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Research paper

The application of predictive stochastic model based on Monte Carlo method in building energy saving renovation

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Abstract: This research has established an energy consumption prediction model based on the Monte Carlo method to resolve the energy-saving transformation problem. First, simplify the building to construct the proposed model. Second, through the principle of building energy balance and Monte Carlo method, the cooling and heat demand model of regional buildings and the energy consumption prediction model of regional buildings are built. Finally, the energy consumption simulation and energy consumption prediction of the regional building complex after energy-saving renovation are carried out. The experiment shows that the building energy consumption in July and August was relatively high, reaching 2.36E+14 and 2.4E+14, respectively. The energy consumption in April and November was relatively low, reaching 1.2E+14 and 1.4E+14, respectively. The highest prediction error was in November, reaching 12%. The lowest prediction error was in January and February, only about 2%. The error of monthly energy consumption predicted by Monte Carlo method is less than 12%, the Root-mean-square deviation is 5%, and the error between predicted and actual annual total energy consumption is only about 2%. By comparing the predicted energy consumption after energy-saving renovation with before, the energy-saving rate reached about 20%. The research results indicate that the proposed Monte Carlo based predictive stochastic model exhibits good predictive performance in building energy-saving renovation, providing theoretical guidance and reference for feasibility studies, planning, prediction, decision-making, and optimization of building energy-saving renovation.

Keywords: energy-saving, Monte Carlo, demand, regional architectural complex, data mining

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1. Introduction

According to the report of the International Energy Agency, global building energy consumption (BEC) has reached one third of the gross energy consumption. Meanwhile, with the sustained and rapid development of the economy and the increasing population, BEC will reach 2–3 times the current total in the coming years. Thus, building energy conservation (B-ECo) has become an important link in energy conservation and emission reduction for countries around the world [1]. Building energy-saving renovation refers to the use of advanced technology, efficient equipment, and management control methods to implement energy-saving renovation and upgrading activities on energy consuming systems or equipment such as enclosure structures, HVAC systems, lighting equipment, hot water supply facilities, and power facilities, in order to improve building energy efficiency and reduce building energy consumption. The existing B-ECo mainly involves transforming individual buildings into large-scale regional building clusters. Due to the complex and diverse functions of regional building clusters, the process of promoting energy-saving renovation (ESR) is particularly complex, with many uncertain factors [2–4]. Traditional energy-saving renovation methods tend to use deterministic models, ignoring many uncertain factors, which may lead to inaccurate predictions of actual performance. Moreover, traditional methods only evaluate building performance based on specific scenarios or assumptions, and cannot provide comprehensive and diverse performance evaluations. Building systems are typically composed of multiple interrelated components, and traditional methods may not fully consider the complex relationships between these components. Therefore, this study proposes a BEC prediction model grounded on Monte Carlo (MC) method. After predicting the energy consumption status of regional building clusters through this model, the accuracy of the prediction is determined by comparing it with actual energy consumption. Then, predict the energy consumption of the improved regional building clusters. The research aims to provide theoretical guidance for the planning, prediction, decision-making, and optimization of building energy-saving renovation by simulating energy consumption and predicting energy consumption after energy-saving renovation through regional building clusters.

2. Related works

Energy Saving Reconstruction of Building (ESRB) refers to the upgrading and management of various power consuming equipment using advanced technology, low energy consumption equipment, and efficient control and management methods to complete the goal of deducting energy efficiency and lifting energy utilization efficiency. Martirano et al.'s research focuses on energy-saving renovation of lighting, which is similar to the energy-saving renovation in this study. The research team has proposed a control circuit algorithm for library lighting equipment, which can adjust the lights according to the situation of library personnel to achieve the effect of saving electricity. The improved lighting fixtures through this method have improved in terms of energy conservation and performance [5]. Lee's research focuses on energy-saving renovation of ventilation systems, which is similar to the energy-saving renovation in this study. The research team used artificial intelligence to construct a building energy-saving renovation model for buildings, which includes equipment control, facility control, and overall building energy-saving, and improves the air conditioning, motors, and socket plugs in the office building through artificial intelligence. This method saves nearly one-third of the energy consumption in terms of facilities and the entire building. This indicates that the method has good energy-saving ability [6].

Morelli et al.'s research focuses on energy-saving renovation, which is similar to the energy-saving renovation in this study. The research team has proposed a design method for building energy-saving renovation measures, which evaluates the durability of potential failures, building maintenance, and energy-saving improvements through analysis. This method combines the impact analysis of fault modes to determine possible faults, and can conduct a comprehensive risk assessment of buildings, such as maintenance plans, durability assessments, etc. [7]. Amani et al.'s research focuses on energy-saving renovation, which is similar to the energy-saving renovation in this study. The research team has designed an optimal personal system based on multi-objective methods to reduce energy waste. This system can save energy and reduce the impact of environmental factors, and there are several options that can greatly reduce BEC. However, due to environmental factors, its performance exhibits instability. The team optimized it and obtained an optimal solution that can reduce energy demand to 30% with good stability [8].

In summary, many scholars have already conducted research in the LS-ESR and achieved significant results. However, they only studied this field separately during their research. Building energy consumption is influenced by various factors, including climate conditions, building structure, equipment efficiency, etc. The model needs to consider these complex interrelationships, which increases the complexity of the modeling process and requires more data to train an accurate model. And some building energy consumption prediction models may perform well under specific conditions, but their generalization ability is limited under other conditions. MC is also used as a high-performance simulation statistical method. Combining LS-ESR with MC can effectively predict energy consumption. By predicting energy consumption of improved regional building clusters, the efficiency and performance of the improvement can be evaluated.

3. Application of predictive stochastic models in ESRB

This chapter simplifies the building and constructs a physical model. Through the principles of building energy balance and Monte Carlo method, a cooling demand model, a heat demand model, and a energy consumption prediction model for regional building clusters are constructed.

3.1. Analysis and research of MC

MC, also known as statistical simulation method and statistical experimental method, is a numerical simulation method that takes rate phenomena as the research object. By increasing the number of samples, the Monte Carlo method can achieve any high accuracy. Calculation accuracy can be controlled as needed to adapt to different problems and application scenarios [9, 10]. For large-scale computing problems, the independent sampling in Monte Carlo methods makes them very suitable for parallel computing, which can effectively utilize computing resources and accelerate the calculation process. Building systems are usually complex and involve multiple interrelated variables. The Monte Carlo method can flexibly adapt to complex systems by simulating the system multiple times, considering various possible combinations and interactions, thereby more comprehensively describing system behavior [11]. And the flexibility of Monte Carlo method enables it to adapt to various models and scenarios. This method does not rely on specific assumptions about system behavior and is therefore applicable to various types of buildings and energy consuming systems. MC is mainly aimed at certain mathematical problems. First, it establishes a Statistical model or Stochastic process, solves the process or model to obtain the probability distribution or mathematical expectation, and then uses the arithmetic mean as the near estimate of the solution. Figure 1 shows the specific process.

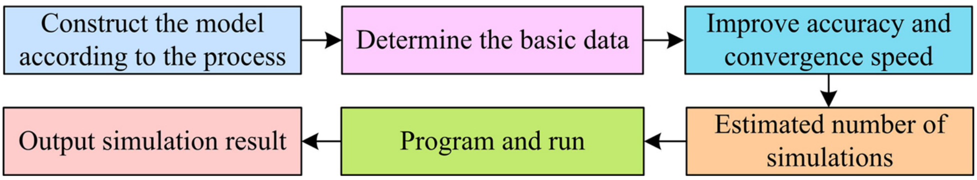

Fig. 1. MC operation flow chart

Figure 1 First build the simulation model according to the simulation process, then determine the required basic data, iteratively update the model simulation accuracy and Rate of convergence, and estimate the simulation times. Afterwards, it is run on a computer to statistically process data and estimate the simulation results and accuracy of the given problem [12,13]. The MC method calculates the integral using random sampling, as Equation (3.1).

$$E(g) = \int_0^\infty g(x) f(x)\, \mathrm{d}x \tag{3.1}$$

In Equation (3.1), $f(x)$ is the distribution density function and g is a random variable. Extract N sub samples, $X_1, X_2, \ldots X_N$, from $f(x)$. The estimated value of the corresponding arithmetic mean is Equation (3.2).

$$\bar{g}_N = \frac{1}{N} \sum_{i=1}^{N} g(X_i) \tag{3.2}$$

Equation (3.2) represents the arithmetic mean of $g(X_N)$. According to the law of large numbers, if the sub sample $g(X_N)$ is independently distributed and has a finite expected value, then the arithmetic mean $\bar{g}_N$ converges to $E(g)$, as shown in Equation (3.3).

$$P\left(\lim_{N\to\infty} \bar{g}_N = E(g)\right) = 1 \tag{3.3}$$

In Equation (3.3), N is the number of sub samples. When the it is sufficiently large, the arithmetic mean will converge to its expected value with a probability of 1. In fact, there is an error in the approximate value obtained through the MC method. Through the central limit law, it can be known that if the random variable is independently distributed and there is a preferential non-zero variance, the conditions must be met as Equation (3.4).

$$\begin{cases} 0 \neq \sigma^2 = \displaystyle\int (x - E(g))^2 f(x)\,\mathrm{d}x < \infty \\ \displaystyle\lim_{N\to\infty} P\left(\frac{\sqrt{N}}{\sigma}|\bar{g}_N - E(g)| < x\right) = \frac{1}{\sqrt{2\pi}} \int_{-x}^{x} e^{-t^2/2}\,\mathrm{d}t,\ x \geqslant 0 \end{cases} \tag{3.4}$$

In Equation (3.4), σ^2 is the non zero variance. When N is sufficiently large, an approximate equation can be obtained as Equation (3.5).

$$P\left(|\bar{g}_N - E(g)| < \frac{\lambda_a \sigma}{\sqrt{N}}\right) \approx \frac{2}{\sqrt{2\pi}} \int_{0}^{\lambda_a} e^{-t^2/2}\,\mathrm{d}t = 1 - a \tag{3.5}$$

In Equation (3.5), a represents the confidence level and $1 - a$ represents the confidence level, λ_a represents the characteristic root of a. Thus obtaining the error of the MC method is Equation (3.6) [14].

$$\varepsilon = \frac{\lambda_a \sigma}{\sqrt{N}} \tag{3.6}$$

In Equation (3.5), ε is the error of MC, and $\dfrac{1}{\sqrt{N}}$ is the order of error Rate of convergence. λ_a corresponds to a, λ represents the characteristic root, and after setting the confidence level, λ_a can be obtained through Normal distribution. The MC can obtain high-quality results in an extremely short time and is suitable for various types of problems, and can handle a large amount of data. Because it can estimate the probability distribution through simulation results, and is simple to use, with fewer steps, and easy to get started.

3.2. Application of MC in ESRB

There are different types of architectures in the central city, and with the continuous expansion of the city, the energy consumption system of buildings is becoming increasingly complex. Due to the many influencing factors of BEC, the principle of energy balance was proposed to simulate BEC and quantify complex buildings. Figure 2 is a physical model of the building.

In Figure 2, due to the differences in buildings, different buildings are simplified into rectangular building models. c is the building length; b is the width; h is the height, and k is the Aspect ratio. Figure 3 is a typical energy flow diagram of a building.

From Figure 3, the external heat load of a typical building includes solar radiation, heat load of the enclosure structure, and fresh air load. The internal heat load includes human body

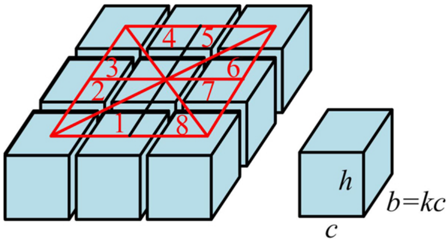

Fig. 2. Typical building physical model

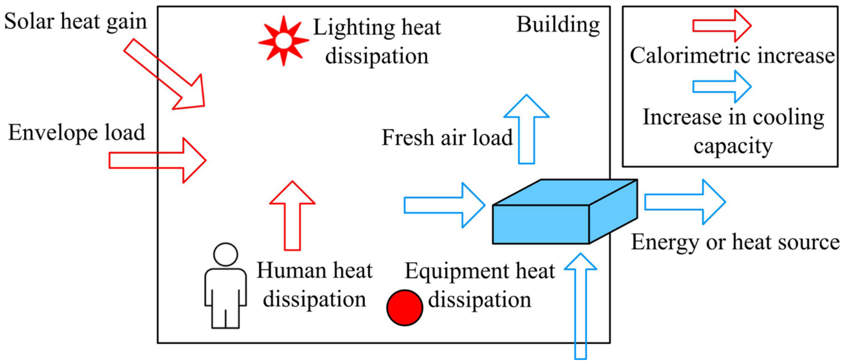

Fig. 3. Typical building energy flow

heat dissipation, equipment and facilities heat dissipation, etc. [15]. If the indoor environment is stable, the overall energy of the building should be constant, so that the energy balance equation of heat gain and heat dissipation can be known. The energy transferred by the envelope is Equation (3.7).

$$Q_{T,t} = U \times (\theta_{\text{out}} - \theta_{\text{in,set}}) \times t \tag{3.7}$$

In Equation (3.7), Q_T is the energy transferred by the enclosure, U is the Heat transfer coefficient, and the unit is W/m^{2}K. θ_{out} is the outdoor temperature, and $\theta_{\text{in,set}}$ means the indoor design temperature. t represents time, measured in hours. The heat transfer of Dedicated outdoor air system is Equation (3.8).

$$Q_{V,t} = L_{fr} \times (h_{\text{out}} - h_{\text{in},j}) \times t \tag{3.8}$$

In Equation (3.8), $Q_{V,t}$ represents the heat transferred by the Dedicated outdoor air system, L_{fr} represents the fresh air flow, unit: kg/s. h_{out} and $h_{\text{in,set}}$ are the outdoor and indoor air enthalpy. The solar radiation heat is Equation (3.9).

$$Q_{S,t} = G_{\text{so}} \times S_{\text{win}} \times \alpha_{\text{soil}} \times \alpha_{sh} \times t \tag{3.9}$$

In Equation (3.9), $Q_{S,t}$ represents the solar radiation heat, Q_{so} represents the solar Radiant intensity intensity, unit: W/m^2, unit: kg/s. S_{win} represents the outer window area, α_{sh} is the shielding coefficient of S_{win}. α_{sol} represents the sunshine's thermal factor. The heat generated inside the building is Equation (3.10).

$$Q_{I,t} = (\alpha_{\text{oc}} q_{\text{oc}} IFA_{\text{oc}} + \alpha_{\text{ap}} q_{\text{ap}} IFA_{\text{ap}} + \alpha_{\text{li}} q_{\text{li}} IFA_{\text{li}}) \times t \tag{3.10}$$

In Equation (3.10), Q_I represents the total energy of the heat sources inner architecture [16]. *IFA* represents the area of the building, α_{oc}, α_{ap} and α_{li} represent the heat dissipation value of indoor occupants, electrical equipment and lighting. q_{oc} represents the people density, and q_{li} represents the power density of lighting. In accordance with the heat balance theorem, the cooling and heating acquirement for buildings is the sum of Equations (3.7) to (3.10). The regional building energy prediction model is jointly determined by building size, building thermophysical properties, building behavior and laws, and climate parameters. It requires the establishment of a regional basic information database to simulate BEC [17], as Equation (3.11).

$$Q_{\text{co},t} = Q_{T,t} + Q_{V,t} + Q_{S,t} + Q_{\text{oc},t} + Q_{\text{li,t}} + Q_{\text{ap},t} = \sum_{i=1}^{M} IFA_i \times \sum_{j=1}^{6} \alpha^i_{j,t} q^i_j \tag{3.11}$$

In Equation (3.11), $Q_{\text{co},t}$ represents the cooling needs of the area, and M means the type of architecture in the area. j is the type of load in the area. $\alpha^i_{j,t}$ Is the load coefficient of Class-j load for Class-i buildings in the area at time-t. q^j_i represents the j-class load indicator of the i-class building in the area, in W/m^2. After determining various loads, establish a random prediction model for heat as Equation (3.12) [18].

$$\begin{cases} Q_{\text{he},t} = Q_{T,t} + Q_{V,t} + Q_{S,t} - Q_{\text{oc},t} - Q_{\text{li,t}} - Q_{\text{ap},t} + Q_{\text{ho},t} + Q_{\text{ve},t} \\ Q_{ho} = \sum_{i=1}^{6} IFA_i \times \alpha^i_{7,t} \times q^i_7 = \sum_{i=1}^{6} IFA_i \times C_p \times \rho \times K^i_h \times dp_{i,t} \times \dfrac{q^i_d}{T^n} \times (T_{\text{hw}} - T_{\text{CL},i,t}) \\ Q_{\text{inf}} = \sum_{i=1}^{6} IFA_i \times \alpha^i_{8,t} \times q^i_8 = 0.28 \times c_p \times \rho \times (\theta_{\text{in}} - \theta_{\text{out},t}) \times L_{\text{inf},t} \end{cases} \tag{3.12}$$

In Equation (3.12), $Q_{\text{he},t}$ represents the heat demand within the building in the area. $Q_{\text{ho},t}$ represents the hot water load inside the building in the area, and $Q_{\text{ve},t}$ represents the infiltration load inside the building in the area. C_p is the air Specific heat at outdoor temperature, and T_{hw} is the water supply temperature of the hot water system. q^i_d represents the daily amount of hot water used by each person, and K^i_h represents the coefficient of change of the hot water system when the load is low. T_{CL} is the hourly temperature of cold water, and $L_{\text{inf},t}$ is the volumetric flow rate of permeated air. The energy consumption calculation model for regional buildings established based on the cooling capacity formula and heat formula is Equation (3.13) [19].

$$EN = EN_{\text{co}} + EN_{\text{he}} + EN_{\text{pu}} + EN_{\text{fa}} + EN_{\text{li}} + EN_{\text{ap}} + EN_{\text{ho}} + EN_{\text{el}} + EN_{\text{inf}} \tag{3.13}$$

Each character in Equation (3.13) represents the energy consumption of different objects in the regional building. EN_{co} is the refrigeration cold source. EN_{he} is the heating source. EN_{pu} is the water pump. EN_{fa} is the fan. EN_{li} refers to other power systems. EN_{ap} and EN_{ho} refer to

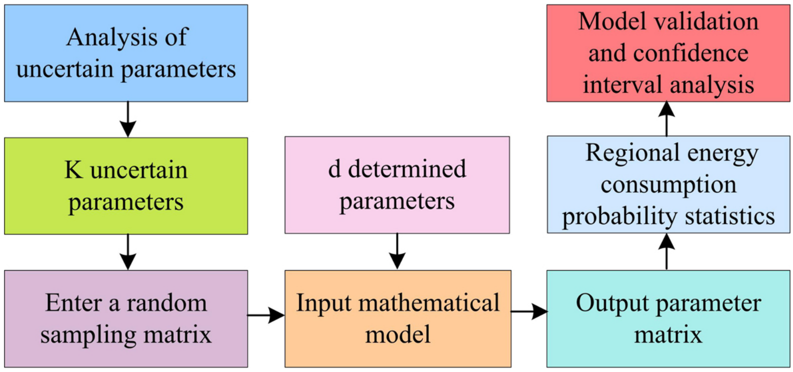

Fig. 4. Regional BEC prediction process based on MC simulation

lighting facilities. EN_{el} means an elevator. EN_{inf} represents electrical facilities [20]. Figure 4 expresses the structure of the model simulated using the MC method.

Figure 4 first analyzes the parameters to determine K uncertain parameters, and then inputs them into the random sampling matrix. By using mathematical models to predict the output parameter matrix of regional BEC prediction models, the probability distribution of regional energy consumption is calculated. Finally, the model is validated and the confidence interval is analyzed.

4. Application analysis of predictive stochastic models in ESRB

The first section of this chapter first verifies the MC's prediction accuracy by predicting the monthly energy consumption of regional buildings and comparing the energy consumption between different facilities with actual energy consumption. The second section uses MC method to transform the energy consumption of air conditioning, lighting sockets and appliances, air conditioning cold and heat sources, and elevators in regional buildings. The energy consumption of various aspects of the renovated regional buildings is predicted to verify the effectiveness of energy-saving improvements.

4.1. Performance testing of BEC prediction model based on MC

This study selected a regional building data information database, which focuses on a typical business district in a central urban area, including basic building information, energy equipment information, energy consumption data, energy parameters, technical measures, etc. This study establishes an energy consumption calculation model based on information about regional buildings, such as energy systems and energy consumption characteristics. Simulate the main energy consumption of regional buildings, such as air conditioning, lighting sockets, and electrical appliances, on a monthly basis, and compare the simulated values with the actual values to verify the accuracy of the model's prediction. Meanwhile, the research introduces BOA-GWO-PSO for comparison [21]. This method combines butterfly optimization algorithm with ray wolf optimizer to improve particle swarm optimization, which can solve the problem of energy allocation and achieve energy conservation. Comparing this method with the method used in this study, the results are shown in Figure 5.

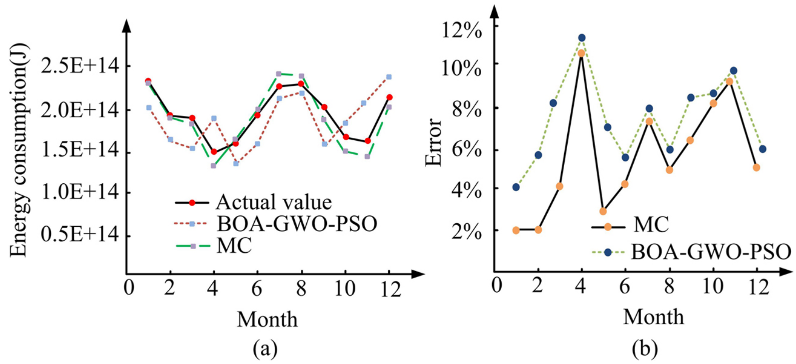

Fig. 5. Simulated and actual values of energy consumption; (a) Monthly energy consumption, (b) Error between actual and predicted values

Figure 5(a) shows the comparison between the actual monthly energy consumption of regional buildings and the monthly energy consumption predicted through Monte Carlo and BOA-GWO-PSO. Figure 5(b) shows the error between the predicted energy consumption and the actual energy consumption. As shown in the figure, the BEC in July and August is relatively high, while the energy consumption in April and November is relatively low; The maximum prediction error reached 12% in November, followed by 11% in April; The smallest errors are in January and February, only around 2%. The results show that the error of monthly energy consumption predicted by MC is less than 12%, and the Root-mean-square deviation (RMSE) is 5%. This indicates that the model has excellent performance and can be utilized to predict the energy-waste and energy-saving potential of regional buildings. Figure 6 predicts the energy consumption of lighting sockets, electrical facilities, air conditioning cold and heat sources, and elevators in regional buildings, and compares them with actual values.

Figure 6(a)–(c) respectively represent the actual and predicted monthly energy consumption of lighting sockets and electrical facilities, air conditioning cold and heat sources, and elevators. Among them, the predicted energy consumption of lighting sockets and electrical equipment showed relatively low energy consumption in February, and high energy consumption in January, March, May, July, and August. The air conditioning cold and heat sources are lower in April, October, and November; The elevator is lower in February. In the energy consumption simulation of lighting sockets, electrical facilities, air conditioning cold and heat sources, and elevators, the average error between them and the actual energy consumption is about 5%, which has a good prediction accuracy. Figure 7 simulates the total energy consumption of regional buildings for one year.

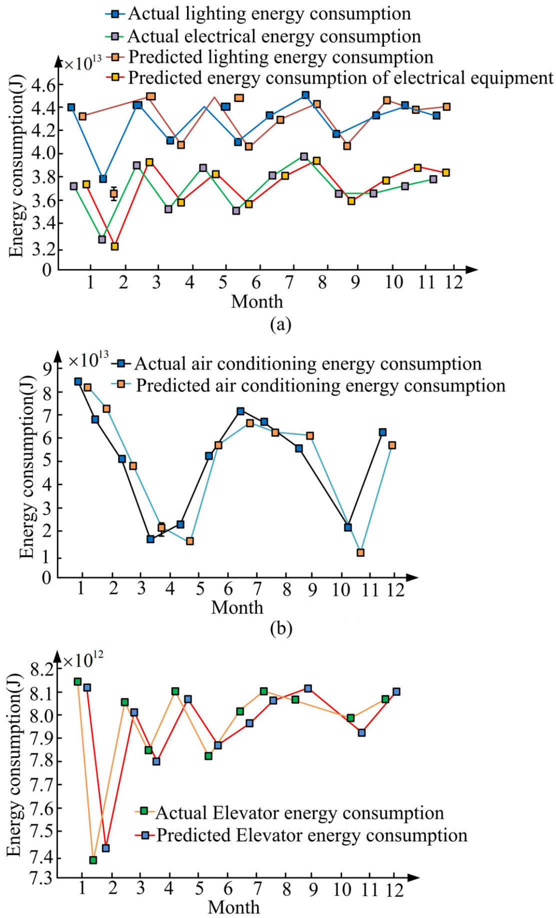

Fig. 6. Actual and predicted monthly energy consumption of different facilities; (a) Energy consumption of lighting and electrical appliances, (b) Energy consumption of air conditioning, (c) Energy consumption of Elevator

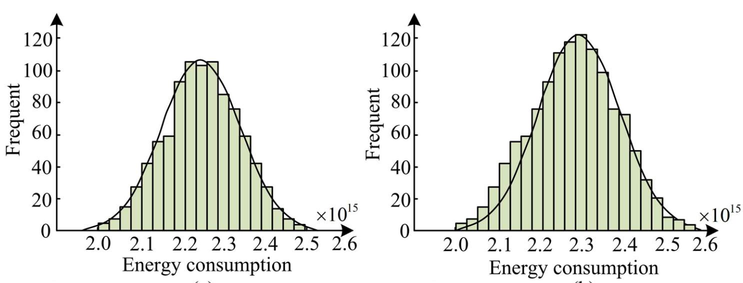

Fig. 7. Energy consumption chart for one year; (a) Predicted total energy consumption of regional buildings, (b) Reality total energy consumption of regional buildings

Figure 7(a) and 7(b) show the predicted and actual annual total energy consumption frequency distribution results. The maximum predicted annual energy consumption is 2.510E+15J, the minimum is 1.90E+15J, the pre average is 2.251E+15J, and the standard deviation is 9.453E+13. The actual annual energy consumption is 2.296E+15J, with a max-value of 2.610E+15J and a min-value of 2.00E+15J. The error between the two is only about 2%, indicating that the model has good prediction accuracy.

4.2. Analysis of the results of predicting BEC after ESR based on MC

This study predicts the energy consumption after regional ESRB using MC. Figure 8 first predicts the monthly energy consumption after the improvement of regional buildings.

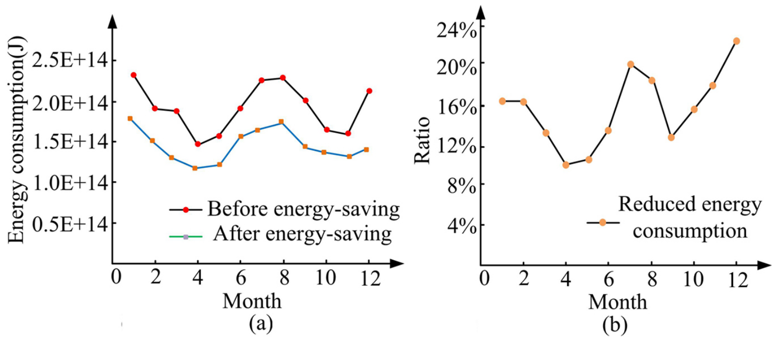

Fig. 8. Energy consumption reduction rate in pre and post energy-saving transformation; (a) Monthly energy consumption, (b) Energy consumption reduction rate

Figure 8(a) shows the monthly energy consumption of regional buildings in pre and post ESR; Figure 8(b) shows the proportion of energy consumption reduction after the renovation. The energy consumption after the renovation has significantly decreased, especially in January, July, and August. And in July and August, energy consumption decreased by 30%, while in April, October, and November, it only decreased by about 10%. The experiment shows

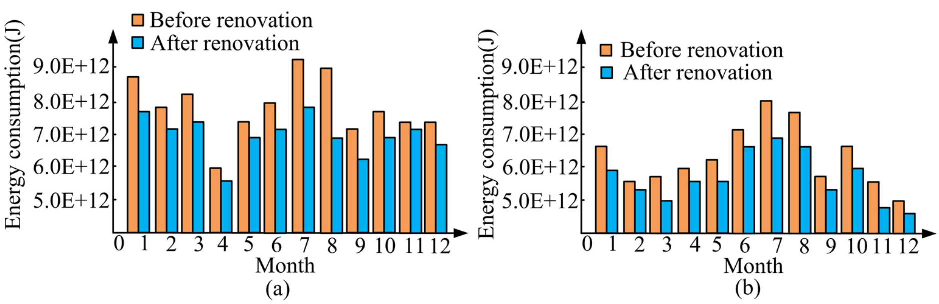

Fig. 9. Energy consumption analysis comparison; (a) Consumption of energy consumption before and after hotel renovation, (b) Consumption of energy consumption before and after restaurant renovation

that the energy consumption after energy-saving transformation predicted by MC decreases every month, with a maximum reduction of 30% and a minimum of 10%, with an average energy consumption reduction rate of 23.7%. This indicates that ESR has a significant effect on reducing energy consumption. Next, ESR analysis was conducted on different kinds of buildings in the selected area: one hotel and one restaurant were selected, with the same floor height and no significant difference in floor area. Figure 9 shows the energy consumption analysis before and after the energy-saving transformation.

Figure 9(a) and 9(b) illustrate that of the hotel and restaurant. The data shows that after ESR, the annual hotels' consumption has reduced by approximately 24.3%, and restaurants have decreased by approximately 19.5%, indicating that ESR has better effects in buildings with higher energy consumption. Figure 10 shows the gross waste in the simulated area after ESRB for one year.

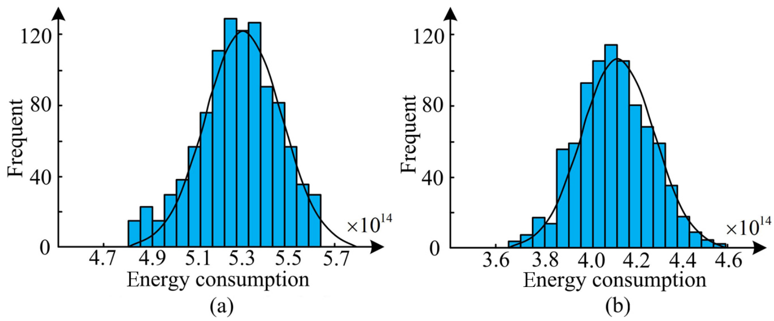

Fig. 10. Comparison of annual energy consumption; (a) Energy consumption before renovation, (b) Energy consumption after renovation

Figure 10(a) and 10(b) show the frequency distribution of total waste before & after regional ESRB. The maximum energy consumption before renovation is 560 TJ, the minimum value is 480 TJ, and the average value is 516 TJ; The maximum value after renovation is 450 TJ, the minimum value is 370 TJ, and the average value is 410 TJ. Compared to the other two, its energy-saving rate has reached around 20%.

5. Conclusions

The LS-ESR of regional building clusters faces many difficulties. This study focuses on the LS-ESR problem of regional building clusters and establishes an energy consumption prediction model based on MC. This model uses the principle of building energy balance and MC to establish a cooling and heat demand model for regional buildings. The energy-wasting simulation of regional building clusters and the energy consumption prediction experiment after ESR show that the monthly energy consumption error predicted using MC is less than 12%, and the RMSE is 5%; The average error of the predicted & actual energy waste of lighting sockets, electrical facilities, air conditioning cold and heat sources, and elevators is about 5%, while the error between the predicted and actual annual total energy consumption is only about 2%. The following conclusions were drawn from this study: (1) A classified typical building energy balance steady-state model was constructed. (2) Build a stochastic model for LSBESR energy consumption prediction based on MC simulation. (3) Analyzed building models, energy parameters, and cooling and heating loads in large-scale renovations. (4) To lay a theoretical foundation for predicting the energy consumption of regional building clusters.

There are still shortcomings in this study, as the selected indicators are not comprehensive enough and only a few relevant factors have been selected. If the range of relevant factors is expanded, the accuracy of the model can be more convincing. Subsequent research can combine GIS technology with established regional energy prediction stochastic models to explore the impact of different building physical forms on energy prediction.

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