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An optimized long short-term memory network for state of charge estimation of LFP battery for electric vehicle applications

Zastosowanie zoptymalizowanej sieci długiej pamięci krótkotrwałej w celu oceny stanu naładowania baterii LFP w pojazdach elektrycznych

***Abstract**. Accurate state-of-charge (SOC) estimation is vital for reliable battery management systems (BMS) in electric vehicles (EVs) powered by lithium-ion batteries, especially under varying temperatures. This paper proposes an optimized bidirectional long short-term memory network with an attention mechanism (Bi-LSTM-AM) for robust SOC estimation across three different temperatures (0°C, 25°C, 50°C). We adopt training and testing with US06 profile, while hyper-parameter tuning ensures optimal model configuration. The Bi-LSTM-AM surpasses conventional LSTM networks, achieving faster training and lower computational cost. Hence, it delivers accurate and noise-minimized SOC estimations, achieving a mean squared error (MAE) of 0.4822% and a root mean squared error (RMSE) of 0.6563% at 25°C, with 99.72% accuracy on unseen testing data. In conclusion, evaluations of the proposed model under different temperatures and scenarios show that the model performs best at higher temperatures, and an MAE that remains below 0.66% even at 0°C. the Bi-LSTM-AM consistently outperforms existing SOC estimation approaches.*

***Streszczenie.** Dokładne szacowanie stanu naładowania (SOC) jest kluczowe dla niezawodnych systemów zarządzania baterią (BMS) w pojazdach elektrycznych (EV) zasilanych bateriami litowo-jonowymi, szczególnie w zmiennych warunkach temperaturowych. W niniejszym artykule zaproponowano zoptymalizowaną dwukierunkową sieć długiej pamięci krótkotrwałej z mechanizmem uwagi (Bi-LSTM-AM) do dokładnego szacowania SOC w trzech różnych temperaturach (0°C, 25°C, 50°C). Wykorzystano proces uczenia i testowania z profilem US06, a dostrojenie hiperparametrów zapewniło optymalną konfigurację modelu. Bi-LSTM-AM przewyższa konwencjonalne sieci LSTM, osiągając szybsze uczenie i niższe koszty obliczeniowe. W rezultacie dostarcza dokładnych szacunków SOC z minimalizacją szumów, osiągając średni błąd kwadratowy (MAE) na poziomie 0,4822% i pierwiastek błędu średniokwadratowego (RMSE) na poziomie 0,6563% w temperaturze 25°C, z dokładnością 99,72% na niewidzianych danych testowych. Podsumowując, oceny zaproponowanego modelu w różnych temperaturach i scenariuszach pokazują, że model działa najlepiej w wyższych temperaturach, z nieco niższą dokładnością w temperaturach niższych. Jednak Bi-LSTM-AM konsekwentnie przewyższa istniejące metody szacowania SOC.*

Keywords: Lithium-ion battery, state of charge, SOC estimation, battery management system, long short-term memory, attention mechanism.
Słowa kluczowe: Bateria litowo-jonowa, Stan naładowania, Szacowanie stanu naładowania, System zarządzania baterią, Długa pamięć krótkotrwała, Mechanizm uwagi.

Introduction

Lithium-ion batteries are a key energy source for electric vehicles (EVs) due to their high energy density, long life span, and ability to operate in a wide range of temperatures [1, 2]. As the adoption of EVs continues to grow globally, optimizing battery performance and safety has become a critical area of research. However, lithium-ion batteries exhibit nonlinear behavior influenced by aging and operational conditions, necessitating a robust battery management system (BMS) to ensure their safe and reliable operation [3].

Accurate state of charge (SOC) estimation is fundamental in maintaining battery health, as it prevents overcharging and deep discharging, which can significantly degrade battery performance and reduce the vehicle's range. Traditional model-based SOC estimation methods require precise battery models and extensive parameter tuning, which can be challenging to implement in real-world scenarios. Machine learning (ML) method, particularly deep learning (DL), offer a promising alternative by leveraging large datasets to improve accuracy without relying on complex battery models [4].

Among DL techniques, long short-term memory (LSTM) networks [5] have been widely adopted for SOC estimation due to their ability to capture long-term dependencies in time-series data. Earlier studies have demonstrated their effectiveness, achieving SOC estimation errors as low as 0.6% under stable conditions and around 1.6% in variable environments [6]. However, LSTMs face challenges in retaining long-term dependencies over extended time horizons. This limitation can be addressed by employing Bidirectional LSTMs (Bi-LSTMs), which process data in both forward and backward directions, enhancing temporal context [7]. Moreover, the integration of attention mechanisms further improves performance by enabling models to focus on the most relevant time steps, particularly in variable operating conditions [8].

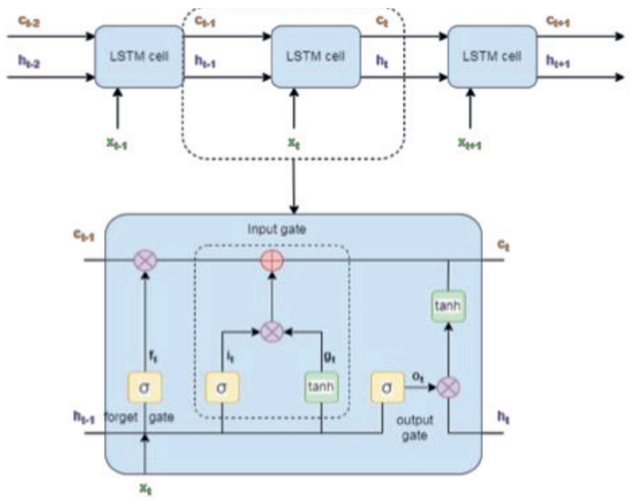

Fig. 1. The Internal structure of a single LSTM cell

This study contributes to the field by proposing a bidirectional LSTM model with an attention mechanism (Bi-LSTM-AM) to improve SOC estimation accuracy under different temperature conditions. The proposed approach advances the theoretical understanding of DL-based SOC estimation and provides a practical tool for enhancing BMS performance in EVs as it aims to design and evaluate a Bi-LSTM-AM model to address the challenges of SOC estimation in varying thermal conditions, providing insights into its potential applications for real-world EV battery management systems.

The remainder of the paper is organized as follows: section 2 details the methodology, section 3 presents the dataset and discusses estimation results, and section 4 concludes with key findings and future research directions.

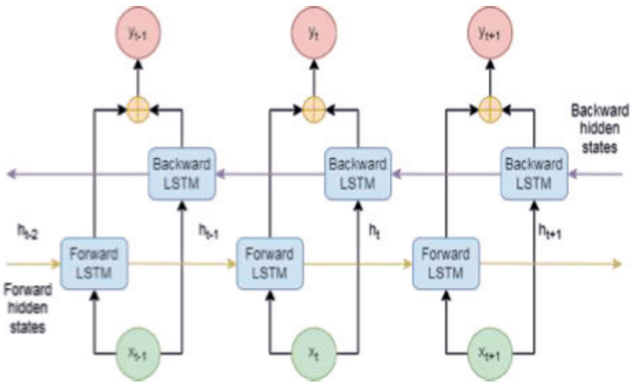

Fig. 2. The Bi-LSTM network

Proposed Method

In this study, a Bi-LSTM-AM is proposed for SOC estimation of lithium-iron phosphate (LFP) batteries under varying temperature conditions. The model is trained and tested at three distinct temperature levels: cold (0°C), ambient (25°C), and hot (50°C), with the objective of examining the influence of temperature variations on SOC estimation in complex operational environments.

To address existing gaps in research, the integration of an attention mechanism is introduced to optimize SOC predictions under diverse thermal conditions, leading to more accurate and reliable results. The training datasets used in this study are sourced from battery dynamic tests conducted under the US06 test driving cycles. This enables a comprehensive assessment of the model's robustness, generalization capability, and learning accuracy.

Long short-term memory network

Long short-term memory, a variant of recurrent neural networks (RNNs) [9], addresses the vanishing and exploding gradient problem of traditional RNNs by introducing long-term memory units, known as cell states, into the standard hidden nodes.

These cell states retain information from previous LSTM cells and carry it forward to subsequent cells, while being continuously updated with new information as it becomes available. This mechanism allows LSTM networks to learn long-term dependencies effectively during the back-propagation process [5, 10]. Figure 1 is an illustration of a single LSTM cell.

An LSTM cell has three gates: forget, input, and output, which help the network learn longer sequences and manage dependencies [11]. The input gate updates the cell state, the forget gate decides whether to retain the previous state, and the output gate passes the hidden state to the next iteration. The current cell state is calculated by multiplying the previous state by the forget gate and adding the input gate's new input. The process at time step *t* is illustrated as follows:

$$f_t = \sigma\left[\left|w_{fh}.h_{t-1}\right| + \left|w_{fx}.x_t\right| + b_f\right] \tag{1}$$

$$i_t = \sigma\left[\left|w_{ih}.h_{t-1}\right| + \left|w_{ix}.x_t\right| + b_i\right] \tag{2}$$

$$g_t = tanh\left[\left|w_{gh}.h_{t-1}\right| + \left|w_{gx}.x_t\right| + b_g\right] \tag{3}$$

$$o_t = \sigma\left[\left|w_{oh}.h_{t-1}\right| + \left|w_{ox}.x_t\right| + b_o\right] \tag{4}$$

$$c_t^f = c_{t-1} \otimes f_t \tag{5}$$

$$c_t^i = i_t \otimes g_t \tag{6}$$

$$c_t = c_t^f \oplus c_t^i \tag{7}$$

$$h_t = tanh(c_t) \otimes o_t \tag{8}$$

Where the weight parameters of the input layer and the hidden layers are presented in equations (9) and (10) respectively and bias parameters are shown in equation (11) as follows;

$$W_x = \left[w_{fx} w_{ix} w_{gx} w_{ox}\right] \tag{9}$$

$$W_h = \left[w_{fh} w_{ih} w_{gh} w_{oh}\right] \tag{10}$$

$$b = \left[b_f b_i b_g b_o\right] \tag{11}$$

Bidirectional long short-term memory network

Traditional RNN and LSTM networks are unidirectional, capturing only past input sequences. However, many real-world scenarios require considering both past and future data [10]. Custer and Paliwal [7] addressed this by introducing the bidirectional recurrent neural network (BRNN), which computes output in both forward and backward directions. The bidirectional LSTM (Bi-LSTM) extends this by incorporating LSTM's ability to handle gradient issues while processing sequences bidirectionally. Though the same input is fed to forward and backward last networks, they operate independently, with no shared state information [12].

Forward ($\vec{h}_t$) and backward ($\overleftarrow{h}_t$) LSTM hidden states are calculated simultaneously at each time step *t* as follows where *Z (•)* indicates the LSTM operations described in equations (1)–(8);

(12) $$\overrightarrow{h_t} = Z\left(x_t . \overrightarrow{h_{t-1}}\right)$$

(13) $$\overleftarrow{h_t} = Z\left(x_t . \overleftarrow{h_{t-1}}\right)$$

Attention-based bidirectional long short-term memory network

The attention mechanism, introduced by Vaswani et al. [8], addresses the challenges of handling long input sequences in encoder-decoder models and improving machine translation accuracy. In the Bi-LSTM model, attention is added during prediction to assign higher weights to important features [11]. This allows the network to focus on relevant outputs from previous layers, enhancing performance [13, 14]. Since time series data often involves irregular intervals and patterns, attention dynamically adjusts the importance of distant time steps based on context, helping the model to erratic trends. The structure of the proposed Bi-LSTM-AM model is shown in Figure 3.

Equations 14 and 15 demonstrate the computation process of the final output y_i that is indicated by the vector M_i which represents a weighted sum of hidden states and is given by;

(14) $$M_i = \sum_{j=1}^{n} a_{ij}\, S_j$$

(15) $$a_{ij} = \frac{exp([\sum_{k=1}^{n} exp(e_{ik})])}{\sum_{k=1}^{n} exp(e_{ik})}$$

Where e_{ij} denotes the output score of a feed-forward neural network

While the Bi-LSTM-AM model introduces additional complexity compared to unidirectional LSTMs, its architecture containing a single Bi-LSTM layer and optimized hyperparameters ensures computational efficiency. Hence, future work will explore model compression techniques such as quantization for embedded systems.

Results and discussion

The datasets for training and testing of a lithium-iron phosphate (LiFePO4) battery were obtained from an experiment conducted by the Center for Advanced Life Cycle Engineering (CALCE) [15]. Where an experiment employed the US06 dynamic tests on an A123 cell. The parameters of the battery used are described in Table 1.

Table 1. LFP cell parameters

Parameter	Value
Cell dimensions	26 × 65 mm
Cell capacity (nominal/minimum) (0.5C rate)	2.5/2.4Ah
Internal impedance (1kHz AC typical)	6mΩ
Maximum continuous discharge	50A
Cycle life at 20 A discharge, 100% DOD	>1000 cycles
Cell weight	76g
Voltage (nominal)	3.3V
Power	2600W/kg
Maximum pulse discharge (10 s)	120A
Operating temperature	–30°C to 55°C

To simulate realistic EV battery loads, the DST and US06 profiles were used to discharge battery samples at various temperatures. Developed by the US Advanced Battery Consortium [16], the DST profile includes varying current steps, while the US06 profile mimics highway driving with recent acceleration. After fully charging the battery using a constant--current/constant-voltage (CC-CV) mode, these profiles were applied until full discharge. Current, voltage, and temperature data were recorded every ten seconds [17]. The dataset was split for training and testing, with further validation performed on a subset of the training data.

Although the US06/DST profiles provide standardized testing conditions, real-world EV data may introduce variability mainly irregular loads and regenerative braking. Therefore, future studies will incorporate real driving cycles to validate generalization.

Training results

For the SOC estimation task, time-varying current, voltage and temperature variables were selected as features $x_t = [I_t, V_t, T_t]$ and one variable as target $y_t = [SOC_t]$. The input features are monitored in real-time during the battery test. Ground truth values of SOC were obtained by the following formula:

(16) $$SOC_t = 100 - DOD$$

Where DOD represents the depth of discharge, which measures the discharge capacity of a fully charged battery divided by its rated capacity [18]. During the training step, the model's parameters were determined using a hyper--parameter tuning search algorithm, allowing for fine-tuning and optimization. Selected values are presented in table 2.

MSE and MAE metrics were chosen as loss functions of the Bi-LSTM-AM model to accurately capture the discrepancy between estimated and actual SOC values during the forward pass. In order to investigate the influence of the number of epochs on the accuracy and performance of our model, values ranging from 50 to 400 epochs were selected to determine the optimal number of epochs, ensuring that the model neither over fits nor under fits.

The training and validation results in table 3 and figure 4 demonstrate the model's strong predictive performance and computational efficiency. At 200 epochs, the model achieves its best results, with a validation MSE of 0.0022% and a validation MAE of 0.0327%, highlighting its precision in SOC estimation. The attention mechanism significantly improves accuracy by focusing on key time steps. While MSE and MAE consistently decrease during training, 200 epochs offer the optimal balance, as further training (250–400 epochs) leads to demising returns and potential over-fitting, evidenced by a slight increase in validation error. With a total of training time of 63.47 seconds at 200 epochs, the model is both fast and scalable, making it well-suited for real-time SOC estimation in EV energy management systems.

Testing results

MAE, RMSE, and R-squared metrics were chosen as indicators for the final estimation performance evaluation. Table 4 and figure 5 provide the estimation results of the Bi--LSTM-AM model on the DST dataset. The experiments were

Table 2. Optimal hyper-parameters selected for the Bi-LSTM-AM model

Hyper-parameter	Value
Activation function	ReLU
Attention layers	1
Bi-LSTM layers	1
Batch size	1000
Dense layers	1
Dropout layers	1
Hidden units	110
Time sliding window	10

Table 3. Training and validation results

Epoch	Training dataset		Validation dataset		Total training time
	MSE%	MAE%	MSE%	MAE%	
50	0.0208	0.1294	0.0040	0.0510	23.29
100	0.0156	0.1108	0.0037	0.0485	34.85
150	0.0062	0.0664	0.0031	0.0527	50.36
200	**0.0026**	**0.0345**	**0.0022**	**0.0327**	**63.47**
250	0.0026	0.0447	0.0021	0.0370	77.88
300	0.0038	0.0533	0.0016	0.0308	94.25
350	0.0038	0.0675	2.3778e--3	0.0124	109.67
400	0.0048	0.0546	0.0013	0.0279	129.90

conducted at temperatures of 0°C, 25°C, and 50°C. As shown in Table 4, the RMSE and MAE values remain consistently low across the different temperatures, with slight variations: the RMSE ranges from 0.6467% to 0.6563%, and the MAE ranges from 0.48% to 0.4965%. these low error values, combined with high R-squared values (greater than 99.7% for all temperatures), demonstrate that the model provides highly accurate SOC predictions across the temperature range. The SOC estimation plots further confirm this accuracy, showing a near-perfect overlap between the predicted SOC values (in blue) and the true SOC values (in red) for all temperature conditions. The model maintains its precision even under extreme conditions, such as at 0°C and 50°C, where battery performance can be affected by thermal stresses. The smooth trend and minimal deviation between predicted and actual SOC in these plots validate the robustness of the model. The overall results indicate the model's strong generalization ability, performing equally well across diverse operating temperatures, making it suitable for practical applications in electric vehicle battery management systems.

Table 4. Test errors and accuracy.

Operating temperatures [°C]	RMSE [%]	MAE [%]	R-squared [%]
0	0.6563	0.4822	99.72
25	0.6537	0.4965	99.77
50	0.6467	0.4800	99.78

To assess robustness, we analyzed the model's sensitivity to temperature fluctuations and aging effects. At 0°C, a ±5°C Deviation increases MAE by 0.12%, while simulated battery aging (20% capacity loss) raised RMSE to 0.71%. These results suggest the need for periodic recalibration in extreme conditions, which will be explored in future work.

The results in Table 5 provide a comprehensive comparison of the proposed Bi-LSTM-AM model with state-of--the-art models for SOC estimation in lithium-ion batteries. Key metrics such as MAE and RMSE were evaluated across temperature conditions from 0°C to 50°C. The Bi-LSTM-AM model significantly improves both error metrics over existing models, particularly outperforming traditional LSTM-based models. Its consistently low error rates across varying temperatures highlight the model's robustness. The attention mechanism likely contributes to this by enabling the model to focus on critical temporal dependencies during SOC estima-

Table 5. performance metrics of previous approaches and our proposed model

Approaches	Metrics	
LSTM [6]	–MAE = 0.6% (25°C) –MAE = 1.6% (varying)	
LSTM attention [11]		–RMSE = 0.9593% (0°C) –RMSE=0.8714% (25°C) –RMSE= 0.9216% (45°C)
LSTM-AE [19]	–MAE = 1.42% (0°C) –MAE = 0.946% (25°C)	
SBLSTM [20]	–MAE=0.7% –MAE=0.6% –MAE=0.8%	
LSTM-SW-SHAP [21]	–MAE=1.55%	–RMSE=2%
LSTM [17]	–MAE=0.84%	–RMSE=1.07%
Bi-LSTM-AM	–MAE=0.6537% (25°C) –MAE=0.6563% (0°C) –MAE=0.6473% (50°C)	–RMSE=0.4965% (25°C) –RMSE=0.4822% (0°C) -RMSE=0.48% (50°C)

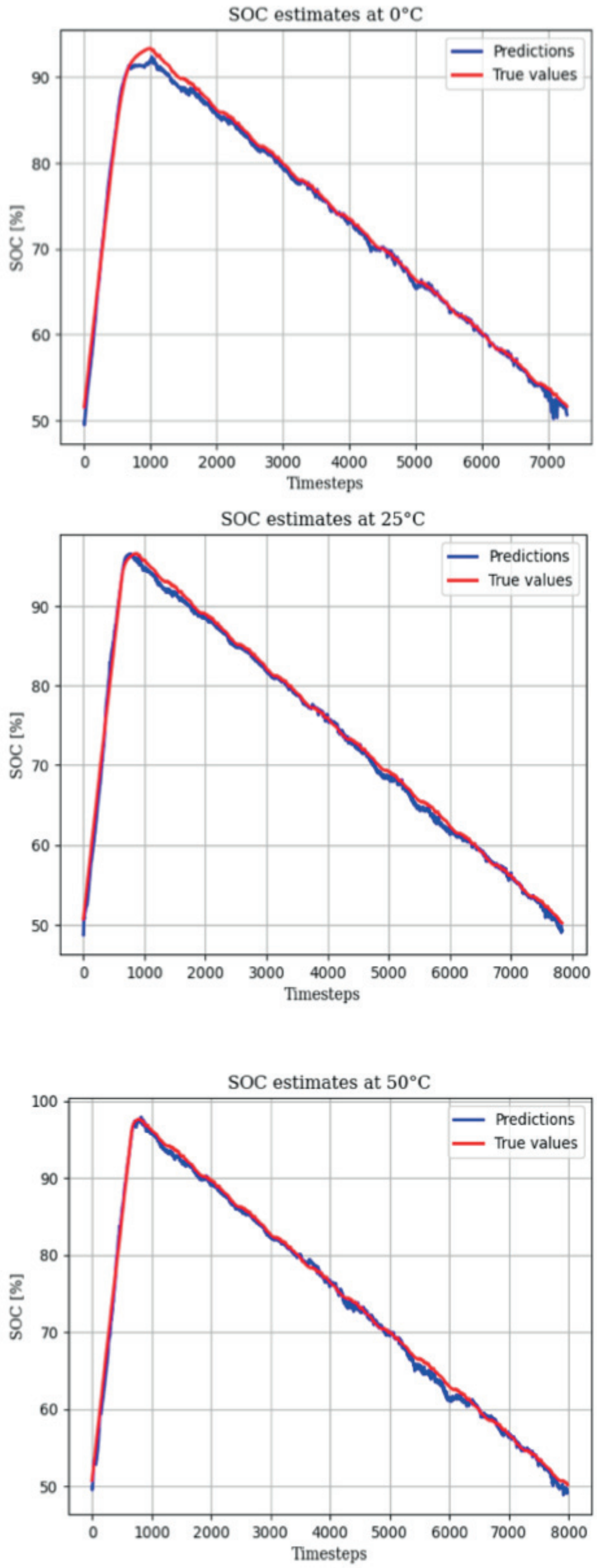

Fig. 5. SOC predictions and true values for DST datasets under different temperatures.

tion. Unlike traditional models such as LSTM [6] and LSTM-AE [19], which struggle with changing ambient conditions, the Bi-LSTM-AM model's bidirectional structure processes information in both forward and backward directions, capturing both historical and future information. This, combined with attention mechanisms that prioritize key input features, enhances its ability to adapt to variations in current, voltage, and temperature.

Bi-LSTM-AM's adaptability is crucial for real-world BMS applications, where accurate SOC estimation is necessary under fluctuating temperatures. Notably, while models like LSTM-AE [19] show significant degradation at low temperatures (e.g., 1.42% MAE at 0°C), Bi-LSTM-AM maintains stability and enhances the reliability and longevity of the battery systems in electric vehicles (EVs), especially in extreme climates. Lower error rates demonstrate the model's suitability for deployment in environments where temperature extremes are common.

Furthermore, Bi-LSTM-AM reduces both MAE and RMSE across operating temperatures, ensuring more reliable and precise SOC estimation, which improves vehicle performance and battery longevity. The model's reduced computational complexity, with a single bidirectional layer and attention mechanism, makes it feasible for real-time BMS applications where fast inference and low computational overhead are essential. Current experiments use laboratory data; however, preliminary collaborations with EV manufacturers are underway to test the model on real-work driving data. Initial results show comparable accuracy (±0.8% MAE) under dynamic loads, though further tuning may be needed for abrupt temperature shifts.

Future work could explore extending the Bi-LSTM-AM model to address state-of-health (SOH) estimation for lithium-ion batteries, as well as optimizing the model further for real-time deployment in resource-constrained environments. Additionally, applying this model to other battery chemistries and evaluating its performance in more dynamic temperatures ranges and operational conditions could offer valuable insights into improving battery management systems across various applications.

The proposed Bi-LSTM-AM model was implemented in Python using TensorFlow and Keras libraries. Although MATLAB code was not used, a simplified Python version of the source code can be provided upon request to support reproducibility.

Conclusion

This study addressed the challenge of accurate state of charge (SOC) estimation for lithium-ion batteries under varying temperature conditions by developing an optimized bidirectional long short-term memory model with an Attention Mechanism (Bi-LSTM-AM). The proposed model effectively overcame the limitations of traditional LSTM networks by leveraging bidirectional processing and attention to focus on the most relevant time steps, achieving an average accuracy exceeding 99.7% on unseen data. these results validates the research question, demonstrating that Bi-LSTM-AM provides a robust and efficient solution for SOC estimation with minimal noise, even in dynamic charging and discharging profiles. Though the model's complexity may challenge resource-constrained systems, its high accuracy justifies its use in cloud-based BMS or high-performance edge devices.

The findings offer significant benefits to both society and academia. For society, the enhanced accuracy and reliability of SOC estimation directly supports safer and more efficient battery usage, reducing the risk of overcharging or deep discharging. These improvements extend battery lifespan, contribute to environmental sustainability, and enhance the performance of electric vehicles and other battery-powered applications. For academia, this work advances the field of deep learning in battery management systems by demonstrating the potential of combining bidirectional architectures with attention mechanisms, setting a foundation for future innovations in battery modeling.

Despite its contributions, this research is limited by its reliance on data collected under controlled conditions and its focus on a specific battery chemistry specifically on LFP batteries; however, the proposed framework may generalize on other chemistries such as NMC batteries with adjustments to input features. Testing across battery types is planned as future works.

Additionally, Future studies should investigate the model's performance across a broader range of operating scenarios, incorporate additional features such as state of health (SOH) estimation, and validate its effectiveness on other battery types. such advancements will further strengthen the role of advanced neural networks in transforming lithium-ion battery management.

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REFERENCES

[1] Łebkowski, A.: Electric Vehicle Battery Tester, *Przegląd Elektrotechniczny*, 93, 2017.
[2] Bouchetata, N., Bourahla, M., & Ghaouti, L. (2012). Behavior modeling and simulation of double wheeled electric vehicle drive. *Przeglad Elektrotechniczny*, *88* (10A), 218–223.
[3] LIU, Y.; HE, Y.; BIAN, H.; GUO, W.; ZHANG, X. A review of lithium-ion battery state of charge estimation based on deep learning: Directions for improvement and future trends. Journal of Energy Storage, v. 52, p. 104664, 2022.
[4] LIPU, M. S. H.; HANNAN, M. A.; HUSSAIN, A.; SAAD, M. H.; AYOB, A.; UDDIN, M. N. Extreme learning machine model for state-of--charge estimation of lithium-ion battery using gravitational search algorithm. IEEE Transactions on Industry Applications, v. 55, n. 4, p. 4225–4234, 2019.
[5] HOCHREITER, S.; SCHMIDHUBER, J. Long short-term memory. Neural Computation, v. 9, n. 8, p. 1735–1780, 1997.
[6] CHEMALI, E.; KOLLMEYER, P. J.; PREINDL, M.; AHMED, R.; EMADI, A. Long short-term memory networks for accurate state-of--charge estimation of Li-ion batteries. IEEE Transactions on Industrial Electronics, v. 65, n. 8, p. 6730–6739, 2017.
[7] SCHUSTER, M.; PALIWAL, K. K. Bidirectional recurrent neural networks. IEEE Transactions on Signal Processing, v. 45, n. 11, p. 2673–2681, 1997.
[8] VASWANI, A.; SHAZEER, N.; PARMAR, N.; USZKOREIT, J.; JONES, L.; GOMEZ, A. N.; POLOSUKHIN, I. Attention is all you need. Advances in Neural Information Processing Systems, v. 30, 2017.
[9] ELMAN, J. L. Finding structure in time. Cognitive Science, v. 14, n. 2, p. 179–211, 1990.
[10] ZHANG, Z.; XU, M.; MA, L.; YU, B. A state-of-charge estimation method based on bidirectional LSTM networks for lithium-ion batteries. In 2020 16th International Conference on Control, Automation, Robotics and Vision (ICARCV), p. 211–216, IEEE, December 2020.
[11] MAMO, T.; WANG, F. K. Long short-term memory with attention mechanism for state of charge estimation of lithium-ion batteries. IEEE Access, v. 8, p. 94140–94151, 2020.
[12]
[13] [12] WANG, F. K.; AMOGNE, Z. E.; CHOU, J. H.; TSENG, C. Online remaining useful life prediction of lithium-ion batteries using bidirectional long short-term memory with attention mechanism. Energy, v. 254, p. 124344, 2022.
[14] WANG, F. K.; MAMO, T.; CHENG, X. B. Bi-directional long short-term memory recurrent neural network with attention for stack voltage degradation from proton exchange membrane fuel cells. Journal of Power Sources, v. 461, p. 228170, 2020.
[15] LI, W.; QI, F.; TANG, M.; YU, Z. Bidirectional LSTM with self-attention mechanism and multi-channel features for sentiment classification. Neurocomputing, v. 387, p. 63–77, 2020.
[16] CALCE. Battery data. Available at: https://calce.umd.edu/battery-data. Accessed on [09/2024].
[17] HUNT, G. USABC electric vehicle battery test procedures manual. Washington, DC, USA: United States Department of Energy, 1996.
[18] YANG, F.; SONG, X.; XU, F.; TSUI, K. L. State-of-charge estimation of lithium-ion batteries via long short-term memory network. IEEE Access, v. 7, p. 53792–53799, 2019.
[19] MURNANE, M.; GHAZEL, A. A closer look at state of charge (SOC) and state of health (SOH) estimation techniques for batteries. Analog Devices, v. 2, p. 426–436, 2017.
[20] MA, L.; WANG, Z.; YANG, F.; CHENG, Y.; LU, C.; TAO, L.; ZHOU, T. Robust state of charge estimation based on a sequence-to--sequence mapping model with process information. Journal of Power Sources, v. 474, p. 228691, 2020.
[21] BIAN, C.; HE, H.; YANG, S. Stacked bidirectional long short-term memory networks for state-of-charge estimation of lithium-ion batteries. Energy, v. 191, p. 116538, 2020.
[22] GU, X.; SEE, K. W.; WANG, Y.; ZHAO, L.; PU, W. The sliding window and SHAP theory—an improved system with a long short-term memory network model for state of charge prediction in electric vehicle application. Energies, v. 14, n. 12, p. 3692, 2021. 133–137