Energy Proceedings
2022
ISSN 2004-2965

Rapid Building Energy Modeling using Prototype Model and Automatic Model Calibration for Retrofit Analysis with Uncertainty#

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ABSTRACT

This paper proposed and implemented a novel method to rapidly generate building energy modeling for existing buildings with measured energy data by integrating the prototype building energy model and automatic model calibration. The generated models were applied for retrofit analysis with uncertainty. First, a prototype model for shopping mall buildings was proposed to generate a baseline EnergyPlus model based on the building's basic information, including vintage, climate zone, total floor area, and percentage of each function type. Next, an automatic calibration algorithm was implemented to calibrate the baseline model based on the monthly electricity and natural gas usage data. Monte Carlo sampling was applied to generate 1000 combinations for fourteen parameters. Multiple solutions that meet the calibration criteria can be found. Moreover, the calibrated energy models were used to evaluate the energy-saving potential of several energy conservation measures. 29 EnergyPlus models that meet the calibration criteria are found. The lighting power density in those 29 models ranges from 11.4 to 14.9 W/m^2 with an average of 13.1 W/m^2; while the chiller COP ranges from 3.45 to 4.79 with an average of 4.00. The electricity energy saving percentage of replacing lights with LED lights ranges from 1.9% to 11.7% with an average of 6.1%; while the electricity energy saving percentage of chiller replacement ranges from 1.6% to 14.1% with an average of 8.4%. The results show a high level of uncertainty when the actual lighting power density and chiller cop information is unknown.

Keywords: AutoBPS, shopping mall, model calibration, EnergyPlus, Monte Carlo

NONMENCLATURE

Abbreviations	
AutoBPS	Automatic Building Performance Simulation
ECM	Energy Conservation Measure
WWR	Window to wall ratio
CityBES	City Building Energy Sustainability
M	Meter
B2/1	Below ground 2/1
F1-F5	Floor 1-5
CVRMSE	The coefficient of variation of the root mean square error
NMBE	The normalized mean bias error
LED	Light Emitting Diode
Fig.	Figure
y_i	data measurement
$\bar{y}$	mean of data measurements
$\hat{y}_i$	Data analog value

1. INTRODUCTION

As urbanization progresses, China's construction scale will continue to expand. Since 2014, the annual completed area of civil buildings in China has reached 4 billion square meters. At the same time, the increase in demand for air conditioning and heating has led to a further increase in building energy consumption. In 2019, China's building construction and operation energy consumption accounted for 33% of the total energy consumption, with building operation accounting for 22% [1]. In 2017, China contributed 28% of global carbon emissions [2] Faced with such a large amount of carbon emissions, China has committed to reaching peak carbon by 2030 and carbon neutrality by 2060.

The high carbon emission is due to the low efficiency of building energy use and the way of energy use. Building energy simulation is an efficient way to analyze the energy saving potential of energy conservation measures. Ye et al. [3] analyzed the sensitivity of nine different energy-saving measures with EnergyPlus to guide the selection of energy-saving measures in

This is a paper for the 8th Applied Energy Symposium - CUE2022, Sept. 24-27, 2022, Matsue, Japan.

different climate regions. Berardi and Soudian [4] simulated the integration of phase change materials into the envelope with EnergyPlus software to study the energy-saving potential of a passive latent heat energy storage system. Hart et al. [5] used EnergyPlus to simulate the potential impact on the thermal performance of replacing the ordinary glass with triple thin glass panes, and obtained the energy-saving potential in different climatic regions of the United States. Peng et al. [6] used DeST energy simulation software to verify the effectiveness and feasibility of different energy-saving measures in an office building. For large buildings, such as shopping malls and large offices, they typically measured whole building or end-use energy consumption data, which can be used to support the generation and calibration of the energy models. Sun et al. [7] used monthly electricity and natural gas consumption to calibrate 111 EnergyPlus building models in the United States, of which 57 were successfully calibrated, they argue that the establishment of the building models and their accuracy have a significant impact on the follow-up research. Hong et al. [8] also regarded the calibration of the building model as one of the ten challenges for future building energy conservation. For manual and automatic calibration, manual calibration requires certain expertise of the calibrator and is a labor-intensive task, which is no longer applicable as the complexity of the building model increases. Advanced mathematical and statistical methods have made the automatic calibration process faster and more efficient than manual calibration [9]. Sun et al. [10] proposed a novel automated calibration method that can replace manual calibration. In the automatic calibration model, the Monte Carlo sampling calibration model is a more commonly used method. Not only can the model be quickly calibrated, but also uncertainty analysis of the model can be performed.

Haarhoff and Mathews [11] presented a simplified Monte Carlo method for finding an approximation of the temperature distribution inside a building, the results show that relatively accurate results can be obtained with very little data. Chambers et al. [12] used a Monte Carlo model to evaluate the effect of color-changing glass on energy saving potential. Sørensen et al. [13] used a Monte Carlo simulation to model the energy performance and indoor climate of buildings considering building physical parameters, including properties of facades, walls, windows, etc., and sift through thousands of combinations of these parameters to find those that meet design criteria. This method could optimize the efficiency of the building design. Zheng et al. [14] proposed a technology-economic-risk decision-making method based on Monte Carlo simulation, which can realize the optimal screening of multiple technology combination strategies. It can also predict regional energy-saving effects and quantitatively analyze energy-saving subsidy policies.

It is a challenging task to manually create a building energy model from scratch. It is beneficial to develop methods that can rapidly and automatically generate building energy models with suitable accuracy. Regarding rapid modeling, part of the research revolves around modeling based on the 3D recognition of buildings [15]. This approach is simpler in principle, but is technically demanding and can only model existing buildings. Elisa and Marincioni [16] proposed a method for rapid modeling of end-users connected to the district heating network. The model can be obtained only by obtaining district heating and building volume measurements. For the measures analyzed, the average error was less than 5%. There is also a part of rapid modeling research around UBEM. There is a new method for rapid automatic calibration of UBEM based on annual electricity and natural gas energy usage data, by learning from an energy performance database, the model calibration is completed after no more than four simulation runs [17]. They also used the retrofit analysis capabilities of City Building Energy Sustainability (CityBES) to automatically generate and simulate UBEM using EnergyPlus based on the city's building dataset and user-selected ECM [18].

This study presented a novel method to automatically generate building energy models by integrating the prototype building energy models and Monte Carlo sampling. First, a prototype model is built with building information such as aspect ratio, floor height, floor area, and proportion of each functional type as input, and the energy consumption model is quickly built with AutoBPS. Secondly, the Monte Carlo method was adopted to calibrate the model, several calibrated models are obtained to analyze the uncertainty of the energy saving rate of energy conservation measures. This study simplifies the modeling process and saves time and effort by proposing a prototype model with a representative model. The generated model can be applied to retrofit analysis with uncertainty, and can also give a reference range for the energy efficiency rate of a building in the absence of building information to give reference in building energy retrofit.

2. METHODS

A shopping mall building in Changsha was selected for the case study. Fig. 1 shows the overall workflow of this study. Frist, the basic building information was collected via on-site visit and the monthly energy consumption data were downloaded from the building management system. Then, a baseline model is generated using the Automatic Building Performance Simulation (AutoBPS) tool based on the basic building information. AutoBPS is a tool developed by Hunan University, China to automatically generate EnergyPlus model using prototype models based on basic building information, including building type, year built, climate zone, number of stories above and below ground, floor to floor height, window to wall ratio (WWR) in each direction, width, height, and so on. Users can customize the building geometry while the building systems (envelope, internal zones, heating, ventilation and air conditioning system) are assigned based on the building type, year built and climate zone to meet the local and national standards. Moreover, Monte Carlo sampling was conducted to calibrate the baseline model using measured monthly electricity and natural gas usage data, which can generate multiple calibrated EnergyPlus models. At last, those calibrated EnergyPlus models are used to perform retrofit analysis with uncertainty.

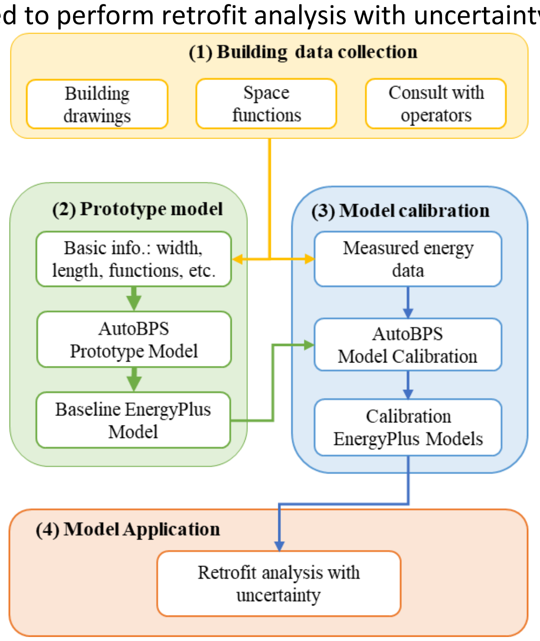


Fig. 1 Overall workflow of the study

2.1 Case study building

Changsha is located in hot summer and cold winter region with high humidity throughout the year. The floor-to-floor height of the shopping mall is 4.7m. The building has windows on the first and second floors with WWR of 0.35 on east, 0.56 on south, 0.35 on west and 0.3 on north. Building area of 210,000 square meters .Fig. 2 shows the floor plans of the building. Through on-site research and the information of the building on Baidu map, the energy performance modeling will be divided into eight functional types for the interior space. including parking, food, office, cinema, corridor, clothing, supermarket, and activity center. The area of each function type is shown in Fig. 3.

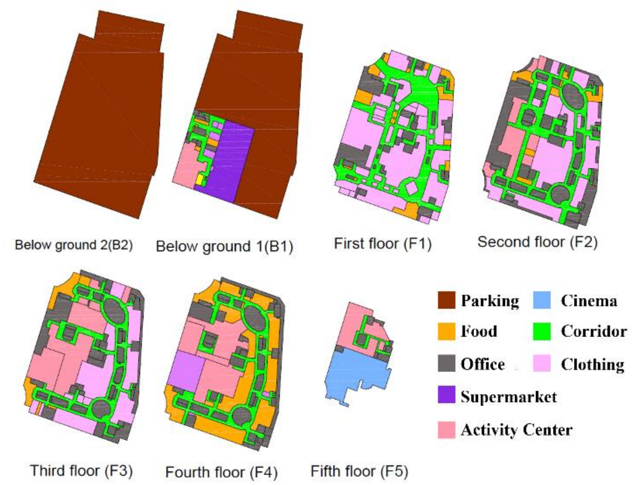


Fig. 1 Distribution of space functions on each floor of the building

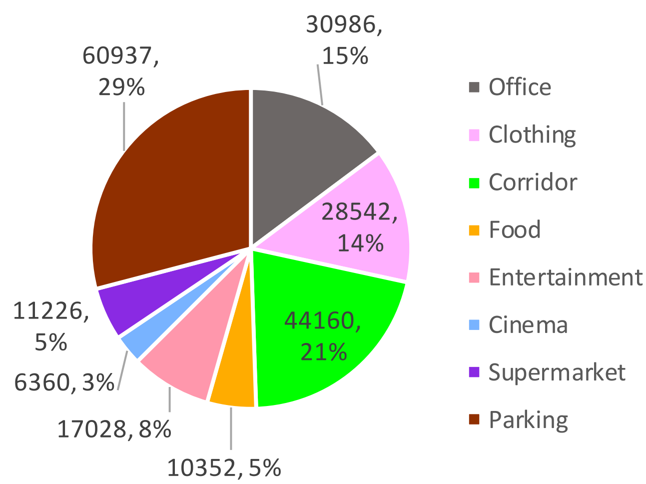


Fig. 2 Area of each function type (m², %)

Fig. 4 illustrates the monthly energy use intensity of electricity and natural gas. The measured annual electricity consumption of the shopping mall is 25.2 GWh, and the electricity use intensity is 120.1 kWh/m2. The annual natural gas consumption of the mall is 14.4×103 GJ, and the natural gas use intensity is 68.6 MJ/m2 (19.1 kWh/m2).

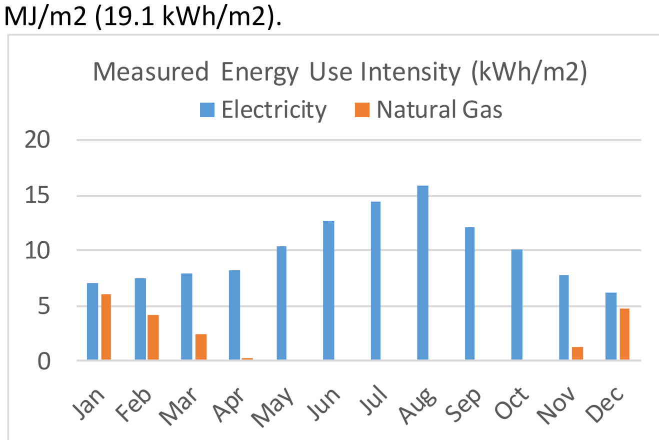


Fig. 3 Monthly measured energy use intensity

2.2 Baseline model generation

As shown in Fig. 5, the shopping mall prototype model in AutoBPS had a rectangular shape with two rings and a core area. The length and width of the building were 238m and 126m. The width of the outer and inner ring areas was 15m and 16.2m. The two rings area were divided into four or more thermal zones each. The spaces in the inner ring were set as the corridor. Other spaces are set up as offices, clothing, food, entertainment, cinemas and supermarkets while ensuring the same floor area as the actual floor area and the basic consistency of floors. There are two parking stories below ground. The area of each function type in the EnergyPlus model was designed to be the same as those shown in Fig. 3. The detailed layout and zoning of each floor of the building are shown in Fig. 5.

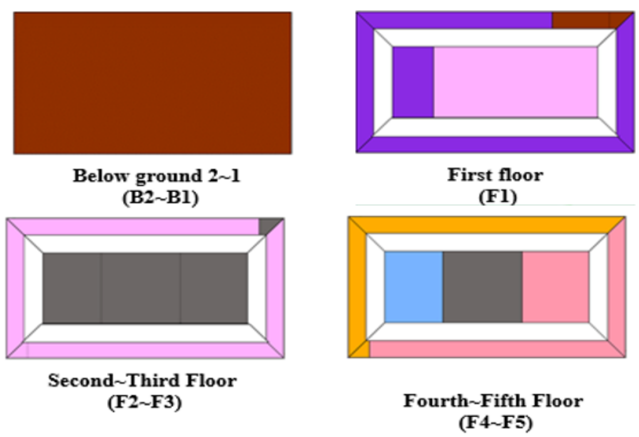


Fig. 4 Thermal zoning of each floor

The building envelope mainly included exterior walls, roofs and exterior windows. With reference to China building energy-saving design standards of "GB50189-2015" and "DBJ43/003-2017", Table 1 lists the heat transfer coefficient of external walls, roof and windows, and the solar heat gain coefficient (SHGC) of windows.

Table 1. Heat transfer coefficient of the envelope

		GB50189-2015 & DBJ43/003-2017	Study building
Heat transfer coefficient ($W/m^2 \cdot k$)	External walls	<0.6	0.58
	Roof	<0.4	0.38
	Window	<2.6	2.5
Window SHGC		0.4	0.4

Table 2 Internal load value table of each thermal zone

Room type	Equipment power density (W/m2)	Lighting power density(W/m^2)	Occupancy (m^2/person)	Heating set-point temperature (℃)	Cooling set-point temperature (℃)
Parking	13	5	8	5	37
Super-market	9	15.5	10	20	25
Corridor	5	9	15	18	28
Food	11	9	10	20	25
Activity center	9	10	5	20	25
Clothing	13	19	8	20	25
Cinema	11	9	5	20	25
Office	10	10	5	20	25

Since the mall contained different functional areas, the heat disturbance settings for each functional area were different. Through on-site research and literature research, the thermal disturbance density of each room type, including equipment, lighting and personnel density, was determined, and the temperature settings in winter and summer in each thermal zone were obtained through literature review. Table 4 demonstrates the value of internal gains of each thermal zone.

2.3 Monte Carlo sampling

The model was calibrated using Monte Carlo sampling. The first thing was to determine the calibrated parameters. In this paper, 14 parameters of Monte Carlo sampling were finally determined for the envelope system, internal gains and air conditioning system, which had a great impact on building energy consumption. For these parameters, their ranges were obtained through literature research and form building standards. In order to ensure the randomness of parameter selection, the initial distribution of most parameters is normal distribution, which was expressed as N(μ,σ2). Among calibrated parameters, the absolute value of infiltration air volume was relatively small, so the randomness distribution of infiltration air volume was selected as triangular distribution. The indoor temperature varies linearly, so the randomness distribution of indoor temperature chose a uniform distribution. Detailed information on parameter distribution is shown in Table 5. The parameters were sampled using the Monte Carlo sampling method to ensure the uniformity of the samples. After obtaining 1000 uniformly distributed samples, there will be a certain error between the simulation results and the actual results. Referring to the standard in ASHRAE 14 in the United States, the monthly

NMBE should not exceed 5%, and the CVRMSE should not exceed 15%.

CVRMSE and NMBE are calculated as follows:

$$CVRMSE = 100 \times \frac{[\sum(y_i - \hat{y}_i)^2/(n-1)]^{\frac{1}{2}}}{\bar{y}}$$

$$NMBE = 100 \times \frac{\sum(y_i - \hat{y}_i)}{(n-1) \times \bar{y}}$$

y_i- measured data

$\bar{y}$- mean of measured data

$\hat{y}_i$- simulated data

In calculating the error of the energy consumption simulation, since the energy consumption of the building is divided into two parts: gas energy consumption and electricity consumption, refer to the formula in Energy Savings Analysis: ANSI/ASHRAE/IES Standard 90.1-2016 for source energy consumption.

$$Source\ energy(GJ) = 3.167 \times Electricity(GJ) + 1.084 \times Natural\ Gas(GJ)$$

Here source energy is defined as an indicator of building energy consumption, including power energy for HVAC (HVAC, refrigeration, fans and pumps), indoor lighting, indoor equipment, and natural gas source energy for heating. The definition of source energy can be used to more easily quantify the error between measured and simulated energy consumption in buildings

2.4 Retrofit analysis with uncertainty

After obtaining the building energy consumption model of the mall, it is necessary to understand the impact of specific energy saving measures on the energy consumption of the mall. This paper explores the impact of replacing LED lighting with optical density and chiller COP on the energy consumption of the mall. The models that meet the error criteria are retrofitted for building energy efficiency. To reduce the energy consumption, here the lighting density is taken as 10 w/m2, and the chiller COP is taken as 6. The energy consumption results of the models after the parameter adjustment are compared with those before the adjustment, and the energy saving rates are calculated. Finally, the energy saving rates of these models were statistically analyzed, and the energy saving rates were calculated as shown below.

$$Energy\ saving\ rate = \frac{A - B}{B}$$

Where A means source energy after adopting energy conservation measures, and B means source energy before adopting energy saving measures.

Table 3 Parameter Distribution Table

Parameter name	Unit	parameter range	Baseline value	GB50189-2015	Distribution type
External wall heat transfer coefficient	W/(m^2·K)	0.37-0.56	0.591	<0.6	Normal
Roof heat transfer coefficient	W/(m^2·K)	0.32~0.4	0.387	<0.4	Normal
Window heat transfer coefficient	W/(m^2·K)	1.93-3.0	2.501	<4.0	Normal
SHGC of the window	none	0.17-0.81	0.5	<0.52	Normal
Occupancy density	m^2/person	4.2-5.8	5	8	Normal
Lighting power density	W/m^2	10-16.2	13.5	10	Normal
Equipment power density	W/m^2	9.56-16.4	13	13	Normal
Infiltration rate per exterior wall area	m^3/s/m^2	0.000336~0.001259	0.0007	none	Triangular
Outdoor air flow rate	m^3/h/person	20~50	35	30	Normal
Fan efficiency	none	0.55~0.65	0.6045	<0.65	Normal
Chiller COP	none	3.0-5.13	5	4-6	Normal
Cooling setpoint temperature	℃	23~26	25	25	Evenly
Heating setpoint temperature	℃	19~23	20	20	Evenly
Boiler thermal efficiency	none	0.81~0.95	0.9	0.9	Normal

3. RESULTS

3.1 *Baseline model simulation results*

Fig. 6 shows the simulated monthly electricity use intensity by end-use. The simulated annual electricity consumption is 25.4 GWh, and the electricity use intensity is 121.1 kWh/m^2. The annual electricity energy use intensities of lights, plug loads, chiller, and others are 28.3, 32.1, 37.7, and 23.1 kWh/m^2, respectively.

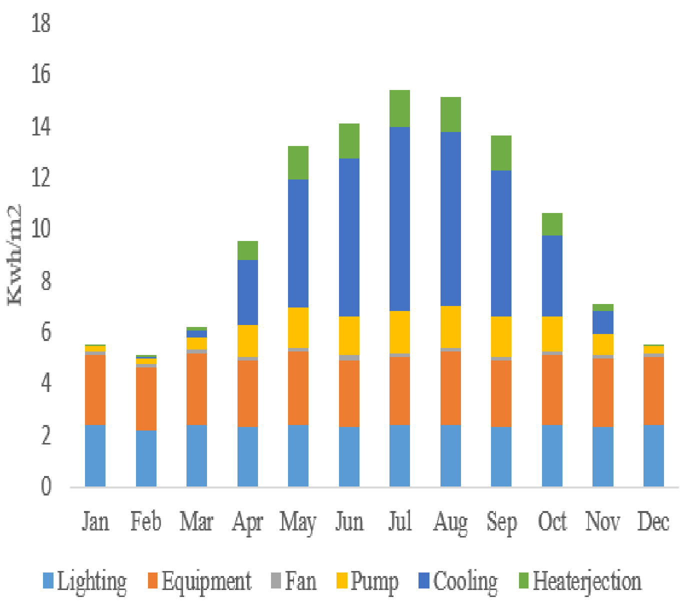


Fig. 6 Simulated monthly electrical energy consumption by end use

Fig. 7 shows the simulated monthly natural gas use intensity by end use. The simulated annual natural gas consumption is 15.4×10^{3}GJ, which is 20.46kWh/m^2. The natural gas is mainly used for space heating during the winter, which accounts for 92% of natural gas consumption.

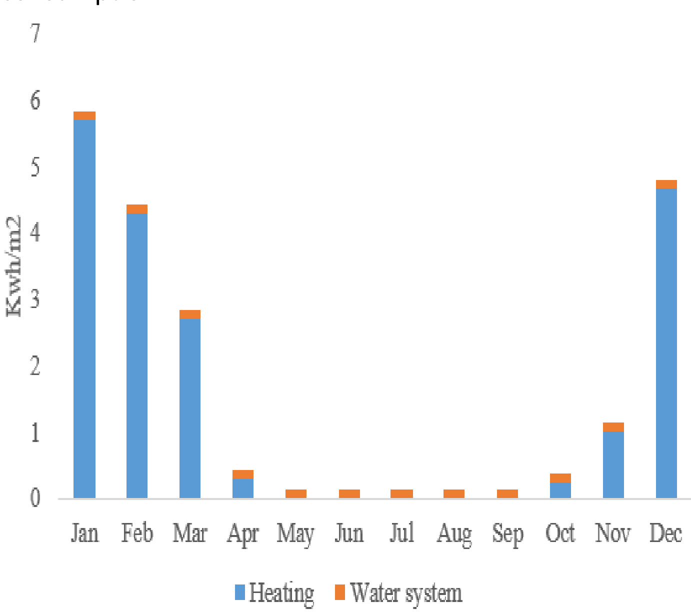


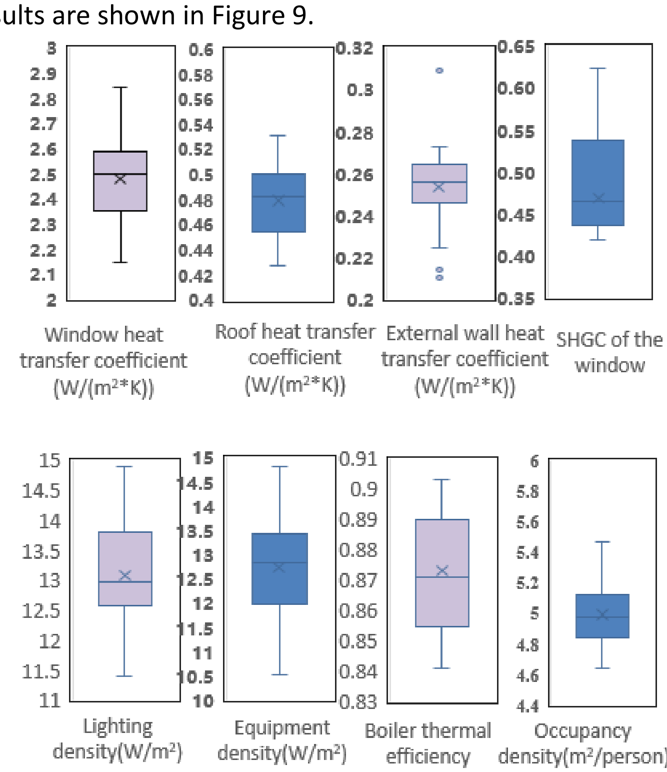
Fig. 7 Simulated monthly natural gas consumption by end-use

After the prototype model was established, the model's energy consumption was compared with the measured energy consumption to ensure that the model matches the actual situation. Using Source energy as the standard for total building energy consumption, the errors between measured and simulated month-by-month energy consumption were calculated, in which the model CVRMSE=14.7%<15% and NMBE=1.54%<5%, both of which meet the standards in ASHRAE 14. The month-by-month energy consumption is shown in Figure 8.

Fig. 8 Source energy consumption calibration results

3.2 Model calibration using Monte Carlo sampling

The prototype model was calibrated with Monte Carlo sampling. A total of 1000 samples were sampled. After screening by ASHRAE 14 criteria, a total of 29 models fit the error range. These 29 models corresponded to 29 combinations of parameters. The 29 values of the 14 parameters were collated and the results are shown in Figure 9.



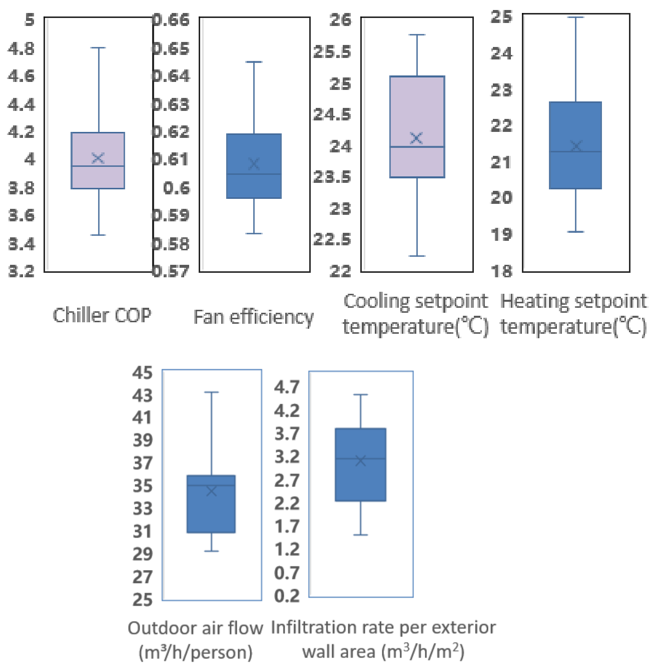


Fig. 9 Box plot of parameter distribution after Monte Carlo sampling

As can be seen in Figure 9, the parameters of all 14 parameters after calibration have changed significantly compared to the assumed parameter ranges before calibration, and the parameters are more concentrated. At the same time, the average values of the parameters all fluctuate above and below the assumed average values, which indicates that the parameter ranges set before calibration are reasonable. The dispersion of different parameters also varies greatly. The smaller ranges of parameters such as chiller COP, fan efficiency, and occupancy density indicate that the distribution of these parameters is more concentrated and the uncertainty is smaller; The large range of heating temperature and boiler thermal efficiency indicates that the distribution of these parameters is scattered and the uncertainty of parameters is large.

3.3 Retrofit analysis with uncertainty

After the model calibration, 29 calibrated EnergyPlus models were obtained. Two energy conservation measures (ECMs) are evaluated, including LED light replacement with the lighting power density of 10W/m2 and chiller replacement with COP of 6. The energy saving rate is calculated in the form of source energy. Fig. 10 shows the distribution of the source energy saving percentage of the two ECMs. The source energy saving percentage of replacing to LED lights ranges from 1.7% to 11.4% with an average of 5.8%; while the source energy saving percentage of chiller replacement ranges from 1.5% to 13.5% with an average of 8.0%. The results show a high level of uncertainty when the actual lighting power density and chiller cop information is unknown. It is necessary to conduct a site visit to figure out the actual lighting power density and chiller COP to narrow down the energy saving results.

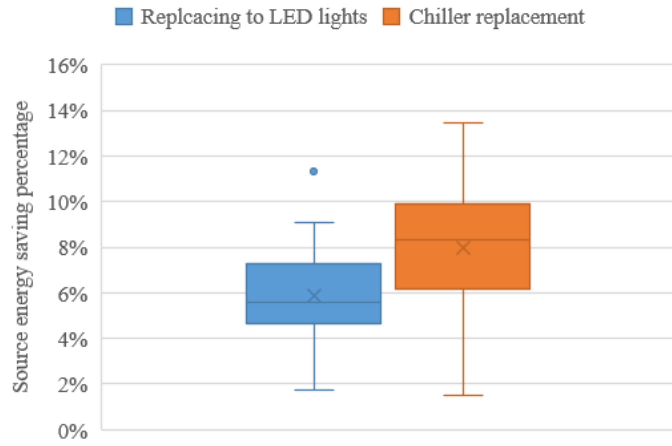


Fig. 10 Source energy saving percentage distribution of the two ECMs

4. CONCLUSIONS

This paper presents a rapid energy modeling method by using AutoBPS to generate a baseline model and calibrates it using Monte Carlo sampling. The calibrated models are then used to perform retrofit analysis with uncertainty. The proposed method could help to find multiple EnergyPlus models that meet the calibration criteria. The retrofit analysis results indicate a high level of uncertainty when applying this method to evaluate the energy saving percentage of the selected ECMs. The method proposed in this study can be better applied to the current building energy retrofit. The prototype model is obtained through rapid modeling, and the final results of the uncertainty of energy-saving measures can provide reliable data support in selecting energy-saving measures for energy-saving retrofit, and help decision-makers to select the most appropriate energy-saving measures.

5. LIMITATIONS AND PROSPECTS

Although model calibration has been automated, current building model simplifications are still manual. Further research will explore the possibility of automated building model simplifications.

In addition, the current energy-saving measures are simplified to numerical transformation, which may be different from the actual energy-saving measures, the follow-up study will be improved.

ACKNOWLEDGEMENT

This paper is supported by the Natural Science Foundation of Hunan Province of China through Grant No. 2020JJ3008.

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