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BUILDING ENERGY CONSUMPTION UNDER OCCUPANTS' BEHAVIOR UNCERTAINTY IN PRE AND POST-RENOVATION SCENARIOS: A CASE STUDY IN ITALY

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Abstract

In Europe, the energy renovation of the existing building stock is a great opportunity to significantly reduce energy consumption and greenhouse gas (GHG) emissions and reach the European sustainability targets. In this framework, building energy simulations (BES) tools are very useful in verifying energy retrofit measures' effectiveness and compliance with national standards. However, an inaccurate numerical prediction, the so-called "performance gap" between measured and numerical performance, is often obtained, mainly due to the inherent uncertainty of model input. Due to its stochastic nature, the occupants' behavior (OB) is considered among the key contributors to this gap. However, the most recent Building Energy Model (BEM) approaches adopt deterministic hourly-defined profiles for characterizing OB, thus neglecting the related uncertainty. In this work, the impact of OB uncertainties on energy consumption (EC) prediction is evaluated by adopting a Karhunen-Loève Expansion sampling technique, used to randomly perturb OB profiles such as heating setpoint (HS), internal thermal loads (IL), and windows opening (NV). Two BEMs of a typical Italian residential building in pre- and post-renovation scenarios are considered and calibrated on real EC data. The results demonstrated that HS uncertainty has the highest impact on EC in all scenarios. Moreover, the higher the energy performance of the building, the higher the impact of OB, especially for IL and NV patterns.

Keywords

Occupants' behavior, Uncertainty analysis, Natural ventilation, Internal loads, Heating setpoint.

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1. INTRODUCTION

In the European Union, 40% of the overall EU energy consumption (EC) and about 35% of the total greenhouse gas (GHG) emissions are attributable to the building sector. This is mainly due to the low energy performance of most of the building stock [1–3], which uses half of this energy for heating households [4]. In the next ten years, the energy demand is expected to increase by more than 20% [5]. Thence, improving the energy performance of these buildings represents an urgent need and opportunity to significantly reduce the European EC and GHG emissions and reach the European sustainability and energy efficiency targets.

In this framework, building energy simulations (BES) are generally used by practitioners to identify the best energy retrofit strategy and to verify its compliance with the requirements set by the National Standards. Still, a discrepancy between the experimental and numerical energy performance called the “energy performance gap” can be found for both new and existing buildings, reaching values up to 250%. This discrepancy can be traced back to the difficulty in obtaining the exact values of all the thousands of inputs needed for characterizing a Building Energy Model (BEM).

Among them, those needed to represent the actual occupants’ behavior and interaction with building systems (OB) are generally the most difficult to be defined. This is mainly due to the stochastic nature of the occupants’ behavior, especially in residential buildings. Several studies found the occupants’ behavior (OB) to be the main responsible for the energy performance gap in residential buildings [6, 7]. Indeed, different occupants’ interactions with thermostats, electric appliances, lighting, domestic hot water appliances, and windows may produce a huge difference in building energy consumption, which can be higher or lower than that forecasted by a building energy model (BEM).

Modeling OB can ease the understanding of occupants’ impact on building energy use. The more recent Building Energy Performance Simulation (BEPS) tools (e.g. [8]), however, model the OB through deterministic hourly-defined profiles, neglecting the OB’s stochastic nature. While simple and easy to understand, this approach does not consider the OB uncertainties, leading to evaluating the energy performance of one of the possible scenarios, which can greatly differ from reality.

The increasing power of the actual computer makes it feasible to conduct parametric BEPS in a reasonable time frame with thousands of simulations and stochastic inputs. As a result, over the past 20 years, the impact of OB uncertainty on building energy use has aroused increasing interest in the research field, where several studies concerning parametric analyses [9, 10] and stochastic OB models [6, 7, 11–13] have been carried out. However, most of these works regard office buildings, while just a few of them focus on residential ones. Moreover, these works mainly investigate the impact of OB on EC by comparing the results obtained through different OB (see e.g. [6]), while few of them consider the inherent uncertainty that can be present in a know, experimentally inferred, OB.

In a common application, indeed, the OB can be qualitatively known since inferred from occupants’ interviews. However, this investigation method leads to OBs’ patterns characterized by a degree of uncertainty that may affect the reliability of the EC prediction. To consider this uncertainty, O’Neill and Niu proposed an interesting approach based on applying a Karhunen-Loève expansion (KLE) sampling technique [7], which allowed them to consider the spatial and temporal uncertainties of a known OB pattern in BES. In particular, they applied this procedure to a US DOE prototype BEM for modeling the uncertainty of occupants’ presence, lighting, heating, and cooling setpoint patterns. However, a very small range of uncertainty of OB (a Coefficient of Variation, CV, of about 3.76%) was assumed, while the uncertainty related to some very important OB, such as windows opening, was neglected [14]. As a result, they found an impact of OB uncertainties on heating consumption of about 4%. Moreover, they conclude that a higher input parameter variation should be used to provide more insights into the impact of different behavior patterns on energy consumption. However, applying this procedure to real residential buildings, calibrated simulations, and window openings is still rare in the literature.

This paper presents an application of the KLE technique to a real, multi-family building in the Italian Marche region (Ancona). A BEM is purposely created and calibrated on observed monthly energy consumption to increase the reliability of the numerical outcomes. Since the impact of OB on EC may vary the buildings’ energy performance levels, both pre (calibrated) and post-energy retrofit scenarios are considered. For each renovation scenario, three uncertainty analyses (UA) are carried out by applying the KLE technique to internal loads (IL), heating setpoint (HS), and window opening (NV) patterns. To provide more insights into the impact of different behavior patterns on energy consumption, a higher input parameter variation than that adopted in [7] is considered. In this way, the robustness of EC prediction related to the three different OB pattern uncertainty is examined.

2. PHASES, MATERIALS, AND METHODS

2.1. PHASES

This work can be subdivided into the following three main phases:

- firstly, a BEM of a real residential building is created and enriched through information about OB collected through questionnaires;
- then, to increase the reliability of the numerical results, the BEM is calibrated to real EC data;
- finally, UAs on OB in both pre and post-retrofit scenarios are performed, having the twofold aim of estimating the impact of OB uncertainties on EC before and after energy renovation, and evaluating the energy prediction robustness to OB uncertainty.

2.2. CASE STUDY

A typical Italian multi-family building built between 1970 and 1975 and placed in the hot-summer Mediterranean climate of Ancona, Italy (Csa climatic zone according to Köppen climate classification [15]) has been selected in this study. The building consists of six stories and 12 dwellings, with a floor area for each story of 280.8 m^2 (Fig. 1a). Each floor has three dwellings except for the first floor, which is unheated and below the ground level, and the second and the last floors, which have one and two dwellings, respectively.

For the aim of this study, the dwelling highlighted in Fig. 1b, belonging to the third story, was selected for calibration and UA. The flat consists of two bedrooms, a bathroom, a kitchen, and a living room, and is occupied by three persons, i.e., a couple with one son. The overall area of the apartment is about 80 m^2.

2.3. NUMERICAL MODELING OF PRE- AND POST-RENOVATION SCENARIOS

The building described in Section 2.2 has been modeled through the DesignBuilder ver. 6.1 [16], which is a graphical interface of the EnergyPlus software (see Fig. 2a). The Conduction Transfer Functions (CTF) have been used as heat balance algorithm, while TRAP and DOE-2 as surface convection algorithm for inside and outside convection, respectively. An IdealLoadsAirSystem model was adopted to compute the HVAC heating energy demand with an infinite heating capacity, and an HVAC Coefficient of Performance (CoP) was used to calculate the heating energy consumption from energy demand [17]. Model inputs, such as thermophysical

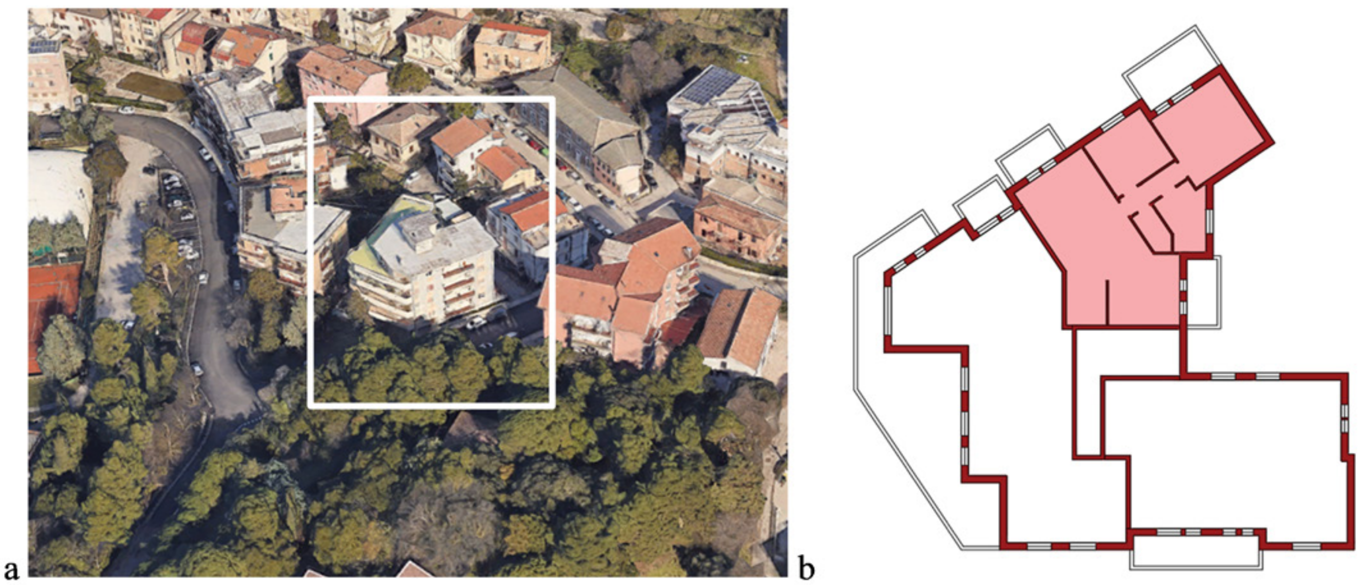

Fig. 1. *(a) Overview of the six-story multi-family building; (b) plan of the third floor with highlighted the case study apartment used for numerical simulations.*

Property	Pre-renovation	Post-renovation
U-value - Exterior walls [W/m^2 K]	0.65 - 0.90	0.32
U-value - Internal walls between flat and stairs [W/m^2 K]	0.65 - 0.90	0.32
U-value - Internal walls between rooms [W/m^2 K]	1.40 – 2.00	calibrated value
U-value - Windows [W/m^2 K]	1.80 – 2.2	1.20
SHGC [-]	0.65 - 0.85	0.35
Infiltration rate [ACH]	0.30 - 0.50	calibrated value
CoP [-]	0.60 - 0.75	0.85
Heating setpoint - Sleeping area [°C]	18 - 20	calibrated value
Heating setpoint - Living area [°C]	18 - 20	calibrated value
Maximum internal thermal gain [W/m^2]	3 - 12	calibrated value
Maximum windows opening area fraction [%]	5 – 100	calibrated value

Tab. 1. *Uniform probability distributions of BEM properties in the pre-renovation scenario and deterministic values in post-renovation scenarios. SHGC: Solar Heat Gain Coefficient; CoP: Coefficient of Performance of the space heating system.*

characteristics of opaque and transparent components, CoP, and infiltration rate, as well as some OB-related inputs, such as maximum internal thermal loads, have been initially estimated from a detailed energy audit, occupants' interview, and literature. Due to the uncertainties in these data, a uniform range of variation has been defined for each relevant property instead of a deterministic value, as summarized in Table 1. These ranges define the search space for the calibration process described in Section 2.4.

Concerning the post-renovation scenario, all the construction elements and heating systems are considered to be upgraded according to the Italian Law on buildings' energy performance [18], significantly improving the thermal performance of the entire building. The deterministic input values considered for the post-renovation scenarios are summarised in Table 1.

The patterns related to the interactions between occupants and building systems, i.e., ILs, HS, and NV, have been inferred from questionnaires submitted to the occupants. The obtained information has been then translated into the estimated daily profiles shown in Fig. 2b, c and d. These data have been used as a starting point for BEM calibration (Section 2.4) and UA (Section 2.5). Concerning the ILs, the pattern in Fig. 2a is multiplied by a maximum value to obtain the related hourly value of ILs, whose range of variation is indicated in Table 1 [19, 20]. Regarding the HS, two different thermostats are in the apartment, i.e., one in the sleeping area and one in the living area. Then, according to occupants' information, two different heating activation profiles were considered, which were multiplied by a different HS. Finally, the NV schedules reported in Fig. 2d indicate the time when the occupants open the windows to ventilate the apartment. According to the ASHRAE book of fundamentals [8, 21], the resulting flow rate from windows is then computed through a superposition process as the combined effect of the airflow driven by wind (Q_W) and the airflow due to stack effects (Q_S). In particular:

$$Q_W = C_W A_0 V \tag{1}$$

$$Q_S = C_D A_0 \sqrt{2gh|T_Z - T_O|/T_Z} \tag{2}$$

where C_W is the opening effectiveness computed as reported in Eq. 3 [8, 21]; A_0 is the opening area of windows, which is unknown and then will be defined in the calibration phase (a range between 10 and 100% of the total opening area is assumed, see Tab. 1); V is the external wind speed; C_D is the discharge coefficient equal to $0.4 + 0.0045|T_Z\text{-}T_O|$; g is the standard gravity; h is the height from the midpoint of the lower opening to the neutral pressure level; T_Z and T_O are the internal and external air dry-bulb temperatures, respectively.

$$C_W = 0.55 - 0.25|Angle\ difference|/180 \tag{3}$$

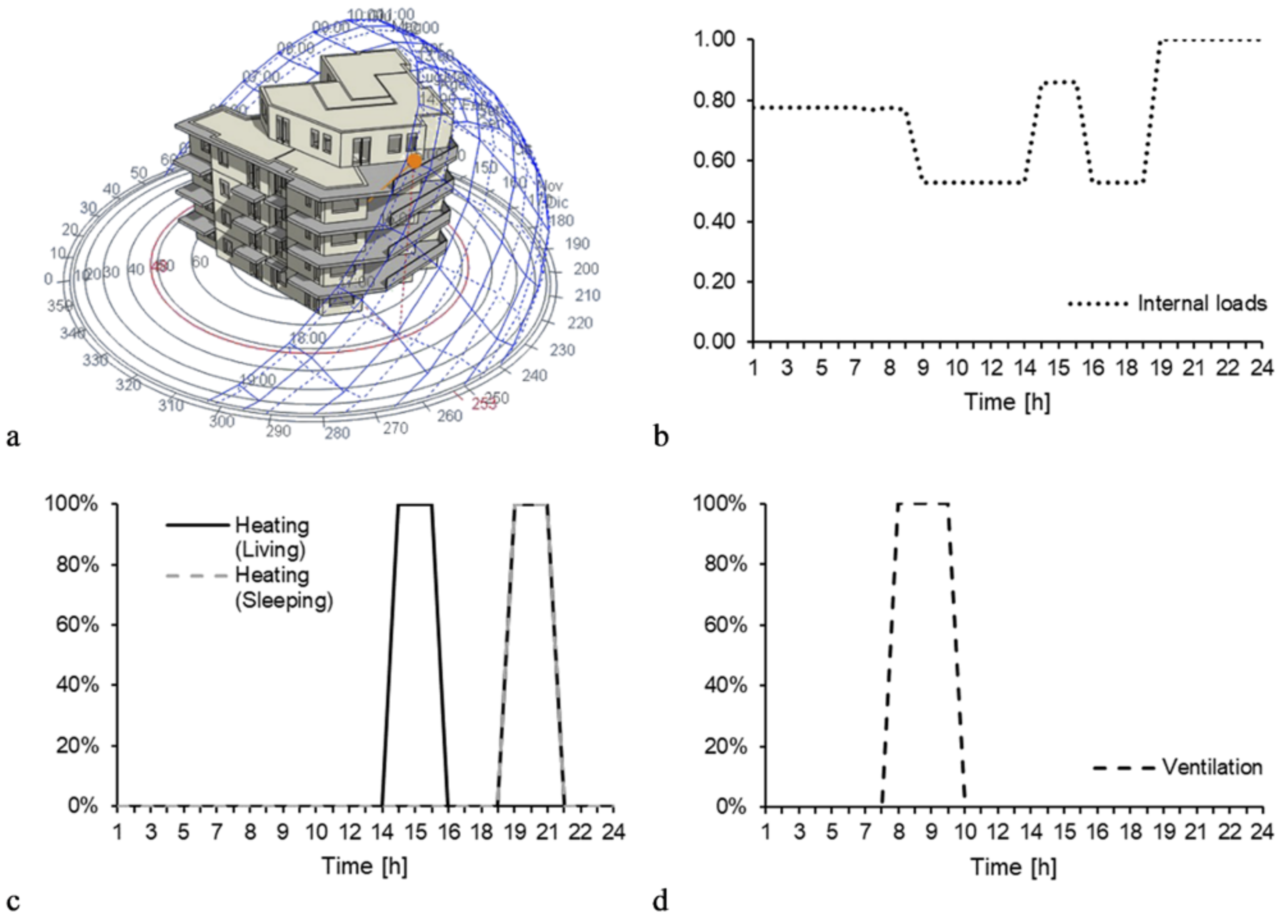

Fig. 2. *(a) BEM of the residential building; (b) OB's patterns for internal gains; (c) OB's patterns for heating; (d) OB's patterns for natural ventilation inferred from occupants' questionnaires.*

2.4. MODEL CALIBRATION

BEMs generally provide inaccurate numerical predictions if not calibrated or validated on real data [22]. Despite this, uncalibrated BEMs are often used in the literature to address the impact of OB on EC [7, 11]. To increase the accuracy of the numerical predictions, the developed BEM has been calibrated against monthly energy consumption in this study, as requested by relevant international Standards on BEM calibration [23]. The selected baseline period for data collection and simulation goes from the 1st of November 2016 to the 24th of March 2017, corresponding to the period during which Italian national authorities allow space heating in Ancona, Italy, i.e., where the building is located. During this period, weather data such as the outdoor air temperature, relative humidity, horizontal global solar radiation, wind velocity, and direction were collected through a weather station placed 1 km away from the building.

An automated calibration tool purposely developed by the authors and based on Artificial Intelligence optimization algorithms has been used to perform the BEM calibration. In particular, the Non-dominated Sorting Genetic Algorithm (NSGA-II) has been implemented for the optimization process, which is one of the most used and efficient for automatic BEM calibration [24]. The tool automatically searches the set of input data that minimizes the error between simulated and measured time-series data, given a search space defined by the input ranges of variation.

Two error functions can be used for assessing the error, i.e., the Coefficient of Variation of the root mean square error (CVRMSE) and the Normalized Mean Bias Error (NMBE). According to the ASHRAE guideline 14 [23], a model is considered calibrated on monthly energy consumption when the CVRMSE and NMBE are below or within specific thresholds, equal to 15% and ±5%, respectively [23].

2.5. UNCERTAINTY ANALYSES

Three distinct "local" uncertainty analyses (UAs) have been carried out on the pre-renovation and post-renovation scenarios to evaluate the impact of OB uncertainties on building EC and then the robustness of the calibrated BEM energy prediction to OB. Each UA concerns the variation of one of the estimated OB patterns shown in Fig. 2b, c, and d, i.e., the internal load pattern (IL-UA), the heating setpoint pattern (HS-UA), and the natural ventilation pattern (NV-UA), respectively. The pattern variation is obtained by adopting the Karhunen-Loève expansion (KLE) sampling technique, which has been successfully used in the literature to evaluate the impact of OB on EC [7, 25].

Similar to the Fourier analysis, a KLE allows representing a stochastic process as an infinite linear weighted combination of orthogonal functions, reducing its dimension by converting time-dependent uncertainty into time-independent stochastic parameters. In practice, the KLE represents a stochastic process x(t) through the following equation:

$$x(t) = \mu_x(t) + \sum_{i=1}^{\infty} \sqrt{\lambda_i}\psi_i(t)y_i \quad (4)$$

where $\mu_x(t)$ is the mean value at the time t, $\psi_i(t)$ is a temporal basis function, and λ_i and y_i are the eigenvalues and eigenfunctions of the covariance function $C(x_1, x_2)$. In particular, y_i is a time-independent stochastic parameter expressed as Gaussian variables characterized by an average equal to zero. The most used types of correlation functions are Gaussian, exponential, or turbulent functions [26]. In this study, the following exponential covariance function is adopted:

$$C(x_1, x_2) = c\, e^{-\left(\frac{x_1 - x_2}{5}\right)^2} \quad (5)$$

where c is a variance scaling parameter corresponding to the Coefficient of Variation (CoV) of each normally distributed hourly value. A different value of c has been adopted for the different OB patterns. Being ILs and NV characterized by high uncertainty, a high value of c, equal to 20%, has been assumed in these cases. Conversely, a smaller c value (2.5%) has been considered for the HS-UA to have plausible values for hourly HS, corresponding to a maximum deviation of ±1°C from the calibrated value.

Assuming that $\mu_x(t)$ is equal to 0, the KLE is used in this work to obtain 1000 sets of 24 "hourly" random coefficients, as shown in Fig. 3a. The sample dimension is chosen to ensure the convergence of the UA result. These coefficients are then used for computing 1000 new hourly patterns for each UA according to the following formulation:

$$X^*(t) = X(t) \cdot \left(1 + x(t)\right) \quad (6)$$

where $X(t)$ is the estimated OB pattern, while the $X^*(t)$ represents the perturbed one. In Fig. 3b, the 1000 patterns obtained for the IL are plotted as an example.

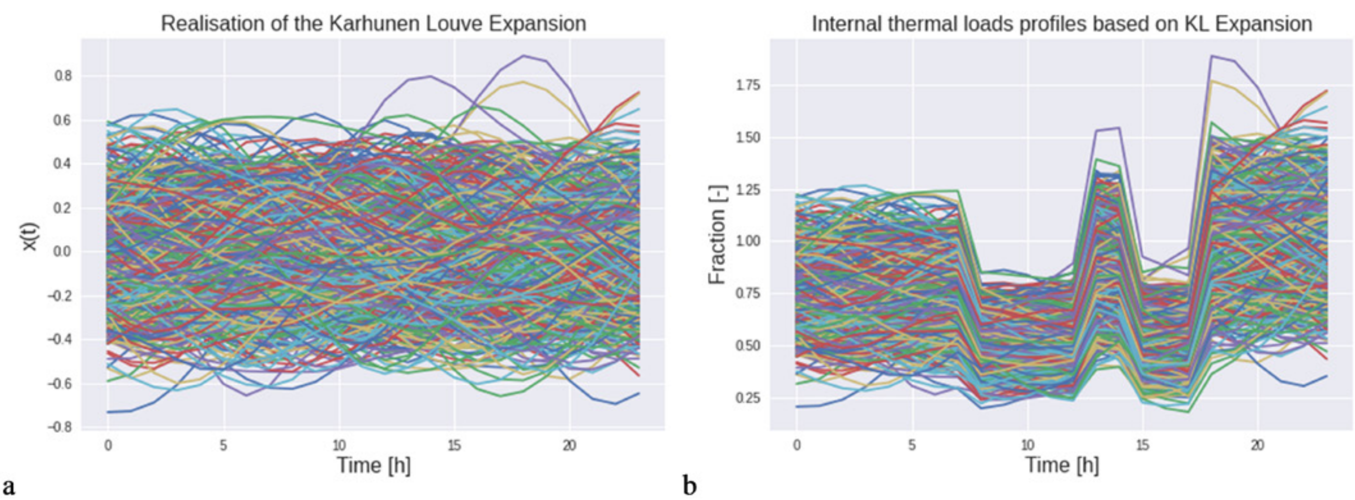

Fig. 3. *(a) 1000 realizations of the KLE; (b) exemplary application of the KLE technique on the internal thermal loads' estimated profile.*

3. RESULTS AND DISCUSSION

3.1. MODEL CALIBRATION

This section reports the results of the model calibration used to increase the reliability of numerical prediction. Figure 4 shows a comparison between observed and predicted EC after BEM calibration, while the calibrated values of the model inputs are reported in Table 2.

The automated calibration tool allowed for reaching a good match between experimental and numerical data. Overall, the obtained CVRMSE and NMBE values are equal to 13.57 and -3.56%, respectively, i.e., lower than the thresholds set in the international Standard to consider a BEM calibrated (equal to 15 and ±5%, respectively, according to the ASHRAE guideline 14 [23]). The obtained model can then be used for reliable EC prediction in both pre and post-renovation scenarios since it represents the actual energy performance of the building [23]. Since observed data are obtained from energy bills and predicted data (from calibrated simulations) are deterministic values, it should be noted that measurement accuracy and confidence interval of numerical predictions cannot be determined in this case.

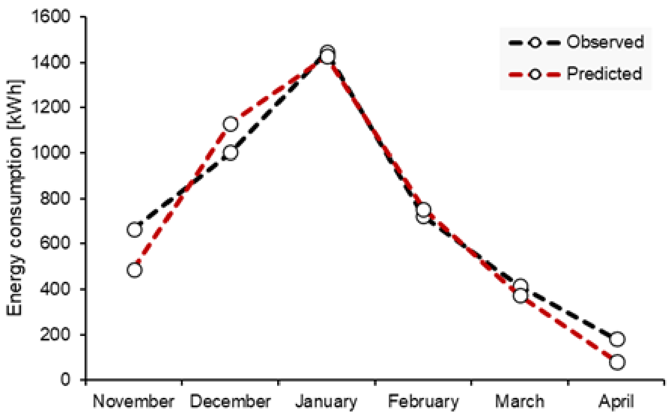

Fig. 4. *Comparison between predicted and observed EC for space heating after BEM calibration.*

3.2. UNCERTAINTY ANALYSIS IN THE PRE-RENOVATION SCENARIO

Starting from the calibrated BEM, a KLE-based UA has been carried out for each considered occupants-related profile, i.e., internal loads (IL-UA), heating setpoint (HS-UA), and natural ventilation (NV-UA). The results of the IL-UA, HS-UA, and NV-UA are reported in terms of yearly EC distribution (Fig. 5a) and monthly EC (plume graph in Fig. 5b). A comparison between calculated and measured monthly EC is also shown in Fig. 5b. It should be noted that only occupants related parameter are varied in the uncertainty analyses carried out in this study since other uncertainty parameters (e.g., building envelope features) have been fixed to deterministic values through the calibration process (see Tab. 2). This allowed us to focus our work on the impact of OB only on numerical results.

For each UA, the yearly EC can be considered normally distributed, characterized by a mean value of

Input parameters	Calibrated values
U-value - Exterior walls [W/m^2 K]	0.66
U-value - Internal walls between flat and stairs [W/m^2 K]	0.67
U-value - Internal walls between rooms [W/m^2 K]	1.43
U-value - Windows [W/m^2 K]	1.96
SHGC [-]	0.65
Infiltration rate [ACH]	0.31
CoP [-]	0.75
Heating setpoint - Sleeping area [°C]	18.1
Heating setpoint - Living area [°C]	20.0
Maximum internal thermal gain [W/m^2]	7.37
Maximum windows opening area fraction [%]	0.06

Tab. 2. *Calibrated values for the pre-retrofit scenarios.*

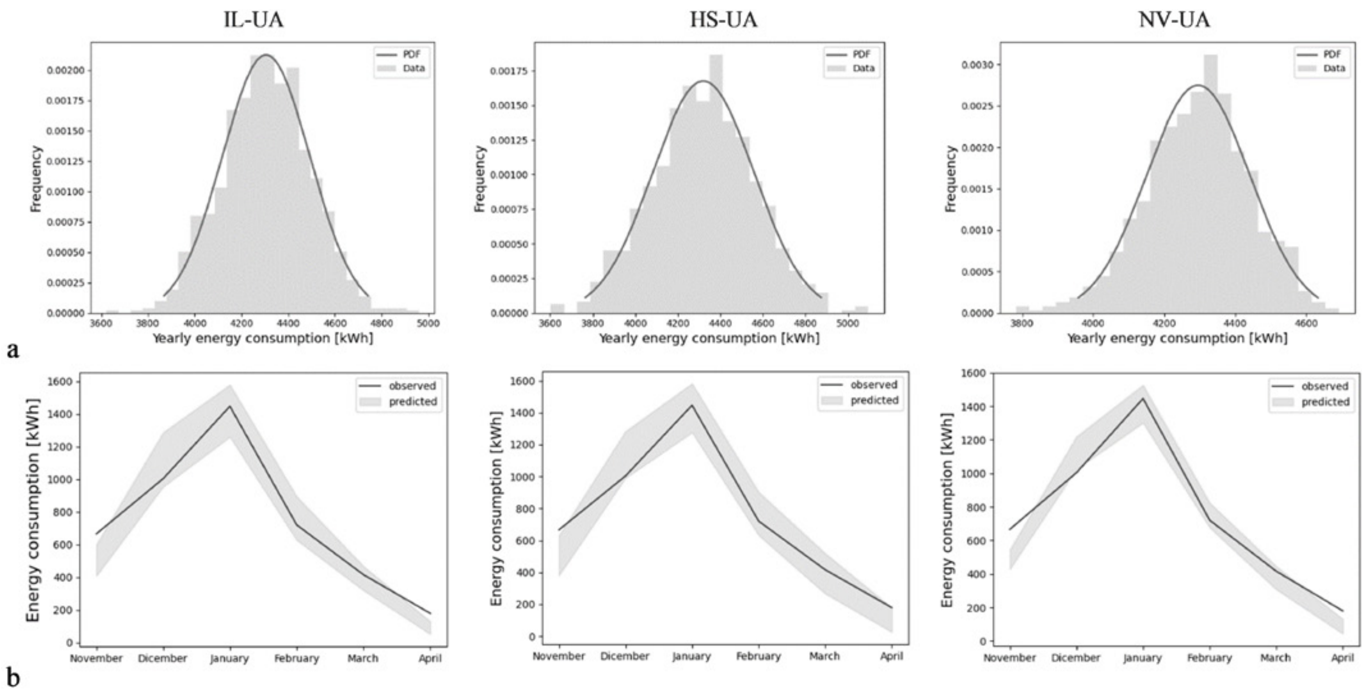

Fig. 5. *(a) Yearly and (b) monthly EC for the three UAs in the pre-renovation scenario.*

about 4300 kWh. Some differences can be noted in terms of standard deviation, equal to 236.5, 189.2, and 141.9 kWh, for HS-UA, IL-UA, and NV-UA, respectively, corresponding to a CoV, equal to 5.5, 4.4, and 3.3%. Thence, in the pre-renovation scenario, the HS schedule uncertainty has the highest impact on the EC, followed by IL and NV uncertainties.

Considering the lower variability assigned to the HS pattern (CoV = 2.5%) compared to that assigned to the IL and NV ones (CoV = 20%), the larger CoV of EC prediction obtained in the HS-UA denotes a high impact of the HS pattern on EC. Conversely, the lower CoVs of EC obtained for IL-UA and NV-UA indicate the lower importance of IL and NV patterns. These results are similar to those obtained in other works. In [7], for example, the author obtained a higher impact of HS pattern uncertainty than that obtained for ILs for office buildings. However, it should be noted that comparing the results among different studies is not an easy task due to the differences that can be found in building characteristics, type of use, OB patterns, and location. This notwithstanding, it can be stated that a correct characterization of the HS profile can be considered fundamental for obtaining realistic predictions of EC in existing buildings with low energy performance.

3.3. COMPARISON BETWEEN PRE AND POST-RENOVATION SCENARIOS

In order to evaluate how the impact of OB on EC may vary from a pre-renovation to a post-renovation scenario, the same three UAs considered in Section 3.2 have been replicated but by considering an improved energy performance of the same case study (see Tab. 1). In Figure 6, the results of the two scenarios are plotted and compared in terms of box plots of yearly energy consumption.

The first evident results regard the expected reduction of the yearly building EC for all the considered UA, which pass from an average of about 4300 kWh in the pre-renovation scenario to about 2800 kWh in the post-renovation, corresponding to a decrease in EC of about 35%. The standard deviation values of the three EC samples are equal to 187.0, 168.5, and 154.0 kWh for HS-UA, IL-UA, and NV-UA, respectively, corresponding to a CoV equal to 6.6, 6.0, and 5.5%. These values are higher than that obtained in the pre-renovation scenarios. The increase obtained in terms of CoV is mainly due to the lower average value of yearly EC, but they differ among different UAs. In particular, the highest increase is obtained for the NV (+67%), followed by the IL and HS (+36% and +20%, respectively). This indicates

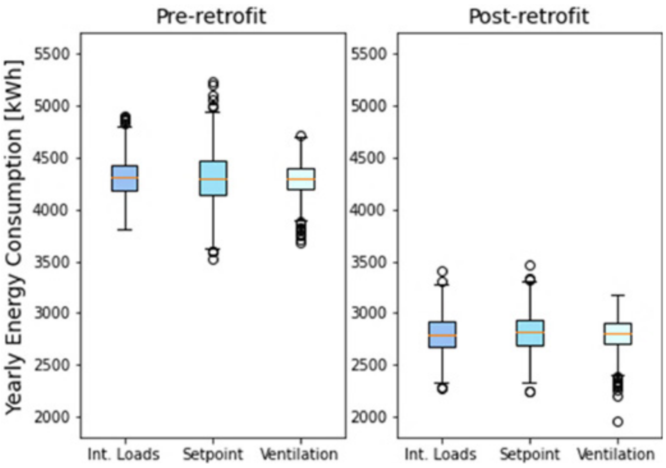

Fig. 6. *Box plot of yearly EC in pre- and post-renovation scenarios.*

that higher building performance can lead to a higher impact of OB uncertainties, particularly those related to heat gains or losses that remain quite constant after renovation, such as internal loads and air changes. Then, this result highlights that the higher the performance of the building, the higher the importance of IL and NV uncertainties in simulations.

4. CONCLUSION

This work allowed us to investigate the impact of uncertainties of known occupants' behavior (OB) information on the energy consumption (EC) of a real existing residential building located in Italy in both pre and post-renovation scenarios. At this aim, a BEM model is created and calibrated on real monthly energy consumption data to increase the accuracy of the numerical prediction. Then, three uncertainty analyses are carried out by expanding, one at a time, occupants' behavior uncertainties related to internal loads (IL), windows opening/natural ventilation (NV), and heating setpoint (HS) patterns through the KLE sampling technique. A pre and post-renovation scenario is also considered to evaluate how the impact of occupants' behavior on energy consumption may change to vary building energy performance levels.

Results demonstrated that the HS uncertainties always have the highest impact on EC regardless of the energy performance level of the building, followed by IL and NV. In particular, the low uncertainty assigned to the HS variation has always led to the largest CoVs of EC, denoting the high importance of the HS pattern uncertainty, regardless of the energy performance of the building. Conversely, the high uncertainty of the IL and NV patterns, and the obtained low variation on EC, denote a low impact of IL and NV uncertainties on EC, especially for the pre-renovation scenario. However, when the energy performance of the building is increased, the importance of IL and NV uncertainties in simulations increases accordingly. Thus, the uncertainty in IL and NV should be accurately considered in high-energy performance buildings.

The main limitation of this work lies in the use of a local UA approach. Thence, further studies are needed to evaluate the overall EC probability distribution by varying all the occupants' patterns. Moreover, more climatic locations and building use/type scenarios should be considered to draw more general conclusions.

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