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# Simulation Modelling of Fuzzy Logic-Based Active Cell Balancing in Battery Systems

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*Abstract*— **Battery energy storage systems are essential for various applications, from electric vehicles to renewable energy integration. However, inherent inconsistencies in cell characteristics lead to capacity degradation and reduced lifespan. Active cell balancing strategies mitigate these issues by redistributing charge among cells, enhancing overall system efficiency. This paper presents a simulation-based study of a fuzzy logic-controlled active cell-balancing system. The proposed approach adjusts balancing currents based on state-of-charge variations, leveraging fuzzy logic inference to improve decision-making under uncertainty. A MATLAB/Simulink-based simulation model is developed to evaluate the fuzzy logic controller's (FLC) performance compared to conventional balancing methods. Results demonstrate that the FLC-based approach achieves superior state-of-charge uniformity, reduced thermal variations, and extended battery health. These findings highlight the potential of intelligent control strategies for optimising next-generation battery management systems.**

*Keywords*— **Active Cell Balancing, Battery Management System, Fuzzy Logic, State of Charge, Simulation Modelling.**

## I. INTRODUCTION

Electric vehicles (EVs) have become a pivotal innovation in mitigating global reliance on fossil fuels and addressing climate change through sustainable energy transitions. They offer zero tailpipe emissions and can utilize renewable energy sources for recharging. EVs have gained popularity in recent years due to advancements in battery technology, which have improved energy density, efficiency, and charging times [1]. These advancements have made EVs more reliable and affordable, encouraging adoption among private consumers and commercial fleets [2].

Electric vehicles (EVs) function through electric propulsion systems driven by rechargeable battery packs. These energy storage systems retain chemical energy, which is subsequently transformed into electrical energy to power the motor. Lithium-ion batteries are the most used because of long cycle life, high energy density, and light weight [2], [3]. The EV ecosystem consists of various components, such as the electric motor, inverter, battery pack, and power management systems, all of which work together to deliver a smooth driving experience.

The Battery Management System (BMS) plays a critical role in maintaining the optimal performance, longevity, and safety of an EV battery pack. Batteries are susceptible to extreme temperature variations, deep discharging, and overcharging which can lead to irreversible degradation if not properly regulated [4]. To prevent such failures, the BMS continuously monitors key battery parameters, including current, voltage, temperature, and State of Charge (SOC), ensuring operation within safe limits. Additionally, it incorporates cell balancing mechanisms, which equalize the charge distribution across all battery cells, thereby enhancing efficiency and extending battery lifespan. The architecture of the BMS is displayed in Fig.1.

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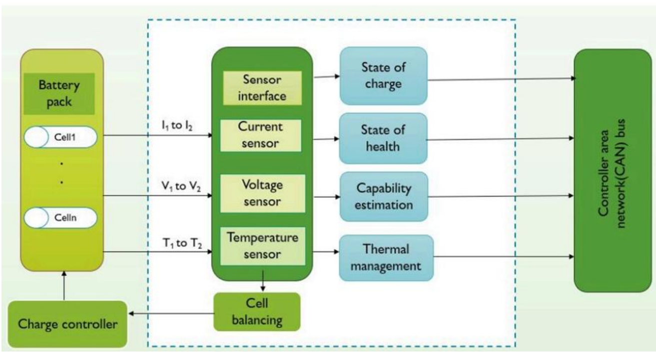


Fig.1. Architecture of Battery Management System

To meet the energy and power requirements of electric vehicles (EVs), however, large-scale battery packs made up of hundreds or thousands of cells coupled in series and/or parallel topologies are required because individual battery cells are limited by capacity and voltage [5]. However, manufacturing differences between individual cells within the battery pack result in inconsistent State of Charge (SOC) and cell voltage [6]. Because of different internal resistances, temperature variations, and differential self-discharge rates, these imbalances gradually get worse after several charge- discharge cycles. This gradual discrepancy reduces the battery pack's usable capacity and may hasten cell deterioration, raising safety concerns about overcharging and over discharging [7]. Battery equalization is essential for preserving balanced SOC levels across all cells in the pack, which helps to reduce these issues and improve battery longevity.

Fuzzy logic control (FLC) has emerged as a promising technique for active cell balancing in BMS, offering a robust and adaptive approach to handling cell inconsistencies. Unlike conventional balancing methods, FLC operates on linguistic rules and membership functions, allowing it to make intelligent balancing decisions even when precise mathematical models are difficult to derive. This capability makes it particularly effective in mitigating state-of-charge (SoC) variations among battery cells [8]. In active cell balancing, FLC enables dynamic charge redistribution by continuously analysing SoC differences and adjusting energy transfer accordingly. This approach minimizes energy loss and improves equalization efficiency compared to conventional methods. The flexibility of fuzzy logic allows it to adapt to real-time variations in cell parameters, ensuring optimal performance across different battery chemistries and configurations [9]. Additionally, fuzzy logic-based balancing enhances battery lifespan by preventing overcharging and deep discharging of individual cells. Maintaining a balanced SoC distribution reduces stress on weaker cells, leading to improved overall system reliability. The integration of FLC in active balancing circuits further optimizes energy flow, making it a viable solution for modern battery management applications [10].

This paper presents the performance of optimization of charging and discharging behavior of active cell balancing using fuzzy logic through simulation modelling. The primary objectives are (1) Design and implement a fuzzy logic controller for active cell balancing. (2) Analyze simulation improvements in battery charging and discharging balancing using fuzzy control based on simulation results. The paper is organized as the simulation modelling methodology described in Section 2, represents the literature review related to BMS and fuzzy logic controller. The configurations and working principles of the active cell balancing in this work are described in depth in Section 3. The simulation results of the active cell balancing using fuzzy logic are indicated in Section 4. The paper's conclusions and future research directions are presented in Section 5.

## II. Literature Survey

Bibiana Lorente Alvarez et al. discuss the development of an active balancing model and BMS for Lithium-Ion batteries used in EV and Hybrid Electric Vehicles (HEV) [7]. The study highlights the importance of balancing the State of Charge (SoC) across cells to improve battery life and efficiency. They introduce a MATLAB R2010b model for active balancing that redistributes energy among cells. The authors also design a modular BMS platform with key components like a master controller and current sensors. Simulations show the effectiveness of this approach in optimizing battery performance before physical implementation.

J. Florence Gnana Poovathy et al. present a fuzzy-based active cell balancing algorithm for Aluminium-Air (Al-Air) batteries used in EVs [8]. The paper highlights the importance of balancing SoC to optimize battery performance and extend lifespan. The authors propose a multi-layered neural network-based adaptive neuro-fuzzy inference system (MLNN-ANFIS) to address cell imbalances and improve efficiency. Simulations and experiments show a 99% convergence in SoC, with the algorithm being twice as fast as conventional methods, reducing energy loss in Al-Air batteries. The study demonstrates the potential of Al-Air batteries and AI/ML techniques for enhanced battery management.

Yan Ma et al. present a nondissipative equalization scheme using fuzzy logic control (FLC) to address the inconsistency of series-connected Lithium-ion batteries in EVs [9]. They propose a two-stage bidirectional equalization circuit with energy transferring inductors to improve cell-to-cell equalization and enhance battery pack performance. The authors use the Thevenin equivalent circuit model and Extended Kalman Filter (EKF) for accurate SOC estimation. The FLC strategy reduces equalization time by 23% and SoC standard deviation by 18.5%, showing significant improvements over traditional methods. The results highlight the potential of the proposed scheme for more efficient and reliable battery management in EVs.

D.A. Martínez et al. developed a BMS using fuzzy logic to enhance the performance and autonomy of lithium-ion batteries in EVs [10]. The paper focuses on energy management challenges and the need for efficient energy storage to optimize performance and extend driving range. The authors model the EV's powertrain and use the New European Driving Cycle (NEDC) to simulate real-world driving conditions. The fuzzy logic controller monitors the SoC and optimizes energy autonomy. Simulations show improvements in SoC behaviour, enhancing energy efficiency and driving range, especially for EVs with high energy demands.

Anuradha D Jadhav et al. presented a BMS design using an FLC to optimize energy management for renewable energy sources, including wind turbines and solar panels [11]. The paper highlights the growing importance of renewable energy due to concerns about fossil fuel depletion and the environment. The authors use MATLAB/Simulink to model and control energy devices, with the FLC managing the discharging and charging of Lithium-ion batteries. Simulations show that the FLC helps maintain optimal SoC, improving battery performance and efficiency. The study suggests that fuzzy logic in BMS can

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enhance energy management and sustainability in power systems.

F.Z. El Mansouri et al. introduce a fuzzy logic control system for managing the charging and discharging of Lithium-Ion batteries powered by photovoltaic (PV) systems, emphasizing the importance of intelligent battery management in both fixed and mobile applications [12]. The system helps prevent overcharging and excessive discharging, which can damage the battery. The proposed fuzzy logic controller offers rapid response and high accuracy in battery regulation. The paper also uses an Incremental Conductance (INC)-based Maximum Power Point Tracking (MPPT) approach to improve power extraction from the PV system, outperforming traditional methods like Perturb and Observe (P&O). Simulations in MATLAB/Simulink validate the system's effectiveness in enhancing battery management and optimizing energy use in renewable energy applications.

## III. METHODOLOGY

The simulation-based research was conducted for inductor-based active cell balancing using fuzzy logic. Two fuzzy logic controllers were developed, each using different membership function shapes. The controllers were used to control the PWM signal's driving duty cycle in simulations of a simpler battery-to-battery balancing circuit. The simulation framework was developed and executed using MATLAB/Simulink to evaluate the performance and efficiency of the proposed control strategies.

### *A. Inductor Based Cell Balancing*

The cell balancing inductor technology, as shown in Fig. 2, is an active equilibrium method that transfers energy between battery pack cells using inductors. The fundamental idea is that excess energy from a larger voltage cell is first momentarily kept within the inductor before being moved to a smaller voltage cell. A microcontroller or similar electronic controller usually controls inductor's switching to handle this operation.

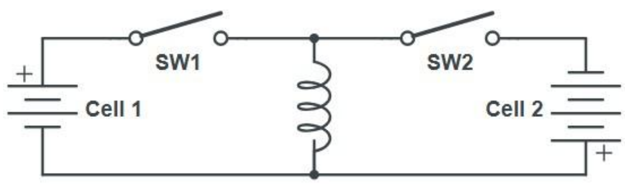


Fig.2. Inductor Based Cell Balancing

Fig. 3 represents the working of cell-cell energy transfer. Assume that the voltage of Cell 1 is greater than that of Cell 2. Initially, with switch SW1 turned on and switch SW2 turned off, battery Cell 1 connects to inductor L, a state called the "inductor charging mode." (Fig. 3.a). During this mode, current flows from Cell 1 into the inductor, storing energy as a magnetic field. Subsequently, when switch SW1 is turned off and switch SW2 is turned on, the energy stored in the inductor is transferred to Cell 2, known as the inductor discharging mode (Fig. 3.b). This cycle repeats at a high switching frequency until the voltage of Cell 2 matches that of Cell 1. The rapid toggling of switches facilitates energy redistribution between the batteries, ensuring balanced voltage levels. The rapid toggling of switches facilitates energy redistribution between the batteries, ensuring balanced voltage levels. By transferring surplus energy from cells with higher energy levels to cells with lesser energy levels, this inductor-based balancing system helps to maintain a consistent state of charge across the battery pack.

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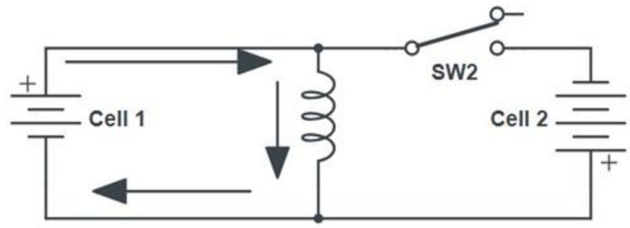
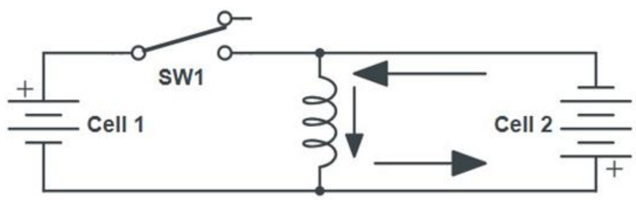



(a)




(b)

Fig.3.Battery to battery transfer of energy: (a) charging mode (b) discharging mode

### B. *Fuzzy Logic Controller*

Fuzzy logic, a distinct branch of mathematical logic, is employed for modelling and analysing systems that exhibit uncertainty or imprecise characteristics. Unlike traditional logic, where an element belongs to a set or does not, fuzzy logic assigns a membership value between 0 and 1, indicating the degree to which an element is associated with a particular set. The operational process of fuzzy logic typically includes the Fuzzifier, which converts precise data entered into fuzzy data, the Inference machine generates outputs using a fuzzy rule foundation, the fuzzy rule is a set of guidelines that specify input should be handled to generate output and Defuzzifier, which translates fuzzy outputs back into precise outputs as shown in Fig.4. Each element of fuzzy logic controller is discussed below in details.

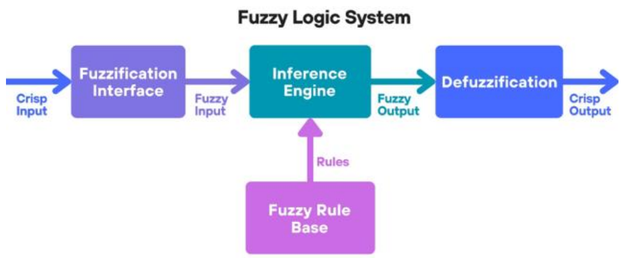



Fig.4. Block diagram of fuzzy logic controller

1. Fuzzy Input: A fuzzy input represents data in a vague or imprecise form using linguistic variables such as "high," "low," or "medium," which are described by membership functions.
2. Fuzzy Output: A fuzzy output is the result of a fuzzy logic system expressed in linguistic terms, derived after processing the input data through fuzzy rules and inference mechanisms.
3. Crisp Input: A crisp input is a precise numerical value that represents the real-world data provided to a fuzzy logic system.
4. Crisp Output: A crisp output is the final, precise numerical result obtained after the defuzzification process in a fuzzy logic system.
5. Fuzzification Interface: The fuzzification interface is the component of a fuzzy logic system that converts crisp input values into fuzzy values using membership functions. This step enables the system to work with imprecise or linguistic data.
6. Inference Engine: The inference engine is the part of a fuzzy logic system that processes fuzzy inputs according to a set of fuzzy rules to produce fuzzy outputs. It determines how input variables interact and influence the system's behaviour.
7. Fuzzy Rule Base: A fuzzy rule base is a collection of "if-then" rules that define the relationship between

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fuzzy inputs and outputs. These rules are the backbone of the fuzzy logic system and guide the decision-making process.

8. Defuzzification Interface: The defuzzification interface converts fuzzy output values into crisp numerical outputs. This process is essential for translating the fuzzy system's results into actionable, real-world data.

Fig. 5 represents the flowchart for working of a fuzzy logic system, starting with fuzzification, where input and output variables are transformed into fuzzy sets. Expert knowledge helps determine membership functions and formulate fuzzy IF-THEN rules, which are processed using MATLAB Simulink (Mamdani method). The fuzzy inference engine tests the rules and the defuzzification process (using the centre of gravity method) converts fuzzy outputs into crisp values. If rules are unsuitable, they are corrected and re-tested until all rules are validated, leading to the completion of the system.

The mathematical representation of fuzzy set A, defined on a universal set X, is represented by a membership function $\mu_A(x)$, which assigns each element x a membership value in the range [0,1]:

$$A= \{(x, \mu_A(x) \mid x \in X\} \qquad (1)$$

Where $\mu_A(x)$ determines the degree to which x belongs to the fuzzy set A and $\mu_A(x)$ lies between 0 and 1, where 0 means no membership, 1 means full membership, and values in between indicate partial membership.

**Membership Function:** A membership function (MF) defines how each element in a set is mapped to a membership value between 0 and 1. It quantifies the degree to which an element belongs to a fuzzy set, enabling the representation of imprecise data in fuzzy logic systems. The membership function contains three subintervals such support, core and boundary represented in equations 2,3 and 4 respectively.

*C.*

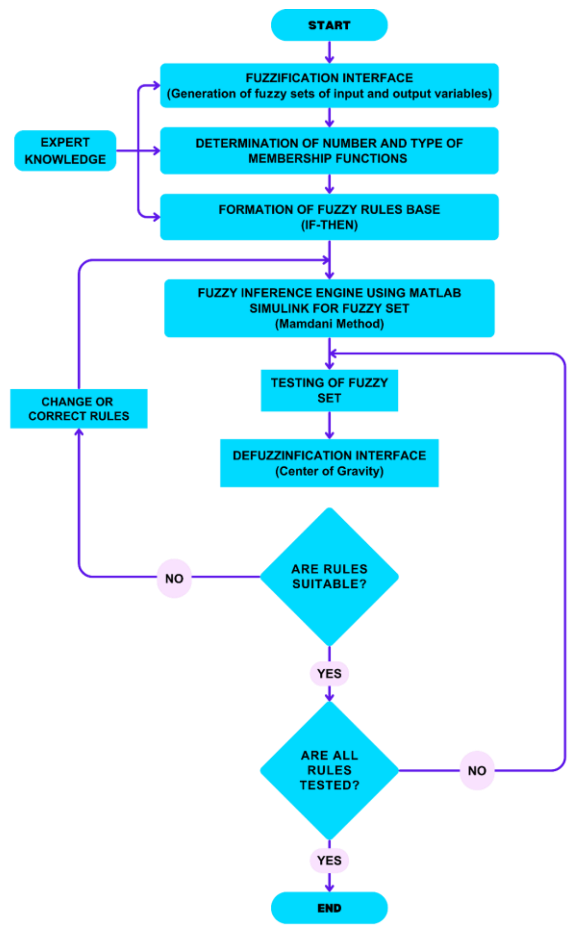


Fig.5. Functional flowchart

$$\text{Support } (A) = \{x \mid \mu A\ (x) > 0\} \qquad (2)$$

$$\text{Core } (A) = \{x \mid \mu A\ (x) = 1\} \qquad (3)$$

$$\text{Boundary } (A) = \{x \mid 1 > \mu A\ (x) > 0\} \qquad (4)$$

The step of implementation of fuzzy logic controller for SoC is mathematically represented as follows

**Set Input:**

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State-of-Charge (SOC) Average: $X_1$ with a Triangular MF for Fuzzy Logic Controller with Trapezoidal and Triangular Membership Function (FLC-TT) and take Gaussian Membership Function for Fuzzy Logic Controller with Sigmoidal and Gaussian Membership Function (FLC-SG).

SOC Difference: $X_2$ with a Trapezoidal Membership Function for Fuzzy Logic Controller with Trapezoidal and Triangular Membership Function (FLC-TT) and take Sigmoidal Membership Function for Fuzzy Logic Controller with Sigmoidal and Gaussian Membership Function (FLC-SG).

Output PWM: Y with a Gaussian Membership Function for both Fuzzy Logic Controller with Trapezoidal and Triangular Membership Function (FLC-TT) and Fuzzy Logic Controller with Sigmoidal and Gaussian Membership Function (FLC-SG).

**Membership Function Equations:**

A triangular membership function is defined as follows by the three parameters {a, b, c}:

$$\mu(x) = \begin{cases} 0, & x \le a \text{ or } x \ge c \\ \dfrac{x-a}{b-a}, & a \le x \le b \\ \dfrac{c-x}{c-b}, & b \le x \le c \end{cases} \tag{5}$$

The x coordinates of the three corners of the underlying triangle MF are determined by the parameters {a, b, c} (where a < b < c).

A trapezoidal MF is specified by four parameters {a, b, c, d} as follows:

$$\text{trapezoid}(x; a, b, c, d) = \begin{cases} 0, & x \le a \\ \dfrac{x-a}{b-a}, & a \le x \le b \\ 1, & b \le x \le c. \\ \dfrac{d-x}{d-c}, & c \le x \le d. \\ 0, & d \le x. \end{cases} \tag{6}$$

The parameters {a, b, c, d} (with a < b <= c < d) determine the x coordinates of the four corners of the underlying trapezoidal MF.

Two parameters are used to specify a Gaussian MF: c and σ determine the completeness of a Gaussian MF, where c is the centre of the MF and σ is its width.

$$\mu_A(x) = e^{-\frac{(x-\mu)^2}{2\sigma^2}} \tag{7}$$

$$\mu_A(x) = \frac{1}{1 + e^{-k(x-c)}} \tag{8}$$

A sigmoidal membership function (MF) is mathematically defined by a parameter a, which governs the slope at the crossover point x = c. Depending on the sign of a, the function exhibits an inherently left-open or right-open nature, making it well-suited for representing linguistic terms like "very large" or "very negative."

**Fuzzy Rule Representation:**

A fuzzy relation establishes a mapping between elements of two universes by defining a membership function over their Cartesian product, representing the degree of association between corresponding elements.

IF X1 is A1 AND X2 is A2 THEN Y is B

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Where A∈X, B∈Y, X and Y are Input Universes and Output Universe respectively. Mamdani inference applies the fuzzy AND operator (minimum function) to compute rule activation:

$$\mu_{rule} = \min\left(\mu_{A1}(X_1), \mu_{A2}(X_2)\right) \qquad (9)$$

The Mamdani Fuzzy Inference System (FIS) is a widely used approach in fuzzy logic for decision-making and control applications. It was introduced by Ebrahim Mamdani in 1975 and is based on linguistic rules that mimic human reasoning. Uses IF-THEN rules where both consequent (THEN part) and antecedent (IF part) are fuzzy sets. In our model, we are using multi-rule multi antecedent.

**Aggregation of Rule Outputs:**

Uses IF-THEN rules where both consequent (THEN part) and antecedent (IF part) are fuzzy sets. Since multiple rules contribute to the final output, their implications must be aggregated. The most common method in Mamdani inference is taking the maximum across all rule outputs:

$$\mu_{output}(Y)=\max\left(\mu B1'(Y), \mu B2'(Y) \ldots \mu Bn'(Y)\right) \qquad (10)$$

This ensures that for each value of Y, the highest truth value across all rules is considered.

**Defuzzification:**

Defuzzification is the mathematical process of mapping a fuzzy set output to a precise scalar value using techniques like centroid, mean of maximum, or weighted average methods for control applications. Since fuzzy logic deals with degrees of membership rather than precise values, defuzzification is necessary to make real-world decisions, such as setting a control signal (e.g., a PWM signal in our case). After aggregation, the output remains a fuzzy set with overlapping membership values. However, in real-world applications, we need a single crisp value to act (e.g., controlling a motor, adjusting voltage). The different type of defuzzification methods are the Lambda cut method, Maxima method, Weighted average method and Centroid method.

Here, we used Centroid method. The Centroid Method (Centre of Gravity, COG) is the most widely used defuzzification method in Mamdani fuzzy inference systems because it provides a balanced and smooth output compared to other methods. Mathematical representation of centroid method is indicated in equation 11.

$$y^* = \frac{\int y \cdot \mu_{output}(y)\, dy}{\int \mu_{output}(y)\, dy} \qquad (11)$$

Mamdani developed two fuzzy logic controllers (FLCs). This initial controller makes use of a hybrid configuration of Trapezoidal and Triangular MFs to define input variables, ensuring an efficient representation of linguistic terms and degree of membership. These functions enhance computational simplicity and adaptability in input-output mapping. The second controller incorporates Sigmoidal and Gaussian membership functions, where the Gaussian function, characterized by its smooth bell curve, facilitates seamless transitions and continuous variations, while the sigmoidal function excels in handling boundary conditions and nonlinear system dynamics. Both controllers are engineered for robust adaptability across diverse input-output relationships.

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The designed FLC incorporates two input variables: the state of charge (SoC) average and the SOC difference. The SoC average, represented by a triangular membership function, is divided into five sub-intervals: very low (VL), slightly low (SL), moderate (M), high (H), and very high (VH). The SOC difference, modelled using a trapezoidal membership function, is divided into four smaller divisions: low (L), high (H), moderate (M), and very high (VH). The output, which regulates the duty ratio of the Pulse Width Modulation, is characterized by a Gaussian membership function split up into five smaller gaps: No Balancing (NB), Low Balancing (LB), Moderate Balancing (MB), Strong Balancing (SB), and Full Balancing (FB). This structured partitioning of input and output membership functions into sub-intervals allows for finer granularity in representing linguistic variables, thereby enhancing the precision and effectiveness of the modelled system.

The Mamdani fuzzy rule table for SOC balancing is created in regard to the following rules displayed in Table.1.

1. When the SOC difference is low and the SOC average is very low (VL), no balancing (NB) is performed since the system requires minimal balancing. As the SOC average increases to slightly low (SL), light balancing (LB) is applied to compensate for the small difference.

TABLE 1
FUZZY RULE

| Rules | VL | SL | M | H | VH |
|---|---|---|---|---|---|
| L | NB | LB | MB | SB | FB |
| M | LB | MB | MB | SB | FB |
| H | MB | MB | SB | FB | FB |
| VH | SB | FB | FB | FB | FB |

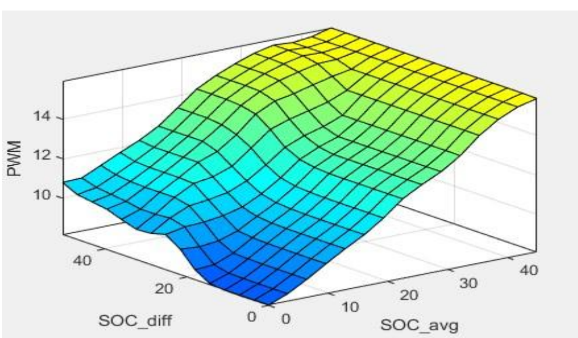
2. For a moderate (M) SOC difference, the balancing level is dynamically adjusted based on the SOC average to optimize charge equalization. If the SOC average is very low (VL) or slightly low (SL), a moderate balancing (MB) strategy is applied, ensuring a gradual reduction of imbalance to prevent excessive energy transfer. However, when the SOC average is moderate (M), high (H), or very high (VH), the balancing intensity is progressively increased from moderate balancing (MB) to strong balancing (SB) and eventually full balancing (FB), aligning with the system’s energy distribution requirements.

3. When the SOC difference is high (H), the balancing becomes more active. For very low (VL) or slightly low (SL) SOC averages, strong balancing (SB) is applied. For moderate (M), high (H), or very high (VH) SOC averages, full balancing (FB) is used to quickly correct the imbalance.

4. If the SOC difference is very high (VH), the system applies the strongest balancing efforts. For very low (VL) and slightly low (SL) SOC averages, strong balancing (SB) is used. For moderate (M), very high (H), and high (H) SoC averages, full balancing (FB) is

applied to ensure effective correction of the imbalance.

Fig.6 illustrates the fuzzy surface within the FLC, offering a graphical representation of the relationship between the SOC average and the SOC differential as input variables and influence the duty cycle of PWM as the output. The surface of fuzzy generates Sigmoidal and Gaussian MFs and demonstrates enhanced smoothness and continuity, in contrast to the surface formed with Trapezoidal and Triangular membership functions, which exhibits sharper transitions.

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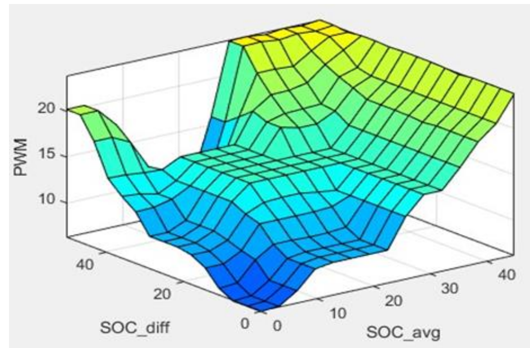



(b)

Fig.6. Surface of fuzzy (a) FLC-TT (b) FLC-SG

## IV. SIMULATION RESULTS AND DISCUSSION

Fig.7 illustrates the active cell balancing process using the FLC-based simulation model. The system utilizes lithium-ion batteries with a capacity of 5400 mAh and a nominal voltage of 3.7 V. The simulation conducted under two distinct operating conditions: discharging mode and charging mode. Initially, State of Charge of Cell 2 and Cell 1 is set at 40% and 50%, enabling an evaluation of the FLC's effectiveness in redistributing energy and achieving charge equalization.

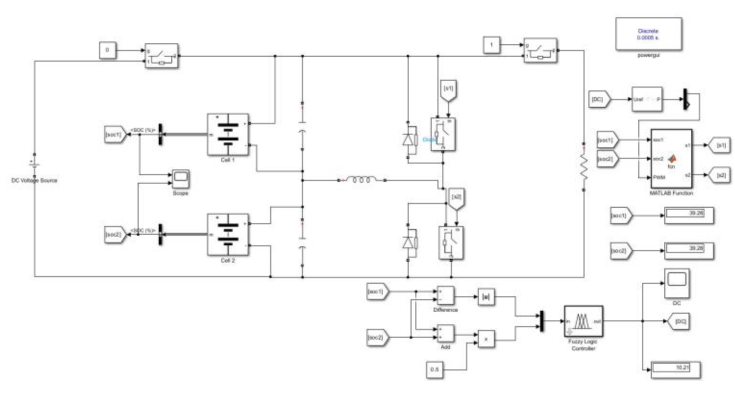
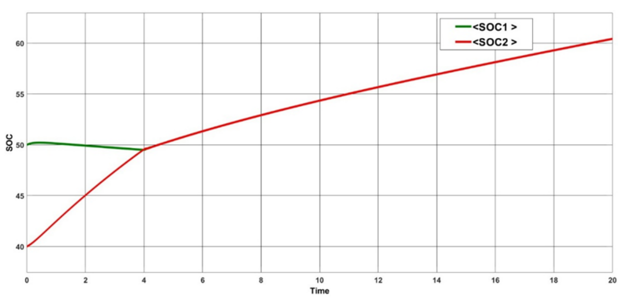


Fig.7. Simulation modelling of active cell balancing using fuzzy logic controller

Fig.8 represents the balance system simulation results under charging circumstances. The analysis reveals that the balancing duration varies across different control strategies: the Fixed Duty Cycle (FDC) method achieves balance in 4.12 seconds (Fig.8.a), the Fuzzy Logic Controller employing Trapezoidal and Triangular membership functions (FLC-TT) reduces the balancing time to 2.84 seconds (Fig.8.b), while the Fuzzy Logic Controller utilizing Sigmoidal and Gaussian membership functions (FLC-SG) further improves efficiency with a balancing time of 2.82 seconds (Fig.8.c). Moreover, upon completion of the process of balancing, both battery cells' state of charge stabilizes and maintains consistency with the expected SOC progression throughout the charging phase.

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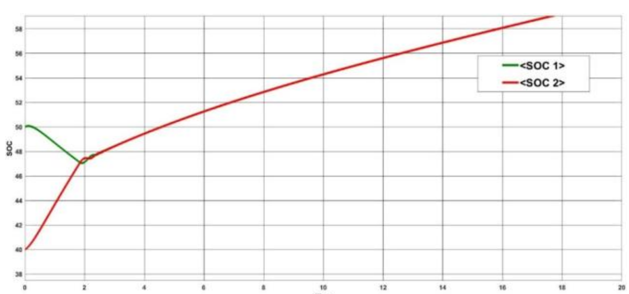


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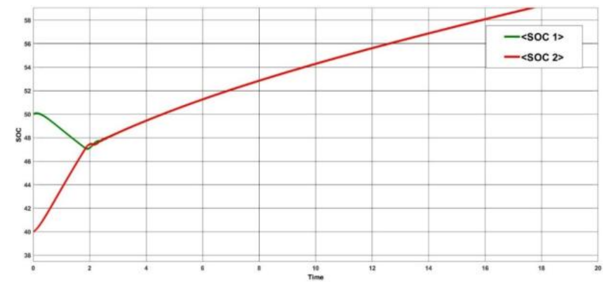


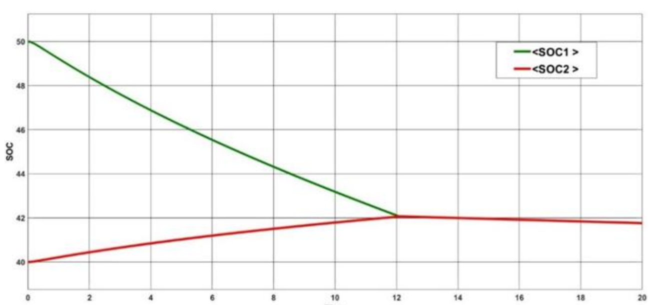

(c)

Fig.8. Simulation results in charging mode (a) FDC (b) FLC-TT (c) FLC-SG

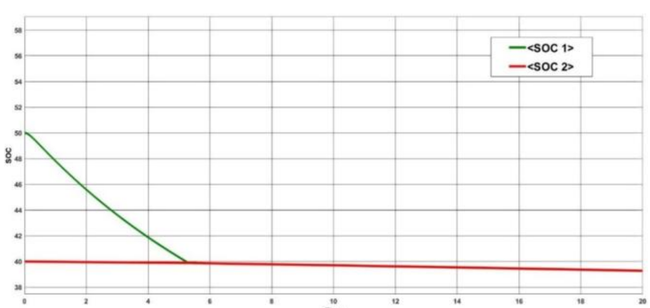
Fig.9 depicts the performance of the balancing system for battery cells during discharge. The results indicate that the balancing duration varies depending on the applied control strategy: the Fixed Duty Cycle (FDC) method completes balancing in 12.02 seconds (Fig.9.a), the Fuzzy Logic Controller with Trapezoidal and Triangular membership functions (FLC-TT) reduces the time to 5.62 seconds (Fig.9.b), and the Fuzzy Logic Controller with Sigmoidal and Gaussian membership functions (FLC-SG) achieves the fastest balancing at 5.53 seconds (Fig.9.c). Following the completion of the equilibrium technique, the SOC of both batteries is stable, aligning with expected SoC reduction observed throughout the discharging phase.

The outcomes of the simulation demonstrate that the FLC-TT and FLC-SG controllers exhibit superior performance in contrast with the FDC approach, achieving significantly greater balancing times. Among them, the FLC-TT controller demonstrates slightly enhanced efficiency over the FLC-SG controller, making it a preferred choice for regulating the duty cycle in battery cell balancing systems that use inductors. This approach is particularly advantageous for large-scale battery packs with multiple cells, where efficient charge redistribution is crucial. Furthermore, the FLC-TT controller offers practical benefits in real-world implementations due to its reliance on simpler membership function shapes, which help minimize computational complexity and reduce processing overhead. This makes it more feasible for embedded systems and real-time applications. A comparative summary of simulation outcomes for all methods presented in Table 2.

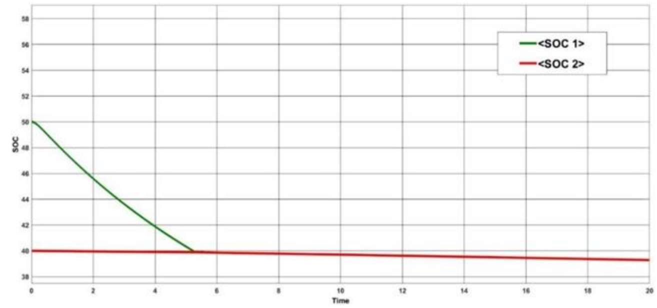
Moreover, various duty ratio is assigned individual inputs by the controller's fuzzy rule inference system. Although the variations are minor, they influence the overall process output. Higher duty cycle values result in increased balancing currents and reduce elapsed times.




(a)




(b)




(c)

Fig.9. Results during discharging (a) FDC (b) FLC-TT (c) FLC-SG

TABLE 2

PERFORMANCE PARAMETERS

| Methods | Testing Condition (Merge time) | |
|---|---|---|
| | **Charging (Sec)** | **Discharging (Sec)** |
| FDC | 4.12 | 12.02 |
| FLC-TT | 2.84 | 5.62 |
| FLC-SG | 2.82 | 5.53 |

## V. CONCLUSION

In this work, two fuzzy logic-based controllers for a BMS cell-to-cell balancing system based on inductors are introduced. The first controller, FLC-TT, employs Trapezoidal and Triangular membership functions, while the second, FLC-SG, utilizes Sigmoidal and Gaussian membership functions. Both controllers are applied with MATLAB/Simulink in a basic two-cell balancing circuit and benchmarked against the conventional Fixed Duty Cycle technique. Outcomes of the simulation indicate that FLC-SG demonstrates slightly better performance than FLC-TT during the charging phase, achieving a 31.55% reduction in merge time compared to 31.07% for FLC-TT.

Similarly, in the discharging phase, FLC-SG achieves a 53.97% reduction, outperforming FLC-TT's 53.24% improvement. However, since the study is conducted in a simulated environment, minor discrepancies in results may arise due to idealized conditions. Future research will focus on enhancing the model and performing real-time experimental validation to assess the controllers' effectiveness in practical applications.

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