On the impact of stochastic modeling of occupant behavior on the energy use of office buildings

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Abstract: The reliability of building performance simulation is hindered by several uncertainties, and aleatory uncertainty due to occupant behavior is one of the most critical ones. The present study aims to assess the propagation of uncertainty due to the adoption of stochastic models for modeling Occupant Presence and Actions (OPAs) available in the literature on the annual electric energy use of a reference office building. To this purpose, a global sensitivity analysis was designed and carried out by analyzing model inputs and energy outputs of 144 permutations of 15 different stochastic models for OPAs for a total of 7200 simulations. Building energy use computed considering stochastic OPAs modeling resulted in being sensibly higher than the reference value estimated assuming scheduled occupancy and rule-based occupant's actions as suggested by reference standards. The median value of the electric energy use was 58.6% higher than the base case electric energy use. Furthermore, the stochastic models used to model window operation have the highest effect on energy output, followed by light switch-off and occupancy models. Light switch-on models showed a lower influence on the overall building energy performance. Furthermore, the Generalized Estimating Equations method was adopted to assess the interdependence among stochastic models for OPA and showed that changing the stochastic model in window operation, occupancy estimation, and light switch-off behavior generates a considerable difference in building's energy performance. Contrariwise, the available stochastic models for light switch-on and blind operation perform quite similarly among each other and have a limited impact on a building's energy performance.

Keywords: Occupant Behavior, Occupant Presence and Actions, Stochastic models, Building Performance Simulation, Office

1 Introduction

Building performance simulation (BPS) is a cost-effective and fast method to better study building variants during the design phase and optimize building renovation concepts according to several and even antagonistic dimensions such as energy, costs, equivalent CO_2 emissions, and occupant comfort [1,2]. Although accurate estimations are an essential requirement for the proper use of BPS, the reliability of its results is hindered by several uncertainties [3–5]. Most of the time, energy modelers solve this issue by simplifying aleatory uncertainties using deterministic variables, a priori schedules, and/or rule-based models [6]. Such simplifications are some of the causes of a disparity between simulated and actual energy use in buildings [7–9]. The phenomenon is called the “performance gap” [1], and its study – started in the mid-90s – is still currently an object of interest for research and software development [10–13]. Carlucci *et al.* [14,15] studied the causes of this disparity, and approximate modeling of Occupant Presence and Actions (OPAs) is accounted as one of its primary causes. People influence building energy use passively through their presence and actively through interactions with the building’s components, such as operable windows, solar shadings, and thermostats, and the use of plug-in appliances and lighting [15]. It is common practice to model occupant presence in BPS via predefined a priori schedules and occupant actions with deterministic rules based on one or more physical variables [6]. However, these simple approaches are not able to account for the diversity between people and conditions and the variability of the interaction between occupants and the building. Thus, several studies have developed more complex models that aim to consider the human-building interaction, as reported in the various reviews conducted in recent years [15–19]. For example, Carlucci *et al.* [15] highlight that, in the last years, data-driven models are attracting increased interest, followed by stochastic OPA modeling techniques and rule-based methods. The growing attention towards data-driven models is related to their capability to deal with large datasets that are becoming more and more available without missing the aleatory nature of OPA in buildings [20–23]. While professionals are reluctant to model occupant-related uncertainty in their simulation [6], the other modeling approach often-adopted in the scientific literature is to represent occupant behavior stochastically, and several probabilistic models are available in the literature to model the different aspects of OPAs [24]. However, further studies on applying stochastic models in energy simulations are required to understand their effect on a building’s energy performance and improve the energy models’ reliability. In this work, the use of the terms *rule-based*, *stochastic*, and *data-driven* models is in agreement with Ref. [15].

The evaluation of the impact of inputs on the BPS results is also becoming a widely studied aspect. In this regard, sensitivity analysis (SA) is a statistical technique that assesses the effect that changes in input or design variables have on the model output variables [25,26]. A better knowledge of the input-output interaction and uncertainty propagation allows estimating reliability of BPS results. Wang *et al.* [27] discussed variants of occupancy models with respect to various outcomes of interest such as HVAC energy consumption and peak demand behavior via a SA. Zhao *et al.* [28] developed a framework to carry out uncertainty analysis (UA) and SA using a Markov model for occupancy in real-time residential building energy demand models. In particular, UA and SA are exploited during the modeling phase to improve simulation outputs. Blight and Coley [29] focused their attention on a SA of the effect of using realistic, quasi-empirical profiles for modeling occupancy, lighting operation, and appliances use on the energy consumption of passive house dwellings. Gaetani *et al.* [30] performed a SA on a medium-size office reference building model [31], introducing variations to building operations (such as HVAC, light, and equipment operation schedules, setpoints, occupancy schedules). Harputlugil and Bedir [32] studied through a SA the impact of presence, space heating, and ventilation controls on the resulting indoor temperature and space heating energy use in Dutch dwellings. Gaetani *et al.* [33], in 2017, carried out a SA varying sixteen occupants-related input variants in an individual office model aiming to assess the influence of different levels of OPAs modeling complexity. Yousefi *et al.* [34] investigated the impact of different OPAs patterns on the energy performance of a multi-family residential building in Iran. Gaetani *et al.* [4] proposed a SA as an intermediate step in a novel methodology to decrease the computational effort to have the first estimate of OPA-related uncertainties in an actual office building in Delft, The Netherlands. Although the literature offers many examples of implementing stochastic models and assessments of the influence of single OPAs models on different performance indicators, the quantifications of interaction effects between models are rarely observed [33]. We believe that this information is essential when setting a building energy model that includes advanced occupant behavior modeling. Thus, starting from the studies and the results reported in previous literature, the present work analyzes the impact of different existing OPAs stochastic models on the energy use of an office building for a more realistic and accurate building energy analysis, and, for the first time, evaluates the interactions between different occupant behavioral models thoroughly, with the purpose of studying uncertainty propagation and estimating confidence intervals of building energy performance, understanding how the impact of a variable depends on the value of the other variables. Moreover, compared to the above-mentioned study of Ref.[33], which considers a single zone, the present research is performed on an entire building made of five thermal zones.

Well-established stochastic models for occupancy, lighting switch-on and switch-off, window and blind operation in office buildings, and clothing insulation levels are selected from the literature. In the present study, a global sensitivity analysis (GSA) is performed by studying 7200 simulations of the ASHRAE 90.1 Small Office model. The model is described in Section 2.2. Since the purpose of this study is to assess the propagation of uncertainty due to stochastic occupant behavior modeling, the small-size office building is used as a test bench, because (1) the large majority of stochastic OPA models were developed from data collected and for use in offices and office-like buildings, and (2) it offers all the types of zones required to model a typical office building and test the different OPA aspects, whereas the medium-size office building does not add any additional parameters to test, but has many more zones, which increase the computational time required for running the simulations. The results are first analyzed in terms of OPAs model performance. Subsequently, the impact of each input variable is highlighted. Finally, the interaction effects between them are presented.

2 Methodology

The objective of this study is the assessment of the impact of different and already available OPAs stochastic models on building energy use. For this reason, an already well-studied building typology was adopted. As emerged from the study conducted by Carlucci *et al.* [15], the vast majority of the OPAs models present in the literature describe occupants' behavior in office buildings (i.e. 45% of the total analyzed models). Hence, the Small Office model from the ANSI/ASHRAE/IES Standard 90.1 Prototype Building Model Package [35–37] is chosen as a virtual test bench for the analysis. This is a conceptual building model whose direct simulation provides the reference performance value, and no actual observations are available to execute either validation or calibration. Widely used stochastic models for modeling occupancy, light/blind adjustments, windows opening/closing, and clothing insulation levels (Table 1) are selected based on the study by Gunay *et al.* [24]. Moreover, since some aspects of the behavior of occupants in a building are triggered by typical weather conditions, we identified the most representative climate zone where occupant data have been so far collected and used to develop stochastic models for OPAs, which is the temperate oceanic climate (Cfb in Köppen-Gieger classification [38]) according to Ref. [15]. The temperate oceanic climate is characterized by moderate temperature year-round and the absence of a dry season. In particular, in the hottest month, the average temperature is below 22 °C, while in the coldest month, it goes from -3 °C to 0 °C. Hence, the Copenhagen IWEC (International Weather for Energy Calculations) climate file is used in this study. Assuming a setpoint temperature of 20 °C for space heating and 26 °C for space cooling, the yearly Heating Degree Days (HDD) for Copenhagen are 4289 HDD_{20} while the Cooling Degree Days is 1 CDD_{26}.

Table 1. Selected OPA stochastic models.

Model code	**Developers**	**OPA**	**Climate zone (Köppen classification)**
C1	Schiavon and Lee, 2013 [39]	Clothing insulation adjustment	-
O1	Reinhart, 2004 [40]	Presence	Cfb
O2	Wang, 2005 [41]	Presence	Csb
O3	Page *et al.*, 2008 [42]	Presence	Cfb
Lon1	Reinhart, 2004 [40]	Light switch-on	Cfb
Lon2	Hunt, 1979 [43]	Light switch-on	Cfb
Loff1	Reinhart, 2004 [40]	Light switch-off	Cfb
Loff2	Boyce, 2006 [44]	Light switch-off	Dfb
B1	Newsham, 1994 [45]	Blinds fully closed or opened	Dfb
B2	Reinhart, 2004 [40]	Blinds fully closed or opened	Cfb
B3	Haldi and Robinson, 2010 [46]	Percentage of closed blinds	Cfb
W1	Yun and Steemers, 2008 [47]	Window positioning	Cfb
W2	Rijal *et al.*, 2008 [48]	Window positioning	Cfa
W3	Haldi and Robinson, 2009 [49]	Window positioning	Cfb
W4	Haldi and Robinson, 2008 [50]	Window positioning	Cfb

The ASHRAE 90.1 Small Office is modeled in EnergyPlus, and the selected OPA stochastic models are implemented in the EnergyPlus Runtime Language. To exploit a GSA, energy simulations are run varying the OPAs input variables through the JEPlus software. Afterward, post-processing of the GSA results is implemented in three steps. Firstly, a simple stochastic projection of the impact of OPAs models on electric energy use is performed. Secondly, statistical analysis is carried out on all the probability distributions of energy use outcomes from all OPAs models using the software package IBM® SPSS® Statistics, version 24. Finally, the Generalized Estimating Equations (GEE) is used to study the main and interaction effects of input variables and their permutations.
For the first step of the analysis, all the distributions are tested for normality using the Kolmogorov-Smirnov statistic given the sample size. Since the test result of the test for all the parameters shows a non-normal distribution for $p \leq 0.05$, non-parametric statistic methods are adopted to explore the differences among different sets of data. The Mann-Whitney U test is utilized to understand the influence of the single variables (occupancy, window, and blind operations, lights switch on and lights switch off models).

2.1 Description of the selected OPAs stochastic models

Table 1 reports all the selected OPAs models, specifying the model's code, developers, and the type of occupant behavior. As highlighted by Lindner *et al.* [51], one of the reasons why OB stochastic models are still rarely used is because existing BPS tools do not provide enough functionality to implement them, and models have to be altered or need assumptions to be implemented. In the present work, the simulation framework developed by Gunay *et al.* [24] with a timestep of 5 minutes has been adopted to implement the stochastic models in EnergyPlus 8.0 through the EnergyPlus Runtime Language.
C1 model estimates the clothing insulation level in clo during the workdays according to the outdoor temperature in the morning and the internal operative temperature at each timestep. The clothing level model's output works just as input in the calculation of predicted mean vote (PMV), which is an input parameter in the W2 window use model. Hence, C1 indirectly affects the building energy use only when the W2 window use model is employed. The occupancy models estimate the probability of occupant presence according to the time of the day. In particular, five different events at the beginning of each workday are initialized: time of arrival, morning coffee break, lunch break, afternoon coffee break, and departure. The duration period for each break is defined as a priori and, in both O1 and O2 models, these events are described by a normal distribution. Moreover, in the O2 model, the break durations are sampled from an exponential probability distribution. O3 model employs two input parameters to forecast the probability of the arrival or departure events: (a) the daily profile of probability of presence and (b) the parameter of mobility that is the ratio of timesteps characterized by a change in the occupancy state considering the probability of arrivals, departures, and breaks. Lon2 is one of the first and most used OPA models available in the literature. It predicts the probability of switch-on the light according to the work plane illuminance[1], as well as the more recent Lon1 model. The main difference

[1] The work plane illuminance has been estimated through the object "Daylighting:Controls" calculated by EnergyPlus in each "Daylighting Reference Points", which are placed at 80 cm above the floor in each thermal zone barycenter.

among them is that the Lon2 model estimates the probability of switch-on light just at arrivals (both morning arrival and arrival after lunch break). At the same time, the Lon1 model allows the action also during intermediate occupancy. Loff1 light switch-off model estimates that occupants undertake an action at departures only (both lunch break departure and departure at the end of the day), not considering intermediate actions or daylight levels. On the contrary, in the Loff2 model, occupants are responsive to daylight. It computes the probability to undertake action during intermediate occupancy according to the duration of absence and the work plane illuminance. Conversely to the lighting models, the implemented blinds and windows operation stochastic models do not diversify the action of opening or closing. The models' developers make use of specific variables (e.g., transmitted direct solar irradiance, direct solar irradiance at the work plane, arrival time, indoor or outdoor temperatures, etc.) to model the probability of state change of the blinds and windows operation. In particular, in the B1 blinds operation model, the blinds are opened at each arrival, and the probability for occupants to close their blinds is calculated according to the transmitted direct solar irradiance value. In the B2 model, closing probability depends on the direct solar irradiance at the work plane (0.8 m above the floor level). B3 blinds operation model uses two different multivariate models, one for arrival period and one for intermediate occupancy period. Unlike the previous ones, the B3 model allows closing action at any occupied period, considering a higher probability to open blinds at arrival. Moreover, B3 permits the blinds' partial closure, while in the B1 and B2 models, the blinds are considered either fully opened or fully closed. In B3, action on blinds is predicted according to the blind unshaded fraction, the outdoor illuminance, and the work plane illuminance. In the W1, W2, W3, and W4 models, windows are fully closed or fully opened, without an intermediate position. All the models consider indoor and outdoor temperatures as primary predictors. Moreover, W3 uses rain as a binary predictor, estimating a lower probability of opening the windows if it is raining.

2.2 The case study

The case study of the present research is the Small Office prototype (Figure 1) from the ANSI/ASHRAE/IES Standard 90.1 Prototype Building Model Package [31].

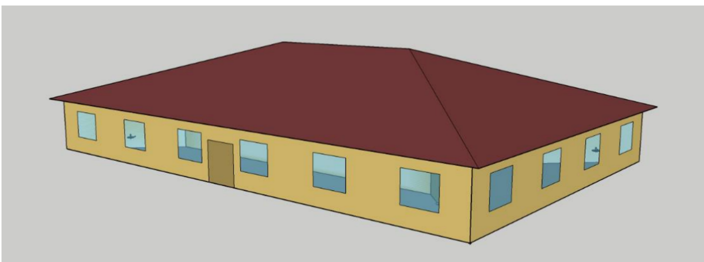

Figure 1. 3D rendering of the ANSI/ASHRAE/IES Standard 90.1 Small Office Prototype.

The Small Office [35–37] is a 511 m^2 single floor building composed of 5 thermal zones. Among the different versions available for the different climate zones and building ages, and in agreement with the Cfb climate zone, the model selected is characterized by the technical features reported in Table 2. Space heating and cooling are provided by an air-source heat pump and the main energy carrier is electricity. In the ASHRAE original model, windows are considered inoperable, and blinds are not available, representing a traditional office building. To have a second term of comparison, these two OPAs have been implemented in the ASHRAE original model through two rule-based models in which blinds close when the internal temperature is higher than 25 °C (i.e., 1 °C less than the setpoint) [52] and windows open during the night (from 9 p.m. to 7 a.m.) if the outdoor temperature is greater than 15 °C exploiting night cooling [53] [54]. These two rule-based models, used in the Copenhagen climate, lead to the functioning of windows and blinds only during the period that goes from April to September. The modified version of the ASHRAE model aims to implement new typical strategies used in office buildings to minimize the cooling load increasing the wellbeing of occupants. In the text, this new model is referred to as "ASHRAE modified".

Table 2. Summary of the ASHRAE 90.1 Small Office model's main features.

Feature	Value or description
Total floor area	511 m^2
Aspect ratio	1.5
Number of floors	1
Window-to-wall ratio	24.4% for south façade 19.8% for the North, East and West façades
Thermal zoning	4 perimeter zones, 1 core zone, 1 attic zone
Floor to floor height	3 m
Floor to ceiling height	3 m
Max number of occupants	31
Available fuel types	Electricity for heating, cooling and SWH (Service Water Heating) plus gas for backup heating
Heating type	Air-source heat pump with gas furnace as backup
Cooling type	Air-source heat pump
Average lighting power density	10.8 W/m^2
Average appliances power density	6.8 W/m^2
Service water heating type	Storage tank
Construction	Wood-frame walls
Structural type	Lightweight
Foundation	20 cm concrete slab poured directly on to the earth
Wall U-value	0.363 $W/(m^2 K)$
Roof U-value	2.858 $W/(m^2 K)$
Floor U-value	2.144 $W/(m^2 K)$
Window U-value	2.371 $W/(m^2 K)$
Window Solar Heat Gain Coefficient	0.397
Window visible transmittance	0.444
Blinds	Inoperable in the original ASHRAE model and close when the internal temperature is higher than 25 °C for the ASHRAE modified

Windows opening	Inoperable in the original ASHRAE model and open during the night (from 9 p.m. to 7 a.m.) if the outdoor temperature is greater than 15 °C for the ASHRAE modified
Other OPAs deterministic schedules	Refer to Score Card available on the ASHRAE website [31]

The ASHRAE Small Office uses electricity for around 99% of its energy consumption, while the remaining 1% is covered by natural gas. Since gas is used only by the backup furnace of the heating system, which relies on electricity as a primary energy source, not considering natural gas energy use does not affect the reliability of the study. If the implementation of stochastic OPAs models influences space heating production, this will be quantified in the electrical energy use for space heating.

2.3 Global Sensitivity Analysis

SA is defined by Saltelli *et al.* as "the study of how uncertainty in the output of a model (numerical or otherwise) can be apportioned to different sources of uncertainty in the model input" [55]. There are two approaches to SA: the local sensitivity analysis (LSA), where the impact of an input variable' variation on a model response is estimated keeping the values of the other input factors constant; and the global sensitivity analysis (GSA), where all the input variables are tested simultaneously. The latter enables assessing the impact on the model output of both individual parameters and interactions between parameters. GSA is performed through a matrix of inputs that sorts all the parameter values.

In this work, GSA is performed to inspect the impact of stochastically modeling the OPAs on the building energy uses. The aim is to identify which of the analyzed behavioral models has the strongest influence in terms of variation of the output energy use. The input variables are the considered occupant behavioral models for each of the six categories: occupant presence, light switch-on, light switch-off, blinds use, windows opening/closing, and clothing insulation level (Table 1). Hence, the variability of the input variables is given by the different stochastic models used for each behavior. The variability in the output variable is due to the stochasticity of implemented OPAs models and the change of the OPAs models. We refer hereby to *stochastic variability* to refer to the former variability source and to *model variability* to refer to the latter source of variability. The scope of this work is to analyze *model variability*; in other words, how the selection of available stochastic OPA models affects the energy performance of the building. Combining all the models in Table 1, the possible permutations are 144. Figure 2 schematizes the permutation paths used in the simulations. The main effect and interaction effect analyses are two useful studies that can be performed on GSA results to assess, in our case, the model variability. The former allows evaluating the impact of single parameter variability on the output while the latter enables evaluating the variability of a couple (or more) of parameters. While the main effect analysis shows the first-order effects, the interaction effect analysis deals with the second-order effects and allows assessing the mutual influence of parameters.

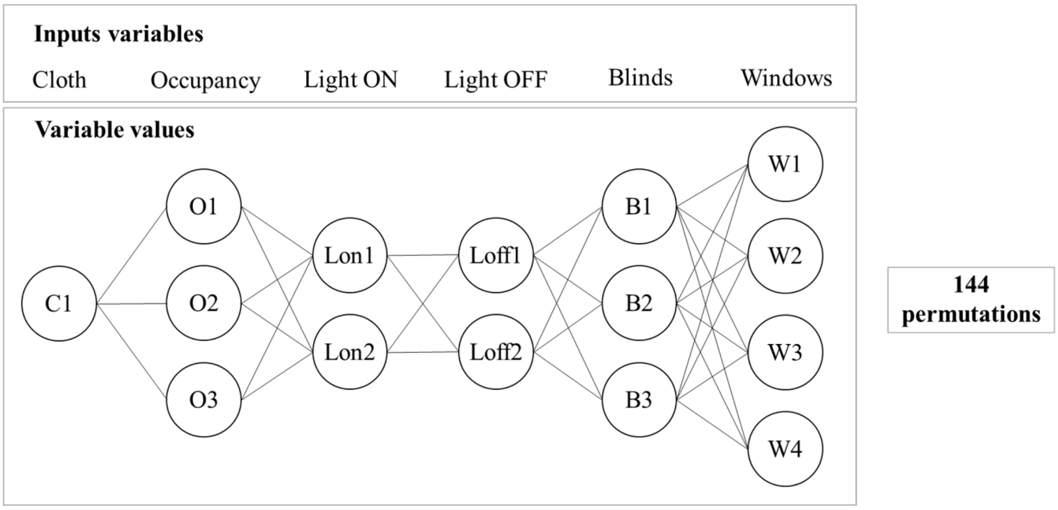

Figure 2. Representation of the GSA's permutations.

2.3.1 Stochastic variability and the number of simulations

Stochastic models have a random variable. A stochastic model is a tool for estimating probability distributions of potential outcomes by allowing for random variation in one or more inputs over time. Distributions of possible outcomes are derived from numerous simulations (stochastic projections), reflecting the random variation in the input(s).

The use of stochastic models for modeling OPA implies that a building's performance is estimated through a probability distribution of the potential outcomes generated by allowing for random variation in the input variables (i.e., the OPA models implemented). The probability distribution of the building's energy use is derived from running several times the same simulation to let the random variation in the input variable propagate. However, the identification of a suitable number of simulations has to consider the trade-off between a proper stochastic propagation and a doable computational time. Feng *et al.* [56] developed an air-conditioning usage probability model based on surveys and measurements and discussed the issues of multiple runs and proper time-step to adopt when simulating stochastic models. Also, this study provided a methodological framework to evaluate the accuracy of the stochastic models' simulation results. They highlighted the importance of mean and standard deviation in assessing the most reliable number of simulations and concluded that 10 simulations were adequate to evaluate mean space cooling energy consumption with a high confidence level. Following a similar approach, in this paper, mean and standard deviation are used to identify the suitable number of simulations for each permutation of the input OPA variables. The principle is to identify the minimum number of simulations at which the mean and standard deviations of the output variable reduce variability and converge to stability. In this regard, five repetitions of 200 simulations are run. An ideal convergence is not achieved in 200 simulations, but stabilization of the mean and standard deviation is reached for more than 50 simulations. This behavior can be explained by the large randomness of the analyzed problem, where six stochastic models are used as input variables for the simulation. This, as expected, shows a high output variability. The standard deviation here presents an average value between 17% and 20%

with respect to the mean, which can be considered an acceptable value for the accuracy required by the study. Based on the results reported by the study of Feng *et al.* [56], research conducted by Gaetani *et al.* [30], and the convergence analysis in Figure 2, 50 simulations per each of the 144 permutations have been chosen for a total of 7200 simulation tasks. This number is considered a reasonable trade-off for allowing stochastic propagation of randomness of input variables in a doable simulation time. The parametrical tool for energy simulations JEPlus has been used to drive the dynamic energy simulation engine EnergyPlus in the simulation tasks. The simulations have been carried out on a remote server equipped with 8 cores (16 threads) Intel® Xenon® E5-1660 v3 with a clock frequency of 3.000 GHz and 16 GB random access memory. Considering an average run-time of 12 minutes for each simulation, approximately 1440 hours were used to run the entire simulation set.

2.3.2 Post-process of GSA results with Mann-Whitney U test and GEE

Mann-Whitney U test is the non-parametric test equivalence of the t-test for independent samples. Rather than comparing the means of the two groups, as in the t-test, the Mann-Whitney U test compares medians. If the significance level (p) provided by the Mann-Whitney U test is lower than 0.05, there is a statistically significant difference between the two tested samples. Gaetani *et al.* [33] performed a sensitivity analysis by means of the Mann-Whitney U test and concluded that the test is a suitable statistical method to determine the aspects of Occupant Behavior (OB) that are influential for the results. For the purpose of this study, the same analysis was used to identify the most important input variables (in our case the OPA categories) in explaining the variability of the response (in our case the building electric energy use).

To account for the dependency between the repeated measures, that is 50 simulations for each of 144 permutations, several methods for repeated methods design can be used [57]. As described in Section 2, probability distributions of responses do not follow a normal distribution. Therefore, the Generalized Estimating Equations (GEE) method was used in this study to account for the potential dependency between the simulations runs of each permutation. The method is developed by Liang and Zeger [58] to produce regression estimates when analyzing repeated measures with non-normal response variables. This allows interpreting the effect of each parameter while accounting for the influence between them. The GEE method has been used in previous OPA studies. Mayer *et al.* [59] applied the method for analysis of user behavior regarding opening windows. The study concluded that window states during a day are correlated, i.e. time-dependent autocorrelation between single window openings. They recommended that for proper modeling, this dependency has to be taken into account and found GEE to be an appropriate method respecting the autocorrelation of the data. Inkarojrit *et al.* [60] conducted a window blind usage field study, where each participant was surveyed 1 to 4 times at approximately every two hours. The GEE method was used to take into account within-subject covariates for their repeated measurements on window blind control behavior. In this study, the GEE analysis was set up in the software package IBM® SPSS® Statistics version 26. The model permutations were treated as subject variables, and the number of runs was considered as within-subject variables. [61].

3 Results and discussion

In this section, the results obtained from the GSA are presented and discussed. The results are reported in terms of total electric energy use that includes electric energy need for heating, cooling, interior and exterior lighting, interior equipment, fans, and water system. Moreover, the heating and cooling electric energy use are analyzed as results. The base case building's total electric energy use considering the Copenhagen climate is 77.3 kWh/(m^2 y), while the electric use for heating and cooling are respectively 5.7 kWh/(m^2 y) and 3.2 kWh/(m^2 y). These represent the reference values of the following analysis, and hereby they will be indicated as the "baseline". At the same time, the ASHRAE modified model shows a total electric energy use of 83.2 kWh/(m^2 y) and an electric use for heating and cooling respectively of 6.8 kWh/(m^2 y) and 2.8 kWh/(m^2 y). Clothing insulation level does not directly impact the electric energy use of the building and it is not considered in the base case scenario. However, in the scenarios where stochastic models are implemented, it works as an input for the PMV calculation that influences the window operation model W2 as described in Section 2.1.

3.1 Stochastic projection of OPA models on the building's energy use

To let the propagation of random input variables of the OPA models, each permutation is run 50 times. Next, all the 144 permutations of Figure 1 are simulated. In Figure 3, the impact of each stochastic OPA model on the building's total electric energy use, electric use for space heating and cooling are presented and compared with the reference performance of the baseline and the ASHRAE modified model. Each boxplot represents the distribution of the values of the building's energy use calculated by choosing one given stochastic OPA model and testing all available stochastic models for the other different aspects of occupant behavior simultaneously.

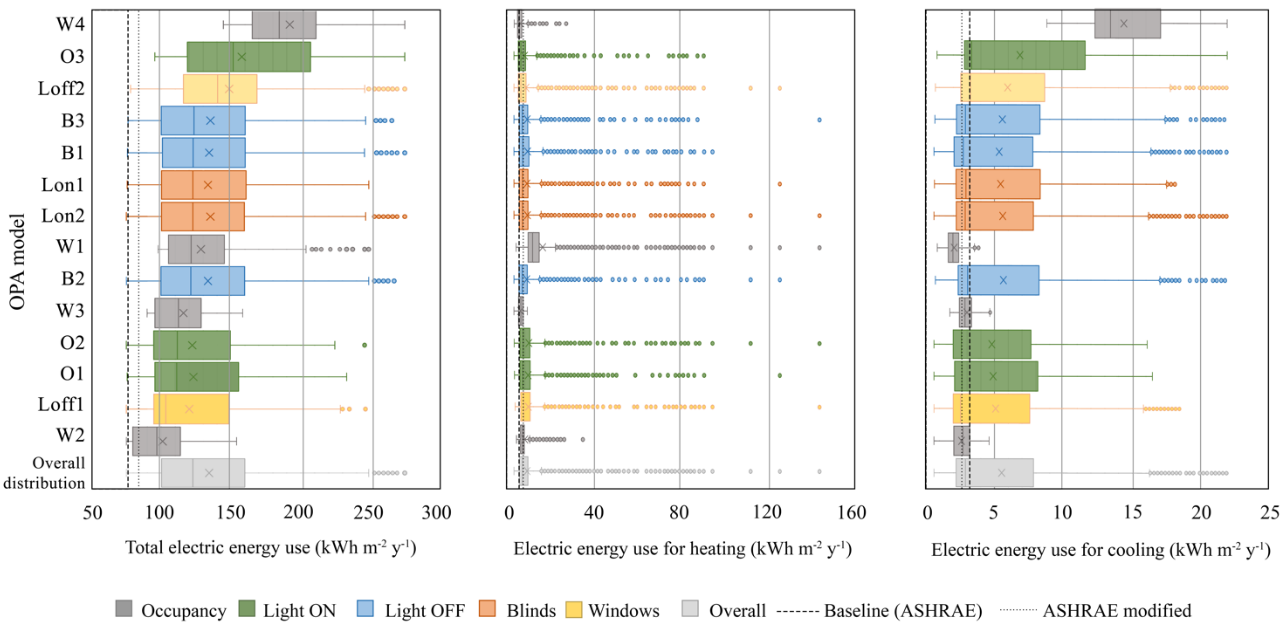

Figure 3. Distribution of the values of building's energy use calculated for each stochastic OPA model when testing simultaneously all available stochastic models for the other different aspects of occupant behavior highlighting the total electric energy use, the

electric use for space heating and cooling.

Analyzing Figure 3, for the total electric energy use, among occupancy models, the O1 and O2 models perform quite similarly. In contrast, the O3 model, which generally estimates higher numbers of occupied hours, causes a larger electric energy use. The median of electric energy use is around 44% higher than the deterministic value for both O1 and O2 models, whereas the median value of the O3 model is 96.1% higher than the reference one. Lon1 and Lon2 are two switch-on models and behave very similarly: they respectively predict an annual electric use with a median that is 58.7% and 58.6% greater than the baseline. On the contrary, the Loff1 and Loff2 switch-off models show different results. Loff1 has a median value of the energy use of 103.31 kWh/(m^2 y), which is 33.6% higher than the base case electric energy use. Loff2 has a median value of the energy use of 140.4 kWh/(m^2 y) which is 81.6% higher than the baseline electric energy use. The three blinds control models perform similarly: the median is 122.8 kWh/(m^2 y) for B1, 121.3 kWh/(m^2 y) for B2, and 123.6 kWh/(m^2 y) for B3. These values are respectively 58.8%, 56.9%, and 59.9% higher than the baseline annual electric energy use. Windows operation models generate more variability in the results compared to other occupants' actions. W1 produces a median that is 57.1% higher than the reference one. W2 and W3 present a median respectively 25.4% and 45.5% higher than the base case value. W4 presents a median value that is 138.7% higher than the reference one, which is the highest median value of annual electric energy use among all the analyzed models. W1, W2, and W3 present narrow and asymmetrical distribution toward lower values. W4 presents the most spread and high distribution of energy use among the windows models. Comparing the distribution of the results of each OPAs model, windows operation models show the narrowest box plots. On the contrary, O3 has the most spread output distribution and a relatively high median value. Finally, the median of the entire distribution of all the results was calculated to be 58.6% higher than the base case energy use.

The electric use for space heating is very similar to the base case except for the W1 model, with the range of the median values between -4% and 27%. Whilst W1's median value is 105% higher than the baseline. A larger difference, in terms of percentages, is registered in the electricity used for cooling. Model W4, O3, and Loff2 bring to a higher electric consumption for cooling, while all the other models have a decreasing effect. Especially W1 and Loff1 change the median electric use for cooling of -38% and -21% respectively. This is since the W1 model allows windows to open more often, and Loff1 triggers a mechanism that drastically decreases the solar gains during the summer period. The largest difference is registered in the electric use for lighting, as a matter of fact, different the OPAs, except the clothing model and the windows opening models, are directly affecting the use of electric lighting (i.e., occupancy is changing the probability of turning on and off the lights, the blinds are changing the radiation impinging on the work plane).

Overall, all the implemented stochastic models always generate a higher total electric energy use than the reference ASHRAE base case. Although the theoretical nature of the case under study did not permit to gather infield data on electric energy use, it is possible to consider that the stochastic modeling of OPAs is more realistic if compared to the deterministic profiles when the modeled actions are effectively possible in a real building. Stochastic simulation allows considering the randomness and the variability of the interaction between people and buildings by estimating the probability to undertake action as a response to one or more input variables. Hence, considering the results of implemented models, it is very likely that the deterministic OPAs simulation underestimates the building energy uses, leading to, eventually, unreliable and overoptimistic building design performance. The underestimation of building energy uses could cause different issues such as wrong-sized systems, incorrect estimation of meeting energy-efficiency targets. Another consideration that can be made is that the selected models were developed from data collected in buildings that are far from the nearly zero-energy target set by EPBD and are located in a climate zone (Cfb) where the summer period is not severe and quite limited. Therefore, if these models are applied in high-performance buildings–like the analyzed case study–, the impact on the energy uses for space heating and cooling is strongly dependent on some decisions imposed by the energy analyst, for example, the duration of the conditioned period or the set-point temperatures, rather than representing the thermal and energy response of the building. The use of these models outside the original climate zone may have a critical impact on the results, but, until now, no systematic work has been developed to study the transferability of these stochastic models to summer-dominated climates. Thus, we recommend careful use of these models in conditions different from those of the original data sources (e.g., climate zone, building use, room type, number of users per thermal zone) because they may completely shift the thermal and energy response of a building.

3.2 Single parameter impact on the variation in overall distribution

The probability distribution calculated for each OPA model is compared to the overall distribution using the Mann-Whitney U test and presented in Figure 4 and Table 3. The test allows assessing the overall most important OPA models by evaluating their effect on the overall distribution variation. We remind that the difference between the medians is considered in this study statistically significant if the *p*-value is not higher than 0.05.

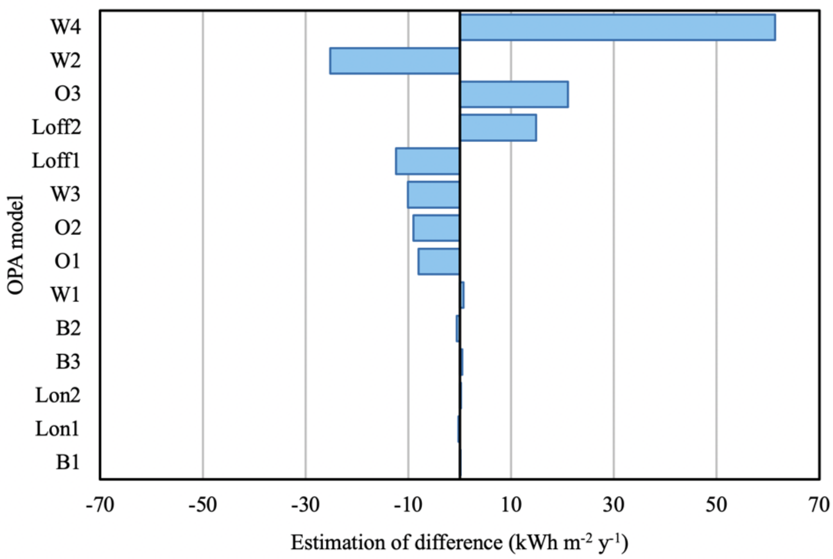

Figure 4. Comparison of probability distribution calculated for each OPA model to the overall distribution using Mann-Whitney U test.

Table 3. Descriptive statistics and estimation for differences between probability distribution calculated for each OPA model to the

overall distribution using the Mann-Whitney U test.

Descriptive Statistics			Estimation for difference		Test
Sample	**N**	**Median**	**Difference**	**95% CI for difference**	***p*-value**
Overall	7200	122.63	-	-	-
W1	1800	121.42	0.72	(-0.70; 2.16)	0.31
W2	1800	96.92	-25.19	(-26.89; -23.75)	0.00
W3	1800	112.45	-10.07	(-11.94; -8.49)	0.00
W4	1800	184.49	61.40	(59.47; 63.25)	0.00
O1	2400	111.14	-8.06	(-9.80; -6.38)	0.00
O2	2400	111.56	-9.03	(-10.76; -7.34)	0.00
O3	2400	151.62	21.07	(19.43; 22.89)	0.00
Lon1	3600	122.68	-0.24	(-1.38; 0.84)	0.65
Lon2	3600	122.60	0.24	(-0.84; 1.39)	0.65
Loff1	3600	103.31	-12.38	(-14.02; -10.71)	0.00
Loff2	3600	140.40	14.84	(13.29; 16.40)	0.00
B1	2400	122.78	0.13	(-1.16; 1.45)	0.82
B2	2400	121.29	-0.63	(-1.98; 0.58)	0.31
B3	2400	123.60	0.51	(-0.72; 1.81)	0.43

As expected, the windows parameter mostly influences the building energy response, followed by occupancy and light switch-off models. Light switch-on and blinds models show an almost negligible effect. This is because, as shown in Section 3.1, the light switch-on models [40,43] and the blinds control models [40,45,46] perform very similar among each other, with a small difference in terms of output distributions. It means that, according to the models selected and the performed analysis, the change in light switch-on and blind models (i.e., changing the stochastic predictive model) does not lead to significant variation in output.

3.3 Parameters' main and interaction effects analyses

The interaction effects analysis allows understanding how the impact of a variable depends on the value of the other variables. To analyze the results from the 7200 simulations, the method of Generalized Estimating Equations (GEE) was exploited. This method allows identifying OPAs models that significantly contributed to the estimated energy use while considering the dependency between the 50 repeated runs of each 144 model permutations. To find the optimal variable combination, a stepwise approach was used in which one variable was added to the model at the time. The contribution of each variable was judged by the goodness-of-fit score Quasi-likelihood under Independence Model Criterion (QIC). According to this criterion, the variable combination giving the lowest QIC value is considered the best [62]. The results of the stepwise approach to finding the best model, including main and interaction effects based on the lowest QIC, are presented in Table 4.

Table 4. Stepwise approach of finding best model judged by the goodness-of-fit score Quasi-likelihood under Independence Model

Criterion (QIC)

	Model combination	QIC
Main Effects	W	592.09
	W, O	543.04
	W, O, Loff	187.32
	W, O, Loff, Lon	203.24
	W, O, Loff, Lon, B	234.95
Main and interaction effects excluding Lon and B models	W, O, Loff, W*Loff	179.46
	W, O, Loff, W*Loff, O*Loff	180.60
	W, O, Loff, W*Loff, O*Loff, W*O	170.15

The analysis found the model with main effects *Windows* (W), *Occupancy* (O), and *Light switch-off* (Loff) to be the best-fitted model with the lowest QIC. This means that changing the stochastic model in one of these variables could generate a considerable difference in the output results. Contrariwise, *Light switch-on* and *Blinds* variables had a low impact on output, meaning that the performance of the stochastic models performs quite similar among each other. This result also reflects the nature of the behaviors themselves: windows operation and occupancy are difficult to predict [63,64]. In contrast, blind operation depends on incident solar irradiance that can be estimated from the windows' orientation and the geometrical feature of the solar device. A similar consideration can be made for the mechanism of switching the lighting on when the available illuminance becomes low.

GEE allows inspecting the variability in output further, considering the interaction effects among input parameters. As expected, the model with the lowest QIC is registered for the permutation of Windows, Occupancy, Light switch-off, and all their interaction effects (W, O, Loff, W*Loff, O*Loff, W*O). The results of interaction effects show again that the simultaneous variation of *Light switch-on* or *Blinds* and the other parameters has a low impact on simulation output. In other words, the impact of the *Light switch-on* or *Blinds* variables does not depend on the other parameters' values.

The interaction analysis revealed the parameters' second-order effects and allowed considerations on the influence between parameters in terms of output variation. This analysis could be a valid help in making a conscious building energy design. When implementing OPAs in building energy model, the interaction between different actions in terms of output is useful information in the actions' and models' selection process.

4 Conclusions and future outlooks

The present work aimed to assess the impact of stochastically modeling occupant presence and actions (OPAs) in building energy simulations. A global sensitivity analysis (GSA) was set up by simulating 144 permutations of all the single OPAs models of each input OPAs category and obtaining 7200 simulations performed in JEPlus. GSA helps to study how the uncertainty in the building electricity use can be apportioned to the different OPAs and analyzed in terms of the impact of every single model, main and interaction effects. 15 stochastic OPAs models have been selected based on their wide use in literature. Specifically, three models of occupant presence [40–42], four models for the lighting switch-on [40,43] and switch-off [40,44], one clothing model [39], three models for blinds opening [40,45,46], and four models for window opening [47–50] were used in the analysis. The ASHRAE Small Office prototype [31] and Copenhagen IWEC weather data were identified as the most suitable to perform this comparative test bench. In the original ASHRAE model, the occupants are modeled in a fully-determinist way. Thus, a modified version of the small office ASHRAE model has been added as a reference. In this modified ASHRAE model, blinds close when the internal temperature is higher than 25 °C and windows open during the night (from 9 p.m. to 7 a.m.) if the outdoor temperature is greater than 15 °C exploiting night cooling.

The analyses of results were performed in terms of annual electric energy use per square meter of net floor area. Concerning the performance of the building model that implemented fixed deterministic profiles (e.g., assuming fixed schedules of occupants' presence) and rule-based behavioral models, the implementation of stochastic models for OPAs always increased the building energy use. From the analysis, it emerged that *windows* models create the highest variability in the results, both in terms of variance and median values compared to the other actions. *Light switch-off* and *Occupancy* models generate notable differences in output results, while regarding *Light switch-on* and the *blinds control* models, only small variations were revealed by implementing the different models.

The dataset from simulations was then analyzed in terms of the variables' main effect and interaction effects through the Generalized Estimating Equations (GEE) approach. In the present GSA, the variables are the implemented behaviors (i.e., *Occupancy*, *Light switch-on*, *Light switch-off*, *Blind control*, and *Window operation*). This analysis confirmed that *Window operation* has the highest effect on output, that is choosing a different stochastic model for windows' operation changes greatly the energy performance of a building, followed by *Occupancy* and *Light switch-off*. *Blind control* and *Light switch-on* variables resulted as the least influential parameters, meaning that their stochastic models compute similar distributions of total energy use required by the building. Moreover, the interaction effects analysis showed that the interaction between *Occupancy* and *Window operation* has an important impact on outputs, meaning that the change of occupancy and windows operation models influence reciprocally beyond impacting individually on the electric energy use. On the contrary, the interaction of the light switch-on models and the other variables showed a very low impact on outputs.

The present study is affected by some limitations. First, results apply to the stochastic models implemented into the analysis; with the development of further stochastic models or data-driven models suitable to be used in the same conditions characterizing this case study, broader conclusions might be obtained. Next, one single control variable for all the occupants as well as one controller for all the lights has been implemented in each thermal zone of the building model. By modeling a higher number of occupancy variables and lights' controllers, more realistic conditions might be represented, although longer simulation times would be required. The improvement of the aforementioned aspects might be helpful in future studies to enhance the generalizability of findings. Moreover, the presented methodology could be used in further research regarding different building typologies (e.g., residential, commercial), implementing related OPAs models.

Finally, we would point out the issue of using stochastic models for occupants' presence and actions in conditions outside the development ones. Few models are currently available for other building types or climate zones, and the reliability of transferring the available stochastic models outside their development conditions has not been evaluated yet. Thus, we recommend careful use of these models in conditions different from those of the original data sources (e.g., climate zone, building use, room type, number of users per thermal zone) because their use may completely alter the thermal and energy response of a building.

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7 APPENDIX A – ASHRAE 90.1 Small Office deterministic models for OPAs

The ASHRAE 90.1 Small Office deterministic models for the OPAs considered in this paper are reported in the charts below. It is worth remembering that in the original building model, blinds use, and windows opening are not considered.

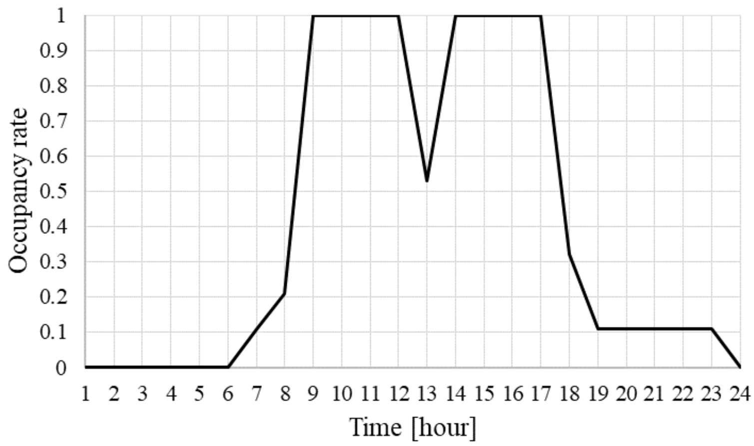

Figure 5. ASHRAE 90.1 Small Office schedule for occupancy rate.

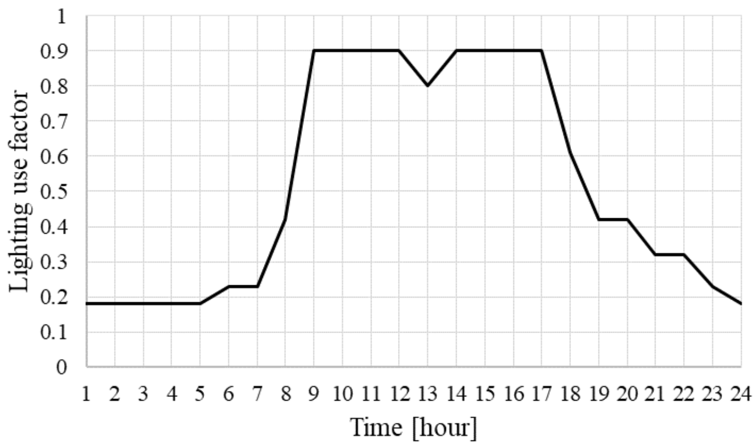

Figure 6. ASHRAE 90.1 Small Office schedule for lighting use factor

For clothing insulation level, ASHRAE 90.1 Small Office considers 1 clo from 30th September to 30th April and 0.5 clo from 1st May to 29th September.

8 APPENDIX B – Stochastic OPAs models results

Figure 7: Timestep values of clothing insulation level, in terms of clo. The daily profile of a random weekday for each month are represented through colored lines.

Results generated by each OPAs model are reported in the charts below. The ASHRAE 90.1 Small Office deterministic profile is reported using a black line.

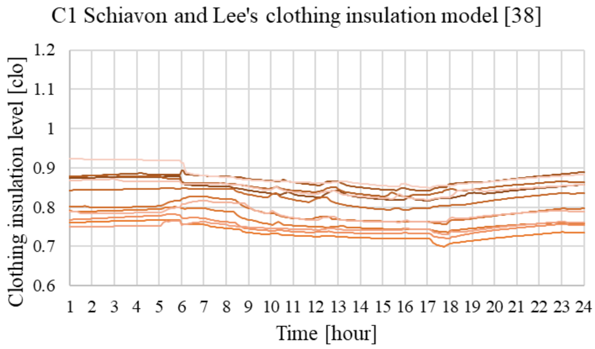

Figure 8. Timestep values of clothing insulation level, in terms of clo. The daily profile of a random weekday for each month are represented through colored lines.

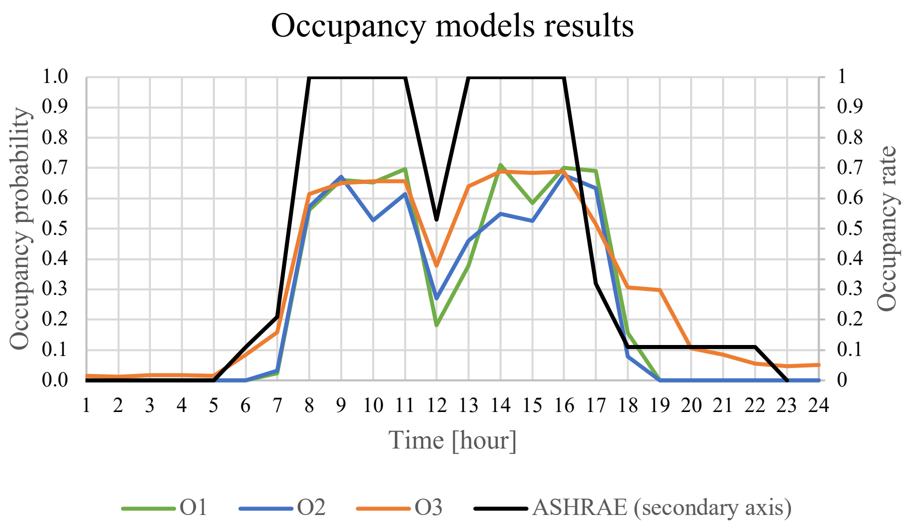

Figure 9. Occupancy profiles obtained from the implementation of O1 model (a), O2 model (b) and O3 model (c). Each colored line represents a daily occupancy profile selected randomly from yearly simulation.

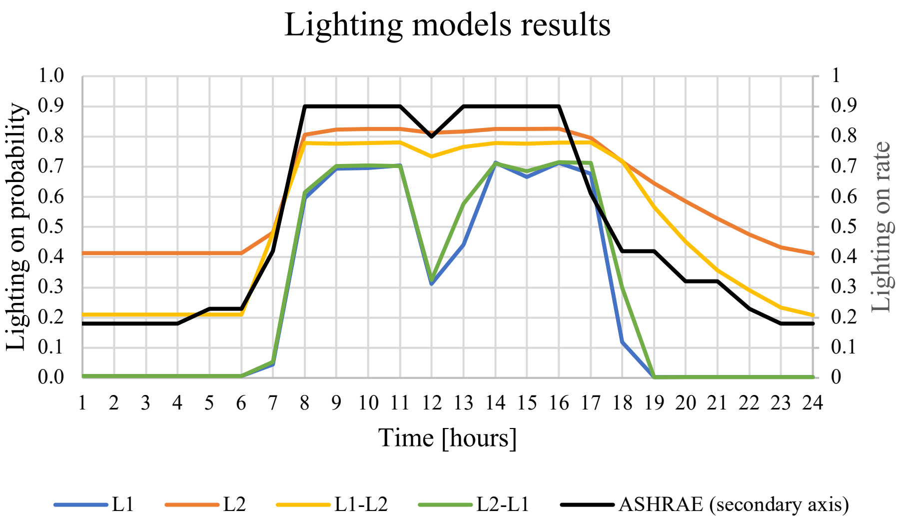

Figure 10. Lighting use profiles obtained from the combination of Lon2+Loff1 (a), Lon1+Loff2 (b), Lon1+Loff1 (c) and Lon2+Loff2 (d). Each colored line represents a daily Lighting use profile selected randomly from yearly simulation.

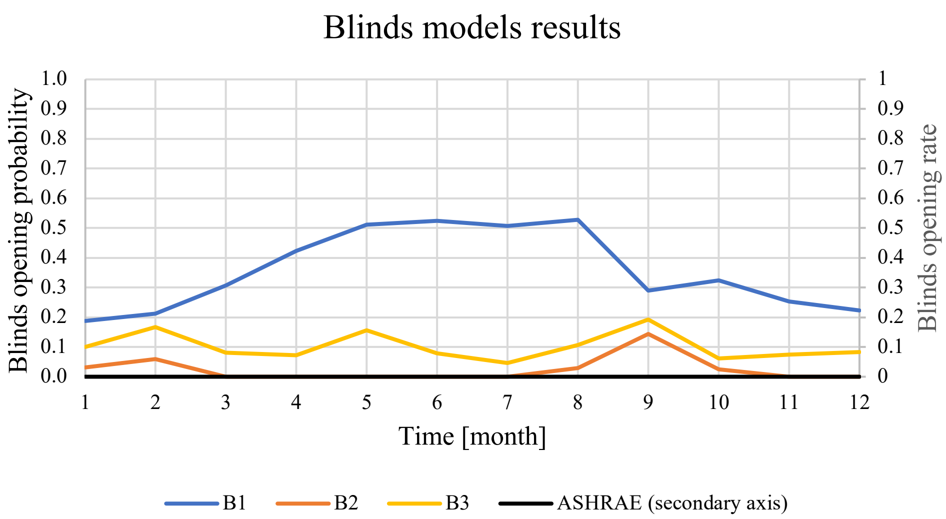

Figure 11. Monthly closed blinds rate obtained implementing B1 model (a), B2 model (b) an B3 model (c). These results represent the monthly rate of hours in which blinds are totally closed. The results are reported for each thermal zone. The values are also reported in tables.

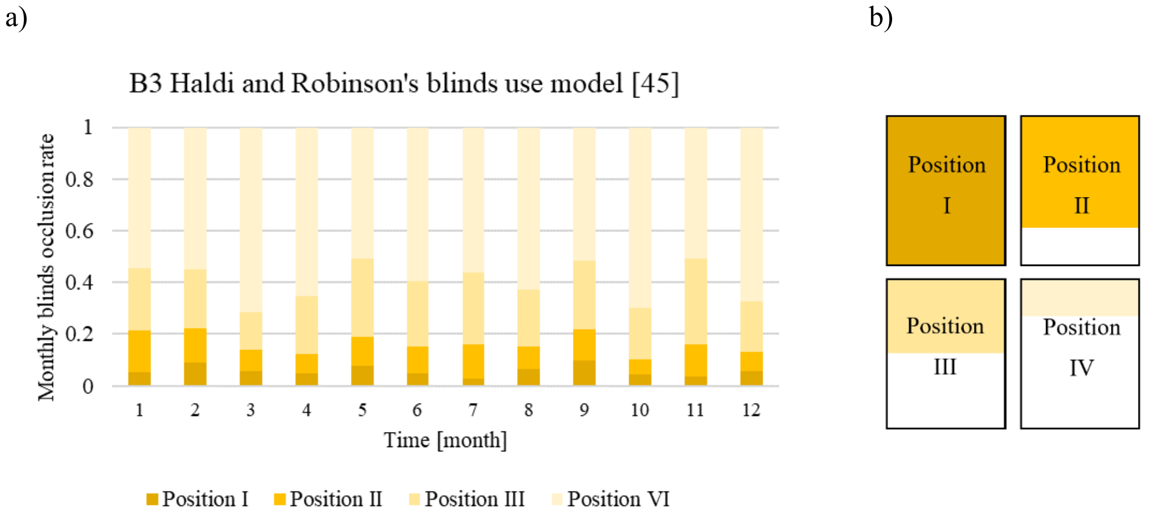

Figure 12. a) Occlusion rate of all the possible blinds position predicted using B3 model. b) representation of all the possible blinds positions colored in accordance with figure a).

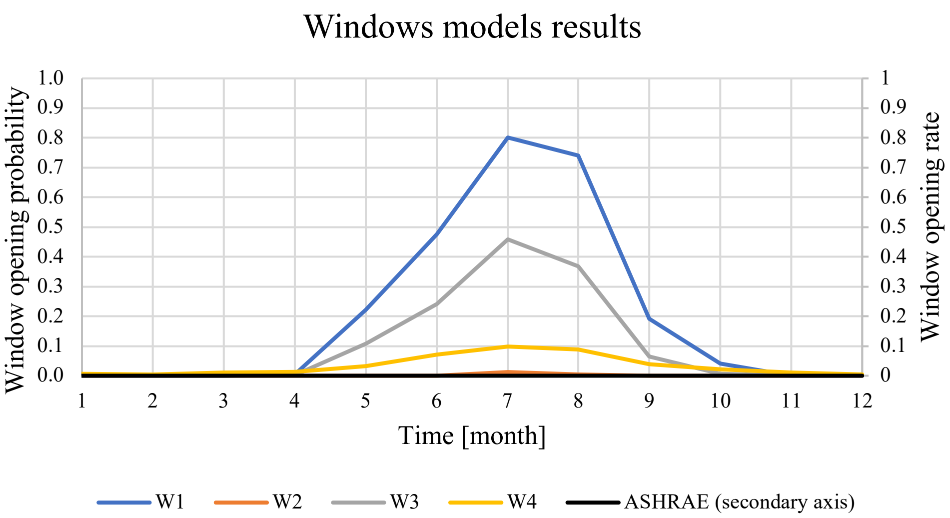

Figure 13. Monthly window opening rate using W1 model (a), W2 model (b), W3 model (c) and W4 model (d). These values represent the monthly rate of hours in which the windows are closed for each thermal zone.