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Data-Driven SOC Estimation for Lithium-Ion Batteries Using Ensemble LSBoost Trees and LSTM Networks

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Abstract: Accurate State of Charge (SOC) estimation is a critical requirement for reliable and efficient Battery Management Systems (BMSs) in lithium-ion battery-powered electric vehicles. However, SOC estimation remains challenging because of the highly nonlinear and temperature-dependent behavior of lithium-ion batteries under dynamic operating conditions. This paper presents a comparative machine learning framework for SOC estimation using Ensemble LSBoost Trees and Long Short-Term Memory (LSTM) networks under multi-temperature operating environments. The proposed framework utilizes the TU Berlin lithium-ion battery dataset containing dynamic drive-cycle profiles at 5°C, 15°C, 25°C, 35°C, and 45°C. A comprehensive preprocessing and feature engineering pipeline consisting of missing-value handling, outlier correction, Savitzky–Golay filtering, derivative feature extraction, moving average current computation, and z-score normalization is implemented to improve estimation robustness and prediction accuracy. To evaluate thermal generalization capability, the models are trained using battery data from 5°C–35°C and tested exclusively on unseen 45°C operating conditions. Experimental results demonstrate that the LSTM model outperforms Ensemble LSBoost Trees because of its superior temporal learning capability and sequential dynamic modeling. The proposed LSTM network achieves an RMSE of 0.0363, MAE of 0.0296, and an R2 score of 0.9823, whereas the Ensemble Trees model achieves an RMSE of 0.0486 and an R2 score of 0.9686. ***Keywords: State of Charge (SOC), Lithium-Ion Battery, Battery Management System (BMS), Long Short-Term Memory (LSTM), Ensemble Trees, Machine Learning, Deep Learning, Electric Vehicles.***

I. INTRODUCTION

Lithium-ion batteries have emerged as the dominant energy storage technology for electric vehicles (EVs), hybrid electric vehicles (HEVs), renewable energy systems, and portable electronic devices because of their high energy density, long cycle life, and low self-discharge characteristics [1], [2]. Accurate estimation of battery State of Charge (SOC) is one of the most critical functions of the Battery Management System (BMS), since SOC directly affects driving range prediction, charging control, battery safety, and energy management strategies [3]. Inaccurate SOC estimation may result in overcharging, deep discharge, accelerated battery degradation, and reduced operational reliability [4].

SOC estimation is a challenging task because lithium-ion batteries exhibit highly nonlinear electrochemical behavior under varying operating conditions [5]. Battery voltage, current response, and internal impedance are significantly influenced by temperature variations, dynamic load profiles, aging characteristics, and charging/discharging conditions [6]. Conventional SOC estimation techniques such as Coulomb counting, open-circuit voltage (OCV) methods, and model-based approaches suffer from several limitations including cumulative integration errors, parameter uncertainty, and sensitivity to environmental conditions [7]. Kalman filter-based techniques such as Extended Kalman Filter (EKF) and Unscented Kalman Filter (UKF) have been widely adopted for SOC estimation; however, their performance strongly depends on accurate battery modeling and parameter tuning [8], [9].

In recent years, machine learning (ML) and deep learning (DL) techniques have emerged as powerful alternatives for battery SOC estimation because of their capability to model complex nonlinear relationships directly from experimental data [10]. Artificial Neural Networks (ANNs), Support Vector Machines (SVMs), Random Forests, and Ensemble Learning methods have demonstrated promising SOC estimation performance under dynamic operating conditions [11], [12]. Deep learning architectures, particularly Long Short-Term Memory (LSTM) networks, have attracted significant attention because they can effectively capture temporal dependencies and sequential battery dynamics [13]. LSTM models are especially suitable for SOC estimation since battery behaviour depends not only on present operating conditions but also on historical current and voltage patterns [14].

Several recent studies have investigated data-driven SOC estimation using deep recurrent neural networks. However, many existing works rely on limited datasets, narrow temperature ranges, or random train-test splitting strategies that do not adequately evaluate model generalization under unseen operating conditions [15]. Moreover, comparative investigations between computationally efficient ensemble learning approaches and deep sequential learning models under thermally varying conditions remain limited in the literature [16].

To address these challenges, this work presents a comparative SOC estimation framework based on Ensemble LSBoost Trees and LSTM networks using the TU Berlin lithium-ion battery dataset under multiple temperature conditions and dynamic drive cycles. A comprehensive preprocessing pipeline consisting of missing-value handling, outlier removal, Savitzky-Golay smoothing, normalization, and feature engineering is developed to improve estimation robustness. Six battery features including voltage, current, temperature, voltage derivative, current derivative, and moving average current are utilized for SOC prediction. The proposed framework evaluates model generalization capability using an unseen high-temperature testing condition, where the models are trained using data from 5°C–35°C and tested at 45°C.

II. Dataset Description and Preprocessing

A. TU Berlin Battery Dataset

The experimental analysis in this work is performed using the lithium-ion battery dataset obtained from Technische Universität Berlin under multiple temperature operating conditions. The dataset contains dynamic battery measurements acquired under realistic drive-cycle conditions and is widely suitable for data-driven battery management system (BMS) research. The battery profiles include synchronized measurements of terminal voltage, current, temperature, and State of Charge (SOC) recorded during charging and discharging operations.

The complete dataset contains 60 battery operating profiles with approximately 9,047,247 total samples after preprocessing and aggregation. To reduce computational complexity while preserving temporal battery dynamics, profile-wise down sampling was performed during dataset partitioning. The final reduced dataset used for machine learning training and testing consisted of 142,734 training samples and 38,240 testing samples for Ensemble Trees, while 141,822 training sequences and 38,012 testing sequences were utilized for the LSTM model. Table I summarizes the characteristics of the utilized battery dataset.

Table I

TU Berlin Battery Dataset Specifications

Parameter	Description
Dataset Source	TU Berlin Lithium-Ion Battery Dataset
Number of Profiles	60
Temperature Conditions	5°C, 15°C, 25°C, 35°C, 45°C
Drive Cycles	BCDC, LA92, US06
Measured Signals	Voltage, Current, Temperature, SOC
Total Samples	9,047,247
Sequence Length	20
Training Temperature Range	5°C–35°C
Testing Temperature	45°C
Ensemble Training Samples	142,734
Ensemble Testing Samples	38,240
LSTM Training Sequences	141,822
LSTM Testing Sequences	38,012

B. Data Preprocessing

Battery datasets collected under dynamic operating conditions often contain measurement noise, transient disturbances, outliers, and missing samples that may degrade the performance of machine learning models [17]. Therefore, a comprehensive preprocessing pipeline was developed to improve the stability and robustness of SOC estimation.

Initially, missing values in voltage, current, temperature, and SOC signals were handled using linear interpolation techniques. Outlier removal was subsequently performed using linear outlier correction methods to eliminate abnormal measurements generated during dynamic battery operation. Since high-frequency fluctuations and sensor noise may adversely affect model convergence, Savitzky–Golay filtering was applied to smooth voltage and current signals while preserving transient battery characteristics [18].

To improve the learning capability of the proposed models, feature engineering was performed using both raw and derived battery variables. In addition to terminal voltage, current, and temperature, derivative-based dynamic features were extracted to better represent battery transient behavior. The voltage derivative and current derivative were computed as follows:

$$dV = V_t - V_{t-1}$$

$$dI = I_t - I_{t-1}$$

where V_t and I_t represent instantaneous voltage and current samples, respectively. Furthermore, a moving average current feature was calculated to capture local current trends and smooth dynamic fluctuations. The final feature vector utilized for SOC estimation is expressed as:

$$X = [V, I, T, dV, dI, I_{avg}]$$

where:

- V denotes battery terminal voltage,
- I represent battery current,
- T corresponds to battery temperature,
- dV and dI denote derivative features,
- and I_{avg} represents moving average current.

Feature normalization was performed using z-score normalization to improve numerical stability and accelerate model convergence [19]. The normalized feature vector was computed as:

$$X_{norm} = \frac{X - \mu}{\sigma}$$

where μ and σ represent the mean and standard deviation of the feature distribution, respectively.

C. Dataset Partitioning Strategy

Unlike conventional random train-test splitting approaches, the adopted partitioning strategy prevents data leakage and enables realistic evaluation of model robustness under unseen thermal conditions [20]. This experimental setup is particularly important for practical electric vehicle battery management systems, where batteries frequently operate under temperature conditions not explicitly observed during model training.

III. PROPOSED SOC ESTIMATION METHODOLOGY

A. Overall Framework

The overall framework of the proposed SOC estimation methodology is illustrated in Fig. 1. The developed framework consists of dataset acquisition, preprocessing, feature engineering, dataset partitioning, machine learning model development, and comparative performance evaluation. The primary objective of the proposed framework is to investigate the effectiveness of Ensemble LSBoost Trees and Long Short-Term Memory (LSTM) networks for lithium-ion battery SOC estimation under varying thermal operating conditions.

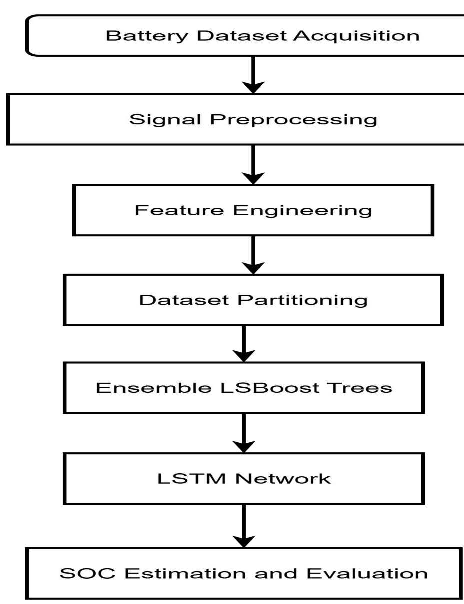

Fig. 1. Overall framework of the proposed SOC estimation methodology using Ensemble LSBoost Trees and LSTM networks.

B. Ensemble LSBoost Trees-Based SOC Estimation

Ensemble learning techniques combine multiple weak learners to improve regression accuracy and generalization capability [21]. In this work, Ensemble LSBoost Trees were utilized for SOC estimation because of their strong nonlinear regression capability and comparatively lower computational complexity. Least Squares Boosting (LSBoost) iteratively combines multiple regression trees to minimize prediction error and improve overall model performance.

The boosting process sequentially trains weak regression learners, where each learner attempts to minimize the residual error generated by the previous learner [22]. The final boosted regression model is expressed as:

$$F_m(x) = F_{m-1}(x) + \gamma_m h_m(x)$$

where:

- $F_m(x)$ represents the boosted regression model at iteration m,
- $h_m(x)$ denotes the weak regression learner,
- and γ_m represents the learning coefficient.

Decision trees were selected as weak learners because of their capability to model nonlinear battery dynamics and variable interactions effectively. The Ensemble LSBoost Trees model was implemented using 150 learning cycles with a learning rate of 0.05. Tree complexity was controlled using a maximum split limit and minimum leaf size to reduce overfitting and improve generalization performance.

One of the major advantages of Ensemble Trees is their comparatively low computational complexity and faster inference capability, making them suitable for real-time battery management applications and embedded BMS implementation [23].C. Long Short-Term Memory Network-Based SOC Estimation

Although Ensemble learning methods demonstrate strong nonlinear regression capability, they do not explicitly capture temporal dependencies in sequential battery behavior. Since lithium-ion battery SOC evolution depends on historical operating conditions, recurrent neural network architectures are more suitable for modeling dynamic battery behavior [24].

Long Short-Term Memory (LSTM) networks are a specialized type of recurrent neural network (RNN) designed to overcome the vanishing gradient problem encountered in conventional RNNs [25]. LSTM networks contain memory cells and gating mechanisms that enable long-term temporal dependency learning, making them highly effective for sequential battery SOC estimation. The LSTM architecture adopted in this work consists of a sequence input layer, an LSTM hidden layer with 64 hidden units, a dropout layer, fully connected layers, and a regression output layer. The LSTM cell utilizes forget, input, and output gates to regulate information flow through the memory state. The forget gate is expressed as:

$$f_t=\sigma(W_f[h_{t-1},x_t]+b_f)$$

The input gate is represented as:

$$i_t=\sigma(W_i[h_{t-1},x_t]+b_i)$$

The cell state update equation is given by:

$$C_t=f_t\odot C_{t-1}+i_t\odot \widetilde{C}_t$$

where:

- $f_t$denotes the forget gate activation,
- $i_t$represents the input gate activation,
- $C_t$denotes the cell state,
- and σrepresents the sigmoid activation function.

In the proposed framework, sequential input windows of length 20 were generated using six engineered battery features over consecutive time steps. Each input sequence is represented as:

$$X_t=[x_{t-19},x_{t-18},\ldots,x_t]$$

where each feature vector $x_t$contains voltage, current, temperature, derivative features, and moving average current information at time step t.

The LSTM model was trained using the Adam optimizer with a mini-batch size of 64 and an initial learning rate of 10^{-3}. Dropout regularization was incorporated to improve generalization capability and reduce overfitting.

IV. EXPERIMENTAL RESULTS AND DISCUSSION

A. Experimental Setup

The proposed SOC estimation framework was implemented in MATLAB using the Deep Learning Toolbox and Statistics and Machine Learning Toolbox. All experiments were conducted on a CPU-based computing environment without GPU acceleration to evaluate the practical feasibility of the proposed models for moderate computational platforms. The experimental setup consisted of preprocessing, feature engineering, dataset partitioning, model training, prediction, and comparative performance evaluation.

To preserve temporal battery dynamics while reducing computational complexity, profile-wise downsampling was performed during dataset partitioning. The final reduced dataset consisted of 142,734 training samples and 38,240 testing samples for Ensemble LSBoost Trees, whereas 141,822 training sequences and 38,012 testing sequences were utilized for LSTM training and evaluation.

The Ensemble LSBoost Trees model was trained using 150 learning cycles with a learning rate of 0.05. Decision tree complexity was controlled using a maximum split value of 30 and a minimum leaf size of 5 to improve model generalization and reduce overfitting. For LSTM-based SOC estimation, a sequence length of 20 was utilized with 64 hidden units, dropout regularization, and the Adam optimizer. The LSTM network was trained using a mini-batch size of 64 and an initial learning rate of (10^{-3}).

B. Ensemble LSBoost Trees Results

The Ensemble LSBoost Trees model demonstrated strong SOC estimation capability under unseen thermal operating conditions. Fig. 2 illustrates the actual and predicted SOC trajectories obtained using the Ensemble Trees model for the testing dataset corresponding to 45°C operating conditions.

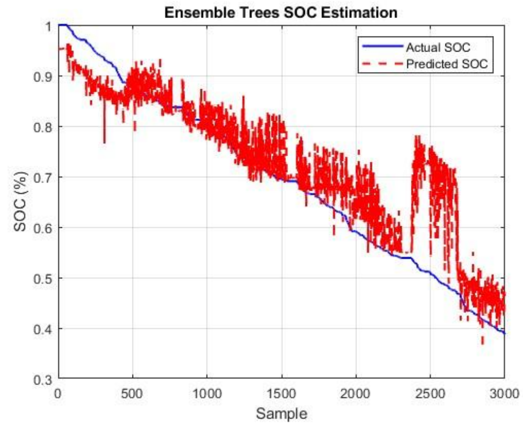

Fig. 2: Actual versus predicted SOC trajectories obtained using the Ensemble LSBoost Trees model under unseen 45°C operating conditions.

The predicted SOC profile closely follows the actual SOC trajectory under most operating conditions. However, localized deviations and transient oscillations are observed during rapid dynamic current transitions, indicating the limited temporal learning capability of tree-based ensemble methods. Since Ensemble Trees operate primarily as static nonlinear regression models, historical sequential battery dependencies are not explicitly captured.

The residual error obtained using Ensemble Trees is presented in Fig. 3. The residual plot indicates that the prediction error remains centered around zero for most operating regions, although larger fluctuations are observed during highly dynamic battery operating intervals. Similarly, the error histogram shown in Fig. 3 demonstrates a relatively wider error distribution compared to the LSTM model, indicating comparatively larger estimation uncertainty.

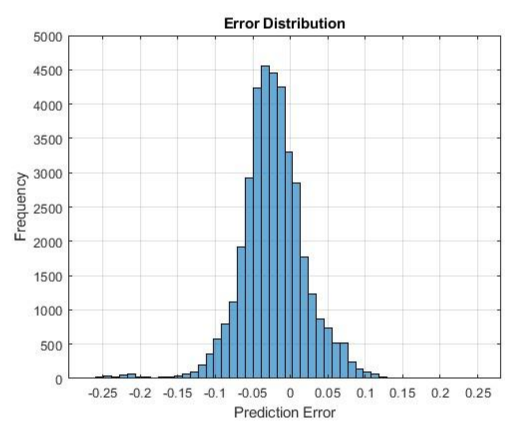

Fig. 3. Prediction error distribution histogram for the Ensemble LSBoost Trees model.

The quantitative performance metrics obtained for Ensemble Trees are summarized in Table III. The model achieved an RMSE of 0.0486, MAE of 0.0376, and an (R^2) score of 0.9686 under unseen high-temperature testing conditions. Furthermore, the model demonstrated very low computational complexity with a training time of approximately 50.89 seconds and prediction time of 0.55 seconds, indicating strong suitability for real-time battery management applications.

C. LSTM-Based SOC Estimation Results

The LSTM model demonstrated superior SOC estimation capability compared to Ensemble Trees because of its ability to learn temporal battery dynamics and sequential operating behavior. The training convergence behavior of the LSTM network is illustrated in Fig. 4. The training curve shows stable convergence with gradual reduction in training loss, indicating effective network optimization and stable learning performance.

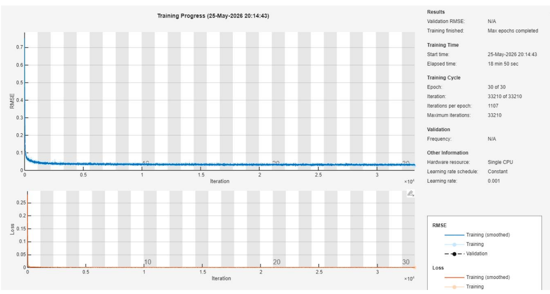

Fig. 4. Training convergence performance of the proposed LSTM network during SOC estimation training.

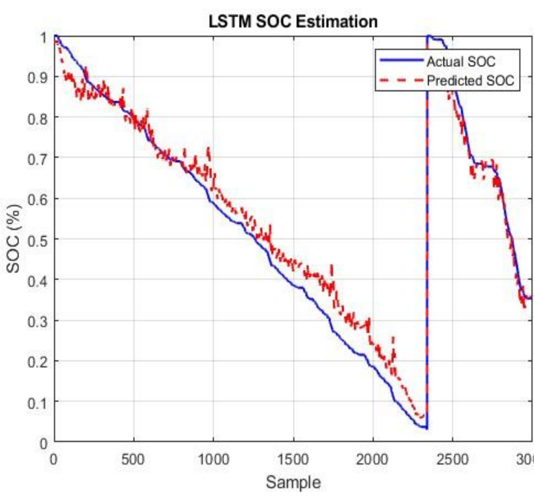

Fig. 5. Actual versus predicted SOC trajectories obtained using the LSTM-based SOC estimation model under unseen 45°C operating conditions.

The actual and predicted SOC trajectories obtained using the LSTM model are shown in Fig. 5. Compared to Ensemble Trees, the LSTM predictions exhibit significantly smoother tracking behavior and improved transient response matching. The predicted SOC closely follows the actual SOC profile even during highly dynamic battery operating conditions, demonstrating the effectiveness of recurrent temporal learning for battery SOC estimation.

The histogram presented in Fig. 6 demonstrates a narrow Gaussian-like error distribution centered around zero, confirming the statistical robustness and unbiased prediction capability of the proposed LSTM model.

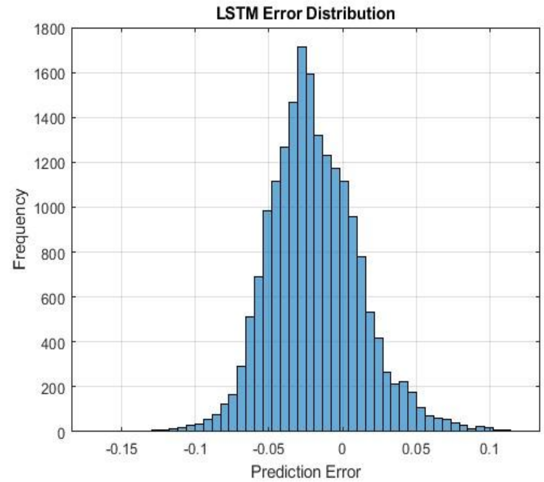

Fig. 6. Prediction error distribution histogram for the proposed LSTM network.

Quantitatively, the LSTM model achieved an RMSE of 0.0363, MAE of 0.0296, MAPE of 11.68%, and an (R^2) score of 0.9823. These results demonstrate significant improvement over Ensemble Trees in terms of estimation accuracy and dynamic tracking capability.

D. Comparative Analysis

The comparative performance analysis between Ensemble LSBoost Trees and LSTM networks is summarized in Table II.

TABLE II

Comparative Performance Analysis of SOC Estimation Models

The obtained results clearly demonstrate that the LSTM network outperforms Ensemble LSBoost Trees in terms of estimation accuracy, residual stability, and dynamic SOC tracking capability. The superior performance of the LSTM model is primarily attributed to its ability to capture sequential battery dependencies and historical operating behavior through recurrent memory mechanisms.

Metric	Ensemble Trees	LSTM
RMSE	0.0486	0.0363
MAE	0.0376	0.0296
MAPE (%)	14.14	11.68
SMAPE (%)	—	10.10
(R^2) Score	0.9686	0.9823
Training Time (s)	50.89	1152

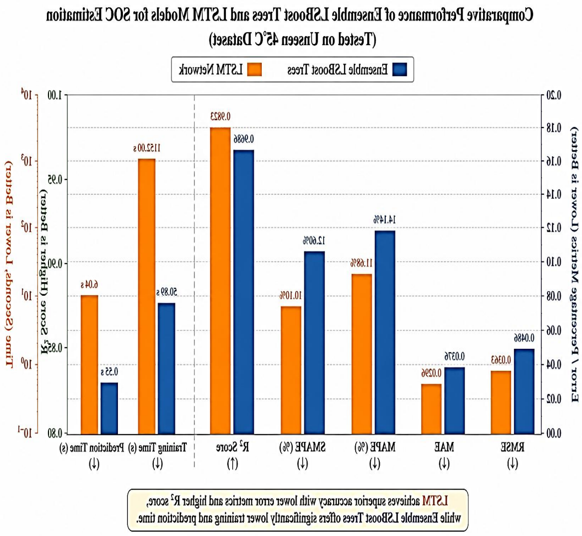

Fig. 7. Performance comparison of Ensemble LSBoost Trees and LSTM models for lithium-ion battery SOC estimation under unseen 45°C operating conditions.

Conversely, Ensemble Trees demonstrated significantly lower computational complexity and faster inference performance, making them more suitable for real-time embedded BMS applications where computational resources are limited. The computational efficiency of Ensemble Trees combined with acceptable SOC estimation accuracy indicates their practical applicability for low-cost battery monitoring systems.

V. CONCLUSION

This paper presented a comparative machine learning framework for lithium-ion battery State of Charge (SOC) estimation using Ensemble LSBoost Trees and Long Short-Term Memory (LSTM) networks under multi-temperature operating conditions. The TU Berlin lithium-ion battery dataset containing dynamic drive-cycle profiles at 5°C, 15°C, 25°C, 35°C, and 45°C was utilized to evaluate the effectiveness and robustness of the proposed SOC estimation models. A comprehensive preprocessing and feature engineering framework consisting of missing-value handling, outlier correction, Savitzky–Golay smoothing, derivative feature extraction, moving average current computation, and z-score normalization was implemented to improve model stability and estimation accuracy.

The obtained results demonstrated that both Ensemble LSBoost Trees and LSTM networks achieved effective SOC estimation performance under dynamic operating conditions. The Ensemble Trees model provided acceptable prediction accuracy with comparatively lower computational complexity, achieving an RMSE of 0.0486 and an R^2 score of 0.9686. Furthermore, the model exhibited significantly lower training and inference time, making it suitable for real-time embedded battery management applications with limited computational resources.

The LSTM model achieved superior SOC estimation performance because of its ability to capture sequential battery dynamics and historical operating dependencies through recurrent memory mechanisms. The proposed LSTM network achieved an RMSE of 0.0363, MAE of 0.0296, and an R^2 score of 0.9823 under unseen high-temperature testing conditions. Residual analysis and error distribution results further confirmed the improved prediction stability and robustness of the LSTM-based SOC estimation framework.

REFERENCES:

[1] J. Chen, Y. Zhang, J. Wu, W. Cheng, and Q. Zhu, "SOC estimation for lithium-ion battery using the LSTM-RNN with extended input and constrained output," Energy, vol. 262, p. 125375, 2023, https://doi.org/10.1016/j.energy.2022.125375.

[2] Xuqing Chai, Shihao Li, Fengwei Liang, A novel battery SOC estimation method based on random search optimized LSTM neural network, Energy, volume 306, 2024, https://doi.org/10.1016/j.energy.2024.132583.

[3] Yong Tian, Rucong Lai, Xiaoyu Li, Jindong Tian, State-of-charge estimation for lithium-ion batteries based on attentional sequence-to-sequence architecture, Journal of Energy Storage, Volume 62, 2023, https://doi.org/10.1016/j.est.2023.106836.

[4] Wu, Y.; Bai, D.; Zhang, K.; Li, Y.; Yang, F. Advancements in the estimation of the state of charge of lithium-ion battery: a comprehensive review of traditional and deep learning approaches. *J. Mater. Inf.* **2025**, *5*, 18. http://dx.doi.org/10.20517/jmi.2024.84

[5] Guanxu Chen, Weiwen Peng, Fangfang Yang, An LSTM-SA model for SOC estimation of lithium-ion batteries under various temperatures and aging levels, Journal of Energy Storage, Volume 84, Part B, 2024, https://doi.org/10.1016/j.est.2024.110906

[6] Mohammed Khalifa Al-Alawi, Ali Jaddoa, James Cugley, Hany Hassanin, A novel enhanced SOC estimation method for lithium-ion battery cells using cluster-based LSTM models and centroid proximity selection, Journal of Energy Storage, Volume 97, Part B,2024, https://doi.org/10.1016/j.est.2024.112866.

[7] D., O.P., Babu, P.S., V., I. et al. Enhanced SOC estimation of lithium ion batteries with RealTime data using machine learning algorithms. Sci Rep 14, 16036 (2024). https://doi.org/10.1038/s41598-024-66997-9

[8] Xichen Fan, Bangxing Li, Yuxin Hao, Qian Tang, Zhenjun Xie, A novel SOC estimation method for lithium-ion batteries using the fusion of deep neural network and physical information model, Journal of Energy Storage, Volume 122, 2025, https://doi.org/10.1016/j.est.2025.116690.

[9] Mei Zhang, Zhihui Wang, SOC estimation for lithium batteries using a CNN-attention-LSTM model, Journal of Energy Storage, Volume 130, 2025, https://doi.org/10.1016/j.est.2025.117479.

[10] Guirguis, J., & Ahmed, R. (2024). Transformer-Based Deep Learning Models for State of Charge and State of Health Estimation of Li-Ion Batteries: A Survey Study. Energies, 17(14), 3502. https://doi.org/10.3390/en17143502.

[11] Zhao, Feng, Yun Guo, and Baoming Chen. 2024. "A Review of Lithium-Ion Battery State of Charge Estimation Methods Based on Machine Learning" *World Electric Vehicle Journal* 15,

no. 4: 131. https://doi.org/10.3390/wevj15040131

[12] Heran Shen, Xingyu Zhou, Zejiang Wang, Junmin Wang, State of charge estimation for lithium-ion battery using Transformer with immersion and invariance adaptive observer, Journal of Energy Storage,Volume 45,2022,https://doi.org/10.1016/j.est.2021.103768.

[13] X. Song, F. Yang, D. Wang and K. -L. Tsui, "Combined CNN-LSTM Network for State-of-Charge Estimation of Lithium-Ion Batteries," in IEEE Access, vol. 7, pp. 88894-88902, 2019, doi: 10.1109/ACCESS.2019.2926517.

[14] Yu Lu, Sida Zhou, Xinan Zhou, Shichun Yang, Mingyan Liu, Xinhua Liu, Heping Ling, Yubo Lian, A novel method of prediction for capacity and remaining useful life of lithium-ion battery based on multi-time scale Weibull accelerated failure time regression, Journal of Energy Storage, Volume 68, 2023,https://doi.org/10.1016/j.est.2023.107589.

[15] S. Chemali, P. J. Kollmeyer, M. Preindl, and A. Emadi, “State-of-charge estimation of Li-ion batteries using deep neural networks: A machine learning approach,” Journal of Power Sources, vol. 400, pp. 242–255, 2018, doi: 10.1016/j.jpowsour.2018.06.104.

[16] R. Xiong, J. Cao, Q. Yu, H. He and F. Sun, "Critical Review on the Battery State of Charge Estimation Methods for Electric Vehicles," in IEEE Access, vol. 6, pp. 1832-1843, 2018, doi: 10.1109/ACCESS.2017.2780258.

[17] Yi Li, Kailong Liu, Aoife M. Foley, Alana Zülke, Maitane Berecibar, Elise Nanini-Maury, Joeri Van Mierlo, Harry E. Hoster, Data-driven health estimation and lifetime prediction of lithium-ion batteries: A review, Renewable and Sustainable Energy Reviews, Volume 113, 2019, https://doi.org/10.1016/j.rser.2019.109254.

[18] Wladislaw Waag, Christian Fleischer, Dirk Uwe Sauer, Critical review of the methods for monitoring of lithium-ion batteries in electric and hybrid vehicles, Journal of Power Sources, Volume 258, 2014, https://doi.org/10.1016/j.jpowsour.2014.02.064.

[19] M. Berecibar, I. Gandiaga, I. Villarreal, N. Omar, J. Van Mierlo, P. Van den Bossche, Critical review of state of health estimation methods of Li-ion batteries for real applications, Renewable and Sustainable Energy Reviews, Volume 56, 2016, https://doi.org/10.1016/j.rser.2015.11.042

[20] Gregory L. Plett, Extended Kalman filtering for battery management systems of LiPB-based HEV battery packs: Part 2. Modeling and identification, Journal of Power Sources, Volume 134, Issue 2, 2004, https://doi.org/10.1016/j.jpowsour.2004.02.032.

[21] G. L. Plett, “Sigma-point Kalman filtering for battery management systems of LiPB-based HEV battery packs: Part 1. Introduction and state estimation,” Journal of Power Sources, vol. 161, no. 2, pp. 1356–1368, 2006, doi: 10.1016/j.jpowsour.2006.06.003.

[22] R. Parmar et al., "A Comparative study on Different ANN Techniques in Wind Speed Forecasting for Generation of Electricity", IOSR Journal of Electrical and Electronics Engineering (IOSR-JEEE), Volume 12, Issue 1 Ver. III (Jan. – Feb. 2017), PP 19-26. DOI: 10.9790/1676-1201031926

[23] J. H. Friedman, “Greedy function approximation: A gradient boosting machine,” Annals of Statistics, vol. 29, no. 5, pp. 1189–1232, 2001, doi: 10.1214/aos/1013203451.

[24] L. Breiman, “Random forests,” Machine Learning, vol. 45, no. 1, pp. 5–32, 2001, doi: 10.1023/A:1010933404324.

[25] S. Hochreiter and J. Schmidhuber, “Long short-term memory,” Neural Computation, vol. 9, no. 8, pp. 1735–1780, 1997, doi: 10.1162/neco.1997.9.8.1735.

[26] R. Parmar and D. K. Sakravdia, "Intelligent Learning Methods for Battery State of Charge Estimation for Electric Vehicles: a Review," 2025 2nd International Conference on Advanced Computing and Emerging Technologies (ACET), Ghaziabad, India, 2025, pp. 1-6, doi: 10.1109/ACET67282.2025.11430296.

[27] C. Jamroen, “The effect of SoC management on economic performance for battery energy storage system in providing voltage regulation in distribution networks,” *Electric Power Systems Research*, vol. 211, p. 108340, Oct. 2022, doi: 10.1016/j.epsr.2022.108340.

[28] P. Shrivastava, T. K. Soon, M. Y. I. B. Idris, and S. Mekhilef, “Overview of model-based online state-of-charge estimation using Kalman filter family for lithium-ion batteries,” *Renewable and Sustainable Energy Reviews*, vol. 113, p. 109233, Oct. 2019, doi: 10.1016/j.rser.2019.06.040.