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Research on the Error Estimation Method for Electric Energy Meters of Electric Vehicle Charging Piles based on Deep Learning

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Abstract: In the context of the increasing spread of electric vehicle (EV) charging stations, the accuracy and reliability of electric energy measurement is becoming increasingly important for consumers. Degradation in the performance of smart meters at these stations is often due to factors such as aging and malfunctions. Traditional approaches to solving this problem usually involve manual on-site inspections, which require significant investment in manpower and materials. To overcome this challenge, this study proposes an error estimation method that integrates highway convolutional neural networks with bidirectional long short-term memory (LSTM) networks, which enables real-time prediction of measurement performance at charging piles. First, the convolutional module is combined with the highway network to extract spatial features from smart meter data for charging facilities while retaining some original information to improve model prediction performance. The features are then fed into a bidirectional LSTM network to obtain temporal characteristics, which improves the accuracy of relative error predictions. Empirical validation of this method at a charging station in the region has shown that it has higher efficiency compared to existing advanced models.

Keywords: electric vehicle charging piles, smart meter, highway network, convolutional neural network, bidirectional long short-term memory network, relative error estimation

1. INTRODUCTION

The growing number of electric vehicle (EV) users has drawn attention to the operation and services of EV charging facilities, particularly in terms of the accuracy of measurement and charging safety. Accurate and reliable energy measurement and fair billing have a direct impact on the interests of the majority of charger users [1], [2]. Currently, the management of EV charging stations from the same batch is usually based on extrapolating the operational status of the entire batch based on a certain proportion of sampled verification results. This approach determines whether the entire batch of meters should be replaced or their use extended. However, the wide distribution, large number and varying quality of charging facilities [3], [4] require considerable human and material resources, which makes it difficult to carry out on-site sampling inspections. In addition, sampling methods are susceptible to false positives and negatives, in which can lead to financial losses for both the operational maintenance departments and users.

The measurement errors in charging piles are primarily due to the deterioration of electric meter performance. Over time, the internal electronic components of the meters are affected by high temperatures, electromagnetic fields, mechanical stresses, and aging, which reduces the reliability of the measurement results [5]. Consequently, researchers have extensively explored error source detection, error modeling, and error assessment [6], to reduce the economic losses caused by these errors. Wei et al. [7] have developed a remote calibration and monitoring system that includes monitoring equipment, a communication network, and a main station. However, the detection of measurement errors requires the installation of numerous standard end devices, which increases investment and operation maintenance costs. The current verification methods do not fully meet the requirements of regular checks, which prompts the exploration of novel technologies and methods to efficiently monitor and control the measurement performance of charging facilities [8].

With the rapid progress in information technology, a large amount of data from electric meters can be collected, transmitted, and stored, which facilitates the online prediction of meter measurement performance [9]. At present, online error analysis of electric meters is mainly divided into two categories, including methods based on least squares and deep learning.

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Least squares based methods primarily use the conservation of energy equation to formulate online error analysis models that offer high interpretability. Liu et al. [10] proposed a linear equation model for remote estimation that uses the k-means clustering method and regularization theory to estimate errors in smart meters. However, the model may yield ill-conditioned equations. To address the ill-conditioning of linear systems, Xie et al. [11] introduced a data optimization algorithm based on a greedy strategy for filtering data and incorporating L2 regularization to mitigate solution variability. At the same time, Kong et al. [12] addressed the problem of data saturation and ill-conditioning by proposing an error estimation method that uses a limited memory recursive least squares algorithm.

However, the electrical environment of charging facilities is complex and has numerous sources of error, including losses in charging piles, transmission lines, and charging stations. Current systems lack refined modeling for each unit, making it difficult to develop accurate mechanistic models for practical use and accurate error estimation in smart electric meters. Furthermore, grid losses are subject to frequent and significant fluctuations due to the influence of load flow and the operational state of the grid. Incorporating these fluctuations into the energy conservation equation can affect the stability, accuracy, and applicability of the model.

In the course of the further development of deep learning, researchers have also used neural networks (NN) to analyze electric meter data [13], [14]. Given the pronounced nonlinear relationship between electric meter data and measurement performance, Amarbayasgalan et al. [15] introduced an unsupervised anomaly detection method based on deep learning principles. Anomalies are detected based on whether the reconstruction error exceeds a predefined threshold. However, the manual setting of the anomaly threshold compromises the robustness of the model. Wang et al. [16] used a backpropagation (BP) neural network to diagnose anomalies in smart meters within an electrical grid system. However, these two methods only provide a qualitative assessment of the meter status as normal or abnormal without providing a quantitative representation of the meter's relative error, so they do not accurately reflect the specific condition of the meter's measurement performance. Chen et al. [17] employed fuzzy C-means clustering for data preprocessing, and categorized the operational status of each measurement before building an error estimation model through an adaptive gradient descent approach. However, the model does not consider the temporal aspects of the electricity usage process, so the temporal evolution of changes in meter performance is not captured. Dong et al. [18] used a hybrid long short-term memory (LSTM) - based model for error analysis on small datasets, but important information was lost during the clustering and denoising phases. Xia et al. [19] developed a relationship model linking the distributed system measurement correction coefficient, network loss, and energy consumption measurement values using the K-means algorithm and BP neural network. However, the approaches have not been specifically tailored to the unique characteristics of smart electric meter data, and their effectiveness has not improved significantly compared to least squares methods or optimization algorithms.

In response to the aforementioned challenges, this paper proposes a spatio-temporal network modeling approach that combines highway convolutional neural networks with bidirectional long short-term memory (H-CNN-BiLSTM) networks. First, the convolutional module is used to extract spatial features between the variables that a highway network combines to reduce information loss. Then, the extracted features are fed into the BiLSTM network to capture temporal patterns. This strategy solves the problems of nonlinearity and autocorrelation present in electric meter data. It enables online prediction of the relative error in EV charging pile meters and reduces the human and material resources required for manual on-site verification.

The following sections of this paper are organized as follows: Section 2 outlines the methods for preprocessing the collected electric meter data and the formula for calculating the relative error. Section 3 explains the model's framework proposed in this study, accompanied by a comprehensive description of the online application process. Section 4 applies the proposed model to an actual charging station and compares it with other existing advanced methods to demonstrate its practicality and superiority. Finally, Section 5 concludes the paper with a concise summary and a look into the future.

2. ELECTRIC METER DATA PREPROCESSING AND CALCULATION OF RELATIVE ERROR

In the domain of field operations, the measurement devices used in new EV charging facilities are susceptible to a number of factors that lead to data gaps, anomalies, and random errors [20]. Therefore, data cleansing is crucial. Since the charging efficiency is subject to considerable fluctuations at the beginning and end of the charging process, which may not accurately reflect the current state of the smart meters, the data used for the calculations refer to cases where a stable charging state is achieved. This dataset includes parameters such as energy, current, voltage, and charging efficiency measured by each smart meter.

As for the electric energy data, it is noteworthy that the smart meters measure the cumulative electricity consumption within their respective branches. Therefore, it is essential to perform a first-order difference calculation with this data. This procedure provides the amount of energy consumed in each branch during a given sampling period:

$$\Delta w_i^k = w_{i+1}^k - w_i^k \tag{1}$$

where w_i^k is the value of electrical energy recorded by the smart meter at the i^{th} sampling period for the k^{th} charging pile. Consequently, the actual relative error of the k^{th} smart meter for the ith sampling period can be calculated using the following formula:

$$\xi_i^k = (\Delta w_i^k - \Delta u_i^k)/\Delta u_i^k \times 100\ \% \tag{2}$$

where Δu_i^k is the actual electrical energy consumed for the k^{th} charging pile during the i^{th} sampling period, which is recorded by a high-accuracy electric energy metering unit installed at the charging gun.

Due to the long sampling period of smart meters used in the field, such as every 15 minutes, it is difficult to obtain precise variations of current, voltage, and charging efficiency between sampling points. Therefore, the average of the data from the previous and subsequent sampling points is used to represent the current, voltage, and charging efficiency for the current sampling period:

$$\bar{x}_i^k = \frac{x_i^k + x_{i+1}^k}{2} \tag{3}$$

where x_i^k is the electrical parameter matrix at the i^{th} sampling period for the k^{th} smart meter, including current, voltage, and charging efficiency.

In the raw data, there is variability in both the units and the dimensions of the different variables, which may cause an uneven distribution of feature weights in the neural network. This imbalance can lead to certain features having a disproportionate influence while others are underestimated, which significantly affects the overall performance of the model. To remedy this, it is important to standardize the input data for the model. This normalization process is instrumental in improving the model's convergence speed and accuracy. The normalization formula used is as follows:

$$v_i = \frac{v_i - v_{min}}{v_{max} - v_{min}} \tag{4}$$

where v_{min} and v_{max} denote the minimum and maximum values of a variable, respectively.

3. ELECTRIC VEHICLE CHARGING FACILITY ELECTRIC METER ERROR ANALYSIS MODEL

In terms of error prediction for operating energy meters, the effectiveness of conventional methods is often unsatisfactory. Therefore, the H-CNN-BiLSTM model is proposed, which mainly consists of a convolutional module and a BiLSTM network module. The modules are used to extract spatial and temporal features from the raw data variables with the ultimate goal of increasing the prediction accuracy. The input to the model is the data processed $\{\bar{x}, \Delta w\}$ as described in Section 2 and the output is the estimated relative error of the electric meter. The network structure is shown in Fig. 1.

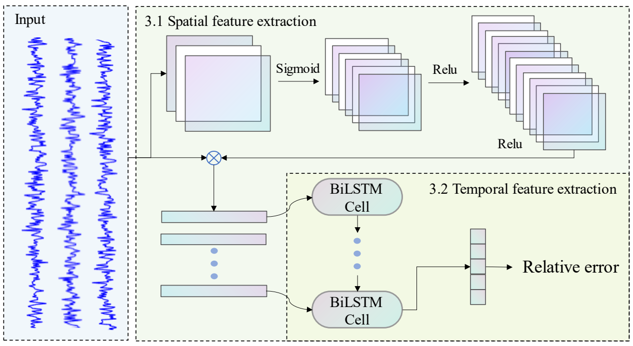


Fig. 1. H-CNN-BiLSTM network structure.

A. *Convolutional module*

The data from smart meters is one-dimensional and contains fewer variables, which severely limits the ability of neural networks to extract the underlying information. However, convolutional neural network stacking is used to enrich data features, which enables in-depth exploration of the intervariable relationships within smart meter data [21], [22]. The convolutional module consists primarily of three one-dimensional convolutional layers. The use of multiple convolutional layers serves the purpose of expanding the feature dimensions and exploring the data to reveal comprehensive information, which consequently expands the channels of the network with minimal parameter involvement.

The *sigmoid* function is chosen as the activation function for the first layer, which is expressed in the following formula:

$$S(x) = \frac{1}{1+e^{-x}} \tag{5}$$

The *relu* function is selected as the activation function for the second and third layers, as shown in the following formula:

$$R(x) = max(0, x) \tag{6}$$

The output of the last convolutional module is combined with part of the original information retained by the highway network, as shown in Fig. 2, and this combination includes two gating structures.

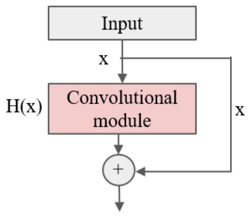


Fig. 2. Highway network structure.

The transformation gate is used to control the degree of transformation of the input signal, allowing the network to adaptively learn the expression of the input signal. The calculation method is as follows:

$$H(x) = \sigma(W_t x + b_t) \tag{7}$$

where x is the input signal. σ denotes the *sigmoid* function. W_t and b_t represent the weight matrix and the bias term of the input gate control function, respectively.

The transmission gate can be regarded as a variant of a gated recurrent unit that controls the retention level of the input signal by learning gate coefficients, which are usually defined as follows:

$$C(x) = 1 - T(x) \tag{8}$$

The final output is therefore given by:

$$F(x) = CNN(x) \otimes H(x) + x \otimes C(x) \tag{9}$$

where $CNN(x)$ represents the output of the convolutional module and $\otimes$ denotes the element-wise multiplication.

B. Bidirectional long short-term memory network module

To capture temporal information comprehensively, the model contains a BiLSTM. In contrast to the LSTM model, the BiLSTM model not only considers the information of the current moment in sequential data, but also integrates information from earlier and later moments, thereby skillfully capturing long-term dependencies within the sequence [23]-[25].

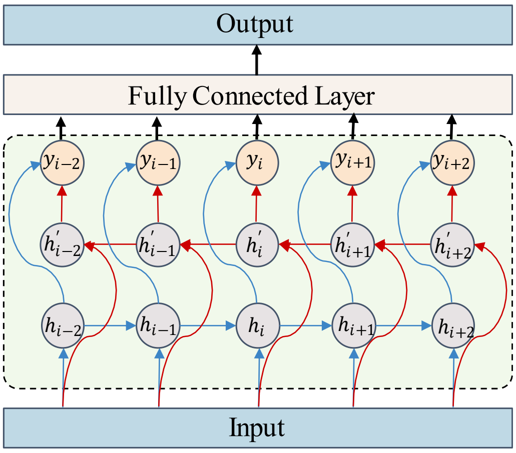


Fig. 3. BiLSTM network structure.

The BiLSTM module consists of two layers of BiLSTM networks, each layer comprising two LSTM units, as shown in Fig. 3. One of the units processes the sequence in the forward direction, while the other processes it in the reverse direction. The outputs of the two LSTM units are concatenated at each time step to generate the final output for that particular time step, and this calculation is represented by the following formula:

$$h_i = LSTM(F(x), h_{i-1}) \tag{10}$$

$$h_i' = LSTM(F(x), h_{i+1}') \tag{11}$$

$$Hs_i = Wh_i + W'h_i' + b_i \tag{12}$$

where $LSTM(\cdot)$ represents the traditional LSTM computation process. h_i and h_i' are the hidden state vectors of the forward and backward LSTM at each time step, respectively. Hs_i is the hidden state vector for each time step, which contains bidirectional temporal information. W and W' are the forward and backward output weights of the BiLSTM, respectively. b_i is the bias parameter.

C. Loss function design

In the field of neural networks, the loss function serves as a metric for quantifying the discrepancy between predicted and observed values. It represents the primary objective function that must be minimized throughout the training process of the neural network, as shown in (13). The loss function consists of two basic components, namely the error function and the regularization term. The error function evaluates the discrepancy between the predictions of the model and the actual values, while the regularization term penalizes the model for overfitting.

$$Loss = \sqrt{\frac{1}{n}\sum_{i=1}^{n} (y_i - f(x_i))^2 + \frac{\lambda}{2}\sum_{i=1}^{m} w_i^2} \tag{13}$$

where n, y_i, and $f(x_i)$ represent the number of samples, the actual values, and the prediction values, respectively. m is the number of weights in the model. w_i represents the determinant of the i^{th} weight and λ is a hyperparameter used to control the weight of the regularization.

D. Model training and online monitoring process

The application process of the error analysis model for EV charger meters based on H-CNN-BiLSTM is shown in Fig. 4 and comprises three components: data preprocessing, offline training, and online prediction. The detailed process is as follows:

1. Data preprocessing: According to the overview in Section 2, the collected raw data is preprocessed. The actual relative error of the electric meter is calculated based on the data from the high-accuracy electric energy metering unit, which serves as the target for the model.
2. Offline training: Starting with the initialization of the network hyperparameters, the preprocessed data is used as input for the model. The loss function is then calculated by comparing the model output with the target value according to (13). The network parameters are then updated using the adaptive moment estimation (Adam) optimization method. The training process ends either when a certain number of iterations is reached or when the loss falls below a predefines threshold.
3. Online prediction: Online prediction does not require the installation of additional electric energy metering units. The collected data is preprocessed and fed directly into the trained model to obtain the estimated relative error of the electric meter. If the error exceeds the national standard, an on-site inspection is carried out to determine whether the electric meter needs to be replaced. However, if the error is within acceptable limits, continuous monitoring is carried out. The aim is to reduce the frequency of on-site inspections and thus minimize the associated costs for personnel and materials.

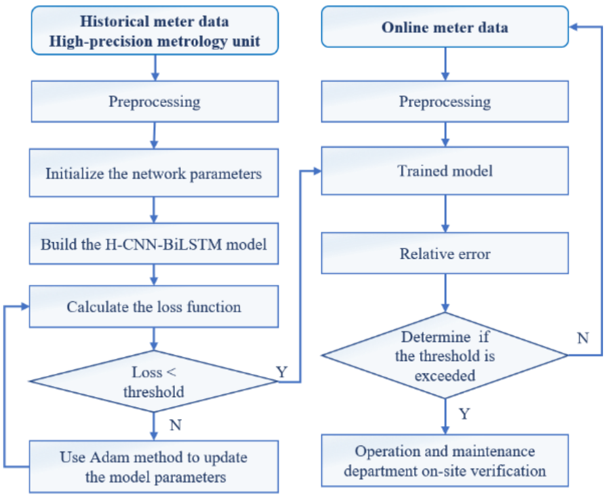


Fig. 4. Flowchart for error estimation in EV charging pile meters.

4. Case study

A. *Data collection*

The proposed model primarily focuses on the error analysis for direct current (DC) charging piles. In order to prove the effectiveness of the proposed method, the data to calculate the relative errors of charging piles is used, which is obtained from DC charging piles at a bus charging station in China. The topological configuration is shown in Fig. 5. Each box-type substation is equipped with a high-accuracy alternating current (AC) electric meter (called master meter), which is responsible for recording the electrical parameters of the grid under the substation. The parameters include charging efficiency, electric energy, and power. Each charging pile is equipped with a DC electric meter (sub-meter) with an accuracy class of 2.0. The sub-meters are installed on the output side of the charging piles to measure the energy supplied to the EV. They record data on voltage, current, electric energy, and power. Both the master meters and the sub-meters have a sampling interval of 15 minutes and are equipped with communication modules that transmit the data to the information collection platform via GPRS/4G. The evaluation focuses on whether the relative error between the electric energy recorded by the sub-meter at the charging pile and the actual energy consumption meets the prescribed accuracy requirements. After preprocessing, a data set of 1550 samples remains. In order to evaluate the effectiveness and practicality of the proposed model, the high-accuracy reference meters were installed in parallel with the charging pile's output-side meter to obtain the actual energy consumption data. The first 1300 samples are assigned to the training set, and the following 350 samples are referred to as the test set.

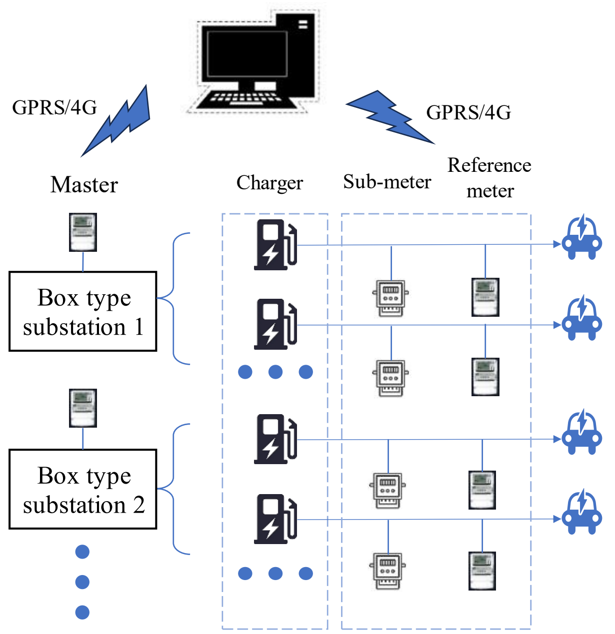


Fig. 5. Topological structure of an electric EV station.

B. *Evaluation metrics*

Root mean square error (RMSE), mean absolute error (MAE), and coefficient of determination (R^2) were selected as metrics for model performance evaluation to demonstrate the accuracy of model predictions, defined as follows:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n} (y_i - f(x_i))^2} \tag{14}$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - f(x_i)| \tag{15}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - f(x_i))^2}{\sum_{i=1}^{n}(y_i - Mean(y))^2} \tag{16}$$

where n represents the number of samples. y_i denotes the actual values. $f(x_i)$ stands for the predicted values, and $Mean(y)$ is the mean value of the target variable.

C. *Experimental results and comparative analysis*

The hyperparameters of the H-CNN-BiLSTM model are specified in Table 1. The model parameters are updated by using the Adam method during the BP process. As shown in Fig. 6, the training process of the proposed model shows that the loss function has reached stability, which means that the model has reached its optimal predictive performance.

Table 1. Hyperparameters of H-CNN-BiLSTM.

Training options	Parameters
Optimizer	Adam
Mini batch size	200
Max epochs	50
Initial learn rate	0.002
Learn rate drop factor	0.1
Learn rate drop period	100

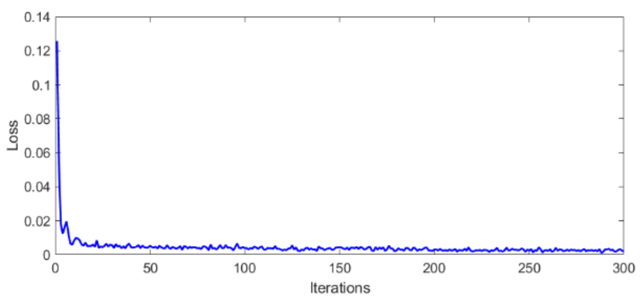
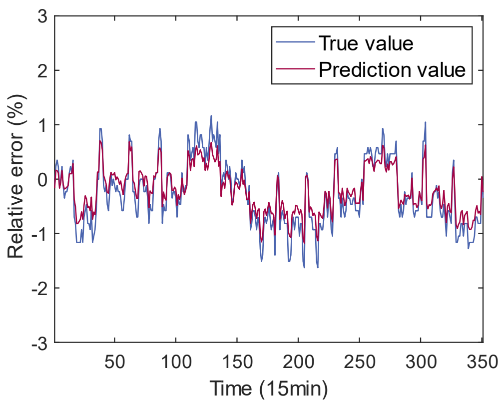
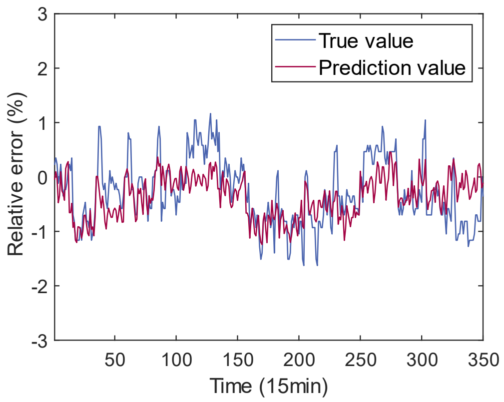


Fig. 6. Model training on the training set.

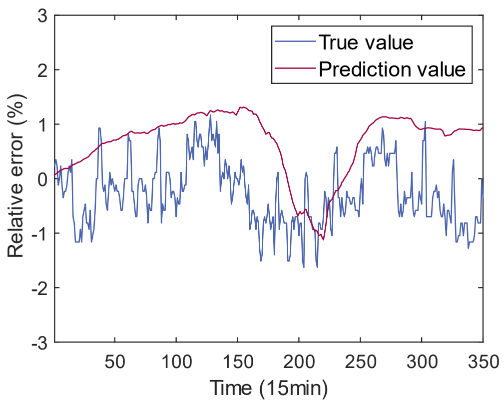
To demonstrate the superiority of the proposed method, it is compared with the limited memory damped recursive least squares with extended Kalman filter (EKF-LMRLS) method, the BP neural network for particle swarm optimization (PSO-BPNN) method, and the generalized damped recursive least squares (GDRLS) method. As shown in Fig. 7, the prediction results demonstrate the superior fitting performance of the proposed method in accurately estimating the fluctuation of the relative errors in the energy meter. In contrast, the PSO-BPNN method neglects the autocorrelation characteristic of



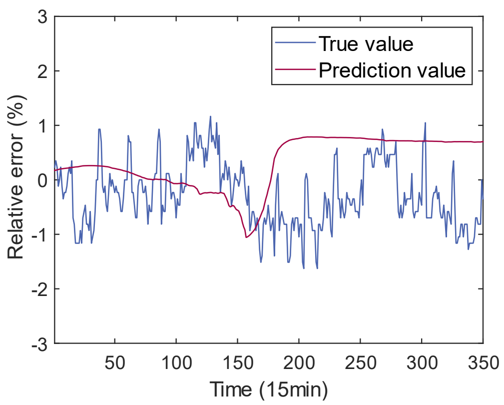
(a) H-CNN-BiLSTM



(b) PSO-BP



(c) EKF-LMRLS



(d) GDRLS

Fig. 7. Prediction results of different models on the test set.

the electric meter data, resulting in inferior estimation performance. On the other hand, both the EKF-LMRLS and GDRLS methods can only predict the general trend of the relative error. Another problem is that the estimated values of GDRLS show significant deviations from the actual values.

To illustrate the predictive capabilities of the proposed model and the comparison models, Table 2 also contains specific model evaluation indices. It is obvious that the prediction accuracy of the model in this paper is the highest. Compared to PSO-BPNN, the RMSE index shows a significant improvement of 130 %. Compared to EKF-LMRLS, the improvement increases to 470 %, and compared to GDRLS, the improvement reaches 410 %. The experimental results show that the method, which considers both the spatial and temporal dimensions, can significantly improve the prediction of relative errors. In addition, a residual boxplot for the H-CNN-BiLSTM model and the comparison models is shown in Fig. 8. It can be seen that the PSO-BPNN method has a larger number of outliers, while the EKF-LMRLS and GDRLS models produce larger boxes. In contrast, the model proposed in this paper has fewer outliers and a smaller box, indicating the stability and accuracy of its predictions.

Table 2. Comparison of the performance evaluation indices of the four models.

Model	R^2	MAE	RMSE
H-CNN-BiLSTM	0.9771	0.1748	0.2093
PSO-BPNN	0.6325	0.3626	0.4635
EKF-LMRLS	0.3934	0.9417	1.1412
GDRLS	0.2024	0.5850	1.0166

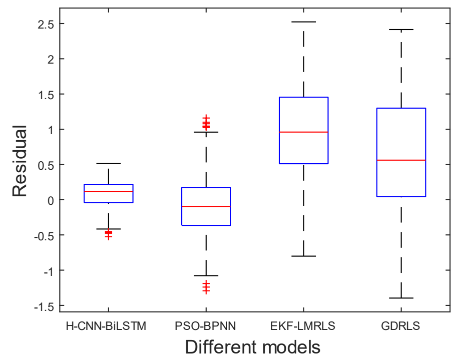


Fig. 8. Residual box plot of different models.

5. CONCLUSION

In response to the inherent limitations of conventional methods in online predictions of the relative error of electric meters, the H-CNN-BiLSTM model is proposed to analyze the relative error of electric meters in EV charging facilities. First, the proposed method utilizes a convolutional module with a highway network to extract spatial features between the meter data while preserving the essential original information. The extracted features are then used as input to a BiLSTM network to learn the change trend of the relative error of the electric meters. Ultimately, the effectiveness of this method is confirmed by its application to a dataset obtained from an EV charging station in a specific region. In contrast to the existing PSO-BPNN, EKF-LMRLS, and GDRLS models, this method provides significantly more accurate prediction results, which can reduce the cost of manpower and materials required for manual on-site verification.

It should be noted that this article is primarily concerned with the influence of the operating condition of DC charging piles on the measurement performance of electric meters and does not include considerations related to AC charging piles or external environmental factors. In future work, the research team intends to combine this model with transfer learning techniques to improve its applicability and generalizability in practical scenarios.

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