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Intelligent Cell Balancing Control for Lithium-Ion Battery Packs

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***Abstract*—This study introduces a balancing control strategy that employs an Artificial Neural Network (ANN) to ensure State of Charge (SOC) balance across lithium-ion (Li-ion) battery packs, consistent with the framework of smart battery packs. The model targets a battery pack consisting of cells with diverse characteristics, reflecting real-world heterogeneous conditions. A fundamental aspect of this approach is the ability to bypass individual cells optimally. This key feature stops current flow to and from the cell, allowing it to rest and cool off while avoiding charging or discharging cycles. The implementation of ANN enables adaptive and dynamic management of SOC, which is essential for optimizing performance and extending the lifespan of battery packs. The results demonstrate the effectiveness of the proposed ANN-based balancing strategy in SOC balancing, demonstrating its potential as a critical solution in enhancing battery management systems for electric vehicles.**

***Index Terms*—The authors shall provide up to 4 keywords or phrases (in alphabetical order and separated by commas) to help identify the major topics of the paper.**

I. INTRODUCTION

The continuous growth in electric vehicles is increasing Li-ion battery deployment. The production process of these batteries, including mixing, coating, calendaring, slitting, and formation [1], often faces challenges in achieving uniformity even within the same production line [2] [3]. This inconsistency may lead to overcharging or over-discharging [4], [5] due to the shortboard effect [6], thereby causing energy and capacity losses. To counter these imbalances, balancing is essential for maintaining cell consistency and efficiency [7].

These batteries are controlled by a Battery Management System (BMS). The BMS's critical role is to manage battery usage within the pack equitably and protect against unfavorable events, notably thermal runaway. A vital function of a standard BMS is to ensure a balanced State of Charge (SOC) across cells. This is often achieved by incorporating active cooling systems to minimize thermal runaway risks.

However, conventional SOC balancing techniques in BMS encounter various challenges, which are mainly divided into dissipative and non-dissipative balancing [8]– [9]. Dissipative balancing, while straightforward, converts surplus energy from higher-energy cells into heat through resistors [10], [11], thus raising efficiency concerns and thermal management risks [8], [12], [13]. Its limitations in battery utilization [14] have led to the exploration of non-dissipative balancing methods [15]-[19]. Non-dissipative balancing strategies aim to redistribute charge within the battery pack without significant encounter challenges.

There are different types of non-dissipative balancing. Capacitor-based systems [15], which, although efficient in balancing, require a large number of components, increasing costs and adding to the system's complexity. Inductor-based strategies [16] offer a higher power handling capability but need to be improved by their intricate control requirements and higher costs. Transformer-based balancing systems [17], noted for their robustness, are often less efficient and bulkier, necessitating complex control systems and incurring higher costs. Common converter-based balancing [18], a comprehensive solution in theory, faces practical challenges such as increased size, complexity, and cost [19]. These constraints of both dissipative and non-dissipative methods underscore the need for a more efficient and simpler solution for SOC balancing in BMS.

This study emphasizes the importance of a low-cost and straightforward control mechanism for SOC balancing [20], utilizing power switches for active cell balancing. The chosen balancing approach modifies the battery pack's current flow through switches, accommodating cells under different conditions. Its success hinges on the strategic design of switch operations to ensure comprehensive cell balance, thereby bypassing the requirement for passive elements like capacitors, inductors, or converters. These advantages inform its choice for this study, with switch control posing the main challenge.

This paper introduces an innovative method that integrates Artificial Neural Networks (ANN) within a smart battery pack framework. In response to these challenges, this paper proposes an innovative method employing ANN within the framework of the smart battery pack. This method is remarkable for its dynamic management of the SOC in series-connected lithium-ion battery cells, facilitated by the precise control of half-bridge switches associated with each cell. A key feature of the proposed approach is the ability to bypass individual cells selectively, thus preventing unnecessary current flow and promoting more efficient SOC balancing. The methodology begins with creating an accurate model of a laboratory lithium-ion battery for real-world behavior simulation. Following this, an ANN is developed and implemented to manage the

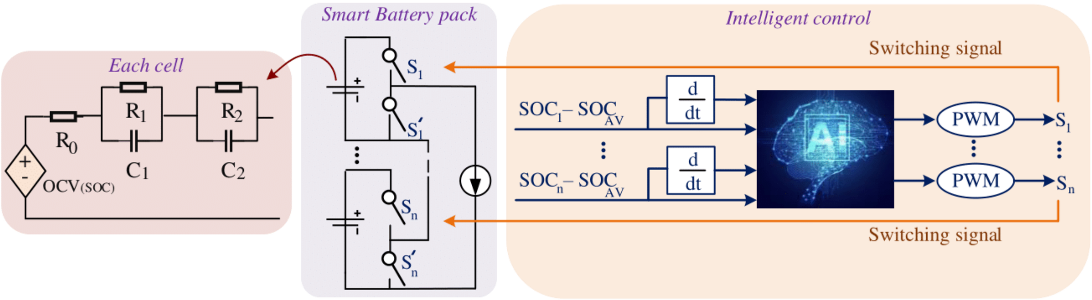

Fig. 1. Electrical schematic of the proposed intelligent balancing system for a battery pack consisting of n serially connected cells.

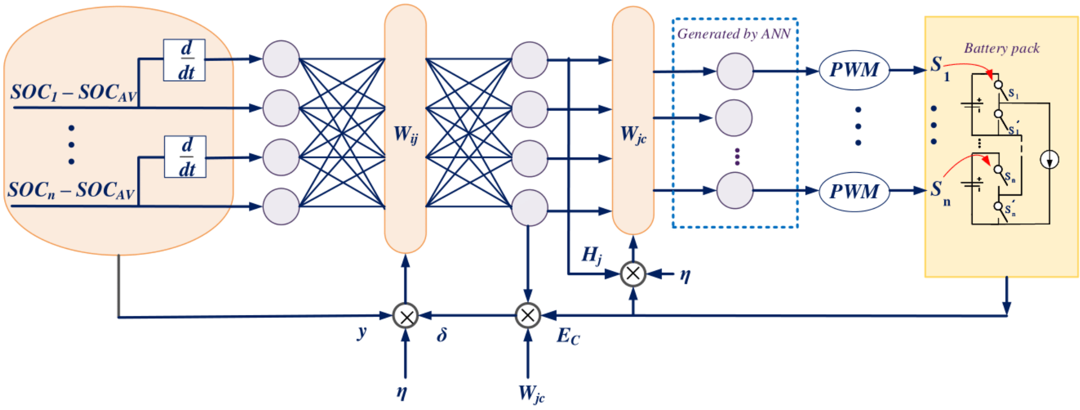

Fig. 2. Schematic of the proposed ANN-based balancing control scheme.

SOC dynamically and accurately, substantially improving the battery pack's overall performance. The findings validate the effectiveness of the suggested intelligent balancing control approach.

II. PROPOSED CONTROL SYSTEM

Every cell is arranged in a series connection within an intelligent battery pack configuration. It incorporates a half-bridge design consisting of two complementary switches, denoted as S_i and S'_i, as illustrated in Figure 1. This design allows for the selective bypassing of individual cells. When the bottom switch, S'_i, is activated, it results in bypassing a cell, particularly useful when a cell's SOC is low to prevent rapid discharge. This bypass function is pivotal for equalizing the health and performance of all cells in the pack. Additionally, this method leads to a pulsed current flow through the cells. Previous studies have shown that pulsed charging can enhance cell longevity. The smart battery pack's architecture in this model is applied not only to improve the cycle life of Li-ion battery packs but also to achieve effective SoC balancing amidst the variations in individual cell characteristics. The individual cells are modeled as circuits, each comprising two Resistor-Capacitor (RC) pairs in series with internal resistance, as depicted in Fig. 1. This model is grounded in an electrical circuit model used for Li-ion cells. The key parameters of the model are extracted from [21]. These specifications were derived from the Electrochemical Impedance Spectroscopy (EIS) test.

The primary goal of the proposed framework is to minimize SOC variations from the average value. ANN generate precise control signals to create PWM signals for switch operation, thus ensuring balanced control.

ANNs utilize processing units known as neurons, notable for their nonlinear nature. Each neuron consists of weights $w_{ij} = [w_{1j}, w_{2j}, \ldots, w_{nj}]$, an activation function $g(j)$, and a bias φ. The choice of activation function varies, including options like the sign, tangent sigmoid, and logarithmic sigmoid. The inputs y_i are processed with these weights, and the output from the hidden layer H_j is derived from the weighted inputs and bias as demonstrated in Equation (1):

$$H_j = g\left(\sum_{i=1}^{n} w_{ij} y_i + \varphi\right) \quad \text{for} \quad j = 1, 2, \ldots, L \tag{1}$$

Here, L illustrates the total number of nodes in the hidden layer.

The outputs are computed as:

$$O_c = \sum_{j=1}^{L} H_j w_{jc} + \varphi \quad \text{for} \quad c = 1, 2, \ldots, m \tag{2}$$

with m denoting the node numbering in the output layer.

The overall functionality of the SOC balancing implementation is shown in a concept diagram in Fig. 1. At first, the average SOC should be calculated as follows:

$$SOC_{\text{AV}} = \frac{1}{n}\sum_{i=1}^{n} SOC_i \qquad \forall i \in n \tag{3}$$

where n represents the number of cells; and SOC_i indicates the SOC of each individual cell. The SOCs of the cells are maintained within a standard operating range of 10-90% to prevent overcharging and overdischarging. This approach specifically avoids the SOC extremes of 0-10% and 90-100%, where aging of the cells tends to accelerate. An ANN-based controller is proposed to generate the control commands for each cell. The ANN takes as input the variance in SOC values of each cell relative to SOC_{AV}, as well as their respective rates of change. It processes these inputs to intelligently generate duty cycle signals for pulse width modulation (PWM). The PWM then generates the switching signals for the half-bridge switches associated with each cell, facilitating precise and adaptive SOC balancing. The schematic of the proposed ANN-based balancing control scheme is shown in Fig. 2.

Various functions, such as sign, logsigmoid, and tansigmoid, can serve as activation functions. In this case, the sign function is adopted as per the methodology in [22]. The objective of the learning process is to reduce the mean squared error (MSE), which is calculated as follows

$$\text{MSE} = \frac{1}{N}\sum_{t=1}^{N}\sum_{i=1}^{n}\left(SOC_i - SOC_{AV}\right)^2 \tag{4}$$

In this model, N denotes the aggregate count of samples. The initial layer of the neural network comprises 12 linear neurons, while the hidden layers are equipped with 50 neurons that exhibit nonlinear characteristics. These nonlinear elements ensure a gradual modification of the weights within the network during operations. The final layer of the neural network is designed with 'n' linear neurons, each representing an individual cell. A back-propagation method under supervised learning conditions is applied to refine the learning process.

$$\begin{aligned} w_{ij}(k+1) &= w_{ij}(k) + \eta\delta y \\ &\text{for } i = 1, 2, \ldots, n; \quad j = 1, 2, \ldots, L \end{aligned} \tag{5}$$

$$\begin{aligned} w_{jc}(k+1) &= w_{jc}(k) + \eta H_j E_c \\ &\text{for } j = 1, 2, \ldots, L; \quad c = 1, 2, \ldots, m \end{aligned} \tag{6}$$

It should be observed in Figure 2 that w_{ij} indicates the weight vector associated with the hidden layer, while w_{jc} is utilized comparably for the output layer. The term E_c represents the error signals, including variations in the SOC and its derivative.

III. RESULTS AND DISCUSSIONS

Simulations were conducted on a battery pack comprising six distinct cells, each varying slightly in terms of capacities and 2RC values. A 3.7V/50Ah NMC LIB from CALB was utilized to perform EIS tests for these tests. In the beginning, the cells exhibited different initial SOC, as depicted in Fig. 3(a). All maintain a uniform initial temperature of 25°C to formalize the testing conditions. Throughout the experimental process, a constant external current of 50 Amps was applied to simulate throughout the tests. As illustrated in Fig. 3(b)-(d), the cell temperatures, voltages, and currents are shown respec-

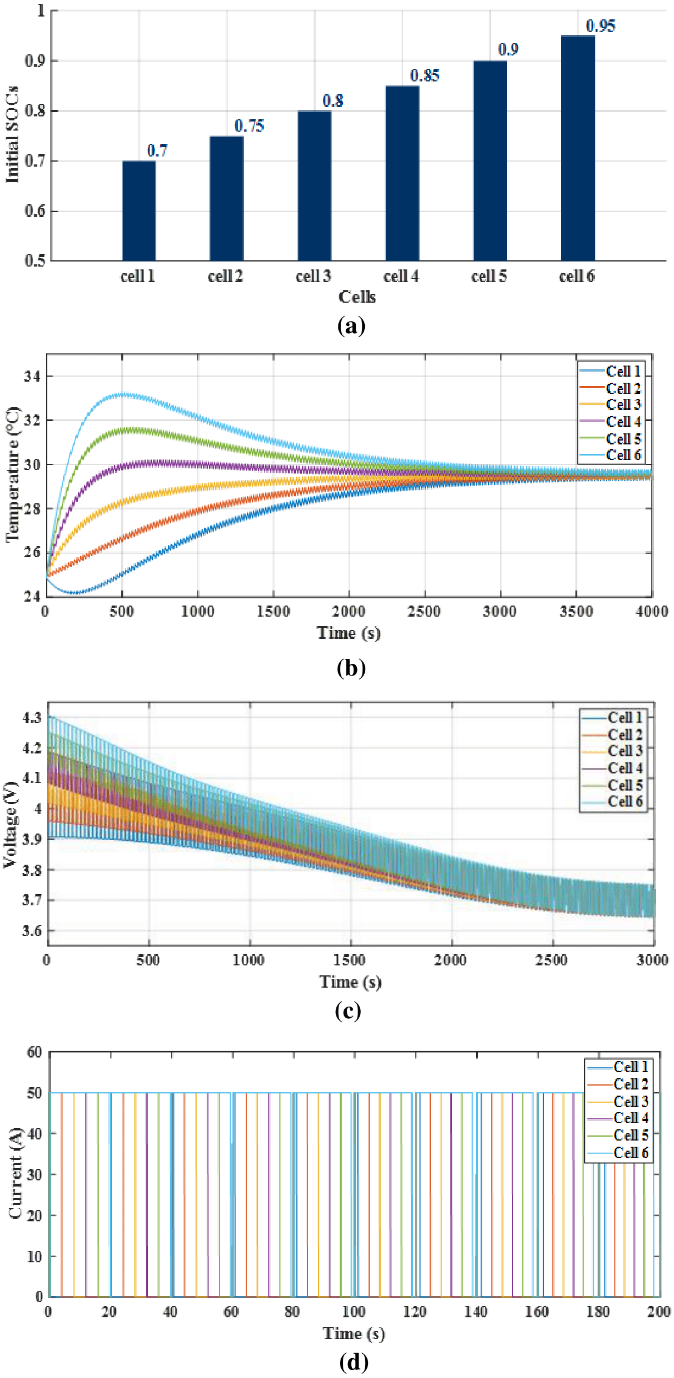

Fig. 3. (a) Initial SOC of each cell, (b) cell temperature, (c) cell voltage, and (d) cell current measurements following the application of the proposed balancing method.

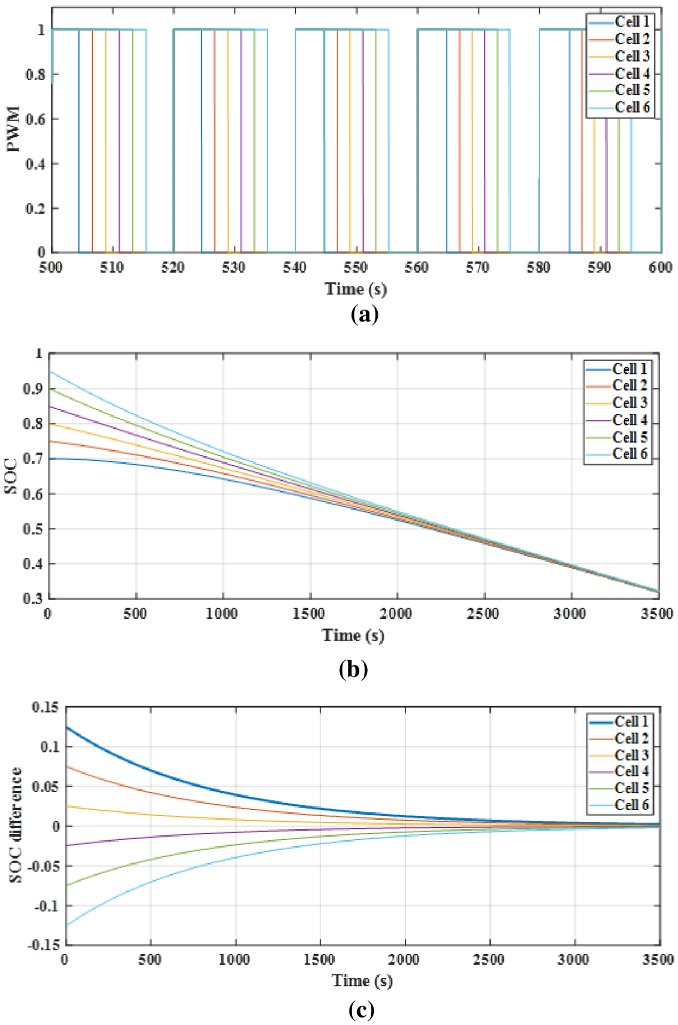

Fig. 4. (a) PWM signal for controlling the switching of each cell, (b) SOC of each cell, and (c) SOC error from the average after applying the proposed balancing method.

tively after applying the proposed control strategy, providing insightful details into the operational dynamics of each cell within the pack. Notably, the maximum temperature observed was 33.1 °C, indicating a controlled thermal environment even significant by the proposed method.

The visual representation of this process, as depicted in Fig. 3 and Fig. 4, offers a clear understanding of the ANN's role in dynamically managing cell characteristics for optimal balance. The prosperous achievement of balanced cell results, as depicted through SOC values and their deviations from the average SOC in Fig. 4(b)-(c), highlights the precision and efficiency of the intelligent balancing control strategy. The cells' SOC convergence to the average, accomplished within a relatively short span of 2500 seconds, stands as a test of the strategy's effectiveness. This rapid convergence is particularly notable, showcasing the system's capability to rectify imbalances and stabilize the pack's operational state quickly. This outcome significantly validates the effectiveness of the proposed intelligent balancing approach, demonstrating its utility in managing complex battery pack dynamics and the method's ability to ensure balanced operation. Moreover, the successful implementation of this strategy underscores the potential of ANN-based systems in advancing battery management technologies, opening avenues for further research and development in this domain.

IV. CONCLUSION

This paper proposed an advanced approach using Artificial Neural Networks (ANN) for State of Charge (SOC) balancing in lithium-ion battery packs within the smart battery pack framework. The study's innovation lies in dynamically managing SOC through precise control of half-bridge switches, a significant step forward in battery management systems. A key aspect of this approach was the selective bypassing of individual cells, which effectively enhanced SOC balancing and overall battery pack performance. The findings demonstrate the effectiveness of the proposed ANN-based balancing control, characterizing it as a vital solution for improving electric vehicle battery systems.

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