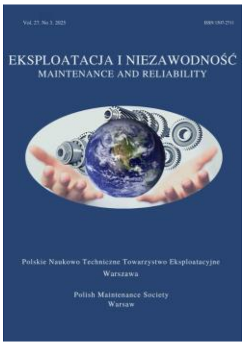

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Improving Reliability in Electric Vehicle Battery Management Systems through Deep Learning-Based Cell Balancing Mechanisms

Indexed by: Web of Science Group

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Highlights

- Improving reliability and efficiency in electric vehicle Battery Management Systems (BMS).
- Applying Deep Learning for enhancement of Cell Balancing (CB) mechanisms.
- MAE, MSE, RMSE, demonstrates a better performance of hybrid model CNN-BiLSTM.
- Charging period, temperature, thermal management and battery chemistry are considered.

Abstract

Cell Balancing (CB) is a crucial aspect of the Battery Management System (BMS), which is used to increase the batteries operate time as well as operational life. The most widely used method is Passive Cell Balancing (PCB) since it is inexpensive and simple to use. This work proposes an algorithm using Deep Learning (DL) that selects the balancing resistor effectively with respect to increasing temperature, C-rate, level of cell imbalance, and balancing duration. Convolution Neural Network (CNN), hybrid method of Convolution Neural Network (CNN)-Long short-term memory (LSTM) (CNN-LSTM) and Convolution Bidirectional LSTM (CNN-BiLSTM) are used to assess the performance of the suggested system. In order to optimize the balancing parameters, the balancing system's error analysis is carried out, and performance indices like Mean Square Error (MSE), Root Mean Square Error (RMSE), and Mean Absolute Error (MAE) are used to compare the suggested algorithms. The hybrid CNN-BiLSTM obtained MAE of 0.0453, MSE of 0.0062 and RMSE value of 0.0671 which is better than other models.

Keywords
battery management system, deep learning, convolution neural network, mean square error, root mean square error.

1. Introduction

Electric vehicles (EVs) are crucial in reducing regional levels of toxins in towns as well as villages. As of right now, EVs offer the greatest options for both practical mode of transportation and safeguarding the environment. High voltage, high efficiency and extended life-span battery systems are required due to the growing reliance on EVs, which calls for improved battery tracking methods [1]. Examining the battery efficiency assessment of the tracking method is crucial to ensuring this and extending the battery pack's overall life cycle. Rechargeable batteries that have no memory operation, minimal self-discharge rate, a favorable power to mass proportion, minimal energy consumption and low cost of maintenance include

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lithium-ion (Li-ion) power supplies. As such, selecting the appropriate battery innovation and making effective use of it are crucial[2]. The chemical composition of batteries is particularly vulnerable to profound release and charging excessively, which can harm the power source and reduce its useful life, as well as which pose security hazards [3].

For EVs, BMS is used in a balancing arrangement to recover the greatest amount of power from the pack of batteries. There are two types of balancing processes that eliminate excess electricity from overestimated cells: passive and active. Dissipative barriers are used in passive structures to drain surplus electricity from extremely charged cells, and energy-storing components are used in active designs to transfer excess charge to low-charged cells, allowing both powerful and fragile cells to support one another [4]. As seen in Figure 1, the cell balancing mechanism used in EVs normally operates in three distinct ways. In order to optimize the amount of electrical power imposed or received by the cell throughout the procedure of charging or discharging manipulate, balancing is used. In the state where the cell is neither charged nor discharged, the idle balancing mode functions [5]. Both voltage- and charge-based coordinating algorithms are employed in the equilibrium and are suitable for both kinds of balancing schemes. The battery voltage is a variable that can be tracked and used as input to the balancing method in the cell maintaining strategy. Algorithms may be developed based on voltage, the inside voltage and state of charge (SOC) history.

Cell balancing is currently studied in great detail using a variety of balancing methods; mainly on DL techniques has transformed the area of e-vehicle BMS to increase the precision of the design metrics and study skills of these approaches is presented in [6-10]. The reduction of maintaining time as well as loss of power in the PCB system's design is discussed in many literatures through control methods.

The author [6] proposes to improve the equilibrium process as well as ideal power loss management, this article proposes a suitable range of maintaining resistor with esteem to scale of cell imbalance, maintaining time, C-rate and increase temperature using a ML based CB regulate method. In the passive balancing structure, adjustable resistors are used to optimize energy loss and achieve ideal heat description. LSTM, radial basis neural network (RBNN), and back propagation neural network (BPNN) are used to assess the effectiveness of the suggested system. To optimize balancing variables, the balancing system's error analysis is carried out, and performance indices like MSE, RMSE and MAE are used to compare the suggested algorithms.

In [7] the author developed modern EVs use a passive cell balancing system that employs secured dissipative resistance to take the excess electricity out of the overestimated cell and evenly distribute it throughout the other cells. The adjustment time of the passive balancer is one of the primary issues. If the car is charged using a traditional charging framework (five to six hours), and there is very little cell imbalance, the lengthy balancing time should be accessible. Passive balancing with a constant resistor is not the best option in situations involving swiftly DC charging or highest imbalance. The PCB with variable balancing resistor is used for both newly created and between cells, depending on the balancing electricity demand under both rapid and gradual charging scenarios.

The author in [8] presents an optimization strategy is divided into two phases. The set of charge transfer groups of cells that will ensure the least amount of electrical energy dissipation is identified by developing the charge adjustment as a Mixed Integer Linear Programming challenge in the initial phase. In order to reach this lower limit in the subsequent phase, we suggest a sequential scheduling method that solves an integer linear programming issue on each iteration. Several scenarios demonstrate that our suggested approach consistently meets the calculated lower limit for the balancing time and results in up to 41% lower electricity dissipation than the most advanced techniques.

The research presented here has demonstrated that, in comparison to uniformly using all the cells, the constrained convex optimization based regulate policy, which takes advantage of the extra degree of freedom of multi-level converter, provides an immense advantage in terms of decreasing temperature and SoC variations, especially under variability in parameters. Therefore, there is a good chance that the multi-level converter will provide another advantage of cell balancing while also serving as an electric motor developed in [9].

The current active cell voltage balancing techniques have a few drawbacks, including inadequate effectiveness, large volume, lack of dependability, and longer cell voltage adjustment times. In this study, an improved active cell voltage balancing technique that depends on a Switched-Capacitor has been suggested to address these drawbacks in active cell voltage balancing. The suggested approach finds the battery pack's easiest route between each cell. As a result, it will lower the battery pack's initial cost while simultaneously increasing the battery pack's acceleration, voltage measurements equalization, and efficiency in general developed in [10].

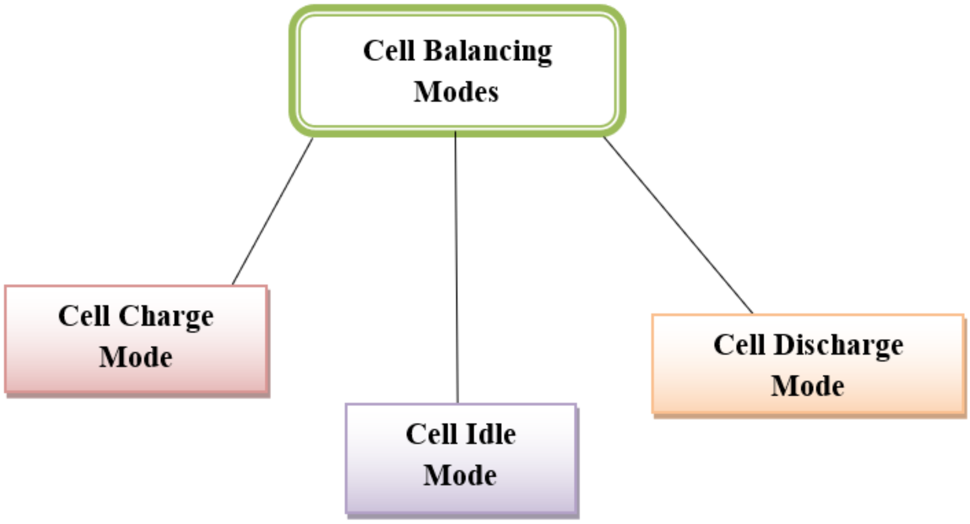


Figure 1. Schematic of cell equalization methods.

The additional components required for designing the dynamic system raises the total expense of battery system, whereas the active circuit backup energy loss in these surpasses the passive strategy power loss. The PCB approach operates on switchable shunt resistance throughout the cell making it simple to establish at low price. According to the studies and evaluations completed thus far, the main issues determined in the existing PCB system are as follows:

- Thermal difficulties in the PCB structure are caused by the balancing resistor's loss of heat.
- The best way to use passive balancing is throughout charging, as its lengthy balancing time may make it impractical in an intense charging situation.

To get around the constraints of the current PCB framework, the suggested algorithm takes into account three crucial balancing factors: rise in temperature, loss of power and maintaining time. The value of the balancing resistor is the primary determinant of each of the parameters. The best choice for the balancing resistor value throughout balancing is determined by a number of real-time factors, including battery utilization, the chemical composition of batteries heat effect, electrical charging temperatures, speed and duration of charge. The primary contribution of the suggested approaches is as follows:

- The application of the best passive balancing method while taking into account the different operational, external factors and chemical composition of batteries factors
- The DL method chooses the right resistor so that the system's maintaining speed is increased lacking significantly raising the system's temperature or energy loss.
- For the purposes of verification and validation, the effectiveness of the suggested DL models is evaluated using the CB resistor power loss, time balance, MSE, RMSE and MAE.

The organization of this study is structured as follows: Section 1, describes the review of existing papers based on CB mechanism and DL. Section 2, provides the suggested passive balancing technique using deep learning method. Section 3, briefs the simulation results and discussion with performance effectiveness of the suggested system. Finally, Section 4, presents the conclusion of the paper.

2. Proposed Passive Cell Balancing Mechanism

Voltage balancing techniques are a prerequisite for both active and passive cell balancing algorithms. The balancing resistor in the passive system eliminates extra power, while an inductor in the active structure transfers excess energy to lower energy cells [11]. The computations determine whether the voltage variation among any two cells is greater than the specified value. By improving the sampling circuit's precision and taking into account the needs of the entire framework, the balancing thresholds could be adjusted more effectively. An ordinary PCB system, which is appropriate for first-level charging methods uses permanent resistors to equalize the extra cell power. It takes a long time to balance the cells because of the tiny maintaining current [12]. The suggested method makes use of an adjustable resistor arrangement, in which customer demand and environmental factors are taken into account when choosing resistors as illustrated in Figure 2.

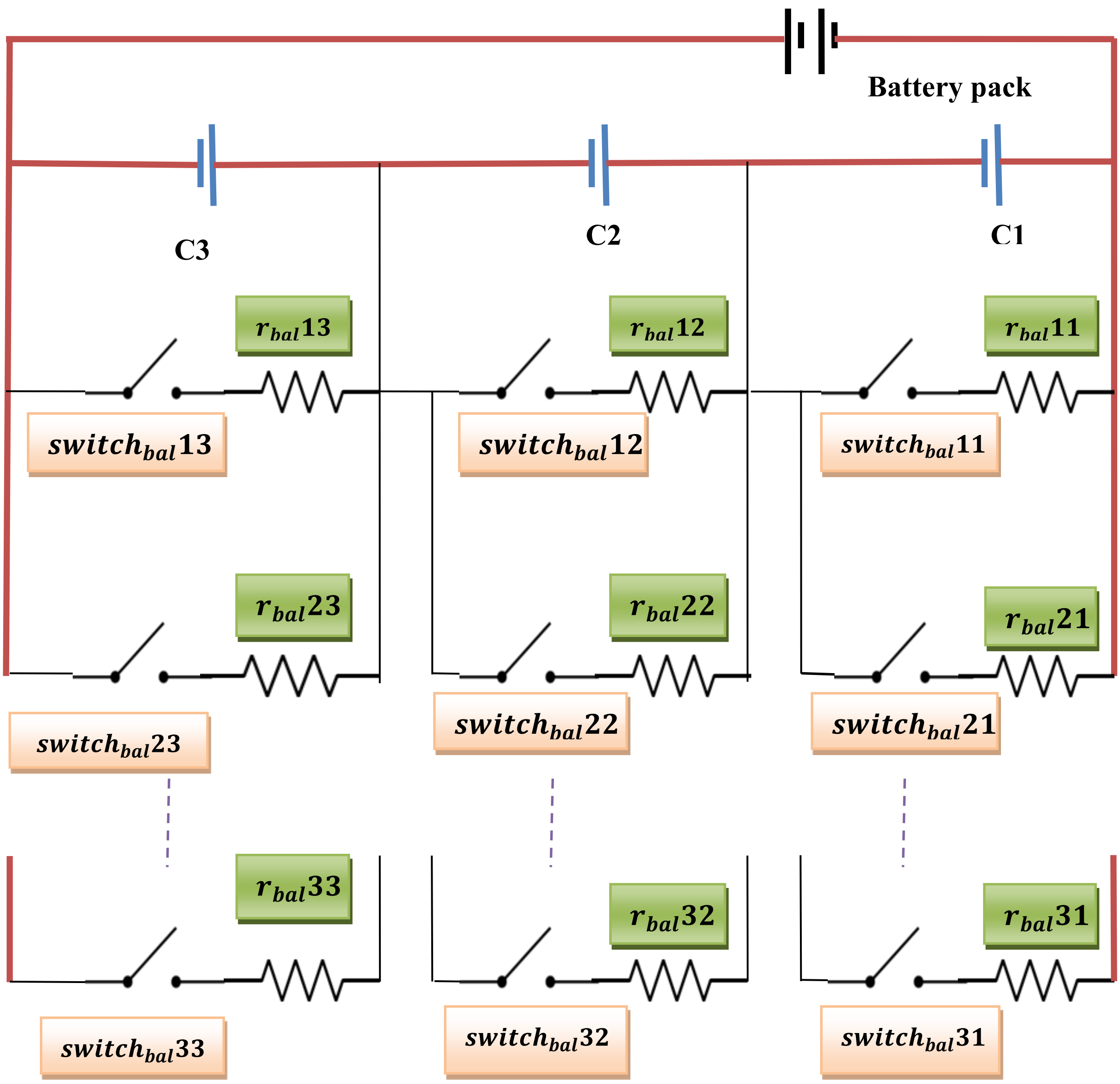


Figure 2. Proposed Passive cell balancing mechanism.

2.1. Battery Representation

In order to facilitate the definition of the optimal CB challenge, the 3RC electrical equivalent circuit model (ECM) is selected as the CB scheme. A Li-ion batteries electrochemical reaction can be explained by an ECM. Thevenin's ECM is one of the ECMs that frequently deals with Li-ion battery operation [13]. It is made up of an inner resistor and an attached parallel RC. The battery model that was chosen for the modeling work based on the research from the 3RC ECM.

$$V_T = V_0 - R_{0I} - V_{R_{e1}C_{e1}} - V_{R_{e2}C_{e2}} - V_{R_{e3}C_{e3}} \quad (1)$$

Where $V_T$represents the battery voltage, V_0 denotes the voltage of open circuit, $V_{R_{e1}C_{e1}}, V_{R_{e2}C_{e2}}, V_{R_{e3}C_{e3}}$ represents the 3RC equivalent network.The AC impedance test is used to examine the impedance features of the battery model. Using a DL model, the simulation data depending on the ECMs is fitted in order to extract the RC model variables [14].

Estimating the SOC is crucial for maximizing battery efficiency and prolonging its lifespan. By measuring the batteries current, voltage and temperature, the power source model SOC is calculated. The SOC and battery temperature affect the model's RC values. Test data is used in the look-up tables to identify the parameter [15]. The parameters that must be taken into account in order to select the best passive balancing layout are power source duration for charging, speed, charging consumption, manufacturing facilities cost, physical components, and balancing current. The following formula is used to determine the cell balancing current.

$$Balancing\ current\ (I_{BA}) = \frac{Imbalance\ voltage \times Capacity}{Blancing\ time} \quad (2)$$

Models of battery voltage behavior fall into the following categories:

Models for analysis, electrochemistry, equivalent circuits, models based on data. The electric behavior of a battery cell is analytically described by mathematical models. This method applies three primary equations: the Sheperd, Nernst, and Peukert equations. Test data, such as SOC, voltage, and current input values, are used to parameterize these models. As a result, a temperature dependency is excluded and a prior SOC estimation is required. By using equations derived from physical and electrochemical laws to model the dynamic behavior, physical-based models can attain a high degree of accuracy. Consequently, a lot of partial differential equations must be solved in real time, which is why they are usually not used in industrial settings. The Butler–Volmer equation is used in common methods, which can achieve high accuracy.

2.2. Balancing Resistor Optimization

The following factors are crucial and heavily influence the best resistor choice.

Charging period: A low current balancing is enough to equalize the cells when the battery is gradually charged. For CB during the charging procedure time, a high balancing energy is necessary if the cell is charged at a high ‘C’ rate [16].

The charging temperature: Because battery pack temperature rises more in warmer regions than in colder climates, outside battery temperature is another crucial factor that must be taken into account when developing the balancing resistor.

The operation strategy of a 48 V system in automotive applications pre-defines a volatile battery operating area. Since stationary states are uncommon, a flexible model must be created. Thus, terminal current, temperature, terminal voltage, and voltage trend were chosen as the model's input features.

Although the terminal voltage calculation doesn't add any new information, it guarantees quicker and more accurate convergence during model training. The voltage level at which the battery is truly functioning can be determined by calculating the average voltage over the previous few steps. Moreover, it can produce the overvoltage polarization trend when paired with the prior current and voltage. In the following step, the overvoltage polarization is determined by the temperature and current. The terminal voltage is recalculated every minute using the most recent sequence of predicted voltages when predicting multiple steps at once. Small errors in voltage prediction are prevented from being sent straight to the next step as input by using a 60-second period. In each iteration, updating terminal voltage could lead to increase error.

The expense of thermal direction: Additional power loss in the circuit balancing for the rapid charging demands, the expenditure for a system to manage temperature is high. Therefore, it is crucial to choose the balancing resistor using the right control scheme in order to guarantee the system's thermal safety. Batteries chemical science: The balancing current and imbalance rate vary considerably depending on the chemistry of the cell [17].

The probability of an imbalance: This variable indicates the age of the rechargeable battery as well as the degree of imbalance. When different batches of cells are manufactured, the level of imbalance is more noticeable. On the other hand, if the manufacturing numerous dimensions are small, this can be managed. With the aging of the cell comes an increased likelihood of imbalance [18].

2.3. Deep Learning Techniques in Cell Balancing

DL also called structured learning or deep set up learning, is a subset of ML techniques based on artificial neural networks [19]. DL is an electronic gadget that simulates the neuronal network of the brain. It's a subfield of machine learning that can be supervised and is known as "deep learning" because it uses deep neural networks. This suggested method introduces a DL algorithm in addition to the traditional PCB strategy to select the balancing resistors optimally based on user interface demands and external variables. However, it ignores the needs for cell balancing [20]. The three DLhybrid techniques applied in this cell balancing mechanism are CNN, hybrid method of CNN-LSTM and CNN-BiLSTM are used to assess the performance of the proposed method.

2.3.1. Convolution Neural Network (CNN)

DL algorithm can take an input image, assign values to different parts of the image and separate one object from another is called a CNN. A Convolutional net requires a lot less preprocessing than other classification algorithms [21]. In basic systems, filters are hand-engineered; however, with sufficient preparation, Convolutional net can learn these filters/characteristics. Convolutional architecture was impacted by the structure of the brain's visual cortex and is akin to the pattern of connecting neurons found in the human brain. Separate neurons only react to stimuli in the area of perception, which is a limited portion of the visual field [22]. The total vision is covered by the overlap of several such fields. CNN is a specific type of neural network.

The batteries voltage, temperature and current sensors provide the inputs. The estimated temperature, battery voltage and charging current are represented by inputs 1, 2, and 3. Cell voltage, charging current and temperature data from cell balancing experiments are fed in as inputs [23]. To choose the value and duration of the balancing resistor, the DL-based model's output is obtained. The performance of the CB system is determined by the algorithm which employs 30 hidden neuron layers.

2.3.2. Convolution Neural Network-Long short-term memory (CNN-LSTM)

A unique type of recurrent neural network (RNN) called LSTM is designed to address the issues of acceleration of gradients and elimination during long pattern training [24]. In longer patterns, LSTM can perform better than a basic RNN. There is only one state in the hidden layer of the initial RNN, and it is highly sensitive to short-term input. There are two primary components to the gate structure's network as shown in Figure 3. The CNN-LSTM block schematic is clearly illustrated in Figure 4.

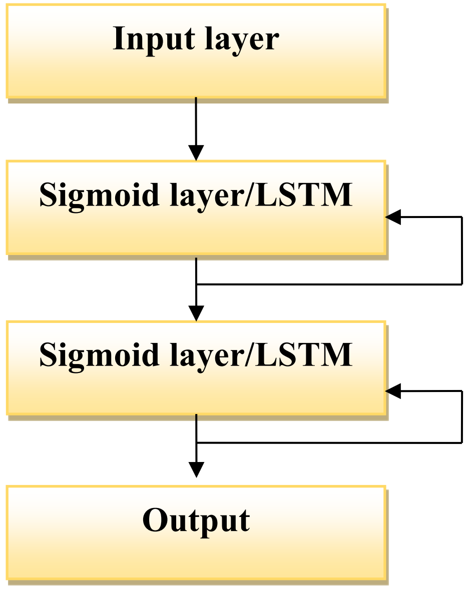


Figure 3. Representation of LSTM.

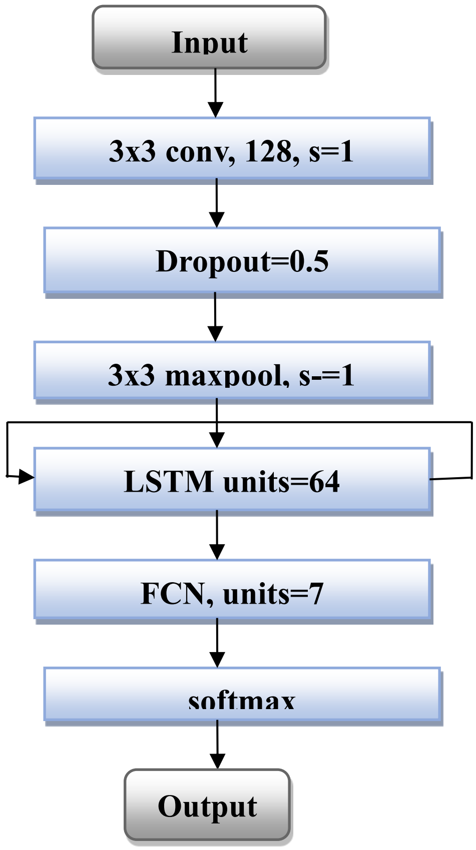


Figure 4. CNN-LSTM block representation.

A sigmoid function, which has an interval of 0 to 1, activates the limit portion of the gate, constraining the quantity and type of data that can pass through. The use of data network, which makes up the other component, is responsible for extracting characteristics from the prior data, such as input data or hidden states. The sequence cell is fully charged using the steady current technique, and the algorithm for passive balancing is activated at the maximum level of charge. The most important battery variables, which have a major influence on balancing achievement, are gathered and described in the existing studies. These variables include voltage, current, and information on temperature. The test is run in a range of room temperature, charging C-rate and cell imbalance circumstances.

For LSTM layer the calculation is denoted as,

$$p_t = \sigma(M_{gi}K_t + M_{pi}H_{t-1} + M_{ci}{}^\circ B_{t-1} + c_i \quad (3)$$

$$l_t = \sigma(M_{gf}K_t + M_{hf}H_{t-1} + M_{cl}{}^\circ B_{t-1} + c_f \quad (4)$$

$$B_t = g_t{}^\circ B_{t-1} + h_t{}^\circ \tanh(M_{gc}H_t + M_{pc}H_{t-1} + c_c) \quad (5)$$

$$a_t = sigma(M_{gd}H_t + M_{pd}H_{t-1} + M_{cd}{}^\circ B_t + c_{o),} \quad (6)$$

$$H_t = a_t{}^\circ tanh B_t \quad (7)$$

The forget gate outcome is determined as follows,

$$a_t = \sigma(M_{g.}[P_{t-1,}m_t] + u) \quad (8)$$

$$J_t = \sigma(Q_{l.}[l_{t-1,}m_t] + u_l) \quad (9)$$

$$\widetilde{B_t} = tanh(M_{d.}[l_{t-1,}m_t] + w) \quad (10)$$

The current cell state can be represented as,

$$B_t = g_t * B_{t-1} + l_t * \widetilde{B_t} \quad (11)$$

Where the value of B_t is (0,1),

$$P_t = O_t * \tanh(B_t) \quad (12)$$

2.3.3. Convolution Bidirectional LSTM (CNN-BiLSTM)

CNNs are frequently utilized for removing features tasks. However, they are also useful for extracting pertinent features from chronological data, such as system states. In this case, the input data's geographic relationships and trends are found by the CNN element of the architecture, which allows it to extract significant features that are essential for further analysis.

Conversely, specialized recurrent neural networks called BiLSTM layers are capable of identifying time-dependent relationships in data sequences. The BiLSTM improve the capacity of the model to comprehend from the sequential original data by taking into account both forward and backward situations. This bidirectional analyzing makes the model involving data processing by ensuring that it will recognize long-term dependencies as well as associations within the data. The real cell balancing outcome and predicted CB results are compared. Unit voltages and electrical charging of the battery make up the six input data sets that are produced by the software and hardware implementation of the PCB mechanism. The PCB control system was used to measure the voltage and current during charging for distinct levels of cell voltage imbalance with various charge currents and temperatures of 1,178 testing patterns and 10,692 training patterns are included in the data.

3. Simulation Results and Discussion

This section describes the simulation results and discussion using various DL models, the outcomes are compared and benchmarked in this innovative statistically based approach to DL. The results of these tests yielded a raw data volume of more than 200 million data points. The following techniques had to be used to pre-process the raw data in order to create a fewer information frame that more accurately reproduced the battery actions before training a model with machine learning computation. The raw information frame for training was reduced to 1,026,917 sequences using under- and over-sampling. To create a varied validation set, an additional 174,393 sequences were included in the validation test set. These sequences were partially chosen by hand and partially chosen at random. In contrast to the validation and training sets, which were derived from test bench measurements, the test procedure was conducted using a test set of 72,800 sequences. Table.1 illustrates the parameter specification of proposed DL.

Table 1. Parameter Specification.

Parameter	CNN	CNN-LSTM	CNN-BiLSTM
Optimizer	Adam	Adam	Adam
Activation function	softmax	softmax	softmax
Dropout	0.3	0.1	0.2
Dense unit	3	3	3
Number of epochs	40	40	40
Number of hidden layers	7	3	1
Loss function	Entropy	Entropy	Entropy
Neurons number	3	3	3

Recurrent Neural Network (RNN) hyperparameter tuning methodology is used. After Epoch 30, the BiLSTM outperformed the RNN by a small margin in terms of mean max error and had a lower MSE. Furthermore, the LSTM's training time per epoch was comparable to the GRU's and three times faster than the RNN's. Two LSTM layers with 128 neurons each and one attached dense layer with 128 neurons were identified empirically as the hidden layers. To address overfitting concerns, a second dropout layer was also employed, with a dropout rate of 0.2. A grid search algorithm was used to empirically determine the model hyperparameters for the suggested models.

Three 3.45 Ah lithium manganese cobalt oxide cells are used in the simulation. The cells nominal cut-off voltages are 3.8, 2.9 and 4.5 volts, respectively, during charging and discharging. A voltage differential that is larger than that of the second cell is maintained for the first and third cells. Initial voltage differences between cell 1 and cell 2 are 50 mV and 104 mV, respectively. There is a 38-mV voltage differential between cells 2 and 3. Because of the nonlinear relationship between battery voltage and SOC, passive balancing primarily occurs during the first and last phases of charging. All the necessary parameters have been taken into account to conduct the investigation design for the PCB system. The results of the CB system performance study have been analyzed and displayed. Balancing current amount is defined as the ratio between capacity consumption to the capacity rated (Ah).

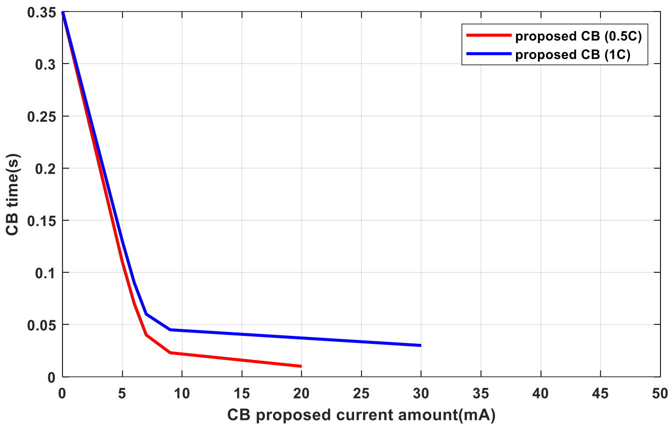


Figure 5. Proposed PCB current vs time variation.

Figure 5, shows that a higher voltage variation between cells corresponds to a higher coordinating capacity ratio. The significant non-linear behavior of the li-ion battery during the first and last stages of charging is the cause of the divergence among the capacity ratio and 1V. As a result, a higher balancing current accelerates balancing and enhances its balancing effect. When the second resistor is turned ON condition, then 1volt drop happen below 100 mV takes place. If both resistors are turned ON condition when the 1Volt is greater than 100 mV takes place.

As demonstrated in Figure 6, when the circuit voltage increases then the balancing battery module voltage rises. With its hybrid combination of GTOA and DRN for adaptive control and optimization of EV battery voltage equalization, the GTOA-DRN technology is new in that it achieves greater efficiency and cost-effectiveness [25]. It has been noted that as the amount of balancing time rises, so does the voltage deviation between the cells. In applications that operate immediately, a suitable increase in the balancing measure can help to achieve a suitable balancing result because the two variables are inversely proportional. Table.2, provides the thorough error analysis, types of error performance based on power and temperature.

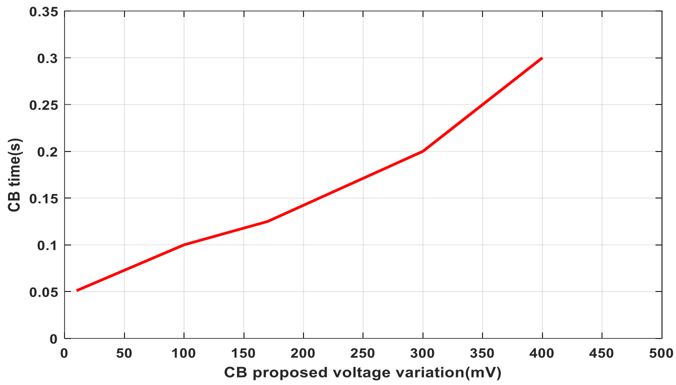


Figure 6. Proposed cell voltage variation.

Table 2. Power and temperature condition of proposed method.

	Training	Validation	Test
Max.Temp	60	57	50
Min. Temp	-23	0	-28
Mean power	-256.6	32.4	-65,4
RMS power	3.8	2.9	1.9
Peak power	16.8	16.4	11.9

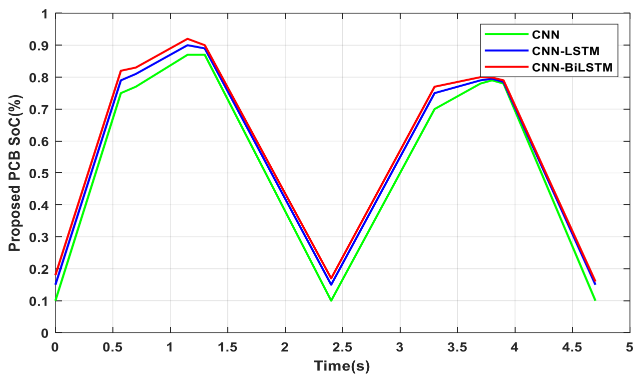


Figure 7. Proposed PCB SoC variation.

As seen in Figure 7, the comparison of proposed CNN, CNN-LSTM and CNN-BiLSTM state of charge cell balancing is determined is clearly shown where the graph illustrates the proposed hybrid CNN-BiLSTM method achieve better results compared proposed CNN, CNN-LSTM models. When x-axis time in seconds is increased, then gradually the SoC of proposed method increases. Using a novel optimization methodology, they show illustrative numerical findings that demonstrate that the analog-to-digital conversion at the RUs has an ideal number of quantization bits [26].

Figure 8, demonstrates the SoC of cell 1, cell2 and cell 2 individual variations based on proposed method. Figure 9, depicts the passive cell balancing reaches the highest peak temperature of 28 degree Celsius and the change in temperature cannot exceed 5 degrees Celsius during the time of charging. According to the suggested plan, it takes cell 1 takes 90 mins and cell 3 takes 60 mins respectively, to reach the balancing threshold. During this time, there is no appreciable rise in temperatures of the batteries or total electrical power loss. As long as the battery temperature remains within acceptable bounds, both resistors are turned on for a higher C-rate. Before switching to the normal mode operation, cell 1 and cell 3 remain in the balancing mode for 3,890 and 1,450 seconds, respectively. Since cell balancing is performed during final charging, when the charging current is limited and the lack of time to balance is the only issue.

Increasing recurrent and epochs will aid in lowering erroneous. At the conclusion of every epoch, the test and train loss are demonstrated. Lastly, the test dataset MAE and MSE are shown in Figure 10. The proposed method achieves a low MAE and MSE as the number of epochs increases. Figure 11, shows the overall performance comparison of proposed CNN, CNN-LSTM and CNN-BiLSTM MSE vs number of hidden units. By determining the obtained results, the proposed hybrid CNN-BiLSTM method achieve better results compared to other models. Table.3 gives the comparison of existing LSTM and proposed models obtained MAE, MSE and RMSE value. By determining the obtained results, the proposed hybrid CNN-BiLSTM method achieve better results compared to existing LSTM, proposed CNN, CNN-LSTM models. To lower the amount of memory needed for each training iteration, the input data from the pre-processing stages was separated into batches. When each batch has been processed once during an iteration, an epoch is deemed complete. Over the trained epochs, the loss and validation loss, respectively. The model continues to learn the relationships between the input data as the loss gradually drops. An increasing validation loss after Epoch 60 is a sign of overfitting. Epoch 35 was when the test set's loss metrics were at their lowest.

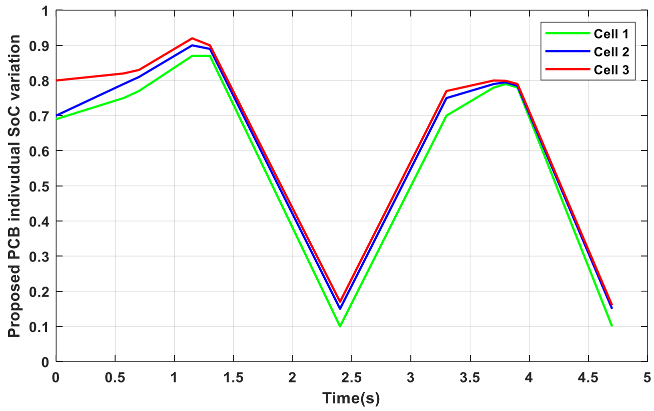


Figure 8. Variation of individual PCB SoC.

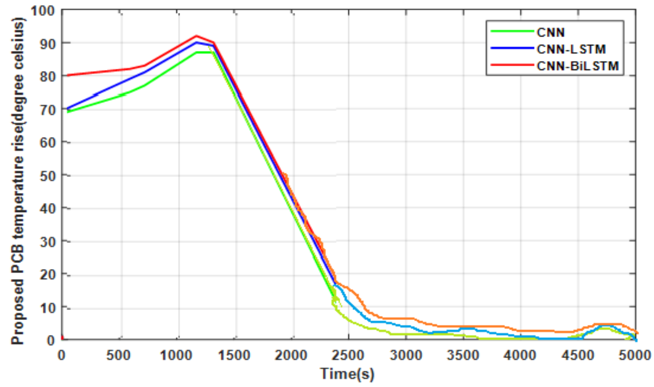


Figure 9. PCB temperature rise.

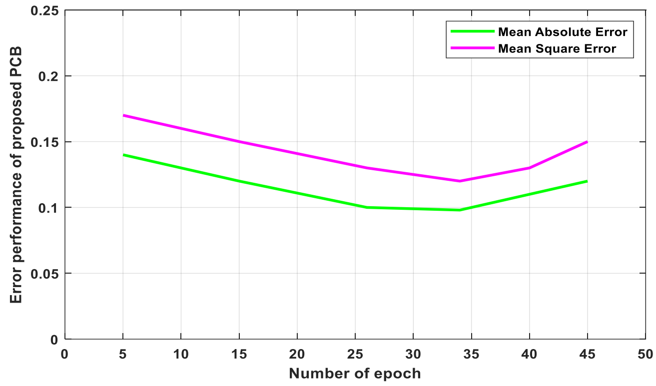


Figure 10. Proposed PCB method error vs epoch performance.

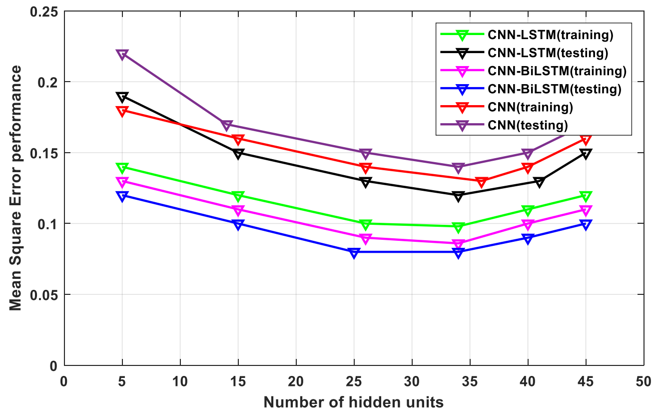


Figure 11. Performance comparison of proposed CNN, CNN-LSTM and CNN-BiLSTM.

Table 3. Comparison of existing LSTM and Proposed CNN, CNN-LSTM and CNN-BiLSTM obtained MAE, MSE and RMSE value.

Model	MAE	MSE	RMSE
LSTM	0.0684	0.0792	0.2964
CNN (Proposed)	0.0576	0.0643	0.2387
CNN-LSTM (Proposed)	0.0521	0.0396	0.1872
CNN-BiLSTM (Proposed)	0.0453	0.0062	0.0671

3.1. Experimental Results

The experimental prototype of the suggested Passive Cell Balancing (PCB) is clearly shown in Figure 12. The dSPACE RTI2102 micro box in the suggested prototype structure produces two complementary PWM signals that power the circuit's MOSFET switches. The AD modules are used to monitor the cell voltages. Utilizing a Tektronix MD3012 oscilloscope, the output results are recorded. Table.2, provides a list of the hardware elements utilized to execute the suggested framework.

Table 2. Experimental setup parameter specification.

Components	Number	Values
Samsung ICR 18550 Lithium-Ion cells	3	3.73V,Ah rating:2650mAh
Transformer	1	2.75V
DC Voltage sensor	3	8trappingg, 230V/12V
Capacitor	5	10mF
Resistor Load	1	20ohm
Switching frequency		28.75kHz
TLP 450 optocoupler	8	

(a) (b)

Figure 12. Experimental setup. (a) Overall Experimental setup, (b) Horizontal and vertical view of Convert setup with load.

Figure 13, displays the MOSFET switches' PWM pulses at a switching frequency of 28.67 kHz with 5V/Div.

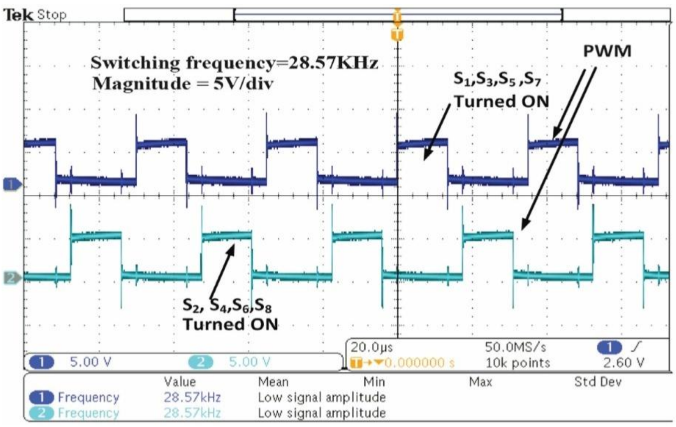
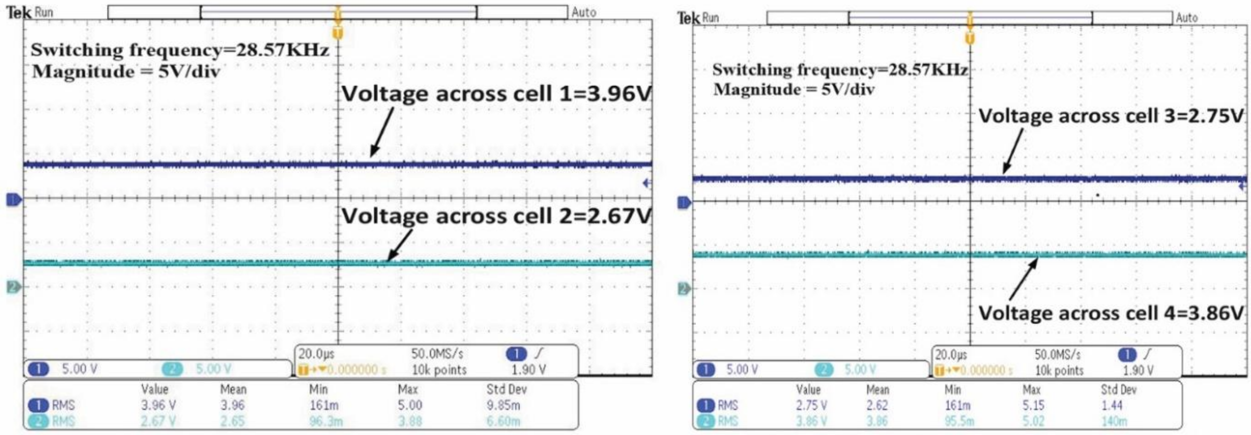


Figure 13. PWM signal Experimental setup.

Figure 14 illustrates the voltage imbalance between the four series-connected cells prior to cell voltage equalization. The initial unequal voltages are P1 = 3.96V, P2 = 2.64V, P3 = 2.65V, and P4 = 3.84V. The cell voltage equalization process in this suggested method is carried out while the load is connected. Thus, cell voltage balancing and cell discharge to load occur simultaneously. Voltage differentials between cells shouldn't be greater than 0.1V for precise PCB. The unbalanced cell voltages are equalized using the suggested passive cell balancing technique. At a switching frequency of 28.57 kHz, cell voltage equalization takes almost 1100 seconds.

The voltages across the cells following equalization are displayed in Figure 15 as P1=3.96V, P2=3.84V, P3=3.96V, and P4=3.84V. Figure 15, displays the entire cell voltage trajectory during cell voltage balancing. Since four cells (4.2V) are connected in series with a 10Ω resistive load in the suggested topology, the theoretical current flowing through the load is 16.8 10 = 1.68A; however, because of overall losses in the hardware prototype, the current actually flows through the resistive load at 1.6558A. The load current passing through the resistive load during active cell voltage balancing is depicted in Figure 16.



(a). the unbalanced voltage across cells B_1 and B_2 (b). the unbalanced voltage across cells B_3 and B_4

Figure 14. Voltage across cells before CB.

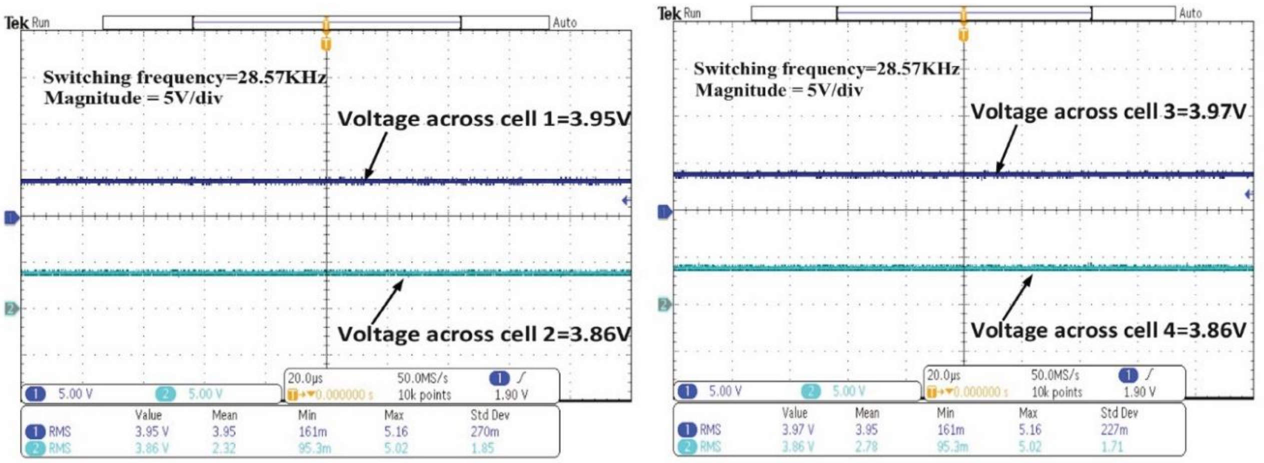


Figure 15. Voltage across cells after CB.

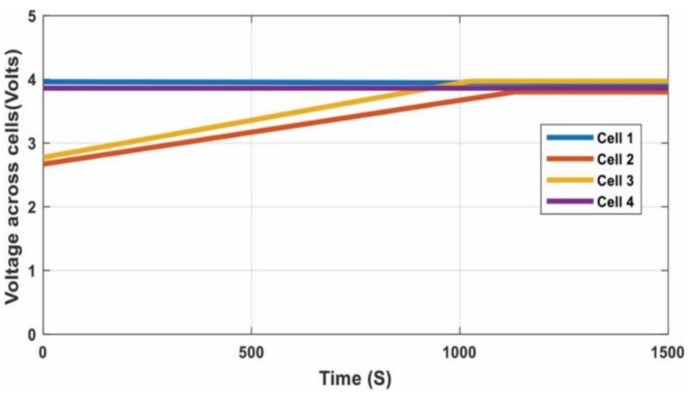


Figure 16. Cell voltage during CB.

4. Conclusion

This study investigates the DL algorithms used to estimate the ideal resistor values for the Li-ion battery pack in order to achieve perfect cell balancing. To reduce difficulty of computation, it is more practical to apply the variable resistor-based PCB algorithm in real time for massive packs of batteries. The proposed three DL algorithms used to assess the performance of the suggested approach. The effectiveness of the optimal cell equalizing control strategy that has been proposed is illustrated by a number of illustrative results. The hybrid CNN-BiLSTM outperforms well in terms of MAE of 0.0453. The CNN-LSTM method performs better than the CNN method with 0.0521 MAE. In contrast to existing method, the suggested system exhibits better balancing speed and a smaller temperature rise. One possible avenue for future research could be to use the cell's higher order voltage deviation. The model inputs are physically measurable parameters, the suggested battery model can be applied in real-time. This guarantees that a BMS can be implemented in a straightforward and precise manner. A wide range of mild-hybrid vehicles can use the developed modeling method because of its accuracy and adaptability to different battery types. Battery CB based on advanced hybrid DL with optimization may be part of future work. Therefore, it is necessary to train a more reliable CB in the peripheral BMS areas.

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