

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

35 1 Introduction

36 Building performance simulation (BPS) is a cost-effective and fast method to better study building variants
37 during the design phase and optimize building renovation concepts according to several and even antagonistic
38 dimensions such as energy, costs, equivalent CO₂ emissions, and occupant comfort [1,2]. Although accurate
39 estimations are an essential requirement for the proper use of BPS, the reliability of its results is hindered by
40 several uncertainties [3–5]. Most of the time, energy modelers solve this issue by simplifying aleatory
41 uncertainties using deterministic variables, a priori schedules, and/or rule-based models [6]. Such
42 simplifications are some of the causes of a disparity between simulated and actual energy use in buildings [7–
43 9]. The phenomenon is called the “performance gap” [1], and its study – started in the mid-90s – is still
44 currently an object of interest for research and software development [10–13]. Carlucci *et al.* [14,15] studied
45 the causes of this disparity, and approximate modeling of Occupant Presence and Actions (OPAs) is accounted
46 as one of its primary causes. People influence building energy use passively through their presence and actively
47 through interactions with the building’s components, such as operable windows, solar shadings, and
48 thermostats, and the use of plug-in appliances and lighting [15]. It is common practice to model occupant
49 presence in BPS via predefined a priori schedules and occupant actions with deterministic rules based on one
50 or more physical variables [6]. However, these simple approaches are not able to account for the diversity
51 between people and conditions and the variability of the interaction between occupants and the building. Thus,
52 several studies have developed more complex models that aim to consider the human-building interaction, as
53 reported in the various reviews conducted in recent years [15–19]. For example, Carlucci *et al.* [15] highlight
54 that, in the last years, data-driven models are attracting increased interest, followed by stochastic OPA
55 modeling techniques and rule-based methods. The growing attention towards data-driven models is related to
56 their capability to deal with large datasets that are becoming more and more available without missing the
57 aleatory nature of OPA in buildings [20–23]. While professionals are reluctant to model occupant-related
58 uncertainty in their simulation [6], the other modeling approach often-adopted in the scientific literature is to
59 represent occupant behavior stochastically, and several probabilistic models are available in the literature to
60 model the different aspects of OPAs [24]. However, further studies on applying stochastic models in energy
61 simulations are required to understand their effect on a building’s energy performance and improve the energy
62 models’ reliability. In this work, the use of the terms *rule-based*, *stochastic*, and *data-driven* models is in
63 agreement with Ref. [15].

64 The evaluation of the impact of inputs on the BPS results is also becoming a widely studied aspect. In this
65 regard, sensitivity analysis (SA) is a statistical technique that assesses the effect that changes in input or design
66 variables have on the model output variables [25,26]. A better knowledge of the input-output interaction and
67 uncertainty propagation allows estimating reliability of BPS results. Wang *et al.* [27] discussed variants of
68 occupancy models with respect to various outcomes of interest such as HVAC energy consumption and peak
69 demand behavior via a SA. Zhao *et al.* [28] developed a framework to carry out uncertainty analysis (UA) and
70 SA using a Markov model for occupancy in real-time residential building energy demand models. In particular,
71 UA and SA are exploited during the modeling phase to improve simulation outputs. Blight and Coley [29]

72 focused their attention on a SA of the effect of using realistic, quasi-empirical profiles for modeling occupancy,
73 lighting operation, and appliances use on the energy consumption of passive house dwellings. Gaetani *et al.*
74 [30] performed a SA on a medium-size office reference building model [31], introducing variations to building
75 operations (such as HVAC, light, and equipment operation schedules, setpoints, occupancy schedules).
76 Harputlugil and Bedir [32] studied through a SA the impact of presence, space heating, and ventilation controls
77 on the resulting indoor temperature and space heating energy use in Dutch dwellings. Gaetani *et al.* [33], in
78 2017, carried out a SA varying sixteen occupants-related input variants in an individual office model aiming
79 to assess the influence of different levels of OPAs modeling complexity. Yousefi *et al.* [34] investigated the
80 impact of different OPAs patterns on the energy performance of a multi-family residential building in Iran.
81 Gaetani *et al.* [4] proposed a SA as an intermediate step in a novel methodology to decrease the computational
82 effort to have the first estimate of OPA-related uncertainties in an actual office building in Delft, The
83 Netherlands. Although the literature offers many examples of implementing stochastic models and assessments
84 of the influence of single OPAs models on different performance indicators, the quantifications of interaction
85 effects between models are rarely observed [33]. We believe that this information is essential when setting a
86 building energy model that includes advanced occupant behavior modeling. Thus, starting from the studies
87 and the results reported in previous literature, the present work analyzes the impact of different existing OPAs
88 stochastic models on the energy use of an office building for a more realistic and accurate building energy
89 analysis, and, for the first time, evaluates the interactions between different occupant behavioral models
90 thoroughly, with the purpose of studying uncertainty propagation and estimating confidence intervals of
91 building energy performance, understanding how the impact of a variable depends on the value of the other
92 variables. Moreover, compared to the above-mentioned study of Ref.[33], which considers a single zone, the
93 present research is performed on an entire building made of five thermal zones.

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

105 2 Methodology

106 The objective of this study is the assessment of the impact of different and already available OPAs stochastic
107 models on building energy use. For this reason, an already well-studied building typology was adopted. As

108 emerged from the study conducted by Carlucci *et al.* [15], the vast majority of the OPAs models present in the
109 literature describe occupants' behavior in office buildings (i.e. 45% of the total analyzed models). Hence, the
110 Small Office model from the ANSI/ASHRAE/IES Standard 90.1 Prototype Building Model Package [35–37]
111 is chosen as a virtual test bench for the analysis. This is a conceptual building model whose direct simulation
112 provides the reference performance value, and no actual observations are available to execute either validation
113 or calibration. Widely used stochastic models for modeling occupancy, light/blind adjustments, windows
114 opening/closing, and clothing insulation levels (Table 1) are selected based on the study by Gunay *et al.* [24].
115 Moreover, since some aspects of the behavior of occupants in a building are triggered by typical weather
116 conditions, we identified the most representative climate zone where occupant data have been so far collected
117 and used to develop stochastic models for OPAs, which is the temperate oceanic climate (Cfb in Köppen-
118 Gieger classification [38]) according to Ref. [15]. The temperate oceanic climate is characterized by moderate
119 temperature year-round and the absence of a dry season. In particular, in the hottest month, the average
120 temperature is below 22 °C, while in the coldest month, it goes from -3 °C to 0 °C. Hence, the Copenhagen
121 IWEC (International Weather for Energy Calculations) climate file is used in this study. Assuming a setpoint
122 temperature of 20 °C for space heating and 26 °C for space cooling, the yearly Heating Degree Days (HDD)
123 for Copenhagen are 4289 HDD₂₀ while the Cooling Degree Days is 1 CDD₂₆.

124

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 <i>et al.</i> , 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 <i>et al.</i> , 2008 [48]	Window positioning	Cfa
W3	Haldi and Robinson, 2009 [49]	Window positioning	Cfb
W4	Haldi and Robinson, 2008 [50]	Window positioning	Cfb

125

126 The ASHRAE 90.1 Small Office is modeled in EnergyPlus, and the selected OPA stochastic models are
127 implemented in the EnergyPlus Runtime Language. To exploit a GSA, energy simulations are run varying the
128 OPAs input variables through the JEPlus software. Afterward, post-processing of the GSA results is
129 implemented in three steps. Firstly, a simple stochastic projection of the impact of OPAs models on electric
130 energy use is performed. Secondly, statistical analysis is carried out on all the probability distributions of
131 energy use outcomes from all OPAs models using the software package IBM® SPSS® Statistics, version 24.
132 Finally, the Generalized Estimating Equations (GEE) is used to study the main and interaction effects of input
133 variables and their permutations.

134 For the first step of the analysis, all the distributions are tested for normality using the Kolmogorov-Smirnov
135 statistic given the sample size. Since the test result of the test for all the parameters shows a non-normal
136 distribution for $p \leq 0.05$, non-parametric statistic methods are adopted to explore the differences among
137 different sets of data. The Mann-Whitney U test is utilized to understand the influence of the single variables
138 (occupancy, window, and blind operations, lights switch on and lights switch off models).

139 2.1 Description of the selected OPAs stochastic models

140 Table 1 reports all the selected OPAs models, specifying the model's code, developers, and the type of
141 occupant behavior. As highlighted by Lindner *et al.* [51], one of the reasons why OB stochastic models are
142 still rarely used is because existing BPS tools do not provide enough functionality to implement them, and
143 models have to be altered or need assumptions to be implemented. In the present work, the simulation
144 framework developed by Gunay *et al.* [24] with a timestep of 5 minutes has been adopted to implement the
145 stochastic models in EnergyPlus 8.0 through the EnergyPlus Runtime Language.

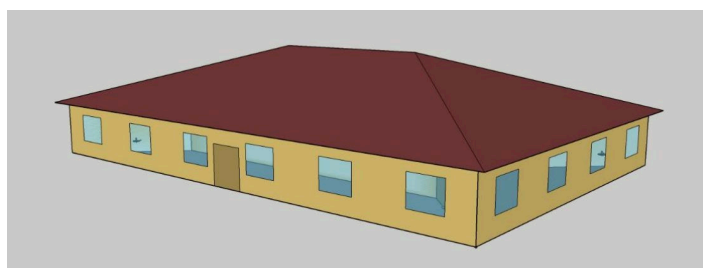
146 C1 model estimates the clothing insulation level in clo during the workdays according to the outdoor
147 temperature in the morning and the internal operative temperature at each timestep. The clothing level model's
148 output works just as input in the calculation of predicted mean vote (PMV), which is an input parameter in the
149 W2 window use model. Hence, C1 indirectly affects the building energy use only when the W2 window use
150 model is employed. The occupancy models estimate the probability of occupant presence according to the time
151 of the day. In particular, five different events at the beginning of each workday are initialized: time of arrival,
152 morning coffee break, lunch break, afternoon coffee break, and departure. The duration period for each break
153 is defined as a priori and, in both O1 and O2 models, these events are described by a normal distribution.
154 Moreover, in the O2 model, the break durations are sampled from an exponential probability distribution. O3
155 model employs two input parameters to forecast the probability of the arrival or departure events: (a) the daily
156 profile of probability of presence and (b) the parameter of mobility that is the ratio of timesteps characterized
157 by a change in the occupancy state considering the probability of arrivals, departures, and breaks. Lon2 is one
158 of the first and most used OPA models available in the literature. It predicts the probability of switch-on the
159 light according to the work plane illuminance¹, 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.

160 among them is that the Lon2 model estimates the probability of switch-on light just at arrivals (both morning
161 arrival and arrival after lunch break). At the same time, the Lon1 model allows the action also during
162 intermediate occupancy. Loff1 light switch-off model estimates that occupants undertake an action at
163 departures only (both lunch break departure and departure at the end of the day), not considering intermediate
164 actions or daylight levels. On the contrary, in the Loff2 model, occupants are responsive to daylight. It
165 computes the probability to undertake action during intermediate occupancy according to the duration of
166 absence and the work plane illuminance. Conversely to the lighting models, the implemented blinds and
167 windows operation stochastic models do not diversify the action of opening or closing. The models' developers
168 make use of specific variables (e.g., transmitted direct solar irradiance, direct solar irradiance at the work plane,
169 arrival time, indoor or outdoor temperatures, etc.) to model the probability of state change of the blinds and
170 windows operation. In particular, in the B1 blinds operation model, the blinds are opened at each arrival, and
171 the probability for occupants to close their blinds is calculated according to the transmitted direct solar
172 irradiance value. In the B2 model, closing probability depends on the direct solar irradiance at the work plane
173 (0.8 m above the floor level). B3 blinds operation model uses two different multivariate models, one for arrival
174 period and one for intermediate occupancy period. Unlike the previous ones, the B3 model allows closing
175 action at any occupied period, considering a higher probability to open blinds at arrival. Moreover, B3 permits
176 the blinds' partial closure, while in the B1 and B2 models, the blinds are considered either fully opened or
177 fully closed. In B3, action on blinds is predicted according to the blind unshaded fraction, the outdoor
178 illuminance, and the work plane illuminance. In the W1, W2, W3, and W4 models, windows are fully closed
179 or fully opened, without an intermediate position. All the models consider indoor and outdoor temperatures as
180 primary predictors. Moreover, W3 uses rain as a binary predictor, estimating a lower probability of opening
181 the windows if it is raining.

182 2.2 The case study

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



185

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

187 The Small Office [35–37] is a 511 m² single floor building composed of 5 thermal zones. Among the different
188 versions available for the different climate zones and building ages, and in agreement with the Cfb climate
189 zone, the model selected is characterized by the technical features reported in Table 2. Space heating and
190 cooling are provided by an air-source heat pump and the main energy carrier is electricity. In the ASHRAE

191 original model, windows are considered inoperable, and blinds are not available, representing a traditional
 192 office building. To have a second term of comparison, these two OPAs have been implemented in the
 193 ASHRAE original model through two rule-based models in which blinds close when the internal temperature
 194 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
 195 7 a.m.) if the outdoor temperature is greater than 15 °C exploiting night cooling [53] [54]. These two rule-
 196 based models, used in the Copenhagen climate, lead to the functioning of windows and blinds only during the
 197 period that goes from April to September. The modified version of the ASHRAE model aims to implement
 198 new typical strategies used in office buildings to minimize the cooling load increasing the wellbeing of
 199 occupants. In the text, this new model is referred to as “ASHRAE modified”.

200

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]

201

202 The ASHRAE Small Office uses electricity for around 99% of its energy consumption, while the remaining
 203 1% is covered by natural gas. Since gas is used only by the backup furnace of the heating system, which relies
 204 on electricity as a primary energy source, not considering natural gas energy use does not affect the reliability
 205 of the study. If the implementation of stochastic OPAs models influences space heating production, this will
 206 be quantified in the electrical energy use for space heating.

207 2.3 Global Sensitivity Analysis

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

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

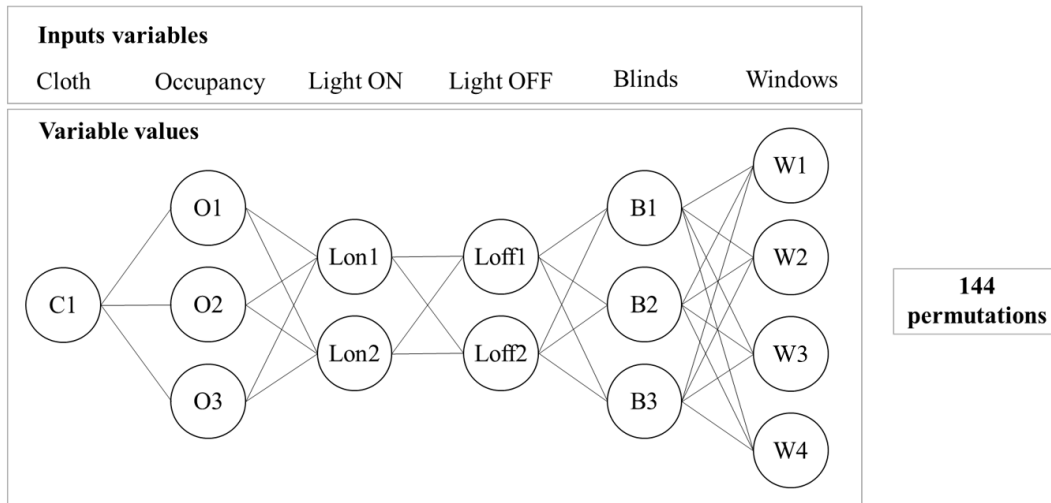


Figure 2. Representation of the GSA's permutations.

231

232

233 2.3.1 Stochastic variability and the number of simulations

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

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

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

267 2.3.2 Post-process of GSA results with Mann-Whitney U test and GEE

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

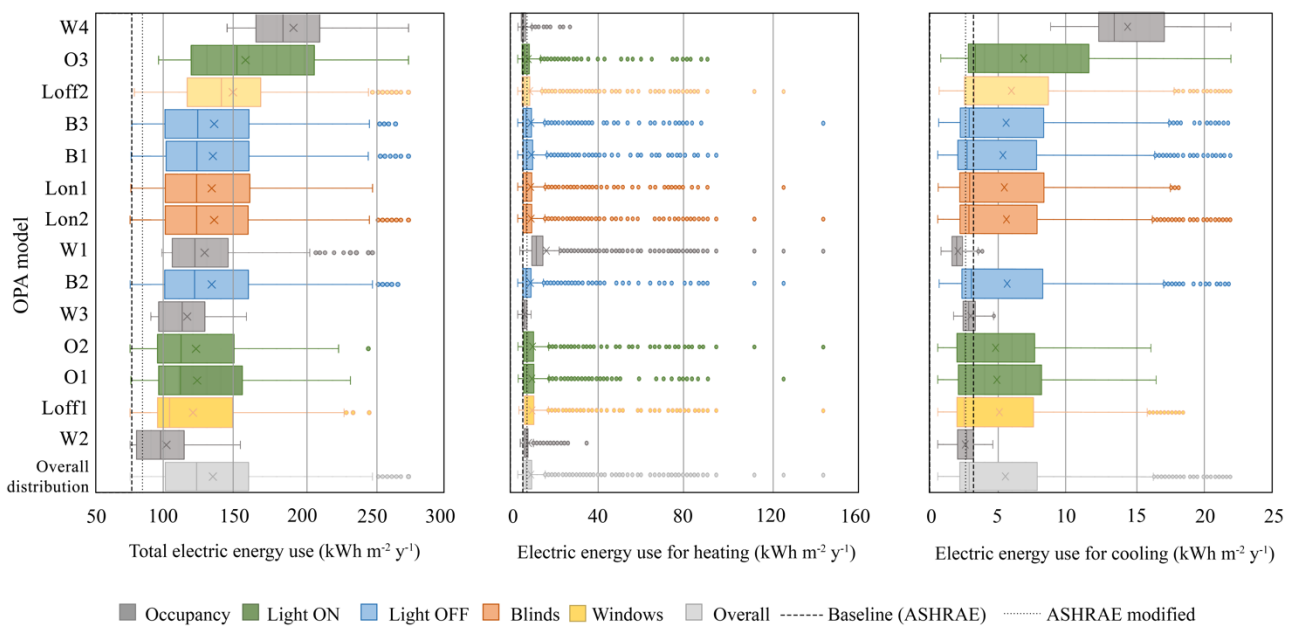
276 To account for the dependency between the repeated measures, that is 50 simulations for each of 144
277 permutations, several methods for repeated methods design can be used [57]. As described in Section 2,
278 probability distributions of responses do not follow a normal distribution. Therefore,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

293 **3 Results and discussion**

294 In this section, the results obtained from the GSA are presented and discussed. The results are reported in terms
 295 of total electric energy use that includes electric energy need for heating, cooling, interior and exterior lighting,
 296 interior equipment, fans, and water system. Moreover, the heating and cooling electric energy use are analyzed
 297 as results. The base case building’s total electric energy use considering the Copenhagen climate is 77.3
 298 kWh/(m²y), while the electric use for heating and cooling are respectively 5.7 kWh/(m²y) and 3.2 kWh/(m²y).
 299 These represent the reference values of the following analysis, and hereby they will be indicated as the
 300 “baseline”. At the same time, the ASHRAE modified model shows a total electric energy use of
 301 83.2 kWh/(m²y) and an electric use for heating and cooling respectively of 6.8 kWh/(m²y) and 2.8
 302 kWh/(m²y). Clothing insulation level does not directly impact the electric energy use of the building and it is
 303 not considered in the base case scenario. However, in the scenarios where stochastic models are implemented,
 304 it works as an input for the PMV calculation that influences the window operation model W2 as described in
 305 Section 2.1.

306 **3.1 Stochastic projection of OPA models on the building’s energy use**

307 To let the propagation of random input variables of the OPA models, each permutation is run 50 times. Next,
 308 all the 144 permutations of Figure 1 are simulated. In Figure 3, the impact of each stochastic OPA model on
 309 the building’s total electric energy use, electric use for space heating and cooling are presented and compared
 310 with the reference performance of the baseline and the ASHRAE modified model. Each boxplot represents the
 311 distribution of the values of the building’s energy use calculated by choosing one given stochastic OPA model
 312 and testing all available stochastic models for the other different aspects of occupant behavior simultaneously.
 313



314

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

318 Analyzing Figure 3, for the total electric energy use, among occupancy models, the O1 and O2 models perform
319 quite similarly. In contrast, the O3 model, which generally estimates higher numbers of occupied hours, causes
320 a larger electric energy use. The median of electric energy use is around 44% higher than the deterministic
321 value for both O1 and O2 models, whereas the median value of the O3 model is 96.1% higher than the reference
322 one. Lon1 and Lon2 are two switch-on models and behave very similarly: they respectively predict an annual
323 electric use with a median that is 58.7% and 58.6% greater than the baseline. On the contrary, the Loff1 and
324 Loff2 switch-off models show different results. Loff1 has a median value of the energy use of 103.31 kWh/(m²
325 y), which is 33.6% higher than the base case electric energy use. Loff2 has a median value of the energy use
326 of 140.4 kWh/(m² y) which is 81.6% higher than the baseline electric energy use. The three blinds control
327 models perform similarly: the median is 122.8 kWh/(m² y) for B1, 121.3 kWh/(m² y) for B2, and
328 123.6 kWh/(m² y) for B3. These values are respectively 58.8%, 56.9%, and 59.9% higher than the baseline
329 annual electric energy use. Windows operation models generate more variability in the results compared to
330 other occupants' actions. W1 produces a median that is 57.1% higher than the reference one. W2 and W3
331 present a median respectively 25.4% and 45.5% higher than the base case value. W4 presents a median value
332 that is 138.7% higher than the reference one, which is the highest median value of annual electric energy use
333 among all the analyzed models. W1, W2, and W3 present narrow and asymmetrical distribution toward lower
334 values. W4 presents the most spread and high distribution of energy use among the windows models.
335 Comparing the distribution of the results of each OPAs model, windows operation models show the narrowest
336 box plots. On the contrary, O3 has the most spread output distribution and a relatively high median value.
337 Finally, the median of the entire distribution of all the results was calculated to be 58.6% higher than the base
338 case energy use.

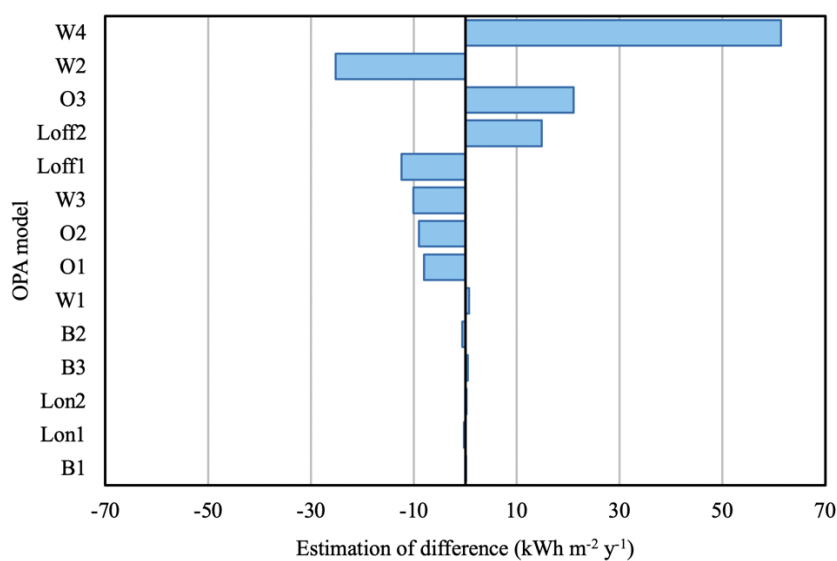
339 The electric use for space heating is very similar to the base case except for the W1 model, with the range of
340 the median values between -4% and 27%. Whilst W1's median value is 105% higher than the baseline. A
341 larger difference, in terms of percentages, is registered in the electricity used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

349 Overall, all the implemented stochastic models always generate a higher total electric energy use than the
350 reference ASHRAE base case. Although the theoretical nature of the case under study did not permit to gather
351 infield data on electric energy use, it is possible to consider that the stochastic modeling of OPAs is more
352 realistic if compared to the deterministic profiles when the modeled actions are effectively possible in a real
353 building. Stochastic simulation allows considering the randomness and the variability of the interaction

354 between people and buildings by estimating the probability to undertake action as a response to one or more
 355 input variables. Hence, considering the results of implemented models, it is very likely that the deterministic
 356 OPAs simulation underestimates the building energy uses, leading to, eventually, unreliable and overoptimistic
 357 building design performance. The underestimation of building energy uses could cause different issues such
 358 as wrong-sized systems, incorrect estimation of meeting energy-efficiency targets. Another consideration that
 359 can be made is that the selected models were developed from data collected in buildings that are far from the
 360 nearly zero-energy target set by EPBD and are located in a climate zone (Cfb) where the summer period is not
 361 severe and quite limited. Therefore, if these models are applied in high-performance buildings—like the
 362 analyzed case study—, the impact on the energy uses for space heating and cooling is strongly dependent on
 363 some decisions imposed by the energy analyst, for example, the duration of the conditioned period or the set-
 364 point temperatures, rather than representing the thermal and energy response of the building. The use of these
 365 models outside the original climate zone may have a critical impact on the results, but, until now, no systematic
 366 work has been developed to study the transferability of these stochastic models to summer-dominated climates.
 367 Thus, we recommend careful use of these models in conditions different from those of the original data sources
 368 (e.g., climate zone, building use, room type, number of users per thermal zone) because they may completely
 369 shift the thermal and energy response of a building.

370 3.2 Single parameter impact on the variation in overall distribution

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



376

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

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

Sample	Descriptive Statistics		Estimation for difference		Test
	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

381

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

388 3.3 Parameters' main and interaction effects analyses

389 The interaction effects analysis allows understanding how the impact of a variable depends on the value of the
390 other variables. To analyze the results from the 7200 simulations, the method of Generalized Estimating
391 Equations (GEE) was exploited. This method allows identifying OPAs models that significantly contributed
392 to the estimated energy use while considering the dependency between the 50 repeated runs of each 144 model
393 permutations. To find the optimal variable combination, a stepwise approach was used in which one variable
394 was added to the model at the time. The contribution of each variable was judged by the goodness-of-fit score
395 Quasi-likelihood under Independence Model Criterion (QIC). According to this criterion, the variable
396 combination giving the lowest QIC value is considered the best [62]. The results of the stepwise approach to
397 finding the best model, including main and interaction effects based on the lowest QIC, are presented in Table
398 4.

399

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

	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	W, O, Loff, W*Loff	179.46
excluding Lon and B models	W, O, Loff, W*Loff, O*Loff	180.60
	W, O, Loff, W*Loff, O*Loff, W*O	170.15

402

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

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

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

422 4 Conclusions and future outlooks

423 The present work aimed to assess the impact of stochastically modeling occupant presence and actions (OPAs)
 424 in building energy simulations. A global sensitivity analysis (GSA) was set up by simulating 144 permutations
 425 of all the single OPAs models of each input OPAs category and obtaining 7200 simulations performed in
 426 JEPlus. GSA helps to study how the uncertainty in the building electricity use can be apportioned to the
 427 different OPAs and analyzed in terms of the impact of every single model, main and interaction effects. 15
 428 stochastic OPAs models have been selected based on their wide use in literature. Specifically, three models of

429 occupant presence [40–42], four models for the lighting switch-on [40,43] and switch-off [40,44], one clothing
430 model [39], three models for blinds opening [40,45,46], and four models for window opening [47–50] were
431 used in the analysis. The ASHRAE Small Office prototype [31] and Copenhagen IWEC weather data were
432 identified as the most suitable to perform this comparative test bench. In the original ASHRAE model, the
433 occupants are modeled in a fully-determinist way. Thus, a modified version of the small office ASHRAE
434 model has been added as a reference. In this modified ASHRAE model, blinds close when the internal
435 temperature is higher than 25 °C and windows open during the night (from 9 p.m. to 7 a.m.) if the outdoor
436 temperature is greater than 15 °C exploiting night cooling.

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

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

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

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

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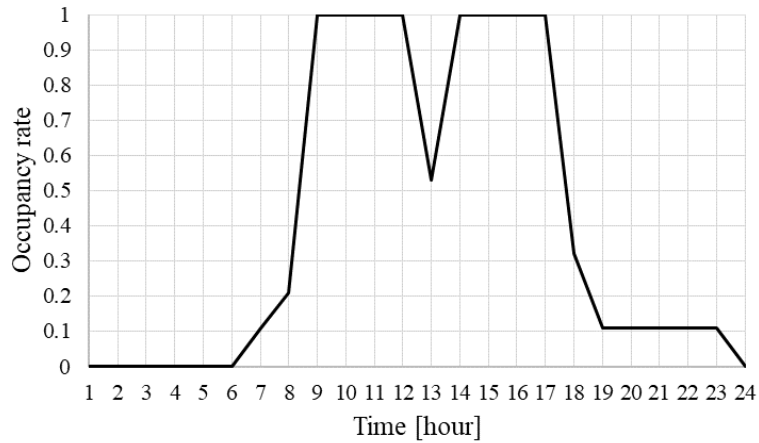
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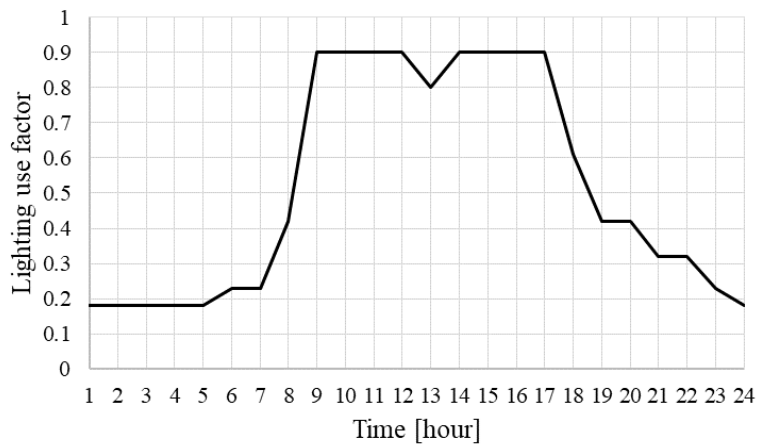
647 7 APPENDIX A – ASHRAE 90.1 Small Office deterministic models for
648 OPAs

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



652

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



654

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

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

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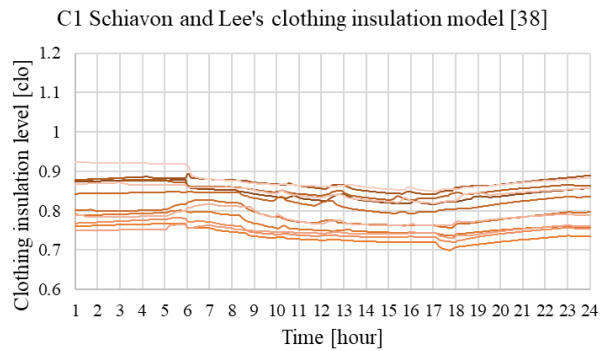
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663 8 APPENDIX B – Stochastic OPAs models results

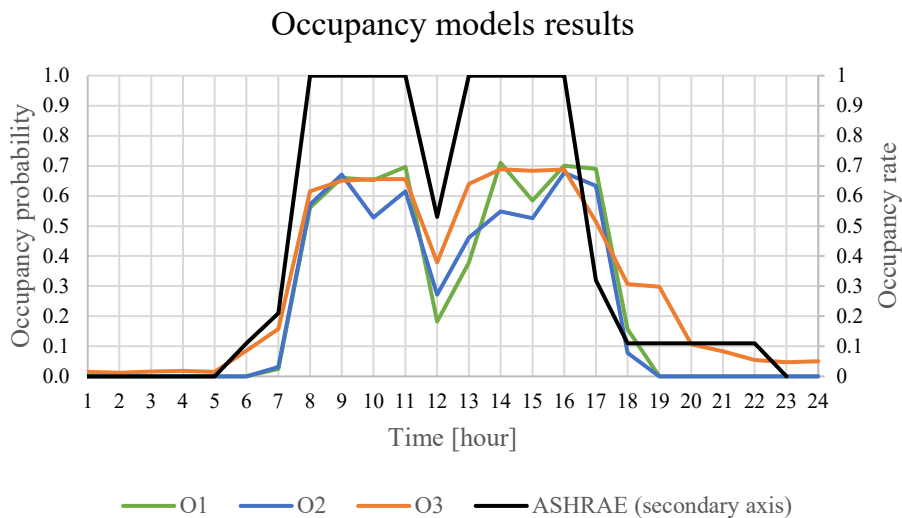
664 *Figure 7: Timestep values of clothing insulation level, in terms of clo. The daily profile of a random weekday for each month are*
 665 *represented through colored lines.*

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



668

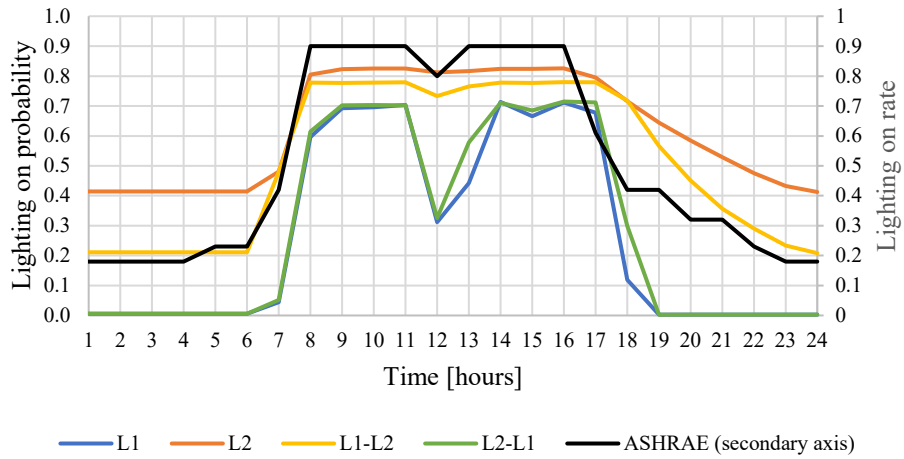
669 *Figure 8: Timestep values of clothing insulation level, in terms of clo. The daily profile of a random weekday for each month are*
 670 *represented through colored lines.*



671

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

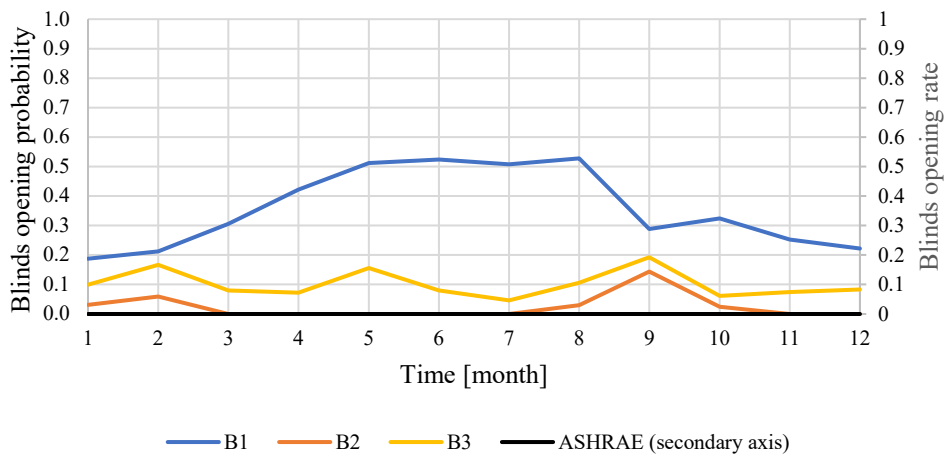
Lighting models results



674

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

Blinds models results



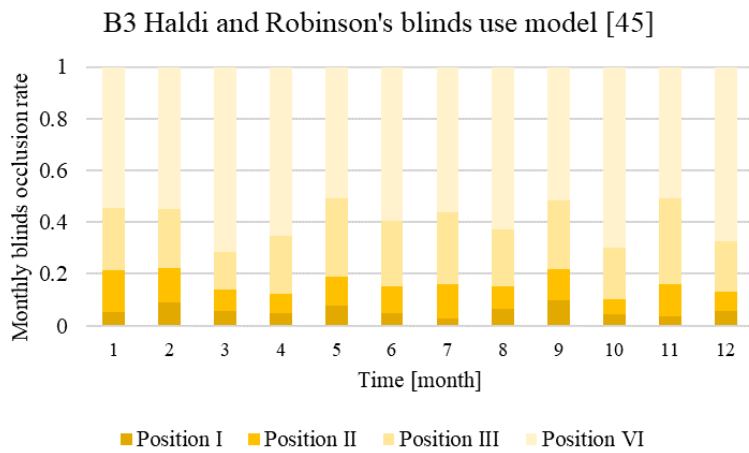
677

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

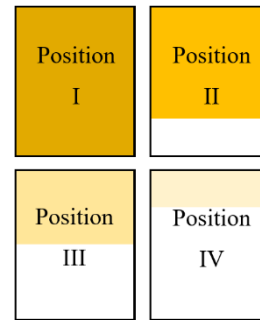
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682

683 a)



b)



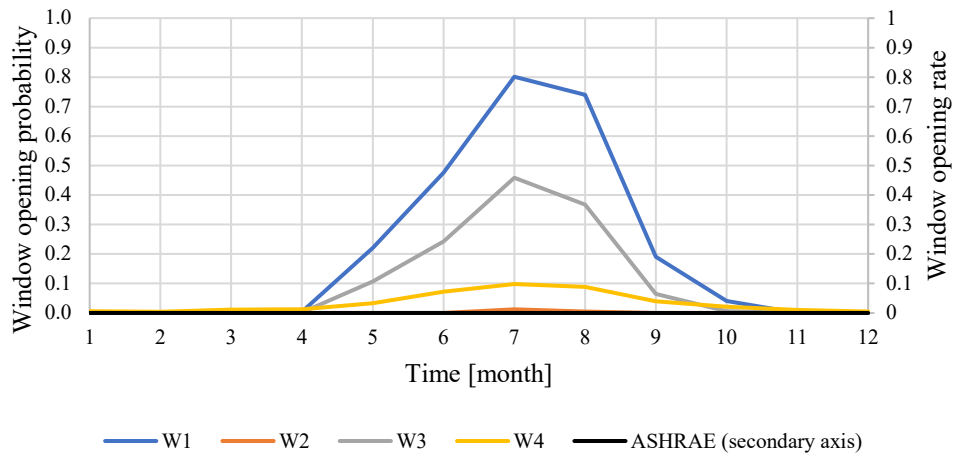
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Figure 12. a) Occlusion rate of all the possible blinds position predicted using B3 model. b) representation of all the possible blinds positions colored in accordance with figure a).

Windows models results



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688

689

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.

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691