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Building energy consumption prediction and management based on artificial intelligence

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Abstract To predict the building energy consumption, a semi-supervised learning outlier detection algorithm is developed to effectively detect and process abnormal energy consumption values. After detecting and processing abnormal energy consumption values, a building energy consumption prediction model based on multi-granularity feature extraction is proposed. The prediction performance of the proposed method is compared with others to explore the accuracy and superiority of the proposed prediction model. The findings indicated that the mean square error and mean absolute error of the local anomaly factor algorithm based on semi-supervised learning were 0.0073 and 0.063, respectively. Compared with the long short-term memory network model, the mean square error, root mean square error, and mean absolute error of the proposed model were significantly reduced by 41.07%, 17.86%, and 30.50%, respectively. Accurately predicting building energy consumption is beneficial for fine planning and management of building energy consumption, making certain contributions to the green development of the building industry and achieving energy conservation and emission reduction.

Index Terms Semi-supervised learning, SL-LOF algorithm, Building energy consumption, Multi-granularity features, Prediction model

I. Introduction

With the rapid development of society, the building energy consumption (BEC) is increasing rapidly. Excessive energy consumption can lead to a large amount of greenhouse gas emissions, resulting in global warming [1]. Therefore, it is particularly important to promote building energy conservation and emission reduction (ECER), and reduce the BEC. The key to achieving building ECER lies in accurately predicting BEC to improve the level of refined management of BEC [2]. Traditional methods for predicting BEC typically use physical algorithms and statistics, which are computationally complex, inefficient, and inaccurate [3]. Therefore, an accurate BEC prediction model is constructed to promote the development of green buildings and implement ECER strategies for buildings [4]. As technology and artificial intelligence (AI) continue to evolve, machine learning (ML) and deep learning (DL) have emerged as a prominent new type of algorithm, with extensive applications across multiple fields, including the prediction of modern BEC [5], [6].

In recent years, ML and DL based on AI have made breakthrough progress in research related to energy consumption. Hou Y et al. used bibliometric methods to characterize the knowledge systems in big data, AI, and energy, and optimized and predicted energy related issues using genetic algorithms and neural networks. The results found that combining ML, DL, and energy conservation could promote energy-saving renovations in buildings [7]. Ngo NT et al. designed a hybrid AI model for predicting time series energy consumption of buildings. The experimental outcomes denoted that the designed model had the highest accuracy, with a root mean square error (RMSE) of 1.77 kWh, an mean absolute percentage error of 9.56%, and a correlation coefficient of 0.914 [8]. Tariq R et al. explored the prediction of BEC using AI-based decision trees, k-nearest neighbors, gradient enhancement, and long-term memory network models. The results found that the average prediction error of decision trees was about 3.58%. The k-nearest neighbor model showed signs of overfitting. Gradient enhancement could accurately predict changes in the training dataset [9]. Ding C et al. developed an AI-based method for assessing and quantifying emissions reductions, estimating energy and emission savings in representative climate zones. The findings indicated that adopting AI could cut down energy consumption and carbon emissions by approximately 8% to 19%. The integration of energy policies with low-carbon power generation has the potential to reduce energy consumption by approximately 40% and carbon emissions by 90%. Wefki H et al. developed a new BEC estimation model based on genetic programming, artificial neural networks, and evolutionary polynomial regression. The efficacy of the model was assessed through RMSE and coefficient of determination. The outcomes denoted that the error of the evolutionary polynomial regression model was 2% [11]. Santos-Herrero JM et al. used artificial neural networks to study digital twins of specific features of buildings. It was found that there was a reasonable correlation between the actual data of working hours and energy consumption, and the model could achieve relatively accurate prediction accuracy in existing public buildings [12].

To effectively refine the management of BEC and implement ECER strategies, many scholars have completed massive research on predictive models for BEC. Mahmood S et al. developed an ML-based green building prediction model aimed at reducing energy consumption. This model utilized regression models such as random forests and decision trees to raise the prediction model. The outcomes denoted that the cooling prediction value was 0.9975 and the heating prediction value was 0.9883, proving that the proposed model had good prediction accuracy [13]. Chaganti R et al. proposed an ML-based building cooling and heating load prediction model, aiming to provide better predictive performance. The experiment extracted various features such as glass window area and relative density. The outcomes denoted that the predictive coefficients for heating and cooling loads of the model were 0.999 and 0.997, respectively [14]. Kim ML et al. developed a DL-based BEC prediction model. The measurement error of occupancy rate counting was analyzed by measuring the occupancy rate. The outcomes denoted that the occupancy rate based on RMSE increased by 71.1% contrast to the original occupancy rate perception. The energy consumption based on occupancy rate prediction increased by 5.2% compared to the original energy estimate [15]. Le T et al. constructed an intelligent BEC prediction model with transfer learning, which used transfer learning and long short-term memory (LSTM) networks to build the prediction model. The experiment compared the performance indicators of different building consumption predictions. The outcomes denoted that the model could be effectively applied to energy management in buildings [16]. Ngo NT et al. proposed a mixed metaheuristic optimization algorithm and ML-based BEC prediction model. The outcomes denoted that the correlation coefficient of the model was 0.90, and the RMSE was 2.02 kWh. The proposed model improved the prediction accuracy by 442.0-1207.9% under RMSE [17].

In summary, many scholars have organized extensive research on BEC prediction models based on AI and have achieved certain research findings. However, existing BEC prediction models do not detect and process abnormal energy consumption (AEC) values before prediction, resulting in low prediction accuracy. This study proposes a semi-supervised learning local outlier factor (SL-LOF) algorithm based on semi-supervised learning, aimed at effectively detecting and processing AEC values to achieve better prediction performance. A multi-granularity-long short-term memory-attention (Mg-LSTM-Attention) model is developed to effectively and accurately predict BEC, to achieve refined management of BEC, by integrating multi-granularity features to address the diverse types of BEC.

The innovation of this research is the improvement of the local outlier factor (LOF) algorithm, specifically with regard to the detection and processing of AEC values. This enhances the accuracy of BEC data and improves the predictive power of the model. An energy consumption prediction model that integrates multi-granularity feature extraction is proposed for large-scale data research. Through multi-granularity feature extraction, the prediction accuracy of the proposed model is improved.

II. Methods and Materials

This part first uses an improved LOF algorithm to detect and process abnormal data of BEC. Then, the study proposes an Mg-LSTM-Attention prediction model. The accurate prediction of BEC values can be achieved through the utilization of granularity partitioning and the extraction of deep features.

II. A. Construction of Building Energy Consumption Data Detection Model Based on Improved LOF Algorithm

In the context of developing green buildings, it is crucial to predict the BECs. By processing, analyzing, and predicting BEC data, refined energy management can be achieved, effectively saving energy [18]. In predicting BEC, first is to preprocess the data of BEC. Due to equipment anomalies during the collection of energy consumption data, the data may become outliers, affecting its authenticity and subsequently impacting the prediction of BEC. Therefore, it is crucial to detect and handle abnormal values. However, the traditional LOF algorithm for detecting outliers may classify the energy consumption during peak electricity periods as outliers and cannot accurately detect outliers, resulting in a decrease in the accuracy of BEC prediction [19]. Therefore, the SL-LOF algorithm was developed to efficiently and accurately detect and process abnormal data of BEC.

The study first uses the LOF algorithm to handle the misjudgment of high energy consumption values during peak periods of building electricity consumption as outliers. The LOF algorithm is used for outlier detection by calculating the local density of nodes, grouping and comparing them with k neighboring local densities [20]. Firstly, it searches for the k distance proximity of the target node x_p using the equation (1).

$$N_k(x_p) = \left\{ x_q \in X, x_q \neq x_p \,\middle|\, d(x_p, x_q) \leq d_k(x_p) \right\} \tag{1}$$

In equation (1), $N_k(x_p)$ means the k distance proximity of point x_p. d_k means the k distance of the sample. x_p and x_q represent the target nodes. Then, the reachable distance of the target node is calculated using equation (2).

$$rd_k(x_p,x_q)=\max\left\{d_k(x_q),d(x_p,x_q)\right\} \tag{2}$$

In equation (2), $rd_k(x_p,x_q)$ denotes the reachable distance between points x_p and x_q. Then, the local reachable density of the target node is calculated using equation (3).

$$lrd_k(x_p)=\left(\frac{1}{|N_k(xl)|}\sum_{q\in N_k(x_p)} rd_k(x_p,x_q)\right)^{-1} \tag{3}$$

In equation (3), $lrd_k(x_p)$ denotes the locally reachable density of point x_p. Finally, the machine damage label will receive your local abnormal factors and LOF score, as shown in equation (4).

$$s(x_p)=LOF_k(x_p)=\frac{1}{|N_k(x_p)|}\sum_{q\in N_k(xl)}\frac{lrd_k(x_q)}{lrd_k(x_p)} \tag{4}$$

In equation (4), $s(x_p)$ expresses the anomaly score of LOF. When LOF, it indicates that point x_p has a higher density value compared to k, indicating that the value is normal. When $LOF_k(x_p)\geq\delta$, it indicates that point x_p has a lower density value compared to k, which is a potential outlier, and δ expresses the threshold. The distribution of outliers detected by the LOF algorithm is shown in Figure 1.

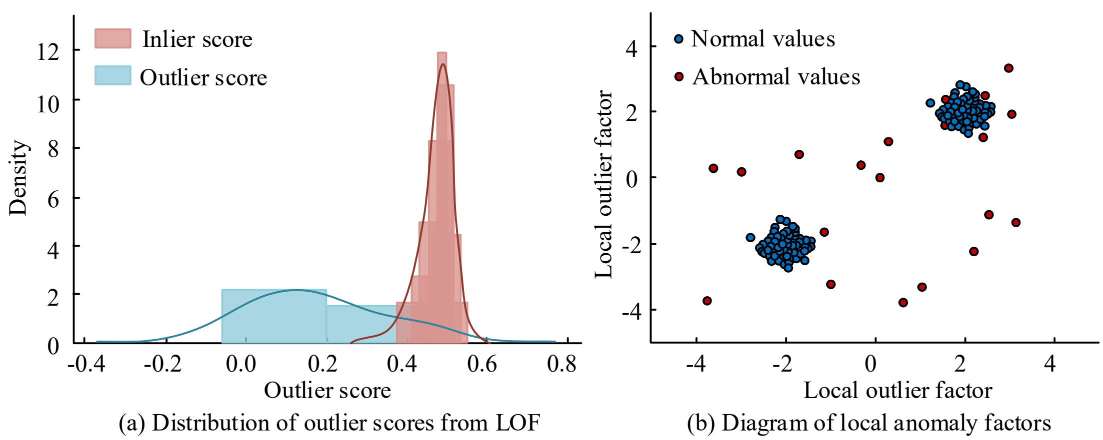


Figure 1: The LOF algorithm detected by the distribution of outliers

After obtaining the LOF score, semi-supervised learning is added to the algorithm. Firstly, the high energy consumption values during peak electricity consumption periods are marked as normal values and added to the normal value list. The particular stages of the SL-LOF algorithm are outlined below: first is to calculate the Euclidean distance between two nodes, as shown in equation (5).

$$dist(y_p,y_q)=\sqrt{\sum_{i=1}^{M}(y_{pi}-y_{qi})^2} \tag{5}$$

In equation (5), y_p and y_q represent the eigenvectors of points x_p and x_q, respectively. y_{pi} expresses the i th feature of the feature vector y_p. M expresses the length of the eigenvector. The average Euclidean distance of points is calculated using equation (6) [21].

$$SL-LOF_{sore}=\frac{\sum_{i=1}^{N} dist(y_p,y_i)}{N}, y_i\in L \tag{6}$$

In equation (6), $SL-LOF_{sore}$ expresses the average Euclidean distance. y_p indicates the eigenvector of point x_p. L indicates a list of energy consumption values during peak electricity usage periods. y_i indicates the eigenvector of point x_i in the L queue. N indicates the length of the list L. Finally, the equation for determining whether point x_p is an outlier is shown in equation (7).

$$\begin{cases} SL-LOF_{sore} \geq \delta, x_p \text{ value appears abnormal} \\ SL-LOF_{sore} < \delta, x_p \text{ value appears normal} \end{cases} \tag{7}$$

In equation (7), δ indicates the set threshold. If x_p is normal, the feature vector y_p corresponding to point x_p is added to the list L of energy consumption values during peak electricity consumption periods. The flowchart of SL-LOF algorithm is denoted in Figure 2. Firstly, the list of energy consumption values during the electricity consumption period are input, and the list of outliers is obtained through the LOF algorithm. On this basis, semi-supervised learning is performed on the abnormal list to calculate the Euclidean distance between target nodes. If $SL-LOF_{sore} < \delta$ is reached, it indicates that there is no abnormality in the energy consumption value and it is added to the normal energy consumption value list. If $SL-LOF_{sore} \geq \delta$, it indicates that the energy consumption value is abnormal, and it should be added to the SL-LOF outlier list. Finally, after detecting and processing the outliers and normal values separately, they will be used for the next stage of BEC prediction.

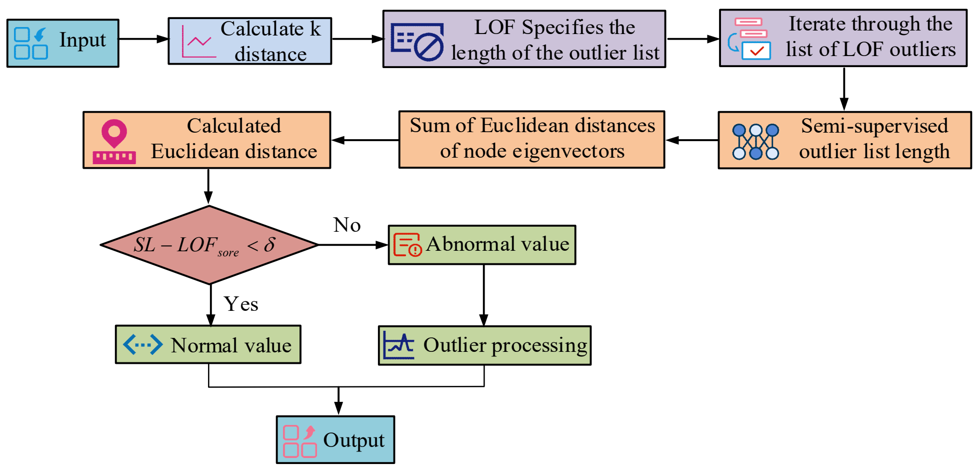


Figure 2: Flow chart of SL-LOF algorithm

II. B.LSTM-Attention Building Energy Consumption Prediction Model Integrating Multi-granularity Feature Extraction

After detecting and processing abnormal data on BEC, further research is conducted to predict it. However, due to the high energy consumption, wide footprint, and multiple sources of energy consumption in buildings, building an accurate BEC prediction model has become a hot research topic [22]. Traditional energy consumption prediction models and algorithms can only predict energy consumption values with few feature types and small data scales, and cannot accurately predict BEC with large datasets or diverse feature types [23]. Therefore, based on DL models, an Mg-LSTM-Attention model integrating multi-granularity feature extraction is constructed to more effectively and accurately predict BEC values. The main process of this model is to perform granularity segmentation on BEC data, extract deep features, obtain long-term correlation information, and predict BEC values.

The multi-granularity feature extraction module incorporates a series of convolutional, batch normalization, pooling, and activation layers. Firstly, the fused feature map is input, and then deep feature maps corresponding to different intensities are output [24]. The calculation for the convolutional layer is shown in equation (8).

$$Y[m,n] = \sum_j \sum_k c[j,k] \times f[m-j, n-k] \tag{8}$$

In equation (8), $c[j,k]$ indicates the convolution kernel's weight matrix. j and k respectively denote the length and width. f and Y indicate the inputting and outputting of the feature map, respectively. The basic goal of the pooling layer is to raise the model's generalization ability, and its operation is indicated in equation (9).

$$\begin{cases} Y_{1/2m,1/2n} = \max(f_{m,n}) \\ Y_{1/2m,1/2n} = average(f_{m,n}) \end{cases} \tag{9}$$

In equation (9), $\max(.)$ means the maximum pooling operation. $average(.)$ stands for average pooling operation. Batching into a layer is used to adjust the weight data distribution of the middle layer, and the activation function can be introduced into the nonlinear prediction model. The post module of the Mg-LSTM-Attention model is long-term correlation capture, which includes an LSTM layer, a fusion attention mechanism layer, and a fully connected layer (FCL). The detailed structure of the LSTM and fusion attention mechanism is shown in Figure 3.

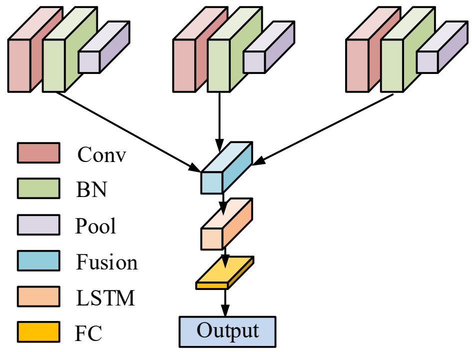


Figure 3: The diagram of LSTM dependencies capture module

The attention mechanism uses a Two-layer Feedforward Neural Network (TFNN) to calculate the attention weights of features, and the weighted average is the fused feature map [25]. The calculation of the TFNN is denoted in equation (10).

$$\tilde{\alpha}_m = \tanh(W_{m2} \cdot \tanh(W_{m1} \cdot V_{grained} + b_{m1}) + b_{m2}) \tag{10}$$

In equation (10), $\tilde{\alpha}_m$ means the outputting of feature maps of various granularities in a TFNN. W_{m1}, W_{m2} and b_{m1}, b_{m2} represent the weights and the bias terms of the first and second feedforward networks. $V_{grained}$ means the vector of input feature transformation. The attention weights are calculated, as shown in equation (11).

$$\tilde{\alpha} = soft\max(\tilde{\alpha}_m) \tag{11}$$

In equation (11), $\tilde{\alpha}$ means the attention weight vector. Through an attention mechanism, the deep and shallow feature maps are fused, as illustrated in Figure 4.

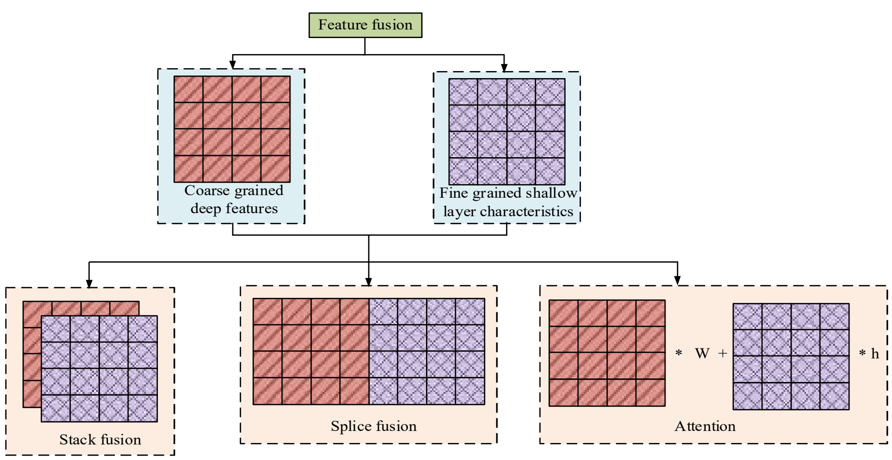


Figure 4: Attention mechanism feature fusion diagram

The calculation equation for the fusion of attention mechanism features is shown in equation (12).

$$v_{fused} = \sum_{v_{grained} \in \{V_{coarse}, V_{middle}, V_{fine}\}} \tilde{\alpha}_m v_{grained} \tag{12}$$

In equation (12), v_{frused} means the fused feature map. $v_{grained}$ means the 1D vector transformed from the input feature map. For FCLs, the prediction value is worked out by inputting the feature vector generated by the LSTM layer, and the loss function is employed to facilitate the calculation of the loss value. The calculation of the predicted BEC is shown in equation (13).

$$y_{pred} = W_m \cdot v_{lstm} + b_m \tag{13}$$

In equation (13), y_{pred} means the predicted BEC value. W_m and b_m respectively represent the weights and bias terms of the FCL. v_{lstm} means the feature vector output by the LSTM layer. The structure diagram of the Mg-LSTM-Attention model is indicated in Figure 5.

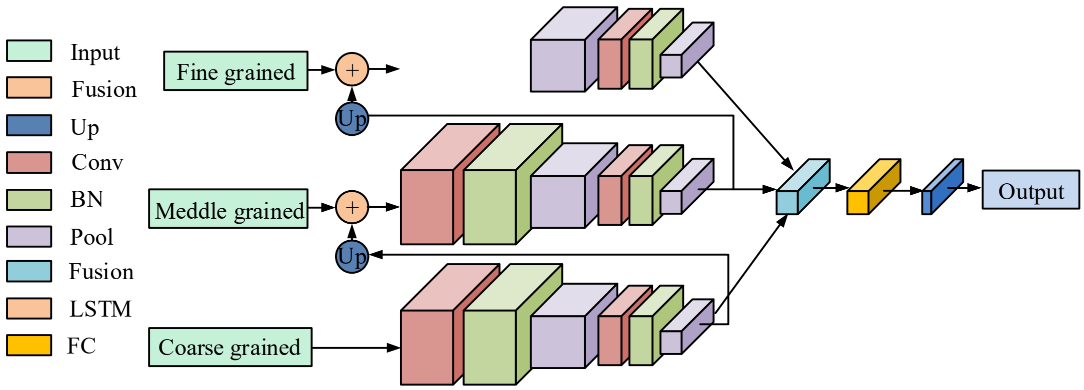


Figure 5: Overall structure diagram of Mg-LSTM-Attention model

During the training of the model, the calculation function is calculated using mean square error (MSE), with objective is to diminish the loss function and facilitate the model's convergence. The calculation of MSE loss is shown in equation (14).

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_{real} - y_{pred})^2 \tag{14}$$

In equation (14), MSE means the MSE loss value. y_{real} means the true value of BEC. A reduction in the MSE will result in an increase in the accuracy of the prediction. The task of predicting BEC is a regression task with time series, and its evaluation indicators usually include MSE, RMSE, and mean absolute error (MAE). The calculation equation is shown in equation (15).

$$\begin{cases} MSE = \frac{1}{N}\sum_{i=0}^{N-1}(y_{real} - y_{pred})^2 \\ RMSE = \sqrt{\frac{1}{N}\sum_{i=0}^{N-1}(y_{real} - y_{pred})^2} \\ MAE = \frac{1}{N}\sum_{i=0}^{N-1}\left|y_{real} - y_{pred}\right| \end{cases} \tag{15}$$

In equation (15), $RMSE$ means the RMSE. MAE denotes the MAE. N denotes the length of the predicted sequence.

III. Results

This part compared and analyzed the detection performance of AEC values using LOF and SL-LOF algorithms. The Mg-LSTM-Attention model using multi-granularity feature extraction was used to predict BEC values. By comparing its performance with other commonly used prediction models, the superiority of the designed prediction model was verified.

III. A. Analysis of the Effect of BEC Data Detection Based on SL-LOF Algorithm

The experiment used two publicly available datasets to analyze and validate the model, including the IHEPC dataset from the ML library and the residential electricity dataset from EERE in the United States. The IHEPC dataset contains 25320 records, with a total of 8520 records in the IHEPC dataset.

Firstly, the energy consumption data detection performance of different neighboring k-value LOF algorithms was analyzed experimentally, and the outcomes are shown in Figure 6. In Figure 6 (a), when the neighboring k value was 3, the total active power consumed was in the range of 0.02-0.65 kW, and the active energy was in the range of 0-0.42 kWh. The LOF algorithm detected a large number of outliers. When the consumption of active power was between 0.65kw and 1.00kw and the consumption of active electrical energy was between 0.42 and 0.85, the LOF algorithm had relatively low detection of energy consumption outliers. The outcomes in Figure 6 (b) indicated that when the neighboring k-value was 5, the total active power consumed was in the range of 0.02-0.68 kW, and a significant number of outliers could be detected in the range of 0-0.25 kWh for active energy. When the consumption of active power was between 0.68kw and 1.00kw and the consumption of active electrical energy was between 0.25-0.85, the LOF algorithm had less detection of AEC values. As the value of k increased, the LOF algorithm significantly reduced the detection of outliers. The experimental outcomes indicate that an increase in neighbouring k-values will impact the ability of the LOF algorithm to detect outliers in energy consumption.

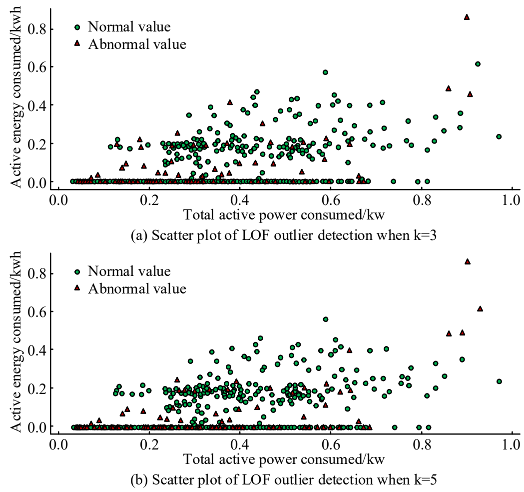


Figure 6: Scatter plots of LOF outliers detection with different k-values

To prove the feasibility and efficacy of the SL-LOF algorithm, a comparative analysis was conducted on the detection efficacy of the LOF and the SL-LOF algorithms for energy consumption outliers. The outcomes are shown in Figure 7. Figure 7(a) illustrates the detection outcomes of the LOF algorithm, which indicate that when the energy consumption time reached 42 minutes, the total active power consumed was 0.69 kW. Furthermore, when the energy consumption time was 109 minutes, the total power consumed reached 0.58 kW. When the energy consumption time was 135 minutes, the total energy consumption power was 0.56 kW. When the energy consumption time reached 195 minutes, the total energy consumption power was 0.63kw. In contrast, the outcomes of the SL-LOF algorithm in Figure 7(b) demonstrated that when the energy consumption time reached 42, 109, 135, and 195 minutes, respectively, there were no abnormal values in the total active power consumption. This indicates that the abnormal values detected by the aforementioned nodes under the LOF algorithm were solely attributable to energy consumption during peak periods. The experiment outcomes denote that the SL-LOF algorithm can detect AEC values during peak hours. Based on the detection of outliers by the LOF algorithm, the SL-LOF algorithm can reduce the number of outliers detected by the LOF algorithm. The experimental outcomes illustrate the efficacy and superiority of the SL-LOF algorithm.

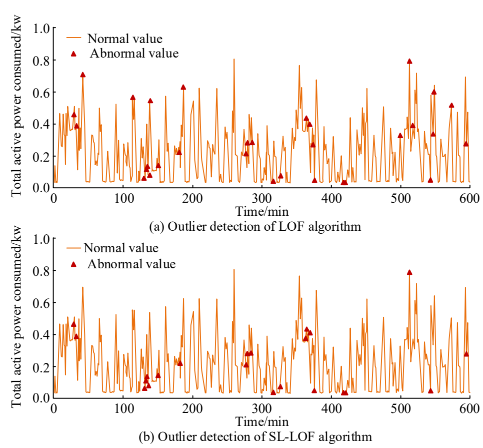


Figure 7: Comparison of LOF and SL-LOF algorithms for outlier detection

To further verify the accuracy of the SL-LOF algorithm in detecting outliers, experiments were conducted to compare the detection efficacy of the algorithm on AEC values under different hyperparameters. The experimental outcomes are shown in Figure 8. Sub-figures (a), (b), and (c) show the detection of AEC values by the SL-LOF algorithm under δ_2 values of 0.5, 0.6, and 0.7, respectively. The outcomes denoted that as the δ_2 value increased, the number of abnormal energy consuming nodes significantly decreased. When it was 0.5, a large number of energy consumption values during peak hours were judged as AEC values. When δ_2 was 0.6, the energy consumption value of electricity during peak hours that were judged as AEC values decreased. When δ_2 was 0.7, the outcomes indicated that a large number of AEC values during peak hours were identified as normal values. In Figure 8 (d), without using AEC value detection, the MSE and MAE values were 0.0083 and 0.002. Under the LOF-based AEC detection algorithm, both values were 0.0079 and 0.068, respectively. In contrast, both values of the SL-LOF algorithm for detecting AEC values were 0.0073 and 0.063, respectively. The experimental outcomes show that using the SL-LOF algorithm to detect AEC values findings in better model performance for predicting BEC.

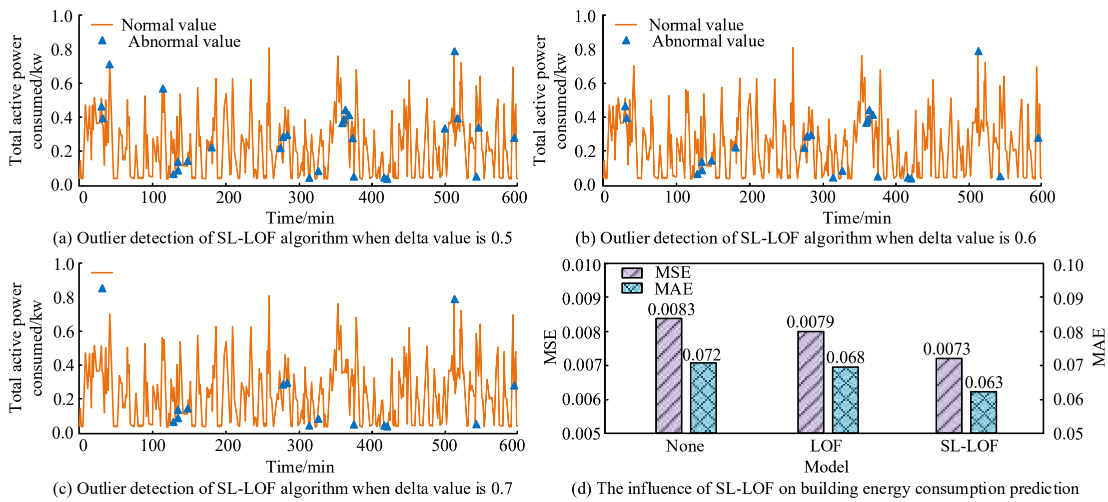
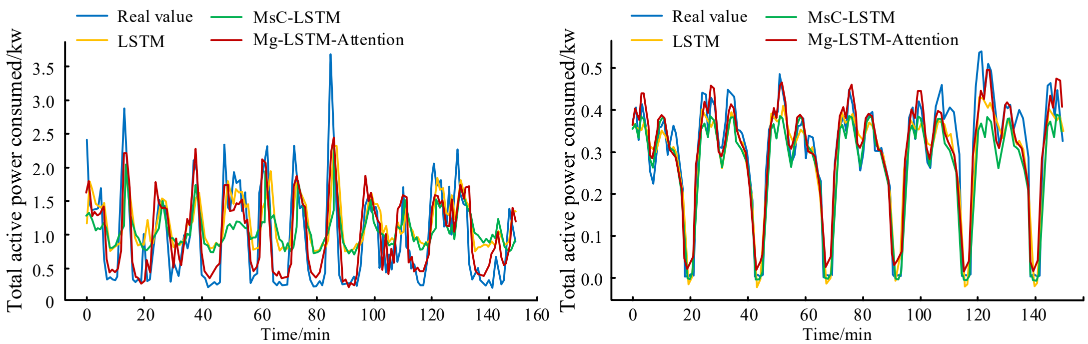


Figure 8: Detection of SL-LOF with different delta values and its influence on prediction

III. B. Performance Verification of Mg-LSTM-Attention Model Integrating Multi-granularity Feature Extraction

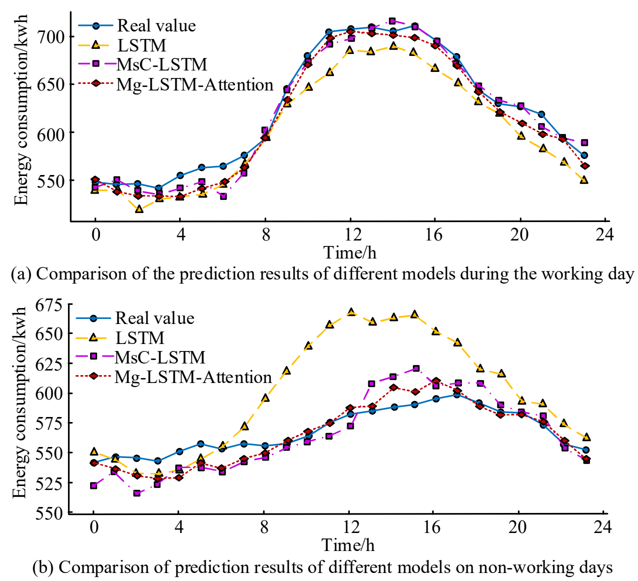
For the BEC prediction model, the programming language used in the experiment was Python 3.6, the processor was AMD R9-5900HX, and the graphics card was NVIDIA GeForce RTX 3060. Firstly, a comparative analysis was completed on the predictive performance of LSTM, Multi-scale Convolutional Long Short-Term Memory (MsC-LSTM), and Mg-LSTM-Attention models on different datasets. The findings are shown in Figure 9. In Figure 9 (a), under the IHEPC dataset, when the time reached 86 minutes, the actual energy consumption during peak hours was 3.61 kW. The energy consumption values predicted by the LSTM model and MsC-LSTM model were 2.25kw and 2.28kw, respectively. The energy consumption prediction value of the Mg-LSTM-Attention model was 2.42kw, which was closer to the true value. When the time reached 122 minutes, the actual energy consumption value was 2.12 kW. The energy consumption values of LSTM, MsC-LSTM, and Mg-LSTM-Attention models were 1.82kw, 1.58kw, and 1.64kw, respectively. In Figure 9 (b), under the EERE dataset, the true energy consumption value was 0.58 kW at 123 minutes. The energy consumption values predicted by LSTM, MsC-LSTM, and Mg-LSTM-Attention models were 0.42kw, 0.37kw, and 0.48kw, respectively. The experimental outcomes denoted that the energy consumption values predicted by the Mg-LSTM-Attention model were close to the true values on both the IHEPC and EERE datasets, demonstrating the greater predictive efficacy.



(a) Prediction graph of the comparison model on the IHEPC dataset (b) Prediction graph of the comparison model on the EERE dataset

Figure 9: Energy consumption prediction curves for different models on different datasets

The experiment was conducted on the IHEPC dataset, comparing the actual energy consumption values on working days and non-working days with the predicted energy consumption values of three models. The findings are denoted in Figure 10. In Figure 10 (a), when the time reached 12 hours, the actual energy consumption value on weekdays was 708.56 kWh, and the predicted energy consumption values of LSTM, MsC-LSTM, and Mg-LSTM-Attention models were 675.35 kWh, 683.42 kWh, and 690.55 kWh, respectively. When the time reached 21.5 hours, the actual value was 623.36 kWh, and the predicted values of LSTM, MsC-LSTM, and Mg-LSTM-Attention models were 586.58 kWh, 612.43 kWh, and 608.74 kWh, respectively. The findings indicated that when the prediction model predicted the energy consumption value during the peak electricity consumption period on weekdays, the Mg-LSTM-Attention model's predicted value was closer to the true value. In Figure 10 (b), when the time was 15 hours, the actual value on non-working days was 580.77 kWh, and the predicted values of LSTM, MsC-LSTM, and Mg-LSTM-Attention models were 656.69 kWh, 605.35 kWh, and 585.74 kWh, respectively. When the time was 21.3h, the actual value was 575.42kWh, and the predicted values of LSTM, MsC-LSTM, and Mg-LSTM-Attention models were 586.33kWh, 580.58kWh, and 578.32kWh, respectively. The experimental findings further demonstrate that the Mg-LSTM-Attention model has good predictive performance.



(a) Comparison of the prediction results of different models during the working day

(b) Comparison of prediction results of different models on non-working days

Figure 10: Comparison of energy consumption prediction of different models in working days and non-working days under IHEPC dataset

The experiment was conducted on the EERE dataset, comparing the actual values on working days and non-working days with the predicted values of three models. The findings are indicated in Figure 11. In Figure 11 (a), when the time was 13.1 hours, the actual value on a working day was 692.37 kWh, and the predicted values of LSTM, MsC-LSTM, and Mg-LSTM-Attention models were 676.44 kWh, 702.63 kWh, and 688.87 kWh, respectively. When the time reached 23.0 hours, the actual value was 575.45 kWh, and the predicted values of LSTM, MsC-LSTM, and Mg-LSTM-Attention models were 547.82 kWh, 589.77 kWh, and 569.42 kWh, respectively. In Figure 11 (b), at 15.4 hours, the actual value on non-working days was 603.57 kWh, and the predicted values of the three models were 651.76 kWh, 608.35 kWh, and 606.74 kWh, respectively. When the time was 17.8 hours, the actual value was 584.66 kWh, and the predicted values of LSTM, MsC-LSTM, and Mg-LSTM-Attention models were 623.48 kWh, 615.78 kWh, and 594.75 kWh, respectively. The findings indicated that the predicted value of the Mg-LSTM-Attention model was closer to the actual value, indicating that the model had a better prediction effect on energy consumption value.

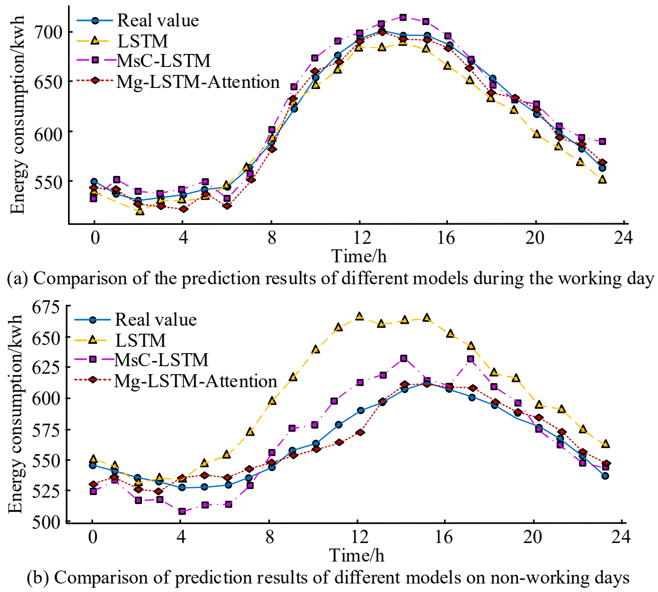


Figure 11: Comparison of energy consumption prediction of different models in working days and non-working days in EERE data set

To further prove the accuracy and superiority of the Mg-LSTM-Attention, the experiment evaluated the predictive performance of different prediction models on different datasets using three indicators: MSE, RMSE, and MAE. The findings are shown in Figure 12. In Figure 12 (a), under the IHEPC dataset, the MSR, RMSE, and MAE of the LSTM were 0.395, 0.627, and 0.492, respectively. The MSR, RMSE, and MAE values of the MsC-LSTM were 0.298, 0.545, and 0.397. In contrast with the SLTM, the three values of the Mg-LSTM-Attention model were significantly reduced by 41.07%, 17.86%, and 30.50%, respectively. The findings in Figure 12 (b) denote that under the EERE dataset, the MSR, RMSE, and MAE values of the LSTM model were 0.034, 0.183, and 0.155. The MSR, RMSE, and MAE value of the MsC-LSTM were 0.053, 0.225, and 0.172. Compared with the SLTM model, the MSR, RMSE, and MAE values of the Mg-LSTM-Attention decreased by 0.016, 0.056, and 0.051, respectively. The findings demonstrate that the designed model can predict energy consumption values and has good predictive performance.

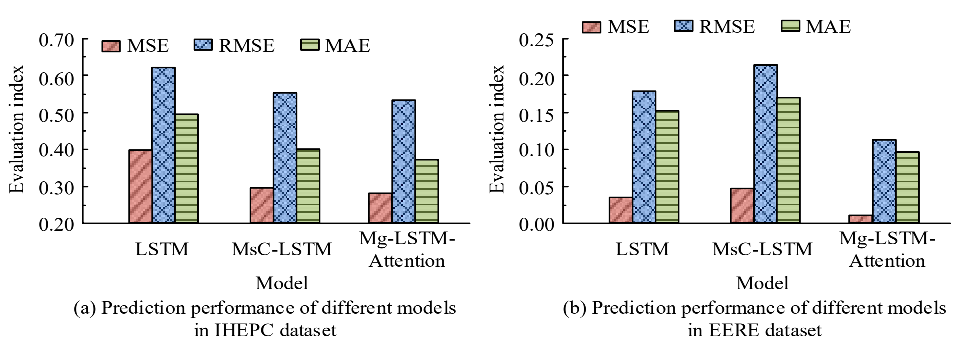


Figure 12: Comparison of prediction performance of different models in IHEPC and EERE datasets

IV. Discussion and conclusion

A semi-supervised learning-based SL-LOF algorithm was developed to detect and process AEC values. A multi-granularity feature extraction Mg-LSTM-Attention model was utilized to predict BEC values, and the predictive efficacy was explored. The experimental outcomes denoted that when the neighboring k-value was 3, the total active power consumed was in the range of 0.02-0.65 kW, and the LOF algorithm detected more outliers. When the k-value was 5, the AEC values significantly decreased. It was found that an increase in neighboring k-values would affect the detection of energy consumption outliers by the LOF algorithm. The detection findings of the SL-LOF algorithm showed that when the energy consumption time reached 42, 109, 135, and 195 minutes respectively, there were no abnormal values in the total active power consumption. The findings indicated that the SL-LOF algorithm could effectively detect AEC values during peak hours. The MSE and MAE values based on the LOF detection algorithm were 0.0079 and 0.068, respectively. The both values of the SL-LOF algorithm were 0.0073 and 0.063, respectively. The outcomes denoted that the SL-LOF algorithm was more accurate in predicting BEC after detecting AEC values. Under the IHEPC dataset, the energy consumption values predicted by the LSTM and MsC-LSTM were 2.25kw and 2.28kw, respectively. The energy consumption prediction value of the Mg-LSTM-Attention was 2.42kw, which was closer to the true value. Under the EERE dataset, the energy consumption values predicted by LSTM, MsC-LSTM, and Mg-LSTM-Attention were 0.42kw, 0.37kw, and 0.48kw, respectively. In the energy consumption prediction of working days and non-working days, the MSR, RMSE, and MAE values of the MsC-LSTM under the IHEPC dataset were 0.298, 0.545, and 0.397, respectively. Compared with the SLTM model, the MSR, RMSE, and MAE values of the Mg-LSTM-Attention were significantly reduced by 41.07%, 17.86%, and 30.50%, respectively. Under the EERE dataset, the Mg-LSTM-Attention showed a decrease in MSR, RMSE, and MAE values of 0.016, 0.056, and 0.051, respectively, compared to the SLTM. The experiment outcomes denote that the proposed model can effectively predict energy consumption values and has good predictive performance. The limitation of the research is that the public dataset used comes from a single building, and subsequent studies can consider predicting the energy consumption of multiple types of buildings.

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