# Early Warning Method of Abnormal Energy Consumption in Public Buildings Based on Multi-Level Analysis and Adaptive Weight

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Abstract. In order to make the energy consumption of public buildings more reasonable, it is necessary to warn the changes of energy consumption. Therefore, an early warning method of abnormal energy consumption of public buildings based on multi-level analysis and adaptive weight is proposed. By analyzing the data variation between different levels, we can find out the existing abnormal data, optimize the abnormal data target and analyze the weight, so as to get the preprocessing results. Calculate the total energy consumption of public buildings in the life cycle, including the abnormal energy consumption of public buildings and the operating energy consumption; Input samples, use the minimum proportional distance to classify, output the weight results, get the output network early warning value, and get the final early warning result of abnormal energy consumption of public buildings. The experimental results show that this method can provide more stable and reliable early warning results, and the results are close to the actual energy consumption results.

Keywords: Multi-level analysis; Adaptive weight; Public buildings; Abnormal energy consumption; Early warning method

# 1 Introduction

Early warning of abnormal energy consumption in public buildings is an important research topic, which is of great significance for improving energy utilization efficiency and reducing energy consumption [1]. Under the background of global energy shortage and increasingly serious environmental pollution, as an important source of energy consumption, how to reduce the energy consumption of public buildings has become an urgent problem, so a new means is needed to evaluate and predict the energy consumption of public buildings more accurately [2]. Multi-level analysis is a common method for complex problem analysis and decision-making [3]. In the analysis of abnormal energy consumption of public buildings, many factors are considered, including the structure of the building itself, the use of equipment, climate and environment [4]. By ranking and quantifying these factors hierarchically, we can find out the key factors affecting energy consumption. At the same time, in order to reduce the error caused by inaccurate estimation, the adaptive weight is adjusted according to the specific situation and data changes.

Reference [5] puts forward a statistical model of total building energy consumption of commercial buildings, discusses how this method develops with time, and summarizes the application of this method in various fields of building energy analysis. Reference [6] proposes an enhanced LSTM community energy consumption prediction model using shared building cluster data sets. By reflecting the inherent behavior pattern of residents in the shared electricity consumption data of single buildings, the power consumption forecasting performance of single buildings is improved. The error is reduced by using the similar energy distribution map of the surrounding buildings. Although the above methods have made some progress, the weights of different factors are often fixed, which can not adapt to the changes of the actual situation. Therefore, on the basis of the above research, an early warning method of abnormal energy consumption of public buildings based on multi-level analysis and adaptive weight is proposed. This method can flexibly adjust the weight according to the real-time data and the changes of the actual environment, so as to evaluate and predict the energy consumption of public buildings more accurately.

# 2 Early warning of abnormal energy consumption of public buildings based on multi-level analysis and adaptive weight

#### 2.1 Pre-processing of abnormal energy consumption data of public buildings

In the preprocessing of abnormal energy consumption data of public buildings, multi-level analysis and adaptive weight are two commonly used methods. Multi-level analysis is a statistical method used to study the hierarchical structure and variation within a group. In the preprocessing of energy consumption data of public buildings [7], the data are grouped according to different levels, and stratified according to building type, floor and time. By analyzing the data variation between different levels, we can find out the abnormal data. The optimization formula of abnormal data target is as follows:

$$Y = A \times X + \lambda \ (1)$$

In the formula, A stands for threshold; X stands for weighting parameter;  $\lambda$  stands for data correlation. According to the characteristics of data, the weights are adjusted adaptively, and by adjusting the weights of integer data points adaptively according to the importance and reliability of data, the influence of abnormal data on the final result is reduced. Each weight value is controlled by the residual size  $\mathcal{E}$ , and the weight expression is as follows:

$$W = F(\chi) \times Y \times \mathcal{E}$$
 (2)

In the formula,  $F(\chi)$  stands for standardized residual. According to the characteristics of weight, the data are weighted by multi-level analysis and adaptive weight method to reduce the influence of abnormal data on the final result, and the expression of pretreatment result is obtained as follows:

$$R = \frac{W}{D} \times G_H \quad (3)$$

In the formula, D stands for smoothing coefficient;  $G_H$  stands for conversion parameter.

Through multi-level analysis and preprocessing of abnormal energy consumption data of public buildings with adaptive weights, abnormal data can be identified and processed more accurately, the accuracy and reliability of energy consumption data analysis can be improved, and scientific basis can be provided for energy consumption management of public buildings.

#### 2.2 Calculation of abnormal energy consumption of public buildings

The energy consumption of public buildings with abnormal building fluctuation fluctuates greatly in a short period of time, which exceeds the normal fluctuation range. This abnormality may be caused by unstable equipment operation, temperature control system failure, abnormal energy supply or human error. The energy consumption of public buildings is the inevitable energy consumption in the process of building operation [8-9]. From this, the calculation model of abnormal energy consumption of public buildings can be obtained, and the expression is as follows:

$$M_{Z} = (M_{1} + M_{2}) \times R \quad (4)$$

In the formula,  $M_Z$  stands for the total energy consumption of public buildings in their life cycle;  $M_1$  stands for abnormal fluctuation energy consumption of public buildings;  $M_2$  stands for energy consumption of public buildings.

#### 2.3 Realization of early warning of abnormal energy consumption in public buildings

Through multi-level analysis and adaptive weight, the original data are transformed cumulatively, which reduces the instability of input and can realize rapid early warning of energy consumption.

Normalize the input and output data, and the normalization formula is as follows:

$$B = \frac{S_{\max} - S_{\min}}{W_{\max} - W_{\min}} \times M_Z \quad (5)$$

In the formula,  $S_{\text{max}}$  represents the maximum value of grayed data;  $S_{\text{min}}$  stands for the minimum value representing the ashing data;  $W_{\text{max}}$  represents the maximum value of original data;  $W_{\text{min}}$  stands for the minimum value of the original data.

For input samples, the minimum proportional distance is used for classification, and the classification formula is as follows:

$$K(E_s) = B \times L_y \times C \qquad (6)$$

In the formula, C stands for the number of data samples, and  $L_{\gamma}$  stands for the number of samples in the Y area. If  $K(E_{\varsigma}) \ge 1$ , the distance between the input sample and the cluster center is re-solved; otherwise, if  $K(E_{\varsigma}) \le 1$ , the width of the hidden layer is solved by the

distance between each cluster center, thus the weight result Q is output, and the calculation formula is as follows:

$$Q = X_n \times Y_n \times Z_n \times K(E_s) \tag{7}$$

In the formula,  $X_n$  represents the length distance between each data point and the cluster center;  $Y_n$  represents the width distance between each data point and the cluster center;  $Z_n$  represents the height distance between each data point and the cluster center. Using the abnormal energy consumption data of public buildings, the output network early warning value is obtained, and the denormalization processing is carried out [10] to obtain the final abnormal energy consumption early warning result of public buildings, and the expression is:

$$P = Q \times \left( G_n^{\ l} + G_n^{\ s} \right) \tag{8}$$

In the formula,  $G_n^l$  stands for missing abnormal data;  $G_n^s$  stands for energy consumption difference data. Through the above contents, we can realize the early warning of abnormal energy consumption in public buildings, identify and deal with abnormal energy consumption in time, and improve energy utilization efficiency and energy conservation and emission reduction level.

## **3** Experimental analysis

Taking the public building of a large shopping mall as the experimental object, the public building has ten floors, which are divided into positive seven floors and negative three floors, of which the second and third floors are underground garages; The first floor to the seventh floor are department stores, clothing, restaurants, electronic products sales areas, gyms, movie theaters and so on. A total of 170 GPRS transmission devices were laid in the public buildings of shopping malls, with 25 on each floor. The standardized original processed samples and ashed samples were used as the input of the early warning model of abnormal energy consumption in public buildings through MATLAB platform software, and 225 groups of data from January 2023 to May 2023 were selected as the training data, of which 25 groups of data were selected every month. Based on the multi-level analysis and adaptive weight technology, a parametric model of public buildings was constructed by using Revit software. The experimental parameters of this model,

| Serial number | Parameter                    | Numerical value       |
|---------------|------------------------------|-----------------------|
| 1             | Area                         | 240,000m <sup>2</sup> |
| 2             | Roofing                      | 0.36                  |
| 3             | External wall                | 0.54                  |
| 4             | Input power /kW              | 41.6                  |
| 5             | Maximum operating current /A | 124                   |
| 6             | Energy regulation level/%    | 75                    |

Table 1. Experimental Parameter Setting Table.





Figure 1. Schematic diagram of experimental data acquisition structure

On the basis of the above experimental parameters and experimental data acquisition structure, the data on the 10th day, 20th day and 30th day are forewarned by the three methods respectively, and the error values of each data are drawn into a box-line comparison chart, and the results are shown in Figure 2.



Figure 2. Comparison results of energy consumption warning errors under three methods.

As can be seen from Figure 2, compared with the early warning error of reference [5] and reference [6], this method shows obvious advantages in early warning error. By drawing the box chart, it can be clearly seen that the box chart area of this method is the shortest, which indicates that the error range is effectively controlled in the smallest and safest area when using this method for early warning. This method has good robustness and can provide more stable and reliable early warning results under different scenarios and data conditions.

Taking January, 2023 as an example, using the methods of reference [5], reference [6] and this paper, the comparative results of abnormal energy consumption and actual energy consumption of public buildings obtained by different methods are analyzed, as shown in Figure 3.



Figure 3. Early warning comparison results of abnormal energy consumption in public buildings

As can be seen from Figure 3, the energy consumption obtained by the method of reference [5] and the method of reference [6] fluctuates greatly, and the result of the method of reference [6] is quite different from the actual energy consumption, indicating that the method of reference is not applicable to the energy consumption early warning of this public building. Under this method, the abnormal energy consumption of public buildings is basically maintained at about  $0.8 \times 104$ , and the daily fluctuation range in January is small. The result of early warning by this method is close to the actual energy consumption value, which shows that this method has a good effect on early warning of abnormal energy consumption.

## 4 Conclusion

An early warning method of abnormal energy consumption in public buildings based on multilevel analysis and adaptive weight is considered. Through experiments, it is concluded that the box diagram of this method has the shortest area and good robustness, and can provide more stable and reliable early warning results under different situations and data conditions. The early warning results of this method are close to the actual energy consumption values and have good early warning effects.

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