Simulation-based Sensitivity Analysis of Energy Performance Applied to an Old Beijing Residential Neighbourhood for Retrofit Strategy Optimisation with Climate Change Prediction

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Abstract

Due to the high energy consumption in the building sector and the ever-increasing urbanisation rate, the demand for retrofitting old buildings in urban areas is increasing in China, especially in metropolitan cities like Beijing. However, despite national and local policies calling for extensive building retrofitting, it is a challenge to determine a cost-effective retrofit strategy. Considering this, the study establishes a novel approach that analyses the sensitivity of building energy consumption on parameters defining the materials used on the building envelope, as well as the solar shading and airtightness of the building. This research builds EnergyPlus models using geometric data captured from the map, building fabric data from local design standards, and a set of varying activity schedules, and carries out simulations to calculate the building energy consumption of a residential neighbourhood in Beijing, China. The energy consumption data is then used for a sensitivity analysis using the Morris Method on 14 building envelope parameters in total. For different building shapes, the sensitivity analysis results highlight that the energy is most sensitive to infiltration, followed by window U-value and window SHGC. The solar absorptances and U-values of external walls and roofs are also found to have a moderate influence on total energy consumption. By using predicted weather files, this research further discusses the changing influences of these parameters considering climate change over the next few decades. The approach of this research is instructive for the analysis of buildings in other cities in cold climate regions due to the generalisability of the studied neighbourhood, and the result has the potential to inform the building management teams and policymakers to determine suitable retrofit strategies.

Keywords: Sensitivity analysis, Climate change prediction, Building retrofitting, Morris Method, Energy simulation

1. Introduction

The building sector is a dominant contributor to global energy consumption and greenhouse gas (GHG) emissions, accounting for approximately 40% of total energy use and one-third of total energy-related GHG emissions, which leads to climate change and global warming, which are great threats of the society (Nejat *et al.*, 2015). In China, with the year-on-year increase, the urbanisation rate in China has reached 64.72% in 2021 (National Development and Reform Commission, 2022), yet the buildings constructed in the early years comply with outdated standards and are no longer optimal for the current conditions due to the advance of building technology and the change of global climate. The GHG emissions from the old buildings also affect the urban microclimate and create a vicious circle causing the urban heat island effect. In addition, the price of coal has continued to rise in China in recent years, while the electricity demand has increased as the national economy has continued to recover and the price of electricity has risen as demand has outstripped supply (Liu *et al.*, 2022). As a result, the building sector, which accounts for a great share of energy consumption, is facing unavoidable challenges.

There are around 60 billion m^2 of existing buildings in China, and only less than 10% are rated to be energy-efficient (Li *et al.*, 2017; Liu, Tan and Li, 2020). In the metropolitan capital Beijing, where the population is more than 20 million and no measures were taken to alleviate the population explosion in the city centre until 2014 (Qiang and Hu, 2022), there exist 1582 old residential neighbourhoods covering 58.5 million m^2, where 16.7% were constructed before 1970, 18.1% were constructed between 1970 to 1979, and 65.2% were constructed between 1980 to 1989 (Gao and Yan, 2021). This indicates a huge potential for energy saving by building retrofit.

With this huge demand for building retrofit in China, technical specifications and design standards need to be optimised. Therefore, the question of this research is to address the need to identify the parameters most beneficial for building energy consumption reduction at building retrofit. Sensitivity analysis (SA), a method that evaluates how the change of building performance simulation outputs is allocated to various input parameters (Pereira, Bögl and Natschläger, 2014), has been widely used to investigate characteristics of parameters in multiple applications such as building design, building retrofit, and the impact of climate change on buildings (Tian, 2012). With a clearer understanding of the sensitivity of design parameters, it can be determined where the time and expenses should be allocated when developing a retrofit strategy, and policymakers can establish design standards for more efficient, effective, and economic development (Sprau Coulter and Leicht, 2014).

Retrofitting for better building energy efficiency has been drawing attention worldwide. Enhancing the energy efficiency of buildings and further driving the reduction of energy consumption throughout the city will contribute to the United Nations Sustainable Development Goals (SDG), especially SDG7, SDG11, SDG12, and SDG13 (Alawneh *et al.*, 2018; Di Foggia, 2018; Wen *et al.*, 2020). Specifically in China, optimising building retrofit strategy is also an important support for the double carbon goal, which aims to peak carbon emissions by 2030 and achieve carbon neutrality by 2060, and currently guides China's social and economic development (Hu, Jiang and Yan, 2022). Since reducing HVAC-related energy use was found to be vital for carbon emission reduction (Li, Jimenez-Bescos, *et al.*, 2023), multiple policies have been proposed by the government. For example, China's 14th Five-Year Plan of Building Energy Conservation and Green Building Development aims to implement energy-saving renovations for no less than 350 million m^2 of existing residential buildings by 2025 (MOHURD, 2022). For the same period, Beijing also issued policies to vigorously transform the old residential areas built before 2000 (The People's Government of Beijing Municipality, 2022). By optimising retrofit strategies and refining retrofit standards, these policies can be implemented with high quality, and the carbon-neutral goal can be supported by the building sector.

This paper studies an old residential neighbourhood located in Beijing, China that needs a retrofit. This neighbourhood contains tightly arranged residential buildings with multiple shapes and is therefore consistent with the trend towards urbanisation with an increasingly large and dense population, and with people having their preferences for building shapes. Meanwhile, this study considers the impact of climate change in the coming decades in terms of temperature increases in the cold climate region (Feng and Du, 2020), examines the impact of increased cooling energy consumption and reduced heating energy consumption on the analysis results, and thus is a considerable guide for other cities in cold climate regions after urbanisation development.

To this end, this study first develops an appropriate methodology through a literature review and then shows an overview of model inputs and the process of EnergyPlus and Python co-simulation. After obtaining the energy simulation results, SA is then carried out for not only the current weather condition but also the predicted weather to explore the reliability of the result due to climate change in the future. Finally, SA results and the implications of these results are discussed.

2. Literature Review

To study and take control of the building energy consumption and retrofit decisions of the old building stock, many techniques have been used by previous researchers. For example, machine learning methods have been used to predict the energy consumption pattern or discover the energy efficiency for buildings using collected energy data over time (Marasco and Kontokosta, 2016; Nilashi *et al.*, 2017; Papadopoulos, Bonczak and Kontokosta, 2018); Ebrahimigharehbaghi *et al.* (2022) used a genetic algorithm to predict homeowners' decisions to retrofit their houses; some studies used building energy simulation tools, either commonly used by the public or newly developed by the researchers, to discover the energy conservation potential using different retrofit strategies (Prabatha *et al.*, 2020; Alavirad *et al.*, 2022; Afshari, 2023). However, these methods all lack the systematic exploration of essences that help reduce energy consumption at building retrofit and do not contribute to the carbon-neutral goal.

Nevertheless, to explore key factors that considerably influence building energy performance, this study uses SA, which has been widely used in the building sector in recent years and various critical parameters were identified. Many studies (Murray and O'Sullivan, 2012; Yu *et al.*, 2013; Ben and Steemers, 2014; Sprau Coulter and Leicht, 2014; Gunay *et al.*, 2019; Silvero, Rodrigues and Montelpare, 2019; Gelesz *et al.*, 2020) used local methods, the methods that explore the effects of individual input variables around the base case one at a time (OAT), and the results showed the most sensitive factors for building energy performance can be system setpoint, operation schedules, system efficiency, or occupant behavioural variables. However, the local methods are not ideal for nonlinear models like building performance simulations (BPS) because interactions between input variables are overlooked (Saltelli and Annoni, 2010).

Some studies (Coffey *et al.*, 2015; Bre *et al.*, 2016; Yang *et al.*, 2016; Gagnon, Gosselin and Decker, 2018; Zeferina *et al.*, 2021; Satola, Houlihan-Wiberg and Gustavsen, 2022) have also attempted to use global methods such as the regression method and variance-based method. Some building thermal properties, such as thermal transmittance, the inertia of walls, and the solar heat gain coefficient (SHGC) of windows, were also found influential for building energy performance, but the former method is limited to linear models or monotonic functions of nonlinear models, while the latter has a considerably high computational cost (Tian, 2012).

Therefore, it is necessary to apply an appropriate method for the SA of a neighbourhood. The Morris Method, also known as the Elementary Effects Method, is a screening method that evaluates the impact of each input parameter individually while making changes from different starting points, thus despite it being considered a global sensitivity analysis method, it combines the benefit of local sensitivity analysis methods and only changes parameter values OAT between consecutive simulations (Saltelli *et al.*, 2008). Weighing its advantages and disadvantages, the Morris Method was chosen for this study because it eclipses all other SA methods in the following aspects:

- It is a global method that can be used for complex nonlinear BPS projects (Saltelli and Annoni, 2010).
- It is computationally cheaper than other global sensitivity methods and thus is suitable for neighbourhood-size BPS where simulations are time-consuming, especially when there are a large number of input variables to investigate (Campolongo, Saltelli and Cariboni, 2011).
- There are various arguments about the distribution of building-related variables. Using the Morris Method, the input factors are taken as several discrete values (Tian, 2012), thus it is unnecessary to use unreliable sources of distributions.
- It provides easy-to-read visualisation in a two-dimensional graph to rank the importance of input parameters and the interactions between them (Tian, 2012).
- Although the Morris Method cannot quantify the uncertainty of the output (Nguyen and Reiter, 2015), it is not an issue since the current study focuses only on ranking the influences of building design variables.

Reviewing SA research using the Morris Method based on different locations around the world, a research gap identified by the authors was the lack of consideration of climate change (Calama-González *et al.*, 2022) so that the identification of influential parameters lacks foresight and can only be used for building retrofitting in the current era. Although the inclusion of climate change in SA has slightly increased in recent years (Nunes and Giglio, 2022; Machard *et al.*, 2023), most are based on case studies in Europe or South America, particularly in cities with warmer climates, and the focus of cold climate regions is lacking. According to the recommendation of previous literature, the investigation of different climate zones should not be overlooked (Silva and Ghisi, 2020; Zhou, Tam and Le, 2023). In addition, the majority of building-energy-related SA was aimed at single case study buildings and was inadequate for concluding generalisability (Bre *et al.*, 2016; Silva and Ghisi, 2020; Goffart and Woloszyn, 2021; Nunes and Giglio, 2022; Machard *et al.*, 2023; Saurbayeva, Memon and Kim, 2023). This research attempts to fill this gap by developing and implementing a smooth SA workflow that is applicable for a building block and meanwhile taking into account the impact of climate change.

3. Methodology

3.1 Energy Modelling of the Neighbourhood

The neighbourhood is located in Chaoyang District in central Beijing (Figure 1). It is representative because it has the composition of the old residential areas commonly seen in Beijing. Buildings in this neighbourhood were constructed from the 1960s to the 2000s, with a few offices and educational buildings inside the neighbourhood and various types of buildings surrounding the neighbourhood. With different heights of 5-20 storeys and different building footprint shapes, the modelling of this neighbourhood takes into account various heat transfer, solar radiation, and shading patterns. This avoids having individual buildings with extremely high or low energy consumption by investigating the average performance of the whole neighbourhood and helps discover the generalisability to inform a wide variety of urban sustainability stakeholders.

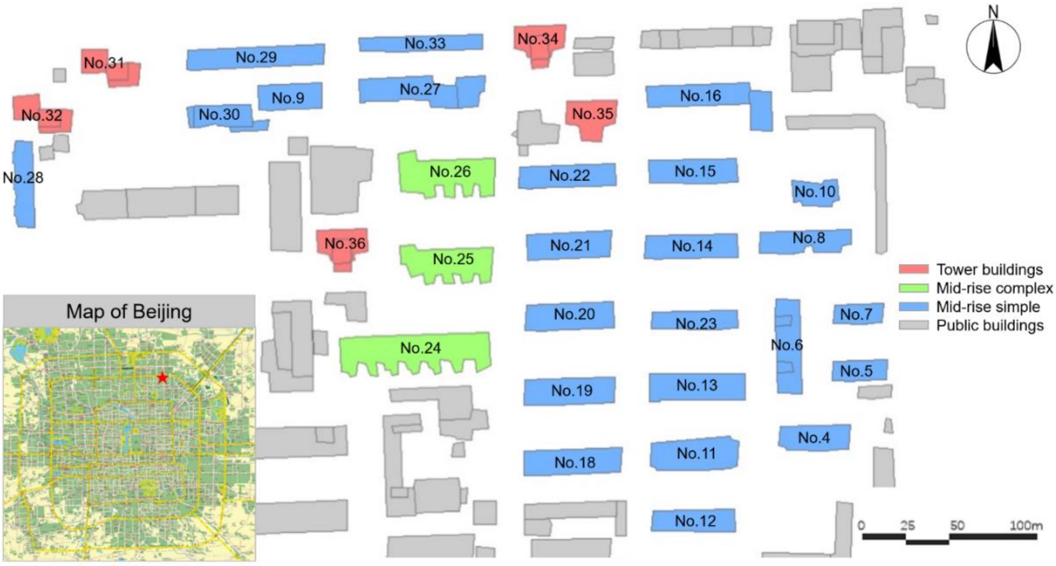

Figure 1. Plan view of the studied neighbourhood with marked residential buildings.

The process of creating energy models for the residential neighbourhood was divided into three steps: data input, model generation and execution, and model calibration. The energy simulation was only carried out for the 32 residential buildings in the neighbourhood, but the geometries were created for all building types.

3.1.1 Data Input

For geometric information, a set of open-source shapefiles containing building footprints and height was extracted from Baidu Map in this study. Some non-geometric information, including the building numbers, the number of floors, and the year of construction of each building, was collected using Baidu Map online platform or local rental websites.

Since building fabric data is not publicly available, it was assumed that the buildings meet the requirements from design standards for Beijing residential buildings of the corresponding year of construction. Because the buildings in 1960 and 1975 were constructed earlier than the first design standard available, these buildings were assumed to have envelope structures similar to the old Beijing residential neighbourhoods investigated by Gao and Yan (2021). An exception is the external windows—since the windows are easy to replace (Liu *et al.*, 2018), it was assumed that all buildings have external windows that comply with the latest standard. The reference standards for each building are presented in Table 1 and the envelope structures are presented in Table 6 in Appendix A.

Table 1. Different types of buildings and the design standards used for them.

Building No.	Type	Year of construction	Quality level	References (building fabrics)	References (other factors)
4, 5, 6, 7, 8, 10, 11, 12, 13, 14,	mid-rise buildings	1960	bad	Statistical data of old residential	GB50736-2012 (MOHURD, 2012),

15, 16, 18, 19, 20, 21, 22, 23				neighbourhoods in Beijing (Gao and Yan, 2021)	Calculation Method for Energy Consumption of Residential Buildings (MOHURD, 2019), GB/T7106-2008 (China Standardization Administration, 2008), JGJ26-2018 (MOHURD, 2018)
9, 30	mid-rise buildings	1975			
31, 32	tower buildings	1982	medium	JGJ26-1986 (China Academy of Building Research, 1986)	
34, 35, 36	tower buildings	1990	good	JGJ26-1995 (China Academy of Building Research, 1995)	
24, 25, 26, 27, 28, 29, 33	mid-rise buildings	2000			

Other non-geometric data such as lighting and equipment power, setpoint temperatures, and infiltration were collected from the latest design standards. For schedules of heating, cooling, occupancy, lighting, and equipment, three usage levels were prepared to mimic varied lifestyles between occupants. While the medium usage schedules followed the latest design standard (MOHURD, 2018b), the high and low usage schedules were assumed to have a one-hour longer or shorter peak period than the medium ones (shown in Figure 2-4).

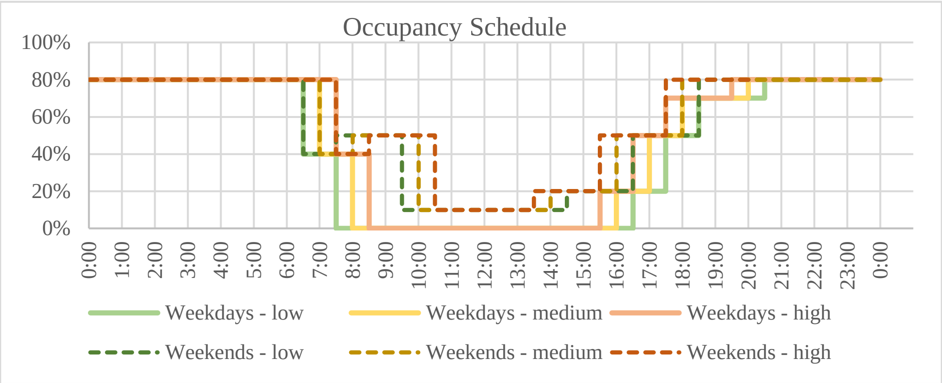

Figure 2. Occupancy schedule used in the energy models.

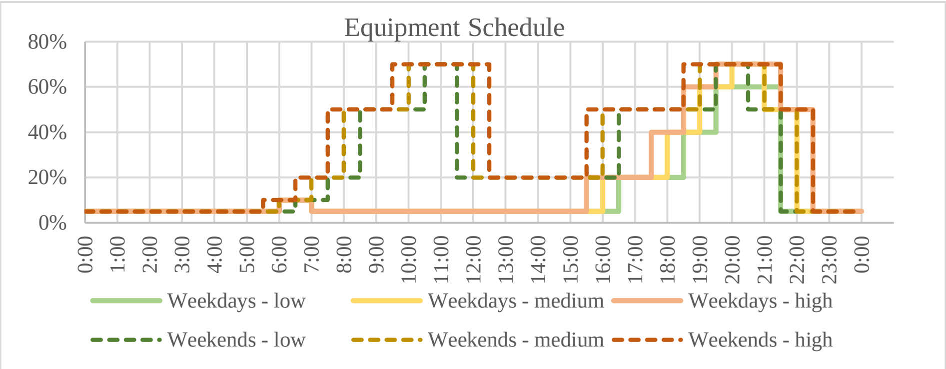

Figure 3. Equipment schedule used in the energy models.

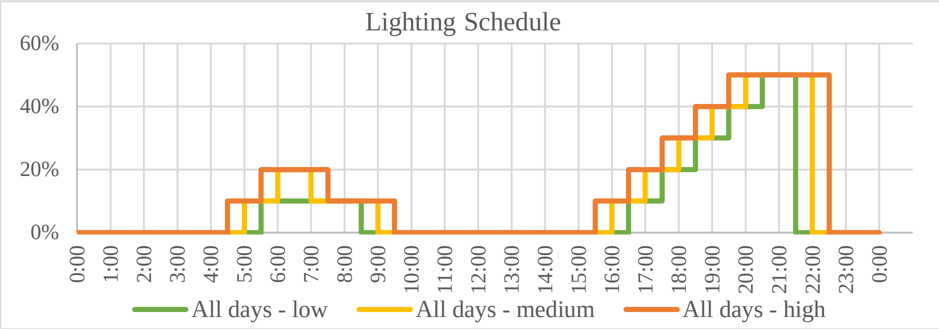

Figure 4. Lighting schedule used in the energy models.

3.1.2 EnergyPlus Model Generation and Execution

To conduct energy simulation for multiple buildings in an automated and organised manner, a modelling platform developed by University College London Energy Institute, SimStock, was used in this study. SimStock gathers data input and automatically generates dynamic building energy simulation models (IDF files) to be executed by EnergyPlus for all buildings within the analysed area, and can perform a wide range of scenario analyses (UCL Energy Institute, 2019). SimStock uses Python codes to complete the whole process.

3.1.3 Model Calibration

Model calibration refers to the check-up and adjustment of the baseline parametric model till the energy outputs are within a reasonable range for Beijing residential buildings. Since the studied neighbourhood consists of buildings constructed in different years, both up-to-date energy benchmarks and statistical energy usage data of old Beijing residential neighbourhoods were investigated as references. The annual energy use indices (EUI) and energy breakdowns are presented in Table 2. Dissimilarities can be noticed between these literature sources, but a reasonable range can be identified.

Table 2. Energy breakdown from reports for Beijing residential buildings.

<table>
<tr><th rowspan="2">Source</th><th colspan="3">Electric energy (kWh/m^2)</th><th rowspan="2">Heating energy (kWh/m^2)</th></tr>
<tr><th>Air conditioner cooling</th><th>Lighting</th><th>Equipment</th></tr>
<tr><td rowspan="2">DB11/T 1413-2017 (Beijing Bureau of Quality and Technical Supervision, 2017)</td><td rowspan="2">8.14</td><td rowspan="2">5.70</td><td rowspan="2">21.16</td><td>33.36 (mid-rise buildings)</td></tr>
<tr><td>27.66 (tower buildings)</td></tr>
<tr><td>Xu et al. (2011)</td><td colspan="3">26.88</td><td>87.22</td></tr>
<tr><td>Cai et al. (2009)</td><td colspan="3">10-30</td><td>57</td></tr>
<tr><td>Li (2018)</td><td colspan="3">15-30</td><td>132.30</td></tr>
<tr><td>Zhao et al. (2014)</td><td colspan="3">/</td><td>63.89</td></tr>
</table>

3.2 Sensitivity Analysis Method

After the establishment of the base case model, SA was developed based on the theories of the Morris Method. To obtain adequate data for SA, the aforementioned simulation was executed a large number of times: the analysed parameters were moved at evenly distributed levels in their domains OAT to form a "trajectory", and the corresponding energy simulation results at each movement were collected. To comprehensively discover the inputs' domain and reveal interactions between parameters (Norton, 2009), a trajectory number of r=20 was used for this study, as recommended in previous studies (Campolongo, Cariboni and Saltelli, 2007).

In each trajectory, moving each parameter plus the base case required a total number of levels $k+1$ (where k is the number of input parameters), indicating a total number of samples $r(k+1)$ required for the complete SA. Although some studies focused on the cost-effectiveness of retrofit or the comfort of the indoor environment (Streicher *et al.*, 2020; Alavirad *et al.*, 2022), this study focused on mitigating the energy usage, which is the main aim of China's carbon-neutral goal. Therefore, the sensitivity of each parameter was judged by their elementary effects (EE) as shown in Equation 1, where i is the parameter index, x_i is the parameter value, Y is the EUI (of total, cooling, and heating energy), and Δ_i is a single step added to the corresponding parameter:

$$EE_i(x) = \frac{Y(x_1, \dots, x_{i-1}, x_i + \Delta_i, x_{i+1}, \dots, x_k) - Y(x_1, \dots, x_k)}{\Delta_i} \quad \text{Equation 1}$$

EE was calculated each time a parameter value was changed, and this process was repeated for 20 trajectories to explore the sensitivity of the energy output across the whole input domain. A new measure μ^* was defined in Equation 2 to assess the overall importance of each parameter by calculating the average EE over the 20 trajectories (Campolongo, Saltelli and Cariboni, 2011). Absolute values of EE were used here to avoid positive and negative impacts cancelling each other out.

$$\mu_i^* = \frac{\sum_{i=1}^{r} |EE_i|}{r} \quad \text{Equation 2}$$

The standard deviation σ was introduced to assess the interactions and non-linear effects between parameters because the output would not vary regardless of how the trajectories moved if there were no interactions. According to de Wit and Augenbroe (2002), a parameter could be considered independent if $\sigma_i \leq 2\mu_i^*/\sqrt{r}$. The standard deviations were calculated using Equation 3.

$$\sigma_i = \sqrt{\frac{\sum_{i=1}^{r} (EE_i - \mu_i^*)^2}{r}} \quad \text{Equation 3}$$

To support the large calculation demand of the Morris Method, the Python library SALib was used. The "Morris" branch of SALib sampling and analysis functions were used when determining groups of input data and after energy simulation respectively to conduct a scientific and complete SA process and in the end, provide clear visualisation for the analysis results.

3.3 Determination of SA Parameters and Their Domains

As the number of required simulations is proportional to the number of input parameters, it is essential to identify and focus on the elements normally considered when retrofitting residential buildings in Beijing to limit computational load.

According to Management Regulations for Retrofitting Projects of Non-energy-efficient Residential Buildings in Beijing (MOHURD, 2011) and Technical Specification for Energy Efficiency Retrofitting of Existing Residential Buildings in Beijing (MOHURD, 2006), retrofit should include the reconstruction of the building envelope (roofs, external walls, external windows, doors), painting of the external walls, window and door air permeability, heat transmission and distribution system, and installation of temperature control and heat meters. In the meantime, encourage the use of shading devices.

In cold climates such as Beijing, the most efficient strategy to increase building energy performance is often considered to be improving the building fabric (Li, Calautit, *et al.*, 2023), while WWR, building orientation, and roof configuration are considered difficult to change for building retrofit. In addition, modifying parameters such as setpoint temperature, heating and cooling schedules and indoor activity were considered unsuitable for residential buildings because the occupants should not be asked to change their lifestyles and preferences. Therefore, this study focuses only on building envelope retrofit.

The 14 parameters considered for this study and their domains for sampling were presented in Table 3. It should be noticed that the thermal properties of walls and roofs were respectively represented by the conductivity, density and specific heat of their brick and cement layers, and the paintings on walls and roofs were represented by the thermal and solar absorptances of their surface layers. The domains for sampling were determined to be symmetrical around the baseline value, widely covering the reasonable range (both ends of the domains could be found in building design guides and standards).

Table 3. Range of the input parameters for SA.

ID	Parameter	Unit	Baseline	Range
1	Brick conductivity	W/m·K	0.85	[0.7, 1]
2	Brick density	kg/m^3	1500	[500, 2500]
3	Brick specific heat	J/kg·K	840	[640, 1040]
4	Cement thermal absorptance	/	0.9	[0.85, 0.95]
5	Cement solar absorptance	/	0.6	[0.3, 0.9]
6	Concrete conductivity	W/m·K	0.4	[0.25, 0.55]
7	Concrete density	kg/m^3	820	[320, 1320]
8	Concrete specific heat	J/kg·K	840	[640, 1040]
9	Ceramic thermal absorptance	/	0.9	[0.85, 0.95]
10	Ceramic solar absorptance	/	0.6	[0.3, 0.9]
11	Window U-value	$W/m^2 \cdot K$	2.5	[1.5, 3.5]
12	Window SHGC	/	0.45	[0.3, 0.6]
13	Shading depth	m	0.3	[0.1, 0.5]
14	Infiltration	$m^3/s \cdot m^2$	0.00125	[0.0008333, 0.0016667]

3.4 Prediction of Future Climate

The impact of future climate change on the SA result can be investigated by using the same parametric model, but replacing the current EPW file with a predicted weather file that can reflect future climate conditions, then repeating the process of using the Morris Method.

The future weather files were predicted using an Excel-based tool CCWorldWeatherGen developed by the University of Southampton Energy and Climate Change Division (University of Southampton, 2021) (Jentsch *et al.*, 2013). The tool creates predicted EPW files for climate change in 2050 and 2080. It transforms the current weather files based on the "morphing" methodology developed by Belcher, Hacker and Powell (2005). The "morphing" methodology starts from the original weather file and applies a shift and a linear stretch to the hourly recorded temperature, wind speed, relative humidity, cloud coverage, precipitation, and downward shortwave flux. The extent of the morphing refers to the global circulation model of the atmosphere and oceans (HadCM3) and the GHG emission projections developed by the UK Climate Impacts Programme (UKCIP02). This methodology was further combined with the Intergovernmental Panel on Climate Change (IPCC) report so that it allows the generation of climate change weather files for worldwide locations.

4. Results and Analysis

4.1 The Calibrated Baseline Model

The EnergyPlus models were established with split air conditioners and heat radiator systems to mimic common HVAC systems in residential buildings in northern China. After executing the simulations, models were visualised to check the configurations of the buildings and shading elements (Figure 5).

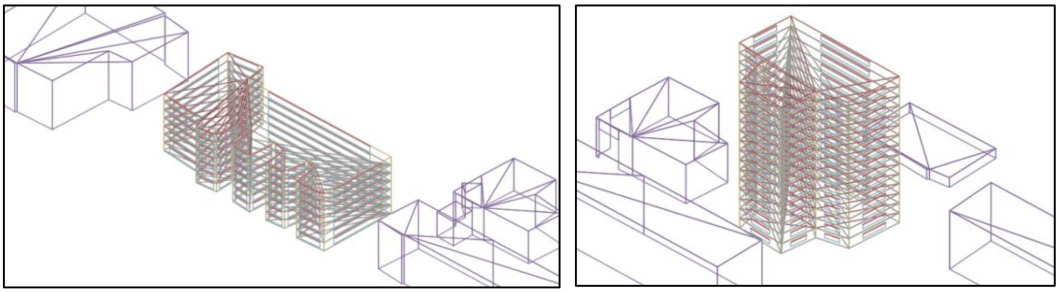

Figure 5. Visualisation of building No.26 (left) and No.35 (right) based on IDF files.

During the calibration process, it was found that only the cooling EUI deviated from the range introduced in Table 2, thus a few parameters were adjusted within reasonable ranges. The building design parameters eventually adopted for the model are shown in Table 4 and the resultant energy breakdown of the studied neighbourhood is presented in Figure 6. It can be noticed that heating is the major energy consumption, which accounts for 74.3% of the total energy. Equipment, lighting, and cooling energy consumption take up 14.1%, 4.8%, and 6.8% of the total energy respectively. This accords with the characteristics of residential buildings in cold northern cities in China.

Table 4. Non-geometric data used in the energy models.

Heating system	Radiator, central heating
Heating period	15th November – 15th March
Heating setpoint	18°C
Cooling system	Split air conditioner
Cooling period	1st May – 31st October
Cooling setpoint	26°C
Horizontal shading depth	0.3 m
Occupancy density	32 m^2/person
Equipment power density	8 W/m^2
Lighting power density	5 W/m^2
Infiltration rate	0.00125 $m^3/s{\cdot}m^2$
Ventilation rate	0.5 ach

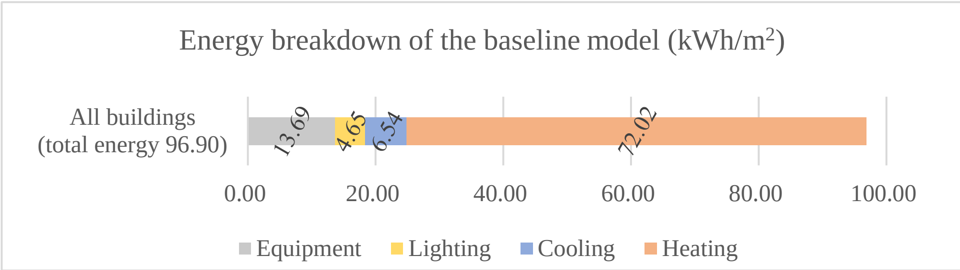

Figure 6. Energy breakdown of all buildings in the studied neighbourhood.

There were different preferences in building shapes in different years of construction, thus the buildings were categorised into three shape types for better analysis. The locations of buildings and their proportions in the total floor area of the neighbourhood are presented in Figure 1 and Table 5.

Table 5. Percentage area for buildings with different shapes.

Building shape	Building No.	Percentage of floor area
Tower building	31, 32, 34-36	24.7%
Mid-rise complex shape	24-26	16.3%
Mid-rise simple shape	4-16, 18-23, 27-33	59.0%

As presented in Figure 7, differences can be noticed between the three shape types, especially in heating energy. The mid-rise complex buildings resulted in lower heating EUI than the other two types, which is inconsistent with the common cognition that buildings with higher shape coefficients tend to have higher heat exchange with the ambient environment, but might be due to the complex shape that is only on the south elevation of these buildings, which maximised solar heat gain in the winter.

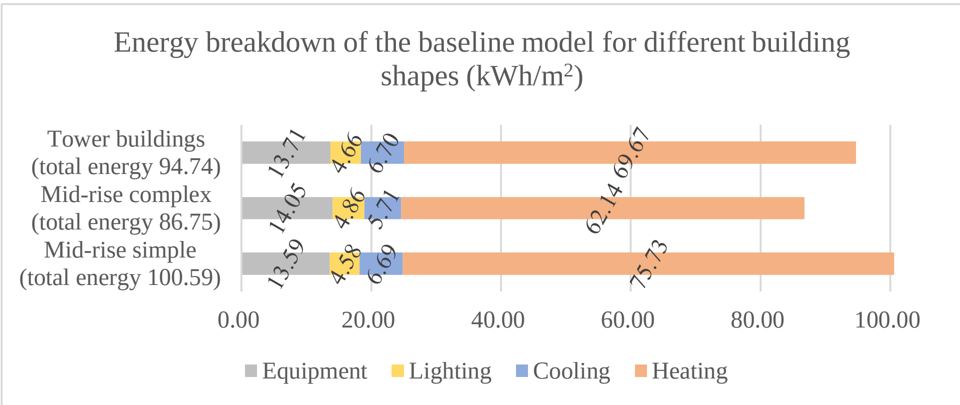

Figure 7. Energy breakdown of different types of buildings in the neighbourhood.

4.2 Sensitivity Analysis Results

Determined by the number of input parameters and trajectories, 300 EnergyPlus simulations were executed in total, using the parameters sampled by the python SALib library as illustrated in Figure 8 while other design factors remained constant. Codes were initiated to sample the parameters from a uniform distribution per the recommendation for retrofitted buildings at the design stage because the design values were equally probable (Tian, 2012; Nguyen and Reiter, 2015). Irregular shapes can be noticed in Figure 8, but the values were sampled with the same probability within the given intervals and did not have an impact on the results.

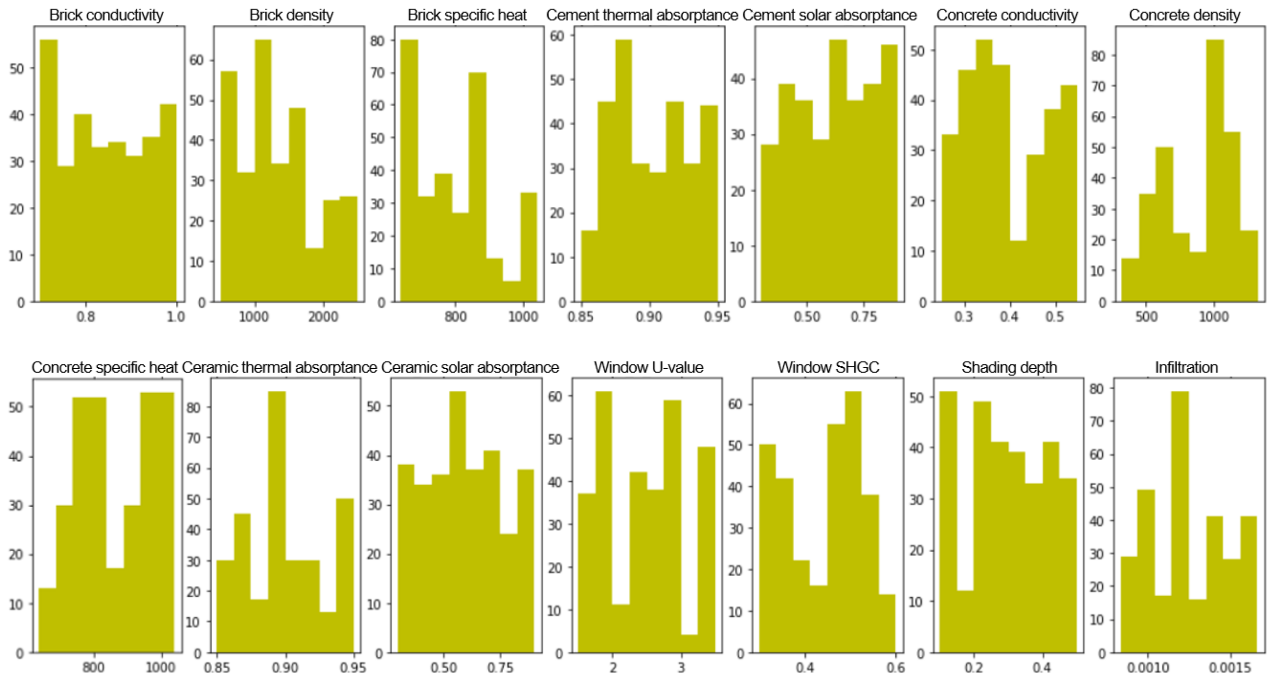

Figure 8. Distribution of the sampled parameters.

The total energy, cooling energy, and heating energy were collected and their corresponding EUIs were calculated for the neighbourhood as a whole, as well as for the three shapes separately. The average elementary effects μ^* and standard deviations σ were calculated, the results are presented in Figure 9-11 and the detailed data are attached in Table 7-9 in Appendix B.

4.2.1 Overall Building Performance of the Neighbourhood

As can be observed from Figure 9, the influences of parameters on the three types of buildings have similar rankings overall. Infiltration is noticeably taking the lead of all parameters with μ of approximately 25kWh/m^2, which means limiting the infiltration rate by 1m^3/s·m^2 can reduce the total energy by 25kWh/m^2. The window properties are the next most influential parameters, followed by the U-value and solar absorptances of external walls and roofs. Other parameters including shading depth, surface thermal absorptance, density, and specific heat of external wall and roof have relatively small influences.

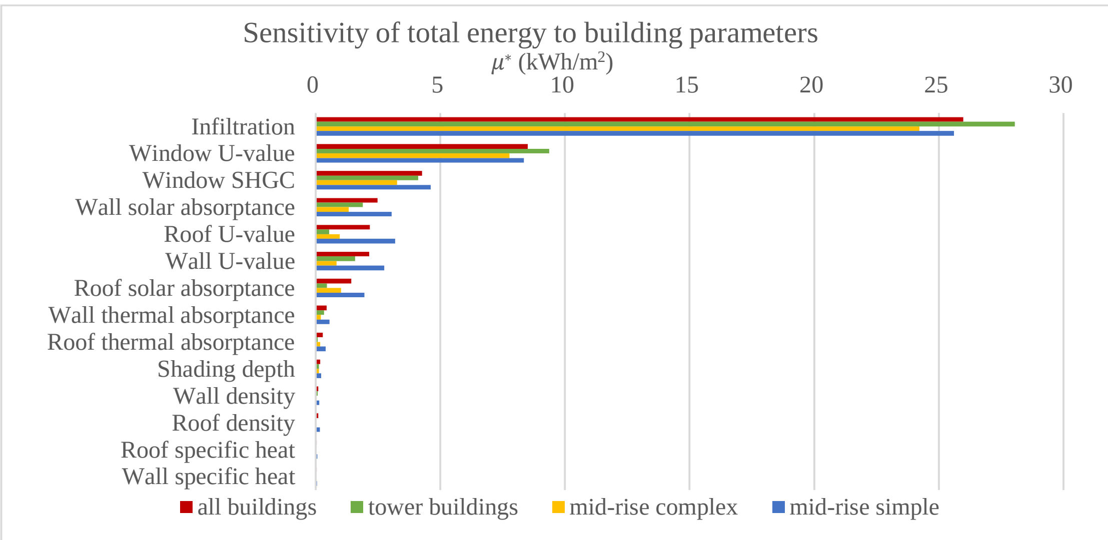

Figure 9. Comparison of the sensitivity of total energy between different building shapes.

Considering the influence on cooling energy alone, the parameters have different rankings. Figure 10 shows that the cooling energy consumption of the neighbourhood is the most sensitive to window SHGC, followed by the wall and roof solar absorptance, which have half of the influence of window SHGC. Following next are the shading depth and window U-value, but other parameters have relatively low influences on the cooling energy. It is noticeable that the most influential parameters for the cooling energy—SHGC, solar absorptance, and shading depth—are all related to solar radiation on the building interior. This implies that either limiting sunlight through windows, reflecting sunlight from building surfaces, or shading the façades can most effectively limit the need for cooling. However, because cooling energy only takes up lower than 10% of the total energy, its corresponding sensitivity is limited.

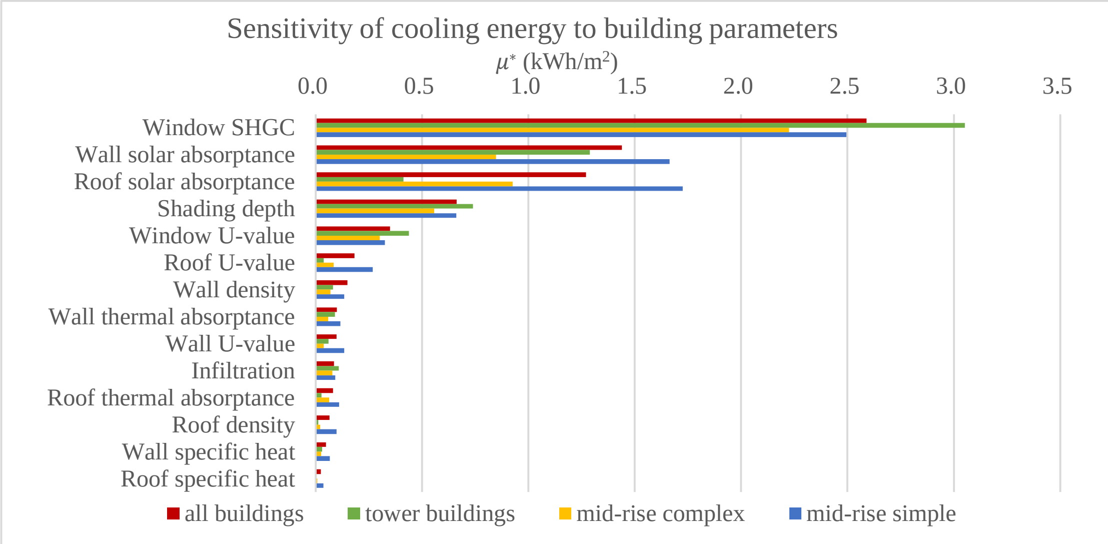

Figure 10. Comparison of the sensitivity of cooling energy between different building shapes.

Because of the large proportion of the total energy attributed to heating, the effects of the parameters on heating energy are similar to that on total energy (Figure 11). However, a difference from total energy is that heating energy has a relatively higher sensitivity to roof solar absorptance and shading depth. This is because of the considerable change in solar radiation on the building due to modification in roof surface solar absorptance and shading depth.

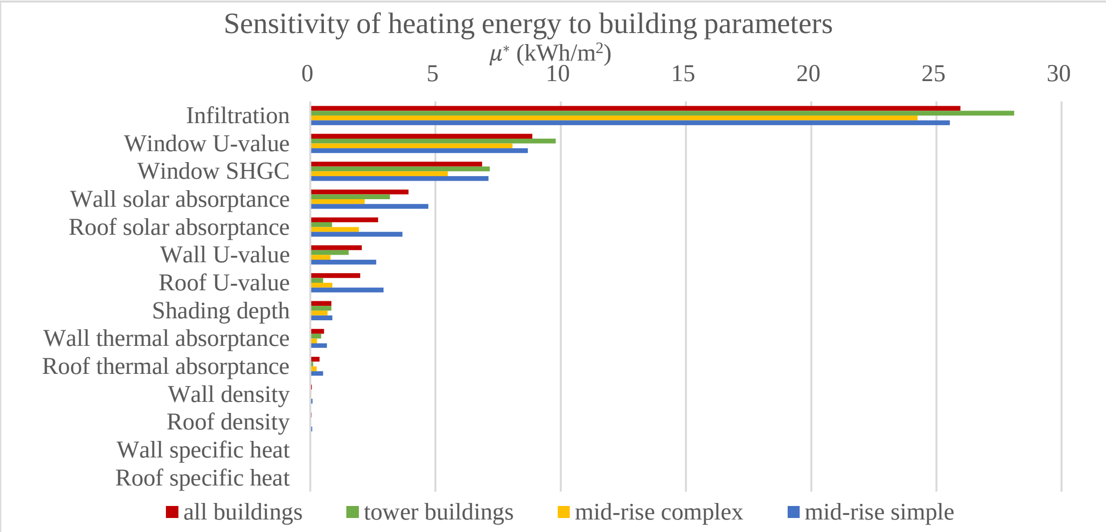

Figure 11. Comparison of the sensitivity of heating energy between different building shapes.

4.2.2 Interaction Between Parameters

The standard deviation σ calculated using the SALib library helps identify interactions between the investigated parameters. In each trajectory, different combinations of parameter values were adopted, thus a smaller σ value demonstrates that this parameter influences the building performance to a similar degree in every trajectory, that is, independent of other parameters. Conversely, a higher σ value indicates that a parameter interacts more with other parameters.

14 points representing the 14 parameters were plotted in Figure 12-14 for total, cooling, and heating energy respectively. In the figures, the right-hand side of the horizontal axis μ^* (the absolute μ) demonstrates larger influence; the upper side of the vertical axis σ demonstrates larger interaction, and the bottom means greater independence. The numbers near these points refer to the parameter ID numbers introduced in Table 3. According to de Wit and Augenbroe (2002), a parameter could be considered independent if $\sigma \leq 2\mu^*/\sqrt{r}$, thus a red line $\sigma = 2\mu^*/\sqrt{r}$ was plotted on each figure as a boundary of independence.

According to the three figures, the most influential parameters can all be considered independent as the points on the right-hand side are all underneath the red line. However, at the bottom-left corner, it can be noticed that the density and specific heat of the wall and roof and shading depth interact with other parameters when influencing total energy; wall U-value, wall specific heat, roof U-value, and infiltration are interactive for cooling energy; the density and specific heat of wall and roof are interactive for heating.

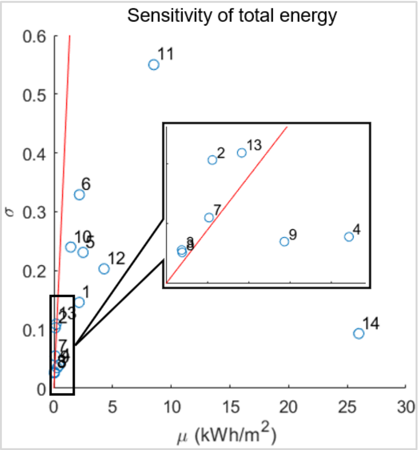

Figure 12. The average and standard deviation of elementary effects, total energy.

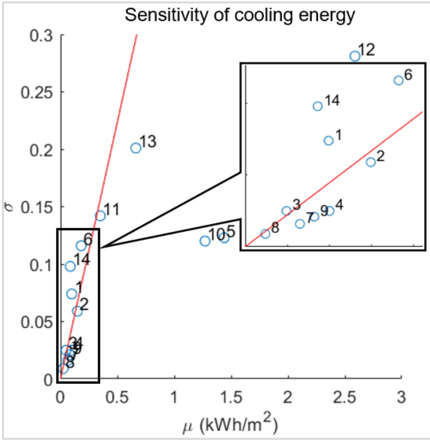

Figure 13. The average and standard deviation of elementary effects, cooling energy.

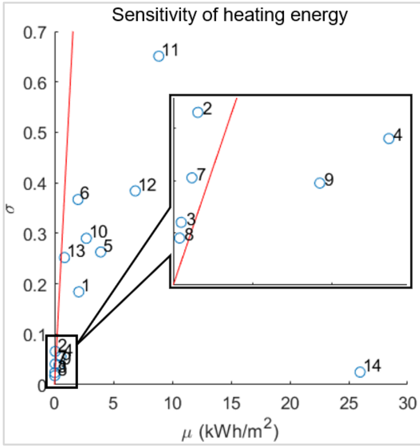

Figure 14. The average and standard deviation of elementary effects, heating energy.

A parameter interacting with others implies that the energy is not saved due to the change of this parameter alone, thus this is a calling for consideration that solely changing this parameter may not be effective as expected. However, because the most interactive parameters are the ones on the left-hand side of Figure 12-14 (i.e. the least influential ones), this interaction does not hinder the progress of identifying key building retrofit parameters.

4.2.3 Analysing Buildings Separately According to Shapes

In addition to analysing the sensitivity of different energy sectors, the buildings were also analysed by different shape types. The total energy is used for the analysis of this part. According to Figure 9, both infiltration and window U-value have larger influences on the tower buildings than the mid-rise buildings. This can be a result of the larger area of windows on the tower buildings, thus more leakage at window frames and more heat transfer through glazing than the mid-rise buildings. Therefore, improving the infiltration and window U-value of these buildings contributes to larger energy savings.

There is an evident tendency that the tower buildings are less likely to be affected by any roof properties (U-value, solar absorptance, thermal absorptance, density, and specific heat) than the mid-rise buildings because they have smaller roof areas relative to façade areas and making changes to other building design parameters is more effective than reconstructing the roof.

All other parameters (i.e., window SHGC, wall solar absorptance, wall U-value, wall thermal absorptance, wall density, and wall specific heat) bring bigger effects to tower buildings than mid-rise complex buildings, but smaller to mid-rise simple buildings. As this is in accordance with the total energy of the three shape types in the baseline model (see Figure 7), these parameters are considered to have no obvious advantages for any specific building shape.

4.2.4 Analysis Using Predicted Weather

Two future weather files were generated using the CCWorldWeatherGen tool for the years 2050 and 2080. From the current and generated weather files, the most noticeable difference is the outdoor dry-bulb temperature. As presented in Figure 15, the temperature throughout the year increases by approximately 3°C from the current weather to the 2050 weather and rises by a further 2°C from 2050 to 2080.

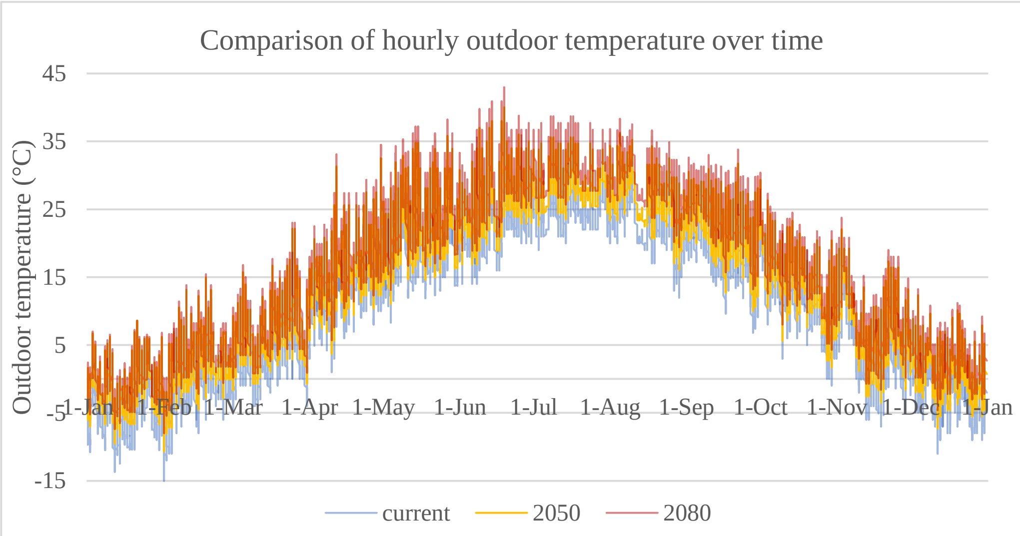

Figure 15. Comparison of hourly outdoor temperatures between different weather files.

Figure 16 shows the comparison of energy breakdown using the baseline building parameters and three different weather files. While the equipment and lighting energy were maintained, the cooling energy noticeably increased and the heating energy gradually decreased because of the predicted temperature rise. As a result, the total energy first increased, then almost remained from 2050 to 2080.

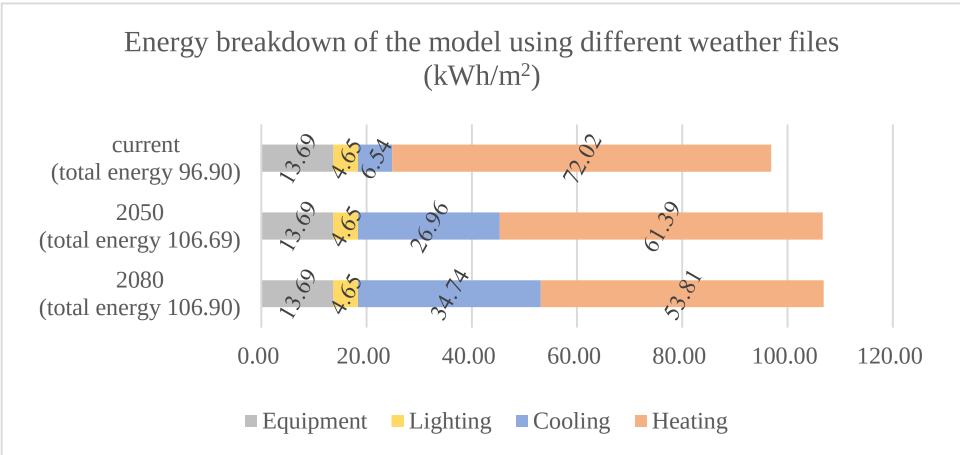

Figure 16. Energy breakdown of the model using current and predicted weather files.

After running the simulation and generating 20 trajectories respectively for the 2050 and 2080 scenarios, Figure 17 presents the comparison of the sensitivity of total energy at different time nodes, and the detailed data were attached in Table 10 in Appendix B. According to Figure 17, most of the parameters have a decreasing μ^* over time. This is because heating energy has a decisive influence on the ranking of most parameters in cold climates, since the heating demand of buildings is reduced in the future due to climate change (Ismail *et al.*, 2021), most μ^* values decrease with the decline of heating energy. However, the most influential parameters do not change over time in general, infiltration and window properties are unchangeably the top three influential parameters for the total energy.

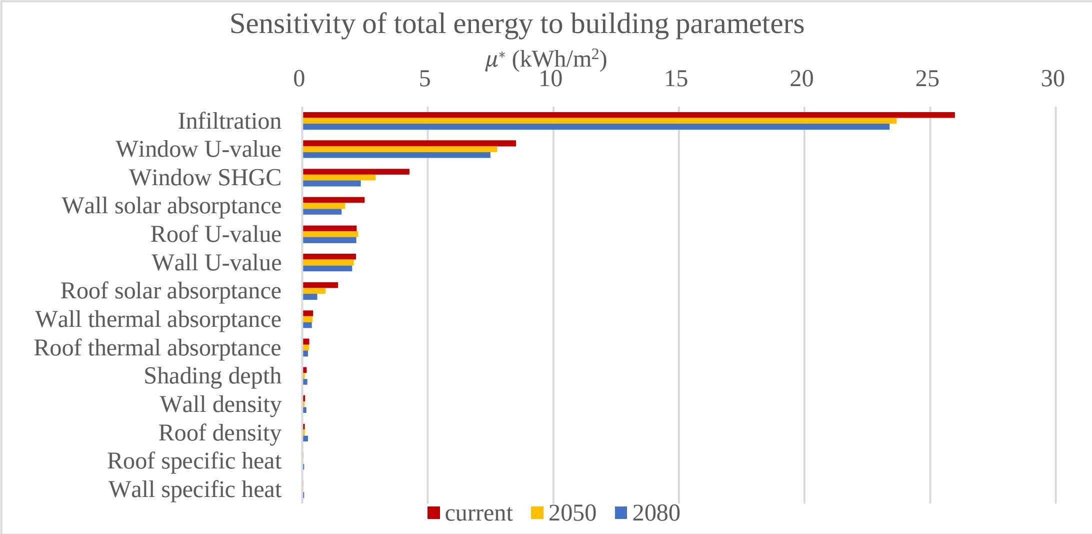

Figure 17. Comparison of the sensitivity of total energy between current and future weather.

Such findings are different from what the authors had previously assumed. According to the assumption, since there is a noticeable temperature rise in 2050 and 2080, some of the lower-ranking parameters such as U-value, density, and thermal absorptance may play an increasingly important role in improving the energy performance of buildings by protecting buildings from overheating. However, being consistent with the conclusions of some other literature (Gercek and Durmuş Arsan, 2019), because infiltration and properties of transparent surfaces are considerably significant for building energy consumption, this priority will not be changed in the next few decades.

A minor change can be noticed that the ranking of wall solar absorptance falls behind roof U-value and wall U-value. It can be summarised that the U-values of the building envelope are the more prioritised parameters, which was also agreed by other studies where improving the U-values of the building envelope has a great possibility to neutralise the impact of climate change on building energy up to 2080 (Chow, Li and Darkwa, 2013). Other parameters, including shading depth, thermal absorptance, density, and specific heat, although having minor changes in ranking, remain to have an insignificant influence on the total energy.

5. Discussion

The sensitivity of the total energy should be used to evaluate whether a building design factor is important in reality because the total energy links to carbon emissions and energy bills. Therefore, improving infiltration and window properties are highly recommended for residential buildings in Beijing due to their high influence. According to the analysis data, infiltration and window U-value have a positive correlation with total energy, whilst window SHGC has a negative correlation, thus the recommendation for building retrofit is to replace external windows with low U-value, high SHGC glazing, and frame with fine sealing. This finding has also been supported by several studies due to the significance of these parameters (Heo, Choudhary and Augenbroe, 2012; Li, Wang and Tang, 2019; Prabatha *et al.*, 2020; Zeferina *et al.*, 2021; Calama-González *et al.*, 2022; Ebrahimigharehbaghi *et al.*, 2022; Zhao, Li and Wang, 2022).

The factors following next on the ranking list are the solar absorptances and U-values of external wall and roof. The solar absorptances of building façades can be improved by repainting the outer surfaces. According to the analysis data, the solar absorptances were found to have a negative correlation with the total energy, thus it is recommended to apply darker and rougher coatings on the outer surfaces. Despite the dissent from previous studies in other climate zones about the benefits of lighter coatings (Nunes and Giglio, 2022; Machard *et al.*, 2023), this study provides insight into the balance of energy conserving in winter and wasting in summer due to solar heat gain specifically in cold climates. In similar studies, solar absorptances were also concluded more influential than those found in this study, which can also be attributed to different climates (Silva and Ghisi, 2020; Saurbayeva, Memon and Kim, 2023). For thermal insulation, lower U-values are desirable for reducing both heating and cooling energy, but the tower buildings are less sensitive to roof properties, thus the refurbishment of the roofs has a low priority for tower buildings.

The other parameters (i.e., the thermal absorptance, density, specific heat, and shading depth), have small influences compared to the former ones and thus these are negligible in practice. The fact that the density and specific heat are barely influential for total energy consumption is beneficial for decision-making as they are difficult to control with the U-value at the same time. Meanwhile, since the correlation between the studied parameters was found to be minimal, it indicated that a parameter is influential majorly because of the characteristics of itself and there is barely dependence on other parameters, which is also beneficial for easier decision-making.

These conclusions can be generally adopted on residential buildings in Beijing in need of retrofit plans because of the representativeness of the studied neighbourhood, in terms of building shape, age, location, etc. These conclusions inform stakeholders about the worthiest parts of the building stock to retrofit and help evaluate to which extent their buildings should be retrofitted according to their budget. Additionally, the conclusions can help policy-making institutions with new policies and building retrofitting standards.

According to the analysis using future weather files, if new retrofit guides or standards are made based on this study, apart from the slightly rising importance of roof and wall U-value, they will be applicable for the next few decades as the ranking of other parameters does not change.

Although the approach presented in this paper shows a comprehensive workflow for building SA projects, there are a few limitations that remain at this point of the study. First of all, the geometric model currently includes internal floors, but more accurate building performance results can be obtained if internal layouts, such as household and room partitions, are considered. Also, this result only represents residential buildings in cold climates because buildings in other climate zones focus differently on heating and cooling, and buildings of other types might tend to focus on different design parameters, e.g., a retail building in a warm climate can focus more on limiting cooling energy, and setpoint temperature can be a critical factor because it is managed by the building facility manager rather than controlled freely by occupants.

The following actions are recommended for future works: the buildings in this study were coarsely divided into three shape types, but it is an interesting topic to quantify building shapes according to their shape coefficients and investigate the relationship between sensitivity and building shapes. In addition, as also mentioned in several papers (Jafari, Valentin and Russell, 2016; Liu *et al.*, 2018; Zhou, Tam and Le, 2023), a few economics-related factors, such as retrofit initial cost, energy cost, discount rate, and the amount of available budget, can be added as SA parameters for future research to minimise the life-cycle cost of buildings, reduce the investment risk, and investigate long-term benefits. As some researchers pointed out (Zeferina *et al.*, 2021; Saurbayeva, Memon and Kim, 2023), using a single SA method is often insufficient and using multiple SA methods simultaneously is recommended to improve the reliability of the SA results.

6. Conclusion

This paper used sensitivity analysis to study a Beijing-based old residential neighbourhood in its retrofit, which is a novel application in China for a metropolis in a cold climate. 32 residential buildings in the neighbourhood were made into EnergyPlus models using geometric data captured from the map and non-geometric data presented by local design standards of the corresponding year of construction, different levels of activity schedules were allocated randomly to the model to imitate the randomness of the occupant activities. The Morris Method with 20 trajectories was used to conduct SA on 14 building-envelope-related parameters, using the current weather file and the predicted climate change weather files. A thorough analysis was carried out by examining the change in cooling, heating, and total EUIs in buildings with different shapes.

In brief, the result showed that for reducing annual energy consumption for residential buildings in Beijing, the recommended retrofit strategies are: (1) seal the frames of external windows and doors; (2) replace old external windows with low U-value and high SHGC windows; (3) repaint the external walls using darker colours and rougher texture; (4) if with adequate budget, add insulation layers at the outer side of the external walls. These recommendations for retrofit strategies will remain reliable in the next few decades, except for a small rise in benefit from improving wall U-value and roof solar absorptance.

Overall, the Morris Method is an effective SA method that demonstrates the prominent sensitivity of infiltration and window properties on building energy consumption through a clear visualization. The result indicates that the sensitivities of some parameters (infiltration and window properties) are consistent across multiple regions, while others are more unique to cold regions. This demonstrates the novelty of this study and fills the gap in research in cold regions. This article also found that various building shapes lead to different results, so it is necessary and effective to average the energy output of a climate zone using a neighbourhood rather than a single building.

Despite limitations in building location and type, this study shows a feasible workflow for determining suitable retrofit strategies for the existing building stock. Having removed the concern of future global warming impact on the results, this workflow is instructive for other developed or developing cities in the cold climate region due to the generalisability of the studied neighbourhood as in a metropolitan city. The results can be used to identify the most efficient, effective, and economic strategies, and also for policy-making or standard-setting in the building retrofit field. Future work is recommended to investigate buildings with different shape coefficients and to include economic factors.

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Appendix A. Building Envelope Structures of Energy Models

Table 6. Material and thermal properties of building construction (outer to inner).

Material	Thickness (m)	Conductivity (W/m·K)	Density (kg/m^3)	Specific heat (J/kg·K)	Thermal absorptance	Solar absorptance
External wall (bad), U-value = 1.97 W/m^2·K						
Cement plaster	0.02	0.72	1760	840	0.9	0.6
Brick (burnt)	0.24	0.85	1500	840	0.9	0.6
Cement plaster	0.02	0.72	1760	840	0.9	0.6
External wall (medium), U-value = 1.51 W/m^2·K						
Cement plaster	0.02	0.72	1760	840	0.9	0.6
Brick (burnt)	0.37	0.85	1500	840	0.9	0.6
Cement plaster	0.02	0.72	1760	840	0.9	0.6
External wall (good), U-value = 0.90 W/m^2·K						
Cement plaster	0.02	0.72	1760	840	0.9	0.6
Brick (burnt)	0.24	0.85	1500	840	0.9	0.6
Urea Formaldehyde Foam	0.024	0.04	10	1400	0.9	0.6
Cement plaster	0.02	0.72	1760	840	0.9	0.6
Roof (bad), U-value = 1.54 W/m^2·K						
Ceramic glazed	0.02	1.4	2500	840	0.9	0.6
Cement plaster	0.02	0.72	1760	840	0.9	0.6
Plaster	0.05	0.35	950	840	0.9	0.6
Cast concrete (medium)	0.13	0.32	1050	840	0.9	0.6
Roof (medium), U-value = 1.01 W/m^2·K						
Ceramic glazed	0.02	1.4	2500	840	0.9	0.6
Cement plaster	0.02	0.72	1760	840	0.9	0.6
Plaster	0.05	0.35	950	840	0.9	0.6
Cast concrete (light)	0.13	0.4	820	840	0.9	0.6
Mineral fibre	0.013	0.038	140	840	0.9	0.6
Roof (good), U-value = 0.80 W/m^2·K						
Ceramic glazed	0.02	1.4	2500	840	0.9	0.6
Cement plaster	0.02	0.72	1760	840	0.9	0.6
Plaster	0.05	0.35	950	840	0.9	0.6
Cast concrete (light)	0.13	0.4	820	840	0.9	0.6
Mineral fibre	0.023	0.038	140	840	0.9	0.6
Internal wall, U-value = 1.48 W/m^2·K						
Cement plaster	0.02	0.72	1760	840	0.9	0.6
Brick (aerated)	0.135	0.3	1000	840	0.9	0.6
Cement plaster	0.02	0.72	1760	840	0.9	0.6
Ceiling, U-value = 2.93 W/m^2·K						
Cast concrete (dense)	0.1	1.4	2100	840	0.9	0.6
Floor, U-value = 2.93 W/m^2·K						
Cast concrete (dense)	0.1	1.4	2100	840	0.9	0.6
Ground floor, U-value = 0.52 W/m^2·K						
Urea Formaldehyde Foam	0.05	0.04	10	1400	0.9	0.6
Cast concrete (dense)	0.1	1.4	2100	840	0.9	0.6
Floor screed	0.07	0.41	1200	840	0.9	0.73
Timber flooring	0.03	0.14	650	1200	0.9	0.78
External window U-value = 3.50 W/m^2·K						
Glazing		SHGC: 0.45			Visible transmittance: 0.7	

Appendix B. Sensitivity Analysis Results

Table 7. Comparison of the average and standard deviation of elementary effects between different building shapes, for total energy.

Total Energy								
Parameters	All buildings		Tower buildings		Mid-rise complex		Mid-rise simple	
	μ	σ	μ	σ	μ	σ	μ	σ
Infiltration	25.983	0.093	28.040	0.121	24.222	0.089	25.608	0.083
Window U-value	8.510	0.550	9.365	0.590	7.771	0.498	8.356	0.548
Window SHGC	-4.271	0.203	4.117	0.226	-3.262	0.187	-4.613	0.206
Wall solar absorptance	-2.485	0.231	-1.895	0.166	-1.321	0.092	-3.052	0.299
Roof U-value	2.173	0.329	0.541	0.102	0.967	0.187	3.187	0.462
Wall U-value	2.148	0.146	1.578	0.114	0.835	0.066	2.749	0.186
Roof solar absorptance	-1.432	0.240	-0.459	0.068	-1.013	0.152	-1.955	0.339
Wall thermal absorptance	0.442	0.039	0.336	0.023	0.211	0.014	0.550	0.054
Roof thermal absorptance	0.286	0.035	0.086	0.009	0.188	0.015	0.397	0.052
Shading depth	0.183	0.109	0.126	0.102	0.137	0.090	0.226	0.119
Wall density	-0.112	0.103	-0.079	0.059	-0.046	0.045	-0.148	0.141
Roof density	-0.104	0.055	-0.015	0.015	-0.021	0.020	-0.166	0.085
Roof specific heat	-0.039	0.026	-0.007	0.008	-0.009	0.012	-0.062	0.040
Wall specific heat	-0.038	0.028	-0.028	0.018	-0.017	0.016	-0.051	0.038

Table 8. Comparison of the average and standard deviation of elementary effects between different building shapes, for cooling energy.

Cooling Energy								
Parameters	All buildings		Tower buildings		Mid-rise complex		Mid-rise simple	
	μ	σ	μ	σ	μ	σ	μ	σ
Window SHGC	2.589	0.281	3.051	0.305	2.226	0.225	2.495	0.290
Wall solar absorptance	1.439	0.123	1.289	0.103	0.848	0.061	1.664	0.155
Roof solar absorptance	1.271	0.120	0.413	0.029	0.926	0.061	1.725	0.177
Shading depth	-0.663	0.201	-0.740	0.222	-0.557	0.165	0.661	0.202
Window U-value	0.350	0.142	0.439	0.161	0.302	0.126	0.326	0.141
Roof U-value	0.182	0.116	0.038	0.026	0.084	0.054	0.269	0.172
Wall density	-0.149	0.059	-0.082	0.037	-0.069	0.044	-0.134	0.095
Wall thermal absorptance	-0.100	0.025	-0.090	0.022	-0.059	0.015	-0.116	0.029
Wall U-value	0.099	0.074	0.060	0.056	0.038	0.039	0.134	0.095
Infiltration	0.086	0.098	-0.109	0.117	-0.079	0.091	0.093	0.093
Roof thermal absorptance	-0.082	0.021	-0.027	0.006	-0.064	0.014	0.111	0.029
Roof density	-0.065	0.016	-0.013	0.003	-0.021	0.005	0.099	0.025
Wall specific heat	-0.049	0.025	-0.030	0.018	-0.026	0.022	-0.066	0.015
Roof specific heat	-0.024	0.009	-0.005	0.002	-0.008	0.004	0.037	0.014

Table 9. Comparison of the average and standard deviation of elementary effects between different building shapes, for heating energy.

Heating Energy								
Parameters	All buildings		Tower buildings		Mid-rise complex		Mid-rise simple	
	μ	σ	μ	σ	μ	σ	μ	σ
Infiltration	25.966	0.025	28.107	0.033	24.254	0.023	25.543	0.027
Window U-value	8.860	0.651	9.803	0.704	8.073	0.585	8.682	0.648
Window SHGC	-6.860	0.384	-7.168	0.400	-5.488	0.340	-7.109	0.391
Wall solar absorptance	-3.924	0.263	-3.184	0.173	-2.170	0.100	-4.716	0.347
Roof solar absorptance	-2.704	0.290	-0.872	0.078	-1.939	0.180	-3.680	0.412
Wall U-value	2.059	0.184	1.529	0.132	0.805	0.078	2.625	0.238
Roof U-value	1.991	0.367	0.504	0.107	0.883	0.199	2.919	0.522
Shading depth	0.845	0.252	0.845	0.251	0.692	0.210	0.886	0.264
Wall thermal absorptance	0.543	0.056	0.427	0.038	0.269	0.026	0.666	0.072
Roof thermal absorptance	0.369	0.039	0.114	0.012	0.252	0.020	0.507	0.058
Wall density	0.062	0.066	0.040	0.047	0.031	0.034	0.082	0.085
Roof density	-0.047	0.041	-0.009	0.013	0.015	0.017	-0.077	0.063
Wall specific heat	0.020	0.024	0.014	0.019	0.012	0.014	0.026	0.029
Roof specific heat	-0.016	0.018	-0.006	0.008	0.008	0.010	-0.028	0.027

Table 10. Comparison of the average and standard deviation of elementary effects between current and future weathers, for total energy.

Parameters	current		2050		2080	
	μ	σ	μ	σ	μ	σ
Infiltration	25.983	0.093	23.672	0.086	23.385	0.235
Window U-value	8.510	0.550	7.764	0.487	7.496	0.493
Window SHGC	-4.271	0.203	-2.915	0.166	-2.335	0.376
Wall solar absorptance	2.485	0.231	1.705	0.182	1.571	0.312
Roof U-value	2.173	0.329	2.238	0.328	2.161	0.310
Wall U-value	2.148	0.146	2.049	0.128	1.993	0.130
Roof solar absorptance	-1.432	0.240	-0.938	0.211	-0.606	0.314
Wall thermal absorptance	0.442	0.039	0.406	0.036	0.384	0.040
Roof thermal absorptance	0.286	0.035	0.272	0.035	0.237	0.042
Shading depth	0.183	0.109	0.107	0.086	0.205	0.140
Wall density	-0.112	0.103	-0.096	0.100	-0.164	0.184
Roof density	-0.104	0.055	-0.108	0.064	-0.227	0.143
Roof specific heat	-0.039	0.026	-0.040	0.029	-0.084	0.062
Wall specific heat	-0.038	0.028	-0.039	0.049	-0.077	0.093