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Short Term Load Forecasting Method of User Level Integrated Energy System Based on Combined Load-CNN-GRU

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Abstract

Aiming at the characteristics of small scale, large load fluctuation and complex energy coupling of user level integrated energy system, a short-term load forecasting method of user level integrated energy system based on combined cooling, heating and electrical loads-convolutional neural networks CNN-gate recurrent unit GRU is proposed. Firstly, the cooling, heating and electrical loads data are spliced into combined load, CNN is used to extract the high-dimensional spatial features of the combined load data. Secondly, the output results of CNN are transformed into one-dimensional feature sequence, Finally, the feature sequence is input into GRU network for high-dimensional temporal feature extraction and the cooling, heating and electrical short-term load forecasting. The integrated energy system data of two independent users of Arizona State University are used for load forecasting. The results show that the CNN-GRU model, which jointly extracts the spatio-temporal coupling characteristics of cooling, heating and electrical loads, has higher prediction accuracy than the CNN model which only uses the combined load to extract the spatial characteristics and the GRU model which only uses the single type load to extract the time characteristics.

Keywords

Short term load forecasting; Integrated energy system; Gate recurrent unit; Convolutional neural networks; Combined load.

1. INTRODUCTION

IES is an integrated energy system that integrates various energy forms such as cold, heat, electricity and gas[1]. According to the size of the region, it can be divided into cross-regional, regional and user-level IES[2].As the smallest unit of IES, user-level IES has many notable features such as complex energy coupling structure, large system scale, and large load fluctuations. For this reason, short-term load forecasting is not only used as its own energy consumption optimization, but also with other IES. The primary premise of developing energy information exchange can no longer be limited to a certain type of single load, and must take into account the whole and multiple energy forms. Moreover, the accurate, real-time and reliable prediction of short-term cooling, heating and electrical loads of user-level IES is of great significance to reduce energy consumption, reduce carbon emissions, and improve economic benefits[3].

The current power load forecasting methods mainly include time series method [4], regression analysis method [5], multiple linear regression method [6], Kalman filter method [7]. The above traditional methods have high requirements on the stationarity of the load sequence, and the prediction effect for nonlinear data is not ideal, so it is difficult to mine the high-

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dimensional time and space characteristics of the time series load. Machine learning algorithms such as support vector machines [8] are significantly better than traditional methods for solving nonlinear problems, but support vector machines have poor processing ability for large-scale data. At the same time, the prediction of cooling, heating and air loads also includes wavelet transform [9], building energy consumption simulation software [10], and various machine learning data mining and other algorithms [11-12].

The above literatures are all for forecasting a single load. The potential spatiotemporal coupling relationship with other energy types has not been considered. In the literature [13] and [14], the wavelet change, ARIMA model and other means are used for the IES to improve the prediction accuracy of the short-term load of the IES, but it is still not fully considered. to the hidden coupling relationship between multiple types of loads. Reference [15] and Reference [16] build prediction models based on the coupling relationship between multiple energy loads analyzed by Pearson correlation coefficient technology and gray correlation method, respectively. However, correlation analysis technology can only filter and artificially intercept some Input variables with strong correlation ignore the characteristics of IES load nonlinearity, poor stability, and strong timing, so it is more difficult to apply to users with large load fluctuations, complex energy time-space coupling, and higher requirements for prediction accuracy. In addition, the results obtained from the correlation are difficult to be directly used as the input of the forecasting model in the subsequent load forecasting, which increases the complexity of the model.

With the transition of computer data storage capacity and computing power, artificial intelligence neural network machine learning algorithm has once again demonstrated its advantages. Among them, CNN and RNN (recurrent neural network) variant series are particularly effective in the field of image processing and natural language processing respectively [17]. CNN extracts spatial features of input data through convolution pooling operation, which reduces the error caused by subjectivity in human feature extraction. In [18], CNN is used to extract load seasonal features for nonlinear sequence data prediction. Good results have been obtained, but for the user-level IES, there are many types of loads, large load fluctuations, and obvious historical laws. Therefore, it is difficult to use the CNN model alone to better grasp the historical laws of the time series load at the current time point and the relationship between the load and the IES. Hidden coupling spatial connections under other types of loads. RNN can effectively extract the temporal features of data. However, when RNN processes long-term sequences, it will gradually lose the information of the early state, causing the gradient to disappear. For this reason, related researchers proposed a variant of RNN, LSTM [19]. LSTM has stronger performance on data of longer time series. adaptive characteristics. However, the LSTM model has many parameters and the convergence speed is slow. GRU is an improved variant based on LSTM. Compared with LSTM, it simplifies model parameters while ensuring model accuracy and improves computational efficiency, so it is widely used in the field of prediction [20-21]. However, although GRU considers the temporal continuity of time series features, it is difficult to fully exploit the hidden temporal coupling relationship between multiple types of energy sources at the same time point in the user-level IES only by a single GRU. Therefore, it must be matched with other models for mining time and spatial coupling information in order to obtain better prediction results.

Therefore, this paper proposes a user-level IES short-term load prediction method based on joint cooling, heating, and electric loads-CNN-GRU, which aims to use CNN and GRU to effectively mine high-dimensional hidden and spatial features of joint load to improve user-level load. Short-term load forecasting accuracy of IES. Taking the cooling, heating and electric load data of two groups of independent users of the Arizona State University Integrated Energy System Dataset as a sample, the prediction is compared with the CNN model that only uses the joint load to extract spatial features and the GRU model that only uses a single type of load for prediction. The model proposed in this paper has higher prediction accuracy and generalization.

2. MODEL ALGORITHM THEORY

2.1. CNN model

The implementation process of a typical CNN is shown in Figure 1.

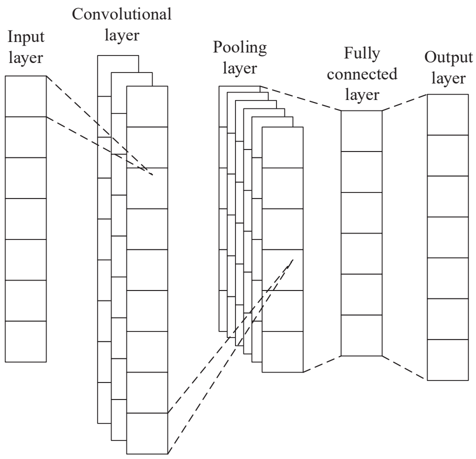

Figure 1. CNN implementation process

Convolutional neural network CNN is mainly composed of convolution layer, pooling layer and fully connected layer. The convolution kernel of the convolution layer, that is, the weight moves on the input matrix with a certain step size to perform the convolution operation, thereby obtaining the input matrix. The feature map is used as the input of the next convolution layer or pooling layer. In this process, the feature of convolution kernel weight sharing can effectively reduce the number of model parameters and improve the efficiency of the algorithm. The pooling layer further extracts the main features of the input matrix. The fully connected layer is generally located in the last layer of the CNN, and the features extracted by the convolutional layer and the pooling layer can be collected together for subsequent analysis and comprehensive judgment.

2.2. GRU model

GRU is one of the variant family of RNN models. RNN will record the current state of the neural network when processing time series, and participate in network operations as part of the next input, but when processing long-term data, there will be a problem of gradient disappearance, so the researchers proposed LSTM model, by forgetting Gate, input gate and output gate to selectively save the current state of the neural network to deal with the gradient disappearance problem of RNN. In order to improve the efficiency of LSTM, related researchers proposed the GRU model, which realized the original function of LSTM by updating the gate and resetting the gate, reducing the model parameters and improving the model convergence speed. The basic structure of GRU is shown in Figure 2, and the mathematical description is shown in equation (1).

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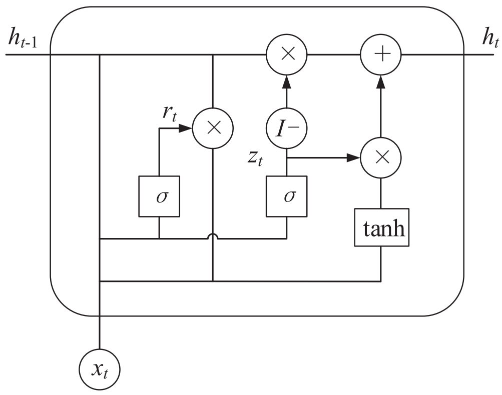

Figure 2. GRU fundamental structure

$$\begin{cases} r_t = \sigma\left(W_r \cdot \left[h_{t-1}, x_t\right]\right) \\ z_t = \sigma\left(W_z \cdot \left[h_{t-1}, x_t\right]\right) \\ \tilde{h}_t = \tanh\left(W_{\tilde{h}} \cdot \left[r_t \times h_{t-1}, x_t\right]\right) \\ h_t = \left(I - z_t\right) \times h_{t-1} + z_t \times \tilde{h}_t \end{cases} \tag{1}$$

In the equation: W_r , W_z , $W_{\tilde{h}}$ respectively represent the update gate, reset gate and candidate set, and r_t , z_t respectively represent the current state of the update gate and the state of the reset gate. h_t , h_{t-1} , $\tilde{h}_t$ represent the state at the current moment, the state at the previous moment and the state of the current candidate set. x_t represents the input variable, I represents the identity matrix, and σ represents the sigmoid activation function.

3. COMBINED LOAD-CNN-GRU PREDICTION MODEL

3.1. Data processing

Due to the possible failures of the acquisition equipment and the interference received, anomalies or errors may occur in the process of acquisition, conversion, storage, and transmission of experimental data sets. Directly discarding the corresponding data will reduce the available information of the prediction model and reduce the prediction performance of the model. For this reason, the method of literature [22] is used to identify abnormal error values and vacancy missing values for the experimental cooling, heating and electric load data sets.

In order to prevent the accuracy of the prediction model from decreasing due to the different data dimensions of the experimental data set, and to avoid the problem of infinity in the comprehensive evaluation index: mean absolute percentage error (MAPE) in the subsequent calculation. The improved normalization method is used as shown in equation (2).

$$x^* = \frac{x - x_{\min}}{x_{\max} - x_{\min}} + 1 \tag{2}$$

In the equation: x is the original cooling, heating, and electrical data, x^* is the normalized data, $x_{\max}$ and $x_{\min}$ are the maximum and minimum values of the sample data.

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3.2. Model architecture

The model architecture is shown in Figure 3.

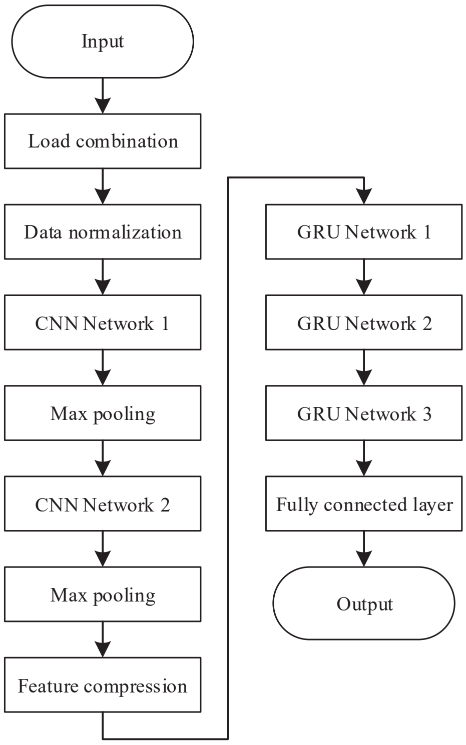

Figure 3. The structure of CNN-GRU model

In this paper, the cooling, heating, and electric load sequences are combined into 3*n joint load sequence data with coupled time-space features, and the combined load is normalized and input to the CNN network for high-dimensional spatial feature extraction and the results are converted into the one-dimensional temporal feature vector is input to the GRU network to extract high-dimensional temporal features, and the eigenvectors combining the hidden time and spatial coupling information of the three loads are used to predict the n+1 cooling(C), heating(H), and electrical(E) loads. In the joint load-CNN-GRU model, the weight parameters are optimized through the error back-propagation algorithm in the whole process.

The model evaluation indicators used mean absolute percent error MAPE and root mean squared error (RMSE). As shown in equation (3).

$$\begin{cases} M_{APE} = \dfrac{1}{N}\sum_{i=1}^{N}\dfrac{|\hat{y}_i - y_i|}{y_i}\times 100\% \\ R_{MSE} = \sqrt{\dfrac{\sum_{i=1}^{N}(\hat{y}_i - y_i)^2}{N}} \end{cases} \tag{3}$$

In the equation: N is the total number of predicted values, $\hat{y}_i$ and y_i are respectively the predicted load value and the actual load value of the i sampling point.

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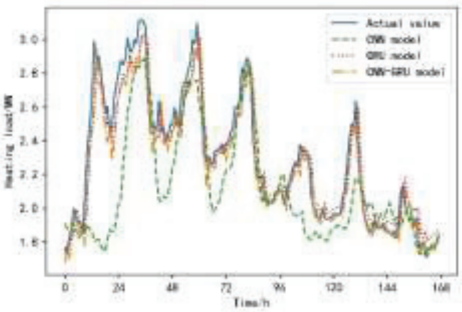
4. EXAMPLE ANALYSIS

The relevant experimental data set in this paper comes from the Campus Metabolism project platform of Arizona State University. The historical loads data of electrical, heating and cooling recorded by the platform from January 2020 to December 2020 of two independent users A and B with a time resolution of 1h are 8784 groups respectively, which are divided into training set and test set according to the ratio of 8:2. The local climatic conditions are warm in winter and hot in summer, and the demand for cooling and electrical loads are relatively large. Therefore, it is assumed that the weight ratio of cooling, heating and electrical loads is 0.4:0.2:0.4.

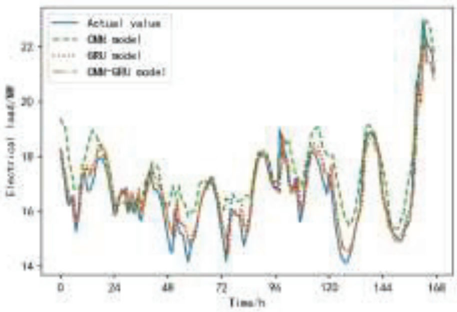
The comparison between the real value of cooling, heating and electrical load of user A for 7 consecutive days and the short-term load prediction curve of different methods is shown in Figure 4 below, and the model evaluation indicators are shown in Table 1.

Table 1. The results of loads prediction in user A

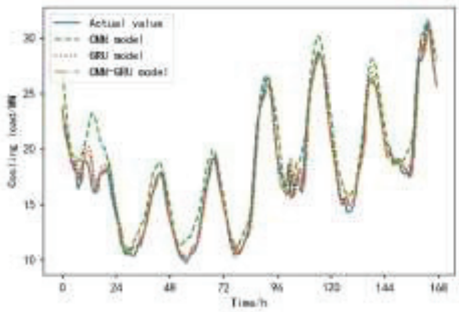
experimental method	RMSE/MW (C/H/E)	MAPE/% C:H:E(0.4:0.4:0.2)
CNN	0.725/1.523/1.076	12.844
GRU	0.604/0.832/0.781	5.045
CNN-GRU	0.568/0.684/0.695	3.499



(a) Heating load prediction



(b) Electrical load prediction



(c) Cooling load prediction

Figure 4. Cooling, heating and electrical loads prediction results of user A

The cooling load has a better prediction effect than the heating and electricity loads, while the heating load has a greater improvement, which indicates that the heating load has obtained more auxiliary hidden information during the spatial coupling process of the joint load sequence data, which proves the effectiveness of the joint load forecasting method proposed in this paper. Since the cooling load and the heating load have a certain inertia, and the electrical

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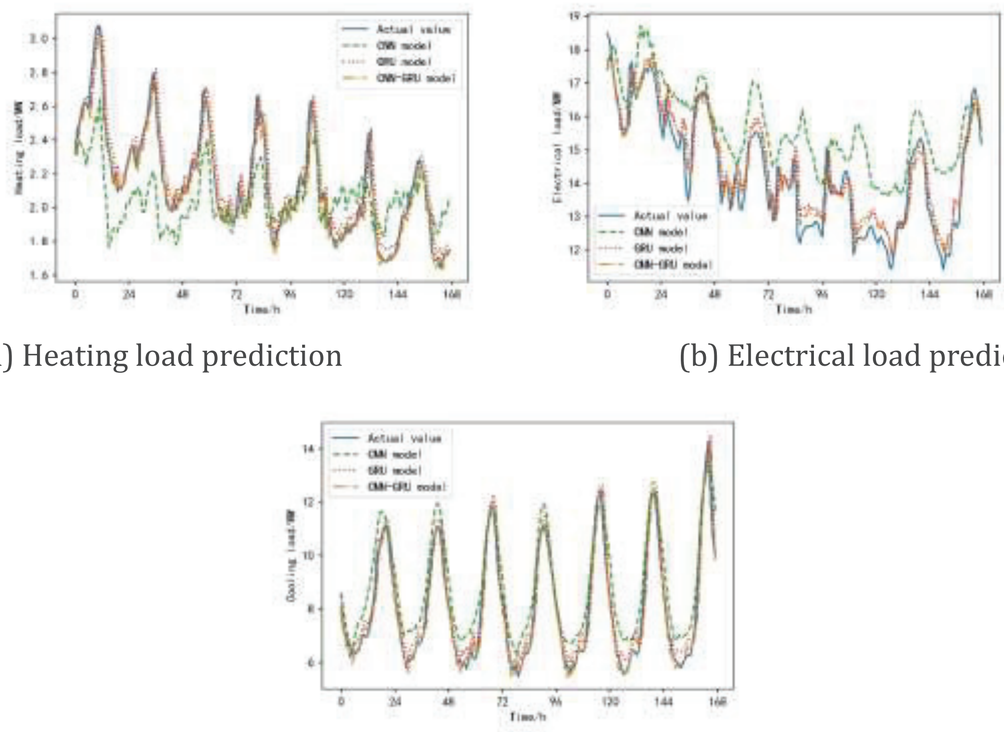
charge changes at the speed of light, the load fluctuation is larger than that of the cooling and heating loads, which makes the prediction more difficult.

At the same time, according to Table 1, compared with the GRU model without the combined load and CNN to extract spatial features, the CNN-GRU method model using the joint load reduces the comprehensive weighted MAPE% value by 1.5%. Lowered by 0.036, 0.148, 0.086.

Compared with the model using only the combined load extraction spatial feature CNN, the comprehensive weighted MAPE% value decreased by 9.3%, and the RMSE values of the cooling, heating and electrical loads were decreased by 0.157 MW, 0.839 MW, and 0.381 MW, respectively, showing a significant effect.

From the RMSE and MAPE values, it can be seen that the effect of the GRU without the combined load is also better than that of the CNN model that uses the combined load to extract spatial features. This is because the cooling, heating, and electrical load data are still fundamentally temporal. Sequence data, so the GRU model that focuses on extracting time series features is more adaptable to sequence data than the CNN model that focuses on extracting spatial features, but from Figure 4, it can be seen from Figure 4 that the combined load is used to extract the cooling, heating, and electrical loads. The CNN-GRU model with hidden time and space coupling features can more accurately track the fluctuation changes of the actual load at the peaks and troughs, which shows that the model proposed in this paper does extract effective time and space coupling information from the joint load, and then the prediction error is reduced and the prediction accuracy is improved.

Figure 5 shows the comparison between the real value of the cooling, heating, and electrical load power of user B and the short-term load prediction curves of different methods for 7 consecutive days, and the prediction accuracy of the model is shown in Table 2.



(a) Heating load prediction (b) Electrical load prediction

(c) Cooling load prediction

Figure 5. Cooling, heating and electrical loads prediction results of user B

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Table 2. The results of loads prediction in user B

experimental method	RMSE/MW (C/H/E)	MAPE/% C:H:E(0.4:0.4:0.2)
CNN	0.696/1.638/1.579	15.294
GRU	0.596/0.796/0.804	4.937
CNN-GRU	0.495/0.597/0.712	3.364

It can be seen from Figure 5 that the CNN-GRU prediction model of joint load proposed in this paper can be closer to the real value, and the prediction accuracy is high. Compared with other models, the method in this paper can not only predict the load change law, but also Peaks and valleys with a wider range of load variation patterns perform better. As can be seen from Table 2, the weighted comprehensive MAPE% value of the CNN-GRU model using the joint load is reduced by 11.9% compared with the CNN model using only the joint load, and the RMSE values of the cooling, heating and electrical loads are reduced by 0.201MW, 1.041MW, 0.867MW. Compared with the GRU model without combined load, the weighted comprehensive MAPE% value decreased by 1.6%, and the RMSE values of cooling, heating and electrical loads decreased by 0.101MW, 0.199MW, and 0.092MW.

Combining the prediction results of user A and user B, it can be seen that in two different user-level IES units, the joint load-CNN-GRU user-level IES short-term load prediction method proposed in this paper has achieved good results, which shows that This method has certain generalization.

To sum up, the combined load is extracted and mined by CNN-GRU, which brings more effective time and space coupling information for the prediction of various loads, and reduces the MAPE and RMSE values of cooling, heating and electrical loads as a whole. Therefore, for the user-level IES with complex energy coupling and large load fluctuation, the CNN-GRU prediction model of combined load can more effectively extract the hidden spatiotemporal relationship between various loads, thereby improving the prediction accuracy of the model.

5. CONCLUSION

This paper proposes a combined load-CNN-GRU short-term load forecasting method for user-level IES. Firstly, a joint load structure is constructed, and then the high-dimensional spatial coupling features of cooling, heating and electrical loads are extracted through CNN convolutional neural network. Secondly, the output result is constructed as a time series feature vector, which is input to the GRU gated recurrent unit for extraction of high-dimensional temporal coupling features, and finally for load prediction. Compared with the CNN model that only uses joint loads to extract spatial features and the GRU model that only uses single-class loads to extract temporal features, the prediction accuracy is higher. In the future, other ways of coupling and combining multi-energy loads can be explored to further improve the model's ability to extract user-level IES high-dimensional time and space information, thereby improving the prediction accuracy.

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