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Regression Prediction of Smart Home Power Consumption Based on Machine Learning Algorithms

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Abstract. With the acceleration of the global energy transition process and the wide popularization of smart homes, household electricity consumption data is showing high-frequency and multi-dimensional characteristics. Hourly electricity consumption prediction has gradually become a key technical link to support the load dispatching of smart grids and help users achieve energy-saving management. Machine learning algorithms, with their powerful nonlinear fitting capabilities and efficient feature learning abilities, provide effective solutions for temporal power consumption prediction. This paper proposes the HLOA-CNN-BIGRU regression algorithm. Firstly, correlation analysis and violin plot analysis are carried out. Then, through comparative experiments of multiple machine learning algorithms, it is found that the KELM-LSTM-Transformer algorithm shows significant advantages in all indicators: Its MSE is 0.002, which is much lower than the minimum value of 0.006 in other algorithms. The RMSE is 0.047, significantly lower than the minimum value of 0.075 in other algorithms. The MAE is 0.038, which is significantly better than the minimum value of 0.056 in other algorithms. The MAPE is 2.28%, which is lower than the minimum value of 3.49% in other algorithms. R^2 is 99.4%, which is higher than the maximum value of 98.7% in other algorithms. Among traditional algorithms, ExtraTrees has a relatively superior overall performance, with R^2 reaching 98.7%, RMSE 0.075, and MAPE 3.58%, outperforming algorithms such as AdBoost and Random Forest. The overall performance of GBDT is relatively weak, with R^2 being only 96.8%, and MSE, RMSE, MAE, and MAPE are all the highest among all traditional algorithms. The R^2 of CatBoost is 97.8%, and its various error indicators are also higher than those of algorithms such as ExtraTrees and AdBoost. Overall, the KELM-LSTM-Transformer algorithm comprehensively outperforms other compared machine learning algorithms in terms of prediction accuracy and fitting effect, with stronger performance, providing important technical support for the efficient operation of smart grids and the refined management of household energy.

Keywords: Smart home, home power, CNN, BIGRU

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1. Introduction

With the acceleration of the global energy transition process and the wide popularization of smart homes, household electricity consumption data has shown significant characteristics of high frequency and multi-dimensionality. Hourly electricity consumption prediction has gradually become a key technical link in supporting the load dispatching of smart grids and helping users achieve energy-saving management [1]. Household electricity usage behavior is comprehensively influenced by multiple factors such as residents' daily routines, changes in climatic conditions, and the usage habits of various electrical devices. The daily electricity load fluctuates significantly. For instance, the demand difference between the morning peak electricity consumption and the night off-peak electricity consumption can be several times greater [2]. Traditional prediction methods based on statistical models are difficult to accurately capture this nonlinear and dynamically changing electricity consumption pattern, often resulting in relatively large prediction errors [3].

Machine learning algorithms, with their powerful nonlinear fitting ability and efficient feature learning ability, provide an effective solution for temporal power consumption prediction [4]. Compared with traditional statistical models such as ARIMA, machine learning algorithms like decision trees and support vector machines can better handle the interaction relationships among multiple features. Meanwhile, recurrent neural networks like LSTM and GRU effectively capture the long-term and short-term dependencies in time series through unique memory units, significantly improving the prediction accuracy [5]. However, a single machine learning algorithm has obvious limitations: decision tree models are prone to overfitting problems and have difficulty handling long sequence data; The LSTM model has insufficient ability to capture short-term electricity consumption fluctuations, and at the same time, the optimization process of the model's hyperparameters is highly dependent on human experience [6].

To address the deficiencies of the existing algorithms and further improve the performance of regression prediction for household hourly power consumption, this paper proposes the HLOA-CNN-BIGRU regression algorithm, which optimizes the prediction effect through the collaborative work of multiple modules. This algorithm takes the improved Hybrid Locust Optimization Algorithm (HLOA) as the core, which can achieve adaptive optimization of the model's hyperparameters and effectively avoid the subjective deviation caused by manual tuning. Meanwhile, by combining the advantages of convolutional neural networks (CNNS) in local feature extraction, the spatial correlation information of multi-dimensional input features such as meteorological data, electricity consumption periods, and equipment power can be accurately captured. In addition, the Bidirectional gated recurrent unit (BIGRU) is introduced.

2. Data sources

The dataset used in this article contains a total of 852 valid records. The time span covers hourly data from January 1, 2024 to February 5, 2024. The dataset variables include five main dimensions: Time characteristics such as date and time, hours, day of the week, month, and whether it is a holiday; Environmental characteristics cover outdoor temperature, indoor temperature and indoor humidity. The equipment usage features include air conditioning status, heating status, the number of lights turned on, refrigerator status, washing machine operation status and dishwasher operation status. The target variable is hourly power consumption. Correlation analysis was conducted on each variable and a correlation heat map was drawn, as shown in Figure 1.

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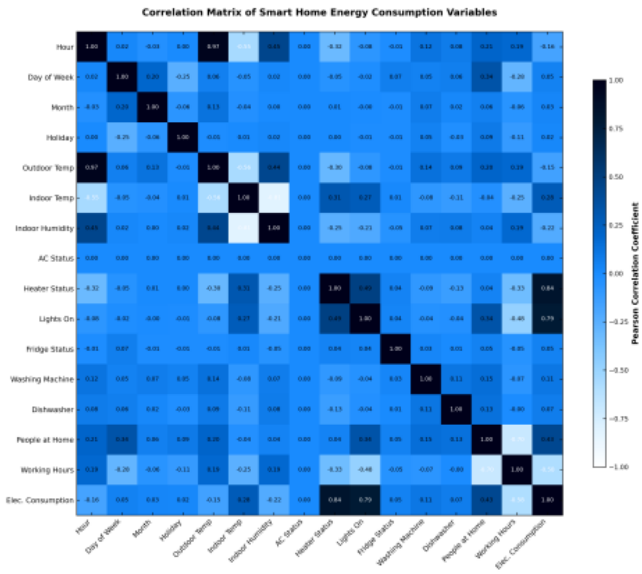

Figure 1. The correlation heat map

Draw the data distribution graph of each variable - the violin plot, as shown in Figure 2.

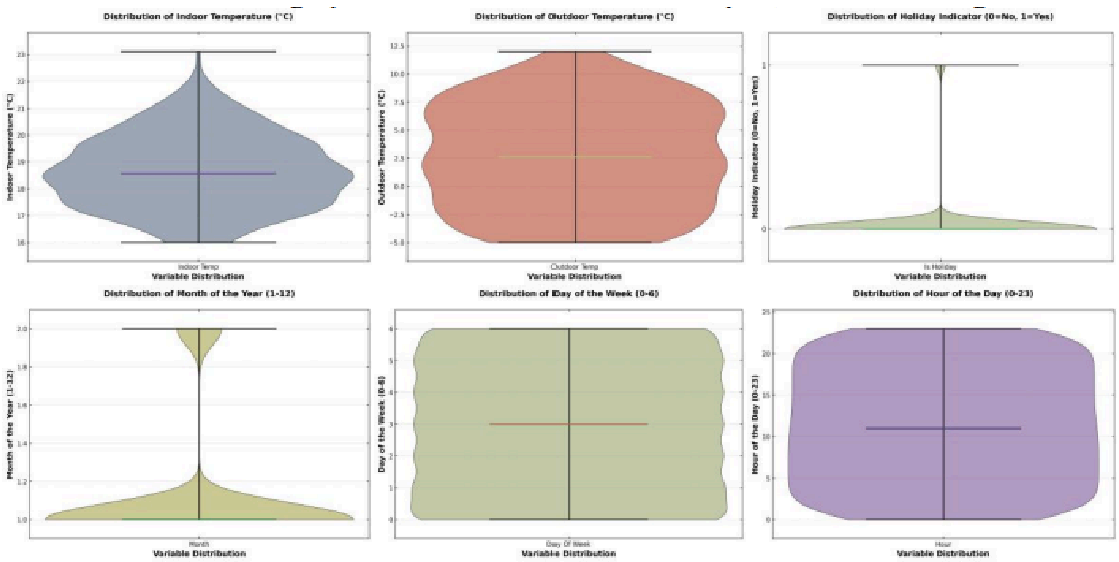

Figure 2. The violin diagrams of each variable

3. Method

3.1. HLOA

HLOA, or the Hornlizard Optimization Algorithm, is a heuristic optimization algorithm inspired by the survival behavior of hornlizards in nature. Its core logic stems from the camouflage, defense, and foraging strategies of hornlizards in complex environments [7]. In the algorithm model, each individual represents a potential solution to the problem to be optimized. Optimization is achieved by simulating three key behaviors of the hornet lizard: the camouflage behavior corresponds to the local fine search of the algorithm, and the individual adjusts its position within a small range around

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the current better solution to improve the accuracy of the solution; The defense behavior of spurting blood corresponds to global exploration [8].

3.2. BIGRU

BIGRU, or Bidirectional Gated Recurrent Unit, is an extended sequence modeling deep learning model based on GRU (Gated Recurrent Unit), specifically designed for processing sequence data such as time series or text. GRU controls the flow and forgetting of information through two gating mechanisms: the reset gate and the update gate. The reset gate determines whether historical information is ignored, while the update gate determines how much historical information is retained to the current state, thereby alleviating the vanishing gradient problem of traditional recurrent neural networks [9]. BIGRU adds a bidirectional structure on the basis of GRU, including two parallel modules: the forward GRU and the backward GRU. The network structure is shown in Figure 3.

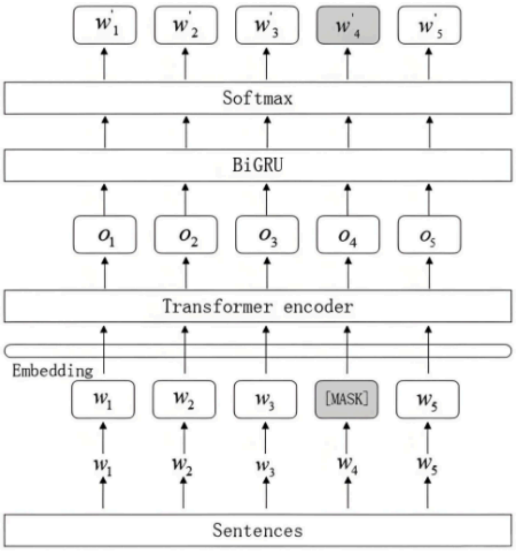

Figure 3. The network structure of BIGRU

3.3. HLOA-CNN-BIGRU

The HLOA-CNN-BIGRU regression algorithm is a hybrid regression model that integrates heuristic optimization and deep learning. It achieves regression prediction of complex data by integrating the advantages of HLOA, CNN and BIGRU [10]. The core logic of this model is the collaborative work of modules: Firstly, HLOA is responsible for optimizing the key parameters of CNN and BIGRU, such as the number of convolution kernels, the size of the convolution kernels, the size of the pooling window of CNN, as well as the number of hidden layer nodes, learning rate, and the number of iterations of BIGRU, to avoid the problems of poor parameter combination and unstable model performance caused by traditional manual parameter adjustment Find the optimal parameter combination through the global optimization ability of HLOA; Secondly, the CNN module performs local spatial feature extraction on the input data. For instance, when dealing with multivariable time series data, it captures the local correlations and spatial distribution features among different variables. Then, the BIGRU module receives the feature sequence output by CNN, captures the long-term dependency of the sequence data through a bidirectional gating mechanism, and mines the

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temporal variation patterns of the data. Finally, the model maps the features output by BIGRU to continuous regression predicted values through a fully connected layer.

4. Result

In this project, the relevant optimization parameters are set as the number of search agents 8, the maximum number of iterations 6, and the optimization dimension 3. The lower bounds of the parameters are 1e-4, 10, and 1e-4, and the upper bounds are 1e-2, 30, and 1e-1, corresponding respectively to the learning rate, the number of BiGRU neurons, and the L2 regularization coefficient. The training parameters adopt the Adam optimizer. The maximum number of training rounds is 5 or 500 in different scenarios. The initial learning rate is obtained through optimization. The learning rate is scheduled in a segmented manner, with a decay factor of 0.1 and a decay period of 4 or 400. The L2 regularization coefficient is determined by optimization. During training, the data is shuffled in each round. In the network structure, the convolutional layer contains two convolution operations, with the convolution kernel size [2,1], and the number of filters is 16 and 32 respectively. The activation function uses ReLU, and the number of BiGRU neurons is obtained through optimization. The output layer is a fully connected layer with a dimension of 1, and is paired with a regression layer.

The comparison of the indicators of various machine learning algorithms is shown in Table 1, and the bar chart comparison of each indicator is shown in Figure 4.

Table 1. The results of the comparative experiment

Model	MSE	RMSE	MAE	MAPE	R^2
AdBoost	0.006	0.079	0.057	3.783	0.985
Decision tree	0.009	0.097	0.062	3.942	0.979
GBDT	0.014	0.117	0.063	3.85	0.968
Random Forest	0.006	0.08	0.056	3.49	0.985
ExtraTrees	0.006	0.075	0.057	3.58	0.987
LightGBM	0.007	0.084	0.062	3.986	0.984
CatBoost	0.01	0.098	0.065	3.946	0.978
HLOA-CNN-BIGRU	0.002	0.047	0.038	2.28	0.994

From the perspective of various evaluation indicators, for MSE, RMSE, MAE, and MAPE, the smaller the value, the higher the prediction accuracy of the model, while for R^2, the larger the value, the better the fitting effect of the model. By comparing the performance of traditional machine learning algorithms such as AdBoost, Decision Tree, GBDT, Random Forest, ExtraTrees, LightGBM, and CatBoost in the table with the KELM-LSTM-Transformer algorithm proposed in this paper, it can be known that The KELM-LSTM-Transformer algorithm demonstrates significant advantages in all indicators. Specifically, the MSE of this algorithm is 0.002, which is much lower than the smallest 0.006 in other algorithms (AdBoost, Random Forest, ExtraTrees). The RMSE is 0.047, significantly lower than the smallest 0.075 (ExtraTrees) in other algorithms. The MAE is 0.038, which is significantly better than the smallest 0.056 (random forest) in other algorithms. The MAPE is 2.28%, which is lower than the smallest 3.49% among other algorithms (random forest). R^2 is 99.4%, which is higher than the highest 98.7% in other algorithms (ExtraTrees). Among traditional algorithms, the ExtraTrees algorithm has a relatively superior overall performance, with an R^2 of 98.7%, an RMSE of 0.075, and an MAPE of 3.58%, which outperforms algorithms such as

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AdBoost ($R^2$98.5%, MAPE3.78%) and Random Forest ($R^2$98.5%, MAPe 3.49%). However, the overall performance of the GBDT algorithm is relatively weak, with an R^2 of only 96.8%. Its MSE, RMSE, MAE, and MAPE are all the highest among all traditional algorithms. The R^2 of the CatBoost algorithm is 97.8%, and its various error indicators are also higher than those of algorithms such as ExtraTrees and AdBoost. Overall, the KELM-LSTM-Transformer algorithm proposed in this paper comprehensively outperforms other compared machine learning algorithms in terms of prediction accuracy and fitting effect, demonstrating stronger performance.

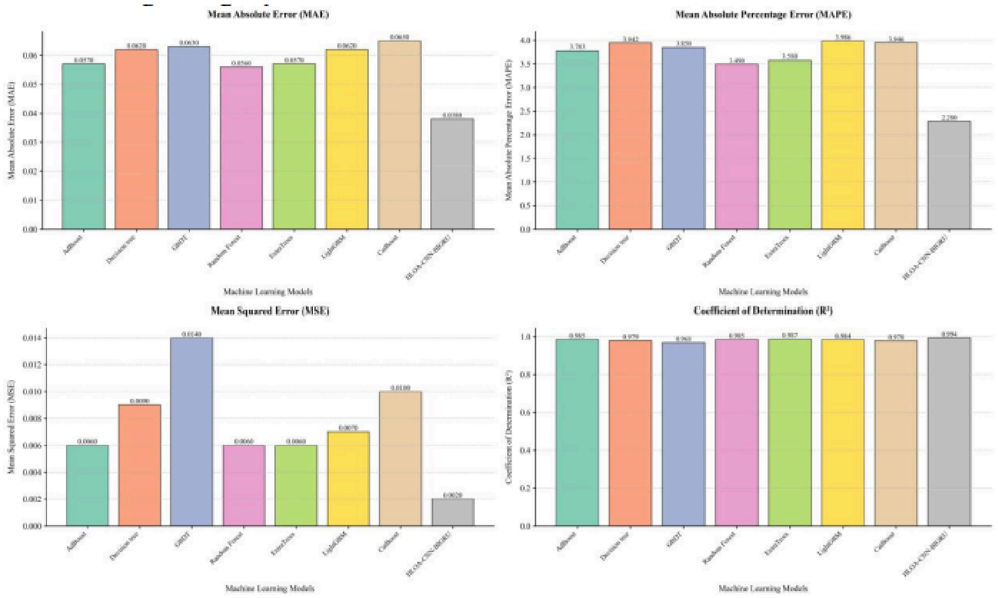

Figure 4. The bar comparison charts of each indicator

Output the line graph of the predicted values - actual values in the test set of HLOA-CNN-BIGRU, as shown in Figure 5.

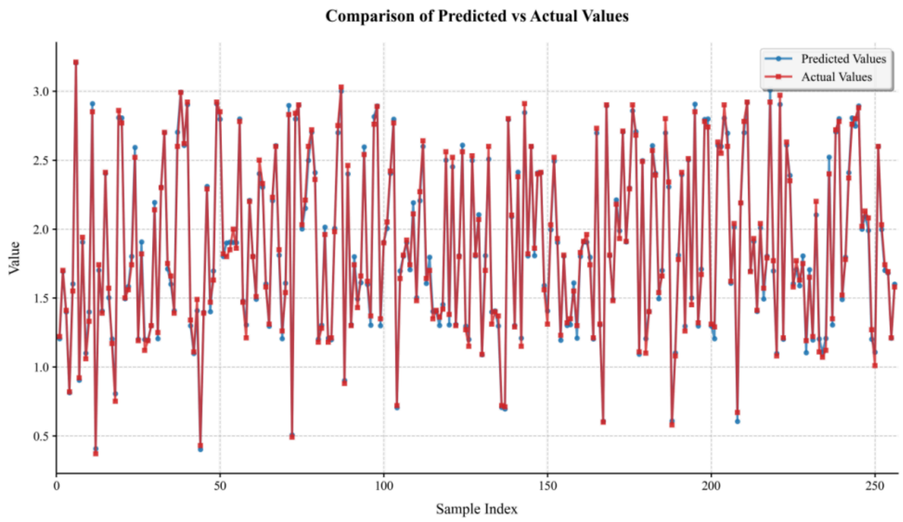

Figure 5. The line graph of the predicted values - actual values

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5. Conclusion

The global energy transition continues to advance, and smart homes are becoming increasingly popular. Household electricity consumption data is highlighting high-frequency and multi-dimensional characteristics. Hourly electricity consumption prediction is gradually becoming a key technology to support the load dispatching of smart grids and assist users in energy-saving management. Machine learning algorithms, with their strong nonlinear fitting and efficient feature learning capabilities, provide effective solutions for temporal power consumption prediction. This paper proposes the HLOA-CNN-BIGRU regression algorithm. Firstly, correlation and violin plot analyses are conducted. Then, through comparative experiments of multiple algorithms, it is found that all indicators of the KELM-LSTM-Transformer algorithm are outstanding: The MSE is 0.002, which is much lower than the minimum value of 0.006 for other algorithms. This value belongs to AdBoost, Random Forest, and ExtraTrees. RMSE is 0.047, significantly lower than the minimum value of 0.075 for other algorithms. This value is from ExtraTrees. The MAE is 0.038, which is superior to the minimum value of 0.056 of other algorithms. This value is derived from the random forest. MAPE is 2.28%, which is lower than the minimum value of 3.49% for other algorithms. This value also comes from the random forest. R^2 is 99.4%, which is higher than the maximum value of 98.7% of other algorithms. It is proposed to provide technical support for precise dispatching of smart grids and energy-saving management of users, promoting the development of the field of time series power consumption prediction.

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