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The Impact of Building Morphology on Energy Use Intensity of High-Rise Residential Clusters: A Case Study of Hangzhou, China

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Abstract: Building operations account for a large amount of energy use and CO_2 emissions, and the morphology of buildings in residential clusters strongly impacts energy efficiency performance. However, little research has focused on the morphology and energy electricity usage of high-rise residential clusters in hot summer and cold winter (HSCW) regions. We investigated 96 residential clusters in Hangzhou, China, and established a corresponding morphology database. Additionally, we obtained annual electricity consumption for 16 of these residential clusters. With this database, we performed optimization of morphological parameters upon energy use intensity (EUI) using a genetic algorithm (GA). Specifically, the cooling, heating, and lighting EUIs of high-rise residential clusters were studied. After implementing the optimized morphological parameters, there was a reduction of up to 7.73% in EUI. According to regression analysis, the average aspect ratio was the most significant factor influencing EUI (r = −0.907), followed by floor area ratio (r = −0.755), average orientation (r = 0.502), and average number of floors (r = −0.453). These results indicate that a higher intensity of land development with a greater floor area ratio, average aspect ratio, and average number of floors can reduce total energy consumption. Additionally, we found that an average building orientation of southwest 15° (with respect to south) is optimal. The findings of this study can assist urban planners and designers in developing more sustainable residential clusters, leading to decreased energy costs and CO_2 emissions.

Keywords: urban residential clusters; energy use intensity; morphological design; cluster optimization; urban sustainability

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1. Introduction

The building sector accounts for approximately 37% of global energy consumption and 34% of energy-related carbon emissions, as reported by the UN Environment Programme (UNEP) [1]. According to the Professional Committee of Building Energy and Emissions (CABEE), energy consumption by buildings in China reached the equivalent of 2.16 billion tons of coal in 2020, with urban residential buildings accounting for 38.68% of this total [2]. Meanwhile, China's CO_2 emissions are soaring, increasing by 750 million tons between 2019 and 2021 [3]. From a global context, the 26th United Nations Climate Change Conference (COP26) resulted in a promise to reduce carbon emissions and achieve net-zero by 2050 [4]. Additionally, the Chinese government promised to achieve peak carbon emissions by 2030 and carbon neutrality by 2050. Thus, the reduction in energy consumption and carbon emissions is a national and global issue, and improving the energy efficiency of buildings is crucial for achieving these goals.

The migration of people from rural to urban areas, commonly referred to as urbanization, has accelerated since the era of industrialization [5]. Over 50% of the global population lived in urban areas in 2018, with projections exceeding 60% by 2030 [6]. The intertwined consequences of urban development and climate change may be more significant in developing countries [7], such as China, where the urbanization rate has rapidly increased from 10.64% in 1949 to 63.9% in 2020 and continues to grow [8]. With increased urbanization, more residential buildings need to be constructed, which leads to higher consumption of resources and larger greenhouse gas emissions. Previous studies have analyzed energy reduction strategies in residential buildings, mainly focusing on low-rise housing [9]. However, under rapid urbanization and land shortages in cities, high-rise residential buildings are becoming more common. Accordingly, cities must take effective measures to reduce the energy consumption of high-rise residential buildings.

Optimization objectives in energy-efficient building design can be broadly categorized into four domains: comfort, energy, cost, and other factors. Among these, energy stands out as the most pivotal objective [10]. At the same time, urban residential building design can significantly impact energy use intensity and the local microclimate [7]. Building form, or morphology, plays a vital role in reducing urban energy demand and usage [11]. It is vital to implement effective urban planning and building design, as these are early steps in urban development and affect later energy efficiency [12]. Energy-efficient building design has demonstrated advantages in reducing energy usage and pollution [13]. Due to the complexity of modeling and simulation of performance, current research on building energy consumption has mostly focused on the scale of individual buildings, such as building envelopes [14], thermal comfort [15–17], and ventilation performance [18]. While there are a few case studies at the urban scale, they primarily rely on simulated data and do not have empirical support from actual energy consumption data. For instance, in Singapore, it was demonstrated that an effective urban typology can bring a 12-fold higher rate of reduction in building cooling demand [19]. In Tehran, it was found that urban morphology significantly influences the energy use intensity of buildings, decreasing cooling demand by more than 10% [20]. Finally, in Northern Europe, researchers discovered that the morphology of urban canyons affected overall performance, with energy efficiency increases of up to 19% for housing [21].

Residential clusters act as basic constituent units of cities and have an impact on their microenvironments, thereby significantly affecting building energy usage. Thus, urban morphology may enhance or mitigate microenvironment effects on clusters and building energy demand [22]. In addition, clusters are smaller in scope and consequently easier to optimize than large urban areas. We therefore investigated the morphological characteristics of residential clusters and propose appropriate design strategies. Due to the complexity of comprehensive modeling and the difficulty in obtaining data on energy consumption, we explore the impact on the energy objective by changing a single variable, adopting a simple model that represents the morphology. Consequently, these models are optimized to account for the lack of the ability to conduct dynamic searches.

Existing research has shown that cities can be effectively represented as several residential clusters with different morphologies [23]. However, factors such as high model complexity, lengthy simulation times, and challenges in obtaining real energy consumption data for residential clusters have hindered progress. Previous studies that simulated and optimized building performance lacked empirical data and primarily focused on the scale of individual buildings, neglecting the impact of relative position between buildings. Furthermore, current building energy optimization research typically involves fixed cases, with limited consideration given to interactions between morphological factors. Given this background, we present a case study on the morphology and electricity consumption of residential clusters in Hangzhou, China, with objectives as follows: (1) build a morphological database for Hangzhou, providing variables and corresponding value ranges for the subsequent optimization model; (2) utilize the electricity consumption data from 16 residential clusters, identify keying morphological indicators influencing consumption;

(3) develop an automated optimization parameter model using Grasshopper, employing the genetic algorithm as its core; and (4) integrate Pareto results and quantitative analysis and examine the relationship between building morphology and energy performance. Finally, we formulate design recommendations for residential buildings in Hangzhou based on the findings.

2. Literature Review

2.1. A Review of Building Morphology Parameters

In exploring energy-efficient strategy, it is crucial to discuss design prototypes for existing buildings [24]. This is because prototypes are the starting point for research in building design, energy efficiency, solar performance, and so on [25]. Hong et al. developed a methodology for single low-rise office building prototypes in Shanghai, specifying the construction year, average orientation, number of floors, window:wall ratio (WWR), and plan form. Through correlation analysis, they determined that the number of floors and WWR are the most influential factors affecting energy consumption [23]. Premrov et al. studied a one-story timber-frame house under different climate conditions, also investigating variations of building geometry, shape factor, and glazing-to-wall area ratio on the south façade [26]. Looking at larger-scale trends, Li et al. built a database of single residential building shapes in Chongqing utilizing satellite images, including characteristics such as aspect ratio, building height, and compactness ratio to define a representative prototype [27]. Similarly, Schaefer et al. built a database on geometrical features of single-family low-income housing in southern Brazil, using quantitative variables such as the dimensions of the façade and floor plan shape and area [28]. Additionally, Bhatnagar et al. identified single building typologies using numerical data like area, aspect ratio, and number of floors [29]. Samuelson et al. identified the design parameters of single residential buildings in urban contexts, including WWR, glass type, building orientation, and building shape [30]. In a similar manner, Li et al. used average building height, floor area ratio, and building cover ratio as quantitative indicators to characterize residential districts [31]. Studying urban forms, Mangan et al. investigated building design parameters of height, height-to-width ratio, and orientation, as well as the typology, plan type, and number of floors [32]. A summary of morphological parameters of buildings is shown in Table 1. Overall, morphological parameters can be classified into three categories: density, geometry, and building type. Accordingly, studies commonly use parameters such as building density, floor area ratio, and average number of floors [33].

Table 1. Summary of morphological parameters of buildings.

Theme	Location	Parameters	References
Establish prototypical buildings using performance index system	Shanghai	Construction year Average orientation Number of floors Window:wall ratio (WWR) Plan form	Hong et al. [24]
Influence of the building shape on the energy performance of timber buildings	Athens and Seville	Building geometry Shape factor Glazing-to-wall area ratio on south façade	Premrov et al. [26]
Developing typical residential reference buildings at district level for bottom-up energy modeling purposes	Chongqing	Aspect ratio Building height Compactness ratio	Li et al. [27]

Table 1. *Cont.*

Theme	Location	Parameters	References
Build a database on geometrical features of houses	Southern Brazil	Dimensions of the façade Floor plan shape Area	Schaefer et al. [28]
Reference building models of office buildings and application of these models by evaluating the energy performance	India	Area Aspect ratio Number of floors	Bhatnagar et al. [29]
Identifying synergies and trade-offs when designing for different energy objectives of high-rise residential buildings	Beijing, New York, and Shenzhen	WWR Glass type Building orientation Building shape	Samuelson et al. [30]
Investigating the relationship between urban morphology parameters and residential building space heating energy performance	Qingdao	Average building height Floor area ratio Building cover ratio	Li et al. [31]
Impact of urban form on building energy and cost efficiency	Istanbul	Height Height-to-width ratio Orientation Typology Plan type Number of floors	Mangan et al. [32]

Research on how morphology affects building performance mostly focuses on either the micro level or the macro level, such as a single building or an entire city, and morphological parameters are often categorized into the building scale or urban scale [34]. However, there is little investigation at the scale of residential clusters, which form the basic building blocks of many cities and showcase a huge influence on microclimate, energy consumption, and comfort.

2.2. A Review of Building Morphology and Energy Performance

Conventional research to enhance the energy efficiency of buildings primarily focuses on the materials and insulation capacity, but rarely considers urban or building morphology [35]. For example, Gan et al. used simulations to optimize the layout of a 40-story housing project in Hong Kong, and achieved a reduction in total energy usage of up to 30–40%. Specifically, they optimized the building orientation to minimize the solar radiation from the east and west and maximized the natural ventilation [9]. In a study across different cities in Italy, Mechri et al. used the analysis of variance (ANOVA) method to conclude that the envelope transparent surface ratio is the most significant parameter for heating and cooling efficiency, accounting for more than 50% of the variance [36]. Albatici et al. also found that buildings in mild and warm climates with the same shape coefficient exhibit lower heating demand if the south façade has a greater area, considering the amount of received solar radiation [37]. Additionally, Li et al. investigated how urban morphology parameters influenced the heating energy performance of residential buildings. Their results showed that a larger floor area ratio (FAR) reduces heating energy consumption due to greater received solar radiation. In particular, the heating energy consumption varied from 43.3 W/m^2 to 20.6 W/m^2 when the FAR rose from 0.07 to 1.55 [31]. Leng et al. analyzed the theoretical energy consumption with an external influence on energy performance of 73 buildings in Harbin. They demonstrated how six urban morphological factors can significantly reduce heating energy use and that the FAR is the most significant, contributing to energy savings of up to 10.820 $kWh/m^2/y$, due to the rise in outdoor environmental temperature [38]. Mangan et al. used 120 urban forms to analyze the effect of design indicators on building performance, specifically energy performance, CO_2 emissions, and economic costs. Their results showed that building height and height-to-width ratio have a great influence on energy and economic performance for three urban forms in Istanbul [32]. Furthermore, Taleghani et al. discussed the energy impact of three urban block configurations (point, slab, and courtyard) in the Netherlands. They demonstrated that the courtyard type exhibits the lowest energy consumption for heating because it has the least exposure to the sun [39]. Building orientation also greatly influences energy consumption [39,40]. For instance, Valladares-Rendón achieved reductions in received solar radiation and cooling demand by optimizing the building orientation and solar control shading systems [40].

Based on this review, there are limitations in the current research on building morphology's impact on energy consumption. For instance, many parameters that characterize block morphology and energy use intensity lack corresponding measurable data, which may lead to inaccurate results. Real energy consumption data is important for verifying morphologies that can reduce energy use intensity, especially in the context of residential cluster morphology. Furthermore, previous studies have usually focused on single building types such as office and residential buildings, but there is little work on residential clusters because of difficulties in acquiring data and long simulation times for modeling. To address these issues, we built a database of residential cluster morphology by surveying 1630 residential buildings from 96 different residential clusters and measured the energy usage of 16 residential clusters in Hangzhou, China. Through clustering and correlation analysis, the key morphological parameters influencing energy consumption were determined, with a genetic algorithm used to optimize the model. Using the optimized model, the correlation between the morphological parameters and energy use intensity was obtained, and suggestions for residential cluster morphology and planning are provided.

3. Methodology

3.1. Research Framework

The framework of this study is shown in Figure 1. This paper constructs an optimization model using the genetic algorithm and real power consumption data, to minimize energy consumption and elucidate an energy-saving design strategy for residential clusters in Hangzhou.

The first step is to determine basic parameters describing the morphology of residential clusters according to literature and relevant standards. These parameters are mainly divided into three categories: urban plans, building geometry, and building types. Using these basic indices, 96 residential clusters and 1630 individual buildings in Hangzhou were investigated. Then, through collecting the corresponding spatial patterns, a morphological database of residential clusters was built to provide variables and corresponding value ranges for the optimization model.

The second step is to perform field research to obtain the electricity consumption of 16 residential clusters in Hangzhou over the last three years. Based on the morphological database of Hangzhou constructed in the first step, we analyze the correlation between the morphological indicators of the clusters and the energy consumption of heating, cooling, and lighting. As a result, we can obtain the key morphological indicators that influence energy consumption.

In the third step, the optimization model is constructed using the key indicators of morphology and the corresponding value ranges clarified in step two. The optimization model uses Grasshopper to build the geometric model, and then Ladybug and Honeybee to simulate energy performance. Finally, through Wallacei, the genetic algorithm is used to automatically adjust the model variables to achieve optimization.

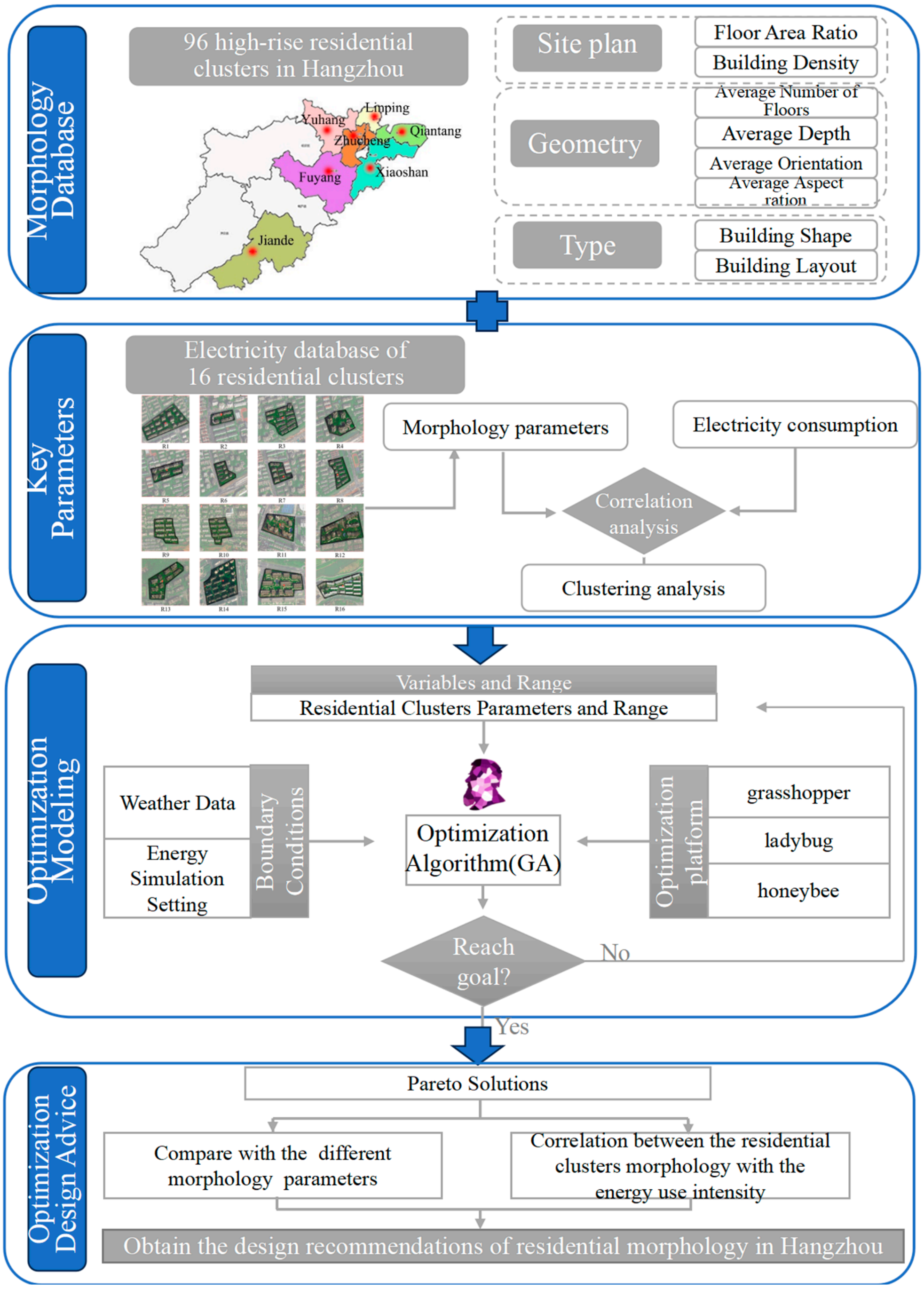


Figure 1. Research framework.

The fourth step is to perform regression analysis on the Pareto solution of the optimization model obtained in step three. Finally, we determine the key parameters and corresponding morphological design strategies for residential clusters that lead to energy savings.

3.2. Study Area

The studied residential clusters are in Hangzhou City, which is located at 29°11′ to 30°34′ north latitude, 118°20′ to 120°44′ east longitude. Hangzhou is the provincial capital of Zhejiang Province in China, and has an urbanization rate of 83.6%. By the end of 2021, the permanent population of Hangzhou was 12.204 million, and the total area of the city is 16,850 square kilometers, yielding a population density of 724 inhabitants/km^2. Hangzhou is located in a hot summer and cold winter (HSCW) climate zone, characterized by an average temperature in January ranging from 0 °C to 10 °C, and an average temperature in July ranging from 25 °C to 30 °C. As a rapidly urbanizing city, Hangzhou has a substantial demand for building energy, particularly for heating and cooling during the winter and summer, respectively.

3.3. Correlation Relationship Analysis

The correlation analysis between the morphology of residential clusters and energy use was conducted using the Pearson correlation coefficient within SPSS Statistics V25 software. The Pearson correlation coefficient serves as a critical index reflecting the extent of correlation between the indicator and the clusters' energy use. Correlation analysis is a statistical means for examining the extent of correlation between multiple variables. The strength of correlation between variables is expressed by the correlation coefficient. Further, the *p*-value determines the significance level of differences between variables. The correlation coefficient r assesses the extent of linear correlation. A positive *r* value indicates a positive correlation, and a negative *r* value indicates a negative correlation. The larger the absolute value of *r*, the stronger the correlation between the variables. Pearson correlation coefficients are calculated using Equation (1):

$$r = \frac{\sum_1^n (x_i - \overline{x}) * (y_i - \overline{y})}{\left[\sum_{i=1}^n (x_i - \overline{x})^2 \sum_{i=1}^n (y_i - \overline{y})^2\right]^{-2}} \tag{1}$$

where r is Pearson's correlation coefficient, x_i, and $\overline{x}$ represent the dependent variable X and its mean, and y_i and $\overline{y}$ represent the dependent variable Y and its mean, respectively.

3.4. The Objective of Optimization

Building energy consumption can be categorized into life-cycle energy consumption and operational energy consumption. In a narrow sense, building energy consumption refers to the energy consumption as part of the operations of a building, such as heating, cooling, lighting, providing hot water, and elevator operations, among other processes. According to the China Building Energy Consumption Report of 2020 [41], on average, the total energy consumption during the operational phase of a building accounts for 46.6% of the total energy consumption throughout the building's life cycle. Additionally, the amount of carbon dioxide released in the operational phase accounts for 42.8% of the total carbon emissions over the entire life cycle of buildings. Therefore, it is vital to reduce the energy use intensity and carbon emissions during the operational phase of a building.

The optimization of this study is to evaluate the impact of morphological parameters of residential clusters on building energy performance. The energy use intensity (EUI) of hot water and elevator operation consumed by residential clusters is less affected by changes in morphology; therefore, we do not include them in the calculation of EUI in this study. Thus, we define the energy consumption of the building as the sum of heating, cooling, and lighting energy consumption. The formula for calculating EUI is shown in Equation (2):

$$EUI = EUI_{heating} + EUI_{cooling} + EUI_{lighting} \tag{2}$$

where EUI is the total energy use intensity, $EUI_{heating}$ is the energy use intensity of heating, $EUI_{cooling}$ is the energy use intensity of cooling, and $EUI_{lighting}$ is the energy use intensity of lighting.

3.5. Optimization Algorithm

The disciplines of building design and performance are inherently distinct areas of expertise. In exploring their interconnected relationship, overcoming disciplinary boundaries poses a significant challenge in research. Recently, the combination of simulation tools and optimization algorithms has been used in the building performance analysis [42], bridging the connection between building morphology and performance. In this building energy performance study, energy simulation is conducted using the Grasshopper–Honeybee platform, which is built on the EnergyPlus engine. Grasshopper 1.0.0007 software, a multi-functional open platform, can efficiently perform simulations of energy consumption, lighting, and solar radiation, thus facilitating the assessment of buildings in early design stages [43,44]. In order to obtain progressively optimized building morphology, a genetic algorithm (GA) is adopted for the optimization task. The morphologies with poor performance are gradually eliminated, and better performance is achieved by adjusting independent variables and generating residential groups in a performance simulation based on the GA (Figure 2). GA-based optimization was first proposed by Holland [45], with Darwin's theory of evolution and Mendel's doctrine of genetics as its foundation. This method draws on evolutionary biology concepts such as heredity, mutation, crossover, and variation, and utilizes the objective function of stochastic search and optimization of solutions [46]. The genetic algorithm can account for the links and mutual influence between various factors, such as architectural morphology in our case, and has an ability to handle complex situations [47]. Meanwhile, Wallacei is an evolutionary objective optimization engine in Grasshopper, using GA as its core, implementing the NSGA-II (non-dominated sorting genetic algorithm II) and the K-means clustering algorithm. To achieve minimum energy use intensity, the values of independent variables are frequently updated, different morphologies are obtained, and the results of the Grasshopper energy consumption simulation are entered in Wallacei. In the subsequent optimization, the total number of optimization generations is set to 100, and the number for each generation is 50.

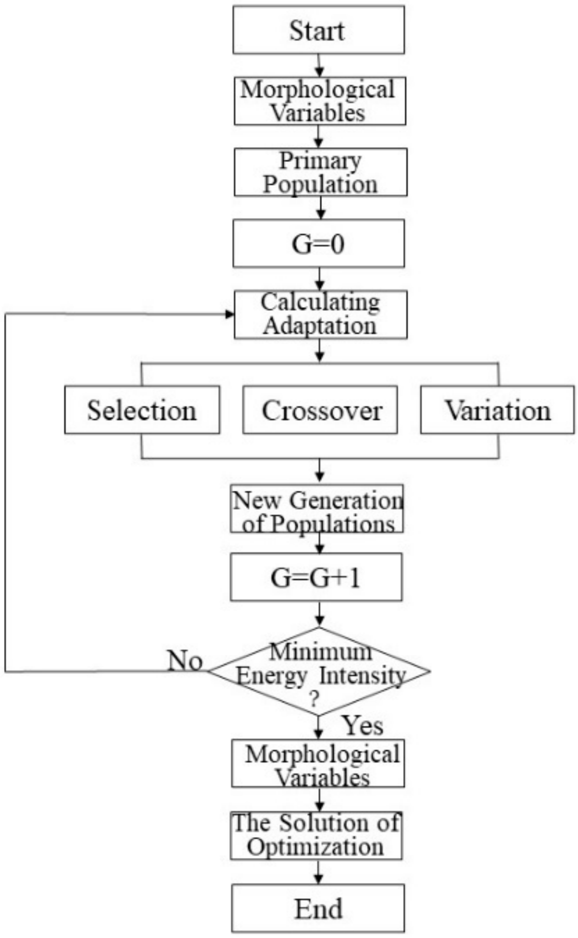


Figure 2. Flowchart of the genetic algorithm approach.

4. Building the Database and Optimization Model

4.1. Morphological Characteristics of Residential Clusters

This paper selects 96 high-rise residential clusters as the basis of the database, with 16 of them used for model validation, as listed in Figure 3. Table 2 shows the parameters of classification for the high-rise residential cluster prototypes, and these indices are based on the previous work described in Section 2.1. The relevant indicators are analyzed statistically to inform the construction of the model. These residential clusters adequately represent the current morphology and development trends of residential clusters in Hangzhou, which makes their analysis useful for the construction of future communities and facilitation of future studies.

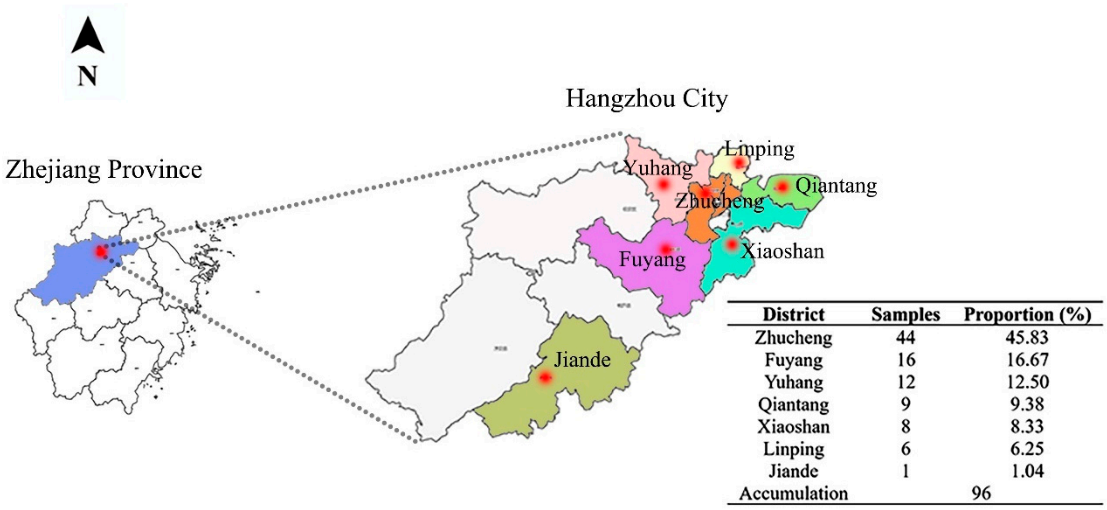


Figure 3. Location of Hangzhou city and distribution of the sample residential clusters.

Table 2. Classification of high-rise residential cluster parameters.

Classification	Core Parameters	Calculation Formula
Site plan	Floor Area Ratio (FAR)	$FAR = \frac{\sum_{i=1}^{n} S_i}{A}$
	Building Density (BD)	$BD = \frac{\sum_{i=1}^{n} F_i}{A}$
Geometry	Average Number of Floors (AF)	$AF = \frac{\sum_{i=1}^{n} S_i}{\sum_{i=1}^{n} F_i}$
	Average Depth (AD)	$AD = \frac{\sum_{i=1}^{n} D_i}{n}$
	Average Orientation (AO)	$AO = \frac{\sum_{i=1}^{n} O_i}{n}$
	Average Aspect Ratio (AAR)	$AAR = \frac{\sum_{i=1}^{n} \frac{L_i}{D_i}}{n}$
Type	Building Shape (BS)	-
	Building Layout (BL)	-

Note: n is the number of buildings; S_i is the gross floor area; A is the area of block; F_i is the gross footprint area; D_i is the depth of the building; O_i is the orientation of the building; L_i is the length of the building.

Then, the basic data of the 96 high-rise residential clusters, comprised of 1630 individual buildings in total, were collected to summarize the basic information related to floor area ratio (FAR), building density (BD), average number of floors (AF), average orientation (AO), building shape (BS), building layout (BL), average aspect ratio (AAR), and average depth (AD) for each residential cluster.

(1) The building shapes

According to the statistical results, it was found that there were 66 slab-type buildings, accounting for 68.75% of the total; Accordingly, there were 30 point-type buildings, accounting for 31.25%. Thus, the slab-type building is the most common among residential groups in the Hangzhou area (Table 3).

Table 3. The number and proportion of different building shapes of residential clusters.

Shapes	Number	Proportion (%)
Slab type	66	68.75
Point type	30	31.25

(2) The building layout

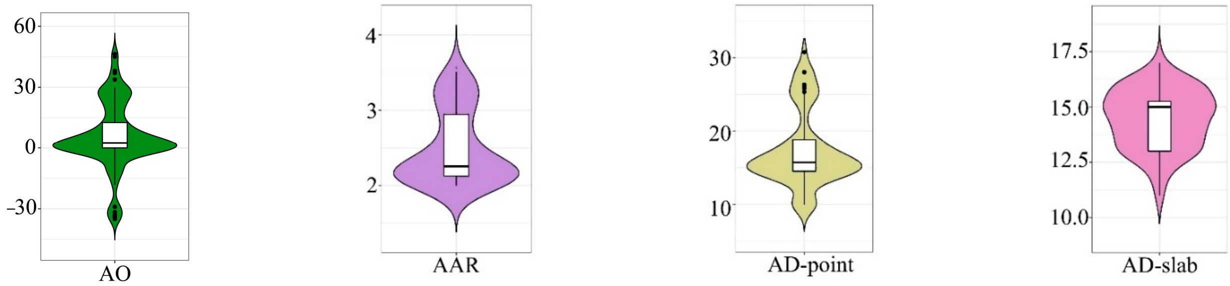
There are three main layout forms for the clusters: parallel, staggered, and courtyard. However, based on field research and analysis of CAD drawings and satellite maps, there are also layout forms that are a mix of the three categories, as well as "free-form" layouts formed by the influence of the base restriction: these are collectively referred to as "other" in this study. According to the statistical results shown in Table 4, among the four types of layout forms, the number and proportion of parallel layout is the largest, with a count of 52 groups and accounting for 54.17% of the total. This is followed by staggered layout, with a count of 26 groups and accounting for 27.08%. The number of courtyard and other layouts is relatively small. Therefore, we select the most typical row and column layouts as the main object for subsequent tests.

Table 4. The number and proportion of different building layouts of residential clusters.

Layout	Number	Proportion (%)
Parallel	52	54.17
Staggered	26	27.08
Courtyard	6	6.53
Other	12	12.5

(3) The average orientation

Statistical analysis of the average orientation (AO) of the research sample is shown in Figure 4a, in which the southeast direction is defined as positive and the southwest as negative (with due south as 0°). The building orientations of residential groups in Hangzhou range from southwest 30° to southeast 30°. In addition, most are concentrated in the range of southwest 10° to southeast 10°. Therefore, we select southwest 30° to southeast 30° as the range of the orientation variable for the subsequent tests.



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

Figure 4. Violin plots of the distribution of morphology parameters of surveyed residential clusters. (**a**) Average orientation (AO) statistical, (**b**) average aspect ratio (AAR) statistical, (**c**) average depth of point-type (AD-point) statistical, (**d**) average depth of slab-type (AD-slab) statistical.

(4) The aspect ratio and depth

Statistical analysis of the average aspect ratio (AAR) for slab-type buildings in the sampled clusters is shown in Figure 4b. It is found that the aspect ratio ranges from 2.0 to 3.5, with most values concentrated between 2.2 and 2.8. Therefore, in subsequent analysis, we adopt 2.0–3.5 as the range of variation for the aspect ratio of slab-type buildings.

The average depths of point-type buildings (AD-point) in the sampled residential clusters studied are shown in Figure 4c. We can see that the depths of point-type buildings range from 10 to 25 m, and they are mainly concentrated around 15 m. Statistics on the depths of slab-type buildings are shown in Figure 4d. The average depths of slab-type buildings (AD-slab) in Hangzhou are mainly distributed between 13 and 16 m, and the most common depth is 15 m, accounting for about 25% of the total. Thus, we use the depth of 15 m as one of the basic parameters for slab-type buildings in our model construction.

4.2. Electricity Usage of Residential Clusters

Electricity consumption of residential clusters is recorded every month by the Hangzhou Electricity Bureau. We collected information on 16 residential clusters in Hangzhou, totaling 176 buildings, as well as their power consumption over the past three years. Information on the morphology of these 16 residential clusters is then summarized according to the previously described indices. Due to the source of data being aggregate values from the Hangzhou Electricity Bureau, it is impossible to get the sub-energy of $EUI_{heating}$ and $EUI_{cooling}$ directly. Therefore, it is necessary to process the obtained data. This involves obtaining the average monthly energy consumption during the transitional seasons (from March to May and September to November) and then subtracting the average energy consumption from the energy consumption during both the heating and cooling seasons separately, thus obtaining $EUI_{heating}$ and $EUI_{cooling}$.

Table 5 and Figure 5 present the total EUI, $EUI_{heating}$, and $EUI_{cooling}$ of the surveyed high-rise residential clusters and corresponding images, respectively. Table 4 shows that the total EUI of residential clusters in Hangzhou ranges from 22.35 to 45.91 kWh/m^2/y, with $EUI_{heating}$ ranging from 1.62 to 6.95 kWh/m^2/y in winter and $EUI_{cooling}$ ranging from 12.39 to 22.35 kWh/m^2/y in summer.

Table 5. The electricity consumption and morphology of the 16 sampled residential clusters.

No.	EUI (kWh/m^2/y)	$EUI_{heating}$ (kWh/m^2/y)	$EUI_{cooling}$ (kWh/m^2/y)	FAR	BD (%)	BS	BL	AD	AF	AO	AAR
R1	32.82	3.49	15.20	2.00	22	1.00	4.00	17.28	18.00	−22.52	4.00
R2	28.72	2.72	13.44	2.15	32	1.00	3.00	18.29	7.00	3.55	3.80
R3	23.74	1.62	12.89	2.15	31	1.00	1.00	26.64	8.00	−17.42	4.00
R4	29.71	4.71	14.87	2.15	31	2.00	3.00	21.93	18.00	0.00	1.00
R5	32.01	4.69	15.25	2.15	31	1.00	1.00	11.35	10.00	−12.69	3.80
R6	36.16	5.26	15.08	2.15	31	1.00	1.00	16.29	8.00	−19.72	3.50
R7	38.33	5.60	15.09	2.15	31	1.00	1.00	11.17	8.50	−16.31	3.60
R8	29.50	4.45	14.88	2.15	31	1.00	1.00	16.93	8.40	−20.70	3.00
R9	33.62	6.95	17.40	1.24	22	1.00	1.00	20.75	6.00	0.00	4.00
R10	34.37	5.40	15.00	1.24	22	1.00	1.00	20.75	6.00	23.10	4.00
R11	30.37	3.21	12.39	2.71	22	3.00	3.00	33.02	19.00	−13.94	1.20
R12	22.35	1.91	13.11	2.60	19	1.00	1.00	14.05	13.00	13.35	2.40
R13	45.91	2.47	12.83	2.20	19	3.00	1.00	13.95	14.00	20.00	3.00
R14	23.83	3.60	17.28	2.71	22	3.00	2.00	14.23	20.00	−25.76	1.10
R15	31.16	3.79	22.35	2.10	25	1.00	1.00	16.00	13.00	−19.79	3.60
R16	30.76	2.58	16.15	2.59	18	1.00	1.00	16.09	12.00	16.96	2.60

Notes: BS: 1, 2, and 3 represent slab, point, and slab-point mixed, respectively; BL: 1, 2, 3, and 4 represent parallel, staggered, courtyard, and other, respectively; AO: negative numbers represent southwest, positive numbers represent southeast, and 0° represents due south direction.

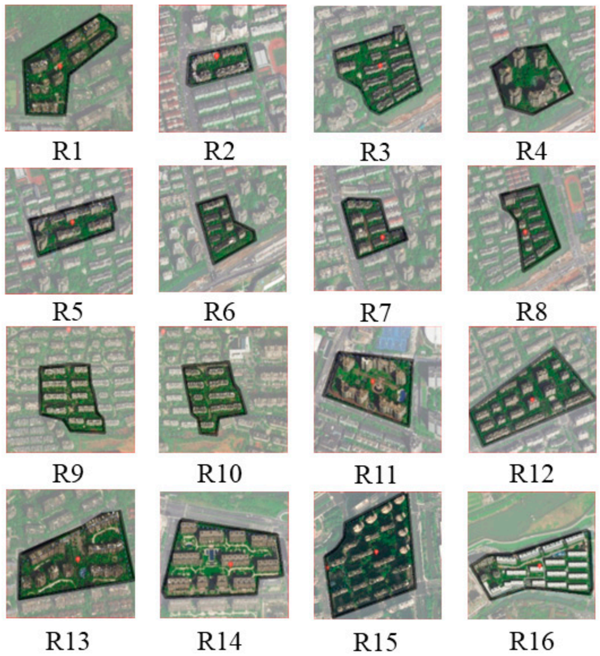


Figure 5. Satellite images of the 16 sampled residential clusters.

4.3. Extracting the Key Parameters of Morphology Based on Energy Use Intensity

Table 6 presents the correlation analysis between the morphology indicators and the electricity consumption. The most impactful parameters are subsequently selected for further classification. The correlation coefficients showcase the following trends, in order of decreasing importance: for $EUI_{heating}$—FAR > AAR > AD > AO > AF > BL > BS > BD; for $EUI_{cooling}$—FAR > AF > BD > BS > AAR > BL > AO > AD; and for total EUI—AD > AO > BS > FAR > BL > AAR > BD > AF. The f-value assesses the collective impact of all the indicators. This result suggests that FAR, AF, AO, and AAR are the most impactful on the energy consumption of the residential clusters.

Table 6. Correlation analysis of residential clusters' average annual electricity consumption per unit floor area for each indicator.

Classification Indicator	Total EUI		$EUI_{heating}$		$EUI_{cooling}$	
	Pearson Correlation	**f-Value (2-Tailed Sig.)**	**Pearson Correlation**	**f-Value (2-Tailed Sig.)**	**Pearson Correlation**	**f-Value (2-Tailed Sig.)**
Floor area ratio (FAR)	−0.359	0.172	−0.654	0.006	−0.209	0.438
Building density (BD)	−0.080	0.767	0.254	0.342	−0.071	0.793
Average number of floors (AF)	−0.176	0.514	−0.345	0.190	0.019	0.945
Average depth (AD)	−0.255	0.341	−0.133	0.625	−0.310	0.243
Average orientation (AO)	0.249	0.353	−0.146	0.589	−0.289	0.277
Average aspect ratio (AAR)	0.306	0.250	0.212	0.432	0.130	0.630
Building Shape (BS)	0.136	0.615	−0.449	0.405	−0.221	0.410
Building Layout (BL)	−0.164	0.544	−0.970	0.550	−0.208	0.440

Table 7 and Figure 6 show a 3 to 4 class K-means clustering of the indices influencing energy consumption. For the 4-class clustering, BS, BL and FAR formed the first cluster; AF and AD formed the second cluster; BD and AAR formed the third cluster; and AO was the last cluster. Under the 3-class clustering, BS, BL, FAR, AF, AD formed the first cluster, BD and AAR formed the second cluster, and AO formed the last cluster.

Table 7. Variable cluster analysis results for the residential clusters.

Classification Indicator	4-Class Clustering	3-Class Clustering
FAR	1	1
BD	2	2
BS	1	1
BL	3	1
AD	3	1
AF	1	1
AO	4	3
AAR	2	2

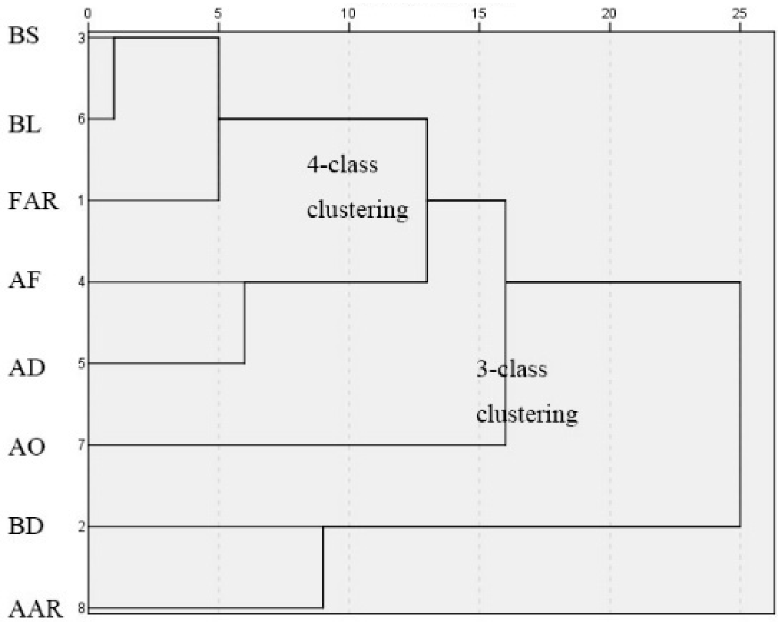


Figure 6. Cluster analysis tree of residential cluster morphology.

By analyzing the 4-class K-means clustering results, we determine that AO, AAR, AF, and FAR are the major factors influencing the total EUI of the residential clusters. Notably, this result aligns with the Pearson correlation analysis described above.

4.4. Optimization Model for the Residential Clusters

Using the key parameters of the residential model for energy use reduction, we can construct a corresponding hypothetical block model. The Standard for Urban Residential Area Planning and Design (GB50180-2018) [48] specifies that the scale of residential clusters should be approximately 150–250 m. Furthermore, Xia et al. found that in the central area of Hangzhou, the distance between road intersections is typically 50–150 m [49]. Thus, this study selected a 150 m $\times$ 150 m block size and a default direction of north—south for the simulation study. Recall from Section 3.3 that Hangzhou residential clusters with a parallel layout accounted for 54.17% of the total. Therefore, we use a parallel layout as the basic layout type, and subsequently perform optimization for high-rise parallel-slab and parallel-point shape classifications.

According to the Neighborhood Land Use and Building Control Index Table from GB50180-2018 [48], the number of floors for high-rises should be 10–18, the floor area ratio 2.2–2.8, the maximum value of building density 22%, the minimum value of the green space rate 35%, and the maximum height 54 m (Table 8).

Table 8. Standard regulations for high-rise residential buildings (GB50180-2018).

Type	FAR	Average Number of Floors	Building Density	Green Area Ratio	Height
High-rise Class I	2.2–2.8	10–18	≤22%	≥35%	≤54

Based on the key residential cluster morphology parameters discussed in Section 3.5 and the corresponding variable value ranges obtained from the standard regulations and survey database, a hypothetical block model is constructed. The variables and their ranges are shown in Table 9, and the model for high-rise residential clusters is shown in Figure 7.

Table 9. High-rise model variables and the range of values.

Factors	Range	Step
AF	[10, 18]	1
FAR	[2.20, 2.80]	0.01
AAR	[2.0, 3.5]	0.1
AD	[10, 25]	1
AO (°)	[−30, 30]	1

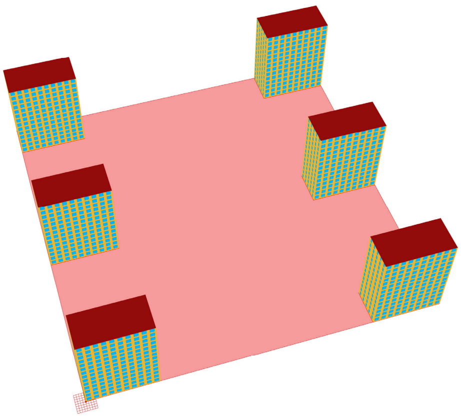


Figure 7. Benchmark model for high-rise residential clusters.

The parameters are largely set according to the Design Standard for Energy Efficiency of Residential Buildings (DB33/1015-2021) [50], with Table 10 presenting these settings for the building energy simulation in Honeybee.

Table 10. Settings for the energy simulation model.

Parameters		Setting
Weather data		Typical meteorological year of Hangzhou in EPW files
Simulation period		From 1 January to 31 December
Constructions	Wall	U value = 0.8 W/(m^2·K)
	Roof	U value = 0.25 W/(m^2·K)
	Floor	U value = 1.2 W/(m^2·K)

Table 10. *Cont.*

Parameters		Setting
	Window	U value = 1.8 W/(m^2·K), SHGC = 0.4
Internal loads	People	Occupant density:0.05 people/m^2
	Lighting	5 W/m^2
HVAC System	Heating/cooling season and setpoints	Heating: 15 December to 20 February, 18 °C Cooling: 15 June to 15 September, 26 °C
	Infiltration	1 ACH

5. Results

5.1. Energy Use Intensity of the Benchmark Model

The optimization trend of each performance indicator is shown in Figure 8. It can be found that the optimization objectives gradually become stable as the number of simulations increases and tend to converge after 600 simulations. This indicates that the simulation data are reasonable and useful for subsequent analysis and research.

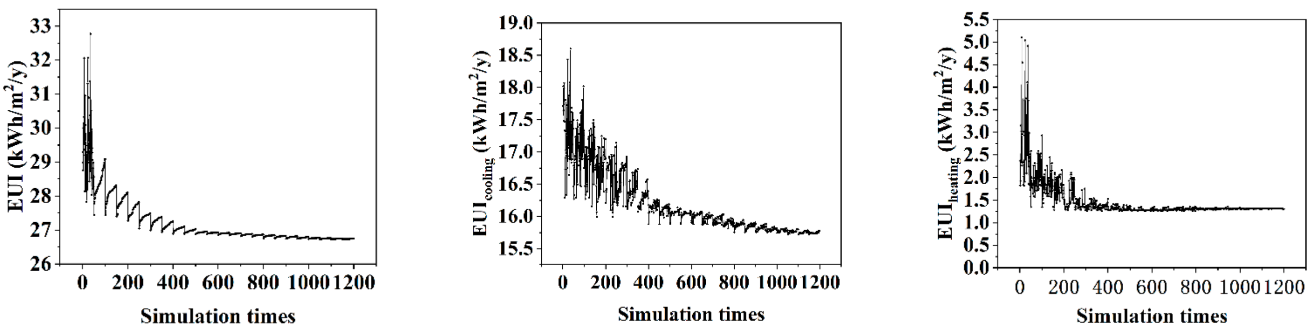


Figure 8. The optimization results with the simulation times.

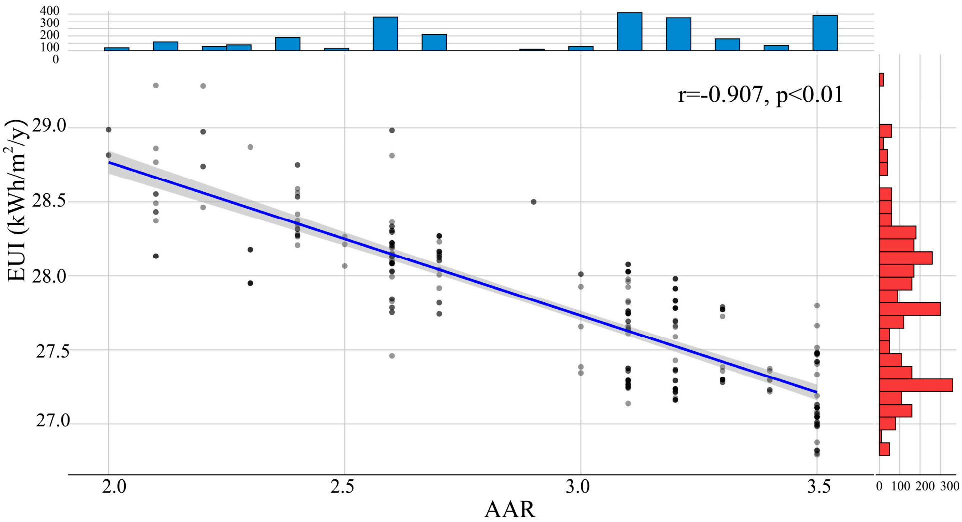
During the optimization process, all morphological parameters and the energy performance at each generation were recorded. The results are shown in Table 11. Comparing the total energy use intensity (EUI) of residential clusters before and after optimization, we find the optimized clusters all have reduced energy usage to differing degrees, and the energy efficiency ratio is 7.73%. For the subcategories of $EUI_{heating}$ and $EUI_{cooling}$, there are reductions compared to the pre-optimization states, but the energy consumption of lighting has increased compared to the pre-optimization states.

Table 11. Optimization results for the various types of energy consumption of residential clusters.

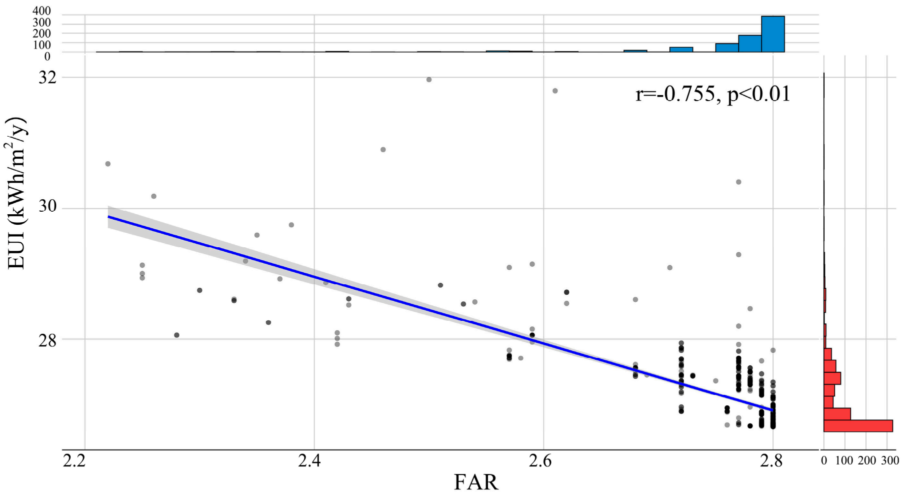
	Benchmark Clusters	Optimization Clusters	Energy Reduction	Efficiency Ratio (%)
Total EUI (kWh/m^2/y)	28.96	26.72	2.24	7.73
$EUI_{cooling}$ (kWh/m^2/y)	17.43	15.72	1.71	9.81
$EUI_{heating}$ (kWh/m^2/y)	2.21	1.32	0.89	40.27
$EUI_{lighting}$ (kWh/m^2/y)	9.32	9.68	−0.36	−3.86

5.2. Correlation between the Morphology Parameters and Energy Use Intensity

To analyze the correlation between the morphological parameters and energy use intensity (EUI), a scatter diagram was generated. The simulation results are shown in Figure 9. All the results were statistically significant at a level of 0.01. The correlation coefficients of AAR, FAR, AF, AO with the EUI of the residential clusters were −0.907, −0.755, −0.453, and 0.502, respectively. In addition, the absolute values of the correlation coefficients of AAR, FAR, and AO with EUI all exceeded 0.5, suggesting strong relationships. The absolute value of the correlation coefficient between AF and EUI exceeded 0.4, suggesting a moderate correlation between them. In the meantime, AAR, FAR, and AF had a significant negative correlation with EUI. Figure 9a–c demonstrate that as AAR, FAR, and AF increase, there is a gradual decrease in the EUI of the residential clusters. FAR and AF reflect the intensity of development and the capacity of the area for construction. Therefore, as the intensity of development of the clusters increase, the EUI will decrease. Also, these results match the conclusion put forward by Liu [34]. Based on the scatterplots, AO between −30° (30° southwest) and 0° shows an EUI of approximately 29.20 kWh/m^2 when averaged at 30° southwest. Shifting AO to 15° southwest, the EUI is reduced to 28.85 kWh/m^2 (Figure 9d). This corresponds to a decrease of about 0.35 kWh/m^2 and an energy saving rate of 1.2%. Therefore, energy consumption decreases and then increases as the building orientation changes from west to east, with the minimum energy consumption occurring at 15° southwest. Within the AO range of 0 to 30°, there is a positive relationship between AO and EUI.

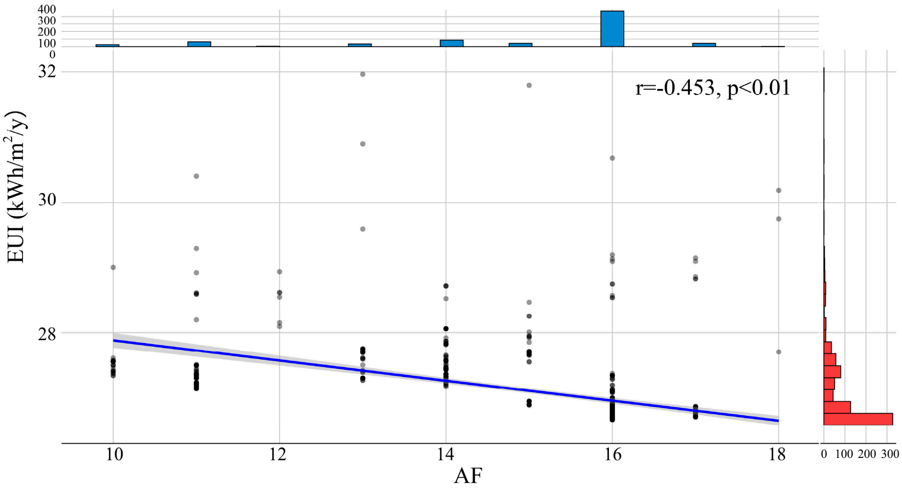


(**a**)



(**b**)

Figure 9. *Cont.*



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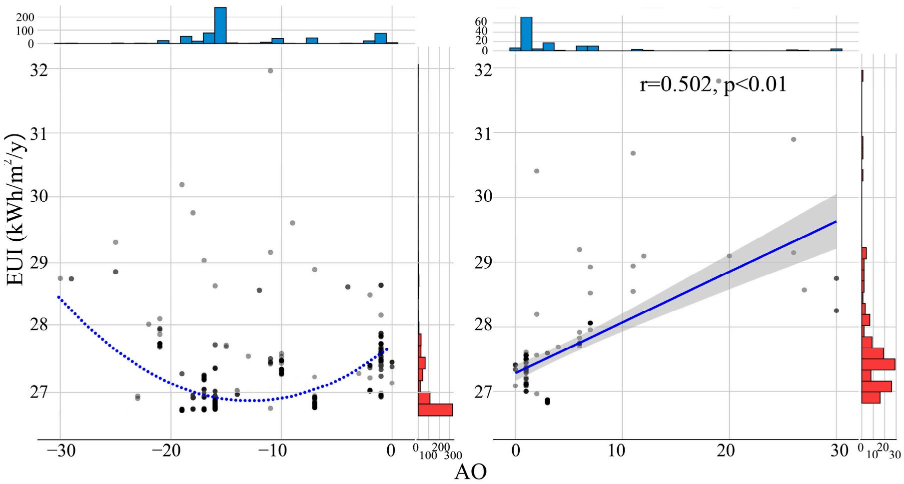

(**d**)

Figure 9. The simulation results of morphologies for the high-rise model. (**a**) Scatterplot and correlation analysis between AAR and EUI. (**b**) Scatterplot and correlation analysis between FAR and EUI. (**c**) Scatter-plot and correlation analysis between AF and EUI. (**d**) Scatter-plot and correlation analysis between AO and EUI.

5.3. Regression between Urban Morphological Parameters and Energy Use Intensity

Based on the results of the correlation analysis, we set the residential cluster morphology variables that exhibited significant correlation as independent variables and EUI as the dependent variable to perform multiple regression analysis. The final regression equation is as follows:

$$EUI = -1.093 * FAR - 0.03 * AF + 0.004 * AO - 0.804 * AAR + 33.254 \tag{3}$$

The regression analysis also produced standardized coefficients, as shown in Table 12. The multiple correlation coefficient R is 0.919, which corresponds to an R^2 of 0.844. In statistical terms, a higher determination coefficient (R^2 value) signifies a better fit of the model to the objective, with a maximum value of 1. Thus, there is a strong fit of the equation and the data, suggesting a linear relationship between the residential cluster morphological parameters and EUI. Furthermore, there is a significance value (Sig.) of 0.000, which demonstrates a high level of statistical significance and reliability.

Table 12. Results of the multiple regression analysis.

Dependent Variables	R Square (R^2)	Sig.	Standardized Coefficients			
			FAR	AF	AO	AAR
EUI	0.844	0.000	−0.162	−0.088	0.062	−0.719

The validity of the model is also confirmed by comparing EUI values calculated using the regression equation with surveyed values of 12 slab-type residential clusters from the database (Table 13). The validation index used is the coefficient of variation of root mean square error (CV(RMSE)) [51]. The equation of CV(RMSE) is as follows:

$$CV(RMSE) = \sqrt{\frac{\sum_{i=1}^{n}(e_i - \hat{e}_i)^2}{n-p}} \quad (4)$$

where $\bar{e}$ represents the mean of measured values, e_i and $\hat{e}_i$ represent measured and predicted values of cluster i, respectively, n is the overall number of buildings, and p is the number of model factors. The CV(RMSE) value resulting from the model predictions is 21.68%. According to ASHRAE Guideline 14, a CV(RMSE) lower than 30% is indicative of a credible model estimation. Therefore, this regression equation can be employed to describe the relationship between residential cluster morphology and EUI in Hangzhou.

Table 13. Validation of the model comparing EUI and morphological parameters of sampled residential clusters.

No.	Measured EUI (kWh/m^2/y)	Predicted EUI (kWh/m^2/y)	FAR	AF	AO	AAR
1	32.82	27.22	2.00	18.00	−22.52	4.00
2	28.72	27.65	2.15	7.0	3.55	3.8
3	23.74	27.38	2.15	8.0	−17.42	4.0
4	32.01	27.50	2.15	10.0	−12.69	3.8
5	36.16	27.78	2.15	8.0	−19.72	3.5
6	38.33	27.70	2.15	8.5	−16.31	3.6
7	29.50	28.16	2.15	8.4	−20.70	3.0
8	33.62	28.50	1.24	6.0	0.00	4.0
9	34.37	28.60	1.24	6.0	23.10	4.0
10	22.35	28.15	2.60	13.0	13.35	2.4
11	31.16	27.60	2.10	13.0	−19.79	3.6
12	30.76	28.04	2.59	12.0	16.96	2.6

Investigating the multiple linear regression results above, one can observe the following.

(a) The high R^2 value of 0.844 indicates that the morphology of residential clusters significantly influences energy use intensity in Hangzhou. Furthermore, the model accounts for 84.4% of the variation in EUI, leaving only 15.6% to be caused by other factors, such as the transparent envelope, materials of enclosure, occupant behavior, and so on.

(b) AAR, FAR, and AF have a negative impact on the annual energy use intensity of residential clusters. Furthermore, when AO ranges from 0 to 30°, AO has a positive impact on EUI, but in the range of −30 to 0°, it has the lowest energy use intensity when AO is 15° southwest.

(c) The magnitudes of the standardized coefficients indicate that among the four morphological parameters, AAR has the strongest influence on the annual energy use intensity of residential clusters (−0.719). Concordantly, FAR (−0.162), AF (−0.088), and AO (0.062) have a smaller impact on energy use intensity.

6. Discussion

The optimization results demonstrate that varying morphologies of residential clusters have different impacts on energy use intensity in Hangzhou, a hot summer and cold winter (HSCW) area. Many researchers, architects, and urban planners are broadly interested in energy-efficient building design [52,53]. However, it is crucial to explicitly quantify how the morphology of residential clusters influences energy use intensity. This study accordingly offers data-driven suggestions for early-stage design of residential clusters, particularly with regard to morphological parameters of residential clusters that significantly impact energy consumption, such as floor area ratio, average number of floors, average orientation, and average aspect ratio.

According to the optimization results, the EUI differs by approximately 7–8% across various morphologies, which is in line with the findings of [54]. From the results of the correlation analysis, it is apparent that AAR, FAR, AF, and AO exhibit notable correlations with the total energy use intensity of the clusters. AAR, FAR, and AF negatively influence energy use intensity. The greater the FAR is, the higher the energy consumption efficiency of the cluster. FAR, AF, and AAR are three principal indicators that characterize the spatial intensity of residential clusters. In cities, the density of land development closely aligns with FAR, AF, and AAR, which is a situation that often entails trade-offs. In general, a high intensity of land development means a greater FAR, a taller AF, and a higher AAR, and a lower intensity of land means smaller values of FAR, AF, and AAR. Thus, residential clusters on land with high-density development are more amenable to reductions in energy use intensity though optimizing building morphology.

Energy flow within a residential cluster is realized through heat conduction, convection, and radiation between the buildings and the outdoor air. Under the constraint of FAR, if the AF or AAR becomes larger, the morphology of clusters will be scattered and the amount of outdoor open space will be larger. When development density of clusters becomes higher, the building compactness within high-rise clusters increases, resulting in a reduction in heat exchange between the building and the outdoor space. For regions with HSCW climates, solar radiation is the main source of heat gain for buildings. However, high-development-intensity clusters gain less solar radiation due to more shade between buildings, which reduces cooling energy consumption in summer. Additionally, in this situation, there is an increase in heat exchange through the external air. This is attributed to the higher buildings, leading to a corresponding acceleration in wind speed [39]. Wang et al. also found that an increase in the distribution of building heights will contribute to increased diversity of the buildings within a parcel of land, facilitating more effective dissipation of heat [55]. Building height significantly influences outdoor temperature distributions, with greater heights resulting in potentially lower outdoor temperatures in the summer [56,57], which can further reduce cooling energy use. During winter, the energy consumption is more significantly affected by the heat exchange in the outdoor space, even though the building façade receives less solar radiation. Also, reasonably deep urban canyons can lead to decreased ventilation efficiency [58]. Accordingly, the space of high-building-intensity settlements is more conducive to the reduction in indoor heat exchange from the building to the outdoor area. Leng et al. showed that a higher spatial intensity of city blocks contributes to improved heating energy efficiency [38]. Additionally, Liu found that for FAR in the range of 0.8–3.0, as FAR increased, the total energy consumption intensity decreased [34]. Additionally, Natanian studied the energy performance of building prototypes across various FAR values. The results showed that as the FAR increases, the energy cooling demand of residential buildings tends to decrease [59]. Previous studies conducted in various climates have also demonstrated that increased building compactness contributes to enhanced building energy efficiency [60,61]. Thus, whether the primary goal is to reduce costs for developers or to increase energy efficiency, a higher development density is preferable for high-rise residential clusters. Consequently, some researchers have proposed high-density development models, especially for residential buildings in urban areas, as a strategy to increase energy savings [61].

From the optimization results, it can be concluded that the ideal AO for the residential clusters was southwest 15°. This is primarily because the prevailing summer wind direction in Hangzhou is southeast, and the southwest orientation of buildings is more conducive for natural ventilation efficiency in the clusters. This natural ventilation can facilitate the removal of internal heat, resulting in lower outdoor ambient temperatures during summer and reducing the cooling energy consumption. At the same time, this orientation is conducive to the building façade gaining more solar radiation in the winter, thus reducing the heating energy consumption in winter. Liu et al. also found that in Jianhu, China, another region with an HSCW climate, a building facing south or southwest at 15° is advantageous for capturing optimal solar radiation and preventing overheating or overcooling [34].

7. Conclusions

As CO_2 emissions increase, it has become increasingly important to construct energy-efficient residential clusters. With an improved understanding of building morphology, urban planners and designers can design more sustainable residential clusters and communities [62]. The main aim of this study was to identify building morphologies for residential clusters that reduce energy use intensity based on modeling and comparisons to real energy use data. Consequently, we quantitatively investigated the collective impact of morphology parameters on the energy use intensity of residential clusters in Hangzhou, China, which is characterized by a hot summer and cold winter (HSCW) climate. We compare 16 residential clusters' real electricity usage data with 780 simulated data cases through a combination of statistical analysis and modeling. Accordingly, we develop a model to predict the energy use intensity of residential clusters.

For the area of Hangzhou, China, a morphological database of 1630 residential buildings from 96 residential clusters and an energy use database of 16 residential clusters were built. The residential clusters were mostly dominated by slab-type buildings, accounting for 68.75% of the total, while the form of building layouts was dominated by parallel layouts, accounting for 54.17%. At the same time, the average orientation ranged from southwest 30° to southeast 30°, and was mainly distributed between southwest 10° and southeast 10°. The average aspect ratios of the building floors ranged from 2.0 to 3.5, while the depths ranged from 10 to 25 m, mainly being concentrated around 15 m. According to the surveyed data, the EUIs of residential clusters in Hangzhou ranged from 22.35 to 45.91 kWh/m^2/y, with $EUI_{heating}$ ranging from 1.62 to 6.95 kWh/m^2/y in winter and $EUI_{cooling}$ ranging from 12.39 to 22.35 kWh/m^2/y in summer.

From analyzing the electricity usage and morphology database, we found that AAR, FAR, AF, and AO are the most crucial factors influencing the energy consumption of residential clusters. Using the optimized morphological parameters, the total EUI can be reduced by 7.73%. The correlation analysis results highlight that AAR is the most significant factor influencing EUI, which is followed by FAR ($r = -0.755$), AO ($r = 0.502$), and AF ($r = -0.453$). AAR, FAR, and AF show negative correlations with EUI. The optimal AO is southwest 15°, which is beneficial in decreasing EUI. When AO ranges from southeast 0 to 30°, it shows a positive correlation with EUI. The crucial morphological parameters influencing the EUI of residential clusters are AAR and FAR, with standard coefficients of -0.719 and -0.162, respectively. Furthermore, the AAR has 4.43 times the impact on EUI compared to FAR. High-intensity land development with greater FAR, taller AF, and higher AAR is therefore suggested to promote energy savings, especially for residential buildings in urban areas.

The findings of this study demonstrate that urban morphology profoundly affects building energy consumption. For policymakers and designers, selecting appropriate cluster morphologies can effectively reduce energy usage, thereby advancing efforts toward achieving carbon emission peaks and promoting sustainable development. By integrating empirical databases with performance simulations, this study aims to enhance understanding of the relationships and mechanisms between morphological parameters and energy consumption. Additionally, the results will offer crucial insights and support for developing energy-efficient urban design strategies in the HSCW climate.

This study also has some limitations. The analysis was conducted on high-rise building data from Hangzhou, China, making the results applicable to the HSCW climate zone of China and high-rise residential clusters. Moreover, this study solely considered morphology as influencing the EUI. Subsequent studies could investigate microclimate, envelope materials, and differing climates to enhance the universality of the model.

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