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Effects of training-test splitting ratio on the performance of LSTM-based battery state of charge estimation model: a comparative study

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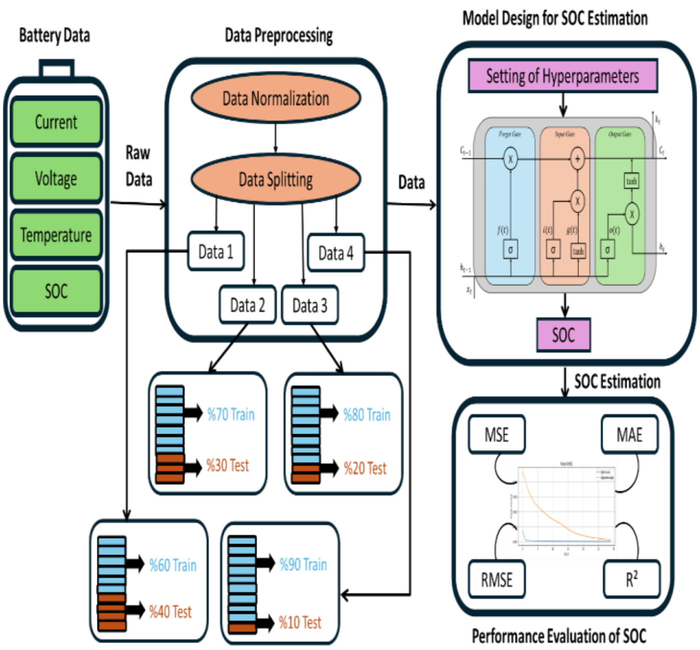
ABSTRACT

Context—Battery state of charge (SOC) estimation is considered a critical parameter in the management of electric vehicle (EV) batteries. Accurate and reliable SOC estimation directly contributes to the effective control of battery charging and discharging processes, optimization of energy management, and extension of battery life. Furthermore, precise SOC estimation demonstrates that EV operates more reliably, sustainably, and with higher efficiency. Therefore, SOC estimation is considered one of the fundamental components of battery management systems (BMS).

Objective—In this study, a long short-term memory (LSTM) model, a deep learning-based approach, was chosen to perform SOC estimation.

Method—The dataset used in the model implementation was divided into training and test datasets with different ratios to evaluate the model's learning and validation performance. To analyze the effect of training and test data ratios on model performance, four different scenarios were created in the first stage. In these scenarios, the training-test split ratios were determined as 60%-40%, 70%-30%, 80%-20%, and 90%-10%, respectively. In the second stage, these four different data splitting scenarios were applied separately to the LSTM model, and the model's estimation performance was examined in detail in each case. In the final stage, the obtained results were analyzed using various error metrics to quantitatively evaluate the model performance. In this context, mean absolute error (MAE), mean square error (MSE), root mean square error (RMSE), and coefficient of determination (R^2) values were calculated and evaluated comparatively.



Results—As a result of the analyses, it was clearly observed that even when the model parameters were kept constant, the training and test data ratios had a significant effect on the SOC estimation performance. According to the findings, the lowest error values were obtained when the training and test data ratio was set at 80%-20%. In this scenario, the MSE value was calculated as 1.3305%, the MAE value as 0.8003%, the RMSE value as 1.1535%, and the R^2 value as 93.53%. In contrast, the highest error values were determined to have occurred at a training-test ratio of 60%-40%. In this case, the MSE was found to be 4.9628%, MAE 1.7788%, RMSE 2.2277%, and R^2 73.27%.

Conclusion—Furthermore, the evaluations showed that as the training data ratio decreased, the model's training time also shortened. However, this negatively impacted the model's estimation accuracy and resulted in lower performance. These findings clearly demonstrate the crucial role of the amount of training data on model performance.

Key Words—Battery state of charge estimation, Electric vehicles, Long short-term memory, Training-test splitting ratio.

I. INTRODUCTION

Today electric vehicle (EV) use has become widespread due to environmental factors. The use of fossil fuels increases the greenhouse gas effect and air pollution. Increased air pollution causes a significant increase in mortality. EV use reduces carbon footprint, decreases noise pollution due to its quiet operation, and allows for living in a cleaner environment. For these reasons, the demand for EVs is constantly increasing. The most critical criterion in EVs is the battery. Battery life and state of charge (SOC) are parameters that directly affect EV use. Efficient battery use and lifespan can be increased with SOC estimation.

Recently, studies on battery state estimation in EVs have been increasing. Studies on battery state estimation are compiled. The focus has been on model-based techniques [1], filtering methods [2], deep learning methods [3] and machine learning techniques [4].

Reliable and accurate battery SOC estimation is crucial. Various studies have been conducted using deep learning methods such as long short-term memory (LSTM) in this regard. Chemali et al. performed SOC estimation by applying LSTM and recurrent neural networks (RNN) on different datasets. The LSTM-RNN model was tested at different temperatures, and the MAE value was obtained between 0.573% and 1.606%. The results were based on 80% training and 20% test data [5]. Yang et al. presented a stacked LSTM model for SOC estimation. The stacked LSTM model with an odorless Kalman filter (UKF) was applied to different training and test datasets, and the results were compared. The error rates of the developed method were RMSE: 2% and MAE: 1%, yielding better results [6]. Song et al. combined the advantages of convolutional neural network (CNN) and LSTM models to perform SOC estimation. When compared with the results of the CNN-LSTM models individually, the CNN-LSTM model yielded higher accuracy results. Error analysis results were found to be MAE<%1 and RMSE<%2 [7]. Wei et al. suggested an LSTM-based exogenous input neural network (NARX) model for battery SOC estimation. The accuracy of the NARX-LSTM hybrid model was demonstrated by comparing it with methods such as LSTM and support vector machine (SVM). The dataset was divided into 70% train, 15% test, and 15% validation data. The RMSE value of the hybrid model was improved by approximately 60% compared to other models [8]. Tian et al. combined LSTM with an adaptive cubic Kalman filter (ACKF) for SOC estimation. These results obtained with LSTM were corrected with ACKF. It was observed that the LSTM-ACKF model gave more accurate results than the LSTM model. MSE<%2.2 and ME<%4 were found [9]. Yang et al. designed the LSTM model for SOC estimation and UKF to reduce estimation errors and noise. According to the error analysis results, RMSE is <1.1% and MAE is <1% [10]. Fasahat et al. proposed the combined autoencoder (AE) and LSTM model. The error rates obtained according to 70% training and 30% test data were found to be less than 1% [11]. Chung et al. proposed the LSTM model for battery SOC estimation at different ambient temperatures. Error analysis results were obtained from 90% training and 10% test data with RMSE<1.5% and MAE<1% [12]. Zhang et al. performed SOC estimation with a hybrid model using LSTM, KF, and attention mechanisms. The estimation results obtained at different driving dynamics and different temperatures were analyzed. RMSE was found to be <1.5% [13]. Hu et al. proposed LSTM and an adaptive extended Kalman filter (AEKF) for SOC estimation. Data cleaned of noise with AEKF was used as input in the LSTM model. Error results for the AEKF-LSTM model were RMSE<0.6% and ME<1.6% [14]. Van et al. contributed to studies on SOC estimation with the LSTM model using real EV data. As indicated by the estimation results of the single-layer LSTM model, RMSE = 1.06%, MAE = 0.77%, and MAPE = 1.4116% were obtained [15]. Praisan et al. presented the LSTM model for real-time SOC estimation. They demonstrated the model accuracy by comparing experimental and simulation results. At ambient temperature, RMSE is 2% [16]. Wong et al. proposed the LSTM-RNN model combined with meta-learning for SOC estimation. The SOC values obtained from the LSTM-RNN 1 and LSTM-RNN 2 models were used as input in the LSTM-RNN 3 model. MAE was found to be 1.42% [17]. Chai et al. created a hybrid model with random search optimization (RS) and LSTM. In the RS-LSTM model, hyperparameters were optimized with RS and then used in the LSTM model. MAE: 0.221% and RMSE: 0.262% were obtained for 80% training and 20% testing data [18]. Xu et al. applied a hybrid EKF, particle swarm optimization (PSO) and LSTM model for SOC estimation. Accuracy was shown with error rates of RMSE: 0.258% and MaxE: 1.559% [19]. Kumar et al. compared the results by estimating SOC with CNN, LSTM and feedforward neural network (FNN) models. The dataset was considered as 70% train, 15% test and 15% validation data. It was stated that the best model was FNN according to the error rates and the model completion time. The lowest MAPE value was found to be 0.7781% [20]. Pu et al. presented a UKF-based LSTM model. They performed battery parameter selection with PSO and SOC estimation with the UKF-LSTM model. It was stated that the MAE and RMSE values were less than 0.7% [21]. Zou et al. used a new model combining transformer encoder and LSTM. The learning and accuracy of the model were increased with the transformer encoder. Using 80% training and 20% test data, MAE: 0.75%, RMSE: 0.93% and R^2: 99.88% were found [22]. Elachhab et al. performed SOC estimation with LSTM and RNN using enhanced input parameters. For the LSTM model, the RMSE and MAE values were 0.83% and 1.06%, respectively; for the RNN model, these values were 1.54% and 1.2%. The train-test data ratios were the same for both models, 80%-20% [23]. Ahn et al. suggested a dual LSTM model for SOC estimation. Mainstream (m–) LSTM and gradient (g–) LSTM, combined in parallel, were able to extract the time-dependent changing trend of the battery. Its accuracy was demonstrated by comparing it with LSTM and vanilla LSTM. MAE, MSE, and RMSE were found to be 0.789%, 1.035%, and 1.017%, respectively [24]. Carrera et al. optimized the LSTM model with a genetic algorithm (GA) and performed a real-time SOC application. In the model using 70% training and 30% test data, the MAE value was found to be 0.181% [25]. Yu et al. combined the EKF and LSTM models, which can capture nonlinear features, for SOC estimation. The EKF-LSTM model yielded better results than the EKF and LSTM models. Its accuracy was demonstrated with error rates less than 1% [26]. Bobobee et al. created a hybrid model using the LSTM (MALSTM) and EKF models with multiple attention mechanisms. The MALSTM-EKF model allowed feature extraction with attention mechanisms and purification of SOC estimation results from noise with filtering. The results of the presented model were compared with the results of the LSTM, AEKF and MALSTM models. The best estimation results were obtained with the MALSTM-EKF model; RMSE, MAE and MAPE values were found to be 0.343%, 0.236% and 1.135%, respectively [27].

This study uses an LSTM model for battery SOC estimation in EVs. First, data preprocessing was performed. Battery data was cleaned and normalized. This normalized data was divided into training and test data. Training and test splitting ratios are important in DL models and can significantly affect the results. Different splitting ratios were used during data splitting. The training and test splitting ratios were determined as 60-40, 70-30, 80-20, and 90-10 percentiles, respectively. These four different training-test splitting ratios were designed as different data sets and used in the LSTM model. Data 1, Data 2, Data 3, and Data 4 were each treated as a new dataset. After data preprocessing, hyperparameter selection and LSTM model design were performed. Model estimation results were compared with error analysis metrics and presented. The estimation results were also visualized with graphs. Figure 1 illustrates the general flowchart of this study.

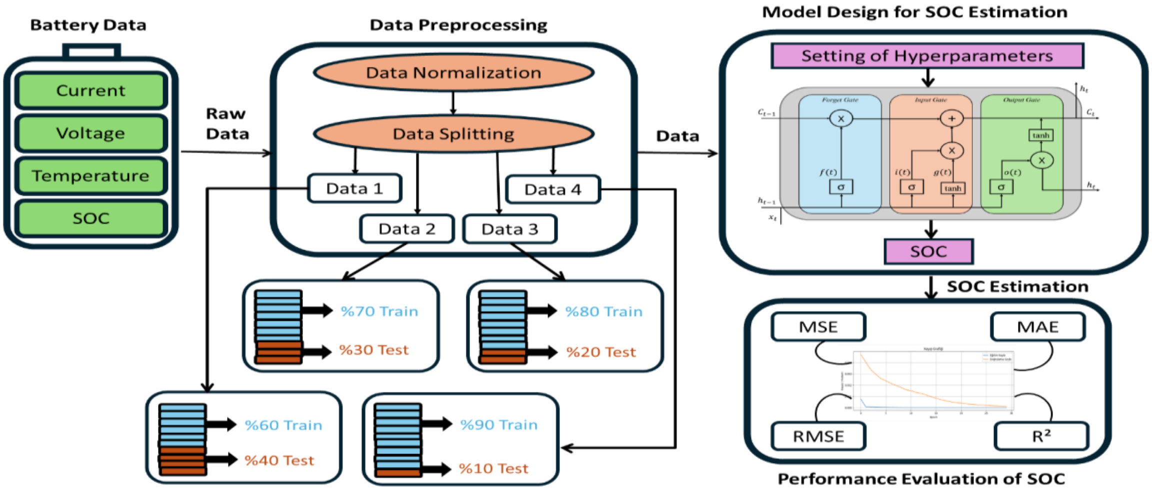


Figure 1. Overall flowchart of this study.

Many SOC estimation studies in the literature have focused on improving estimation accuracy using hybrid DL models, optimization algorithms, KF approaches, and attentional mechanisms. Generally, studies have used fixed training-test split ratios such as 70%-30% and 80%-20%. Furthermore, the effects of different training-test split ratios on the learning behavior, generalization ability, and estimation performance of LSTM-based SOC estimation models have not been analyzed. This study focuses specifically on evaluating the effect of different training-test splitting ratios on the SOC estimation performance of a LSTM model. Therefore, the main objective of the study is not to compare different machine learning or deep learning models. The aim is to investigate how the amount of training-test data affects the estimation accuracy, training time, and generalization behavior of the LSTM model with the same model settings. The contributions of this research paper are presented below:

- The aim of this paper is to demonstrate the effects of training and test split ratios on the LSTM model for SOC estimation. Studies examining the effects of different training and test split ratios on SOC estimation results were not found in the literature.
- Studies were conducted with a new battery dataset that has been presented in the literature but has not yet been used for SOC estimation.
- Changes in model completion time were observed at different training and test split ratios.

II. LSTM MODEL for SOC ESTIMATION

A. Dataset description

The battery dataset used in this study consists of data obtained over 5 years from 28 portable battery systems using Lithium-Iron-Phosphate (LFP) batteries, with a nominal capacity of roughly 160 Ah and a voltage of 24 V. The dataset was obtained from a system with 8 cells each connected in series, totaling 224 cells [28]. The 8 batteries connected in series formed a battery system and are shown in Fig. 2.

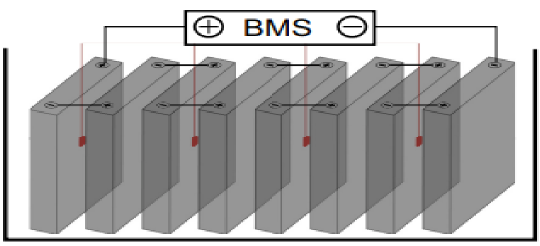


Figure 2. A system consisting of 8 batteries connected in series [28].

Each system includes a load current sensor and a voltage sensor in each cell. Four temperature sensors are placed between adjacent cells, meaning each temperature sensor is shared by two cells. Active cell equalization is also present in battery systems. The battery dataset consists of time-series data including voltage, current, temperature, and actual SOC values. Current, voltage, temperature, and actual SOC values were used to estimate SOC. Current, voltage, and temperature are input variables, while SOC is considered the target output. SOC estimation is a sequential estimation problem. Therefore, the data are chronologically ordered in all training-test split scenarios. Random shuffling was not performed to prevent temporal information leakage between training and test samples. System and data characteristics are shown in Table 1.

Before the model training phase, missing data and inconsistent values were checked. Input variables were normalized using the MinMax normalization method. The normalization was applied to improve the convergence stability and training performance of the LSTM model. Normalization parameters were calculated only from the training subset to prevent data leakage. Then they were applied to the corresponding test subset. After the normalization process, the data were converted into successive samples using a sliding window approach. The window size refers to the number of previous time steps used to predict the next SOC value of the model. Additionally, batch size was defined to ensure efficient model training. Batch size refers to the number of data points that will be processed simultaneously during the model's weight update phase.

B. Structure of the LSTM model

The LSTM algorithm, which has a recurrent (feedback-based) neural network architecture, is distinct from conventional neural networks. It was developed as an advanced form of recurrent neural network (RNN) structures. By enhancing the memory capability of RNNs, LSTM can accurately learn and preserve long-term dependencies within sequential data, enabling more robust learning performance [29].

Table 1. System and data characteristics.

Nominal voltage	24 V
Nominal capacity	160 Ah
Number of systems	28
Number of cells	8 (series)
Total number of cells	224
Battery chemistry	LFP
Data type	Time-series
Input variables	Voltage, current, temperature
Output variable	SOC
Splitting strategy	Sequential

LSTM networks can store information over extended periods by controlling the processes of reading, writing, and removing data from memory. During training, the model evaluates the importance of input features and decides which information should be retained or discarded based on learned weight parameters. In this way, LSTM dynamically determines the relevance of information for future use [30].

These mechanisms are governed by three main gates within the LSTM architecture: the input gate $i(t)$, the output gate $o(t)$, and the forget gate $f(t)$. In essence, LSTM is a specialized neural network model that can leverage past information in future estimations without losing critical knowledge. The LSTM model structure is illustrated in Fig. 3, and the model formulas are shown in (1)-(6):

$$i(t) = \sigma(W_{xi}x_t + W_{hi}h_{t-1} + b_i), \quad (1)$$

$$f(t) = \sigma(W_{xf}x_t + W_{hf}h_{t-1} + b_f), \quad (2)$$

$$g(t) = tanh(W_{xg}x_t + W_{hg}h_{t-1} + b_g), \quad (3)$$

$$o(t) = \sigma(W_{xo}x_t + W_{ho}h_{t-1} + b_o), \quad (4)$$

$$c(t) = f(t)c(t-1) + i(t)g(t), \quad (5)$$

$$h(t) = \sigma\ c(t)o(t). \quad (6)$$

When determining the hyperparameters for the LSTM model, configurations commonly used in SOC estimation studies were considered. Different hyperparameter configurations were experimentally evaluated during the model development process. The hyperparameters selected for the best results are shown in Table 2. The number of hidden neurons was set to 64 to provide sufficient learning capacity without increasing model complexity. The window size was set to 72, the batch size to 32, and the learning ratio to 0.0005. The Huber loss function was used as the loss function. The Huber loss function was preferred because it is more robust against anomalous estimation errors.

The model was implemented in Python using the TensorFlow deep learning framework. All experiments were conducted in Python version 3.10.11. An ASUS X555LN laptop equipped with an Intel Core i7 processor, 8 GB RAM, and a 64-bit operating system was used during the experiments. To ensure accurate and reliable comparison between different training-test split ratios; preprocessing procedure, model architecture and hyperparameters were used identically in all scenarios. Also, fixed random seed values were used during the experiments to improve reproducibility.

Cross-validation was not applied because SOC estimation is a time series problem, as it could lead to temporal information leakage between the training and test subsets. Therefore, a chronological splitting strategy was used. Four different training-test splitting scenarios were created: 60%-40%, 70%-30%, 80%-20%, and 90%-10%. In all scenarios, the earlier part of the dataset was used as training data and the later part as test data. This approach allowed a model trained on past battery data to estimate future SOC values. Thus, the proposed splitting strategy better reflects the SOC estimation process. In practical BMSs, future SOC values are estimated using previously observed operational data. For this reason, preserving the sequential of the dataset provides a more realistic evaluation framework for real-world SOC estimation applications.

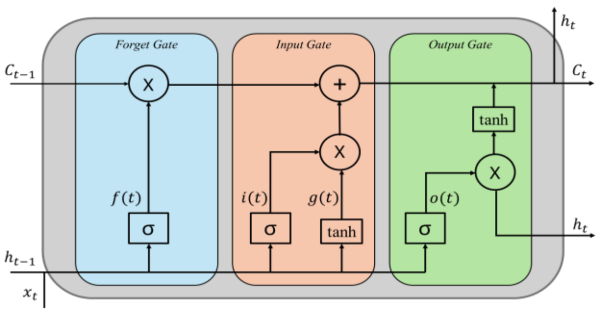


Figure 3. Structure of the LSTM model.

C. Error metrics

Data 1, Data 2, Data 3, and Data 4 were used in the LSTM model to obtain SOC estimation results. Model performance for each data was analyzed using MSE, MAE, RMSE, and R^2 error metrics. The formulas for these error metrics are shown in (7)-(10):

$$MSE = \frac{1}{T}\sum_{t=1}^{T}\left(SOC(t) - \widehat{SOC}(t)\right)^2, \quad (7)$$

$$MAE = \frac{1}{T}\sum_{t=1}^{T}\left|SOC(t) - \widehat{SOC}(t)\right|, \quad (8)$$

$$RMSE = \left[\frac{1}{T}\sum_{t=1}^{T}\left(SOC(t) - \widehat{SOC}(t)\right)^2\right]^{1/2}, \quad (9)$$

$$R^2 = 1 - \frac{\sum_{t=1}^{T}\left(SOC(t) - \widehat{SOC}(t)\right)^2}{\frac{1}{T}\sum_{t=1}^{T}\left(SOC(t) - \overline{SOC(t)}\right)^2}, \quad (10)$$

where $SOC(t)$ represents the true SOC value, $\widehat{SOC}(t)$ expresses the predicted value, and $\overline{SOC(t)}$ denotes the average of the true SOC values.

III. APPLICATION and RESULTS

In this section, LSTM model estimation results are compared with error analysis metrics. Estimation results are also presented visually with graphs. Actual-predicted SOC graphs are shown along with loss graphs for each data point.

The highest error rates were obtained for Data 1, with MSE: 4.9628%, MAE: 1.7788%, RMSE: 2.2277%, and R^2: 73.27%. The analysis time for Data 1 was 45 minutes. Error rates for Data 2 were found to be MSE: 4.1343%, MAE: 1.7511%, RMSE: 2.0333%, and R^2: 78.35%. The analysis time for Data 2 was 50 minutes. The lowest error rates were obtained for Data 3, with MSE: 1.3305%, MAE: 0.8003%, RMSE: 1.1535%, and R^2: 93.53%. The analysis time for Data 3 was 54 minutes. Error rates for Data 4 were found to be MSE: 2.5153%, MAE: 1.2155%, RMSE: 1.5860%, and R^2: 87.12%. The analysis time for Data 4 was 60 minutes. Figure 4 shows the loss graph for Data 1, Data 2, Data 3 and Data 4. Figure 5 presents the estimation performance for Data 1, Data 2, Data 3 and Data 4 by showing the actual and estimated SOC values.

To evaluate the overfitting behavior of the LSTM model, training and validation loss curves were also examined. In general, a large difference between training loss and validation loss can indicate overfitting.

In this study, the difference between training and validation losses varied depending on the training-test split ratio. An 80%-20% split ratio provided the best balance between learning capacity and generalization performance. While the 90%-10% scenario used the largest training subset, test performance was lower than the 80%-20% scenario. This suggests that increasing

Table 2. Hyperparameters of the LSTM.

Layers	1 × LSTM, 1 × Dense
Hidden neuron	64
Activation function	tanh, linear
Optimization algorithm	Adam
Loss function	Huber Loss
Epoch	30
Batch size	32
Window size	72
Learning rate	0.0005

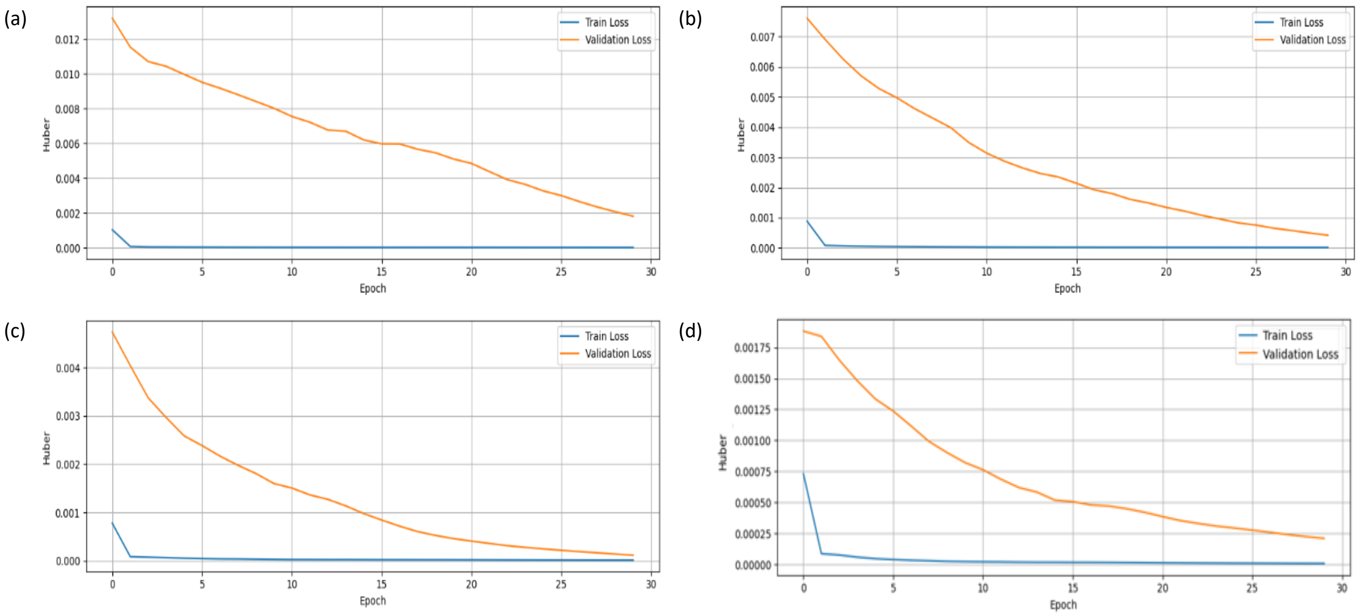


Figure 4. Loss graph for (a) Data 1, (b) Data 2, (c) Data 3, (d) Data 4.

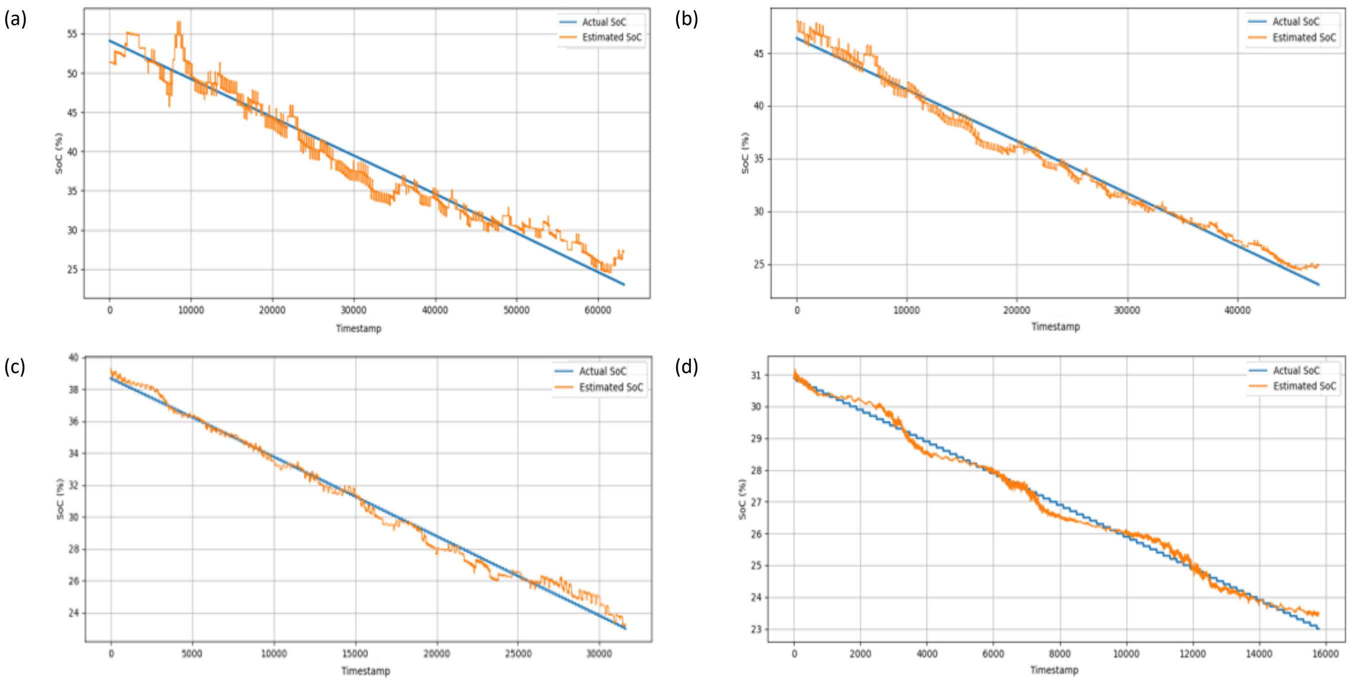


Figure 5. SOC estimation performance for (a) Data 1, (b) Data 2, (c) Data 3, (d) Data 4.

the training data ratio may not necessarily lead to better generalization. Therefore, the 80%-20% split ratio was found to be the most suitable configuration for the current dataset. Additionally, lower training ratios may limit the model's learning capacity and negatively affect its ability to capture nonlinear battery behavior. Insufficient training can lead to difficulties in capturing battery dynamics. Besides, the smoother convergence behavior observed in the 80%-20% scenario demonstrates a more stable learning process with reduced overfitting tendency compared to the other splitting configurations.

The error analysis results obtained for each data in the LSTM model are compared in Table 3. Furthermore, the results are visualized and presented in Fig. 6. Compared to SOC estimation studies in literature, the results obtained are consistent with the performance metrics in previous LSTM-based SOC estimation studies. Some hybrid and optimized models in the literature have been shown to have lower error values. However, the aim of this study is to analyze the effect of training-test splitting ratios on a vanilla LSTM model, not to develop a new hybrid architecture. Therefore, the results obtained demonstrate that the data splitting strategy has a direct impact on SOC estimation performance.

Additionally, similar to LSTM-based SOC estimation studies in the literature, the proposed model achieved acceptable estimation accuracy despite using a simpler vanilla LSTM architecture. This suggests that data splitting strategy can significantly impact model performance, even without the use of hybrid or optimized models. Table 4 presents the previous studies with related to SOC estimation.

Table 3. Error analysis results.

Dataset	MSE (%)	MAE (%)	RMSE (%)	R^2 (%)
1	4.9628	1.7788	2.2277	73.27
2	4.1343	1.7511	2.0333	78.35
3	1.3305	0.8003	1.1535	93.53
4	2.5153	1.2155	1.5860	87.12

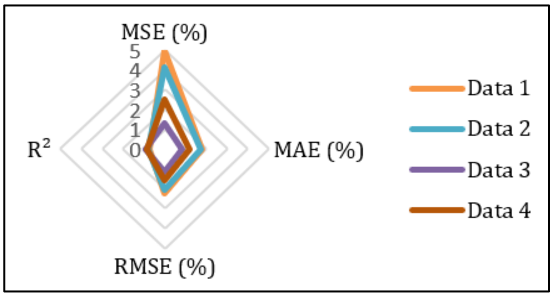


Figure 6. Error analysis results.

Table 4. Previous studies on SOC estimation.

Refs.	Model	Results (%)	Train-Test Ratio (%)
[5]	LSTM-RNN	MAE:0.573–1.606	80-20
[12]	LSTM	RMSE:<1.5; MAE:<1	90-10
[18]	RS-LSTM	MAE:0.221; RMSE:0.262	80-20
[22]	Transformer-LSTM	MAE:0.75; RMSE:0.93; R^2: 99.88	80-20
[23]	LSTM-RNN	RMSE:0.83; MAE:1.06	80-20
[25]	GA-LSTM	MAE: 0.181	70-30
Our Study	LSTM	MSE: 1.3305; MAE:0.8003; RMSE:1.1535; R^2:93.53	80-20

IV. CONCLUSION

The effect of training-test splitting ratios on SOC estimation results was investigated. It was observed that while keeping the LSTM model parameters constant, changing the training and test split ratios resulted in different outcomes and altered estimation performance. Furthermore, reducing the percentage of training data allowed the model to be completed in a shorter time. The best estimation result was obtained with Data 3. Data 4 and Data 2 yielded the second and third best results respectively. Data 1 showed the highest error rates and the lowest estimation performance. No studies were found on the effects of different training-test splitting ratios on SOC estimation performance. This study is expected to contribute to future SOC estimation studies by highlighting the critical influence of training-test splitting strategies on LSTM-based model performance.

AUTHOR STATEMENT

Plagiarism Check—The article has been scanned with iThenticate and found to be compliant with the journal's plagiarism policy.
Conflict of Interest—There is no conflict of interest with any person/ institution in this article prepared.
Ethics Committee Approval—There is no need to obtain permission from the ethics committee for the article prepared.
Use of Artificial Intelligence Tools—In this study, no artificial intelligence tools were used. All content reflects the original contribution of the author.
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Data availability—The dataset used in this study is publicly available and can be accessed through the Zenodo repository [31].
CRediT Author Contribution—Conceptualization, Methodology, Investigation, Software, Writing - Original Draft, Validation (**Leyla Efe**); Methodology, Investigation, Writing - Review & Editing, Validation, Supervision (**Abdülsamed Tabak**).
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