually made of carbon-based materials such as graphite, while the cathode consists of lithium metal oxides (e.g., $LiCoO_2$, $LiFePO_4$). The electrolyte is a solution of lithium salts dissolved in organic solvents, which enables the movement of lithium ions between the electrodes.

During charging, lithium ions move from the cathode to the anode through the electrolyte. In the discharge process, this movement is reversed. While ions flow internally through the electrolyte, electrons travel externally via the circuit to supply electrical energy (Figure 1).

Another critical aspect of lithium-ion batteries is their sensitivity to environmental conditions over time, which may cause each cell to behave differently. Such inconsistencies often result in voltage imbalances among cells. Overcharging or early discharging of individual cells can reduce overall battery lifespan and compromise safety. To address these issues, BMS and cell balancing mechanisms are employed.

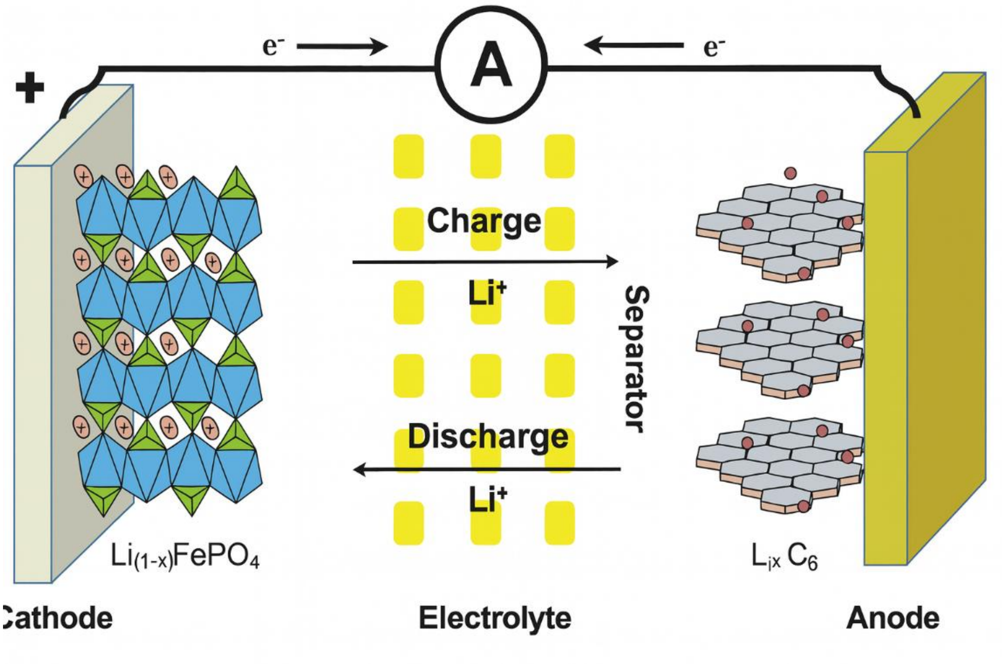

Figure 1. Basic structure of a lithium-ion battery

2.2. Intercell Voltage Imbalance Problem

One of the key functions of BMS is to ensure the balanced operation of all individual cells within a battery pack. Although cells connected in series share the same current, variations in their internal structures and responses to environmental conditions can lead to discrepancies over time. These discrepancies manifest as differences in voltage, capacity, and temperature among the cells—collectively referred to as intercell imbalance.

Voltage imbalance negatively impacts both the performance and safety of energy storage systems. For example, during charging, if one cell reaches full charge earlier than others, the charging process must be terminated to avoid overcharging, even though other cells may still have capacity. Similarly, during discharging, if one cell depletes faster, the entire pack must stop operation to prevent deep discharge. This leads to inefficient utilization of the total battery capacity (Krishna et al., 2024).

Additionally, cells that frequently operate near the upper or lower limits of voltage range experience accelerated aging and uneven thermal stress, which can lead to reduced lifespan or even safety hazards such as overheating, swelling, or fire (Janjua et al., 2024). Therefore, early detection and mitigation of cell imbalance is essential for reliable battery operation.

To address these issues, BMS includes balancing circuits that monitor the voltage of each cell and act accordingly. These circuits help equalize voltages among cells, ensuring the battery system operates more safely and efficiently. The importance of intercell balancing is especially pronounced in applications such as electric vehicles, renewable energy systems, and portable power supplies, where long-term performance and safety are critical (Karlsen et al., 2019; Parameswari & Usha, 2024).

In the model developed within this study, the intercell imbalance issue is examined in detail. Voltage discrepancies arising from different charge levels across cells are addressed through a passive balancing method, guided by an intelligent control system based on artificial intelligence. Two heuristic algorithms—PSO and GWO—are employed to dynamically manage the balancing decisions, allowing real-time adaptability and improved system efficiency (Samaddar et al., 2020; Shukla & Patel, 2022).

2.3. Battery Management System (BMS)

Lithium-ion batteries have become integral to numerous applications, ranging from electric vehicles to renewable energy systems. Ensuring the safe, efficient, and long-term operation of these battery packs necessitates the use of advanced monitoring and control mechanisms. These systems are collectively referred to as BMS.

A BMS is an electronic control unit responsible for monitoring all cells within a battery pack, managing imbalances between them, tracking critical parameters such as temperature and voltage, and protecting the system when safety thresholds are exceeded (Janjua et al., 2024). It is designed to enhance both operational safety and battery longevity.

The core functions of a typical BMS include:

- Monitoring cell voltages and temperatures,
- Estimating the SOC and SoH,
- Protecting against overcharging, overdischarging, short circuits, and thermal runaway,
- Executing cell balancing functions (either passive or active),
- Exchanging data with external systems through communication interfaces (Krishna et al., 2024).

Depending on the complexity of the system, BMS architectures can be centralized, distributed, or modular. In centralized designs, all sensing and control tasks are managed by a single unit. In contrast, distributed systems feature individual monitoring modules attached to each cell, enabling more scalable and precise solutions (Karlsen et al., 2019; Turgut, 2018).

Furthermore, integrating artificial intelligence techniques into BMS design has shown promise in enhancing SOC/SoH estimations and enabling more intelligent balancing decisions. In this context, artificial neural networks and machine learning algorithms are being increasingly explored for BMS applications (Parameswari & Usha, 2024).

In this study, a BMS model was developed in the MATLAB/Simulink environment for a battery system consisting of three series-connected lithium-ion cells. In the designed system, individual SOC values are monitored for each cell, cell balancing is performed, and data is transmitted to a centralized control block. As shown in Figure 2, the architecture collects data from each cell and relays it to the central controller via the BMS, classifying it as a modular or semi-distributed system. Moreover, the control of the balancing process is carried out using two heuristic algorithms—GWO and PSO. Depending on the voltage deviations between cells, passive balancing circuits are activated, thereby improving both energy distribution and overall system safety and efficiency.

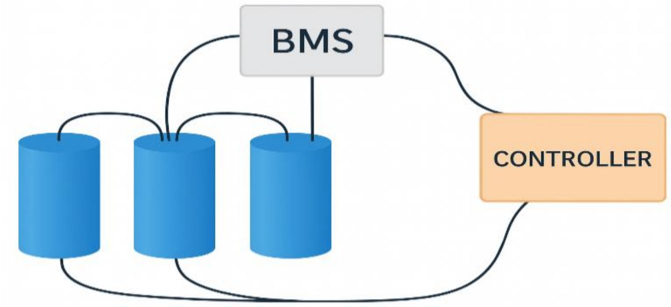

Figure 2. Schematic illustration of the connection between BMS and a three-cell lithium-ion battery pack.

2.4. Cell Balancing Methods

In lithium-ion battery systems, especially those with multiple cells connected in series, discrepancies in the SOC between individual cells can develop over time. These imbalances typically arise due to variations in manufacturing tolerances, internal resistance, and environmental conditions. When left unaddressed, the cell with the lowest capacity dictates the overall capacity of the battery pack, thereby reducing system performance and shortening the battery's lifespan (Shukla & Patel, 2020).

To mitigate this issue, BMS are equipped with cell balancing mechanisms that redistribute energy to equalize cell voltages. These balancing strategies are generally categorized into two types: passive balancing and active balancing.

In passive balancing, excess energy from higher-voltage cells is dissipated as heat through resistive elements. This method is widely adopted in commercial applications due to its simplicity and cost-effectiveness (Janjua et al., 2024). However, it suffers from poor energy efficiency because the dissipated energy is not recovered or reused.

On the other hand, active balancing transfers excess charge from higher-voltage cells to lower-voltage ones using energy transfer components such as capacitors, inductors, or DC-DC converters (Parameswari & Usha, 2024). Although more complex and expensive, active systems offer higher efficiency and are better suited for large-scale or high-capacity battery packs.

In the present study, a passive balancing strategy was implemented in a Simulink-based model for a battery pack consisting of three lithium-ion cells. Each cell voltage is continuously monitored, and when a predefined threshold is exceeded, a corresponding resistor circuit is activated to dissipate the excess energy. The entire process is dynamically managed using two heuristic algorithms: PSO and GWO. These algorithms intelligently determine when and where balancing should occur, based on real-time voltage differences between the cells. This approach improves system reliability and battery longevity, while also minimizing the need for complex and costly hardware solutions.

2.5. Application of Artificial Intelligence Algorithms in BMS

Conventional battery management strategies often utilize fixed thresholds or rule-based control logic to perform cell balancing. Although these approaches are simple and easy to implement, they tend to lack the adaptability required for dynamic and nonlinear battery behavior, especially under varying load conditions. To address these limitations, artificial intelligence (AI)-based optimization algorithms have been increasingly employed in BMS, offering greater flexibility and improved accuracy in control.

AI-driven methods continuously monitor key battery parameters such as cell voltage, temperature, and SOC, allowing the system to respond more precisely to real-time conditions. Among these, metaheuristic algorithms like PSO and GWO are particularly notable for their effectiveness in managing cell balancing processes.

PSO, inspired by the collective behavior of bird flocks or fish schools, enables particles to explore the solution space by learning from their own experience and that of their neighbors. Its fast convergence and low computational complexity make it suitable for real-time applications (Kennedy & Eberhart, 1995). However, in complex optimization problems, it may suffer from premature convergence, leading to suboptimal results.

GWO, on the other hand, is based on the leadership hierarchy and hunting mechanisms of grey wolves, which allows for more diversified search capabilities and better balance between exploration and exploitation phases (Mirjalili et al., 2014). This structure enhances the algorithm's ability to avoid local minima, making it more robust in scenarios with complex decision spaces, such as large-scale battery systems.

In the context of BMS, both algorithms have demonstrated effectiveness in dynamically adjusting the balancing control signals based on real-time SOC deviations. While PSO tends to perform well in systems requiring fast decision-making, GWO offers improved stability and broader search coverage, which is advantageous in achieving uniform SOC distribution across cells. The choice between the two should be guided by the specific design criteria of the system, including computational resources, system complexity, and desired control accuracy.

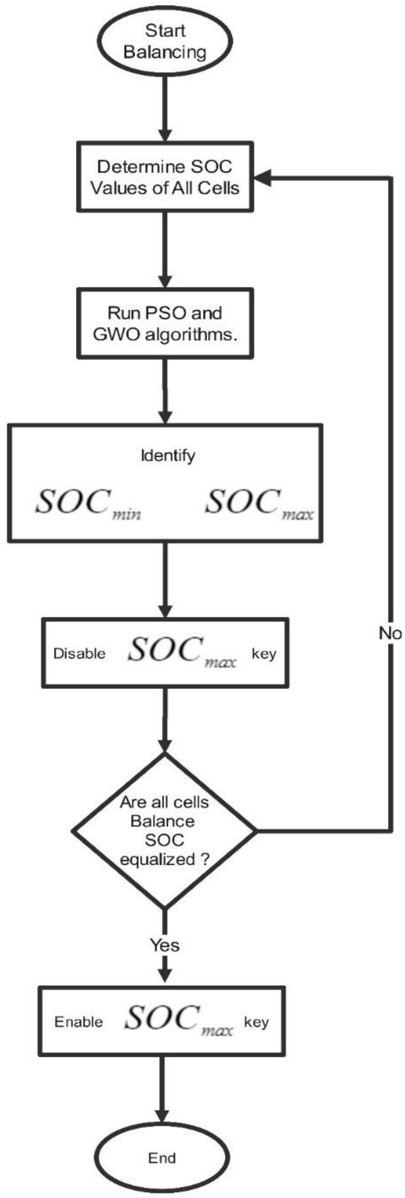

Figure 3. Flowchart of the passive balancing controller based on PSO and GWO algorithms

The balancing strategy employed in this study operates based on a real-time control algorithm utilizing PSO or GWO methods. The overall control structure is illustrated in the flowchart in Figure 3.

The process begins with an initialization step where the system starts the balancing operation. In the first stage, the SOC values of all battery cells are measured and used as inputs for the optimization algorithm. Depending on the selected method—either PSO or GWO—an optimal discharge rate is calculated for each cell (g_1, g_2, g_3). These rates determine which IGBT switches are activated, enabling current to flow through the passive discharge resistors.

Following this, the controller identifies the maximum and minimum SOC values among the cells. If the difference between these values exceeds a predefined tolerance, the cell with the highest SOC is discharged by closing its respective switch. The controller then checks whether the SOC levels of all cells have converged within the acceptable range.

If the SOC balancing condition is not met, the system loops back to remeasure the cell states and repeats the process. Once the SOC levels are sufficiently equalized, the controller opens the switch of the previously discharging cell, and the process concludes with the termination of the balancing operation.

This flow-based architecture is identical for both the PSO and GWO controllers; the only difference lies in the optimization method used to compute the control actions. The algorithm's iterative and feedback-driven structure ensures that balancing continues until SOC convergence is achieved.

Methodology

In this section, the performance of two heuristic optimization algorithms—PSO and GWO—is compared within a passive cell balancing framework for a three-cell lithium-ion battery pack. The algorithms are evaluated based on SOC convergence, voltage stability, current behavior, switching frequency, and energy consumption (Güven et al., 2024).

Figure 4 presents the general block diagram of a passive balancing architecture designed for a BMS consisting of three series-connected lithium-ion cells. The system is composed of four main functional units:

- **SOC Measurement Unit**: This unit estimates the SOC of each individual cell based on real-time measurements of cell voltage and temperature.
- **Control Block**: The estimated SOC values are processed using either the PSO or GWO algorithm, implemented within a MATLAB Function block. As a result, individual discharge control signals (g1, g2, g3) are generated for each cell.
- **Passive Balancing Switches**: Insulated Gate Bipolar Transistors (IGBTs) are employed as switching elements. These switches are controlled via the signals from the control block, and operate by connecting the appropriate discharge resistor to the high-SOC cell when required.
- **Discharge Resistors**: These resistors serve to reduce the SOC disparity among cells by dissipating excess energy from cells with higher SOC levels, allowing the pack to reach a balanced state over time.

In the diagram, the main supply line is illustrated along the common positive rail and ground, shared among all three series-connected cells. Each cell has an independent balancing branch controlled separately via its corresponding switch. This architecture preserves hardware simplicity while enabling software-based optimization. As a result, the SOC values of all cells converge gradually over time, enhancing pack uniformity and prolonging battery life.

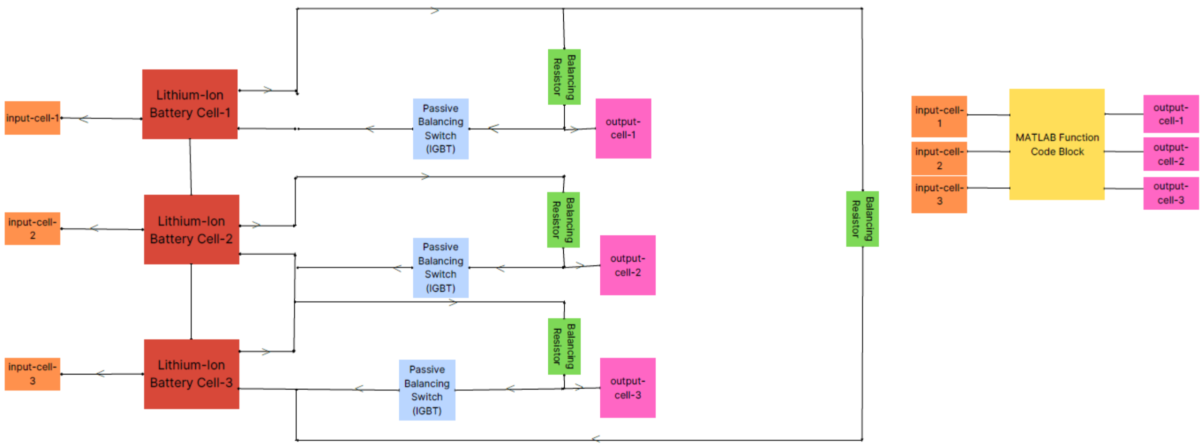

Figure 4. General block diagram of the passive balancing architecture for a three-cell lithium-ion battery pack

The passive balancing system for the three-cell lithium-ion battery pack was implemented in a Simulink environment. The model includes battery blocks that reflect the dynamic behavior of the cells, a passive balancing circuit, and two independent controller structures based on PSO and GWO algorithms.

To evaluate the effectiveness of the algorithms under unbalanced conditions, the simulation was initialized with unequal SOC values across the three cells. The nominal voltage of all cells was set to 3.7 V. This setup enabled the analysis of the balancing performance and stability of the optimization algorithms in systems with varying initial charge levels.

The simulation parameters are summarized as follows:

- Initial SOC values were set to 20%, 25%, and 28% for Cell 1, Cell 2, and Cell 3, respectively.
- The total simulation time was 680 seconds.
- The balancing method applied was passive balancing via IGBT-controlled discharge resistors.
- Both PSO and GWO algorithms were tested, with each using a maximum iteration count of 100 and a population size of 60 agents/particles.
- A response delay of 30 seconds was introduced to model battery dynamics more realistically.

This modeling framework allows for a comparative assessment of the optimization-based balancing algorithms, highlighting their ability to reduce SOC differences among the cells over time under identical hardware conditions.

Each lithium-ion cell was modeled using the “Lithium-Ion Battery” block available in the Simscape Electrical library. This block allows for the accurate representation of cell dynamics based on manufacturer-specific parameters, such as cell capacity, internal resistance, and the open-circuit voltage (OCV) versus SOC characteristic curve. The block outputs the cell voltage, current, and SOC values, which are extracted through a Bus Selector and visualized using Scope blocks within Simulink.

To interface with the control algorithms, physical signals from the battery model are converted to Simulink-compatible format using the PS-Simulink Converter. These converted signals are fed into the MATLAB Function block, where AI-based controllers—namely PSO and GWO—process the data to calculate optimal discharge decisions based on current SOC estimations.

Each modeled lithium-ion cell has a nominal voltage of 3.7 V and a maximum capacity of 5.4 Ah. The fully charged voltage is 4.3068 V, while the cutoff voltage is set at 2.775 V. The nominal discharge current is 2.3478 A, and the internal resistance is 6.8519 mΩ. The voltage response time is approximately 30 seconds, matching the dynamic behavior typically observed in commercial lithium-ion cells.

Additional model parameters include a capacity of 4.8835 Ah at nominal voltage and an exponential zone beginning at 3.9974 V with a capacity of 0.2653 Ah. The discharge behavior was further characterized using multiple current profiles: 6.5 A, 13 A, and 32.5 A, to capture the nonlinearities of the cell response under different load conditions.

This modeling approach ensures that the battery behavior under various operating conditions is accurately captured, providing a reliable simulation platform for evaluating the balancing algorithms.

Passive Balancing Circuit and Optimization-Based Controllers

The passive balancing circuit is implemented independently for each cell. It consists of a Controlled Switch (IGBT) that receives a gate signal from the controller and a fixed series-connected resistor with a value of 1 Ω. When the controller issues an "on" command, the switch closes, allowing current to flow through the resistor and discharge the corresponding cell. Otherwise, the switch remains open, isolating the cell from the discharge path.

Both PSO- and GWO-based controllers are implemented within MATLAB Function blocks in the Simulink environment. These controllers receive real-time SOC values (SOC1, SOC2, SOC3) as inputs and generate appropriate gate control signals (g1, g2, g3) to regulate the passive discharge switches.

In the PSO-based controller, a set of particles represents candidate discharge ratios. At each simulation step, particles are evaluated using a cost function that minimizes the SOC deviation among cells. Based on individual and global best positions, the particle velocities and positions are updated accordingly. The final discharge ratio values are assigned to the respective cells as control signals.

The GWO-based controller follows a similar logic, where the top three candidate solutions are labeled as alpha, beta, and delta wolves. These leaders guide the remaining population through position updates driven by adaptive coefficients that balance exploration and exploitation. The updated positions determine the discharge ratios used to drive the balancing switches.

Both controllers operate at a 30-second sampling interval and are configured under identical conditions to allow fair comparison in terms of balancing accuracy, speed, and stability.

The implementation of the passive balancing circuit for each cell is illustrated in Figure 5. Each branch contains an IGBT switch and a 1 Ω discharge resistor, which are controlled individually based on SOC levels.

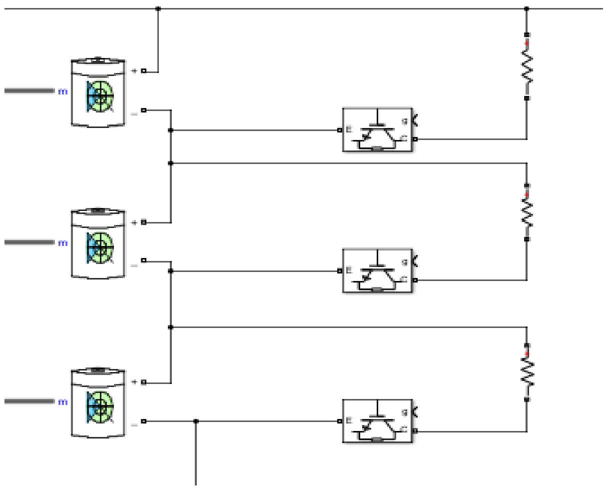

Figure 5.Passive Balancing Circuit

Findings and Discussion

The performance comparison between the PSO and GWO algorithms was conducted under identical initial conditions, with the initial SOC values set to 20%, 25%, and 28% for the three lithium-ion cells, and a nominal voltage of 3.7 V applied across all cells. The evaluation focused on three primary aspects: SOC convergence behavior, voltage stability, and discharge current characteristics.

As shown in Figure 6 and Figure 7, the SOC values of all cells progressively increased and converged around the 600th second. In the case of the GWO-based system, the final SOC values reached approximately 36.05%, 36.03%, and 36.12%, indicating a small but measurable difference among the cells. In contrast, the PSO-based controller achieved a more precise convergence, with all three cells reaching a final SOC of exactly 36.06%. This demonstrates that the PSO algorithm provided a more accurate and uniform balancing outcome.

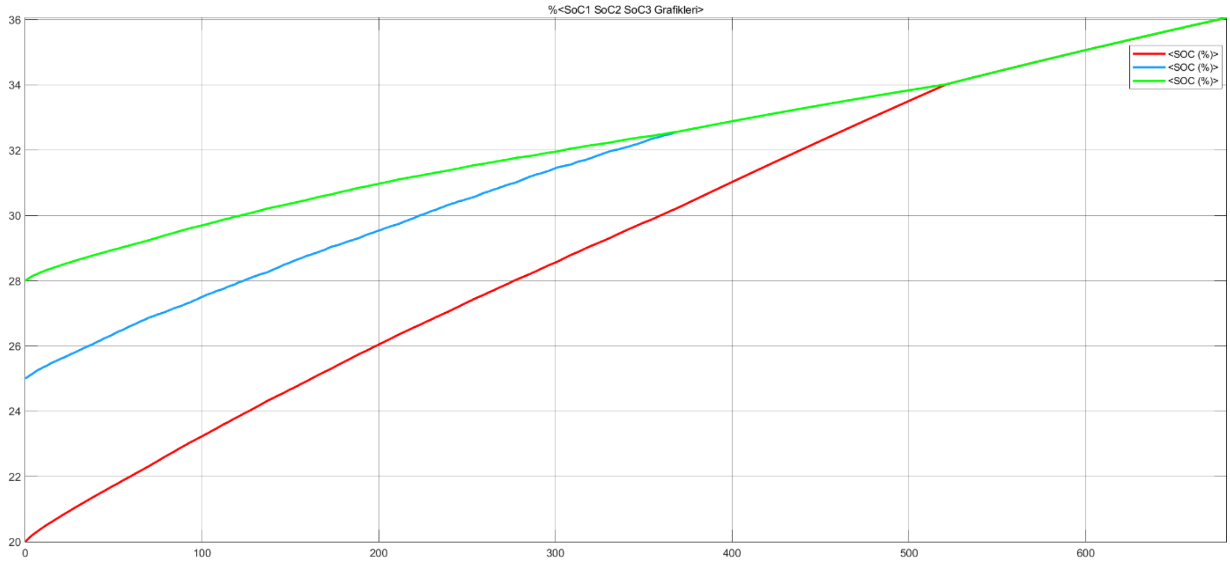

Figure 6. SOC graph of the system using the PSO algorithm

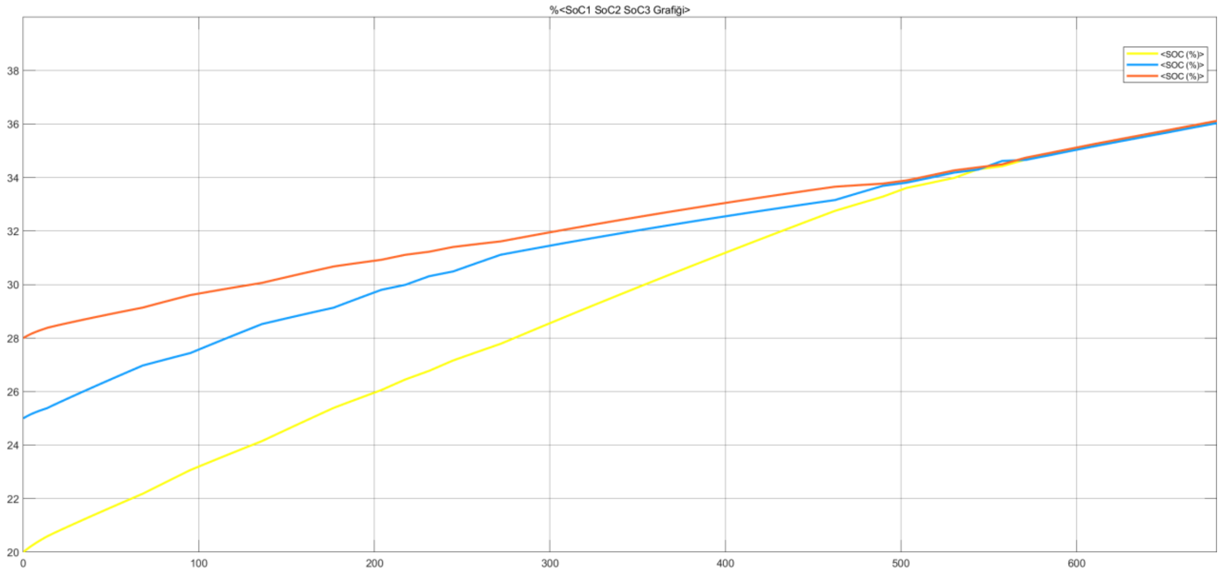

Figure 7. SOC graph of the system using the GWO algorithm

The voltage profiles presented in Figure 8 and Figure 9 offer further insight into the system dynamics. Under the PSO algorithm, cell voltages exhibited irregular, high-frequency oscillations due to rapid switching commands. These fluctuations are attributed to the frequent engagement and disengagement of IGBT switches, driven by PSO's constant exploration of the solution space. While this behavior supports effective balancing, it also introduces voltage instability and potential hardware stress.

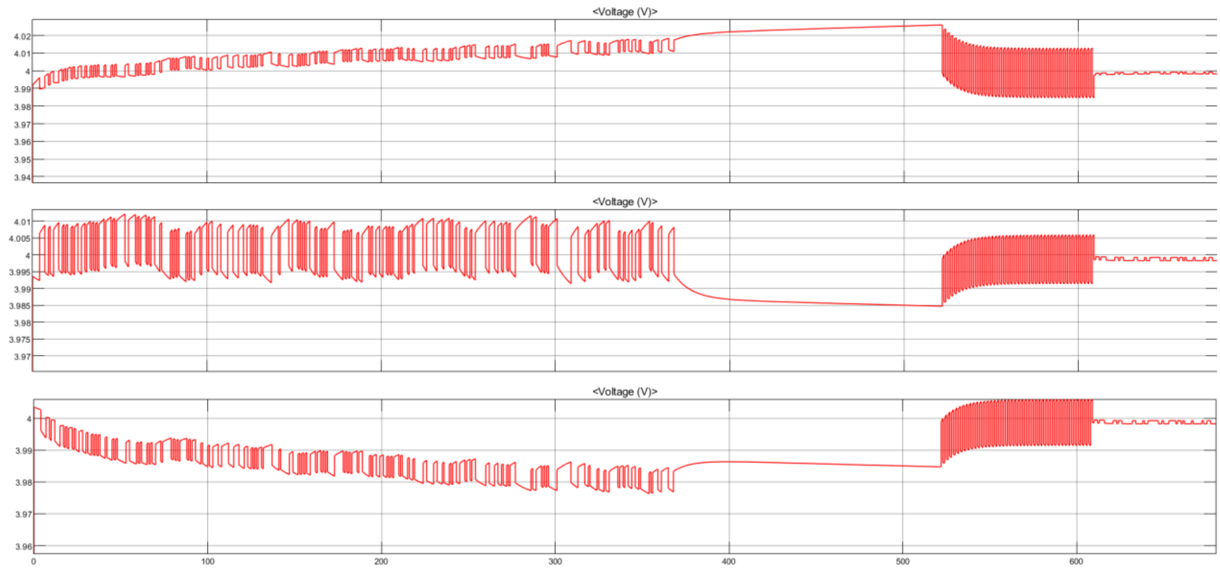

Figure 8. Voltage Graph of the System Using the PSO Algorithm (for cells 1, 2 and 3, respectively)

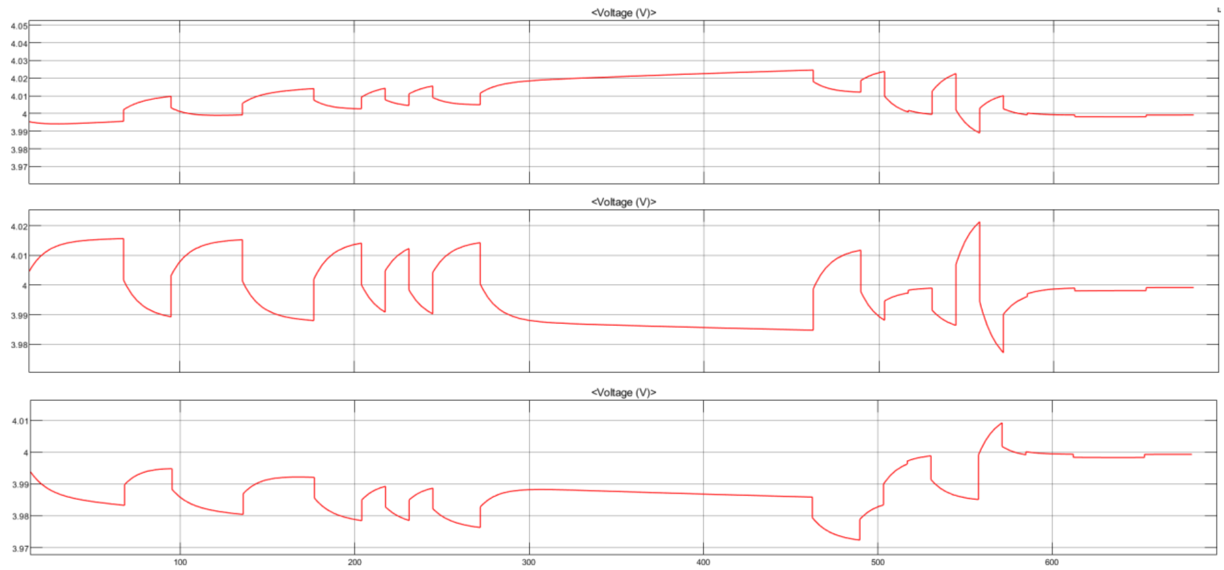

Figure 9. Voltage Graph of the System Using the GWO Algorithm (for cells 1, 2 and 3, respectively)

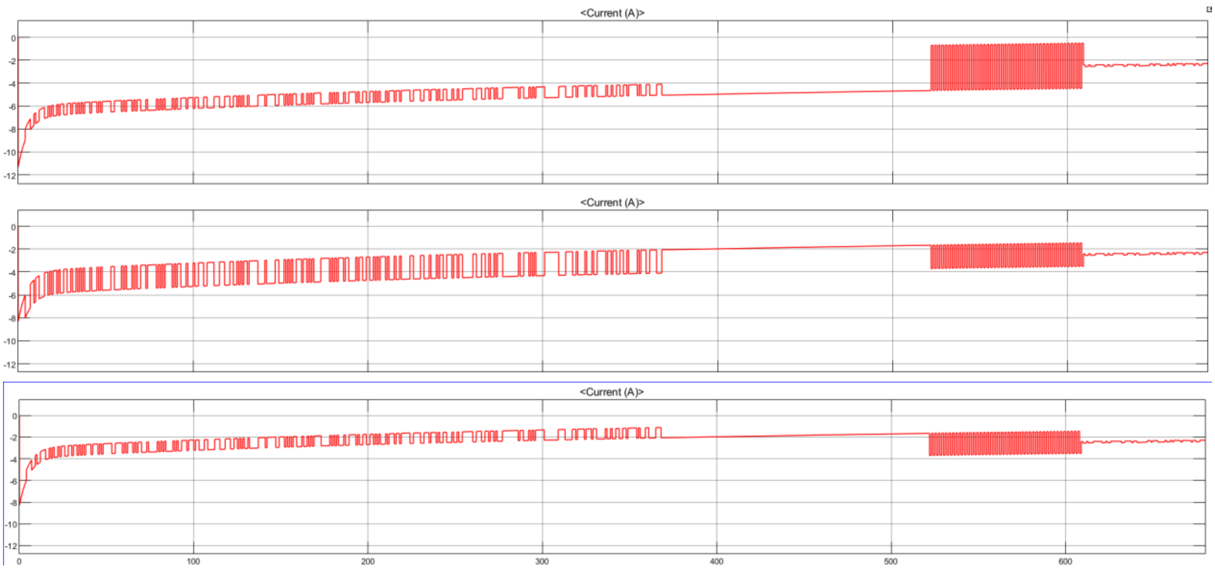

Figure 10. Flow Graph of the System Using the PSO Algorithm (for cells 1, 2 and 3, respectively)

Conversely, the GWO-based system displayed smoother voltage transitions and reduced oscillation frequency. The algorithm's more stable and lower-frequency decision-making process resulted in fewer switching events, allowing the voltages to converge toward steady-state values in a more controlled manner. This behavior contributes to lower thermal and electrical stress on circuit components, enhancing the overall stability and robustness of the system.

When examining discharge current behavior, Figure 10 and Figure 11 show that the average current applied per cell was −2.298 A for the PSO controller and −2.385 A for the GWO controller. This indicates that GWO employed a more aggressive discharge strategy, consuming slightly more energy in an attempt to speed up balancing. However, this did not translate into improved accuracy; in fact, the final SOC values were slightly less uniform compared to those achieved by PSO. This trade-off highlights that faster balancing is not always synonymous with better performance, especially when hardware longevity and control precision are critical considerations.

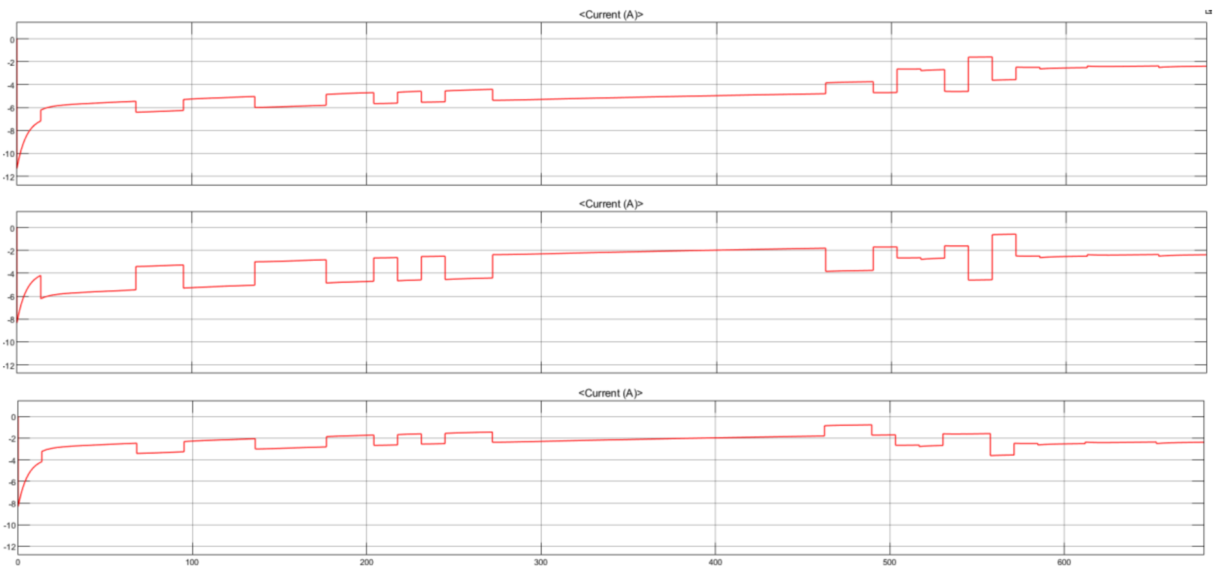

Figure 11. Flow Graph of the System Using the GWO Algorithm (for cells 1, 2 and 3, respectively)

Overall, while both optimization algorithms demonstrated effective balancing capabilities, the PSO algorithm provided more precise convergence and a uniform SOC distribution. In contrast, the GWO algorithm offered better voltage stability and less switching noise but at the cost of higher energy consumption and marginally less accurate SOC alignment. These findings suggest that the choice of algorithm should consider not only convergence speed but also the electrical and thermal implications for the hardware platform.

The convergence times of the PSO and GWO algorithms were observed to be nearly identical, with both methods reaching SOC equilibrium in approximately 600 seconds. However, PSO achieved this convergence with smoother transitions and lower discharge currents. This behavior indicates that PSO employs a more energy-efficient and stable balancing strategy, leading to reduced stress on system components (Güven and Yörükeren, 2022).

In evaluating the effectiveness of passive balancing, not only the success of SOC equalization but also the energy efficiency and impact on system stability must be considered. To this end, the average voltage and current values obtained during simulation were used to estimate the total energy dissipated through the discharge resistors.

In a passive balancing system, energy is dissipated as heat across a fixed resistor when a cell is discharged. The amount of energy consumed by each cell can be estimated using the fundamental electrical energy equation shown in Equation (1):

$$E = V \cdot I \cdot \Delta t \tag{1}$$

Where:

- V is the average cell voltage,
- I is the average discharge current,
- Δt is the duration of the balancing period.

Simulation results indicated that the average cell voltage for both algorithms was approximately 3.98 V. The average discharge current was −2.385 A for GWO and −2.298 A for PSO, over a balancing duration of 600 seconds. Using Equation (1), the energy dissipated per cell for each algorithm was computed as follows:

$$E_{GWO} = 3.98 \times 2.385 \times 600 = 5.715{,}3\ Joule \tag{2}$$

$$E_{PSO} = 3.98 \times 2.298 \times 600 = 5.493{,}2\ Joule \tag{3}$$

Multiplying by the number of cells (three), the total energy consumed by the system is:

$$\mathbf{E_{GWO\_total}}: 3 \times 5.715{,}3 = 17.145{,}9\ J \tag{4}$$

$$\mathbf{E_{PSO\_total}}:: 3 \times 5.493{,}2 = 16.479{,}6\ J \tag{5}$$

The relative energy difference between the two methods can be calculated using Equation (6):

$$\Delta E(\%) = \left(\frac{17.145{,}9 - 16.473{,}6}{17.145{,}9}\right) \times 100 = 3{,}9 \tag{6}$$

According to this result, the PSO algorithm demonstrated approximately 3.9% less energy consumption compared to GWO. This advantage can be attributed to the more moderate discharge currents used by PSO and its less aggressive switching behavior. In contrast, GWO's more forceful control actions resulted in increased energy dissipation and greater power demand during switching operations.

In summary, while both algorithms exhibited similar balancing durations, the PSO-based approach clearly outperformed GWO in terms of energy efficiency. This makes PSO a more suitable choice for applications where minimizing energy loss and preserving hardware longevity are critical.

The switching frequency of power electronic components such as IGBTs or MOSFETs plays a critical role in the design and longevity of a passive balancing system. These components operate based on control signals (g_1, g_2, g_3) generated by the balancing algorithm, which determines the activation and deactivation of the discharge paths. As such, the signal profile produced by the algorithm directly affects the number of switching events and, consequently, the thermal and electrical stress on the hardware.

In the simulation environment, each cell is associated with a unique control signal. The number of transitions between logic states ("0" to "1" and vice versa) over time represents the switching activity of that signal. Lower switching frequency is generally favorable, as it reduces energy loss, thermal stress, and the degradation rate of switching devices.

The control signals generated by the GWO-based controller, as illustrated in Figure 12, exhibit relatively low switching activity. The signals remain stable for extended periods, with infrequent transitions observed. For instance, the g_3 signal switches only about 10 times throughout the entire simulation, while g_1 and g_2 switch approximately 6–7 and 12 times, respectively. This low-frequency switching behavior reflects a stable control approach that minimizes unnecessary activity and supports hardware efficiency.

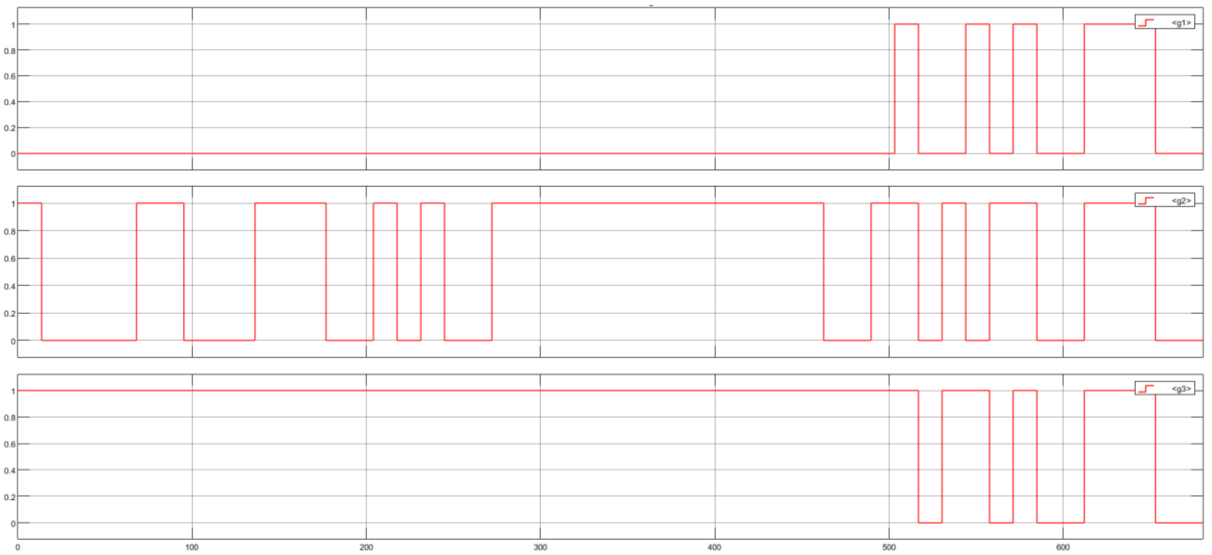

Figure 12. Switching Graph of the System Using the GWO Algorithm

In contrast, the PSO-based system demonstrates a significantly higher switching rate, as seen in Figure 13. The control signals generated by PSO exhibit high-frequency toggling, with each signal undergoing over 80 to 100 transitions during the simulation period. While this behavior allows for finer control and more precise SOC equalization, it introduces substantial electrical and thermal burden on the switching devices. Such intense switching activity can accelerate component wear, increase the risk of overheating, and necessitate more robust cooling mechanisms.

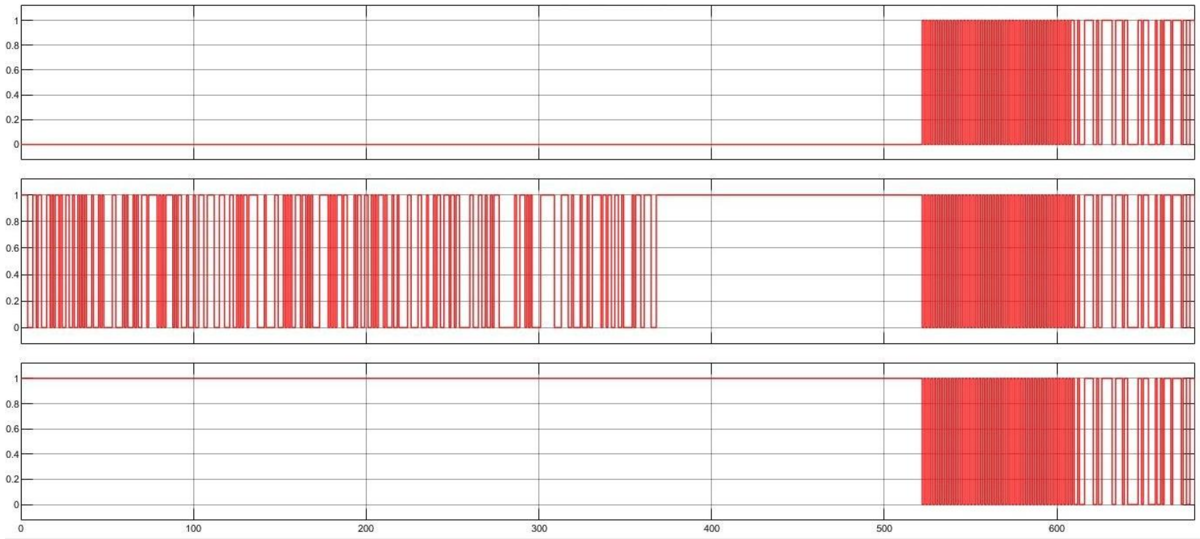

Figure 13. Switching graph of the system using the PSO algorithm

In summary, the GWO algorithm offers a notable advantage in terms of hardware friendliness by minimizing switching frequency while still maintaining acceptable balancing performance. On the other hand, PSO, despite providing slightly more accurate SOC convergence, imposes a higher switching load that could potentially shorten the operational lifespan of key power components. Therefore, the choice of control algorithm should also consider the switching profile it generates, especially in systems where reliability and thermal constraints are critical.

The number of switching events generated by each controller was also analyzed to better understand the computational and hardware load introduced by the algorithms. As presented in Table 1, the PSO-based controller triggered more than 280 transitions across the three discharge signals (g_1, g_2, g_3), while the GWO-based controller generated only about 28–30 transitions in total. This indicates that PSO exhibits approximately 10 times more switching activity compared to GWO.

Table 1. Number of switching events for each control signal

Algorithm	g_1 Transitions	g_2 Transitions	g_3 Transitions	Total Transitions
GWO	6–7	12	10	28–30
PSO	80+	100+	100+	280+

Such a high switching frequency in PSO suggests a more sensitive balancing mechanism capable of detecting and responding to SOC differences at finer scales. While this enhances balancing precision, it also imposes additional electrical and thermal stress on the switching elements. PSO's frequent signal updates stem from its underlying structure, which involves continuous position updates and random exploration within the solution space. This causes even small fluctuations in SOC values to trigger switching actions, leading to more frequent activations of the discharge resistors.

In contrast, the GWO algorithm applies a leader-based search and decision mechanism, which results in a more structured and stable control response. Because of this, balancing actions are less frequent and more deliberate. The reduced number of switching events contributes to lower thermal stress, extended hardware lifetime, and simplified control operation.

Although both algorithms achieve successful SOC balancing, they differ significantly in terms of control effort and hardware load. These differences suggest that algorithm selection should be based not only on performance metrics but also on system constraints and operational priorities. For applications where energy efficiency and fine-tuned balancing are critical, PSO may be the preferred choice. However, for systems that prioritize simplicity, lower switching stress, and extended component lifespan, GWO offers a more suitable alternative.

In the broader scope of this study, a passive balancing strategy was implemented on a three-cell lithium-ion battery pack, with control provided by two nature-inspired optimization algorithms: PSO and GWO. The goal was to minimize the SOC differences among cells while evaluating the impact of each algorithm on system behavior, energy efficiency, and hardware demand.

Simulation results confirmed that both PSO and GWO successfully balanced the SOC levels across the cells. However, detailed analysis revealed key differences. In terms of energy efficiency, PSO consumed approximately 3.8% less energy compared to GWO, largely due to its more optimized discharge control. Regarding SOC convergence, PSO achieved more symmetrical and precise balancing in a shorter time, attributed to its high-resolution decision-making and dynamic particle updates. On the other hand, switching activity was significantly higher in PSO, introducing potential disadvantages in terms of thermal stress and hardware wear. GWO, with its structured decision model, required far fewer switching operations and therefore presented a lower impact on system components.

These findings indicate that algorithm selection should be application-specific. Systems that demand high accuracy and energy performance may benefit from PSO, while applications constrained by limited hardware resources or requiring longer component lifespan may be better served by GWO.

From a real-time implementation perspective, the computational requirements of each algorithm must also be considered. PSO's frequent position updates and dense control signals require a more powerful processor and larger memory space, making it more suitable for high-performance embedded systems. In contrast, GWO’s simpler structure and lower parameter count enable easier integration into low-power microcontroller-based platforms. Furthermore, GWO’s lower switching frequency reduces power consumption and thermal stress, improving reliability in resource-constrained environments. Thus, for real-time BMS with limited hardware capability, GWO may present a more practical and sustainable control solution.

Conclusion and Recommendations

In this study, a passive cell balancing strategy was developed and evaluated in a simulation environment for a battery pack composed of three lithium-ion cells. The proposed BMS utilized two nature-inspired optimization algorithms—PSO and GWO—to dynamically adjust the discharge behavior of each cell based on real-time SOC measurements. Both control strategies successfully reduced the SOC and voltage imbalances among the cells, enhancing the uniformity of charge distribution and, consequently, improving the safety and lifespan of the battery system.

Simulation results demonstrated that both algorithms were capable of achieving full SOC convergence in approximately 600 seconds. PSO offered finer balancing precision and greater energy efficiency, consuming approximately 3.8–3.9% less energy than GWO, due to lower average discharge currents and more optimized control actions. Moreover, PSO resulted in nearly perfect SOC alignment among the three cells. However, this came at the cost of significantly higher switching activity—over 280 transitions compared to GWO's 28–30 transitions—potentially leading to increased thermal stress and faster degradation of power components such as IGBTs.

In contrast, GWO demonstrated a more hardware-friendly profile, with significantly lower switching frequency and a stable control pattern. This lower-frequency operation reduces thermal cycling and extends component life, making GWO a compelling option in systems where simplicity, robustness, and low hardware stress are prioritized.

The comparison between these algorithms highlights that optimization performance must be considered in conjunction with system-level metrics such as energy efficiency, switching frequency, and real-time feasibility. From a practical perspective, PSO may be better suited for high-performance systems where processing capacity is not a limiting factor and where precision control is critical. GWO, on the other hand, with its lower computational and switching demands, offers a viable solution for real-time applications on low-power microcontrollers, embedded platforms, or cost-sensitive systems.

For future work, experimental validation on physical hardware is recommended to assess the real-time performance and robustness of the proposed balancing strategies under dynamic operating conditions. Important factors such as temperature fluctuations, high current scenarios, and cell aging effects should be incorporated into the evaluation framework. Furthermore, integrating active or hybrid balancing circuits could significantly enhance energy recovery and overall system efficiency.

Another promising direction is the incorporation of battery health (SoH) estimation algorithms and AI-based prediction models to enable adaptive control schemes that respond to changing battery conditions in real time. Cloud-based monitoring systems and wireless communication interfaces could also be explored to extend the BMS architecture toward scalable, smart grid–compatible energy management solutions. These developments will be essential for advancing battery system intelligence, sustainability, and integration into future electric vehicles and energy storage platforms.

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