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Multi-Objective Optimization-Driven Research on Rural Residential Building Design in Inner Mongolia Region

Dezhi Zou [1,2,3,4,*], Cheng Sun [1,2] and Denghui Gao [3,4]

[1] School of Architecture and Design, Harbin Institute of Technology, Harbin 150001, China; suncheng@hit.edu.cn
[2] Key Laboratory of Cold Region Urban and Rural Human Settlement Environment Science and Technology, Ministry of Industry and Information Technology, Harbin 150001, China
[3] School of Architecture, Inner Mongolia University of Technology, Hohhot 010051, China; gdh060838@163.com
[4] Key Laboratory of Green Building at Universities of Inner Mongolia Autonomous Region, Hohhot 010051, China
* Correspondence: zdz@imut.edu.cn; Tel.: +86-13947173235

Abstract: According to the China Building Energy Consumption and Carbon Emissions Research Report (2023), the construction industry accounts for 36.3% of total societal energy consumption, with residential buildings contributing significantly due to their extensive coverage and high operational frequency. Addressing energy efficiency and carbon reduction in this sector is critical for achieving national sustainability goals. This study proposes an optimization methodology for rural dwellings in Inner Mongolia, focusing on reducing energy demand while enhancing indoor thermal comfort and daylight performance. A parametric model was developed using Grasshopper, with energy consumption, thermal comfort (PPD), and Useful Daylight Illuminance (UDI) simulated through Ladybug and Honeybee tools. Key parameters analyzed include building morphology, envelope structures, and indoor thermal environments, followed by systematic optimization of building components. To refine multi-objective inputs, a specialized wall database was established, enabling categorization and dynamic visualization of material properties and construction methods. Comparative analysis demonstrated a 22.56% reduction in energy consumption, 19.26% decrease in occupant thermal dissatisfaction (PPD), and 25.44% improvement in UDI values post-optimization. The proposed framework provides a scientifically validated approach for improving energy efficiency and environmental adaptability in cold-climate rural architecture.

Keywords: multi-objective optimisation; rural residential building; building performance optimisation; energy efficiency retrofit

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1. Introduction

According to official statistics, the building sector accounted for 36.3% of China's total energy consumption and 38.2% of energy-related carbon emissions in 2021 [1]. Energy efficiency improvement and carbon emission reduction have consequently become imperative pathways for sustainable development in China's construction industry. Nevertheless, budget constraints and technological limitations in construction practice have resulted in energy-intensive yet suboptimal-comfort dwellings prevailing in rural areas. This reality positions residential building energy conservation as a critical domain for implementing national decarbonization strategies. However, the exclusive pursuit of energy minimization may adversely affect interrelated indoor environmental quality metrics,

particularly thermal comfort and daylighting performance. Given the inherent conflicts among optimization objectives, single-criterion design approaches could lead to significant performance trade-offs.

Therefore, multi-objective optimization is required to simultaneously address the tripartite objectives of energy efficiency, thermal comfort, and daylight adequacy. This process integrates key design parameters as input variables to optimize building components through computational iterations, ultimately seeking solutions that satisfy multiple performance criteria: enhanced building thermal performance, minimized energy demand, superior indoor environmental quality, daylight optimization, and improved ecological sustainability.

2. Literature Review

2.1. Multi-Objective Optimisation of Building Energy Efficiency

Multi-objective optimization in architecture encompasses a broad range of strategies and methodologies designed to enhance the performance of building design and operation, while balancing competing design and performance criteria through multi-objective optimization applications. Scholars worldwide have progressively conducted explorations to address diverse objective orientations in optimization processes.

Shao Teng and Zheng Wuxing et al. developed a multi-objective optimization design model for rural residences in cold regions by integrating MOBO optimization software, the NSGA-II algorithm, and multi-attribute decision-making methods. Case study analyses demonstrated that the optimal solution achieved a 54.0% building energy savings rate and a 56.7% improvement in the predicted percentage of dissatisfied occupants (PPD) [2]. Chengjin Wu et al. proposed an optimization framework combining Bayesian optimization, extreme gradient boosting trees, and the NSGA-II algorithm for multi-objective optimization of residential building performance. Post-optimization results showed a 44.1% reduction in energy consumption, a 10.9% improvement in thermal comfort indices, and a 1.7% enhancement in daylighting performance [3]. Yue Pan and Yuxuan Shen et al. established a multi-objective optimization framework comprising evaluation metric systems, deep neural network model training, and automated optimal solution generation via a deep deterministic policy gradient (DDPG) model. Application to an educational facility in Shanghai demonstrated the framework's superiority over conventional genetic algorithms, yielding a 13.19% improvement in building performance [4]. Ming Liu et al. implemented multi-objective optimization using Grasshopper and related plugins to reduce energy consumption while enhancing thermal comfort in a university student centre. The optimized design achieved a 58.8% reduction in annual comprehensive energy consumption and extended indoor thermal comfort duration by 53.0% [5].

Zhouchen Zhang et al. analyzed the impact of occupant behavior stochasticity on energy efficiency and multi-objective optimization. Their Pareto frontier-based energy conservation strategy demonstrated a 20.2% energy reduction while maintaining indoor thermal comfort through occupant behavior integration in design [6]. Huanbo Lyu and Daniel Herring et al. developed a novel multi-objective optimization framework for flexible building space utilization. Leveraging real sensor data and machine learning models for energy cost estimation, the framework optimized energy consumption and thermal comfort, with effectiveness validated through two representative case scenarios [7]. Zhikun Ding et al. proposed a multi-objective optimization method for building envelope retrofitting under future climate conditions. The approach integrated random forests and general circulation models for future weather data generation, combined Monte Carlo methods with NSGA-II to establish Pareto frontier solutions, and conducted comprehensive decision-making analyses across meteorological datasets [8]. Bingying Yao et al. performed

multi-objective optimization of office egg-crate shading control parameters using EnergyPlus simulations and JEPLUS software for design variable integration. Results indicated significant reductions in energy consumption alongside improvements in thermal and visual comfort [9].

Fabrizio Ascione, Nicola Bianco et al. developed a novel multi-objective optimization framework that incorporates building geometry, envelope structure, and energy systems as input parameters. The framework aims to optimize buildings with objectives of maximum sustainability, cost-effectiveness, and minimum investment. When applied to the design of a typical office building in Milan, the framework significantly reduced the building's primary energy consumption, global cost, and CO_2-equivalent emissions while improving indoor thermal comfort [10]. Sara Ouanes developed a methodology integrating sensitivity analysis and multi-objective optimization (NSGA-II) to enhance residential building energy performance and thermal comfort. Latin hypercube sampling and multiple linear regression were employed to evaluate the significance of design parameters. Results indicated that window characteristics, thermal insulation, and roof reflectivity were the most influential factors, achieving significant improvements in annual heating demand (13.2–49.5%) and a reduction in thermal discomfort exceeding 26% [11]. Abdelhakim Walid Makhloufi et al. evaluated energy consumption, cost, and carbon emissions under various climate scenarios using multi-objective optimization. They found that integrating passive design, active systems, and renewable energy strategies significantly reduced energy consumption and building carbon emissions [12]. Ali Khani and Mehdi Khakzand et al. applied the NSGA-II genetic algorithm to perform multi-objective optimization on variables including window characteristics, shading devices, and building orientation in classroom models, aiming to reduce energy consumption and improve visual and thermal comfort. Based on optimization results, they proposed design recommendations for classrooms, providing references for educational building design in hot–humid climates [13]. Ana Vukadinović et al. optimized structural and architectural parameters of detached residential buildings with sunspaces using the NSGA-II algorithm. Key parameters included window-to-wall ratio, glazing type, wall structure, and shading systems. Energy simulation software was used for optimization, providing references for passive solar building design with sunspaces [14]. Ahmet Serhan Canbolat and Emre İsa Albak conducted multi-objective optimization on building envelope insulation materials using NSGA-II, with objectives of minimizing cost and CO_2 emissions. The study analyzed four design variables (wall thickness, wall material, insulation material, and heat source) under four climatic conditions [15]. Badr Chegari et al. proposed a multi-objective optimization algorithm based on BPO technology by integrating artificial neural networks (ANN) and metaheuristic algorithms. By considering building envelope thermal parameters and shading devices as input variables, a database was created through TRNSYS simulations for ANN training. With the objectives of minimizing thermal demand and discomfort hours, the optimization results demonstrated a 74.52% reduction in energy demand and a 4.32% improvement in thermal comfort [16].

2.2. Village Housing Performance Study

With the global energy crisis and climate change becoming increasingly severe, promoting the low-carbon and intelligent transformation of residential buildings has become a core topic of research in the field of architecture. In recent years, driven by digital technology, the research on residential performance optimisation has shown an innovative trend of multidisciplinary cross-fertilisation, and scholars at home and abroad have made breakthroughs in the fields of energy saving and carbon reduction, thermal comfort enhancement, and the application of intelligent algorithms. Ying Zhou et al. developed a health- and ther-

mal comfort-oriented automated spatial layout generation system for residential buildings, providing an efficient and practical tool for future design processes [17]. Yao Sheng and Jiang Zezhi et al. proposed a rural housing performance optimization method based on tree-structured Gaussian process global sensitivity analysis. The optimized design achieved 35.62% annual average effective daylight illuminance and 10% energy consumption reduction [18]. Shao Teng and Zhang Ni et al. established a residential optimization framework integrating SVM and NSGA-II algorithms, targeting energy consumption, carbon emissions (1000 kgCO2/m^2 reduction), thermal comfort (44% improvement), daylighting (7.4% enhancement), and cost efficiency (63 CNY/m^2 savings). Case validation demonstrated 76% energy savings [19]. Ryan Hepple et al. investigated phase change material (PCM) integration in residential exterior walls through positional optimization. Results indicated that interior PCM placement maximized thermal loss reduction effectiveness [20]. Hui Xi et al. evaluated six high-performance machine learning models for indoor thermal comfort prediction, employing SHAP values and partial dependence plots (PDP) to identify critical influencing factors [21]. A. Carratt, G. Kokogiannakis, and D. Daly evaluated a novel minimal-input model calibration method for post-retrofit performance prediction. Comparative analysis using monitored data from three social housing retrofits demonstrated superior accuracy over conventional calibration approaches [22]. Aline Schaefer et al. developed a cluster analysis-based method to identify reference models from real UK low-income housing systems, providing benchmarks for future thermal and energy performance studies [23].

Xi Luo and Lina Du developed a stochastic model incorporating behavioral differences in energy use among family members through field investigations, aiming to enhance the accuracy of energy consumption simulation in rural residential buildings. The study demonstrated that classifying household energy use patterns based on family member behaviours through this simulation model could more accurately reflect actual energy consumption scenarios. Compared with the "average resident" approach, the model exhibited significant seasonal variations in energy consumption simulations across different household types, particularly during summer and winter periods [24]. Yuqi Fu and Cynthia Changxin Wang established a multi-objective mixed-integer nonlinear programming model to optimize roof material selection for Australian residences, balancing carbon emissions and thermal performance while integrating thermal mass into the optimization framework [25]. Karim Boumlik et al. implemented an optimization analysis methodology to assess and enhance the design of Moroccan residential buildings, aiming to improve energy efficiency and achieve near-zero energy consumption. Integrating whole-building simulation with sequential search techniques, the research identified the most cost-effective energy efficiency measure combinations under various climatic conditions. The optimized designs achieved 51–67% annual energy reduction in Moroccan residential buildings [26]. Shen XY and Ye X established an environmental performance-based parametric design framework for Singaporean HDB flats. Utilizing 3D cellular automata and parametric performance simulation, the study optimized housing layouts to achieve multi-objective equilibrium in daylighting, energy consumption, and thermal comfort [27]. Zeyad Amin Al-Absi et al. investigated phase change material (PCM) applications in Saudi Arabian desert-climate residences. By optimizing PCM transition temperatures, placement, and HVAC setpoints, the analysis revealed 24.1–30.4% annual energy reduction through improved thermal performance across seasons [28].

Literature review reveals that studies on multi-objective optimization in buildings predominantly employ the NSGA-II algorithm, focusing on building envelope performance, spatial layout, and equipment systems. The core optimization objectives are primarily concentrated on three key indicators: energy efficiency, thermal comfort, and daylight

sufficiency. In severe cold regions, the synergistic optimization of these three indicators holds particular significance. Enhanced energy efficiency is directly linked to reduced heating energy consumption, while improved thermal insulation of the building envelope and passive utilization of solar radiation gains can simultaneously decrease energy demand, enhance indoor thermal comfort, and achieve efficient natural light utilization through daylighting design. The coupled relationship among "energy conservation, comfort, and luminous environment" becomes especially pronounced under cold climatic conditions. However, existing research pays insufficient attention to rural residential buildings in Inner Mongolia, which are characterized by a large population base, severe cold climate, and unique construction patterns. Critical issues such as thermal defects in building envelopes, poor winter thermal comfort, and low utilization of natural daylight remain unresolved through systematic multi-objective optimization. There is an urgent need to explore technical pathways for coordinated improvement of these three aspects in this region.

3. Methodology

3.1. Overview of the Study

This study employs Rhino-Grasshopper to develop a parametric platform integrating key performance indicators including energy consumption, daylighting, and thermal comfort. The platform enables simultaneous simulation and calculation of residential buildings' energy consumption, daylighting performance, and thermal comfort conditions. Multi-objective optimization is implemented through the Wallacei plugin embedded in the platform. By iteratively adjusting building morphological parameters, envelope structure parameters, and indoor thermal environment variables, while monitoring real-time feedback on energy consumption, thermal comfort, and daylighting impacts, the system identifies optimal parameter combinations to achieve balanced multi-objective solutions, thereby providing robust technical support for sustainable design of rural residential buildings in Inner Mongolia.

3.2. Multi-Objective Optimisation Model Creation

3.2.1. Residential Wall Database Construction

Based on field investigations of rural residential building envelopes in Inner Mongolia, this study establishes foundational data which will be incorporated into the regional building material database. The investigation focuses on systematic documentation and categorization of locally available construction materials, including concrete, cladding materials, mortar, and thermal insulation materials. This phase involves comprehensive evaluation of material performance parameters, cost-effectiveness, and local availability to ensure compliance with both technical specifications and economic feasibility for building envelope systems. Table 1 presents the catalogue of conventional wall materials identified in rural residential constructions across Inner Mongolia.

Subsequently, a comprehensive identification and classification of wall systems in rural residential buildings was conducted, encompassing load-bearing walls, non-load-bearing walls, partition walls, and their respective functional applications in architectural configurations. Each wall type was systematically categorized based on four critical dimensions: structural functionality, material composition, construction methodology, and environmental adaptability.

Table 1. Common wall materials for rural houses in Inner Mongolia.

	Name of Material	Thermal Conductivity W/(m·K)	Vapour Permeability Coefficient G/(m·h.Pa)	Densities Kg/m³	Heat Storage Capacity W/(m²·K)
Insulation material	Extruded polystyrene sheet	0.030	—	35	0.34
	Moulded Polystyrene Sheet	0.039	—	30	0.36
	Moulded Polystyrene Sheet	0.041	—	20	0.36
	Rock wool	0.040	4.880	180	0.70
	Aerogel	0.016	—	3.55	—
Concrete	Shale ceramsite concrete	0.500	0.435	1100	6.70
	Haydite concrete	0.84	0.315	1600	10.36
	Volcanic ash, sand, cement concrete	0.57	0.395	1700	6.30
	Fly ash ceramsite concrete	0.44	1.350	1100	6.30
Finishing materials	Marble	2.91	0.113	2800	23.27
	Granite	3.49	0.113	2800	25.49
	Woodwork	0.35	3.000	700	6.93
Mortar	Vitrified microsphere insulation slurry	0.080	—	350	—
	Rubber powder polystyrene particle thermal insulation mortar	0.070	—	300	—

Typical regional materials including concrete composites, thermal insulation layers, and mortar mixtures were processed through a Self-Organizing Map (SOM) neural network model. The model's adaptive information processing system employed statistical analysis and mathematical modelling to decipher multivariate datasets from the material database, revealing intrinsic correlations between material properties. A hierarchical clustering algorithm with multi-objective optimization capabilities was implemented to refine preliminary clustering outcomes. Through iterative processing, the algorithm fed optimized clusters into subsequent neural network layers for progressive refinement, ultimately deriving high-performance composite wall systems. The optimization framework integrated both individual material performance enhancement and synergistic effects of material combinations, coupled with parametric tuning for holistic system optimization. Optimized wall configurations were subsequently integrated into the database to enhance its comprehensiveness and practical utility.

A database constitutes a structured repository for systematic organization, storage, and management of architectural data. Two predominant data models exist: relational and non-relational databases [29]. This research employs MySQL, a representative relational database management system (RDBMS). MySQL is characterized by robust functionality, intuitive operation, high-speed processing, and secure reliability, supporting multi-language programming interfaces for database access [30]. Figure 1 illustrates the procedural framework of the developed rural wall system database for Inner Mongolia.

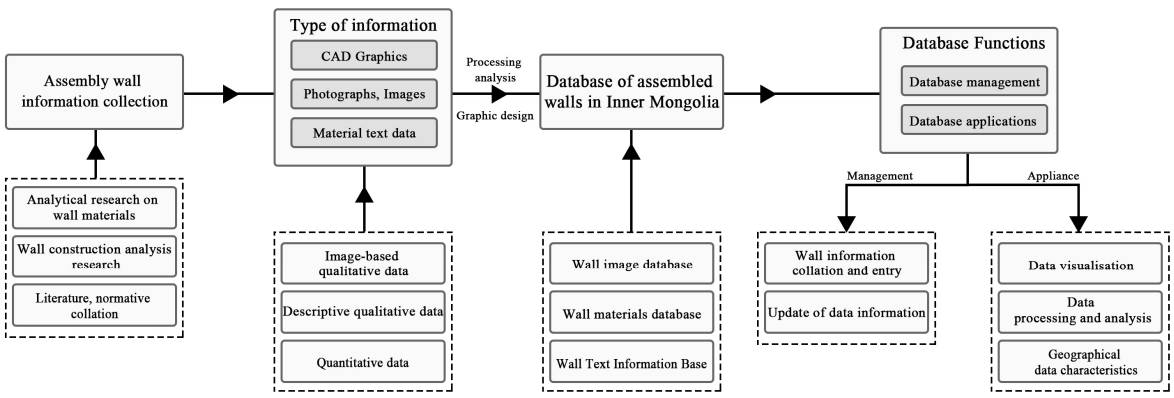


Figure 1. Wall database process architecture.

Taking the rural residential wall database table of Inner Mongolia as an exemplar, the MySQL table schema is structured as follows: The schema primarily stores critical parameters including wall assembly nomenclature, unique identifiers, digital imagery references, performance datasets, and material composition specifications, as detailed in Table 2.

Table 2. Description of the structure of the wall database for Rural Residential Building in Inner Mongolia region.

	Field Name	Data Type	Null Value	Clarification
No.	id	Int	N	
Wall Name	w-name	varchar	N	Record the name of the wall
Wall Number	w-num	varchar	N	Numbering the walls
Image Name	img-name	varchar	N	Recording of wall construction images
Image Data	img-path	mediumblob	N	Data path for recording images
Image Number	img-num	varchar	N	Numbering the images
Material Number	m-num	varchar	N	For wall construction materials
Material Content	material	tinytext	Y	Description of wall construction materials, remarks text

The database system enables systematic categorization, processing, and analytical evaluation of collected wall material compositions and structural configurations from rural residential buildings in Inner Mongolia. This is coupled with multidimensional visualization capabilities through both static graphical representations and dynamic interactive dashboards, which serves as critical input parameters for subsequent multi-objective optimization processes.

3.2.2. Multi-Objective Optimisation Theory and Model Creation

In optimization design, multi-objective optimization involves the simultaneous pursuit of optimal solutions for multiple objectives, whereas single-objective optimization focuses on optimizing a singular objective. Practical engineering problems frequently entail multiple conflicting objectives, necessitating the adoption of multi-objective optimization to balance these objectives and identify the optimal trade-off. The application of multi-objective optimization has proliferated in machine learning and deep learning domains, as it offers an effective approach to reconcile multiple performance metrics, thereby achieving enhanced overall performance in complex real-world applications.

Grasshopper and its optimization plugin Wallacei demonstrate unique advantages in multi-objective building performance optimization, primarily manifested in domain specificity and design process integration. The visual programming environment of Grasshopper significantly lowers the threshold for architects to engage in complex optimization processes, with node-based logical chains enabling seamless integration between parametric design and algorithmic invocation. Wallacei incorporates the NSGA-II algorithm and supports dynamic Pareto front visualization [31], allowing designers to intuitively balance multi-objective conflicts within the 3D geometric interface. Deep integration with the Rhino platform facilitates real-time geometric feedback, eliminating latency caused by data conversion in conventional tools and substantially enhancing iterative efficiency. While general-purpose multi-objective optimization tools (e.g., ModeFRONTIER, jMetal) demonstrate superior algorithmic diversity and computational scalability, their code-driven or modular interfaces struggle to directly accommodate the unstructured problems inherent in architectural design. Furthermore, architectural performance optimization often requires coupling with external simulation engines. Grasshopper achieves a streamlined workflow through its Ladybug/Honeybee plugins, whereas generic tools necessitate additional interface development, thereby escalating technical complexity. A detailed comparative analysis is presented in Table 3.

Table 3. Comparative analysis of Grasshopper with Wallacei and other multi-objective optimisation tools.

Comparison Dimension	Grasshopper + Wallacei	Other Multi-Objective Optimisation Tools
User Interface and Interactivity	Based on a visual programming environment (Grasshopper), it supports node-based parametric operations and is suitable for users with a non-programming background.	Mostly traditional GUIs or code-driven interfaces (e.g., jMetal requires programming), with a steeper learning curve.
Optimisation algorithm flexibility	Based on NSGA-II algorithm, supports customised fitness functions; suitable for small to medium sized problems.	Provide a broader library of algorithms (e.g., MOEA/D, SPEA2) and support large-scale multidisciplinary optimisation (e.g., ModeFRONTIER).
Visualisation and post-processing	Built-in interactive 3D visualisation and dynamic Pareto Frontier analysis supports simultaneous exploration of design space and target space.	Reliance on external tools (e.g., MATLAB R2023a, ParaView 5.12) for advanced visualisation and process fragmentation.
Domain Applicability	For building and engineering design optimisation, it supports the coupled analysis of morphology generation and environmental performance simulation.	More versatile and suitable for traditional engineering fields such as mechanical and aerospace, but needs to be customised to suit construction needs.

In conclusion, the combination of Grasshopper and Wallacei provides a highly accessible solution for multi-objective optimization in architecture, particularly suitable for rapid exploration and interdisciplinary collaboration during schematic design phases. However, for ultra-large-scale or high-dimensional problems, it remains necessary to integrate traditional optimization tools or customized algorithms to extend capability boundaries.

The Wallacei plugin requires each optimization objective to be a single value. In residential building performance optimization, the annual cumulative load is analyzed to evaluate energy consumption, with the primary objective of minimizing total energy demand for heating, cooling, and lighting systems. Energy consumption inherently correlates with occupant comfort requirements, which exhibit spatial variability depending on room functionality. Significant discrepancies in solar radiation exposure across building orientations differentially impact thermal performance of spatial zones. The computational model accounts for both functional zoning and orientation characteristics across building floors to ensure accurate energy simulation. In this simulation for severe cold regions, critical HVAC system parameters are defined: design indoor temperature (20 °C), air exchange rate (0.5 h^{-1}), equipment/lighting power densities (3.5 W/m^2 and 5 W/m^2, respectively), with continuous 24-h heating operation.

Occupant presence rate constitutes a crucial parameter in building energy modelling, directly determining internal thermal loads and energy consumption patterns. Variations in occupancy rates induce dynamic shifts in indoor hygrothermal conditions, necessitating adaptive control strategies for HVAC systems. Elevated occupancy rates amplify sensible heat gains from occupants and equipment, consequently increasing heating/cooling demands and energy consumption. Conversely, reduced occupancy may decrease thermal loads, yet suboptimal rates risk energy waste through unnecessary system operation during unoccupied periods. Accurate occupancy rate modelling is therefore imperative for achieving energy efficiency optimization, cost savings, and enhanced indoor environmental quality. The occupancy rate schedule implemented in this study is detailed in Table 4.

Table 4. Room occupancy rate.

Time	Bedroom	Living Room	Kitchen	Toilet	Ancillary Rooms
00:00	1.0	0.0	0.0	0.0	0.0
01:00	1.0	0.0	0.0	0.0	0.0
02:00	1.0	0.0	0.0	0.0	0.0
03:00	1.0	0.0	0.0	0.0	0.0
.....	.....	.....	.....	.....	.....
21:00	0.5	0.5	0.0	0.5	0.1
22:00	1.0	0.0	0.0	0.1	0.1
23:00	1.0	0.0	0.0	0.0	0.0
24:00	1.0	0.0	0.0	0.0	0.0

The digital energy-efficiency design strategy adopts the maximum Useful Daylight Illuminance Percentage (UDI) as the daylight performance optimization target in case study implementation. When a measurement point achieves full natural illuminance for a given hour, it is recorded as compliant. Subsequently, the percentage of compliant hours relative to annual operational hours is calculated for all measurement points. The arithmetic mean of these percentages across all points is then established as the quantitative daylight performance objective in simulations.

As the PPD simulation in Grasshopper generates spatially distributed data points across evaluation grids rather than a comprehensive index, additional methodology is required to define the integrated thermal comfort metric. To holistically characterize thermal comfort optimization outcomes, this study employs the average PPD value per functional space as the thermal comfort performance objective. The integrated optimization platform configuration and objective parameterization are systematically detailed in Table 5.

Table 5. Optimisation of platform and target setting.

Optimisation Platforms	**Rhino-Grasshopper and Wallacei**		
Optimisation goals	Building energy consumption	Indoor thermal comfort	Indoor Lighting
Optimisation of target indicators	EUI	PPD	UDI

3.2.3. Model-Related Parameter Settings

Building energy consumption, daylight availability, and thermal comfort are inherently influenced by multiple interdependent factors encompassing both indoor/outdoor environmental conditions and inherent building characteristics, including envelope thermal performance, microclimate parameters, internal heat sources, and occupant demographics with associated behavioral patterns. The energy-efficient design optimization framework strategically selects variables from three primary domains: architectural morphology parameters, building envelope specifications, and indoor thermal environment regulation.

Multi-objective optimization incorporates the following variables: shading overhang dimensions, shading element light transmittance, interior surface reflectivity (walls, ceilings, floors), internal wall thickness, floor thermal resistance, window thermal transmittance coefficient, glazing solar heat gain coefficient, supplemented by the established rural residential wall material database. The comprehensive variable configuration is systematically presented in Table 6.

Following the establishment of the multi-objective optimization framework, parameter configuration within the Wallacei platform was implemented. The evolutionary computation framework was configured with 50 generations and a population size of 20, resulting in 1000 total fitness evaluations (50 generations $\times$ 20 individuals). Platform-default values were retained for other parameters, with complete input specifications detailed in Table 7.

Table 6. Input Parameters and Initial Values and Ranges of Parameters.

No.	Parametric	Starting Value	Range of Values
1	Shading overhang dimensions	0.11 m	0.3–1.5 m
2	Shading element light transmittance	0.62	0–1
	Reflectivity of internal walls	0.10	0–1
3	Ceiling reflectivity	0.5	0–1
	Ground reflectivity	0.8	0–1
4	Internal wall thickness	0.17 m	0.1–0.4 m
5	Floor thermal resistance	3.0 m^2·K/W	0.7–6 m^2·K/W
6	Window thermal transmittance coefficient	0.9 (W/m^2·K)	0–2.5 (W/m^2·K)
7	Glazing solar heat gain coefficient	1.0	0–1
8	Wall database	-	-

Table 7. Wallacei parameter settings.

Parameter Name	Set Value
Population Size	20
Generation count	50
Crossover probability	0.8
Mutation probability	1/r
Crossover distribution index	20
Mutation distribution index	20
Random seed	1

Through meticulous parameter configuration and optimization platform setup, this study is designed to enable multi-objective optimization algorithms to conduct comprehensive yet efficient exploration within the multi-dimensional solution space. The ultimate objective is to identify Pareto-optimal solutions that simultaneously satisfy critical performance criteria: energy consumption minimization, daylight availability optimization, and thermal comfort enhancement.

3.3. Parameter Sensitivity Analysis

3.3.1. Optimisation Parameter Correlation Analysis

This study employs global sensitivity analysis to quantify the independent effects of input parameters on objectives, aiming to provide prioritization references for subsequent optimization rather than directly eliminating parameters. This step facilitates the understanding of nonlinear relationships between parameters and objectives, while establishing a basis for parameter weight allocation in optimization algorithms.

The multi-objective optimization parameters for typical case buildings initially comprised 10 variables (e.g., shading overhang dimensions, ground reflectance, and internal wall thickness). However, because the wall database could not be quantified for sensitivity analyses, it was excluded, resulting in nine parameters for sensitivity analyses in this section. Prior to analysing parameter correlations, the Shapiro–Wilk test was conducted to assess normal distribution compliance. Parameters demonstrating p-values <0.05 (with values approaching 0) indicate non-normal distributions [32]. As shown in Table 8, all parameters exhibited p-values approaching 0, confirming their non-normal distributions. Consequently, parameter correlations were analyzed using Spearman's rank correlation coefficient method.

Python (version 3.11) was employed to compute Spearman correlation coefficients between parameters and generate the correlation diagram shown in Figure 2 (parameter names are represented by initials in the figure). The correlation matrix displays Spearman rank correlation coefficients among nine variables: shading overhang dimensions, light transmittance, reflectivity of internal walls, ceiling reflectance, ground reflectance, interior wall thickness, floor thermal resistance, window thermal transmittance coefficient, and

glazing solar heat gain coefficient. The Spearman correlation coefficient quantifies the strength and direction of monotonic relationships between variables, ranging from −1 (perfect negative correlation) to +1 (perfect positive correlation).

Table 8. Optimisation parameters Shapiro Wilk analysis results.

Parametric	*p*-Value	Parametric	*p*-Value
Shading overhang dimensions	1.74×10^{-14}	Internal wall thickness	5.56×10^{-10}
Shading element light transmittance	2.28×10^{-24}	Floor thermal resistance	5.32×10^{-19}
Reflectivity of internal walls	2.08×10^{-15}	Window thermal transmittance coefficient	1.23×10^{-14}
Ceiling reflectivity	1.92×10^{-13}	Glazing solar heat gain coefficient	2.53×10^{-14}
Ground reflectivity	6.1×10^{-19}	-	-

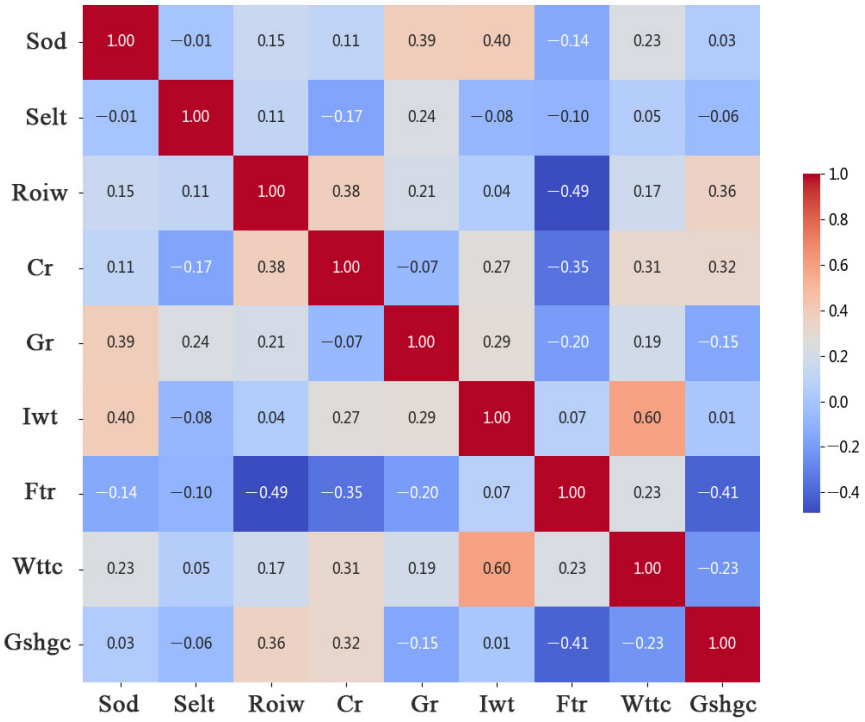


Figure 2. Correlation matrix of parameters for multi-objective optimisation.

The analysis reveals a significant positive correlation (coefficient = 0.60) between interior wall thickness and window heat transfer coefficient, while a moderate negative correlation (coefficient = −0.49) is observed between ground thermal resistance and interior wall reflectance. Weak correlations among certain parameters suggest no substantial linear relationships, leading to the conclusion that the optimization parameters exhibit limited intercorrelation.

Given the weak parameter correlations, global sensitivity analysis was conducted using permutation importance and gradient boosting tree methods to comparatively evaluate parameter sensitivities regarding building energy consumption, thermal comfort, and daylighting performance. Two distinct global sensitivity analysis approaches were implemented to assess the impact of optimized design parameters on building performance metrics, with comprehensive comparative analysis performed to derive more precise and holistic conclusions.

3.3.2. Sensitivity Analysis of Building Energy Consumption

The Permutation Importance method was employed to analyze the sensitivity of optimized parameters on building energy consumption in typical cases. The calculated

coefficient of determination (R^2) reached 83.46%, demonstrating the model's robust explanatory power and statistical significance of the computational results.

Gradient Boosting Trees (GBT) were utilized to assess parameter sensitivity on energy consumption. During random search optimization, n_estimators was incrementally adjusted from 50 to 1000 in steps of 10, while max_depth ranged from 2 to 50 with increments of 2. The min_samples_leaf parameter was tested at values of 1, 2, and 4, with min_samples_split configured at 2, 5, and 10. Through systematic optimization, the optimal parameter combination was determined as: n_estimators = 100, max_depth = 6, min_samples_leaf = 2, and min_samples_split = 5. This configuration achieved a coefficient of determination (R^2) of 88.69%. The comparative sensitivity profiles of parameters on building energy consumption derived from both methodologies are comprehensively illustrated in Figure 3.

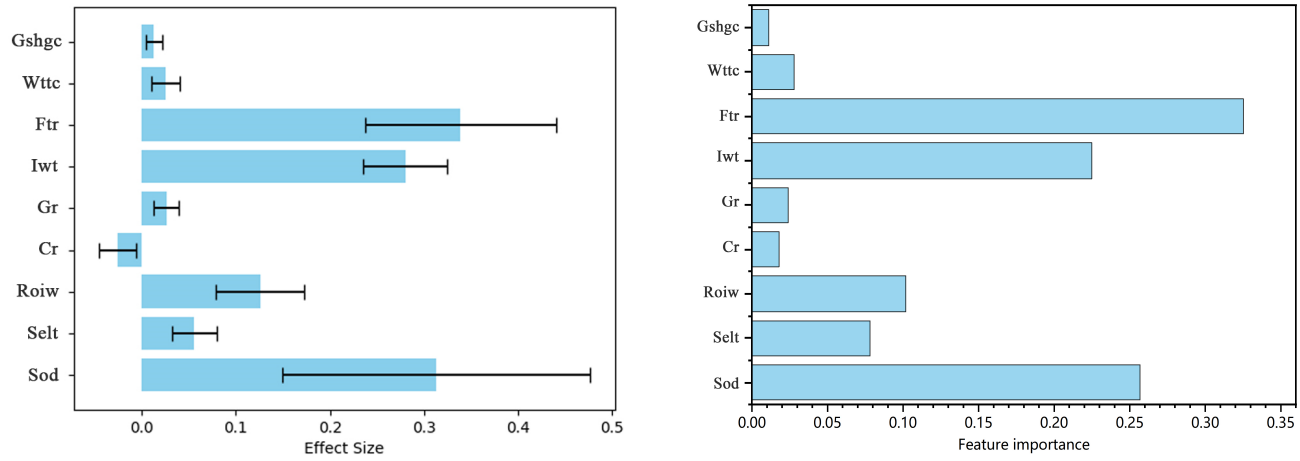


Figure 3. Effect of optimisation parameters on the sensitivity of building energy consumption: (**a**) Permutation Importance method; (**b**) Gradient Boosting Trees.

As shown in Figure 3a, the permutation importance method reveals that floor thermal resistance and shading overhang dimensions exhibit significant impacts on building energy consumption, while ceiling reflectivity demonstrates a moderate negative correlation with energy demand. Figure 3b illustrates the gradient boosting tree analysis results, identifying floor thermal resistance as the most influential parameter on building energy consumption, followed by shading overhang dimensions. The quantified parameter importance rankings are systematically presented in Table 9.

Table 9. Comparative analysis of the significance results of energy consumption related features.

Parametric	Permutation Importance Method	Gradient Boosting Trees
Shading overhang dimensions	0.313 (± 0.164)	0.2569
Shading element light transmittance	0.056 (± 0.024)	0.0782
Reflectivity of internal walls	0.126 (± 0.047)	0.1018
Ceiling reflectivity	−0.026 (± 0.020)	0.0182
Ground reflectivity	0.026 (± 0.013)	0.0243
Internal wall thickness	0.280 (± 0.045)	0.2249
Floor thermal resistance	0.339 (± 0.101)	0.3253
Window thermal transmittance coefficient	0.025 (± 0.015)	0.0284
Glazing solar heat gain coefficient	0.013 (± 0.009)	0.0112

The results of the two analyses were ranked very similarly, with the top three influences being floor thermal resistance, shading overhang dimensions, and internal wall thickness.

3.3.3. Sensitivity Analysis of Thermal Comfort

Indoor thermal comfort, as a crucial building performance indicator, encompasses human subjective perceptions of temperature, humidity, air movement, and thermal radiation within indoor environments. Thermal comfort significantly impacts occupants' quality of life, health status, and work productivity. Consequently, sensitivity analysis of optimization parameters was performed using permutation importance method, yielding a coefficient of determination (R^2) of 81.58%. Gradient boosting tree analysis identified optimal hyperparameters: n_estimators = 150, max_depth = 8, min_samples_leaf = 2, and min_samples_split = 5, achieving an R^2 value of 84.96% for thermal comfort sensitivity evaluation. Both methods demonstrated substantial explanatory power and statistical significance in the analysis. The comparative sensitivity profiles of parameters affecting indoor thermal comfort from both methodologies are illustrated in Figure 4.

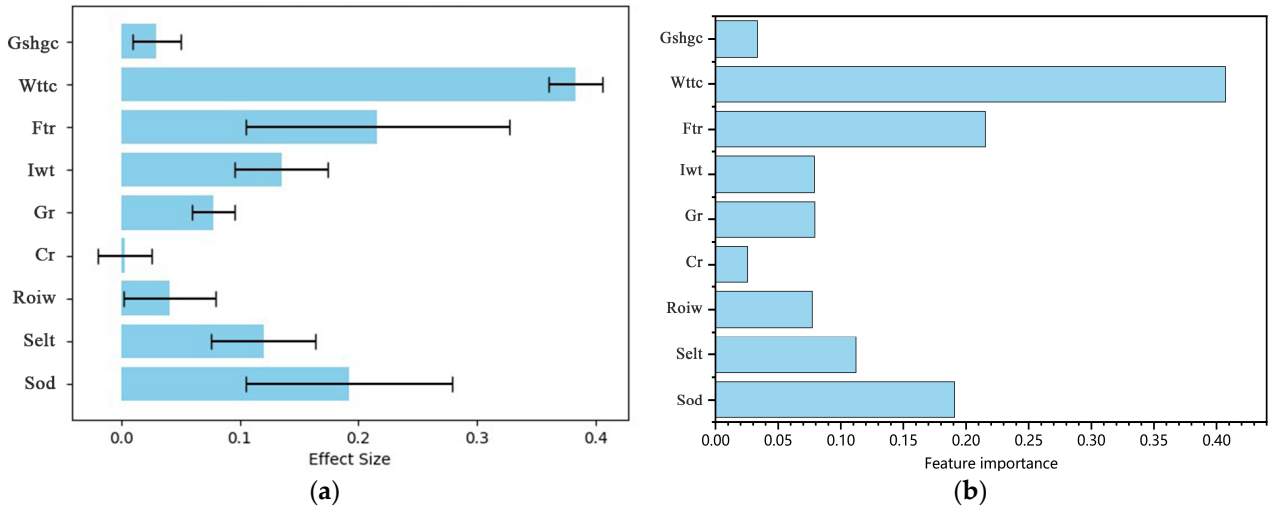


Figure 4. Effect of optimisation parameters on the sensitivity of indoor thermal comfort: (**a**) Permutation Importance method; (**b**) Gradient Boosting Trees.

As illustrated in Figure 4a, the window thermal transmittance coefficient and floor thermal resistance exhibit significant impacts on indoor thermal comfort under the permutation importance method. Figure 4b demonstrates that gradient boosting tree analysis identifies the window thermal transmittance coefficient as the most influential parameter for indoor thermal comfort, followed by floor thermal resistance. The relative importance ranking of these parameters regarding building energy consumption is detailed in Table 10.

Table 10. Comparative analysis of the significance results of thermal comfort related features.

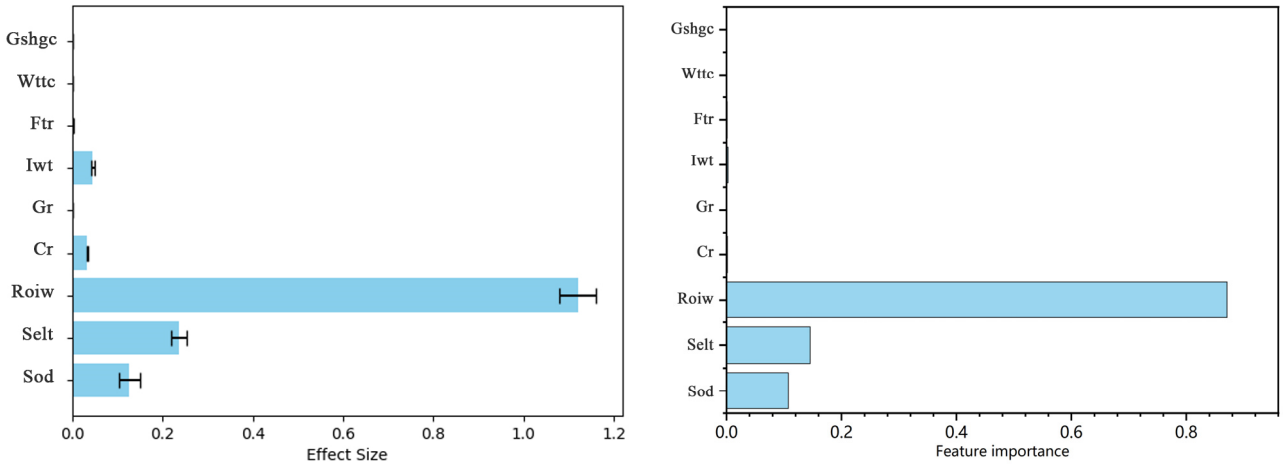
Parametric	Permutation Importance Method	Gradient Boosting Trees
Shading overhang dimensions	0.192 (±0.087)	0.1908
Shading element light transmittance	0.120 (±0.044)	0.0120
Reflectivity of internal walls	0.041 (±0.039)	0.0773
Ceiling reflectivity	0.003 (±0.023)	0.0255
Ground reflectivity	0.078 (±0.018)	0.0792
Internal wall thickness	0.135 (±0.039)	0.0788
Floor thermal resistance	0.216 (±0.111)	0.2154
Window thermal transmittance coefficient	0.383 (±0.023)	0.4071
Glazing solar heat gain coefficient	0.030 (±0.020)	0.0334

The ranking results from both permutation importance and gradient boosting tree methods exhibit significant consistency. The top three influential parameters are window thermal transmittance coefficient, floor thermal resistance, and shading overhang

dimensions. However, discrepancies were observed in the ranking order for internal wall thickness and ground reflectivity between the two methods. Given that these parameters demonstrated relatively minor impacts (with lower coefficient values) on indoor thermal comfort, they are excluded from further discussion. Through comprehensive analysis of both methodologies, it is evident that the most critical parameters affecting indoor thermal comfort (excluding building exterior walls) are window thermal transmittance coefficient, floor thermal resistance, and shading overhang dimensions.

3.3.4. Sensitivity Analysis of Indoor Lighting

Natural daylighting plays a critical role in occupant health, comfort, and work efficiency. To evaluate the impact of various optimization parameters, permutation importance and gradient boosting tree methods were employed to analyze parameter sensitivity in daylighting performance. The permutation importance analysis yielded a coefficient of determination (R^2) of 89.48%,while the gradient boosting tree analysis identified optimal hyperparameters (n_estimators = 100, max_depth = 8, min_samples_leaf = 2, min_samples_split = 5) achieving R^2 = 99.76% for thermal comfort sensitivity assessment. These results demonstrate robust statistical significance for both approaches. The comparative sensitivity rankings of parameters affecting indoor thermal comfort obtained through both methodologies are illustrated in Figure 5.



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

Figure 5. Effect of optimisation parameters on the sensitivity of indoor lighting: (**a**) Permutation Importance method; (**b**) Gradient Boosting Trees.

As illustrated in the figure above, both methodologies demonstrate consistent ranking orders of parameters: reflectivity of internal walls, shading element light transmittance, and shading overhang dimensions. The relative importance of each parameter on building energy consumption is detailed in Table 11.

The global sensitivity analysis conducted through two methodologies revealed that, when excluding exterior walls, the most significant factors affecting building energy consumption were floor thermal resistance, shading overhang dimensions, and interior wall thickness. For indoor thermal comfort, the dominant parameters were window thermal transmittance coefficient, floor thermal resistance, and shading overhang dimensions. Regarding daylighting performance, reflectivity of internal walls, shading element light transmittance, and shading overhang dimensions exhibited the greatest influence.

Table 11. Comparative analysis of the significance results of indoor lighting related features.

Parametric	Permutation Importance Method	Gradient Boosting Trees
Shading overhang dimensions	0.125 (±0.0023)	0.1073
Shading element light transmittance	0.235 (±0.018)	0.1453
Reflectivity of internal walls	1.120 (±0.011)	0.8708
Ceiling reflectivity	0.033 (±0.001)	0.0013
Ground reflectivity	0.0002 (±0)	0.00006
Internal wall thickness	0.045 (±0.003)	0.0026
Floor thermal resistance	0.001 (±0.001)	0.0010
Window thermal transmittance coefficient	0.0005 (±0)	0.0002
Glazing solar heat gain coefficient	0.0008 (±0)	0.0005

Global sensitivity analysis enables quantification of the impact degree of various design parameters on comprehensive building performance. This analytical approach facilitates the identification of critical factors influencing energy consumption, thermal comfort, and daylighting performance, thereby supporting decision-making for overall building energy efficiency and carbon reduction.

3.4. Case Study

3.4.1. Case Overview

A two-story rural residence located in Chifeng, Inner Mongolia was selected as the case study. The building features a north–south orientation with 3.6-m floor-to-ceiling heights. The ground floor comprises a kitchen adjacent to the dining area, a living room serving as the central circulation hub, and a guest room. The living space maintains visual and physical connectivity with all functional zones. The upper floor contains a master bedroom with cloakroom, secondary guest quarters with shared bathroom, balcony, and study room. The floors are conveniently connected by stairs and the floor plan is shown in Figure 6.

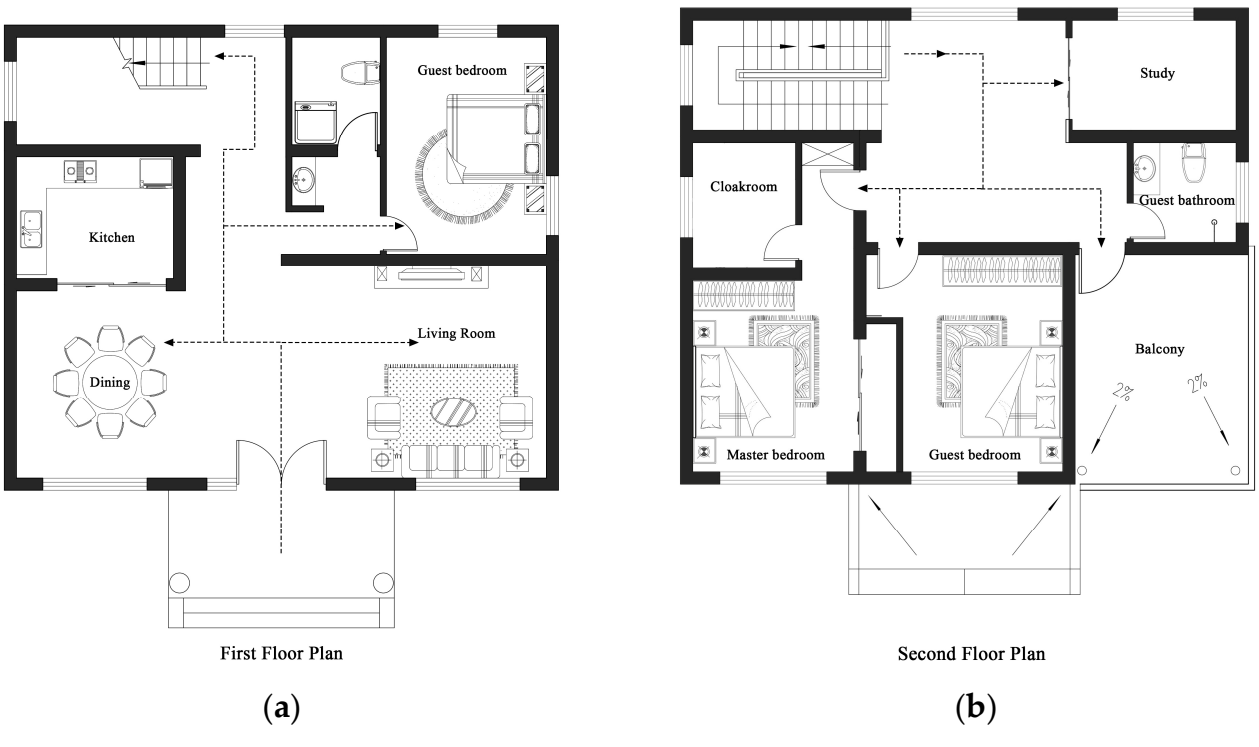


Figure 6. Typical Case Floor Plan: (**a**) First Floor Plan; (**b**) Second Floor Plan.

3.4.2. Case Building Related Parameters

The relevant thermal parameters of the buildings were adjusted in accordance with the Design Standard for Residential Buildings in Severe Cold and Cold Areas (JGJ26-2018) [33], as well as the building design codes, standards, and atlases of Inner Mongolia. The thermal parameters of the enclosure structures for residential buildings in the above typical villages and towns are shown in Tables 12 and 13.

Table 12. Thermal parameters of non-transparent building envelope structure.

Classification	Composition	Thermal Conductivity Thermal Resistance ($m^2 \cdot K/W$)	Thermal Inertness Index	Heat Transfer Coefficient [$W/(m^2 \cdot K)$]
Roof	Cement mortar 2 mm + asphalt felt 6 mm + cement mortar 40 mm + extruded polystyrene board 75 mm + clay ceramsite concrete 200 mm	2.727	4.068	0.347
Floor	Cement mortar 25 mm + reinforced concrete 80 mm + cement mortar 20 mm	0.098	1.262	3.054
External wall	Cement mortar 10 mm + extruded polystyrene board 60 mm + shale multi-hollow brick 240 mm + lime cement mortar 20 mm	2.332	0.402	4.245

Table 13. Thermal parameters of transparent building envelope structure.

Classification	Name	Heat Transfer Coefficient [$W/(m^2 \cdot K)$]	Visible Light Transmittance
Window	Aluminium alloy-70 series flat window (5 + 12A + 5Low-E)	1.9	0.8
Gate	Single-layer solid wooden outer door	1.972	-

3.5. Performance Analysis of Typical Rural Buildings

3.5.1. Analysis of Building Energy Consumption

In the building energy consumption simulation analysis conducted in this study, energy consumption calculations were performed for heating, cooling, artificial lighting, and other equipment throughout the annual 8760-h period. Following the establishment of the aforementioned building energy consumption module, the simulation yielded an annual cumulative Energy Use Intensity (EUI) of 226.449 kWh/m^2 for the building, the distribution of specific values is shown in Figure 7.

The categorized building load demand components are systematically summarized in Table 14. Quantitative analysis demonstrates that heating load dominates the energy profile at 82.41%, followed by equipment load with 7.98%, lighting load at 6.48%, and cooling load constituting the smallest proportion of 3.13%.

Table 14. Case building annual subloads.

Type of Energy Consumption	Heating Load	Cooling Load	Lighting Load	Equipment Load
EUI (kWh/m^2)	186.622	7.086	14.672	18.07
Percentage	82.41%	3.13%	6.48%	7.98%

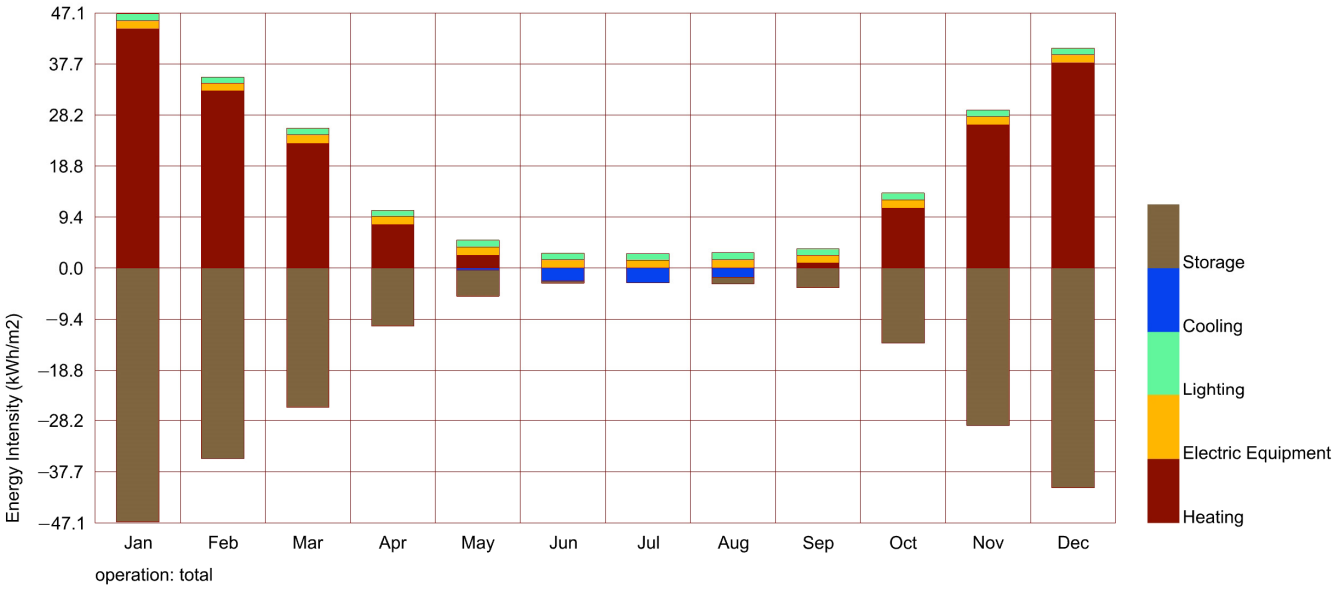


Figure 7. Month-by-month energy consumption distribution of Case building.

Table 15 presents the monthly load distribution of the case building. Heating-dominated months (Nov-Mar) collectively account for 79.28% of annual load, whereas cooling months (Jun-Aug) represent merely 5.87%.

Table 15. Case Building Month-by-Month Load Demand Analysis.

Months	**January**	**February**	**March**	**April**	**May**	**June**
Percentage	20.70%	15.59%	11.45%	4.72%	2.44%	2.28%
Months	**July**	**August**	**September**	**October**	**November**	**December**
Percentage	2.39%	1.20%	1.59%	6.10%	12.85%	18.69%

3.5.2. Building Thermal Comfort Analysis

During the indoor thermal comfort analysis phase, systematic calculations were conducted for spatial temperature distributions and the PPD index across all functional spaces in the case building. Table 16 presents the pre-optimization spatial distribution of thermal metrics obtained through comprehensive simulation, detailing zone-specific operative temperatures and PPD values.

Table 16. Spatial distribution of case building data.

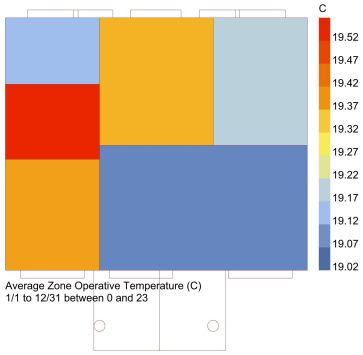
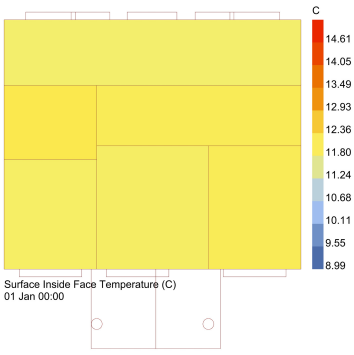
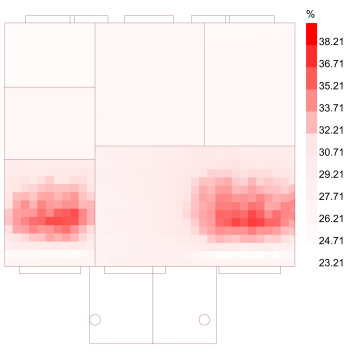
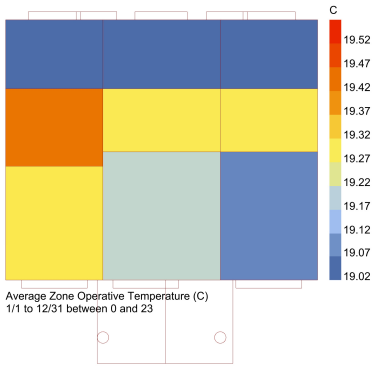
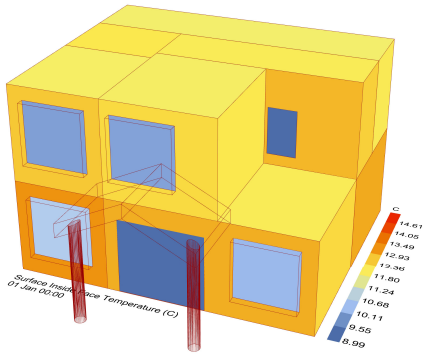
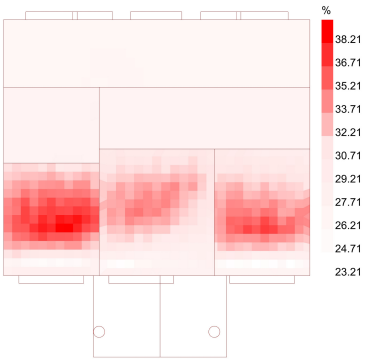
Indoor Space Temperature	**Outer Surface Temperature of Building**	**PPD**
		

Table 16. *Cont.*

Indoor Space Temperature	Outer Surface Temperature of Building	PPD
		

As shown in Table 15, the primary heated spaces on the first and second floors exhibit uniform temperature distribution, fully complying with thermal comfort standards for heated rooms in severe cold regions during winter. However, the top-floor spaces demonstrate lower temperatures with notable spatial heterogeneity. The exterior surface temperature corresponds to thermal measurements recorded at 00:00 on January 1st. Simulation results indicate an average Predicted Percentage of Dissatisfied (PPD) value of 27.828% across all rooms, signifying suboptimal thermal comfort conditions where over a quarter of occupants experience discomfort.

3.5.3. Building Interior Lighting Analysis

The daylight simulation of the case building yielded a Useful Daylight Illuminance (UDI) value of 48.77%. Analysis of UDI spatial distribution patterns, as shown in Figure 8, demonstrates the daylighting performance across interior spaces.

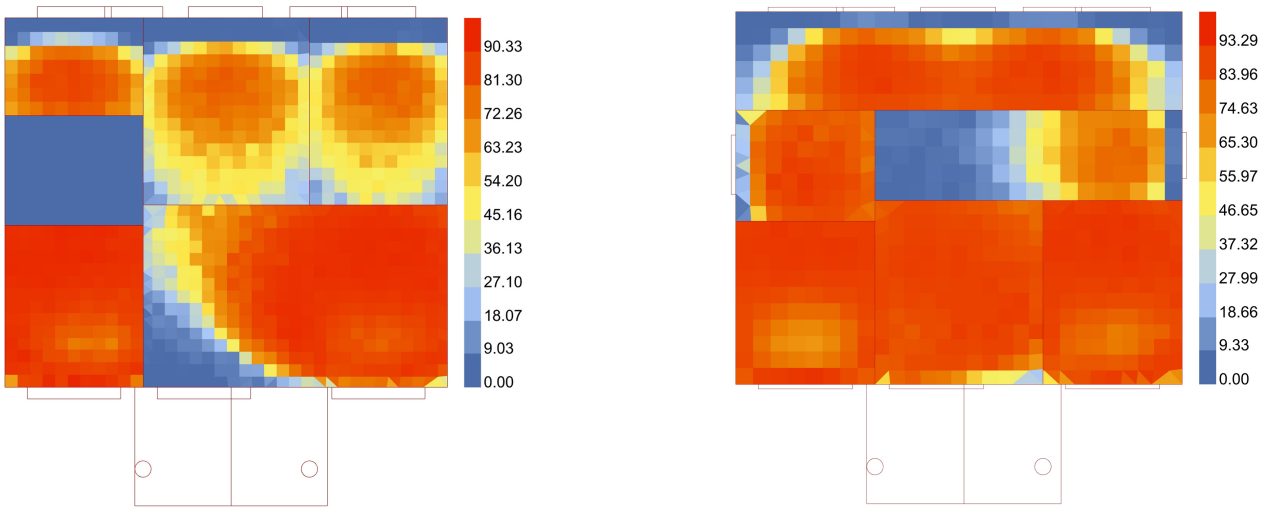


Figure 8. Useful Daylight Illuminance: (**a**) First Floor Plan; (**b**) Second Floor Plan.

As illustrated in the figure above, significant variations in daylighting performance are observed across different building locations. The decreasing trend in numerical values indicates non-uniform daylight distribution, where certain interior zones of the residential building exhibit sufficient illumination while others remain relatively dim.

Simulation analysis reveals three primary deficiencies in this rural residential building: energy consumption, indoor thermal comfort, and daylighting performance. Specifically, the building demonstrates elevated energy consumption levels, particularly during winter heating periods. The inadequate thermal insulation performance of traditional building envelopes contributes to substantial heat loss, consequently increasing overall energy expenditure. Concurrently, suboptimal indoor thermal comfort is manifested through significant temperature fluctuations during winter months, failing to meet established human comfort criteria. Furthermore, the suboptimal daylighting design results in insufficient natural illumination in specific rooms during daytime hours. This deficiency necessitates supplementary artificial lighting, which not only escalates energy consumption but also adversely impacts occupants' quality of life.

4. Results and Discussion

4.1. Analysis of Pareto Solution Set Distribution

The spatial distribution of feasible solutions obtained through multi-objective genetic algorithm computation is presented in Figures 9 and 10. During the optimization simulation, the emergence of convergence tendencies in the solution structure enables effective identification of Pareto front solutions. Each red spherical marker in the diagrams corresponds to a feasible solution generated during optimization iterations, whereas those encapsulated by the red curved surface represent Pareto-optimal solutions identified in this optimization process. The proximity of each feasible solution to the origin of the three-dimensional coordinate system quantitatively reflects its closeness to the predefined objective values.

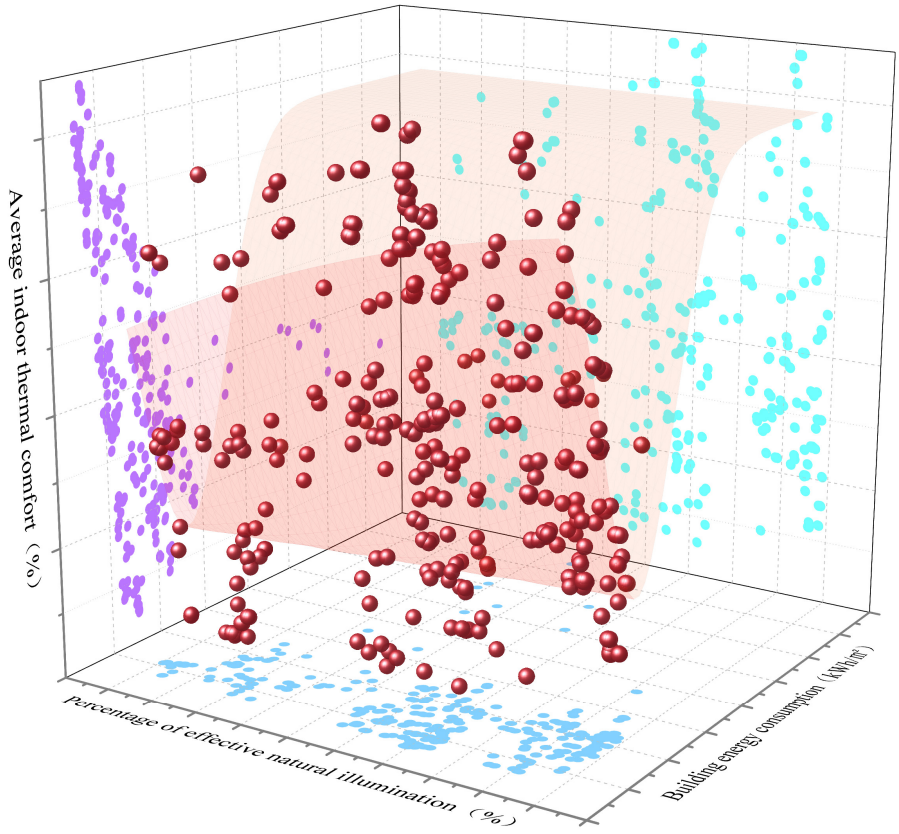


Figure 9. Multi-objective optimisation algorithm solution set.

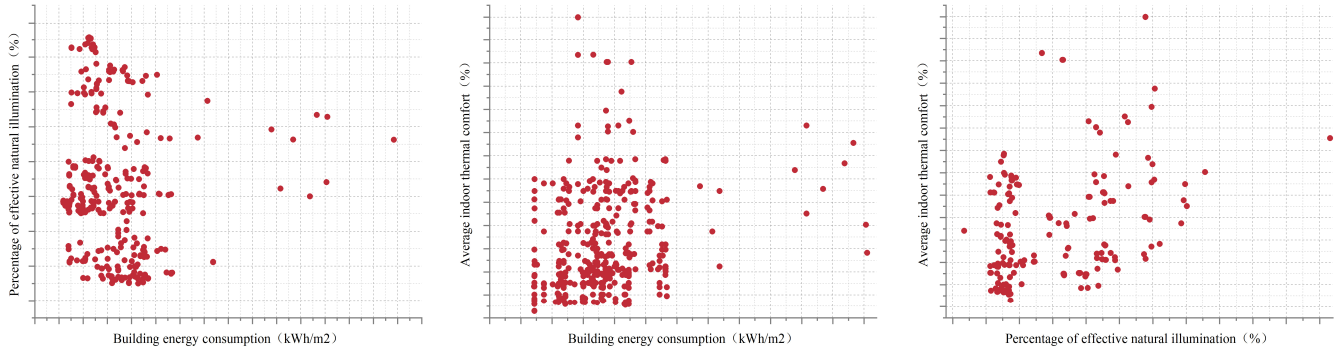


Figure 10. Multi-objective optimisation algorithm solution set (Plane view).

The Wallacei Analytics module enables visual analysis of objective performance trends during the optimization process. As illustrated in Figure 11, the iterative variation trends of three performance objectives during the optimization phase are demonstrated. In multi-objective optimization processes, the default optimization direction is set to minimize the objective values. Consequently, when integrating the optimization module, the Useful Daylight Illuminance (UDI) percentage is processed as a negative value.

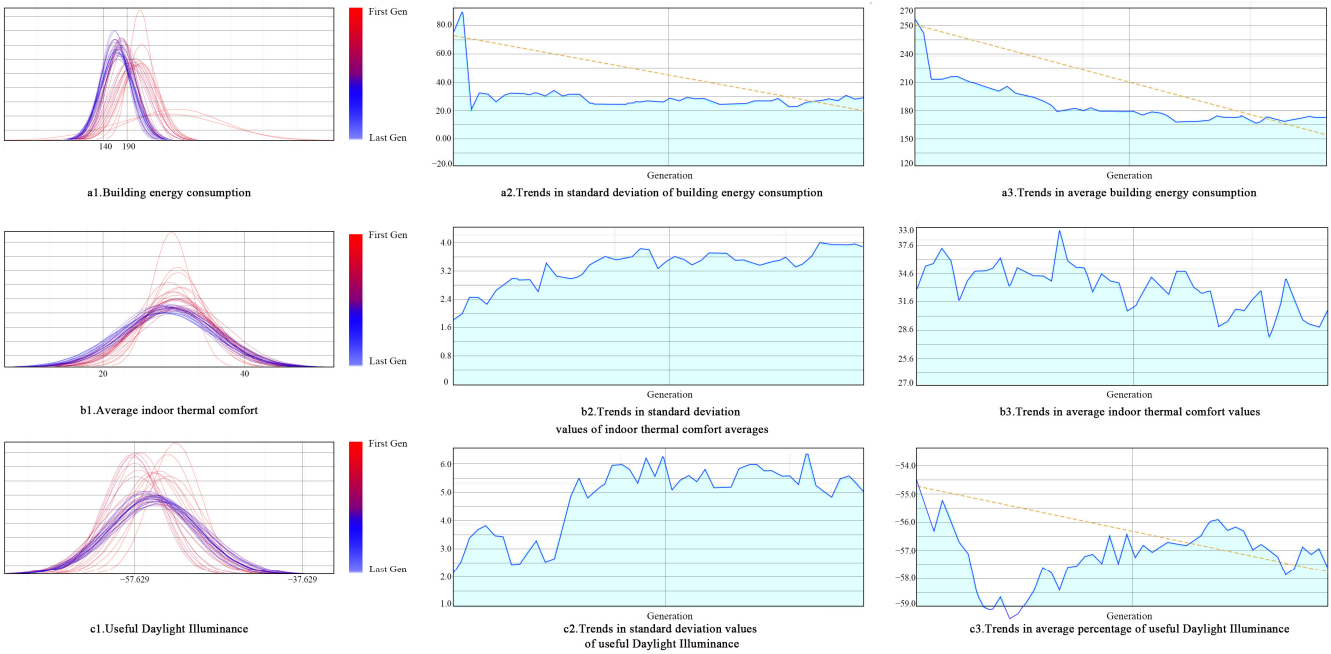


Figure 11. Multi-objective optimisation of trends in different objectives: (**a1**–**a3**) Building energy consumption; (**b1**–**b3**) Average indoor thermal comfort; (**c1**–**c3**) Useful Daylight Illuminance.

During the multi-objective optimization process, the red curve representing initial iterations progressively transitions into the blue curve corresponding to final iterations, accompanied by a leftward shift of the entire curve profile. This phenomenon demonstrates that building energy consumption undergoes continuous optimization throughout iterations, exhibiting a decreasing trend. In later optimization stages, the magnitude of positional shifts in the curve diminishes, while the reduction in curve height signifies increased variability in energy consumption values, reflecting greater deviations from the mean consumption level. Furthermore, analysis of the mean energy consumption trend reveals negligible changes during the first four generations of iterations. However, a marked decline in building energy consumption is observed starting from the fourth generation, ultimately stabilizing at a relatively constant level.

Analysis of the variation trend in the average indoor thermal comfort values (Figure 11) reveals that the curve exhibits an overall leftward shift from the initial to final iteration, indicating a progressive reduction in the mean thermal comfort level during the iterative process Concurrently, the expanded span and reduced peak amplitude observed in the final iteration curve suggest enhanced dispersion of performance objective values during optimization, accompanied by increased deviations from the global mean value.

Furthermore, the observed variation trend in the average Predicted Percentage of Dissatisfied (PPD) values across all rooms demonstrated an overall decline, despite intermittent fluctuations. Specifically, the target value decreased from 27.828% to 21.178%, indicating a significant improvement in indoor thermal comfort. This implies a substantial reduction in the proportion of occupants expressing dissatisfaction with the thermal environment under identical conditions. These findings collectively validate the effectiveness of the multi-objective optimization results.

When analysing the variation trend of Useful Daylight Illuminance (UDI), it can be observed that during the iterative process from the initial generation to the final generation, the curve height gradually increases while the enclosed area decreases. This trend indicates that as the optimization process progresses, the UDI values tend to converge with reduced dispersion. Specifically, the UDI percentage demonstrates a remarkable improvement from 48.770% in the initial generation to approximately 63.747% in the final generation, highlighting the effectiveness of optimization measures in enhancing indoor daylighting quality. The distribution of optimized solution sets for the case building is presented in Table 17.

Table 17. Case building optimised solution set distribution.

Objectives	Starting Value	Single Best Value	Optimisation Rate
EUI (kWh/m^2)	226.449	129.406	42.85
PPD (%)	27.828	21.178	23.90
UDI (%)	48.770	63.747	30.71

Under the multi-objective optimization framework established in this study, comprehensive analyses were conducted on three critical building performance indicators: energy consumption, daylighting performance, and indoor thermal comfort. The results demonstrate that all three performance objectives achieved substantial improvements during the optimization process. Notably, the convergence trend observed in objective values with progressing iterations highlights the stabilization characteristics of the optimization system, which carries significant implications for subsequent analytical evaluations.

4.2. Solution Set Options

To reduce building energy consumption, enhance indoor thermal comfort and daylighting performance, and establish a preferred solution set for rural residential buildings in Inner Mongolia, this study systematically analyses the characteristics of the optimal comprehensive performance solution.

The selection process of optimized solutions begins with the Pareto front solution set, where target values are illustrated in Figure 12. Distinct coloured polylines represent various non-dominated solutions. The analysis reveals inherent trade-offs between indoor thermal comfort (PPD), Useful Daylight Illuminance (UDI) percentage, and building energy consumption. In the Pareto solution distribution plot, vertical coordinates denote target value magnitudes, with lower positions indicating superior performance for corresponding objectives. Initial energy consumption solutions averaged 226.449 kWh/m^2, while the optimized target achieved 129.406 kWh/m^2, demonstrating a 42.85% reduction through genetic

algorithm optimization. The Predicted Percentage Dissatisfied (PPD) index decreased from 27.828% to 21.178%, indicating significant improvement in occupant thermal satisfaction. The Useful Daylight Illuminance percentage showed marked enhancement, progressing from 48.770% to 63.747% across optimization generations.

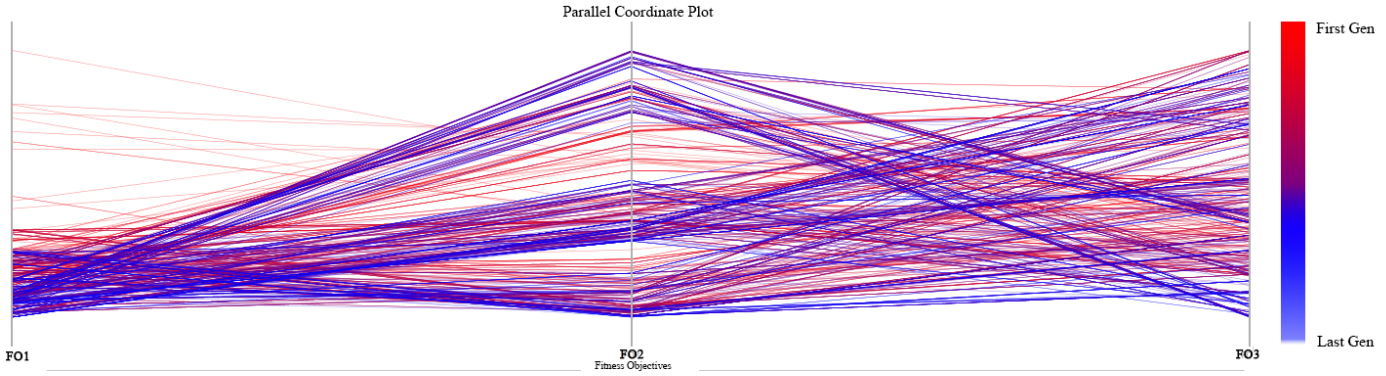


Figure 12. Distribution of Objective Values for Pareto Frontier Solution Sets.

However, due to the contradiction between the three objective values, a single result cannot simultaneously achieve optimal performance across all objectives. In this study, different solution sets were extracted, as shown in Table 18, after eliminating suboptimal solutions that do not satisfy the expected conditions.

Table 18. The Pareto frontier solution sets the optimal target value for each performance ranking.

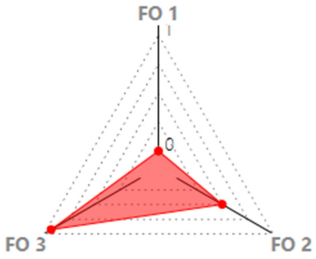
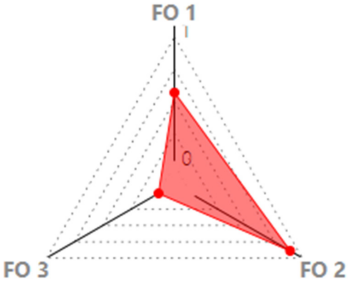
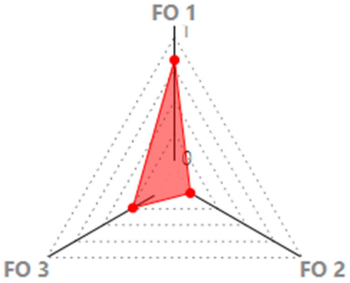
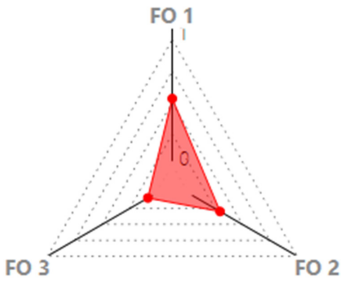
Performance Ranking Optimum	EUI (kWh/m^2)	PPD (%)	UDI (%)	Diamond Radar Chart
Optimal building energy consumption	129.406	39.659	57.884	
Optimal indoor thermal comfort	206.831	25.152	63.747	
Optimal Useful Daylight Illuminance	177.913	21.178	48.504	

Table 18. *Cont.*

Performance Ranking Optimum	EUI (kWh/m^2)	PPD (%)	UDI (%)	Diamond Radar Chart
Programmes with the highest average ranking	175.348	22.467	61.178	

A comparative analysis of the optimal comprehensive performance indicators for the multi-objective optimisation of the case building—relative to the initial sample—is presented in Table 19. Improvements were noted across all three metrics: energy consumption, thermal comfort, and indoor lighting, with enhancement rates of 22.56%, 19.26%, and 25.44%, respectively.

Table 19. Case building optimized solution set distribution.

Objectives	Starting Value	Integrated Optimal Value	Optimisation Rate
EUI (kWh/m^2)	226.449	175.348	22.56
PPD (%)	27.828	22.467	19.26
UDI (%)	48.770	61.178	25.44

The heating, air conditioning, lighting, and equipment load components of the multi-objective optimization comprehensive performance optimal solution for the case building were analyzed and compared with the initial samples, as detailed in Table 20. Analysis of the optimization effects reveals an overall reduction in annual cumulative load. Regarding individual load components, the lighting and equipment subsystems exhibited the least optimization improvement, followed by heating load, whereas the air conditioning load demonstrated the most significant optimization performance.

Table 20. Case Building Load Subdivision.

Objectives	Starting Value	Integrated Optimal Value	Optimisation Rate
Heating	186.622	138.95	25.54%
Air Conditioning	7.086	3.657	48.39%
Lighting	14.672	14.669	0
Equipment	18.07	18.07	0

In the detailed monthly load variation analysis of optimal solution samples, this study defines cooling load as air conditioning load, heating load as thermal load, with electrical load being the sum of lighting and equipment loads. The corresponding load distribution patterns are detailed in Figure 13. The in-depth analysis of graphical data reveals that the case building exhibits significant annual load fluctuations. Particularly in January, February, and December, the load values substantially exceed other months, with heating load constituting the predominant proportion. Notably, January demonstrates the annual peak load, characterized by exceptionally prominent heating demand.

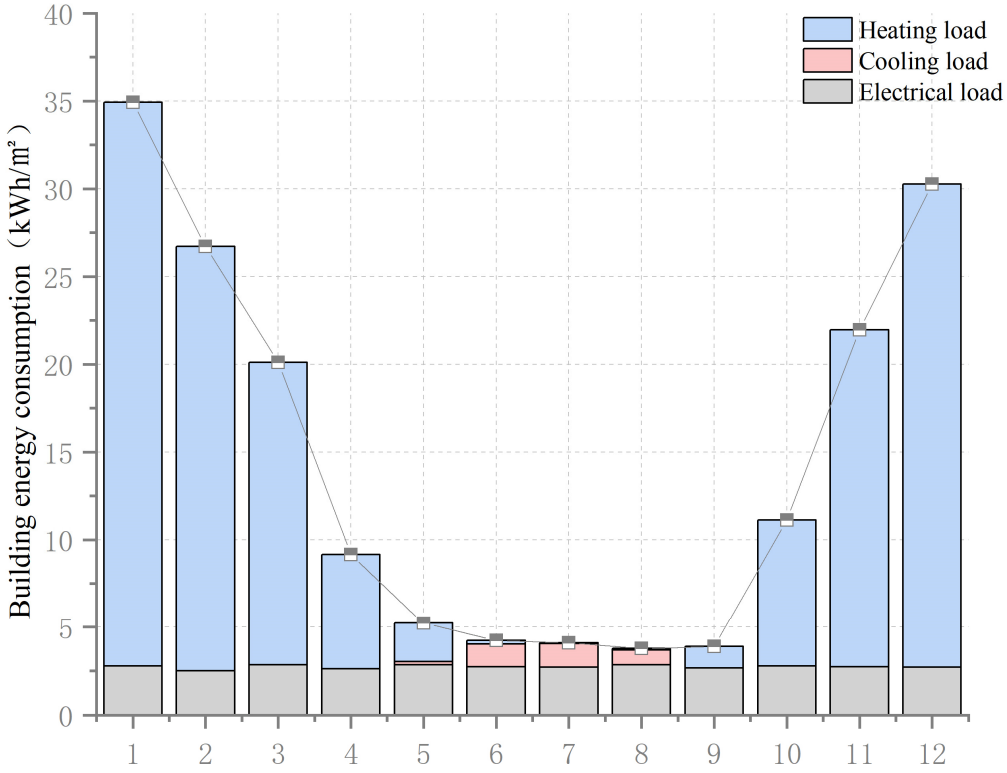


Figure 13. Case Building Optimal Solution Month-by-Month Load Variation.

Furthermore, during June and August, the building's load profile is predominantly composed of electrical and cooling loads. The winter heating season, particularly in January, witnesses the maximum thermal load intensity.

An in-depth analysis of the hourly load distribution throughout the year in the case study building reveals significant fluctuations in cooling and heating loads. Specifically, the building's cooling load peaked at 0.0631 kWh/m^2 on July 24th at 10:00, while the heating load reached its annual maximum of 0.1616 kWh/m^2 on December 19th at 8:00. In contrast, the electricity load demonstrates relatively stable variation characteristics with distinct periodic fluctuations.

4.3. Design Parameter Optimisation Solution Set

To reduce energy consumption in rural residential buildings while improving indoor thermal comfort and daylighting, the previous section derived a solution set demonstrating the highest average ranking across three objectives: building energy consumption, effective daylight illuminance percentage, and indoor thermal comfort. The corresponding output values are presented in Table 21.

Table 21. Case building optimisation solution set parameter values.

No.	Parametric	Optimal Value
1	Shading overhang dimensions	0.10
2	Shading element light transmittance	0.90
	Reflectivity of internal walls	0.10
3	Ceiling reflectivity	0.20
	Ground reflectivity	0.20
4	Internal wall thickness	0.19
5	Floor thermal resistance	0.7
6	Window thermal transmittance coefficient	1.3
7	Glazing solar heat gain coefficient	0.6
8	Wall database	254

Through 1000 simulation-based optimization calculations, Wall No. 254 was selected from the existing rural residential wall database in Inner Mongolia, demonstrating balanced performance across multiple metrics. The specific construction details of this wall are presented in Table 22.

Table 22. Multi-objective optimisation for selection of wall constructions.

No.	Composition	Heat Transfer Coefficient [W/ (m^2·K)]
No. 254	1.10 mm exterior finish 2.90 mm extruded polystyrene sheet 3.240 mm shale ceramic concrete 4.20 mm internal plaster on external wall	0.326

A preliminary cost analysis of Wall No. 254 indicates a 18% increase in material costs compared to traditional methods, yet the 22.56% energy savings could offset this within 4–6 years, based on local energy tariffs.

4.4. Comparison of Cases and Exploration of Universality

To validate the universality and regional adaptability of the proposed method, this study conducted a multi-dimensional comparative analysis (Table 23) of optimization cases selected from three climatic zones: Severe Cold, Cold, and Hot Summer–Cold Winter regions. The systematic investigation revealed both commonalities and distinctions in multi-objective optimization strategies across diverse geographical contexts.

Table 23. Comparative analysis of different cases.

Comparison Dimension	This Study in Inner Mongolia	Zalantun Case [34]	Northwest Territories Cases [2]	TianJin Case [35]	Xuzhou Case [36]
Climate zone	Severely Cold Zone	Severely Cold Zone	Cold Zone	Cold Zone	Summer Hot and Winter Cold Zone
Optimisation goals	Energy consumption, Indoor thermal comfort, Indoor Lighting	Energy consumption, Costs	Energy consumption, Indoor thermal comfort, Costs	Energy consumption, Indoor thermal comfort	Indoor thermal comfort, Carbon emission, Costs
Core algorithm	NSGA-II (Wallacei)	NSGA-II (MOBO)	NSGA-II (MOBO)	SPEA-2, HypE	Krill Herd Algorithm
Core variables	Enclosure, Form	Enclosure insulation	Orientation, External windows, Insulation	Architectural form	Window–wall ratio, Heat transfer coefficient
Energy saving rate increase	22.56%	34.1~72.0%	54%	22.8%	Reduced by 55.84 kWh/m^2
Range of cost increments	Small increase	92.3–645.5 CNY/m^2	182.4 CNY/m^2	-	-
Thermal comfort improvement	PPD decreased by 19.26%	-	APDD increased by 57.6%	Reduction in the number of hours of thermal discomfort by 8.8%	APD decreased by 25%

The present study, along with Zalantun, is situated within the severe cold climate zone. Both cases focus on core variables related to building envelope and thermal performance (e.g., wall insulation), whereas the Xuzhou case in the hot summer/cold winter climate zone prioritizes optimization parameters such as window-to-wall ratio and thermal transmittance coefficient. This comparative analysis demonstrates that climatic conditions exert a significant influence on variable selection in architectural optimization. Unlike previous studies [2,34,35] that focused solely on energy consumption or cost optimization, this research integrates daylighting performance into multi-objective optimization criteria for cold regions, thereby expanding the quantitative assessment framework in environmental quality dimensions to some extent.

The Zalantun case adopted a weighted sum method to determine equilibrium solutions, achieving a 72% energy-saving rate while incurring a marked cost increase. This high-cost strategy complements the low-increment approach proposed in our study, demonstrating that technical templates should be selected based on regional economic capacities.

While both this study and the Northwest Territories case [2] employ NSGA-II, the latter focuses on orientation and window design optimization under cold zone conditions, achieving a higher energy-saving rate (54%) with moderate cost increments (182.4 CNY/m^2). This suggests that passive design strategies (e.g., orientation adjustment) may complement envelope insulation in severe cold regions.

The Tianjin case [35] shares similar climatic zoning requiring enhanced thermal insulation performance with this study, with both optimization objectives encompassing the balance between energy consumption and thermal comfort. This demonstrates that thermal environment stability constitutes the central challenge for performance optimization in cold/severe cold regions. Aligning with our research methodology, the Tianjin case prioritizes architectural morphology (e.g., building shape coefficients) as key variables, achieving thermal loss reduction through morphological optimization. The comparable energy-saving rates (22.8% vs. 22.56% in this study) corroborate the universal applicability of morphological regulation in cold climate zones.

The Xuzhou case [36] proposes a co-optimization strategy for window-to-wall ratio and thermal transmittance of exterior windows to address dual challenges of summer heatwaves and winter cold extremes. Utilizing genetic algorithms to balance carbon emissions, retrofit costs, and thermal comfort, this approach reveals the necessity for reconciling seasonal energy efficiency conflicts in hot-summer/cold-winter zones, presenting a distinct contrast to the year-round insulation prioritization typical in severe cold regions.

Although the aforementioned cases have validated the cross-regional potential of multi-objective optimization approaches, the findings of this study are constrained by Inner Mongolia's specific climatic conditions and economic development level. Future research should integrate regional meteorological data with occupant behavior patterns to establish a dynamic optimization framework, thereby enhancing the generalizability of the methodology.

5. Limitations and Future Research Directions

5.1. Limitations

The proposed methodology has achieved promising results; however, several limitations remain.

(1) Regional Specificity: The methodology and results are tailored to the severe cold climate and architectural practices of Inner Mongolia. The applicability of optimized solutions to other climatic zones or cultural contexts remains untested. (2) Data Constraints: The wall material database relies on localized field investigations, potentially omitting emerging construction techniques and introducing sampling biases. (3) Model Simplifications: To

balance computational efficiency and practicality, fixed occupancy schedules (based on field surveys) and static HVAC parameters were adopted. While this approach enabled tractable optimization, it excluded dynamic behavioral patterns and climate fluctuations, potentially underestimating energy demand in transitional seasons. (4) Economic Feasibility: The economic viability of optimized solutions (e.g., material costs, stakeholder acceptance) was not evaluated, potentially hindering rural implementation of high-performance materials.

5.2. Future Research Directions

In addition to improving on the limitations mentioned above, this study may be further developed in the following four aspects in the future.

(1) Investigate the synergistic effects of integrating renewable energy systems with optimized building envelopes. Quantify energy autonomy potential and carbon offset capabilities under severe cold climate conditions.

(2) Leverage IoT sensors and machine learning to collect real-time occupancy patterns, thermal preferences, and energy-use behaviours in rural households. Establish region-specific behavioral profiles to replace static assumptions.

(3) Propose low-cost automation frameworks to optimize building operations in response to real-time environmental data. Evaluate the scalability of smart systems in resource-limited rural contexts.

(4) Future studies should prioritize integrated implementation strategies that bridge theoretical optimization and rural construction practices through standardized guidelines, workforce capacity-building, and multi-stakeholder collaboration frameworks.

6. Conclusions

This research focuses on rural residential buildings in Inner Mongolia, proposing an optimized design methodology for regional vernacular architecture. The rationality of this method was validated through case studies, yielding the following conclusions:

(1) Current rural dwellings in Inner Mongolia exhibit substantial energy-saving potential due to prevalent high energy consumption and suboptimal thermal comfort levels, primarily constrained by construction budgets and technical limitations.

(2) A comprehensive database for rural residential wall systems was established through systematic investigation of building materials and application of self-organizing neural network modelling. This database systematically categorizes, processes, and analyses the collected wall materials and structural configurations of residential buildings in Inner Mongolia. The MySQL-based platform enables visualization through static/dynamic diagrams and serves as critical input for subsequent multi-objective optimizations.

(3) Utilizing Rhino-Grasshopper with Wallacei multi-objective optimization module, parametric analysis was conducted with key architectural parameters including: exterior wall composition, window thermal transmittance coefficients, and sunshade configurations (length and reflectivity). This methodology demonstrates dual functionality: guiding preliminary energy-efficient design decisions and informing retrofit strategies for existing buildings. Comparative analysis reveals significant performance enhancements in optimized solutions, with EUI, PPD, and UDI metrics improving by 22.56%, 19.26%, and 25.44%, respectively, confirming the method's feasibility and robustness.

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