Research on Energy Consumption Data Monitoring of Smart Parks Based on IoT Technology

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Abstract. Intelligent park energy consumption data monitoring is the basis of effective energy management. By monitoring energy consumption data, you can understand the energy consumption of each equipment, system and region in the park, and analyze and evaluate energy use. This helps identify energy consumption problems, optimize energy use, and develop sound energy management practices. Therefore, a smart park energy consumption data monitoring method based on Internet of Things technology is proposed. The perception layer of the Internet of Things technology is used to control the energy of the smart park through the collection, transmission and control of monitoring data. The energy consumption data of each layer of the large-scale smart park is collected through the sensor network. The host computer uses USB interface to obtain data from the gateway. Based on this, the energy consumption data is preprocessed by using power error data correction and missing data fitting compensation steps. By using Gaussian function to analyze the characteristics of energy consumption sample data of the smart park, a multiple linear regression model is constructed to complete the monitoring of energy consumption data of the smart park. The experimental results show that the smart park energy consumption sequence under the proposed method is more stable in fit degree, more accurate in prediction and shorter in response time.

Keywords: Internet of Things Technology · Smart Park · Zigbee · Grey Short - and Long-Term Memory Network

1 Introduction

Smart Park [1] is a modern park based on information technology, fully utilizing technologies such as the Internet of Things, cloud computing, big data, artificial intelligence, and blockchain to achieve intelligent facilities management, enterprise services, urban governance, and other aspects of the park. Through the application of Internet of Things technology, smart parks have achieved functions such as intelligent perception, interconnection, and autonomous decision-making of items, thereby improving the operational efficiency and enterprise service level within the park. For example, by deploying intelligent monitoring equipment to monitor and analyze the use of various resources (water,

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electricity, gas, etc.) in the park in real time, energy efficiency has been improved and waste has been reduced. In addition, smart parks can also utilize big data and artificial intelligence technology for data analysis and prediction, optimize park planning and operational decision-making, and achieve information management of various internal links in the park. At the same time, smart parks can also work closely with urban management departments to achieve intelligent urban governance. In short, smart parks are a new direction for the development of modern parks and an important means of promoting the economic development of parks and enhancing the level of urban intelligence.

At present, many scholars have gradually proposed new energy consumption methods. For example, Ji et al. [2] proposed an energy consumption prediction method based on convolutional neural networks. Convolutional kernels can continuously extract time series features to obtain accurate results. However, in practical applications, reasonable output weights are not set, resulting in slow network training speed and weak generalization ability. Xiao et al. [3] proposed a support vector machine method for predicting energy consumption, which verifies the input variables of the model through univariate validation. Although the support vector machine considers the temporal correlation of prediction, when the sample data is small, the energy consumption prediction error of the method is relatively large.Kladas A et al. [4] in order to realize efficient photovoltaic research, proposed an energy data detection method, which combined the Ramer-Douglas-Peucker algorithm with the Timescaledb compression method to reduce the space of time series data to ensure the maximum saving of disk space. The monitoring speed is slow. Nascimento GFS et al. [5] adopted non-invasive load monitoring (NILM) technology to compress building data sets to reduce energy consumption, and used factorial hidden Markov model to complete data detection. However, in the actual application process, the calculation amount is large and the detection efficiency is low.

To improve the drawbacks of the above methods, this article proposes a smart park energy consumption data monitoring method based on Internet of Things technology.The main innovations of this research are reflected in the following aspects:

(1) Use the perception layer of the Internet of Things technology to collect energy consumption data of each layer of the smart park through the sensor network. This paper adopts advanced wireless sensor technology to realize real-time monitoring and collection of energy consumption data of smart park.
(2) The steps of power error data correction and missing data fitting compensation are proposed, and the collected data is preprocessed. The innovation of this step lies in the ability to effectively deal with errors and omissions in the data, improving the accuracy and integrity of the data.
(3) Gaussian function was used to analyze the characteristics of the energy consumption sample data of the smart park. This analysis method can reveal the underlying patterns and regularities in the data, providing a basis for subsequent modeling and prediction.
(4) Construct multiple linear regression model for energy consumption monitoring. This paper uses multiple linear regression model to monitor the energy consumption data of smart parks. This model can comprehensively consider the influence of many factors on energy consumption and provide more comprehensive and accurate energy consumption monitoring results.

2 Smart Park Energy Consumption Data Monitoring

2.1 Energy Control and Information Transmission in Smart Parks Based on the Internet of Things

This article utilizes IoT technology to achieve energy management and control in smart parks. The Internet of Things mainly plays a monitoring role in this system, with the perception layer being the most critical. It generally includes sensors, sink nodes, upper computers, etc., which use the cooperative relationship of nodes to transmit the acquired information through the routing of other nodes, and finally send it to the sink node, and then use the external network to send it to the control center, so as to complete the collection, transmission and control of monitoring data.

Develop an overall concept for the energy management and control system, dividing it into three layers: acquisition, transmission, and application through a layered approach. The overall architecture is shown in Fig. 1.

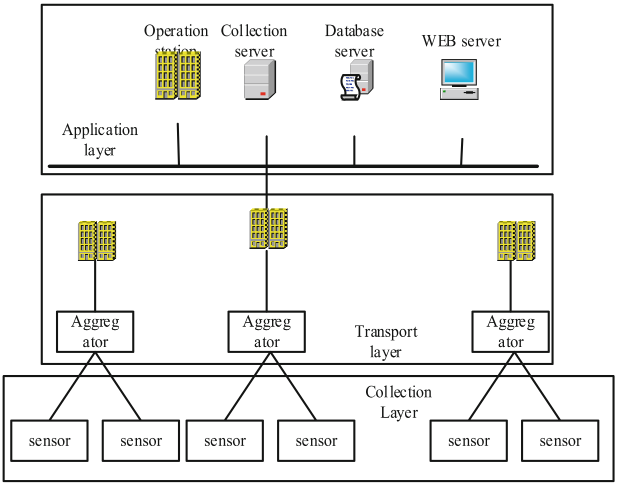

Fig. 1. Overall Architecture of the Control System

(1) Collection layer

The system acquisition part mainly uses different types of sensors, such as smart meter [6] and temperature sensing devices, through which various energy consumption information and environmental information are tested.

Power supply information collection: including data such as electricity quantity, voltage, power, and harmonics, providing a basis for the system's electricity analysis.

Water supply information collection: divided into water temperature, flow rate, and pH value, which can enable users to timely understand water use information and water quality.

Boiler information collection: mainly collects steam temperature, fuel consumption, etc., and can provide real-time data for system efficiency evaluation.

(2) Transport layer

The system transmission section includes on-site level and management level, with the former communicating through Zig Bee [7] and the latter using Ethernet for communication.

Among them, Zig Bee is suitable for short distance wireless communication due to its advantages such as low cost and good security. Its two biggest characteristics are: good self-organization performance, no need for manual operation; Strong self-healing ability, when a node fails, the network can repair itself to ensure normal communication, and this process does not require manual operation.

(3) Application layer

It has multiple functions such as information collection, analysis, organization, and prediction. Through information collection, real-time understanding of energy utilization status, and utilizing functions such as analysis and organization, the energy utilization status is organized to identify problems; Finally, predict the use of energy consumption, grasp energy consumption trends, achieve effective control, and reduce energy waste.

2.2 Monitoring Information Transmission Based on the Internet of Things

The monitoring method in this article consists of three parts: sensor nodes, gateways, and hosts. Multiple sensors and ZigBee [8] form a sensor network, whose main task is to collect energy consumption data from various layers of large smart parks. By processing the data of the power system, sensor nodes send data to the gateway, and the upper computer uses USB interface to obtain data from the gateway, forming a visual human-machine interface, which facilitates users to observe the numerical changes of electrical equipment in real time on a PC. Based on the three-layer architecture of the Internet of Things, energy consumption monitoring is achieved through technologies such as wireless sensors and the Internet. It consists of three main modules: perception layer, communication layer, and application layer.

The perception layer is the lowest level of the system and the center of the entire monitoring. The main function of the sensing layer is to collect energy consumption data, and a wireless sensor network is established using ZigBee technology. The perception layer of this unit is located indoors in a large smart park, consisting of various indoor sensors and wireless communication nodes. And analyze, preprocess, and store the wireless sensor nodes connected to it, completing the configuration of ZigBee and the establishment of the wireless Mesh network.

The communication layer consists of two main parts: inbound communication and remote data transmission, with the function of transmitting energy consumption information. Utilizing an embedded gateway, the ZigBee communication protocol for close proximity is converted into remote GPRS to meet the needs of remote data transmission;

The GPRS communication network is a bridge between the application layer information management center and the perception layer. Through the embedded gateway of the communication layer, the collected energy consumption data of the smart park is connected to the wireless GPRS network through the GPRS module. Then, the GPRS base station of the mobile operator is connected to the internet to complete the storage and management of the data, which is finally sent to the monitoring management information center through various switches and routers. The application layer is the energy consumption management center, whose main role is to analyze and integrate energy consumption data. And the parameter information of each energy consumption measurement point is transmitted to the database through the network of the communication layer, which is managed by the administrator.

2.3 Pre Processing of Historical Energy Consumption Data in Smart Parks

This article takes electricity as the energy consumption of smart parks that needs to be predicted. During the process of collecting electricity data, due to statistical errors and other reasons, a large number of errors and missing information may appear in the data used for prediction. Therefore, it is necessary to preprocess the original dataset, which includes the correction of electrical energy error data and the fitting compensation of missing data.

The external factors that affect the overall energy consumption of smart parks include: urban development capacity, smart park area, temperature changes, thermal conditions of smart parks, power of smart park electrical equipment, etc. However, there has been no actual change in the thermal situation of smart parks in many regions over the years, and the power equipment in smart parks has always been an original piece of equipment, without any actual changes.

Therefore, the main influencing factors for the overall power consumption prediction of urban smart parks only need to consider three external factors: urban development capacity, urban smart park area, and temperature changes. Characteristic indicator analysis is needed for these three external factors. The different indicators of these three external factors and the variable indicator R of smart park power consumption are as follows:

$$R = \sum (X - \overline{X})(Y - \overline{Y})/\sqrt{(X - \overline{X})^2(Y - \overline{Y})^2} \tag{1}$$

In the formula, X represents indicator sample 1, $\overline{X}$ represents indicator sample 2, Y represents the mean of indicator sample 1, and $\overline{Y}$ represents the mean of indicator sample 2.

Based on the absolute value of variable indicators, the power consumption of smart parks for various influencing factors was determined, and six indicators were obtained: monthly sequence variables, monthly cycle variables, per capita disposable income of urban and rural people, smart park area, average summer hour, and average winter hour. The relationship between various indicators and the electricity consumption of the smart park is shown in Table 1.

2.4 Energy Consumption Prediction of Smart Parks Under Long-Term and Short-Term Memory Networks

In the traditional recurrent neural network, when any hidden layer memory unit calculates the weight matrix and activation function, the obtained memory data will be fleeting,

Table 1. Relationship between various indicators and electricity consumption in smart parks

Impact variable indicators	The relationship between power consumption and smart park
Smart Park Area	This indicator has a linear relationship with the total electricity consumption of the smart park, increasing in the same proportion
Per capita disposable income	This indicator is highly correlated with the total power consumption of the smart park
Month cycle variable	This indicator can display the cycle length of power consumption in smart parks
Month sequence variable	This indicator can display the growth of power consumption in smart parks
Average Summer Hour	This indicator is clearly biased towards the air conditioning and cooling power consumption in the smart park's electricity consumption
Winter average hour	This indicator is clearly biased towards the heating and heating electricity consumption in the smart park's electricity consumption

while the long-term and short-term memory network makes the memory data disappear instantaneously without being affected by the fusion of memory data and current input data. The short-term memory network can store and use historical data by introducing input gates and output gates into the model, and adjust the output of different time series to bring stable processing to the subsequent actions of the energy consumption prediction model [9, 10].

Although the long-term and short-term memory network [11] has excellent nonlinear fitting ability, its prediction deviation is high when there are few samples. The energy consumption cycle of smart parks is unstable, making it difficult to find similar fitting curves for replacement. By using the grey theory method [12, 13] to cumulatively transform the raw data and reduce input instability, rapid prediction of energy consumption can be achieved. The optimized energy consumption prediction model process is shown in Fig. 2.

In the process of establishing the prediction model of grey long and short term memory network, it is necessary to accurately calculate the relevant parameters in the network. By using the Gaussian function to analyze the characteristics of the energy consumption sample data of the smart park, the optimized prediction model uses the K-means clustering method [14, 15] to calculate the height and central coordinate point of the Gaussian function, complete the reasonable allocation of resources, and make the central coordinate point of the prediction model coincide with the central point of the input sample.

Grey process the output and input data, and normalize the formula:

$$T = T_{\min} + \frac{T_{\max} - T_{\min}}{E_{\max} - E_{\min}}(E - E_{\min}) \tag{2}$$

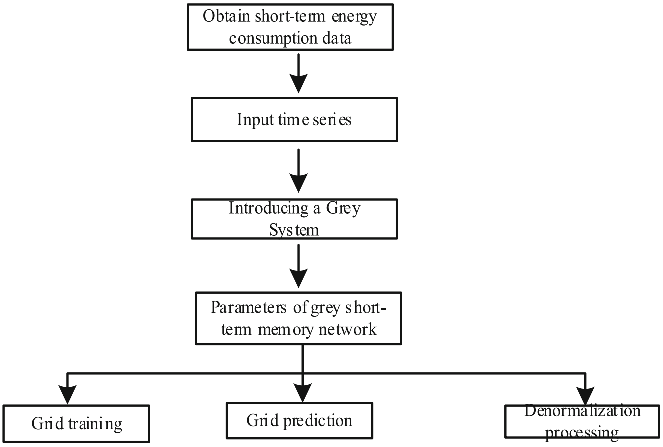

Fig. 2. Flow chart of energy consumption prediction of grey short-term memory network

In the formula, E represents raw data, T represents ashed data, E_{max} represents the maximum value of raw data, E_{min} represents the minimum value of raw data, T_{max} represents the maximum value of ashed data, and T_{min} represents the minimum value of ashed data. The data samples are constructed by using the position sliding method, and the corresponding weights and parameters are obtained through the learning and training of the gray long-term and short-term memory network.

2.5 Energy Consumption Data Monitoring for Smart Park Operation

From a statistical perspective, the possibility of the existence of lower limit data samples for energy consumption monitoring in smart parks was analyzed, and a multiple nonlinear regression model was used to analyze the energy consumption and influencing factors of smart parks. In order to obtain the actual monitoring values of energy consumption in smart parks, reasonable sample energy consumption data for smart parks can be determined more scientifically, which is of great significance for the determination of accurate monitoring models for energy consumption in smart parks.

The multiple linear regression model [16, 17] is one of the most commonly used methods in dealing with variable relationships at present. The expression for a multiple regression model with m variables is as follows:

$$Z = \beta_0 + \beta_1 v_1 + \beta_2 v_2 + \ldots + \beta_m v_m + e \tag{3}$$

In the formula, A represents the regression coefficient, B represents random error, and v represents the variable influencing factor of the smart park. The variables of the smart park and any one of them need to satisfy a linear relationship, and the formula for solving the linear correlation coefficient is as follows:

$$r = \frac{\sum_{i=1}^{m} (v_i - \overline{v})(u_i - \overline{u})}{\sqrt{\sum_{i=1}^{m} (v_i - \overline{v})^2 \sum_{i=1}^{m} (u_i - \overline{u})^2}} \tag{4}$$

Substitute the energy consumption data of the smart park operation without missing values into the formula, set the linear coefficient between CPU utilization and power as $r_{cpu} = 0.9603$, and the linear coefficient between memory utilization and power as $r_{men} = 0.9537$. The expression of the multiple linear regression energy consumption model is:

$$Q = \beta_0 + \beta_1 U_{cpu} + \beta_2 U_{mem} \tag{5}$$

Due to the mutual influence of different energy consumption during the data monitoring process of smart parks, and the non absolute and complete nonlinear relationship between operating power and the presented utilization rate, in order to improve the accuracy of the smart park energy consumption monitoring model in this article, a nonlinear relationship is introduced for discussion and analysis.

Using a polynomial model as the basic function, a nonlinear energy consumption model is obtained. The expression for monitoring energy consumption in smart parks using the smart park energy consumption model is as follows:

$$Q = \beta_0 + \beta_1 U_{cpu} + \beta_2 U_{cpu}^2 + \beta_3 U_{mem} + \beta_4 U_{mem}^2 \tag{6}$$

The number of energy efficiency equipment in the smart park and the area of the smart park are the main influencing factors of energy consumption monitoring in the smart park. The actual value of $\beta_0, \beta_1, \beta_2, ...\beta_m$ is obtained by polynomial regression analysis.

In order to ensure the accuracy of the monitoring results, the energy consumption data monitoring results of the smart park are calibrated through relative deviation and average relative deviation. The relative deviation can obtain the monitoring accuracy of each smart park impact factor, and the relative deviation can reflect the error of model monitoring. The expression for the relative deviation and average relative deviation [18, 19] of energy consumption data monitoring in smart parks is as follows:

$$Q_{\text{relative deviation}} = \frac{Q_{\text{predictive value}} - Q_{\text{true value}}}{Q_{\text{true value}}} \tag{7}$$

$$Q_{\text{Average relative deviation}} = \frac{\sum_{i=1}^{m} (Q_{\text{deviation}})}{m} \tag{8}$$

During the monitoring process, there may also be some data anomalies that cause changes in energy consumption values and cannot reflect the actual situation, as shown in Table 2.

Table 2. Data Classification of Energy Consumption Supervision Platform

Data type	Data characteristics	Cause of occurrence	Processing method
Real data Distorted data	Normal data usage	business as usual	retain
	Using abnormal data	Abnormal energy usage behavior, equipment failure	Reserved, marked
data type	Mutation data	Measurement transmission failed	Eliminate
	0 data	There is a problem with the transmission or recording device	Eliminate

From Table 1, it can be seen that based on whether the data can reflect the actual energy consumption of buildings, they can be divided into two types: real data and distorted data [20].

(1) Real data
  1) Normal data: When the monitored energy consuming equipment is operating normally, the recorded data is the measured data and calculated energy consumption results.
  2) Abnormal energy usage data: The collected electrical energy values and consumption data in the event of abnormal use of energy consuming devices. The abnormal operation of the device is caused by human energy consumption behavior and the failure of the electrical device.

(2) Distorted data
  1) Catastrophic data: measuring the quality of the equipment itself.
     Adjacent electromagnetic interference [21] can cause a significant increase or decrease in measurement results, but it quickly returns to normal. This result cannot truly reflect the actual situation of energy consumption.
  2) 0 data: When the measuring instrument or transmission device malfunctions, the collected data will be displayed as 0. If not detected or repaired in a timely manner, it will result in all collected data being 0 for a period of time.

To improve the data quality [22] of energy consumption monitoring platforms, it is necessary to screen and integrate the identified zero data and mutation data. Therefore, an intelligent data supplementation method using energy mode is proposed.

Assuming there is a continuous problem data with 0 and mutation data [23, 24]. The problem data includes m type of energy usage data, j type of energy usage data has h_j problem data points. Before the problem data occurs, the cumulative display value A' on the time meter is displayed, and after the problem data occurs, the cumulative display value B' on the time meter is displayed. By analyzing the time, temperature, and other information of the problem data, the energy consumption types of each problem data are determined, and the mathematical expectation μ and variance Δ of energy consumption are obtained. The supplement of problem data can be represented by the following mathematical problems.

A' and B' represent the energy consumption numbers included in the missing part, while E_j follows the layout of $F\left(\mu_j, \Delta_j\right)$; Among them, E_j describes the compensation number for the problem data under the j-type energy consumption situation. The equation used in this problem is not closed, and the $\sum_{j=1}^{m}\left(\frac{E_j-\mu_j}{\Delta_j}\right)^2$ minimum limit is introduced to measure the supplementary quality of the data.

Obtain the calculation result using the pull method, expressed as:

$$E_j = \mu_j + \frac{h_j\Delta_j^2}{\sum_{j=1}^{m}\left(h_j\Delta_j^2\right)}\left(B' - A' - \frac{\sum_{j=1}^{m} h_j\mu_j}{\sum_{j=1}^{m} h_j}\right) \tag{9}$$

Integrate the obtained energy consumption data of each item into one monitoring result. If it is greater than the variance data, the energy consumption is not in a normal state and requires the intervention of the technical department to check whether there is a fault or simply excessive electricity consumption [25], in order to take corresponding measures.In order to improve the readability and understandability of the article, the method flow chart is presented below. By observing the flow chart, you can quickly understand the overall framework of the research method, which helps readers to understand and master the research content faster. The flow chart is shown in Fig. 3:

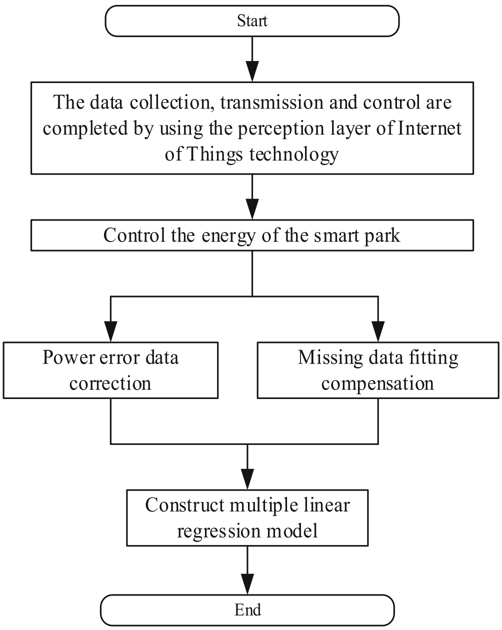

Fig. 3. Smart park energy consumption data monitoring flow chart

3 Experimental Design and Result Testing

Conduct experiments to demonstrate the effectiveness of the proposed method. Select a large shopping mall smart park as the monitoring target, the use of IBM Watson IoT iot platform to obtain real data, with advanced data storage and processing capabilities, can safely store the energy consumption data of the mall's smart park, and provides strong security measures to ensure the confidentiality, integrity and availability of data, support a variety of communication protocols and data formats, Real-time access to various energy consumption data of the mall's smart park,and the specific experimental parameters are shown in Table 2. The 6-story building is from the positive 5th floor to the negative 1st floor, with the negative 1st floor being the underground garage; The first floor is the department store sales center; The second floor is for shoe sales; The third floor is for clothing sales; The fourth floor is for food and beverage sales, and the fifth floor is for electronic product sales and movie theaters. A total of 120 GPRS transmission devices will be installed in the mall, with 20 devices per layer (Table 3).

Table 3. Experimental Parameters

Name	Data
the measure of area	250000 m^2
position	Located in the North China region
Number of layers	6th floor
Cargo Lift	4 parts
Elevator	7 parts
Getting on and off the elevator	12 parts
Business Hours	9:00–21:00

According to the laws of local climate change, set April, May, October, and November as the transitional seasons; Set January, February, March, and December as the heating season; Set June, July, August, and September as the cooling season. The energy consumption monitoring results during the heating season, cooling season, and transition season using the proposed energy consumption monitoring method are shown in Fig. 4.

From Fig. 4, it can be seen that the energy consumption of lighting, sockets, and power is in a stable state during the heating, cooling, and transition seasons, with particularly small changes in amplitude, indicating the non seasonal relationship between lighting energy consumption, socket energy consumption, and power energy consumption. The annual fluctuation of air conditioning power consumption is relatively severe, indicating the seasonality of air conditioning energy consumption. Due to the fact that most student dormitories and office buildings use non electric heating methods such as gas for heating, the use of air conditioning for refrigeration is greater than that of air conditioning for heating, and the energy consumption monitoring is completely consistent with the actual situation.

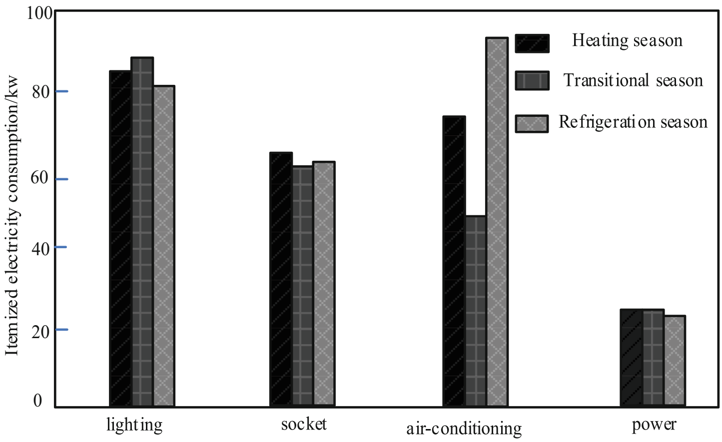

Fig. 4. Energy consumption during heating, cooling, and transition seasons

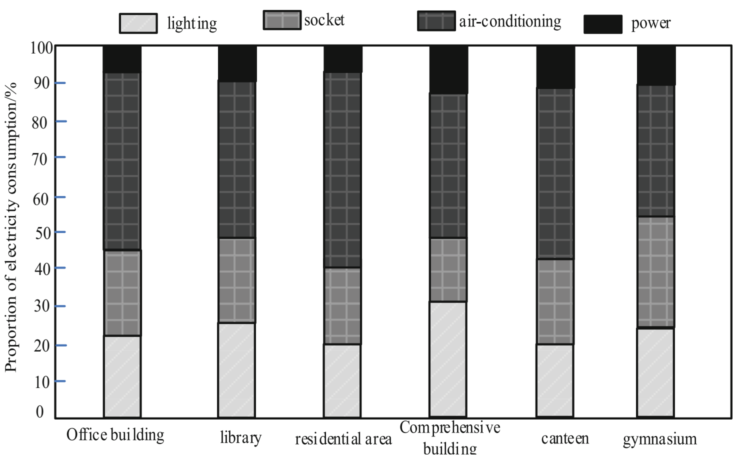

Fig. 5. Proportion of energy consumption by sub projects in the smart park

From Fig. 5, it can be clearly seen that lighting energy consumption, socket energy consumption, and air conditioning energy consumption are the main energy consumption sub items. In various types of smart parks, the proportion of these three items is far greater than power energy consumption. Among them, the highest proportion of energy consumption for air conditioning is in office smart parks, student dormitories, and canteens. This is because these locations have frequent student access, high mobility, and higher indoor air quality compared to other smart parks.

Through the MATLAB platform software, the standardized original processing samples and the ashed samples are used as the input of the long-term and short-term memory network prediction model, of which 125 groups of daily data from January 1, 2021 to May 5, 2021 are used as training data. Comparing the method proposed in this paper with the energy consumption prediction method based on convolutional neural networks proposed in reference [2] and the energy consumption prediction method based on support vector machines proposed in reference [3], Fig. 6 shows the comparison results of the three models.

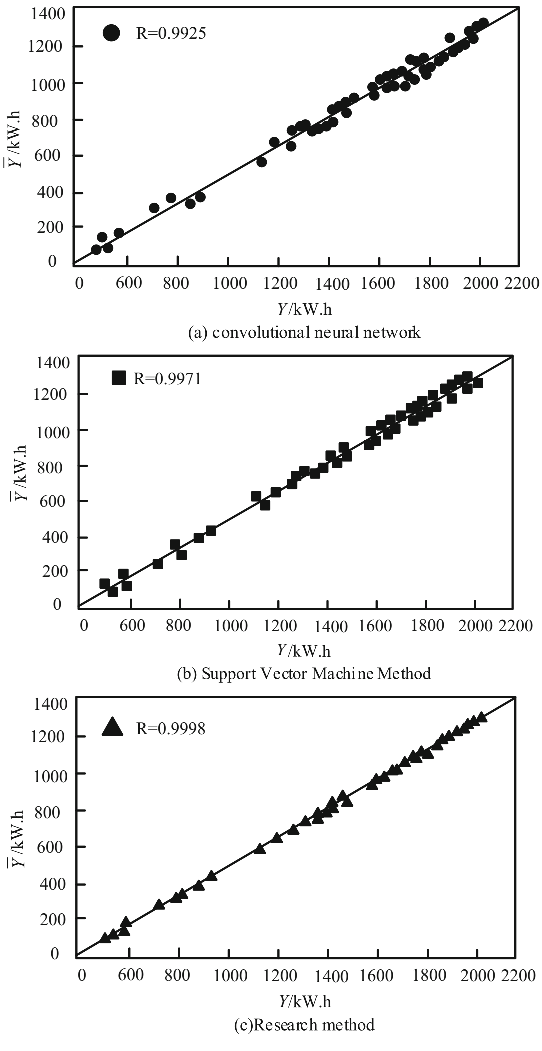

Fig. 6. Comparison of three building prediction models

Figure 6 shows the correlation distribution between the predicted value $\overline{Y}$ and the actual value $\overline{Y}$ of all models, where R represents the Pearson correlation function, the Pearson correlation coefficient value predicted by the neural network model is $R = 0.9925$, the Pearson correlation coefficient value predicted by the adaptive neural network model is $R = 0.9971$, and the Pearson correlation coefficient value predicted by the method in this paper is $R = 0.9998$. The correlation coefficient value of the method in this paper is significantly higher than that of other methods, The predicted values of the smart park prediction model proposed in this article have always been within the standard linear range, and the fit of the smart park energy consumption series is more stable, resulting in more accurate prediction results.

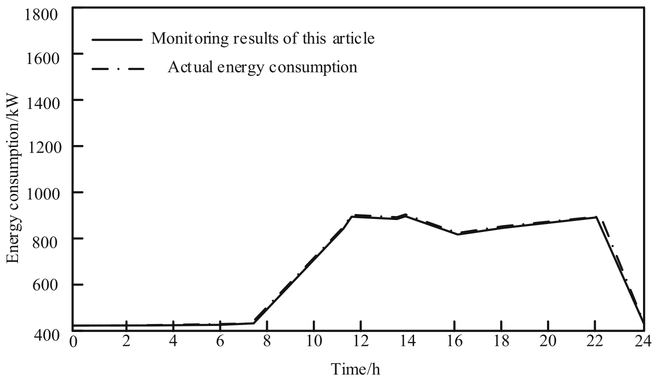

Fig. 7. Comparison of Energy Consumption and Actual Monitoring on the First Floor

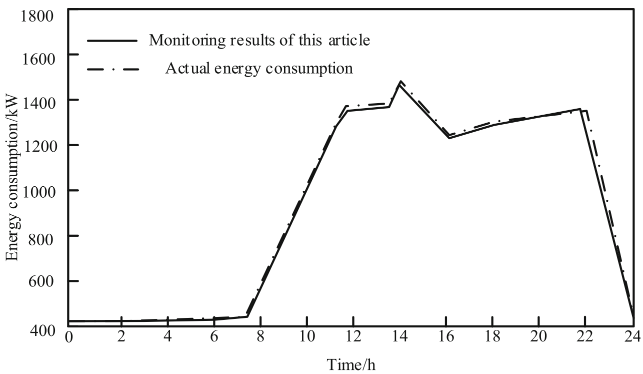

Fig. 8. Comparison of Energy Consumption and Actual Monitoring on the 2nd Floor

From Fig. 7 and Fig. 8, it can be observed that the positive 1st and 2nd floors are basically in a flat state from 0 to 7, and the energy consumption gradually increases after 7 o'clock, reaching a peak at 11 o'clock and 14 o'clock. This indicates that the power consumption of the 1st and 2nd floors is relatively high at this time, and the energy consumption increases.

Observing Fig. 9, it can be seen that the energy consumption of the third floor is relatively high at 12:00 and 19:00, which is during lunch and dinner time. Oil fumes can cause an increase in indoor temperature and a higher demand for air conditioning. As the meal time ends, energy consumption also decreases.

By observing Fig. 10, it can be seen that the energy consumption on the fourth floor is relatively high throughout the day, especially from 12:00 to 14:00 and from 20:00 to

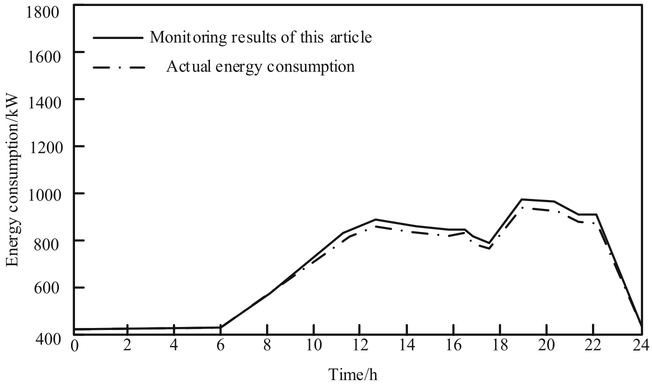

Fig. 9. Comparison of Energy Consumption and Actual Monitoring on the 3rd Floor

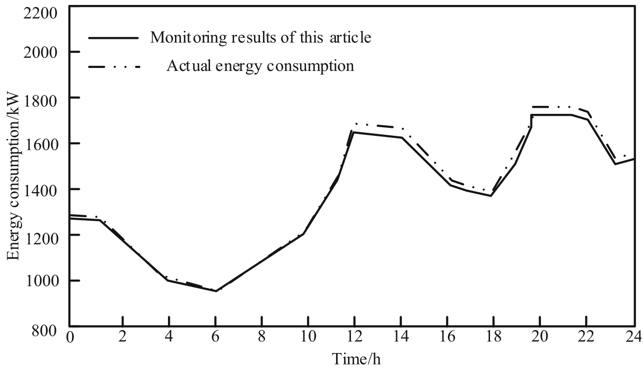

Fig. 10. Comparison of Energy Consumption and Actual Monitoring on the 4th Floor

22:00. At this time, the movie theater on the fifth floor is open 24 h, which is not consistent with the business hours of the mall. In addition, the electronic product sales area is open, resulting in an overall increase in energy consumption. As the opening hours of the mall end, the energy consumption in the electronic product sales area decreases, but at this time, the cinema is still in business hours, and night movies are more popular, so the energy consumption is only slightly reduced. From the experimental results obtained in the above figure, it can be seen that there is an error between the actual energy consumption and the monitoring results in this article, but the numerical value is very small, and overall, the accuracy is high.

Energy consumption monitoring in smart parks requires timely acquisition and processing of energy consumption data to achieve real-time monitoring and management of energy consumption. Therefore, the performance of evaluation methods should have a short response time and be able to quickly respond to and process energy consumption data. The method in this paper, the energy consumption prediction method based on Convolutional neural network proposed in literature [2] and the energy consumption prediction method based on support vector machine proposed in literature [3] are used as comparison methods to test the response time of different methods. The specific test results are shown in Fig. 11.

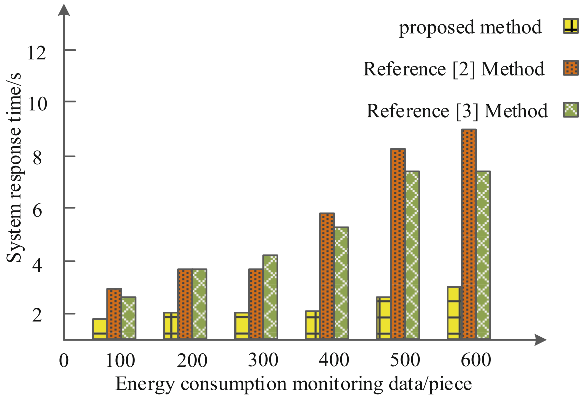

Fig. 11. Comparison of Response Time Testing for Three Methods

Analyzing the data in Fig. 11, it was found that with the increase of energy consumption monitoring data, the response time of the three methods increased to varying degrees. However, the response time of the method in this paper was always lower than that of the other two methods. When monitoring 600 energy consumption data, the method in this paper only took 3 s, while the methods in reference [2] and [3] took 9 s and 7 s, respectively. This verifies that the method proposed in this paper has the fastest response speed, indicating its practicality.

4 Conclusion

The Internet of Things technology can achieve real-time monitoring and analysis of different resources for better planning and utilization, to minimize waste and improve resource utilization efficiency. In this context, a smart park energy consumption data monitoring method based on Internet of Things technology is proposed. Based on the pre processed energy historical data of the smart park, improve the long-term and short-term memory network to predict the energy consumption of the smart park, and build a nonlinear regression model to monitor the energy consumption of the smart park.

However, smart parks often involve multiple departments and enterprises, involving issues such as data privacy and security. Therefore, in the future, it is necessary to consider whether the security and privacy of data can be ensured during the energy consumption data monitoring process.

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