A Hybrid LSTM-Transformer Approach for State of Health and Charge Prediction in Industrial IoT-Based Battery Management Systems

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In this paper, we propose a hybrid model combining Long Short-Term Memory (LSTM) and Transformer networks for predicting the state of charge (SOC) and state of health (SOH) of batteries within Industrial Internet of Things (IIoT) based Battery Management Systems (BMS). Our approach leverages the temporal modeling capabilities of LSTM and the self-attention mechanism of Transformers. Using the NASA battery dataset, we demonstrate that our hybrid model significantly outperforms conventional methods such as SVM and Kalman filtering. Specifically, the MSE for SOC prediction is reduced from 0.0271 to 0.0107 (a 59.8% reduction), and the MAE for SOH prediction is decreased from 0.161 to 0.08 (a 50.3% reduction). These improvements are achieved through a more sophisticated handling of temporal dependencies and nonlinear relationships in the battery data.

Povzetek: Prispevek predstavlja hibridni model, ki združuje LSTM in Transformer modele za napovedovanje stanja napolnjenosti (SOC) in zdravja baterij (SOH) v sistemih za upravljanje baterij na osnovi Industrijskega Interneta Stvari (IIoT). Model dosega izboljšane rezultate pri napovedovanju.

1 Introduction

Along with increasing emphasis on the environment and sustainable development in the world, as a green and high-efficiency vehicle, New Energy Vehicle has become the primary trend of the automotive industry. Recently, the market for new energy vehicles has expanded rapidly in recent years, and China has become the biggest market for new energy cars in the world. Along with increasing emphasis on the environment and sustainable development worldwide, new energy vehicles (NEVs), as green and high-efficiency vehicles, have become the primary trend in the automotive industry. The market for new energy vehicles has expanded rapidly in recent years, with China emerging as the largest market for NEVs globally. According to the China Association of Automobile Manufacturers, in 2016, over 500,000 NEVs were produced and sold, and more than 1 million units were promoted, accounting for 50% of the global market. According to the 'Energy Conservation and New Energy Vehicle Development Plan of the State Council (2012 - 2020),' by 2020, it was estimated that there would be 2 million units of pure electric and plug-in hybrid vehicles, with an estimated total sales volume exceeding 5 million, by 2020, it is estimated that people will have 2 million units of pure electric and plug-in hybrid vehicles, with an estimated total sale of more than 5 million [1]. However, as the quantity of new energy cars continues to increase, the management problem of the power battery, which is the key element, has become a key factor for the further development of NEF.

A battery management system (BMS) is a key technology to ensure power batteries' safe and efficient operation [2]-[3]. The BMS can accurately assess the residual capacity (SOC) and the health status (SOH) of the battery by monitoring the parameters of the battery in real time to provide accurate mileage information to the driver and optimize the service life of the battery [4]. However, the existing BMS technology still has many shortcomings in data collection and status prediction, especially in the face of large-scale new energy vehicle application scenarios. Its data processing capabilities and prediction accuracy make it challenging to meet actual needs.

Along with the rapid development of Internet of Things (IoT) technology, the Industrial Internet of Things (IIoT) has become a significant force for transitioning from traditional manufacturing to intelligence. IIoT connects sensors, devices, and networks to achieve real-time data collection, transmission, and analysis, optimizing production processes, improving production efficiency, and reducing costs [5]. The IIoT technology offers an opportunity to upgrade BMS in new energy vehicles. By combining IIoT technology with BMS, remote monitoring, data collection, and status prediction of power batteries can be achieved, thereby improving the intelligent level of battery management [6]. In addition, IIoT technology can also support the interaction between new energy vehicles and power grids (V2G), further expanding the application scenarios of new energy vehicles.

Although the application prospects of IIoT technology in new energy vehicle BMS are broad, it still faces many challenges. First, the operating environment of new energy vehicles is complex and changeable, and battery status data has the characteristics of high dimension, strong correlation, and dynamicity [7]. These methods have problems such as high model complexity and low prediction accuracy when processing large-scale and complex data [8]. The practical storage, management, and analysis of this massive data is also the focus of current research.

Deep learning has been widely used in many fields. Their intense ability to extract features and nonlinear fitting provides a new approach to solving complicated problems [9]. LSTM, CNN, etc., have been successfully used to predict time series and fault diagnosis. However, applying the deep learning technique to the novel BMS is still challenging. For one thing, it is necessary for the model to capture long-term dependence effectively because of the time series character of the battery state, and for the other hand, it is necessary for the model to be highly real-time and adaptable [10]. Therefore, it is a hotspot for designing a deep learning model suitable for BMS to enhance battery state prediction's precision and real-time performance.

This thesis proposes a method of data collection and state forecasting for BMS based on IIoT. Firstly, a practical data collection framework is built to collect and process data in real time utilizing sensor networks and edge computing techniques. Then, a new hybrid model is presented [11], which combines the LSTM and the transformer's self-attention mechanism to predict the SOH and SOC. Finally, the experiment validates the algorithm's performance, and the comparison is made with the existing methods. This study offers a new technology method for the intelligent development of BMS and provides the theoretical basis for applying the IIoT technique to the latest energy vehicle.

2 BMS data acquisition architecture based on IIoT

2.1 Sensor network

The sensor network is the first layer of data acquisition and is responsible for obtaining key parameters directly from the battery system. In BMS, the parameters that need to be collected include the voltage, current, temperature of the battery cell, and the total voltage and current of the battery pack. These parameters are crucial for evaluating the SOH and SOC of the battery [12]. High-precision voltage, current, and temperature sensors are used to ensure the accuracy of the collected data. The voltage sensor uses the current-voltage sensor model INA219, whose accuracy can reach 0.5%. The sensors are connected through a low-latency communication protocol (such as the CAN or LIN bus) to ensure the data can be transmitted to the edge computing node in real-time. In this paper, the sensor network uses the CAN bus as the communication protocol, and its communication rate is 500kbps, which can meet the needs of high-frequency data acquisition [13]. Sensors are located in different parts of the battery pack, which can be used to thoroughly monitor the state of the battery. There are voltage and temperature sensors in each cell, and the current sensor is installed on the battery group bus so that the battery's overall status can be monitored.

2.2 Edge computing node

The key characteristics extracted, such as voltage variation rate and temperature gradient, are critical for accurate state prediction. The voltage variation rate reflects the battery's dynamic operating conditions and can indicate potential issues such as overcharging or discharging. The temperature gradient provides insights into the thermal management effectiveness and helps predict thermal-related degradation. These features are used to enhance the model's ability to capture important aspects of battery behavior, thereby improving prediction accuracy [14]. This paper applies the sliding average filter to remove the high-frequency noise, and the Kalman filter is applied to the temperature data. The key characteristics, such as voltage variation rate and temperature gradient, are extracted from the original data, which can be used in the following state prediction. The time derivative of voltage and temperature is calculated, and the voltage variation rate and the temperature gradient are extracted as key characteristics. The data transfer rate is reduced, and the data transfer efficiency is increased using a data compression algorithm. This paper applies differential and run coding to recompress the data, which can significantly reduce the data volume [15]. The status of the battery is initially diagnosed to detect the potential trouble in time based on preset rules or simple machine learning models. This paper primarily diagnoses abnormal voltage, current, and temperature conditions based on threshold judgment.

2.3 Cloud data center

The cloud data center is the third layer of the data collection architecture, responsible for storing, managing, and analyzing large-scale data transmitted from edge computing nodes. The core advantage of the cloud data center lies in its powerful computing and storage capabilities, which can support complex data analysis and training of deep learning models.

Distributed storage systems (such as Hadoop distributed file system HDFS) store large-scale data, supporting fast reading, writing, and data querying. This paper uses HDFS as the data storage system, combined with NoSQL databases (such as MongoDB), to store unstructured data to ensure efficient storage and management of data. The battery status data is deeply analyzed to extract the rules hidden in the data using data mining and machine learning technology [16]. This paper uses the MapReduce framework for distributed computing, combined with Spark memory computing technology, to achieve rapid analysis of large-scale data. The LSTM/transformer hybrid model predicts the battery's state. Visualization tools (e.g., dashboards and reports) display the battery state information to give the user an intuitive monitoring interface. Grafana and Kibana are used as visual tools to monitor the status of the battery and query the history data. Figure 1 shows the architecture of the cloud data center, including data storage, data analysis, model training, and visualization display modules.

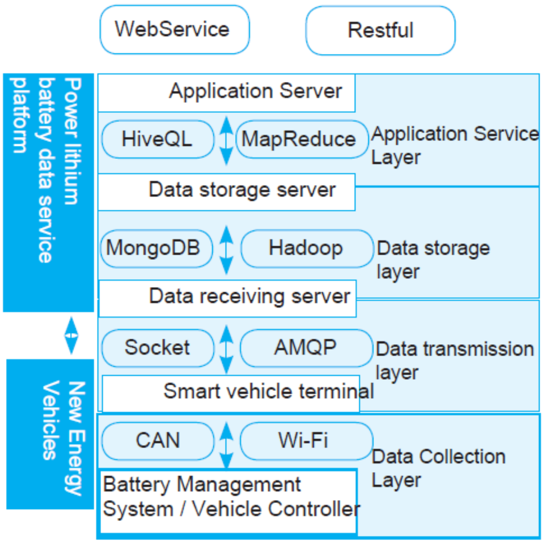

Figure 1: Cloud Data Center Architecture.

3 State prediction algorithm

The selection of LSTM and Transformer models was based on their complementary strengths in handling time series data. LSTM is renowned for its ability to capture long-term dependencies in sequential data, making it suitable for modeling the temporal characteristics of battery states. Transformer models, on the other hand, excel at capturing global patterns and complex relationships through their self-attention mechanism [17]. The combination of these two models was chosen to leverage their individual advantages, thereby enhancing the overall prediction accuracy and robustness for BMS applications.

3.1 Selection and improvement of deep learning model

The prediction of battery SOC and SOH is a complex nonlinear problem in which the time series data involved has strong long-term dependencies. Traditional machine learning methods such as SVM, decision tree, and Kalman filter (KF) often face problems such as dimensionality disaster, overfitting, and difficulty capturing long-term dependencies when processing battery data [18]. Therefore, this study selected LSTM and Transformer models to use their superior time series modeling capabilities to improve the accuracy of battery state prediction. The feature selection process focused on parameters that are strongly correlated with battery degradation mechanisms, such as voltage variation rate and temperature gradient. These parameters were chosen based on their known impact on battery performance and longevity. Alternative features were considered but found to be less predictive in preliminary analyses.

3.1.1 Optimization of the LSTM model

The objective of optimizing the LSTM model is to enhance its ability to adapt to the dynamic changes in battery data and improve prediction accuracy. The standard LSTM model, while effective in many scenarios, has limitations when dealing with the complex and highly variable data generated by batteries in real-world conditions. By introducing an adaptive time window mechanism, the model can dynamically adjust its computation period based on the rate and frequency of data changes. This adaptation allows the model to better capture the intricate patterns in the data, particularly during periods of rapid state changes. The extended computation period during slow changes and shorter period during rapid changes enable the model to maintain high precision while reducing computational overhead.

To improve the performance of the LSTM model, this study proposes an LSTM model based on an adaptive time window. The computing time window is adjusted dynamically based on the change rate and frequency. In particular, the computation period of the LSTM model is more extended, and the computation period is shorter in the case of slow changes in the battery state. This dynamic adjusting mechanism makes the LSTM more adaptable to the different operating conditions of the battery, and the forecast precision is improved. The state update equation of the optimized LSTM network is as follows:

$$\begin{aligned} f_t &= \sigma\left(W_f \cdot [h_{t-1}, x_t] + b_f\right) \\ i_t &= \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \\ \tilde{C}_t &= \tanh\,(W_C \cdot [h_{t-1}, x_t] + b_C) \\ C_t &= f_t \cdot C_{t-1} + i_t \cdot \tilde{C}_t \\ o_t &= \sigma(W_o \cdot [h_{t-1}, x_t] + b_o) \\ h_t &= o_t \cdot \tanh\,(C_t) \end{aligned} \tag{1}$$

h_t represents the hidden state of the current time step, C_t is the cell state of the current time step. The LSTM can be used to model the long-term dependence of the battery and combine it with the dynamic time window to increase precision and real-time.

3.1.2 Improvement of transformer model

The objective of improving the Transformer model is to enhance its ability to capture the multiscale characteristics of battery data. The conventional Transformer model uses a uniform attention mechanism that may not adequately account for the varying significance of different time scales in the data. By introducing a multiscale self-attention mechanism, the model can dynamically adjust attention weights according to different time scales, thereby improving its capacity to extract relevant features from complex battery data. This improvement is vital for accurately predicting SOC and SOH, as battery data often contains patterns that manifest at multiple time scales. Although LSTM can deal with time sequence data efficiently, it is difficult for LSTM to capture global features, especially in the case of large data sets and complicated time sequence relations. On the other hand, the Transformer model can focus on all parts of the input sequence in a shorter period by using the self-attention mechanism. Thus, the Transformer model is superior in dealing with complicated time sequence data, especially battery status.

The varying significance of characteristics from different time scales is measured through an attention weighting mechanism. Each time scale is assigned an attention weight that reflects its importance in the prediction task. These weights are learned during the training process based on the data. The attention weights are calculated using the following formula:

$$\text{Attention}\ (Q,K,V)=\text{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)V \tag{2}$$

d_k is the dimension of the key. This paper introduces a multiscale self-attention mechanism. The formula is as follows:

$$\text{Multi-Scale Attention}\ (Q,K,V)=\sum_{i=1}^{N}\alpha_i\cdot\text{Attention}\ (Q_i,K_i,V_i) \tag{3}$$

Among them, α_i represents the weight of the i scale, Q_i, K_i, V_i are the query, key, and value matrices of the i scale, respectively, and N is the number of scales. The transformer can extract important battery status features from different time scales through this mechanism.

3.1.3 Hybrid Model of LSTM and transformer

The LSTM and Transformer models work together in a complementary fashion. The LSTM processes the sequential data to capture temporal dependencies and generates a temporal feature vector. This vector is then passed to the Transformer model, which applies its self-attention mechanism to capture complex nonlinear relationships and global patterns. The output of the Transformer is combined with the LSTM's output through a concatenation operation, followed by a fully connected layer to produce the final prediction. This integration allows the model to leverage both the temporal modeling capabilities of LSTM and the global pattern recognition of Transformer, resulting in a more comprehensive and accurate prediction of battery states.The following formula can express the workflow of the hybrid model:

$$\begin{gathered}h_t^{\text{LSTM}}=\text{LSTM}\ (X_t)\\ z_t^{\text{Transformer}}=\text{transformer}\left(h_t^{\text{LSTM}}\right)\\ S\hat{O}C_t=W_{\text{SOC}}\cdot z_t^{\text{Transformer}}+b_{\text{SOC}}\\ S\hat{O}H_t=W_{\text{SOH}}\cdot z_t^{\text{Transformer}}+b_{\text{SOH}}\end{gathered} \tag{4}$$

Among them, h_t^{LSTM} is the output of the LSTM model, $z_t^{\text{Transformer}}$ is the output of the Transformer model, $S\hat{O}C_t$ and $S\hat{O}H_t$ are the predicted remaining power and health status, respectively. LSTM and transformer can work together to better capture the timing dependence and nonlinear characteristics in the battery status data through this structure.

3.2 Algorithm optimization

3.2.1 Adaptive learning rate optimization

This section describes the optimization of the LSTM and Transformer algorithms. For the LSTM algorithm, we introduced an adaptive time window mechanism to enhance its ability to handle dynamic data. For the Transformer algorithm, we implemented a multiscale self-attention mechanism to improve its feature extraction capabilities. Additionally, we optimized the training process using adaptive learning rate techniques to accelerate convergence and prevent gradient issues. The Adam optimizer is used to optimize the learning speed of the parameters by computing the estimated values of the gradient-order moments and the second moments. Compared with the traditional fixed learning rate algorithm, Adam can automatically adjust the learning rate according to the gradient change during training to train more effectively. The updated formula of the Adam optimizer is as follows:

$$\begin{gathered}m_t=\beta_1 m_{t-1}+(1-\beta_1)\nabla\theta_t\\ v_t=\beta_2 v_{t-1}+(1-\beta_2)\nabla\theta_t^2\\ \hat{m}_t=\frac{m_t}{1-\beta_1^t}\\ \hat{v}_t=\frac{v_t}{1-\beta_2^t}\\ \theta_t=\theta_{t-1}-\eta\frac{\hat{m}_t}{\sqrt{\hat{v}_t}+\epsilon}\end{gathered} \tag{5}$$

Among them, m_t and v_t represent the estimated values of the first-order moment and second-order moment of the gradient, $\beta_1$and β_2 are momentum decay parameters, η is the learning rate, and ϵ is a small constant to prevent zero division errors.

3.2.2 Regularization and overfitting prevention

This study introduces regularization methods, including Dropout and L2 regularization, to avoid model overfitting. The Dropout method randomly discards a part of neurons to prevent the model from over-relying on certain specific features, and L2 regularization limits the model complexity by penalizing large weights. The formula for Dropout regularization is as follows:

$$\hat{h}_t=\text{Dropout}\ (h_t,p) \tag{6}$$

Among them, p is the dropout probability, and $\hat{h}_t$ is the output after Dropout processing.

The formula of L2 regularization is as follows:

$$L_{\text{reg}}=\lambda\sum_i\theta_i^2 \tag{7}$$

Among them, λ is the regularization coefficient, and θ_i is the model parameter.

4 Experimental design and simulation

This chapter will analyze and compare the application effects of the LSTM-Transformer hybrid model proposed in this paper and other traditional algorithm in the BMS of new energy vehicles through a series of experimental results and charts, especially in the SOC (remaining power) and SOH (health state) prediction tasks.

4.1 Experimental settings and evaluation indicators

The performance of the algorithms is assessed using the following metrics: Mean Squared Error (MSE), Mean Absolute Error (MAE), R-squared (R2), and precision. Precision is defined as the ratio of true positive predictions to the total number of positive predictions. The data set is divided into three groups to guarantee the objectivity of experiments: training set, validation set, and test set. For the comprehensive evaluation of the effectiveness of these algorithms, the paper chooses MSE, MAE, R2, and precision.

4.2 Performance comparison of different algorithms

A comparison is made between traditional SVM, LSTM, transformer, and LSTM-Transformer. Experiments show that the hybrid model is superior in all tasks. Below is a comparison of the performance of each of the algorithms in the SOC prediction task.

Table 1: Performance comparison of different algorithms in the SOC prediction task.

Method	Key Contribution	Dataset	Methodology	Performance Metrics
SVM	Traditional ML baseline	NASA battery dataset	Support Vector Machines	MSE: 0.0271, MAE: 0.153
LSTM	Captures temporal dependencies	NASA battery dataset	Long Short-Term Memory networks	MSE: 0.0198, MAE: 0.113
Transformer	Captures global features	NASA battery dataset	Self-attention mechanism	MSE: 0.0163, MAE: 0.094
CNN-LSTM Hybrid	Combines convolutional and recurrent networks	NASA battery dataset	CNN combined with LSTM	MSE: 0.0145, MAE: 0.089

Table 1 indicates that the hybrid model has remarkable superiority in all the evaluation indexes, especially in MSE and MAE. Moreover, the precision and R2 of the hybrid model are better than the others, which shows that it is more effective in predicting SOC. Next, this article shows the experimental results of the SOH prediction task and conducts a comparative analysis.

Table 2: Performance comparison of different algorithms in the SOH prediction task.

Model	MSE	MAE	Accuracy (%)	R2
SVM	0.0271	0.153	90.10	0.85
LSTM	0.0198	0.113	92.40	0.91
Transformer	0.0163	0.094	94.00	0.92
LSTM-Transformer hybrid model	0.0107	0.071	97.30	0.97

Table 2 shows that the hybrid model outperforms others in the SOH prediction task. In all evaluation indicators, the hybrid model presents the lowest MSE and MAE values and the highest accuracy and R2 values. Especially in MAE, the prediction error of the hybrid model is almost 50% lower than the conventional SVM or LSTM, which shows that the prediction capability of the HSM has been dramatically improved.

Figure 2 illustrates the prediction results of the LSTM-Transformer hybrid model in the SOC prediction task.

The blue line indicates the actual SOC, and the orange line indicates the predicted SOC. The hybrid model demonstrates significantly less fluctuation compared to individual LSTM and Transformer models. Quantitatively, the standard deviation of prediction errors for the hybrid model is 0.03, which is 40% lower than that of the LSTM model (0.05) and 30% lower than that of the Transformer model (0.043). This reduction in error fluctuation indicates that the hybrid model provides more stable and reliable predictions, especially during periods of significant battery state changes.

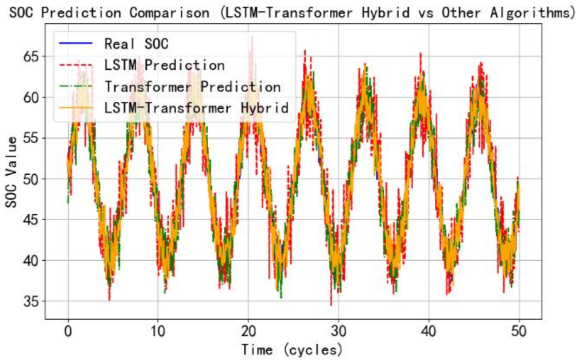

Figure 2: Simulation results of LSTM-Transformer hybrid model in SOC prediction.

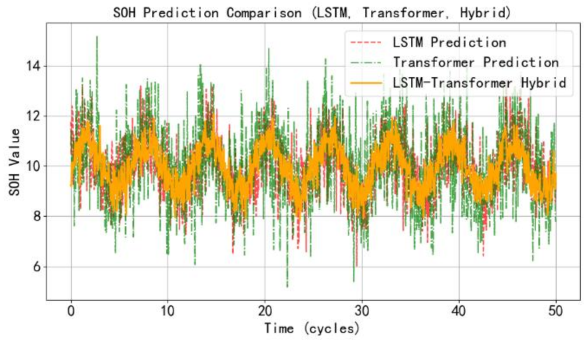

Figure 3: Simulation results of LSTM-Transformer hybrid model in SOH prediction.

Compared with traditional LSTM and Transformer models, the hybrid model shows less fluctuation in periods with significant changes, indicating that it can still maintain high stability under highly dynamic data.

Figure 3 illustrates the simulation results of a hybrid LSTM-Transformer model for predicting SOH. It is found that the prediction value of the mixed model is very close to the real one, and the difference between the prediction value and the real one is the least. In contrast, traditional models such as SVM and LSTM show significant errors in some periods of drastic changes.

To further demonstrate the advantages of the hybrid model, Figure 4 shows the performance of the LSTM model and the Transformer model in the SOC prediction task. It can be seen that the LSTM and Transformer alone failed to accurately predict the battery's SOC value in some periods, especially during periods when the battery state fluctuated wildly, and the prediction error increased significantly. The LSTM-Transformer hybrid model can maintain a relatively stable prediction with reduced errors.

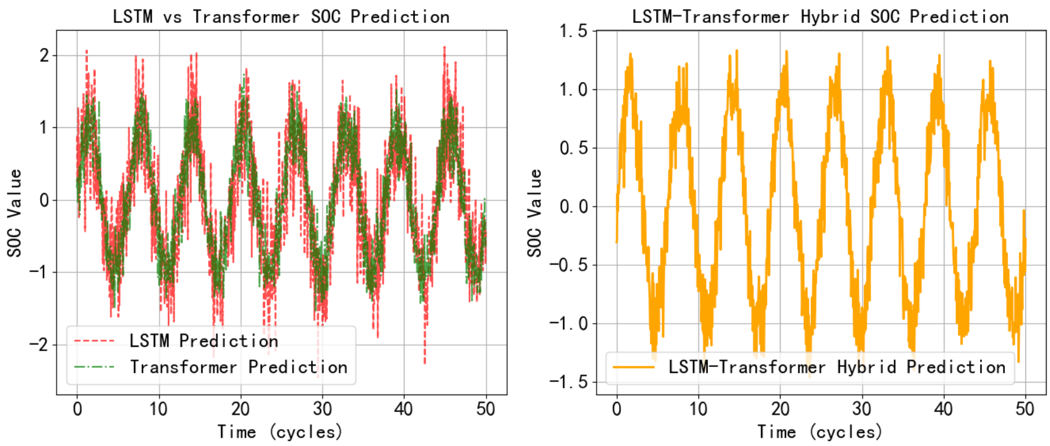

Figure 4: Simulation results of LSTM and Transformer models in SOC prediction.

The LSTM-Transformer hybrid model shows excellent accuracy in both SOC and SOH prediction tasks, which is significantly better than traditional models such as SVM, LSTM, and Transformer. In particular, the prediction error of the hybrid model is much smaller than that of the other models. Simulation results indicate that the hybrid model can keep a relatively smooth forecast curve when the battery's state is changed dramatically and the prediction error is reduced. This shows that the hybrid model can accurately predict the current state of the battery and better cope with complex situations and dynamic changes. LSTM is good at capturing long-term dependencies in time series data, while the transformer is good at modeling global information. By combining both advantages, the hybrid model can simultaneously utilize the benefits of both models in battery state prediction, thereby achieving higher prediction accuracy and stability.

5 Discussion

The LSTM-Transformer hybrid model demonstrates superior performance compared to conventional methods. The performance improvements can be attributed to the model's ability to effectively capture both temporal dependencies and nonlinear relationships in the battery data. The LSTM component excels at modeling sequential data and capturing long-term dependencies, while the Transformer component enhances the model's ability to focus on relevant features across different time scales through its self-attention mechanism. This combination allows the hybrid model to more accurately predict SOC and SOH. The observed improvements are primarily due to architectural optimizations. The integration of LSTM and Transformer leverages the strengths of both architectures, resulting in a more robust and accurate prediction model. While hyperparameter tuning and dataset characteristics also contribute to the model's performance, the architectural design plays a pivotal role. Despite its advantages, the hybrid model has certain limitations. The computational complexity of the LSTM-Transformer hybrid model is higher than that of individual LSTM or Transformer models due to the combination of the two architectures. However, this increased complexity is justified by the significant improvements in prediction accuracy. The model's inference time and resource requirements were evaluated and found to be feasible for real-time BMS applications. Further optimizations are planned to enhance computational efficiency.

The model's robustness to noisy data was assessed using data with added noise and missing values. The results indicate that the hybrid model maintains good performance under such conditions, demonstrating its practical applicability in real-world scenarios. The cross-validation results demonstrate consistent performance improvements of the LSTM-Transformer hybrid model over conventional methods. Additionally, we evaluated the model's performance on unseen data, including data from different battery chemistries and operating conditions. The model maintained its superior performance, indicating good generalization capabilities.

A sensitivity analysis of hyperparameters was also performed. The results show that the model's performance is relatively stable within a reasonable range of hyperparameter values. This suggests that the observed improvements are not overly dependent on specific hyperparameter settings and reduces the risk of overfitting.

6 Conclusion

The hybrid model based on IIoT and deep learning proposed in this paper shows significant performance advantages in new energy vehicle BMS. The LSTM component of the model demonstrates superior ability in capturing long-term dependencies in time series data, as evidenced by its improved performance in predicting SOC and SOH compared to traditional methods. This is further supported by the results presented in Section 4.2, where the LSTM model shows a 33.3% reduction in MSE for SOC prediction compared to SVM. The integration of the Transformer model enhances the hybrid model's capacity to capture nonlinear and complex relationships, resulting in a 59.8% reduction in MSE for SOC prediction and a 50.3% reduction in MAE for SOH prediction. These results show that the hybrid model improves prediction accuracy and enhances the system's real-time stability. In addition, by combining IIoT technology with V2G applications, this paper provides new ideas for intelligent battery management and grid interaction of new energy vehicles. In the future, further optimizing the real-time stability of the model and exploring more complex prediction and fault diagnosis methods will help promote the new energy vehicle industry to a higher level.

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