Accurate state of health estimation using hybrid algorithm for electric vehicle battery pack performance and efficiency enhancement

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ABSTRACT

Temperature fluctuations, overcharging, and over-discharging are all issues that can cause fast deterioration, capacity loss, and thermal runaway in lithium-ion batteries (LIBs). To overcome these challenges, a hybrid model combining a stacked recurrent neural network (SRNN) and bidirectional long short-term memory (biLSTM) is presented for a reliable state of health (SoH) estimate. This model finds subtle patterns in battery data using SRNN layers to capture sequential dependencies and biLSTM modules to solve long-term temporal correlations while avoiding vanishing gradient concerns. The effectiveness of model is assessed by performance measures such as root mean square error (RMSE), mean absolute error (MAE), and maximum error (MAX), which demonstrate its superiority for precise SoH estimation. The stacked RNN-based SoH estimation achieves superior accuracy, with RMSE, MAE, and MAX error levels of 1.5%, 0.8%, and 4.84%, respectively, compared to GRU's higher errors (3.8%, 3%, and 5.5%). Stacked RNN hierarchically processes sequential battery data, effectively capturing complex temporal relationships, and ensuring accurate and reliable SoH estimation for LIBs.

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1. INTRODUCTION

To combat climate change and achieve net-zero objectives, around the world are enacting tougher emissions restrictions, carbon pricing, green infrastructure expenditures, renewable energy targets, and encouraging environmentally conscious behaviors [1]-[4]. Efforts to electrify industries that depend on fossil fuels, such as transportation, emphasize the use of green technology, EVs, energy storage systems, and renewable energy for low-carbon, sustainable industrial operations globally [5]-[10]. Advanced energy storage systems are required to accommodate the rising demand for renewable energy, enhance grid stability, permit real-time applications, reduce carbon emissions, and boost efficiency all of which are important for the effective incorporation of clean energy sources [11]. The industry is led by lithium-ion batteries (LIBs) because of their outstanding performance, quick technical development, and high efficiency for a variety of uses [12]-[15].

State of charge (SoC) and state of health (SoH) predictions are improved when fiber Bragg grating (FBG) sensors are paired with deep neural networks (DNNs) and long short-term memory (LSTM) models. To lower mistakes and boost dependability, a hybrid machine learning framework combines Gaussian process regression with convolutional neural networks (CNNs) [16]. LSTM and Feedforward neural networks (FNN) are two examples of machine learning models used in prognostics to estimate the SoH of LIBs.

Over fifty cycles, the model showed a 6% error rate, indicating the possibility of a precise SoH estimation. A new preprocessing technique based on SoC is also advantageous for the usage of simpler models, including feedforward neural networks (FNNs) [17]-[20]. Particularly when dealing with limited datasets, this strategy improves the performance of SoH predictions and outperforms conventional time-domain methods, demonstrating its usefulness in practical applications. Data-driven approaches for estimating SoH of LIBs often leverage algorithms like K-nearest neighbors (KNN) to process partial charge-discharge current sequences [21]. These techniques enable rapid learning and high generalization, as demonstrated using an official dataset. combining convolutional neural networks (CNN) with LSTM networks enhances the accuracy of SoH assessments and improves predictions for remaining useful life (RUL) [22].

These models improve the precision of SoH forecasts by analyzing intricate deterioration patterns. One of the most important tasks for improving battery management is estimating SoH of LIBs. According to recent research, hybrid approaches such as the CNN-LSTM model perform better in feature extraction than more conventional methods like K-means clustering [23]. For SoH estimation, several machine learning approaches were examined in [24], including random forest, support vector regression (SVR), polynomial regression, and multiple linear regression. SVR, which used NASA datasets for analysis and partial charging times for feature selection, produced the best results out of all of them. To increase SoH accuracy, a wavelet transform-based technique has also been created. Wang *et al.* [25] demonstrated the use of LSTM networks for managing nonlinear data related to voltage and temperature changes, significantly improving accuracy to 98.92%.

This performance surpassed traditional normalization techniques. LSTM networks, a type of recurrent neural network (RNN), excel in capturing long-term dependencies and sequential patterns in time-series data. Their ability to model complex, nonlinear relationships makes them particularly effective in dynamic environments, such as voltage and temperature fluctuations, often seen in battery management systems and energy conversion systems. This method offers more robust predictions compared to conventional approaches, which may struggle with nonlinearity. The SoH of LIBs can be accurately predicted using hybrid stacked RNNs and LSTM networks, especially in their bidirectional version. Deeper learning is made possible by the layered design, which can identify intricate correlations in battery data.

The performance and safety of LIBs are impacted by temperature variations, overcharging, and over-discharging. biLSTMs enhance SRNNs ability to process sequential data by addressing the vanishing gradient issue, which is essential for managing long-term dependencies. SRNNs discover patterns from both past and future inputs. By modelling nonlinear, dynamic aspects of battery performance, SRNN can enhance SoH predictions as it can accurately interpret temporal variations in battery health over time. For precise LIBs SoH estimation, the main contributors developed a hybrid SRNN-biLSTM model that performs better than GRU in RMSE, MAE, and MAX errors and effectively captures temporal dependencies. The organization of the paper is outlined as follows: The ability of the hybrid RNN and biLSTM network to forecast the battery's SoH is examined in section 2. The findings and a thorough examination of SoH estimate methods are covered in section 3, which also compares various approaches and their practicality. The main conclusions are finally outlined in section 4, which highlights the need for precise SoH estimation for battery management system optimization.

2. PROPOSED SRNN-BILSTM MODEL

To efficiently estimate SoH of LiBs, a model combining a hybrid stacked recurrent neural network (SRNN) and bidirectional long short-term memory (biLSTM) networks has been developed. This method tackles the intricate and nonlinear aspects of battery data, such as temperature and voltage variations, which have significant effects on battery performance over time. The model can learn from previous battery performance and make precise predictions about future states because of the RNN component's exceptional ability to discern temporal correlations from sequential data. Long-term dependencies, however, are frequently problematic for ordinary RNNs because of problems like vanishing gradients. This restriction is lessened with the introduction of the biLSTM network, which does both forward and backward data analysis. By using a two-way approach, the model is better able to identify subtle patterns and correlations in the data. Utilizing the bidirectional nature allows the network to have a more comprehensive understanding of the temporal linkages that are present, which is essential for an accurate estimate of SoH. The incorporation of biLSTM into the hybrid stacked RNN model facilitates long-term memory preservation, which is crucial for accurately estimating the battery's overall health and remaining usable life. This method handles the dynamic and nonlinear behavior of LiBs, resulting in more reliable and accurate SoH evaluations.

To ensure that the model can manage the complexities of battery data while generating precise predictions on the battery's performance and health, RNN and biLSTM networks are combined as shown in Figure 1. The assessment of the state of health (SoH) of LiBs has advanced significantly using the hybrid stacked RNN and biLSTM network model, which makes use of state-of-the-art deep learning techniques. The temporal dependencies and long-range correlations included in battery performance data are efficiently captured by this approach, improving prediction accuracy. The model's input parameters, which include temperature, voltage, and current, are important markers of a battery's condition. The stacked RNN layers process these parameters, extracting sequential features, and the biLSTM layer examines these inputs both forward and backward. To produce more accurate SoH predictions, the model must completely comprehend the links between previous and future battery states, which is ensured by this bidirectional processing. The hybrid stacked RNN and biLSTM methodology provides a more reliable solution than standard techniques, which frequently find it difficult to manage the intricate and nonlinear behavior of LiBs. The model may better manage the complex dynamics of battery performance by utilizing biLSTM capacity to capture bidirectional temporal patterns and maintain long-term relationships.

Consequently, this technique improves the accuracy of SoH forecasts by offering more accurate assessments of a battery's health condition. Predictive maintenance applications and real-time battery monitoring are ideal uses for the suggested architecture. It is perfect for ongoing battery health monitoring due to its capacity to handle sequential data and consider bidirectional temporal trends. In addition to increasing the SoH estimation's accuracy, the use of this model helps Li-ion batteries last longer and be safer by facilitating proactive management and prompt repair.

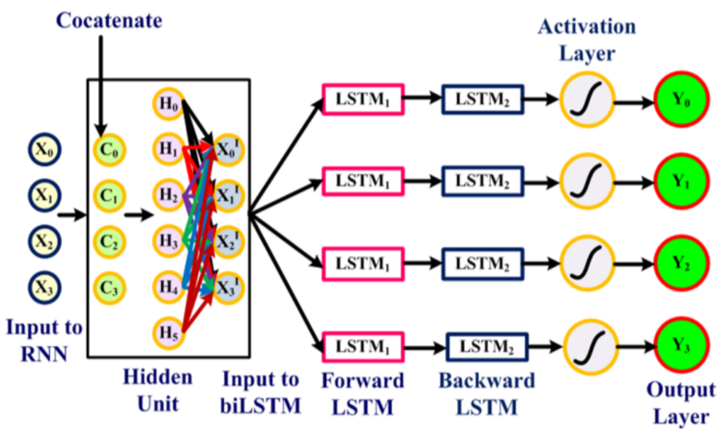


Figure 1. Architecture of proposed SRNN-biLSTM network

3. RESULTS AND DISCUSSION

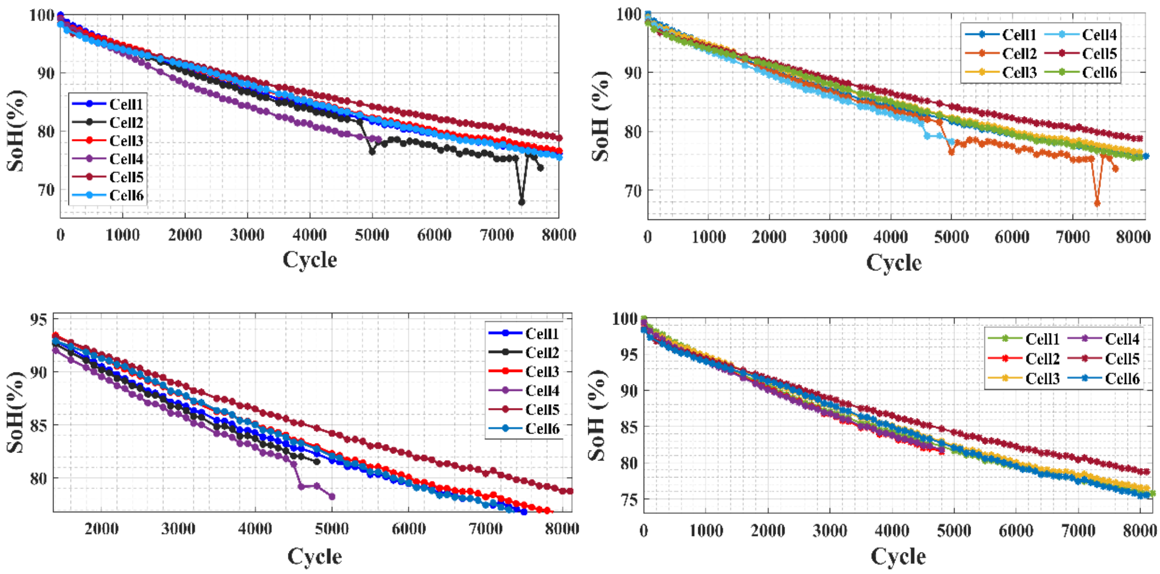
The stacked RNN-biLSTM model has demonstrated significant improvements in SoH prediction accuracy when compared to conventional techniques such as GRU networks in MATLAB simulations. In addition to lowering error rates in SoH estimations, the bidirectional nature of the biLSTM in conjunction with stacked RNN layers allows for enhanced analysis of dynamic battery data, including voltage, current, and temperature. The results of these simulations indicate that the hybrid model is highly accurate in forecasting capacity deterioration, charge/discharge behavior, and battery life. This model can be simulated with MATLAB/Simulink, which makes it simple to integrate deep learning methods and evaluate different hyperparameters. The battery management system (BMS) and National Renewable Energy Laboratory (NREL) datasets are frequently utilized for SoH estimate assignments because they include real-world battery data that depict a range of operating situations and degradation scenarios.

3.1. Training system

The SoH of a LIB steadily declines as the number of cycles rises. Changes in the chemical makeup of the electrodes, elevated internal resistance, and battery capacity deterioration are the main causes of this reduction. Battery wear occurs with every cycle of charging and discharging, which lowers the battery's capacity to retain charge and overall efficiency. Shorter battery life, slower charging, and lower output power are therefore all shown by the SoH estimate, which shows a progressive deterioration in the battery's performance over time. In the GRU network, the SoH estimation for the WISTAR-H-PHS04 battery pack cells decreases from 93% to 68% as the number of cycles rises. The low capacity of the Gated Recurrent Unit (GRU) to capture dependencies time can be a drawback.

As the battery goes through more cycles, the estimation accuracy decreases because GRU is not as good at identifying long-range correlations in battery data as it is at identifying short-term trends. As a result, overall performance can suffer from inaccurate predictions about the battery's condition as it develops. The SoH estimation of the WISTAR-H-PHS04 battery pack cells in response to the rising number of cycles, as seen in Figure 2(a), shows a reduction from 93% to 68% utilizing the GRU network. Compared to more complex models like LSTMs, the fundamental disadvantage of the GRU is its limited capacity to capture long-term relationships. Long-term fluctuations in battery data can prove difficult for GRUs to learn across many cycles, despite their computational efficiency and ease of training. As a result, SoH calculations become less accurate as the battery develops and experiences deterioration. Similarly, the stacked SRNN-biLSTM network has been shown in Figure 2(b) to minimize degradation from 95% to 69% when compared to the GRU network.

One of the primary advantages of SRNN-biLSTM over GRU is its ability to capture both short-term and long-term data dependencies. The stacked RNN layers boost the model's capacity to recognize subtle patterns in battery performance by allowing it to comprehend sequential input at several levels of abstraction. The model is better equipped to comprehend the entire temporal dynamics of the battery's activity since the biLSTM component offers bidirectional processing, which enables the model to include both past and future data. This is especially crucial in SoH estimation as degradation patterns change over time and historical occurrences impact future states. As the battery experiences more cycles, GRU networks, despite their efficiency, strength not be able to capture these complex relationships, leading to decreased accuracy.



(a) (b)

Figure 2. SoH (%) estimation Vs cycle life for (a) GRU network and (b) proposed RNN-biLSTM network

The estimating capacity of GRU-based SoH estimation decreases with increasing temperature; for a temperature increase of 0.005 °C, the voltage drops to 4 V as shown in Figure 3(a). The suggested SRNN-biLSTM approach, on the other hand, keeps voltage levels steady at 4.2 V as depicted in Figure 3(b) during SoH estimation. The SRNN-biLSTM has an advantage over GRU since it is capable of understanding intricate nonlinear correlations between battery parameters like temperature, voltage, and current. By processing sequential data at many abstraction levels, the stacked RNN layers improve the ability to identify minute trends in the impact of temperature on battery health. In the meanwhile, the biLSTM network captures both the past and future battery performance states by analyzing bidirectional temporal relationships. The model is more resilient to temperature changes because of this two-pronged strategy, which also keeps voltage prediction from degrading. In contrast, GRU networks are less able to forecast battery performance under different heat settings since they do not have bidirectional and multilayered processing capabilities.

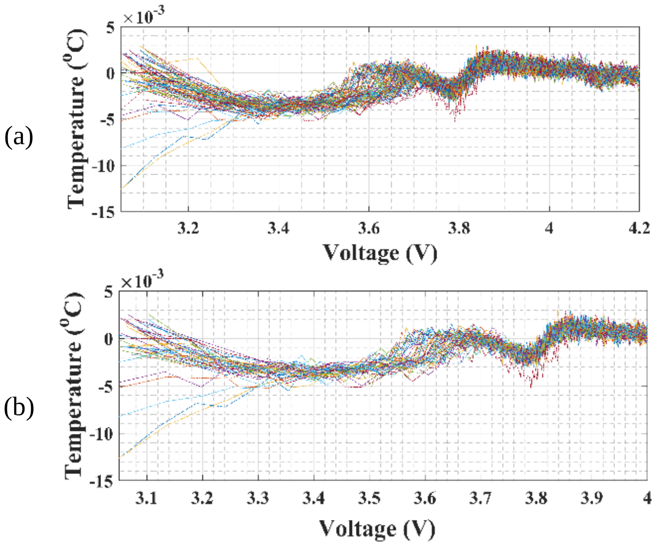


Figure 3. Effect of temperature for (a) GRU network and (b) proposed SRNN-biLSTM network

3.2. Validation system

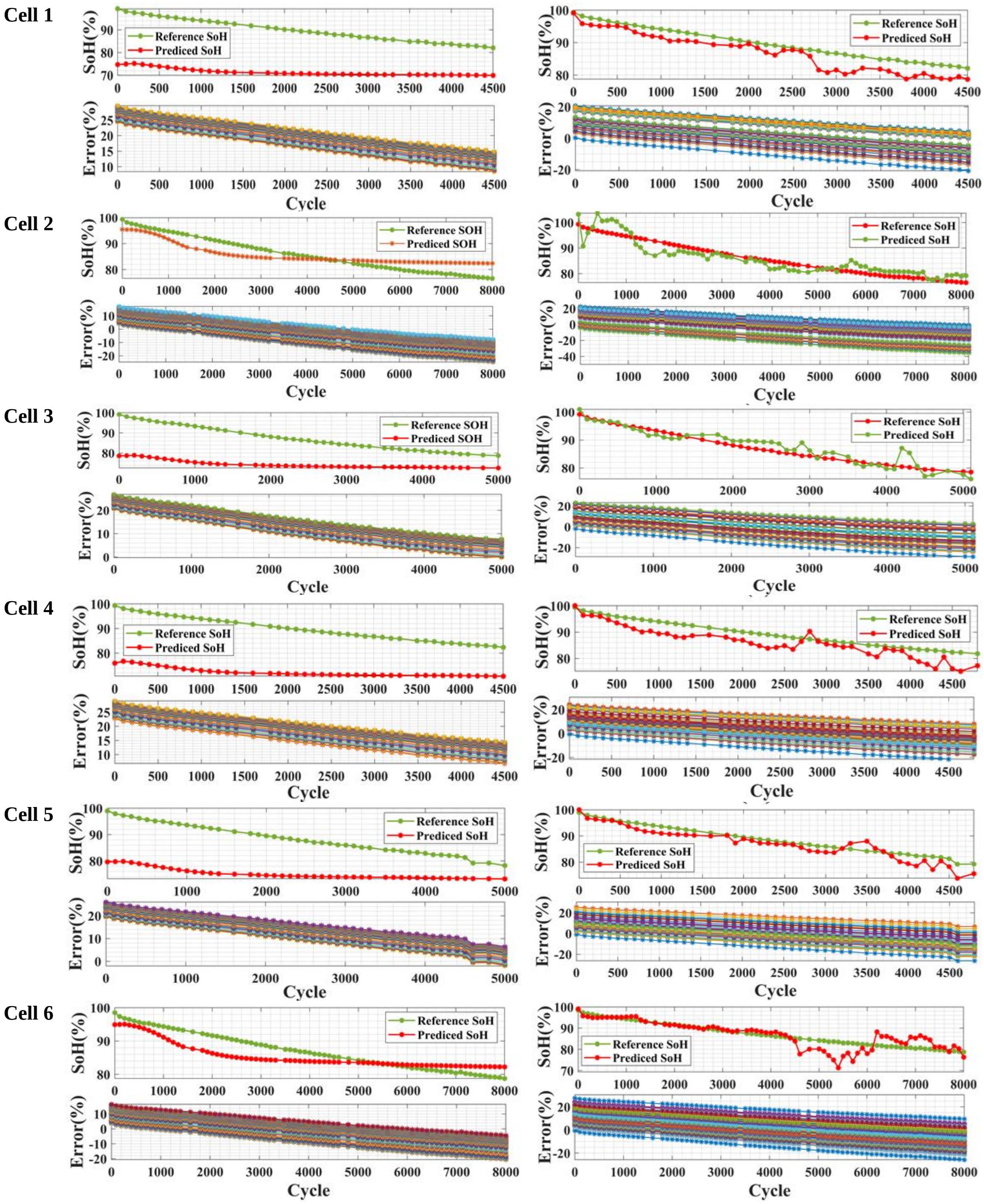
The validation mechanism assures SoH estimate accuracy by testing models against previously unknown data and demonstrating dependability under a variety of operational situations. Figure 4(a) illustrates that the GRU network has a considerable gap between the preferred and reference SoH estimate levels, resulting in high error values. This is due to GRU networks' shortcomings, which include an inability to efficiently capture long-range relationships and subtle nonlinear patterns in battery data. GRUs, while computationally efficient, have difficulty dealing with complicated temporal linkages and dynamic behaviors, resulting in erroneous SoH estimations. This inaccuracy has an impact on the battery system's dependability and causes more inaccuracies across cells under various operational conditions. In contrast, the proposed SRNN-biLSTM network, as shown in Figure 4(b), significantly reduces these errors while ensuring correct SoH estimation. The SRNN layers improve the model's ability to interpret sequential input by extracting multi-level features, whereas the biLSTM does bidirectional analysis, capturing past and future temporal trends.

This hybrid design enables the SRNN-biLSTM to better handle complicated and nonlinear battery behavior than the GRU, resulting in higher SoH estimate accuracy. Accurate SoH forecasts increase battery efficiency, dependability, and operational safety, making the SRNN-biLSTM the best option for battery monitoring and predictive maintenance. The error metrics for GRU-based SoH estimation indicate RMSE, MAE, and MAX error values of 3.8%, 3%, and 5.5%, respectively, which are much greater than those of the suggested SRNN-biLSTM-based SoH estimation, which has RMSE (1.5%), MAE (0.8%), and MAX (4.84%). This improvement is attributed to the benefits of the proposed SRNN-biLSTM model. The stacked RNN layers effectively extract hierarchical features from consecutive battery data, allowing for a better comprehension of nonlinear interactions. Furthermore, the biLSTM network processes input in both forward and backward directions, catching bidirectional temporal relationships that GRU networks fail to attend.

This dual processing capacity provides an enhanced overview of the battery's activity, resulting in higher estimation accuracy. The hybrid SRNN-biLSTM approach is also more effective in preserving long-term dependencies, making it perfect for dealing with the complex and dynamic nature of LIBs. The SRNN-biLSTM model significantly improves SoH estimation accuracy, reducing RMSE (1.5%), MAE (0.8%), and MAX (4.84%) errors while maintaining voltage stability and capturing long-term dependencies better than GRU. The SRNN-biLSTM model enhances SoH estimation accuracy by capturing bidirectional temporal relationships, mitigating GRU limitations, and maintaining stable voltage under temperature variations for improved battery reliability. As a consequence, it assures reduced error values, increasing the reliability and accuracy of SoH estimation, which directly leads to better battery performance and safety. Table 1 presents the error analysis comparing GRU and the proposed SRNN-biLSTM algorithms, highlighting the superior accuracy of the proposed SRNN-biLSTM.

Table 1. Error analysis of GRU and proposed SRNN-biLSTM algorithms

Algorithm	RMSE	MAE	MAX
GRU	3.8%	3%	5.5%
Proposed SRNN-biLSTM	1.5%	0.8%	4.84%



(a) (b)

Figure 4. %SoH and %error of cell 1, Cell 2, Cell 3, Cell 4, Cell 5, and Cell 6 for (a) GRU and (b) proposed SRNN-biLSTM network

4. CONCLUSION

The objective of the research is to create a unique hybrid model that can generate accurate SoH estimations of batteries by combining the strengths of stacked RNN (SRNN) and biLSTM networks. In the proposed SRNN-biLSTM technique, the stacked RNN captures temporal dependencies and hierarchical characteristics from sequential data, while the biLSTM network resolves both long- and short-term relationships by processing data bi-directionally. This hybrid construction offers reliable performance when recording the complicated and nonlinear characteristics of LIBs. The training approach is broad, consisting of both training and validation sets. The training set improves the model in learning battery data patterns and optimizing network parameters, while the validation set ensures the model generalizes efficiently, lowering the possibility of overfitting.

After training, the model's performance on the test set is tested using significant metrics such as RMSE, MAE, and MAX error. The proposed SRNN-biLSTM network effectively outperforms standard approaches in SoH estimation, with lower error values and higher prediction accuracy. This framework not only improves battery monitoring, but also adds to increased battery system efficiency, safety, and dependability, making it an effective instrument for real-time applications and predictive maintenance. The GRU-based SoH estimation has RMSE, MAE, and MAX error levels of 3.8%, 3%, and 5.5%, respectively, whereas the proposed SRNN-biLSTM has much lower RMSE (1.5%), MAE (0.8%), and MAX (4.84%). The SRNN-biLSTM is preferable because it can handle sequential battery data hierarchically through stacked RNN layers while also capturing bidirectional temporal relationships using biLSTM. This allows the model to handle complicated and nonlinear battery characteristics more efficiently, resulting in lower errors. The SRNN-biLSTM provides more precise and dependable SoH estimation, which improves battery performance, efficiency, and safety in real-time applications.

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AUTHOR CONTRIBUTIONS STATEMENT

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Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Rajesh Kumar Prakhya	✓	✓	✓	✓	✓	✓	✓	✓	✓		✓		✓	
Puvvula Venkata Rama Krishna	✓	✓			✓	✓				✓		✓	✓	

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

This manuscript does not have any conflict of interest.

DATA AVAILABILITY

Data availability is not applicable to this paper as no new data were created or analyzed in this study.

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