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Abstract:

Urban building energy model (UBEM) is a powerful tool to simulate performance and evaluate efficiency of upgrades for a group of buildings under the urban context. However, the larger the scale/number of buildings, more parameters must be collected to create energy models that cover each individual building, causing more uncertainties. To reveal this, this study created a UBEM for the mixed modern and historic buildings at a campus in China and produced a set of UBEMs that consider variations of key model parameters, with the modeled results meeting the 20% error range. The calibrated set of UBEMs were then used to evaluate uncertainties of energy-savings of four building energy retrofit (BER) measures. The first measure, BER 1, was to preserve the historic values of buildings; BER 2 to meet green building design standard; BER 3 to achieve 20% more savings than BER 2; and BER 4 to utilize renewable photovoltaic energy. For BER 1, BER 2, and BER 3, the energy savings of buildings of different ages varied within 10%–44%. For BER 4, the energy savings of buildings varied within 49%–505%, respectively, where the reason for higher than 100% is energy production is much higher than energy demand. Similar results can be concluded for building functions, for BER 1, BER 2, and BER 3, the energy-saving potentials varied within 6%– 45%, while 97%–492% to BER 4. This study can provide an important and significant reference to apply UBEM in evaluating energy-efficient retrofits as well as other energy-related studies that consider uncertainties.

Keywords: Urban building energy model, uncertainties, energy retrofit, model calibration, university campus

1. Introduction

With urbanization accelerating, cities host 65.22% of mainland China's population by the end of 2022 (National Statistical Bureau of the People's Republic of China, 2023). This urban sprawl has produced profound changes in the urban physical environment, consequently increasing urban energy consumption and global carbon emissions (Gonzalez, 2005; Rahaman et al., 2022). Debates concerning environmental upheaval and energy usage highlight the urgent need for more sustainable development in the building sector. Considering the large number of buildings in the existing stock and the high cost of demolition and reconstruction, it is more technically feasible and financially effective to retrofit buildings than to construct new ones. Multivarious energy retrofits already have been proposed in many research and engineering fields and applied in modern urban buildings with passive or active retrofit approaches (Rodrigues & Freire, 2021).

As known, the widely applied passive approach proposed to minimizes heat loss through building envelope, by reducing thermal conductivity, improving airtightness, maximizing daylight, and so on (Suárez & Fernández-Agüera, 2015). While active approach is also popular to upgrade heating, ventilation, and air-conditioning systems (Xin et al., 2018), replace high-energy appliances (Gupta & Gregg, 2016; Hinnells, 2008), renewable energy (Luddeni et al., 2018; Zhou et al., 2013), smart buildings (Ibaseta et al., 2021), and so on. In many retrofits to achieve higher energy efficiency, both active and passive approaches are often adopted in one retrofit project (Hu et al., 2021). Hu et al. combined the retrofits of wall insulation and photovoltaic (PV) installation to achieve an zero-energy residential building (Luddeni et al., 2018). Mata et al. found that the combination of various retrofit methods, including wall insulation, window replacement, and recovery system improvement, could achieve a 53% reduction of energy demand in Swedish residential building (Mata et al., 2013).

Those mentioned above have been adopted a lot to the modern buildings and those approaches are also highly beneficial for older buildings (Na & Shen, 2021). Historical buildings are typically recognized as having relatively poor energy efficiency performance, therefore, an alternative to retrofitting should be considered (Cho et al., 2020). In historic buildings, available energy-saving retrofit measures are more constrained than in modern buildings, and thus are fewer. For example, preservation of historic buildings must not damage the facade, and also, it is essential to understand the influence of the future climate on a historical building, e.g., its artwork, construction, and so on (Muñoz González et al., 2020). Also, Qu et al. proposed a novel holistic building retrofit approach and emphasized the role of saving materials and avoiding complicated installation on retrofit measures of histolic buldings (Qu et al., 2020). Even so, some studies also have investigated the retrofits on historic buildings (Ascione et al., 2017; Schibuola et al., 2018). Rota presents that the historical museum buildings can be retrofit, seeking to balance the “passive” energy performance of the building envelope and the “active” performance of the energy systems (Rota et al., 2015). Coelho and Henriques used passive retrofit measures in the view of conservation of high-valued artefacts with a hygrothermal model (Coelho & Henriques, 2021). Milone investigated energy-savings of two different retrofits of the building envelope of a heritage house, and thought viable and best available technologies for historic buildings should be non-invasive or passive (Milone et al., 2015).

No matter passive or active retrofits for modern and historic buildings, having an accurate estimation of a building’s energy consumption is quite important when making decisions on its renovation or retrofits (Kalogeras et al., 2020; Todorović et al., 2015). This requires validation of the energy model with measurement and simulation, which are frequently employed as efficient ways to assess the potential of various energy-saving methods before initiating a retrofit program for existing buildings (Hong et al., 2014). It usually requires detailed and accurate building energy model input and calibration, such as local weather, building schedule, envelope characteristics, and so on. However, this is a very time-consuming task and is also one of the 10 challenges discussed in Hong et al. (Hong et al., 2020). One thing that can’t be avoided is the uncertainty of a building energy simulation model (Ohlsson & Olofsson, 2021), which is due to unknown parameters that users have to guess at in the energy models. The uncertainty is enlarged in urban building energy model (UBEM) at a larger scale (Dilsiz et al., 2023). To create the energy model, a series of those inputs and parameters is usually set up (Sun & Hong, 2017). In the trial-and-error process, the inputs can be divided into known parameters that are easily acquired, such as building size, function, and equipment, and some unknown parameters that are difficult and costly to acquire, such as schedule, thermal conductivity, and operation. In such cases to deal with unknown parameters, common strategies are to apply existing well-established templates or representative constructions (Coakley et al., 2014). Some researchers even creatively proposed representative communities (blocks) to evaluate future energy uses of comprehensively considering the influences of urban development, building retrofits, and so on (Oraiopoulos et al., 2023). Such simplified methods may save time in the early design stage, but would consequently further widen the gap between the simulated and actual values, for accurate retrofit projects (Li et al., 2015).

Another solution is to conduct an on-site survey to calibrate the simulation model, minimizing the discrepancy between simulated and observed energy data (Manke et al., 1996). Numerous calibration approaches based on manual iterative parameter tuning have been developed, including using open data (Sun et al., 2022), collecting supplemental evidence (Pan et al., 2007), and applying graphical comparisons with an iterative trial-and-error process (Pedrini et al., 2002; Yang et al., 2016), trying to find a more reliable energy model. Chaturvedi and Rajasekar generated 15000 model configurations to assess weather, physical and operational uncertainties on the annual and peak cooling energy demands for a residential building, finding that simulations predicted 0.22–2.17 and 0.45–1.62 times variation on acutal demand (Chaturvedi & Rajasekar, 2022). To reduce uncertainties, González and Bandera recommended high-fidelity physical model to calculate and calibrate the energy models, which can improve 22.9% of energy simulation accuracy (González & Bandera, 2022). Zhu et al. combined approximate Bayesian computation and machine learning algorithms to consider calibration of building energy models under uncertainty (Zhu et al., 2020), and a similar approach to analyze uncertainties can be also found in (Calama-González et al., 2021). A nested Fuzzy Monte-Carlo approach also was applied to quantify uncertainties from various inputs and parameters in building energy models (Shamsi et al., 2020). The reduced-order grey box energy model also has become widely recognized as an issue in building energy-saving retrofitting that needs to be considered, no matter what kinds of objectives and constraints (Gabrielli & Ruggeri, 2019) are being addressed.

However, two retrofit issues still need more investigations: the feasibility for the mixed modern and historic buildings at urban block level, and concomitantly uncertanties for decision of urban block retrofit measures when using energy simulation estimation of energy savings at a larger scale. On one hand, historic buildings are usually not separate in the urban context; rather, they are mixed with modern buildings. Therefore, full consideration of the larger-scale mixed urban block rather than individuals should be taken in urban building retrofit projects (Valencia et al., 2022). Meanwhile, different retrofit measures should be proposed for both modern and historic buildings. However, this is rarely investigated in the current literature. On the other hand, UBEM is the efficient and necessary tool to quantify energy performance on a larger spatial scale (Reinhart & Cerezo Davila, 2016). As the scale increases, accurate and detailed data acquisition becomes more difficult, and more unknown data needs to be determined by estimation and calibration. Therefore, the uncertainty of UBEM should be considered significantly.

To address the above issues, a campus of Southeast University was selected as the case study. It has a mix of modern and national historical buildings with different functions and ages varying from 1922 to 2004. Several passive and active energy retrofit measures were proposed for both modern and historical buildings to meet different energy-saving targets. The UBEM of the campus was created with on-site survey and different feasible inputs were determined by a validation process using actual energy records. To consider the uncertainties, multiple sets of calibrated models that meet the error level of 20%, were adopted rather than one calibrated model, to evaluate the energy-savings of different retrofit measures. Finally, this study analyzed the impact of uncertainties from calibrating UBEM on energy-saving potentials of different retrofits for different-age and -type buildings.

2. Methodology

2.1 Framework of the methodology

Fig. 1 illustrates the general framework of conducting a building energy retrofit process with the UBEM tool. The first stage is to create the parameterized simulation model of the building group using the Rhino tool and its built-in Grasshopper platform. On-site survey were to obtain the detailed building information, such as building shapes, floors, window-to-wall ratios, and so on. The second stage is to configure the UBEM, including determining the key inputs and dynamic simulation outputs (heating, cooling, and so on). In this stage, this study collected local microclimate data as the weather input from an on-site experiment to create the Energyplus Weather (EPW) file, and energy records to calibrate the UBEM. In stages 3 and 4, several energy-saving retrofit measures are proposed to combine different measures for modern and historical buildings. With the calibrated UBEM, the energy-saving potentials of each retrofit measure was evaluated for different types of buildings. Finally, this study analyzed and determined the optimal energy retrofit solution and the uncertainties from different parameters.

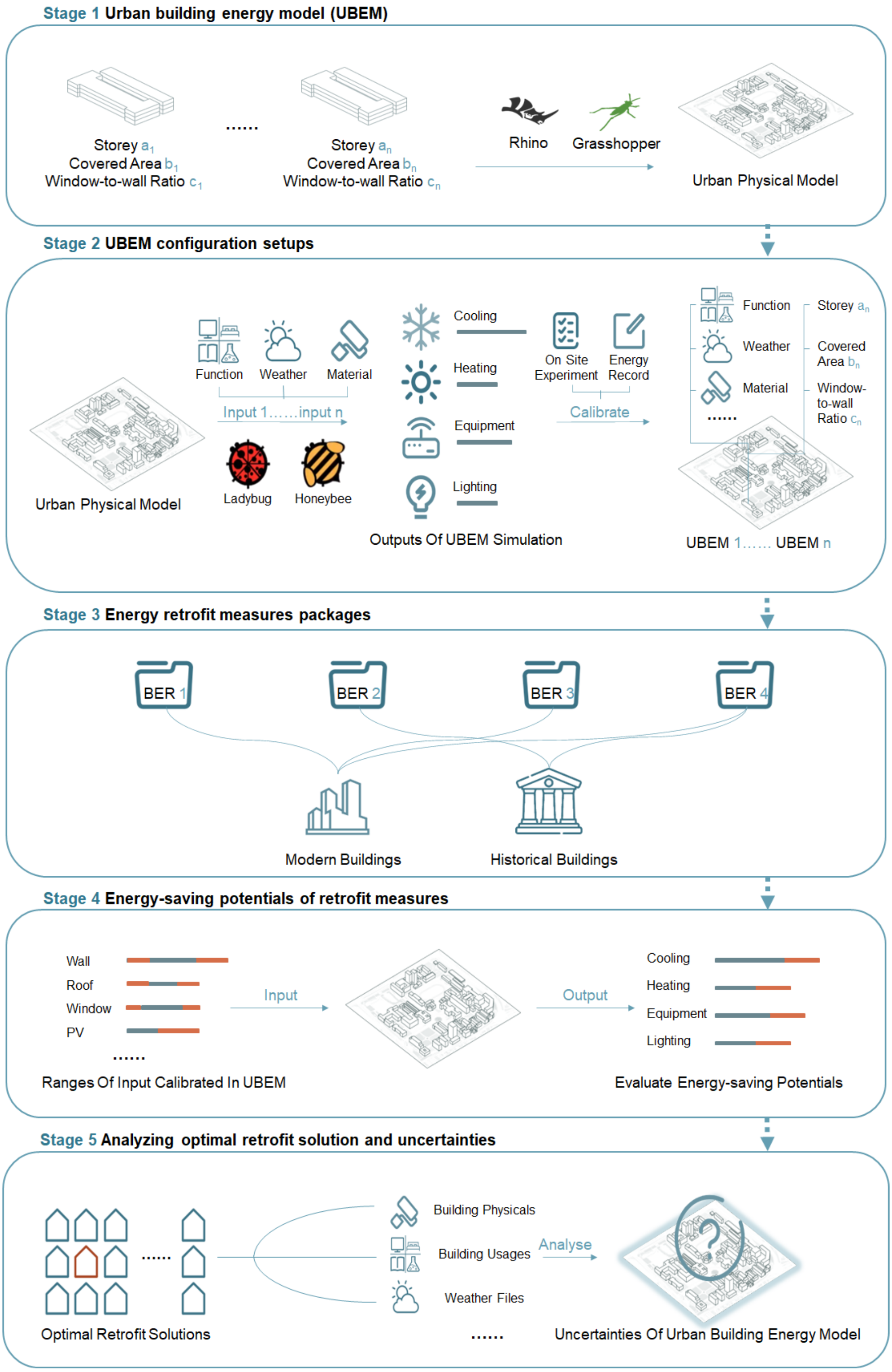

Fig. 1. The general framework of a building energy retrofit assisted with UBEM

2.2 Case campus building group

Southeast University (SEU, Fig. 2) was selected as the case urban block. It is located in the center of Nanjing City, Jiangsu Province, China. SEU has been built since 1900s and is a complex of historic and new buildings with a total land area of 411,309 m^2. Since the buildings of SEU are of different ages, the architectural functions, sizes, and energy consumption of each building also varies greatly (Fig. 3). In this study, 19 SEU buildings with real electricity consumption data were selected for energy retrofit trials, including office buildings, laboratories, educational buildings, and public buildings. Table 1 summarizes information of the selected buildings. Except Liwenzheng Building, and two-thirds of the buildings are brick-concrete structures, and the rest are reinforced concrete structures. Brick is mostly used as an exterior wall material, and cement block is used as exterior facade material. Before the 1960s, the buildings all adopted the form of a pitched roof, and vice versa after the 1980s. After the 1980s, the number of building floors is generally higher than before the 1980s.

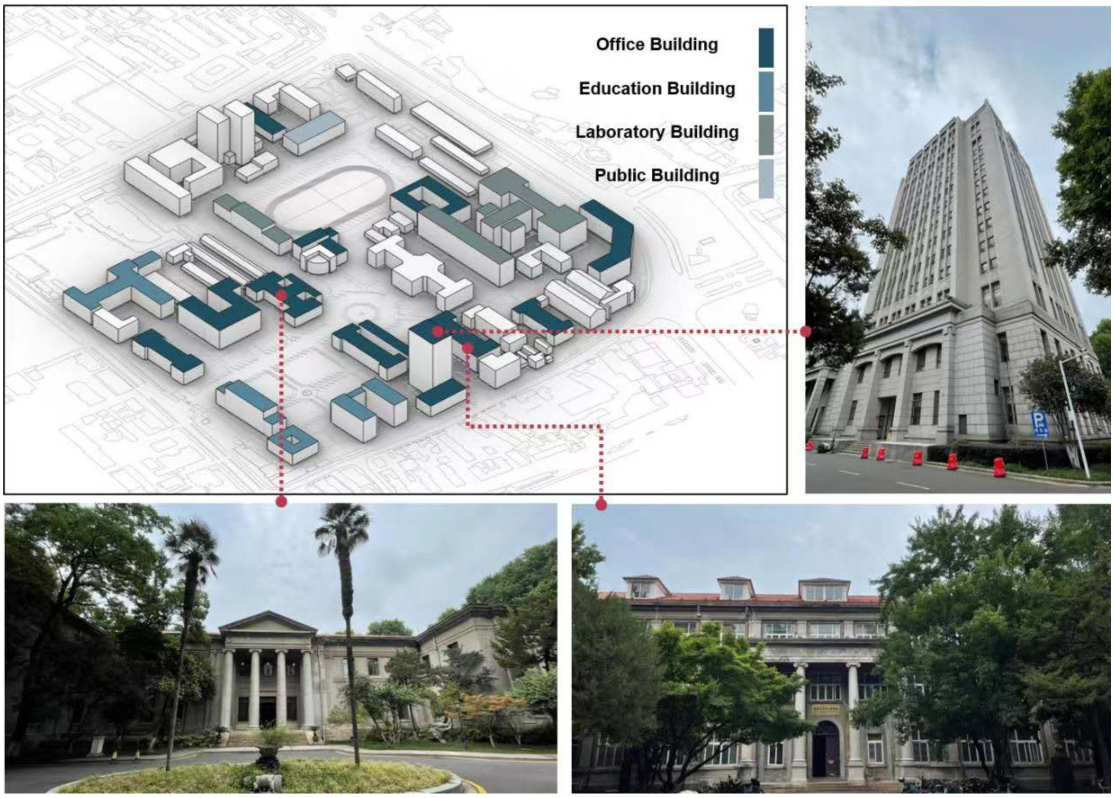

Fig. 2. The building plan of the Southeast University campus and actual images of three examples of office buildings

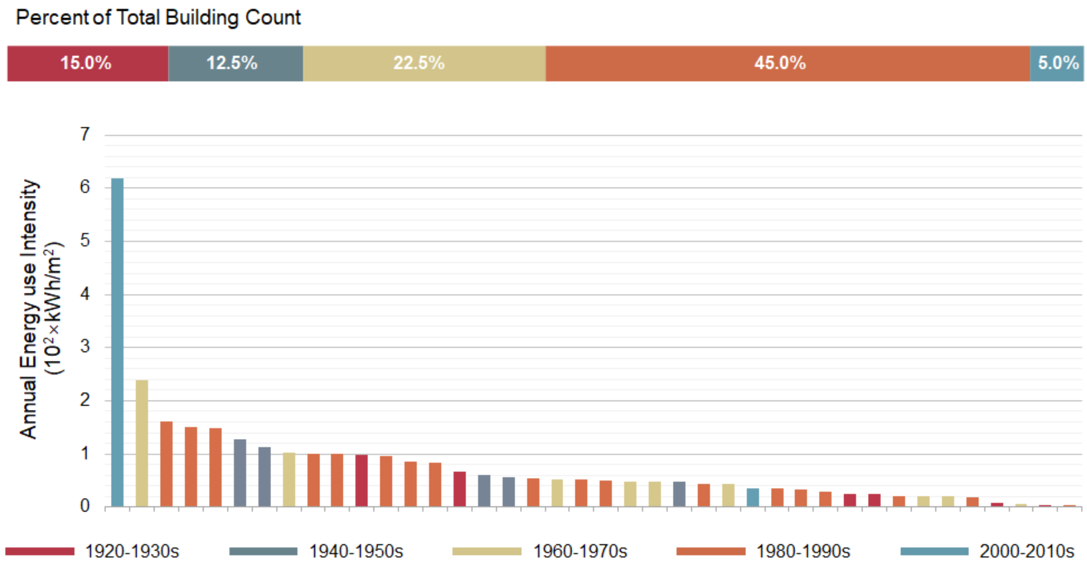

Fig. 3. Annual energy usage of buildings in Southeast University campus

Table 1. Summary information of buildings in the Southeast University campus

Name	Year	Structure	Wall	Roof	Storey	Floor area (m^2)	Window-wall ratio	Function
Gymnasium	1922	Brick-concrete	Brick	Slope	3	3,602	0.13	Public
The Old Library	1922	Brick-concrete	Brick	Slope	2	4,500	0.27	Office
Jianxiong	1927	Reinforced concrete	Brick	Slope	3	5,072	0.40	Office
Zhongda	1929	Brick-concrete	Brick	Slope	3	6,516	0.22	Office
Jinling	1937	Brick-concrete	Brick	Slope	3	3,471	0.24	Office
Wusi	1954	Brick-concrete	Brick	Slope	3	4,497	0.35	Office
Wuwu	1955	Reinforced concrete	Brick	Slope	4	8,584	0.34	Office
Hehai	1957	Brick-concrete	Brick	Slope	2	1,766	0.18	Office
Nangao	1957	Brick-concrete	Brick	Slope	4	3,938	0.20	Lab
Dongli	1957	Reinforced concrete	Brick	Slope	4	11,326	0.30	Education
Zhongxin	196X	Reinforced concrete	Brick	Flat	6	10,902	0.20	Lab
Zhongshan	1982	Brick-concrete	Brick	Flat	6	7,482	0.22	Education
Dongnan	1982	Brick-concrete	Brick	Flat	3	2,859	0.33	Education
Library	1985	Brick-concrete	Brick	Flat	5	8,145	0.42	Office
Qiangong	1987	Brick-concrete	Brick	Flat	6	5,595	0.18	Education
Publisher	1990	Reinforced concrete	Cement block	Flat	4	2,086	0.14	Office
Cezhen	1994	Brick-concrete	Brick	Flat	4	2,993	0.16	Office
Architecture Design Institute	199X	Reinforced concrete	Cement block	Flat	4	7,106	0.30	Office
Liwenzheng	2004	Brick-concrete	Cement block	Flat	6	30,000	0.21	Lab

2.3 On-site experiment

In this study, we installed one microclimate station on the roof of a seven-floor building (Qiangong, lat: 32.06; long: 118.80) in SEU. The microclimate station (Fig. 4) was from the Onset Computer Corporation (www.onsetcomp.com). It was charged by an AC adapter and equipped with a solar panel to produce power stored in the battery. The data can be stored locally as well as transferred to an online server through a Wi-Fi channel. The parameters used in this study consist of the temperature (°C), relative humidity (RH, %), direct normal solar radiation (watts per square meter [W/m^2]), wind speed (meters per second [m/s]) and direction (°). Table 2 shows the basic information about the version, operating temperature, accuracy, resolution, measurement range, and size of the selected sensors in this study.

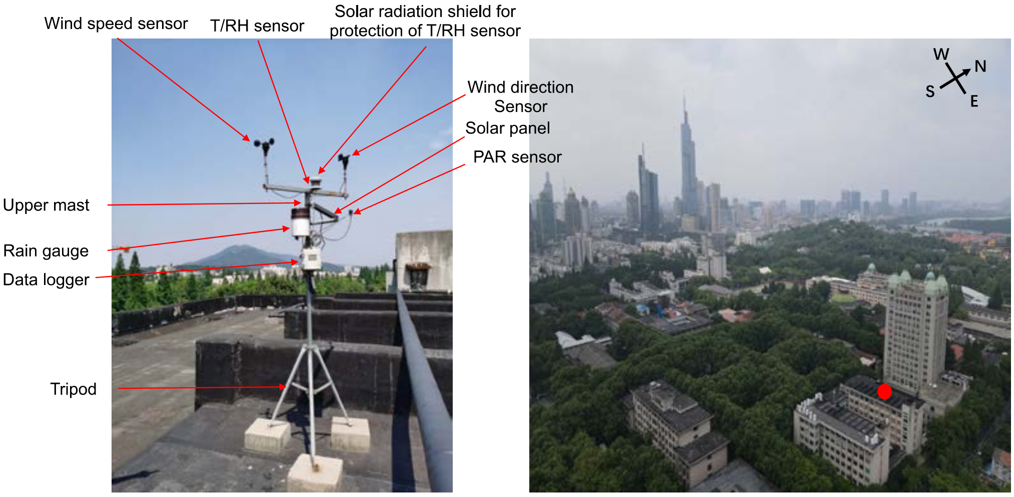

Fig. 4. The presentation of the microclimate station for the experiment in this study

Table 2. The basic information of sensor set used in this study

	Data Logger	Temperature/ Humidity	Wind Speed	Wind Direction	Solar Radiation
Version	RX3003	S-THB-M002	S-WSB-M003	S-WDB-M003	S-LIB-M003
operating temperature	40~+60℃	-40~+75℃	-40~+75℃	-40~+70℃	-40~+75℃
Accuracy	-	T: ±0.21℃ RH: ±2.5%	±1.1m/s or ±4%	±5°	±10 W/m^2 or ±5%
Resolution	-	T: 0.02℃ RH: 0.1%	0.5 m/s	1.4°	1.25 W/m^2
Measure-ment range	-	T: -40~+75℃ RH: 0~100%	0~76 m/s	0~355°	0~1280 W/m^2
Size	186mm(H)×181 mm(L) × 118 mm(W)	10 mm × 35 mm	410 m × 16 mm	460 mm × 200 mm	41 mm(H) × 32 mm(Φ)

2.4 UBEM configuration

2.4.1 The tool for UBEM

The UBEM simulation in this study was mainly based on the Rhino platform. Rhino is a 3D modeling software widely used in architectural design, industrial manufacturing, and other fields. Its built-in visual programming plug-in Grasshopper can realize the simulation operation link to Rhino design model, which is convenient for architectural designers to adjust their design simultaneously thourgh building performance simulation. Among them, Ladybug and Honeybee are free open-source plug-ins for Grasshopper, and those tools can simulate energy consumption with an Energyplus engine in a Grasshopper environment, which can help create all sets of uncalibrated energy simulation models for next analysis. The UBEM configuration is divided into four modules: the parameter setting module, morphology generation module, performance simulation module, and data record module (Fig. 5).

The parameter setting module mainly needs information of site weather, building physical parameters and building thermal parameters. The first step is to input the waeather information by creating an EPW file with the on-site micro-climate station and to obtain the building physical parameters through field investigation. Then, this study establishes the energy simulation model with Honeybee.

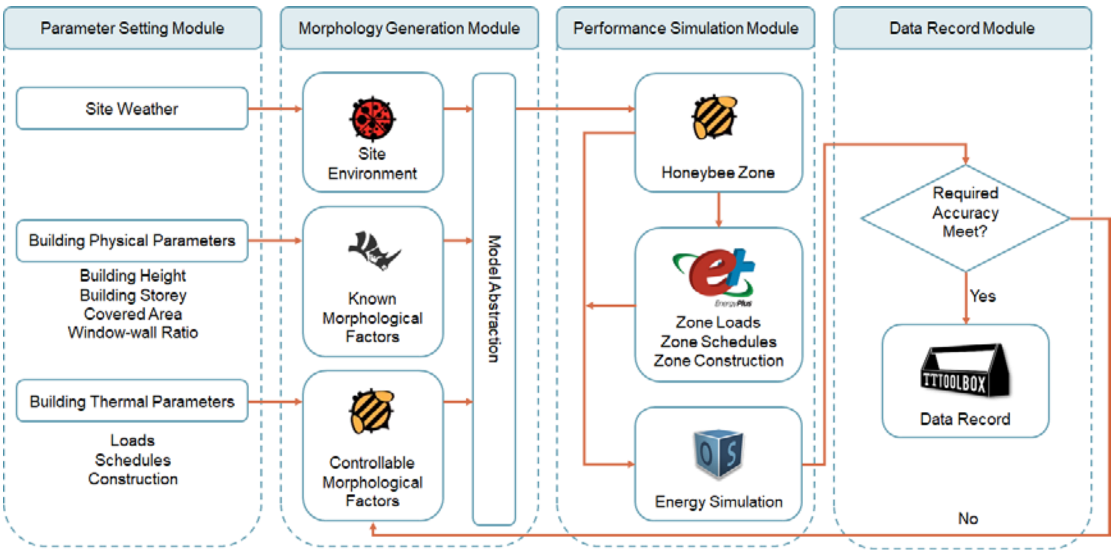

Fig. 5. Energy consumption simulation process with UBEM

2.4.2 Parameter settings for UBEM

Considering that building thermal parameters are difficult to obtain through experiments, this study selects several references for different inputs based on the actual situation (Table 3). Wall and window construction can be obtained through on-site survey. Roof and floor construction refer to the Honeybee's typical value. For equipment load, lighting density, and number of people, this study referred to the *Design Standard for Energy Efficiency of Public Buildings GB 50189-2015*, which also conforms to the energy usage habits of Chinese public buildings. ASHRAE 90.1 is a recommended default standard in Honeybee for further customization of the model inputs. Table 4 shows the performance characteristics for different building types. The certain value ranges for UBEM validation in Table 5 are assigned through trial-and-error based on Table 4. The typically ±50% input range ensures most simulation results covering real energy data. Other parameters' settings are concluded in Table 4 and 5.

Considering the characteristics of campus buildings, this study set up a timetable to distinguish the hourly room occupancy rate during the semester, summer and winter vacation, weekdays, and weekends (Fig. 6). We made sure the input range of the parameters was large enough for the tolerance of UBEM validation. After the parameters were input, the building physical model was established through Rhino and Grasshopper, thermal parameters were input through Honeybee and Ladybug, and finally the data were integrated to Energyplus engine for energy simulation. When the accuracy of the simulation results met the requirements, the following data were recorded.

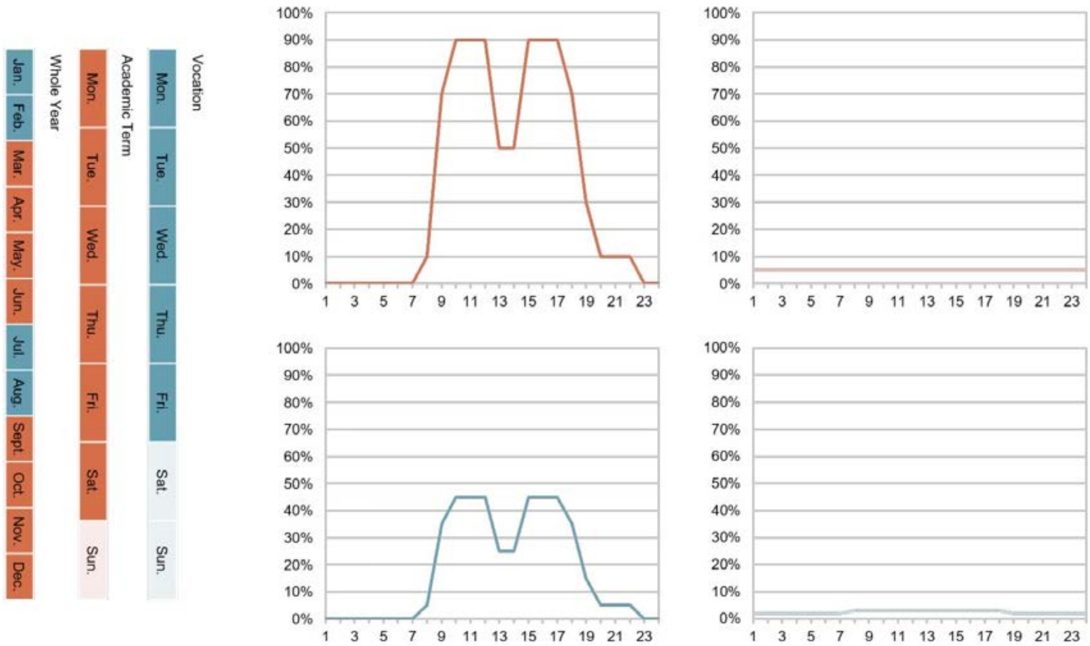

Fig. 6. The whole year occupancy schedules of Southeast University campus

Table 3. The reference of input parameters

Input Parameters	**Reference**
Wall Construction	On-Site Survey
Window Construction	Typical Value of Single Pane
Roof Construction	Typical Value of Honeybee
Floor Construction	Typical Value of Honeybee
Equipment Load Per Area	*Design Standard for Energy Efficiency Of Public Buildings GB 50189-2015*
Lighting Density Per Area	*Design Standard for Energy Efficiency Of Public Buildings GB 50189-2015*
Air Infiltration Rate	ASHRAE standard 90.1
Number of People Per Area	*Design Standard for Energy Efficiency Of Public Buildings GB 50189-2015*
Ventilation Per Person	ASHRAE 90.1

Table 4. Load settings for different types of buildings

Input Parameters	**Office**	**Education**	**Laboratory**	**Public**
Equipment Load Per Area (W/m^2)	7.5	15	22.5	7.5
Lighting Density Per Area (W/m^2)	9	9	10	7
Air Infiltration Rate (ACH)	0.5	0.5	0.5	0.5
Area Per Number of People (m^2/ppl)	10	6	10	6
Ventilation Per Person (m^3/s)	30/3,600	30/3,600	30/3,600	30/3,600

Table 5. Performance characteristics during the UBEM configuration

Input Parameters	**Default**	**Unknown Parameter Values**

			Low	Typical	High
Wall Construction (W/(m^2*K)		-	0.2	0.4	0.6
Window Construction	U-Value(W/(m^2*K))	2.5	-	-	-
	Solar Heat Gain Coefficient (%)	60	-	-	-
	Visible Transmittance (%)	55	-	-	-
Roof Construction(W/(m^2*K))		0.5	-	-	-
Floor Construction(W/(m^2*K))		1.5	-	-	-
Equipment Load Per Area(W/m^2)		-	7.5	15	22.5
		-	15	30	45
Lighting Density Per Area(W/m^2)		-	4.5	9	13.5
Air Infiltration Rate (ACH)		-	0.05	0.5	0.95
Number of People Per Area(m^2/person)		-	12	6	4
		-	20	10	3/20

Note： '-' means the 'not applicable' in the corresponding setting.

2.4.3 Calibration process of UBEM

Fig. 7 shows the validation process for iterations of UBEM. This study also referenced the 20% error requirement used in the energy consumption simulation conducted by Nagpal et al. at Harvard University (Nagpal & Reinhart, 2018). The simulation outputs are compared with the real energy consumption to judge whether accuracy is accepted. If yes, the parameter settings should be output. Otherwise, it is necessary to repeat the simulation to adjust the controllable unknown input parameters, and the Grasshopper slider is used to automatically iterate the input parameter. In the process, each building will have multiple sets of feasible inputs with modeled energy results in an acceptable range. The set of these models will be used in Section 2.5.

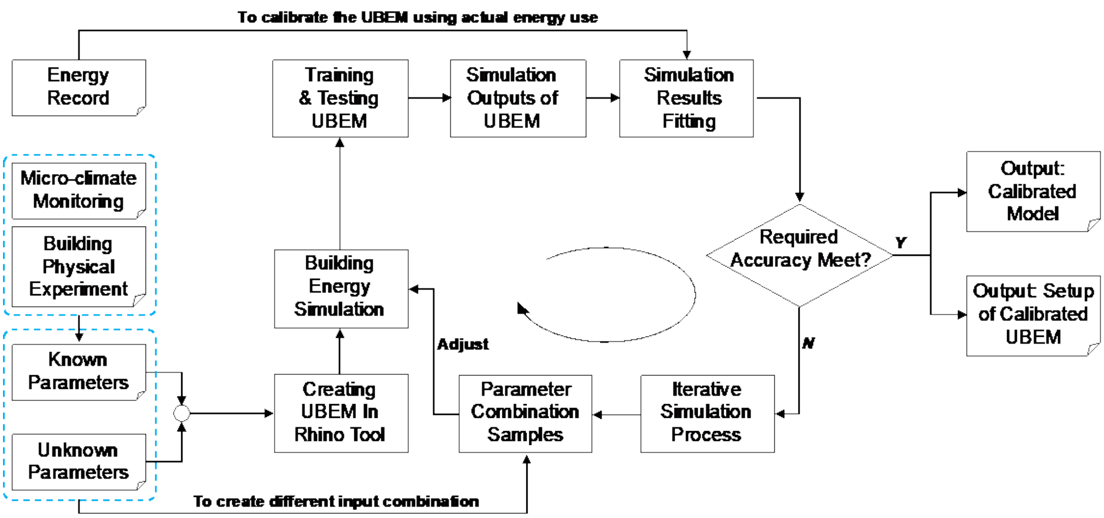

Fig. 7. Flowchart illustrating the UBEM calibration methodology

2.5 Building energy retrofit measures

Once the feasible calibration models received, they will be used to energy simulation for different building energy retrofit measures. As a mixed historic urban block, the energy retrofit of SEU needs to consider the needs of both historical and modern buildings. Therfore, this study puts forward four retrofit targets with different energy-saving targets as well as four building energy retrofit (BER) measures. Multiple calibrated models of each building will be applied according to these retrofit measures and multiple simulations will be conducted to generate multiple sets of energy savings under BERs. Based on the current requirements of green building and the buidling characteristics of the mixed campus, the following four targets were proposed:

- Target 1 maintains the historic campus style without damaging the building structure and transforms the parts that are easy to change.
- Target 2 enables building energy consumption to meet the requirements of China's *Assessment Standard for Green Building GB/T 50378-2019.*
- Target 3 further improves upon Target 2 to achieve China's *Technical Standard for Nearly Zero Energy Buildings GB/T51350-2019*.
- Target 4 uses renewable energy technology in the buildings.

According to these targets, this study puts forward the energy-saving retrofit measures (Table 6). Both active and passive retrofit measures are included in our BER measures, and the specific include roof, wall, window replacement, Leed light and HVAC system upgrade, and photovoltaic (PV) installation. BER 1 uses active technique such as replacing Leed lighting and upgrading HVAC systems. BER 2 adds passive measures to replace roofs, walls and windows for lower U-value on the basis of BER 1. BER 3 is the advanced version of BER 2 and asks for the much more lower U-value. Based on BER 3, BER4 adds the step of installing PV. Although passive technique is encouraged for historical buildings retrofit and all the measures are fit for modern buildings, this study update all the feasible inputs of each building according to the measures above and the energy simulation results after retrofit will be used to analyze the impact of uncertainties from calibrating UBEM.

Table 6. BER measures for the four different targets

	Target		Target 1	Target 2	Target 3	Target 4
	BER measures	**Value**	**BER 1**	**BER 2**	**BER 3**	**BER 4**
Passive	Roof insulation	U-value 0.5→0.32	-	◯	-	-
	Wall insulation	U-value ≤0.48	-	◯	-	-
	Window system	U-value ×80%	-	◯	-	-
Active	Led lights	LPD-value × 0.389	◯	◯	◯	◯
	High-efficiency HVAC system	COP＆EER-value 3.08→3.4	◯	◯	◯	◯
	Photovoltaic (PV) panel	-	-	-	-	◯
High Standards	Roof insulation	U-value 0.5→0.2	-	-	◯	◯
	Wall insulation	U-value ≤0.3	-	-	◯	◯
	Window system	U-value ×50%	-	-	◯	◯

Note: '◯' means the BER measure used in 3.5, while '-' the opposite.

3. Results

3.1 Results of campus building energy model calibration

The four buildings in the southeast corner of the campus were used as samples to conduct the UBEM calibration (Fig. 8). The calibration results of the building energy consumption model mainly have the following characteristics:

a) The peaks and troughs of the annual energy consumption of different buildings appear at different times. Taking summer as an example, the energy consumption of each building tends to increase with increaseing temperature and decrease with decreasing utilization rate during holidays. However, the Zhongshan, Dongnan, and Qiangong buildings reached peak energy demand in June, while the summer peak of the Zhongda building was delayed, occurring in July.

b) During the year, the changes in energy consumption are different; some are stable, and some buildings have obvious changes, with the Dongnan and Qiangong buildings being the most typical. The annual energy consumption of the Dongnan building is relatively small, and the energy consumption is relatively stable throughout the year with the extreme difference is about 15,000 kilowatt-hours (kWh). However, the energy consumption of the Qiangong building is large in scale, changes drastically, and the biggest difference is the largest, reaching 70,000 kWh.

c) Inputting the same parameters, the energy simulation results of some buildings are closer to their maximum value, while others are the opposite. The minimum energy consumption results of Dongnan can only be maintained the same as the real energy consumption, while the real energy consumption of Zhongda is closer to the maximum simulated energy consumption, and even higher in one month.

The main reason for this feature is the difference in the actual usage of buildings. Due to the various functions, building scales, and usages, the actual energy trend is quite different. However, the energy simulation results based on the same series of parameters can only show the same trend. The simulation results cannot fully consistent with the real energy consumption of atypical building. Although some monthly energy consumption exceeds the simulation range, the error can be accepted considering the overall energy consumption.

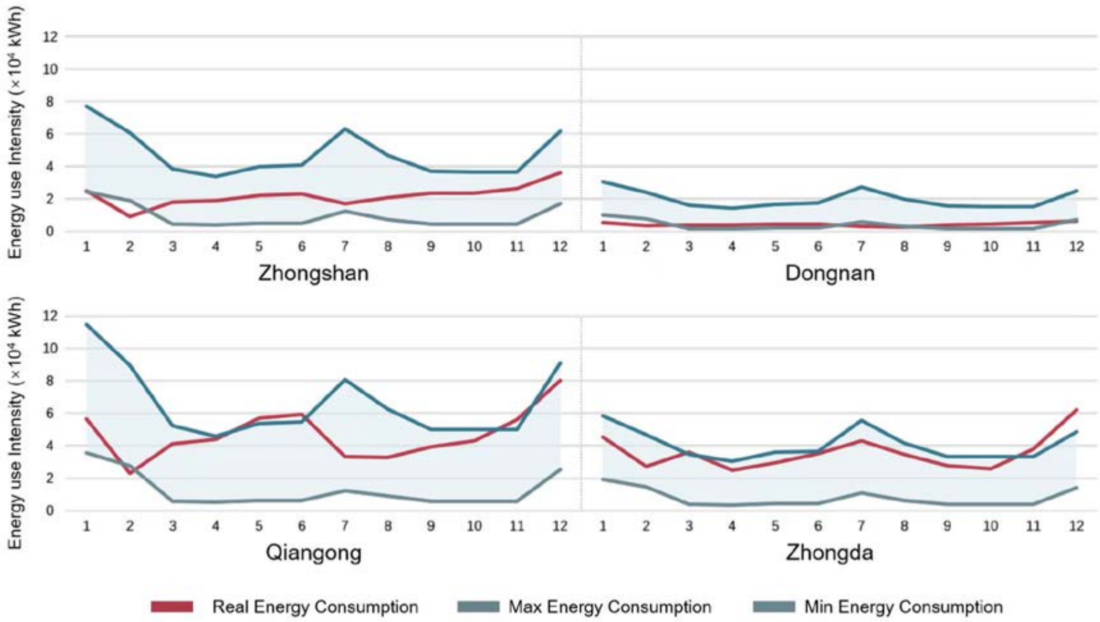

Fig. 8. Comparison of the simulated monthly energy use distribution with observed data for the four buildings

Fig. 9 shows the simulated energy consumption results with the error range of 20%. The tolerance can calculated by the perceptage that divides the measured energy by difference between simulated energy and measured energy. Points with the same measured energy use belong to the same building. Each column represents the simulated results of the same building, and each point represents the annual energy consumption from one set of feasible inputs. For example, points in the red box represent the simulated annual energy of Dongli Building. The points in the grey area meet the accuracy requirements, and the corresponding inputs will be used in the procedure of assessing energy-savings of retrofits. As seen in Fig. 9, all buildings have their energy models that meet the 20% error requirement. This study also classified the buildings according to their ages and conducted the energy simulation calibration for each building. Except for the Architectural Design Institute and the Zhongxin building in the 1980–1990s, the energy consumption of the buildings in the 1920–1930s was the least, followed by most of the buildings in the 1980–1990s, the energy consumption of the buildings in the 1960–1970s was higher, and the energy consumption of the buildings in the 1940–1950s was between the two. This is related to the scale and materials of the building at that time and the use of it today.

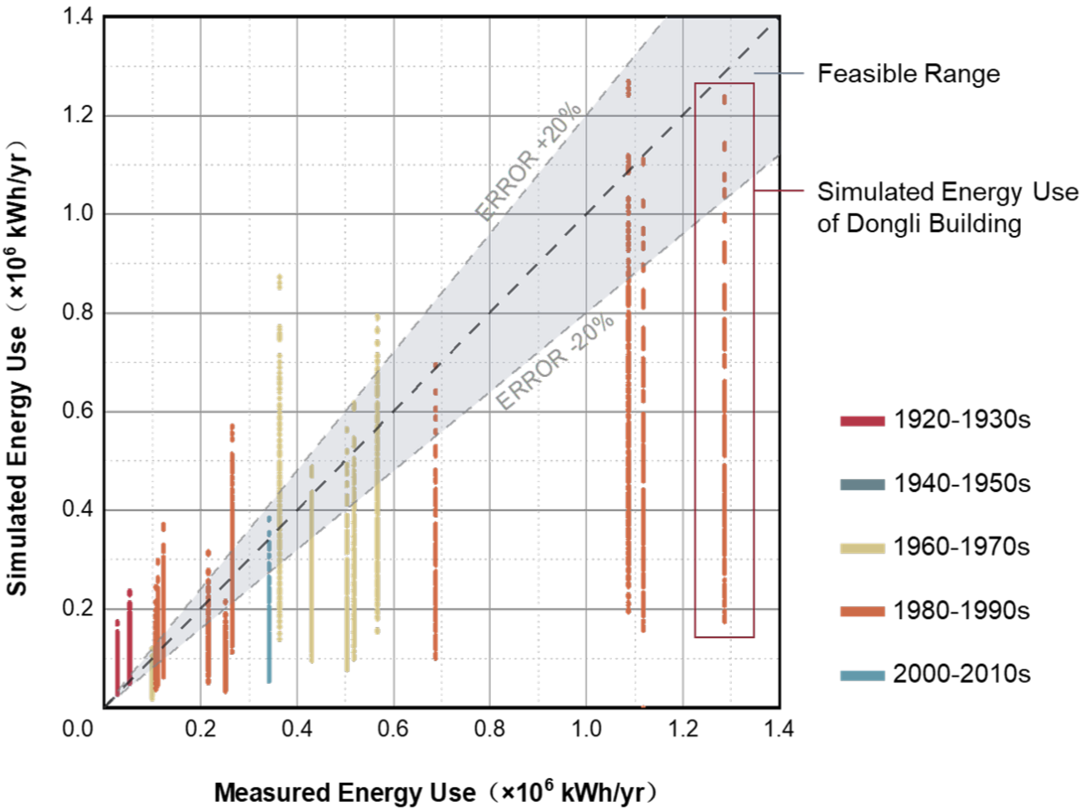

Fig. 9. Correlation of measured versus modeled energy use for individual buildings

3.2 Results of building energy retrofit measures

3.2.1 Results of BER 1

According to BER 1, LED lights and a high-efficiency HVAC system are used for energy retrofits. The energy-saving results are shown in Fig. 10. Each building's energy-saving potential is presented in box and bubble plots. Box plot can express the different energy-saving potentials of multiple sets of feasible inputs from the same building. In the bubble plot, one bubble comes from the average energy-saving potential of the same building and the diagram compares the relationship between real energy consumption, energy-saving potential, and building scale.

The average energy-saving potential of all buildings reaches 10%; the highest is about 40% for the Dongnan building, and the lowest is 10% for the gymnasium, both built in the 1920–1930s. The average energy-saving potential of the building group is about 25% (of which 12 buildings below the average energy-saving potential), and the simulated energy-saving potential of 7 buildings above the average value. For example, the energy-saving potential span of the library is large, with a range of near 50%, while the energy-saving potential span of the Cezhen building is the smallest, less than 5%. The overall building energy-saving potential is between 30%–50%. Among all the energy-saving potentials, the Qiangong and Zhongshan buildings have the largest energy-saving potential (57%), and the Jianxiong building has the smallest energy-saving potential (-7%). There are negative numbers in the energy-saving potential data of some buildings, because when the input parameters of energy-saving retrofits are selected, the corresponding simulation results are higher than the current energy consumption.

Also, we found that the average simulated energy consumption increases along with the larger corresponding building area, and energy-saving potentials of large buildings fluctuate less and are closer to the average energy-saving potential. Although the energy consumption of the original building has an age concentration, for BER 1 the energy-saving potential does not show an obvious pattern. It shows that there are no typical results for the lighting energy consumption and the energy efficiency levels of the equipment used in buildings of different ages. As shown in Fig. 10, for office buildings, the energy-saving potentials are more stable and closest to the average energy-saving potential. However, the energy-saving potential of educational buildings, laboratory buildings, and public buildings fluctuates greatly. This is consistent with the fact that the lighting energy consumption of office buildings is relatively stable, and the actual usage of other functional buildings is significantly different.

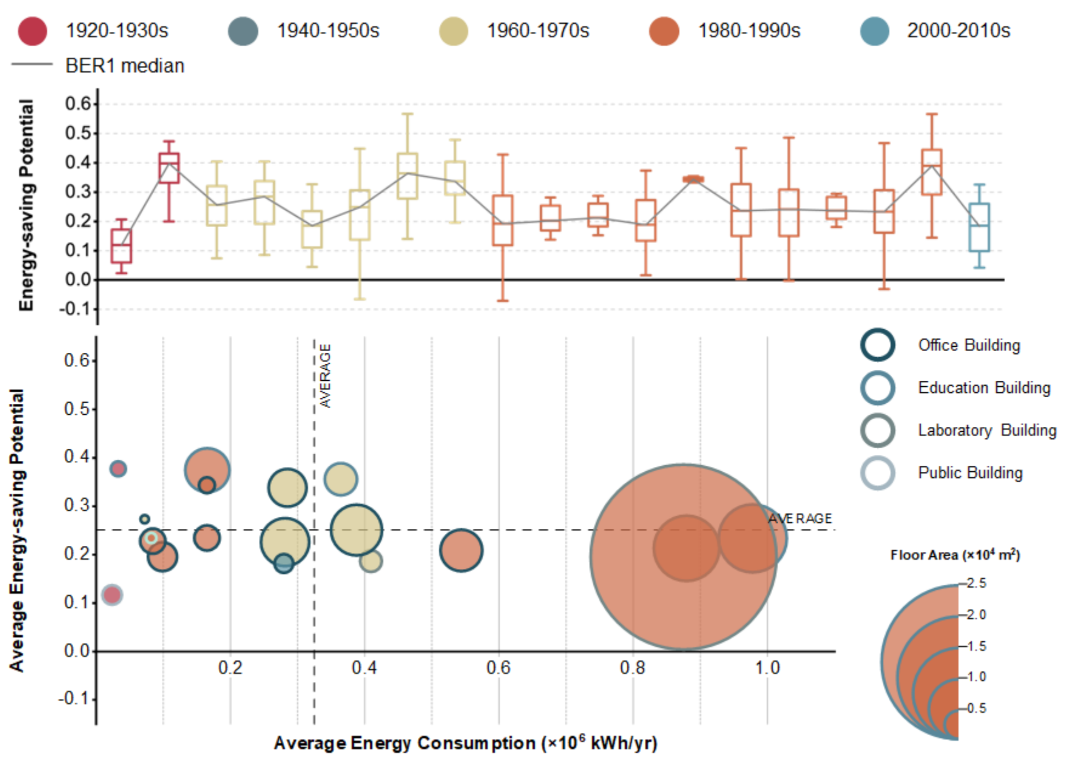

Fig. 10. Energy consumption and energy-saving potential after applying BER 1

3.2.2 Results of BER 2

The BER 2 measures are mainly carried out through the reduction of heat transfer coefficients of roofs, walls, and windows in the renovation of passive energy-saving technology, as well as through the use of LED lighting and a high-efficiency HVAC system. Fig. 11 shows the energy-saving potentials. Overall, the energy-saving potentials are larger than those of BER 1, and the median value of the energy-saving potentials of all the building samples reach 15%. The highest is still 40% for the Dongnan building, and the lowest is 15% for the gymnasium. The average energy-saving potential is 26% for the building group, of which 13 buildings below the average energy-saving potential, and the simulated energy-saving potential of 6 buildings above the average value. The basic situation of the extreme value of energy-saving potential is similar to that of BER 1. The largest and smallest spans are still the library and the Cezhen building. The range of the overall building energy-saving potential is also mostly between 30%–50%. Among all energy-saving potentials, the maximum energy-saving potential of the Qiangong and Zhongshan buildings slightly increased, but it is still about 57%, and the minimum energy-saving potential of the Jianxiong building is -6%. The variation of BER 2 is also similar to that of BER 1, indicating that the efficiency of passive technology renovation on the overall building complex is relatively uniform, and there is no obvious individual difference.

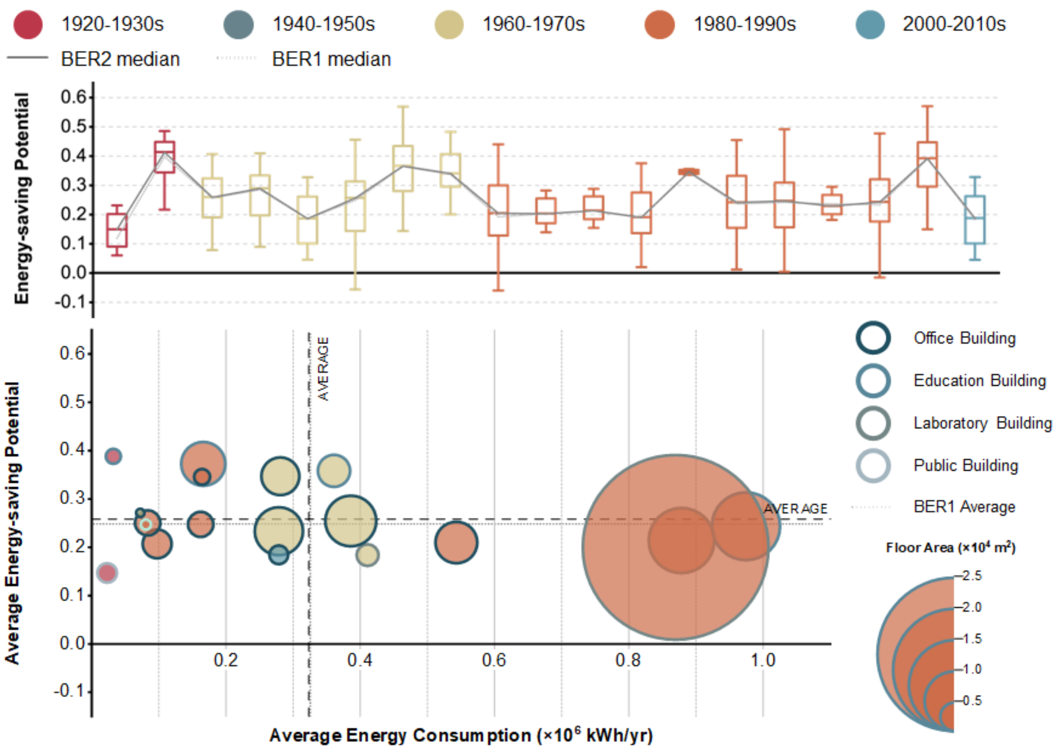

Fig. 11. Energy consumption and energy-saving potential after applying BER 2.

3.2.3 Results of BER 3

Upon BER 2, BER 3 strengthens the intensity of passive energy-saving technology renovation, and the heat transfer coefficient of the roof, walls, and windows has been significantly reduced. The results are presented in Fig. 12. The overall energy-saving potential data of BER 3 is larger than it of BER 2, and the simulation energy consumption results are smaller. The average energy-saving potential of the building group is about 27%; there are 13 buildings with less than the average energy-saving potential, and the simulated energy-saving potential of 6 buildings is higher than the average. The highest median value of the energy-saving potential of the building complex is still about 43% for the Dongnan building, while the lowest is only 19% for the Jinling building.

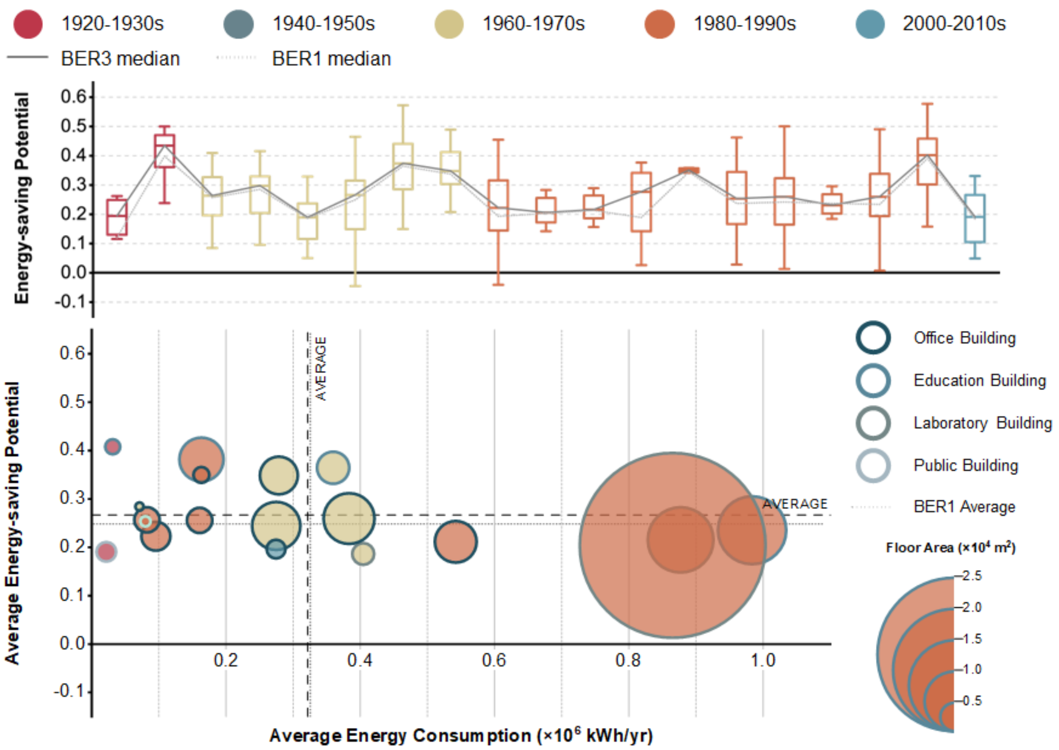

Fig. 12. Energy consumption and energy-saving potential after applying BER 3

3.2.4 Results of BER 4

Based upon BER 3, BER 4 adds active renovation technology, and configures PV panel production capacity on the roof. The energy consumption simulation result and change of BER 4 are quite different from the previous ones, indicating that the active energy-saving technology has a greater impact on the building complex. As shown in Fig. 13, the energy-saving potential of the building complex has a large span. The gymnasium, which has always shown a low energy-saving potential, improves significantly, reaching the same level as the Dongnan building and the old library, which have always had considerable energy-saving potential. The energy-saving potential of other buildings is between 50%–300%. Among them, the energy-saving potential of the Jinlin building is still the smallest, only 50%.

The active technology has a very strong energy-saving effect on the campus building complex. After applying BER 4 measures, the average energy-saving potential of the building complex is 191%, and the average energy consumption simulation result is less than 0, whereas the energy consumption simulation results have negative numbers. On the one hand, due to the small overall scale of the campus building complex and the low population density, the energy consumption scale is relatively small. On the other hand, the campus buildings are mostly low-rise buildings. When the building area is the same, the area where solar PV panels can be installed on the roof will be larger, and the production capacity will be more, potentially even offsetting the building energy consumption.

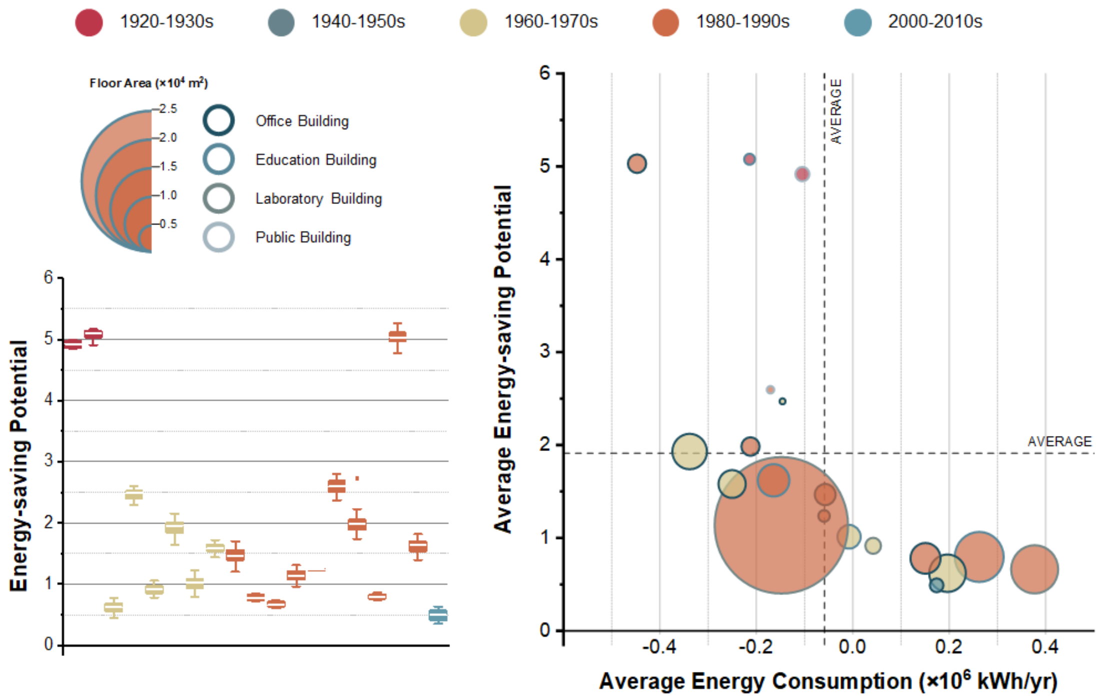

Fig. 13. Energy consumption and energy-saving potential after applying BER 4.

For the vast majority of buildings, as the average simulated energy increases, the energy-saving potential decreases, as shown in Fig. 13. The main reason for this result is that the energy consumption offset by active technology accounts for a large proportion of the building's original energy consumption, resulting in a certain positive correlation between the final energy consumption simulation results and the energy-saving potential. Some buildings do not fully meet the positive correlation, mainly because their original construction area is small and the floors are low, as well as the energy demand of the building, therefore, installing the PV panels on the roof can produce larger the energy-saving potential.

3.2.5 Overall analysis of all BERs

Overall, from the perspective of energy-saving retrfot measures 1 to 3, passive energy-saving technology has a relatively strong energy-saving effect on buildings in the 1920–1930s, and the energy-saving potential changes significantly, while it is relatively stable for buildings in the 2000–2010s. The main reason is that the walls of the buildings in the 1920–1930s were all brick walls, while the buildings in the 2000–2010s were cement walls; changing the heat transfer coefficient had a different impact on the building energy consumption. The differences in the energy consumption simulation results of BER 4 are mainly reflected in two aspects: On the one hand, the overall layout of the building energy simulation data results has changed greatly, but the consumption simulation results are only in the average position. On the other hand, the energy-saving potential of the buildings has changed greatly, which is reflected not only in the fact that the energy-saving potential no longer has negative values, but also because the overall span has increased, ranging from 5% to 500%. There are also obvious changes in the layout of the energy-saving potential of different buildings. This is mainly because the active energy-saving technology is related to the form and area of the building roof, and energy-saving renovation measures 1 to 3 mainly take into account the influence of building structure, materials, and equipment lighting. There is no direct connection between the two, so there is different energy consumption.

For all buildings, the energy-saving potentials of BER 1 to BER 3 are similar; the difference is mainly reflected in BER 4. As shown in Fig. 14(a), the energy-saving potential variation of buildings in 1980–1990s is large, and this may due to the larger number of buildings and the different structure, wall and roof materials, building area, window-to-wall ratio, functions and so on. In contrast, for buildings in the 1920–1930s and 2000–2010s, the difference is smaller, and there are fewer buildings. As for Fig. 14(b), there are many office buildings on the campus with obvious differences in scale and usage, resulting in a large variation of energy-saving potentials. For laboratory buildings and public buildings, the data are more concentrated.

The differences in building energy consumption classified by building years come mainly from the differences in the physical properties of buildings, which consist of not only the overall building scale and floor height, but also the structure, materials, and window-to-wall ratio settings used. As shown in Fig. 14(a), for buildings of all ages, the energy-saving potentials of BER 1 to BER 3 are relatively stable, ranging from 18%–44% for buildings in the 1920–1930s, 20%–37% for buildings in the 1960–1970s, 16%–35% for buildings in the 1980–1990s and 10%–26% for buildings in the 2000-2010s. The energy-saving potential of BER 4 for buildings in different eras varies greatly. The energy-saving potential of buildings in the 1920–1930s is roughly 505%, buildings in the 1960–1970s are between 93%–196%, buildings in the 1980–1990s are between 140%–258%, and buildings in the 2000–2010s is roughly 49%.

As shown in Fig. 14(b), for BER 1 to BER 3, the energy-saving potentials of buildings with different functions are stable. The energy-saving potential of office buildings is 16%–33%, it of educational buildings is 27%–45%, it of laboratory buildings is 13%–29%, and it of public buildings is 6%–25%. Among the buildings with BER 4, public buildings have the largest energy-saving potential, at roughly 492%; office buildings and educational buildings have a wide range of energy-saving potentials, at 145%–255% and 100%–166%, respectively, and experimental buildings have stable energy-saving potential of about 97%.

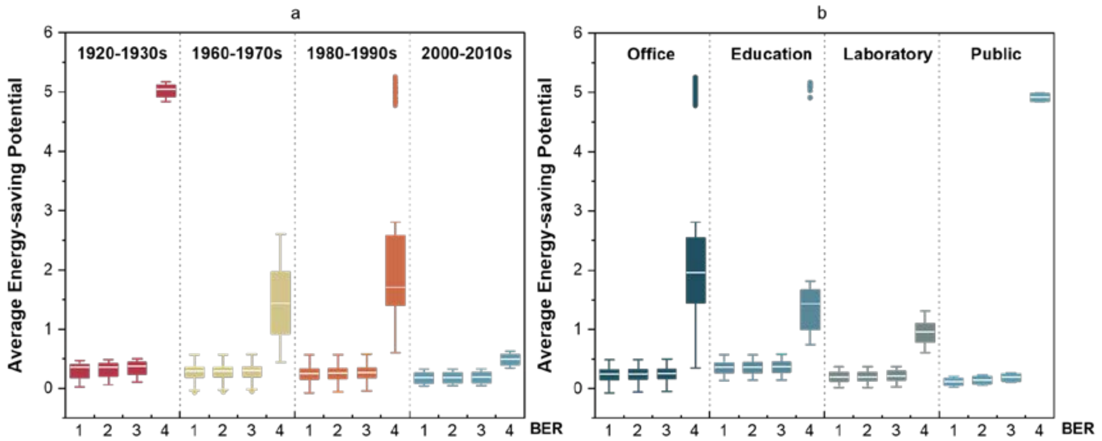

Fig. 14. Distributions of energy-saving potentials within (a) different building years and (b) building type.

4. Discussion

This study provided a reference that calibrates building energy model at the urban level, and relieves the impact of the uncertainty of the calibiration on the energy-saving potential of retrofitting historic buildings. While creating UBEM for decision of different retrofit measures at urban scale, many inputs must be obtained, some of which are easy to obtain as known paramters while some of which are difficult to obtain as unkonw parameters. That says, for the same building, there are multiple sets of feasible inputs that bring the simulation results close to the real energy use, in turn, multiple groups of energy models can be produced from model calibration. As dicussed in

Literature review, multi-parameter inputs or multi-systems (retrofit measurements or energy systems) will produce uncertainties of energy models (Ruan et al., 2023). Therefore, two methods of dealing with uncertainty can be summarized. One is to reveal the impact of uncertainty sources at inputs of energy models, such as, uncertainties from climatic changes (Liu et al., 2023), building form, and its physical parameters (Dilsiz et al., 2023), occupancy density (Shin & Park, 2022), or those combined with efficiency of energy systems (Ye et al., 2021). The second is to reveal the impact uncertainty on the application of energy models, for example, early to take uncertainty into account, Heo et al. proposed a scalable probabilistic methodology of calibrating building energy models for large-scale investments in building energy retrofits (Heo et al., 2012). The works in our study also applies to the second one, which is also a contribution to make up for the lack of considering uncertainties for energy model at urban block level.

This study also have those contributions and implications. First, establishing and calibrating UBEM was time-consuming and labor-intensive, and most of the research time was spent on the field investigation, data query, and iterative calibration. This study provided an idea of classifying building groups of different functions and ages, and calibrated one building of those groups to obtain various sets of feasible inputs. As seen from the calibration results, all the buildings can have their possible feasible energy models. This idea might help save the time for related research. Second, energy simulation, especially at urban scale, faces many inputs, and it is very difficult to obtain accurate data for each input. Uncertainty is therefore common, and has great impact of energy-related decisions. This study can provide a good case study of applications of UBEM that tunes the models and considers uncertainties. Third, urban renewal is now the main theme of China's urban construction and an important aspect of urban sustainable development. This study provided an important and significant reference for those considering to apply UBEM in evaluating energy-efficient retrofits in mixed historic urban blocks, and further for exploring the impact of general uncertainties of UBEM on evaluating the potential of energy-efficient retrofits at an urban block scale. This study can also be referred to those activities such as low-carbon urban design, design of energy system, urban energy planning, which also needs to consider uncertainties to make more scientific decisions.

However, this study also had some limitations. First, in the process of energy simulation, landscape design, especially the impact of trees on the environmental microclimate, was not considered. This omission could reduce the accuracy and authenticity of energy consumption simulation results, which also could be an important consideration in future work to include such impact on retrofit choices. Second, the main idea of this study analyzed the energy-savings of different building energy measures at urban scale, however, no in-depth analysis of how to implement those energy-efficient retrofit measures. For example, this study did not consider to apply PV panels on historic buildings, however, when installing PV on modern buildings, how much the tall trees will affect the roof PV. Finally, this study created all parameterized sets of UBEM by adjusting slider tool in Grasshopper slider, which help only reduce the workload of manual adjustment, but cannot reduce the amount of calculation. Therefore, an important future work needs to introduce optimization or machine learning algorithms to speed up the simulation process and improve calibration efficiency.

5. Conclusion

This study investigated energy retrofit under uncertainties of urban building energy model for mixed modern and historic buildings on a university campus. An urban building energy model was created with an on-site survey in the Rhino Grasshopper tool, and real electricity data were used to calibrate the models to ensure the modeled results were within 20% tolerance of the measured energy data. The calibrated set of UBEMs rather than one were used to evaluate four energy retrofit measures that target China green building energy standards, China ultra-low energy building standards, and active use of photovoltaic energy generation. Four different building energy retrofit (BER) measures: BER 1 to maintain the historic values, BER 2 to achieve green building design standard, BER 3 to achieve energy savings 20% higher than BER 2, and BER 4 to utilize renewable energy. The different energy-saving potentials of four BER measures can be used as a reference for future energy-saving retrofits of related buildings.

The multiple set of calibrated energy models were applied to simulate the energy-saving potentials of the four BER measures. For different building ages, the energy-saving potentials of BER 1 to BER 3 are relatively stable, ranging from 18%–44% for buildings in the 1920–1930s, 20%–37% for buildings in the 1960–1970s, 16%–35%

for buildings in the 1980–1990s and 10%–26% for 2000-2010s buildings. Differently, the energy-saving potentials of BER 4 varies greatly, which is 505% for buildings in the 1920–1930s is roughly, 93%–196% for buildings in the 1960–1970s, 140%–258% for buildings in the 1980–1990s, and about 49% for buildings in the 2000–2010s, respectively. Similar results can be concluded for building functions, for BER 1 to BER 3, the energy-saving potential of office buildings is 16%–33%, 27%–45% for educational buildings, 13%–29% for laboratory buildings, and 6%–25% for public buildings. Among the buildings with BER 4, public buildings have the largest energy-saving potential, at roughly 492%; office buildings and educational buildings have a wide range of energy-saving potentials, at 145%–255% and 100%–166%, respectively, and experimental buildings have stable energy-saving potential of about 97%.

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References

Ascione, F., Ceroni, F., De Masi, R. F., de' Rossi, F., & Pecce, M. R. (2017). Historical buildings: Multidisciplinary approach to structural/energy diagnosis and performance assessment. *Applied Energy*, *185*, 1517–1528. https://doi.org/10.1016/j.apenergy.2015.11.089

Calama-González, C. M., Symonds, P., Petrou, G., Suárez, R., & León-Rodríguez, Á. L. (2021). Bayesian calibration of building energy models for uncertainty analysis through test cells monitoring. *Applied Energy*, *282*(April 2020). https://doi.org/10.1016/j.apenergy.2020.116118

Chaturvedi, S., & Rajasekar, E. (2022). Application of a probabilistic LHS-PAWN approach to assess building cooling energy demand uncertainties. *Building Simulation*, *15*(3), 373–387. https://doi.org/10.1007/s12273-021-0815-6

Cho, H. M., Yun, B. Y., Yang, S., Wi, S., Chang, S. J., & Kim, S. (2020). Optimal energy retrofit plan for conservation and sustainable use of historic campus building: Case of cultural property building. *Applied Energy*, *275*(June), 115313. https://doi.org/10.1016/j.apenergy.2020.115313

Coakley, D., Raftery, P., & Keane, M. (2014). A review of methods to match building energy simulation models to measured data. In *Renewable and Sustainable*

Energy Reviews (Vol. 37, pp. 123–141). Elsevier Ltd. https://doi.org/10.1016/j.rser.2014.05.007

Coelho, G. B. A., & Henriques, F. M. A. (2021). Performance of passive retrofit measures for historic buildings that house artefacts viable for future conditions. *Sustainable Cities and Society*, *71*(May), 102982. https://doi.org/10.1016/j.scs.2021.102982

Dilsiz, A. D., Ng, K., Kämpf, J., & Nagy, Z. (2023). Erratum to: Ranking parameters in urban energy models for various building forms and climates using sensitivity analysis (Building Simulation, (2022), 10.1007/s12273-022-0961-5). *Building Simulation*. https://doi.org/10.1007/s12273-023-0988-2

Gabrielli, L., & Ruggeri, A. G. (2019). Developing a model for energy retrofit in large building portfolios: Energy assessment, optimization and uncertainty. *Energy and Buildings*, *202*, 109356. https://doi.org/10.1016/j.enbuild.2019.109356

Gonzalez, G. A. (2005). Urban sprawl, global warming and the limits of ecological modernisation. *Environmental Politics*, *14*(3), 344–362. https://doi.org/10.1080/09644010500087558

González, V. G., & Bandera, C. F. (2022). A building energy models calibration methodology based on inverse modelling approach. *Building Simulation*, *15*(11), 1883–1898. https://doi.org/10.1007/s12273-022-0900-5

Gupta, R., & Gregg, M. (2016). Do deep low carbon domestic retrofits actually work? *Energy and Buildings, 129*, 330–343. https://doi.org/10.1016/j.enbuild.2016.08.010

Heo, Y., Choudhary, R., & Augenbroe, G. A. (2012). Calibration of building energy models for retrofit analysis under uncertainty. *Energy and Buildings*, *47*(2012), 550–560. https://doi.org/10.1016/j.enbuild.2011.12.029

Hinnells, M. (2008). Technologies to achieve demand reduction and microgeneration in buildings. *Energy Policy*, *36*(12), 4427–4433. https://doi.org/10.1016/j.enpol.2008.09.029

Hong, T., Chen, Y., Luo, X., Luo, N., & Lee, S. H. (2020). Ten questions on urban building energy modeling. *Building and Environment*, *168*, 106508.

Hong, T., Yang, L., Hill, D., & Feng, W. (2014). Data and analytics to inform energy retrofit of high performance buildings. *Applied Energy*, *126*, 90–106. https://doi.org/10.1016/j.apenergy.2014.03.052

Hu, X., Xiang, Y., Zhang, H., Lin, Q., Wang, W., & Wang, H. (2021). Active–passive combined energy-efficient retrofit of rural residence with non-benchmarked construction: A case study in Shandong province, China. *Energy Reports*, *7*, 1360–1373. https://doi.org/10.1016/j.egyr.2021.02.045

Ibaseta, D., García, A., Álvarez, M., Garzón, B., Díez, F., Coca, P., Pero, C. Del, &

Molleda, J. (2021). Monitoring and control of energy consumption in buildings using WoT: A novel approach for smart retrofit. *Sustainable Cities and Society*, *65*, 102637. https://doi.org/10.1016/j.scs.2020.102637

Kalogeras, G., Rastegarpour, S., Koulamas, C., Kalogeras, A. P., Casillas, J., & Ferrarini, L. (2020). Predictive capability testing and sensitivity analysis of a model for building energy efficiency. *Building Simulation*, *13*(1), 33–50. https://doi.org/10.1007/s12273-019-0559-8

Li, N., Yang, Z., Becerik-Gerber, B., Tang, C., & Chen, N. (2015). Why is the reliability of building simulation limited as a tool for evaluating energy conservation measures? *Applied Energy*, *159*, 196–205. https://doi.org/10.1016/j.apenergy.2015.09.001

Liu, S., Wang, Y., Liu, X., Yang, L., Zhang, Y., & He, J. (2023). How does future climatic uncertainty affect multi-objective building energy retrofit decisions? Evidence from residential buildings in subtropical Hong Kong. *Sustainable Cities and Society*, *92*(December 2022), 104482. https://doi.org/10.1016/j.scs.2023.104482

Luddeni, G., Krarti, M., Pernigotto, G., & Gasparella, A. (2018). An analysis methodology for large-scale deep energy retrofits of existing building stocks: Case study of the Italian office building. *Sustainable Cities and Society*, *41*(December 2017), 296–311. https://doi.org/10.1016/j.scs.2018.05.038

Manke, J., Hittle, D., & Hancock, C. (1996). *Calibrating building energy analysis models using short term test data*. https://doi.org/CONF-9603117- ISBN 0-7918-1765-2; TRN: IM9711%%132

Mata, É., Sasic Kalagasidis, A., & Johnsson, F. (2013). Energy usage and technical potential for energy saving measures in the Swedish residential building stock. *Energy Policy*, *55*, 404–414. https://doi.org/10.1016/j.enpol.2012.12.023

Milone, D., Peri, G., Pitruzzella, S., & Rizzo, G. (2015). Are the Best Available Technologies the only viable for energy interventions in historical buildings? *Energy and Buildings*, *95*, 39–46. https://doi.org/10.1016/j.enbuild.2014.11.004

Muñoz González, C. M., León Rodríguez, A. L., Suárez Medina, R., & Ruiz Jaramillo, J. (2020). Effects of future climate change on the preservation of artworks, thermal comfort and energy consumption in historic buildings. *Applied Energy*, *276*(June), 115483. https://doi.org/10.1016/j.apenergy.2020.115483

Na, R., & Shen, Z. (2021). Assessing cooling energy reduction potentials by retrofitting traditional cavity walls into passively ventilated cavity walls. *Building Simulation*, *14*, 1295–1309.

Nagpal, S., & Reinhart, C. F. (2018). A comparison of two modeling approaches for establishing and implementing energy use reduction targets for a university campus. *Energy and Buildings*, *173*, 103–116.

https://doi.org/10.1016/j.enbuild.2018.05.035

National Statistical Bureau of the People’s Republic of China. (2023). *Statistical Bulletin of the People’s Republic of China on National Economic and Social Development in 2022*.

Ohlsson, K. E. A., & Olofsson, T. (2021). Benchmarking the practice of validation and uncertainty analysis of building energy models. *Renewable and Sustainable Energy Reviews*, *142*(February 2020), 110842. https://doi.org/10.1016/j.rser.2021.110842

Oraiopoulos, A., Hsieh, S., & Schlueter, A. (2023). Energy futures of representative Swiss communities under the influence of urban development, building retrofit, and climate change. *Sustainable Cities and Society*, *91*(January), 104437. https://doi.org/10.1016/j.scs.2023.104437

Pan, Y., Huang, Z., & Wu, G. (2007). Calibrated building energy simulation and its application in a high-rise commercial building in Shanghai. *Energy and Buildings*, *39*(6), 651–657. https://doi.org/10.1016/J.ENBUILD.2006.09.013

Pedrini, A., Westphal, F. S., & Lamberts, R. (2002). A methodology for building energy modelling and calibration in warm climates. *Building and Environment*, *37*(8–9), 903–912. https://doi.org/10.1016/S0360-1323(02)00051-3

Qu, K., Chen, X., Ekambaram, A., Cui, Y., Gan, G., Økland, A., & Riffat, S. (2020). A novel holistic EPC related retrofit approach for residential apartment building renovation in Norway. *Sustainable Cities and Society*, *54*(November 2019). https://doi.org/10.1016/j.scs.2019.101975

Rahaman, Z. A., Kafy, A. Al, Saha, M., Rahim, A. A., Almulhim, A. I., Rahaman, S. N., Fattah, M. A., Rahman, M. T., S, K., Faisal, A. Al, & Al Rakib, A. (2022). Assessing the impacts of vegetation cover loss on surface temperature, urban heat island and carbon emission in Penang city, Malaysia. *Building and Environment*, *222*(June), 109335. https://doi.org/10.1016/j.buildenv.2022.109335

Reinhart, C. F., & Cerezo Davila, C. (2016). Urban building energy modeling - A review of a nascent field. *Building and Environment*, *97*, 196–202. https://doi.org/10.1016/j.buildenv.2015.12.001

Rodrigues, C., & Freire, F. (2021). Environmental impacts and costs of residential building retrofits – What matters? *Sustainable Cities and Society*, *67*(July 2019), 102733. https://doi.org/10.1016/j.scs.2021.102733

Rota, M., Corgnati, S. P., & Di Corato, L. (2015). The museum in historical buildings: Energy and systems. the project of the Fondazione Musei Senesi. *Energy and Buildings*, *95*, 138–143. https://doi.org/10.1016/j.enbuild.2014.11.008

Ruan, Y., Qian, F., Sun, K., & Meng, H. (2023). Optimization on building combined cooling, heating, and power system considering load uncertainty based on scenario generation method and two-stage stochastic programming. *Sustainable Cities and Society*, *89*(October 2022). https://doi.org/10.1016/j.scs.2022.104331

Schibuola, L., Scarpa, M., & Tambani, C. (2018). Innovative technologies for energy retrofit of historic buildings: An experimental validation. *Journal of Cultural Heritage*, *30*, 147–154. https://doi.org/10.1016/j.culher.2017.09.011

Shamsi, M. H., Ali, U., Mangina, E., & O'Donnell, J. (2020). A framework for uncertainty quantification in building heat demand simulations using reduced-order grey-box energy models. *Applied Energy*, *275*(June), 115141. https://doi.org/10.1016/j.apenergy.2020.115141

Shin, H., & Park, C. S. (2022). Parameter estimation for building energy models using GRcGAN. *Building Simulation*, *2*, 629–639. https://doi.org/10.1007/s12273-022-0965-1

Suárez, R., & Fernández-Agüera, J. (2015). Passive energy strategies in the retrofitting of the residential sector : A practical case study in dry hot climate. *Building Simulation*, *8*, 593–602. https://doi.org/10.1007/s12273-015-0234-7

Sun, K., & Hong, T. (2017). A framework for quantifying the impact of occupant behavior on energy savings of energy conservation measures. *Energy and Buildings*, *146*, 383–396. https://doi.org/10.1016/j.enbuild.2017.04.065

Sun, K., Hong, T., Kim, J., & Hooper, B. (2022). Application and evaluation of a pattern-based building energy model calibration method using public building datasets. *Building Simulation*, *15*(8), 1385–1400. https://doi.org/10.1007/s12273-022-0891-2

Todorović, M. S., Ećim-Crossed D Signurić, O., Nikolić, S., Ristić, S., & Polić-Radovanović, S. (2015). Historic building's holistic and sustainable deep energy refurbishment via BPS, energy efficiency and renewable energy - A case study. *Energy and Buildings*, *95*, 130–137. https://doi.org/10.1016/j.enbuild.2014.11.011

Valencia, A., Hossain, M. U., & Chang, N. Bin. (2022). Building energy retrofit simulation for exploring decarbonization pathways in a community-scale food-energy-water-waste nexus. *Sustainable Cities and Society*, *87*(May), 104173. https://doi.org/10.1016/j.scs.2022.104173

Xin, L., Chenchen, W., Chuanzhi, L., Guohui, F., Zekai, Y., & Zonghan, L. (2018). Effect of the energy-saving retrofit on the existing residential buildings in the typical city in northern China. *Energy and Buildings*, *177*, 154–172. https://doi.org/10.1016/j.enbuild.2018.07.004

Yang, T., Pan, Y., Mao, J., Wang, Y., & Huang, Z. (2016). An automated optimization method for calibrating building energy simulation models with measured data: Orientation and a case study. *Applied Energy*, *179*, 1220–1231.

https://doi.org/10.1016/j.apenergy.2016.07.084

Ye, Y., Hinkelman, K., Lou, Y., Zuo, W., Wang, G., & Zhang, J. (2021). Evaluating the energy impact potential of energy efficiency measures for retrofit applications: A case study with U.S. medium office buildings. *Building Simulation*, *14*(5), 1377–1393. https://doi.org/10.1007/s12273-021-0765-z

Zhou, L., Li, J., & Chiang, Y. H. (2013). Promoting energy efficient building in China through clean development mechanism. *Energy Policy*, *57*, 338–346. https://doi.org/10.1016/j.enpol.2013.02.001

Zhu, C., Tian, W., Yin, B., Li, Z., & Shi, J. (2020). Uncertainty calibration of building energy models by combining approximate Bayesian computation and machine learning algorithms. *Applied Energy*, *268*(September 2019), 115025. https://doi.org/10.1016/j.apenergy.2020.115025