

Remaining Useful Life Prediction of Lithium-Ion Batteries Based on Transfer Learning and DAE-LSTM

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Abstract: Predicting the Remaining Useful Life (RUL) of lithium-ion batteries is one of the core tasks in battery health management. This study aims to enhance the accuracy of RUL prediction by proposing a battery RUL prediction method that integrates source domain battery iteration transfer with Long Short-Term Memory (LSTM) neural networks. Firstly, multiple batteries with known degradation trends are utilized as source domain batteries, and combined with full-lifetime capacity degradation data to construct the Source Domain Battery Iterations Module (SIM) to obtain the optimal LSTM pre-training model. Secondly, the pre-trained model is transferred to the target domain and fine-tuned using the target domain training set. Finally, the fine-tuned LSTM pre-training model is applied to the task of predicting the capacity of target domain batteries, thereby completing the RUL prediction. The effectiveness of the algorithm is validated on three open-source datasets. Experimental results demonstrate that in scenarios where the source domain and target domain battery types are the same, the absolute error of RUL prediction is less than 2 cycles. Moreover, in cases where the battery types differ, except for the 20% prediction starting point, the RUL prediction error is less than 10 cycles, indicating a high level of prediction accuracy.

Keywords: Lithium-ion battery, Remaining life prediction, Long Short-Term Memory neural network, Transfer learning, Source domain battery iteration module (SIM).

1. Introduction

Lithium-ion batteries are widely employed in various fields such as consumer electronics, electric vehicles, and aerospace due to their high energy density, long lifespan, and environmental friendliness [1]. However, factors such as frequent charging and discharging cycles and changes in environmental temperature can significantly affect their lifespan [2]. Battery aging is primarily characterized by a decrease in capacity and an increase in equivalent internal resistance [3]. Timely replacement of batteries is crucial once they reach their designated end-of-life threshold to ensure the safety of both the battery and its operating system [4]. Therefore, accurate prediction of the Remaining Useful Life (RUL) of lithium-ion batteries is essential.

In recent years, with the rapid development of machine learning and deep learning, data-driven methods for predicting the RUL of lithium-ion batteries have gained significant attention. Compared to traditional methods based on equivalent circuits [5] and physical models [6], data-driven approaches are more flexible and can eliminate the complex process of physical modeling. They utilize historical data from battery operation to effectively predict the remaining useful life of batteries [7]. Recurrent neural networks, with their unique memory structure, have demonstrated significant advantages in handling time-series data and are thus commonly used in various life prediction tasks [8]. Zhang Yongzhi et al. [9] employed Long Short-Term Memory (LSTM) neural networks to capture the long-term correlations between the degradation capacities of lithium-ion batteries. By segmenting capacity data using a sliding window and iteratively predicting future capacity degradation data, this method of sliding window segmentation and iterative prediction is one of the most commonly used techniques in predicting the remaining useful life of lithium-ion batteries. P. Khumprom et al. [10] proposed an LSTM-based prediction

model for battery life prediction, using capacity data at 50% and 70% of the lifecycle for model training and subsequent remaining life prediction. Experimental results showed that the model trained with 70% lifecycle data had higher accuracy. This is not only related to the amount of training data but also to the degradation characteristics of lithium-ion batteries. The degradation curve of batteries is nonlinear, with the degradation rate in the early to middle stages much slower than in the later stages [11]. Thus, modeling only the slow degradation rate in the early stages of the battery and then predicting the life using autoregression often leads to significant prediction errors. Furthermore, lithium-ion batteries often exhibit capacity rebound during the degradation process [12], and factors such as electromagnetic interference and differences in charge-discharge rates during experiments can introduce noise into the battery capacity data, which greatly interferes with the establishment of data prediction models. Therefore, denoising of battery capacity data is necessary. Qiao Jianshu et al. [13] used an Adaptive Bi-exponential Model Smooth (ABMS) and Complete Ensemble Empirical Mode Decomposition with Adaptive Noise (CEEMDAN) algorithm to denoise battery capacity data and then used an LSTM network for capacity prediction. Compared to predictions using undenoised data, prediction models with data preprocessing demonstrated higher accuracy.

Wang Zhuqing et al. [14] used Local Tangent Space Alignment (LTSA) to extract features from battery capacity data, reduce fluctuating data in degradation, and employed an adaptive sliding window LSTM model for life prediction. Experimental results showed that prediction models with data denoising were more accurate in predicting RUL.

(1) Although most existing prediction models have demonstrated impressive predictive capabilities, they generally suffer from three main issues:

(2) Model limitations: Predicting the life of lithium-ion batteries using only local degradation data has certain

limitations due to the different degradation rates at different life stages.

(3) Denoising prediction correlation: In many prediction methods, data denoising and capacity prediction are often treated separately as two independent tasks, ignoring the correlation between them. Sparse degradation data: Deep learning-based training methods require a considerable amount of data as support. However, real-world degradation data for batteries are limited, which affects the establishment of prediction models.

To address these issues, this study proposes a novel RUL prediction model for lithium-ion batteries named TL-LSTM-SIM, which integrates transfer learning (TL), Long Short-Term Memory neural networks (LSTM), and the Source domain battery Iterations Module (SIM). Firstly, through the SIM module, multiple source domain batteries with known degradation trends are used to iteratively train the LSTM model, enabling the pre-training of a high-precision model on a large-scale dataset. Subsequently, the pre-trained model is transferred to the target domain using transfer learning techniques and fine-tuned on the target domain training set to adapt to the characteristics and environment of the target domain batteries. Through iterative training of LSTM via the SIM module, the predictive performance of the model after the fusion of transfer learning and LSTM is further improved.

Experimental results demonstrate that the proposed TL-LSTM-SIM model maintains high prediction accuracy when predicting the RUL of different types of lithium-ion batteries.

2. LSTM and Transfer Learning theory

2.1. LSTM

Since the data collected from lithium-ion batteries is acquired during charging and discharging cycles, they belong to the category of time-series data. Recurrent Neural Networks (RNNs) are well-suited for handling time-series data and processing sequential information in an ordered manner. In order to address the issue of vanishing or exploding gradients in RNNs, the LSTM network structure was proposed, which replaces the classical RNN's state units with LSTM recurrent units.

A special type of RNN model is the LSTM (Long Short-Term Memory). Compared to traditional RNNs, LSTM can better handle long-term dependencies in sequential data. LSTM consists of three gate controllers: the forget gate, the input gate, and the output gate. Figures 1-1 and 1-2 illustrate the architecture of an LSTM unit.

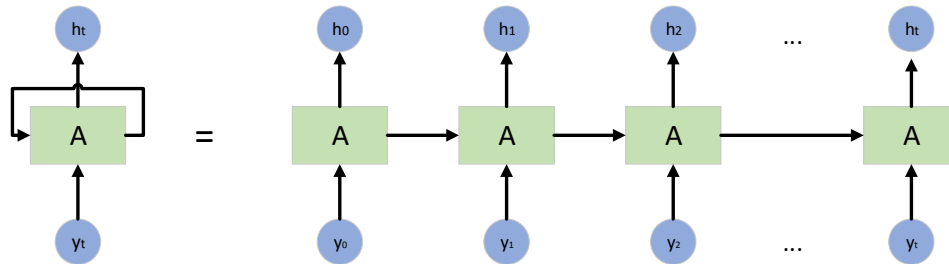


Figure 1. Structure of the recurrent neural network with chain-like features

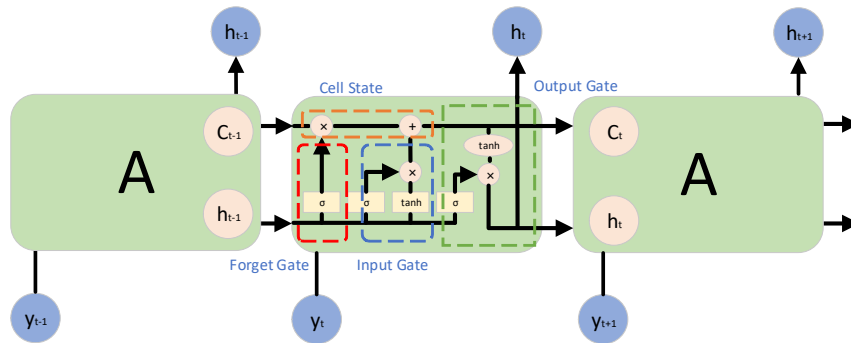


Figure 2. The LSTM neural network structure

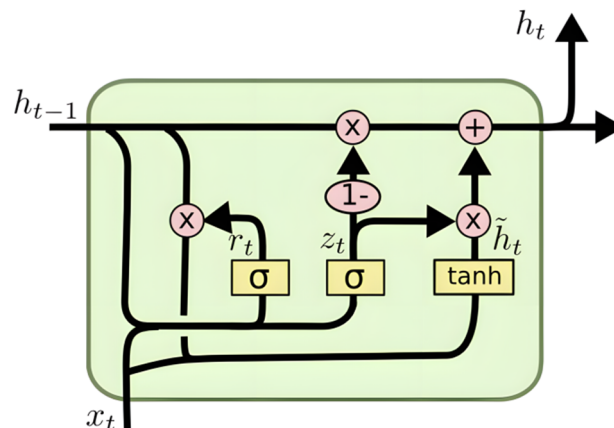


Figure 3. Local amplification plot of the LSTM neural network

The main function of the forget gate is to retain information about when to forget a unit value, as given by the following equation:

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

Where y_t represents the input value; h_{t-1} represents the output value; W_f and b_f respectively denote the weight and bias, and σ is the activation function. The input gate stores these values into a memory cell, and its operation principle is as follows:

$$i_t = \sigma(W_i \cdot [y_t, h_{t-1}] + b_i) \quad (2)$$

$$\tilde{C}_t = \tanh(W_c \cdot [y_t, h_{t-1}] + b_c) \quad (3)$$

Where W_i , W_c represents the weight; \tanh represents the activation function, which \tilde{C}_t is a one-dimensional matrix with values ranging from 0 to 1. Combining the outputs of the forget gate and the input gate, the updated information for C_t is calculated as:

$$C_t = f_t \cdot C_{t-1} + i_t \cdot \tilde{C}_t \quad (4)$$

The put gate controls reading of memory cell values:

$$o_t = \sigma(W_o \cdot [y_t, h_{t-1}] + b_o) \quad (5)$$

Where W_o and b_o are the weight and bias of the output gate respectively, and o_t represents the output of the LSTM. The hidden state at time step t is updated as follows:

$$h_t = o_t \cdot \tanh(C_t) \quad (6)$$

The internal structure of the LSTM network is illustrated in Figures 3-4. Compared to RNN, LSTM structure not only includes activation functions but also adds sigmoid functions to form gating mechanisms for controlling information flow paths and updating transmitted information. This creates an internal network structure that filters information states, allowing for selective memory or forgetting of information.

2.2. Transfer Learning

Transfer learning is a machine learning method similar to knowledge transfer and inductive learning, which aims to learn the similarity between knowledge and utilize existing knowledge to accomplish new tasks. Its principle is based on the universality of convolutional neural networks in learning shallow features. When the amount of data for the target task is insufficient, transfer learning transfers the universal features from a pre-trained base model to the target task, thereby improving the training effectiveness of the target task. The domain from which features are transferred is called the source domain, and the domain to which features are transferred is called the target domain. Transfer learning leverages the information learned from existing source domain data and applies it to similar but different target domains, thus avoiding training new tasks from scratch and reducing the need for large amounts of training data.

(1) Domain

Domain D can be understood as a specific field at a certain time. For example, book reviews and TV series reviews can

be regarded as two different domains. Domain D consists of a feature space X and an edge probability distribution $P(X)$. In general, if two domain are different, then they should have different feature spaces or different edge probability distributions.

$$D = \{X, P(X)\} \quad (7)$$

X Represents the feature space and $P(X)$ represents the marginal probability distribution, where $X = \{x_1, \dots, x_n\}$.

(2) Task

The task is what needs to be done, such as sentiment analysis and entity recognition, which are two different tasks. For a specific domain $D = \{X, P(X)\}$, the task consists of a label \mathcal{Y} space and a target prediction function $f(\cdot)$.

$$T = \{\mathcal{Y}, f(\cdot)\} \quad (8)$$

Where $f(\cdot)$ is not observed, but can be learned from the training data containing the data $\{x_i, y_i\}$, where $x_i \in X$ and $y_i \in \mathcal{Y}$. From a probability perspective, $f(\cdot)$ can be written as $P(y|x)$.

In essence, task T depends on domain D , meaning that if two tasks are different, it could be because the domains are different or because the tasks on the same domain are different, i.e., either \mathcal{Y} different $f(\cdot)$ or different. Moreover, different domains D could have two possibilities: either different feature spaces or different marginal probability distributions, as illustrated in the figure.

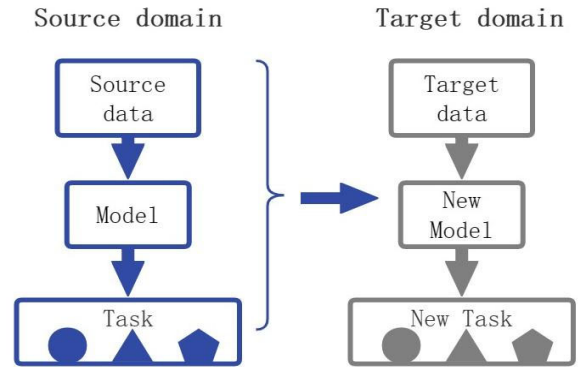


Figure 4. Schematic diagram of transfer learning

The combination of the two can be defined as: given the source domain D_s and learning task T_s , target domain D_t and learning task T_t , the purpose of transfer learning is to obtain the knowledge in the source domain D_s and learning task T_s to help improve the learning of the prediction function $f_t(\cdot)$ in the target domain, where $D_s \neq D_t$ or $T_s \neq T_t$.

2.3. Pre-training and Fine-tuning

In deep learning algorithms, the accuracy of prediction models largely depends on the effectiveness of training on the training dataset, necessitating the use of more training dataset data during the training phase. However, in practical applications of RUL prediction for lithium-ion batteries, prediction models need to exhibit good predictive performance across different battery degradation stages. Especially in early-stage battery prediction, where the

prediction starting point is set in the early degradation stage of the battery, the reduction in the volume of training dataset data affects the model's predictive accuracy.

To address the above issues, transfer learning is widely applied due to its ability to share information between the source domain and target domain [14]. In transfer learning, the source of transfer information is referred to as the source domain (Ds), and the destination of transfer information is the target domain (Dt). The purpose is to transfer features from the source domain dataset to the target domain dataset by using datasets with similar characteristics, thereby improving the performance of the model when predicting target domain data. As shown in Figure 2, the pre-training-fine-tuning transfer learning method first uses all data in the source domain as the training set to pre-train the LSTM and saves the pre-trained model. Then, by copying the information of the first N-1 layers of the pre-trained model, it is transferred to the target domain, and fine-tuning of the pre-trained model is performed using the training set of the target domain data. Finally, the pre-trained-fine-tuned LSTM model is used as the prediction model for the target domain data prediction.

During the capacity degradation process of different lithium-ion batteries, there are both common degradation trends of overall capacity decline and degradation characteristics caused by interfering factors such as changes in environmental temperature and differences between battery cells. Therefore, in the transfer of aging information, a pre-trained LSTM model suitable for the source domain batteries is first trained using source domain data. Subsequently, this pre-trained model is transferred to the target domain and fine-tuned using the training set of the target domain data, enabling the pre-trained model to be applicable to target domain batteries [12]. The pre-training-fine-tuning approach considers both the general characteristics of source domain batteries and the unique characteristics of target domain batteries, allowing the pre-trained model to pre-learn the general characteristics of battery aging before predicting battery RUL and indirectly expanding the training dataset, thereby improving the model's predictive accuracy for target domain batteries.

3. TL-LSTM-SIM Prediction Model Construction

3.1. The Method Framework of the TL-LSTM-SIM Model

As illustrated in Figure 3, the proposed framework for RUL prediction consists of two main components: Source Domain Battery Iterations Module (SIM): Multiple batteries with known full-lifetime capacity degradation data are initially utilized as source domain batteries for pre-training the LSTM model. Through multiple iterations, a pre-trained model with high predictive accuracy is obtained.

Prediction of Remaining Useful Life (RUL) for Target Domain Batteries: The optimal LSTM pre-trained model obtained from the source domain is transferred to the target domain. After fine-tuning using the target domain training set, the model predicts the capacity degradation curve for target domain batteries, subsequently calculating the RUL of the target domain batteries.

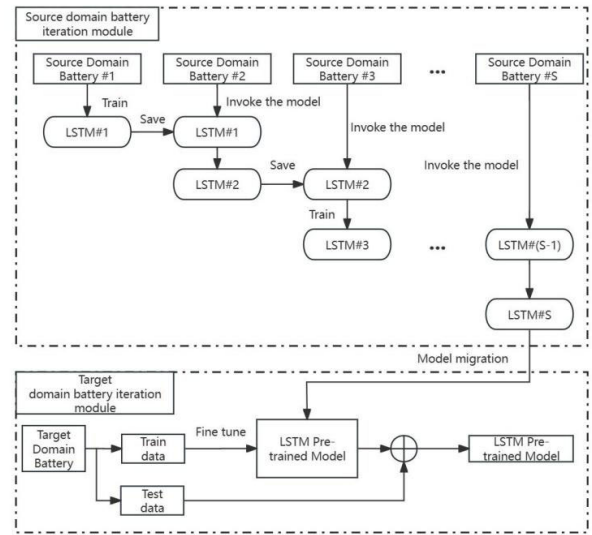


Figure 5. The framework of TL-LSTM-SIM method.

3.1.1. Source Domain Battery Iterations Module (SIM)

In conventional transfer learning, typically, a single-source domain battery data is used for model pre-training [12], resulting in significant discrepancies between source and target domain batteries, which greatly affect the predictive accuracy of the model. To address this issue, this paper introduces the Source domain battery Iterations Module (SIM) based on transfer learning (TL), which iteratively trains the LSTM model using capacity data from multiple lithium-ion batteries, and saves the optimal LSTM pre-trained model obtained during training, which is later invoked for predicting target domain batteries.

The training process of the SIM module is illustrated in Figure 3. Firstly, all capacity data of Source domain battery #1 are used as the training set to pre-train the LSTM model and saved as LSTM#1. Subsequently, all data of Source domain battery #2 are used as the training set to continue training LSTM#1, and LSTM#2 is obtained. This process continues until Source domain battery #S, achieving iterative training using multiple source domain batteries. During the iteration, except for the first source domain battery, subsequent batteries call upon the previously saved pre-trained model. Finally, the LSTM pre-trained model "LSTM#S" obtained after training is used as the output of the SIM module for the RUL prediction process. Through multiple experiments, this paper selects batteries N1-N7 from the MIT dataset as the source domain batteries used in the SIM module, i.e., after 7 iterations, the SIM module outputs the LSTM pre-trained model.

3.1.2. RUL Prediction

As shown in Figure 4, the RUL prediction process of the TL-LSTM-SIM model is depicted. The specific prediction process is as follows:

(1) Partitioning of source domain batteries and target domain batteries. The SIM module is constructed using batteries N1-N7 from the MIT dataset.

(2) Pre-training the LSTM model using the SIM module. The LSTM model is trained using all capacity data of source domain batteries, and after 7 iterations, the optimal LSTM pre-trained model is obtained.

(3) Transfer the optimal LSTM pre-trained model to the target domain and fine-tune the model using the target domain training set. With the prediction starting point (SP) as the

boundary, the capacity data of the target domain batteries are divided into training and testing sets, where the training set is used for fine-tuning the pre-trained model.

(4) Invoking the fine-tuned LSTM pre-trained model to predict the capacity of target domain batteries. The prediction ends when the capacity prediction curve descends to the end-of-life (EOL) point, and outputs the capacity prediction curve and the RUL prediction value. EOL corresponds to the number of cycles at the failure threshold of the lithium-ion battery. The RUL calculation formula is as follows:

$$RUL = EOL - SP \quad (9)$$

SP is the starting point.

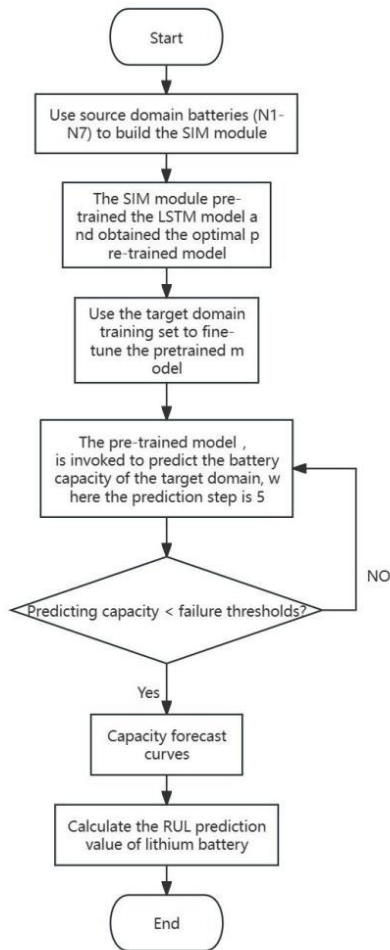


Figure 6. The RUL prediction process based on the TL-LSTM-SIM model.

3.2. Introduction of the experimental datasets

Validation of the algorithm's performance was conducted using two types of lithium-ion batteries with different electrode materials and aging environments. The first type of battery was sourced from the MIT dataset as described in reference [15]. This dataset comprises 124 sets of lithium-ion battery aging data, from which 8 batteries were selected for model construction and validation, designated as N1-N8. These batteries have a rated capacity of 1.1Ah and a rated voltage of 3.3V. The second type of battery was sourced from the CALCE dataset [16], and CS36 was chosen for model validation. These batteries also have a rated capacity of 1.1Ah and a rated voltage of 3.4V.

3.3. Experimental design and evaluation criteria

In terms of experimental design, we conducted research on the RUL prediction performance of the TL-LSTM-SIM model across three experimental groups, aiming to validate the predictive accuracy of the model by predicting different types of target domain batteries. All three experimental groups utilized the Source domain battery Iterations Module (SIM) for pre-training the LSTM model, with the construction of the SIM module using the N1-N7 data from the MIT dataset. To validate the predictive capability of the SIM module across different types of batteries, lithium-ion batteries from two categories of datasets were selected as the target domain batteries. The specific configurations of the experimental groups are shown in Table 1. In Experiment Group 1, the target domain battery N8 originates from the same dataset as the batteries used in constructing the SIM module. In existing studies, the RUL prediction starting point is typically set at either 30% or 50% of the capacity data [11].

To further test the model's RUL prediction performance during the early degradation stages of batteries, we selected the 20%, 30%, and 50% capacity data points of the target domain battery as the prediction starting points. The prediction starting points for each category of target domain batteries are presented in Table 2.

Table 1. Experimental groups of source-domain batteries and target-domain batteries.

Experimental group	Source domain battery	Target domain battery
1	Source Domain Battery Selection Module (SIM)	N8
2	Source Domain Battery Selection Module (SIM)	CS36

Table 2. Settings of start points for each stage.

Starting point of prediction	N8	CS36
20%	200	200
30%	300	300
50%	400	400

To evaluate the predictive accuracy of the model, root mean square error (RMSE), mean absolute error (MAE), and absolute error of the RUL prediction (RUL_{er}) are utilized as performance metrics for assessing both the capacity prediction curve and RUL prediction values. The formulas are as follows:

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^N (y_k - y_i)^2} \quad (10)$$

$$MAE = \frac{1}{N} \sum_{k=1}^k |y_k - y_i| \quad (11)$$

$$RUL_{er} = |RUL_{pr} - RUL_{tr}| \quad (12)$$

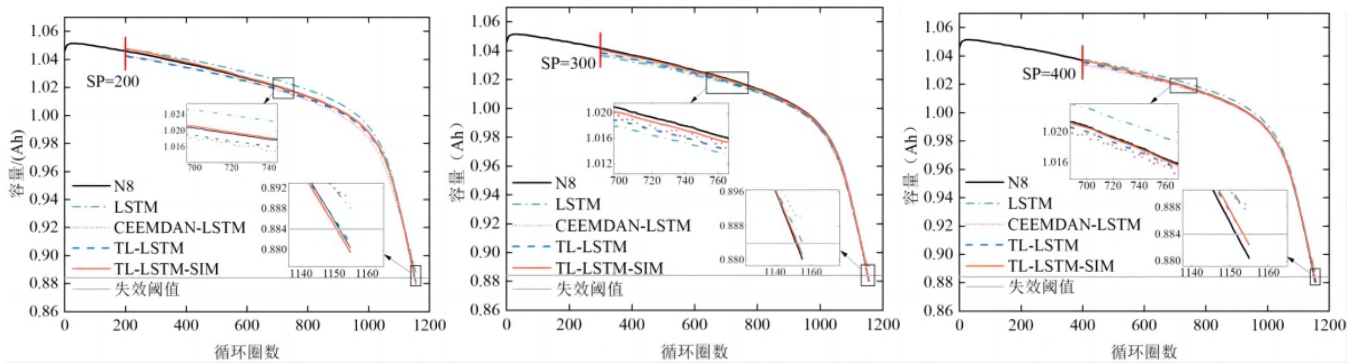
In the equation, N represents the number of prediction cycles, y_i denotes the actual capacity, y_k represents the predicted capacity, RUL_{pr} denotes the predicted Remaining Useful Life (RUL), and RUL_{tr} represents the actual RUL.

4. Interpretation

To validate the predictive performance of the TL-LSTM-SIM model proposed in this paper, we selected three RUL prediction models, namely LSTM, CEEMDAN-LSTM [11], and TL-LSTM [12], to jointly predict the RUL of target domain batteries in the three experimental groups listed in Table 2. Among them, the TL-LSTM algorithm only utilizes a single target domain battery for pre-training[13], while the model proposed in this paper utilizes the SIM module for pre-training. Each model predicts the RUL at three prediction starting points of 20%, 30%, and 50% for lithium-ion batteries, and the prediction results are compared and analyzed using three accuracy metrics: RMSE, MAE, and RULer.

As shown in Figure 6 and Table 4, the prediction results of each model for Experiment Group 1 are displayed, where the battery types in both source and target domains are identical.

It is noteworthy that the aging experiment of the MIT battery was terminated near the failure threshold. Therefore, if the predicted values fail to decrease to the failure threshold in a timely manner during capacity prediction, it is considered a prediction failure[14-18]. In Figure 6, the capacity prediction curves of the LSTM and CEEMDAN-LSTM models fail to decrease to the failure threshold before battery failure, hence they are deemed as prediction failures. In contrast, both TL-LSTM and TL-LSTM-SIM models successfully predict the RUL, with the prediction curve of TL-LSTM-SIM being closer to the actual curve. In Table 4, the RUL prediction fails for the LSTM and CEEMDAN-LSTM models, while the RULer (Remaining Useful Life error) for TL-LSTM and TL-LSTM-SIM are both less than 3. Furthermore, the root mean square error (RMSE) of the TL-LSTM-SIM model is significantly lower than that of other models, demonstrating superior performance.



(a) N8 battery, SP=200 (20%) (b) N8 battery, SP=300 (30%) (c) N8 battery, SP=400 (50%)
Figure 7. The capacity prediction curves for experimental group 1.

Table 3. Prediction results of experimental group 1 under different prediction start points.

Module	RMSE(Ah)	MAE(Ah)	RLpr	RULer
LSTM	0.0037	0.0036		
CEEMDAN-LSTM	0.0032	0.0030		
20%				
TL-LSTM	0.0022	0.002	953	
TL-LSTM-SIM	0.0009	0.0007	51	
LSTM	0.0032	0.0030		
CEEMDAN-LSTM	0.0024	0.0022		
30%				
TL-LSTM	0.0015	0.0014	854	
TL-LSTM-SIM	0.0007	0.0006	853	
LSTM	0.0025	0.0023		
CEEMDAN-LSTM	0.0016	0.0014		
50%				
TL-LSTM	0.0008	0.0007	54	
TL-LSTM-SIM	0.0004	0.0003	754	2

Figures 7 and 8 display the capacity prediction curves for Experiment Group 2 and Experiment Group 3, respectively. From Figures 7(a)-(c), it can be observed that in the predictions of Experiment Group 2, all four models exhibit relatively accurate capacity prediction curves. Particularly at

the 20% prediction starting point, the TL-LSTM and TL-LSTM-SIM models demonstrate the best fitting, indicating that the TL-LSTM-SIM model manifests its advantages more prominently in the early stages.

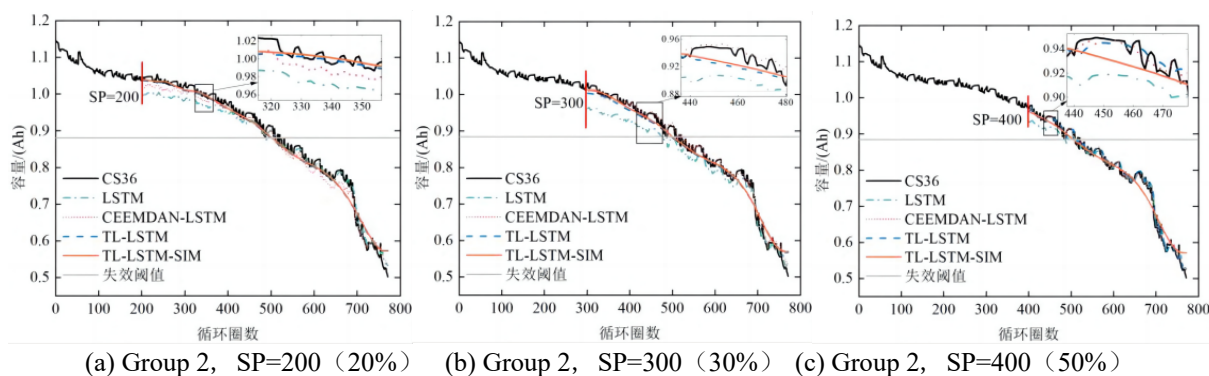


Figure 8. The capacity prediction curves for experimental group 2.

The results above demonstrate that TL-LSTM-SIM achieves promising performance in predicting the RUL of lithium-ion batteries under various conditions. Particularly, it maintains high prediction accuracy when dealing with batteries of different types. To further substantiate the

reliability of TL-LSTM-SIM in predicting the RUL of lithium-ion batteries, this study conducted 100 cycles of experiments for two groups, yielding the final results as shown in Table 4.

Table 4. TL-LSTM-SIM model 95% confidence interval prediction results.

Experimental group	1			2		
Starting point of prediction	200	300	400	200	300	400
96% confidence interval	[949,954]	[853,855]	[753,755]	[280,315]	[180214]	[86,114]

5. Conclusion

This paper proposes a TL-LSTM-SIM model based on transfer learning, which pre-trains the LSTM model by constructing the Source domain battery Iterations Module (SIM), and applies the optimized LSTM pre-trained model to predict the RUL of target domain batteries. Recognizing the limitations of existing transfer learning methods that solely rely on single-source domain battery data for model pre-training, this study introduces the SIM module to enable iterative training of the LSTM model using data from multiple source domain batteries. Subsequently, RUL predictions are conducted for batteries sourced from three open datasets, with prediction starting points set at 20%, 30%, and 50% respectively. Compared with other models, the TL-LSTM-SIM model demonstrates superior prediction accuracy across various battery types, particularly exhibiting significant advantages when predicting from a 20% starting point. The specific conclusions are as follows:

The proposed TL-LSTM-SIM model enhances the transfer learning approach by introducing the SIM module, enabling iterative pre-training of the LSTM model using full-lifetime capacity degradation data from multiple source domain batteries, thereby further improving prediction accuracy.

The TL-LSTM-SIM model achieves high prediction accuracy when predicting both same-type source and target domain batteries, as well as different types of batteries. In cases where the battery types are the same, the absolute error of RUL predictions is less than 2 cycles; while for different battery types, the RUL prediction errors are all less than 10 cycles except when predicting from a 20% starting point.

The TL-LSTM-SIM model maintains high prediction accuracy across different starting points, particularly demonstrating advantages during the early degradation stages of lithium-ion battery capacity compared to other algorithms.

In future research, the utilization of multi-source domain

transfer learning will be considered to extract aging characteristics from a wider range of battery types, aiming to further enhance prediction accuracy and ensure consistency in predicting various battery types.

Funding

This work was supported by “the Fundamental Research Funds for the Central Universities”, Southwest Minzu University (2022NYXXS096).

Acknowledgment

In particular, thanks to the NASA Ames Center of Excellence Diagnostic Center and MIT-Stanford-Toyota Research Center for providing the experimental data.

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