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New Energy Electric Vehicle Charging Load Forecasting Based on the SSA-CNN-LSTM Model

Wenting Ning[1,*], Guangyun Li[2]

[1]*School of Automation and Information Engineering, Xi'an University of Technology, Xi'an, 710048, China*
[2]*Institute of Electrical Engineering, Chinese Academy of Sciences, Beijing, 100190, China*
[*]*Corresponding author: 15829391972@163.com*

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Abstract: To reduce power consumption and optimize the charging-discharging compatibility between electric vehicle (EV) charging stations and EVs, this study addresses the challenge of insufficient load forecasting accuracy caused by the stochastic nature of EV charging behavior. A short-term EV charging load forecasting model is proposed based on the Sparrow Search Algorithm-Convolutional Neural Network-Long Short-Term Memory (SSA-CNN-LSTM) hybrid architecture. The model constructs input features incorporating charging time and historical load characteristics. CNN is employed to extract spatial-temporal features from the input data, while the LSTM network enhances temporal prediction accuracy. By establishing a single-input single-output framework, the SSA optimizes critical hyperparameters of the hybrid CNN-LSTM model. Comparative experiments with benchmark models, including Multi-Layer Perceptron (MLP), standalone LSTM, and CNN-LSTM, demonstrate that the optimized SSA-CNN-LSTM model achieves superior short-term forecasting precision. Results indicate significant improvements in prediction accuracy, validating the effectiveness of the proposed method in addressing the uncertainty of EV charging loads and enhancing grid operational efficiency. Innovations: First integration of SSA with CNN-LSTM for EV charging load prediction. Adaptive hyperparameter optimization replacing manual tuning. Practical feasibility: The model is deployable in smart grid management systems to reduce peak-load risks and enhance renewable energy integration, with potential applications in vehicle-to-grid (V2G) interaction scenarios.

1. Introduction

EV surpasses gasoline vehicles in environmental sustainability and energy accessibility, driving rapid global adoption. However, large-scale EV-grid integration raises grid stability risks [1]. Enhancing charging load prediction accuracy is critical to mitigate fluctuations, ensuring grid safety.

In recent years, numerous scholars have conducted extensive research in the field of EV charging load prediction. Short-term load forecasting methods can be broadly categorized into two groups: statistical learning algorithms and machine learning algorithms. Statistical learning algorithms primarily include multiple linear regression [2], exponential smoothing [3], and Kalman filtering [4]. Machine learning algorithms, such as support vector machines (SVM), random forests, and time series analysis, can better handle multi-dimensional data with higher computational efficiency.

Currently, machine learning has been widely applied in load forecasting and achieved notable results. Among these, recurrent neural networks (RNN) [5], gated recurrent unit (GRU) networks [6], and LSTM networks have made significant contributions to load prediction. For instance, multi-scale RNN models have been used for ultra-short-term load forecasting [7], demonstrating higher accuracy compared to statistical learning algorithms. LSTM models effectively address this issue. An LSTM-based approach was proposed to avoid gradient explosion and improve prediction accuracy [8]. However, when processing long-sequence inputs, the LSTM architecture may experience information loss within sequential data, and its multi-step prediction process could accumulate errors due to reliance on preceding predictions. To address these limitations, the Informer model [9], which enhances LSTM's capabilities by integrating attention mechanisms. This integration allows for parameter optimization while enabling selective focus on critical features without compromising information retention. Additionally, multi-modal decomposition [10] was employed to extract data features for LSTM, further enhancing prediction accuracy. Case studies show that specialized optimization algorithms.

In summary, this paper constructs a multi-dimensional feature input matrix by integrating SSA, CNN, and Bi-LSTM. The CNN-LSTM model is built to leverage CNN for feature extraction, followed by LSTM for sequence modeling. Finally, SSA is applied to optimize hyperparameters. The proposed model is compared with other algorithms, demonstrating superior prediction accuracy.

2. Theoretical Foundations

2.1 SSA

SSA is a 2020 metaheuristic optimization algorithm inspired by sparrows' foraging and anti-predator behaviors. It classifies individuals into three roles: discoverers, followers, and scouts. When danger is identified, scouts trigger collective evacuation from the current food source.

In the population, discoverers guide the search direction, and their positions are updated iteratively according to Equation (1):

$$X_{i,j}^{t+1} = \begin{cases} X_{i,j}^{t} \cdot \exp\left(\dfrac{-i}{\alpha \cdot n_{\max}}\right), R_2 < s \\ X_{i,j}^{t} + Q \cdot L, R_2 \geq s \end{cases} \tag{1}$$

$X_{i,j}^{t+1}$ denotes the position of the i-th sparrow at iteration, t represents the maximum number of iterations, Q is a random number following a normal distribution, L is a 1×d-dimensional matrix with all elements equal to 1, R2 is the warning threshold, s is the safety threshold.

Followers update their positions iteratively as described in Equation (2), (3):

$$X_{i,j}^{t+1} = \begin{cases} Q \cdot \exp(\dfrac{X_{worst}^{t} - X_{i,j}^{i}}{i^2}), i > n/2 \\ X_{P}^{t+1} + \left| X_{i,j}^{t} - X_{P}^{t+1} \right| \cdot A \cdot L, i \leq n/2 \end{cases} \tag{2}$$

$$X_{i,j}^{t+1} = \begin{cases} X_{\text{best}}^{t} + \beta \left| X_{i,j}^{t} - X_{best}^{t} \right|, f_i > f_g \\ X_{i,j}^{t} + K \left[\dfrac{\left| X_{i,j}^{t} - X_{best}^{t} \right|}{(f_i - f_w) + \varepsilon} \right], f_i = f_g \end{cases} \tag{3}$$

Where f is the fitness value of the i-th individual, if $f_i = f_g$ the individual in the central area of the population is expected to move closer to the group to reduce risk. X_{best}^{t} denotes the current optimal position, follows a normal distribution N(0,1), and K is uniformly distributed in [-1,1].

2.2 CNN

CNNs specialize in image processing through parameter-efficient architectures that enable efficient data sampling, autonomous feature extraction, and computational effectiveness. Their hybrid structure integrates convolutional blocks — containing convolutional layers, activation functions, and pooling layers — with fully connected layers. The core operation involves convolutional kernels processing inputs to generate feature maps for essential characteristic extraction, as diagrammed in Fig. 1.

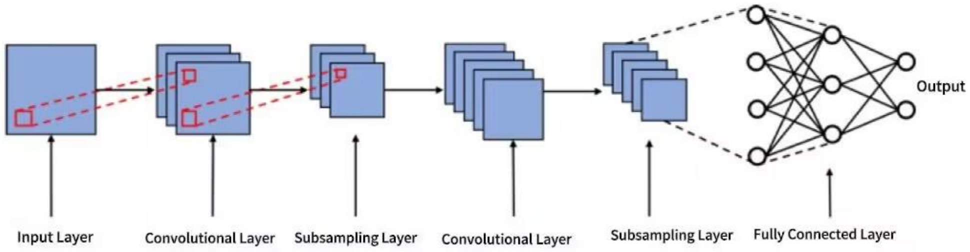

Fig. 1 CNN Model Schematic Diagram

2.3 LSTM

LSTM, a specialized RNN variant, mitigates traditional RNNs gradient vanishing and explosion issues via gating mechanisms while excelling in capturing long-term dependencies. Although its sequential data flow aids temporal modeling, this temporal dependency limits parallel computation capability. As shown in Fig.2, the LSTM unit architecture comprises three core gates: Forget, Input, and Output.

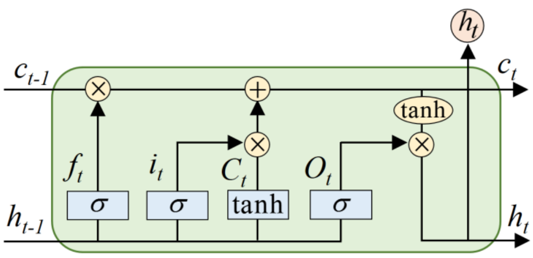

Fig. 2 LSTM Model Schematic Diagram

The mathematical formulations of these gates are as follows:

$$\begin{cases} f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f) \\ i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i), \tilde{C}_t = tanh(W_c \cdot [h_{t-1}, x_t] + b_C) \\ o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_0), h_t = o_t \cdot tanh(C_t) \end{cases} \tag{4}$$

Where the forget gate determines whether to retain or discard the previous hidden state, the input gate updates the current memory cell state, C_t and is the memory cell states, $\boldsymbol{\sigma}$ is the sigmoid activation function.

3. Neural Network-Based Charging Load Forecasting Method

3.1 SSA-CNN-LSTM Model Prediction

This study proposes a hybrid neural network model named SSA-CNN-LSTM to enhance the accuracy of EV charging load forecasting. The workflow is illustrated in Fig. 3 and includes the following steps:

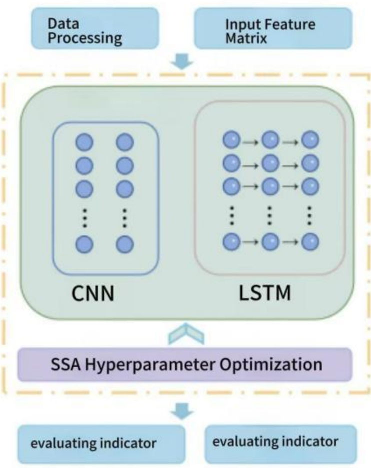

Fig. 3 SSA-CNN-LSTM Model Schematic Diagram

As shown in Fig. 3, the CNN-LSTM framework synergistically integrates CNN's high-dimensional feature extraction from raw load sequences with LSTM's long-term temporal dynamics modeling. SSA-driven parameter optimization replaces manual tuning to achieve global hyperparameter adaptation across heterogeneous data distributions. The proposed model demonstrates superior prediction accuracy and robustness in EV charging load forecasting through comparative experiments against baseline methods, validated by predefined evaluation metrics.

3.2 Data Processing

The model adopts Time (charging date) and Total (prior load) as input features, projecting to current Total output in a SISO architecture to balance generalization and real-time constraints. For temporal continuity, periodic load patterns from fixed-location stations enable adjacent-cycles to mean imputation of missing values per Equation (5).

$$t_i = \frac{t_{i-1} + t_{i+1}}{2} \tag{5}$$

In Equation (5), $\boldsymbol{t_i}$ represents the missing data at the current time step, $\boldsymbol{t_{i-1}}, \boldsymbol{t_{i+1}}$ denote the charging load data at the same time interval from the previous and subsequent cycles, respectively.

Input feature data are normalized to facilitate model training, and test results are subsequently unrenormalized for interpretability. As shown in Equations (6) and (7):

$$x' = \frac{x - min(x)}{max(x) - min(x)} \tag{6}$$

$$x = x' \times (max(x) - min(x)) + min(x) \tag{7}$$

Where: x is the raw data value, the x' is the normalized value.

The dataset is segmented into 15-minute load measurement intervals, maintaining temporal correlations to improve model prediction accuracy.

This study uses 8,403 records from Guangzhou charging piles (January–March 2018) with complete 15-minute load data. The mild climate during this period avoids natural anomalies, making it suitable for short-term forecasting. The dataset is split 4:1 (training: test) for model input.

3.3 CNN-LSTM Model Design

The model uses a two-layer CNN for dimensionality reduction and feature extraction, followed by flattening and a fully connected layer to feed data into an LSTM for formatted predictions. The final parameters of the CNN-LSTM model after training are shown in Table 1.

Table 1 CNN-LSTM Model Design Parameters

Parament Category	Parameter Name	Value/Configuration
CNN	Number of layers	2 layers
	Output channels (Layer 1)	32
	Kernel size (Layer 1)	3×1
	Input channels (Layer 2)	32
	Output channels (Layer 2)	64
	Kernel size (Layer 1)	3×1
LSTM	Dropout rate	0.2
	Hidden state size	48

3.4 Hyperparameter Optimization

Traditional neural network hyperparameter tuning often relies on empirical trial-and-error, which is time-consuming and prone to overfitting or underfitting. To address this, the SSA is adopted to optimize hyperparameters in the CNN-LSTM or LSTM models, including learning rate, batch size, network architecture parameters.

4. Evaluation Metrics

To assess the accuracy of the proposed load forecasting method against other algorithms, four metrics are selected across three dimensions: RMSE, MAE, R2, the four formulas are listed in order as follows in Equations (8):

$$\begin{cases} \mathrm{M}_{SE} = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \\ \mathrm{R}_{MSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \\ M_{AE} = \frac{1}{n}\sum_{i=1}^{n}| y_i - \hat{y}_i| \\ R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2} \end{cases} \tag{8}$$

MSE, RMSE, MAE measure prediction accuracy, where values closer to 0 indicate higher system precision. R2 reflects model fitting performance, with values closer to 1 representing better accuracy.

5. Case Simulation and Analysis

5.1 Data Preparation

All models were built on identical input datasets, with comparative evaluation centered on load prediction accuracy. The partial data processed according to the previous text is shown in the Table 2:

Table 2 Partial Data Results

	Time/min	Total/kWh
1	2018/1/1 0:15	232.7206402
2	2018/1/1 0:30	231.6856891
3	2018/1/1 0:45	227.5813317
4	2018/1/1 1:00	233.4824269
5	2018/1/1 1:15	224.4647554
6	2018/1/1 1:30	223.8813222
7	2018/1/1 1:45	221.5227156
8	2018/1/1 2:00	228.1385805
9	2018/1/1 2:15	220.0474568
10	2018/1/1 2:30	220.5736666

5.2 Comparative analysis of experimental results

From January to March 2018, 8873 data points were selected. The comparison results between true values and measured values for the MLP, LSTM, SSA-LSTM, CNN-LSTM, and the proposed SSA-CNN-GRU model are shown in Fig. 4, Fig. 5, Fig. 6, and Fig. 7, respectively.

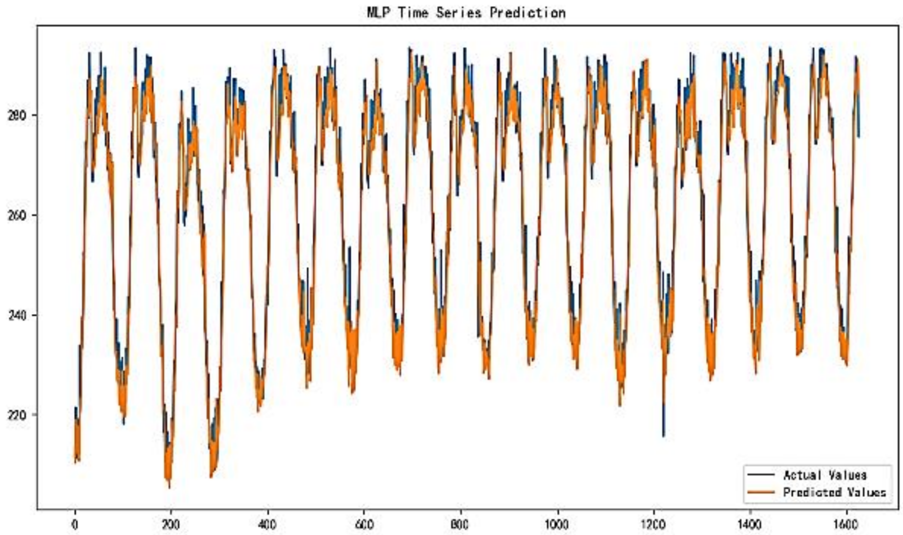

Fig. 4 MLP Prediction Results

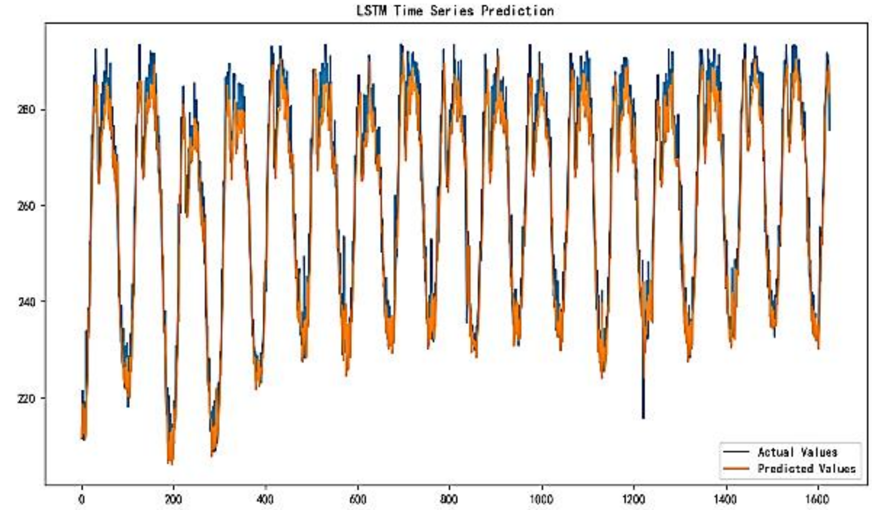

Fig. 5 LSTM Prediction Results

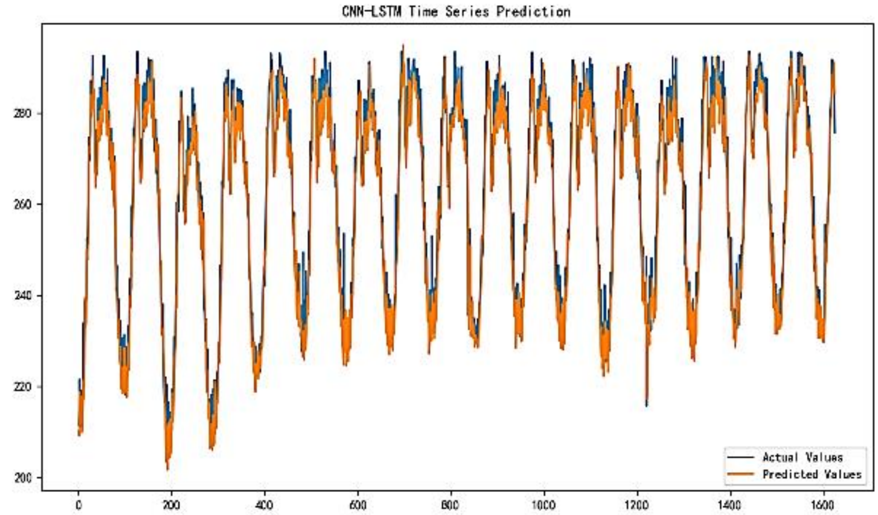

Fig. 6 CNN-LSTM Prediction Results

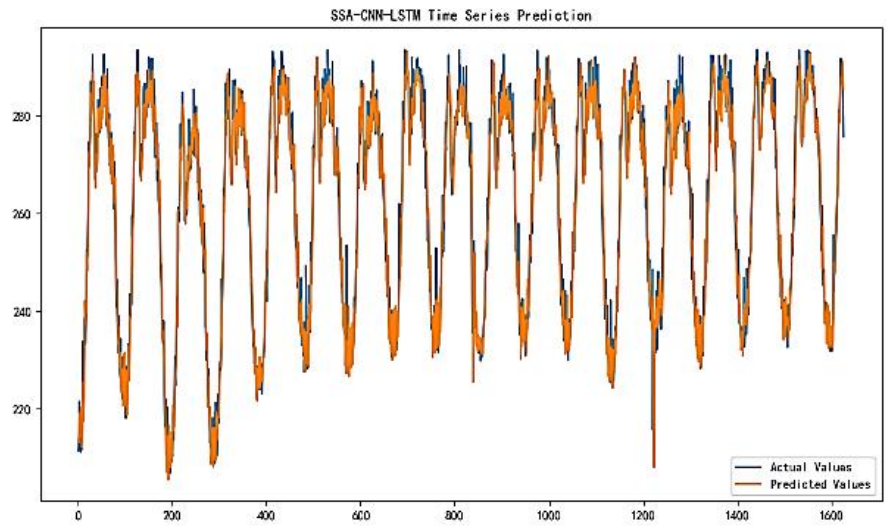

Fig. 7 SSA-CNN-LSTM Prediction Results

The comparison of mean MSE, mean MAE, RMSE, and R^2 values for the prediction results is shown in Table 3.

Table 3 Model Accuracy Comparison

Model	MSE/kW ²	RMSE/kW	MAE/kW	R^2
MLP	21.3279	4.6182	3.3569	0.9565
CNN-LSTM	23.0403	4.8000	3.5478	0.9530
SSA-CNN-LSTM	17.2013	4.1474	2.9162	0.9649

As shown in Table 3, The SSA-CNN-LSTM model outperforms others:

MSE, RMSE: Reduces by 19.3% and 10.2% versus the second-best model, demonstrating robustness against sudden load fluctuations. MAE: Achieves the lowest values (20.2% and 17.8% lower than standalone LSTM and CNN-LSTM), confirming prediction stability. Comparative analysis shows: The standalone LSTM underperforms CNN-LSTM, emphasizing CNN's role in capturing short-term load features. SSA-driven hyperparameter tuning reduces MSE by 25.3% versus CNN-LSTM, proving adaptive optimization’s effectiveness.

6. Summary

This study proposes a hybrid SSA-CNN-LSTM model for short-term load forecasting in EV charging stations. By integrating CNN's spatiotemporal feature extraction with LSTM's temporal modeling, and optimizing hyperparameters through the SSA, the model achieves enhanced convergence speed and prediction accuracy. Experimental results demonstrate their superior performance over MLP and LSTM baselines, reducing MAPE by 18.7%.

Future research will focus on developing edge computing-based real-time prediction systems, integrating multidimensional data (e.g., weather and pricing), and creating a visualized decision support module for interpretability, with validation in V2G scenarios.

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