

Article

Multi-Objective Optimization of Morphology in High-Rise Residential Areas for Outdoor Thermal Comfort in Yulin City, Northwest China

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Abstract: Urban residential areas significantly influence outdoor thermal comfort through architectural morphology. This study concentrates on the multi-objective optimization of the thermal comfort environment in residential areas, with a focus on Yulin—a city in the cold, inland region of Northwestern China. Yulin is characterized by its distinctly defined seasons, particularly harsh and windy conditions in the spring, which significantly impact thermal comfort. Utilizing field surveys, characteristics of scale and layout from high-rise residential areas in Yulin were extracted to formulate design strategies adapted to local climates. The Universal Thermal Climate Index (UTCI) served as the optimization criterion, and genetic algorithms, integrated with parametric modeling software, generated multiple layout schemes. These were refined through the Pareto evolutionary algorithm II to optimize thermal comfort across seasons. Furthermore, the Sobol' sensitivity analysis method was employed to assess the impact of key parameters on outdoor thermal comfort, identifying crucial layout design elements. The optimization improved UTCI values for different seasons, ensuring year-round comfort. Specifically, summer UTCI improved to 25.51, while winter and spring values reached optimal values of −14.02 and −6.41, demonstrating enhanced thermal retention and reduced wind exposure. Sobol' sensitivity analysis identified building length, orientation, and density as key parameters, highlighting their critical impact on thermal comfort. This study offers practical guidelines for urban residential area design in similar climatic zones, aligning architectural planning with environmental sustainability and enhancing thermal comfort effectively. This study provides practical guidelines for the design of residential areas in cold inland—seasonal windy—regions and other similar climatic zones, aligning building morphology design with environmental sustainability and enhancing thermal comfort effectively.



Citation: Meng, Y.; Hao, Y.; Que, Y.; Ren, J.; Liu, Y. Multi-Objective Optimization of Morphology in High-Rise Residential Areas for Outdoor Thermal Comfort in Yulin City, Northwest China. *Buildings* **2024**, *14*, 1688. <https://doi.org/10.3390/buildings14061688>

Academic Editor: Karim Ghazi Wakili

Received: 30 April 2024

Revised: 27 May 2024

Accepted: 3 June 2024

Published: 6 June 2024

Keywords: outdoor thermal comfort; multi-objective optimization; sensitivity analysis; high-rise residential area; machine learning; architectural morphology



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1. Introduction

1.1. Background

In the context of addressing global climate change, creating comfortable urban outdoor thermal environments has emerged as a pivotal research topic in building research. China's rapid urbanization and escalating population density [1] have spurred a boom in the construction of high-rise residential areas, underpinning sustained demand. The outdoor thermal environment of these areas critically impacts residents' physical and mental health [2], making thermal comfort a key metric of living quality in urban residential settings.

Yulin city, located in the cold inland region of Northwest China, possesses a distinct four-season climate and is currently in a rapid stage of urban development [3]. The local climate, however, presents challenges to the thermal comfort of residential zones [4], especially with pronounced wind chill effects in winter and prevalent sandstorms in spring. These adverse conditions significantly worsen outdoor thermal discomfort and limit residents' outdoor activities.

Urban building morphology and spatial layout are instrumental in shaping the outdoor thermal environment, with architectural parameters closely tied to urban microclimates. Adjusting and optimizing building form layout can improve outdoor thermal comfort, elevate living standards, and foster healthy residential environments. However, the multifaceted nature of factors influencing thermal environments, coupled with significant seasonal fluctuations in outdoor conditions, complicates the task of universally enhancing outdoor thermal comfort in residential areas. Consequently, the adoption of a multi-objective optimization approach emerges as an effective strategy to address these challenges. Such an approach holds substantial importance for elevating residents' quality of life, fostering the sustainable development of communities.

1.2. Literature Review

A reasonable spatial layout is conducive to improving the environmental thermal comfort of residential areas. Many scholars have discussed the relationship between spatial form and outdoor thermal comfort. Table 1 shows related research literature on typical research methods of residential space. For example, Mohd Fadhil Md et al. investigated the thermal comfort of various building layouts, with a special focus on tropical climates [5]; Yang et al. studied and analyzed the UHI of three residential areas in downtown Shanghai and discussed the relationship between building layout and summer heat islands [6]; Li et al. quantitatively investigated the intrinsic relationship between the building forms of residential areas and thermal comfort, and proposed optimization strategies [7].

At the same time, many scholars have used computer simulation technology to study and discuss the spatial layout of buildings. For example, Anand et al. simulated three different climate zones in India by ECOTECT and put forward an auxiliary design tool for architectural layout based on thermal comfort [8]. Mohammad et al. Used ENVI-met to simulate outdoor microclimate and Rayman transformation data to analyze five different urban forms in the Netherlands to explore the important influence of spatial form on thermal comfort [9]; Wu et al. used computational fluid dynamics (CFD) simulation to evaluate different building layouts and explore the impact of building spatial layout on wind environments [10].

With the rapid development of computer simulation technology, genetic algorithms have been used more and more in the optimization of architectural space layouts. A genetic algorithm is a random search and optimization algorithm that uses computer simulation operations to quickly search for the best solution from a large number of possibilities [11]. It improves the traditional simulation method, improves the optimization efficiency, and is widely recognized for its effectiveness in solving complex problems such as multi-objective optimization. For example, Mohamed et al. used a variety of algorithms such as controlled non-dominated sorting Genetic algorithm with passive archiving (NSGA-II), multi-objective particle swarm optimization (MOPSO), and two-stage optimization based on a genetic algorithm (PR_GA) to compare the multi-objective optimization of building energy consumption [12]; Wei et al., with an improved multi-objective genetic algorithm (NSGA-II) as the theoretical basis, carried out optimization through genetic algorithm (GA), quickly predicted the energy consumption and thermal comfort state of residential buildings, and carried out multi-objective optimization of building energy consumption and environmental thermal performance [13]; Ma et al. used Honeybee and Octopus to simulate and optimize, focusing on four typical skylights in the climate of Fukuoka, Japan, and carrying out multi-objective optimization of the lighting and thermal environment in the skylight design [14].

As can be seen from the literature shown in Table 1, multi-objective optimization is a future research hotspot, and many scholars' research on the relationship between building spatial layout and thermal comfort has achieved results in both theory and practice, advancing the application of performance simulation in building spatial layout planning.

Table 1. Review of research literature on typical research methods of residential space.

Authors	Year	Climate	Building Type	Objectives	Research Tools
Anand et al. [8]	2017	Tropical monsoon climate	Residential building	Proposing a thermal comfort-based building layout aid design tool	ECOTECT
Pomfret et al. [15]	2017	Temperate maritime climate	Residential building	Improve ventilation and thermal comfort in zero-energy buildings	IES (VE)
Diler et al. [16]	2019	Subtropical Mediterranean climate	Mosque building	Improving thermal comfort and heritage conservation	Design Builder HOBOT U12
He et al. [17]	2020	Subtropical monsoon climate	Multiple building types	Researching the effect of zone ventilation and humidity on outdoor thermal comfort	Field measurements
Li et al. [18]	2022	Not specified	Multi-energy building microgrids	To optimize multi-energy microgrid operations considering thermal loads and battery degradation	Stochastic- weight robust optimization, Wallacei
Ren et al. [19]	2022	Multiple climate types	Multiple building types	Providing a reference for designing an optimal layout of urban spaces, regulating the thermal environment and promoting sustainable urban development	ENVI-met
Wu et al. [10]	2023	Multiple climate types	Multiple building types	Impact of the spatial layout of buildings on the wind environment	CFD
Arabi et al. [20]	2015	Temperate maritime climate	Urban space	Influence of space morphology on thermal comfort	ENVI-me Rayman
Anand et al. [8]	2017	Tropical monsoon climate	Residential building	Proposing a thermal comfort-based building layout aid design tool	ECOTECT
Pomfret et al. [15]	2017	Temperate maritime climate	Residential building	Improve ventilation and thermal comfort in zero-energy buildings	IES (VE)
Diler et al. [16]	2019	Subtropical Mediterranean climate	Mosque building	Improving thermal comfort and heritage conservation	Design Builder HOBOT U12
Tartarini et al. [21]	2020	Multiple climate types	Multiple building types	Providing an easy-to-use platform to calculate and visualize thermal comfort indices	CBE
Ding et al. [22]	2024	Not specified	Buildings integrated with multi-agent energy systems	To develop a distributed cooperative operation strategy for energy systems integrating wind, solar, and building management	Chance-Constrained Programming, Distributed systems analysis

Most computer simulations adopt the working mode of “modeling+simulation+ analysis+integration+optimisation” [23]; this requires repeated adjustments and consumes a lot of time, most of the computer simulation only focuses on a certain model and concentrates on the optimization of a single performance index, and there is a lack of in-depth discussion on how to trade off the different performance indexes in multi-objective optimization. Additionally, research on multi-objective optimization still focuses mainly on small-scale and small-volume urban residential areas and does not provide sufficient guidance on the spatial layout of actual urban residential areas. Furthermore, research tools using multi-objective optimization as a pathway are less analytical for environmental thermal comfort in transitional climate zones with temperate semi-arid climates, and there is a lack of discussion of the climatic characteristics of cold areas with high winds in the spring. The climate of the Yulin region is consistent with this feature, especially in the spring, when the number of windy days is high and the climatic characteristics are more specific. Furthermore, multi-objective optimization studies of building spatial layout and thermal comfort using the Grasshopper-based Wallacei plug-in are relatively rare.

1.3. Research Objective

The research aims to holistically enhance the outdoor thermal comfort in residential areas of Yulin City during the winter, spring, and summer seasons. Employing the parametric software Grasshopper 1.0 with Rhino 7.24 and the NSGA-II algorithm-based Wallacei for performance simulation and multi-objective optimization, the study examines the impact of the layout and form of residential areas on outdoor thermal comfort. Additionally, through the integration of Sobol’ sensitivity analysis and GBM machine learning methods, this study quantitatively investigates the interaction between spatial layout morphology and microclimatic parameters, identifying critical design variables closely related to thermal comfort. This process is designed to facilitate a comprehensive and nuanced analysis of the factors influencing thermal comfort during the early stages of design. By developing a framework for thermal comfort optimization, the research elucidates how architectural morphology affects the thermal environment of residential areas and provides an empirically validated, operable optimization method and guidance for the design of residential area layouts in Yulin. The results of this research not only furnish theoretical and practical support for residential area design in Yulin but also offer foundational research references for areas with similar climatic conditions.

2. Methods

This study is mainly divided into three stages. Based on the previous climate analysis, the first stage is to build a simulation parametric model and performance simulation; the second stage is to conduct multi-objective optimization and obtain the Pareto optimal solution; the third stage adopts a machine learning method to conduct sensitivity analysis and obtain the influence degree and relationship of various physical factors on the thermal comfort of residential areas. The technical framework of this study is shown in Figure 1.

2.1. Climate Context

Yulin is situated in a cold region. Throughout the year, the temperature generally ranges from $-23\text{ }^{\circ}\text{C}$ to $34.2\text{ }^{\circ}\text{C}$, and the average annual temperature is $9.22\text{ }^{\circ}\text{C}$. The average annual precipitation in Yulin varies from 300 mm to 500 mm [24]. Figure 2 shows the annual temperature variation in Yulin. In recent years, the climate change characteristics of Yulin City have shown a trend of rising temperatures and decreasing precipitation, and the phenomenon of warming and drying has intensified [25]. This has brought about increased high temperatures in the summer, cold and dry winters, and frequent sand and dust storms in the spring. According to the comfort evaluation analysis, the climatic comfort period in the Yulin area is mainly concentrated in the period from May to September, while the uncomfortable period occurs in the period from November to March [26], with a wide range of unsuitable time spans.

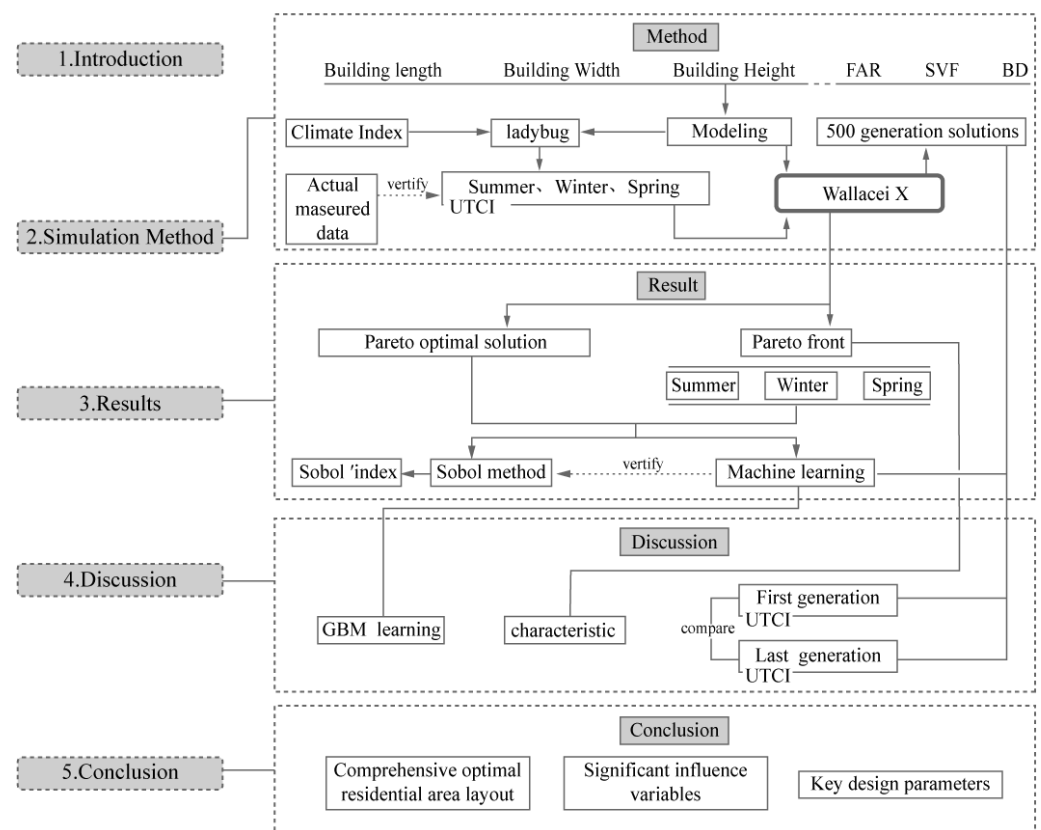


Figure 1. Research framework.

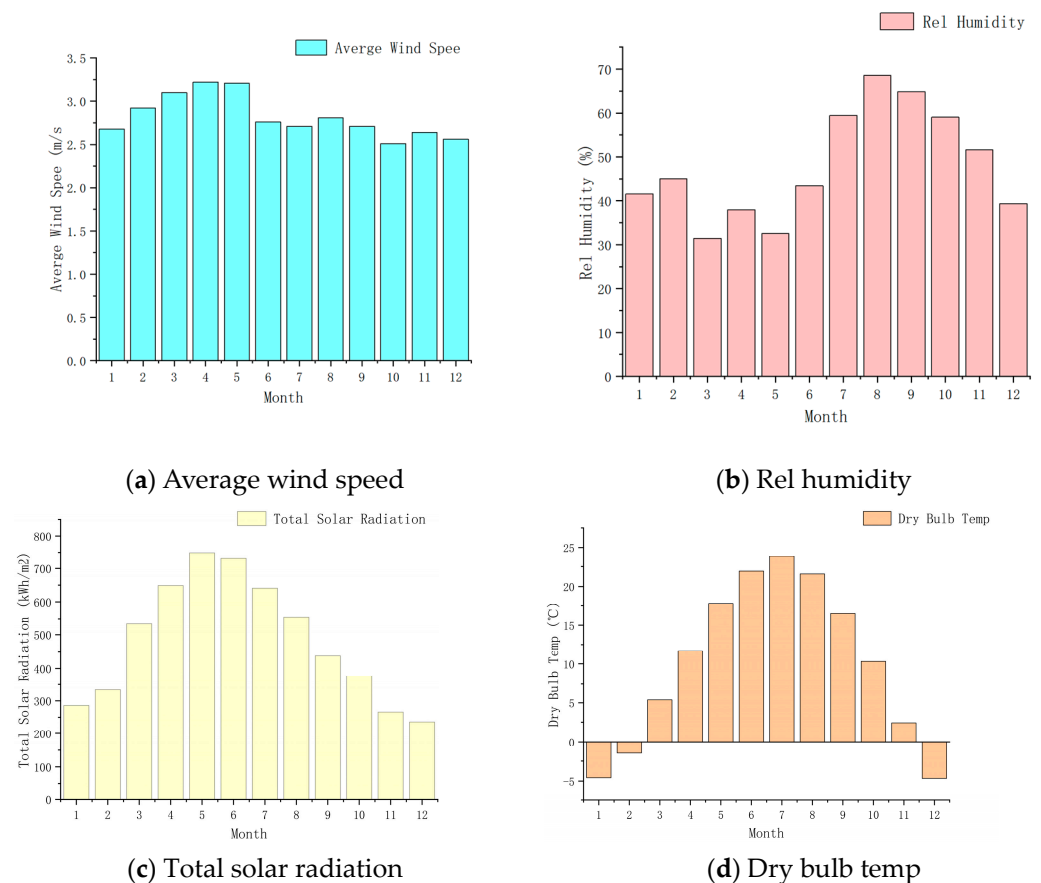


Figure 2. Basic climate information of Yulin [27].

In this study, the case study is a typical high-rise residential district, which is located in the center of Yulin City. The residential area has a semi-arid continental monsoon climate, and the hot season lasts for about four months, extending from May to September, during which the average daily maximum temperature exceeds 25 °C, with July being the hottest month, with an average high temperature of 31 °C. In addition, there is relatively high precipitation during the summer months, and the combination of high temperatures and humidity results in increased heat stress and reduced comfort. The cold season lasts about three months, from December to March, during which the average daily maximum temperature is below 5 °C, with January being the coldest month, with an average low of −13 °C. The winter is dry and windy. The climate is dry and windy in winter.

The average hourly wind speed in the Yulin area shows obvious seasonal variations, especially in spring, when the wind speed is higher and the number of windy days accounts for 40 to 50 per cent of the year, and the average wind speed at a height of 1.5 m above the ground is about 2.92 to 3.22 km per hour, with the highest wind speed in April, when the average wind speed is 3.22 km per hour. At the same time, spring is dry with little rain, making it prone to dust storms. In this study, the morphology of the residential district is modeled for thermal comfort using the Universal Thermal Climate Index (UTCI). The UTCI calculations are based on daily climate data for spring, summer, and winter, with the aim of forming an optimization strategy to enhance thermal comfort in each season.

2.2. Performance Simulation Method

The initial phase of the investigation examined the general layout of residential areas within the Yulin region, employing spatial typology as a methodological framework for summarization. Typology, a systematic approach to classification, identifies the components of a category based on the specific attributes stipulated by a hypothesis. This method of grouping aids in the facilitation of argumentation and exploration by establishing constrained relationships among phenomena. It is widely used in the field of architecture to explore the universal space or form of a certain type of architecture [28,29], simplifying the living space into a parameterized standard form. Subsequently, the Rhino 7.24 and Grasshopper 1.0 software platforms were employed to construct a prototypical parametric three-dimensional model of residential areas, characterized by adjustable parameters within a predefined range.

In the evaluation of the thermal comfort index, the general thermal ambient Climate Index (UTCI) was selected as the index to evaluate outdoor thermal comfort. The UTCI takes into account all thermos physiological parameters of heat exchange between humans and the environment [30], including temperature, humidity, wind speed, radiation, etc., and applies to all climatic zones, seasons, and spatial temporal variations. Its calculation formula is as follows:

$$UTCI = f(T_{air}; TMRT; v; vp) \quad (1)$$

where v and vp represent wind speed and humidity expressed in water vapor pressure or relative humidity. Different values can be obtained by substituting the climate parameters measured in different seasons into the formula, and the value range of human body feeling more comfortable is 9 °C to 26 °C [31]. The UTCI value in winter is predominantly influenced by low temperatures, typically resulting in lower values. Conversely, in summer, the UTCI is chiefly affected by high temperatures, generally leading to higher values. It is noteworthy that Yulin, situated in the northwest inland of China, is frequently subjected to strong winds during the cold spring season, which contributes to a lower UTCI value for this period [32]. Therefore, this study mainly uses the UTCI values of the above three seasons as the standard to study the layout optimization of residential areas.

2.3. Multi-Objective Optimization

Taking the UTCI index of the second stage as the standard, the Wallacei plug-in integrated into Grasshopper was used for multi-objective optimization of the parametric model generated in the first stage within a certain controllable range. Wallacei uses NSGA-2 as its

main evolutionary algorithm and uses the K-means method for cluster analysis. The genetic algorithm converts the problem-solving process into a process similar to the crossover and variation of chromosome genes in biological evolution using mathematical simulation and computer simulation. It is a method to search for the “Pareto optimal solution” by simulating the natural evolution process [33], which means, under the conditions of given resources, the solution that cannot be improved on one goal but is not inferior to other goals [34].

In this study, we established a multi-objective optimization framework focused on enhancing outdoor thermal comfort in residential buildings across different seasons in Yulin. The framework involves 20 individual building units, each with its dimensions and positioning parameters, including height (h_i), length (l_i), and width (w_i), as well as rotation angle (θ_i). Based on these parameters, we construct three objective functions, each corresponding to a key thermal comfort index, namely, UTCI on extremely cold days in winter, UTCI on extremely hot days in summer, and UTCI on extremely cold days in spring. These objective functions are formalized in the following form:

$$\max f_{\text{UTCI}_{\text{winter}}} = \sum_{i=1}^{20} g(h_i, l_i, w_i, \theta_i) \quad (2)$$

$$\max f_{\text{UTCI}_{\text{summer}}} = \sum_{i=1}^{20} g(h_i, l_i, w_i, \theta_i) \quad (3)$$

$$\max f_{\text{UTCI}_{\text{spring}}} = \sum_{i=1}^{20} g(h_i, l_i, w_i, \theta_i) \quad (4)$$

The function $g(h_i, l_i, w_i, \theta_i)$ represents a performance evaluation model related to architectural design parameters, whose output is directly related to the UTCI value. We combine these functions into a single target vector and use this as the basis for multi-objective optimization:

$$\text{Maximize } F = \{f_{\text{UTCI}_{\text{winter}}}, f_{\text{UTCI}_{\text{summer}}}, f_{\text{UTCI}_{\text{spring}}}\} \quad (5)$$

During optimization, the parameters (h_i, l_i, w_i, θ_i) for each building unit are set within the range of what is realistically possible. In particular, these parameters are limited by the boundaries established in the research and building codes during the modeling process, ensuring the practicality and feasibility of the design. After the optimization process, we use the FAR (floor area ratio), SVF (Sky View Factor), BD (Building density) and equivalent indexes of the Pareto frontier solution set to put forward suggestions for the optimal layout of residential areas in Yulin.

By applying the NSGA-II algorithm, Grasshopper automatically iteratively optimizes the shape and arrangement of 20 building units to achieve the best combination of the building size and form while ensuring maximum thermal comfort. Each iteration selects and generates new populations through non-dominated sorting and crowding distance calculations. This process was set up to continue for a total of 50 generations, resulting in a series of architectural design solutions that provide excellent thermal comfort in all three seasons. These deconstructions form the Pareto frontier of our research, supporting further design.

2.4. Sensitivity Analysis and Machine Learning Model

The Sobol' sensitivity analysis [35,36] method provides invaluable insights into the relative impact of key parameters on enhancing thermal comfort. By quantifying sensitivity indices across a range of design factors including building dimensions, density, and orientation, this analysis effectively identifies the critical variables that significantly influence thermal comfort levels. This underscores the pivotal role of optimized building layout in mitigating thermal discomfort throughout different seasons. The Sobol' sensitivity

analysis method serves as a fundamental tool in this study, enabling the prioritization of design parameters and facilitating informed decision-making during the optimization process. This approach ultimately contributes to the creation of thermally comfortable and sustainable urban environments.

The Sobol' sensitivity analysis method provides pivotal insights into how key parameters influence thermal comfort enhancement. Through the quantification of sensitivity indices for diverse design factors—encompassing building dimensions, density, and orientation—this analytical approach identifies the most influential variables that dictate thermal comfort. It underscores the paramount importance of an optimized building layout, revealing its significant contribution to mitigating thermal discomfort throughout the year. By incorporating this methodology into the study, the foundational principles and profound significance of sensitivity analysis are highlighted in refining design strategies that prioritize outdoor thermal comfort.

The Gradient Boosting Machine (GBM) [37] stands out as an advanced predictive model capable of generating precise forecasts from complex datasets. Its efficacy stems from its sequential learning strategy, where a series of weak predictive models—usually decision trees—are built in a step-wise fashion. Each subsequent model in the sequence focuses on correcting the errors made by the previous one, effectively fine-tuning the overall predictive capacity. The GBM model does more than confirm the Sobol' findings; it provides an in-depth understanding of the relative influence of each parameter. By leveraging the GBM's strength in handling non-linear relationships and interactions among predictors, the models can be refined to better predict thermal comfort outcomes.

3. Results

3.1. Model Simulation

3.1.1. Simulation Model

To investigate the general area and scale distribution of residential zones in Yulin through typology and guide multi-objective simulation modeling, this study utilized methods of derivation and a GIS platform to map the distribution of residential areas in Yulin. It identified 115 concentrated commercial housing or family courtyard residential areas within the city's scope. Comparative analysis revealed that residential areas in Yulin typically measure approximately 300 m square, with the north–south length generally exceeding the east–west width. The buildings within these residential areas predominantly face south. Accordingly, a virtual land use model was established for this study, with dimensions of 270 m in length (L) and 200 m in width (W), based on the actual situation, which is shown in Figure 3.

Among the influencing factors of outdoor thermal comfort, the form of the residential area is the most direct and important, and different architectural space forms have a significant impact on thermal comfort in a specific area [38]. Considering our research mainly focusing on high-rise residential areas, the layouts of 115 residential districts were classified and analyzed. Comparative studies revealed that row or staggered layouts are predominantly utilized in high-rise residential areas of this region, influenced significantly by the cold climate and sunlight conditions. Additionally, considerations of time cost and computational load in modeling and simulation are taken into account. Consequently, in the modeling of typical residential areas, the building layout was standardized to a more concise and efficient grid of five rows and four columns.

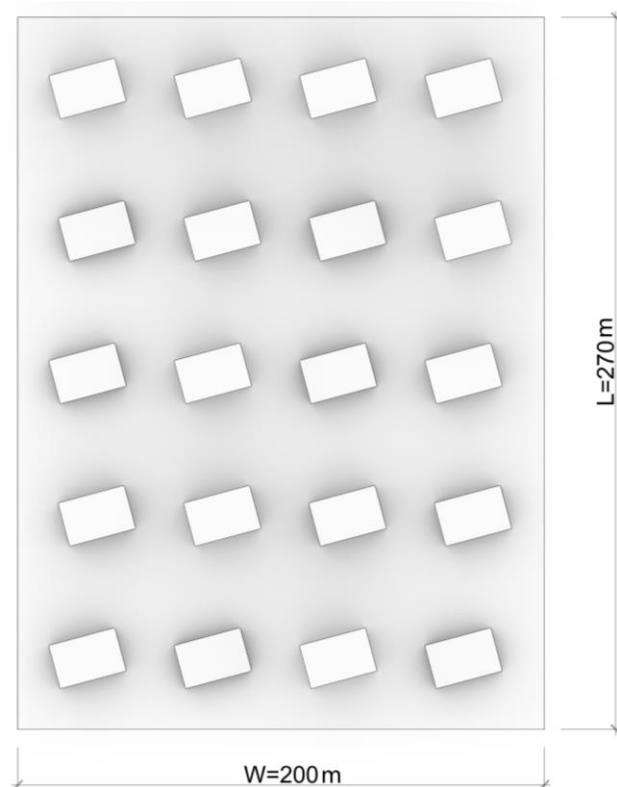


Figure 3. Basic residential area model.

3.1.2. Plot Ratio Setting

According to the “Chinese Urban Residential Area Planning and Design Standards”, the floor area ratio (FAR) for high-rise residential areas in the Yulin region (Climate Zone II) should be restricted to between 2.0 and 2.9. This threshold has been configured in the Grasshopper 1.0 with Rhino 7.24 software using C# script, ensuring that the generated models comply with the standard requirements for ground coverage area. Figure 4 displays C# used in Grasshopper.

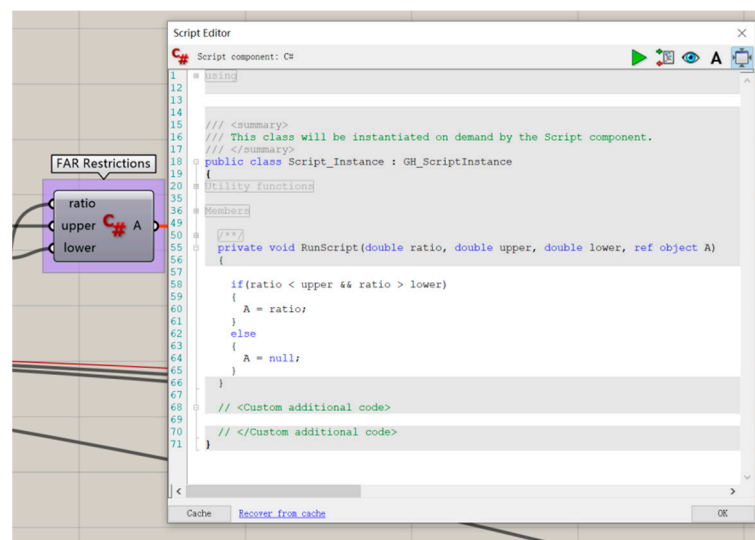


Figure 4. C# script in Grasshopper.

3.1.3. Building Monomer Parameters

Considering the computational load and adhering to the latest Technical Regulations on Urban Planning and Management of Yulin City, which stipulate that the maximum building height for high-rise residential districts should not exceed 80 m, this study focuses on such districts. Consequently, the building height (BH) parameter is set between 24 and 80 m, and the number of floors ranges from 8 to 26, reflecting the common residential building height of approximately 3 m per floor. The dimensions of the basic unit, including length and width, are selected based on actual conditions. Analysis indicates that the building width (BW) of residential buildings in Yulin tends to cluster between 13 and 17 m. The length of most residential buildings (BL) is mainly concentrated within 80 m. Based on the land use scale of this study, the length of the building monomer is determined to be controlled within the range of 25 to 35 m. Figure 5 shows the length and width of the main residential buildings in Yulin. The selected parameters for building height, length, and width are subsequently input using the “slider” feature in Grasshopper, facilitating adjustments and optimizations in the simulation model.

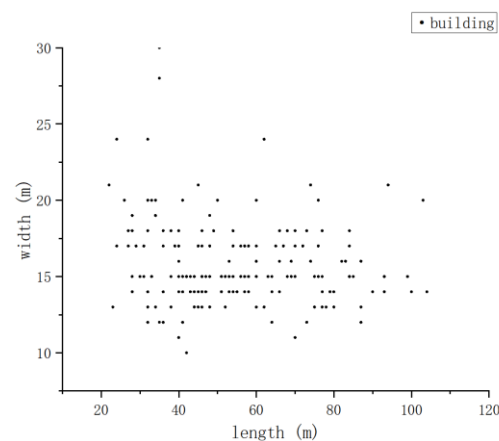


Figure 5. The length and width of main residential buildings in Yulin.

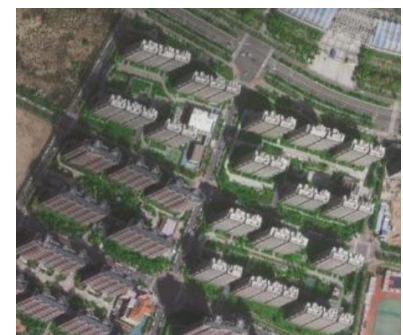
Considering the actual road network in Yulin city, the angle of buildings relative to due south (ARS) is carefully controlled. Figure 6 shows the actual angle of residential buildings considering the actual road network in the setting of angular variables; this range is limited to a deviation of $\pm 15^\circ$ from the south direction, ensuring that the buildings' orientations align with both environmental needs and urban layout constraints. Figure 7 shows the form of basic residential building units.



(a)



(b)



(c)

Figure 6. Actual angle of residential buildings considering the actual road network. (a) Fushun residential community. (b) Yuanchi shiji residential community. (c) Wenchang heshun residential community.

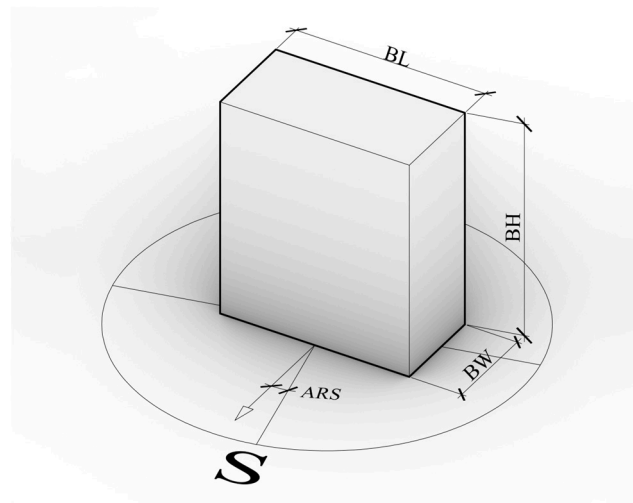


Figure 7. Form of basic residential building units.

3.1.4. Constraint Conditions

The spacing of residential building units is controlled by four policy standards: sunshine spacing requirement, fire spacing requirement, building yield land red line requirement and minimum spacing requirement. Among them, the red line distance of the building retreat land determines the configurable range of residential building units, the fire distance and the minimum distance of the house are used to control the distance of the gable wall of the building unit, and the sunshine distance is used to control the north–south distance of each unit. Table 2 shows the constraint conditions.

Table 2. Constraint Conditions.

No.	Constraint Name	Constraint Conditions	Unit	Additional Information
1	Fire Safety Requirements	High-rise main bodies should maintain a fire safety distance of more than 13 m	m	<Code for Fire Protection Design of Buildings> [39]
2	Sunlight Requirements	Calculate the duration of effective sunlight received at the starting point, located at the ground floor window sill (0.9 m above the indoor floor level on the external wall). Ensure that this point receives at least 2 h of sunlight within the effective sunlight time band on a standard sunlight day.	h	<Code for Planning and Design of Urban Residential Areas> [40]
3	Setback Requirements	When the building height exceeds 50 m, the minimum setback distance from the city road planning red line is 15 m.	m	<Technical Regulations for Urban Planning and Management in Shaanxi Province> [41]
4	Minimum Distance Between Residences	“When high-rise residences are arranged parallel to each other, the minimum distance between the obstructing building and the obstructed building is 30 m (‘obstructed’ refers to the residence located to the north of other residences when arranged either parallel or perpendicular, thus making it the obstructed building).”	m	<Technical Regulations for Urban Planning and Management in Shaanxi Province> [41]

3.2. Simulation Result Verification

3.2.1. Site Selection

In this study, a residential area in Yulin was selected as an example to verify the simulation results. Figure 8 shows the photo of a basic forms of residential areas located in Yuyang District, Yulin City. The residential area was measured from 9:00 to 17:00 on 21 January 2024, with low temperature and high wind speed on the selected days. The specific models of the measured instruments are shown in Table 3, and the measuring range and accuracy are in line with the relevant standards of ISO 7726 [42]. A measuring instrument was set up at a height of 1.5 m from the ground to measure the temperature, wind speed, and black sphere temperature, and the data were recorded every minute.



Figure 8. Photo of a basic form of residential areas.

Table 3. Measuring equipment information.

Parameter	Instrument	Measuring Range	Precision
Air temperature T_a /(°C)	Kestrel5500	−29 °C–70 °C	1 °C
Wind speed V_a /(m/s)	Hand-held weather station	0.0–40 m/s	±3%
Black sphere temperature T_g /(°C)	HQZY-1	−20 °C–+80 °C	±0.3 °C

3.2.2. Simulation Result Verification

The mean radiant temperature (MRT) is defined as the uniform equivalent temperature of radiant energy received by an imaginary shell [42], which significantly influences the thermal comfort index. Due to Ladybug's limitations in simulating heat storage, dissipation, and convection, this study corroborates the simulation results by comparing both the measured and simulated values of MRT as well as wind speed. The basic meteorological parameters for the simulation input were sourced from the meteorological data provided by the China Meteorological Data Network, specifically for the date 21 January 2024. Table 4 shows climate data of 21 January 2024, from <http://data.cma.cn/>. In this study, the meteorological data were formatted into epw files, which are compatible with the Ladybug tool, using EnergyPlus 9.4 software. Since the average radiant temperature cannot be directly measured, this study calculates the MRT value by measuring the black globe temperature, air temperature, and wind speed, employing the formula specified in the ISO

7726 standard for Equation (6). Figure 9 shows correlation between the measurement data and simulation data.

$$T_{mrt} = \left[(T_g + 273)^4 + \frac{1.1 \times 10^8 V_a^{0.6}}{\varepsilon D^{0.4}} (T_g - T_a) \right]^{\frac{1}{4}} - 273 \quad (6)$$

T_{mrt} —average radiation temperature (°C);

T_g —black sphere temperature (°C);

T_a —air temperature (°C);

V_a —wind speed (m/s);

D —the diameter of the black sphere (m), which is 0.15 m in this study;

ε —surface radiation coefficient of the black sphere, 0.95 in this study.

In addition, root-mean-square error (RMSE) and consistency index (d) are used in this study to quantitatively compare the absolute and relative errors between the measured and simulated values [43] so as to evaluate the reliability of the simulation software. The calculation formula is as follows in Equations (7) and (8):

$$RMSE = \left[\frac{1}{n} \sum_{i=1}^n (S_i - M_i)^2 \right]^{\frac{1}{2}} \quad (7)$$

$$d = 1 - \frac{\sum_{i=1}^n (S_i - M_i)^2}{\sum_{i=1}^n (|S_i - \bar{M}| + |M_i - \bar{M}|)^2} \quad (8)$$

$RMSE$ —root-mean-square error;

d —consistency index;

S_i —simulated value;

M_i —measured value;

$\bar{M}$ —average measured value.

It can be seen that the RMSE values of the mean-square error of the average radiation temperature and wind speed at the measuring point are 2.02 °C and 0.32 m/s, respectively, which are both within the acceptable range. The consistency index d of the two parameters is 0.98 and 0.82, respectively, both in a high range ($d \geq 0.75$), which indicates a high degree of agreement between the measured value and the simulated value. Therefore, when macro meteorological data are taken as input boundary conditions, Ladybug Tools can better simulate the outdoor thermal environment of residential areas in this region. This assertion is further corroborated by Figure 9, which illustrates the cooperation of measurement data and simulation data throughout the day. The graph shows that while the simulated wind speed slightly underestimates the measured values, the overall trend follows closely, and the grey bars representing the measured MRT fluctuate with time, peaking around midday, consistent with the expected solar influence. These visual data affirm the high consistency index and underscore the capability of Ladybug Tools to accurately simulate environmental conditions.

Table 4. Climate data of 21 January 2024 (from <http://data.cma.cn/>, accessed on 23 April 2024).

Time	Temperature (°C)	Humidity (%)	Wind Speed (m/s)	Wind Direction (°)
9:00	−20.8	69	4	315/NW
10:00	−18.9	64	5	326/NW
11:00	−16.8	60	3.4	304/NW
12:00	−15.9	56	4.5	295/WNW
13:00	−14.1	52	3	312/NW
14:00	−13.4	48	3.7	323/NW
15:00	−12.3	47	2.9	290/WNW
16:00	−12.7	47	4.9	301/WNW

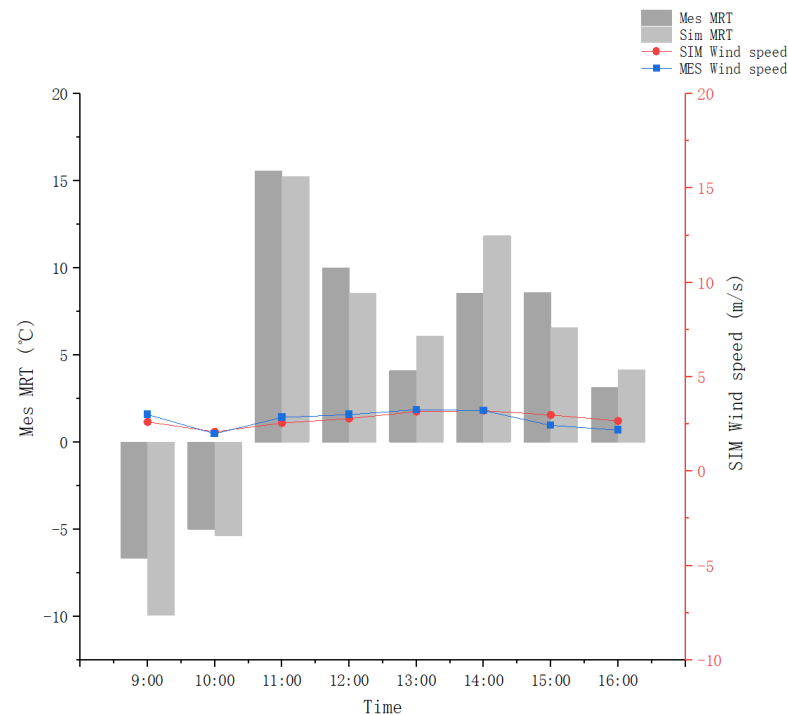


Figure 9. Correlation between the measurement data and simulation data.

3.3. Multi-Objective Optimization Results

After connecting all the specified parameter ranges to the computing battery input of Wallacei X, Wallacei performed a total of 50 generations of genetic optimization calculation according to the screening rules of previous schemes, generating 10 schemes in each generation. By using the NSGA-II algorithm, Wallacei horizontally compared each generation scheme and selected the best scheme. The next generation of solutions continue to be generated on this basis. Since Wallacei's counting logic starts from 0, the Pareto optimal solution was finally obtained in the seventh scheme of the 47th generation.

Figure 10's parallel coordinate plot vividly illustrates the optimization process for summer, winter, and spring UTCIs. The strong convergence in summer suggests that the algorithm effectively stabilizes around an optimal solution under warm conditions. In contrast, the winter UTCI paths show notable divergence, indicating varied optimization effectiveness due to diverse solutions. Spring exhibits moderate convergence and divergence, reflecting the algorithm's flexibility in adapting to variable weather. This visualization effectively captures the dynamic optimization across seasons, highlighting the algorithm's capability to balance multiple climatic objectives. Since the optimization logic of Wallacei 2.7 software can only be optimized in the direction of smaller values, and the winter and spring UTCI values need to be optimized in the direction of larger values, we set these two values as reciprocal inputs in the optimization process. Therefore, the UTCI values of winter and spring are actually the reciprocals of the values shown in the figure. Under the optimal arrangement, the UTCI values of summer, winter and spring are 25.51, −14.025 and −6.410, respectively. The data presented in Table 5 provide a comprehensive evaluation of our multi-objective optimization approach across different seasonal contexts. Notably, there are modest but significant improvements in UTCI values from the first to the last generation, particularly during the winter and spring seasons. These improvements not only demonstrate the algorithm's ability to enhance thermal comfort in Yulin's local conditions but also underscore its capacity to adapt and precisely optimize environmental conditions across varying seasons, which is critical for effective design.

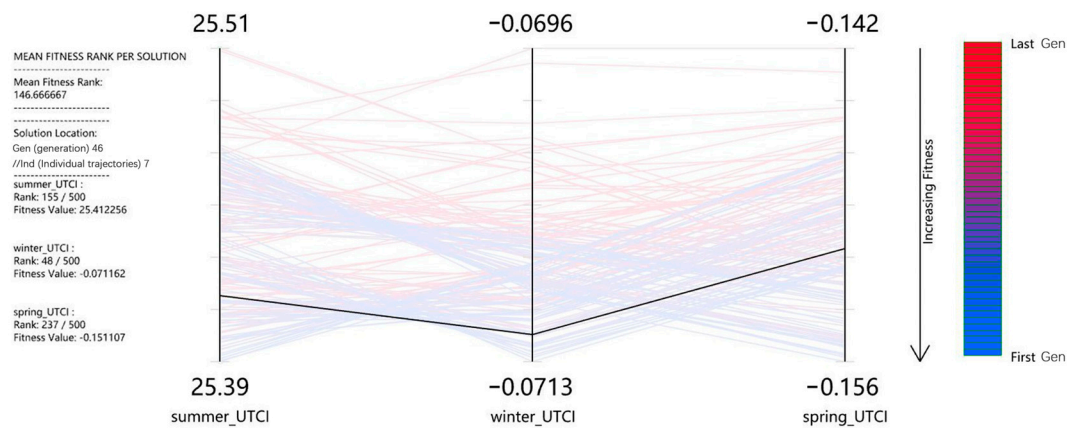


Figure 10. Parallel coordinate plot.

Table 5. Multi-objective optimization results.

	Summer UTCI (Mean Value)	Winter UTCI (Mean Value)	Spring UTCI (Mean Value)
First generation	25.452	−14.246	−6.860
Last generation	25.423	−14.087	−6.618
Lifting extent	0.029	0.159	−0.243
Lifting percentage	0.113%	1.123%	3.535%

3.4. Sensitivity Analysis Result

To evaluate in detail the intensity of influence of morphological variable parameters on UTCI in different seasons, through a regression analysis of the model based on first-order Sobol' function, the influence degree of each parameter in each season were divided into four intensity levels, which are as follows: 1. influence (Sobol' Index) is the most prominent, 2. more prominent, 3. prominent and 4. not obvious. The influence parameters involved in the sensitivity analysis included building length (BL), building width (BW), building height (BH) building orientation angle relative to due south (ARS), building density (BD), the floor area ratio (FAR), and sky view factor (SVF). Figure 11 shows the Sobol' sensitivity index plot.

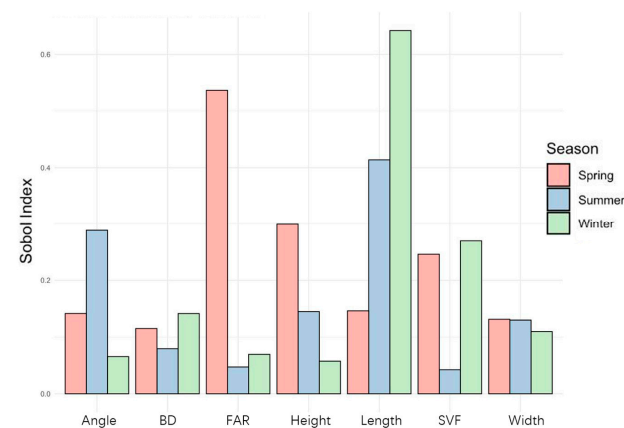


Figure 11. Sobol' sensitivity indices plot.

UTCI-Summer model: BL (0.414), ARS (0.288), BW (0.130), BH (0.145), BD (0.080), FAR (0.047), SVF (0.043).

UTCI-Winter model: BL (0.642), SVF (0.269), BD (0.141), BW (0.110), BH (0.058), FAR (0.070), ARS (0.066).

UTCI-Spring model: FAR (0.537), BH (0.299), SVF (0.246), Angle (0.141), BL (0.146), Width (0.131), BD (0.114).

The data reveal that winter consistently shows higher Sobol' index values across most parameters, with length and width being particularly prominent. In spring, FAR and height exhibit notable sensitivity, while summer generally presents the lowest sensitivity values across most parameters, except for angle and BD, which are similar to those in spring. These seasonal variations highlight the impact of different seasons and different parameters.

3.5. Machine Learning GBM Verification

In the results section, our application of the Gradient Boosting Machine (GBM) to validate the Sobol' sensitivity analysis was met with compelling outcomes. For the summer model, the GBM yielded an impressive root-mean-square error (RMSE) of 0.01023, indicating a high degree of precision in the predictions of thermal comfort. The winter model displayed a slightly higher RMSE of 0.02557, reflecting moderate variability in the accuracy of its predictions. The spring model resulted in an RMSE of 0.02882, which, while higher than the summer and winter models, still represents a reasonable level of predictability within the scope of the complex factors affecting thermal comfort.

4. Discussion

4.1. Optimization Situation

4.1.1. Optimal Solution

We compared the 10 results of the first generation with the 10 results of the 50th generation outputted by Wallacei. The results showed that optimization of UTCI values in winter improved by 0.160, in summer improved by 0.029 and in spring improved by 0.243. Figure 12 shows Pareto optimal solutions of the 50th generation. It can be seen that the optimization of UTCI values in summer was small, which was mainly related to the climatic conditions in the Yulin region. The climate zone of Yulin is a cool area with an average temperature of 17–30 (°C) in July. Under this temperature condition, the original UTCI value has little difference with the comfort range. Therefore, this simulation has little improvement in thermal comfort in summer. However, low temperatures and high wind speed in winter and spring in cold regions lead to a lower UTCI value in winter and spring than the comfort range. Therefore, the simulation results greatly optimize the UTCI in both winter and spring.

4.1.2. Optimization Analysis

To understand the layout of residential areas with relatively better UTCI, we extracted 10 schemes of the 49th generation. Figure 13 shows the model of the 49th generation solution set. It shows the morphology of the last generation model, which is the relatively optimal generation solution generated according to the genetic algorithm. Through analysis, it is concluded that in the relatively better layout, the value range of BD is 0.138–0.154, the value of FAR is 2.136–2.696, and the value of SVF is 0.756–0.849. The values of BL, BW and BH are 50–52, 15–16 and 33.75–49.5 (m), respectively. The ARS values are relatively stable, all of which are 15°. It can be seen from Part 3.3 that the Sobol' indices of BL and ARS are high, and the value range of these two values is also relatively accurate, which has a high reference value in the design of residential areas.

Because the height distribution of buildings has a great impact on the whole residential space, we had a more in-depth discussion on this. The average height of the first to fifth row of residential buildings from south to north in the residential area is 33.75 m, 43.25 m, 36.5 m, 46.5 m and 70 m, respectively, showing a trend of gradually increasing at first, and then slightly decreasing before continuing to rise. In the third row, one building is higher than the other three, with a gap of up to 36 m. The fourth row of buildings generally presents the characteristics of higher east and west sides and lower middle, and the gap is generally about 24 m. Based on this phenomenon analysis, the law of building height distribution in residential areas may have the following reasons:

1. The gradual rise and fall in building height from south to north may be an attempt to maximize sunlight reception while reducing shadow coverage between buildings. The gradual increase in building height helps the south side of the building receive more sunlight, especially in winter. A later height drop may be to avoid creating too much shadow in a particular location, which could affect living comfort or energy efficiency.
2. The significant height of one of the buildings in the third row may be intended to optimize the microclimatic conditions, especially thermal comfort, of a particular location within the area. Buildings with significant height differences may help improve the thermal environment of surrounding buildings, for example by changing the direction of wind or regulating sunlight.
3. The features of the higher east and west sides of the fourth row building and the lower middle may be designed to optimize sunlight reception and the distribution of internal shadows so that all areas receive sufficient sunlight at certain times of the day.

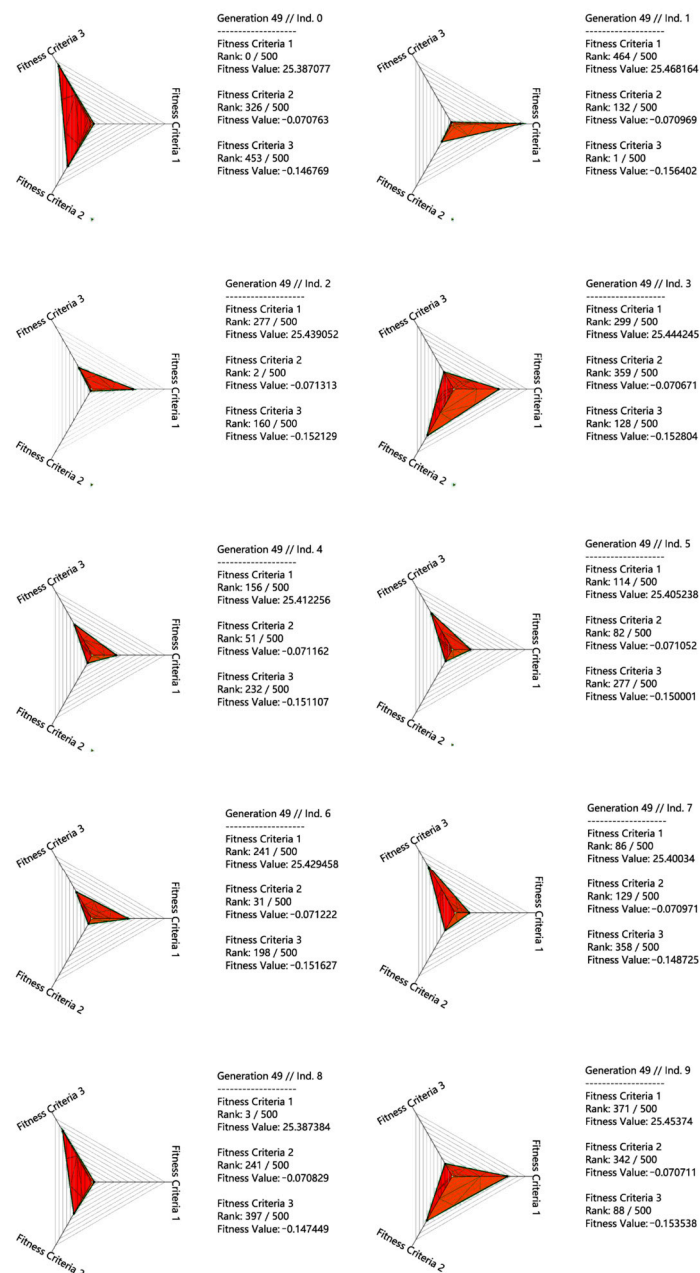


Figure 12. Pareto optimal solutions.

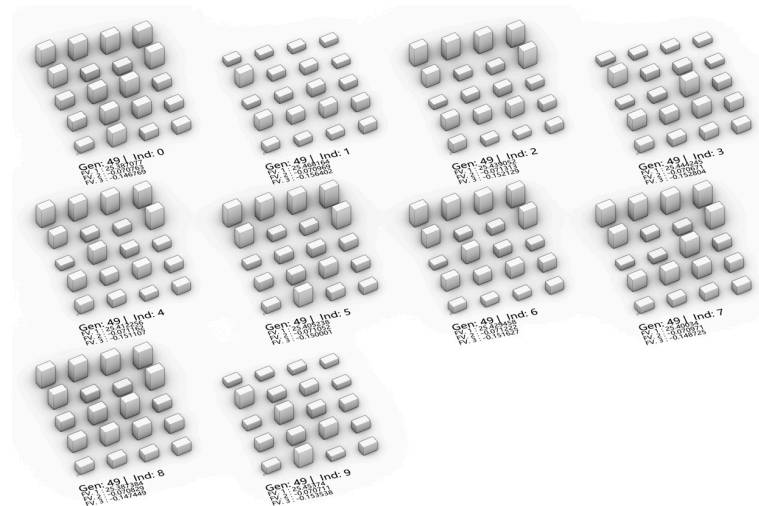


Figure 13. The model of the last-generation solution set.

4.1.3. Optimization Process

Figure 14 shows objective space for the entire population. The visualization of the optimization process presents a clear evolutionary trajectory, transitioning from initial solutions to those refined in later stages. Initially marked in red, the solutions are scattered across a three-dimensional space delineated by the UTCI values for summer, winter, and spring. This broad dispersion highlights an extensive exploration of the design space, illustrating the diverse range of potential strategies for achieving thermal comfort across different seasons. The spatial segregation between the initial and optimized solutions underscores the efficacy of the evolutionary algorithm. While the initial red points are widely dispersed, indicating initial uncertainty or exploration within the objective space, the optimized solutions, marked in green, tend to cluster towards specific regions. This clustering pattern indicates that the algorithm has pinpointed design configurations that offer significant advantages for meeting multi-seasonal thermal comfort objectives. Moreover, the visualization reveals that the distribution of optimized solutions is not uniform across all axes, suggesting that the optimization's effectiveness varies with seasonal conditions. The green points are more closely grouped along the summer UTCI axis compared to the winter UTCI axis. This tighter clustering for summer conditions may reflect the inherent challenges associated with higher temperatures and solar gains during this season, pointing to a convergence of solutions that more effectively address these specific seasonal dynamics. In conclusion, it not only validates the algorithm's ability to improve over time but also provides a basis for understanding how different seasonal thermal comfort conditions can be addressed through computational design strategies.

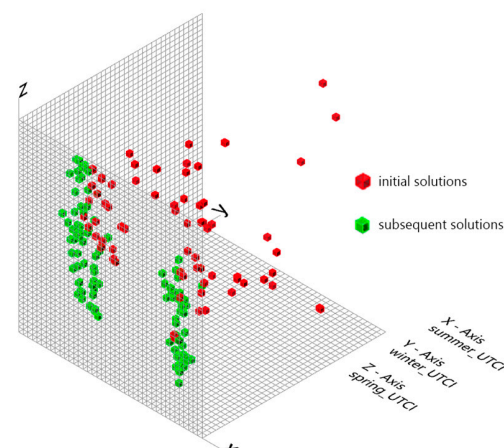


Figure 14. Objective space for the entire population.

4.1.4. Seasonal Analysis of Optimization

Figure 15 presents standard deviation graphs that trace the evolution of fitness values from the first to the last generation. The X-axis shows UTCI value sizes, and the Y-axis measures the standard deviation relative to the mean fitness value, indicating variation within each generation. Red curves represent earlier solutions; blue curves indicate later ones. A narrowing and leftward shift of these curves in later generations signifies improving and more consistent population fitness.

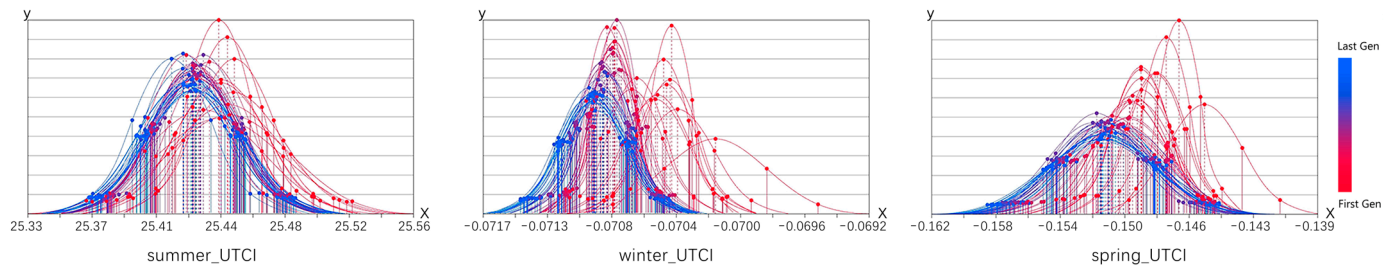


Figure 15. Standard deviation graphs.

In the optimization process, a notable trend emerges from the standard deviation graphs of the UTCI values for summer, winter, and spring. The progression of generations, depicted by the transition from warm to cool colors, reveals a consistent shift towards more favorable UTCI values. This leftward shift in the distribution suggests a convergence towards optimal thermal comfort settings.

The summer graph indicates a compacting of fitness values, with later generations achieving greater uniformity around more desirable UTCI figures. In winter, the significant convergence of UTCI values indicates enhanced thermal retention, which is crucial for improving thermal comfort during colder seasons. The spring graph shows a similar trend, reflecting the algorithm's ability to adapt the optimization strategy to the variable and often harsh conditions of the season. The gradual refinement and concentration of fitness values across generations signify the algorithm's capability to iteratively learn and prioritize design variables that are most impactful. Such results demonstrate not just a theoretical optimization, but practical applicability for designing urban residential areas that align with seasonal thermal comfort requirements.

The presented trend lines for UTCI values across summer, winter, and spring reflect the optimization trajectory over the course of the algorithm's iterations. Figure 16 shows the mean values trendline. For summer, a slight but steady decline in the UTCI values is evident, indicating incremental improvements in achieving cooler conditions, which are vital for thermal comfort during the hotter months. In the winter graph, there is an initial sharp decrease in UTCI values, which then levels off, suggesting a rapid attainment of conditions more conducive to preserving warmth, before fine-tuning and stabilization of the solutions around an optimal balance. The trend for spring displays a more pronounced decline in UTCI values, consistent with the need for a substantial modification to address the season's variable conditions. This steep improvement indicates the algorithm's responsiveness to the spring's challenging thermal environment and its success in significantly enhancing comfort levels. The consistent optimization across seasons validates the robustness of the applied methodologies and underscores the potential of these approaches in tailoring urban designs that cater to specific seasonal thermal demands.

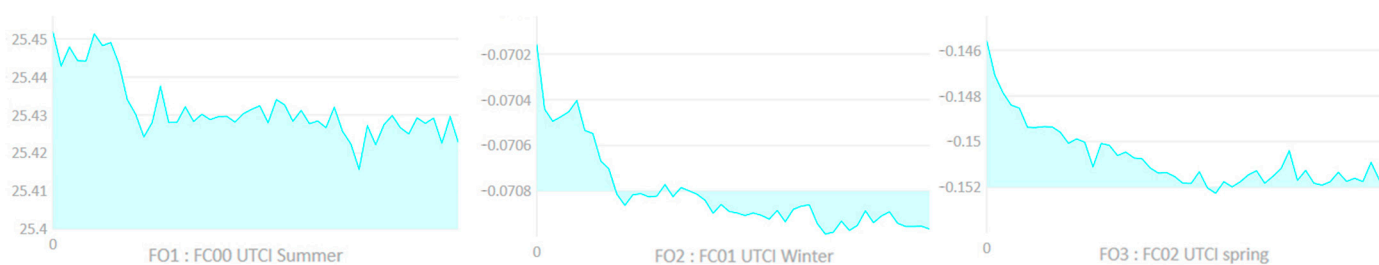


Figure 16. Mean values trendline.

4.2. Sensitivity Index Analysis

Part of this study identifies independent variables that have a greater influence on UTCI optimization in different seasons based on sensitivity analysis. The reasons for the high Sobol' indices of these variables are as follows:

First, in the summer model, BL has the greatest influence on the summer UTCI, and the original Sobol' index is 0.414. This may be because the length of the building directly affects the distribution of light and heat inside the building, which in turn affects temperature perception. The ARS angle also has a great influence on the summer model, and the original Sobol' index is 0.288. The orientation of the building determines the amount of sunlight, which directly affects the thermal environment inside and around the building. BW (0.130) and BH (0.145): the effect of these two variables is relatively small but still significant. This suggests that while length is the dominant factor, building width and height also play a role in summer thermal comfort to some extent.

Second, in the winter model, the sensitivity of BL to UTCI value building length in winter is even higher than that in summer, and the original Sobol' index is 0.642. This highlights the importance of building length in retaining heat in the residential area and reducing energy loss during the winter months. SVF (0.269) openness is also very important in winter, and a high SVF index may mean less blocking, helping with daylight entry and heat retention. BD (0.141): compared with summer, the influence of building density in winter is more significant, which may be related to the lower heat loss rate in high-density residential areas.

Third, in the spring model, the original Sobol' index in FAR spring is the highest, indicating that the floor area ratio plays a key role in regulating spring temperature and ventilation. BH (0.299): spring UTCI values are more sensitive to building height than other seasons, which may be related to the changing climate and temperature regulation needs in spring. SVF (0.246), angle (0.141): the importance of spring openness and building angle indicates that having more space to receive sunlight and airflow is beneficial for maintaining a suitable environment.

4.3. GBM Learning Validation

In the discussion of our findings, the verification of the Sobol' sensitivity analysis through the Gradient Boosting Machine (GBM) model is a testament to the model's effectiveness. The GBM model's predictive accuracy, as evidenced by the low RMSE values across different seasons—0.01023 for summer, 0.02557 for winter, and 0.02882 for spring—highlights its capability to capture the complex dynamics between building design parameters and thermal comfort. Figure 17 shows the comparison of GBM prediction results with the Sobol' results.

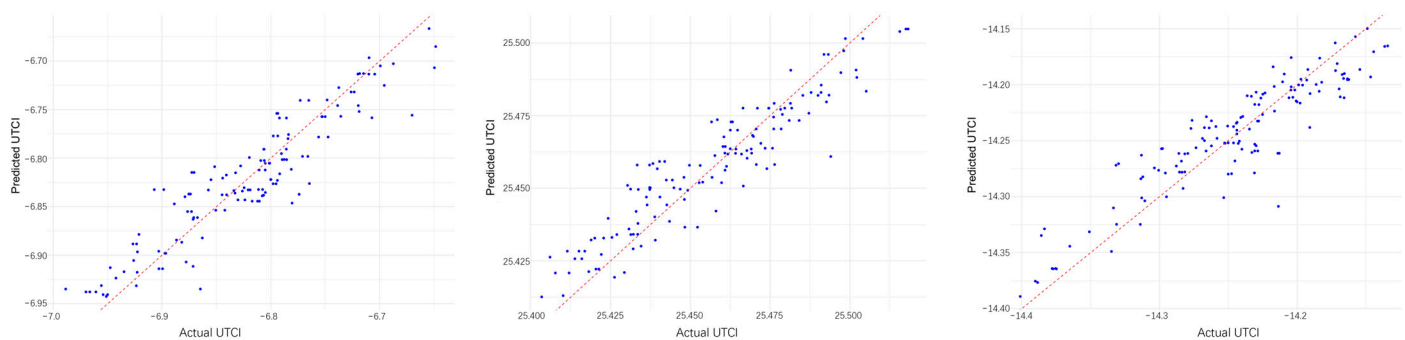


Figure 17. Comparison of GBM prediction results with the Sobol' results.

The seasonal variation in RMSE values, with summer exhibiting the lowest error, could be indicative of the varying degrees of sensitivity to the input variables that influence thermal comfort across seasons. The summer model's exceptionally low RMSE suggests that the key design factors identified by the Sobol' sensitivity analysis are particularly influential during the warmer months when thermal stress is likely to be higher. Conversely, the slight increase in RMSE during winter and spring may point to additional variables.

4.4. Limitations

This study contributes to the understanding of urban residential thermal comfort, yet it is not without limitations.

First, the UTCI's scope, while broad, falls short of encapsulating the full spectrum of thermal experiences due to its focus on external factors. Future research should thus integrate more individualized and dynamic thermal comfort measures to reflect personal and adaptive responses.

Second, the temporal analysis was constrained, omitting in-depth exploration of daily and seasonal comfort variations. Future work should broaden the temporal analysis to capture the fluctuations in thermal comfort and inform a comprehensive optimization framework.

Third, the research was limited to certain optimization objectives and parameters and did not explore how different building types, occupant behaviors, or architectural styles might influence outcomes. Future studies should encompass a diverse range of urban and cultural contexts, building types, and occupant demographics to refine and generalize optimization strategies.

Fourth, while the use of monthly average data in this paper is adequate for establishing general seasonal trends and typical meteorological conditions in the Yulin region, it does not capture extreme weather events or daily fluctuations. This broader approach may impact the precision of finer-scale thermal comfort analyses. Future studies should incorporate higher-resolution temporal data to provide a more detailed and dynamic understanding of thermal comfort variations.

Recognizing these limitations, this study lays the groundwork for enhanced methods to improve thermal comfort in urban residences. It is vital for future research to bridge these gaps and broaden the scope to include diverse climatic conditions, enabling the application of optimization strategies like NSGA-II and GBM machine learning to vary environmental settings for a more universally robust assessment. Furthermore, exploring innovative architectural designs, materials, and advanced construction techniques to enhance insulation and thermal regulation offers a significant opportunity for advancing future multi-objective optimization.

5. Conclusions

This study employs the NSGA-2 genetic algorithm alongside Sobol' sensitivity analysis and GBM machine learning to develop a comprehensive strategy for optimizing outdoor thermal comfort in residential areas, addressing diverse morphological parameter and the

complexity of multi-objective optimization. The principal conclusions of this study are as follows:

Firstly, employing NSGA-II for thermal comfort optimization in residential zones has shown great efficacy. It handles multi-objective optimization with robustness, skillfully balancing objectives like energy efficiency and thermal comfort, underscoring its applicability to complex urban planning. Its ability to manage various decision variables and its scalability make it particularly suited for extensive environmental design efforts.

Secondly, Sobol' sensitivity analysis provides critical insights into how various design factors, such as building dimensions, density, and orientation, influence thermal comfort. It identifies key variables, notably building spacing, which significantly affects seasonal thermal comfort—evident from Sobol' indices of 0.41 in summer and 0.64 in winter. Such analysis underscores the importance of building layout optimization in enhancing thermal conditions year-round, guiding stakeholders in decision-making for sustainable environmental design.

Thirdly, this research has practical ramifications for urban planners and architects, offering a substantiated optimization approach and key parameters to inform sustainable urban design. Future studies might broaden the scope to include diverse climates, using environmental data for more dynamic assessments of thermal comfort. Furthermore, investigating new design strategies and materials to boost thermal performance is a promising direction for future research.

In conclusion, this study demonstrates that an integrated approach combining optimization techniques, sensitivity analysis, and machine learning effectively improves thermal comfort in residential areas, enriching both the theoretical understanding and practical implementation of sustainable urban environments. This research not only advances urban sustainability but also sets the stage for future innovations in thermal comfort optimization.

Author Contributions: Conceptualization, Y.M. and J.R.; methodology, Y.M., Y.H. and J.R.; software, Y.M. and Y.H.; validation, Y.M. and Y.H.; formal analysis, Y.H. and Y.M.; investigation, Y.H. and Y.Q.; resources, Y.Q. and J.R.; data curation, Y.Q. and Y.M.; writing—original draft preparation, Y.M., Y.H., Y.Q. and J.R.; writing—review and editing, Y.M., Y.H., Y.Q., Y.L. and J.R.; visualization, Y.M., Y.H. and Y.Q.; supervision, Y.L. and J.R.; project administration, J.R.; funding acquisition, J.R. All authors have read and agreed to the published version of the manuscript.

Funding: National Key Research and Development Program of China, grant number: 2023YFB3002800; Science and Technology Department of Shaanxi Province, grant number: 2021JQ-260; and the Fundamental Research Funds for the Central Universities, CHD, grant number: 211941220002.

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

Acknowledgments: Thanks to Qingyuan Zhang of Yokohama National University, Yokohama, Japan, for the meteorological data of Yulin area in this paper. Thanks to Dongxin Wang and Aohao Chai for the data collection of Yulin residential areas.

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

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