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Development of new baseline models for U.S. medium office buildings based on commercial buildings energy consumption survey data

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Building energy estimation for the building sector under various scenarios are needed for building energy regulation and policy making. This often starts with representative baselines (either empirical baseline or modeled baseline). Commercial Buildings Energy Consumption Survey (CBECS) data is a widely used empirical baseline for U.S. commercial buildings, but none of the existing baseline model are developed to represent the CBECS data. This paper aims to develop new baseline models for the U.S. medium office buildings, which can produce modeled baselines consistent with the CBECS data. First, we introduced the methodology to create baseline models and the criteria to evaluate the performance of baseline models. The methodology consists of three phases: (1) identification of model inputs, (2) model calibration, and (3) model validation with uncertainty analysis. The evaluation index is the *coefficient of variation of the root-mean-square deviation* (*CV(RMSD)*) of site energy use intensities (EUIs) between the modeled baseline and empirical baseline. Then 30 new baseline models for two vintages (pre- and post-1980) and 15 climate zones were created. The evaluation shows that the *CV(RMSD)* is lower than 0.05 for the modeled baselines produced by the new baseline models. As a comparison, the *CV(RMSD)* is higher than 0.1 for the existing modeled baselines generated by DOE Commercial Reference Building Models. Further analysis shows that the new baseline models are able to capture the uncertainties of the representative features of existing buildings.

Introduction

The commercial building sector was responsible for approximately 18.2% of U.S. primary energy use in 2018 (EIA 2019a). Furthermore, the primary energy consumption of U.S. commercial buildings was projected to increase approximately 5% by 2050. On the other side, great energy saving potentials were found in commercial buildings (Glazer 2017; Griffith et al. 2008; Kneifel 2010, 2011; Li, Yang, and Lam 2013; Torcellini et al. 2006). For example, Griffith et al. (2008) compared site energy use intensities (EUIs) in existing buildings and high-efficiency buildings without photovoltaic (PV) panels. The results showed that high-efficiency buildings can in average reduce 45% of site EUIs. Moreover, Glazer (2017) reported that 50% of the site energy can be reduced for commercial buildings in the U.S. Thus, it is crucial to encourage building owners to select suitable energy efficiency measures in order to improve the energy efficiency of U.S. commercial buildings.

To improve building energy efficiency, a rich set of building energy evaluation programs were developed to evaluate the energy performance of U.S. commercial buildings. For example, ENERGY STAR Portfolio Manager, created by the U.S. Environmental Protection Agency, allows building owners to compare their actual energy use with baselines representing the U.S. Stock (EPA 2013). ASHRAE's Building Energy Quotient (bEQ) (ASHRAE 2019) program aims to evaluate the building energy performance by comparing with baselines considering different building characteristics. The Building Energy Asset Score (BEAS) (DOE 2019a; Wang et al. 2018) encourages building owners to improve energy related building characteristics

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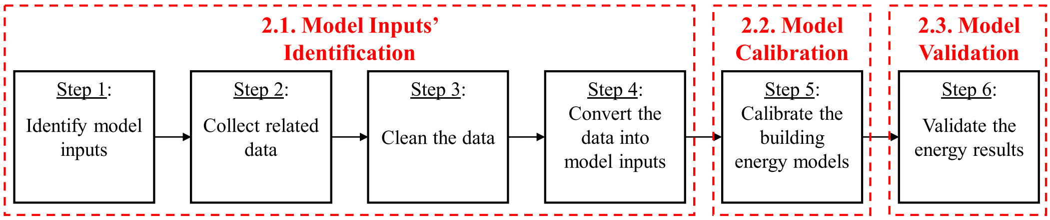

Fig. 1. Methodology to create baseline models.

by comparing their building's infrastructure against modeled baseline. The Leadership in Energy and Environmental Design (LEED) (USGBC 2014) gives energy credits by referring to the ASHRAE 90.1 modeled baseline for new construction.

Building energy evaluation programs use baselines as reference to evaluate the energy performance of the studied buildings. Baselines are classified into empirical and modeled baselines. Empirical baselines are often developed based on survey data sources, such as the Commercial Buildings Energy Consumption Survey (CBECS) (EIA 2019b), California Commercial End-Use Survey (CEUS) (CCEC 2006), and Building Performance Database (BPD) (DOE 2019b, Mathew et al. 2015). The ENERGY STAR Portfolio Manager and ASHRAE's bEQ program use empirical baselines. Modeled baselines are developed using baseline models, such as the DOE Commercial Reference Building Models (DOE 2011) and DOE Commercial Prototype Building Energy Models (DOE 2019c). The BEAS and LEED use modeled baselines.

To ensure consistent energy performance evaluation, it is important to reconcile the modeled baselines to empirical baselines so that the EUIs predicted by the baseline models match the EUIs in the empirical baselines. To achieve this goal, researchers are devoting efforts to reconcile the modeled baselines to the empirical baselines by modifying baseline models. They usually adjust the model inputs and calibrate the models to match the empirical energy data. For example, ASHRAE TRP-1771 aims to provide greater consistency between the empirical baselines and the modeled baselines. Furthermore, its objective is to complement empirical baselines with modeled baselines. Baseline models for several building types, such as U.S. religious worship buildings (Ye, Hinkelman, et al. 2019), U.S. college/university buildings (Ye, Zuo, et al. 2018), and U.S. mechanical workshop (Ye, Wang, et al. 2018), have already been created.

In support of ASHRAE TRP-1771, this paper aims to develop the new baseline models for U.S. medium office buildings, which have consistent energy estimation with the empirical baselines. These models will be used for building energy regulation and policy making. This paper is organized as follows. Section "Methodology" introduces the methodology to create the baseline models. Section "Baseline model creation" creates new baseline models for U.S. medium office buildings. Section "Model Comparison" then compares the performance of the new baseline models with the existing DOE Commercial Reference Building Models (DOE 2011). Finally, Section "Conclusion" is the conclusion section.

Methodology

This section introduces the methodology to create the baseline models based on the previous literature (Ye, Hinkelman, et al. 2019). For each climate and vintage, one model with dedicated inputs will be created. This will result in a set of models to represent each type of commercial building in different climates and vintages. As shown in Figure 1, the methodology consists of three phases: (1) identification of model input which is discussed in Subsection "Method of model inputs' identification," (2) model calibration detailed in Subsection "Model calibration method," and (3) model validation in Subsection "Model validation method." In addition, identifying model inputs can be further divided into four steps: identify model inputs, collect related data, clean the data, and convert the data into model inputs.

Method of model inputs' identification

To create a building energy model, six categories of model inputs are required: (1) weather condition, (2) geometry, (3) envelope, (4) schedule, (5) internal load, and (6) system (Ye, Hinkelman, et al. 2019). Weather condition provides the information about the microclimate surrounding the studied building. Geometry provides dimensional and shape parameters, such as total floor area and window location. Envelope provides the construction layers of walls, floors, roof, windows, and doors, and material for each layer. Schedule records the occupancy behavior, internal load density, and system operation. Generally, detailed building energy modeling programs require hourly or 15-minute schedules. Internal load provides the nominal values for lighting, electric equipment power density and so on. System includes the parameters of heating, ventilation, and air conditioning (HVAC), lighting, domestic hot water, and refrigeration systems.

Existing survey data sources provide related data for model inputs. Ye, Zuo, et al. (2019) divided the existing survey data sources into in-depth and large-scale sources. The in-depth sources, such as the CBECS, provide detailed building characteristics and energy use data for each building sample (EIA 2019b). The large-scale sources, such as the BPD, only provide key building characteristics and energy data of a rich set of building samples (DOE 2019b). However, both types of data sources do not provide all required information for model inputs. Huang and Franconi (1999) separated the model inputs into three groups: (1) physical building characteristics, which include the geometry and envelope, (2) HVAC system characteristics, which include the mechanical system, and (3) building's internal

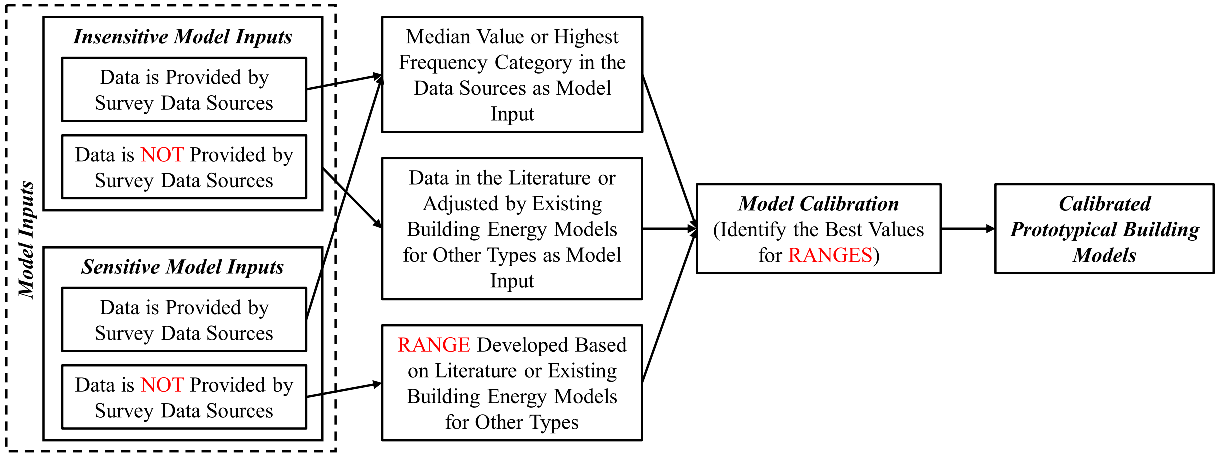

Fig. 2. Rules to determine the values and ranges of model inputs.

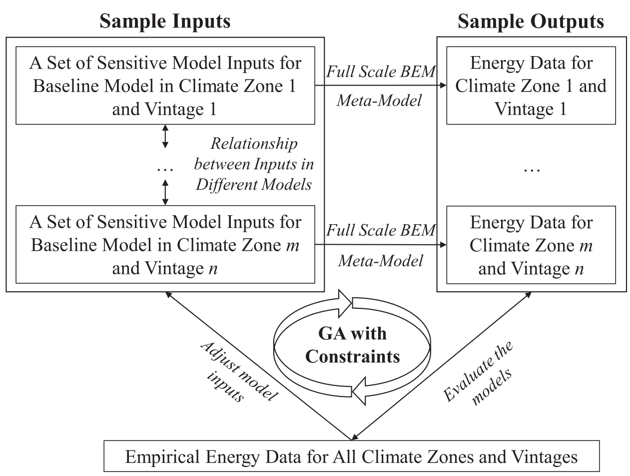

Fig. 3. Methodology to calibrate the building energy models.

conditions and operational patterns, which include the internal load and schedule. They identified that it is easy to obtain the related information for physical building characteristics from survey data sources. However, it is difficult to collect related data for HVAC system characteristics, and building's internal conditions and operational patterns. To collect all required information, data in other sources also is used to identify model inputs. For example, Griffith et al. (2008) determined the values of model inputs by collecting data from various building energy-related papers and reports, which can be used in New Models. Furthermore, model inputs in existing prototypical building energy models, such as DOE Commercial Reference Building Models, can also be used as reference (DOE 2011).

Since collected data may contain some errors and some building samples may not be suitable, it is necessary to clean the data. Ye, Hinkelman, et al. (2019) provided detailed method to clean the data. First, the building samples with missing key variables or errors are eliminated. For example, if a building sample does not provide the data for energy consumption, this sample will be eliminated from the sample set. Second, the unsuitable building samples are eliminated. For example, there are some multi-function buildings in the sample set, which are not dominated by office (office-function area is less than 30%). These samples are unsuitable for this study and they are eliminated. After eliminating unsuitable building samples, we get the remaining data.

Furthermore, we need to convert the remaining data into model inputs, since the remaining data have different formats. Figure 2 shows the rules to determine model inputs depending on their sensitivity to site EUIs. First, by reviewing existing research, the six categories of model inputs can be divided into two types: insensitive model inputs and sensitive model inputs. For both sensitive and insensitive model inputs, if the data is directly provided by the survey data sources, the median value or highest frequency value of data is selected. If the data is not provided by the survey data sources but it is insensitive, the values provided by the literature or adjusted by existing building energy models are used as the model inputs. For the rest of the model inputs, which are sensitive but not provided by the survey data sources, the ranges of model inputs are designed based on the remaining data and engineering judgment. Since some model inputs only have ranges, it is necessary to identify the best values among these ranges by calibrating models, which will be introduced in Subsection "Model calibration method."

Model calibration method

The objective of model calibration is to identify the best values among the ranges of model inputs so that the new baseline models can produce site EUIs close to the empirical baselines. Since empirical baselines only provide the yearly site EUI, we cannot calibrate models by using monthly utility bills or real-time sensors' data. However, since we have EUIs for buildings at different climate zones and different vintages, the relationship between different building models are considered in the model calibration process. Furthermore, an optimization algorithm, genetic algorithm (GA) with constraints, is developed for this process. Assuming there are m climate zones and n types of vintages, the workflow is shown in Figure 3.

Since model inputs in different climate zones and different vintages are related, they are used to connect and

Table 1. Relationship of model inputs in different models for one type of U.S. commercial buildings in case of sensitive model inputs without data provided.

Type of relationship	Example	Index
Values are the same in all climate zones and both vintages.	Aspect ratio	Type 1
Values are the same in all climate zones; Values for post-1980 models are not higher than pre-1980 models.	Electric equipment power density	Type 2
Values are the same in all climate zones; Values for post-1980 models are not lower than pre-1980 models.	Rated cooling COP	Type 3
Values in climate zones 5–8 are not higher than the other climate zones; Values between the two vintages have no constraint.	Window U-factor	Type 4
Values in climate zones 5–8 are not lower than the other climate zones; Values between the two vintages have no constraint.	Exterior wall insulation R-value	Type 5

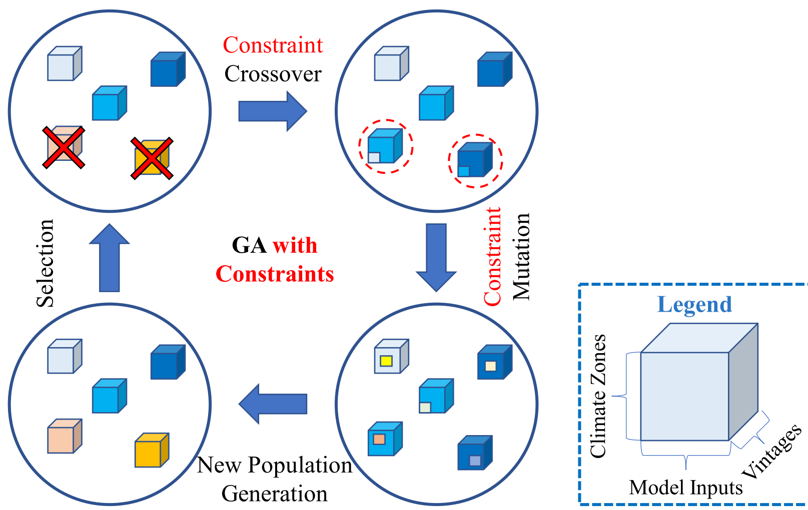

Fig. 4. Schematic diagram and flow chart of the GA with constraints.

aggregate separated models into a sample for the GA with constraints. During the model calibration, an input of the sample will be changed by referring to the inputs in other climate zones and vintages. Here, we use the baseline models for U.S. commercial buildings as an example, which are created for each ASHRAE climate zone and consider two vintages (pre- and post-1980). By analyzing the CBECS data using engineering judgments, we identified five types of relationship of model inputs, which is summarized in Table 1.

Type 1 includes the model inputs with the same value for all climate zones in both vintages, such as aspect ratio. If a model input is the same for all climate zones, but may be different for different vintages, it is either Type 2 or Type 3 as the new construction is expected to be more energy efficient than the older construction. If the newer construction (post-1980) do not have higher value than the older one (pre-1980), it is Type 2. An example is electric equipment power density. Otherwise, it is Type 3, such as rated cooling COP.

Types 4 and 5 are considered to use different values in various climate zones based on the comparison between climate zones 5–8 (cold climate) and the rest. If the value of a model input in climate zones 5–8 is not higher than it in the other climate zones, it is Type 4, such as window U-factor. Otherwise, it is Type 5, such as exterior wall insulation R-value.

The next step is to adjust the model inputs using a genetic algorithm (GA) so that the model outputs match the empirical energy data for all climate zones. The model outputs can be calculated by using full scale building energy modeling (BEM) programs, such as EnergyPlus (Crawley et al. 2008; Crawley et al. 2001; DOE 2017). However, since the model adjustment with GA is an iterative process and needs a large number of simulations, it is too time consuming to use full scale BEM programs. To reduce the computational time, meta-models are used to generate sample outputs with different inputs. The meta-models are data-driven models, which are trained based on the key model inputs and outputs calculated by full scale BEM programs.

During the process, a GA with constraints is developed to identify the best values among the ranges of model inputs. Its schematic diagram is shown in Figure 4. Inputs in a sample have three dimensions: (1) model inputs, (2) climate zones, and (3) vintages. However, the three dimensions are not independent since there are rule-based relationships of model inputs in different climate zones and vintages, as described in Table 1. Conventional GA provides a range for each variable and the sample is generated within the range without any other constraints. To reflect the rule-based relationships of model inputs for this application, constraints are adopted for the sample generation in crossover and mutation

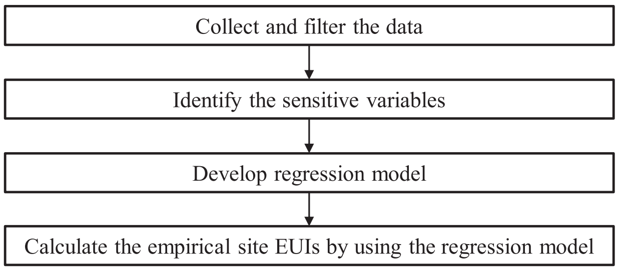

Fig. 5. Methodology to create empirical baselines.

steps of the GA (shown in red color in Figure 4). The process will not stop until the models predict consistent site EUI with empirical site EUI using an evaluation criterion defined in section "Evaluation results." As shown in Figure 4, the constraint is realized using an iteration to ensure all accepted samples meet the constraints.

After completing model calibration by using the GA with constraints, some model inputs will be further refined based on the engineering judgment. For example, U-factor of window is a discrete value based on the window. In the optimization, it is a continuous value. Thus, the final value of U-factor in the model should be selected from the closest discrete value based on an existing window type. Finally, the calibrated sample will be recorded, and the baseline models are selected from the calibrated sample.

Model validation method

To validate the performance of the baseline models, there are three steps: (1) create empirical baselines, (2) create evaluation criteria, and (3) evaluate the models by using the evaluation criteria. This subsection will elaborate the methods adopted in the first two steps.

Empirical baselines

ENERGY STAR provides a method to create empirical baselines for U.S. commercial building (EPA 2013) which is shown in Figure 5. This method is adopted to create the empirical baseline for the U.S. medium office buildings in our study.

The methodology consists of four steps: (1) collect data from the 2003 CBECS (EIA 2006b) and filter the data based on the designed rules; (2) conduct sensitivity analysis to identify sensitive variables; (3) create regression model based on the sensitive variables; and (4) identify representative values of the sensitive variables and calculate the empirical site EUIs by using the regression model.

Evaluation criteria

The *coefficient of variation of the root-mean-square deviation* (*CV(RMSD)*) is used to evaluate whether the baseline models have consistent energy estimation with the empirical baseline. To calculate the *CV(RMSD)*, we have to calculate the *root-mean-square deviation* (*RMSD*) firstly. The *RMSD* is calculated by using the following equation:

$$RMSD_{Vint} = \sqrt{\frac{\sum_{i=1}^{15} \left(\widehat{EUI}_{i,Vint} \quad EUI_{i,Vint} \right)^2}{15}} \tag{1}$$

where *Vint* is vintages, which consists of pre- and post-1980; i is climate zone i, $i = 1, 2, \ldots, 15$; *EUI* is the empirical site EUI; $\widehat{EUI}$ is the modeled site EUI.

Based on the results of *RMSD*, we can calculate the *CV(RMSD)* by using the following equation:

$$CV(RMSD_{Vint}) = \frac{RMSD_{Vint}}{max(EUI_{i,Vint}) \quad min(EUI_{i,Vint})} \tag{2}$$

where $max(EUI_{i,Vint})$ is the maximum value of the empirical site EUI in the vintage *Vint*; $min(EUI_{i,Vint})$ is the minimum value of the empirical site EUI in the vintage *Vint*.

When the *CV(RMSD)* is lower than 0.05, the baseline models have consistent energy estimation with the empirical data (Pan, Huang, and Wu 2007). Otherwise, we consider the baseline models fail to predict the site EUI to match the empirical baseline.

Uncertainty analysis

The new baseline models are designed to provide representative features of existing buildings instead of developing for a specific building. Since different buildings have varied features, it is necessary to identify the capability of the baseline models to capture the uncertainties of building energy consumption caused by the uncertainties of model inputs. Figure 6 lists the uncertainties of the model inputs.

The uncertainties of thousands of the model inputs affect the uncertainties of building energy consumption. The detailed and board onsite survey is required to collect all information for designing the uncertainties of all model inputs. To simplify the uncertainty analysis, this paper selects a subset of the model inputs and designs the uncertainties for them based on the 2003 CBECS data and engineering judgment. By referring to the methodology and results concluded by Wang et al. (2018), this paper designs the criteria to evaluate the results of the uncertainty analysis: (1) the uncertainties of the modeled site EUIs should be identified by providing the uncertainties for the subset of the model inputs; (2) the highest probability of the modeled site EUI should be similar to the 2003 CBECS data; (3) the median site EUI for the models should be similar to the 2003 CBECS data.

Baseline model creation

This section creates the baseline models for U.S. medium office buildings by implementing the three-phase methodology introduced in Section "Methodology." Subsection "Identification of model inputs" introduces the identification of model inputs. Subsection "Model calibration" presents the model calibration and description. Subsection "Model validation" conducts the model validation.

Identification of model inputs

Table 2 shows examples about determining the values or ranges of sensitive model inputs. If the 2003 CBECS provides data for a model input, the data type is value. In this case, we can use the median value or the highest frequency

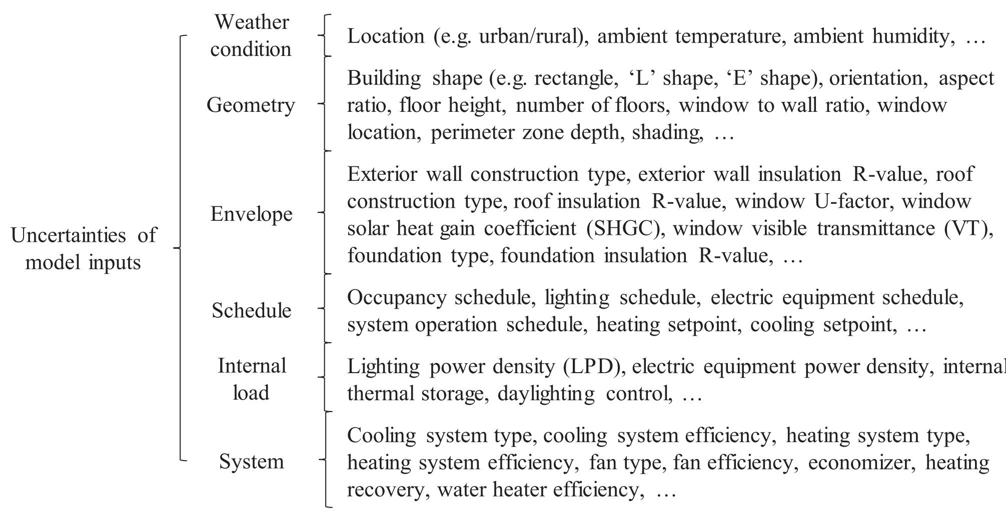

Fig. 6. List of model inputs' uncertainties.

Table 2. Examples of the values or ranges of sensitive model inputs.

Category	Sensitive model input	Whether data provided by the 2003 CBECS	Data type	Type of relationship[a]
Geometry	Total floor area	Yes	Value	–
	Aspect ratio	No	Range	Type 1
	Floor-to-floor height	No	Range	Type 1
	Window-to-wall ratio	Yes	Value	–
	Glazing sill height	No	Range	Type 1
Envelope	Exterior wall insulation R-value	No	Range	Type 5
	Roof insulation R-value	No	Range	Type 5
	Window U-factor	No	Range	Type 4
	Window SHGC	No	Range	Type 5
	Foundation insulation R-value	No	Range	Type 1
	Infiltration rate	No	Range	Type 1
Schedule	Hourly schedule	Design the schedule based on Figure 7	Value	–
Internal load	People density	No	Range	Type 1
	Lighting power density	No	Range	Type 2
	Electric equipment power density	No	Range	Type 2
System	Rated cooling COP	No	Range	Type 3
	Burner efficiency	No	Range	Type 3
	Fan total efficiency	No	Range	Type 3
	Ventilation	No	Range	Type 1
	SWH thermal efficiency	No	Range	Type 3

[a]Type of relationship has been introduced in Table 1.

value of the selected sample data from the 2003 CBECS as the model input (EIA 2006b). For example, the 2003 CBECS provides the values of total floor area for all building samples. Then, the median value (3,130 m^2) is used as the model's total floor area.

The data type of the hourly schedule is also considered as value in this paper. The 2003 CBECS provides the total weekly operating hours, which is not the model-required format. Griffith et al. (2008) provided a methodology to design the hourly operating schedules by using the 2003 CBECS data. Based on the methodology, this paper determines the operation hours for U.S. medium office buildings, which is shown in Figure 7.

In Figure 7, the numbers shown above boxes and ovals are the quantities of remaining building samples in the 2003 CBECS after being classified. Based on the workflow, the models should open all five workdays as evenly as possible. Then we calculate the median value of total weekly

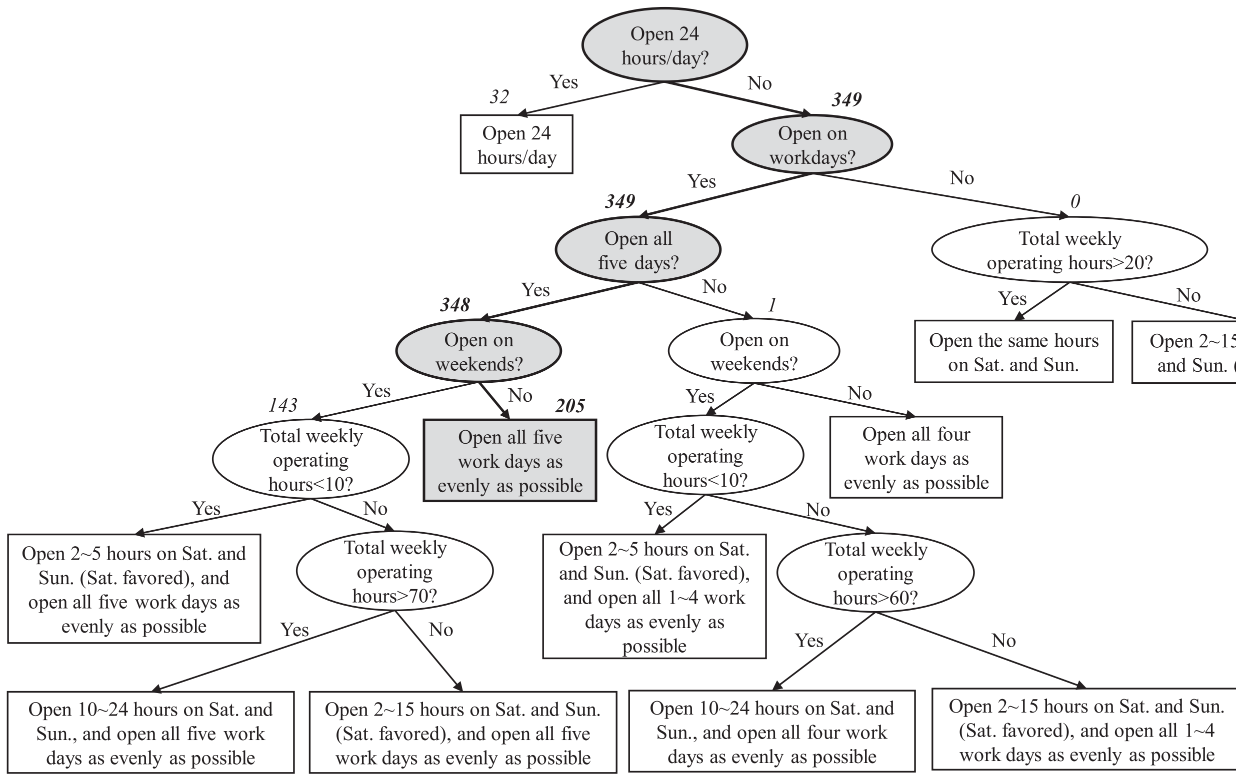

Fig. 7. Workflow to determine operating hours for U.S. medium office buildings.

operating hours for the selected building samples in the 2003 CBECS and the median value is 50 hours (EIA 2006b). After that, the operating schedules are arranged by referring to DOE Commercial Reference Building Models, and using engineering judgment (DOE 2011, 2019c). Finally, in all new baseline models of medium office buildings, the occupants stay from 8am to 6 pm and the system is operated from 7am to 6 pm.

If the 2003 CBECS does not provide data for a model input, the data type is range. Based on Table 1, the features of relationship type reflect in the range of the model input. For example, a model input for Type 1 has the same range for all climate zones and both vintages. Furthermore, the related data in the 2003 CBECS and publications is used to identify the range of the model input (Deru et al. 2011; Griffith et al. 2008; Huang and Franconi 1999; NREL 2018; Sharp 1996; Wang, Goel, and Makhmalbaf 2013; Wang et al. 2015; Winiarski, Jiang, and Halverson 2006; Winiarski, Halverson, and Jiang 2007). Table 3 provides examples for ranges of sensitive model inputs without data provided.

For example, the 2003 CBECS does not include information about the aspect ratio. However, Winiarski, Halverson, and Jiang (2007) provides the values of the aspect ratio for office buildings. Furthermore, the Type 1 relationship shown in Table 1 is that values are the same in all climate zones and both vintages. Thus, based on the information provided by Winiarski, Halverson, and Jiang (2007), the range for the aspect ratio is [1.6, 2.4] for all climate zones and both vintages.

Another example is that the 2003 CBECS provides the materials of exterior walls and roof for each building sample. However, the EnergyPlus model requires the detailed information of exterior walls and roof, such as the insulation R-value, thickness of each layer, and conductivity of each layer. Winiarski, Halverson, and Jiang (2007) provides required information about building envelope construction based on the 2003 CBECS and other data sources. First, the related data is collected from the 2003 CBECS. Second, the information provided by Winiarski, Halverson, and Jiang (2007) is used to determine the ranges of model inputs for the detailed information of exterior walls and roof.

Model calibration

This subsection calibrates the models within the ranges of model inputs identified in Subsection "Identification of model inputs." The model calibration selects the best values among the ranges of approximately 18 model inputs. EnergyPlus and Boosted Tree meta-model are used to calculate energy data (Chen and Guestrin 2016; Chen et al. 2015; Crawley et al. 2000). The meta-model is trained by the EnergyPlus model. Based on the validated results, the relative errors are all lower than 1%, which the meta-model is qualified to generate more samples. The GA with constraints uses *CV(RSMD)* of site EUIs between modeled baselines and empirical baselines as the indicator to evaluate the performance for each calibration loop. The optimization process is converged after approximately 1,000 iterations. Then, based on the engineering judgment, some model inputs, such

Table 3. Examples for the ranges of sensitive model inputs.

Type of relationship[a]	Sensitive model input	Range
Type 1	Aspect ratio	[1.6, 2.4] for all climate zones and both vintages
Type 2	Electric equipment power density	Pre-1980: [9.24, 14.81] W/m^2 Post-1980: [7.98, 13.34] W/m^2
Type 3	Rated cooling COP	Pre-1980: [2.52, 3.39] Post-1980: [2.61, 3.50]
Type 4	Window U-factor	Pre-1980: Climate Zones 1–4: [4.67, 7.00] W/m^2-K Climate Zones 5–8: [2.82, 4.23] W/m^2-K Post-1980: Climate Zones 1–4: [3.27, 7.00] W/m^2-K Climate Zones 5–8: [2.36, 4.03] W/m^2-K
Type 5	Exterior wall insulation R-value	Pre-1980: Climate Zones 1–4: [0.61, 1.18] m^2-K/W Climate Zones 5–8: [0.89, 1.69] m^2-K/W Post-1980: Climate Zones 1–4: [0.76, 2.26] m^2-K/W Climate Zones 5–8: [1.72, 4.69] m^2-K/W

[a]Type of relationship has been introduced in Table 1.

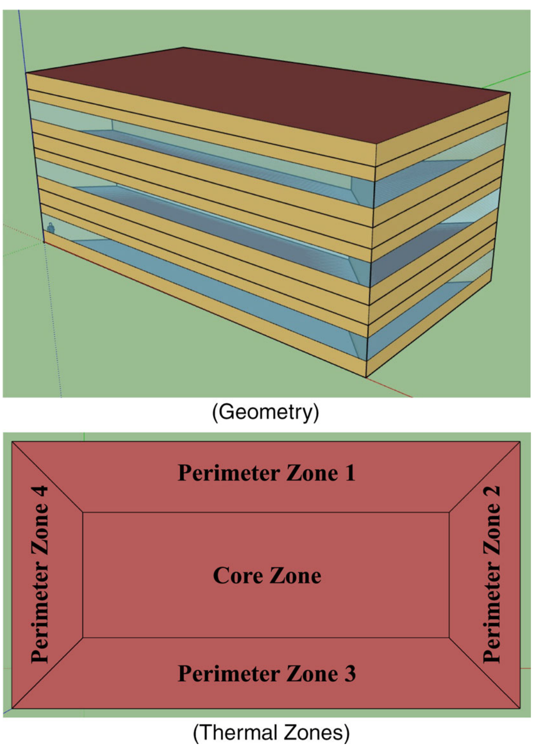

Fig. 8. Geometry and thermal zones of the new baseline models for the U.S. medium office buildings.

as U-factor and SHGC of windows are adjusted based on the window types in the real world.

Based on the model inputs obtained from the calibration process, the new baseline models for U.S. medium office buildings are identified. The geometry and thermal zones of the new baseline models are shown in Figure 8. New baseline models have three floors and there are five thermal zones in each floor.

The key model inputs of the new baseline models are listed in Table 4. The first column shows the category of each input. The second column shows the name of each input. The third column shows the values of each input. Some model inputs for envelopes are listed in Table 5, which have different values for various climate zones and vintages.

Model validation

To validate the performance of models, we create empirical baselines. Then we create the evaluation criteria. After that, the models are evaluated by using the evaluation criteria. Since the evaluation criteria have been created in Subsection "Evaluation criteria," this subsection details the empirical baseline creation (Subsection "Empirical baseline creation") and evaluation results (Subsection "Evaluation results").

Empirical baseline creation

This subsection creates empirical baselines for 15 climate zones. CBECS data does not classify buildings into 15 climate zones. Instead, it only has data for 5 climate zones. So, we cannot get the empirical baseline for each climate zone by simply using CBECS data. Therefore, we will use CBECS data to create a regression model to get the empirical baselines for 15 climate zones.

First, we collect the data from the 2003 CBECS (EIA 2006b) and filter the data by using the criteria created by ENREGY STAR Portfolio Manager (EPA 2013). After collecting and filtering the data from the 2003 CBECS, we select 240 and 231 building samples for pre- and post-1980 medium office buildings respectively. Then, the site EUIs for these building samples are calculated. After that, based on the sensitivity analysis conducted in the literature, we identify seven sensitive variables. They are listed as follows (The variable names and descriptions refer to the 2003 CBECS codebook (EIA 2006a)):

(1) SQFT8: Square footage;
(2) WKHRS8: Total weekly operating hours;
(3) NWKER8: Number of employees during main shift;
(4) PCNUM8: Number of computers;
(5) HDD658: Heating degree days (base 65 F);
(6) CDD658: Cooling degree days (base 65 F);
(7) PBAPLUS8: More specific building activity.

Since the seven sensitive variables are not independent, the sensitive variables are modified into the independent ones referring to the ENERGY STAR Portfolio Manager (EPA 2013). The final version of the sensitive variables is listed as follow, which are used to create the regression model for the empirical baseline:

Table 4. Key model inputs of the baseline models for the U.S. medium office buildings.

Category of input	Name of input	Value of input		
Weather condition	Location	1A, Miami, FL		
		2A, Houston, TX	2B, Phoenix, AR	
		3A, Atlanta, GA	3B, El Paso, TX	3C, San Francisco, CA
		4A, Baltimore, MD	4B, Albuquerque, NM	4C, Seattle, WA
		5A, Chicago, IL	5B, Denver, CO	
		6A, Minneapolis, MN	6B, Helena, MT	
		7, Duluth, MN		
		8, Fairbanks, AK		
Geometry	Total floor area	3,130 m^2		
	Building shape	Rectangle		
	Aspect ratio	2.01		
	Number of floors	3		
	Window fraction	27.50%		
	Window location	Equal percentages on all sides		
	Floor height	4.47 m		
	Shading	No		
	Skylight	No		
Envelope	Exterior wall type	Steel frame wall		
	Insulation R-value of Exterior walls	Show in Table 5		
	Roof type	Insulation entirely above deck (IEAD)		
	INSULATION R-VALUE OF ROOF	Show in Table 5		
	Foundation type	Slab-on-grade		
	R-value of foundation	0.64 m^2-K/W		
	U-value of windows	Show in Table 5		
	SHGC of windows	Show in Table 5		
Schedule	Occupancy schedule	8 am–6 pm		
	System schedule	7 am–7 pm		
Internal Load	Occupant density	20.48 m^2/person		
	Electric equipment power density	Pre-1980: 14.74 W/m^2	Post-1980: 11.83 W/m^2	
	Lighting power density	Pre-1980: 16.34 W/m^2	Post-1980: 11.95 W/m^2	
	Infiltration rate	0.00031 m/s for the whole building (Flow per exterior surface area)		
System	Ventilation requirement	0.0242 m^3/s-person for the whole building		
	Cooling system type	Packaged A/C Units		
	Rated COP for cooling system	Pre-1980: 3.11	Post-1980: 3.17	
	Cooling temperature setpoint	24.0 °C		
	Heating system type	Gas furnace		
	Efficiency for heating system	Pre-1980: 0.68	Post-1980: 0.78	
	Heating temperature setpoint	21.0 °C		
	Efficiency for water heating equipment	Pre-1980: 0.68	Post-1980: 0.78	

(1) Total floor area (SQFT8);
(2) Total weekly operating hours (WKHRS8);
(3) Number of employees per area (NWKER8/SQFT8);
(4) Number of computers per area (PCNUM8/SQFT8);
(5) Percentage of heated area Heating degree days (HEATP8 HDD658);
(6) Percentage of cooled area Cooling degree days (COOLP8 CDD658);
(7) Whether it is a bank (If PBAPLUS8 = 3, it is a bank; else, it is not a bank).

The values for these variables are selected for the whole climate, but different for two vintages (Pre- and 1980). After that, we create the regression model by using a weighted ordinary least squares regression method. The regression model can be expressed as:

$$Site\ EUI = \sum a_i f(Variable_i) + b \tag{3}$$

where *Site EUI* is the site EUI for each building sample; $Variable_i$ is the value of each sensitive variable in each building sample; $f(Variable_i)$ is a function of $Variable_i$, which could be polynomial, exponential, rational, and logarithmic functions; a_i is the coefficient for variable i; b is the residual value of the regression model. The objective of this step is to find out the values of all a_i, $f(Variable_i)$, and b,

Table 5. Model inputs for envelopes.

Name of input	Unit	Vintage	Climate zone 1A	2A	2B	3A	3B	3C	4A	4B	4C	5A	5B	6A	6B	7	8
Insulation R-value	m^2-K/W	Pre-1980	0.76	0.88	0.88	0.90	0.90	0.90	0.91	0.91	0.91	1.01	1.01	1.23	1.23	1.31	1.37
of exterior walls		Post-1980	0.83	0.89	0.89	1.08	1.08	1.08	1.07	1.07	1.07	1.28	1.28	1.39	1.39	1.44	1.56
Insulation R-value	m^2-K/W	Pre-1980	1.80	1.86	1.86	1.92	1.92	1.92	1.93	1.93	1.93	2.05	2.05	2.09	2.09	2.28	2.31
of roof		Post-1980	2.55	2.56	2.56	2.70	2.70	2.70	2.71	2.71	2.71	2.74	2.74	2.86	2.86	2.86	2.88
U-value of windows	W/m^2-K	Pre-1980	5.96	5.11	5.11	5.11	5.11	5.11	5.11	5.11	5.11	4.26	4.26	4.26	4.26	3.80	3.80
		Post-1980	6.13	5.00	5.00	5.00	5.00	5.00	4.26	4.26	4.26	4.26	4.26	3.69	3.69	3.52	3.52
SHGC of windows	–	Pre-1980	0.40	0.40	0.40	0.40	0.40	0.40	0.60	0.60	0.60	0.60	0.60	0.60	0.60	0.77	0.77
		Post-1980	0.25	0.27	0.27	0.27	0.27	0.27	0.35	0.35	0.35	0.35	0.35	0.35	0.35	0.49	0.49

Table 6. Empirical baselines.

	Climate zone: Site EUI (Unit: MJ/m^2-yr)							
Pre-1980	1A 908.83	2A 886.99 2B 935.48	3A 851.66 3B 863.82 3C 726.35	4A 894.70 4B 868.40 4C 786.81	5A 940.47 5B 897.18	6A 1,032.64 6B 939.41	7 1,132.51	8 1,375.41
Post-1980	1A 726.15	2A 701.28 2B 736.86	3A 695.41 3B 689.42 3C 569.30	4A 747.91 4B 682.56 4C 646.08	5A 808.07 5B 734.53	6A 914.88 6B 804.76	7 995.50	8 1,215.80

Table 7. Evaluation of the new baseline models.

		Pre-1980		Post-1980	
Evaluation index	Unit	Ref Model[a]	New Model[b]	Ref Model[a]	New Model[b]
CV(RSMD)	–	0.194	0.016	0.123	0.009

[a]DOE Commercial Reference Building Models.
[b]New baseline models created in this paper.

which minimizes the distance between the real values of site EUIs and the estimated values calculated by the regression model.

Finally, the empirical baseline can be calculated by using the representative values of the sensitivity variables. The heating degree days and cooling degree days use the values of the studied cities, and the other variables use the median values or the highest frequency values. The results of the empirical baselines for the 15 climate zones and two vintages (pre- and post-1980) are summarized in Table 6.

Evaluation results

As introduced in Subsection "Evaluation criteria," we use *CV(RSMD)* as an indicator to evaluate the performance of baseline models. Table 7 presents the *CV(RSMD)* for these new baseline models (New Model). The DOE Commercial Reference Building Models (Ref Model) are used as reference (DOE 2011).

The *CV(RSMD)* for the new baseline models are only 0.016 and 0.009 for pre- and post-1980 models, compared to 0.194 and 0.123 for the DOE Commercial Reference Building Models. This indicates that new baseline models have more consistent energy estimation with the empirical baselines compared with DOE Commercial Reference Building Models. Instead of meeting the 2003 CBECS data, the DOE Commercial Reference Building Models are designed to provide a starting point to measure the progress of energy efficiency for U.S. commercial buildings (Deru et al. 2011). However, there are needs for models which can match 2003 CBECS data (Turner and Frankel 2008). Based on the results shown in Table 7, the new baseline models meet the criteria and have consistent energy estimation with the empirical baselines. Thus, it is more suitable to use the New Model as baseline models if the energy estimation is required to meet the 2003 CBECS data.

Table 8. Uncertainties of selected model inputs.

No	Selected model input	Climate dependent/ independent	Vintage dependent/ independent	Discrete/ continuous	Distribution type	Unit	Range
1	Total floor area	Independent	Independent	Continuous	Exponent	m^2	[929, 9290]
2	Aspect ratio	Independent	Independent	Continuous	Norm	–	±20% Default value
3	Window fraction	Independent	Independent	Continuous	Norm	–	[5%, 50%]
4	Glazing sill height	Independent	Independent	Continuous	Norm	m	[0.9, 1.1]
5	Floor height	Independent	Independent	Continuous	Norm	m	[4, 5]
6	Exterior wall insulation R-value	Dependent	Dependent	Continuous	Uniform	m^2-K/W	±20% Default value
7	Roof insulation R-value	Dependent	Dependent	Continuous	Uniform	m^2-K/W	±20% Default value
8	Foundation insulation R-value	Independent	Independent	Continuous	Uniform	m^2-K/W	±20% Default value
9	Window U-value and SHGC	Dependent	Dependent	Discrete	Uniform	U: W/m^2-K SHGC: -	Window samples are selected from database
10	Building occupied start time	Independent	Independent	Continuous	Uniform	–	[7:00 am, 9:00 am]
11	Building occupied finish time	Independent	Independent	Continuous	Uniform	–	[5:00 pm, 7:00 pm]
12	Occupant density	Independent	Independent	Continuous	Norm	m^2/person	±20% Default value
13	Electric equipment power density	Independent	Dependent	Continuous	Norm	W/m^2	±20% Default value
14	Lighting power density	Independent	Dependent	Continuous	Uniform	W/m^2	±20% Default value
15	Infiltration rate	Independent	Independent	Continuous	Uniform	m/s	±20% Default value
16	Ventilation requirement	Independent	Independent	Continuous	Uniform	m^3/s-person	±20% Default value
17	Fan efficiency	Independent	Dependent	Continuous	Uniform	–	±20% Default value
18	Rated COP for cooling system	Independent	Dependent	Continuous	Uniform	–	±20% Default value
19	Efficiency for heating system	Independent	Dependent	Continuous	Uniform	–	±20% Default value
20	Efficiency for water heating equipment	Independent	Dependent	Continuous	Uniform	–	±20% Default value

Uncertainty analysis

This subsection conducts uncertainty analysis based on the methodology provided in Subsection "Uncertainty analysis." Twenty model inputs are selected, and the distributions of them are determined based on the data provided by the 2003 CBECS and engineering judgment. Table 8 lists the uncertainties of these selected model inputs. Two aspects are considered in this table: One is the dependence of the model inputs on climate and vintage. For those dependent on climate and vintage, the different ranges should be selected; otherwise, the same range is used for all climate zones and vintages. The other is the type of the data (discrete or continuous) and their distribution (uniform, normal, or exponent).

Since the numbers of buildings in different climate zones are different, we estimate the weights of medium office buildings in different climate zones and vintages based on the 2003 CBECS data and existing research (Deru et al. 2011). The weights of buildings are listed in Table 9. The numbers of medium office buildings in pre-1980 and post-1980 are almost same; so the weights of medium office buildings for pre-1980 and post-1980 are both 50%.

Based on the collected data, we select approximately 5,000 building samples and conduct simulation. The uncertainties of modeled and empirical site EUIs are shown in Figure 9.

By providing the uncertainties for the 20 studied model inputs, the uncertainties of modeled site EUIs for both pre- and post-1980 medium office buildings are identified. The modeled site EUIs with the highest probabilities are 957 MJ/m^2-yr for pre-1980 medium office buildings and 814 MJ/m^2-yr for post-1980 medium office buildings. The values are similar to the highest probabilities of the site EUIs for the

Table 9. Weights of medium office buildings in different climate zones for both pre 1980 and post 1980 (unit: %).

	Climate zone														
Vintage	1A	2A	2B	3A	3B	3C	4A	4B	4C	5A	5B	6A	6B	7	8
Pre 1980	1.07	6.72	2.41	6.33	5.91	1.12	9.84	0.30	1.62	8.76	2.83	2.47	0.29	0.27	0.06
Post 1980	1.07	6.72	2.41	6.33	5.91	1.12	9.84	0.30	1.62	8.76	2.83	2.47	0.29	0.27	0.06

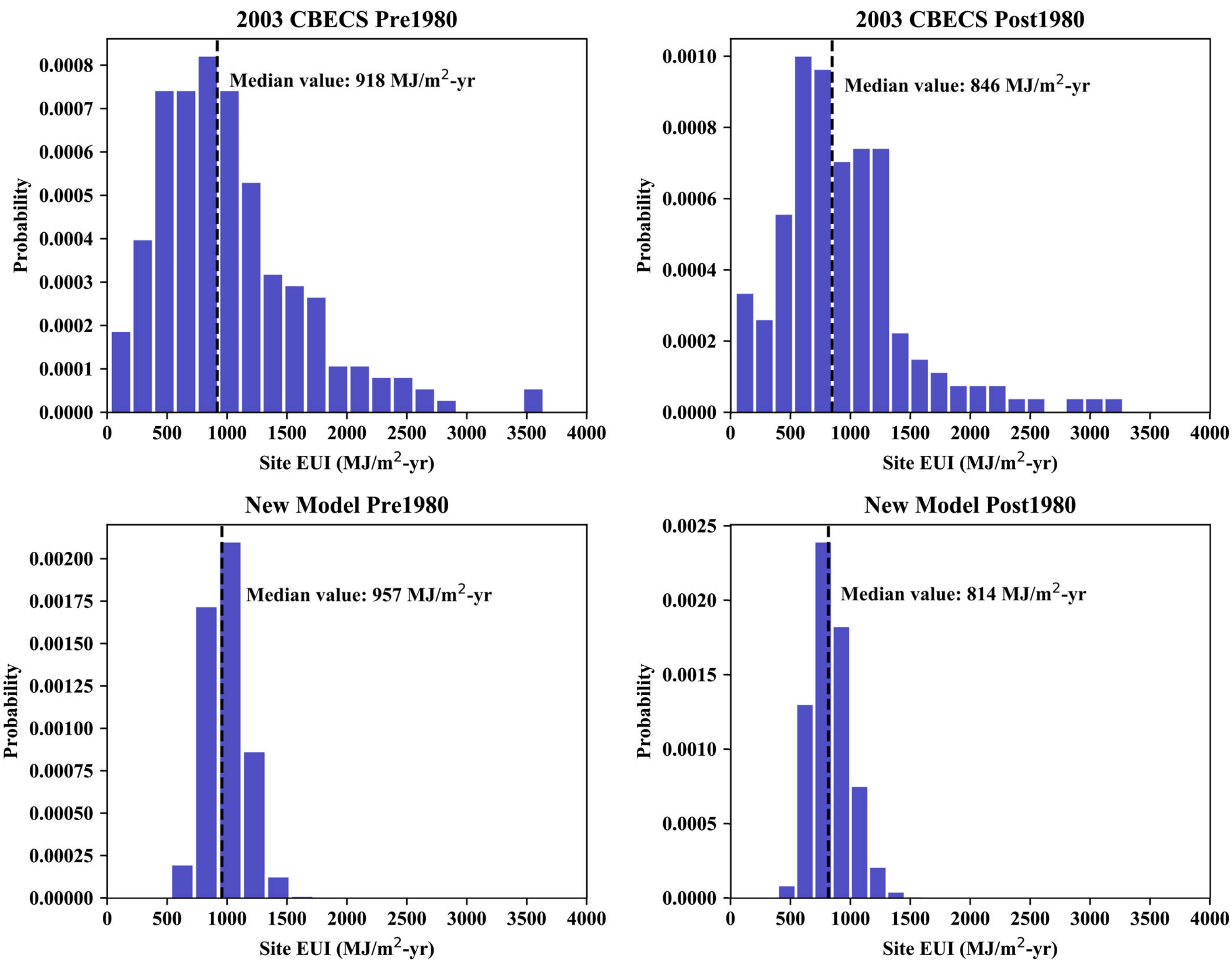

Fig. 9. Uncertainty analysis of the New Model.

2003 CBECS. Furthermore, the relative errors of the median site EUIs between models and the 2003 CBECS are lower than 5% for both pre- and post-1980 buildings. Thus, the models meet the requirement of the criteria introduced in Subsection "Uncertainty analysis." When the uncertainties of all model inputs are identified, the uncertainties of the building energy consumption will be captured by the models.

Model comparison

This section further compares the energy results of the New Model with the Ref Model. Their performance is evaluated based on the empirical data from the 2003 CBECS. Subsection "Comparison of site EUIs" compares the site EUIs between the New Model and the Ref Model, and Subsection "Comparison of cooling and heating EUIs" compares the cooling and heating EUIs.

Comparison of site EUIs

Figure 10 shows the comparison results between the New Model and the Ref Model. The black bars are the site EUIs for the Ref Models and the white bars are the New Models created in this paper. The symbols, "X"s, are empirical baselines listed in Table 6.

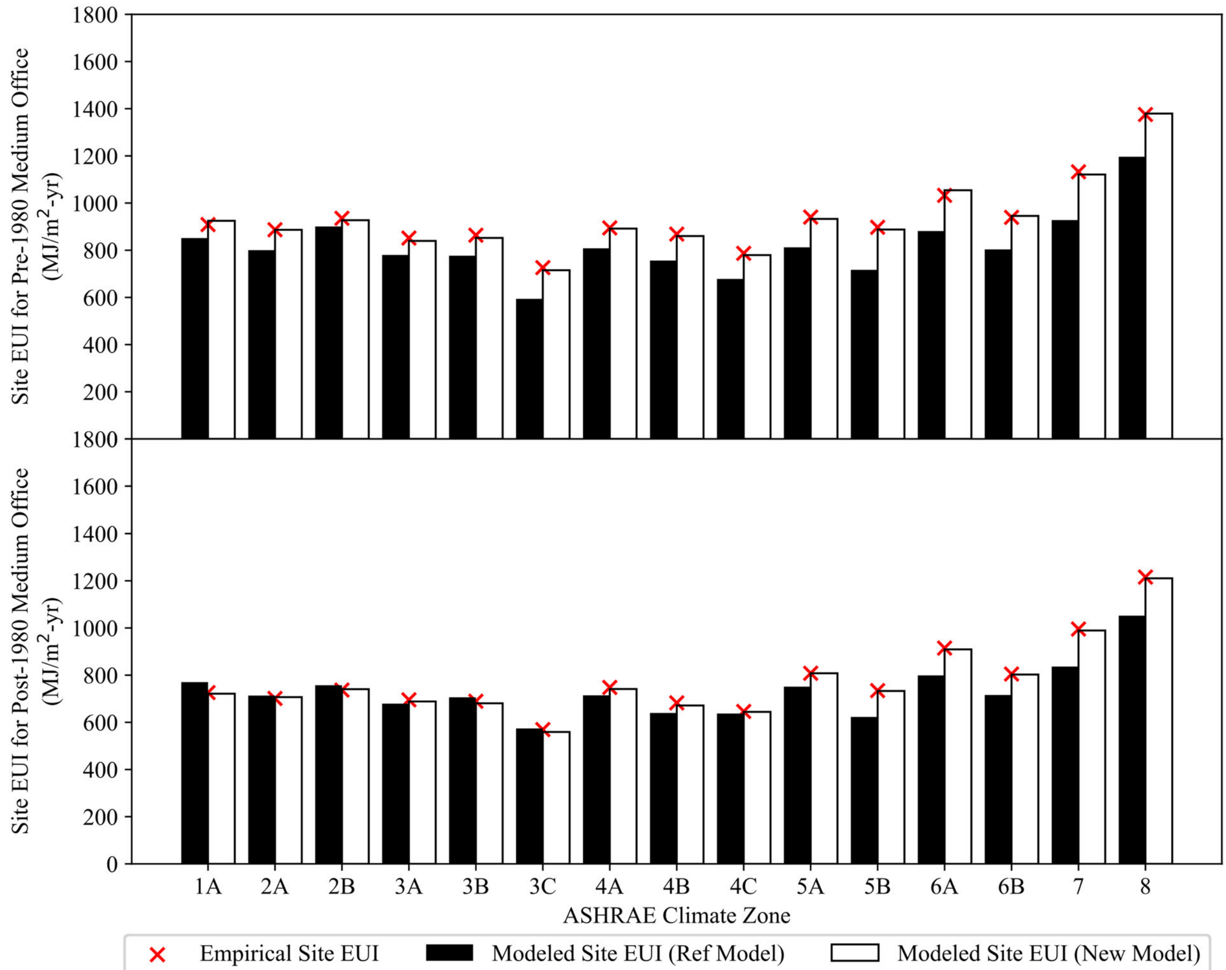

Fig. 10. Comparison of site EUIs for the Ref Models and New Models.

The results show that the New Models predict site EUI consistent with the empirical site EUIs in all climate zones and both vintages. For the pre-1980 models, the site EUIs of the Ref Models are lower than the empirical values in all climate zones. For the post-1980 models, the Ref Models have higher site EUIs in climate zone 1 A and lower site EUIs in climate zones 4–8 by comparing with the empirical site EUIs. However, the New Models have similar site EUIs to the empirical values in all climate zones and both vintages.

To understand the causes of the difference in predicted site EUIs between Ref Model and New Model, Table 10 compared the model inputs of Ref Model and New Model using the pre-1980 models in climate zone 5 A as an example. Based on Subsection "Method of model inputs' identification," the model inputs are divided into six categories. Since both Ref Model and New Model in this example are in the same location, the weather condition is the same. Based on the Ref Model, we change the model inputs in one category into the values in the New Model at one time and the model inputs for other categories are not changed. The New Model is used to evaluate the energy impact based on the site EUI of the Ref Model. The column, Energy Impact, calculates the relative errors of site EUIs between the New Model and Ref Model. It can be expressed as the following equation:

$$Energy\ Impact_i = \frac{Site\ EUI_{Upgr,i} \quad Site\ EUI_{Ref}}{Site\ EUI_{Ref}} \quad 100\% \qquad (4)$$

where $Site\ EUI_{Upgr,i}$ is the site EUI of the New Model which model inputs in Category i are the values in the New Model; $Site\ EUI_{Ref}$ is the site EUI of the Ref Model.

The results show that changing the model inputs for geometry and system greatly increases the site EUI. Furthermore, changing the model inputs for envelope and schedule greatly decreases the site EUI. Based on the aggregative effect, the pre-1980 New Model in climate zone 5 A has higher site EUI than the Ref Model.

Comparison of cooling and heating EUIs

Previous subsection shows that the changes in cooling and heating system leads to the largest changes on site EUI. Thus, further analysis on the impact of cooling and heating EUIs of Ref Model and New Model are also compared. CBECS 2003 only divided the US into 5 climate zones and both the Ref and New Models are designed for 15 climate zones. To make the model results and the 2003 CBECS data comparable, building samples are classified into different categories based on their cooling degree day 65 F (CDD65)

Table 10. Example of model input comparison (Pre-1980 building model in climate zone 5 A).
Baseline Site EUIs generated from Empirical data, Ref Model, and New Model:
Empirical Baseline: 940.47 MJ/m^2-yr
Ref Model: 812.26 MJ/m^2-yr
New Model: 932.75 MJ/m^2-yr

	Item	Unit	Input value		Energy impact
			Ref Model	New Model	
Geometry	Total floor area	m^2	4,982	3,130	+19.5%
	Aspect ratio	–	1.50	2.01	
	Window fraction	–	33.00%	27.50%	
Envelope	Exterior wall insulation R-value	m^2-K/W	1.13	1.01	–4.82%
	Roof insulation R-value	m^2-K/W	2.50	2.05	
	Window U-value	W/m^2-K	3.53	4.26	
	Window SHGC	–	0.41	0.60	
	Infiltration	m^3/s-m^2	0.00113	0.00031	
Schedule	Schedule	–	The schedules are simplified in the New Model		–7.03%
Internal load	Lighting power density	W/m^2	16.90	16.34	+0.35%
	Electric equipment power density	W/m^2	10.76	14.74	
	People density	m^2/person	18.58	20.48	
System	Ventilation rate	m^3/s-person	0.0125	0.0242	+23.85%
	Rated cooling COP	–	3.38	3.11	
	Heating efficiency	–	0.78	0.68	
	Water heater efficiency	–	0.80	0.69	

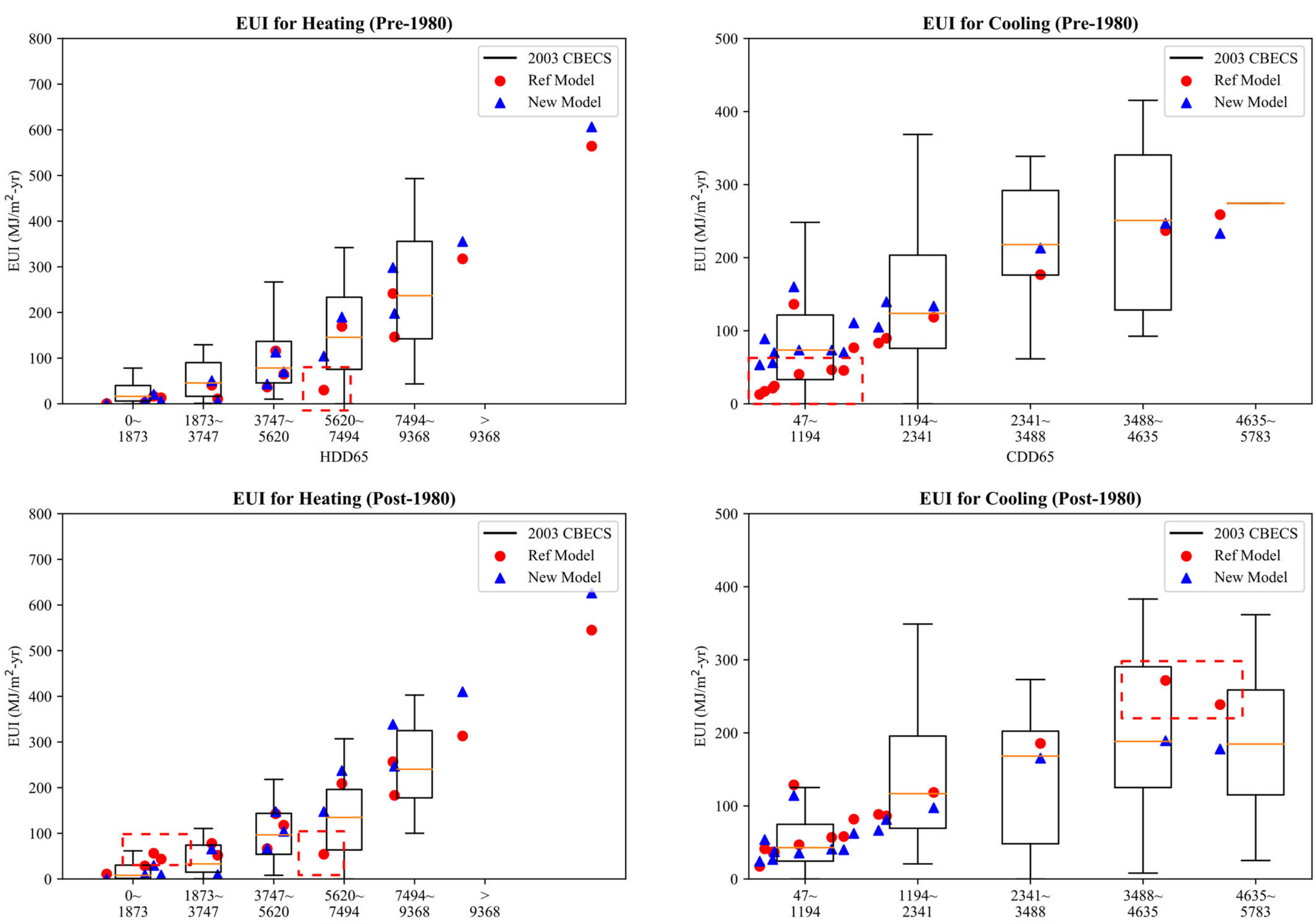

Fig. 11. Comparison of the heating and cooling EUIs for the reference and new baseline models.

Table 11. Pearson's chi-squared test for the heating and cooling EUIs predicted by New and Ref Models to the CBECS data.

	Pre-1980 Heating	Pre-1980 Cooling	Post-1980 Heating	Post-1980 Cooling
Ref Model	37.5	33.7	137.7	61.3
New Model	14.3	7.2	37.5	11.3

and heating degree day 65 F (HDD65) (Ye, Hinkelman, et al. 2019).

The buildings in CBECS, Ref and New Models can be divided into six categories based on their HDD65 and can also be divided into five categories based on their CDD65, as shown in Figure 11. Figure 11 shows the results of comparison of the heating and cooling EUIs between Ref Models and New Models. The boxplots are created to present the EUI of buildings from 2003 CBECS data, and the red horizontal lines are the median values for boxplots. The red circles and blue triangles are site EUIs predicted by Ref Models and New Models, respectively.

The results show that, the EUIs for heating and cooling in the New Model are closer to the median values of the 2003 CBECS data than the Ref Model. For example, in Figure 11a, EUI for Heating (Pre-1980) at HDD65, one case for a Ref Model in the red box, has significantly lower EUI (65 MJ/m^2-yr) than the 75% of 2003 CBECS data (> 90 MJ/m^2-yr). Furthermore, as shown in Figure 11b, the pre-1980 Ref Models tend to have lower EUIs for cooling in the cases with 47–1194 CDD65 by compared with the 2003 CBECS data. Moreover, as shown in Figure 11c, the post-1980 Ref Models tend to have higher EUIs for heating in the area with low HDD65. Figure 11d shows that the post-1980 Ref Models and higher EUIs for cooling in the area with high CDD65. Furthermore, the Pearson's chi-squared test (Greenwood and Nikulin 1996) is used to evaluate the similarity of the modeled EUIs to the CBECS EUIs. The similarity is expressed as the following:

$$\chi^2 = \sum_{i=1}^{n} \frac{EUI_{New,i} \quad EUI_{Emp,i}}{EUI_{Emp,i}}^{2} \qquad (5)$$

where n is the number of categories in Figure 11; $EUI_{New,i}$ is the heating or cooling EUIs predicted by the New Model in category i; $EUI_{Ref,i}$ is the heating or cooling EUIs in the CBECS data in category i.

Table 11 shows the values of chi-squared test for the New Model and Ref Model against CBECS data. All results for the New Models are lower than the Ref Models, which indicates that the New Models predict the EUIs closer to the CBECS data than the Ref Models.

Conclusion

This paper develops new baseline models for the U.S. medium office buildings, which have consistent energy estimation with the empirical baselines. Extracting model input data from the 2003 CBECS and calibrating models make the energy estimation consistent. The results show that the *CV(RMSD)* between the new modeled baselines and the empirical baselines is lower than 0.05, which meets the criteria to evaluate the performance of the baseline models. By compared with the DOE Commercial Reference Building Models, the energy performance (site EUIs, cooling EUIs, and heating EUIs) of new baseline models is significantly closer to the empirical data provided by the 2003 CBECS.

The new baseline models created in this paper can be used for the research of building energy simulation, which has a requirement of matching empirical data. For example, these baseline models can be used for building sector energy estimation under various scenarios, which will help for making energy regulation and policy. Furthermore, the methodology to create and validate baseline models can be used for other building types.

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