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Analysis of synergistic influence of multi-scale design parameters on nearly-zero energy office blocks performance based on architectural morphological classification and parametric modeling

Research Article

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Abstract

Design parameters at different scales in the pre-design phase could significantly impact both building energy consumption and photovoltaic (PV) power generation potential. However, existing studies often overlook the synergistic effects of design parameters across multiple scales (block-building-facade scales) when evaluating these aspects. This paper aims to propose a workflow for the assessing building energy consumption and PV power generation potential of office blocks applicable in the pre-schematic design phase considering the synergistic influence of multi-scale design parameters, using building typology and parametric modelling approach. The study proposed a multi-scale design parameter classification system combined with parametric modelling. The study investigated 80 office blocks in Wuhan as the study case, which were classified into array type and enclosed type. Correlation analysis and multiple regression equations were used to quantify the single versus synergistic effects of different scale design parameters. Results suggest that focusing solely on a single scale during the pre-design stage is typically inadequate for understanding building energy potential. In contrast, multi-scale synergistic analysis boosts energy use intensity (EUI) by 7.56% and net energy use intensity (NEUI) by 33.96%. Under multi-scale synergistic conditions, the EUI of array type is more influenced by the building design parameters, while the NEUI is effected by the balance of multi-scales design parameters. While the EUI of enclosed types exhibit balanced effects across multi-scale design parameters, with NEUI results aligning closely with PV power generation potential. Multiple regression equations highlight building density and shape factor as key influencers for both array and enclosure layouts. This study offers designers a flexible and scalable workflow for evaluating building energy consumption and PV power generation potential in the pre-design phase. The findings can guide nearly-zero energy urban block planning to achieve a balance between energy supply and demand.

Keywords

nearly-zero energy
office blocks
multi-scale design parameters
synergistic influence
energy consumption
PV power generation potential

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1 Introduction

Current research indicates that the overall circumstances related to global energy consumption is not positive (Valdes 2021), the human demand for and usage of fossil fuels continues to increase rapidly (Ghorbani et al. 2024). As a major contributor to energy consumption, the construction industry could account for up to 40% of total carbon emissions (Chen and Tsay 2022). In China, public buildings occupy 21.7% of the total national building area, with a significant carbon footprint (CABEE 2021), and office buildings contribute 25% to the total carbon emissions of

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Abbreviations

AVBD	average building depth (m)	EUI_{HEAT}	heating energy consumption per unit building area per year (kWh/(m²·y))
BD	building density (%)	EUI_{LIGHT}	lighting energy consumption per unit building area per year (kWh/(m²·y))
BD(EW)	east-west building distance (m)	FAR	floor area ratio
BD(SN)	north-south building distance (m)	FH	floor height (m)
BDe	building depth (m)	H-WR	building height-to-width ratio (%)
BDe1–BDe4	building depth of enclosed block (m)	LHS	Latin hypercube sampling
BH	average building height (m)	L-WR	building length-to-width ratio (%)
BS	building number of floors	NEUI	energy use intensity after PV deployment (kWh/(m²·y))
BW	building width (m)	OB	orientation
BW1(ES)	east-west building width (m)	OI1(EW)	east-west opening interval-1 (m)
BW1-1(ES)	north-south building width (m)	OI1(SN)	north-south opening interval-1 (m)
BW2(EN)	east-west building width (m)	OI2(EW)	east-west opening interval-2 (m)
BW2-2(EN)	north-south building width (m)	OI2(SN)	north-south opening interval-2 (m)
BW3(WS)	east-west building width (m)	PV	photovoltaic
BW3-3(WS)	north-south building width (m)	SF	shape factor (%)
BW4(WN)	east-west building width (m)	SFA	standard floor area
BW4-4(WN)	north-south building width (m)	TL(BI)	total opening length (m)
CD(EW)	east-west courtyard distance (m)	TL(E)	total length of enclosure (m)
CD(SN)	north-south courtyard distance (m)	WH	window height (m)
DOE	enclosure degree (%)	WH-WR	window aspect ratio (%)
EAI	PV power generation potential per unit building area per year (kWh/(m²·y))	WSH	window sill height (m)
EUI	Energy consumption per unit building area per year (kWh/(m²·y))	WW	window width (m)
EUI_{COOL}	cooling energy consumption per unit building area per year (kWh/(m²·y))	WWR	window-to-wall ratio (%)

public buildings (CABEE 2022). Therefore, energy-savings research in office buildings is crucial for reducing carbon emissions. In response, the Chinese government has implemented corresponding policy plans, such as the 2035 long-term vision plan (Xinhua Net 2020), to achieve these goals, and nearly zero-energy buildings (NZEB) are gradually becoming a significant focus of research.

Nearly zero-energy buildings could significantly reduce carbon emissions and enhance sustainability. This was mainly achieved by improving the performance of building envelope, optimizing its form, and incorporating renewable energy sources to achieve near-zero energy consumption in buildings (Park et al. 2021). Among these, renewable energy sources often include solar thermal systems (SWH) and photovoltaic systems (PV) (Skandalos and Karamanis 2021; Niveditha and Rajan Singaravel 2022). For instance, Feng et al. (2019) studied the near-zero energy consumption method for office buildings in tropical regions, surveyed 34 building cases and established a predictive model. Compared with the base model, the PV self-consumption and the building self-sufficiency were improved by 19.5% and 10.6%, respectively. Hachem-Vermette (2022) considered unit combinations and various renewable energy sources (solar, wind, waste-to-energy) for sustainable zero-energy communities in North America, with solar PV systems being identified as a primary means to achieve community near-zero energy consumption goals. Therefore, this paper primarily adopted PV systems as the renewable energy source for office blocks.

Research indicated that key design parameters influencing building energy consumption and other performance factors were determined during the pre-design stage (Konis et al. 2016). The process of designing and constructing a building could be divided into three stages: schematic design, construction, and operation and maintenance. With the completion of construction, the cost of optimizing building performance sharply increases (as shown in Figure 1). Therefore, achieving near-zero energy consumption goals for a building required intervention as early as possible, preferably in the early pre-design stage (Lin et al. 2021). At this stage, there is a need to minimise building energy consumption and maximise PV power generation potential

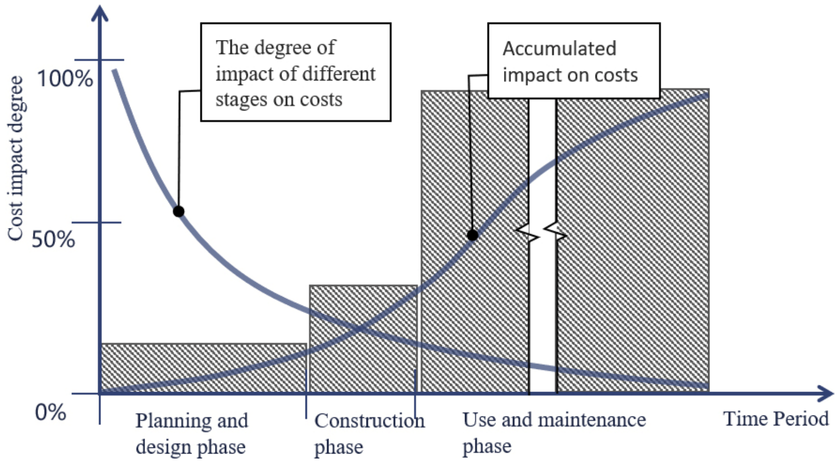


Fig. 1 Relationship between optimization potential and performance of building solutions (Kohler and Moffatt 2003; Yang 2006)

through multi-scale design parameters regulation.

The increasing needed to consider building energy consumption and PV system application at the planning stage has brought about a series of challenges to architects, requiring them to make predictions and decisions for the pre-design stage: first, the method of considering the building energy consumption and PV power generation in an integrated way; second, what scale (block scale, building scale, facade scale) design parameters that needed to be considered in the pre-design stage; third, the workflow of comprehensively considering the building energy consumption and PV power generation potential at multiple scales synergistic influence in the pre-design stage.

Design parameters at different scales would have an impact on building energy consumption. At the block scale, existing research mostly approached this from a morphological perspective. Leng et al. (2020) found that urban form indicators such as floor area ratio, building height, and road height width ratio affected the heating energy consumption of buildings. Among them, floor area ratio was the most critical factor in saving heating energy, with a maximum of 10.82 kWh/(m^2·y). As a result, architects and block planners recognized that optimizing block form could be an effective way to reduce building energy consumption. The research results aim to determine which block form influencing factors have a greater impact on building energy consumption. Shareef and Altan (2022) explored the impact of block form and height diversity on block-scale energy consumption in the UAE (The United Arab Emirates) and found that optimizing orientation and height diversity could reduce cooling energy consumption by 6.4% and 4.6%, respectively. Mangan et al. (2021) studied the design parameters of block buildings and the study found that building height and building aspect ratio were more important than orientation, and the utilization rates of energy-saving strategies were also different under different climate conditions. Wong et al. (2011) studied the impact of Singapore's urban form on building energy consumption and found that improving green space ratio and sky view factor could reduce urban energy consumption by 4.5%. In short, the block scale mainly focused on assessing the impact of morphological factors on building energy consumption, and formulating corresponding energy-saving strategies based on this.

The research on building energy consumption at the building scale was relatively established, and most of them consider the impact of building and facade scale design parameters on building energy consumption and indoor environment as a whole. Hong et al. (2020) studied the correlation between building parameters of low-rise office buildings in Shanghai and building energy consumption. The study found that the building plan form, orientation, number of floors, and window-to-wall ratio were the main factors affecting building energy consumption. Chen et al. (2017) studied various parameters of an individual building from a design perspective, and the results showed that the building's outline form, atrium form, plane form, and orientation all have an impact on building energy consumption. It could be found that the morphological factors at the building scale have a very obvious impact on building energy consumption, and optimizing parameters at this scale was of great significance to building energy conservation. Some studies have also developed the effect of facade-scale design parameters on building energy consumption. For example, de Rubeis et al. (2018) evaluated the impact of different room geometries, window shapes, window-to-wall ratios and lighting types on building energy consumption. According to the results, the combination of rectangular classrooms, rectangular south-facing windows, 12% WWR and LED lights provided the best energy performance for the academic classrooms designed in L'Aquila. Mahdavinejad et al. (2024) studied the impact of different facade geometries on the visual comfort of office buildings and building energy consumption. The results showed that the window-to-wall ratio and inclined wall played a crucial role in balancing indoor lighting and building energy consumption. Maleki and Dehghan (2021) compared window design variables such as window-to-wall ratio, shape, location, and orientation to reduce building energy consumption and improve lighting performance. The results showed that a 40% window-to-wall ratio for the north square window and a 30% window-to-wall ratio for the upper central horizontal window were recommended. In summary, existing studies at the facade scale mainly consider the impact of parameters such as window-to-wall ratio and window form on the building energy consumption and indoor environment performance.

For PV power generation potential, scholars have studied the issue at different scales, whether at the block, building, or facade scale. At the block scale, researchers paid more attention to the impact of block morphological parameters on PV power generation potential. Tian and Xu (2021) evaluated the PV power generation potential of residential blocks in Wuhan City. The study found that the average PV installation potential of roofs, south facades, and west facades were 96%, 32%, and 39%, respectively. In high-rise and mixed residential block types, the total facade PV installation exceeds 66%. Xie et al. (2023) studied the correlation between the block form of university dormitories on building energy consumption and PV power generation potential in Wuhan. It was concluded that the H-type block had the greatest energy savings potential, and the tower block could reduce PV power generation potential by 72.05% after adopting PV panels, and found that block and building forms have a significant impact on building energy consumption and PV power generation potential. Some scholars have also conducted comprehensive research regarding building energy consumption and PV power generation potential. For example, Xu et al. (2023b) studied how different types of residential morphological factors affect building energy consumption, PV power generation potential, and PV substitution rate in residential blocks in Wuhan under the guidance of a near-zero energy consumption goal. It was found that the floor area ratio, building depth, and shape factor simultaneously affected building energy consumption and PV power generation potential. It could be seen that the design parameters of block and building affected the PV power generation potential, and which were similar to the parameters affecting building energy consumption.

At the building and facade scales, existing research focused on exploring how to obtain greater PV power generation potential. Reffat and Ezzat (2023) studied the importance of building facades for PV installation, and the results demonstrated that the roof area was limited and it was necessary to increase the installable area of the facade, especially on the south and east-west facades, to improve the PV power generation potential by finding the optimal inclination angle. Asfour (2018) studied the relationship between shading integrated PV devices and PV power generation potential in hot areas, and the results showed that the installation of fixed PV equipment could increase the effectiveness of PV power generation. The above research focused on the necessity of the building facade as a PV installation carrier. Therefore, it was imperative to combine the facade window shape, window-to-wall ratio and other design parameters for PV power generation potential.

However, in existing research, the evaluation of building energy consumption and PV power generation potential in the early stage of design mostly focused on a single scale (block scale, building scale or facade scale), and less consideration of the synergies impact of multi-scale design parameter on building energy consumption or PV power generation potential. Considering only the effect of single-scale design parameters was not a good guide to the performance-based design of pre-design solutions. At the same time, there was a lack of workflow involved in the pre-design stage, making it difficult for designers to complete a rapid building energy use and PV power generation potential evaluation of the design scheme, requiring parameterized models as a support.

This study aims to develop a multi-scale design workflow for pre-design stage of office blocks. This process would allow to quickly generate parametric models of different morphology based on design parameters at different scales. Simultaneously, the synergistic relationship between multi-scale design parameters would be considered when evaluating building energy consumption and PV power generation potential. This research helps to provide designers with a building energy consumption and PV power generation potential assessment workflow that considers multi-scale synergistic effects, allowing them to flexibly change input data according to different use environments and draw design opinions under different environments. At the same time, adding corresponding optimization modules could directly generate optimization plans, providing corresponding technical tools and rule summaries for future research.

2 Methodology

The methodology of this study, as depicted in Figure 2, including four primary stages: Step 1, office block classification and prototype extraction, with field survey and architecture typology; Step 2, based on the results of real block cases survey, divide the original design parameter system into multiple scales, and analyze the range of characteristics of the above parameters in actual buildings; Step 3, generate a

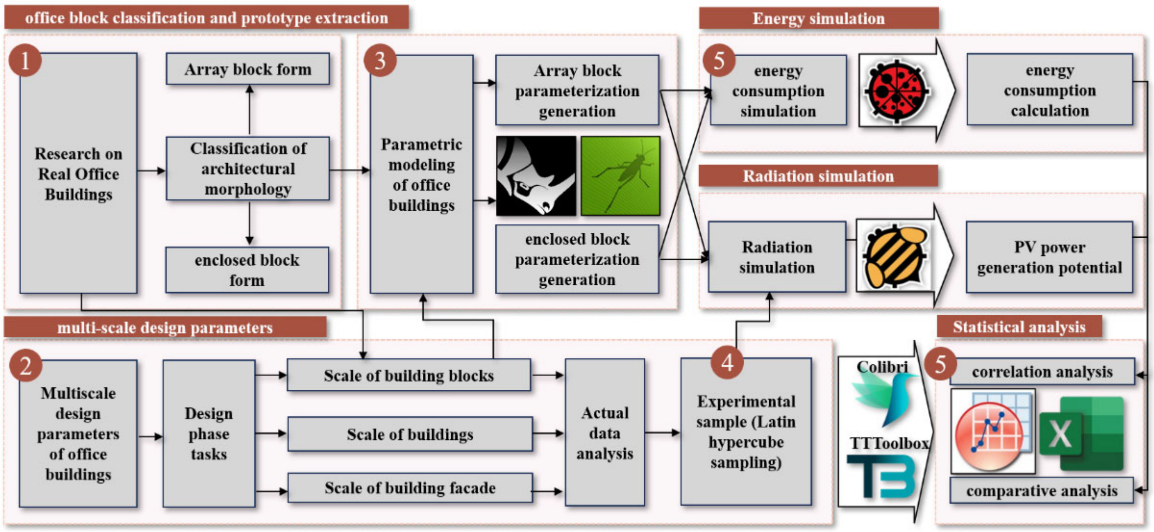


Fig. 2 Framework of the holistic approach

multi-scale parametric model, which is use to simulate building energy consumption and PV power generation potential; Step 4, use the Latin hypercube sampling (LHS) method to obtain an experimental model of the synergistic influence of multi-scale design parameters; Step 5, based on the simulation results of office blocks building energy consumption and PV power generation potential, correlation and multiple regression methods are used to analyze the influence relationship between multi-scale design parameters and EUI, EAI, and NEUI.

2.1 Multi-scale prototype extraction of typical office blocks—a case study in Wuhan

In order to establish multi-scale design parameters and models of office blocks, this section utilized case research to extract simulation sites and architectural prototypes of office blocks, taking Wuhan as a case study, which is a megacity in central China, a hot summer and cold winter climate zone of China. This city has a large number of blocks types and a large number of office blocks cases. This paper used a combination of satellite maps and field surveys to obtain parameter information of office blocks.

2.1.1 *Architectural prototype*

A total of 80 block cases were selected for the field survey (Figure 3), which were classified into three morphological types: pavilion type, slab type, and enclosed type. However, in the above classification, the parametric modelling generation logic and layout of the pavilion and slab types were consistent, while the enclosed type had a large number of variations. Therefore, this paper had made appropriate adjustments and summarized the research objects into two types: array types and enclosed types. The array and enclosed prototypes were shown in Figure 4. Under this classification method, array types included pavilion types and slab types. Enclosed types were divided into fully enclosed and non-fully enclosed. Non-fully enclosed was divided into three categories: two-building enclosed, three-building enclosed, and four-building enclosed. Based on this, a total of 16 prototypes were obtained, including 4 array types, numbered Z1–Z4, and 12 enclosed types, numbered W1–W12.

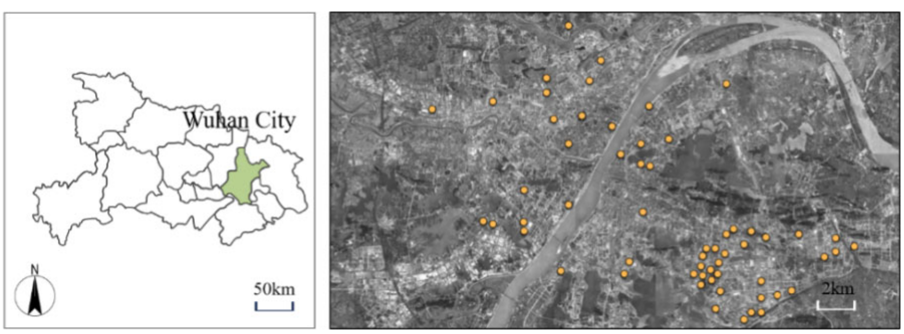


Fig. 3 Wuhan City's geographical location and cases selection distribution

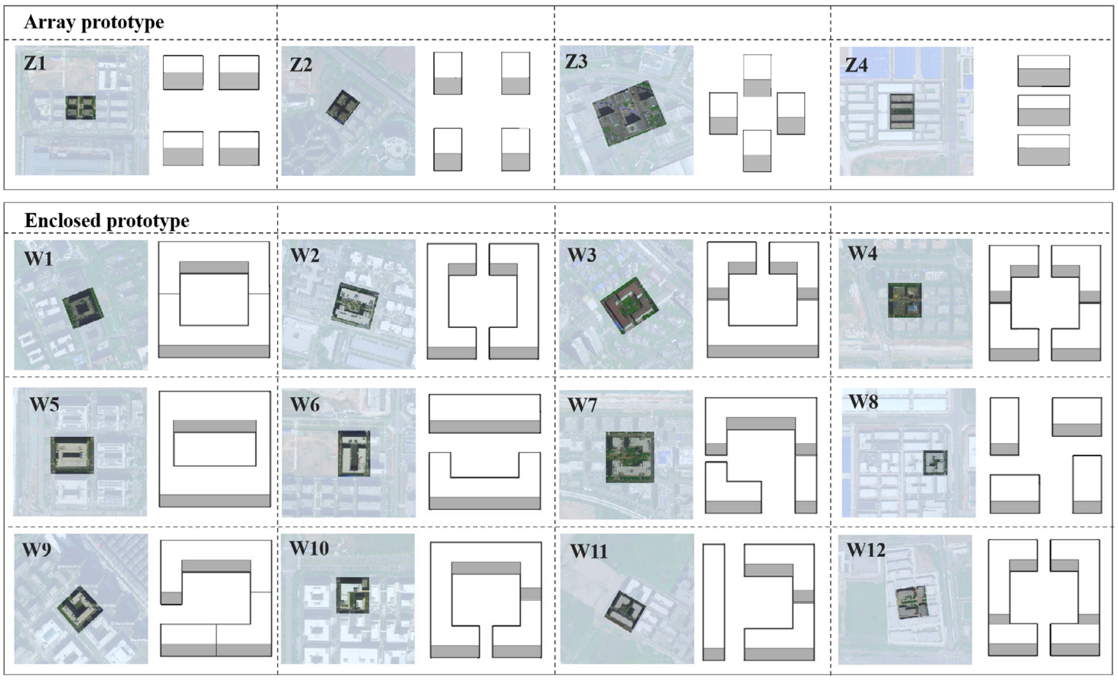


Fig. 4 Array and enclosed prototype extraction

2.1.2 Site prototype

Through the investigation of the office blocks site size in Wuhan, this study selected the 100 m × 100 m range as the ideal block, which was a component of a large comprehensive urban block. In order to identify clearly the synergistic influence of multi-scale design parameters on building energy consumption and PV power generation potential of different morphological types, the surrounding blocks involved in the simulation process also adopted the same morphological type as the main block and changed according to the changes in the main simulated block (Figure 5). The survey found that among the above classification, the building height in the array office blocks was mostly consistent and evenly arranged; while the building height of enclosed office blocks was mostly consistent and change complexly, so this article studied them separately and made a horizontal comparison.

2.2 Classification of multi-scale design parameters for office blocks

Multi-scale design parameters in the pre-design stage were divided into control parameters and descriptive parameters. Control parameters referred to parameters that accurately control the generation of parametric models. While descriptive parameters denoted parameters that could not be used to directly generate a parametric model. They were used to describe the morphological characteristics of the blocks at different scales (note that this characteristic includes blocks, building, and facade scales). For example, floor area ratio (FAR), building density (BD), building length-to-width ratio (L-WR), height-to-width ratio (H-WR), etc. were obtained through secondary calculation after inputting control parameters. The control parameters entered into the model during the simulation process were all derived from the

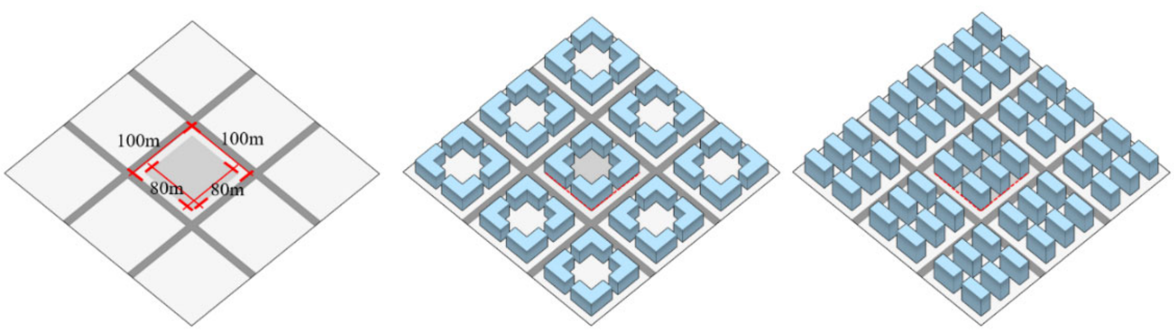


Fig. 5 Simulation site and surrounding environment settings

survey results of 80 real block cases, and their range and simulation step length were shown in Tables 1 and 2.

2.2.1 Multi-scale design parameters of array office blocks

For the block scale, control parameters referred to parameters that directly affect the layout form in the pre-design stage (Figure 6 – right), which included north-south building distance (BD(SN)), east-west building distance (BD(EW)), and site orientation (OB). The descriptive parameters were mainly construction intensity indicators, which generally reflected the development intensity in the planning stage, including floor area ratio (FAR) and building density (BD). In addition, there was the average building height (BH), which was calculated at the building scale and represented the average building height characteristics at the block scale (Table 1).

For the building scale, controllable parameters referred to parameters that control the generation of building form in the pre-design stage and were directly input into the parametric model, including standard floor area (SFA), number of building floors (BS), floor height (FH), and building depth (BDe). Descriptive parameters mainly denoted parameters that describe typical building morphological characteristics, which included building length-to-width ratio (L-WR), building height-to-width ratio (H-WR), building shape factor (SF), and building width (BW). The building width was included in the descriptive parameters because it was obtained by calculating the standard floor building area (SFA) and building depth (BDe) (Table 1).

Regarding the facade scale, the controllable parameters were mainly the window design parameters of the building facade, and their variable range covered the curtain wall facade and window wall facade system to meet the morphological requirements of different individual buildings. Specific parameters included window sill height (WSH), window height (WH), window width (WW) and window-to-wall ratio (WWR). Descriptive parameters were indirect design parameters at the facade scale. Due to the richness

Table 1 Multi-scale design parameters and simulation range of array office blocks

Parameter type	Control parameter	Range	Step size	Descriptive parameter
Block scale	North-south building distance (BD(SN))	7 to 29 m	1	Floor area ratio (FAR)
	East-west building distance (BD(EW))	6 to 19 m	1	Building density (BD)
	Orientation (OB)	−80° to 90°	5	Average building height (BH)
Building scale	Standard floor area (SFA)	650 to 1100 m^2	50	Building width (BW)
	Number of floors (BS)	3 to 21	1	Building length-to-width ratio (L-WR)
	Floor height (FH)	3.8 to 5.4 m	1	Building height-to-width ratio (H-WR)
	Building depth (BDe)	3 to 21 m	1	Shape factor (SF)
Facade scale	Window sill height (WSH)	0.1 to 1.2 m	0.1	Window height-to-width ratio (WH-WR)
	Window height (WH)	1.5 to 5 m	0.1	
	Window width (WW)	1 to 4 m	0.1	
	Window-to-wall ratio (WWR)	0.24 to 0.65	0.05	

Note: Controlling parameters: directly input parameter models to control model generation.
Descriptive parameters: calculate based on the input parameters to obtain the description of the model.

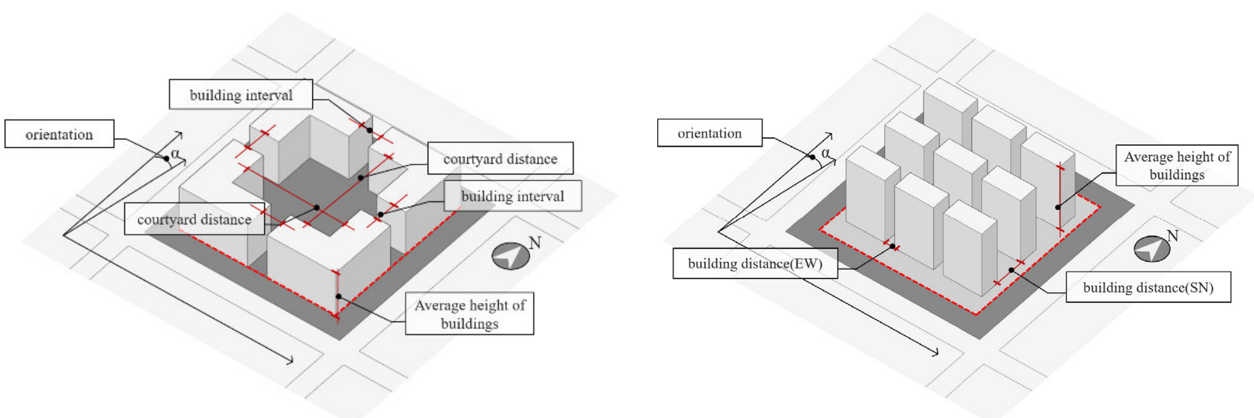


Fig. 6 Block-scale enclosed design parameters (left) and array design parameters (right)

of facade design, the window length and width vary widely, so the window height-to-width ratio (WH-WR) was needed to guide the design (Table 1).

2.2.2 Multi-scale design parameters of enclosed office blocks

For the block scale, control parameters referred to parameters that directly affect the layout form in the pre-design stage. However, unlike the generation logic of the array type, the enclosed type considered the courtyard distance. Control parameters mainly included the distance between the north and south courtyards (CD (SN)), the distance between the east and west courtyards (CD(EW)), and the orientation (OB). Descriptive parameters were divided into three categories: construction intensity indicators, opening spacing, and overall enclosure description parameters. Among them, the construction intensity indicators were the same as in the array type. The opening spacing denoted the building spacing at the break of the enclosure (Figure 6 – left). The overall enclosure description parameter was used to describe the enclosure degree of the entire building, which decreased as the opening spacing increased. Specifically, description parameters included floor area ratio (FAR), building density (BD), average building height (HB), north-south opening interval 1 (OI1(SN)), north-south opening interval 2 (OI2(SN)), and east-west opening interval 1 (OI1(EW)), interval between east-west openings 2 (OI2(EW)), total enclosure length (TL(E)), enclosure degree (DOE), total opening length (TL(BI)) (Table 2).

For the building scale, the control parameters mainly fall into three categories: the area of the four enclosed buildings, the height parameter, and the width and depth of the building. All four enclosed buildings could be changed, so four sets of parameters needed to be input to generate a complex single building form, including standard floor area (SFA), number of building floors (BS), floor height (FH), building depths of each building (BDe1, BDe2, BDe3, BDe4), east-west building surface width of each building in the block ((BW1(ES)), (BW2(EN)), (BW3(WS)), (BW4(WN))). There were mainly two categories of descriptive parameters. One was the surface width data obtained based on the input

Table 2 Multi-scale design parameters and simulation range of enclosed office blocks

Parameter type	Control parameter	Range	Step size	Descriptive parameter
Block scale	North-south courtyard distance (CD(SN))	21 to 40 m	1	Floor area ratio (FAR) Building density (BD) Average building height (BH) North-south opening interval-1 (OI1(SN)) North-south opening interval-2 (OI2(SN)) East-west opening interval-1 (OI1(EW)) East-west opening interval-2 (OI2(EW)) Total length of enclosure (TL(E)) Enclosure degree (DOE) Total opening length (TL(BI))
	East-west courtyard distance (CD(EW))	24 to 40 m	1	
	Orientation (OB)	−75° to 90°	5	
Building scale	Standard floor area (SFA)	650 to 1100 m^2	50	North-south building width (BW1-1(ES)) North-south building width (BW2-2(EN)) North-south building width (BW3-3(WS)) North-south building width (BW4-4(WN)) Total enclosed building area (SFA(A)) Average depth (AVBD) Building shape factor (SF)
	Number of building floors (BS)	3 to 21	1	
	Floor height (FH)	3.8 to 5.4 m	1	
	Building depth (BDe1)	16 to 26 m	1	
	Building depth (BDe2)	16 to 26 m	1	
	Building depth (BDe3)	16 to 26 m	1	
	Building depth (BDe4)	16 to 26 m	1	
	East-west building width (BW1(ES))	0 to 26 m	1	
	East-west building width (BW2(EN))	0 to 26 m	1	
	East-west building width (BW3(WS))	0 to 26 m	1	
	East-west building width (BW4(WN))	0 to 26 m	1	
Facade scale	Window sill height (WSH)	0.1 to 1.2 m	0.1	Window aspect ratio WH-WR
	Window height (WH)	1.5 to 5 m	0.1	
	Window width (WW)	1 to 4 m	0.1	
	Window-to-wall ratio (WWR)	0.24 to 0.65	0.05	

Note: Controlling parameters: directly input parameter models to control model generation

Descriptive parameters: calculate based on the input parameters to obtain the description of the model depth parameter, and the other was the average depth and building shape factor that described the overall depth characteristics. It specifically included the north-south building width of each building in the block ((BW1-1(ES)), (BW2-2(EN)), (BW3-3(WS)), (BW4-4(WN))), total enclosed building area (SFA(A)), average depth (AVBD), and shape factor (SF) (Table 2).

As for the facade scale, the enclosed type and the array type were exactly the same, so the details would not be reiterated.

2.3 Generation of multi-scale parametric models for office blocks

By entering design parameters at multiple scales, parametric models were accurately generated that cover the block layout to the facade skin. Huang et al. (2022) studied the relationship between wind environment and block form, whose parametric models mainly generated by setting limit boundaries. Sun et al. (2022) conducted a simplified modeling of urban blocks, which mainly controlled the specific design scheme generation through input parameters. This article mainly adopted the second type for parametric modeling, but in comparison, the model covered multiple scales synergistic active and paid more attention to the design specifications in pre-design stage.

2.3.1 Multi-scale parametric model generation of array office blocks

1) Block-scale parametric model generation

According to the design task requirements, the parametric model generation of block scale was mainly divided into the following steps: First, considered the block setback line according to the specification (Wuhan Municipal Bureau of Natural Resources and Urban-Rural Development 2014) to obtain the design scope. Second, calculated the number of buildings that could be arranged based on the design scope and building design parameters. Finally, design criteria inspection and judgement. The last step was divided into two parts: The first part was to determine whether the building layout was outside the design scope. It could be judged by the script and automatically reduced by one row or column. The second part was, when the input spacing did not comply with the building fire protection regulations, it could be automatically judged and adjusted to the minimum spacing that met the regulations based on the building height to ensure that the generated block model met the requirements.

The calculation logic of the design criteria inspection and judgement was to determine the site layout by calculating the number of buildings T_1 and T_2 (Figure 7(C)). When inputting the following parameters: north-south distance

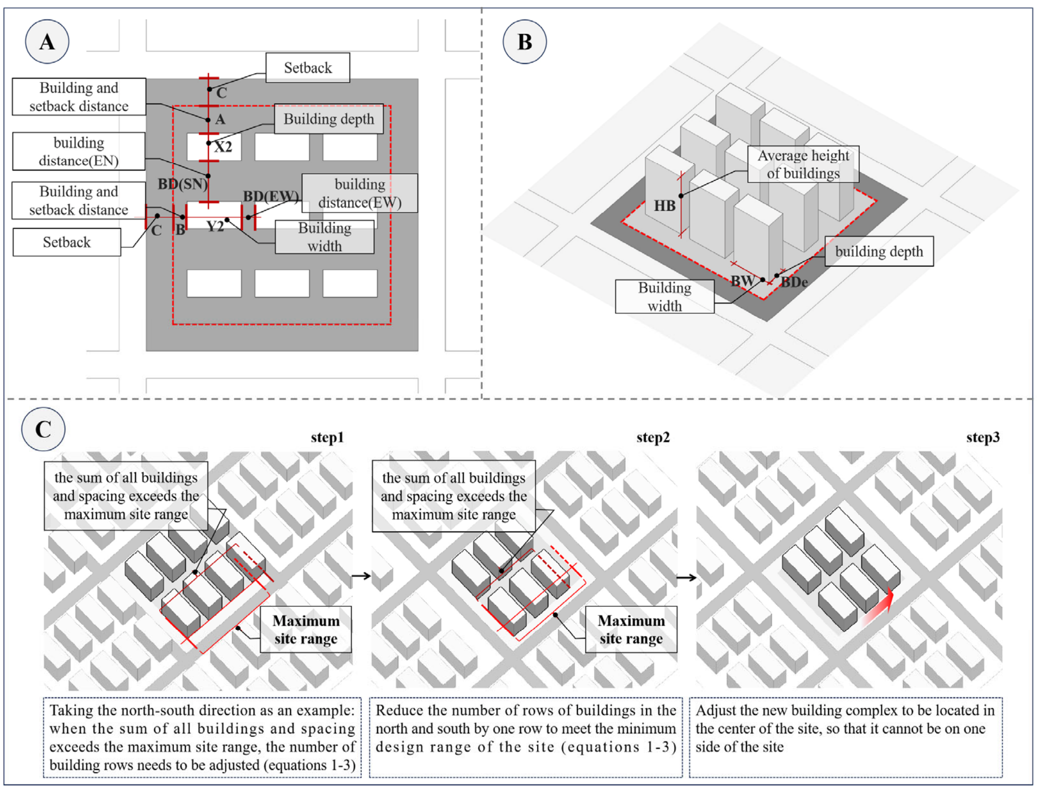


Fig. 7 (A) Schematic diagram of the building scale design parameters of the array type; (B) schematic diagram of spacing correction; (C) schematic diagram of the main spacing of the array

between buildings BD(SN), east-west distance between buildings BD(EW); building width (BW), building depth (BDe), the equations were as follows:

$$T_2\mathrm{BW} + (T_2 - 1)\mathrm{BD(EW)} + 2B \le Y - 2C \quad (1)$$

$$T_1\mathrm{BDe} + (T_1 - 1)\mathrm{BD(SN)} + 2A \le X - 2C \quad (2)$$

$$\mathrm{SFA} = \mathrm{BW} \times \mathrm{BDe} \quad (3)$$

where, T_1: the maximum number of buildings arranged in the north and south of the site; T_2: the maximum number of buildings arranged in the east and west of the site; X: the distance between the north and south of the site; Y: the distance between east and west of the site; BD(SN): the north-south distance between buildings; BD(EW): the east-west distance between buildings; BDe: the building depth; BW: the building width; A: the north-south distance between the building and the setback line; B: the east-west distance between the building and the setback line; C: the distance between the boundary of the site and the setback line; SFA: the standard floor area. And the conditions need to meet when $H \geq 24$ m; BD(SN) and BD(EW) ≥ 13 m; when $H < 24$ m; 6 m $\leq$ BD(SN); and BD(EW) ≤ 13 m (Figures 7(A) and (B)).

2) Building-scale parameterized model generation

According to the design task requirements, the parametric model generation of building scale was mainly divided into the following steps: First, the building plan form was obtained based on the input standard floor area (SFA) and building depth (BDe), and then the building height (BH) was generated based on the floor height (FH) and number of floors (BS). At the same time, these parameters were input into the block-scale model calculation, and the block design parameters would be adjusted and calculated based on the building design parameters (Equations (1)–(3)). Combining the building scale design parameters and block layout, the resulting changes were shown in Figure 8.

3) Facade scale parameterized model generation

According to the design task requirements, the parametric model generation of facade scale was mainly divided into the following steps: First, input the WWR of different facades to determine whether to generate a curtain wall system or a window wall system. Then input the window parameters (WSH, WH, WW) to directly generate a homogeneous facade. The size of the windows was not affected by the WWR, which only changed the number of windows.

2.3.2 Multi-scale parametric model generation enclosed office blocks

1) Block-scale parametric model generation

Based on the design task requirements of the block-scale, the parametric model generation was mainly divided into the following steps: First, according to the specification (Wuhan Municipal Bureau of Natural Resources and Urban-Rural Development 2014), the distance of building setback was considered to obtain the design scope, which was the same as the array type. Second, the building distance between the inner courtyards of the enclosed building was taken into account. The generation logic of the enclosed type and the array type was different. The enclosed block consists of four buildings by default. By changing the form of the four enclosed buildings, different design schemes were generated. The last step was to maintain building

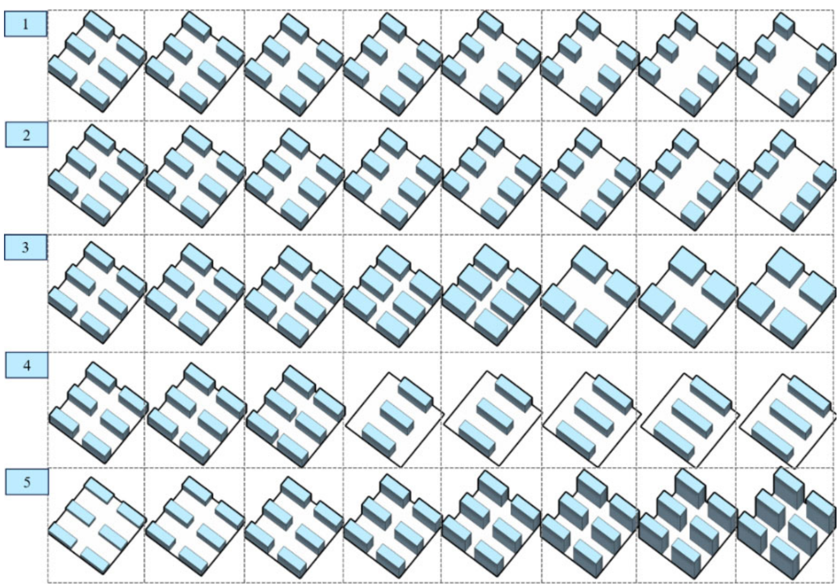


Fig. 8 Schematic diagram of morphological changes in the array type blocks

control, which was also divided into two parts. One was that the enclosed buildings cannot exceed the design scope, and the other was that the spacing between four different enclosed buildings needed to meet the minimum building regulations.

The calculation logic of the building control part was to control the sum of the width and spacing of each side to not exceed the design range. The first category was the distance between the north and south courtyards and the distance between the east and west courtyards. The second category was the building area of the four enclosed buildings. The third category was the width and depth parameters of the four enclosed buildings. The fourth category was the building height and morphology parameters. Finally, the maximum number of buildings arranged in the north and south of the site T_1 and the maximum number of buildings arranged in the east and west of the site T_2 were defaulted to 2. These parameters must meet the calculation Equations (4)–(9).

$$T_2\mathrm{BDe(EW)}+(T_2-1)\mathrm{CD(EW)}+2B\le Y-2C \tag{4}$$

$$T_1\mathrm{BDe(SN)}+(T_1-1)\mathrm{CD(SN)}+2A\le X-2C \tag{5}$$

$$\mathrm{SFA}_1=(\mathrm{BW1(ES)}\times\mathrm{BW1\text{-}1(ES)})-(\mathrm{BW1(ES)}-\mathrm{BDe(EW)})\times(\mathrm{BW1\text{-}1(ES)}-\mathrm{BDe(SN)}) \tag{6}$$

$$\mathrm{SFA}_2=(\mathrm{BW2(EN)}\times\mathrm{BW2\text{-}2(EN)})-(\mathrm{BW2(EN)}-\mathrm{BDe(EW)})\times(\mathrm{BW2\text{-}2(EN)}-\mathrm{BDe(SN)}) \tag{7}$$

$$\mathrm{SFA}_3=(\mathrm{BW3WS}\times\mathrm{BW3\text{-}3(WS)})-(\mathrm{BW3(WS)}-\mathrm{BDe(EW)})\times(\mathrm{BW3\text{-}3(WS)}-\mathrm{BDe(SN)}) \tag{8}$$

$$\mathrm{SFA}_4=(\mathrm{BW4(WN)}\times\mathrm{BW4\text{-}4(WN)})-((\mathrm{BW4(WN)}-\mathrm{BDe(EW)})\times(\mathrm{BW4\text{-}4(WN)}-\mathrm{BDe(SN)}) \tag{9}$$

where, T_1: the maximum number of buildings arranged in the north and south of the site (set to 2); T_2: the maximum number of buildings arranged in the east and west of the site (set to 2); X: the north and south distance of the site; Y: the east and west distance of the site; CD(SN): distance between north and south courtyard; CD(EW): distance between east and west courtyards; BDe(SN): building depth between north and south; BDe(EW): building depth between east and west; BW1(ES), BW2(EN), BW3(WS), BW4(WN), BW1-1(ES), BW2-2(EN), BW3-3(WS), BW4-4(WN): building width; A: distance between building and setback; B: distance between building and setback; C: block setback line; SFA1–SFA4: standard floor building area. And the conditions need to meet: when $H \ge 24$ m, BI1, BI2, BI3, BI4≥ 13 m; when $H < 24$ m, 6 m ≤ BI1, BI2，BI3, BI4 ≤ 13 m (Figures 9(A) and (B)).

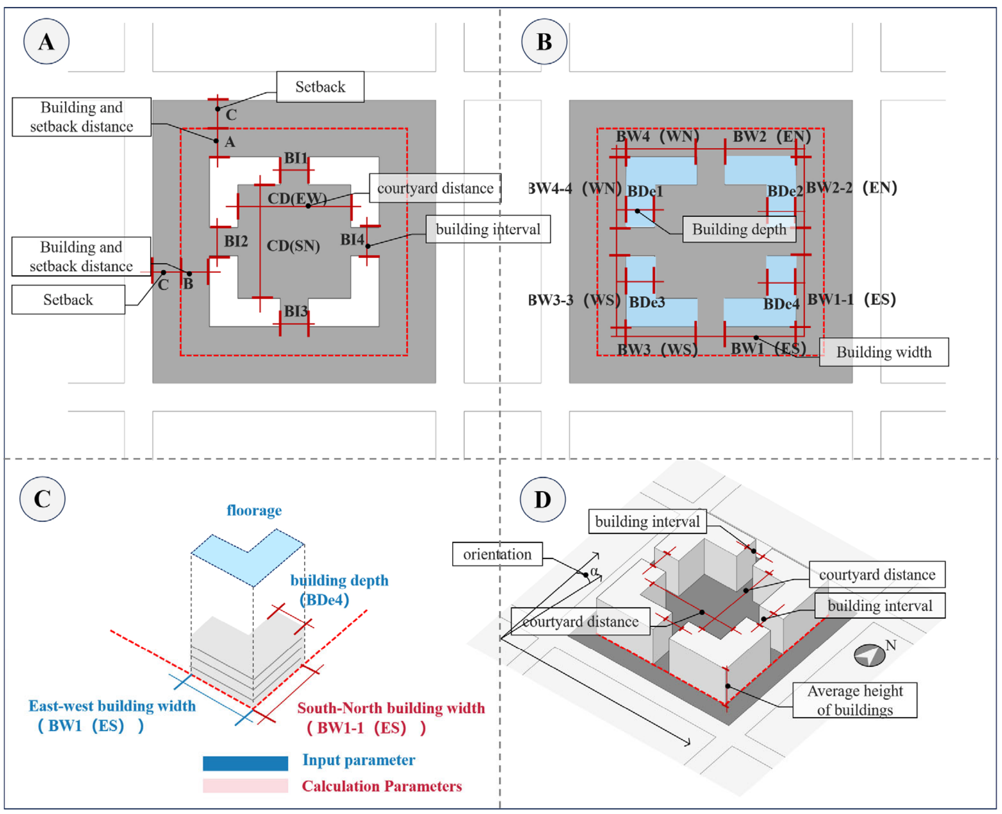


Fig. 9 (A) Schematic diagram of the main spacing of the enclosed type; (B) schematic diagram of the design parameters of the enclosed single unit; (C) control method of enclosed building type; (D) design parameters of the enclosed all units

2) Building scale parametric model generation

According to the design task requirements of the building scale, the parametric model generation was mainly divided into the following steps: First, confirmed the standard floor area of the four buildings to determine the overall volume of the enclosed building. Second, input the building width and building depth parameters of one side separately, and then calculated the building width parameters of the other side (Figures 9(C) and (D)). In order to achieve the diversity of design schemes, when any two buildings contacted each other due to changes in surface width, they could be merged into one building through Boolean operations, thereby achieving different plane form combinations (Nos. 3, 4, 5, 6 in Figure 10). The building depth parameters were grouped in pairs to form a new enclosed building (Nos. 8 and 9 in Figure 10). Finally, the building height and number of floors determined the building height form. In this way, the specific design scheme of the four enclosed buildings was accurately generated. Under this generative logic, the architectural design schemes changes were very extensive (No. 10 in Figure 10).

3) Facade scale parameterized model generation

As for the facade scale, the enclosed types and the array

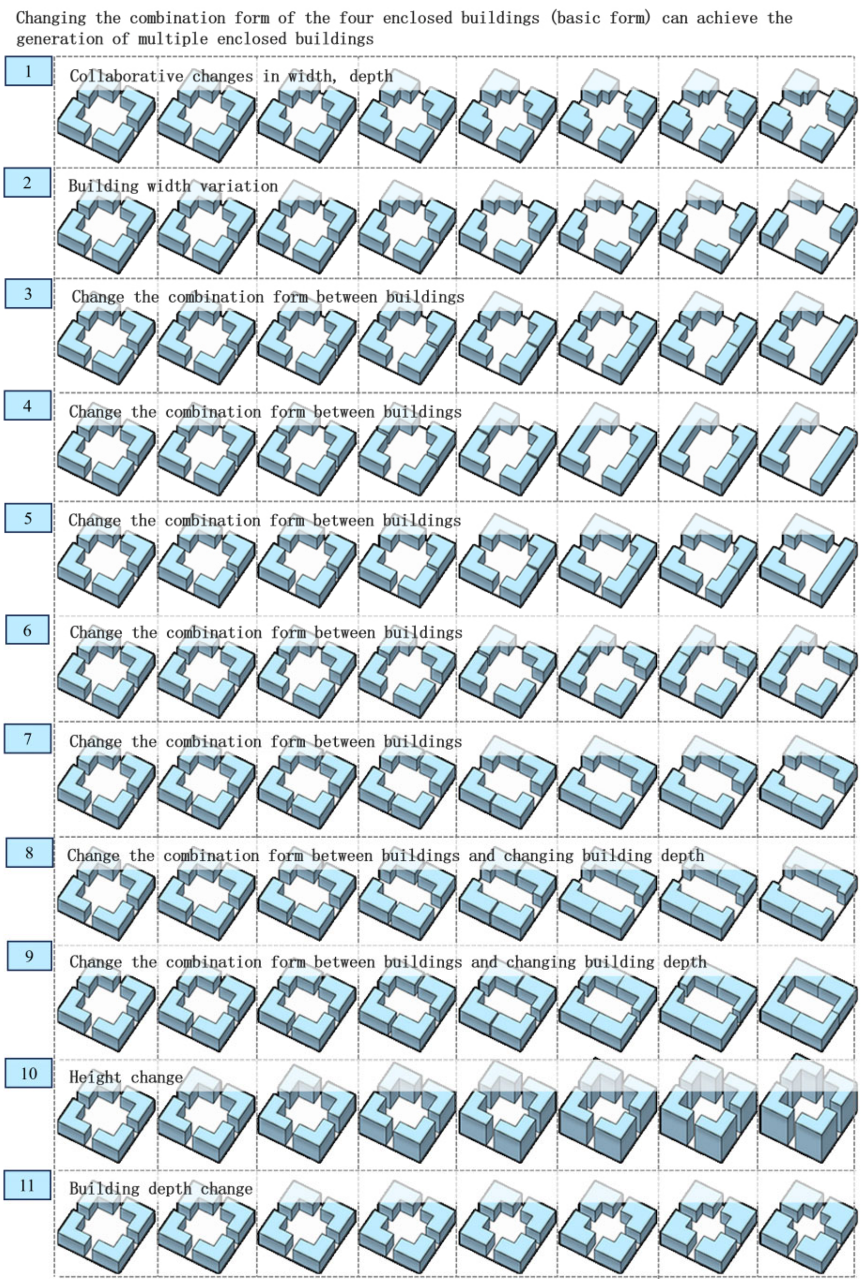


Fig. 10 Schematic diagram of morphology changes of enclosed type

types were the same as explained in Section 2.3.1. Based on this, for the two office building types summarized above, this section generated parametric models under the influence of different design parameters at three scales: block, building, and facade scales. This generative model was used to comprehensively evaluate the synergistic influence relationships between design parameters at different scales.

2.4 Building energy consumption and PV power generation potential evaluation indicators

2.4.1 Building energy consumption calculation and simulation method

This section mainly described the building energy consumption calculation and simulation methods. The simulation of office blocks mainly employed the Ladybug and Honeybee tools on the Rhinoceros incorporated with the Grasshopper platform. The tools were connected to the EnergyPlus simulation engine for energy consumption simulations (Figure 11), which took into account the solar radiation heat reflected by surrounding buildings or their own components, as well as the wind environment in the site, to reflect the impact of occlusion and wind on building energy consumption (Wang and Wang 2020). The parametric model was edited and generated through Grasshopper's basic engine, which covered all parameters from block layout to individual building generation and facade changes, and then obtained the total building energy consumption of office blocks under the synergistic influence of multiple scales design parameters, and calculate the annual energy use intensity (EUI) (Equation (10)). In order to make the parameters set for the simulation conform to the actual situation of the office blocks in Wuhan, the geometric and non-geometric parameters of the energy consumption simulation were set by combining satellite maps, field research, and design standards (China Academy of Building Research 2015). For example, the geometric parameters of the case were obtained through satellite maps combined with field research to establish a 3D model. Obtain the operation schedule of cases through field survey. The building envelope parameters and equipment parameters settings were shown in Table 3. The simulated energy consumption data was output through the battery, and the data was input into Excel and SPSS software for later data analysis.

$$\mathrm{EUI} = \frac{E}{S_{\mathrm{A}}} \tag{10}$$

where, EUI: energy consumption per unit building area (kWh/(m^2·y)); E: total energy consumption of office block buildings (kWh·y); S_{A}: total building area of office blocks (m^2).

2.4.2 PV power generation potential calculation and simulation method

PV power generation potential was affected by different parameters, the block scale was mainly affected by block morphological parameters. According to Izquierdo et al. (2008) research, PV power generation potential assessment mainly included five levels: physical potential, geographical potential, technical potential, economic potential and social potential. According to research by Tian and Xu (2021), this article focused on the calculation of PV power generation potential into three levels, including radiation potential (physical potential), installation potential (geographical potential), and technical potential.

Firstly, the radiation potential refers to solar radiation distribution on building surfaces, determined by using the Grasshopper platform workflow with a proven high accuracy

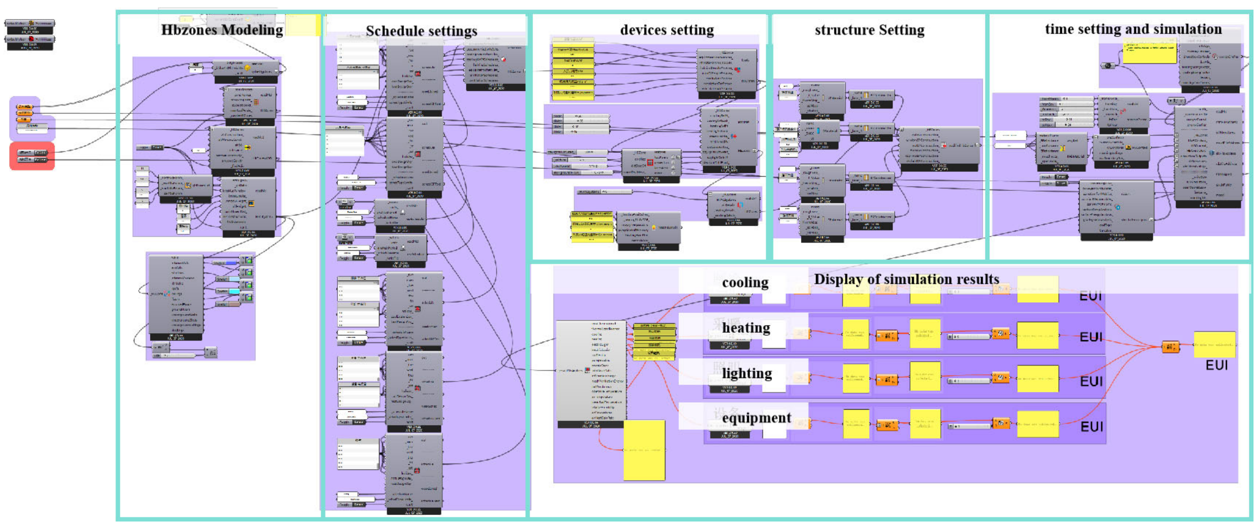
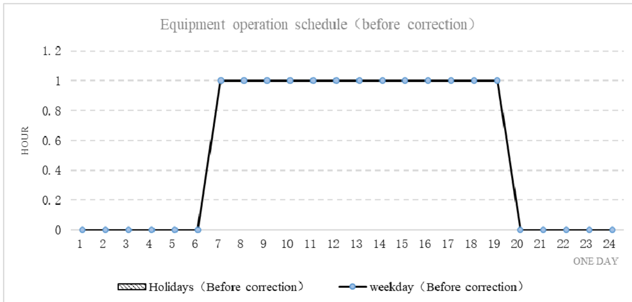
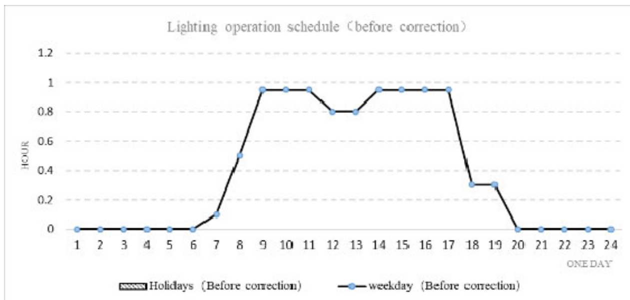
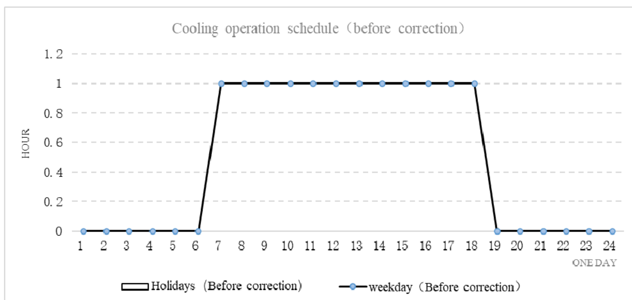
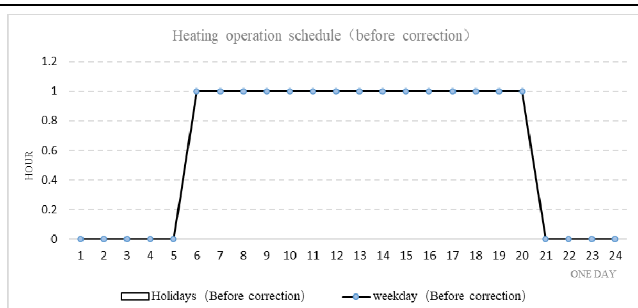


Fig. 11 The simulation workflow for building energy consumption

Table 3 Parameters settings of building energy consumption simulation

Parameter setting	Set value	Construction type	Material type
Heating setpoint	18°	Doors and windows	Aluminum alloy doors and windows
Cooling setpoint	26°	Exterior wall	Steel reinforced concrete
Occupant density	10 m^2/P	Interior wall	B05 aerated concrete block
Lighting power	9 W/m^2	Roof	Polystyrene foam board
Equipment power	15 W/m^2	Floor slab	Extruded polystyrene foam board
Equipment schedule			
Lighting schedule			
Cooling schedule			
Heating schedule			

in prior studies (Tian and Xu 2021). For solar radiation simulation, The Ladybug and Honeybee used the Radiance module to simulate solar radiation. The Perez scattered radiation model used in the Radiance program was very adaptable to the calculation of building surface radiation in an urban environment. In addition, Radiance also used complex light tracing algorithms based on the physical behavior of light in the 3D model, so it could perform radiation calculations on the facade and roof of buildings (Tian and Xu 2021). When calculating the installation potential, it was mainly affected by the equipment and windows on the building surface. Not all surfaces could be installed with PV modules. Therefore, this article investigated the proportion of PV panels that could be installed on different facades and roofs of office blocks in Wuhan. The roof effective area ratio of office buildings was 0.42, the facade effective area ratio was 0.45, the corresponding roof installation factor was 0.58, and the exterior wall installation factor was 0.65. During simulation calculation, this value changed with the WWR. The remaining parameters settings were as shown in Tables 4 and 5.

When calculating technical potential, according to relevant research (Campbell et al. 2008), the technical potential parameters setting of PV system was shown in Table 5. The PV power generation potential was calculated by Equation (11).

$$E_{\mathrm{p}} = H_{\mathrm{A}} \times A_{\mathrm{pv}} \times \eta_i \times K \times (1 - R_{\mathrm{d}})^{N-1} \tag{11}$$

where, E_{p}: annual power generation of PV system (kWh·y); H_{A}: annual effective solar radiation (kWh·y); A_{pv}: installable area (PV module area) (m^2); η_i: PV module efficiency (%); K: comprehensive efficiency coefficient (%); R_{d}: degradation rate of the PV system (%); N: life cycle of the PV system (year).

Finally, the obtained annual power generation of the PV system was converted into the PV power generation potential per unit building area (EAI), which was the final PV power generation potential of the block, calculated according to Equation (12).

$$\mathrm{EAI} = \frac{E_{\mathrm{p}}}{S_{\mathrm{B}}} \tag{12}$$

Table 4 Parameter setting of solar radiation simulation

Parameter setting	Value
Weather data	CHN_Hubei.Wuhan.574940_CSWD
Simulation period	00:00 on January 1 to 24:00 on December 31
Grid size	1 m × 1 m
Building surface diffuse reflectance	0.2
Ground surface diffuse reflectance	0.2

Table 5 Parameter setting for technical potential calculation

Parameter setting	Value	Unit
PV module efficiency	17.73	%
Integrated efficiency factor	85	%
Attenuation rate of PV power generation	0.06	%
Durable years of PV equipment	25	year

where, EAI: PV power generation potential per unit building area per year (kWh/(m^2·y)); E_{p}: total PV power generation (kWh·y); S_{B}: total building area (m^2).

2.4.3 NEUI calculation method

There is difference in the impact of block form on building EUI and EAI. This study used net energy use intensity (NEUI) as a comprehensive evaluation indicator after PV system deployment, which represented the energy use intensity after PV power generation energy was connected to the grid. It was a commonly used indicator used to reflect the annual net energy consumption per unit area after considering for PV power generation potential (Zhang and Xu 2019).

$$\mathrm{NEUI} = \mathrm{EUI} - \mathrm{EAI} \tag{13}$$

where, EUI: Energy consumption per unit building area (kWh/(m^2·y)); EAI: PV power generation potential per unit building area per year (kWh/(m^2·y)).

2.5 Experimental design and statistical analysis methods

2.5.1 Experimental design

In order to study the synergistic influence of multi-scale design parameters on building energy consumption and PV power generation potential, the previously mentioned design parameters need to be placed in the same simulation environment for analysis, and so many research variables would produce a huge number of results under different combinations. Adopting a one-by-one simulation method resulted in a large amount of calculation. Therefore, this paper used Latin hypercube sampling (LHS) to input all controlling design parameters into the parametric model to generate different solutions. For the array and enclosed experimental samples, 500 cases were selected to be simulated and recorded one by one. The input data range was derived from 80 actual block cases survey results.

2.5.2 Sampling method

This article used the LHS method, which firstly divided all parameter intervals into multiple equal-probability regions, and then randomly samples them separately to avoid sample problems caused by aggregation of data. LHS sampling was an advanced Monte Carlo sampling method that could effectively fill space and fit nonlinear curves. Compared with other sampling methods, LHS sampling could cover not only the probability results of all parameter spaces, but also had a relatively small amount of calculation and saves time (Helton et al. 2006). Normally, the number of sampling times for different variable combinations obtained by LHS sampling was 5–10 times the number of variables (Tian 2013).

2.5.3 *Single factor analysis and multi-factor analysis*

Single factor analysis aims to explore the correlation degree of a single factor on the results without considering the mutual influence between factors. The main method was to perform Pearson correlation analysis. This was a method of analyzing the correlation between two variables, which explored the correlation degree of a single factor on the result. The calculation Equation was as follows:

$$r=\frac{n\sum xy-\sum x\sum y}{\sqrt{n\sum x^2-\left(\sum x\right)^2}\sqrt{n\sum y^2-\left(\sum y\right)^2}} \tag{14}$$

where, r: correlation coefficient; x: independent variables; y: dependent variables.

Among them, when the correlation coefficient $r = 0$, it means that there is no correlation between x and y; when $r > 0$, it means that y increases with the increases of x; when $r < 0$, it means that y decreases with the increases of x.

Multi-factor analysis was adopted to explore the joint effects of multiple independent variables on the results, taking into account the interaction between design parameters. The main method was multiple regression analysis. Multiple regression analysis was a common statistical method that treated multiple variables as independent variables and one variable as the dependent variable. It explored the influence between multiple independent variables and one dependent variable, and finally could fit a regression model with certain explanatory power. The expression of the general multiple regression model was as follow:

$$y=\beta_0+\beta_1x_1+\beta_2x_2+\cdots+\beta_nx_n+\varepsilon \tag{15}$$

where, β: regression coefficient; β_0: constant term (intercept term); β_1, β_2, …, β_n: partial correlation coefficients; x: independent variables; y: dependent variables; ε: error value.

2.6 A workflow for considering the synergistic influence of multi-scale design parameters in the early stage of office building

This section summarized the office building simulation workflow in the pre-design stage, taking into account the synergistic influence of multi-scale design parameters on building energy consumption and PV power generation potential. Taking Wuhan City as an example, the city's typical office building forms were classified into array types and enclosed types. According to the multi-scale design parameter system established in this article, the range characteristics of the above two morphological types were analyzed, and the range of the input parameters was mainly determined. Then LHS was performed to obtain simulation samples for simulation. Finally, correlation analysis and multiple regression analysis were performed on the simulation results to obtain the key parameters and design strategies in the pre-design stage, as well as the influence weights at different scales (Figure 2).

3 Results and discussions

3.1 Validation of multi-scale parametric models and evaluation tools

3.1.1 *Practical case verification of multi-scale parametric models*

In order to prove the accuracy and practicality of the parametric models, this section selected two representative cases of array types and enclosed types to verify the multi-scale parametric models (Figures 12–15). The results showed that after inputting the actual data obtained through the survey into the parametric models, the generated form of the real office building was obtained and analyzed, such as the FAR and OB at the block scale, the BW and BDe at the building scale, and the WWR and WH at the facade scale, etc. A parametric model that was highly consistent with the actual solution was obtained through this. This article utilized this model to study the synergistic effects

(A) *Optics Valley Core Center e-area*

North-south distance (BD (SN))	*20m*	*Building depth (BDe)*	*23m*
East-west distance (BD (EW))	*15m*	*Window sill height (WSH)*	*1m*
Orientation (OB)	*-15°*	*Window height (WH)*	*3.8m*
Standard floor area (SFA)	*700 m²*	*Window width (WW)*	*3.2m*
Building floors (BS)	*5*	*Window-to-wall ratio (WWR)*	*0.4m*
Floor height (FH)	*4.8m*		

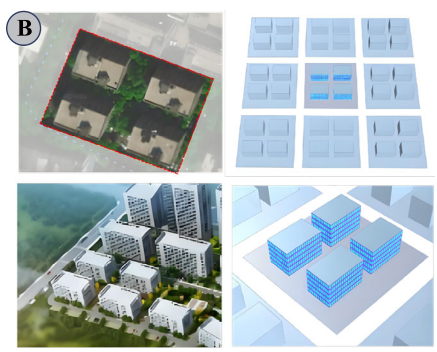


Fig. 12 Case 1: Optics Valley Core Center e-Area: (A) control parameters table; (B) comparison between actual and model images

A

Daijiashan Intellectual Property Ecological Town Science and Technology Innovation Exchange Center			
North-south distance (BD (SN))	15m	Building depth (BDe)	18m
East-west distance (BD (EW))	0m	Window sill height (WSH)	1.1m
Orientation (OB)	25°	Window height (WH)	2.4m
Standard floor area (SFA)	900 m²	Window width (WW)	2.1m
Building floors (BS)	11	Window-to-wall ratio (WWR)	0.35m
Floor height (FH)	4.5m		

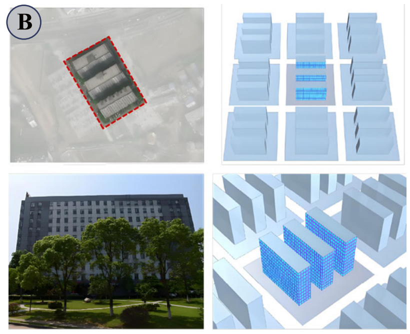


Fig. 13 Case 2: Daijiashan Intellectual Property Ecological Town Science and Technology Innovation Exchange Center: (A) control parameters table; (B) comparison between actual and model images

A

Gemdale Weixin Jiangxia Intelligent Manufacturing Park			
North-south courtyard distance (CD (SN))	38m	East-West building width (BW1 (ES))	25m
East-west courtyard distance (CD (EW))	28m	East-West building width (BW2 (EN))	43m
Orientation (OB)	0°	East-West building width (BW3 (WS))	43m
Standard floor area (SFA)	1200 m²	East-West building width (BW4 (WN))	25m
Building floors (BS)	4	Window sill height (WSH)	0.2m
Floor height (FH)	4.8m	Window height (WH)	4.1m
Building depth (BDe1)	25m	Window width (WW)	2.2m
Building depth (BDe2)	25m	Window-to-wall ratio (WWR)	0.4m
Building depth (BDe3)	25m		
Building depth (BDe4)	25m		

Fig.14 Case 3: Gemdale Weixin Jiangxia Smart Garden: (A) control parameters table; (B) comparison between actual and model images

A

Wuhan Biomedical Accelerator Industrial Park			
North-south courtyard distance (CD (SN))	40m	East-West building width (BW1 (ES))	42m
East-west courtyard distance (CD (EW))	40m	East-West building width (BW2 (EN))	42m
Orientation (OB)	0°	East-West building width (BW3 (WS))	42m
Standard floor area (SFA)	900 m²	East-West building width (BW4 (WN))	24m
Building floors (BS)	5	Window sill height (WSH)	1.2m
Floor height (FH)	5m	Window height (WH)	3m
Building depth (BDe1)	22m	Window width (WW)	2.8m
Building depth (BDe2)	22m	Window-to-wall ratio (WWR)	0.42m
Building depth (BDe3)	22m		
Building depth (BDe4)	24m		

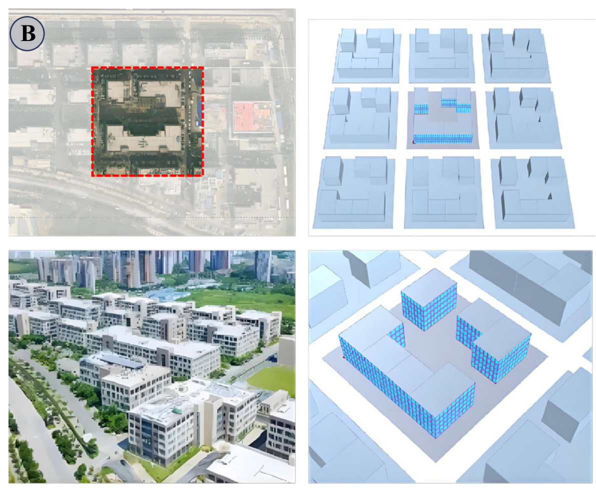


Fig. 15 Case 4: Wuhan Biomedical Accelerator Industrial Park: (A) control parameters table; (B) comparison between actual and model images

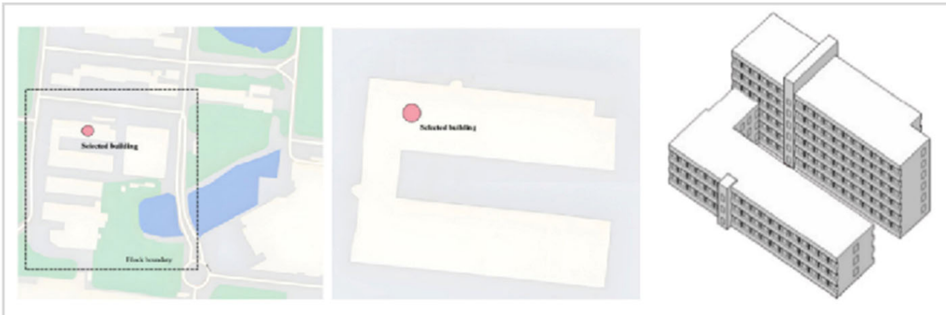
of multi-scale design parameters on building energy consumption and PV power generation potential.

Figures 12 and 13 show the comparison between actual array cases and multi-scale parametric models. Figures 14 and 15 show the comparison between enclosed actual cases and multi-scale parameterized models.

3.1.2 Verification of building energy consumption and PV power generation potential assessment tools

The simulation computing platform developed in this study mainly employed the computing core of EnergyPlus, and its simulation accuracy had been validated by many studies (Yang et al. 2015). This study followed the lab group's previous building examples and used the technical tools in Section 2.5 for simulation (Xu et al. 2023a). The comparison showed that the simulation accuracy of the tool was within the 10% error range, and the R^2 value between monthly energy consumption simulation and monthly measured energy consumption was 0.88 (Figure 16(A) and Figure 17), proving the rationality and accuracy of the

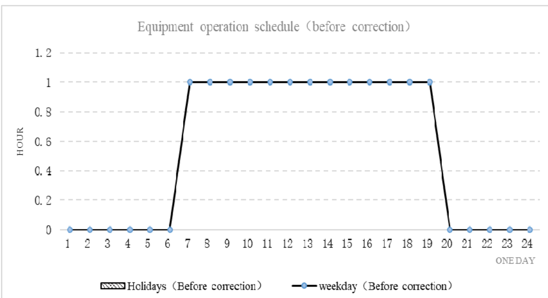
A →

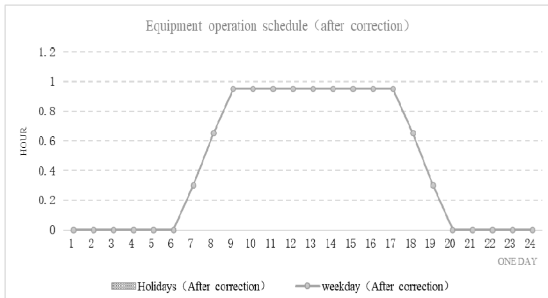


B ↓

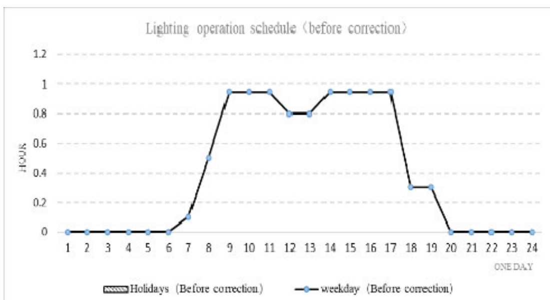
Parameter setting	Set value	Construction type	Material type
Heating setpoint	18°	Doors and windows	Aluminum alloy doors and windows
Cooling setpoint	26°	Exterior wall	Steel reinforced concrete
Occupant density	10 m²/P	Interior wall	B05 aerated concrete block
Lighting power	9 W/m²	Roof	Polystyrene foam board
Equipment power	14 W/m²	Floor slab	Extruded polystyrene foam board

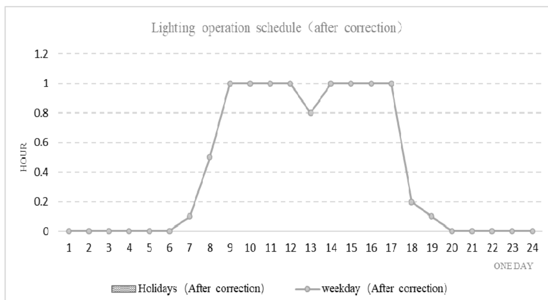
Equipment schedule



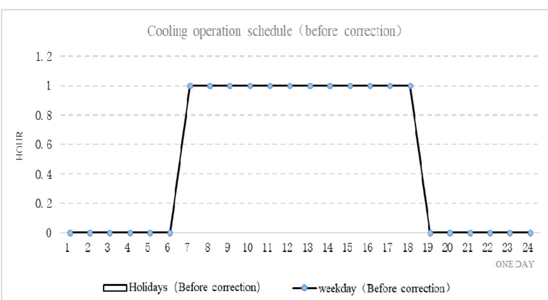


Lighting schedule





Cooling schedule



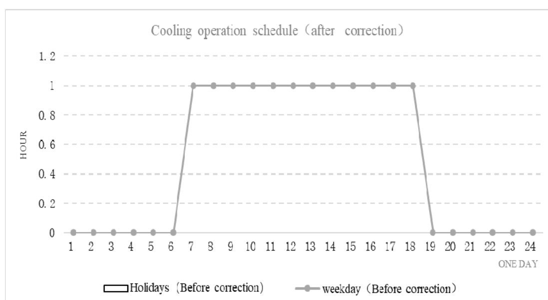


Fig. 16 (A) The location, floor plan, 3D model; (B) data correction

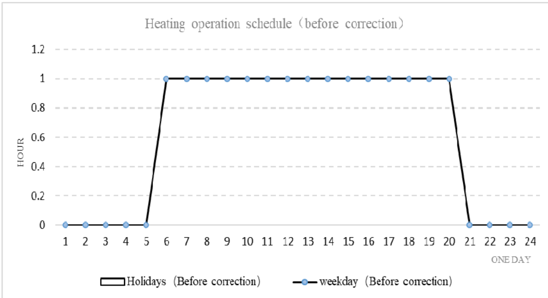
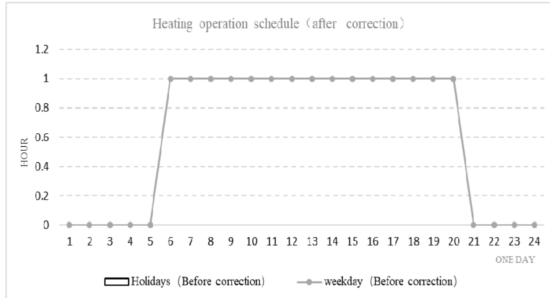
Heating schedule		
	before correction	after correction

Fig. 16 (A) The location, floor plan, 3D model; (B) data correction (Continued)

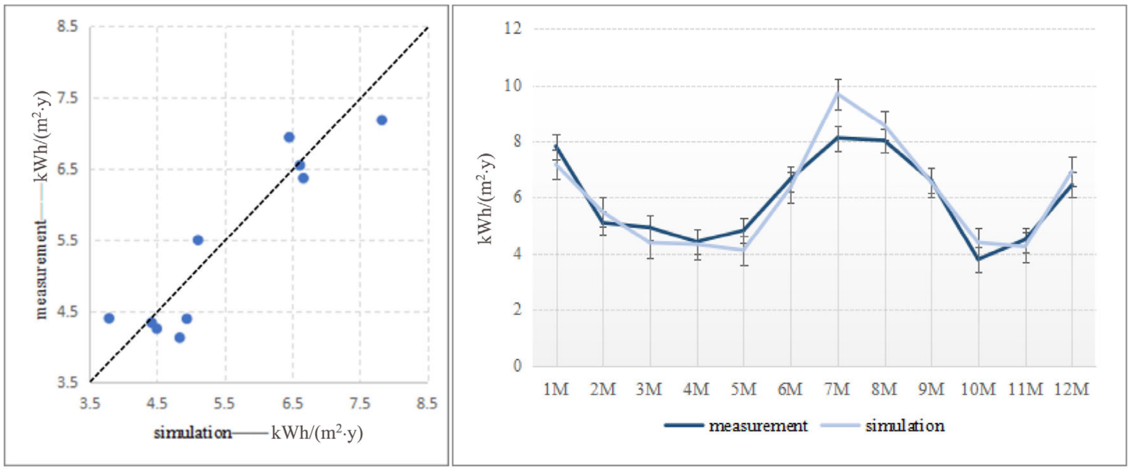


Fig. 17 Comparison of measured and simulated EUI

building energy consumption simulation and calculation method used in this study. The parameter settings during the validation of the simulation tool were as follows, geometric and non-geometric parameters were investigated for an office building in an urban environment, including the building's length, width, height, window-to-wall ratio, and operation schedule (Figures 16(B)). Month-by-month building energy consumption data was measured. The geometrical and non-geometrical parameters of the building were realistically recovered in the simulation tool according to the results of the research, and then the energy simulation was carried out, and the simulation results were compared and analyzed with the measured results.

When evaluating the PV power generation potential, the main part of the simulation was the solar radiation received by building surfaces. The radiation potential calculation in this article was mainly employed the Ladybug and Honeybee plug-ins of the Rhinoceros-Grasshopper platform to calculate the solar radiation received by building surfaces, while taking into account the mutual shading of block environment. Liao et al. (2019) verified the accuracy of this tool through a miniature model of a city block, and the overall error was less than 10%, which was acceptable.

3.2 The synergistic impact of multi-scale design parameters on building energy consumption and PV power generation potential

3.2.1 *Simulation results and correlation analysis of array*

The simulation results demonstrated that the total building energy consumption (hereinafter referred to as EUI) ranged from 58.21 to 69.33 kWh/(m^2·y), the PV power generation potential (hereinafter referred to as EAI) ranged from 6.04 to 51.16 kWh/(m^2·y), and the building net energy consumption (hereinafter referred to as NEUI) ranged from 12.25 to 60.56 kWh/(m^2·y). The results were generally consistent with the normal distribution (Figures 18 (A)–(D)).

1) Correlation analysis of array multi-scale design parameters

The array simulation used 10 block-scale design parameters, eight building-scale design parameters, and five facade-scale design parameters, and comprehensively analyzed the correlation between the above parameters and EUI, EAI, and NEUI. According to the definition of significant correlation, when the significance value was less than 0.05,

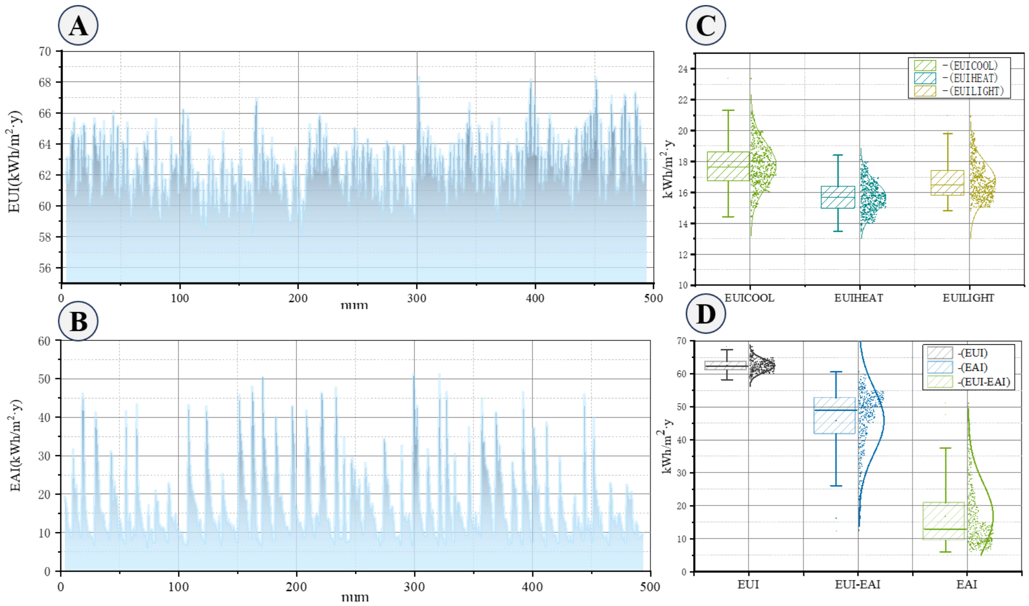


Fig. 18 (A) and (B): EAI and EUI simulation results of array type; (C) and (D): box diagram of array block EUI_{COOL}, EUI_{HEAT}, EUI_{LIGHT}, EUI, EAI, NEUI simulation results

the independent variable and the dependent variable were significantly related. This article retained relevant parameters for discussion.

This section analyzed the EUI correlation results at different scales. Table 6 shows the correlation between the seven design parameters and EUI. Among them, only building density (BD) was significantly correlated with EUI at the block scale, with a correlation coefficient of 0.195. There was a correlation between six design parameters and EUI at the building scale. Among them, the parameter with the highest correlation was the FH (r = 0.7), which showed a positive correlation with EUI. And this was followed by SF (r = 0.367), BDe (r = −0.352), SFA (r = −0.28), L-WR (r = 0.254), and BW (r = 0.124). In the facade scale, no design parameters were related to EUI, but the WWR of different facades were related to EUI_{COOL} and EUI_{LIGHT}, which had an impact on cooling and lighting energy consumption. In summary, EUI was more affected by building-scale design parameters, but both block scale and building scale design parameters had an impact on EUI and need to be considered at the same time.

Regarding the block scale, compared with the study of cold regions in China by Leng et al. (2020), regarding the relationship between heating energy consumption and block form, the block scale parameters BD and FAR had a significant impact on EUI. However, the importance of block-scale design parameters was reduced when considering the impact of the synergistic effect of block-scale and building-scale design parameters on building energy consumption. In order to analyze the difference between single block scale and multi-scale results, this part was studied separately in Section 3.3. Regarding the building scale, in contrast to the energy consumption simulation results of office blocks at the building scale (Hong et al. 2020), the design parameters such as orientation had no significant correlation with building energy consumption in the multi-scale simulation environment in this study.

This section analyzed the correlation between design parameters and EAI at different scales. Table 6 shows the correlation results between 11 design parameters and EAI. Among them, six design parameters at the block scale were related to EAI. The design parameter with highest correlation was the BH (r = -0.831), which showed a negative correlation with EAI. And this was followed by FAR (r = −0.783), BD(EW) (r = 0.208), BD (r = −0.134), and OB (r = −0.098). Except for the east-west building distance BD(EW), all other design parameters showed negative correlation with EAI. At the building scale, only two design parameters were correlated with EAI, namely the SF (r = 0.79), which was positively correlated, and the building H-WR (r = −0.749), which was negatively correlated. There was a correlation between four design parameters of the facade scale and EAI, all of which were the WWR of the four different facades. Among them, the correlation coefficients were the same for the WWR of north and south facades (r = −0.95), and the correlation coefficients for the WWR of east and west facades were the same (r = −0.92).

The block-scale design parameters had a greater impact on EAI. Comparing the relationship between block form and EAI by Mohajeri et al. (2016), it was found that increased building heights led to increased shading effects between buildings, reducing the PV power generation

Table 6 Correlation analysis results of array type

Block scale		EUI	EUI_{COOL}	EUI_{HEAT}	EUI_{LIGHT}	EAI	NEUI
FAR	*r*	−0.023	−0.624**	−0.150**	0.826**	−0.783**	0.795**
	P	0.613	0	0.001	0	0	0
BD	*r*	0.195**	−0.261**	0.024	0.606**	−0.134**	0.175**
	P	0	0	0.6	0	0.003	0
BH	*r*	0.002	−0.437**	0.006	0.516**	−0.831**	0.848**
	P	0.964	0	0.891	0	0	0
OB	*r*	−0.032	−0.058	−0.048	0.055	−0.098*	0.094*
	P	0.48	0.202	0.292	0.219	0.03	0.037
BD(SN)	*r*	−0.064	0.216**	−0.012	−0.350**	0.053	−0.067
	P	0.158	0	0.782	0	0.238	0.139
BD(EW)	*r*	0.006	0.176	0.084	−0.229*	0.208*	−0.209*
	P	0.955	0.091	0.424	0.027	0.046	0.044
Building scale		**EUI**	**EUI_{COOL}**	**EUI_{HEAT}**	**EUI_{LIGHT}**	**EAI**	**NEUI**
BDe	*r*	−0.352**	−0.266**	−0.352**	0.034	0.035	−0.104*
	P	0	0	0	0.455	0.442	0.021
BW	*r*	0.124**	0.065	0.121**	0.025	−0.066	0.092*
	P	0.006	0.151	0.007	0.584	0.141	0.042
FH	*r*	0.700**	0.459**	0.778**	−0.046	−0.014	0.151**
	P	0	0	0	0.306	0.75	0.001
SFA	*r*	−0.280**	−0.216**	−0.267**	0.02	−0.038	−0.016
	P	0	0	0	0.654	0.404	0.721
L-WR	*r*	0.254**	0.153**	0.244**	0.03	−0.07	0.121**
	P	0	0.001	0	0.506	0.118	0.007
H-WR	*r*	−0.03	−0.434**	−0.033	0.493**	−0.749**	0.758**
	P	0.504	0	0.468	0	0	0
SF	*r*	0.367**	0.587**	0.372**	−0.406**	0.790**	−0.736**
	P	0	0	0	0	0	0
Facade scale		**EUI**	**EUI_{COOL}**	**EUI_{HEAT}**	**EUI_{LIGHT}**	**EAI**	**NEUI**
WWR(S)	*r*	0.017	0.122**	0.01	−0.126**	−0.095*	0.100*
	P	0.714	0.007	0.828	0.005	0.035	0.026
WWR(N)	*r*	0.017	0.122**	0.01	−0.126**	−0.095*	0.100*
	P	0.714	0.007	0.828	0.005	0.035	0.026
WWR(E)	*r*	0.015	0.233**	−0.03	−0.228**	−0.092*	0.097*
	P	0.743	0	0.501	0	0.04	0.031
WWR(W)	*r*	0.015	0.233**	−0.03	−0.228**	−0.092*	0.097*
	P	0.743	0	0.501	0	0.04	0.031

* The correlation is significant at the 0.05 level (2-tailed).

** The correlation is significant at the 0.01 level (2-tailed).

potential. The building scale had a smaller impact on EAI, and the design parameters that affected the PV power generation potential of buildings were all related to building height. In the facade scale, it was mainly the WWR of each facade that was significant. An increase in the WWR would reduce the installed area of PV modules on the building facade.

This section analyzed the correlation results between NEUI and design parameters at different scales. Table 6 shows the correlation between 14 design parameters and NEUI. Among them, five design parameters at the block scale were correlated with NEUI. The one with highest correlation was the BH (r = 0.848), which showed a positive correlation with NEUI. And this was followed by FAR (r = 0.795), BD(EW) (r = −0.209), BD (r = 0.175), and OB (r = 0.94). Except for the BD(EW), all other parameters showed positive correlation. There was a correlation between five design parameters at the building scale and NEUI. Among them, the design parameter with highest correlation was the building H-WR (r = 0.758), which showed a positive correlation. And this was followed by SF (r = −0.736), FH (r = 0.151), L-WR (r = 0.121), and BDe (r = −0.104), where only the shape factor (SF) and building depth (BDe) showed a negative correlation. There was a correlation between four design parameters at the facade scale and NEUI, all of which were WWR of four different facades. Among them, the correlation coefficients were the same for the WWR of north and south facades (r = 0.1), and the correlation coefficients for the WWR of east and west facades were the same (r = 0.97), which were all positively correlated.

Compared with the correlation results between design parameters and EUI and EAI, NEUI was relatively balanced and affected by the design parameters of the three scales under the synergistic influence of multiple scales. Among them, the block scale design parameters had the most obvious impact on NEUI. In the research of Xie et al. (2023) on the real architectural form of Wuhan university dormitories, when the block scale also considered the effects of morphological parameters on EUI and EAI, changed in EAI had a greater impact on the NEUI. At the building scale, except for the SFA, all other design parameters were correlated with the NEUI, which was also affected by EAI, and the correlation of the design parameters originally related to EUI became smaller. The influence of design parameters of facade scale on NEUI was completely consistent with EAI. An increase in the WWR would lead to an increase in NEUI, mainly due to the reduction in PV power generation potential.

2) Arrayed multiple regression analysis

The correlation analysis method was used to calculate the correlation between each morphological parameter and energy efficiency indicators (EUI, EAI, and NEUI). However, this method could not fully explain the comprehensive impact of morphological parameters on building energy consumption and PV power generation potential. To address this problem, this study selected morphological parameters with strong correlation and conducted multiple regression analysis based on correlation analysis.

According to the results in Table 7, when considering the multi-scale synergistic influence of design parameters on EUI, the SF, BD, FH, H-WR and EUI of array office blocks were positively correlated, and the BDe, SFA and EUI were negatively correlated. The above parameters had a synergistic impact on the EUI of office blocks in hot summer and cold winter climate zones of China, among which the shape factor (SF) and floor height (FH) had the greatest impact.

$$\mathrm{EUI} = 42.988 - 0.195 \times \mathrm{BDe} - 0.002 \times \mathrm{SFA} + 10.842 \times \mathrm{BD} + 45.982 \times \mathrm{SF} + 3.06 \times \mathrm{FH} + 0.424 \times \mathrm{H\text{-}WR} \quad (16)$$

According to the results in Table 8, when considering the multi-scale synergistic influence of design parameters on NEUI, the SF, BD, H-WR, and north and east facade WWR of array office blocks were positively correlated with NEUI, and the BDe and FH had a negative correlation with NEUI. The above parameters had a synergistic impact on the NEUI of office blocks in hot summer and cold winter climate zones of China. Among them, the design parameters with the greatest impact were also the shape factor (SF) and building depth (BDe).

$$\mathrm{NEUI} = 112.332 - 1.647 \times \mathrm{BDe} + 36.196 \times \mathrm{BD} + 290.893 \times \mathrm{SF} - 1.109 \times \mathrm{FH} + 7.513 \times \mathrm{H\text{-}WR} + 4.831 \times \mathrm{WWR(N)} + 5.248 \times \mathrm{WWR(E)} \quad (17)$$

Overall, the correlation analysis results showed that under the synergistic influence of the multiple scales (block-building-facade scales), a design strategy that comprehensively considered building energy consumption and PV power generation potential should be considered. For example, the block scale needed to appropriately reduce the floor area ratio (FAR), average building height (BH), building density (BD), and adopted low angle orientation (OB). The building scale needed to reduce the building floor height (FH), shape factor (SF), building height-to-width ratio (H-WR), and aspect building length-to-width ratio (L-WR).

3.2.2 *Simulation results and correlation analysis of enclosed*

The simulation results showed that the total building energy consumption (hereinafter referred to as EUI) ranged from 56.56 to 68.84 kWh/(m^2·y), the PV power generation potential (hereinafter referred to as EAI) ranged from 7.62 to 46.08 kWh/(m^2·y), the building net energy consumption (hereinafter referred to as NEUI) ranged from 13.69 to

Table 7 Multiple regression results of array EUI

	Unstandardized coefficient		Standardized coefficient			Collinearity statistics	
	B	Standard error	Beta	*t*	Significance	Tolerance	VIF
(Constant)	42.988	0.835		51.473	0		
BDe	−0.195	0.009	−0.322	−22.905	0	0.733	1.364
SFA	−0.002	0	−0.111	−5.908	0	0.414	2.418
BD	10.842	0.418	0.323	25.938	0	0.933	1.071
SF	45.982	2.516	0.485	18.277	0	0.206	4.85
FH	3.06	0.049	0.784	62.383	0	0.919	1.088
H-WR	0.424	0.072	0.144	5.881	0	0.242	4.132
Dependent variable: EUI							

Table 8 Multiple regression results of array NEUI

	Unstandardized coefficient		Standardized coefficient			Collinearity statistics	
	B	Standard error	Beta	*t*	Significance	Tolerance	VIF
(Constant)	112.332	2.642		42.513	0		
BDe	−1.647	0.045	−0.529	−36.904	0	0.785	1.273
BD	36.196	2.275	0.21	15.913	0	0.926	1.08
SF	290.893	9.091	−0.597	−31.998	0	0.464	2.157
FH	−1.109	0.264	−0.055	−4.193	0	0.929	1.077
H-WR	7.513	0.272	0.497	27.61	0	0.498	2.01
WWR(N)	4.831	0.583	0.106	8.282	0	0.984	1.016
WWR(E)	5.248	0.58	0.115	9.05	0	0.995	1.005
Dependent variable: NEUI							

57.14 kWh/(m^2·y), and the results were generally consistent with normal distribution (Figures 19(A)–(D)).

1) Correlation analysis of enclosed multi-scale design parameters

This section analyzed the correlation results between EUI and design parameters at different scales. Table 9 shows the correlation results between 9 design parameters and EUI. Among them, five design parameters at the block scale were correlated with EUI. Among them, the design parameter with the highest correlation was BD (r = −0.346), which showed a negative correlation with EUI. And this was followed by FAR (r = −0.27), DOE (r = −0.133), CD(SN) (r = 0.133), and TL(E) (r = 0.121). There was a correlation between four design parameters at the building scale and EUI. Among them, the design parameter with the highest correlation was the FH (r = 0.652), which showed a positive correlation with EUI. And this was followed by SF (r = 0.485), SFA (r = −0.346), and BDe (r = −0.133). In the facade scale, no design parameters were related to EUI, but the WWR of different facades were related to EUI_{COOL} and EUI_{LIGHT}, which had an impact on cooling and lighting energy consumption. In summary, EUI was affected by a combination of block and building scale design parameters.

Regarding the block scale, comparing the research on energy consumption of enclosed buildings by Manioğlu and Oral (2015) and Asfour (2020), it was found that existing research mostly considered the energy consumption characteristics of full enclosure or specified enclosure morphology, and considered complex morphological changes to a lesser extent. The energy consumption results under these conditions rarely took the DOE of enclosed buildings as a research object, while this study found that there is a negative correlation between the DOE and EUI.

This section analyzed the correlation results between EAI and design parameters at different scales. Table 9 shows the correlation between the four design parameters and EAI. Among them, two design parameters at the block scale were related to EAI, namely the BH (r = −0.833) and the FAR (r = −0.828), both of which showed negative correlations. At the building scale, only one design parameter had a correlation with EAI, which was the SF (r = 0.897) and positively correlated. There was only one significant design parameter related to the facade scale and EAI, which was the west facade WWR (r = −0.109).

Among them, block-scale design parameters had a greater impact on EAI. This was validated by the study by Mohajeri et al. (2016), where the impact of block form on PV power generation potential of building surface was studied, and it was found that as the shading environment increases, the acceptable radiation from the building facade decreases significantly. The shading effect caused by the increased height of enclosed buildings was the most obvious factor affecting EAI. The building scale and facade scale had little impact on EAI, and the impact was mainly by the SF and the west facade WWR.

This section analyzed the correlation results between NEUI and design parameters at different scales. Table 9 shows the correlation between the six design parameters and NEUI. Among them, four design parameters at the block scale were correlated with NEUI. The design parameter with the highest correlation was the BH (r = 0.867), which

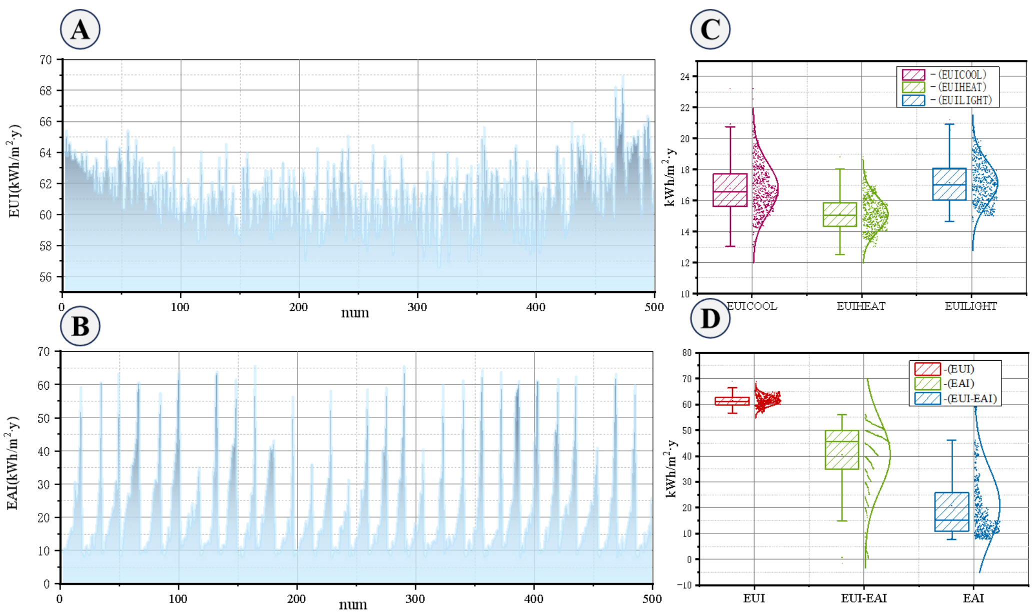


Fig. 19 (A) and (B): EAI and EUI simulation results of enclosed type; (C) and (D): box diagram of enclosed block EUI_{COOL}, EUI_{HEAT}, EUI_{LIGHT}, EUI, EAI, NEUI simulation results

Table 9 Correlation analysis results of enclosed

Block scale		EUI	EUI_{COOL}	EUI_{HEAT}	EUI_{LIGHT}	EAI	NEUI
FAR	*r*	−0.270**	−0.727**	−0.515**	0.859**	−0.828**	0.828**
	P	0	0	0	0	0	0
BD	*r*	−0.346**	−0.450**	−0.414**	0.343**	−0.08	0.033
	P	0	0	0	0	0.075	0.466
BH	*r*	−0.045	−0.535**	−0.263**	0.767**	−0.833**	0.867**
	P	0.322	0	0	0	0	0
DOE	*r*	−0.133**	−0.06	−0.08	−0.062	0.074	−0.097*
	P	0.003	0.181	0.076	0.169	0.103	0.032
TL(E)	*r*	0.121**	0.044	0.063	0.077	−0.076	0.097*
	P	0.007	0.325	0.162	0.087	0.093	0.031
CD (SN)	*r*	0.133**	0.074	0.077	0.049	−0.04	0.062
	P	0.003	0.099	0.089	0.274	0.377	0.172
Building scale		**EUI**	**EUI_{COOL}**	**EUI_{HEAT}**	**EUI_{LIGHT}**	**EAI**	**NEUI**
SFA (A)	*r*	−0.346**	−0.450**	−0.414**	0.343**	−0.08	0.033
	P	0	0	0	0	0.075	0.466
FH	*r*	0.652**	0.412**	0.645**	−0.029	−0.002	0.097*
	P	0	0	0	0.516	0.998	0.032
AVBD	*r*	−0.133**	−0.242**	−0.220**	0.260**	−0.04	0.022
	P	0.003	0	0	0	0.373	0.62
SF	*r*	0.485**	0.754**	0.626**	−0.660**	0.897**	−0.868**
	P	0	0	0	0	0	0
Facade scale		**EUI**	**EUI_{COOL}**	**EUI_{HEAT}**	**EUI_{LIGHT}**	**EAI**	**NEUI**
WWR(S)	*r*	−0.084	0.140**	−0.045	−0.252**	−0.044	0.033
	P	0.063	0.002	0.324	0	0.334	0.461
WWR (N)	*r*	0.037	0.104*	0.048	−0.105*	−0.006	0.012
	P	0.409	0.021	0.283	0.02	0.886	0.785
WWR(E)	*r*	0.004	0.199**	0.017	−0.240**	0.01	−0.01
	P	0.927	0	0.713	0	0.821	0.823
WWR (W)	*r*	−0.076	0.087	−0.061	−0.165**	−0.109*	0.103*
	P	0.094	0.052	0.177	0	0.015	0.022

* The correlation is significant at the 0.05 level (2-tailed).

** The correlation is significant at the 0.01 level (2-tailed).

showed a positive correlation with NEUI. And this was followed by FAR (r = 0.828), DOE (r = −0.97), and TL(E) (r = 0.97). Among them, the DOE showed a negative correlation, and the other parameters showed a positive correlation. There were two design parameters at the building scale were correlated with NEUI, namely SF (r = −0.868) and FH (r = 0.097). Only one design parameter of the facade scale had a correlation with NEUI, which was the west facade WWR (r = 0.103).

Compared with the correlation results of EUI and EAI, NEUI was greatly affected by the block scale under the synergistic influence of multiple scales design parameters. The layout morphology of enclosed block was an important design indicator. The key design parameters affecting NEUI were parameters such as DOE and BH, which created a shading effect. As to building scale design parameters, the BH was related to NEUI. The facade scale design parameter influenced NEUI was completely consistent with those affecting EAI.

2) Enclosed multiple regression analysis

According to the multiple regression results in Table 10, when considering the synergistic influence of multi-scale design parameters, AVBD, FAR, TL(E), SF, FH and EUI of enclosed office blocks were positively correlated with EUI, while the BD was negatively correlated. The above parameters had a synergistic impact on the EUI of office blocks in hot summer and cold winter climate zones of China, among which the shape factor (SF) and floor height (FH) had the greatest impact.

Table 10 Multiple regression results between EUI and design parameters of enclosed

	Unstandardized coefficient		Standardized coefficient			Collinearity statistics	
	B	Standard error	Beta	*t*	Significance	Tolerance	VIF
(Constant)	32.703	0.581		56.333	0		
AVBD	0.056	0.02	0.063	2.801	0.005	0.366	2.732
FAR	0.754	0.031	0.577	24.283	0	0.328	3.052
BD	−9.591	0.808	−0.246	−11.874	0	0.43	2.324
TL(E)	0.01	0.002	0.121	5.894	0	0.438	2.285
SF	67.079	1.659	0.991	40.443	0	0.308	3.245
FH	3.186	0.058	0.782	55.248	0	0.923	1.083
Dependent variable: EUI							

$$\begin{aligned} \mathrm{EUI} = 32.7.3 + 0.056 \times \mathrm{AVBD} + 0.754 \times \mathrm{FAR} - 9.591 \\ \times \mathrm{BD} + 0.01 \times \mathrm{TL(E)} + 67.079 \times \mathrm{SF} + 3.186 \times \mathrm{FH} \end{aligned} \quad (18)$$

According to the multiple regression results in Table 11, when considering the synergistic influence of multi-scale design parameters, the FAR, BD, TL(E), SF and west facade WWR of enclosed office blocks were all positively correlated with NEUI. The above parameters had a synergistic impact on the NEUI of office blocks in hot summer and cold winter climate zones of China, among which the design parameters with the greatest influence were the SF and BD.

$$\begin{aligned} \mathrm{NEUI} = 97.368 + 3.279 \times \mathrm{FAR} - 108.749 \times \mathrm{BD} + 0.083 \\ \times \mathrm{TL(BI)} + 315.542 \times \mathrm{SF} + 0.88 \times \mathrm{WWR(W)} \end{aligned} \quad (19)$$

Overall, when calculating the net energy consumption (NEUI) by increasing the potential for PV power generation (EAI), its balance was influenced by three scale design parameters, and it was more affected by the block scale design parameters. The block scale needed to be appropriately reduced floor area ratio (FAR) and average building height (BH), and a low degree of enclosure (DOE) layout form should be adopted. The building scale required a reduction in building floor height (FH) and shape factor (SF) to reduce complex forms. The facade scale could be selected as low window to wall ratio vertical strip windows and point windows, reducing the window to wall ratio on the west facade.

3.2.3 *Differences in EUI, EAI, and NEUI results between array and enclosure types*

In general, the EUI simulation results range of array types and enclosed types was similar, and the correlation analysis results of the two were affected by a combination of the block and building scale design parameters. However, the minimum EUI of the enclosed types was 2.91% less than that of the array types. In terms of correlation results, the EUI of array types was more affected by the building scale design parameters, mainly the FH, SF and BDe, while the EUI of enclosed types needed to be paid more attention by the influence of block scale design parameters, such as DOE and OI, due to the large changes in block morphology. As the DOE increases, building energy consumption would decrease accordingly.

In general, the array types had a wider range of EAI simulation results than the enclosed type, with an increase of 17% compared to the EAI of enclosed type, where the maximum EAI increases by 11.02%, and the overall EAI was also greater. This was due to the fact that the mutual shading of buildings in an enclosed type block led to a reduction in the amount of solar radiation received by the

Table 11 Multiple regression results between NEUI and design parameters of enclosed

	Unstandardized coefficient		Standardized coefficient			Collinearity statistics	
	B	Standard error	Beta	*t*	Significance	Tolerance	VIF
(Constant)	97.368	3.134		31.068	0		
FAR	3.279	0.208	0.373	15.741	0	0.344	2.906
BD	108.748	4.889	−0.415	−22.243	0	0.555	1.803
TL(E)	0.083	0.01	0.147	8.174	0	0.597	1.674
SF	315.542	10.986	−0.694	−28.723	0	0.332	3.014
WWR(W)	0.88	0.867	0.014	1.016	0.031	0.995	1.005
Dependent variable: NEUI							

building surfaces. As the enclosure increased, the EAI decreased, this trend contradicted to the EUI and needed to be weighed up when considering performance-based design in the pre-design schemes. In terms of correlation results between design parameters and EAI, the block scale design parameters that had an impact on EAI were similar to the building scale design parameters in array versus enclosed blocks, with building height being the key design parameter. While the facade scale design parameters was different, where the WWR of the east, west, south, and north facades of the array type were all related to EAI, while the enclosed type was only related to the WWR of the west facade.

Overall, the array types NEUI range increases by 11% compared to the enclosed types. This was because the NEUI was more affected by the EAI results. The array types had greater PV power generation potential. Arrayed block layout were more advantageous if the pre-design scheme had a higher demand for PV power generation potential. As for the results of the correlation analysis between the design parameters and NEUI, there was a large difference between the array and enclosed blocks, with the NEUI of the array blocks influenced by the combined effect of all three scale design parameters at the same time; however, the NEUI of the enclosed blocks was mainly influenced by the block scale design parameters.

As for the design scheme, the array types were more had greater significance on correlation results. There was a big difference between the array types and the enclosed types. The array types were evenly affected by the design parameters of three scales, while the enclosed types were more obviously affected by the block scale.

3.3 Comparison of simulation results between multi-scale design parameters and single scale design parameters—using array design as an example

This article took an array office block as an example to compare the simulation differences between multi-scale design parameters and block single-scale design parameters on building energy consumption and PV power generation potential. The experiment set the design parameters at the building and facade scales to fixed values, and set them to the typical mophology in the office building survey data. Only the design parameters at block scale were changed. Based on this, a sampling test was conducted, and 500 experimental samples were selected to simulate, the simulation results data was used as a data base to compare and analyze the synergistic effect of multi-scale design parameters with single-scale design parameters on EUI, EAI and NEUI.

This section analyzed the synergistic impact of multi-scale design parameters on energy efficiency indicators (EUI, EAI and NEUI) in comparison with the single-scale design parameters of the block from the distributional characteristics of indicators. Figure 20 showed the simulation results under the impact of single-scale design parameters, which were different from the synergistic influence of multi-scale design parameters. The first discrepancy was the range of variation in the three indicators, including EUI, EAI, and NEUI. Only considering the impact of block scale design parameters, the range of variation of EUI results was 62.97–65.77 kWh/(m^2·y); the range of variation of EAI was 7.15–46.38 kWh/(m^2·y); and the variation range of NEUI was 18.55–58.32 kWh/(m^2·y). While considering the synergistic active of multi-scale design parameters, the EUI variation range was 58.21–69.33 kWh/(m^2·y); the EAI variation range was 6.04–51.16 kWh/(m^2·y); and the NEUI result variation range was 12.25–60.56 kWh/(m^2·y) (Figures 20(A) and (B)). Compared with the single scale of the block, considering the synergistic active of multi-scale design parameters, the EUI variation range was increased by 297.14%, where the maximum energy saving potential was increased by 7.56%, the EAI variation range was increased by 15.01%, and the maximum EAI was increased by 10.3%. For NEUI results,

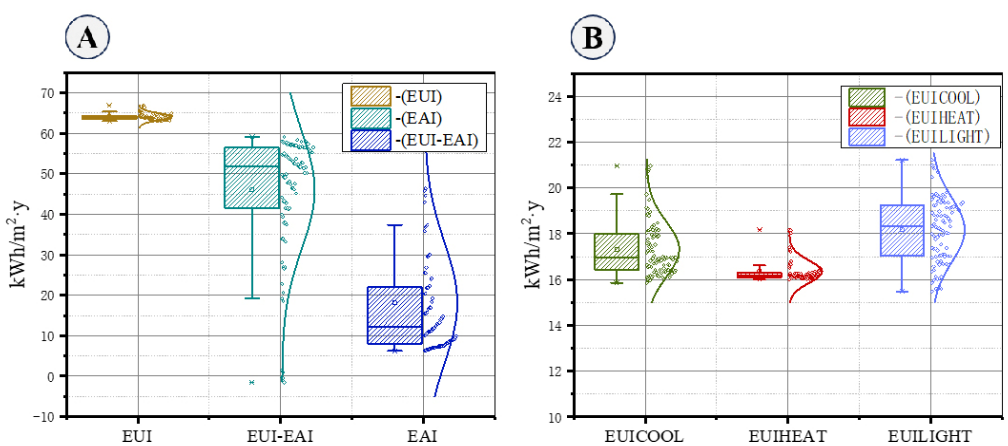


Fig. 20 Box plot of single-scale EUI, EAI, NEUI, EUI$_{COOL}$, EUI$_{HEAT}$, EUI$_{LIGHT}$, simulation results of array blocks

the range increased by 21.47%, and the energy savings potential after the PV modules deployed increased by 33.96%. The potential for energy savings was greater with the synergistic effect of multi-scale design parameters than when only a single block-scale design parameter was considered. The performance-based design of the scheme at the pre-design stage required the tuning of design parameters to maximise energy efficiency gains (Lin et al. 2021). Therefore, it is important to consider the synergistic effect of multi-scale design parameters for programme design.

This section compared and analyzed the differences in the synergistic effect of multi-scale design parameters versus single block scale design parameters on energy performance indicators, including EUI, EAI and NEUI, from a correlation analysis perspective. Regarding the correlation results of EUI, Table 12 shows that there were five design parameters of single block scale related to EUI. The design parameter with the highest correlation was BD (r = 0.824), and this was followed by BD(SN) (r = −0.679), FAR (r = −0.348), BD(EW) (r = 0.348), and OB (r = 0.288). Among them, two design parameters, FAR and BD(SN), showed negative correlation with EUI, while all other parameters showed a positive correlation with EUI.

Comparative analysis with the results of the correlation of the single block scale design parameters on EUI revealed that only building density (BD) was related to EUI, under the synergistic influence of multi-scale design parameters in Table 6. It could be found that the correlation between design parameters and energy performance indicators (EUI, EAI and NEUI) became stronger if only single block scale design parameters were considered. Therefore, the synergistic effect of multi-scale design parameters should be considered in the performance-based design of the pre-design solution, and there is a limitation in considering the effect of only a single-scale design parameter on the energy performance indicators (EUI, EAI and NEUI).

Regarding the correlation results of EAI, Table 12 shows four design parameters related to EAI. The design parameter with the highest correlation was BH (r = −0.889), which showed a negative correlation, and this was followed by FAR (r = −0.836) and BD(EW) (r = −0.836). Comparing the correlation between the synergistic effect of multi-scale design parameters and the correlation between single-scale design parameters and EAI, it can be found that there is a consistency in the design parameters affecting EAI, but considering only the effect of single block scale design parameters on EAI, the correlation coefficients of the same design parameter with EAI were even larger, e.g. BH.

Regarding the NEUI correlation results, Table 12 shows four design parameters related to NEUI. The design parameter with the highest correlation was BH (r = 0.898), which showed a positive correlation, and this was followed by FAR (r = 0.865) and BD(EW) (r = 0.865) This result was similar to the impact result of EAI. Comparing the correlation results of block-scale NEUI under the synergistic influence of multiple scales design parameters in Table 6, it was found that the correlation coefficient of a single block scale would become higher.

3.4 Discussion

This work mainly had the following two advantages. First of all, it had simulation flexibility. For office buildings in different climate zones, according to the climate characteristics and corresponding building design

Table 12 Single-scale correlation analysis results of array blocks

Block scale		EUI	EUI_{COOL}	EUI_{HEAT}	EUI_{LIGHT}	EAI	NEUI
FAR	r	−0.348**	−0.926**	−0.524**	0.961**	−0.836**	0.865**
	P	0.002	0	0	0	0	0
BD	r	0.824**	−0.239*	0.288*	0.539**	−0.045	0.099
	P	0	0.036	0.011	0	0.699	0.39
BH	r	0.049	−0.912**	−0.662**	0.824**	−0.889**	0.898**
	P	0.67	0	0	0	0	0
OB	r	0.288*	−0.041	0.144	0.148	−0.092*	0.093*
	P	0.011	0.722	0.21	0.199	0.967	0.903
BD(SN)	r	−0.679**	0.168	−0.277*	−0.414**	0.004	−0.049
	P	0	0.144	0.015	0	0.973	0.674
BD(EW)	r	0.348**	−0.926**	−0.524**	0.961**	−0.836**	0.865**
	P	0.002	0	0	0	0	0

* The correlation is significant at the 0.05 level (2-tailed).

** The correlation is significant at the 0.01 level (2-tailed).

specifications, thermal parameters, human behavior schedule parameters, indoor thermal disturbance parameters, etc. It can be adjusted according to local climate conditions and design specifications to optimize the corresponding form parameters. Secondly, this workflow was scaleable, and the above analysis results could also be used to generate solutions. It would only be required to access the multi-objective optimization engine to obtain concrete design solutions and application scenarios. This mode could also replace different building data to simulate different types of buildings, which universal and scaleable. At the same time, due to the contradiction between building energy consumption and PV power generation potential, this method could balance the performance between the two and lay the foundation for future research.

This study has several limitations that should be addressed in future research: the results of this study mainly explored the synergistic influence of multi-scale design parameters on building energy consumption and PV power generation potential in the pre-design stage of office blocks. Many parameters that affect building energy consumption, such as building envelope, human behavior, and parameters that affect PV power generation potential, such as PV module installation angles, PV module types, etc., have been simplified and standardized accordingly. In addition, the parametric model constructed in this paper was mainly to study the synergistic effect of multi-scale design parameters on building performance indexes (EUI, EAI and NEUI), serving the performance-based design of the pre-design schemes. Complex architectural details were not considered, and future research could deepen the design scheme based on the optimisation results of the pre-design schemes to meet other usage needs, such as cultural needs and aesthetic demands.

4 Conclusion

In order to provide designers with a workflow for building energy consumption and PV power generation potential assessment, which considers the synergistic effect of multi-scale design parameters in the pre-design stage, this paper develops a workflow from parametric modelling of design solution generation to performance evaluation and performance-based comparison and selection of design solutions, under the synergistic influence of multi-scale design parameters, taking Wuhan City as an example. Specifically, this paper divides office blocks into two categories: array types and enclosed types through field survey and architectural typology, then establishes a multi-scale design parameter system and parametric model for office blocks, and conducts sampling simulations based on this to obtain multi-scale design parameters. Differences in the synergistic effect of multi-scale design parameters versus block scale design parameters on the three performance indicators (EUI, EAI and NEUI) are compared. The main conclusions of the main research are as follows:

(1) Taking the array types as an example, considering the synergistic influence of multi-scale design parameters, the energy saving potential of the building is increased by 7.56% compared with the block scale, and the energy savings potential is increased by 33.96% when PV modules are deployed. There are significant differences in the correlation results between building energy consumption and PV power generation potential.

(2) For array office blocks, considering only a single block scale design parameter is more relevant to EUI than the synergistic effect of multi-scale design parameters on EUI. The parameter with the strongest correlation is the floor height (FH). The NEUI receives the combined effect of all three scale (block, building and facade scales) design parameters, with the most influential design parameter being building height (BH).

(3) For enclosed office blocks, the EUI is affected by the combined effect of block and building scale design parameters under the synergistic effect of multi-scale design parameters, of which the most influential design parameter is the floor height (FH). After the PV modules are deployed, the NEUI is affected by a combination of three scale design parameters, where the most influential design parameter is the shape factor (SF).

(4) A comparative analysis of the EUI, EAI, and NEUI simulation results of the array and enclosed office blocks under the synergistic effect of multi-scale design parameters reveals that the EUI of the two block types are similar. While the EAI range of the arrayed block is increased by 17% and the maximum PV power generation potential is increased by 11% compared to the enclosed type. The range of NEUI results for the array type increases by 11% over the enclosed type. At the same time, the results of the study also indicate that arrayed blocks are more suitable for the installation of PV modules than enclosed blocks.

(5) Considering the synergistic effect of multi-scale design parameters, the results of the EUI and NEUI multiple regression analyses of arrayed and enclosed office blocks indicate that building density (BD) and shape factor (SF) are the design parameters that most affect the two performance indicators.

This study found that it is extremely necessary to consider the synergistic influence of multi-scale design parameters in the pre-design stage. Compared to block single scale, the correlation results of multi-scale are more accurate, which have greater energy-saving potential as well, and it is more effective in assisting designers to judge the performance-based advantages and disadvantages of pre-design solutions. This research provides designers in the pre-design stage with a simulation workflow for building energy consumption and PV power generation potential that takes into account the synergistic effect of multi-scale design parameters, allowing them to flexibly change the input data according to different use environments, and draw conclusions and design opinions under different design requirements. At the same time, corresponding optimization modules could be added to the simulation workflow, which can directly generate optimization solutions and provide corresponding technical tools and rule summaries reference for future research.

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Declaration of competing interest

The authors have no competing interests to declare that are relevant to the content of this article.

Author contribution statement

Shen Xu: conceptualization, methodology, resources, data curation, project administration, funding acquisition; Han Yang: conceptualization, data curation, formal analysis, investigation, methodology, software, validation, visualization, writing—original draft; Rongpeng Zhang: conceptualization, methodology, writing—review & editing, supervision; Minghao Wang: writing—review & editing; Ying Long: writing—review & editing, supervision; Thushini Mendis: writing—review & editing, supervision; Gaomei Li: conceptualization, methodology, data curation, writing—review & editing, supervision.

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