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Sustainable Architecture for Future Climates: Optimizing a Library Building through Multi-Objective Design

Yijia Miao [1,2], Zebin Chen [3], Yiyong Chen [3] and Yiqi Tao [1,3,4,*]

1 Center for Human-Oriented Environment and Sustainable Design, Shenzhen University, Shenzhen 518060, China; miaoyj@connect.hku.hk
2 Faculty of Architecture, The University of Hong Kong, Hong Kong 999077, China
3 School of Architecture and Urban Planning, Shenzhen University, Shenzhen 518060, China; 2210325065@email.szu.edu.cn (Z.C.); chenyiy@szu.edu.cn (Y.C.)
4 State Key Laboratory of Subtropical Building and Urban Science, Shenzhen University, Shenzhen 518060, China
* Correspondence: taoyiqi@szu.edu.cn

Abstract: In the context of the escalating challenge of climate change, optimizing buildings' energy performance has become a critical research area, yet studies specifically targeting library buildings are scarce. This study addresses this gap by investigating the impact of multi-objective optimization on energy efficiency and occupant comfort in educational library buildings under future climate scenarios. Utilizing the Non-Dominated Sorting Genetic Algorithm II (NSGA-II), this research optimizes a range of building parameters, including the cooling and heating setpoints, air change rates, shading device depths, window visible transmittance, and window gas types. The optimization aims to balance energy consumption and comfort, using simulations based on future weather data for the years 2020, 2050, and 2080. The results indicate that the optimized solutions can significantly reduce the heating energy by up to 95.34% and the cooling energy by up to 63.74% compared to the baseline models, while maintaining or improving the occupant comfort levels. This study highlights the necessity for dynamic, responsive architectural designs that can adapt to changing environmental conditions, ensuring both sustainability and occupant well-being. Furthermore, integrating these building-level optimizations into a City Information Model (CIM) framework can enhance urban planning and development, contributing to more resilient and energy-efficient cities. These findings underscore the importance of sustainable design practices in the context of climate change and the critical role of advanced optimization techniques in achieving energy-efficient, comfortable educational spaces.

Keywords: energy performance; multi-objective optimization; library building; NSGA-II; climate change response

Citation: Miao, Y.; Chen, Z.; Chen, Y.; Tao, Y. Sustainable Architecture for Future Climates: Optimizing a Library Building through Multi-Objective Design. *Buildings* **2024**, *14*, 1877. https://doi.org/10.3390/buildings14061877

Academic Editor: John C. Brigham

Received: 18 April 2024
Revised: 9 June 2024
Accepted: 12 June 2024
Published: 20 June 2024

1. Introduction

The escalating impacts of climate change on the built environment necessitate a reevaluation of architectural design practices, especially for educational infrastructure such as libraries, which require a delicate balance of functional, sustainable, and occupant comfort. As climate variability intensifies, the design of these buildings demands innovative approaches that not only address immediate environmental sustainability goals but also ensure long-term adaptability and resilience [1,2]. In this field, multi-objective optimization (MOO) has emerged as a vital tool. MOO facilitates the simultaneous balancing of various performance criteria, responding adeptly to the dynamic environmental conditions [3–5].

The incorporation of MOO into architectural design addresses the complexities of achieving optimal energy efficiency alongside enhanced occupant comfort [6]. This approach is essential in navigating competing objectives, such as maximizing natural light while minimizing heat gains [7,8] or improving ventilation at the expense of increased energy use [9,10]. For example, the work of Xiong and Tzempelikos [11] illustrates the application of dynamic façades with integrated lighting and shading control systems in office spaces. This approach, aimed at enhancing visual comfort and reducing lighting energy consumption, employed different types of sensors for glare control and focused on metrics such as the daylight glare probability (DGP), daylight luminance, and vertical illuminance, leading to improved shading functionality. Similarly, Kohansal et al. [12] delved into the optimization of building insulation. Their research identified the optimal thickness and type of insulation material for different climatic zones, achieving improved energy efficiency and reduced heating and cooling demands. Papadopoulos et al. [13] conducted a study on the enhancement of thermal comfort and energy efficiency in commercial buildings. Their research involved balancing the use of HVAC systems with maintaining ideal indoor temperature ranges, demonstrating potential for energy savings while minimally impacting occupant comfort across seven climate zones in the US.

Despite significant advancements in the commercial and residential sectors, the application of MOO in designing school libraries for future climate scenarios remains less explored. School libraries serve dual functions as educational and communal spaces, demanding specific considerations for energy efficiency and indoor environmental quality. These facilities must support diverse activities and provide a conducive learning environment, which introduces unique challenges that necessitate focused investigation and specialized design strategies [14]. The general principles of sustainable architecture are well established, yet applying these principles to school libraries requires tailored approaches, particularly due to their significant roles in educational outcomes and community well-being [15]. The research by Liu and Ren [16] underscores the evolving needs of academic libraries, highlighting the necessity for flexible designs that adapt to changes in user behavior and technological advancements. Furthermore, research on predictive and adaptive design strategies in libraries is less prevalent, indicating a gap in the literature. Incorporating future climate data into the design process is essential in developing buildings that remain functional and efficient as the environmental conditions evolve [17,18]. This forward-thinking approach ensures that investments in educational infrastructure are resilient, sustainable, and capable of serving future generations.

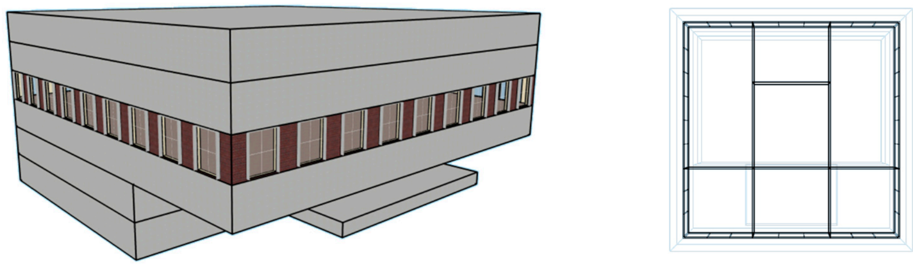
Addressing the identified research gap, this study proposes an analytical framework incorporating nine design variables and targeting three primary objective functions: the annual heating energy consumption, annual cooling energy consumption, and annual uncomfortable hours. This approach is further augmented by the inclusion of predictive future climate data, ensuring that the proposed solutions remain relevant under changing climatic conditions. The initial analyses in this study were conducted using the JEPLUS v2.1 software. This was followed by a sensitivity analysis and the application of a genetic algorithm for optimization, executed through the JEPLUS + EA platform. The weighted sum method was employed to extract optimal solutions from the Pareto front generated by the optimization process. This methodology allows for the assessment of the potential of various design strategies, not only in isolation but in a coordinated manner that addresses multiple aspects of building performance. By doing so, the proposed solutions are ensured to be effective in a wide range of scenarios, offering a thorough and practical guide for sustainable architectural practices in educational infrastructures.

The major innovation of this paper lies in its specific focus on educational library buildings, a building type that has unique requirements and has been less explored in the context of future climate scenarios. Furthermore, this study integrates predictive future climate data into the optimization process, ensuring that the solutions are robust and adaptable to long-term climatic changes. By addressing both current and future environmental challenges, this study aims to offer practical, adaptable solutions for the creation of energy-efficient and comfortable educational spaces in the face of evolving climate conditions.

2. Methodology

2.1. Building Description

The building model utilized in this study is a simplified adaptation of the Shenzhen University Library and serves as a representative example of the common academic library architecture in China. The structure comprises six floors, with each floor having a 4 m ceiling height and a floor area of 2500 square meters. To balance model complexity and computational efficiency, the analysis is concentrated on a single, standard floor within the building. This simplification reduces the computational time while maintaining useful accuracy for multi-objective optimization studies [19]. The standard floor consists of seven zones, each with the same function (primarily seating and reading spaces). Figure 1 shows the floor plan and the simulation model of the studied library.



(**a**) (**b**)

Figure 1. The simulated model: (**a**) model perspective view; (**b**) model plan.

The project was evaluated using EnergyPlus v9.4. EnergyPlus is a widely recognized building energy simulation software program developed by the US Department of Energy [20]. Known for its precision, EnergyPlus effectively simulates the energy performance of multizone buildings, incorporating key aspects such as building design, climate data, and other relevant parameters. For the evaluation of heating and cooling energy consumption, the Ideal Loads Air System object in EnergyPlus was selected. This system is widely used for its efficiency in energy simulation, offering a simplified yet effective approach to modeling HVAC dynamics [21]. The model allows us to define hourly desired internal conditions for temperature and humidity and estimates the suitable inlet conditions for the primary air to maintain these conditions without detailed HVAC system modeling. It uses an ideal unit that mixes air at the exhaust zone with a specified amount of outdoor air and then adds or removes heat and moisture at 100% efficiency to produce a supply air stream at the required conditions [22]. The energy required for conditioning is metered and reported as district heating and district cooling, which represent the external sources of heating and cooling energy supplied to the system. Consequently, the results depend solely on the building envelope, ventilation flow rates, internal gains, and solar gains and are not influenced by the HVAC system performance. It is important to note that the Ideal Loads Air System in EnergyPlus does not set a specific coefficient of performance (COP) or efficiency energy ratio (EER). Instead, it assumes perfect efficiency (100%), meaning that the thermal energy required to condition the air directly equals the reported energy use. Therefore, while the term "energy consumption" is used, it represents the idealized energy required to meet the thermal loads without the inefficiencies of real HVAC systems. This methodology provides a simplified approach to assessing building performance, focusing on the impact of the building envelope, ventilation rates, internal gains, and solar gains, under idealized conditions.

The occupancy and operating profiles were set to reflect typical library usage. The occupancy density was set to 0.15 persons per square meter. The HVAC system operated from 9 a.m. to 6 p.m. daily, providing heating, cooling, and ventilation during these hours, and was turned off during the night. The model parameters for the energy simulation were meticulously set in line with key standards: the "Design Standard for Energy Efficiency of Public Buildings [23]", the "Design Code for Heating Ventilation and Air Conditioning of Civil Buildings", and the "Technical Standards for Nearly Zero Energy Buildings [24]". For a detailed representation of the building envelope and the specific parametric settings, refer to Tables 1 and 2.

Table 1. Construction and thermophysical properties of the baseline building.

Component	Construction (Outside to Inside Layer)	U-Value (W/m^2·K)
Roof	20 mm cement mortar, 110 mm insulation material, 100 mm reinforced concrete, 20 mm cement mortar	0.346
External wall	20 mm cement mortar, 80 mm insulation material, 200 mm aerated concrete, 20 mm cement mortar (solar absorptance is 0.7)	0.351
Internal wall	20 mm gypsum plasterboard, 100 mm concrete block, 20 mm gypsum plasterboard	1.231
Internal floor	20 mm cement mortar, 150 mm reinforced concrete, 20 mm cement mortar, 12 mm terrazzo	2.929
Window	3 mm glazing (solar transmission is 0.837, visible transmittance is 0.898), 13 mm air gap, 3 mm glazing	2.716

Table 2. Building parameters for the baseline model used in the simulations.

Input Variable	Unit	Value
Cooling setpoint	°C	26
Heating setpoint	°C	20
Air change rate	ac/h	3
Depth of shading devices on windows (south, west, and east)	m	0.4

2.2. Future Weather Data

This research mainly focuses on the building performance in hot and humid subtropical climates, where Shenzhen (22.54° N, 114.05° E) was chosen as a representative. The EnergyPlus Weather (EPW) file utilized in this study was sourced from the EnergyPlus website. Future weather files were generated in accordance with the Intergovernmental Panel on Climate Change (IPCC) Special Report on Emissions Scenarios (SRES) A2 climate change scenario, employing the Climate Change World Weather File Generator (CCWorldWeatherGen) tool [25]. This tool employs a morphing methodology to produce new EnergyPlus Weather (EPW) files based on the original EPW files initially fed into the system [26,27].

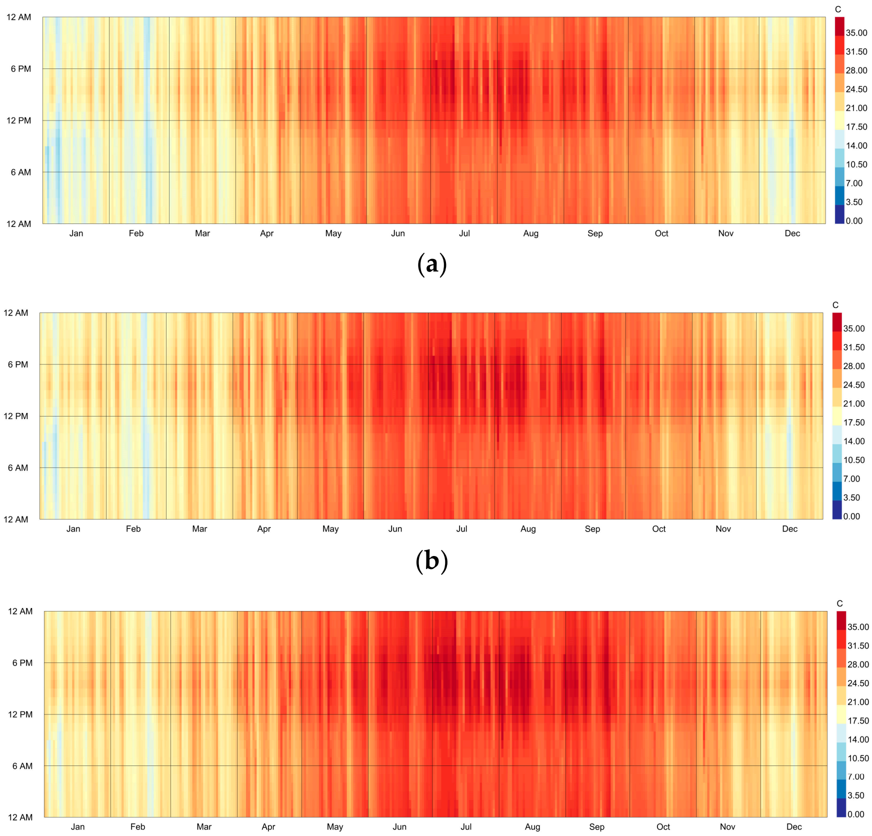
In this study, the CCWorldWeatherGen tool was employed to generate weather data for three distinct future scenarios: the years 2020, 2050, and 2080. These scenarios depict varying potential future climates for Shenzhen, offering a basis for the design of a climate-resilient library building, specifically to cope with future heatwaves. Figure 2 shows an ascending trend in the dry bulb temperature for the years 2020, 2050, and 2080, indicating an increase in the frequency of future climatic overheating events. Table 3 provides representative climate statistics for these years, including minimum, maximum, and average values for the air temperature, relative humidity, and solar radiation.

Table 3. Representative climate statistics for the years 2020, 2050, and 2080.

Year	2020	2050	2080
Min Temperature (°C)	10.1	12	13.7
Max Temperature (°C)	34.7	35.4	36.6
Avg Temperature (°C)	23.8	24.7	26

Table 3. *Cont.*

Year	2020	2050	2080
Min Relative Humidity (%)	19	19	19
Max Relative Humidity (%)	100	100	100
Avg Relative Humidity (%)	78	77.9	78
Min Solar Radiation (W/m^2)	0	0	0
Max Solar Radiation (W/m^2)	1036	1033	1014
Avg Solar Radiation (W/m^2)	197.1	197.3	195.8
Heating Degree Days (°C·days)	2739.7	1270.8	377.4
Cooling Degree Days (°C·days)	53,360.1	60,151.7	70,800.5



(**a**)

(**b**)

(**c**)

Figure 2. Dry bulb temperature for three weather scenarios: (**a**) year 2020; (**b**) year 2050; (**c**) year 2080.

2.3. Parameter Selection

In optimizing buildings' energy efficiency and occupant comfort, particularly within library environments, selecting appropriate design parameters is crucial. Table 4 lists the nine parameters chosen for their significant impact on building performance and indoor environmental quality. The selection of these nine input variables for multi-objective optimization is based on their critical roles in influencing both the energy consumption and occupant comfort in buildings. The heating and cooling setpoints (P1 and P2) directly impact the indoor thermal environment and energy use for heating and cooling systems. Optimizing these setpoints can significantly reduce the energy consumption while maintaining the thermal comfort. The air change rate (P3), which includes both ventilation and air change rates, affects the indoor air quality, thermal comfort, and energy use. Properly managing the air change rate is essential in maintaining a healthy indoor environment and optimizing the energy performance. The depth of shading devices on different facades (P4, P5, and P6) plays a vital role in controlling the solar heat gain, reducing the cooling loads, and improving occupant comfort by preventing glare and overheating. The window solar transmittance (P7) impacts the amount of solar radiation entering the building, affecting both the lighting and thermal loads. The type of gas used in the windows (P8) influences the overall thermal performance of the building envelope, as different gas fills (Air, Argon, Krypton, Xenon) have varying insulation properties. The wall solar absorptance (P9) affects how much solar energy is absorbed and subsequently radiated as heat, impacting the building's thermal balance. Optimizing this parameter helps to manage the building's heat gain and loss, contributing to reduced heating and cooling energy consumption, while maintaining comfortable indoor conditions. These parameters, encompassing both continuous and discrete variables, allow for detailed customization to optimize the environmental conditions within libraries. By carefully selecting and optimizing these parameters, this study aims to develop strategies that not only effectively reduce the heating and cooling energy consumption but also minimize the number of hours characterized by discomfort. This comprehensive and integrated approach ensures that the optimization solutions address both energy efficiency and occupant comfort, demonstrating the study's ability to tackle the challenges posed by climate change.

Table 4. Input variables and their distributions.

No.	Input Variable	Unit	Probability	Range [Minimum:Step:Maximum]
P1	Heating setpoint	°C	Continuous	[18:1:23]
P2	Cooling setpoint	°C	Continuous	[24:1:28]
P3	Air change rate	ac/h	Continuous	[1:0.2:3]
P4	Depth of shading devices for east-facing windows.	m	Continuous	[0.2:0.2:1]
P5	Depth of shading devices for west-facing windows	m	Continuous	[0.2:0.2:1]
P6	Depth of shading devices for south-facing windows	m	Continuous	[0.2:0.2:1]
P7	Window solar transmittance	-	Continuous	[0.6:0.03:0.9]
P8	Window type	-	Discrete	Air, Argon, Krypton, Xenon
P9	Wall solar absorptance	-	Continuous	[0.3:0.1:0.8]

2.4. Multi-Objective Optimization

One of the best-known algorithms in the field of multi-objective optimization is the Non-Dominated Sorting Genetic Algorithm (NSGA). Its enhanced iteration, known as NSGA-II, was introduced in 2002 [28] and is recognized for its effectiveness in solving complex optimization problems involving multiple objectives [29].

The NSGA-II algorithm enhances multi-objective optimization with its fast non-dominated sorting and efficient crowding degree mechanisms, including a crowding degree comparison operator and an elite strategy. It improves upon the original NSGA's time complexity of $O(MN^3)$ to $O(MN^2)$, where M is the number of objectives and N is the population size, thus offering a higher sorting speed. The elite strategy in NSGA-II involves carrying forward superior individuals from the parent population to the offspring, ensuring the retention of genetic excellence in subsequent generations. This strategy eliminates the need for manually specified shared parameters, thus maintaining the population diversity more effectively. In scenarios where non-dominated solutions surpass the designated population size, NSGA-II employs a crowding distance measure for pruning, ensuring an optimal balance in the population [30].

Additionally, since most optimization problems involve multiple objective functions that may exhibit conflicting or opposing trends, this algorithm offers a set of optimal choices that are not superior to each other along a curve. This curve is known as the Pareto front [31,32].

In this study, NSGA-II is employed as the optimization method. The multi-objective optimization used the NSGA-II algorithm to improve the adaptive fit of the candidate populations using non-dominated sorting and Pareto dominance. The population reproduces and evolves to produce individuals that are more suitable to obtain the optimal solution. The leading parameters for the optimization were the annual energy consumption for heating, annual energy consumption for cooling, and annual discomfort hours. The annual discomfort hours were determined based on the "Time Not Comfortable" metric as defined by the Simple ASHRAE 55-2004 standard in EnergyPlus. The population size was 10, parallel simulations were conducted, and the maximum number of generations was 200. The crossover probability and mutation probability were 100% and 20%, respectively, resulting in a compromise between the computational complexity and accuracy. Table 5 summarizes the NSGA-II initialization parameters.

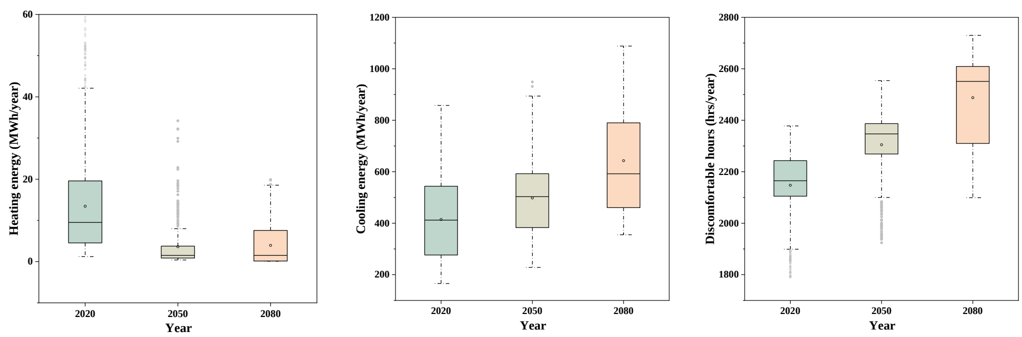
Table 5. Parameter settings of NSGA-II.

Parameter	Value
Population Size	10
Crossover Rate	1.0
Mutation Rate	0.2
Maximum Generation	200

The JEPlus v2.1(Java + EnergyPlus) software was utilized in conjunction with NSGA-II to define the design parameters and outputs, facilitating the identification of decision variables and objective functions relevant to the optimization process.

3. Results and Discussion

Figure 3 presents a comparison of the building energy and comfort metrics under the three weather scenarios. The analysis of the box plots for heating energy, cooling energy, and discomfort hours across different years reveals significant insights into the impact of climate change on the building's energy consumption and occupant comfort. The box plots summarize the results of all 2000 run simulations, highlighting the range and distribution of the outcomes. A discernible trend towards increased cooling energy consumption and discomfort hours, likely due to rising temperatures, underscores the need for climate-responsive building designs and efficient cooling systems. Conversely, the variability in heating energy consumption suggests changing heating requirements, highlighting the importance of adaptable heating solutions. These trends collectively emphasize the critical need for sustainable and resilient architectural practices that prioritize both energy efficiency and occupant comfort in response to evolving climatic conditions.



(**a**) (**b**) (**c**)

Figure 3. Comparation of building energy and comfort metrics under three weather scenarios: (**a**) heating energy (electricity); (**b**) cooling energy (electricity); (**c**) discomfort hours. (Note: ° means the average value).

Figure 4 introduces a parallel coordinate plot (PCP) that illustrates the interrelationships between the different joint configurations in this study. This figure effectively displays the multi-dimensional nature of the dataset, allowing for an examination of how various building parameters interact and influence each other [33]. Each line in the PCP represents a specific joint configuration, while the axes correspond to the different building parameters used in the optimization process. By plotting the data in this manner, it becomes easier to identify patterns and correlations between parameters, as well as to understand the trade-offs involved in the multi-objective optimization. In addition, Figure 5 showcases the three-dimensional Pareto fronts resulting from the Non-Dominated Sorting Genetic Algorithm II (NSGA-II) optimization process, applied across the three distinct weather scenarios. The "best solutions" demarcated in the figure are those that have achieved a Pareto-optimal status, where no other solution is superior in all three objectives simultaneously. These solutions occupy a region of the Pareto front that balances lower energy use with minimized discomfort hours, indicative of optimized building performance. The spread of the solutions along the Pareto front underscores the variability in the performance trade-offs that can be achieved through architectural and control strategy modifications. The density of points near the "best solutions" region suggests that while many configurations can reduce the energy consumption and discomfort hours, only a few do so optimally.

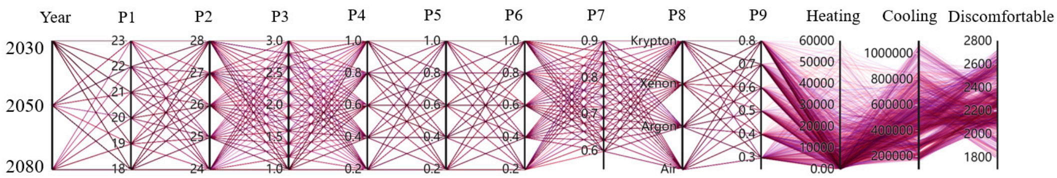


Figure 4. Parallel coordinate plot for different joint configurations.

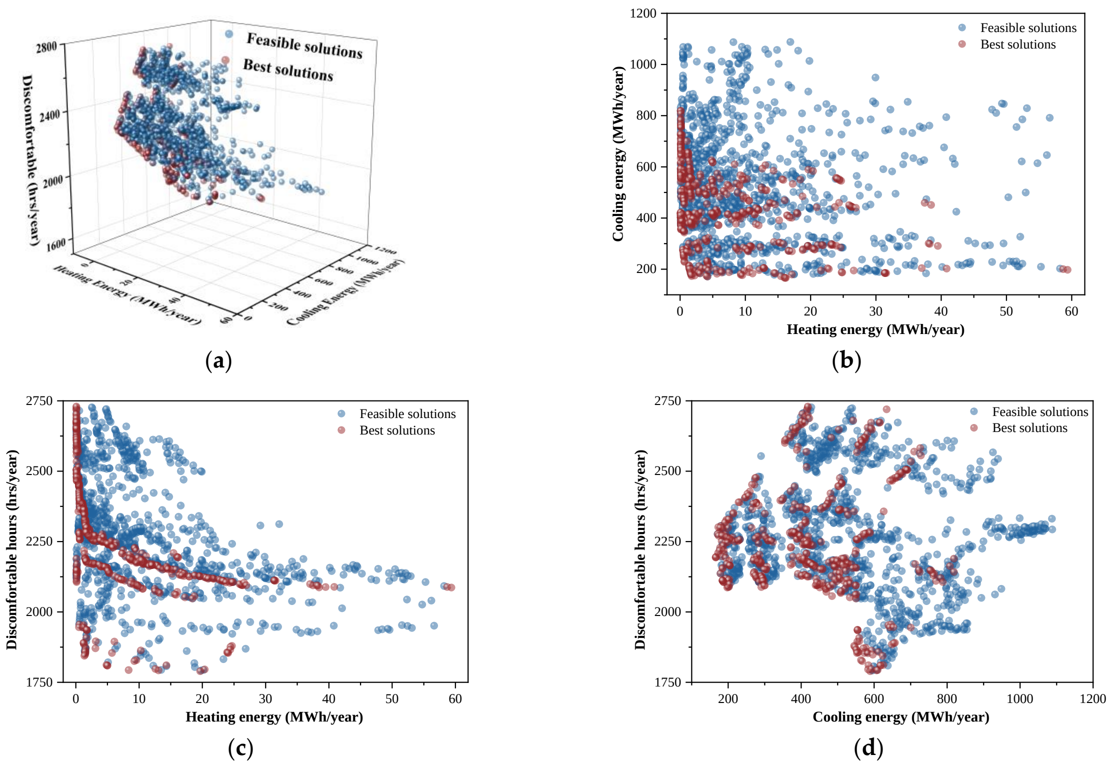


Figure 5. Optimal solutions and three-view projections of the Pareto front: (**a**) 3D View of feasible and best Solutions; (**b**) Cooling Energy vs. Heating Energy; (**c**) Discomfortable Hours vs. Heating Energy; (**d**) Discomfortable Hours vs. Cooling Energy.

To identify the most effective solutions to optimize the building performance, the Weighted Sum Method (WSM) [34,35] is utilized to identify optimal solutions from the three-dimensional Pareto front generated by NSGA-II optimization, enabling a balanced evaluation across multiple objectives. The method evaluates multiple objectives: heating energy (T_1), cooling energy (T_2), and discomfort hours (T_3). Recognizing that heating and cooling energy both pertain to energy consumption, they are combined in the objective function. The formulation of the objective function, denoted as $f_{ws}(x)$, is

$$f_{ws}(x) = a_1\left(\frac{T_1(x)-T_1(x)^{min}}{T_1(x)^{max}-T_1(x)^{min}} + \frac{T_2(x)-T_2(x)^{min}}{T_2(x)^{max}-T_2(x)^{min}}\right) + a_2\left(\frac{T_3(x)-T_3(x)^{min}}{T_3(x)^{max}-T_3(x)^{min}}\right) \tag{1}$$

where $f_{ws}(x)$ is the weighted sum score of the solution x; $T_1(x), T_2(x), T_3(x)$ are the values of heating energy, cooling energy, and discomfort hours for the solution x. $T_1(x)^{min}, T_2(x)^{min}, T_3(x)^{min}$ and $T_1(x)^{max}, T_2(x)^{max}, T_3(x)^{max}$ represent the minimum and maximum values of these objectives across all solutions; a_1 and a_2 are the weights assigned to the objective function.

The weights a_1 and a_2 are assigned to the objective functions as follows:

$$a_1 = a_2 = \frac{1}{2} \tag{2}$$

This adjusted weighting strategy guarantees an equal emphasis on energy consumption (encompassing both heating and cooling energy) and the comfort level (quantified as discomfort hours) in the evaluation of the solutions. This methodological approach ensures a holistic assessment, balancing the imperatives of energy efficiency and occupant comfort. By considering both energy and comfort metrics comprehensively, this approach provides a more integrated view of building performance. Consequently, solutions exhibiting the lowest weighted sum scores are identified as the optimal choices for each specific weather scenario—2020, 2050, and 2080. The detailed outcomes of this analysis are presented in Table 6, where the best solutions under each weather scenario are systematically tabulated, elucidating their efficacy in meeting the stipulated objectives.

Table 6. Ranking of the top three solutions for each weather scenario.

Year	P1	P2	P3	P4	P5	P6	P7	P8	P9	Heating Energy (MWh/year)	Cooling Energy (MWh/year)	Discomfort Hours (h/year)
2020	21	28	1.6	0.4	0.8	0.8	0.63	Krypton	0.8	14,402	184,685	2156
2020	20	28	1.4	0.4	0.6	0.6	0.66	Xenon	0.5	7510	187,935	2220
2020	20	28	1.2	0.4	0.4	0.4	0.63	Krypton	0.7	6373	186,575	2235
2050	18	25	1	0.6	0.6	0.8	0.72	Argon	0.6	578	546,434	1955
2050	18	28	1	1	1	1	0.6	Xenon	0.3	679	228,495	2390
2050	18	28	1	0.4	0.6	0.8	0.6	Xenon	0.7	579	247,468	2407
2080	18	25	1	0.8	0.8	0.8	0.6	Krypton	0.8	132	723,020	2149
2080	18	25	1	0.8	0.8	0.8	0.69	Krypton	0.4	118	769,437	2110
2080	18	28	1	1	0.8	1	0.6	Xenon	0.8	147	355,400	2600

Table 6 reveals significant trends in building design strategies that respond to the changing climatic conditions from 2020 to 2080. A clear trend across all scenarios is the escalating cooling energy consumption from 2020 to 2080. This is primarily driven by rising external temperatures due to climate change. As the temperatures increase, the demand for cooling energy intensifies, reflecting the need for more efficient cooling systems and building designs that can mitigate heat gains. Conversely, the heating energy requirements show a significant reduction over time, with the largest reductions observed in the year 2080. This decrease is a direct result of the warmer external temperatures, reducing the need for heating. The discomfort hours, which indicate the periods when the indoor conditions fall outside the comfort range, generally increase from 2020 to 2080. This trend suggests that maintaining occupant comfort becomes increasingly challenging as the climate warms. The increase in discomfort hours highlights the necessity for adaptive and resilient design strategies to ensure occupant comfort without excessively high energy consumption.

In the 2020 scenario, the heating and cooling setpoints (P1, P2) lean towards higher thresholds for cooling and lower for heating. This indicates a strategy to minimize the reliance on air conditioning and heating systems. By 2080, a shift in focus towards cooling is evident, aligning with the expected rise in average temperatures and the occurrence of heatwaves, demonstrating a strategic response to the anticipated warmer conditions.

The air change rates (P3) across the solutions do not exhibit a uniform trend, suggesting a site-specific or design-specific approach. Higher air change rates enhance the indoor air quality and occupant comfort by allowing more fresh air into the building. However, they can increase the energy consumption as the heating and cooling systems seek to condition the incoming air. Conversely, lower air change rates improve the energy efficiency by reducing the entry of unconditioned air but may lead to poorer indoor air quality due to inadequate ventilation. The variation in the air change rates across the different weather scenarios suggests a need for adaptive building designs. These designs would dynamically adjust the air change rates to optimize both the energy performance and indoor air quality, a crucial consideration in the face of the evolving climatic challenges.

The depth of shading devices for various window orientations (P4, P5, P6) also varies. In the year 2020, moderate depths are commonly selected, implying a strategy to balance the solar gains with natural lighting. For 2050 and 2080, an adaptation to warmer conditions is noticeable with slightly increased depths, particularly for south-facing windows, to mitigate the increased solar gains expected from more intense and frequent heat events.

The window solar transmittance (P7) is a critical parameter in building design, influencing both the energy consumption and indoor comfort levels. Solar transmittance refers to the fraction of solar radiation that passes through a window. Higher solar transmittance allows more sunlight and heat to enter the building, which can be beneficial in colder climates by reducing the heating demands. However, in warmer conditions, this can lead to increased cooling loads and occupant discomfort. Therefore, balancing the solar transmittance with advanced shading and glazing technologies is crucial in optimizing the energy efficiency and comfort in future-proof building designs. Considering the significantly higher cooling loads observed in the simulations, the effective management of the solar transmittance becomes even more important to mitigate the impact on the energy consumption and maintain thermal comfort.

In assessing the thermal insulation efficiency of window gases (P8) for the years 2020 and 2050, Xenon stands out as the most effective, followed by Krypton. This is largely attributed to Xenon's higher density and lower thermal conductivity, which considerably diminishes heat transfer through windows. However, the situation changes in 2080. Using air, which has weaker insulating properties, surprisingly results in the lowest cooling energy consumption, although the heating energy requirement is slightly higher compared to Krypton and Xenon. This shift can be explained by the increased solar radiation in 2080, significantly affecting the indoor temperatures. Windows, especially those facing direct sunlight, may absorb substantial solar heat. The strong insulating properties of Krypton and Xenon could lead to the accumulation of this heat indoors, necessitating greater cooling energy to maintain comfortable temperatures. Interestingly, the number of discomfort hours is nearly identical across all three gases, suggesting that the type of gas used has a minimal effect on the overall comfort level inside the building in terms of temperature regulation.

The wall solar absorptance (P9) is a critical parameter in building design, as it affects both the energy consumption and indoor comfort levels. The solar absorptance of a wall refers to the fraction of solar radiation that is absorbed by the wall's surface. Higher absorptance values mean that more solar energy is absorbed, which can contribute to higher indoor temperatures and potentially increase the cooling loads. Conversely, lower absorptance values reflect more solar energy, which can reduce the cooling demands but may increase the heating needs in colder conditions. In this study, the optimal value for wall solar absorptance (P9) is not fixed across the top solutions for each weather scenario. This variability suggests that different combinations of the parameters, including the wall solar absorptance, can achieve the best overall performance in terms of energy consumption and occupant comfort. For instance, a higher absorptance value might be beneficial when paired with other parameters that enhance the cooling efficiency or reduce the direct solar gain, while a lower absorptance value could be optimal in scenarios where the heating efficiency is prioritized.

Figure 6 illustrates a comparison of the optimization solutions with the baseline building. In the 2020 scenario, the optimization solutions achieve a reduction in heating energy of approximately 0.56% to 56.01% and in cooling energy of 62.92% to 63.56% compared to the baseline building. This significant decrease in both heating and cooling energy consumption demonstrates the effectiveness of the adopted optimization strategies. Additionally, the discomfort hours show a minor reduction in the best-case scenario, indicating that the improvements in energy efficiency do not come at the cost of occupant comfort. For the 2050 scenario, the optimization solutions reduce the heating energy consumption by 90.84% to 92.19% and the cooling energy consumption by 13.29% to 63.74%. These results highlight the substantial energy savings achievable with the optimization solutions. However, the discomfort hours vary, with a reduction of 15.15% in one scenario and slight increases of up to 4.46% in others, suggesting that while the energy efficiency is greatly enhanced, some scenarios might require additional measures to maintain or improve the occupants' thermal comfort. In the 2080 scenario, the optimization solutions show a dramatic reduction in heating energy consumption of 94.19% to 95.34% and a cooling energy consumption reduction of 4.11% to 55.72%. The discomfort hours generally decrease, with reductions of up to 17.78%, although one scenario shows a slight increase of 1.32%. These findings underscore the long-term benefits of the optimization strategies in terms of energy savings and enhanced occupant thermal comfort.

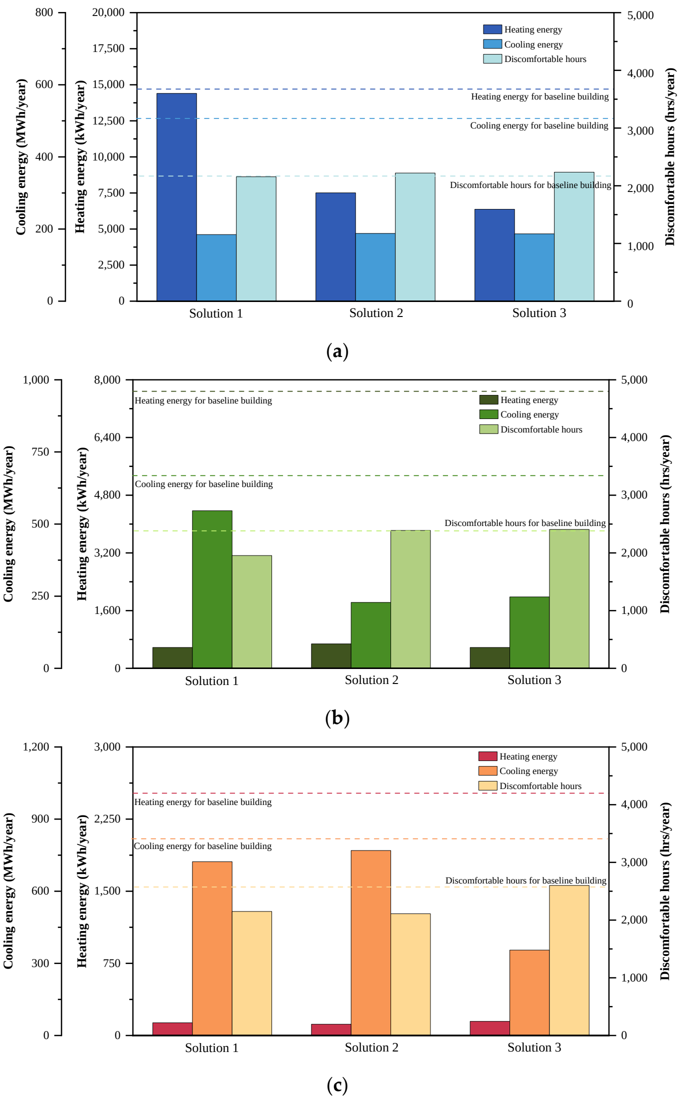


Figure 6. Comparison of top three optimization solutions for each weather scenario (refer to Table 6) with baseline building: (**a**) year 2020; (**b**) year 2050; (**c**) year 2080.

This comparative analysis reveals that the optimization solutions significantly reduce the overall energy consumption across various scenarios while maintaining occupant comfort at levels comparable to the baseline scenario. These outcomes not only underscore the effectiveness of the research methodology and the optimization strategies employed but also highlight their ability to address the challenges posed by climate change. In some instances, a slight increase in discomfort hours is observed, representing a judicious compromise given the notable energy savings achieved. This balance between energy efficiency and occupant comfort is critical in the realm of sustainable and resilient architectural practices.

In conclusion, the solutions from the study showcase a strategic and nuanced selection of building parameters, indicative of a trend towards tailored building designs that dynamically respond to the environmental conditions and occupant needs. The use of high-performance materials such as Krypton and Xenon in windows, coupled with a deliberate approach to shading device deployment, emphasizes the focus on thermal management and energy efficiency. These findings demonstrate the potential of sustainable building practices in creating environments that are both energy-efficient and comfortable, underlining the importance of harmonizing these aspects in the face of the evolving climatic challenges.

4. Conclusions

This study demonstrates the significant potential of multi-objective optimization strategies in reducing energy consumption and enhancing occupant comfort in educational buildings under future climate scenarios. The optimization solutions achieved substantial reductions in both heating and cooling energy consumption while maintaining or slightly improving the comfort levels. Specifically, compared to the baseline building, in the 2020 scenario, the heating energy was reduced by approximately 0.56% to 56.01%, and the cooling energy was reduced by 62.92% to 63.56%. In the 2050 scenario, the heating energy consumption was reduced by 90.84% to 92.19%, and the cooling energy consumption by 13.29% to 63.74%. For the 2080 scenario, the heating energy consumption showed a dramatic reduction of 94.19% to 95.34%, and the cooling energy consumption decreased by 4.11% to 55.72%. These results highlight the substantial energy savings achievable with the optimization solutions. The discomfort hours generally decreased, with reductions of up to 17.78%, indicating a balanced approach to energy efficiency and occupant comfort.

However, the study had several limitations. The optimization solutions were based on specific climate scenarios and building parameters, which may not account for all possible future conditions or variations in building use. Additionally, the simulations assumed ideal HVAC system performance, which may not fully represent real-world operational inefficiencies.

Looking ahead, integrating building-specific energy performance data into a City Information Model (CIM) framework can enhance urban planning and development. This study provides valuable insights into the energy dynamics at the building level, crucial for informed decision-making in urban development and sustainability strategies. Future research should focus on validating the optimization solutions with real-world data, exploring the impact of operational inefficiencies, and expanding the analysis to other building types and climate scenarios.

Author Contributions: Conceptualization, Y.M. and Y.T.; funding acquisition, Y.C. and Y.T.; investigation, Z.C.; writing—original draft, Y.M. and Y.T.; writing—review and editing, Y.M., Z.C., Y.C. and Y.T. All authors have read and agreed to the published version of the manuscript.

Funding: This study was funded by the National Key Research and Development Program of China, (No. 2022YFC3800600), the National Natural Science Foundation of China (No. 52108018), and the Shenzhen Science and Technology Program (No. 20231122115018001 and No. ZDSYS20210623101534001).

Data Availability Statement: The data presented in this study are available on request from the corresponding author.

Acknowledgments: The authors would like to acknowledge the support of the Center for Human-Oriented Environment and Sustainable Design, Shenzhen University.

Conflicts of Interest: The authors declare no conflicts of interest.

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