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Article

Analysis of parameter adjustment and efficiency improvement of optimized energy-saving retrofit of building clusters using the least-squares approach

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Abstract: The energy-saving performance of large building clusters has gradually become a focus of attention in the construction of green and low-carbonized cities. In this paper, we select K university building cluster as a research sample, collect its building outline, city information point (POI) and area boundary information, and generate its building cluster energy consumption model through spatial analysis and building type identification. For the prediction of energy consumption and energy-saving renovation of the building cluster, the multi-criteria decision optimization theory is introduced to predict the energy consumption of the energy-saving scheme, and the least squares method is used to establish the functional relationship between building energy consumption and outdoor climate, and to comprehensively build the energy consumption prediction and optimization model of the building cluster. The model can fully take into account the energy-saving technologies applied to many different types of buildings in K university, and the difference between the predicted and actual energy-saving performance data is controlled within 3.00%, which shows high feasibility in promoting the optimization and enhancement of energy-saving effect of buildings.

Keywords: least squares method; multi-criteria decision optimization; energy consumption prediction and optimization; energy saving of building groups; parameter adjustment

1. Introduction

With the development of economy and society, the phenomenon of energy shortage has become a worldwide topic. Along with the intensification of energy problems, people also pay more and more attention to energy saving and environmental protection, in order to realize sustainable development, energy saving, consumption reduction and emission reduction have become the main mode of social development, and related policies and supervision measures are proposed [1-3]. Building, industry and transportation are the three main areas of energy consumption, of which building energy consumption accounts for about one-third of the total energy consumption of the society, and carbon emission reduction in the field of building will become an important part of the realization of the “dual-carbon” strategy [4-6].

The energy consumption of the building mainly comes from the operation period energy consumption, such as heating, cooling, ventilation, cooking, lighting, office life electricity, etc., and take energy-saving design or the implementation of energy-saving renovation of the original building can significantly reduce the energy consumption during the operation period of the building, is an important means of sustainable development of the building [7-10]. The Energy Efficiency Improvement of Existing Buildings (ESRB) is a series of renovation projects aimed at effectively enhancing the energy utilization efficiency of buildings. The main measures include active energy-saving and intelligent energy-saving systems mainly focusing on improving the energy efficiency of energy-consuming facilities such as HVAC systems within buildings and developing and utilizing renewable energy. And passive energy-saving measures mainly such as improving the thermal performance, airtightness and adjustable solar heat gain of building envelopes [11-15]. Various energy saving measures work together to contribute to building energy consumption reduction. However, most traditional ESRB methods have obvious shortcomings in parameter tuning, multi-objective synergy, and retrofit effect evaluation due to factors such as policy uncertainty and project financial support [16-18].

Literature [19] calculates the energy consumption of building group heating and screening of retrofit solutions through EnergyPlus software and entropy value method respectively, introduces the comprehensive benefit assessment optimization scheme, and adjusts the retrofit parameters to propose the optimal retrofit solution with more energy efficiency assessment results. Literature [20] used the non-dominated sorting genetic algorithm (NSGA-II) based on polynomial operations to determine the optimal solution of energy consumption, cost and carbon emission in ESRB, and this multi-objective solution method effectively reduces the energy consumption, cost and carbon emission of the building, and improves the efficiency of ESRB. Literature [21] for optimizing the energy efficient design of building maintenance structure in ESRB, with the help of NSGA-II to estimate the winter building energy consumption, lighting energy consumption, and thermal comfort, and introduce the Pareto method to select the effective building parameters. Literature [22] constructed a building energy consumption simulation model, combined the multi-objective whale optimization algorithm with GA-backpropagation algorithm to train the retrofit parameters, and introduced the entropy weight-approximation ideal solution ranking method method to obtain the best retrofit solution. Literature [23] carried out energy-saving and low-carbon retrofitting of educational buildings, focusing on adjusting the selection of envelope materials and shading schemes, and predicting and optimizing the three objectives of sustainable energy use, useful daily illumination, and total building carbon emissions under GA combined with the retrofitting XGBoost algorithm, so as to obtain the retrofitting scheme of high light + low energy consumption + low carbon emissions. Literature [24] constructed an ESRB framework based on machine learning, heuristic optimization algorithm and entropy weighting method, using the framework to balance the energy consumption, carbon emission and cost in the retrofitting process, and these three targets were successfully reduced by 56.62%, 51.60% and 24.27%.

Least Squares (LS) is a method commonly used in statistics and mathematics, and its main purpose is to determine a function by performing an optimal fit on a given set of data sets [25]. In practice, LS is commonly used in curve fitting, regression analysis, data fitting, and many other aspects, this is due to the fact that it can be realized using simple manual calculations as well as efficient calculations using modern computer technology, and has shown a wide applicability of application value in the field of engineering [26-29].

The diverse applications of LS in building energy management point the way to optimize the parameter adjustment and performance improvement of energy efficiency retrofit in building stock. Literature [30] developed a baseline assessment model based on convex nonparametric LS regression analysis for evaluating building energy performance influencing factors, which provides a reference for parameter adjustment of ESRB projects. Literature [31] used generalized LS to analyze three kinds of environmental regulatory measures for cross-regional energy consumption in China, with different strengths of regulatory measures in different regions and differences in the requirements for building energy efficiency retrofits, and this analysis points out the direction of optimizing the retrofit program for ESRBs. Literature [32] created a numerical model of central air-conditioning system based on DOE-2 (Department of Energy) model and regression method, determined the objective function and constraints of air-conditioning under the guidance of nonlinear programming, and introduced sequential LS to develop the optimal energy consumption point operating parameter program. Literature [33] developed a data-driven model based on adaptive learning for predicting the hourly energy consumption of a building, which contains various adaptive methods such as recursive LS, multiple linear regression, and Gaussian mixed model regression. Literature [34] administered dynamic thermal simulation with Latin hypercubic sampling methodology and used a weighted LS-based analysis to assess the impact of the building on CO2 emissions, air-conditioning cooling energy consumption, and lighting energy consumption under a passive design strategy. Literature [35] designed an energy prediction model based on LS support vector machine optimized by genetic algorithm for predicting the energy consumption of heating, ventilation and air conditioning in buildings with an accuracy of 97.2%. Literature [36] is the use of LS to optimize the efficiency strategy of energy management in buildings and combines predictive modeling, machine learning, and factorial design to predict the energy consumption patterns and the factors affecting the peak electricity demand, which reduces the peak electricity consumption while achieving energy management. Literature [37] used biased LS-structural equation modeling to analyze the relationship between the challenges faced in retrofitting residential buildings to net zero carbon, and this study is of practical value for the development of effective programs and improvements for ESRBs as well as the development of industry standards for ESRBs.

In this paper, appropriate buffer distances and buffer percentages are determined for the building complex zones of K-High School based on GIS data information such as building contours, urban information points, and area boundaries. On this basis, the building types of its building contours are identified and validated through major use identification and subtype clustering analysis, and its building cluster energy consumption benchmark model is initially established. Subsequently, the theoretical contents of multi-criteria decision optimization and the least squares method are explained in detail, and the prediction and optimization model of building cluster energy consumption is proposed by combining the characteristics of the current building cluster energy consumption data. Then, we sort out the environmental information, building room characteristic information and building energy performance of the building cluster of K University in order to complete the research preparation for the application analysis of the proposed prediction and optimization model. Finally, the regression coefficients of the fitting factors of the model are compared with those of similar models, and the similarity between the predicted values of the model and the actual energy consumption information of the K-college building cluster is verified.

2. Generation of energy consumption models for building clusters

The building cluster of K University is selected as the research object, and the spatial analysis of geographic information of the neighborhood where the building cluster is located, building use discrimination and cluster analysis are carried out in this chapter, so as to generate the energy consumption model of the building cluster.

2.1. Spatial analysis of GIS data

After collecting the building contours, POIs and area boundary contours, spatial analysis was performed with the help of GIS software QGIS, then the main attribute POIs were defined to determine the main uses of the buildings, and then unsupervised cluster analysis was utilized to determine the subtypes of each building use.

QGIS is a software developed in C++ based on the graphical user interface (GUI) development toolkit Qt and is available on multiple platforms Windows, Mac OS X, Linux and Unix. It supports multiple data formats such as database, raster and vector data, and is widely used to view, edit and analyze geospatial data. A raster data model divides the surface of the earth into individual cells and numerically represents the location and shape of features by numerizing the information within each cell. This data model is often similar to image data such as digital photographs. The raster data model is represented by a collection of regularly arranged grid-like pixels, and common raster data types include satellite imagery, aerial photographs, and digital elevation models (DEMs). Vector data models consist of points, lines, and surfaces (polygons); line data are represented by connecting multiple points, and polygon data are represented by creating surfaces by connecting three or more points with lines. These vector spatial data are usually managed by relational databases and some attribute information is stored in tables.

The raw POI data in csv format is imported through the QGIS "Add Separated Text Layer" function, and in the dialog box, you can choose to display the data in point coordinates, select longitude values for the X-axis and latitude values for the Y-axis, and then save it in the common Shapefile vector data format. Similarly, import the raw data of regional boundary points in csv format into QGIS, and use the function of "Scatter to Line" to get the outline of regional boundary.

The latitude and longitude of POI data and area boundary contours are currently in GCJ02 coordinate system (also known as Mars coordinate system), which is encrypted and shifted from WGS84 coordinate system, which is the coordinate system established for the use of the Global Positioning System (GPS), and the building contour data are in WGS84 coordinate system. Therefore, the first step is to convert the coordinate system with the help of QGIS plug-in tool and standardize it to WGS84 coordinate system. Assigning different attributes to the building contour is shown in Fig. 1. spatial connection between POIs and building contour is performed as shown in Fig. 1(a). For POIs inside the building contour, the attributes of POIs can be directly assigned to the building contour after point-plane intersection by using the "Connect Attributes by Position" function in QGIS. However, for POIs outside the building contour, it is necessary to consider the buffer analysis of spatial location offset. The shortest distance from the POI to the boundary of the neighboring building contour is used as the buffer distance. To determine the buffer distance, a neighborhood is selected to check whether the external POI belongs to the building contour before assigning the POI attribute to the building contour.

Figure 1(b) shows the spatial connection between the region boundary and the building contour. For building contours that are within the area boundary, the type of the area boundary is directly assigned to the building contour after the face-plane intersection through QGIS. Similarly due to offsets, the building contours located on the boundary are also analyzed for buffering. The same neighborhood was selected and the percentage of building contour area within the boundary to the total contour area was calculated to determine the percentage of building contours when they actually fall within the area boundary.

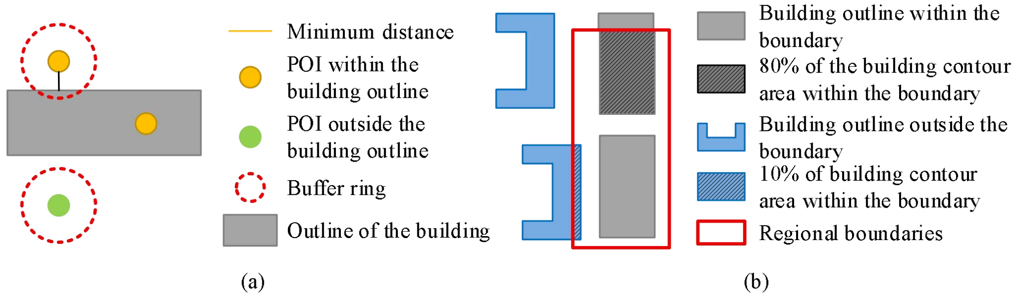


Figure 1. Assign different attributes to the building outline.

After passing through the point-plane intersection, 175,580 out of 296,351 POIs (57.56%) fall within the building contours. As the buffer distance increases, more POIs are assigned to nearby building contours. Table 1 shows the variation of accuracy with buffer distance. Accuracy is defined as the number of POIs that actually belong to the neighboring building contours divided by the number of external POIs corresponding to a given buffer distance. There are 946 POIs outside the building contours of the selected neighborhoods.The accuracy decreases dramatically when the buffer distance exceeds 4 m. The accuracy of the POIs is determined by the number of POIs outside the building contours of the selected neighborhoods. Therefore, in this study, the buffer distance was set at 4 m. Then, 210,231 out of 296,351 POIs (70.94%) were assigned to the building contours. Among the 70004 building contours, 21288 (30.41%) had one or more POIs.However, about 55000 (25%) POIs were still more than 10 m away from neighboring building contours. Most of these POIs are located in the fringe areas of the university building complex neighborhoods, which are mainly rural suburbs, and therefore no building outline data are available for the time being in their areas.

Table 1. The accuracy varies with the buffer distance.

Buffer distance	The number of POIs corresponding to the buffer distance	The number of POIs belonging to the outline of adjacent buildings	Accuracy
1m	234	212	90.9
2m	394	359	91.5
3m	481	439	91.7
4m	548	490	89.9
5m	600	504	84.4
6m	639	518	81.4

After the face-to-face intersection, there are 41,126 building contours within the region boundary and another 5007 building contours intersecting the region boundary line. Therefore the ratio of the area of building contours within the region boundary to the total building contour area is defined as the buffer percentage. Table 2 shows the variation of accuracy with buffer percentage. Accuracy is defined as the number of building contours that actually belong to the area boundary divided by the number of intersecting building contours at the corresponding buffer percentage. In the selected neighborhoods, there are 681 building contours intersecting the area boundary. When the buffer percentage is below 70%, the accuracy is below 90%. Therefore, the buffer percentage was set at 70% in this study. Then, 3112 out of 5007 building contours were considered to be within the regional boundary. Within the regional boundary then there are a total of 43831 building contours.

Table 2. The accuracy varies with the buffer percentage.

Buffer percentage	The number of building contours corresponding to the buffer percentage	The number of building Outlines within the regional boundary	Accuracy
90%	292	274	94.3
80%	329	302	92.2
70%	352	319	91
60%	371	327	88.5

2.2. Building primary use discrimination and subtype clustering

Due to the fact that the raw POI data are categorized more and contain multiple levels of subcategories under each major category, certain types are not categorized comprehensively enough, e.g., insurance and securities companies are located in financial and insurance services, and firms are located in life services, which should also belong to corporate enterprises. The main building types discriminated in this paper are residential, office buildings, shopping malls, hotels, schools, hospitals, cultural and art galleries and comprehensive buildings, so the original data need to be selected and reclassified. For example, business office buildings and residential areas are picked out from business buildings, government and institutions above the township level, industrial and commercial tax institutions and public prosecutors and law enforcement agencies are picked out from government institutions and social organizations, and department stores, shopping centers and hypermarkets are picked out from shopping services. The POI data is finally regrouped into 12 categories: commercial office buildings, government agencies, residential buildings, shopping malls, hotels, schools, hospitals, culture and art museums, companies and enterprises, catering services, retail shopping, entertainment and leisure.

POI data only show point information, but not area or volume information. When the building outline contains any POI attribute of business office, governmental organization, shopping mall, residence, hotel, school, hospital, culture and art museum, the main use of the building can be directly identified, so these eight attributes are defined as the main attributes.

After obtaining the number of POIs and boundary attributes contained in the outline of each building, the first distinction is made based on the presence or absence of a main attribute. When there is one main attribute, the main use of the building can be determined directly. When there are multiple main attributes, the building is determined to be a mixed type. When there is only one area boundary attribute and no POI main attribute, the building type is determined based on the corresponding boundary attribute.

In addition to the main attributes, commercial buildings usually have many other commercial POIs.Therefore, subtype clustering analysis is used to further categorize building uses. Building subtypes are buildings with other mixed uses. Clustering is a process of grouping similar data in a dataset into the same class or cluster, which is unsupervised learning and does not require any prior given criteria and automatically classifies the data based on the sample data. K-means clustering is one of the most widely used clustering algorithms, with applications in air conditioning energy use pattern recognition, typical building classification, and so on. K-means clustering first arbitrarily selects K objects from the data set as the center of mass of the initial cluster; then calculates the distance between each object and the center of mass of each cluster and divides the object into clusters closest to it; recalculates the average of each cluster and updates the center of mass of each new cluster; and repeats the first two steps until the objects in the clusters no longer change. Figure 2 shows the iterative process of clustering into two clusters. It is characterized by simplicity and efficiency, but at the same time sensitive to initial values and isolated point data. In this paper, K-means algorithm is used to deal with numerical attribute data.

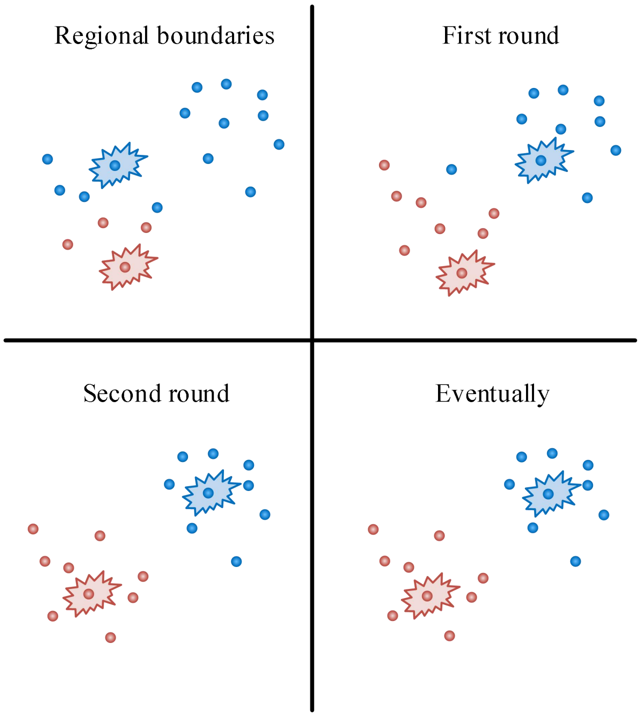


Figure 2. An example of the iterative process of the K-means algorithm.

When there is only one main attribute POI within the building profile, the number of food and beverage services, companies and businesses, retail shopping, entertainment and leisure, and that main attribute are used as inputs for clustering. For building profiles that do not contain any primary attribute, the number of POIs in the other four categories is used as the input for clustering.The K-means algorithm is a division-based clustering algorithm that uses distance as a measure of similarity between data objects, with the smaller the distance, the more likely they are to be in the same type of cluster. The commonly used distance is the Euclidean distance, which is calculated as in equation (1). The number of clusters K needs to be preset, and the optimal value is determined by the Davidson Boulding Index (DBI), which is expressed as the sum of the average intra-class distances of any two classes divided by the distance between the centers of the two clusters to find the maximum value, and is calculated as in Equation (2).

$$d(x,y)=\left(\sum_{i=1}^{n}(x_i-y_i)^2\right)^{\frac{1}{2}} \tag{1}$$

$$DBI=\frac{1}{k}\sum_{i=1}^{k}\max_{i\neq j}\frac{s_i+s_j}{d_{ij}} \tag{2}$$

Where $x=(x_1,x_2,\ldots,x_n), y=(y_1,y_2,\ldots,y_n)$ represents two columns of n -dimensional vectors; s_i represents the average distance from the data within a class to the class center, and d_{ij} represents the distance between two class centers.The smaller DBI means the smaller the distance within a class, and at the same time, the larger the distance between classes, the better the clustering effect.

3. Model for predicting and optimizing the energy consumption of a building complex

This chapter mainly explains the operation steps and principles of multi-criteria decision optimization and the least squares method, in which the multi-criteria decision optimization theory is able to carry out the prediction calculation of energy consumption of the building group, and the least squares method is able to establish the weight coefficients of energy consumption according to the comprehensive energy consumption, and to establish the functional relationship between total energy consumption of the building and the outdoor climate. Under the data framework of the model established in Chapter 2, the prediction and optimization model of building group energy consumption is constructed by combining the two.

3.1. Multi-criteria decision optimization theory

The research literature on decision-making in building energy efficiency retrofit is divided into multi-attribute decision-making and multi-objective optimization, and the optimization theory of regional large-scale retrofit decision-making is especially important for pre-feasibility analysis.

(1) Multi-attribute decision-making

The essence of the multi-attribute decision-making problem is to establish the mathematical relationship between the decision-making target and attributes, eliminate the differences between the attributes in terms of magnitude as well as type through dimensionlessness, and process them into dimensionless uniform indicators. Attribute weights are calculated by expert judgment, judgment matrix, projection method, gray correlation method, etc. Finally, through the decision-making model, the multi-attribute is evaluated comprehensively. Let's set the set of alternative energy-saving retrofit strategies in a multi-attribute decision-making problem as $G=\{g_1,g_2,\ldots,g_n\}$, and the set of evaluating attributes as $U=\{u_1,u_2,\ldots,u_n\}$, and let $A=\{a_1,a_2,\ldots,a_n\}\left(a_i\geq 0,\sum a_i=1\right)$. x_{ij} denotes the value of the decision indicator for the jth attribute of the ith energy efficiency retrofit strategy, whose value can be either a deterministic or an indeterminate fuzzy number.

The high level of uncertainty and ambiguity in regional energy efficiency retrofits requires the use of fuzzy integrated assessment methods. Fuzzy decision making is also a method of doing quantitative probability analysis of non-quantitative events. This method constructs an affiliation function that conforms to each attribute by establishing a hierarchical evaluation (AHP) structural diagram, and for the element X in the set, the value of $\mu(X)$ is called the affiliation function of X corresponding to the fuzzy set, which involves Gaussian-type, generalized bell-type, S-shape, trapezoidal and other affiliation functions, and the following figure shows the trigonometric affiliation function with partially overlapping regions, which allows for fuzzy judgments of different energy-saving retrofitting strategies.

Considering the uncertainty of subjective judgment, combining empirical judgment and quantitative calculation, in the study of regional retrofit decision-making and willingness to scientifically deal with uncertainty in the decision-making factors, and express subjective or objective descriptions with fuzzy numbers on the domain of real numbers, and the key to this is the construction of the affiliation function, and the establishment of fuzzy relationship from X to U as in equation (3):

$$R=\begin{bmatrix} r_{11} & r_{12} & \cdots & r_{1n} \\ r_{21} & r_{22} & \cdots & r_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ r_{n1} & r_{n2} & \cdots & r_{nn} \end{bmatrix} \tag{3}$$

where r_{ij} denotes the degree of affiliation of the jth evaluation attribute corresponding to the evaluation value of the ith energy saving strategy.

Applying the composite operation of the matrix, the fuzzy comprehensive decision-making model Eq. (4) can be obtained:

$$B=A\times R \tag{4}$$

(2) Multi-objective optimization

Multi-objective optimization problem is in a very important position in the study of building energy efficiency renovation, the actual problem of regional energy efficiency renovation is usually very complex. There are many decision-making factors for regional energy-saving retrofit, and the attributes of some factors conflict with each other, and multi-objective optimization is the problem of getting the best optimization for multiple objectives under the given conditions.

This paper proposes that the multi-objective optimization model of large-scale building group energy-saving retrofit can consider the optimization strategy of time, technology, building three-dimensional, regional large-scale retrofit conventional multi-objective optimization model to consider the decision variables for the optimal control value of the multi-dimensional indexes of energy, economy, etc., as in equation (5):

$$\min -\omega_1 \frac{AES}{AES_{go}} - \omega_2 \frac{NPV}{NPV_{go}} + \ldots + \omega_3 \frac{PP}{PP_{g0}}$$
$$s.t. \begin{cases} \sum x_{i,j}(0) \le q_i, i = 1,2,\ldots,I \\ AES \ge AES_{go}, AES = \sum\sum\sum a_{i,j} x_{i,j}(t) \\ \ldots\ldots \\ \sum\sum\sum b_{i,j} x_{i,j}(t) \le IN(t) \\ PP \le PP_{go} \end{cases} \tag{5}$$

where i represents the number of categories of energy-saving measures; j represents alternative energy-saving measures; t represents the year; $x_{i,j}$ denotes the input scale of the ith measure; $a_{i,j}$ is the energy saving generated by the unit investment of the ith measure; $b_{i,j}$ is the unit investment of the ith measure; $\omega_1 + \omega_2 + \omega_3 = 1$; $IN(t)$ is the upper limit of the retrofit investment index; PP is the payback period.

3.2. Introduction to the Principle of Least Squares

In the study of statistical methods in scientific experiments, it is often necessary to find the functional relationship between the independent variable and the dependent variable $y = F(x)$ from a set of experimental data $(x_i, y_i)(i = 0,1,\cdots,m)$. In the context of this paper, the independent variable is set as outdoor climate change, and the dependent variable is set as energy consumption of the building stock. It is not required that $y = F(x)$ passes through all points (x_i, y_i) but only that the error $\delta_i = F(x_i) - y_i (i = 0,1,\cdots,m)$ is minimized according to some criterion at a given point x_i, and Euclid's paradigm $\|\delta\|_2$ is usually used as the error measure. A general formulation of the least squares method is that for a given set $(x_i, y_i)(i = 0,1,\cdots,m)$ of data, it is required to find a function $y = S^*(x)$ in the function space $\phi = span\{\varphi_0, \varphi_1, \ldots, \varphi_n\}$ such that the sum of squared errors is as in equation (6):

$$\|\delta\|_2^2 = \sum_{i=0}^{m} \delta_i^2 = \sum_{i=0}^{m} \left[S^*(x_i) - y_i\right]^2 = \min_{S(x)\in\varphi} \sum_{i=1}^{m} \left[S(x_i) - y_i\right]^2 \tag{6}$$

Here is equation (7):

$$S(x) = a_0\varphi_0(x) + a_1\varphi_1(x) + \ldots + a_n\varphi_n(x) \quad (n < m) \tag{7}$$

This is the general least squares approximation in the case of considering the characteristics of the energy consumption data of a building group, and when using it to find the fitting curve, the first thing to do is to determine the form of $S(x)$. Usually, the form of $S(x_i)$ is determined from the law of motion of the problem as well as from the given data tracing and the better result is selected by calculating the general expression of $S(x)$ is the linear form of Eq. (7), and if $\varphi_k(x)$ is a kth degree polynomial, $S(x)$ is an nth degree polynomial, and in order to make the problem is more general, it is usual to consider all $\|\delta\|_2^2$ in the least squares method as a weighted sum of squares as in Eq. (8):

$$\|\delta\|_2^2 = \sum_{i=0}^{m} \omega(x_i)\left[S(x_i) - y_i\right]^2 \tag{8}$$

Here $\omega(x)$开0 is a weight function on $[a,b]$ which represents the different weights of the data at different points (x_i, y_i). The problem of finding the fitted curve by least squares is to find a function $y = S^*(x_i)$ in $S(x)$ that minimizes the value of equation (9), which translates into finding the multivariate function:

$$I\left(a_0,a_1,\ldots a_n\right)=\sum_{i=0}^{m}\omega\left(x_i\right)\left[\sum_{j=0}^{n}a_j\varphi_j\left(x_i\right)-y_i\right]^2 \tag{9}$$

of the extremum $\left(a_0^*,a_1^*,\ldots a_n^*\right)$ problem. From the necessary conditions for finding the extremum of a multivariate function, we have equation (10):

$$\frac{\partial I}{\partial a_k}=2\sum_{i=0}^{m}\omega\left(x_i\right)\left[\sum_{j=0}^{n}a_j\varphi_j\left(x_i\right)-y_i\right]\varphi_k\left(x_i\right)=0 \quad (k=0,1,\cdots,n) \tag{10}$$

If equation (11) is noted:

$$\left(\varphi_j,\varphi_k\right)=\sum_{i=0}^{m}\omega\left(x_i\right)\varphi_j\left(x_i\right)\varphi_k\left(x_i\right) \tag{11}$$

Then we have equation (12):

$$\left(y,\varphi_k\right)=\sum_{i=0}^{m}\omega\left(x_i\right)y_i\varphi_k\left(x_i\right)\equiv d_k \quad (k=0,1,\cdots,n) \tag{12}$$

Then equation (13):

$$\left(y,\varphi_k\right)=\sum_{i=0}^{m}\omega\left(x_i\right)y_i\varphi_k\left(x_i\right)\equiv d_k \quad (k=0,1,\cdots,n) \tag{13}$$

can be rewritten as equation (14):

$$\sum_{j=0}^{n}\left(\varphi_k,\varphi_j\right)a_j=d_k \quad (k=0,1,\cdots,n) \tag{14}$$

This equation is called the normal equation and it can be written in matrix form as in equation (15):

$$Ga=d \tag{15}$$

which has the formula (16):

$$a=\left(a_0,a_1,\ldots,a_n\right)^T,d=\left(d_0,d_1,\ldots,d_n\right)^T$$
$$G=\begin{bmatrix}\left(\varphi_0,\varphi_0\right)\left(\varphi_0,\varphi_1\right)\ldots\left(\varphi_0,\varphi_n\right)\\ \left(\varphi_1,\varphi_0\right)\left(\varphi_1,\varphi_1\right)\ldots\left(\varphi_1,\varphi_n\right)\\ \\ \left(\varphi_n,\varphi_0\right)\left(\varphi_n,\varphi_1\right)\ldots\left(\varphi_n,\varphi_n\right)\end{bmatrix} \tag{16}$$

Since $\varphi_0,\varphi_1,\ldots\varphi_n$ are linearly independent, $|G|\neq 0$, there exists a unique solution to the system of equations as in Equation (17):

$$a_k=a_k^* \quad (k=0,1,\cdots,n) \tag{17}$$

The least squares solution of the function y is thus obtained as equation (18):

$$S^*(x)=a_0^*\varphi_0(x)+a_1^*\varphi_1(x)+\ldots+a_n^*\varphi_n(x) \tag{18}$$

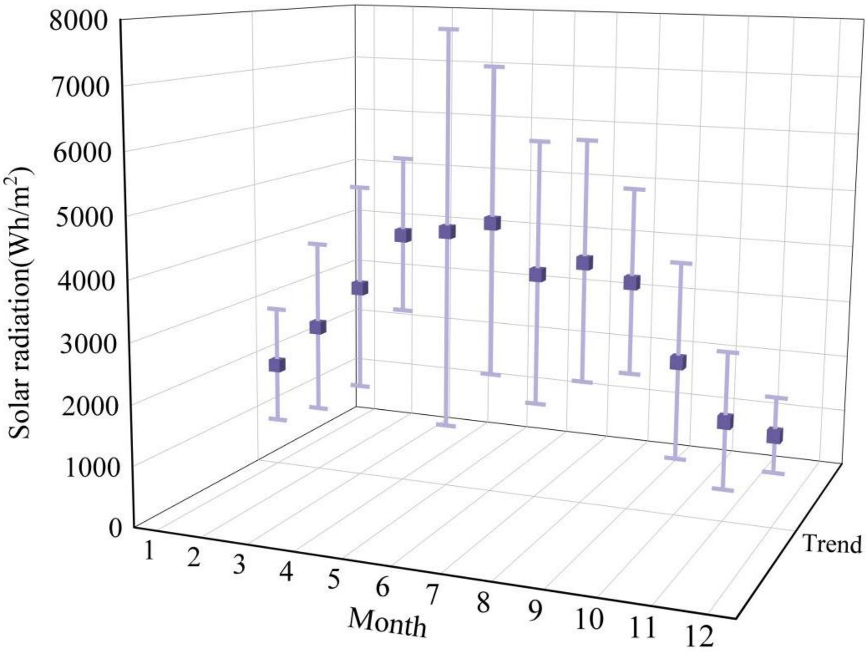
4. Testing and Application of Energy Consumption Prediction and Optimization Models

Based on the geographic location information of the building complex of University K summarized above, this chapter further combs its building information and energy performance. Its building clusters are mainly (TB) Teaching Building, (AB) Administration Building, (LB) Library, (DB) Dormitory Building, and so on. According to statistics, the campus of University K contains 6 academic buildings (TB1-6), 15 administrative buildings (AB1-15), three libraries (LB1-3), and 45 dormitory buildings (DB1-45), which are categorized to carry out the following research and analysis.

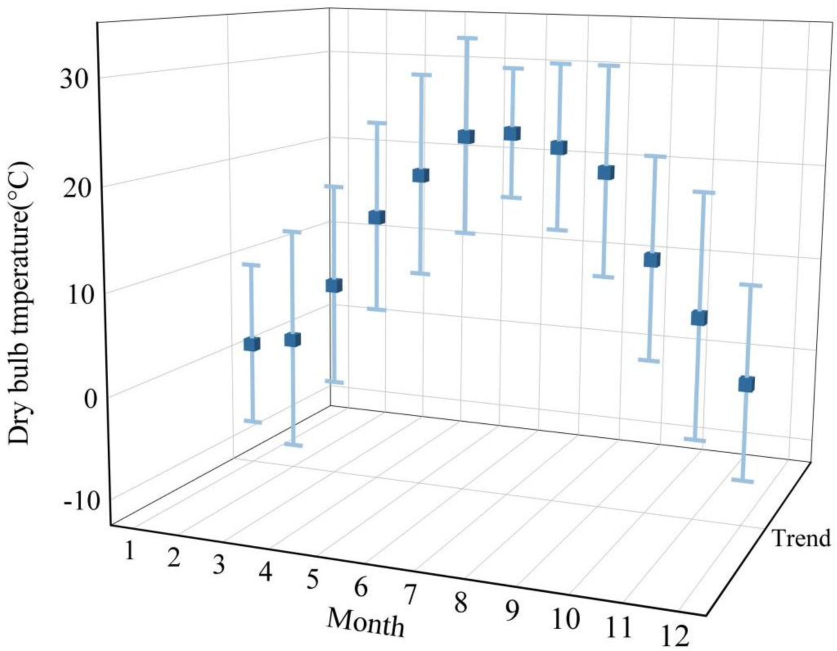
4.1. Sample parameter collection and processing

4.1.1. Environmental information

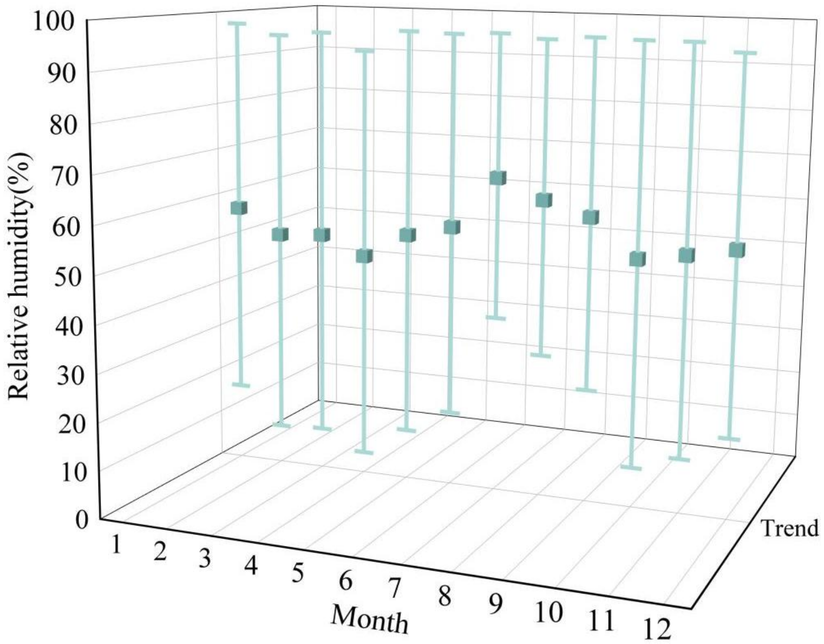
Figures 3(a)-(c) show the variation intervals and trends of total solar radiation, average daily dry bulb temperature and average daily relative humidity in the area where the K-University complex is located, in that order.



(a) Total solar radiation



(b) Average daily dry bulb temperature



(c) Average daily relative humidity

Figure 3. Solar radiation, dry bulb temperature and relative humidity.

It can be seen that the total daily terrestrial radiation in the area where College K is located is concentrated in the months of April-September, with a difference of about 5,500 Wh/m², while the solar irradiation in winter is relatively small (about 1,800 Wh/m²). The average dry bulb temperature in the summer months is >28°C, while the average dry bulb temperature in the winter months is <-3°C. The region also has a high relative humidity throughout the year, and the climate is humid, with relative humidity averaging 50% and above in the summer months.

4.1.2. Building room characterization information

Statistical collation of the following characteristic information of the study building rooms: (R1) room area (m²), (R2) area of single facade facade (m²), (R3) area of single window (m²), (R4) number of windows, (R5) peak occupant density (m²/person), (R6) lamp power (W), and (R7) total number of lamps in a single room and the power density of the lamps (W/m²) are listed in the part of the The measured data for the building rooms are shown in Table 3.

Table 3. The measurement parameters of room(part).

Room	TB1-203	AB3-609	LB1-405	DB32-612
R1	80.16	201.66	200.56	16.5
R2	43.91	94.11	61.11	5.4
R3	6.4	3.6	2.2	2
R4	5	16	10	1
R5	1.9	6.7	2	4.3
R6	30	30	30	30
R7	20	100	66	3

Combining the data collected from the standard database and the actual measurements, a relatively complete parameter information of the university building complex of K was obtained, and some of the information is shown in Table 4, where the parameter variables are: (P1) building number, (P2) floor area, (P3) number of storeys of the building, (P4) storey height, (P5) U-value of heat transfer from the external wall (W/m²*K), (P6) U-value of floor heat transfer (W/m²*K), (P7) U-value of roof heat transfer (W/m²*K), (P8) U-value of window heat transfer (W/m²*K), (P9) U-value of window heat transfer (W/m²*K), and (P10) U-value of roof heat transfer (W/m²*K), and (P11) U-value of window heat transfer (W/m²*K).) Roof heat transfer U-value (W/m²*K), (P8) Window heat transfer U-value (W/m²*K), (P9) Solar heat gain coefficient, (P10) Window-to-wall ratio, (P11) Air infiltration rate, (P12) Personnel density (person/m²), (P13) Peak lighting power density (W/m²), (P14) Peak time equipment power density (W/m²), (P15) Indoor solar irradiance (lux), (P16) Fresh air volume per capita (m²/s*person). The peak power of the equipment in the teaching building (TB1-203) and the administration building (AB3-609) is higher, respectively 18, 15W/m²>10W/m², while the peak power of the equipment in the library (LB1-405) and the dormitory building (DB32-612) is lower than 10W/m², which is basically consistent with the actual situation of the school.

Table 4. Partial information about the buildings on campus K.

Number	Parameter variable information			
P1	TB1-203	AB3-609	LB1-405	DB32-612
P2	1312.65	1492.25	1546.05	346.95
P3	8	15	6	7
P4	3.8	3.8	3.1	3.1
P5	0.4	0.4	0.47	0.47
P6	0.58	0.58	0.58	0.58
P7	0.34	0.34	0.44	0.44
P8	2.75	2.75	2.75	2.75
P9	0.73	0.73	0.73	0.73
P10	0.25	0.25	0.26	0.26
P11	0.5	0.5	1.1	1.1
P12	7	4	5	2
P13	15	15	13	13
P14	18	15	9	3
P15	432	432	432	432
P16	0.01	0.01	0.01	0.01

The temporal data of building operation on a typical weekday are shown in Table 5, in which the operation peaks of office teaching buildings such as the teaching building, administration building and library are between 09:00 and 18:00, and the peaks of dormitory building personnel in the room are: 22:00 to 07:00 the next day, and 12:00 to 14:00, which are in line with the actual situation of the school.

Table 5. The typical data of workday.

Architectural	TB and AB,LB		DB	
Time	Workday	Holidays	Workday	Holidays
01:00	0	5	100	90
02:00	0	5	100	90
03:00	0	5	100	90
04:00	0	5	100	90
05:00	0	5	100	90
06:00	0	5	100	90
07:00	20	5	60	90
08:00	55	5	40	90
09:00	95	5	10	90
10:00	95	5	10	40
11:00	95	5	10	40
12:00	85	5	30	40
13:00	80	5	60	50
14:00	90	5	30	50
15:00	95	5	20	20
16:00	95	5	20	20
17:00	95	5	20	20
18:00	60	5	30	20
19:00	55	5	50	20
20:00	50	5	50	20
21:00	35	5	50	20
22:00	30	5	100	20
23:00	10	5	100	60
24:00	0	5	100	60

4.1.3. Existing energy-saving technologies and energy-saving performance

Currently, the energy-saving technologies used in K university building complexes are mainly divided into passive energy-saving technologies and active energy-saving technologies, of which passive energy-saving technologies include: optimization of thermal performance of the envelope structure and setting up of shading, and active energy-saving technologies include: improving the efficiency of the HVAC system and reducing the energy consumption of the equipments. The application ratio of different energy-saving technologies varies according to different building types, for example, library and teaching buildings focus on the use of active energy-saving technologies.

Therefore, in this subsection, the number and percentage of indoor unsatisfactory hours of the building under HVAC system for the whole year are counted from a total of four aspects: envelope, lighting, HVAC performance and equipment. The effects of climate change and individual building energy efficiency technologies on the annual indoor unsatisfactory hours during heating and cooling periods are summarized in Table 6.Overall, the percentage of indoor unsatisfactory hours is small (<5.00%) and fluctuates little in different building models in different years. The percentage of unsatisfactory hours during heating is between 0.006% and 0.195%, while the percentage of unsatisfactory hours during cooling is between 1.200% and 1.608%. That is, the indoor thermal comfort belongs to the same level, which is conducive to the following comparative analysis of energy consumption.

Table 6. The number and proportion of unsatisfactory hours indoors.

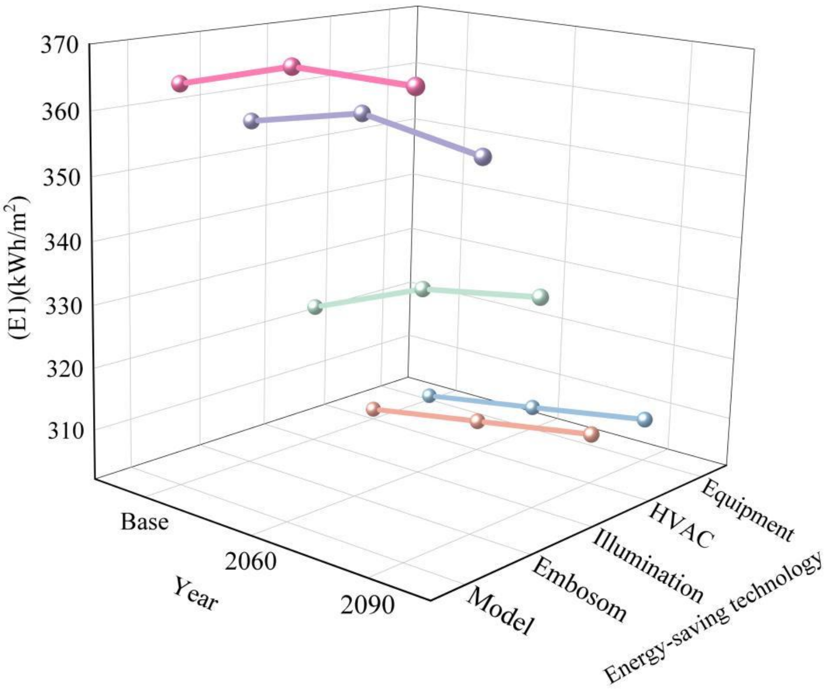
System operation period	Heating period			Refrigeration period		
Year	Base year	2060	2090	Base year	2060	2090
Embosom	35h	20h	18h	3296h	3371h	3392h
	0.022%	0.007%	0.006%	1.47%	1.504%	1.513%
Illumina tion	116h	49h	36h	2931h	3138h	3201h
	0.098%	0.035%	0.023%	1.304%	1.398%	1.427%
HVAC	185h	74h	60h	3486h	3577h	3600h
	0.195%	0.086%	0.07%	1.568%	1.598%	1.608%
Equipment	159h	68h	50h	2702h	2901h	2966h
	0.138%	0.053%	0.036%	1.200%	1.291%	1.32%

Based on the benchmark model of energy consumption of the K-University building complex generated in Chapter 2, the comparison of (E1) total primary energy consumption, (E2) electricity consumption and (E3) gas energy consumption under different building skill technology applications are shown in Fig. 4(a)-(c) in order. Compared with the base year, the energy saving performance of the K-University building complex under different building skill technology applications is shown in Table 7.

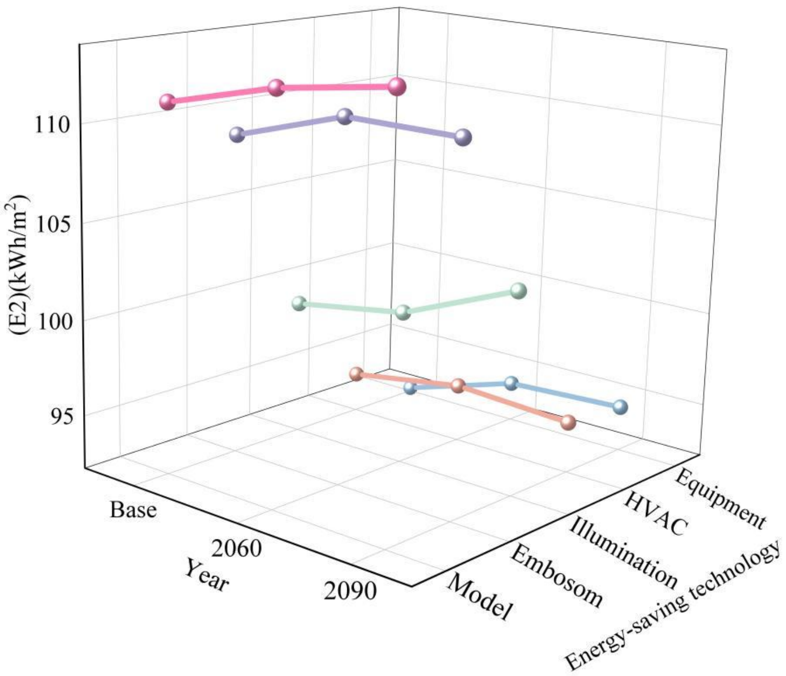
Based on Fig. 4, it can be calculated that for (E1) total primary energy consumption, compared with the baseline model, the energy saving rate of “Reduce equipment energy consumption” is the highest, and its energy saving rates in the baseline year, 2060 and 2090 are 18.221%, 17.99% and 17.08% in that order, which are all 17.00% and above. The second highest energy saving rate is the “Improve HVAC System Efficiency” technology, with energy saving rates of 16.25%, 17.04%, and 17.45% in the base year, 2060, and 2090, respectively, ranging from 16.00% to 17.50%. The energy saving rates for the “shading” and “envelope thermal performance optimization” technologies are relatively low, ranging from 5.00% to 15.00%.

For (E2) electricity consumption, the energy-saving rate of different technologies is the same as that of (E1) total primary energy consumption, and the energy-saving rate of “reducing equipment energy consumption” still remains at 17.00% and above, while the energy-saving rate of the technology of “improving the efficiency of the HVAC system” decreases to 15.14%~15.00%. The energy saving rate of the “improve HVAC system efficiency” technology is somewhat lower, ranging from 15.14% to 117.32%. The energy saving rate of “installing sunshade” technology and “optimizing thermal performance of envelope” technology is also in the range of 5.00% to 15.00%.

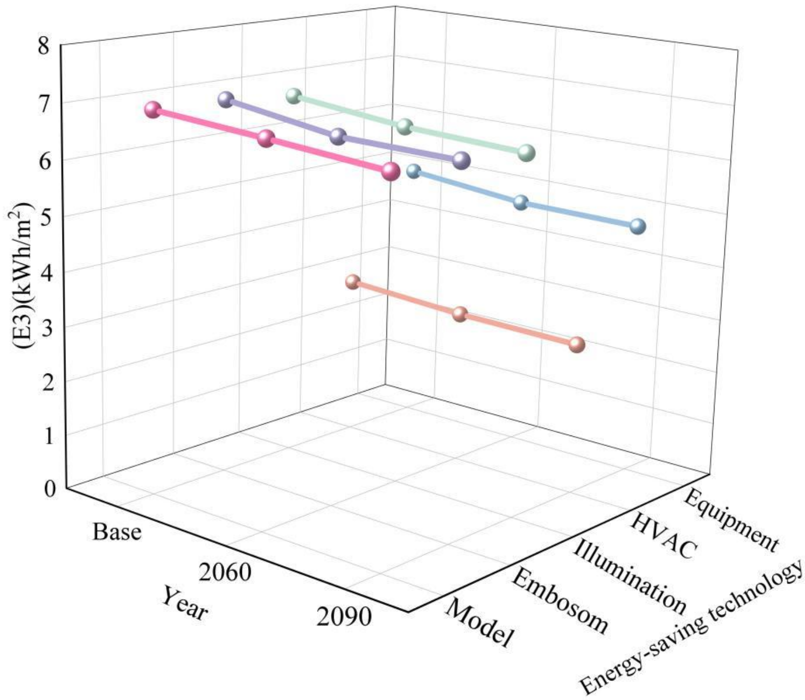
In terms of (E3) gas energy consumption, the performance of different energy-saving technologies, from high to low, is the same: reducing equipment energy consumption, improving the efficiency of the HVAC system, installing sun shading and optimizing the thermal performance of the enclosure. The difference is that only the first two technologies have a more significant and improved energy saving rate, ranging from 31.89% to 57.68%. The latter two techniques had little effect, both below 5.00%.



(a) (E1)Total primary energy consumption



(b) (E2) Electricity consumption



(c) (E3) Gas energy consumption

Figure 4. Energy-saving performance of the K University building complex.

In addition, it is known from Table 7 that climate change has less impact (<4.74%) on the building energy performance for the building models using the same building energy efficiency technology. The reason for this is that only the HVAC system operational energy consumption is more affected by climate change.

Table 7. Energy-saving performance compared with the base year.

Building energy-saving technology		E1		E2		E3	
		2060	2090	2060	2090	2060	2090
Embosom	Variation (kWh/m^2)	5.92	5.97	2.29	2.33	0.44	0.38
	Amplitude of variation	1.93%	1.9%	2.11%	2.15%	-1.14%	-2.07%
Illumination	Variation (kWh/m^2)	6.85	9.09	2.6	3.33	0.39	0.33
	Amplitude of variation	2.28%	2.9%	2.57%	3.29%	-1.87%	-2.8%
HVAC	Variation (kWh/m^2)	2.52	3.62	1.21	1.56	0.51	0.47
	Amplitude of variation	1.18%	11.48%	1.24%	1.6%	-1.13%	-2.57%
Equipment	Variation (kWh/m^2)	6.64	8.95	2.55	3.3	0.36	0.36
	Amplitude of variation	2.38%	3.07%	2.68%	3.49%	-3.54%	-4.74%

4.2. Comparative analysis and validation of models

4.2.1. Comparison of model fitting factors

Although the fitting effect of the model can be determined based on the statistical values, considering the relevant knowledge in the field of construction and the influencing factors of heat consumption indexes, it is necessary to compare the independent variables introduced by each of the (M1) stepwise regression model, (M2) principal component regression model, and (M3) least-squares-based model for prediction and optimization of energy consumption of building clusters.

Combining the above analysis with the existing studies, the heat consumption influencing factors selected in this paper are (F1) heat transfer coefficient of external walls, (F2) heat transfer coefficient of external windows, (F3) window-to-wall ratio, (F4) body shape coefficient, (F5) occupant density, and average indoor temperature. A comparison of the performance of the three model fitting factors is shown in Table 8.It can be seen that the (M2) principal component regression model and the (M3) least squares based model for predicting and optimizing the energy consumption of the building stock introduce all the influencing factors of heat consumption into the model and determine the linear relationship. And the regression coefficients of (M3) Least Squares-based model regression for prediction and optimization of energy consumption of building complexes on all fitted factors are better than (M2) Principal Component Regression Model, which indicates that the model in this paper is more capable of interpreting the data. The regression coefficient of the factor "(F1) heat transfer coefficient of external wall" in the (M1) stepwise regression model is 0, which is not introduced into it. Therefore, the (M3) least-squares-based model for predicting and optimizing energy consumption of building clusters is selected as the optimal model for further application analysis.

Table 8. Model fitting factors.

Influence factor	Partial regression coefficent		
	M1	M2	M3
F1	0	0.81	0.92
F2	2.59	3.15	3.55
F3	7.95	3.8	4.84
F4	19.24	24.69	25.36
F5	-31.075	-28.91	-27.36
Constant term	0.61	0.44	0.45

4.2.2. Model prediction accuracy

The fitting performance of the predicted and actual values of the prediction and optimization model based on the least squares method is shown in Fig. 5, and the slope of the fitted straight line between the predicted and actual observed values is 0.996>0.990, which tends to be close to 1, indicating that the predicted values are almost overlapped with the actual observed values and the degree of restoration is high.

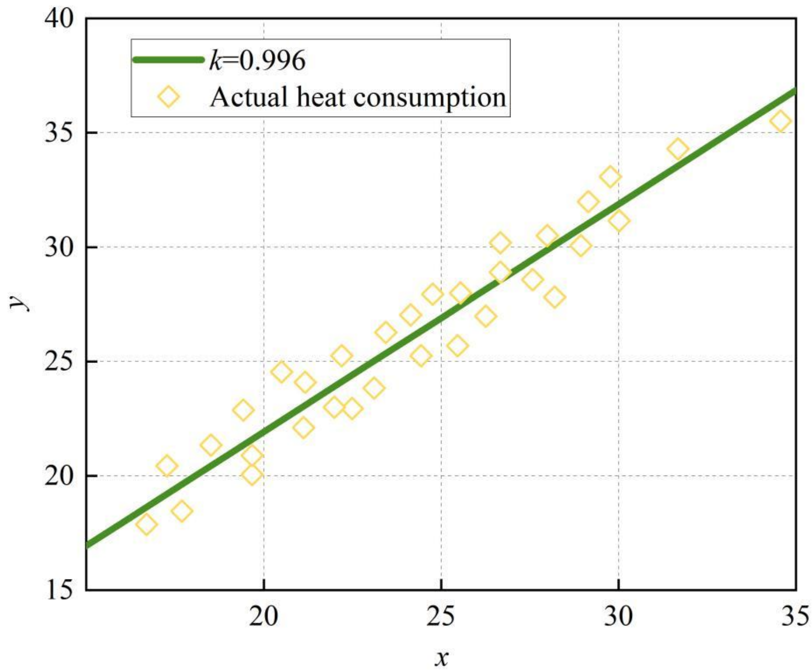


Figure 5. Model prediction and the actual value of linear fitting.

4.2.3. Validation of actual data information

Based on the building information of University K sorted out above, 5 buildings each of teaching building (TB1-5), administrative building (AB3-7), library (LB1-5) and dormitory building (DB32-36), and a total of 20 buildings were extracted, and the proposed least squares model was used to predict the heat consumption and list the error of the heat consumption with that of actual heat consumption of the baseline model as shown in Table 9.The model prediction of this paper's heat consumption error is in the range of 0.15 to 41.24kW, and the error rate is in the range of [0.01,2.47] (<3.00%). On the whole, the model in this paper can calculate and predict the heat consumption of K university buildings more accurately, and provide more real data reference for the adjustment of energy-saving parameters and the improvement of its efficiency.

Table 9. Calculation results and error validation sample.

Serial number	Predicted heat consumption(kW)	Actual heat consumption(kW)	Error(kW)	Error rate(%)
TB1	2218.18	2223.20	-5.02	-0.23
TB2	1560.15	1559.57	0.58	0.04
TB3	1448.60	1444.61	3.99	0.28
TB4	1120.21	1124.57	-4.36	-0.39
TB5	1025.85	1021.32	4.53	0.44
AB3	2039.33	2020.38	18.95	0.94
AB4	1427.16	1399.01	28.15	2.01
AB5	898.58	889.51	9.07	1.02
AB6	1554.82	1565.51	-10.69	-0.68
AB7	2101.50	2104.01	-2.51	-0.12
LB1	1075.97	1076.12	-0.15	-0.01
LB2	2037.50	1996.26	41.24	2.07
LB3	1806.29	1819.78	-13.49	-0.74
LB4	1626.32	1619.12	7.20	0.44
LB5	2104.99	2113.16	-8.17	-0.39
DB32	1163.03	1163.69	-0.66	-0.06
DB33	855.40	881.81	-26.41	-2.99
DB34	1387.10	1389.66	-2.56	-0.18
DB35	995.51	982.92	12.59	1.28
DB36	935.20	912.66	22.54	2.47

5. Conclusion

This paper takes the K university building cluster as the research sample and establishes a benchmark model for energy consumption of the corresponding building cluster. Combined with the multi-criteria decision optimization theory and the least squares method, a building group energy consumption prediction and optimization model with a wide range of applications, excellent fitting effect and reliable prediction accuracy is proposed. The regression coefficients of the proposed model on the five important building heat consumption influencing factors are the best among similar models, and the slope of the straight line between the predicted and observed values is as high as 0.996, and the errors between the output predicted values and the sample benchmark model data are in the range of [0.01,2.47] in the verification of the actual application.

By accurately predicting the energy consumption performance of different types of buildings under different energy-saving technologies, the least-squares-based energy consumption prediction and optimization model of building clusters is able to provide abundant data references for the adjustment and optimization of energy-saving technologies, which can assist in the improvement of the energy utilization rate of buildings and the sustainable development of the urbanization process.

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