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AN ENERGY CONSUMPTION PREDICTION SYSTEM FOR COMMUNICATION TOWER STATION EQUIPMENT ROOMS BASED ON THE COMBINATION OF GCN AND LSTM

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Abstract: This study designs an energy consumption monitoring and optimization system for communication tower station equipment rooms, based on a combination of Graph Convolutional Networks (GCN) and Long Short-Term Memory Networks (LSTM). The system aims to address issues such as low energy consumption data acquisition accuracy, high monitoring latency, and delayed energy-saving measures in traditional equipment rooms. The system collects energy consumption data through split-route acquisition, using hardware devices such as power transformers and AD7606 chips to monitor the energy consumption of key equipment in real-time. By integrating GCN and LSTM, the system can analyze the energy consumption relationships and trends of devices in the equipment room, providing accurate predictions of energy consumption for the next cycle. The research results show that this system can effectively predict node energy consumption, and provide an intelligent solution for the green transformation and energy-saving emission reduction in the telecommunications industry.
Keywords: Communication tower station equipment room; Graph Convolutional Networks; Long Short-Term Memory Networks; Energy-saving optimization

1 INTRODUCTION

With the intensification of global climate change, green and low-carbon development has become a common focus of attention worldwide. As the infrastructure of social operations, public institutions account for a significant proportion of the total national energy consumption and possess substantial energy-saving potential[1]. By optimizing the energy consumption management of public institutions, not only can carbon emissions be directly reduced, but it can also serve as a demonstration and driving force for energy conservation and emission reduction[2]. Therefore, conducting research on energy consumption optimization and low-carbon technology applications for public institutions not only aligns with global trends in environmental protection and energy conservation but also fits with the core concept of sustainable development.

However, literature reviews and analyses reveal that most energy consumption management systems in communication tower station equipment rooms are still based on traditional monitoring models, relying primarily on simple data collection and display[3]. These systems lack deep data mining and intelligent prediction capabilities, making it difficult to achieve dynamic optimization of energy consumption[4]. Traditional energy monitoring methods face issues such as low data collection accuracy, high monitoring atency, and delayed energy-saving measures in practical applications, making it difficult for systems to meet the current demands for refined and intelligent management. Given the rapid development of 5G technology and the growing energy consumption demands of the telecommunications industry, improving the real-time capability, accuracy, and intelligence level of energy consumption monitoring systems has become an urgent issue to address[5].

This study aims to develop an energy consumption monitoring and prediction system for public institutions based on a combination of Graph Convolutional Networks (GCN) and Long Short-Term Memory Networks (LSTM). The scientific novelty of this system lies in its use of GCN to capture the spatial dependencies between energy consumption nodes, combined with LSTM to process temporal sequence changes, enabling accurate predictions of future energy consumption trends. Unlike traditional energy monitoring methods, the GCN-LSTM fusion model extracts both spatial and temporal features, significantly enhancing prediction accuracy and model adaptability[6]. This research not only achieves intelligent and refined energy consumption management for public institutions but also provides innovative solutions and technological pathways for the low-carbon technology field both domestically and internationally, driving technological progress in green and low-carbon transformation.

2 DATA SOURCES AND PREPROCESSING

The system uses power transformers, AD7606 chips, precision ADC (Analog-to-Digital Conversion) technology, and RTU chip modules for split-route energy consumption data collection. The various hardware components collect energy consumption data in real time from different facility units, including air conditioning units, Battery Backup Units (BBU), and Remote Radio Units (RRU)[7]. These devices enable multi-channel, high-precision data collection and processing, providing reliable data support for subsequent energy consumption monitoring and analysis. Once the data collection is completed, it is packaged and sent to the server, then transmitted to the AI IoT cloud service platform[8-10].

The collected data mainly includes the current and voltage of the AC unit, and the current, voltage, active power, and reactive power of the three-phase meter of the DC unit. Since the dimensions and types of the data vary, it is necessary to convert the data into a numerical matrix format that can be applied to GCN. For both AC and DC data, Min-Max normalization is used to scale the feature values between 0 and 1.

$$H_n = \frac{H_{mn} - \min(H)}{\max(H) - \min(H)} \tag{1}$$

Where H_n is the original feature matrix, $\min(H)$ and $\max(H)$ are the minimum and maximum values in H, and H_n is the normalized feature matrix.

3 RESEARCH METHODOLOGY

3.1 Graph Convolutional Network

After obtaining the preprocessed dataset, it is necessary to perform normalization on the features. The data format includes the feature matrix H and the adjacency matrix of the graph. Each row of the node feature matrix represents the feature vector of a node, while the adjacency matrix represents the connections between nodes.

(1) Define the node affiliation by numbering the energy consumption data nodes in the DC and AC units within the communication tower station equipment room: X_1, $X_2, \cdots X_{19}, \cdots X_n$ (n represents the number of energy consumption data nodes).

(2) The energy consumption data corresponding to each node is represented as I_k^n, where n denotes the n-th node, and k represents the k-th time period of the day (with a time granularity of 20 minutes). For example, $k = 0$ represents the energy consumption data at 00:00 on the given day. Since the model input is a vector, the energy consumption data for each node is vectorized as follows:

$$I^n = [I_0^n, I_1^n, \cdots, I_k^n], K = 72 \tag{2}$$

(3) A graph structure is used for representation, as shown in Figure 1:

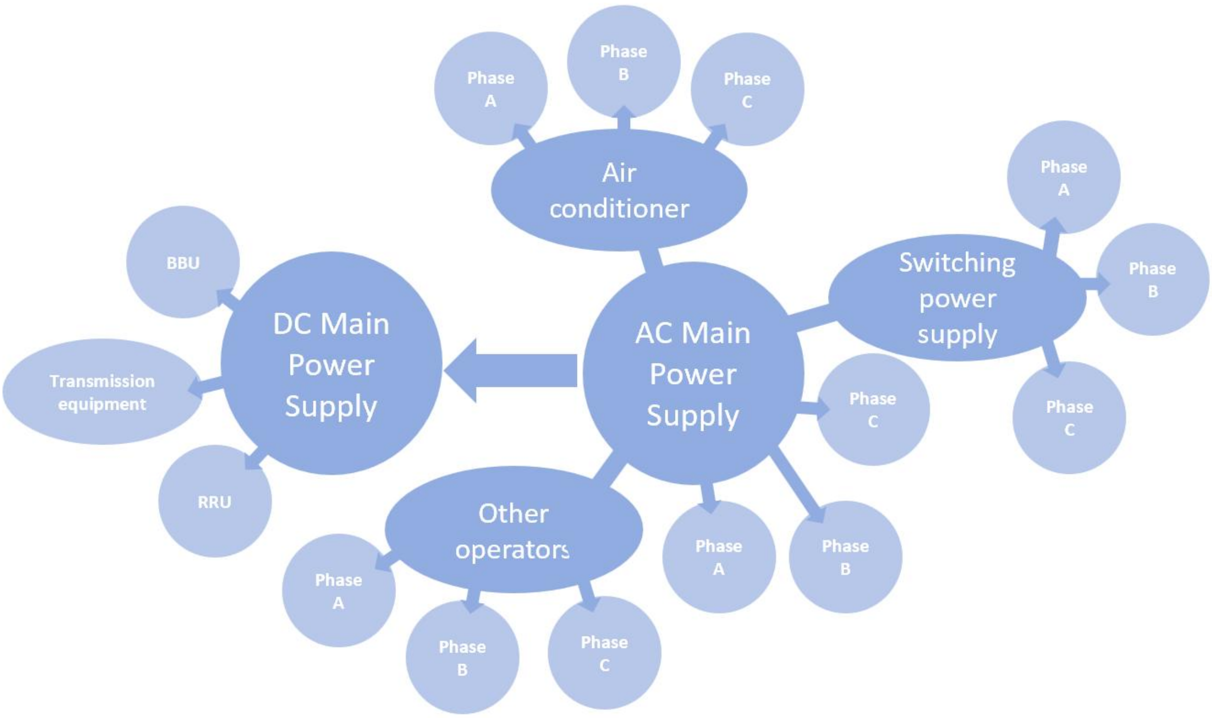

Figure 1 Node Relationship Diagram

(4) Generate the adjacency matrix A based on the affiliation relationships between the nodes, as shown below:

$$A = \begin{bmatrix} a_{11} & \cdots & a_{1n} \\ \vdots & \ddots & \vdots \\ a_{m1} & \ldots & a_{mn} \end{bmatrix} \tag{3}$$

Where,

$$a_{mn} = \begin{cases} 1 & if\ m = n \\ 1 & if\ m\ and\ n\ are\ connected \\ 0 & if\ m\ and\ n\ are\ not\ connected \end{cases} \tag{4}$$

(5) Rearrange the energy consumption data of each node into matrix form as the input to the network, as shown in the following formula:

$$X = \begin{bmatrix} I_0^0 & \cdots & I_K^0 \\ \vdots & \ddots & \vdots \\ I_0^n & \ldots & I_K^n \end{bmatrix} \tag{5}$$

Where n represents the total number of nodes, and k denotes the length of the input vector for each node. The rearranged matrix is then input into the network for prediction.

(6)The server-side uses the Graph Convolutional Network (GCN) to perform comprehensive analysis and judgment on the monitored energy consumption data. Based on the input features and the current weights of the network, it calculates the predicted values[3].

The forward computation process is as follows:

$$H^{l+1} = f\left(H^l, A\right) = \sigma\left(AH^l W^l\right) \tag{6}$$

Where H^l represents the l-th layer of the network, and the total number of layers in the network is 3, i.e., the input layer, hidden layer, and output layer. $H^0 = X$ represents the input layer, A is the adjacency matrix of the graph, W^l is the weight parameter matrix of the l -th layer, and $\sigma(.)$ is the nonlinear activation function. The hidden layer uses the RELU function, and the output layer uses the Sigmoid function. The output value $\left[p_0, p_1, \cdots p_n\right]$ represents the predicted energy consumption of each data node.

(7) Loss function definition:

To measure the difference between the model's predicted values and the actual values, the Mean Squared Error (MSE) Loss function is used as the Loss, as shown below:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}\left(y_i - \hat{y}_i\right)^2 \tag{7}$$

Where n is the number of input energy consumption data samples, y_i is the actual measured value of the energy consumption data, and $\hat{y}_i$ is the predicted value from the GCN. The MSE measures the average squared error between the model's predicted values and the actual values. The smaller the Loss, the higher the prediction accuracy of the model.

The backpropagation weight update uses the momentum gradient descent method (SGDM) to compute the gradient of the Loss function with respect to the weights, and this gradient is used to update the network weights. The Loss is optimized, and the model's parameters are updated automatically until the Loss no longer converges, at which point the updates stop.

$$W^{(l)} = W^{(l)} - \mu \nabla_{W^{(l)}} \mathrm{Loss} \tag{8}$$

3.2 Long Short-Term Memory (LSTM) Network

LSTM is used to identify the temporal features in energy consumption data and capture the load variation trends of the equipment. By using LSTM to dynamically update the weight matrix in GCN, the weight matrix of GCN is replaced by the hidden state of LSTM. At each monitoring period T , the weight matrix of GCN is updated based on the current input and historical information, thereby better capturing the dynamic features and changes in the time-series data.

$$\begin{cases} i_t = \sigma\left(W_{xi}x_t + W_{hi}h_{t-1} + W_{ci}c_{t-1} + b_i\right) \\ f_t = \sigma\left(W_{xf}x_t + W_{hf}h_{t-1} + W_{cf}c_{t-1} + b_f\right) \\ g_t = \tanh\left(W_{xg}x_t + W_{hg}h_{t-1} + b_g\right) \\ o_t = \sigma\left(W_{xo}x_t + W_{ho}h_{t-1} + W_{co}c_{t-1} + b_o\right) \\ c_t = f_t \odot c_{t-1} + i_t \odot g_t \\ h_t = o_t \odot \tanh\left(c_t\right) \end{cases} \tag{9}$$

Where, x_t is the input feature at the current time step; h_t is the hidden state at the current time step; c_t is the memory cell at the current time step; i_t, f_t, o_t and g_t represent the input gate, forget gate, output gate, and memory cell update gate, respectively; W and b are the model's weight and bias parameters; σ is the Sigmoid activation function; $\odot$ denotes element-wise multiplication.

3.3 GCN-LSTM Model Structure

The GCN-LSTM model combines the Graph Convolutional Network (GCN) for extracting spatial dependencies and the Long Short-Term Memory (LSTM) network for learning temporal features. It processes the energy consumption relationships between device nodes using graph convolution, followed by LSTM to capture dynamic temporal features. The model first inputs the standardized meter data and custom edge indices into the GCLSTM unit to obtain the temporal features associated with the nodes, and then uses a Multi-Layer Perceptron (MLP) to further extract nonlinear features, enabling accurate prediction of energy consumption for future time periods.

4 RESULTS

Select data from some nodes within a certain time period, and compare the GCN predicted values with the actual measured results. The comparison of the GCN prediction results and actual data is shown in Figure 2 (where red represents the predicted values, and blue represents the actual measured values). The results show that the measured values are highly consistent with the predicted values, the system has high accuracy, and can effectively predict the node energy consumption in the next time period.

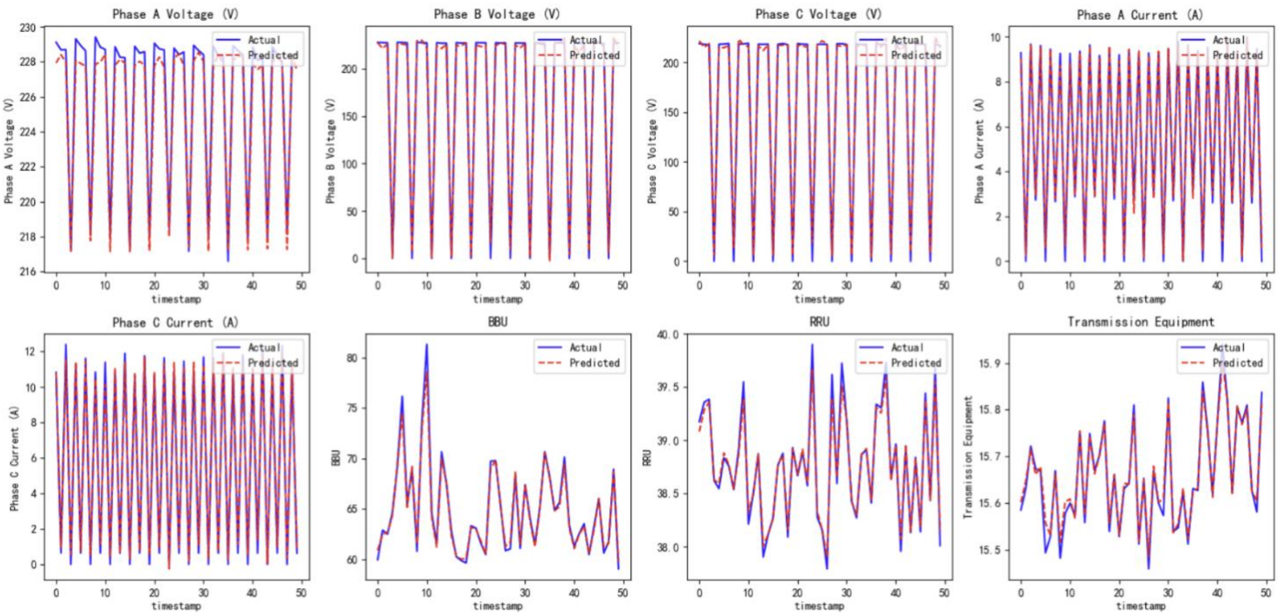

Figure 2 Comparison of GCN Predicted Values and Actual Data

After 200 epochs of iteration, the Loss converges as shown in Figure 3. The Loss function starts to stabilize after 75 iterations and finally converges to 0.0675, indicating a good training performance.

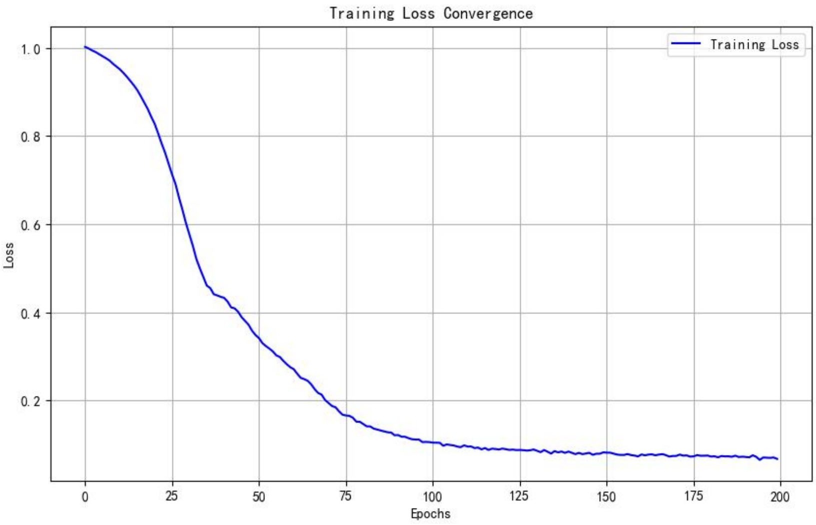

Figure 3 Loss Function Variation Over Time

5 CONCLUSIONS

This study proposes and designs a communication tower room energy consumption monitoring and optimization system based on the combination of Graph Convolutional Networks (GCN) and Long Short-Term Memory (LSTM) networks. The system constructs an energy consumption prediction model that integrates both spatial and temporal features, enabling accurate analysis and dynamic optimization of energy consumption data. The results show that the system can effectively predict the energy consumption of nodes with high overall accuracy, and provides an innovative technical path and solution for the communication industry to achieve intelligent and refined energy consumption management.

COMPETING INTERESTS

The authors have no relevant financial or non-financial interests to disclose.

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