Active Cell Balancing Control Strategy for Parallelly Connected $LiFePO_4$ Batteries

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***Abstract*—While several recent studies have focused on eliminating the imbalance of energy stored in series-connected battery cells, very little attention has been given to balancing the energy stored in parallel-connected battery cells. As such, this paper aims at presenting a new balancing approach for parallel $LiFePO_4$ battery cells. In this regard, a Backpropagation Neural Network (BPNN) based technique is employed to develop a Battery Management System (BMS) that can assess the charging status of all cells and control its operations through a DC/DC Buck-Boost converter. Simulation results demonstrate the effectiveness of the proposed approach in balancing the energy stored in parallel-connected battery cells in which the state of charge (SoC) estimation error is found to be only 1.15%.**

***Index Terms*—Active cell balancing, battery management system, DC/DC buck-boost converter, state of charge estimation.**

I. INTRODUCTION

IN the past decades, smart grids (SGs) and electric vehicles (EVs) have become popular industry trends around the globe due to their cost effectiveness in the long run. For both technologies, a Battery Energy Storage System (BESS) will play a significant role for grid stabilization [1]–[3]. However, a BESS has to overcome several challenges, including cell to cell factorial delinquencies and cell performance over its entire operational life. Several Battery Management Systems (BMS) have been proposed to observe the cell parameters, i.e., current, voltage, state of charge (SoC) and temperatures to maintain the reliability of the cells [4], [5].

The primary role of a BMS is to protect the cells from over-charging and/or deep-discharging and hence extending the battery-life cycle. Usually, cells are predisposed in a battery pack with a minimum parameter variation for the sake of smooth and long operations. The performance of a battery pack is significantly impacted due to imbalance in the energy stored among its cells. Generally, only 10%∼20% to 60%∼70% SoC is permitted for a cell to maintain its performance. Outside this range, the cells exhibit over-charge and depth of discharge (DoD) [6]–[8]. Fig. 1 shows five battery cells of different levels of SoC. Upon connecting these cells in series/parallel, the cells with the highest SoC become over-charged during the charging period while the batteries with the lowest SoC experience deep-discharge during the discharging period. Several recent studies proposed different approaches to reduce the imbalance of the SoC among series-connected cell strings [9]–[11]. However, not much attention was given to balancing the SoC of parallel-connected cells as shown in Fig. 2. Parallel cells should have the same terminal voltage, despite voltage variations which ultimately initiate circulating current and SoC variations among the cells [12], [13].

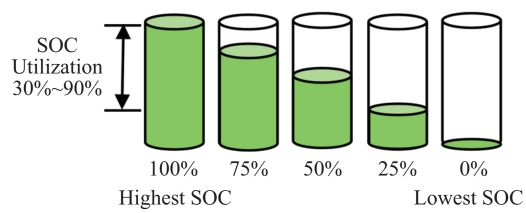

Fig. 1. Different leveled state-of-charges for battery-cells.

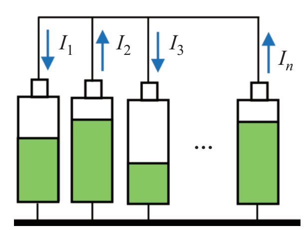

Fig. 2. Current circulation among the parallel connected cells due to imbalanced state-of-charge.

Subsequently, this paper presents a new approach to eliminate the unbalancing factors of parallel allied Lithium Ion Battery (LIB) cells. Reference [14] investigated the performance of parallel-connected cell strings and proposed a method to balance the different levels of SoC. Reference [15] considered normal battery module capacity and charge voltage shift for parallel-connected $LiFePO_4$ cells and calculated the battery pack capacity using a proposed BMS. The proposed method

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resulted in a standard integration difference in the range of 0%∼0.35%. Reference [16] tested the cells internal resistance and its impact on the battery life cycle for parallel-connected Lithium Ion battery (LIB) cells. Results concluded that only 20% of the internal resistance variation could reduce 40% of the battery life cycle.

Reference [17] classified cell balancing topologies into two categories: passive and active cell balancing. In the case of the passive cell balancing technique, current flows through a resistor which results in energy loss. In an active cell balancing method, energy is allocated equally among the battery cells. Thus, power losses can be reduced in many ways, including an active charge equalization scheme for battery cells [18], [19]. Usually, cell terminal voltage, open-circuit voltage (OCV) and SoC parameters are required for active cell balancing techniques. However, the problem of fluctuation of cell terminal voltage cannot be expressly accomplished for the equalization structure.

A minor difference of OCV among the cells causes a significant variation of the system performance as OCV is directly related to SoC. In general, LIB comprises a flat terminal voltage in the range of 20% to 80% of the SoC. As shown in Fig. 3, the voltage variation in this range is less than 0.09 V. Such slight voltage variation is hard to be used to persuade a proper charging and discharging process. Consequently, this paper focuses on active cell balancing tactics for online SoC assessment. Furthermore, a Backpropagation Neural Network (BPNN) is widely used for SoC estimation due to its self-handling characteristics. BMS observes the condition of the cells through assessing their SoC and issues a charging/discharging/islanding signal via a DC/DC buck-boost converter. In consequence, BPNN is adopted in this paper to develop a proper BMS for parallel-connected cells.

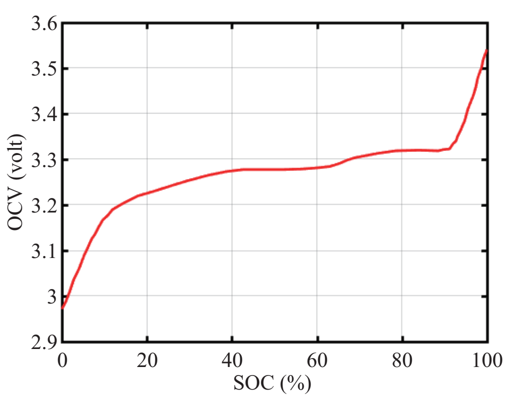

Fig. 3. OCV vs SOC for LiFePO$_4$.

The rest of this paper is arranged as follows: Section II explains the entire methodology of the proposed model. Battery Equivalent Circuit Model (ECM) and SoC estimation are presented in sections A and B. Section C describes the DC/DC Buck-Boost converter while the active cell balancing method is demonstrated in section D. Numerical simulation and discussion are deliberated in Section III. The conclusion is presented in Section IV.

II. Proposed Methodology

A. Cell Modeling

A thevenin equivalent circuit model (ECM) is an effective way to describe the internal characteristics of the battery cell. To avoid calculation complexity, the first-order Thevenin model shown in Fig. 4 is proposed in this paper. In this figure, $R_1//C_1$ models the time-delayed polarization resistance and capacitance, charge transfer activation and diffusion concentration [19], [20]. The OCV (V_{OC}) of the equivalent circuit model is:

$$V_{\mathrm{OC}} = V_R + V_P + V_{\mathrm{out}} \tag{1}$$

$$V_{\mathrm{out}} = (V_R + V_P) - V_{\mathrm{OC}} \tag{2}$$

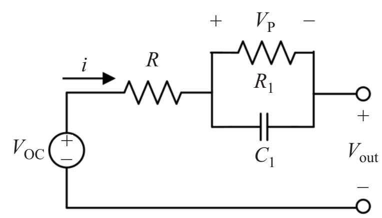

Fig. 4. First-order equivalent circuit model.

Here, R and $V_R = iR$ is the ohmic resistance and ohmic voltage drop respectively, which is related to the cell temperature, operating current and SoC. V_P is the polarized voltage for $R_1//C_1$ and V_{out} is the terminal or output voltage. The variations of the charging and discharging conditions are determined as follows.

$$C_1 \frac{\partial V_P}{\partial t} = i - \frac{V_P}{R_1} \tag{3}$$

Here, the functioning polarization is written off from the equivalent capacity $C_1 = t/R_1$ of $R_1//C_1$; where t is the polarization time factor. The aforementioned elements can be easily identified using pulse tests [21].

B. SOC Estimation

For cell strings, reliable SoC estimation is important to confirm its protection scheme and avoid over-charging and deep-discharging. However, accurate SoC estimation is quite challenging due to the nonlinear electrochemical reactions. Among existing SoC estimation techniques, Artificial Neural Network (ANN) especially BPNN shown in Fig. 5 is widely used due to its self-handling characteristics [22], [23]. As can be seen in Fig. 6, the proposed SoC method in this paper employs the current, voltage and temperature of each cell to estimate the SoC of individual cells by using (4) to (7) to minimize the Root Mean Square Error (RMSE) of the estimated SoC, BPNN structural weights are adjusted to achieve the desired minimum error [24].

$$netj_n = \sum_{j=1}^{3} a_j w_{jn} + p_n \tag{4}$$

Here, $netj_n$ is the input of the hidden layer neuron n, the input to the hidden neuron is a_i, and w_{in} is the weight between input neuron j to hidden neuron n, bias of the hidden neuron n is p_n.

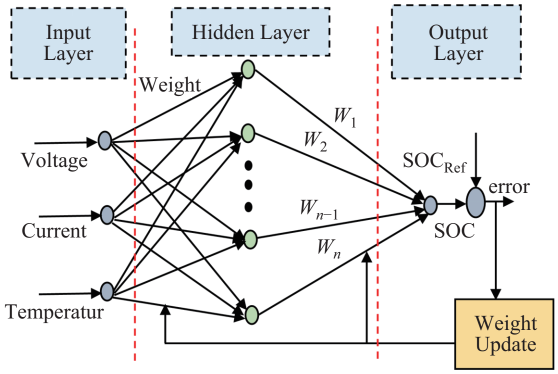

Fig. 5. BPNN structure for SOC estimation.

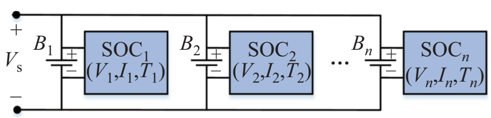

Fig. 6. SoC estimation for individual cells.

$$h_n = f\left(netj_n\right) = \frac{1-\exp\left(-2netj_n\right)}{1+\exp\left(-2netj_n\right)} \tag{5}$$

$$nety = \sum\nolimits_{m=1}^{n} h_m g_m + q \tag{6}$$

where h_n is the applied tangent activation function of the hidden layer neuron n, total input of the output neuron S is $nety$, h_m contains the value for hidden neuron to output neuron S, g_m shares weight for hidden neuron m to output neuron y, and q is the bias of the output layer neuron y. The Sigmoid function is the implemented activation function for the output layer neuron. Output function S can be calculated from:

$$S = f(nety) = \frac{1}{1+\exp(nety)} \tag{7}$$

C. Buck-boost Converter

A circuit diagram of the implemented synchronous Buck-Boost converter is shown in Fig. 7 [25], [26]. For standardizing the energy conveyance of cell sequences, four MOSFET switches ($M_1 \sim M_4$) are involved in the DC/DC converter. The converter can be utilized as a Buck, Boost or Buck-Boost converter. The converter is set-back to buck and boost mode procedure according to the anticipated cell voltage. To carry out the Buck mode, M_3 is permanently turned off while M_4 is turned on. On the other hand, the operation of M_1 and M_2 are subject to a governor formula. In Fig. 7, the source power charges the inductor by closing and opening the MOSFET switches M_1 and M_2 respectively. The capacitor delivers the output current at charging duration. M_2 and M_1 would be closed and opened respectively during the inductor discharging period. For charging the load, the inductor provides reserved energy to the capacitor. The average terminal voltage $V_{\text{Ter}} = DV_{\text{SC}}$, can be attained by adjusting the duty cycle D to be less than 1. Conversely, during Boost mode action, MOSFET switches M_1 and M_2 are permanently turned on and off respectively, while M_3 and M_4 are closed and opened continuously following the inductor charging status. This action is inverted during the discharging period.

Average output voltage V_{out} is $1/(1-D)V_{\text{SC}}$ while the output voltage during the Buck-Boost operation is $V_{\text{out}} = D/(1-D)V_{\text{SC}}$. For this mode, MOSFET switches M_1 and M_3 are turned off while M_2 and M_4 are turned on to charge the inductor. This action is reversed during inductor discharging.

D. Proposed Cell Balancing Technique

Battery pack capacity can be increased by connecting cell strings in parallel or in series. Theoretically, the terminal voltages of individual parallel cells should be identical [18], [26]. To maintain the reliability of the battery pack, charging and discharging cycles are triggered as soon as a cell SoC reaches a pre-defined cut-off region, even if its terminal voltage is the same as the other cells. An active cell balancing scheme is developed to diminish the SoC deviation among the cells. BMS estimates the SoC from each cell and issues a balancing signal through the DC/DC synchronous Buck-Boost converter shown in Fig. 7. In this technique, the average SoC ($\bar{S}$) of the parallel-connected cells is compared to the SoC of each cell (S_i). If the difference is more or less than a predefined value (S_{thr}), BMS commands the converter to proceed with the charging/discharging action as per the equation below:

$$\begin{cases} S_i - \bar{S} > S_{\text{thr}} & \text{Discharging} \\ S_i - \bar{S} < S_{\text{thr}} & \text{Charging} \\ \text{Others} & \text{Islanding} \end{cases} \tag{8}$$

III. Simulation and Discussion

The proposed active cell-balancing topology, along with the battery equivalent circuit model, as shown in Fig. 8 is simulated in the MATLAB/SIMULINK environment to validate the effectiveness of the proposed BMS. A $LiFePO_4$ cell is employed to assess the proposed active cell balancing methodology. Three parallel-connected A123 Li-iron-phosphate ANR26650 M1 cells, with nominal voltage of 3.3 V and 2.3 Ah capacity of which the OCV vs SoC, are presented in literature as shown in Fig. 3 [27]. The collected battery data is trained using the MATLAB/Simulink toolbox. As can be seen in Fig. 9, the overall regression for Training, Validation, Testing and Overall regression (R) is over 99%. Consequently, the actual and estimation SoC are almost similar as can be

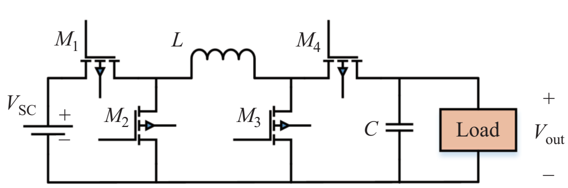

Fig. 7. Four switched DC/DC Buck-Boost converter.

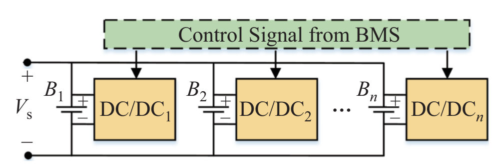

Fig. 8. Active charge equalization structural design.

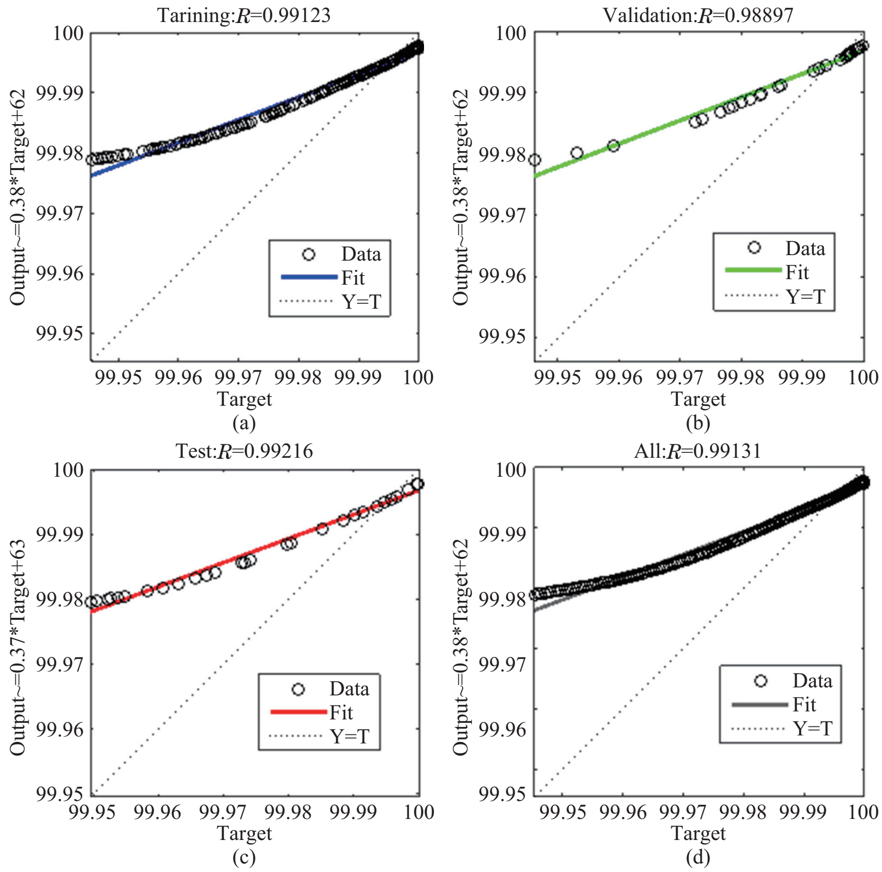

Fig. 9. (a) Training (b) Validation (c) Testing and (d) Overall regression for SoC estimation.

seen from Fig. 10. Fig. 11 shows 1.15% RMSE for the SoC estimation using the proposed BPNN. Compared with the estimation methods published in literature that include the Invariant-Imbedding Method (IIM), Extended Kalman Filter (EKF) and Unscented Kalman filter (UKF), the estimation error of the proposed BPNN in this paper is the lowest, as can be observed from Table I.

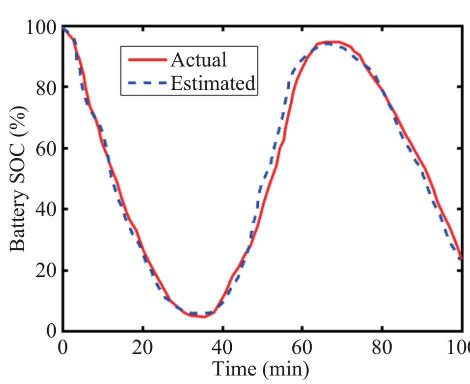

Fig. 10. Actual and Estimated Battery SoC.

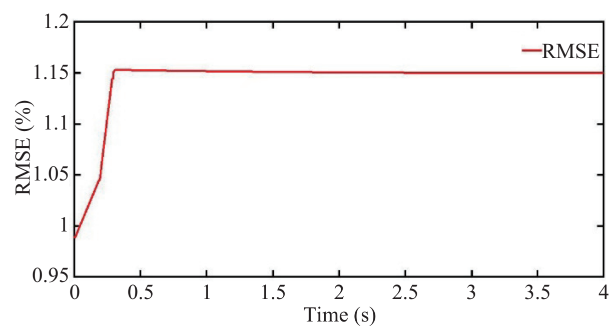

Fig. 11. RMSE of the BPNN proposed model.

TABLE I
UNITS COMPARISON OF SOC ESTIMATION METHODOLOGIES

Ref.	Year	Battery Model	SOC Estimation Algorithm	Error (%)
[28]	2016	2^{nd} order	IIM	2
[29]	2017	1^{st} order	BPNN	1.2478
[30]	2017	1^{st} order	EKF	6.5
[31]	2018	1^{st} order	UKF	1.5
[24]	2019	1^{st} order	BPNN	1.2
Proposed	2020	1^{st} order	BPNN	1.15

To validate the robustness of the proposed balancing technique, three cells are assumed to initially exhibit different SoC; 54%, 52%, and 50%. The proposed BMS analyzes these SoC levels and issues a signal to the DC/DC Buck-Boost converter to either charge or discharge its individual stored energy in order to achieve SoC balance among the three cells. Fig. 12 to Fig. 14 illustrate the effectiveness of the proposed active cell balancing technique through the cells' voltages, currents and SoC without and with the implementation of the proposed methodology. Fig. 12(a) shows that although

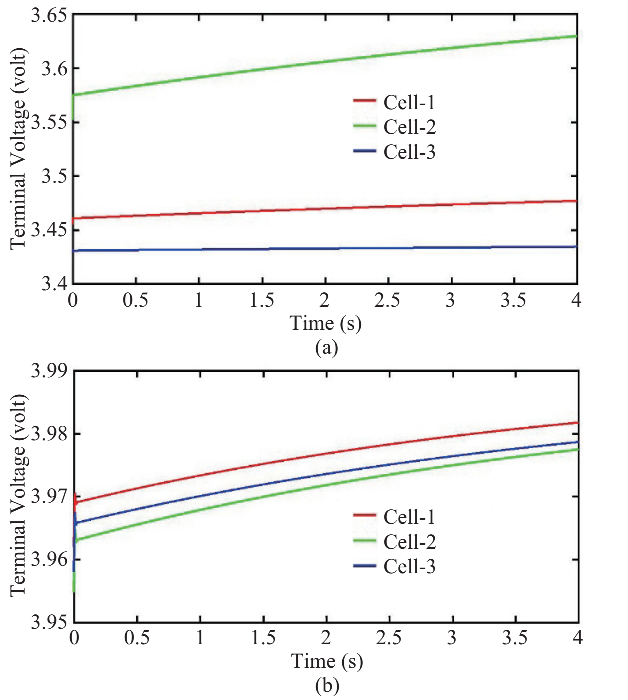

Fig. 12. Cells voltages (a) without and (b) with the application of the proposed method.

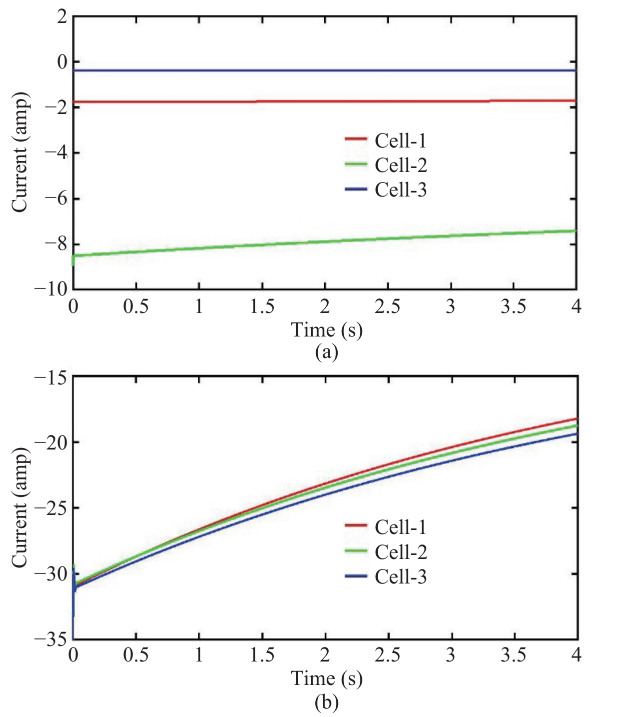

Fig. 13. Cells currents (a) without and (b) with the application of the proposed method.

the terminal voltage for the three parallel cells should be the same, due to different SoC, the terminal voltages are different without the implementation of any BMS scheme which may result in circulating current among the cells as can be observed in Fig. 13(a). Employing the proposed BMS will bring cell voltages to almost the same level as can be seen in Fig. 12(b) which can limit the circulating current as

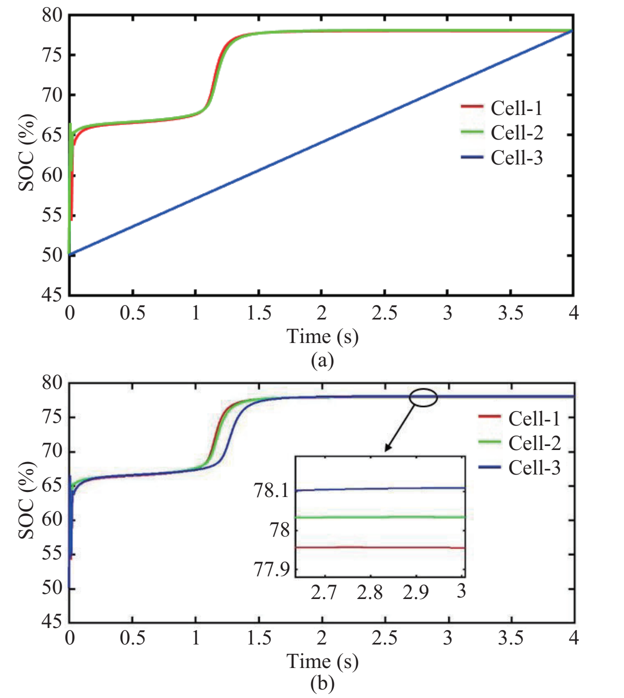

Fig. 14. Cell SoC (a) without and (b) with the application of the proposed method.

can be seen in Fig. 13(b). Fig. 14 shows the SoC before and after the implementation of the proposed technique. Before the implementation, the three cells exhibit imbalance to escalate the SoC levels of 54% 52%, and 50%, as can be shown in Fig. 14(a). With the implementation of the proposed technique, the SoC of the three cells become closer and rise up to 78% as shown in Fig. 14(b). The detailed flowchart of the proposed topology is shown in Fig. 15.

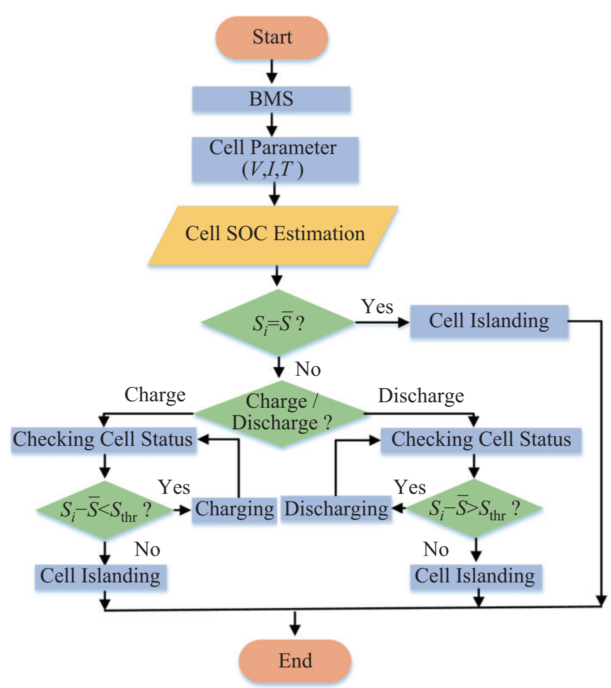

Fig. 15. Flowchart of the proposed active cell balancing scheme.

IV. CONCLUSION

An active cell balancing methodology based on adaptive BPNN to estimate the state of charge of battery cells is presented and implemented on $LiFePO_4$ battery cells connected in parallel. The proposed BMS assesses the SoC level of each cell and drives an activation signal to the DC/DC Buck-Boost converter to equalize the SoC of all cells. The activation signal triggers charging, discharging or islanding cell modes succeeding the direction of BMS. The key conclusions of the obtained results are as follows:

- The proposed BMS can minimize the SoC estimation error to 1.15% which surpasses the accuracy of other estimation models published in literature.
- The proposed active cell balancing approach eliminates the SoC discrepancies among the connected cells, eliminating the circulating current among parallel connected cells.
- The proposed technique is simple and easy to implement within parallel connected cells and can be modified for series connected cells as well. This technique is essential to maintain the reliability of series/parallel connected cells and improve its performance by lengthening its operational life cycle.
- If the proposed scheme fails to moderate the charging levels, and SoC of a battery string, it is suggested to replace the weakest cell of the battery pack.

Further research to validate the proposed technique will be conducted experimentally to prove its practical feasibility.

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