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Authors

Chen, Y

Deng, Z

Hong, T

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Yixing Chen^{1,2}, Zhang Deng^{1,2}, Tianzhen Hong³

¹ College of Civil Engineering, Hunan University, Changsha 410082, China

² Key Laboratory of Building Safety and Energy Efficiency (Hunan University), Ministry of Education, China

³ Building Technology and Urban Systems Division, Lawrence Berkeley National Laboratory, Berkeley, CA 94720, USA

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Automatic and Rapid Calibration of Urban Building Energy Models by Learning from Energy Performance Database

Yixing Chen^{1,2,*}, Zhang Deng^{1,2}, Tianzhen Hong^{3,*}

1. College of Civil Engineering, Hunan University, Changsha 410082, China

2. Key Laboratory of Building Safety and Energy Efficiency (Hunan University), Ministry of Education, China

3. Building Technology and Urban Systems Division, Lawrence Berkeley National Laboratory, Berkeley, CA 94720, USA

* Corresponding author E-mail: yixingchen@hnu.edu.cn; thong@lbl.gov

Abstract

Urban building energy modeling (UBEM) is attracting increasing attention in the energy modeling field. Unlike modeling a single building using detailed building systems information, UBEM generally uses limited high-level building stock data to infer default assumptions about building characteristics and operations. This practice inherently brings uncertainty to UBEM. This study introduced a novel method of automatic and rapid calibration of UBEM based on the annual electricity and natural gas energy use data by learning the correlations between crucial model input parameters and the building energy use from the reference building models. A case study was presented to calibrate 72 large office buildings built before 1978 in San Francisco. Seventeen model parameters were selected and Monte Carlo sampling was used to create 1000 samples that reasonably represent the parameter space. Then 1000 simulations were performed for the reference building model to create an energy performance database. The results showed that by learning from the energy performance database, it took less than four simulation runs on average to calibrate a building model. After the calibration, the distributions of each parameter were obtained to replace their single predefined default values. For example, the default lighting power density of 21.39 W/m² was calibrated to be 7.50 W/m² on average. The case study successfully demonstrated the effectiveness of the novel calibration method for UBEM in the mild climate. The method will be further tested in future for other climate zones and other building types.

Keywords

Urban Building Energy Modeling; Model Calibration; EnergyPlus; Reference building model; CityBES

Nomenclatures

Abbreviations

CBES: commercial building energy saver
CityBES: City Building Energy Saver
COP: coefficient of performance
CVRMSE: Coefficient of variation of the root mean square error
ECMs: energy conservation measures
EUI: energy use intensity
EUIs: energy use intensities
GHG: greenhouse gas
GOF: good of fitness
HVAC: heating, ventilation, and air-conditioning
LED: light-emitting diode
NMBE: normalized mean bias error
PV: Photovoltaics
SHGC: solar heat gain coefficient
UBEM: Urban building energy modeling;
VAV: variable air volume
WWR: windows to wall ratio

Symbols

End_Use: Any end-use energy use intensity
w: source factor
y: energy use intensity result
GOF_{real}: the real GOF calculated based on EnergyPlus simulation results

Subscripts

tb: target building
rb: reference building
min: minimum
max: maximum
e: electricity
g: natural gas
guess: guessed results
simulate: simulated results

1 Introduction

1.1 Background and motivation

Today's cities consume more than two-thirds of the world's primary energy and account for more than 70% of global greenhouse gas (GHG) emissions. The building sector in cities can consume up to 75% of the total

primary energy. In the United States, half of the commercial buildings [1] and 55% of the residential buildings [2] were built before 1980, while 82% of both commercial and residential buildings were built before 2000. Retrofitting the existing building stock to improve energy efficiency and reduce energy use is a crucial strategy for cities to reduce GHG emissions and mitigate climate change [3].

There are many building energy conservation measures (ECMs), such as enhancing the performance of envelope system (e.g., adding thermal insulation or using high-performance windows), installing photovoltaics on roof [4], improving the energy efficiency of equipment, using natural ventilation, optimizing building operation and controls [5], and promoting energy-saving occupant behavior [6]. The energy saving potential of some ECMs is apparent and easy to evaluate, e.g., replacing the existing lighting system with light-emitting diode (LED) lamps [7]. However, the energy saving potential of some ECMs may significantly vary by climate zones. For example, the external wall thermal insulation performs better in a cold climate than a hot and mild climate [8]. Some ECMs may not save energy when the system is not well designed and operated. For example, if the district cooling system is oversized, the system may operate under inefficient low-load conditions and thus may not save energy. It is, therefore, essential to evaluate the performance of ECMs before implementing them, mainly when the resources are limited [9].

Urban Building Energy Modeling (UBEM) refers to the application of bottom-up physics-based building energy models to predict operational energy use as well as indoor and outdoor environmental conditions for groups of buildings in an urban context [10]. UBEM is an excellent tool to explore opportunities for ECMs when applying to a large group of buildings in the urban context [11]. UBEM can also be used to evaluate the district-scale technologies [12]. Unlike modeling a single building, which will use detailed information, UBEM generally uses existing building stock data consisting of high-level building information. The details of building systems are rarely available for a large number of buildings at the city scale. Typically, the building systems and their efficiency values are determined based on the building type, vintage, size, and climate zone, which represent the average conditions among peer groups [13].

The use of archetype may lead to smaller ranges of site and source energy use intensities (EUIs) distribution for simulated results compared with measured data [14]. Many cities in the United States begin to enforce energy ordinance for existing buildings and provide open data via web portals [15]. Those contained energy data typically at the annual resolution, can be used to calibrate the UBEM and reduce the discrepancy between simulated results and measured data. The model calibration is commonly defined as an inverse approximation because of the need for tuning necessary inputs to reconcile the outputs by a simulation

program, as closely as possible to the measured energy data [16]. It is impossible to calibrate the model to be exact as the real building. However, after the calibration, the results are believed to be better than without calibration [17].

1.2 Related works and knowledge gaps

There are several automatic calibration methods developed to calibrate individual building, including optimization-based methods [18], pattern or rule-based methods [19], and Bayesian calibration methods [20]. Those calibration methods iteratively adjust the values of selected parameters until the difference between the simulated and measured energy use meets the calibration criteria, which typically requires numerous simulation runs and can be computationally intensive. Those methods were well demonstrated for individual buildings. Although they can be directly applied to calibrate UBEM, the number of simulations required to calibrate the UBEM is proportional to the number of buildings; thus, the total number of simulation runs can be enormous. When simplified reduced-order models (e.g., resistance-capacitance network models) were used in UBEM, each simulation run may only take several milliseconds. So sophisticated calibration methods such as Bayesian calibration can be applied [21]. However, for detailed physics-based energy models, it may take several minutes or more to run a simulation. It is therefore very important to reduce the number of simulations when calibrating physic-based energy models at a large scale (e.g., with hundreds or thousands of buildings).

There are limited studies on UBEM calibration. Nagpal et al. [22] showed a methodology for auto-calibrating UBEM using surrogate modeling techniques. For each building, about 200 EnergyPlus simulations were performed to generate samples for training the surrogate models. The surrogate models can then generate new representative data samples without the need for computationally expensive energy simulations. The surrogate models can be combined with optimization algorithms to determine the combinations of unknown parameters. Sokol et al. [23] presented a Bayesian-based calibration method for defining residential archetypes in UBEM. Three hundred ninety-nine homes with monthly electricity and gas data were used as a training set to generate the probability distributions of uncertain parameters, then applied to a broader test set of 2263 homes to validate the models. Each building was simulated with 1000 samples from the posterior distribution.

Moreover, Cerezo et al. [24] proposed a Bayesian calibration technique to determine the frequency distributions for occupancy, lighting power density, plug load density, and cooling temperature setpoints.

This calibration method was applied to 164 residential building with annual energy data, then validated by 159 metered buildings in the same district. Each building was simulated using 100 samples by a Latin Hyper Cube approach. Santos et al. [25] described an automated UBEM calibration process to calibrate five parameters using a genetic algorithm for 56 buildings with monthly electricity data. The parameters were converged after 4680 iterations using the reference rural weather file. When the local weather file generated by the Urban Weather Generator [26] was used, the models took 2650 iterations to converge. Most of the current UBEM calibration studies performed the calibration method for each building separately. However, buildings in the UBEM are usually similar in characteristics and operations. The UBEM calibration should not be the simplified scale-up of the methods used for calibrating individual buildings, which require computationally intensive iterations and monthly or more detailed energy use data usually not available for a large group of buildings.

1.3 Objective of this study

This paper introduces a novel UBEM calibration method by learning from a pre-simulated performance database of the reference building models to automatically and rapidly calibrate 72 energy models of large office buildings built before 1978 in San Francisco with the annual electricity and natural gas data.

2 Method

Figure 1 shows the main steps to calibrate the UBEM in this study. First, we collected the building information of a district in San Francisco. Seventy-two buildings with the annual electricity and natural gas consumption data were selected as target buildings for the UBEM calibration. Secondly, we created the UBEM for the buildings using City Building Energy Saver (CityBES), an open data and computing platform for urban buildings [27]. The geometries of the building energy models are created based on the building footprint, building height, and the number of stories. On the other hand, the system types and energy efficiency values are generated according to the prototypes/archetypes in CityBES, which are based on the minimum energy efficiency requirements of California's building energy efficiency standards Title 24. The third step is to adjust those prototype models based on the measured energy data, so they can better represent the case study buildings. The fourth step is to select the parameters for calibration and perform the UBEM calibration to obtain the post-calibration distribution of the parameters. The third and fourth steps are related, but different. Take the modeling of daylighting controls as an example. The third step is to develop the methods to model the daylighting controls, including the location of daylight sensors and the dimming

control based on the design illuminance levels. The fourth step can take the “Has daylighting control or not” as a parameter for calibration and determine the percentage of buildings that have daylighting control after calibration. The last step is to validate the calibration algorithms. One thousand simulations per building (72,000 in total) are run to verify the performance of the calibration algorithms. The details of each step are introduced in the following section.

Figure 1. Main steps of the UBE M calibration

2.1 Identify the buildings for UBE M calibration

Figure 2 shows the buildings selected for UBE M calibration in this study. Those buildings are located in San Francisco, which belongs to ASHRAE climate zone 3C (Warm – Marine). Figure 2 (a) shows 8665 buildings in the northeast district, including 278 large office buildings. The building dataset was generated by integrating the diverse data sources from multiple city departments of San Francisco [15]. San Francisco Environment Code Chapter 20 [28] requires that each non-residential building larger than 929 m² and each residential building larger than 4645 m² must be benchmarked using Energy Star Portfolio Manager [29]. Seventy-two large office buildings built before 1978 with the available annual electricity and natural gas data were selected for calibration in this study. Figure 2 (b) shows the 72 buildings color-coded by their simulated electricity EUIs. For the UBE M calibration, the 72 large office buildings are modeled and calibrated with the consideration of shading impacts from all the 8665 buildings in the same district.

Figure 2. (a) 8665 buildings in the northeast district of San Francisco; (b) the selected 72 large office buildings with measured energy data (color-coded by the simulated electricity EUIs)

Figure 3 shows the boxplots of the basic information of the 72 target buildings. The number of stories ranges from 3 to 38 with a median of 10, while the gross floor area ranges from 1161 to 101,822 m² with a median of 11,361 m². The border of a building is referred to as the smallest rectangular shape with a proper orientation that can entirely contain the building footprint [14]. The footprint area to border area ratio ranges from 0.52 to 1.00, with a median of 0.95, which indicates that most of the target buildings have a rectangular shape.

Figure 3. Boxplot of the basic characteristics of the 72 target buildings

2.2 Create the UBEM

CityBES is used to create the UBEM for the 72 target buildings with the consideration of shading impacts from the 8593 buildings in the same district. CityBES [27] integrates the Commercial Building Energy Saver (CBES) [30] to create building energy models in EnergyPlus [31] for each building. The geometry of the energy model is created based on the building footprint, the building height, the number of stories, the function type of each story, and the windows to wall ratio (WWR). The function type of each story and the WWR, as well as the building system types and efficiency levels, are determined based on the building type, gross floor area, year built, and climate zone. Figure 4 shows the EnergyPlus models of two example buildings created by CityBES. Figure 5 compares the measured and simulated annual electricity and natural

gas energy use intensity (EUI) before calibration. The system efficiencies are determined based on the 'before 1978' vintage; however, the energy efficiencies of lights and other equipment have been significantly improved since 1978. That is why the simulated electricity EUIs are much higher than the measured ones for most buildings, as shown in Figure 5 (a). On the other hand, the measured natural gas EUIs are higher than the simulated results for many buildings. The next section introduces the adjustment of the prototype building models in CBES and CityBES to better represent the target buildings in reality. In this study, the unit of kWh/m²/year is used for the electricity EUI, the natural gas EUI, as well as the end-use EUIs so that we can have a better comparison.

Figure 4. EnergyPlus models of two example buildings created by CityBES

(a) Electricity EUI

Figure 5. Comparison of the measured and simulated annual electricity and natural gas EUI before calibration

2.3 Initial prototype models and parameter ranges

A building energy model can be split into three parts: the geometry, the building systems, and the efficiency values of the building systems. Here, the building systems refer to the physical components, equipment, or elements in the buildings. When modeling a single building, detailed information is typically used to create the geometry and the building systems, and the measured energy use data can be used to calibrate the efficiency values of the building systems. However, for UBEM, both the building systems and their efficiency values are unknown and needed to be calibrated using the measured energy data.

Table 1 shows the initial list of parameters and their ranges of values or options for calibration. The parameters 1 to 8 are related to conventional building systems that exist in almost all the buildings, including occupancy & operation, lighting, plug loads, and envelope & infiltration. The parameters 9 to 13 are related to the heating, ventilation, and air-conditioning (HVAC) system and domestic hot water system. For the large office buildings in San Francisco, the prototype building model assumes they use chillers, natural gas boilers, and central variable air volume (VAV) systems for space cooling and heating and the natural gas boiler for the domestic hot water system. The parameters 14 and 15 are related to daylighting control systems and air economizers, which may only be installed in a portion of the 72 buildings.

Table 1. Initial list of parameters and their value options for calibration

ID	Code	Name (Unit)	Option 1	Option 2	Option 3	Option 4
1	OCD	Occupancy density (person/m ²)	0.05	0.13	0.22	0.30
2	LPD	Lighting power density (W/m ²)	6.46	13.58	20.69	27.81
3	EPD	Equipment power density (W/m ²)	8.91	12.30	15.69	19.08
4	WWR	Window to wall ratio	0.25	0.38	0.52	0.65
5	WIN	Window glazing [SHGC, U-Factor (W/m ² ·°C), Visible transmittance]	[0.175, 1.43, 0.42]	[0.46, 2.67, 0.81]	[0.61, 4.37, 0.81]	[0.82, 6.98, 0.81]
6	INF	Infiltration rate (L/s·m ² wall area)	0.302	0.579	0.856	1.133
7	SET	Temperature setpoint (°C)	19 - 26	20 - 25	21 - 24	
8	SCH	Operational schedule (days)	4	5	6	6+
9	FAN	Fan efficiency	0.65	0.61	0.57	0.54
10	COP	Cooling efficiency (COP)	5.15	4.46	3.76	3.07
11	EFF	Heating efficiency	0.95	0.89	0.84	0.78
12	OAF	Outdoor air flow rate (L/s·person)	5.56	8.33	11.11	13.89
13	SHW	Gas water heater efficiency	0.93	0.85	0.78	
14	ECO	Air economizer	Yes	No		
15	DLT	Daylighting control	Yes	No		

COP: coefficient of performance, SHGC: solar heat gain coefficient, U-Factor: overall heat transfer coefficient, 6+: 6 working days and HVAC always on, HP: heat pump water heater

2.4 Adjust the prototype models and parameter ranges

For UBEM calibration, the calibrated parameters and their ranges are typically determined before calibration. When two simulations are run with upper and lower limits, the ranges of the calibration results can be roughly determined. The measured results may be higher than the upper limits or smaller than the lower limits, which requires the modeler/user to change the range of the parameters for calibration or update the modeling methods to include more features based on the real cases.

Figure 6 shows the workflow to adjust the prototype models and parameter ranges. First, two simulations (minimum and maximum efficiency cases) are run for each building to define the results boundary. The prototype models and parameter ranges are suitable for a building if the measured energy data of the building fall within its result boundary. The next step is to determine whether the prototype models and the parameter ranges are good enough based on the percentage of buildings, where their measured energy data are within their results boundaries. If the prototype models are not good enough, manual processes are required to check the parameter ranges by reviewing more recent information and update the

prototype models to include more building systems.

Figure 6. Workflow to adjust the prototype models and parameter ranges

Figure 7 shows the simulation results of the minimum and maximum cases with the initial prototype model and the parameter ranges. 71% of the measured electricity EUIs are within the simulated result boundaries, and the rest 29% are all smaller than the minimum results. For natural gas EUIs, 69% of the measured data are within the range, while the rest 31% is higher than the maximum results. There are 54% of the buildings, where both measured electricity and natural gas EUIs are within the simulated boundary. The initial prototype models and parameter ranges result in higher electricity consumption and smaller natural gas consumption compared with the measured energy data.

Figure 7. Simulation results of the minimum and maximum cases for the initial prototype models and parameter ranges

A detailed review of the Commercial Prototype Building models was conducted to check the ranges of the parameters. Those prototype models are mainly developed by Pacific Northwest National Laboratory to support the commercial building energy codes and standards (ANSI/ASHRAE/IES Standard 90.1 and IECC) [32]. Table 2 lists the parameter values in three different Standard 90.1 prototype building models and the proposed new value options. Nine parameters (WWR, INF, SET, SCH, FAN, EFF, SHW, ECO, DLT) are kept the same. For occupancy density (OCD), the value of new option 2 is set to be the same as that of the 90.1 prototype models, while the other values of OCD are updated to have a narrower range compared to the initial options. For the lighting power density (LPD), the 2019 California Energy Commission Title 24 allowed LPD is 7.00 W/m² for office buildings. In this research, a lighting system with 25% more efficient than the 2019 title 24 limits is used as the new option 1 (5.27 W/m²), while the new option 4 is set to be the same as Standard 90.1-2004 models. The new options 1, 2, and 3 of window glazing (WIN) are set to be the same as the three 90.1 models, and the new option 4 is the same as the initial option 3. The equipment power density (EPD), cooling COP (COP), and outdoor airflow rate (OAF) are slightly updated based on the reviewed results.

Besides the updated parameter ranges, two new building systems are included. The first system is to model the Photovoltaics (PV) on the roof (PVR) as more buildings install PV to meet the city and the state's clean energy goal with the support of incentive programs. The City of San Francisco launched the GoSolarSF

program to provide a monetary incentive to help residents and businesses install solar panels on rooftops [33], and the California Solar Initiative offers cash back for installing solar panels [34]. In this study, it is assumed that 60% of the roof area can be used for PV. A PV module has an area of 1.65 m² with a maximum current of 7.5 A and a maximum voltage of 30 V. The short circuit current is 8.3 A, and the open-circuit voltage is 36.4 V. The tilt angle from horizontal is set to 31.8. The second system is to model the first floor as a full-service restaurant. The setting of the restaurant is based on the Standard 90.1 prototype models for the full-service restaurant. As most of the target buildings are located in downtown San Francisco, many of them may have restaurants or coffee shop on the first floor. Electricity equipment, gas equipment, and exhaust fan are modeled in addition to the conventional systems for the restaurant.

Table 2. Parameter values in Standard 90.1 prototype building models and the new value options

ID	Code	90.1 - 2016	90.1 - 2010	90.1 - 2004	New option 1	New option 2	New option 3	New option 4
1	OCD	0.05	0.05	0.05	0.04	0.05	0.06	0.07
2	LPD	8.50	9.69	10.76	5.27	7.10	8.93	10.76
3	EPD	8.07	8.07	8.07	5.99	8.07	10.15	12.23
4	WWR	0.40	0.4	0.40	0.25	0.38	0.52	0.65
5	WIN	[0.24, 2.90, 0.31]	[0.29, 2.85, 0.20]	[0.37, 4.91, 0.22]	[0.24, 2.90, 0.31]	[0.29, 2.85, 0.20]	[0.37, 4.91, 0.22]	[0.61, 4.37, 0.81]
6	INF	0.57	0.57	1.02	0.30	0.58	0.86	1.13
7	SET	21-24	21-24	21-24	19 - 26	20 - 25	21 - 24	
8	SCH	5	5	5	4	5	6	6+
9	FAN	0.61	0.61	0.6	0.65	0.61	0.57	0.54
10	COP	5.33	5.17	4.9	5.70	5.30	4.90	4.50
11	EFF	0.81	0.81	0.79	0.95	0.89	0.84	0.78
12	OAF	8.02	8.02	9.44	6.60	8.02	9.44	10.86
13	SHW	0.80	0.8	0.8	0.93	0.85	0.78	
14	ECO	Yes	Yes	Yes	Yes	No		
15	DLT	Yes	Yes	No	Yes	No		
16	PVR*	No	No	No	Yes	No		
17	RES*	No	No	No	Yes	No		

Note: PVR - Photovoltaics (PV) on the roof; RES - Restaurant on the first floor

Figure 8 shows the simulation results of the minimum and maximum cases with the updated prototype models and the updated parameter ranges. Both measured electricity and natural gas EUIs are within the simulated boundary for all the 72 buildings. The updated prototype models and the updated parameter ranges

can better represent the target buildings. It will be great if we can continue to improve the prototype models and the parameters ranges; however, it will require on-site visits, interviews, or surveys to understand more information about the target buildings, which is out of this study's scope. The main objective of this study is to evaluate the UBEM calibration algorithms; therefore, the updated prototype models with the new parameter ranges (Table 2) are used in the UBEM calibration process.

Figure 8. Simulation results of the minimum and maximum cases for the updated prototype models and parameter ranges

2.5 Calibrate the UBEM

The proposed UBEM calibration method includes four main steps (Figure 9). The first step is to identify a list of parameters, which are uncertain and significantly influence building energy performance. In this study, seventeen parameters are selected with two to four value options, as shown in Table 2. The full combination of the parameters leads to a massive number of simulations. In the previous UBEM calibration studies, 100 samples [24], 200 to 400 samples [22], and 1000 samples [23] were generated for each building. So, the Monte Carlo Sampling technology is used to create 1000 samples as a reasonable representation of the parameter space. Monte Carlo sampling is a class of techniques for randomly sampling a probability distribution, where the distribution of individual parameters will be the same as the inputs. The second step is to create the energy performance database of the reference building model. One EnergyPlus model of the

reference building is created for each parameter combination sample. The 1000 sets of simulation results of the reference building model are stored to create the energy performance database. Each set of EnergyPlus simulation results includes the annual electricity and natural gas energy usage as well as the end-uses, including the electricity consumption for the space cooling, interior and exterior lighting, interior and exterior equipment, fans, pumps, and refrigeration, and the natural gas consumption for space heating, water heating, and gas equipment (restaurant).

Figure 9. Workflow of the UBEM calibration method

The third step is to guess the candidate samples without running EnergyPlus simulations. This step is an essential part of this UBEEM calibration process. The minimum and maximum cases are run for each target building to evaluate the performance of the prototype models and parameter ranges in the previous section. Those results are used together with the energy performance database and the minimum and maximum results of the reference building to guess the target buildings' results for the 1000 samples. Any end-use result of a target building for a sample ($End_Use_{tb,sample}$) can be calculated based on equation (1). The $End_Use_{tb,max}$ and $End_Use_{tb,min}$ are the end use results of the target building's minimum and maximum cases, while the $End_Use_{rb,max}$ and $End_Use_{rb,min}$ are the end use results of the reference building's minimum and maximum cases. The $End_Use_{rb,sample}$ is the end use result of the reference building for the sample, which is stored in the energy performance database., the end-use results are guessed and aggregated to generate the annual electricity and natural gas EUIs using equation (1).

$$\frac{End_Use_{tb,sample} - End_Use_{tb,min}}{End_Use_{tb,max} - End_Use_{tb,min}} = \frac{End_Use_{rb,sample} - End_Use_{rb,min}}{End_Use_{rb,max} - End_Use_{rb,min}} \quad (1)$$

For individual building, energy model calibration, the Coefficient of variation of the root mean square error (CVRMSE) and the normalized mean bias error (NMBE) are normally used as the calibration metrics when monthly or more detailed energy data are available. As suggested by ASHRAE Guideline 14 [35], CVRMSE and NMBE should be less than 15% and 5% for monthly calibration data and 30% and 10% for hourly calibration data. In this study, only annual electricity and natural gas EUIs are available. So, the good of fitness (GOF) is used instead in this study. For the guessed sample result, the good of fitness (GOF) is calculated based on equation (2). A threshold of 5% is used to determine whether the sample is a candidate solution or not.

$$GOF_{guess} = \sqrt{\frac{w_e^2 \times (y_e - y_{e,guess})^2 + w_g^2 \times (y_g - y_{g,guess})^2}{w_e^2 y_e^2 + w_g^2 y_g^2}} \quad (2)$$

where w_e is the source factor for electricity (3.14), w_g is the source factor for natural gas (1.05), y_e is the measured electricity EUI, y_g is the measured natural gas EUI, $y_{e,guess}$ is the guessed electricity EUI of the target building for the sample, and $y_{g,guess}$ is the guessed natural gas EUI of the target building for the sample.

After step 3, a list of candidate solutions for each target buildings is generated. Moreover, the last step is to determine the valid solution(s). A sample from the guessed candidate samples is randomly selected, and one EnergyPlus model of the target building is created based on the sample parameter values. The real GOF is calculated based on Equation (3). When the real GOF is less than 5%, the solution is deemed adequate and valid. All the samples in the guessed solutions are later tested to evaluate the performance of the proposed method. The average number (expected value) of simulation runs to calibrate a building is calculated using Equation (4).

$$GOF_{real} = \sqrt{\frac{w_e^2 \times (y_e - y_{e,simulate})^2 + w_g^2 \times (y_g - y_{g,simulate})^2}{w_e^2 y_e^2 + w_g^2 y_g^2}} \quad (3)$$

$$ClibrationRuns_{tb} = \frac{\text{Number of Guessed Solutions}}{\text{Number of validated Solutions}} \quad (4)$$

where $y_{e,simulate}$ is the simulated electricity use intensity of the target building for the sample, and $y_{g,simulate}$ is the simulated natural gas use intensity of the target building for the sample.

3 Results

The simulation results of the minimum and maximum cases for the updated prototype models and parameter ranges are shown in Figure 8. The following section shows the simulation results of the reference building model, the number of candidate solutions per building, and the validated solutions per building.

3.1 Reference building full-scale simulation results

Monte Carlo sampling is used to generate 1000 parameter combination samples for the 17 parameters listed in Table 2. Figure 10 shows the distribution of the electricity and natural gas EUIs of the reference building results. The electricity EUIs range from 50.84 to 180.84 kWh/m²/year, with a median of 101.02 kWh/m²/year. The natural gas EUIs can be split into two groups: with and without modeling the first floor as a restaurant. When the first floor is modeled as a restaurant, the natural gas EUIs range from 37.46 to 65.21 kWh/m²/year, with a median of 42.13 kWh/m²/year. The ranges are 2.59 to 37.62 kWh/m²/year without modeling the restaurant. The electricity and natural gas EUIs for the minimum case are 50.37 and 4.76 kWh/m²/year

accordingly, while the values are 197.94 and 63.69 kWh/m²/year for the maximum case.

Figure 10. Distributions of the electricity and natural gas EUIs of the reference building simulation results

3.2 Candidate solutions

Figure 11 shows the distribution of the number of guessed candidate solutions for the 72 buildings. Forty-nine buildings (68%) have more than ten guessed solutions. Ten buildings have less than four guessed solutions, which may be difficult to find valid solutions. There are 1735 guessed solutions in total for the 72 buildings.

Figure 11. Distribution of the number of guessed candidate solutions

3.3 Valid solutions

There are 1108 valid solutions out of the 1735 guessed solutions, which means 64% of the guessed solutions are valid solutions. Figure 12 shows the average number of EnergyPlus runs to calibrate the 72 buildings. Sixty-one buildings (85%) out of the 72 buildings only need to run one or two simulations to calibrate the model. The expected value of the total simulations to calibrate the 72 buildings is 122, equivalent to 1.7 simulation runs per building on average.

Figure 12. Average number of calibration runs per building

3.4 Parameter distribution after calibration

The 72 buildings belong to the same archetype based on their building type, size, and vintage. These buildings are assigned with the same default values for the selected parameters before calibration. Table 3 shows the distributions of the parameter values after calibration, as well as the default and the calibrated average values. The calibrated values of lighting power density (LPD) and equipment power density (EPD) are 65% and 46% smaller than the default prototype values, which will strongly impact the retrofit saving estimation of ECMs for lighting and plug-load systems. The window-to-wall ratio (WWR) is 26% larger than the default prototype value, while the infiltration rate (INF) is 36% smaller than the default prototype value. The outdoor air flowrate (OAF) is 26% higher than the default value. The calibration results show that 65% of the buildings may have restaurants on the first floor. In contrast, about half of the buildings may have air economizer (ECO), daylighting sensors (DLT), or photovoltaics on the roof (PVR).

Table 3. Parameter values after calibration

ID	Code	Option 1	Option 2	Option 3	Option 4	Default value	Calibrated average	Percentage difference
1	OCD	25%	26%	26%	24%	0.11	0.055	-50%
2	LPD	36%	25%	20%	19%	21.39	7.50	-65%
3	EPD	44%	27%	17%	12%	14.68	8.00	-46%
4	WWR	17%	25%	27%	32%	0.38	0.48	26%
5	WIN	20%	19%	31%	30%	Option 4		NA
6	INF	25%	24%	25%	26%	1.13	0.72	-36%
7	SET	18%	21%	61%		Option 3		NA
8	SCH	28%	32%	22%	18%	Option 2		NA
9	FAN	27%	26%	21%	26%	0.6	0.59	-1%
10	COP	31%	21%	30%	18%	5.11	5.16	1%
11	EFF	24%	24%	28%	24%	0.76	0.86	14%
12	OAF	23%	24%	22%	31%	7.08	8.90	26%
13	SHW	32%	32%	36%		0.78	0.85	9%
14	ECO	54%	46%			Option 2		NA
15	DLT	53%	47%			Option 2		NA
16	PVR	54%	46%			Option 2		NA
17	RES	65%	35%			Option 2		NA

3.5 Validation of the UBEM algorithm

A full-scale (1000 simulations per building) simulation runs are performed for all the 72 target buildings for calibration to validate the UBEM algorithms. A total of 72,000 EnergyPlus simulations are run, and the results are used to evaluate the performance of the proposed UBEM calibration method.

3.5.1 Validation of the post-calibration parameter distributions

Table 4 shows the distributions of the parameter values for the 1866 valid solutions out of the 72,000 EnergyPlus simulation runs. It also shows the differences in parameter value distribution between the 1108 valid solutions and the full 1866 valid solutions. The post-calibration parameter distributions are very close to those obtained from full-scale simulation runs. The absolute differences higher than 2.5% are highlighted in Table 4. It requires 72,000 EnergyPlus simulations in total to find the full 1866 valid solutions, while it only takes 1735 EnergyPlus simulations to find the 1108 valid solutions. The proposed UBEM calibration algorithms can generate high accuracy results with a small number of simulations.

Table 4. Differences in distribution between the 1108 valid solutions and the total 1866 valid solutions

ID	Code	Total 1866/72000 valid solutions				1108/1735 vs 1866/72000			
		Option 1	Option 2	Option 3	Option 4	Option 1	Option 2	Option 3	Option 4
1	OCD	24%	25%	26%	25%	0.3%	0.9%	-0.2%	-0.9%
2	LPD	35%	26%	20%	19%	1.1%	-0.6%	0.0%	-0.5%
3	EPD	44%	24%	19%	14%	0.7%	2.7%	-1.7%	-1.7%
4	WWR	18%	27%	25%	31%	-0.5%	-2.4%	1.9%	1.0%
5	WIN	21%	19%	29%	30%	-1.2%	-0.6%	2.0%	-0.2%
6	INF	23%	25%	28%	24%	1.4%	-0.4%	-3.1%	2.0%
7	SET	18%	24%	58%		0.1%	-2.8%	2.6%	
8	SCH	31%	30%	21%	18%	-2.9%	2.3%	0.5%	0.1%
9	FAN	26%	26%	22%	26%	0.4%	0.5%	-1.2%	0.4%
10	COP	31%	21%	30%	19%	0.0%	0.7%	0.2%	-0.9%
11	EFF	24%	24%	26%	26%	0.0%	0.2%	1.7%	-1.9%
12	OAF	25%	23%	22%	29%	-2.7%	0.5%	0.5%	1.7%
13	SHW	34%	33%	33%		-1.5%	-0.7%	2.2%	
14	ECO	52%	48%			1.6%	-1.6%		
15	DLT	54%	46%			-0.9%	0.9%		
16	PVR	57%	43%			-2.4%	2.4%		
17	RES	64%	36%			0.9%	-0.9%		

3.5.2 Validation of the valid solutions

Table 5 shows the comparison of the guessed and real GOFs. There are 1735 guessed solutions and 1866 valid solutions in total. Through the UBEM calibration process, 1108 valid solutions were found, which is 64% of the guessed solutions and 59% of the total valid solutions. The result indicates that the UBEM calibration algorithm can find a significant number of valid solutions without a massive number of simulations. Figure 13 shows the distribution of real GOF for the 1735 guessed solutions. The real GOF is less than 10% for 97% of the guessed solutions, which indicates that most of the guessed solutions are very close to the valid solutions.

Table 5. Comparison of the guessed and real GOFs

	$GOF_{guess} \leq 5\%$	$GOF_{guess} > 5\%$	Total
$GOF_{real} > 5\%$	627	69507	70134
$GOF_{real} \leq 5\%$	1108	758	1866
Total	1735	70265	72000

Figure 13. Distribution of the real GOF for the 1735 guessed candidate solutions

Table 6 shows the distributions of the parameter values for the 1735 guessed solutions and the difference in parameter distributions between the 1735 guessed solutions and the 1866 valid solutions. The maximum difference is 4.9% for the temperature setpoints (SET), and only five differences are higher than 2.5%. The 1735 guessed solutions are calculated based on simple algebraic equations and logics, as introduced in Figure 9, which can be done within a second for each building. It does not require EnergyPlus simulations in this case. The parameter distributions generated from the guessed solutions can be used before running a large number of calibration runs.

Table 6. Differences in distribution between the 1735 guessed solutions and the 1866 valid solutions

ID	Code	1735 guessed solutions				1735 vs 1866/72000			
		Option 1	Option 2	Option 3	Option 4	Option 1	Option 2	Option 3	Option 4
1	OCD	25%	27%	24%	24%	1.0%	1.6%	-2.2%	-0.4%
2	LPD	36%	25%	20%	19%	1.1%	-0.7%	-0.1%	-0.2%
3	EPD	43%	28%	17%	12%	-0.3%	3.3%	-1.4%	-1.7%
4	WWR	18%	24%	26%	31%	0.3%	-2.5%	1.7%	0.5%
5	WIN	22%	19%	30%	29%	0.7%	-0.5%	0.7%	-0.8%
6	INF	25%	24%	25%	26%	1.9%	-0.9%	-3.4%	2.4%
7	SET	16%	21%	63%		-1.8%	-3.1%	4.9%	
8	SCH	29%	29%	21%	20%	-1.6%	-0.8%	0.2%	2.2%
9	FAN	27%	23%	21%	28%	1.2%	-2.4%	-1.3%	2.4%
10	COP	30%	21%	31%	17%	-0.3%	0.9%	0.8%	-1.4%
11	EFF	22%	26%	27%	25%	-1.8%	2.1%	0.6%	-1.0%
12	OAF	26%	22%	21%	31%	0.6%	-1.0%	-1.3%	1.8%
13	SHW	33%	33%	35%		-1.4%	0.2%	1.2%	
14	ECO	52%	48%			-0.4%	0.4%		
15	DLT	55%	45%			0.2%	-0.2%		
16	PVR	58%	42%			1.5%	-1.5%		
17	RES	65%	35%			1.3%	-1.3%		

4 Discussion

As shown in Figure 11, most of the buildings have multiple candidate models. For each calibration run, different candidate models may be selected, which may result in different parameter combinations after calibration. The problem will be worse when calibrating only a few buildings. In the future, we will perform multiple calibration runs to check whether the parameter distribution can converge to a unique set.

For UBEM calibration, the first step is to adjust the prototype models, so the prototype model can represent most or all the target buildings. This step is not introduced in most of the existing UBEM calibration studies. In the case study, the simulation results of the initial prototype models lead to higher electricity EUIs and lower natural gas EUIs. So, an adjustment of the prototype models is required. The initial prototype models treated all the stories as office space; however, there are many buildings in downtown San Francisco where the first floor is a restaurant or coffee shop. These restaurant spaces may consume higher natural gas for cooking and lead to higher natural gas consumption. Therefore, the mixed-use building type of office and restaurant is developed to model the first floor as restaurants.

The guessed solutions calculated based on the energy performance database, and the minimum and maximum simulation runs of each target building can generate very close results compared to the full-scale simulation runs. The parameter distribution generated from the guessed solutions can be simultaneously obtained when the users input the annual energy data of the buildings.

5 Conclusions

The case study successfully demonstrated the effectiveness of the novel urban building energy model (UBEM) calibration method for a group of large office buildings in the mild climate. The main findings of this study are summarized as follows:

- For UBEM calibration, it is important to perform two simulations with upper and lower limits of key parameters for each building to determine whether the prototype models can represent the target buildings. If not, an adjustment of the prototype models is needed before performing the calibration.
- By learning from the pre-simulated energy performance database of city reference buildings, it only took an average of 3.7 simulation runs to calibrate each building model, including the two simulations for the minimum and maximum cases.
- After the calibration, the distribution of each parameter was obtained, which was very different from the single default value based on building vintage and corresponding energy code.
- The parameter distributions generated from the guessed solutions without detailed EnergyPlus simulations are very close to those generated from the valid solutions.

The proposed UBEM calibration method can be adopted in most UBEM programs to improve the accuracy of simulation results with affordable computational resources. With more cities worldwide adopt policies to require disclosure of annual building energy use, such data can be directly used in the proposed Group-Learning UBEM Calibration method.

This study tested the proposed UBEM calibration algorithm in the mild climate of San Francisco for large office buildings. In the future, the UBEM calibration method will be further validated for other climate zones and other building types to demonstrate the validity of the method or needs of improvements.

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