

Article

A Multi-Stage Decision Framework for Optimal Energy Efficiency Measures of Educational Buildings: A Case Study of Chongqing

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Abstract: Buildings consume large amounts of energy resources and emit considerable amounts of greenhouse gases, especially existing buildings that do not meet energy standards. Building retrofitting is considered one of the most promising and significant solutions to reduce energy consumption and greenhouse gas emissions. However, finding suitable energy efficiency measures for existing buildings is extremely difficult due to the existence of thousands of retrofit measures and the need to meet various objectives. In this paper, a multi-stage decision framework, including a multi-objective optimization model, and a ranking method are proposed to help decision-makers select the optimal energy efficiency measures. The multi-objective optimization model considers the economic and environmental objectives, expressed as the retrofit cost and energy consumption, respectively. The entropy weight ideal point ranking method, an evaluation and ranking method that combines the entropy weight method and ideal point method, is adopted to sort the Pareto front and make a final decision. Then, the proposed decision framework was implemented for the retrofit planning of an educational building in Chongqing, China. The results show that decision-makers can quickly identify near-optimal energy efficiency measures through multi-objective optimization and can select suitable energy efficiency measures using the ranking method. Moreover, energy consumption can be reduced by building retrofitting. The energy consumption of the case building was 64.20 kWh/m² before retrofitting, and the value can be reduced by 6.79% through retrofitting. Furthermore, the reduction in building energy consumption was significantly improved by applying the decision framework. The highest value of energy consumption was 59.84 kWh/m², while the lowest value was 27.11 kWh/m² when implementing the multi-stage decision framework. Thus, this paper provides a useful decision framework for decision-makers to formulate suitable energy efficiency measures.

Keywords: multi-stage decision framework; optimal energy efficiency measures; educational buildings; building retrofitting; energy consumption; retrofit cost



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1. Introduction

The building sector is one of the three largest energy-consuming sectors, in addition to the industry and transportation sectors, and is a major source of CO₂ emissions [1]. According to the IEA, the building sector accounts for one-third of the global energy consumption and nearly 40% of CO₂ emissions [2]. In China, building energy consumption has reached more than 46% of the total final energy consumption [3,4]. At the same time, the carbon emissions of the building sector constituted 21.7% of the total, with an average annual growth rate of 6.03% [5]. Therefore, the building sector is recognized as the main contributor to environmental degradation, and thus, reducing the energy consumption and CO₂ emissions of buildings is an important way to achieve carbon peak and neutrality targets and sustainable development.

There are different methods available to address energy overuse and the CO₂ emission problem in the building sector. One effective method is energy saving and emission reduction for new buildings, for example, by improving energy efficiency standards. The other way is energy efficiency improvement for existing buildings by retrofitting. Building retrofitting is considered the primary and fundamental approach since most existing buildings do not meet energy efficiency standards [6]. Moreover, many studies have demonstrated that existing buildings hold enormous potential to reduce energy consumption and CO₂ emissions and generate positive environmental impacts through energy retrofitting [7–9]. Retrofit, refurbishment and renovation are often used to describe the renewal of buildings. Refurbishment work includes the improvement, renovation, retrofit and repair of existing buildings [10]. Refurbishment and renovation are often focused on aesthetics and tenant amenities [11]. Thus, renovation is sometimes used interchangeably with refurbishment, but renovation applies especially to buildings, whereas refurbishment does not [11]. However, retrofit typically means the addition of features for the improvement in performance in particular areas such as energy efficiency [12]. Thus, retrofit is adopted in this paper, and the means of building retrofitting is the process of adopting various measures to renovate the envelope, equipment systems and operation methods of buildings.

There is a wide range of energy efficiency measures (EEMs) for building retrofitting. As with a set, EEMs can contain only one ‘element’ or several distinct ‘elements’. For example, the EEM can contain only one measure, such as the change in insulation materials for external walls, or the EEM can contain several measures, such as the change in insulation materials for external walls, the change in insulation materials for roofs and the change in the thickness of insulation layers. Thus, the elements can be envelopes, equipment systems, the behavior of humans indoors, etc. The envelope contains the insulation materials and thickness for walls, roofs, types of windows and the window-wall ratio (WWR). The insulation materials can be expanded polystyrene (EPS) boards, extruded polystyrene (XPS) boards, rigid polyurethane (PU) boards, etc. The insulation layer thickness can be 10 mm, 20 mm, 30 mm, etc. Examples of equipment systems include heating, ventilation and air conditioning (HVAC) systems, lighting systems, hot water systems, etc. Hundreds and thousands of elements will generate billions of combinations (EEMs), resulting in a large space for solutions and further making the decisions regarding EEMs more difficult and complicated [13,14].

The problem of selecting EEMs is a multi-objective optimization problem [15]. The most important purpose of building retrofitting is to improve energy efficiency and reduce carbon emissions. However, different decision-makers may have different objectives, such as retrofit cost, comfort indoors, high quality, etc. Many of these objectives are conflicting and cannot be compared under equivalent conditions [16], which adds complexity to the decision problem and does not have one EEM but a set of EEMs. Thus, the main challenge in building retrofitting is the selection of the optimal EEMs [17].

The main purpose of this work is to use advanced algorithms and dynamic building simulation tools to select optimal EEMs among different EEMs for an educational building. The structure of this paper is as follows: In Section 1, the background is analyzed and introduced; in Section 2, related works on how to select the optimal EEMs are summarized; Section 3 presents an appropriate methodological framework for supporting building retrofitting decisions; and Section 4 focuses on the results and discussion of the case building. Finally, the conclusions are drawn.

2. Literature Review

Selecting suitable and optimal EEMs is an extensive research area, and therefore, numerous studies have been carried out on this topic. One common way to determine the best EEMs is the “scenario by scenario” method [18], wherein engineers make comparisons among several EEMs based on experience and dynamic simulation tools. Dynamic building energy simulation tools are powerful tools for calculating and analyzing building energy

performance, which include EnergyPlus [16,19], DesignBuilder [20,21], TRNSYS [22,23], etc. For example, Cho et al. used EnergyPlus to simulate building energy savings to make decisions among six packages of building energy efficiency measures [24]. Chae and Kim used ECO-CE3, an energy performance analysis tool that originated in South Korea, to select the best EEMs among eight energy efficiency measures for an 80-year-old heritage school [25]. The selection results of “scenario by scenario” methods mainly depend on dynamic building simulation tools and the experience and knowledge systems of engineers, architects or building designers, who have a certain subjectivity. Moreover, the number of analyzed scenarios of this method is typically very low, often resulting in a suboptimal solution [15,18].

Another common method used to select the optimal EEMs is the combination of dynamic building simulation tools and optimization algorithms, which offers the ability to evaluate trade-offs among different stakeholders (expressed as objective functions) across thousands of EEMs (expressed as decision variables). Unlike the “scenario by scenario” method, this method provides an efficient algorithm to select the optimal EEMs among thousands of EEMs while considering different objectives, such as environmental, economic and social objectives. Thus, this method offers the possibility of finding the optimal EEMs quickly and more effectively.

Research on multi-objective optimization for existing buildings has gradually drawn scholarly attention. Environmental, economic and social objectives are considered simultaneously under this method, such as energy consumption [26–28], retrofit cost [20,21,29] and thermal comfort [19]. He et al. evaluated the trade-offs among NPV, energy consumption reduction and retrofit investment for a high-rise residential building by adopting a genetic algorithm [30]. Ghalambaz, Yengejeh and Davami carried out a multi-objective optimization for an office building using a grey wolf optimizer to simultaneously minimize energy consumption by lighting, heating and cooling [31]. For decision variables, the multi-objective optimization for building retrofitting involves envelopes [32–34], HVAC [35,36] and other control measures [37]. For the envelope, the EEMs discussed most frequently are the insulation materials, insulation thickness, window types and WWR [26,38]. For HVAC measures, a heating system, cooling system and hot water system are commonly used [39,40]. For the control measures, temperature set-point, HVAC loads and control zone strategies are often studied [41,42].

Furthermore, different building types have been analyzed in recent articles. The building types for most of the above articles include residential buildings [43–46], office buildings [47–50], hospital buildings [51], commercial buildings [52], historical or industrial buildings [53,54], etc. Many studies make decisions among different EEMs by adopting metaheuristic algorithms, such as evolutionary algorithms [55] and swarm-based algorithms [56]. For instance, Chang used the genetic algorithm (GA) to support the decision of selecting the optimal envelope EEMs to meet multiple objectives for a residential building in Tokyo [26]. Solmaz, Halicioglu and Gunhan used the particle swarm optimization algorithm to determine the best EEMs for an existing public school building in Turkey [17].

In accordance with previous studies, few studies use the optimization algorithm to assist in the designing and decision making of educational buildings, which occupy a large proportion of existing buildings. Furthermore, previous studies offered a multi-objective optimization process for existing building retrofitting. A complete and comprehensive decision-making framework to help decision-makers select optimal EEMs remains largely under-researched. Therefore, it is crucial to investigate and define optimal energy efficiency measures (EEMs) for educational building retrofitting by adopting a comprehensive and quick framework, which can guide building owners to make decisions more effectively and efficiently. Based on the above research conclusions, the aim of this paper is to create an effective multi-stage decision framework to formulate the optimal EEMs to minimize the retrofit cost and energy consumption. An educational building in hot summer and cold winter zones in China was adopted as the reference case to implement the multi-stage decision framework and determine the optimal EEMs.

3. Methodology

A multi-stage decision framework that minimizes energy consumption and retrofit cost to identify reliable optimal EEMs for existing buildings was developed and implemented. The framework developed included four main stages, as shown in Figure 1: (1) developing the building model; (2) defining the optimization problems; (3) performing the multi-objective optimization; and (4) ranking the Pareto front. The first stage aimed to develop the building model by Sketchup software, OpenStudio software and EnergyPlus software, which collected data on the building, climate, occupant behavior, etc. Then, the optimization problems were defined (stage 2), which included decision objectives and decision variables (EEMs). The major task of stage 3 was to produce near-optimal EEMs (also called the Pareto front) by performing a multi-objective optimization process. After that, the Pareto front was ranked by the entropy weight ideal point ranking method [57], and the decision results were generated. Based on the results of ranking EEMs, decision-makers can also carry out decisions based on other decision objectives. For example, decision-makers can select the optimal EEMs based on the expected lifespan or the difficulty of implementing the EEMs. The multi-stage decision framework is explained in detail in the following four stages:

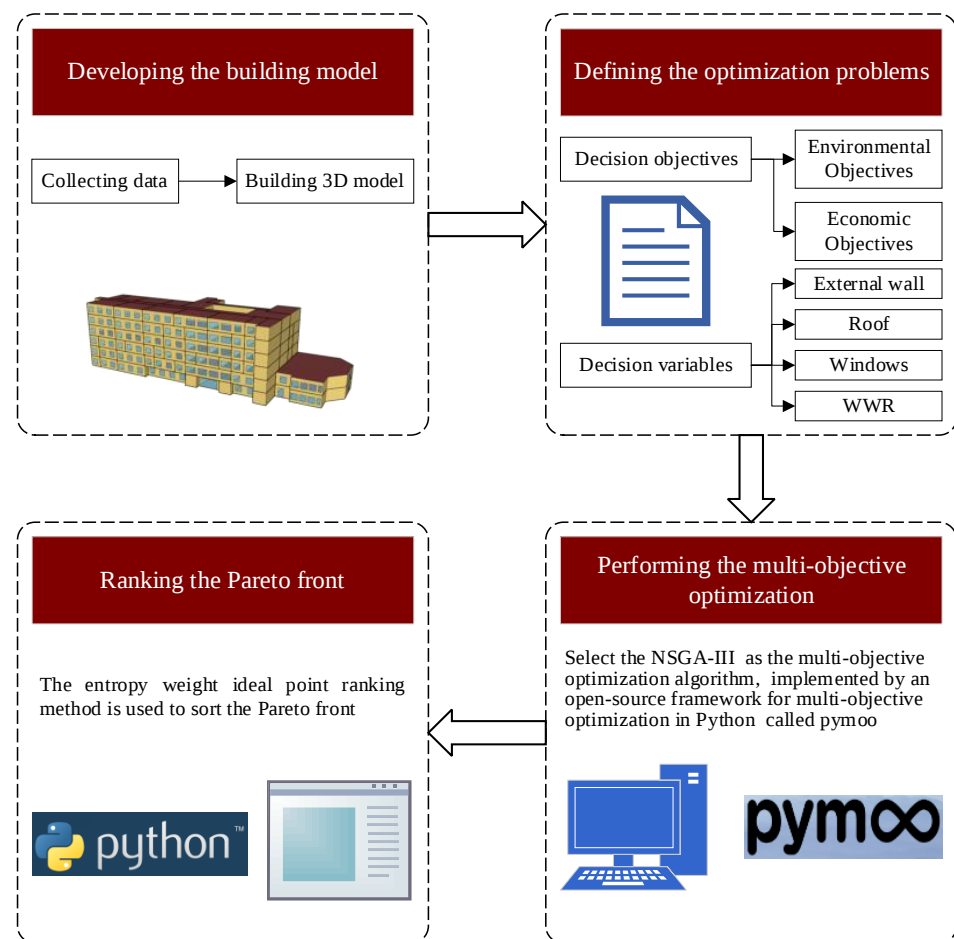


Figure 1. Framework of building multi-objective optimization.

3.1. Developing the Building Model

The first task of creating a building model is to collect input data, including meteorological data for the location of the building, building characteristic data and building occupant behavior data. Meteorological data of the building location can generally be downloaded from 'Weather' on the EnergyPlus website. Building characteristic data mainly include information such as the geometric features of existing buildings, building envelope and energy supply systems. Building information files mainly include building construction

drawings, equipment drawings and other necessary information, which are used to set up an accurate building model. Personnel behavior information and appliance operation files should be collected, including personnel activity files, per capita building areas occupied by different functional rooms, ventilation times, equipment power density, etc. The second task is to construct the building model after the building-related data are gathered. The main objective of this task is to ensure that the building performance difference between the model and the real building is limited to a certain range. A 3D geometric model of the building was created by transforming the gathered building information into Sketchup 2019. Finally, the 3D geometric model was imported into OpenStudio and EnergyPlus to define the parameters of the envelope, energy supply system and occupant behavior in detail.

The case building selected in this paper is in Chongqing, China, which has a hot summer and cold winter climate. It is a six-story educational building with a total height of 22.8 m and a building gross floor area of 7680 m². Detailed information on the building is shown in Table 1. The plan for the first and second floors is shown in Figure 2, and the plan for the building above the second floor is presented in Figure 3. A 3D modeling software package, Sketchup 2019, was used to render the building geometry and divide the thermal zones. Figure 4 shows an architectural schematic view of the case building. The 3D model was imported into OpenStudio and EnergyPlus to define the envelope and energy supply system.

Table 1. Basic information on the case building.

Basic Information	Data
Shape	Rectangle
Length	81.9 [m]
Width	26.7 [m]
Floor number	6
Average floor height	3.6 [m]
Ground floor area	1350 [m ²]
Total area	7680 [m ²]
Window–wall ratio	
North	18.27%
East	1.97%
South	18.55%
West	2.37%

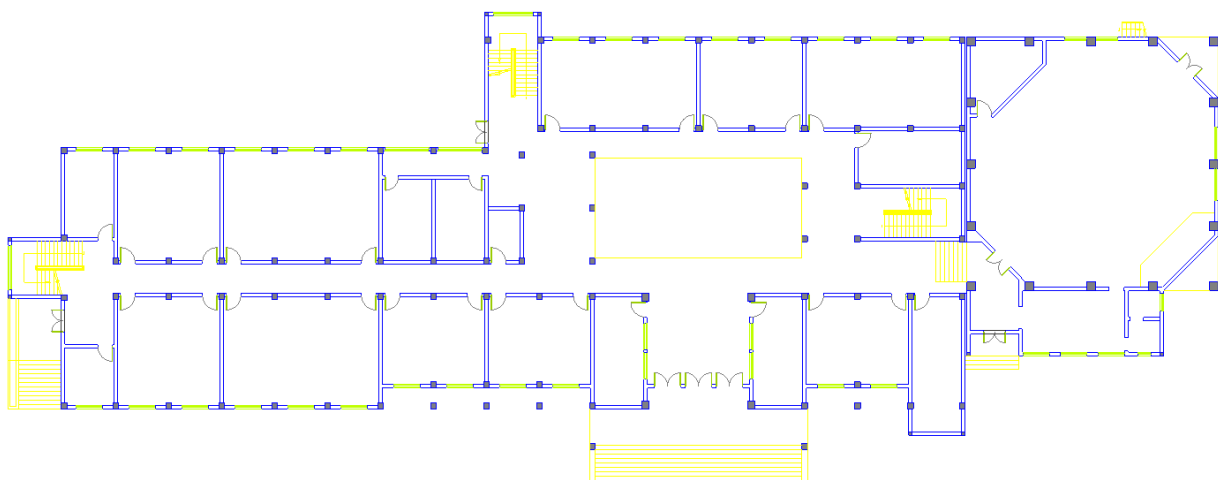


Figure 2. First- and second-floor plan.

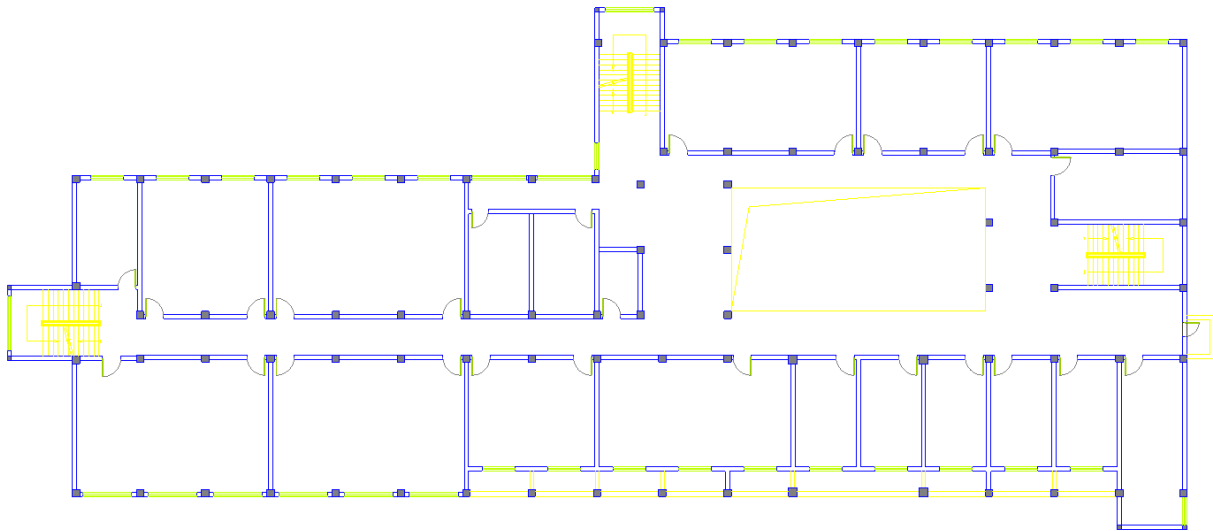


Figure 3. Third-floor to sixth-floor plan.

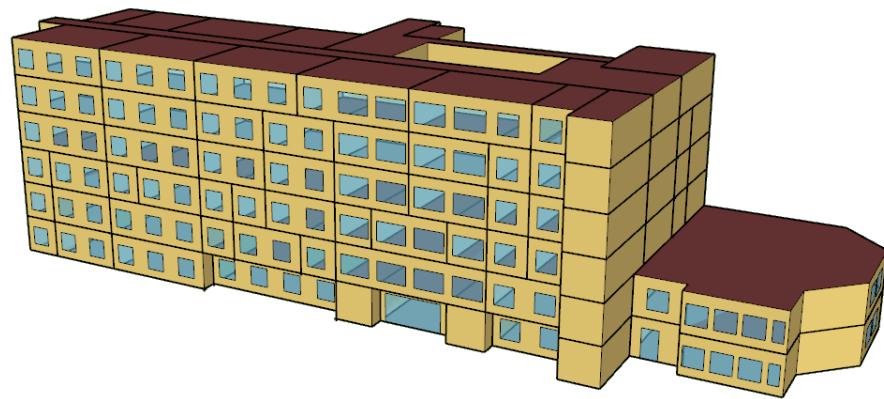


Figure 4. Schematic view of the 3D model for the case building.

3.2. Defining the Optimization Problems

Based on the results of the literature review, a multi-objective optimization model was devised considering the environmental aspects (energy consumption) and economic aspects (retrofit cost).

3.2.1. Objective Functions

A. Energy Consumption (f_1)

In this paper, the building's energy consumption was adopted as an objective and calculated using the dynamic building energy simulation program of EnergyPlus 9.4:

$$EC = \frac{1}{A} \times [EC_c + EC_h + EC_l + EC_w + EC_e] \quad (1)$$

where EC is the building's energy consumption (kWh/m²); A is the air-conditioning area of the existing building (m²); EC_c is the energy consumption used for cooling (kWh); EC_h is the energy consumption used for heating (kWh); EC_l is the energy consumption used for lighting (kWh); EC_w is the energy consumption used for domestic hot water (kWh); and EC_e is the energy consumption used for appliances (kWh).

B. Retrofit Cost (f_2)

Retrofit cost is an important indicator for evaluating economic viability and is defined as the cost of an EEM, which visually reflects the economic impacts of every EEM. The retrofit cost can be calculated using the following equations:

$$C = \frac{(C_w + C_r + C_{win})}{A}$$

$$C_w = \sum_{l=1}^L C_{w,l} \times T_l \times A_w$$

$$C_r = \sum_{k=1}^K C_{r,k} \times T_k \times A_r$$

$$C_{win} = C_{win,v} \times A_{win} \quad (2)$$

where C is the building's total retrofit cost (RMB/m²); C_w is the retrofit cost of the external wall (RMB); C_r is the retrofit cost of the roof (RMB); C_{win} is the retrofit cost of the external windows (RMB); $C_{w,l}$ is the unit price of insulation materials l for the external wall (RMB/m³); T_l is the thickness of the insulation layer (m); A_w is the surface area of the external wall (m²); $C_{r,k}$ is the unit price of insulation materials k for the roof (RMB/m³); T_k is the thickness of the insulation layer (m); A_r is the surface area of the roof (m²); $C_{win,v}$ is the unit price of the window type (RMB/m²); and A_{win} is the surface area of the windows (m²).

3.2.2. Decision Variables

Nearly 50% of building energy consumption is related to the building envelope [26], of which 30% are external walls, roofs represent 30%, floors represent 20%, 10% include doors and windows and 10% relate to air tightness measures [7]. Through the energy retrofit of the envelope of existing buildings, the annual energy consumption can be reduced by approximately 50% [52,58]. Therefore, this study selected insulation materials (x_1) and insulation layer thickness (x_2) for the external wall, insulation materials (x_3) and insulation layer thickness (x_4) for the roof, window types (x_5) and window–wall ratio (WWR_North as x_6 and WWR_South as x_7) as the decision variables. Tables 2–4 show the range of variation and the unit price of decision variables used in this study.

Table 2. Decision variables for the external wall.

Variable Name	EEM Description	Value	Comments	Cost (RMB/m ³) ^a
x_1 [0, 8]	Change insulation material type	0	XPS	600
		1	EPS	425
		2	PU	740
		3	Rock wool board (RW)	500
		4	Glass wool board (GW)	200
		5	Rubber board (RP)	1300
		6	Graphite polystyrene board (SEPS)	190
		7	Glazed hollow bead board (VB)	780
		8	Mineral binder and expanded polystyrene (R3P)	450
x_2	Change insulation layer thickness	[0, 100] (Unit: mm)		

a: The cost of building materials was obtained from [59].

Table 3. Decision variables for the roof.

Variable Name	EEM Description	Value	Comments	Cost (RMB/m ³)
x_3 [0, 4]	Change insulation material type	0	XPS	580
		1	EPS	425
		2	PU	740
		3	RW	500
		4	GW	200
x_4	Change insulation layer thickness	[0, 300] (Unit: mm)		

Table 4. Decision variables for the window and WWR.

Variable Name	EEM Description	Value	Comments	Cost (RMB/m ²)
x_5 [1, 21]	Change external window type	1	Float white glass (FWG) 6 mm	34
		2	FWG 8 mm	45
		3	FWG 12 mm	70
		4	5 mm Toughened glass (TG) + 6 mm Air (6A) + 5 mm TG	135
		5	5 mm TG + 9A + 5 mm TG	140
		6	6 mm TG + 9A + 6 mm TG	155
		7	6 mm TG + 12A + 6 mm TG	165
		8	8 mm TG + 9A + 8 mm TG	190
		9	8 mm TG + 12A + 8 mm TG	197
		10	5 mm Toughened glass with Low-E (TGLO) + 6A + 5 mm TG	143
		11	5 mm TGLO + 9A + 5 mm TG	150
		12	6 mm TGLO + 6A + 6 mm TG	165
		13	6 mm TGLO + 9A + 6 mm TG	170
		14	8 mm TGLO + 9A + 8 mm TG	205
		15	10 mm TGLO + 9A + 10 mm TG	234
		16	5 mm Toughened glass with coated (TGC) + 6A + 5 mm TG	139
		17	5 mm TGC + 9A + 5 mm TG	144
		18	6 mm TGC + 9A + 6 mm TG	170
		19	6 mm TGC + 12A + 6 mm TG	180
		20	8 mm TGC + 12A + 8 mm TG	198
		21	10 mm TGC + 12A + 10 mm TG	234
x_6	Change north window–wall ratio	[0.1, 0.55]		
x_7	Change south window–wall ratio	(0.1, 0.55]		

Therefore, the multi-objective optimization problem is defined as follows:

$$\text{Min}\{f_1(\bar{x}), f_2(\bar{x})\}, \bar{x} = [x_1, x_2, \dots, x_n]$$

$$f_1(\bar{x}) = EC$$

$$f_2(\bar{x}) = C \quad (3)$$

where f_1 in Equation (3) is the first objective function, f_2 is the second objective function, $\bar{x}$ is a combination of variables (retrofitting measures), $x_1, x_2, \dots, x_n$ and n are the numbers of retrofitting EEMs.

3.3. Performing the Multi-Objective Optimization

The multi-objective problem defined above consists of two conflicting objectives: energy consumption and retrofit cost (e.g., the application of EEMs can reduce building energy consumption, but it usually leads to an increase in the cost of retrofitting). Thus, the multi-objective problem does not have one optimal EEM but a set of solutions called the Pareto front. The EEMs on the Pareto front are unable to select the optimal solutions from an objective perspective. For example, the energy consumption of one EEM is lower than another, but its retrofit cost is higher.

Among many methods of solving multi-objective optimization problems, non-dominated sorting genetic algorithms (NSGAs) and multi-objective particle swarm optimization (MOPSO) algorithms have often been used by researchers. The elite non-dominated sorting genetic algorithm (NSGA-II) and reference-point-based non-dominated sorting genetic algorithm (NSGA-III) in NSGAs have been widely used in many fields. NSGA-II is more capable of contributing all the effective solutions compared to MOPSO [32], whereas NSGA-III achieves a better performance than NSGA-II in terms of iteration speed and hypervolume index [60]. Thus, NSGA-III was used as the multi-objective optimization algorithm for educational building retrofitting in this paper. NSGA-III was implemented using an open-source framework for multi-objective optimization in Python called pymoo, which includes the problem module, optimization module and analysis module [61]. First, the optimization parameters were imported into pymoo according to the objective functions and decision variables. Second, the IDF file in EnergyPlus was modified by changing the value of the decision variable (changing the EEMs), and the EnergyPlus software was run to obtain the building energy consumption and retrofit cost corresponding to different EEMs in real time. Finally, the Pareto front was generated.

3.4. Ranking the Pareto Front

After performing the process of multi-objective optimization, the sets of EEMs (Pareto front) are obtained, and decision-makers should select the optimal EEMs satisfying their requirements. This paper offers an efficient and effective approach to help decision-makers. The entropy weight ideal point ranking method is an evaluation and ranking method that combines the entropy weight method (EWM) and the ideal point method. The entropy weight is an objective weighting method [62] that can produce a more reasonable and reliable index weight according to the measured data [57]. The entropy weight method overcomes the shortcomings of strong subjectivity, such as Expert Raters and the Analytic Hierarchy Process (AHP). The ideal point method determines the order of the pros and cons of each EEM (Pareto front) by calculating the distance (expressed as closeness degree) from each EEM evaluation to the ideal point [62]. The ideal point is a vector consisting of all the maximum values of each valuation index [63]. The entropy weight ideal point ranking method introduces the concept of “entropy” into weight calculation, and the entropy weight is used to fix the subjective weight to obtain a more reasonable weight. Then, the ideal point method is adopted to evaluate and select the alternative solutions, and arrive at the final decision [63]. Thus, this method is an effective combination of subjective and objective methods and is more scientific and rational.

This ranking method sorts the Pareto front by weighing different decision objectives and then calculating the closeness degree of each solution in the Pareto front. The ranking procedure includes five phases:

(1) Data normalization.

Suppose that there are n individuals among the Pareto front (retrofit EEMs) and m decision objectives, which are denoted as $B = \{B_1, B_2, \dots, B_n\}$ and $C = \{C_1, C_2, \dots, C_m\}$, respectively. Let x_{ij} represent the objective function value of the individuals B_i with respect

to the objective C_j ; then, the original objective function value matrix can be constructed as follows:

$$X = (x_{ij})_{m \times n} = \begin{pmatrix} x_{11} & \cdots & x_{1n} \\ x_{21} & \cdots & x_{2n} \\ \vdots & \ddots & \vdots \\ x_{m1} & \cdots & x_{mn} \end{pmatrix}, (i = 1, 2, \dots, m, j = 1, 2, \dots, n) \quad (4)$$

Then, the initial objective value matrix $X = (x_{ij})_{m \times n}$ is transformed into a normalized objective value matrix $R = (r_{ij})_{m \times n}$ using Equation (5):

$$r_{ij} = \frac{x_{ij} - \inf(x_{ij})}{\sup(x_{ij}) - \inf(x_{ij})} \quad (5)$$

where $\sup(x_{ij})$ and $\inf(x_{ij})$ denote the maximum value and minimum value of x_{ij} on the j th objective, namely, the maximum value and the minimum value on the j th column.

(2) Calculation of the entropy value.

The value of entropy can be calculated as follows:

$$H_i = - \frac{\sum_{j=1}^n f_{ij} \cdot \ln f_{ij}}{\ln n} \quad (6)$$

$$f_{ij} = \frac{1 + r_{ij}}{\sum_{j=1}^n (1 + r_{ij})}, (i = 1, 2, \dots, m; j = 1, 2, \dots, n)$$

(3) Calculation of entropy weights of different objectives.

The entropy weight ω_i of different objectives are calculated using Equation (7):

$$\omega_i = \frac{1 - H_i}{\sum_{j=1}^n (1 - H_i)}, (j = 1, 2, \dots, n) \quad (7)$$

Then, the characteristic matrix of the objectives is calculated using the following equations:

$$A = (a_{ij}) = \begin{pmatrix} a_{11} & \cdots & a_{1n} \\ a_{21} & \cdots & a_{2n} \\ \vdots & \ddots & \vdots \\ a_{m1} & \cdots & a_{mn} \end{pmatrix} = \begin{pmatrix} \omega_1 r_{11} & \cdots & \omega_1 r_{1n} \\ \omega_2 r_{21} & \cdots & \omega_2 r_{2n} \\ \vdots & \ddots & \vdots \\ \omega_m r_{m1} & \cdots & \omega_m r_{mn} \end{pmatrix} \quad (8)$$

(4) Identification of ideal points.

According to Equation (9), the ideal point matrix P^* is as follows:

$$P^* = (P_1^*, P_2^*, \dots, P_m^*) \quad (9)$$

where P_j^* denotes the maximum value of every row.

(5) Calculation of the closeness degree.

The closeness degrees between individuals B_i and ideal points P^* can be calculated using the following:

$$T_j = 1 - \frac{\sum_{i=1}^m a_{ij} \cdot P_i^*}{\sum_{i=1}^m P_i^{*2}}, (j = 1, 2, \dots, n) \quad (10)$$

where $T_j \in [0, 1]$; the smaller the value, the better the performance of the individuals.

The entropy weight ideal point ranking method is written in the programming language and run in Python based on the above five phases. First, the initial objective value matrix is transformed into a normalized objective value matrix and the entropy and entropy weights of the different objectives are calculated. Second, the ideal point matrix is identified according to Equation (9). Finally, the closeness degree is calculated. When the program is terminated, the weights of the different objectives and the closeness degrees of the individuals are the output.

4. Results and Discussion

In this section, the results of implementing the multi-stage decision framework for educational case building are presented. The results mainly include the multi-objective optimization process (see Section 4.1) and the Pareto front ranking process (see Section 4.2).

4.1. Results of Multi-Objective Optimization

The multi-objective optimization process was carried out on a computer with an Intel® Core™ i5-7500 CPU @ 3.40 GHz processor and 8.00 GB RAM, and the whole calculation took 102 h.

Figure 5 shows the objective function values for the first three and last three generations of individuals generated in the optimization process. It is obvious that the value of the objective function for the first three generations is higher than the value of the last three generations, which demonstrates that the objective functions (energy consumption and retrofit cost) are gradually optimized with the progress of the optimization. The results show that by carrying out multi-objective optimization of existing buildings, it is possible to ensure that energy consumption and retrofit cost can reach a relatively satisfactory level to be in line with the preferences of decision-makers as much as possible. It is also worthwhile to mention that the building's energy consumption and retrofit costs from the figure are conflicting [15,16]; that is, as one objective decreases, the other objective increases. In other words, it is impossible to minimize the building's energy consumption and retrofit cost simultaneously, which can be verified by the values of the objective functions in Table 5.

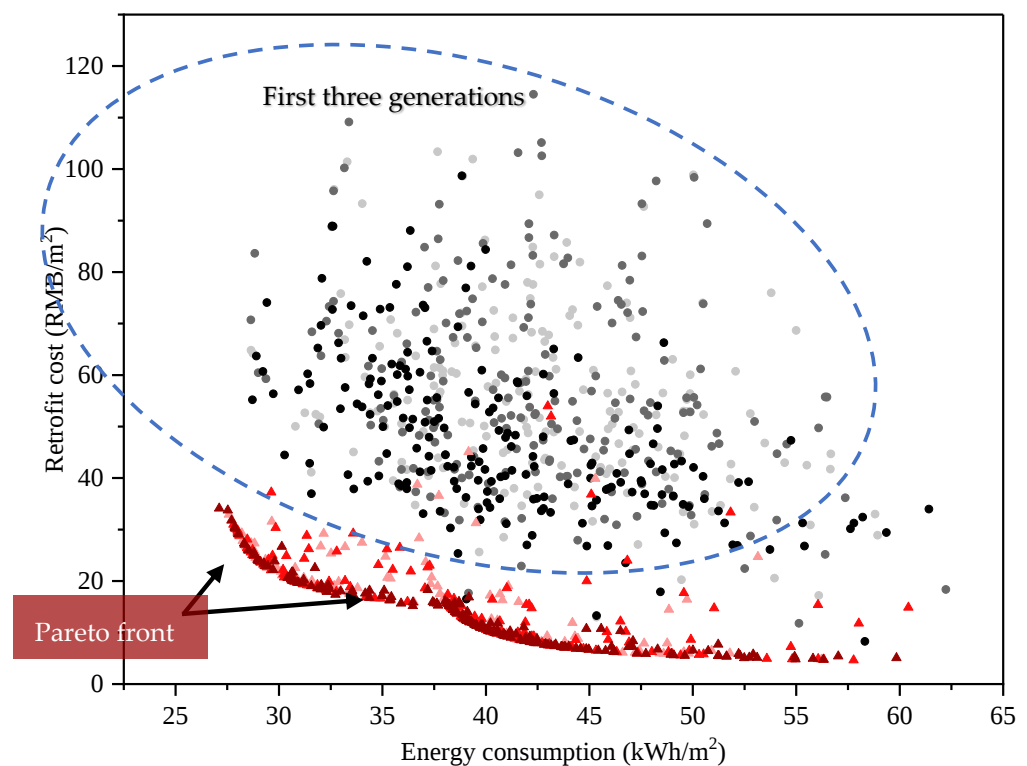


Figure 5. The values of the building energy consumption and retrofit cost.

Table 5. Descriptive statistical analysis indicators.

	Total (N)	Mean	Standard Deviation	Sum	Minimum	Median	Maximum
Energy Consumption (kWh/m ²)	200	39.30	7.08	7859.13	27.11	39.40	59.84
Retrofit Cost (RMB/m ²)	200	13.64	6.87	2728.77	4.78	11.86	34.11

Table 5 shows the descriptive statistical analysis indicators of the Pareto front generated by multi-objective optimization. It can be determined that building energy consumption increases from 27.11 kWh/m² to 59.84 kWh/m², and the value of the retrofit cost decreases from 34.11 RMB/m² to 4.78 RMB/m². The values of the objective functions varied greatly, indicating the significance of the multi-objective optimization for building retrofitting. Furthermore, the means for building energy consumption and retrofit cost are 39.30 kWh/m² and 13.64 RMB/m², respectively. It can be observed that the distribution of building energy consumption is uniform, and the distribution of retrofit cost is focused on approximately 10 RMB/m² as the optimization process progresses.

Table 6 shows the energy consumption before retrofitting and the simulation values after optimization. The building energy consumption before the retrofit is 64.20 kWh/m², while the highest value of energy consumption in the Pareto front is 59.84 kWh/m² and the minimum value is 27.11 kWh/m², all lower than the value before the retrofit. Therefore, the energy savings can range from 4.36 kWh/m² to 37.09 kWh/m², which are reduced from 6.79% to 57.78% by running the multi-objective optimization algorithm. Thus, the annual reduction in energy consumption can range from 33,920.80 kWh to 288,560.20 kWh every year, respectively. These results demonstrate that energy consumption can be reduced by energy retrofits; moreover, the degree of reduction can be greatly increased by implementing multi-objective optimization.

Table 6. Energy savings after optimization.

	Energy Consumption (kWh/m ²)	Energy Savings after Optimization (kWh/m ²)	Annual Energy Savings (kWh)
Reference building	64.20	-	-
Maximum of Pareto front	59.84	4.36	33,920.80
Minimum of Pareto front	27.11	37.09	288,560.20

4.2. Results of Pareto Front Ranking

According to the entropy weight ideal point ranking method, the weight of two objective functions can be obtained as $\omega = (\text{energy consumption}, \text{retrofit cost}) = (0.62, 0.38)$. Then, 200 individuals of the Pareto front set are ranked, and the top 10 individuals with the smallest closeness degree (T_j) are selected. The data for the decision variables and objective function values are given in Table 7.

Table 7. Optimum retrofit options for the reference building retrofit.

Individual	T_j	x_1 Insulation Materials for External Wall	x_2 Insulation Layer Thickness for External Wall (mm)	x_3 Insulation Materials for Roof	x_4 Insulation Layer Thickness for Roof (mm)	x_5 Window Types	x_6 WWR_North	x_7 WWR_South	f_1 Energy Consumption (kWh/m ²)	f_2 Retrofit Cost (RMB/m ²)
112	0.3628	6-SEPS	40	4-GW	170	14	0.10	0.10	27.11	34.11
122	0.3670	6-SEPS	100	4-GW	270	15	0.11	0.10	27.53	33.75
22	0.4078	6-SEPS	90	4-GW	250	15	0.11	0.10	27.71	31.80
76	0.4352	6-SEPS	70	4-GW	240	15	0.11	0.10	27.86	30.48
1	0.4379	6-SEPS	70	4-GW	240	15	0.10	0.10	27.87	30.35
200	0.4408	6-SEPS	70	4-GW	230	15	0.10	0.10	27.89	30.21
45	0.4630	6-SEPS	60	4-GW	240	15	0.10	0.10	28.04	29.13
117	0.4992	6-SEPS	70	4-GW	180	15	0.10	0.11	28.32	27.35
147	0.5048	6-SEPS	60	4-GW	185	15	0.10	0.10	28.34	27.09
162	0.5270	6-SEPS	50	4-GW	185	15	0.10	0.10	28.53	25.99

As seen in Table 7, the insulation materials of the 10 individuals for the external wall are SEPS, and those of the roof are GW. However, the window type, insulation layer thickness, and WWR differ among individuals. The window type can be 8 mm TGLO + 9A + 5 mm TG or 10 mm TGLO + 9A + 10 mm TG. The insulation thickness of the external wall increased from 40 mm to 100 mm, and the insulation thickness of the roof increased from 170 mm to 270 mm. The WWR in the north and south was either 0.10 or 0.11. In addition, the value of building energy consumption increased from 27.11 kWh/m² to 28.53 kWh/m², and the retrofit cost decreased from 34.11 RMB/m² to 25.99 kWh/m². From the results of the table, it can be concluded that different EEMs result in different building energy consumption and retrofit costs.

It is interesting to note that all the decision variables of individual No. 147 and individual No. 162 are the same, except for the insulation thickness of the external wall, which is reduced from 60 mm to 50 mm. However, the objective functions of energy consumption and retrofit cost were changed, of which energy consumption decreased from 28.53 kWh/m² to 28.34 kWh/m², while the retrofit cost increased from 25.99 RMB/m² to 27.09 RMB/m². A similar phenomenon is observed when the insulation thickness of the roof is increased from 230 mm to 240 mm, whereas other decision variables remain unchanged for individual No. 1 and individual No. 200. From the results, it can be clearly inferred that increasing the thickness of the thermal insulation layer can reduce the energy consumption of the building, but it leads to an increase in the cost of retrofitting. In addition, this also validates the results, indicating that the building's energy consumption and retrofit cost are competitive objectives.

Moreover, it should be noted that the smallest value of the closeness degree is observed for individual No. 112 in the Pareto front set, which is the optimal EEM. From the table, the optimal EEMs mainly include 40 mm SEPS in the external wall, 170 mm GW in the roof and 8 mm TGLO + 9A + 5 mm TG of the window. From the perspective of retrofit cost, the retrofit costs of SEPS for external wall, GW for roof and window type are 425 RMB/m³, 200 RMB/m³ and 205 RMB/m², respectively, based on the first issue of the 2021 journal *Chongqing Engineering Cost Information* from the website of Chongqing Engineering Cost Information. According to the results of EnergyPlus and the value of WWR, the surface areas of the external wall, roof and window type are 3008.23 m², 1792.98 m² and 731.08 m², respectively. Thus, the retrofit cost of the optimal EEM is 34.11 RMB/m² $((3008.23 \times 0.04 \times 425 + 1792.98 \times 0.17 \times 200 + 731.08 \times 205)/7680 = 34.11)$. From the results of EnergyPlus, the building's energy consumption is 27.11 kWh/m².

For the evaluation of the multi-objective optimization results, the entropy weight ideal point ranking method was used in this paper. Decision-makers can also select the optimal EEMs for other decision objectives, such as the expected lifespan of the EEMs, the difficulty of implementing the EEMs, the degree of comfort after retrofitting, etc.

Then, we provide our perspective on the impacts that the multi-stage decision framework can have on policy-makers, building owners and engineers. The major implication of all the above results is that the optimal EEMs generated by the proposed decision framework reduce building energy consumption and improve decision-making efficiency. However, the implementation of the multi-stage decision framework is difficult due to the uncertainties with respect to the high upfront investment required, the availability of green technologies, the lack of building retrofit awareness and the limited retrofitting experience [64]. Thus, policy-makers can develop corresponding policy instruments based on the decision-making framework to promote the implementation of the framework. On the one hand, economic incentives and technical measures can be employed to improve the building owners' interest in carrying out the decision framework. On the other hand, the cultivation of interdisciplinary talents can be strengthened.

5. Conclusions

In this paper, a systematic multi-stage decision framework to help decision-makers select the optimal EEMs is suggested for building retrofitting. A multi-objective opti-

mization algorithm, NSGA-III, was applied, which consists of two objectives: minimizing energy consumption and retrofit cost. A ranking algorithm called the entropy weight ideal point ranking method was used to rank the Pareto front generated from multi-objective optimization. Then, a six-story educational building in Chongqing, China, was chosen as a real-world case study to investigate the optimal EEMs. The insulation materials and insulation layer thickness of the external walls, as well as the insulation materials and insulation layer thickness of the roof, window types and WWR of the building, were selected as decision variables, which were extracted from the building draws to be used as the input data. The case building was simulated using EnergyPlus software to implement the retrofit measures and investigate the effects on energy consumption and retrofit cost. The multi-objective optimization problem and ranking algorithm were solved using Python. The main findings are summarized as follows.

The energy savings were high after retrofitting. For the case building, the building energy consumption was 64.20 kWh/m² before retrofitting. However, the value can be reduced from 59.84 kWh/m² to 27.11 kWh/m² by implementing multi-objective optimization, which was able to reduce the annual energy consumption from 6.79% to 57.78%. The annual energy savings of buildings can reach 288,560.20–33,920.80 kWh.

The reduction in building energy consumption was significantly improved. The highest value of energy consumption was 59.84 kWh/m², while the lowest value was 27.11 kWh/m² when implementing the multi-stage decision framework.

When keeping the other decision variables unchanged, increasing the thickness of the insulation layer can reduce building energy consumption; however, it will lead to an increase in retrofit costs. The results indicate that different EEMs lead to different energy consumption and retrofit costs.

The framework allows decision-makers to select the optimum building retrofit measures to minimize energy consumption and retrofit costs. However, there are some improvements that could be considered to enhance the accuracy of the proposed framework by add to the number of case study buildings. Therefore, additional case buildings with different characteristics should be considered in future research to address the limitations of the case study. On the other hand, this paper only considers the envelope as the decision variable. Other variables such as lighting, the HVAC system and renewable energy also need to be considered in future research.

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Nomenclature

Nomenclature

AA	Characteristic matrix of the objectives	EC_l	Energy consumption used for lighting, kWh
A_{ac}	Air-conditioning area, m ²	EC_w	Energy consumption used for domestic hot water, kWh
A_r	Surface area of roof, m ²	F	Decision objectives
A_w	Surface area of external wall, m ²	f_1	Energy consumption
A_{win}	Surface area of windows, m ²	f_2	Retrofit cost
B	Matrix of retrofit EEMs	H_i	Entropy
C	Building's total retrofit cost, RMB/m ²	k	Insulation materials for roof
C_r	Retrofit cost of roof, RMB	l	Insulation materials for external wall
$C_{r,k}$	Unit price of insulation materials k for roof, RMB/m ²	P^*	Ideal point matrix
C_w	Retrofit cost of external wall, RMB	R	The normalized matrix for objective function
C_{win}	Retrofit cost of external windows, RMB	T_j	Closeness degrees
$C_{w,l}$	Unit price of insulation materials l for external wall, RMB/m ³	T_k	Thickness of insulation layer, m
$C_{win,v}$	Unit price of the window type, RMB/m ²	T_l	Thickness of insulation layer, m
EC	Building's energy consumption, kWh/m ²	ω_i	Entropy weights of different objectives
EC_c	Energy consumption used for cooling, kWh	X	Original objective function value matrix
EC_e	Energy consumption used for appliances, kWh	$\bar{x}$	Combination of variables
EC_h	Energy consumption used for heating, kWh		

Acronyms

A	Air	PU	Rigid polyurethane
EEMs	Energy efficiency measures	RP	Rubber board
EPS	Expanded polystyrene	RW	Rock wool board
EWM	Entropy weight method	R3P	Mineral binder and expanded polystyrene granule
FWG	Float white glass	SEPS	Graphite polystyrene board
GA	Generic algorithm	TG	Toughened glass
GW	Glass wool board	TGC	Toughened coated glass
HVAC	Heating, Ventilation and Air Conditioning	TGLO	Toughened glass with Low-E
MOPSO	Multi-objective particle swarm optimization	VB	Glazed hollow bead board
NSGAs	Non-dominated sorting genetic algorithms	WWR	Window–wall ratio
NSGA-II	Elitist non-dominated sorting genetic algorithm	XPS	Extruded polystyrene
NSGA-III	Reference-point based non-dominated sorting genetic algorithm		

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