

Passive Shading Optimization for University Buildings in Southwest China: A Simulation-Based Transferability Assessment with Heatwave Stress Testing

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Abstract: This study examines the transferability of a passive shading optimization approach under extreme-heat conditions in Southwest China. A university-building prototype serves as the geometric reference, and its envelope and operation settings are then adapted for Chengdu and Chongqing in accordance with the relevant building standards. The workflow combines weather-data preprocessing, a simplified overhang-based shading representation, dynamic thermal-response calculation, and differential-evolution-based parameter search. To separate routine and extreme-condition performance, the analysis was organized into three parts: an annual benchmark under typical meteorological year (TMY) conditions, a 2023 extreme-summer scenario comparison, and a Monte Carlo robustness analysis. Under the Southwest China cases, the optimized scheme reduced cooling energy use by approximately 43–45% and peak load by more than 50% in the reported scenarios. The Orlando reference scenario showed a smaller improvement, indicating that the performance gain depended strongly on climate context and baseline envelope characteristics. The Monte Carlo analysis further showed that the optimized scheme remained superior to the baseline across the sampled perturbation cases, with lower-tail energy-saving performance remaining above 40%. The retained annual, extreme-summer, and perturbation results all point in the same direction: the workflow is more useful as a comparative stress-testing tool than as a substitute for measured building validation. The study does not claim full real-world validation: the weather-adjustment procedure is treated as a scenario-construction assumption, and the simplified shading model does not fully represent façade-specific projection geometry.

Keywords: passive shading; dynamic thermal model; extreme-summer stress test; Monte Carlo robustness; scenario-based weather adjustment

1. Introduction

Net-zero-energy campus buildings show how building design can contribute to climate-change mitigation and carbon-neutrality goals [1]. As climate conditions become less stable, however, energy-saving measures may



not perform equally well across different climate zones. This makes it necessary to test whether building-optimization methods remain effective under both local and extreme climate

The problem becomes more acute in Southwest China, where extreme heatwaves have become increasingly frequent. During June–August 2023, the Sichuan-Chongqing region experienced record-breaking temperatures exceeding 40 °C for multiple consecutive days, with peak values reaching 42 °C in Chongqing and 40 °C in Chengdu. These events occurred under high-humidity conditions (average relative humidity of $58 \pm 7\%$ during peak hours), creating a combined “high-temperature-high-humidity” stress environment that challenges predictions of building energy performance.

The meteorological data used in this study are derived from the NASA POWER reanalysis platform (v2.0) at $1^\circ \times 1^\circ$ resolution for Chongqing (29.56° N, 106.55° E) and Chengdu (30.57° N, 104.07° E). These datasets provide hourly temperature and humidity records during the 2023 heatwave period, enabling accurate simulation of real-world extreme conditions. Temperature thresholds were compared against official reports from the China Meteorological Administration (CMA), with the stress-test thresholds in the present study set to 42.0 °C for Chongqing and 40.0 °C for Chengdu.

Passive shading is a standard strategy to reduce solar heat gain and cooling demand. Building optimization methods have been extensively studied. But when these methods are employed for extreme heat conditions in Southwest China, there are three main gaps.

Many existing studies still rely on typical meteorological year (TMY) data when assessing building performance. Although such data provide a useful basis for routine annual comparisons, they do not reproduce the chronology of a specific record-breaking event. The present study therefore evaluates the optimized scheme under both typical-year reference conditions and the 2023 extreme-summer scenarios for Chengdu and Chongqing.

Another unresolved issue concerns the climate boundary conditions of shading models. Current studies have not clearly determined whether a shading optimization model can or cannot be used under extreme heatwave conditions. This is a critical concern for the climate of Southwest China. In this region, summers are hot and humid, and winters are cold and damp. Because of this seasonal conflict, conventional fixed shading systems might not meet requirements year-round [2].

Practical implementation has received less attention than performance under fixed benchmark conditions, which still forms the basis of many shading studies. In actual buildings, however, deviations in shading depth, glazing SHGC, and envelope thermal properties may alter the simulated response, and installation deviation particularly during extreme summer conditions. The robustness analysis addresses this issue by perturbing these parameters to determine whether the optimized scheme retains its advantage over the baseline when parameter variability is introduced.

In response to these issues, the present study is framed as an extension of a conceptual passive-shading building prototype into a simulation-based transferability assessment for Southwest China. The university-building prototype is used as the geometric reference, after which weather adaptation, extreme-summer scenario comparison, and robustness analysis are introduced for the Southwest China cases. The analysis is reported in three parts: an annual benchmark under TMY conditions, a comparison under the 2023 extreme-summer scenario, and a perturbation-based robustness analysis. This structure is intended to clarify what the model can and cannot show, and under which climate and data assumptions the reported results should be interpreted.

The main contributions of this study are as follows:

- (1) A simulation-based extension of a conceptual passive-shading framework is developed to examine how a reference university-building prototype performs when adapted to hot-humid conditions in Southwest China, with separate evaluation under typical-year reference and 2023 extreme-summer scenarios.
- (2) The modeling procedure is organized into explicit stages, including weather-data preparation, shading-geometry calculation, dynamic thermal-response analysis, and differential-evolution-based parameter search, so that the assumptions, inputs, and output indicators can be reported more transparently.
- (3) The study evaluates the stability of the optimized scheme under parameter perturbations. It clarifies the limits of the present framework, especially the use of scenario-based weather adjustment and a simplified overhang-based shading representation.

2. Materials and Methods

A self-developed dynamic thermal model built around physical heat-balance relationships is used here to assess the proposed shading strategy. The model was used for comparative scenario analysis rather than direct replication of measured utility data. The geometric reference case follows the conceptual setting of a two-story

university academic building prototype, with the principal geometric characteristics and baseline envelope assumptions summarized in Table 1.

Table 1. Principal Baseline Assumptions and Model Inputs.

Parameter	Value	Source
Stories	2	—
Wall U-value	0.45 W/(m ² ·K)	GB 50176-2016 [3]
Roof U-value	0.35 W/(m ² ·K)	GB 50176-2016 [3]
Window U-value	2.8 W/(m ² ·K)	ASHRAE 90.1-2019 [4]
Baseline glazing SHGC	0.75	ASHRAE 90.1-2019 [4]
Improved glazing SHGC	0.45	ASHRAE 90.1-2019 [4]
South facade window-to-wall ratio	45%	ASHRAE Handbook—Fundamentals [5]
Other facade window-to-wall ratio	30%	ASHRAE Handbook—Fundamentals [5]
Lighting	5 W/m ²	ASHRAE Handbook—HVAC Applications [6]
Equipment	8 W/m ²	DOE Reference Building [7]
Cooling setpoint	24 °C	ASHRAE Standard 55 [8]
Natural ventilation	Operable windows (>28 °C)	GB 50736-2012 [9]
Infiltration	0.5 ACH	ASHRAE Handbook—Fundamentals [5]

The principal reproducible contribution of the present study lies in the Southwest China cases, for which the weather inputs, parameter settings, and processing steps can be documented explicitly. The Orlando case is retained mainly as a reference benchmark context for cross-scenario comparison rather than as the principal source of reproducible evidence.

Figure 1 summarizes the workflow used to connect building geometry, envelope assumptions, hourly weather data, and the subsequent optimization and robustness analysis. Hourly weather data are then prepared for the Orlando reference scenario and the Southwest China stress-test scenarios, after which solar geometry, facade radiation, and overhang occlusion are calculated. The resulting gains and exchanges are coupled within the dynamic thermal model, and the shading variables are finally evaluated through differential evolution under annual benchmark, heatwave-window, and perturbation conditions.

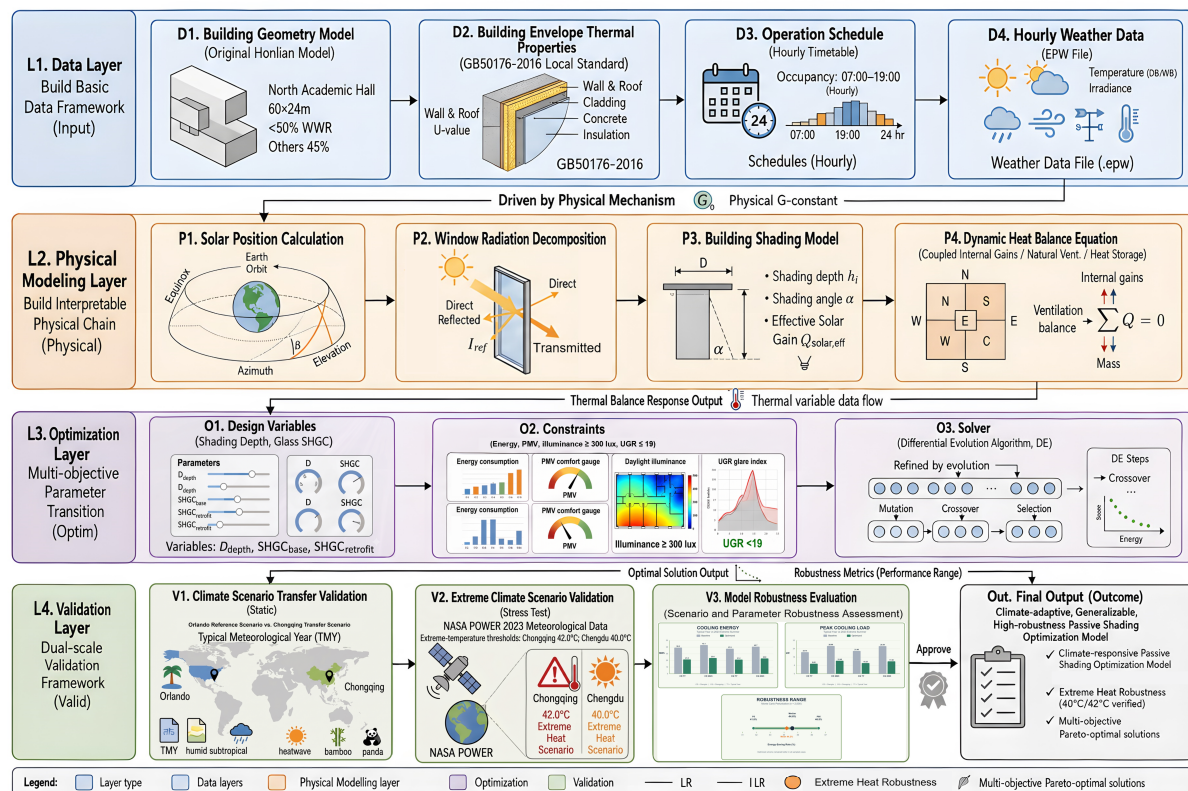


Figure 1. Computational workflow of the self-developed passive shading assessment model.

2.1. Study Design and Computational Workflow

The study was organized as a simulation-based comparative workflow built on a fixed conceptual university-building prototype. This prototype was used across all scenarios so that the effects of climate inputs, shading configurations, and envelope settings could be compared on a consistent geometric basis. Within this workflow, the principal reproducible extension of the study lies in the Southwest China weather processing, extreme-summer scenario construction, and robustness-assessment stages. The workflow proceeded as follows. (1) The building geometry, facade window-to-wall ratios, envelope thermal properties, and internal-load assumptions were defined. (2) Hourly weather data were prepared for the Orlando reference scenario and the Southwest China stress-test scenarios. (3) Hourly solar geometry and facade radiation were calculated, and a simplified overhang-based shading representation was used to estimate the reduction in incident solar gain at the window surface. (4) The resulting solar gains, internal gains, ventilation heat exchange, and conductive heat transfer were coupled within a dynamic thermal-response model to estimate hourly cooling demand and indoor thermal response. (5) The shading variables were optimized by differential evolution, and the resulting design was evaluated under annual benchmark, heatwave-window stress-test, and Monte Carlo perturbation scenarios.

Figure 2 illustrates the geometric basis of the simplified overhang-based shading model used in this study. Under high summer solar altitude, the overhang blocks a larger proportion of direct solar radiation incident on the south-facing window. In contrast, under lower winter solar altitude, a greater portion of solar radiation can still enter the window. This simplified geometric relationship provides the basis for the hourly shading-occlusion calculation described in the subsequent section.

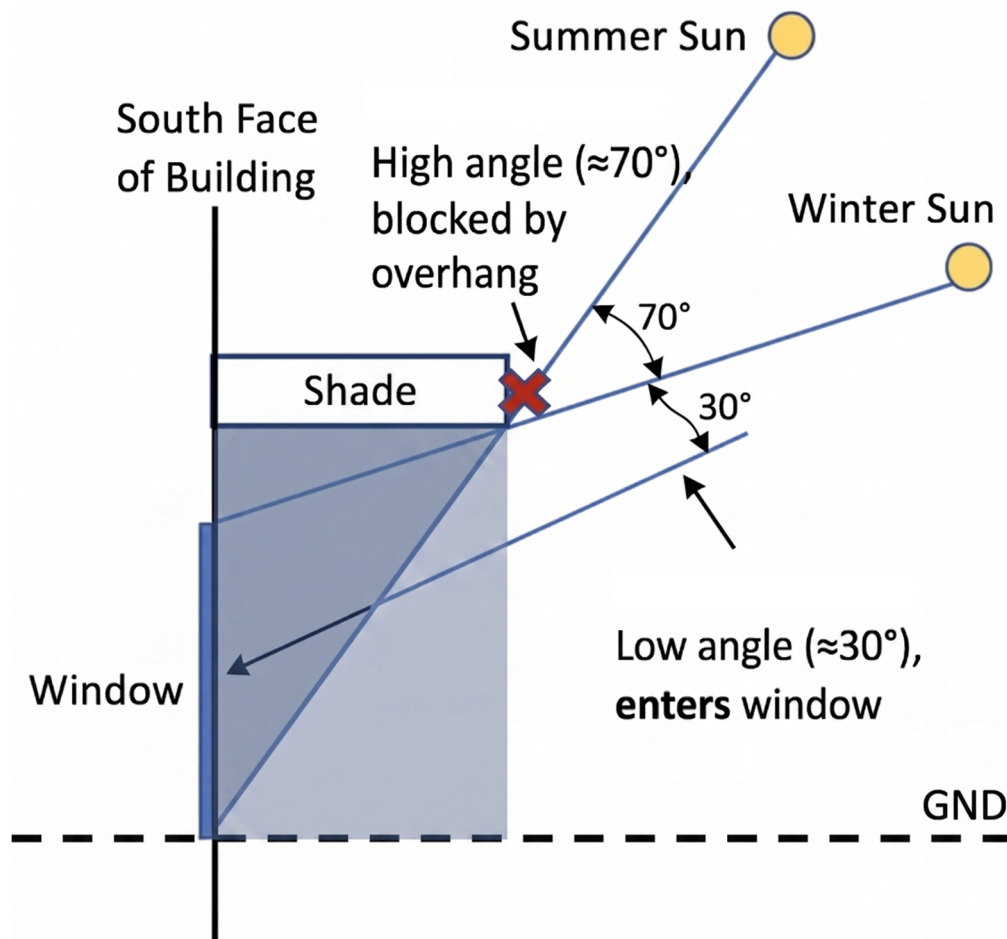


Figure 2. Passive Solar Shading Principle: Winter and Summer Sun Angles on Solstices.

2.2. Selection and Processing of Extreme-Event Data Sources

Multiple weather datasets were combined to define the climatic boundary conditions used in this analysis. The Orlando dataset was retained as the reference weather context associated with the original conceptual prototype, whereas the Southwest China datasets constitute the main climate-specific extension developed in the present study. For Chengdu and Chongqing, the typical-year reference scenario was constructed from the hourly

mean of NASA POWER records over 2014–2022, with leap-day entries excluded, whereas the 2023 records were used to represent the extreme-summer scenario.

To construct the extreme-summer stress-test scenario, the hourly temperature series was proportionally adjusted so that the maximum daily temperature reached the thresholds defined for Chengdu and Chongqing. The adjustment was used only to create a severe-heat test condition and was not intended to calibrate the NASA POWER dataset or reconstruct the observed weather event.

2.3. Solar Radiation Calculation Module

Solar-radiation inputs were derived from the hourly weather datasets described in Section 2.2. The total solar radiation incident on each window surface was calculated using standard solar geometry and irradiance-component decomposition methods for direct, diffuse, and tilted-surface radiation [10]:

$$\delta = 23.45^\circ \times \sin \left[\frac{360^\circ}{365} \times (284 + n) \right] \quad (1)$$

$$\omega = 15^\circ \times (LT - 12) \quad (2)$$

$$\sin \alpha_s = \sin \phi \times \sin \delta + \cos \phi \times \cos \delta \times \cos \omega \quad (3)$$

where n is the day of the year, LT is local solar time (h), and ϕ is the latitude of the corresponding scenario location. Based on these geometric variables, the total radiation incident on the window surface, I_{total} was decomposed into direct radiation, diffuse radiation, and ground-reflected radiation, as expressed in Equations (4) and (5).

$$I_{\text{total}} = I_{\text{dir}} \times \cos \theta + I_{\text{diff}} \times F_{\text{sky}} + I_{\text{ref}} \times F_{\text{ground}} \quad (4)$$

$$F_{\text{ground}} = (\rho/\pi) \times \left[\frac{1}{\cos \alpha_s} - 1 \right] \quad (5)$$

where I_{dir} , I_{diff} , and I_{ref} are the instantaneous radiation intensities (W/m^2); θ is the incidence angle between the solar beam and the normal direction of the window surface (degrees); F_{sky} is set to 0.85 based on typical campus layouts in Southwest China; and F_{ground} is calculated using Equation (5), with $\rho = 0.25$ as the ground albedo for typical campus environments (e.g., asphalt and concrete).

2.4. Shading Geometric Occlusion Module

Shading performance changes nonlinearly with solar altitude. In the present model, overhang depth is used to estimate the reduction in direct solar gain at the window surface. The comparative retrofit cases are summarized in Table 2.

Table 2. Definition of the comparative retrofit cases.

Case	SHGC	Overhang Depth L (m)	Description
Baseline	0.75	0.5	Original configuration
Scheme A	0.45	0.5	Glazing improvement only
Scheme B	0.75	1.2	Overhang adjustment only
Scheme C	0.45	1.8	Combined retrofit

These cases were defined to distinguish the effects of changes in glazing and overhang, and their combined application. The normalized occlusion ratio η was calculated as:

$$\eta = \min \left(1, \max \left(0, \frac{h_{\text{shadow}}}{H} \right) \right) \quad (6)$$

$$h_{\text{shadow}} = L \cdot \tan \alpha_s \quad (7)$$

Here H denotes the window height. $\eta = 0$ indicates no occlusion, whereas $\eta = 1$ indicates full occlusion. The ratio is restricted to the interval $[0, 1]$ to avoid nonphysical values. The effective solar heat gain after shading is:

$$I_{\text{eff}} = I_{\text{total}} \times (1 - \eta) \times \text{SHGC} \quad (8)$$

Figure 3 shows the difference between the baseline and optimized overhang settings used in the present analysis. It is included only to clarify the relative shading depth and its effect on solar obstruction. In the present study, the simplified shading representation is used primarily to examine the effect of overhang depth on the reference window configuration rather than to reproduce a full multi-façade geometric optimization.

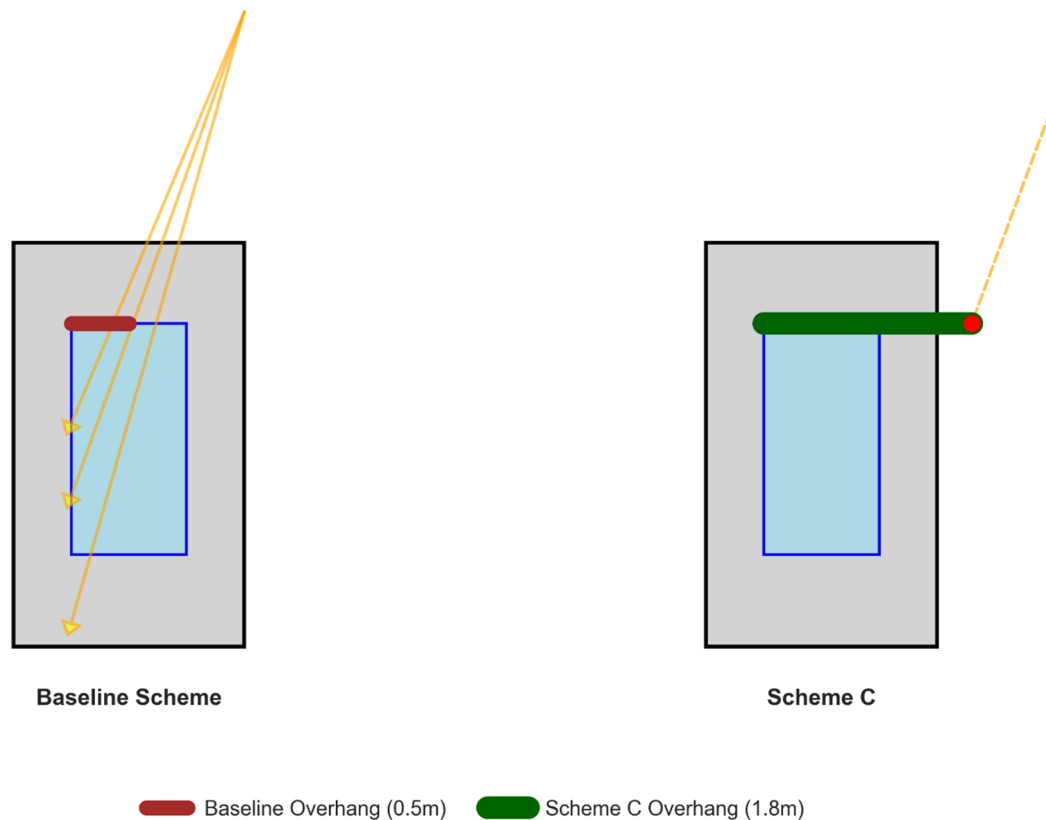


Figure 3. Schematic comparison of the baseline and optimized overhang configurations used in the shading-occlusion analysis.

2.5. Building a Dynamic Thermal Model

Before the final scenario comparisons were performed, one-factor screening experiments were used to examine the sensitivity of cooling and total energy demand to whole-building and south-facing WWR and SHGC settings. These scans were used to guide the choice of feasible search intervals rather than to define the final optimized scheme directly.

The study building follows the conceptual setting of the North Academic Hall prototype at Sungrove University (60 m × 24 m). Table 3 summarizes the parameter ranges used in the subsequent analysis. These ranges were defined based on the original conceptual framework and adapted to the university-building context of the Sichuan–Chongqing region.

Thermal response was calculated with a self-developed dynamic heat-balance model. The building was divided into five thermal zones, and the heat-balance equation for each zone included effective solar heat gain, internal gains, ventilation heat exchange, conductive heat transfer, and cooling removal, as expressed in Equation (9).

Table 3. Experimental parameter ranges for parametric studies.

Parameter	Range (Step)	Unit	Experiment ID
Window-to-wall ratio (WWR)	0.30–0.70 (0.10)	-	exp1
Solar heat gain coefficient (SHGC)	0.20–0.50 (0.05)	-	exp2
South-facing WWR	0.40–0.80 (0.10)	-	exp3
South-facing SHGC	0.20–0.40 (0.05)	-	exp4

$$C_i \frac{dT_i}{dt} = Q_{\text{solar},i} + Q_{\text{int},i} + Q_{\text{vent},i} + Q_{\text{cond},i} + Q_{\text{HVAC},i} \quad (9)$$

where C_i is the equivalent thermal capacitance of the thermal zone (J/K), T_i is the indoor air temperature of the thermal zone ($^{\circ}\text{C}$), $Q_{\text{solar},i}$ is the effective solar heat gain calculated using Equation (8), $Q_{\text{int},i}$ is the internal heat gain assigned according to the typical academic-building schedule in Southwest China, and $Q_{\text{vent},i}$ is the heat exchange due to natural ventilation (W).

$$Q_{\text{vent},i} = \rho_a \times c_p \times V_{\text{vent}}(T_{\text{out}} - T_i) \quad (10)$$

where $\rho_a = 1.2 \text{ kg/m}^3$ is the standard air density, $c_p = 1005 \text{ J/(kg} \cdot \text{K)}$ is the specific heat capacity of air, $T_i = 24 \text{ }^{\circ}\text{C}$ is the occupied-period cooling setpoint, T_{out} is the outdoor dry-bulb temperature ($^{\circ}\text{C}$) and V_{vent} is the dynamic ventilation rate (m^3/s).

The model adopted simplified operational control rules under hot-weather conditions. When the outdoor temperature exceeded $32 \text{ }^{\circ}\text{C}$, the ventilation rate was reduced to 30% of its baseline to limit hot-air intrusion. The baseline ventilation rate was calculated as follows:

$$V_{\text{vent}} = \begin{cases} 2.0 \times C_d A_{\text{open}} \sqrt{\frac{2\Delta P}{\rho}} & \text{if } T_{\text{out}} \leq 28 \text{ }^{\circ}\text{C} \\ 0.3 \times C_d A_{\text{open}} \sqrt{\frac{2\Delta P}{\rho}} & \text{if } T_{\text{out}} > 32 \text{ }^{\circ}\text{C} \\ C_d A_{\text{open}} \sqrt{\frac{2\Delta P}{\rho}} & \text{otherwise} \end{cases} \quad (11)$$

where ΔP is the total pressure difference jointly induced by wind pressure and thermal pressure (Pa):

$$\Delta P = \Delta P_{\text{wind}} + \Delta P_{\text{thermal}} \quad (12)$$

$$\Delta P_{\text{wind}} = 0.5 \rho_a v_{\text{ref}}^2 C_p \quad (13)$$

$$\Delta P_{\text{thermal}} = \rho_a g h_{\text{ref}} \frac{T_i - T_{\text{out}}}{T_i} \quad (14)$$

2.6. Optimization Objectives, Constraints, and Retrofit Scheme

In energy-related optimization, differential evolution is commonly applied to problems with nonlinear behavior and continuous design variables [11]. In the present study, it was adopted to search for low-energy shading configurations under thermal and visual constraints.

The optimization problem was formulated around heatwave-period performance during the 2023 Sichuan-Chongqing extreme-summer event, with the aim of reducing cooling energy demand while maintaining thermal and visual performance constraints.

$$\min[\alpha E_{\text{cool}}^{\text{extreme}} + \beta(H^{\text{over}}) + \gamma(G^{\text{glare}})] \quad (15)$$

where $E_{\text{cool}}^{\text{extreme}} = \sum_{t \in T_{\text{heatwave}}} E_{\text{cool},t}$ is the total cooling energy consumption during heatwave periods, T_{heatwave} is within the 2023 Sichuan-Chongqing heatwave events: 116 h for Chengdu, 51 h for Chongqing, H^{over} is the number of indoor temperature exceedance hours ($T_{\text{in}} > 28 \text{ }^{\circ}\text{C}$) during T_{heatwave} , G^{glare} is the glare exceedance index evaluated during T_{heatwave} . The weighting coefficients α , β , and γ were selected to reflect the relative importance of cooling demand, thermal exceedance, and glare control, with reference to ISO 7730 and CIE 117. The constraints are uniformly constructed as:

$$\begin{cases} H^{\text{over}}(T_{\text{in}} > 28 \text{ }^{\circ}\text{C}) \leq 15\% \times |T_{\text{heatwave}}| \\ D^{\text{daylight}} \geq 80\% \\ \text{UGR} \leq 19 \end{cases} \quad (16)$$

where:

H^{over} is the cumulative number of hours during T_{heatwave} when $T_{\text{in}} > 28 \text{ }^{\circ}\text{C}$;

D^{daylight} is the temporal proportion during the daytime heatwave period, from 8:00 to 18:00, when the work-plane illuminance is $\geq 300 \text{ lux}$;

UGR is the unified glare rating (CIE 117-1995), with the calculation period limited to 10:00–15:00, corresponding to the peak solar radiation period.

Unless otherwise stated, the optimization objective defined in this subsection is evaluated over the selected 2023 heatwave window. Annual benchmark metrics are reported separately for reference comparison and are not part of the heatwave-period optimization objective. The annual scenario comparisons reported later in Section 3.2 should therefore be interpreted as post-optimization assessment results rather than as direct outputs of the heatwave-window objective function.

To improve reproducibility, the retained workflow logic, parameter-screening structure, design-variable ranges, scenario definitions, and robustness-analysis settings are summarized explicitly in Algorithm 1 and Tables 4 and 5. Some implementation-specific solver settings from the original conceptual model were not fully archived and are therefore not reported here as exact recovered values. The revised manuscript therefore emphasizes the reproducibility of the workflow structure and scenario-processing logic rather than claiming complete recovery of all solver-level implementation details.

Algorithm 1. Climate-responsive passive shading optimization framework

Input: climate data C , building geometry G , envelope parameters E , design-variable bounds B , population size N , and maximum generations $G_{\max}$.

Output: optimal retrofit scheme P^* and performance indicators R^* .

1: Preprocess the climate input C by handling missing values, screening abnormal values, and separating solar radiation into its principal components.

2: Initialize population P_0 within bounds $B = \{L, SHGC\}$.

3: **For** generation $g = 1$ **to** $G_{\max}$ **do**

4: **For** each candidate p in P_g **do**

5: Calculate facade solar radiation and shading occlusion ratio η .

6: Compute effective solar heat gain $Q_{solar,eff}$.

7: Run the five-zone dynamic thermal model.

8: Evaluate heatwave-period cooling energy, indoor-temperature exceedance, daylight, and glare constraints.

9: **End For**

10: Generate offspring using differential mutation and crossover.

11: Select feasible low-energy candidates to form P_{g+1} .

12: **End For**

13: Identify the optimal scheme P^* from the final population.

14: Assess P^* under the annual benchmark, the 2023 heatwave stress-test, and Monte Carlo perturbation scenarios, and return R^* .

Table 4. Optimization settings and robustness-assessment parameters.

Variable	Symbol	Search Range/Value
Overhang depth	L	0–3.0 m
Search step for sensitivity	ΔL	0.1 m
Baseline SHGC	SHGCbase	0.75
High-performance glazing SHGC	SHGCOpt	0.45
Envelope U-value uncertainty	U	$\mu = 2.0 \text{ W/m}^2\cdot\text{K}$, $\sigma = 0.2 \text{ W/m}^2\cdot\text{K}$
SHGC uncertainty	SHGC	$\mu = 0.45$, $\sigma = 0.04$
Overhang-depth uncertainty	L	$\mu = 1.8 \text{ m}$, $\sigma = 0.15 \text{ m}$
Monte Carlo samples	M	2000
Assessment scenarios	—	Chengdu 2023 heatwave (116 h) Chongqing 2023 heatwave (51 h) annual benchmark (TMY) Monte Carlo perturbation

Table 5. Retained implementation settings and reproducibility information.

Item	Description
Geometric reference case	Conceptual university academic building prototype derived from the original Sungrove problem setting
Weather data source (Southwest China)	NASA POWER hourly datasets for Chengdu and Chongqing
Typical-year reference construction	Hourly mean of NASA POWER records over 2014–2022, with leap-day entries excluded

Table 5. *Cont.*

Item	Description
Extreme-summer scenario	2023 NASA POWER weather records, with stress-test temperature adjustment applied
Solar-radiation inputs	GHI, DNI, DHI, air temperature, humidity, pressure, wind speed, and wind direction
Thermal model	Self-developed dynamic heat-balance model with five thermal zones
Optimization variables	Overhang depth and glazing SHGC
Optimization objective	Heatwave-period cooling-energy minimization with thermal and visual constraints
Monte Carlo sample size	2000
Monte Carlo random seed	20260526
Monte Carlo perturbation variables	Overhang depth, glazing SHGC, envelope thermal transmittance
Retained implementation limits	Some implementation-specific solver settings from the original conceptual model were not fully archived

2.7. Weather-Data Adjustment and Extreme-Summer Stress-Test Scenario Construction

A simplified climate-morphing procedure was applied to the NASA POWER hourly weather sequences in order to construct extreme-summer stress-test scenarios for Southwest China, which form one of the main methodological extensions of the present study. The purpose of this procedure was not to reconstruct station observations but to generate a scenario that reflects historically reported peak temperature levels during compound extreme-heat events. The corrected temperature sequence was calculated as:

$$T_{\text{extreme}} = T_{\text{power}} \times \frac{T_{\text{historical,max}}}{T_{\text{POWER,historical,max}}} \quad (17)$$

where T_{extreme} is the corrected temperature sequence (°C), T_{power} is the original temperature from NASA POWER data (°C), $T_{\text{historical,max}}$ is the historically reported extreme temperature used as the stress-test reference, namely 42.0 °C for Chongqing and 40.0 °C for Chengdu, from the Blue Book on Climate Change in China (2023), $T_{\text{POWER,historical,max}}$ is the corresponding multi-year historical maximum temperature at the relevant station in the NASA POWER data, namely 38.2 °C for the Chongqing station and 36.5 °C for the Chengdu station. For scenario-construction purposes, the same scaling factor was also applied to relative humidity, solar radiation, and wind speed.

This treatment should be interpreted as a synchronized perturbation used to construct a compound extreme-heat scenario rather than as a full physical reconstruction of observed meteorological coupling. The resulting adjusted dataset, with the scenario-construction parameters summarized in Table 6, was then used to evaluate the performance and robustness of the optimized shading design under extreme-summer conditions.

Table 6. Summary of the extreme-summer scenario construction for Chengdu and Chongqing.

City	NASA POWER Historical Maximum (°C)	Stress-Test Reference Threshold (°C)	Adjustment Purpose
Chengdu	36.5	40.0	Constructed extreme-summer stress-test scenario
Chongqing	38.2	42.0	Constructed extreme-summer stress-test scenario

The purpose of this adjustment is not to reproduce observed station records exactly, but to generate a bounded extreme-summer stress-test scenario in which the temperature threshold matches historically reported peak conditions while the remaining variables are adjusted in a synchronized exploratory manner.

The principal conclusions were interpreted with caution because the synchronized adjustment of humidity, radiation, and wind speed was used only to construct a compound stress-test scenario, not to infer exact physical coupling at the station level.

3. Results

3.1. Archived Annual Benchmark and Selected-Week Illustration under the Orlando Reference Scenario

Archived annual benchmark results were retained for the baseline scheme and Scheme A under the Orlando reference scenario. The baseline scheme recorded an annual cooling energy consumption of 38,823 kWh, a total energy consumption of 38,992 kWh, and 751 comfort hours. Scheme A reduced annual cooling energy

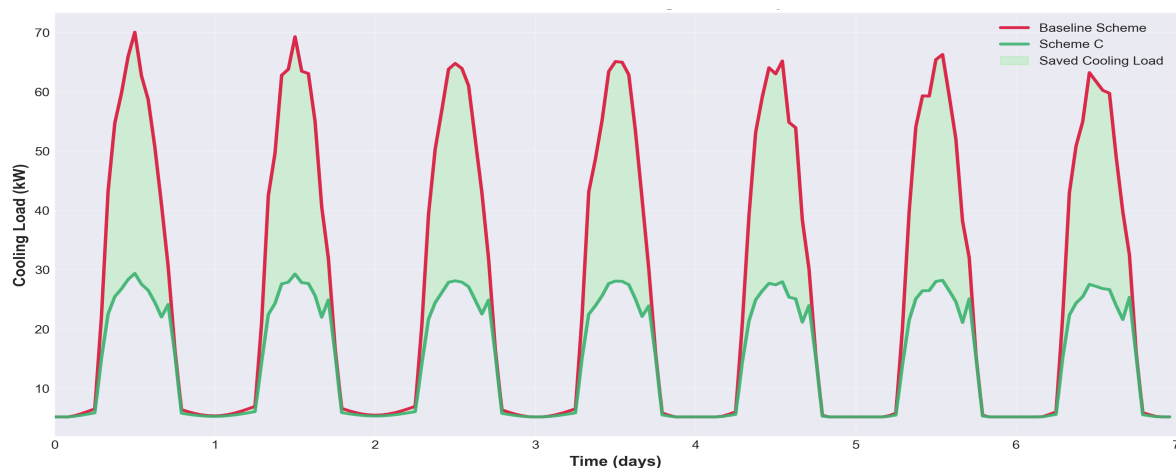
consumption to 36,004 kWh and increased annual comfort hours to 952, corresponding to an annual cooling-energy saving of approximately 7.3%. These archived annual results indicate that glazing improvements alone resulted in a measurable reduction in cooling demand under the Orlando reference condition. These Orlando results are presented as reference outputs associated with the original conceptual benchmark context, whereas the main climate-specific extension of the study is developed in the Southwest China scenarios discussed below.

Archived annual outputs for Schemes B and C were not fully retained in the available records. Accordingly, Table 7 reports only the traceable annual benchmark results for the baseline scheme and Scheme A. Scheme C is discussed separately below because the retained evidence for that case was available only as selected-week graphical outputs rather than as a complete annual summary.

Table 7. Archived annual benchmark comparison of the baseline scheme and Scheme A under the Orlando reference scenario.

Scheme	Heating Energy Consumption (kWh)	Annual Cooling Energy Consumption (kWh)	Total Energy Consumption (kWh)	Comfort Hours (h)	Cooling-Energy Saving Rate (%)
Baseline scheme	169	38,823	38,992	751	0
Scheme A: high-performance glazing replacement only	232	36,004	36,236	952	7.3

For Scheme C, the retained evidence is limited to selected-week graphical outputs rather than a complete annual summary. The case is therefore interpreted as a short-period illustration, not as a full annual benchmark result. Figure 4 shows the baseline–Scheme C comparison over the selected 7-day period under the Orlando reference scenario. Over the selected 7-day analysis period, the baseline scheme consumed approximately 4414.7 kWh of cumulative cooling energy, whereas Scheme C consumed approximately 2432.5 kWh, corresponding to a weekly cooling-energy saving of 44.9% (1982.2 kWh). The selected-week cooling-load profiles also indicate a substantial reduction in peak cooling load, with the baseline scheme approaching 70 kW and Scheme C remaining below approximately 30 kW during the analyzed period.



(a) Cooling-load comparison

Figure 4. Cont.

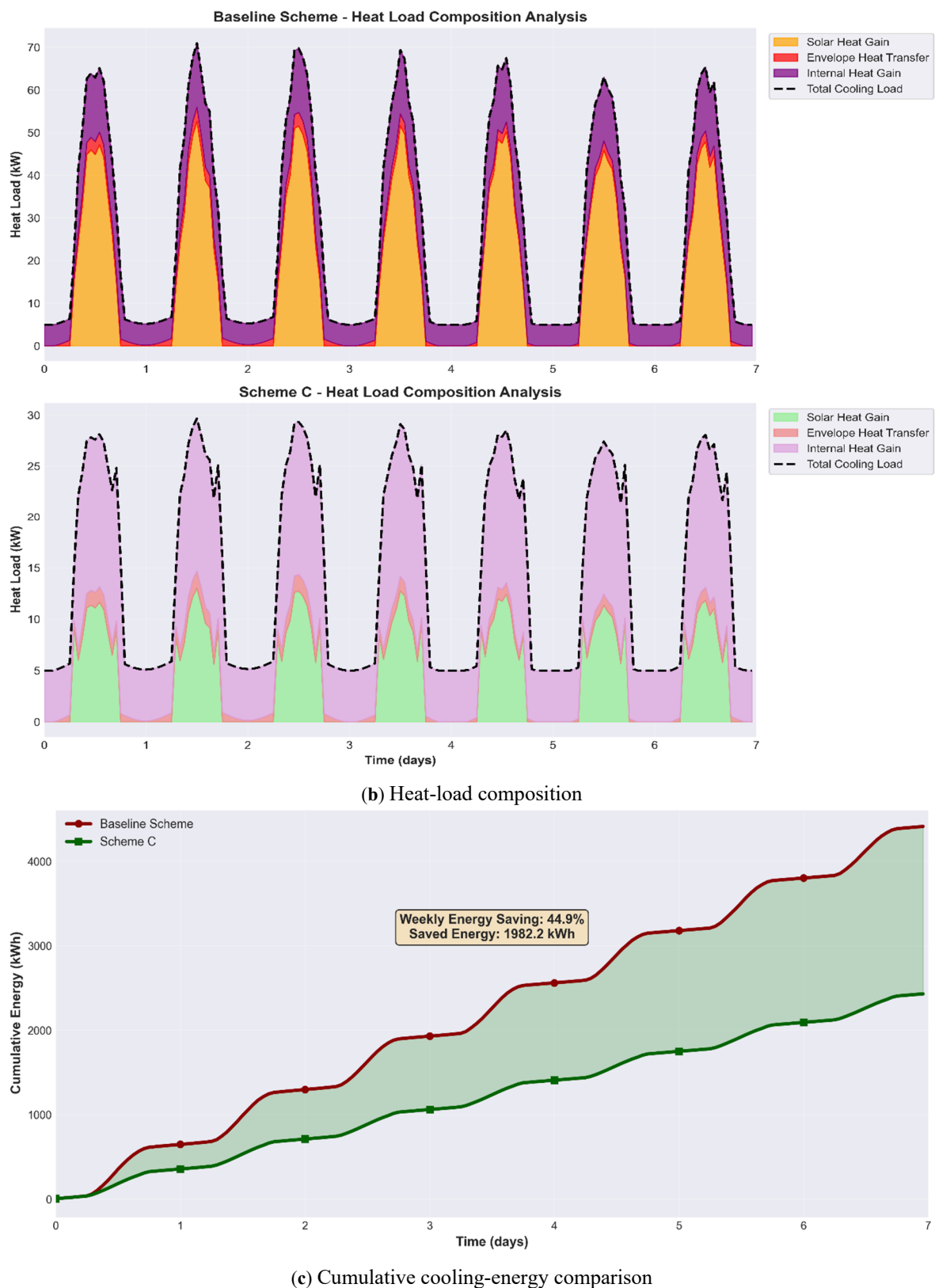


Figure 4. (a–c). Selected-week illustration under the Orlando reference scenario: (a) cooling-load comparison between the baseline scheme and Scheme C; (b) heat-load composition of the baseline scheme and Scheme C; and (c) cumulative cooling-energy comparison over the 7-day analysis period.

3.2. Typical-Year Reference and 2023 Extreme-Summer Scenario Comparison for Chengdu and Chongqing

The Chengdu and Chongqing comparisons were used to examine whether the optimized shading scheme retained its relative advantage when the weather input shifted from the typical-year reference to the 2023 extreme-summer scenario.

A direct comparison was conducted between the typical-year reference case and the 2023 extreme-summer scenario for Chengdu and Chongqing. As shown in Figure 5 and Table 8, both cities exhibited higher cooling energy demand and higher peak cooling load under the 2023 extreme-summer condition than under the corresponding typical-year baseline. At the same time, the optimized scheme maintained a stable relative advantage over the baseline scheme in both cities. For example, in Chengdu, the cooling energy-saving rate changed only slightly, from 45.3% under the typical-year baseline to 45.2% under the 2023 extreme-summer scenario, while the peak-load reduction rate remained above 50%.

In both Chengdu and Chongqing, the optimized scheme continued to reduce cooling energy use and peak cooling load relative to the baseline under the 2023 extreme-summer scenario.

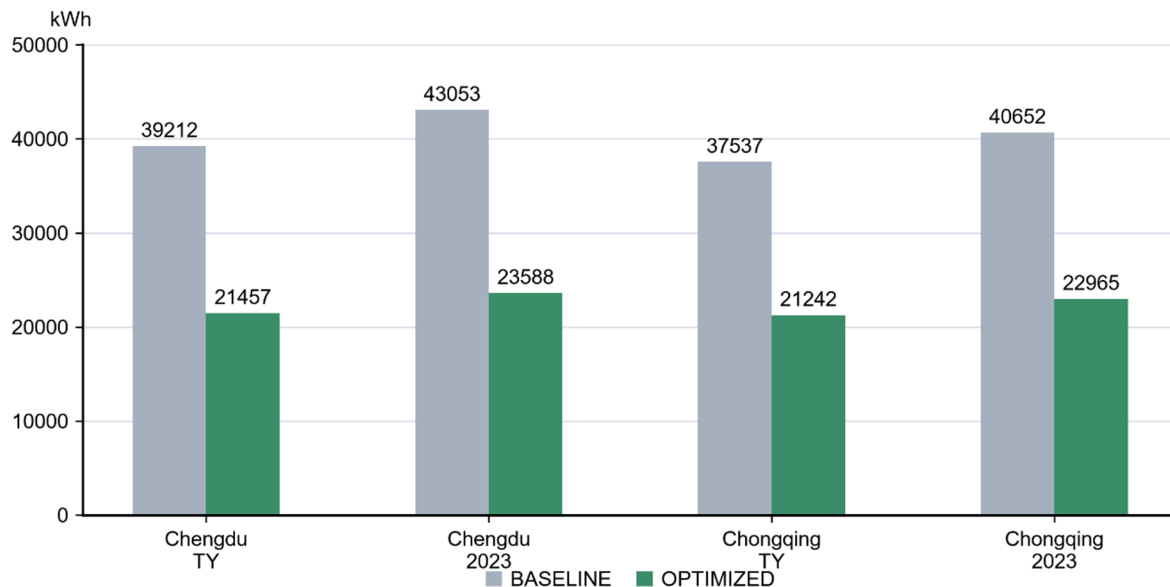


Figure 5. Annual cooling energy use in Chengdu and Chongqing under the typical-year reference and the 2023 extreme-summer scenario.

Table 8. Cooling energy consumption and peak cooling load under typical-year reference and 2023 extreme-summer conditions for Chengdu and Chongqing.

Scenario	Baseline Cooling (kWh)	Optimized Cooling (kWh)	Energy-Saving Rate	Baseline Peak Load (kW)	Optimized Peak Load (kW)	Peak Load Reduction Rate
Chengdu's typical-year	39,212	21,457	45.3%	20.74	9.65	53.5%
Chengdu 2023 extreme year	43,053	23,588	45.2%	26.66	12.49	53.2%
Chongqing's typical-year	37,537	21,242	43.4%	21.90	10.25	53.2%
Chongqing 2023 extreme year	40,652	22,965	43.5%	26.54	11.92	55.1%

3.3. Robustness Assessment under Parameter Perturbation

The robustness checks focused on whether the optimized scheme still performed better than the baseline after perturbing shading depth, glazing SHGC, and envelope thermal transmittance. Independent truncated-normal perturbations were applied within $\pm 10\%$ of the nominal values, and 2000 samples were generated using a random seed of 12,345. Each perturbed optimized case was compared with a correspondingly perturbed baseline case under the same scenario conditions. The robustness analysis was performed on the extended Southwest China scenario framework rather than on the original conceptual reference setup alone.

Figure 6 relates shading-depth perturbation to total cooling energy, Figure 7 shows the resulting energy-saving distribution, and Table 9 reports the corresponding summary statistics. In all 2000 sampled cases, the optimized scheme outperformed the paired baseline. The median energy-saving rate was 44.6%, and the 5% quantile was 41.8%.

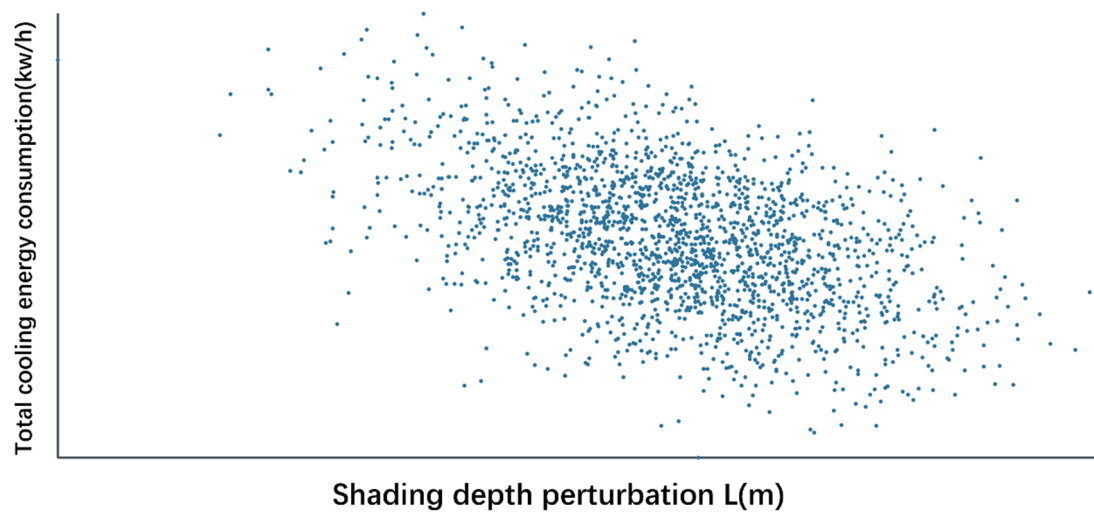


Figure 6. Relationship between shading-depth perturbation and total cooling energy in the Monte Carlo simulation.

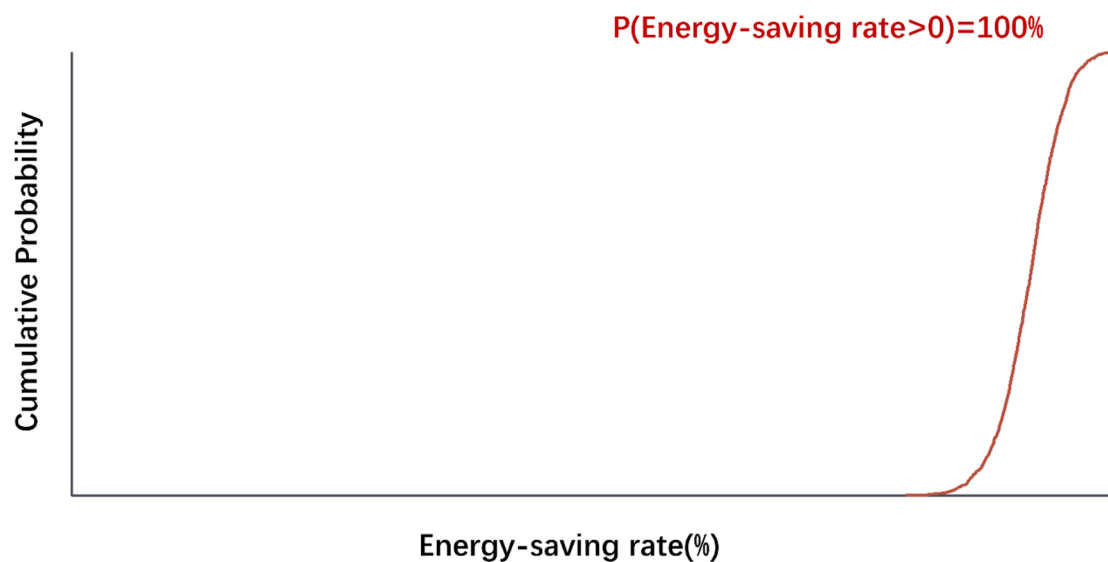


Figure 7. Distribution of the energy-saving rate under Monte Carlo perturbation.

Table 9. Statistical summary of the Monte Carlo robustness assessment.

Indicator	Value
Number of samples	2000
Mean energy-saving rate	44.2%
Median energy-saving rate	44.6%
5% quantile	41.8%
95% quantile	46.5%
Random seed	12,345
Distribution type	Independent truncated normal perturbations
Truncation bounds	$\pm 10\%$ of nominal values
Parameter correlation	Independent
Baseline perturbation	Yes (paired perturbation under the same scenario conditions)

4. Discussion

4.1. Severe-Summer Performance in Chengdu and Chongqing

When the weather input was changed from the typical-year reference to the 2023 extreme-summer scenario, the optimized shading scheme continued to perform better than the baseline in both Chengdu and Chongqing. In Chengdu, the cooling-energy saving rate changed only from 45.3% to 45.2%; in Chongqing, it changed from 43.4% to 43.5%. Peak-load reduction remained above 50% in all four comparisons.

This does not mean that the 2023 scenario had little effect on building performance. On the contrary, both annual cooling energy demand and peak cooling load increased in the hotter scenario. What remained stable was the optimized scheme's relative advantage over the baseline. Under the assumptions of the present model, the optimized design continued to outperform the baseline even as summer conditions became more severe.

4.2. Interpretation of the Orlando Reference Benchmark

The Orlando case requires more cautious interpretation because the retained outputs are not equally complete across schemes. Archived annual benchmark results were retained only for the baseline scheme and Scheme A. These results show that the glazing-only modification reduced annual cooling energy consumption from 38,823 kWh to 36,004 kWh and increased comfort hours from 751 to 952, corresponding to an annual cooling energy saving of about 7.3%.

Scheme C, however, is documented differently. For that case, the retained evidence is limited to selected-week graphical outputs rather than a complete annual summary. The selected-week illustration shows a weekly cooling-energy saving of 44.9%, with cumulative cooling energy decreasing from approximately 4414.7 kWh to 2432.5 kWh and peak cooling load dropping from approximately 70 kW to below 30 kW during the analyzed week. These values are informative, but they should be read as a short-period illustration rather than as a complete annual benchmark result for Scheme C. For that reason, the Orlando case in the revised manuscript serves mainly as a reference benchmark context. In contrast, the principal reproducible evidence of the study is concentrated in the Southwest China scenarios.

4.3. Robustness under Parameter Perturbation

Within the tested uncertainty range, the Monte Carlo results do not show a loss of the optimized scheme's relative advantage. In all 2000 perturbation cases, the optimized scheme outperformed the paired perturbed baseline. The median energy-saving rate was 44.6%, and the 5% quantile remained at 41.8%.

These values should still be interpreted with caution. They do not guarantee field performance, but they do suggest that moderate variation in shading depth, glazing SHGC, and envelope thermal transmittance did not remove the simulated benefit of the optimized design. Within the present perturbation setting, the retrofit therefore appears reasonably tolerant to the tested parameter uncertainty.

4.4. Limitations and Future Work

The most important limitation of the present study is that all conclusions remain simulation-based. No measured building data were available for direct comparison, so the current results should be read as comparative model outputs rather than as verified field performance. The Southwest China weather inputs were also adjusted to stress-test scenarios rather than reconstructed from station observations, meaning that the resulting extreme-summer sequences are scenario assumptions rather than exact reproductions of observed meteorological coupling. In addition, the archived annual outputs for Schemes B and C under the Orlando reference scenario were not fully retained, so the annual benchmark comparison is incomplete. The model itself also remains simplified, particularly in its overhang-based shading representation and its operational control assumptions.

Future work should compare the adjusted weather sequences with higher-resolution observations and test the workflow against monitored building data. UAV-based thermal monitoring may also support this type of comparison in the built environment [12].

5. Conclusions

The present study extends a conceptual passive-shading building prototype into a simulation-based comparative and stress-testing framework for Southwest China under extreme-summer conditions rather than as a substitute for measured validation in real buildings. Under the Orlando reference scenario, the archived annual benchmark results show that Scheme A reduced annual cooling energy consumption from 38,823 kWh to 36,004 kWh and increased comfort hours from 751 to 952, corresponding to an annual cooling energy saving of approximately 7.3%. In addition, the retained selected-week records for Scheme C indicated a weekly cooling-energy saving of 44.9%, with cumulative cooling energy decreasing from approximately 4414.7 kWh to 2432.5 kWh and peak cooling load dropping from approximately 70 kW to below 30 kW during the analyzed week. Second, in Chengdu and Chongqing, the optimized scheme remained effective under both typical-year reference and 2023 extreme-summer conditions. The cooling energy-saving rate remained between 43.4% and 45.3%, while the peak-load reduction rate remained between 53.2% and 55.1%, indicating stable comparative performance

under severe summer conditions in Southwest China. Third, the Monte Carlo analysis showed that the optimized scheme outperformed the baseline perturbed in 100.0% of sampled cases, with a median energy-saving rate of 44.6% and a 5th percentile of 41.8%.

The current results support the workflow as a comparative design and stress-testing tool, but the conclusions remain bounded by scenario-based weather assumptions and the simplified model structure.

Author Contributions

R.Y.: conceptualization, methodology, investigation, formal analysis, writing—original draft preparation; X.L.: conceptualization, writing—review and editing, supervision; C.Y.: writing—review and editing; G.Z.: writing—review and editing; W.Z.: writing—review and editing; I.B.Z.: writing—review and editing, supervision. All authors have read and agreed to the published version of the manuscript.

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Data Availability Statement

Data will be made available on reasonable request.

Conflicts of Interest

The authors declare no conflict of interest.

Use of AI and AI-Assisted Technologies

During the preparation of this work, the authors used Gemini to obtain preliminary suggestions for the graphical layout of Figure 1. After using this tool/service, the authors independently redrew, reviewed, and edited the figure using Microsoft PowerPoint as needed and took full responsibility for the content of the published article.

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