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Uncertainties in Energy Consumption Introduced by Building Operations and Weather for a Medium-Size Office Building

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Abstract

Deviations between predicted and actual building energy consumption can be attributed to uncertainties introduced by four components of such projections: (1) the accuracy of the underlying models in simulation tools, (2) the accuracy of input parameters describing the design conditions of building envelope and HVAC systems, (3) actual weather, (4) variations in building operation practices. This study investigates uncertainties in energy consumption due to actual weather and building operational practices, using a simulation-based analysis of a medium-size office building. The combined effect of poor practice in building operations across multiple parameters results in an increase in energy use of 49-79% across four selected cities, while good practice reduces energy use by 15-29% across the cities. The impact of year-to-year weather fluctuation on energy use ranges from -4% to 6%. To determine the uncertainty distribution profile for annual energy use, a Monte Carlo method is applied to sample the possible combinations. This study finds that the uncertainty distribution in annual energy consumption approximately follows a log-normal distribution, and shows that the uncertainty range due to operational factors even at an 80% confidence level can dwarf the impact of design features.

Keywords: Building operations, Uncertainties, EnergyPlus, Monte Carlo Analysis

1. Introduction

The prediction of building energy consumption is a complicated task. In addition to first principle models required to characterize building systems and components, detailed information about the building envelope, HVAC systems, and weather must be taken into consideration. The dynamic behavior of weather conditions and building operations, and the impact of multiple building characteristics, call for the use of simulations to facilitate design and operation for better building performance. However, significant deviations in terms of building energy consumption between measured performance and model-predicted results at design stage are reported for low-energy buildings[1]. Deviations between predicted and actual building energy consumption can be attributed to uncertainties introduced by four components of such projections: (1) the accuracy of the underlying models in simulation tools, (2) the accuracy of input parameters describing the design conditions of building envelopes and HVAC systems, (3) actual weather, (4) actual building operations. An estimate of the degree of uncertainties contributed from each factor is of importance to improve the robustness of simulation models and help the modeler and customer have a better understanding of building simulation results.

In the last decade, there have been several important research efforts focused on the investigation of uncertainties in input parameters for building design support. However, a review of the literature shows there are limited data available describing uncertainties for design parameters in building simulation. Macdonald and Strachan [2] applied a Monte Carlo uncertainty analysis for thermal properties of construction materials, weather, internal heat gains, and infiltration rate to evaluate the variation of energy consumption using assumed uncertainty distribution patterns. Holm and Kuenzel [3] evaluated the impacts of materials properties and surface coefficients on hygrothermal building simulation using a Monte Carlo analysis. De Wit and Augenbroe [4] addressed the effects of uncertainty in two important factors —wind-pressure coefficients and room air-temperature distribution— on simulation results for design evaluation. Macdonald and Clarke [5] integrated uncertainty algorithms within the engine of ESP-r simulation tool. The predicted uncertainty in conductivity, heat capacity, and thickness using an integrated approach within the simulation code was compared with Monte Carlo and differential analysis. Their study also discussed the issue of non-convergence of building simulations. This non-convergence was caused by the introduction of new terms for uncertainty analyses that were uncorrelated to previously existing terms. Cóstola et al. [6] investigated the effect of uncertainties in wind-pressure coefficients (Cp) on air infiltration and ventilation simulations. Breesch and Janssens [7] conducted uncertainty and sensitivity analyses in climate and design-related parameters for thermal comfort evaluations of passive cooling in office buildings. Domínguez-Muñoz et al. [8] studied the impacts of uncertainties in 20 design-related parameters on the simulated peak-cooling loads using a Monte Carlo analysis. Hopfe and Hensen [9] described a case study of uncertainty analysis in building simulation introduced by design parameters. Tian and de Wilde [10] explored the uncertainties in climate, construction material properties, infiltration rate, internal loads, and equipment efficiency for building simulations of an office building in the UK.

Few studies have been done to investigate the effects of uncertainties in building operations-related parameters on building energy consumption for HVAC systems. In fact, building operations-related parameters that are based on the interpretation and assumptions of ideal operation from energy modeling at the design stage can lead to a wide range of uncertainties in building energy simulation. Combining building operations scenarios can yield significantly different building energy consumption results should any of these scenarios change. Ardehali and Smith [11] evaluated HVAC system operation strategies for energy conservation of constant-volume systems including night purge, system optimum start-and-stop, chilled water reset, and condenser water reset. Huang *et al.* [12] reported 17% energy savings by adjusting five energy management control functions for HVAC system. Using the eQUEST building simulation tool, NBI [13] studied the impact on building energy consumption of 28 building features, which include three operations-related parameters.

This study investigates the uncertainties in building energy consumption introduced by building operations and weather using a simulation approach for a commercial reference office building [14]. The study was conducted as part of a Department of Energy (DOE) project to examine the impact of incorporating energy efficiency metrics into the commercial building mortgage valuation process [15]. Uncertainty in energy use causes volatility of net operating income, which in turn affects the value of commercial building mortgages. In this study, the design-related parameters such as window- to-wall ratio, U-value, nominal equipment efficiency, etc., are considered as fixed values. Its primary purpose is to understand the degree of uncertainty in energy consumption due to identified individual operation parameter and interactive effects among operations parameters.

2. Building model description

The commercial building reference model for a medium-size office building is modified in compliance with ASHRAE 90.1-2007 and is used as a baseline for the study to investigate the impacts of operation parameters and weather on building energy consumption. There are three stories and 15 thermal zones (four perimeter zones and one core zone for each floor) in the medium-size office reference model. The window to wall ratio (WWR) is 0.48 for four orientations. Both lighting-power density and electric plug-load density is 10.76W/m^2. A multi-zone VAV system, with a two-speed DX cooling coil and a gas burner, is used to provide the conditioned environment for each floor. An electric reheating coil is available for each thermal zone.

3. Uncertainties in annual energy use due to weather variation

Most building energy models are simulated using TMY (typical meteorological year). There are three major reasons why TMY data rather than actual weather data are widely used by building designers: (1) TMY represents hourly meteorological values that typify conditions at a specific location over a long period of time, such as 30 years. (2) Most public weather stations are located outside of cities, so that the measured weather conditions may not be applicable to the designed site [16], and local weather data for solar radiation are often not available. (3) It is costly to acquire a weather station with accurate sensors and to ensure the quality of measured data.

However, for the purpose of investigating the uncertainties in energy consumption due to weather fluctuations, historical data are needed. Weather files for a period of 10-15 years were created according to the required format of EnergyPlus, using actual weather data obtained from a commercial vendor. Key parameters including dry-bulb temperature, dew-point temperature, relative humidity, wind speed, wind direction, and sky cover are obtained directly based on data recorded hourly by weather stations in each city, while hourly direct solar radiation and diffuse solar radiation data estimates are provided by meteorologists.

The annual site energy consumption using TMY3 weather files is used as a baseline for comparison with the simulated annual site energy consumption using historical weather files. Four cities —Washington DC, Chicago, Atlanta, and San Francisco— are chosen to represent four climates in the United States. The box-and-whisker chart (Figure 1) illustrates the statistical spread of the uncertainties of total site energy consumption introduced by weather. The tips of the whiskers represent the maximum and minimum variations of total energy consumption. The bottom and top of a box represent 25th and 75th percentiles of the energy variations, respectively. A negative or positive percentage of a variation indicates that, in a particular year, the predicted annual site energy consumption using an actual weather file for that year is, respectively, less than or greater than that using TMY weather file. The ranges of uncertainties in annual energy consumption vary according to climate. For example, there is less variation of annual energy consumption for San Francisco, located in warm-marine climate, than the ranges in uncertainties for other cities. The uncertainty range due to weather of San Francisco is from -0.5% to 3.0%. This could be attributed to the fact that the climate in San Francisco is relatively mild and requires less heating and cooling than other climates. The variation of annual energy consumption for Atlanta is from -2.2% to 5.1%. Based on the annual energy prediction using TMY data, the uncertainties in annual energy consumption introduced by actual weather variations during the period of 10-15 years, depending on the availability of weather data, ranged from -4.0% to 6.1% for the four typical climatic zones. The uncertainties due to weather for the 25th and 75th percentiles are in the range of -2.5% and 1.8%.

These results show that the impacts of year-to-year weather variations may be significant for the purpose of evaluating energy saving retrofits, but they are relatively minor compared to the uncertainty due to operational parameters, as explained in the next section.

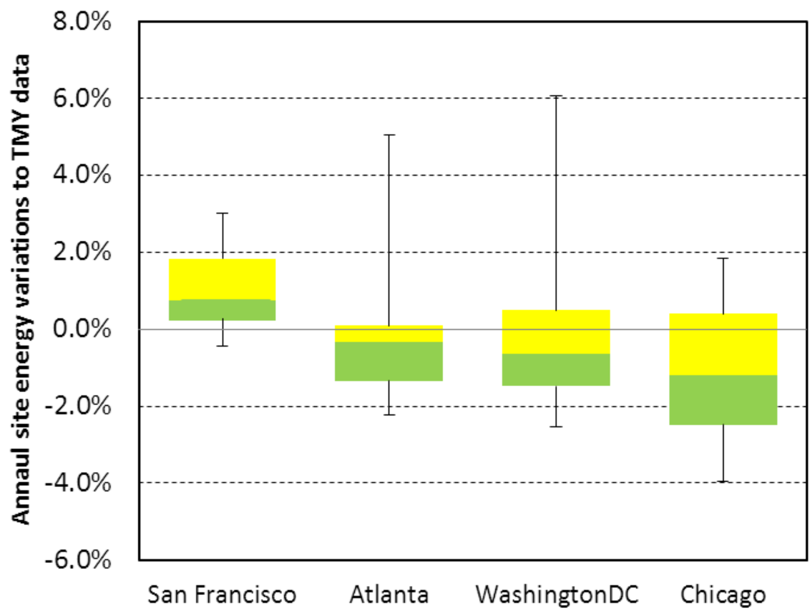

Figure 1. Uncertainties in annual site energy consumption due to actual weather, relative to TMY weather data

4. Uncertainties in annual energy use due to building operations

The way in which a building is operated plays an important role in its energy consumption. While still maintaining the same level of indoor thermal environment, various operation practices for buildings may result in significantly different energy use. Based on inputs from commissioning providers, we categorized common operation practices into three different levels of practice —good, average, poor —and identified key parameters to describe the characteristics of building operations. The uncertainties in annual energy consumption introduced by each parameter and combination of multiple parameters are investigated using building energy simulation. For each simulation, thermal comfort parameters were checked to ensure that indoor thermal comfort requirements were met for all scenarios.

4.1 Development of baseline model and range of practices

A range of practice for key building operations, listed in Table 1, is defined in the study to evaluate the impact of each parameter on building performance.

Table 1. Range of practice in building operations for a medium-size office building

Operation parameters	Good practice	Average practice	Poor practice
Lighting control	Dimming control based on illuminance setpoint and	Light on/off based on occupancy sensor	Manual switch on/off
Plug-in equipment control	Turn off when occupants leave	Sleep mode by itself	No energy saving measures
HVAC equipment operation schedule	6am to 8pm and one hour warm-up period	6am to 10pm and one hour warm-up period	5am to midnight and two hours warm-up period
Room temperature setpoints for occupied hours	20 ℃ for heating; 25 ℃ for cooling	21 ℃ for heating; 24 ℃ for cooling	22 ℃ for heating; 23 ℃ for cooling
VAV box minimum-flow setting	15% of design flow rate.	30% of design flow rate.	50% of design flow rate.
Economizer cycle	Integrated economizer with dry bulb temperature control	Non-integrated economizer with dry-bulb temperature control	No economizer
Night setback	12.7 ℃ for heating set point and 30 ℃ for cooling set	15.6 ℃ for heating set point and 28.4 ℃ for cooling	18.3 ℃ for heating setpoint and 26.7 ℃ for cooling setpoint for
SAT control	SAT reset based on warmest zones	SAT reset based on stepwise function with outdoor air	Constant SAT
Vacant spaces	Range of room setpoints: 12.8 ℃ -32.2 ℃; no lighting/plug loads	N/A	Rooms setpoints are the same as occupied space, no plug loads, 30% of design lighting loads

4.1.1 Lighting control

Lighting load represents about 30% of overall building energy consumption. Advanced lighting control is one of most effective measures for building retrofits [17]. The uncertainties in energy consumption that result from different lighting controls for a facility with the capability of automatic daylight and occupancy sensors were explored in the study. In good practice, electric lights continuously dim in perimeter zones when daylight illuminance increases, at reference points located 2 m from the facade inside thermal zones, up to the illuminance setpoint (500 lx). In good practice, interior shades may also be implemented to prevent discomfort glare. Interior shades will be pulled down when the glare index is above 20. In average practice, occupancy sensors automatically switch the lighting on or off, as demonstrated in the operations schedule shown in Figure 2. In poor practice, occupants keep lights turned on throughout occupancy hours as shown in Figure 3.

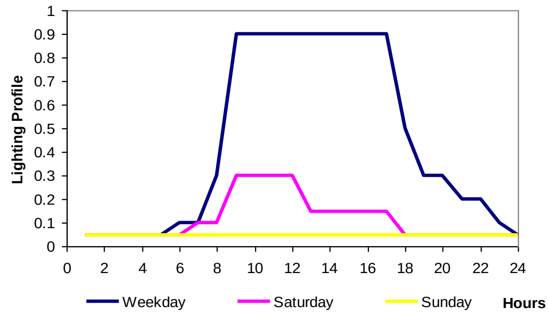

Figure 2. Lighting schedule with occupant sensor control

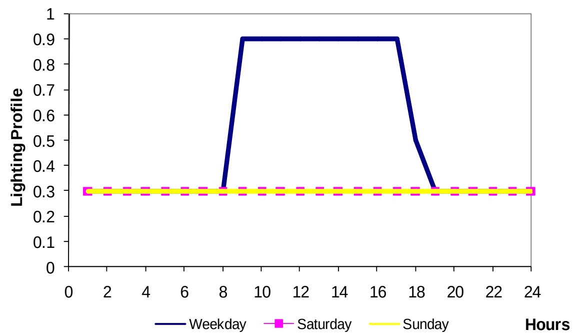

Figure 3. Lighting schedule with manual controls

4.1.2 Plug loads

Plug loads can account for a significant percentage of energy consumption in commercial buildings. The levels of practice correspond to the degree to which plug loads are turned off at night. The plug-load schedules for the range of practice are shown in Figure 4.

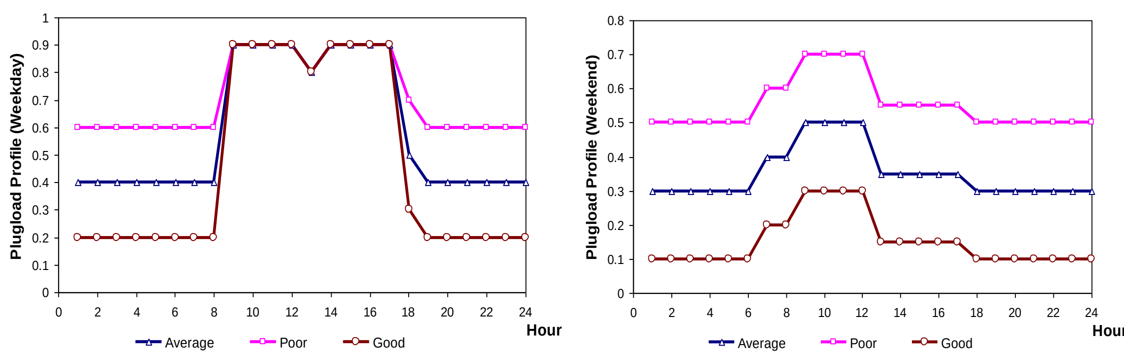

Figure 4. Hourly plug-load profile for weekdays and weekends

4.1.3 HVAC equipment operation schedule

The HVAC operation schedule is set to enable the HVAC equipment to provide comfort conditions for a given occupancy schedule. The range of practices for HVAC operation schedules used in this analysis are listed in Table 1. Good practice is represented in the table by the case of a building operator who carefully tracks the occupancy schedule and sets the HVAC schedule as close to it as possible without sacrificing comfort. Average practice is represented by the HVAC operation schedule in the reference model. Poor practice is represented by the case of a building operator who sets the HVAC to run for a period much longer than the occupancy schedule.

4.1.4 Night setback

Setting the heating setpoints a few degrees lower, and the cooling setpoints a few degrees higher for unoccupied hours at night and during weekends, can significantly reduce heating and cooling energy. The period for night setback is from 10:00 pm- 5:00 am for weekdays. The cooling and heating setpoints for the period of night setback for the range of practices are summarized in Table 1. There is about a 3.3 °C temperature difference for the cooling setpoint and 5.6 °C temperature difference for the heating setpoint across the good, average, and poor practice setpoints for night setback.

4.1.5 VAV box minimum flow setting

Variable air volume (VAV) terminal boxes modulate VAV damper positions to adjust the supply airflow and reheat valve (if equipped) in sequence to maintain the zone temperature setpoints. In cooling mode, the supply airflow is modulated between its maximum and minimum settings to maintain the zone cooling setpoint. In heating mode, the supply airflow is typically set to minimum and the reheat valve is modulated to maintain the zone heating setpoint. Setting of the minimum airflow is tricky because there is a trade-off between indoor comfort and energy use. A higher minimum airflow setting can provide better ventilation in the space, but as a consequence of simultaneous heating and cooling, it comes at the expense of high fan power as well as extra heating and cooling energy use. Minimum airflow fractions of 15%, 30%, and 50% of the maximum airflow are used to represent the range of practice in this parametric study.

4.1.6 Supply air temperature reset

In good practice, the supply air temperature is reset based on the cooling demands of the warmest zone. In average practice, the supply air temperature is reset based on outdoor air temperature, to minimize simultaneous heating and cooling. Note that fan energy could increase when the supply air temperature is reset to a higher temperature. The stepwise function of the supply air temperature reset is shown in Figure 5. The cooling loads for the core zones in a commercial office building may not vary with outdoor air temperature. In poor practice, the supply air temperature is kept as a constant temperature at 12.8 °C for a single duct VAV system.

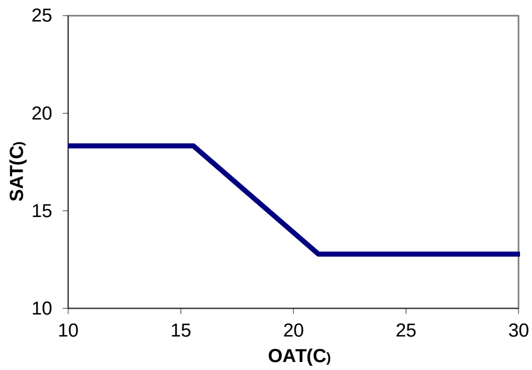

Figure 5. Stepwise function for supply air temperature reset based on outdoor air temperature

4.1.7 Airside economizer

Economizers are one of the most important components to reduce energy use in buildings whenever outdoor air conditions are more favorable for cooling than return air conditions. In average and good practice scenarios, the economizer operation is controlled by the differential temperature between outdoor air and return air. Both an integrated economizer approach and a non-integrated economizer approach are simulated for good and average practice respectively. In non-integrated economizer mode, the outdoor air damper will be turned down to the minimum position once free cooling cannot meet the required cooling capacity. In the integrated economizer mode, mechanical cooling works together with free cooling in economizer mode to meet the required cooling capacity, and the system stays in integrated economizer mode until outdoor conditions reach the high-limit shutoff setting. For poor practice, it is assumed that the outdoor air economizer is disabled.

4.1.8 Room temperature setpoints for occupied hours

Adjustment of room temperature setpoint bands during occupied hours can have an impact on building energy consumption. Occupant behavior, e.g., clothing adjustments that adapt to the local environment, can lead to a higher cooling setpoint and lower heating setpoint, reducing energy use. For average practice, the room temperature setpoint is 21 °C for heating and 24 °C for cooling. For good practice, the room temperature setpoint is decreased by 1 °C for heating and is increased by 1°C for cooling. For poor practice, the room temperature setpoint is increased by 1 °C for heating and is decreased by 1°C for cooling.

4.1.9 Operations of vacant spaces

Office-building vacancy is an unpredictable factor, and management of energy use in vacant spaces has an impact on total building energy consumption. In the study, it is assumed that the area of vacant space was ~10% of total office area. In good practice, there is a wide band for room setpoints ranging from 12.8 °C to 32.2 °C, lights are turned off and there are no plug loads in the vacant spaces. For poor practice, the room temperature setpoints in the vacant spaces are the same as occupied space, and 30% of the lighting is left on.

4.2 Uncertainties in annual energy use due to individual operation parameters

In this section, the uncertainties in annual energy consumption due to individual building operation parameters are investigated using EnergyPlus simulations. The baseline model is defined as the building operation using average practice in Table 1. Eighteen scenarios, with individual operation parameters defined in good or poor practice listed in Table 1, were created using the reference model for each city.

Three end-use categories —lighting controls, plug loads and HVAC operations— play important roles in building energy consumption. Annual site energy consumption for each scenario, including electricity and gas consumption, is summarized, and the variation of annual site energy consumption for Atlanta—based on the energy consumption predicted by the baseline model— is shown in Figure 6. A negative value represents the percentage of energy savings, while a positive value represents the percentage of energy penalty. Plug loads can introduce a -11.3% to 6.8% variation of annual site energy consumption based on the range of defined hourly profiles. The range of lighting control practice accounts for variation of annual energy consumption from -5.3% to 8.4%. In HVAC end use, VAV damper minimum position, supply air temperature reset, air side economizer, and room temperature setpoints are the most influential parameters for medium-size office buildings with DX units. In Atlanta, the annual energy use for the scenario without supply air temperature reset is 2% higher than that of the scenario with the supply air temperature reset based on warmest zone. The purpose of using the supply air temperature reset is to avoid reheating at terminal units and keep DX units off as long as possible in cold weather, and also to return to a low setpoint in warm weather when DX units are likely to be on. The variations of VAV damper minimum settings introduce uncertainties of -5.7% - 9.5% in annual site energy consumption. Minimum damper positions for VAV terminal units are adjustable. A higher minimum damper setting (e.g., 50%) can result in a significant energy penalty due to thermal comfort issues and simultaneous heating and cooling. The application of a dual maximum strategy [18] and 15% minimum airflow for VAV boxes can lead to a 3.2% energy savings for California climates. The uncertainties in annual site energy consumption due to airside economizer operation range from -1.4% to 2.4%.

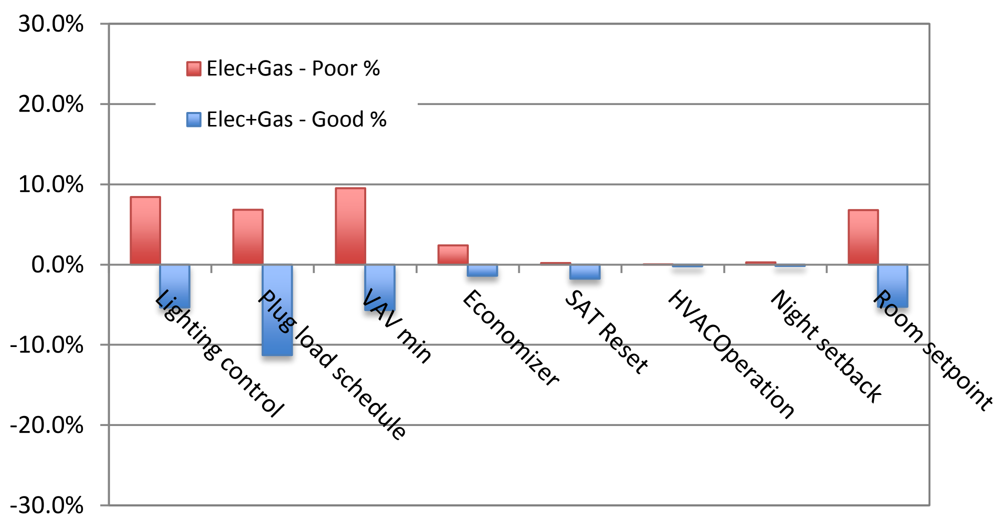

Figure 6. Uncertainties in annual site energy use due to individual building operation parameters for a reference building in Atlanta.

If 10% of an office area is vacant, the annual site energy consumption is always lower than baseline due to the reduced lighting and plug loads for those vacant spaces. The management of lighting and HVAC operation for vacant spaces directly impacts energy consumption. The annual energy use for the reference building with a 10% vacancy and poor practice is 3.9 % higher than when good practice is used. Increased vacant spaces in buildings would enlarge the impacts of operation practices for vacant spaces on annual energy use.

Figure 7 summarizes the uncertainties in annual site energy due to individual operation parameters across the four climates. The uncertainties are based on the annual site energy consumption of baseline models for each city. For medium-size office building models simulated in different climates, the parameters with the largest uncertainties are lighting control, plug load controls, VAV min settings, supply air temperature reset and air side economizer control. Notably, the uncertainties stemming from economizer control in a mild climate (San Francisco) are greater than those in other climates using the same control strategies. This is due to the fact that, during more than 90% of the year in San Francisco, outdoor air conditions are favorable for economizer mode. Therefore, for the airside economizer scenarios considered during normal operation, a wider range of uncertainties is reported for San Francisco than that for the other cities. It is worth noting that the uncertainties in annual site energy consumption discussed in this paper are for a limited set of operational parameters. If there are faults in the existing operation systems (such as stuck damper, sensor offset, etc.), uncertainty ranges would be even larger.

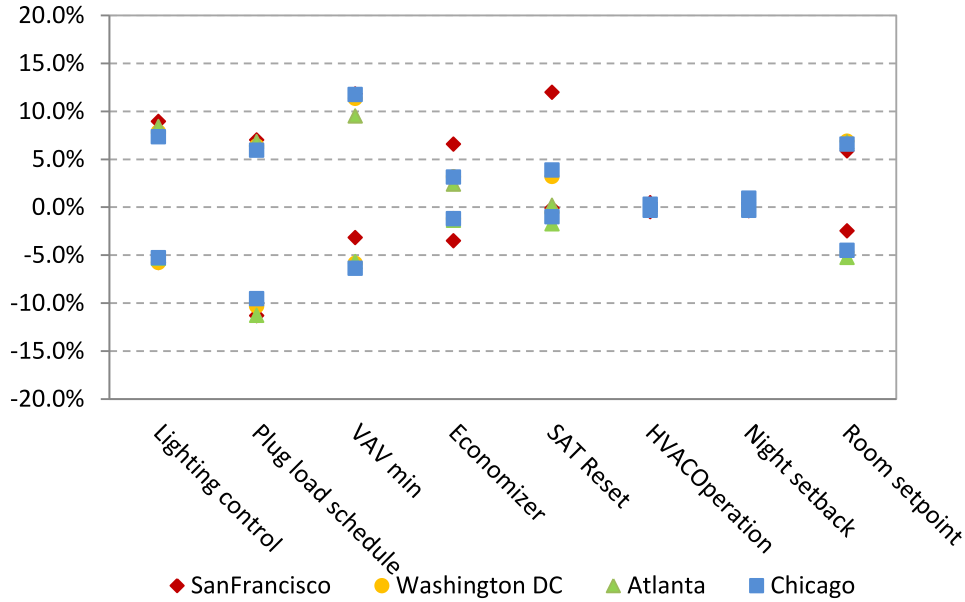

Figure 7. Uncertainties in annual site energy use due to individual building operation parameters for reference buildings in four climates.

4.3 Uncertainties in annual energy consumption due to combined effect of multiple operation parameters

The uncertainties in annual site energy consumption contributed by the combined effects of multiple operation parameters are investigated in this section. As a first step, extreme scenarios with maximum variation of site energy consumption for the given parameters are studied for each city. In the second step, a Monte Carlo method is applied to analyze the annual energy consumption impacts of all possible combinations for given operation parameters.

The extreme scenarios of all the parameters in good or poor practices are simulated using EnergyPlus. When all the evaluated parameters are combined, the variations in annual site energy consumption ranges from -29% to 79% for San Francisco; -15% to 49% for Atlanta; -28% to 57% for Washington, D.C.; and -27% to 58% for Chicago. Notably, the combined effect of poor practices across all HVAC parameters is larger than the sum of individual effects for each HVAC parameter reported in the previous section. The variation of annual energy consumption represents a wide range of uncertainties in annual site energy consumption.

A Monte Carlo method is applied to compose various simulation scenarios and identify the uncertainty distribution within this range. The Monte Carlo method uses prior distributions of input uncertainties to sample randomly a range of possible inputs for simulating the same problem. In this study, the Monte Carlo method is applied to create all possible combinations simulated for the San Francisco climate. The ranges of possible inputs are the ranges of practices defined in Table 1. The analysis assumes discrete uniform distribution for each operation practice. In this uncertainty analysis, the probability of occurrence is equal for each combination scenario, a reasonable assumption for the parameters investigated here. For any specific building, it is possible that the occurrence of one scenario might be more probable than the occurrence of others. The uncertainty distribution can be obtained by analyzing the variations of energy consumption according to the baseline and frequency of the variations.

The frequency distribution of uncertainties for various possible combinations is shown in Figure 8. Results show that the uncertainty distribution in annual site energy consumption nearly follows a log-normal distribution. The geometric mean of the log-normal distribution curve approximates 1.0, which indicates the baseline scenario. For the San Francisco climate, when the system is operating normally, the range of uncertainties for the medium-size office reference building is from -29% to 79%; at a 95% confidence interval, the range of uncertainty is from -20% to 42%; and at an 80% confidence level, the range of uncertainty is from -15% to 18%.

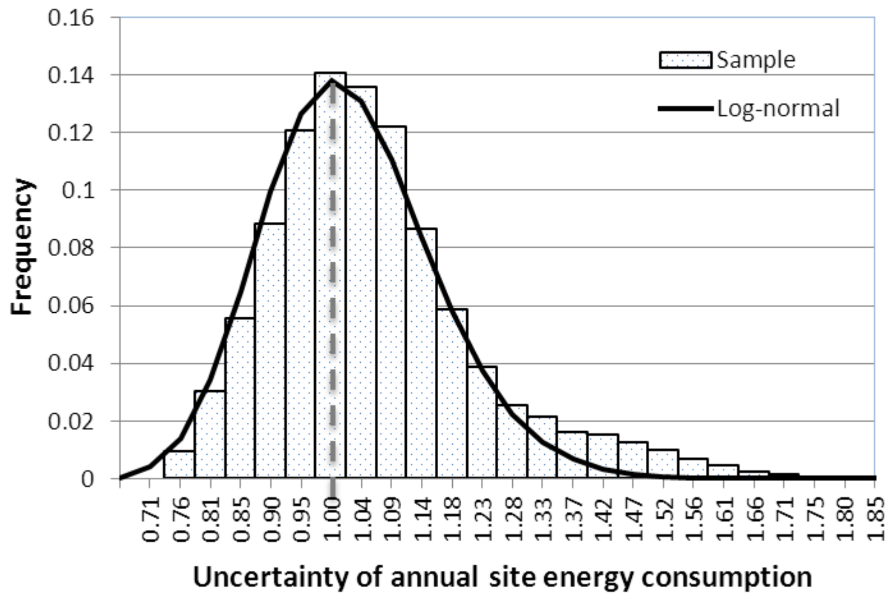

Figure 8. Uncertainty distribution profile for annual energy use in San Francisco

5. Conclusion and recommendations

This paper investigates the uncertainties in annual site energy consumption due to weather variation and operation parameters for a medium-size reference office prototype. The range of uncertainties for each category is summarized in Figure 9. The uncertainties in annual site energy consumption for the defined operation parameters range from -28.7% to 79.2%, while the uncertainties due to weather variation range from -4.0% to 6.1%. Among building end uses, HVAC operation is most influential, introducing -15.3 to 70.3% variation in annual site energy consumption.

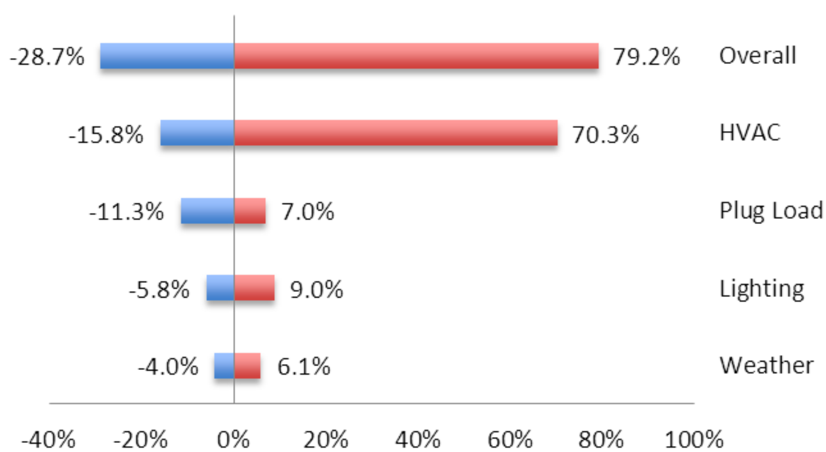

Figure 9. Uncertainties in annual site energy consumption by category

This study contributes to the understanding of the impacts of key operation parameters on energy consumption. The energy penalty of the combined scenarios with poor practice is larger than the sum of the energy penalties of poor practice in individual parameters. For medium-size office building models simulated in different climates, the parameters with the largest impacts are lighting control, plug-load controls, VAV minimum settings, supply air temperature reset, and air side economizer control. In future research, it would be interesting to compare the uncertainties derived from simulation against empirical data from commissioning projects [19].

Notably, the uncertainty distribution in annual site energy consumption for all possible combinations of operations parameters approximately follows a log-normal distribution. As a result, the range of uncertainties in building energy consumption at a given confidence level can be reported. The uncertainty range due to operational factors, even at an 80% confidence level, can dwarf the impact of design features.

This analytical approach can also be applied to other stages in a building's life cycle. For example, during the design stage, a rational range of predicted energy use based on uncertainties can be reported at specific confidence levels. Instead of predicting building energy use based only on interpretations and assumptions of ideal operation, it is important that building simulation can predict actual building performance within a rational range based on uncertainties in actual operations, and thereby improve the reliability of energy simulations.

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