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An Improved Cascaded Forward Back Propagation Neural Network for State of Energy Estimation of Lithium-ion Batteries

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Abstract. The SOE of batteries is crucial for power system energy scheduling and new energy vehicle industry innovation, with scientific research significance. To achieve precise SOE estimation, this study introduces a data - driven high - precision SOE estimation model. First, a moving - average data enhancement technique is proposed to reduce noise and increase data diversity, improving estimation efficacy. Then, a Cascaded Forward Back Propagation Neural Network is built, and the ESC parameter optimization algorithm is used to optimize network weights and thresholds. Finally, the model is validated with CALCE battery team's public dataset. Experimental results show the model's superior performance: across different temperatures, MAE averages 0.015, MSE averages 0.0006, MAPE averages 2.29%, and R^2 averages 0.9828. The methodology's effectiveness is confirmed, providing a reliable reference for the new energy vehicle industry..

Keywords: Lithium-ion battery, State of Energy, Cascade Forward Back Propaganda Neural Network, Extremum Seeking Control for Parameter Optimization, State estimation.

1. Background and related work

Lithium-ion batteries, a relatively mature and prevalent technology in the realm of clean energy, have emerged as the preferred option for new energy vehicle batteries, attributed to its low production and maintenance costs, high energy density per unit, multiple cycling capabilities, minimal charge loss rates, and user-friendliness. Research endeavors in lithium-ion batteries are anticipated to steer, propel, and facilitate innovations, implementations, and advancements within the new energy vehicle industry. In the context of new energy vehicles, the battery energy state (SOE) constitutes a pivotal parameter, directly mirroring the residual available energy of the battery. Accurate estimation of SOE can not only augment the precision of vehicle range prediction, but also optimize the battery management system, and as well as enhance the safety and reliability profiles of new energy vehicles.

The State of Energy (SOE) functions as an indicator of a battery's residual energy, precisely representing the ratio of its current remaining energy (i.e., the energy that can be discharged) to its rated energy. Nevertheless, simultaneously, the SOE is distinguished by more complex models and

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demands a higher computational burden. The operation and iteration of the SOE reference value are shown as Formula (1).

$$\begin{cases} SOE = \frac{E_{now}}{E_n} \\ SOE_t = \frac{\eta \int_0^t U_t I_t dt}{E_N} + SOE_0 \end{cases} \tag{1}$$

In this formula, η represents the charging and discharging efficiency, which is usually taken as 1, E_{now} indicates the energy stored in the battery at this moment, E_N is the rated capacity of the battery, SOE_0 is the initial value of SOE.

From the perspective of research methods, the main ones are: direct calculation method, model-based method and data-driven estimation method. The three methods each have their advantages and disadvantages.

Table 1. Comparison of different SOE estimation methods

Method type	Specific examples	Advantages	Limitations
direct calculation method	power integration the AC impedance method the open-circuit voltage method	intuitive and easy to implement	can't actively mitigate errors difficult to obtain precise initial values for estimation other data, causing error accumulation
model-based method	electrochemical principle-based equivalent circuit-based	accurately understand the electrochemical reactions in lithium-ion batteries suitable for online real-time estimation	make real-time state estimation challenging
data-driven method	statistical learning machine learning	eliminating the need to consider the battery's electrochemical mechanism	needs a large amount of data

Previous research encompasses direct methods (e.g., voltage integration [1-2]), electrochemical models [3-4], and data-driven approaches (Kalman filters [5-6], LSTM [7-8]). Although these methods are effective, they encounter accuracy-complexity trade-offs that our method aims to address. Consequently, there exist certain improved estimation methods in relevant research that utilize data-driven techniques. The algorithm founded on the Neural Timedelta Kernel (NTK) and Unscented Kalman Filter (UKF) demonstrates favorable performance in multi-state estimation [9-10]. By incorporating adaptive filters for state estimation and adjusting parameters to mitigate noise interference, the robustness and accuracy of the model can be augmented under high-temperature and variable-load conditions [11-12]. Additionally, the Kepler Optimization Algorithm (KOA) can optimize the optimization index of lithium-ion batteries [13]. Optimizing polynomial coefficient parameters and the LM - SH - CKF algorithm can also enhance the accuracy and robustness of the model [14-15].

Generally speaking, the data-driven SOE estimation method has great research potential, with advantages like no need for complex mechanism modeling, strong adaptability, real-time execution and high multivariable coupling processing ability. However, it has shortcomings such as limited generalization ability, significant data dependence and complexity in long-term estimation. Therefore, this paper adopts the data-driven estimation method, specifically formulating the estimation method based on cascaded forward and backward propagation neural networks. This

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method is expected to achieve high accuracy and accurately determine the SOE of lithium-ion batteries without overly increasing the experimental workload.

This paper takes three common lithium-ion batteries as the research objects and conducts research on the target of accurately estimating the SOE of lithium-ion batteries. The main ideas and contributions are as follows.

Sample data from the CALCE battery team's public dataset were used, and a series of data preprocessing procedures were performed. These included grouping working conditions and setting a default initial SOE value of 1. Moreover, data enhancement processing was done on the current dataset, and the average slider data enhancement method was proposed. Data enhancement of the original data can increase dataset diversity, prevent overfitting, make the modeling effect more realistic, and maintain the integrity of the original data.

Based on the traditional BPNN model, the cascade forward mechanism is introduced and applied to lithium battery SOE estimation. This innovation breaks through traditional linear assumption constraints, accurately portrays battery dynamic characteristics, integrates diverse parameter inputs, mitigates the impact of noise and abrupt operating - condition changes, reduces reliance on mechanistic models, and adapts to slow time - varying processes like battery aging and cycle life degradation. As a result, it enables precise estimation of the battery's energy state.

To address the issue that specific parameter configurations of the Cascaded Forward Back Propagation Neural Network (CFBPNN) affect the estimation efficacy, the ESC parameter optimization algorithm is introduced. By combining data - driven methods with real - time feedback mechanisms, it enables adaptive parameter adjustments and parameter optimization during the SOE estimation process.

2. Mathematical analysis

2.1. Analysis of the overall estimation framework

The basic work content and process of this research are shown in the following figure.

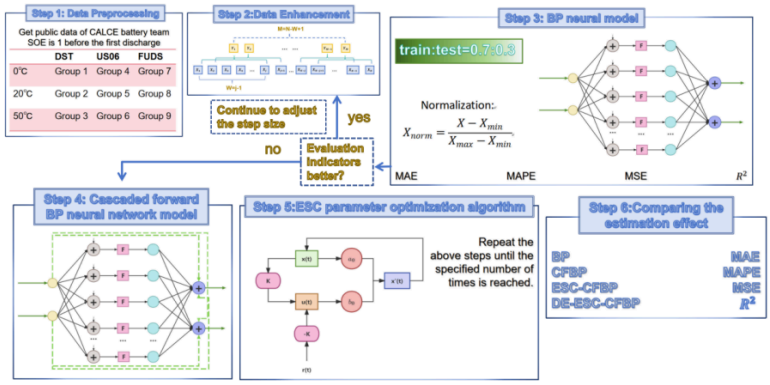


Figure 1. Flowchart of the overall estimation framework

2.2. Data enhancement method

The moving average data enhancement technique efficiently mitigates high-frequency noise, by computing the mean value of the data within a specified window, while preserving the low-frequency trend characteristics of the signal. The slider average data enhancement method is shown

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in Formula (2) as follows. Sliding-window averaging (w=700) reduces noise while preserving discharge trends.

$$y_i = \frac{1}{W} \sum_{j=0}^{W-1} x_{i+j} \tag{2}$$

This paper adopts the proposed method to perform data enhancement on the voltage data obtained from nine groups of operating conditions. Subsequently, the enhanced data and the non-augmented data were categorized into two primary groups, totaling 18 subsets, which were then incorporated into the respective models for estimating the SOE of lithium-ion batteries.

2.3. Hybrid optimization method

In this study, we use both Cascaded Forward Back Propagation Neural Network (CFBPNN) and ESC parameter optimization methods to optimize the model.

The CFBPNN is a special kind of feedforward structure. Its distinctive characteristic lies in the fact that the input of each layer is derived not only from the output of the preceding layer but also directly receives the original input signal, thereby forming a cascaded connection. This unique structure augments the model's capacity to preserve the original features and proves advantageous for learning intricate patterns. In this investigation, a cascading forward neural network was employed to directly acquire the original input signals pertaining to voltage and current, while concurrently utilizing the SOE output from the preceding layer as the input signal for the current layer. The outcomes indicate that the Cascading Forward Back Propagation Neural Network exhibits relatively precise estimation results for the SOE of lithium-ion batteries.

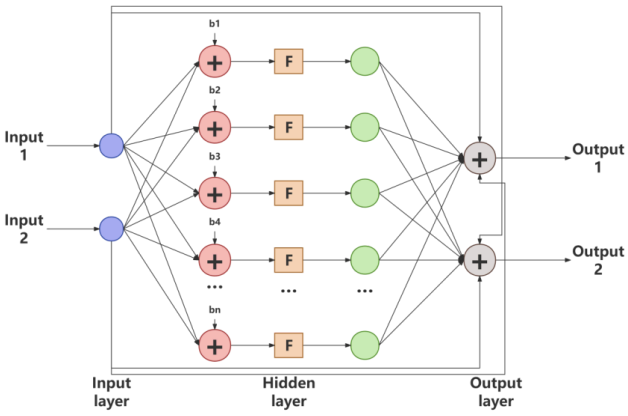


Figure 2. Cascaded Forward Back Propagation Neural Network model

The formula of the Cascaded Preceding Back Propagation Neural Network is as follows.

Suppose the cascaded forward back propagation neural network has multiple hidden layers, the output of the i-th neuron in the first hidden layer can be obtained as shown in Formula (3).

$$y_{2,j} = f_2\left(b_{2,j} + \sum_{i=1}^{M} w_{2,i}\left(f_1\left(b_{1,i} + \sum_{i=1}^{N} w_{1,i}x_i\right)\right) + \sum_{j=1}^{N} w_{j,1}x_j\right) \tag{3}$$

ESC represents a potent real - time optimization methodology. Its purpose is to select the system's initial state and control input to pursue the optimal matching coefficient. The core advantage of ESC resides in its capacity to adjust system parameters online and adaptively, thereby attaining the

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optimal performance. This algorithm does not necessitate an exact system model. It measures the response of system performance indicators in real - time by superimposing minuscule periodic detection disturbances on the operating parameters. The crucial adaptive mechanism is as follows: the algorithm continuously analyzes the phase/amplitude relationship between the disturbance and the response and, accordingly, automatically and dynamically adjusts the controller parameters. This adaptive parameter adjustment empowers ESC to automatically track the system's optimal operating point. Even when the system's dynamic characteristics or the optimal set - point vary over time, it can sustain efficient and robust optimization performance, significantly enhancing the system's autonomous adaptability.

3. Experimental analysis

Given the extensive content and substantial volume of data within the CALCE Battery team's public dataset, this paper primarily focuses on selecting three typical experimental conditions for lithium-ion batteries: DST, FUDS, and US06. Additionally, data collected at temperatures of 0℃, 20℃, and 50℃ are considered and further categorized into nine groups of conditions. When other scholars employ various models for estimation and modeling, they commonly observe that incorporating data enhancement and parameter optimization algorithms can enhance the accuracy of estimation results. Consequently, this paper also adopts data enhancement and ESC parameter optimization algorithms, integrating them with the CFBPNN model to achieve more precise estimation results for the SOE of lithium-ion batteries.

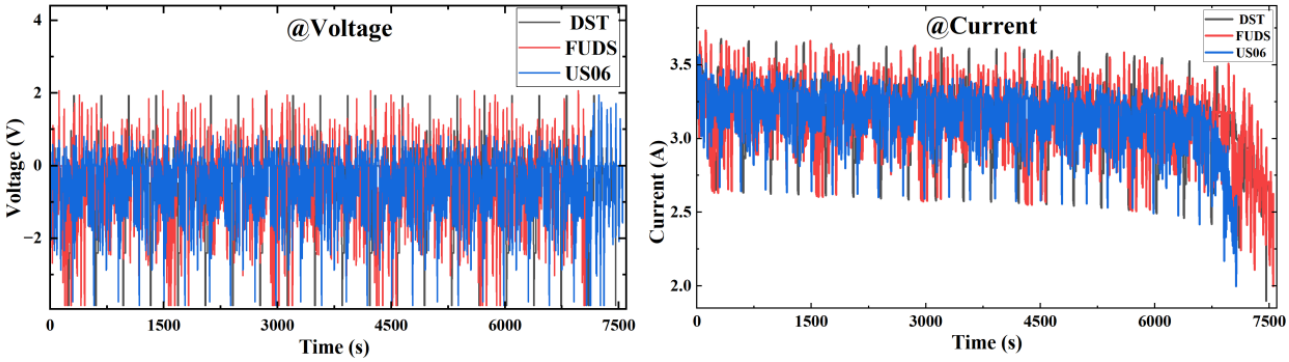


Figure 3. Original data of voltage and current under partial working conditions

Set different slider sizes, insert the enhanced data into the BPNN model, analyze and compare four evaluation indicators. Following a preliminary evaluation, it is observed that when the slider size is set to 700, the data enhancement effect is optimal. Under the vast majority of operational conditions, with a slider size of 700, the R2 value of the BPNN model typically exceeds 0.97. However, there is a slight deficiency in some data pertaining to the FUDS operational condition, with an R2 value hovering around 0.93.

The SOE estimation results and errors under 20℃ of DST/US06/FUDS conditions are shown in Figures 4 to 6.The data results of 0 ℃ and 50 ℃ are similar to those of 20 ℃.

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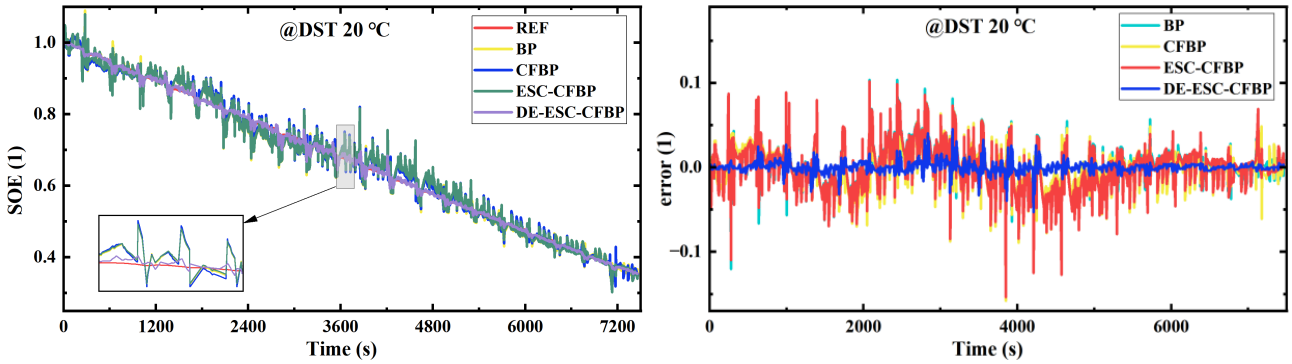


Figure 4. Estimation results and errors of DST working condition at 20℃

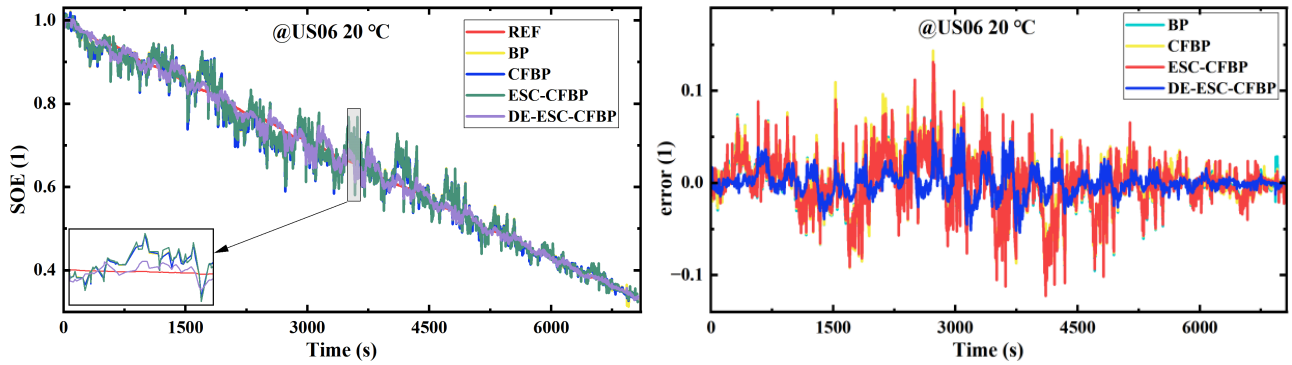


Figure 5. Estimation results and errors of US06 working condition at 20℃

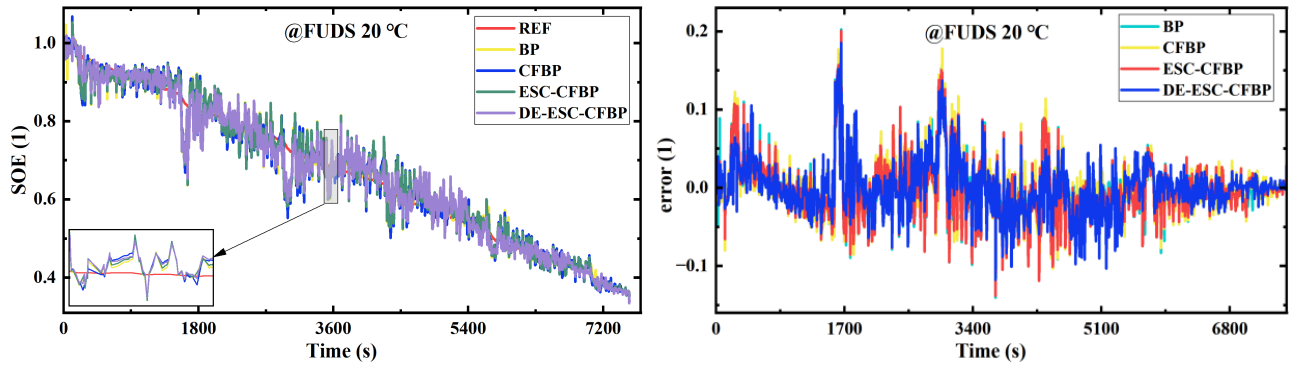


Figure 6. Estimation results and errors of FUDS working condition at 20℃

Owing to the complexity of classifying diverse working conditions and the diversity of evaluation indices, the evaluation indices for all working conditions are presented herein in the form of a composite table. In comparison with naked - eye observation, the comparison table can more clearly reflect the estimation capability of the model under different working conditions. The four evaluation indices for all working conditions are presented in Table 2. Through this composite table, we can make a single-level comparison of different temperatures, different models, different battery types and different evaluation angles, and we can also make an overall evaluation by integrating multiple dimensions. By comparing the evaluation indices of different working conditions, numerous novel findings have been obtained.

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Table 2. Comparison table of evaluation indexes for all working conditions

	DST	0℃	20℃	50℃	FUDS	0℃	20℃	50℃	US06	0℃	20℃	50℃
BP	MAE	0.0247	0.0201	0.0215	MAE	0.0336	0.0239	0.0253	MAE	0.0325	0.0218	0.0220
	MAPE	3.63%	3.03%	3.50%	MAPE	5.04%	3.48%	4.07%	MAPE	4.99%	3.28%	3.56%
	MSE	0.0012	0.0007	0.0009	MSE	0.0024	0.0013	0.0012	MSE	0.0018	0.0009	0.0009
	R^2	0.9595	0.9192	0.9803	R^2	0.9237	0.9608	0.9718	R^2	0.9457	0.9747	0.9811
CFBP	DST	0℃	20℃	50℃	FUDS	0℃	20℃	50℃	US06	0℃	20℃	50℃
	MAE	0.0244	0.0193	0.0232	MAE	0.0321	0.0265	0.0244	MAE	0.0316	0.0220	0.0230
	MAPE	3.62%	2.86%	3.94%	MAPE	4.78%	3.92%	3.87%	MAPE	4.87%	3.32%	3.82%
	MSE	0.0012	0.0006	0.0010	MSE	0.0023	0.0014	0.0011	MSE	0.0017	0.0009	0.0009
	R^2	0.9607	0.9808	0.9779	R^2	0.9277	0.9568	0.9731	R^2	0.9477	0.9745	0.9799
ESC-CFBP	DST	0℃	20℃	50℃	FUDS	0℃	20℃	50℃	US06	0℃	20℃	50℃
	MAE	0.0266	0.0210	0.0223	MAE	0.0346	0.0243	0.0239	MAE	0.0311	0.0211	0.0197
	MAPE	4.00%	3.17%	3.59%	MAPE	5.18%	3.56%	3.73%	MAPE	4.99%	3.19%	3.24%
	MSE	0.0013	0.0008	0.0009	MSE	0.0026	0.0013	0.0011	MSE	0.0017	0.0009	0.0008
	R^2	0.9554	0.9779	0.9792	R^2	0.9209	0.9607	0.9731	R^2	0.9482	0.9760	0.9833
DE-ESC-CFBP	DST	0℃	20℃	50℃	FUDS	0℃	20℃	50℃	US06	0℃	20℃	50℃
	MAE	0.0183	0.0042	0.0069	MAE	0.0286	0.0229	0.0224	MAE	0.0106	0.0098	0.0131
	MAPE	2.70%	0.63%	1.10%	MAPE	4.21%	3.41%	3.52%	MAPE	1.57%	1.46%	2.07%
	MSE	0.0008	0.0001	0.0003	MSE	0.0017	0.0010	0.0009	MSE	0.0002	0.0002	0.0004
	R^2	0.9731	0.9987	0.9929	R^2	0.9454	0.9676	0.9778	R^2	0.9934	0.9949	0.9913

The estimation performance under the FUDS working condition is marginally inferior to that of the other two operational modes. And it can be observed that the CFBPNN, when enhanced with data and integrated with the ESC optimization parameter algorithm, exhibits superior estimation conditions across diverse working scenarios in comparison to other configurations. Notably, the fitting efficacy subsequent to data enhancement has undergone substantial enhancement. This disparity may be attributed to the initial suboptimal efficacy of the data enhancement component.

Examining the combined error graph, errors of various models are generally comparable. However, the ESC parameter optimization algorithm with data enhancement and cascading precursors can limit errors to a narrower margin. Specifically, DST at 20°C and 50°C, US06 at 0°C and 20°C, and FUDS at 0°C and 20°C perform better. This may be because at these temperatures, the battery's internal chemical reactions can maintain a better degree and rate. Conversely, under other conditions, unsuitable temperatures may lead to inadequate reaction effects and inaccurate estimation results.

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The average MAPE values are 0.0413, 0.0294, and 0.0333 respectively, and the estimation accuracy is best at 20℃, which supports the above conclusion. The average MSE index values at 0℃, 20℃, and 50℃ are 0.0016, 0.0015, and 0.0016 respectively, showing a further narrowing of the disparity. Evidently, the model's estimation performance is relatively stable across different temperatures and has a wide range of applications. The average coefficient of determination (R^2) values at the three temperatures are 0.9506, 0.9752, and 0.9806 respectively, suggesting that the model can better interpret abnormal data and achieve better estimation results at higher temperatures.

Therefore, in future research, we can try to focus on controlling the battery working temperature, which may improve the service life and other properties of lithium - ion batteries.

It can be observed from the evaluation index graphs pertaining to these distinct working conditions that the incorporation of the cascade forward mechanism, the implementation of data enhancement, and the introduction of the ESC parameter optimization algorithm within the Back Propagation Neural Network (BPNN) model all exert certain influences on the estimation results of the SOE for lithium-ion batteries. The DE-ESC-CFBP model, which is the focus of this research endeavor, demonstrates a favorable SOE estimation performance. Precisely, the average value of the Mean Absolute Error (MAE) evaluation index across the three temperature settings in the BPNN is 0.0232. Upon the introduction of the cascade forward mechanism, this average value increases slightly to 0.0252, albeit within a very narrow range. Notably, the MAE evaluation index exhibits a relatively high sensitivity to interference, thereby accounting for scenarios where the MAE does not decrease but rather increases under certain operational conditions. Following the integration of the ESC parameter optimization algorithm, the average MAE values decrease to 0.0249. With the utilization of enhanced data, the average MAE further diminishes to 0.0152, indicating a marked improvement in estimation accuracy.The results of MAPE are basically the same as those of MAE.

The average values of the coefficient of determination (R^2) for the four groups of evaluation indices are 0.9641, 0.9643, 0.9639, and 0.9828, respectively. These findings suggest that, while incorporating the cascaded forward mechanism into the model may increase data fluctuation, it enhances the model's capacity to explain abnormal data scenarios. The addition of the ESC parameter optimization algorithm mitigates the data fluctuation augmentation induced by the cascaded forward mechanism. Ultimately, the introduction of slider average data enhancement, which further enriches the data sample, optimizes the estimation effect to its peak performance.

4. Conclusion

Our hybrid model demonstrates temperature-robust SOE estimation (R^2>0.98) through cascaded feature learning and adaptive optimization, which provides a new idea and scheme for this topic. Future work will explore multi-battery systems and thermal compensation.

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