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Short-Term Load Forecasting of Electric Vehicle Charging Stations Accounting for Multifactor IDBO Hybrid Models

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Abstract: The charging behavior of electric vehicle users is highly stochastic, which makes the short-term prediction of charging load at electric vehicle charging stations difficult. In this paper, a data-driven hybrid model optimized by the improved dung beetle optimization algorithm (IDBO) is proposed to address the problem of the low accuracy of short-term prediction. Firstly, the charging station data are preprocessed to obtain clear and organized load data, and the input feature matrix is constructed using factors such as temperature, date type, and holidays. Secondly, the optimal CNN-BiLSTM model is constructed using convolutional neural network (CNN) and Bi-directional Long Short-Term Memory (BiLSTM), which realizes the feature extraction of the input matrix and better captures the hidden patterns and regularities in it. Then, methods such as Bernoulli mapping are used to improve the DBO algorithm and its hyperparameters; for example, hidden neurons of the hybrid model are tuned to further improve the model prediction accuracy. Finally, a simulation experiment platform is established based on MATLAB R2023a to validate the example calculations on the historical data of EV charging stations in the public dataset of ANN-DATA, and comparative analyses are carried out. The results show that compared with the traditional models such as CNN, BiLSTM and PSO-CNN-BiLSTM, the coefficient of determination of the model exceeds 0.8921 and the root mean square error is maintained at about 4.413 on both the training and test sets, which proves its effectiveness and stability.

Keywords: data driven; electric vehicle; charging load; convolutional neural network; gated recurrent neural network; dung beetle optimization algorithm

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1. Introduction

The advancement of global decarbonization has driven the rapid development of electric vehicles (EVs), which has played an important role in achieving the global carbon neutrality target. The rapid popularization of new energy EV not only effectively promotes the transformation revolution of non-renewable energy sources such as fossil energy but also injects new vitality into environmental protection and sustainable development. With the continuous maturation of technology and policy support from governments [1,2], electric vehicles have seen rapid growth in ownership in recent years due to their low-carbon and environmentally friendly features, and the global sales of battery-powered vehicles and plug-in hybrids have shown a continuous growth trend [3,4] as shown in Figure 1. According to the International Energy Agency (IEA), the global stock of electric vehicles will reach 145 million in 2030. Further projections show that the electricity demand for electric vehicles is expected to reach 510 TWh by 2050 when electric vehicles replace 60% of conventional gasoline vehicles [5].

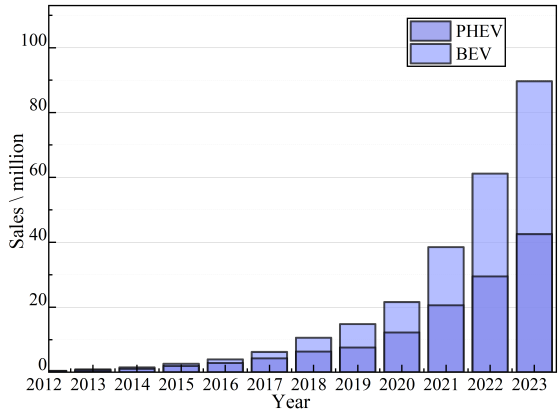

Figure 1. Trend of global sales of battery-powered vehicles.

A large number of EV charging stations will be constructed to meet the growing demand of EV users [6,7]. Compared with electric load forecasting, the historical data of EV charging loads have numerous zero sampling points due to the randomness of charging behavior, making it more difficult and complex to forecast [8]. Uncontrollable EV charging leads to large load variations in the grid, affecting the power quality of the distribution network [9]. This, in turn, can have significant adverse effects on the existing power system, including high load peaks, increased energy consumption, and degradation of power quality [10–15]. Ref. [16] has investigated the impact of uncontrollable EV charging on the distribution grid, which may result in power demand and line currents exceeding distribution transformer ratings, as well as distributed voltage dips beyond required levels. The application of Grid-to-Vehicle (G2V) technology can help to mitigate the possible fluctuation of grid burden caused by EV charging loads, as well as improving the scheduling and optimization of EV charging behavior [17]. Therefore, improving the accurate prediction of EV charging loads is crucial for the effective application of G2V technology, realizing the orderly charging of EVs, and ensuring the safe and stable operation of the power grid [18,19].

Research methods for EV charging load forecasting are mainly categorized into probabilistic and data-driven based methods [20]. Among the probabilistic methods, there are Monte Carlo stochastic simulation methods based on statistical probability [21], stochastic simulation methods based on queuing theory [22], simulation methods based on travel chains and Markov processes [23,24], and Hidden Markov Models [25]. However, modeling methods are limited to the lack of real charging load data, and mostly use mathematical modeling or simulation for approximating real behavioral simulation, and there are limitations in the realism of their prediction results. Data-driven methods mainly use artificial intelligence algorithms for charging load prediction. Traditional AI algorithms such as random forest (RF) [26], support vector machine (SVM) [27], and XGBoost [28], although they have good non-linear data fitting ability and parameter learning ability, they are unable to learn the temporal features in the time-series data similar to the charging load historical data well. The development of deep learning [29] provides new methods for EV charging load prediction. Ref. [30] cascaded a convolutional neural network (CNN) with a fully connected network, and showed that it has better accuracy and generalization in power load forecasting 24 h in advance in power systems; ref. [31] proved that the Bi-directional Long Short-Term Memory (BiLSTM) model, which has a network structure that extracts features from time-series data in both directions, has better forecasting ability than the one-way LSTM model in time-series analysis, and can be used for power load forecasting. However, little research has been performed on the problem of combining the advantages of different machine learning methods to predict the charging load of electric vehicle charging stations, based on which this paper establishes a hybrid network model to solve the problem. Ref. [32] proposed a hybrid model based on CNN-BiLSTM for power load forecasting, and the proposed CNN-BiLSTM hybrid model is superior compared with the single-structured LSTM model and CNN-LSTM hybrid model. The hyperparameters of neural networks are often manually adjusted based on experience, and the effect is difficult to guarantee, while the use of optimization algorithms for hyperparameter tuning can significantly improve the performance of neural networks. Ref. [33] proposed a new combined method for the short-term load forecasting of power systems based on the fuzzy mean (FCM) clustering support vector regression (SVR) technique and applied PSO to optimize the model parameters to further improve the accuracy of the method.

In summary, this paper combines CNN and BiLSTM to take advantage of CNN in feature extraction and BiLSTM in time-series prediction, and overcome the difficulty of insufficient features and regularity of charging data due to the highly stochastic nature of EV user behavior. And focusing on the short-time load prediction of EV charging stations, the improved dung beetle optimization algorithm is used to find the optimal hyperparameters for the CNN-BiLSTM hybrid model, trying to provide a solution to the low prediction accuracy. The innovations are reflected in the following aspects: on the one hand, this paper compares and analyzes the hybrid models of CNN and BiLSTM and selects the optimal structure, which makes full use of the advantages of each of the two, and thus improves the generalization ability of the model; on the other hand, the dung beetle optimization algorithm (IDBO) is improved by using Bernoulli chaos mapping, part of the idea of the fish hawk optimization algorithm, and the adaptive t-distribution perturbation strategy, which improves the performance of the algorithm without increasing the complexity of the algorithm, and the performance and the prediction accuracy of the CNN-BiLSTM hybrid model tuned by this method are greatly improved.

The structure of this paper is shown as follows: Section 2 describes the basic concepts and principles of the convolutional neural network, bidirectional gated recurrent neural network, and dung beetle optimization algorithm. Section 3 describes the structural design of the CNN-BiLSTM model and the optimization method for the dung beetle algorithm. Section 4 describes the hybrid model for optimizing CNN-BiLSTM based on IDBO. Section 5 optimizes the hyperparameters of the hybrid CNN-BiLSTM model with the improved IDBO algorithm, and uses the tuned model to perform an example simulation on the historical charging load data of electric vehicle charging stations in the public dataset of ANN-DATA in the USA to validate the effectiveness of the model. Section 6 concludes the paper. The technology roadmap of this paper is shown in Figure 2.

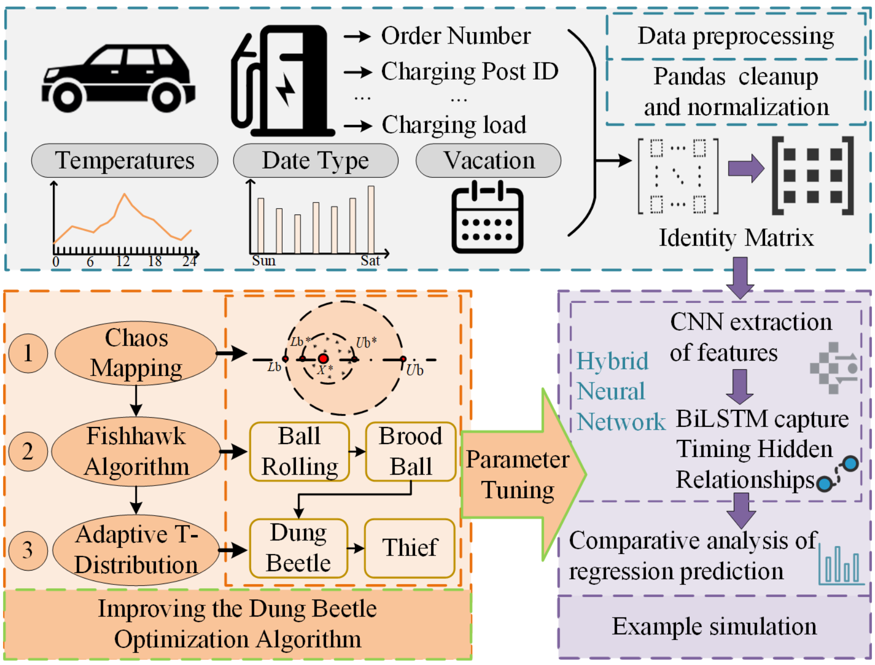

Figure 2. Technology roadmap.

2. Theoretical Foundations

2.1. Convolutional Neural Network

In this paper, a CNN is utilized to identify and learn the spatial structure in the input data matrix so as to capture the correlation between in the input features and the electric vehicle charging load. The convolutional neural network is a multilayer supervised learning neural network. The CNN network structure generally consists of a number of convolutional blocks. The convolutional blocks generally include a convolutional layer, pooling layer, activation function, and fully connected layer [34]. Among them, the convolutional layer and the maximum pooling sampling layer are the core modules to realize the feature extraction function. The fully connected layer is used to summarize the underlying features and information obtained from the convolutional block. The schematic diagram of feature extraction is shown in Figure 3.

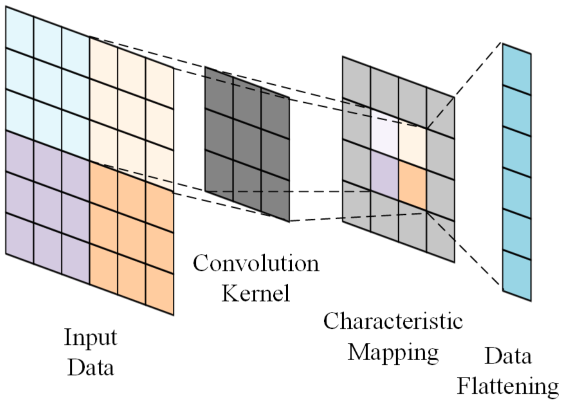

Figure 3. Schematic diagram of CNN for feature extraction.

2.2. Bi-Directional Long Short-Term Memory

Charging load data from EV charging stations are characterized by randomness and periodicity, so this paper utilizes BiLSTM neural networks to receive feature representations extracted by CNNs to capture and learn long-term dependencies in time-series data through its bi-directional structure, and to better extract the hidden patterns and regularities in the time-series from the historical data so as to more accurately make predictions. The LSTM algorithm adds a gating mechanism to the recurrent neural network (RNN). BiLSTM is composed of multiple LSTM blocks in forward and backward orders, which can be used to efficiently extract time-series data features [35]. The ability to obtain information from both past and future time steps compensates for the key features that may be neglected by LSTM [36] when only considering the current information. The structure is shown in Figure 4.

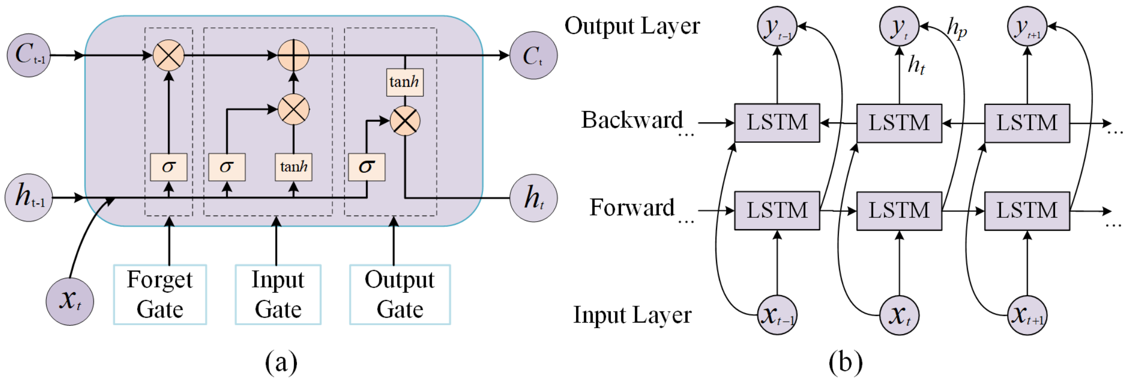

Figure 4. Structure of neural network. (**a**) LSTM; (**b**) BiLSTM.

BiLSTM implicit layer is derived from the weighted splicing of the forward LSTM implicit layer and the backward LSTM:

$$h_t^{'} = \alpha_t h_t + \beta_t h_p \tag{1}$$

where, $h_t^{'}$ is BiLSTM implicit layer; h_t is backward LSTM hidden layer; h_p is LSTM hidden layer; α_t and is β_t weight coefficient.

2.3. Basic Dung Beetle Algorithm

In this paper, analogous to the behavioral characteristics and optimization strategies of dung beetles in the dung beetle optimization algorithm to find the best food source within the initial exploration range, the electric vehicle users adjust their behaviors to find the best charging strategies according to their own different charging needs to maximize the charging efficiency and energy saving under the time and space constraints.

In the dung beetle optimization algorithm (DBO), the dung beetle population is divided into four different roles according to the ratio of 6:6:7:11 to simulate the behaviors of ball rolling, foraging, stealing and reproduction, and to perform global search and local exploitation for the purpose of intelligent optimization. Among them, the ball-rolling behaviors are divided into two cases, without and with obstacles as shown in Equations (2) and (3) below, respectively:

$$X_i^{t+1} = x_i^t + \partial \cdot k \cdot x_i^{t-1} + b \cdot \left| x_i^t - x_{worst}^t \right| \tag{2}$$

$$X_i^{t+1} = x_i^t + \tan\theta \cdot \left| x_i^t - x_i^{t-1} \right| \tag{3}$$

where t denotes the current number of iterations, x_i^t denotes the position of the ith dung beetle in the population at the tth iteration, and k is the deflection coefficient. ∂ denotes whether the direction is biased or not, and is assigned the value of 1 or -1; b is a constant value; and x_{worst}^t denotes the current worst position. Only the value of $\tan\theta$ in $[0,\pi]$ is considered, and it is specified that the position is not updated when $\theta = 0$, π or 2π.

After the rolling behavior, the breeding behavior is simulated by the boundary selection strategy, and the location of the daisy is updated as shown in Equations (4) and (5) below:

$$\begin{cases} Lb^* = max\left\{ x_{\text{gbest}}^t \cdot (1-R), Lb \right\} \\ Ub^* = min\left\{ x_{\text{gbest}}^t \cdot (1+R), Ub \right\} \end{cases} \tag{4}$$

$$B_i^{t+1} = x_{\text{gbest}}^t + b_1 \cdot \left(B_i^t - Lb^* \right) + b_2 \cdot \left(B_i^t - Ub^* \right) \tag{5}$$

where x_{gbest}^t denotes the local optimal position; Ub^* and Lb^* denote the upper and lower bounds of the propagation region; Ub and Lb denote the upper and lower bounds of the optimization problem, respectively; $R = 1 - t/T_{max}$, and T_{max} is the maximum number of iterations; B_i^{t+1} is the position of the ith daisy at the tth iteration; b_1,b_2 are the independent random vectors of $1 \times D$; and D is the optimization dimension.

The optimal foraging areas and locations of foraging dung beetles are updated as shown in Equations (6) and (7):

$$\begin{cases} Lb^I = \max\left\{ x_{\text{lbest}}^t \cdot (1-R), Lb \right\} \\ Ub^I = \min\left\{ x_{\text{lbest}}^t \cdot (1+R), Ub \right\} \end{cases} \tag{6}$$

$$x_i^{t+1} = x_i^t + c_1 \cdot \left(x_i^t - Lb^I \right) + c_2 \cdot \left(x_i^t - Ub^I \right) \tag{7}$$

where x_{lbest}^{t} denotes the current local optimal position; Lb^I and Ub^I denote the upper and lower bounds of the foraging area; c_1 is a random number obeying a normal distribution; and c_2 is a $1 \times D$ random vector belonging to the range (0,1).

The location information of the dung beetle thief that stole the dung ball is updated as shown under Equation (8):

$$x_i^{t+1} = X_{\text{lbest}}^t + s \cdot g \cdot \left(\left| X_i^t - x_{\text{gbest}}^t \right| + \left| x_i^t - X_{\text{lbest}}^t \right| \right) \tag{8}$$

where g denotes a random vector of size $1 \times D$ obeying a normal distribution; and s denotes a constant value.

By combining a CNN with a bidirectional long and BiLSTM, an appropriate structure is selected to construct an efficient deep learning framework aimed at solving complex time-series prediction challenges. To further enhance the performance of this combined model, the DBO algorithm is used to optimize the model parameters, which not only significantly accelerates the convergence process of the model training but also improves the model's generalization ability and prediction accuracy in complex environments. The optimization model can effectively cope with the uncertainty and sudden change in the charging load when forecasting the short-term load of charging stations of charging vehicles, which provides more accurate and stable data support for the operation and management of charging stations and the load dispatch of power grids.

3. Model Building and Optimization Process

In this paper, considering the multiple factors affecting the charging load of electric vehicle charging stations, a CNN is used to identify and learn the spatial structure in the input feature matrix so as to capture the correlation between the input features and the EV charging load, and then a BiLSTM neural network is used to receive the features extracted by the CNN, from which the long-term dependency relationships in the time-series data are obtained as well as the hidden ones. The CNN-BiLSTM hybrid neural network model is thus constructed to realize a short-term prediction model of the EV charging load at charging stations with better generalization performance and prediction accuracy.

3.1. Design of CNN-BiLSTM Model Structure

In order to select the optimal structure of the proposed CNN-BiLSTM hybrid neural network, the CNN and BiLSTM structures with different numbers of network layers are trained to predict the dataset in the example of this section with the same number of neurons in each layer, the maximum number of training times of each network, and the batch of samples and other parameters. It is assumed that the model structure is one to five layers of CNN and one to five layers of BiLSTM with a total of 25 layer structures. The training results are ranked in descending order according to the size of the coefficient of determination R^2, and the accuracy of the top five predictions is shown in Table 1.

Table 1. Comparison of prediction accuracy of models with different number of layers.

Framework (CNN-BiLSTM)	Second	MSE	RMSE	MAE	R^2
3-1	69.34	27.18	5.21	3.80	0.8116
4-1	95.86	28.42	5.32	3.91	0.8071
2-1	55.72	29.78	5.46	4.05	0.8062
5-1	116.87	29.93	5.46	4.00	0.8049
3-3	73.11	31.04	5.57	4.03	0.7983

In the above table, it can be visualized that the model structured as a three-layer CNN model with one layer of BiLSTM has the minimum MSE, RMSE, MAE, elapsed time, and the maximum coefficient of determination R^2. Hence, this combination is used as a charging load prediction model for EV. As shown in Figure 5, the structure is designed as 6 layers, and all the CNN-BiLSTM hybrid models mentioned later are this model.

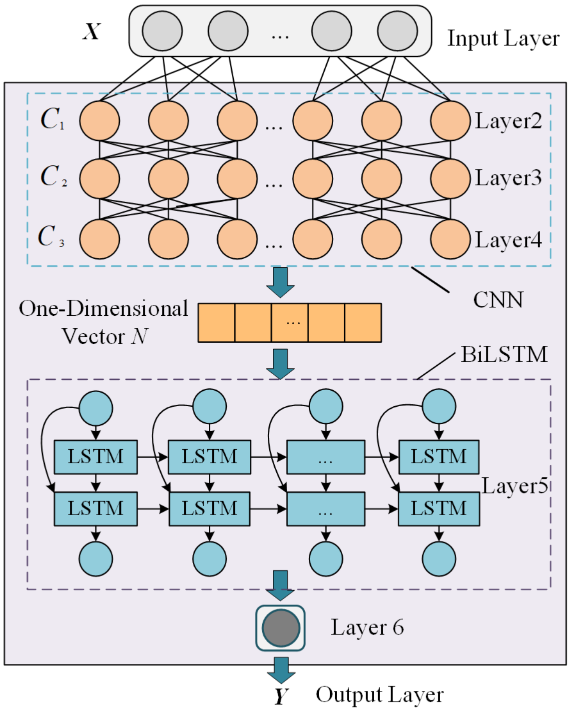

Figure 5. CNN-BiLSTM hybrid model structure.

In addition to the input and output layers, the other layers of the CNN-BiLSTM load prediction model are described below.

Layer 2, Layer 3 and Layer 4: All are convolutional blocks, the input data are convolved by their translation to extract feature information and capture the correlation between the input features and the EV charging load. In this case, the Layer 2 convolutional kernel size is set to 3 × 3, the Layer 3 convolutional kernel size is set to 3 × 2, the Layer 4 convolutional kernel size is set to 2 × 2, and both vertical and horizontal steps are 1. Pooling is average pooling, and the activation function is the ReLU function. The output is a one-dimensional vector array N of the extracted feature maps flattened by the CNN network.

Layer 5: It receives inputs from a one-dimensional vector array N, and then efficiently captures the long-term dependencies in the sequence by running the forward and backward BiLSTM networks simultaneously to better extract the hidden patterns and regularities in the time series from the historical data.

Layer 6: It is a fully connected layer, responsible for integrating the BiLSTM results and then outputting the predicted values in the specified format, with the number of neurons matching the number of model outputs. The number of neurons in the fully connected layer is 1 because the output is a single moment load prediction.

3.2. Improvement of DBO Optimization Algorithm

Neural network model hyperparameter values are often experimented with empirically and gradually adjusted until they approach the optimal values. However, without the support of deep expertise, it is difficult to achieve good results, prone to overfitting and underfitting phenomena, and time-consuming. Therefore, in this paper, the IDBO algorithm is used for the hyperparameter tuning of CNN-BiLSTM models.

The IDBO algorithm is derived from the standard dung beetle optimization algorithm by integrating Bernoulli chaotic mapping, the global exploration strategy of the fish hawk optimization algorithm, and the adaptive t-distribution perturbation strategy. Through the improvement of these three strategies, the IDBO algorithm shows excellent diversity and comprehensiveness in the optimization process. First, the use of Bernoulli chaotic mapping as a means of population initialization effectively increases the exploration of the search space, providing broader possibilities for the subsequent optimization stages. Second, through the global exploration strategy of the fish hawk optimization algorithm, the IDBO algorithm is able to quickly and comprehensively search the solution space, find potential high-quality solutions, and obtain more rapid convergence and global development capability in the early iteration stage. Finally, the introduction of the adaptive t-distribution perturbation strategy enables the IDBO algorithm to have a better global development capability in the early iteration stage, while in the late iteration stage, it is able to carry out a more in-depth local exploration and meticulously adjust the population in order to improve the accuracy and convergence of the solution. The details of the three optimization strategies are as follows:

(1) Bernoulli Chaotic Mapping

The traditional dung beetle optimization algorithm in the population initialization stage adopts the way of generating random numbers to initialize the population position, which leads to the mixed position of dung beetles in the population, and at the same time, it cannot traverse all the positions in the environment, which leads to its poor optimization search and low convergence speed. Considering that the initial position in the charging process of EV has high spatio-temporal randomness, this paper proposes to introduce Bernoulli mapping in the initialization stage of the population [37], and the mathematical expression of Bernoulli mapping can be expressed as:

$$Z_{k+1} = \begin{cases} Z_k/(1+\rho) & Z_k \in (0, 1-\rho] \\ (Z_k - 1 + \rho)/\rho & Z_k \in (1-\rho, 1) \end{cases} \tag{9}$$

where Z_k is the current value of the kth generation of the generated chaotic sequence, and ρ is a control parameter.

(2) Fusion Fish Hawk Optimization Algorithm

Considering that EVs are limited in space–time conditions, different charging pile usage, charging speed, and connection methods are considered as comprehensively as possible to obtain the optimal charging strategy. The global exploration strategy of the fish hawk optimization algorithm [38] can make up for the drawbacks of the dung beetle algorithm that only relies on the worst value in the rolling behavior, cannot communicate with other dung beetles in time, and has more parameters. Its formula is as follows:

$$x_{i,j}^{P1} = x_{i,j} + r_{i,j} \cdot \left(SF_{i,j} - I_{i,j} \cdot x_{i,j}\right) \tag{10}$$

where SF is the fish selected by the fish hawk, r is a random number between [0,1], and the value of I is one of 1,2.

(3) Adaptive T-distribution Perturbation Strategy

Considering the charging phase of the electric vehicle charging process, users will try to maximize the behavior of fully charging quickly in order to quickly return to use, as well as the impact of other issues such as avoiding overcharging during the charging process on the charging load of the charging station. In this paper, the t-distribution variant perturbation [39] with the iteration number variant formula as the t-distribution of the degree of freedom parameter is used to perturb the foraging behavior of the small dung beetle so that the dung beetle algorithm has a better global exploitation ability in the preiteration period, a good local exploration ability in the late iteration period, and improves the convergence speed of the algorithm in the following way for the specific location updating:

$$X_{\text{new}}^{i} = X_{\text{best}}^{i} + t(C\_\text{iter}) \cdot X_{\text{best}}^{i} \tag{11}$$

where X_{new}^{i} is the population position after adaptive t-distribution perturbation, X_{best}^{i} is the position of population i in the tth iterative equation, and $t(C\_\text{iter})$ is the adaptive t-distribution function parameterized by the number of iterations as degrees of freedom.

This IDBO algorithm, which combines the properties of global search and local optimization, shows excellent robustness and high efficiency in solving complex problems, and provides a comprehensive and effective solution for optimizing model hyperparameter problems. The IDBO optimization algorithm, Particle Swarm Optimization (PSO) [40], Sparrow Search Algorithm (SSA) [41], Northern Goshawk Optimization (NGO) [42], and the standard DBO algorithm to find the optimal solution for the single-peak function (F1), the basis function (F3), the hybrid function (F6), and the combined function (F9) in the cec2021 test function are used to perform a comparative analysis, whose convergence curves are shown in Figure 6.

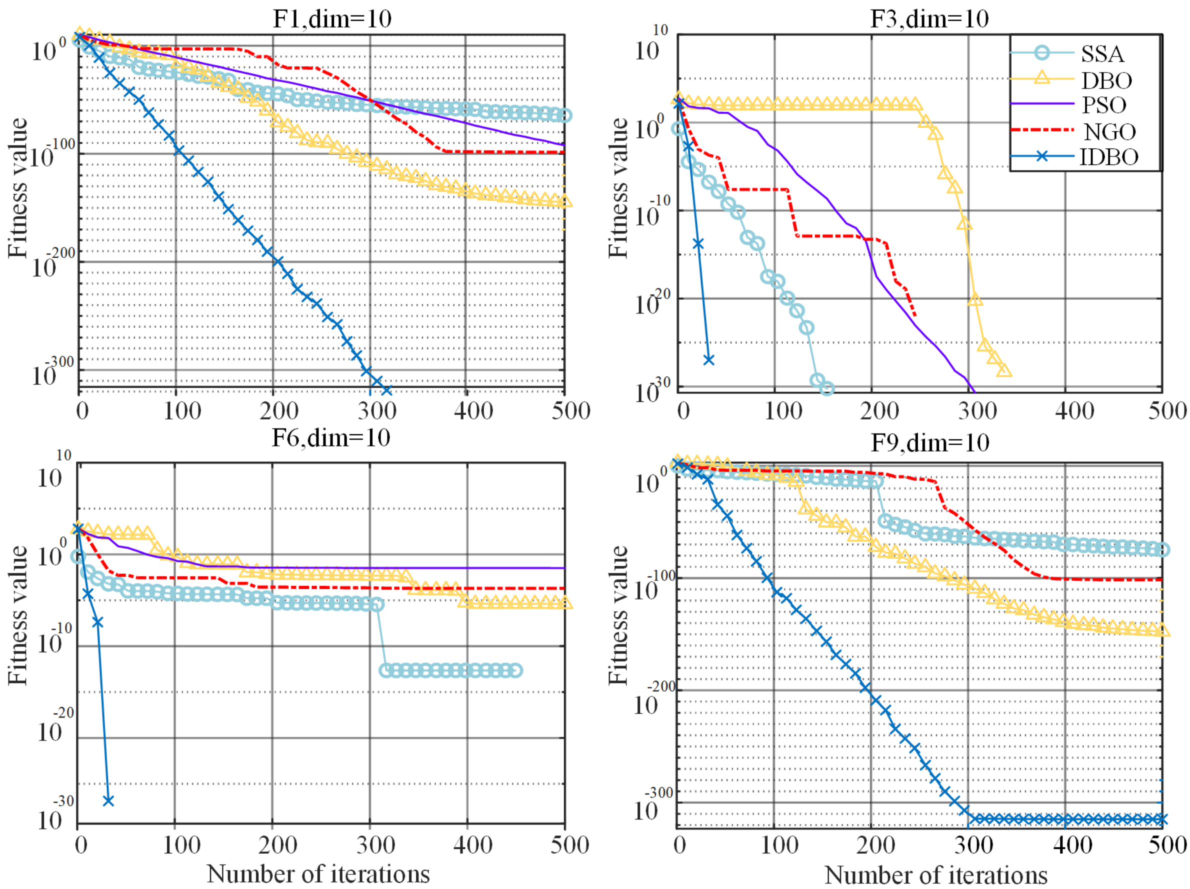

Figure 6. Test function evolution curve.

Figure 6 shows that compared with other optimization algorithms, the convergence curve of the IDBO algorithm shows stable and fast convergence characteristics, which effectively guides the optimization process towards the direction of the optimal solution and converges rapidly. The effectiveness of the IDBO algorithm in dealing with various kinds of complex and practical optimization problems is verified. Therefore, the IDBO algorithm can be applied to practical deep learning models, exploring the hyperparameter space through iterations, evaluating the performance of the model under different configurations, and gradually approximating the optimal solution to improve the performance of the model on practical tasks so as to better predict and deal with the potential load peaks of EV charging stations, avoiding grid congestion, overloading, and other safety risks, thus reducing the pressure on the power grid and improving its stability and security.

4. IDBO Optimized CNN-BiLSTM-Based Hybrid Model

4.1. Data Preprocessing

Since the proposed prediction method predicts the charging load of the charging station every hour, and the historical charging data exported by the charging station data collection system contain much invalid information such as order number and charging pile ID, the data are filtered and cleaned by using the Pandas package in Python v3.9.2, and only the charging load and charging start- and end-time information are retained. After that, the load is split into 24 moments of charging load per day. In addition, the original charging load data collected by the charging station often contains some null values, while the EV charging load data of the charging station have a certain degree of continuity, and the load data have a high degree of consistency at similar time periods. Therefore, Equation (9) is used to fill in for the null values:

$$y_t = \frac{y_{t-1} + y_{t+1}}{2} \tag{12}$$

where y_t is the missing moment fill data; y_{t-1} is the previous moment charging load value; and y_{t+1} is the latter moment charging load value.

In order to accelerate the convergence of the network loss function and improve the speed of model training, it is necessary to carry out one-hot coding of the date-type and holiday-type data, and normalize the historical load and temperature data. The normalization formula is

$$x_{\text{one}} = \frac{x - x_{\min}}{x_{\max} - x_{\min}} \tag{13}$$

where x_{one} is the value after normalization, and $x_{\max}$ and $x_{\min}$ are the maximum and minimum values in the sample data before normalization, respectively.

In this paper, the historical data of 24 h before the moment to be predicted are used to form the input feature matrix in order to make the charging load prediction for the next 1 h, and the input feature matrix X of its model is

$$X = \left[D_{(m+1)\times 7}, H_{(m+1)\times 2}, T_{(m+1)\times 1}, w_{(m+1)\times 1}\right] \tag{14}$$

where each training sample X is a matrix of order (m + 1) × 11 with m = 23; and $D_{(m+1)\times 7}$ and $H_{(m+1)\times 2}$ are one-hot coding matrices of weekly date and holiday types, respectively. $t_{(m+1)\times 1}$ and $w_{(m+1)\times 1}$ are air temperature and historical charging load sequences in units of °C and kW, respectively. After that, the whole input dataset is divided into training, validation, and test sets in the ratio of 7:2:1 for model prediction performance testing.

4.2. Evaluation Indicators

To assess the prediction accuracy of the model proposed in this paper, Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and Coefficient of Determination R^2 are selected as evaluation indexes. The formulas are

$$\text{MAE} = \frac{1}{q}\sum_{k=1}^{q}(|w_k - \hat{w}_k|) \tag{15}$$

$$\text{RMSE} = \sqrt{\frac{1}{q}\sum_{k=1}^{q}(w_k - \bar{w}_k)^2} \tag{16}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(w_k - \hat{w}_k)^2}{\sum_{i=1}^{n}(w_k - \bar{w})^2} \tag{17}$$

where w_k is the real data of the charging load at moment k; $\hat{w}_k$ is the predicted charging load data at moment k; $\bar{w}_k$ is the average value of the real data of the charging load; and q is the number of data points in the test dataset.

4.3. IDBO-CNN-BiLSTM Hybrid Model Construction

In summary, this paper proposes a hybrid prediction model of IDBO-CNN-BiLSTM, whose flowchart is shown in Figure 7 and is realized as follows.

Step 1. Use Pandas to preprocess the raw charging station data to get the charging load data at each moment, and construct the feature matrix as the input matrix with the data of factors such as air temperature, date type, and holidays.

Step 2. Combine the advantages of CNN feature extraction and BiLSTM to capture the hidden relationship of the time-series data, and construct the optimal layer CNN-BiLSTM hybrid model after experimental comparison.

Step 3. Optimize the initial position of the population, dung beetle rolling behavior, and small dung beetle foraging behavior in the dung beetle optimization algorithm.

Step 4. Use the improved dung beetle optimization algorithm to hyperparameter tune the CNN-BiLSTM hybrid model.

Step 5. Each type of dung beetle updates its position according to the formula, and then detects its boundaries, stops when it reaches a certain fitness value or the maximum number of iterations, and outputs the optimal hyperparameters.

Step 6. The resulting optimal hyperparameters are brought into the CNN-BiLSTM hybrid model, and then the feature input matrix in Step1 is substituted to obtain the predicted dataset.

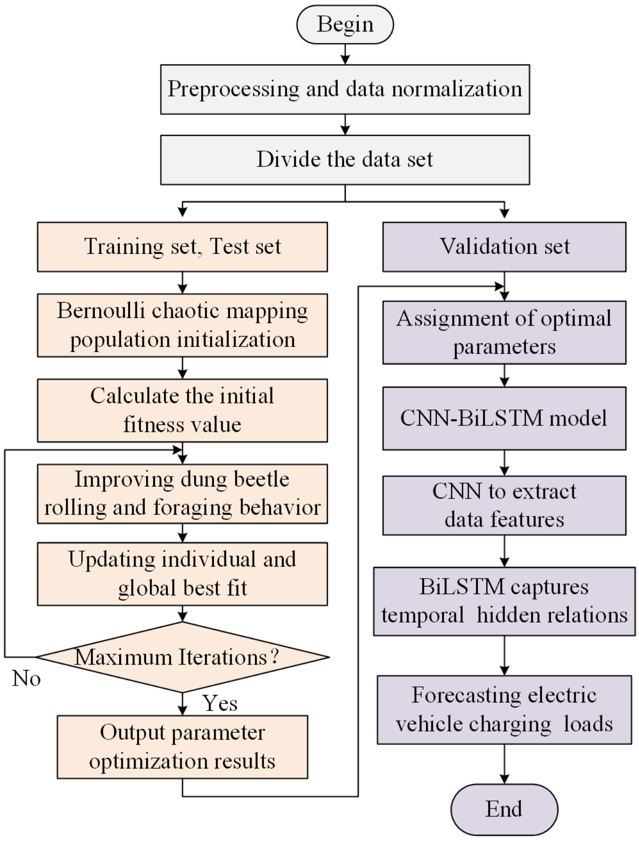

Figure 7. Principle flowchart of charging load forecasting method.

5. Example Simulation

In this paper, the historical charging load data of an EV charging station located on the campus of California Polytechnic State University in the U.S. ANN-DATA public dataset is selected for the experiment [43], and the historical charging load data of all 54 charging piles in the charging station from 1 January 2019 to 31 December 2019 are selected and collated to obtain 8760 sampling points. Temperature data were obtained using historical meteorological data for the city of Los Angeles, where Cal Poly is located, obtained from publicly available data on the National Oceanic and Atmospheric Administration website. The weekly dates and holiday types were set based on local realities. The IDBO-optimized CNN-BiLSTM hybrid model introduced in the previous section and other models are used to predict the charging load for the next 1 h of this data, and the results are analyzed and compared to verify the accuracy and validity of the prediction method of the proposed model.

5.1. IDBO Hyperparameter Optimization Results

The number of convolutional kernels of the three-layer CNN layer, the number of hidden neurons of the single-layer BiLSTM layer, the maximum number of iterations, the batch sample size and the learning rate in the CNN-BiLSTM model are set as hyperparameters to be optimized. The number of convolutional kernels of the three-layer CNN layer is optimized in the range of [8,64], the number of hidden neurons of the single-layer BiLSTM layer is optimized in the range of [8,128], and the maximum number of iterations is optimized in the range of [30,100]. The proposed IDBO and SSA, PSO and unoptimized DBO algorithms are used to optimize the above hyperparameters, and all four optimization methods take the minimum MSE of the prediction results of the validation set as the objective function, and the hyperparameter optimization results are shown in Table 2.

Table 2. Hyperparameter optimization results.

Parameterization	Limit	PSO	SSA	DBO	IDBO
Convolution Kernels 1	[8,64]	42	41	55	56
Convolution Kernels 2	[8,64]	48	30	29	27
Convolution Kernels 3	[8,64]	42	48	42	46
Hidden Neurons 1	[8,128]	48	42	52	45
Maximum Iterations	[10,100]	73	84	78	95
Batch Sample Size	[32,128]	101	74	65	107
Learning Rate	[0.001,0.1]	0.0013	0.0041	0.0016	0.0029

5.2. Comparative Analysis of Experimental Results

For the four models without hyperparameter tuning, the training predictions were repeated 100 times with the same parameters such as batch sample size and learning rate, as well as under different optimization algorithms for hyperparameter tuning of the CNN-BiLSTM hybrid model. The mean comparisons of MAE, RMSE, and R^2 for the prediction results of each model are shown in Table 3. As shown in Table 3, the CNN-BiLSTM hybrid model performs better than the CNN and BiLSTM models alone in processing time-series data. The proposed IDBO-CNN-BiLSTM model has the highest prediction accuracy among the CNN-BiLSTM models tuned with hyperparameters of the optimization algorithm. Compared with the DBO optimization algorithm, the IDBO-optimized hybrid model reduces the MAE by 8.22%; the RMSE reduces the RMSE by 13.34%; and the R^2 mean value improves the R^2 mean value by 5.62%.

Table 3. Comparison of model prediction accuracy.

Predictive Model	MAE Average	RMSE Average	R^2 Average
IDBO-CNN-BiLSTM	3.299	4.313	89.21%
CNN	4.563	6.215	74.18%
LSTM	4.333	5.832	76.92%
BiLSTM	4.064	5.474	79.23%
CNN-BiLSTM	3.801	5.214	81.66%
PSO- CNN-BiLSTM	3.766	5.433	84.94%
SSA-CNN-BiLSTM	3.755	5.134	83.86%
DBO-CNN-BiLSTM	3.703	5.093	84.44%

Figure 8 shows the prediction error box plots for each model, where C, L, B, CB, PCB, SCB, DCB, and IDCB represent CNN, LSTM, BiLSTM, CNN-BiLSTM, PSO-CNN-BiLSTM, SSA-CNN-BiLSTM, DBO-CNN-BiLSTM, and DBO-CNN- BiLSTM prediction models. As seen in Figure 8, the box corresponding to the prediction result error of the hybrid model based on IDBO optimization CNN-BiLSTM is flatter, the median line is located in the center of the box, and the upper and lower dashed lines are the shortest, which indicates that the error volatility of its prediction result is the smallest, which confirms that the model has a good ability to process the data.

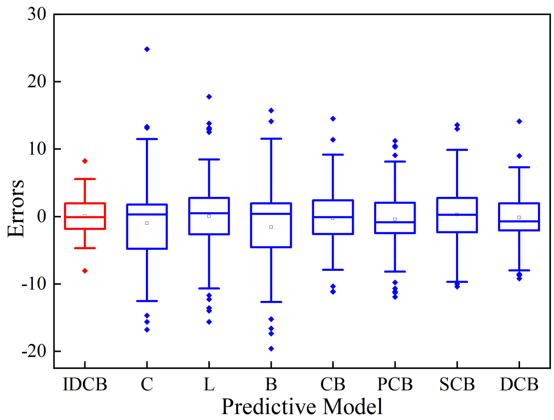

Figure 8. Model prediction error box plots.

In order to better verify the effectiveness of the IDBO algorithm on model performance improvement, the prediction results of the unoptimized CNN-BiLSTM hybrid model and the CNN-BiLSTM hybrid model are compared with the real values, and the prediction plots of their test sets are shown in Figures 9 and 10. From Figure 9, it can be seen that when the real values change, the prediction of the CNN-BiLSTM hybrid model has a certain lag and instability, which leads to a large error value, and most of the errors are concentrated in the range of [−5,10]. This indicates that the model needs to be improved in capturing data changes and predicting trends, and further optimization and improvement are needed to improve its prediction accuracy.

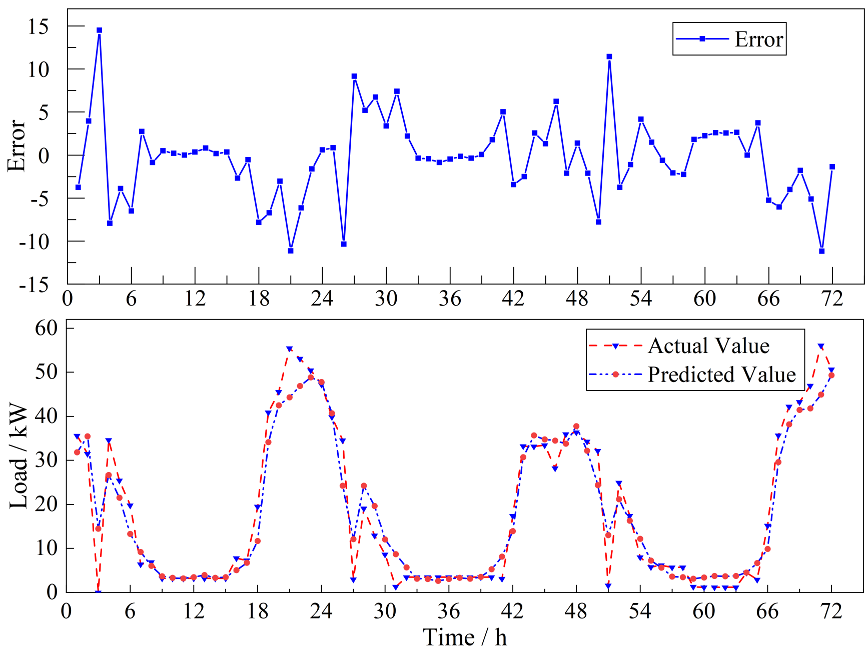

Figure 9. Plot of CNN-BiLSTM model predicted values against actual values.

According to Figure 10, it can be seen that the IDBO-CNN-BiLSTM model has a sharper prediction response to the actual numerical changes. Compared with the CNN-BiLSTM hybrid model, the error value of this model is significantly reduced, and most of the errors are distributed within the range of [−1.5,1.5]. This phenomenon indicates that the optimized CNN-BiLSTM model by IDBO shows high accuracy and stability in responding to the data changes, keeping the prediction errors within a small range.

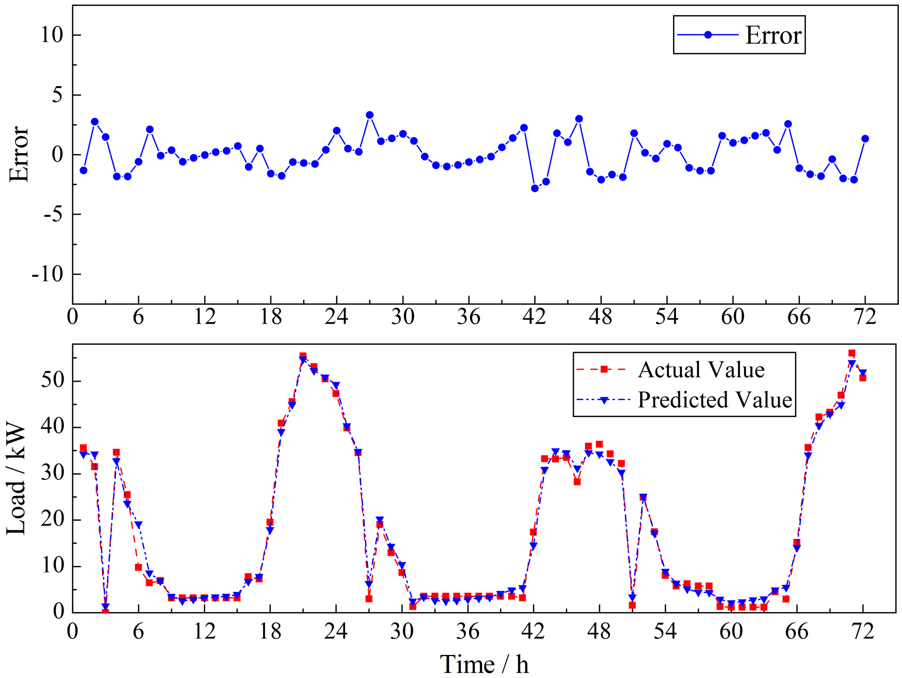

Figure 10. Plot of predicted versus actual values of IDBO-CNN-BiLSTM model.

In order to comprehensively evaluate the performance of the hybrid CNN-BiLSTM model optimized by the IDBO algorithm, this paper analyzes the model by comparing it with several baseline models including independent CNN, LSTM, and BiLSTM models, with a special focus on the model's prediction ability in the presence of complex charging load variations. The results are illustrated in two parts as shown in Figure 11. In part (a) of Figure 11, the performance of the CNN, LSTM and BiLSTM models in response to dramatic fluctuations in the charging load profile is shown. It can be clearly seen that the accuracy of these models in predicting the charging load especially at peaks and troughs is insufficient, and there is a large error between the predicted value and the true value, which indicates a limitation in their ability to capture the dynamic changes in the charging load. On the contrary, when the hybrid CNN-BiLSTM model is employed, the prediction results show a more accurate load-following trend, especially when dealing with peak charging loads, and the match between the predicted and real load curves is significantly improved.

In further evaluation, as shown in part (b) of Figure 11, the results of the CNN-BiLSTM hybrid model after tuning with different optimization algorithms are compared and analyzed. The results show that although all the tuned models can simulate the general trend of the charging load profile better, the CNN-BiLSTM model optimized based on the IDBO algorithm exhibits the best performance in terms of details. In particular, when predicting the peaks and valleys of charging loads, the model not only has the highest accuracy but also is able to closely follow the dramatic turns of the actual load curve, showing a high degree of adaptability and prediction accuracy regarding the complex dynamics of EV charging loads. These comparative results clearly show that the hybrid CNN-BiLSTM model optimized by the IDBO algorithm has significant advantages in the complex and variable EV charging load prediction task.

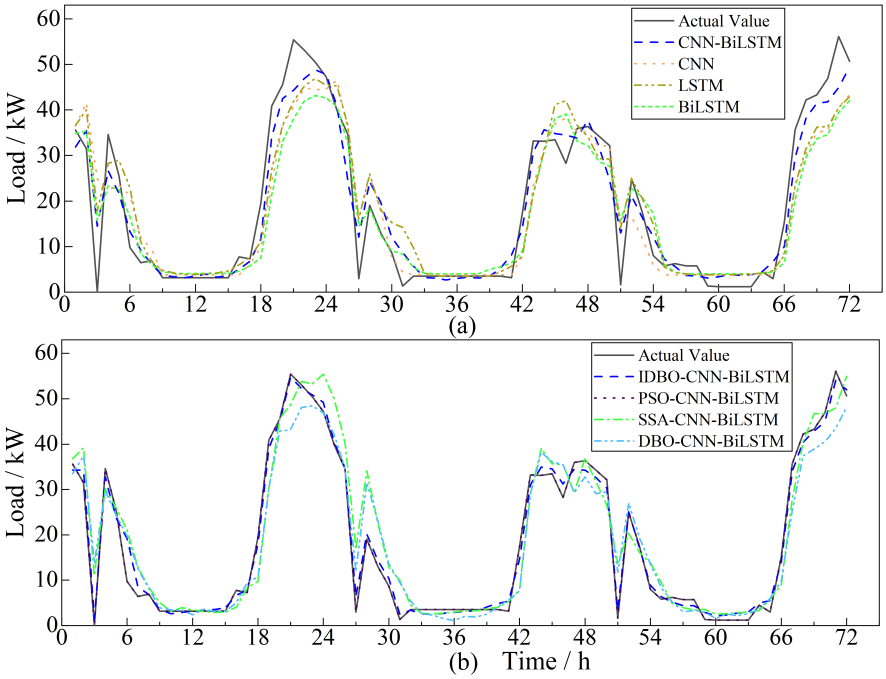

Figure 11. Plot of different model predictions.

Through the above comparative analysis, it can be found that the prediction accuracy of the model after parameter optimization is higher, and the MAE, RMSE, and R^2 indexes of the IDBO-CNN-BiLSTM model have been improved to different degrees, which fully reflects the importance of the CNN-BiLSTM hybrid model, as well as the importance and effectiveness of the IDBO algorithm for parameter optimization. This stable and accurate prediction ability provides a reliable basis for EV charging station load prediction.

5.3. Field Application

A comprehensive and integrated regression analysis and prediction of the charging loads of 31 EV charging stations in a specific urban area was carried out using the proposed model, and the distribution of electric vehicle charging stations in urban areas is shown as red dots in Figure 12.

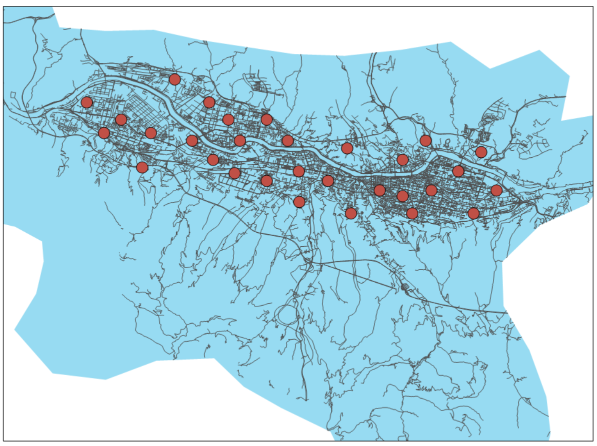

Figure 12. Distribution of EV charging stations.

The charging load data of all charging stations in the region were exhaustively counted and analyzed, and the prediction results for one day in the region are shown in Figure 13. The overall error of the prediction is within the acceptable range of [−20 kW, 20 kW], which not only confirms the validity of the model but also highlights its high accuracy and practical value in practical applications. By accurately predicting the charging load, the model is expected to provide powerful data support and decision-making reference for grid load management, charging station planning and construction, and optimal deployment of EV charging facilities. This study not only demonstrates the application of advanced research methods and technologies, but also provides concrete cases and practical proofs for the operation and management of EV charging stations and related policy formulation.

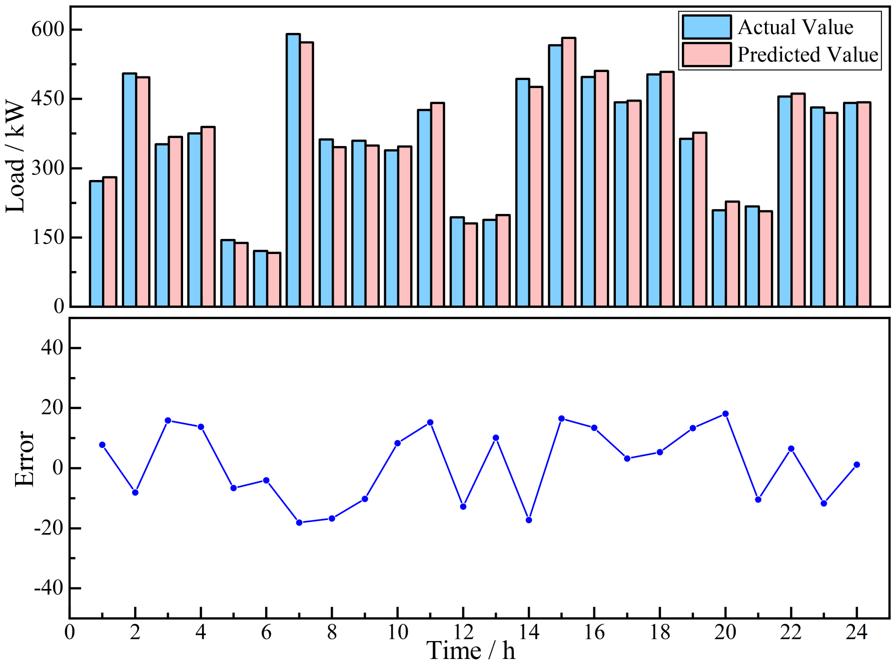

Figure 13. Load statistics of electric vehicle charging stations.

6. Conclusions

In this paper, in order to solve the problem of short-term charging load predictions of EV charging stations under a multifactor situation, a data-driven hybrid model based on an organic combination of CNN, BiLSTM and tuning using IDBO, the improved dung beetle algorithm, is proposed to realize the prediction of the short-term load of electric vehicle charging stations. The following conclusions are mainly obtained:

(1) The optimal hybrid neural network model with three CNN convolutional layers and a single BiLSTM layer as the main structure is designed and built. Through the analysis and comparison of different combinations of layers, and the comparison and analysis of other single models, the results show that the hybrid model is better than other models.

(2) Optimization of the four functions in the cec2021 test function by each algorithm and comparative analysis. The convergence curves obtained by the IDBO algorithm show the characteristics of stable and fast convergence. It reflects that the IDBO algorithm shows excellent robustness and high efficiency in solving complex problems, and provides an effective solution to the hyperparameter problem of the optimization model.

(3) Through the comparative analysis of regression prediction of several different algorithms and base models, the optimized CNN-BiLSTM hybrid model based on IDBO has been greatly improved in prediction accuracy. Compared with the DBO algorithm, its MAE and RMSE are decreased by 8.22% and 13.34%, respectively, and R^2 is improved by 5.62%. It proves that the hybrid model based on the algorithm under the DBO algorithm has higher prediction accuracy and stability, and provides a new method for the short-time prediction of electric vehicle charging loads.

In the next study, the influence of meteorological conditions such as temperature and barometric pressure, incentive policies, electricity price and other factors on the charging load of electric vehicles at charging stations will be further considered, and a more comprehensive feature input dataset will be constructed to improve the prediction accuracy of the proposed prediction method as much as possible. Although the model proposed in this paper has achieved a certain degree of accuracy, with the growth in the number of electric vehicles and the development of deep learning technology, the model still needs to be updated through the algorithm and technology to further improve the model accuracy and prediction efficiency to meet the needs of reality, so the system needs to be optimized and improved in the future.

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Abbreviations

The following abbreviations are used in this manuscript:

CNN	Convolutional Neural Network
BiLSTM	Bi-directional Long Short-Term Memory
DBO	Dung Beetle Optimization
IDBO	Improved Dung Beetle Algorithm

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