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1 **A statistical-based optimization method to integrate thermal**
2 **comfort in the design of low energy consumption building**

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15 **A statistical-based optimization method to integrate thermal** 16 **comfort in the design of low energy consumption building**

17 **Abstract**

18 It is necessary to design energy-efficient buildings so that a trade-off between energy-savings
19 and occupants' thermal comfort is fulfilled. Advanced thermal comfort-based control
20 strategies have been proposed for this purpose. However, such an approach could consume
21 energy as the conventional one if the building is poorly designed. The aim of this study is to
22 propose a method that integrates thermal comfort in the design of energy-efficient buildings.
23 The use of sensitivity analysis and an optimization approach to identify the values of design
24 parameters represent its core steps. The meta-modeling approach based on the design of
25 experiments technique is adopted to perform the sensitivity analysis. Then, the obtained meta-
26 models are used to optimize building design for the intended objectives. A case study is
27 selected to test the proposed method. The results indicated that implementing the suggested
28 strategy leads to about 20 % of heating energy-savings compared to the base case while
29 significantly enhancing occupant thermal comfort. Moreover, the results indicated that a
30 reduction of about 22% of heating energy can be achieved compared to the comfort controlled
31 case while it consumes 4% more if the comfort control is applied to the optimized design
32 while maintaining consistent thermal comfort conditions.

33 **Keywords:** thermal comfort, energy savings, design of experiments, sensitivity analysis,
34 Optimization, Analysis of Variance.

35 **1. Introduction**

36 In developed countries, the building sector accounts for about 40% of the final energy
37 consumption and more than 30% of the greenhouse gas emissions ahead of transport and
38 industry sectors [1]. Although progress is being made towards sustainable buildings,
39 improvements are still not in line with a growing building sector and the increasing demand

40 for energy services. The break-down of final energy consumption by end-use in the building
41 sector demonstrates that Heating, Ventilation, and Air conditioning (HVAC) systems account
42 for about 34% to 40% of the total energy use in residential and commercial buildings,
43 respectively [2]. However, these percentages may vary considerably from one region to
44 another [3].

45 These concerns have led to the establishment of various standards and regulations
46 aimed at prompting sustainable construction growth, such as zero energy buildings [4]. Such
47 principles focus on improving building envelope design, using efficient equipment and
48 deploying renewable energy resources [5]. Nevertheless, it is important to bear in mind that
49 the main purpose of buildings is to provide a comfortable indoor environment to their
50 occupants because people spent most of the day indoors, and uncomfortable indoor climate
51 results in lower work efficiency and an indirect impact on energy consumption [6]. Therefore,
52 improving the energy performance of buildings must consider thermal comfort alongside
53 energy-savings measures, hence energy efficient-buildings must be designed so that a trade-
54 off between is achieved.

55 Thermal comfort is defined as “*the condition of the mind in which satisfaction is*
56 *expressed with the thermal environment*” [7]. Amid all the suggested thermal comfort indices,
57 the Predicted Mean Vote (PMV) and Percentage of Persons Dissatisfied (PPD) are the most
58 appropriate indices for evaluating thermal comfort in an air-conditioned environment [8]. It is
59 calculated based on four environmental parameters defined as relative humidity, air velocity,
60 air temperature and mean radiant temperature and two occupant related parameters renowned
61 as metabolic rate and clothing insulation. Various national and international standards, such as
62 ISO 7730 [9], ASHRAE 55 [7,10], and CEN CR 1752 [11], adopted the PMV index. To
63 ensure a comfortable indoor environment, it is recommended to maintain the PMV at 0 with a
64 tolerance of 0.5 [9].

65 The used indices to evaluate occupants' thermal comfort in air-conditioned buildings
66 demonstrate that occupants' thermal comfort is more than just an indoor air temperature. Most
67 standards, however, adopt a static set-point temperature for the control of the indoor
68 environment, alongside energy-efficient measures. For instance, in France, the RT2012
69 recommends a set-point temperature of 19 °C during the winter season [12]. This legislation
70 was created to encourage efficient energy use and to decrease environmental risks. Although
71 this measure reflects good progress towards reducing building energy consumption, it is not
72 satisfactorily considering occupant thermal comfort.

73 To overcome this limitation, numerous research groups focused on developing
74 innovative and advanced techniques for building control. For this purpose, thermal comfort
75 based control strategies have been suggested and studied over the past decades [13]. These
76 strategies are intended to maintain consistent indoor thermal comfort rather than fixed indoor
77 temperature. For this aim, an advanced control scheme is utilized to regulate the monitored
78 environmental parameters, so that the pre-defined PMV is preserved.

79 Liang and Du [14] developed a direct neural network model to predict the PMV index
80 using the abovementioned six parameters and showed how to incorporate such a model into
81 the control system of a building. Ferreira et al. [15] applied a model-based predictive control
82 using the branch and bound method to control an HVAC system, using the PMV index, in a
83 university building. Castilla et al. [16] suggested an approximation of the PMV index using
84 neural networks. The authors indicated that this approximation allows a reduction in the
85 number of sensors required and the ability to control the HVAC system. Hussain et al. [17]
86 compared the performance of a comfort-based fuzzy control with traditional ON/OFF control
87 using simulation studies. The study reported decreases in heating and cooling energy
88 consumption when using the comfort based control system. Garnier et al. [18] utilized a
89 simulation-based neural predictive HVAC control approach to investigate the energy-saving

90 and occupant comfort benefits compared to two other non-predictive approaches. The
91 proposed method achieved energy-savings during both the heating and cooling seasons.
92 Ruano et al. [19] proposed an improved model predictive control based on the PMV index for
93 an existing HVAC system. The authors reported a significant economic savings, compared
94 with conventional control, while satisfying thermal comfort conditions. Xu et al. [20]
95 developed and tested a novel periodic event-triggered mechanism based on the PMV index.
96 The authors reported energy and cost savings for the buildings and demand reduction for the
97 power grid. Yoon and Moon [21] proposed a performance-based thermal comfort control
98 model based on the Gaussian process regression and deep Q-learning algorithm. The authors
99 indicated that the suggested approach provided the optimal control that maximizes the energy-
100 savings while maintaining acceptable thermal comfort conditions.

101 The reviewed studies show that many research groups are orienting their work toward
102 the use of advanced and intelligent control methods. This is due to the poor performance of
103 conventional methods when dealing with complex, dynamic and non-linear systems [22].
104 Nevertheless, the literature proof of the advantage of these advanced control systems over
105 traditional ones is scarcely adequate to persuade the building industry to substitute
106 conventional controllers with advanced smart ones.

107 All the above studies were conducted with a purpose of showing (i) the interest of the
108 comfort-based control compared to the conventional one, mostly by numerical approaches
109 and much understanding from real situation investigations is still needed, without (ii)
110 changing the design parameters of the case study such as the building envelope parameters.
111 There is no reason why these two aspects could not be studied simultaneously. In addition, the
112 literature still lacks experimental studies that quantify the costs associated with the use of
113 these advanced control strategies compared with conventional control ones, namely because
114 predictive models require a consistent input data about the indoor environment to be able to

115 make predictions. Also, some studies indicated that a poor design of the building has a direct
116 impact on energy consumption regardless of the utilized control approach [23]. Therefore, the
117 building design represents the first and crucial strategy to reduce energy consumption in the
118 building sector. In addition, integrating occupant thermal comfort during the design process
119 can be a step forward towards achieving energy-savings and maintaining satisfactory thermal
120 comfort conditions.

121 In this regard, the objective of this study, which in fact is an extension to the authors'
122 previous works [24–26], is to propose a new method to integrate occupant thermal comfort in
123 the design of energy-efficient buildings to achieve optimally designed buildings for both
124 energy consumption and thermal comfort. The study of Merabtine et al [24] investigates the
125 actual thermal comfort condition without considering a new approach to enhance the thermal
126 performance of the building. Besides, the investigation of Hawila et al [25,26] relies solely on
127 numerical simulation to confirm the advantages of the thermal comfort control strategy, while
128 in practice it is still a questionable approach as discussed above. And bearing in mind that a
129 poor design influences the overall thermal performance of the building despite the utilized
130 control strategy, the investigations in this study are oriented towards integrating occupant
131 thermal comfort in the design process rather than the control method.

132 The main aims intended through this method are: i) to understand the relationship
133 between thermal performance and design parameters, ii) to provide realistic and accurate
134 predictions of the thermal performance throughout the design process, and iii) to identify the
135 parameters and interaction between parameters that significantly affect the design goals. For
136 this purpose, the combined use of dynamic numerical simulations and meta-modeling
137 approach based on the Design of Experiment (DoE) technique are adopted to analyze the
138 sensitivity of both energy consumption and thermal comfort to design parameters, as well as
139 to develop meta-modeling relationships. These last are then validated and utilized to optimize

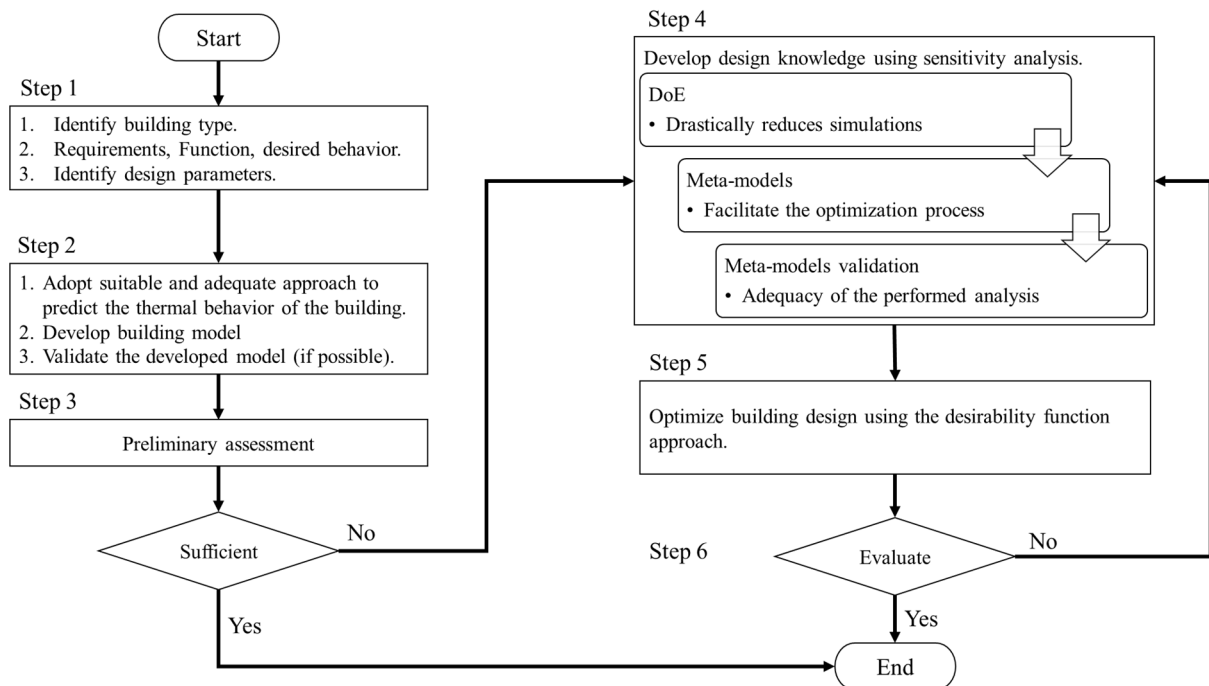
140 building design for a trade-off using the desirability function approach. The proposed method
 141 differentiates from other approaches by allowing a significant reduction in the number of
 142 simulations, thanks to the DoE technique, to develop the mathematical relationship between
 143 response variables and design parameters. These mathematical relationships convert the
 144 discretized domain into a continuous one, thus leading to enhancing the accuracy of the
 145 optimal solutions. Moreover, the obtained meta-models can be utilized as an alternative of
 146 numerical simulations as a rapid and easy approach to predict the thermal performance and to
 147 optimize the building design in similar case studies.

148 2. Methodology

149 The proposed methodology to integrate occupant thermal comfort in the design of
 150 energy-efficient buildings comprises six main steps, as discussed in the following sections.

151 Figure 1 illustrates the framework of the proposed method.

152



153

154

Figure 1 : The framework of the proposed method.

155 **2.1 Identifying building type, desired behavior and design parameters**

156 The first step of the proposed method is concerned with identifying the building type
157 under the design process. A key starting point is then to define the requirements, which lead
158 to the exploration of functions and, eventually, the desired behavior of the building. The
159 requirements and functions of the building are defined via a communicative interaction
160 between the stakeholders of the building. Based on these requirements and functions, the
161 expected behavior is then obtained from the existing standards and regulations.

162 Subsequently, the design process and design parameters takes place. In this early
163 stage, the stakeholders aim to find a joint decision for building design solution. This is first
164 done by identifying the factors influencing the building's thermal behavior, which can be
165 divided into five categories i) Climate, ii) Building-associated characteristics, such as area,
166 orientation, envelope, iii) Occupant-related features, such as occupancy schedules, iv)
167 Building services systems and operation, such as HVAC systems, and v) Occupants' behavior
168 and activities.

169 Afterward, it is important to set the values of the design parameters to achieve the
170 desired thermal behavior. First, the designer or engineer might set the values based on
171 previous experience or similar case studies. Second, an evaluation study must be performed to
172 confirm if the considered parameters achieved the desired behavior or not. Indeed, the
173 analysis process requires a suitable and adequate approach to predict the thermal behavior of
174 the building, as well as clear evaluation criteria to evaluate the performance of the building.

175 **2.2 Adopting suitable and adequate approach to predict the behavior of the building**

176 The prediction of building thermal performance requires models that accurately
177 describe the physical phenomena. Numerous models were developed in the literature to
178 predict the building performance, including dynamic simulation methods, statistical methods

179 and artificial intelligence-based techniques. Each approach has its advantages and drawbacks.
 180 The combined use of dynamic simulation and statistical models is adopted in the proposed
 181 approach because building performance simulations are capable of providing adequate
 182 conclusions with less time and cost, as well as it enables analyzing different scenarios during
 183 the design phase without the need for an existing building. Besides, statistical and artificial
 184 intelligence methods require sufficient historical performance data to develop prediction
 185 models [27]. Indeed, the prediction capability of numerical models is an influential factor to
 186 reflect the reliability of the results, and model calibration and validation are required. For this
 187 purpose, the normalized mean bias error (NMBE), the coefficient of variation of the root
 188 mean square error (CVRMSE), and the coefficient of determination (R^2) are used in this
 189 study, as recommended by the ASHRAE Guideline-14 (G-14) [28].

190 NMBE is a measure of how close the predicted data, s_i , fits the measured data, m_i ,
 191 and is expressed in percentage (%), as expressed in Equation (1), where n is the total number
 192 of measured data. It is the ratio of the sum of discrepancies between actual and predicted data
 193 to the mean of all measured data. Positive or negative value signifies that the model under- or
 194 over-predicts the measured data.

$$NMBE = \frac{1}{\bar{m}} \times \frac{\sum_{i=1}^n (m_i - s_i)}{n} \times 100 \quad (1)$$

195 CVRMSE measures the dispersion of the residuals between measured and predicted
 196 data, it is calculated using Equation (2). It is a measure of the ability of the model to fit the
 197 measured data. A lower value indicated that the model is a better fit. This index is not
 198 subjected to the cancellation phenomenon.

$$CVRMSE = \frac{1}{\bar{m}} \times \sqrt{\frac{\sum_{i=1}^n (m_i - s_i)^2}{n}} \times 100 \quad (2)$$

199 The coefficient of determination (R^2) shows how close the predicted values are to the
 200 regression line of the measured data. This index is ranged between 0, which means that the

201 predicted and measured data do not fit, and 1, which means that the predicted values match
 202 perfectly the measured data. Table 1 summarizes the criteria of ASHRAE G-14 [28] to
 203 validate a model as calibrated.

$$R^2 = \left(\frac{n \times \sum_{i=1}^n m_i \times s_i - \sum_{i=1}^n m_i \times \sum_{i=1}^n s_i}{\sqrt{(n \times \sum_{i=1}^n m_i^2 - (\sum_{i=1}^n m_i)^2) \times (n \times \sum_{i=1}^n s_i^2 - (\sum_{i=1}^n s_i)^2)}} \right)^2 \quad (3)$$

204 Table 1 : Threshold limits of statistical criteria for calibration in compliance with ASHRAE
 205 G-14 [28].

Statistical indices	Monthly Calibration	Hourly Calibration
NMBE (%)	±5	±10
CVRMSE (%)	15	30
R^2	> 0.75	> 0.75

206 2.3 Preliminary assessment

207 The proposed design needs to be evaluated to check whether the building meets the
 208 predefined requirements. Indeed, during the design process, it is more important to compare
 209 design alternatives and use benchmarking than evaluating absolute values. A benchmark can
 210 be defined as a reference point against which building performance may be assessed. Two
 211 main approaches are used for building performance benchmarking: a) comparison of building
 212 behavior against historical performance, or b) comparison of behavior with the performance
 213 of similar buildings.

214 Afterward, the results should be either satisfactory or unsatisfactory. The first implies
 215 that the considered design parameters are adequate to achieve the desired objectives, hence
 216 the design process can be terminated. An unsatisfactory result, however, implies that the
 217 deemed designed parameters need to be altered to achieve the desired objective. In this case,
 218 several iterations and comparisons must be performed to attain the main objectives. Indeed,
 219 this process requires considering and evaluating several scenarios. Here, sensitivity analysis
 220 can be used to develop design knowledge to understand and formulate the relationship

221 between the considered design parameters and the desired objectives. This formulation allows
222 optimizing the building design for the predefined requirements.

223 **2.4 Developing design knowledge using sensitivity analysis**

224 Sensitivity analysis (SA) is a valuable approach for identifying the key parameters
225 influencing the thermal performance of buildings for both observational and energy
226 simulation studies [29]. There are numerous techniques to employ SA in building
227 performance studies. The meta-modeling approach based on the Design of Experiments
228 (DoE) technique is adopted in the proposed framework. DoE allows the designer or engineer
229 to derive mathematical formulation, noted as meta-models, between the studied variable and
230 design parameters by drastically reducing the number of simulations. The developed meta-
231 models are then used to simplify and accelerate the parametric studies to find an optimal
232 design to achieve the desired behavior.

233 The most common meta-models are the first-order linear model, the linear model with
234 interaction terms, the pure quadratic model, and the complete quadratic model. The
235 coefficients of the meta-model is determined by simple matrix multiplication using the least-
236 squares method. Indeed, the validity of the obtained meta-models is vital to reflect the
237 adequacy of the performed analysis. The significance of the obtained meta-model and model
238 terms can be tested using the ANOVA approach in combination with Fisher's statistical test
239 (P-value < 0.05). In addition, graphical analysis of residuals can be applied to check the
240 adequacy of the obtained meta-models, and as a result, the performed analysis.

241 **2.5 Optimization**

242 The next step is to use the validated meta-models to find the value of design
243 parameters that outcome the predefined behavior of the building, such as minimizing or
244 maximizing a response variable. However, in the case of building design, the desired behavior

245 is a function of more than one response, such as minimizing energy consumption and
 246 maintaining acceptable thermal comfort levels. A compromise solution is thus desired and a
 247 simultaneous optimization procedure is needed.

248 In this consequence, the desirability function approach represents a suitable method to
 249 optimize multiple responses. It aims to simultaneously optimize multiple equations by
 250 converting a multiple response problem into a single one. First, each response (y_i) is
 251 converted into an individual desirability function (d_i) depending on the desired objective, as
 252 expressed by Equations (4-6), if the objective is to achieve a target value, minimize, or
 253 maximize the response value, respectively. Then, the obtained function are combined in the
 254 Global Desirability Function (GDF), as indicated in Equation (7), where T, L and U are the
 255 target, the lower and the upper limits, respectively, and r_i is a weighting parameter. The
 256 Nelder-Mead simplex method is then used to search for the set of input factors to maximize
 257 the GDF [30].

$$d_i^{target} = \begin{cases} 0 & \text{if } y_i < L \\ \left(\frac{y_i - L}{T - L}\right)^{r_1} & \text{if } L \leq y_i \leq T \\ \left(\frac{U - y_i}{U - T}\right)^{r_2} & \text{if } T \leq y_i \leq U \\ 1 & \text{if } y_i > U \end{cases} \quad (4)$$

$$d_i^{min} = \begin{cases} 0 & \text{if } y_i > U \\ \left(\frac{U - y_i}{U - T}\right)^r & \text{if } T \leq y_i \leq U \\ 1 & \text{if } y_i < T \end{cases} \quad (5)$$

$$d_i^{max} = \begin{cases} 0 & \text{if } y_i < L \\ \left(\frac{y_i - L}{T - L}\right)^r & \text{if } L \leq y_i \leq T \\ 1 & \text{if } y_i > T \end{cases} \quad (6)$$

$$D = (d_1 \times d_2 \times \dots \times d_n)^{1/n} = \left(\prod_{i=1}^n d_i \right)^{1/n} . \quad (7)$$

259 **2.6 Final evaluation**

260 Indeed, after identifying the values of design parameters, a final evaluation step must
261 be performed. Here the evaluation process follows the same approach as indicated in step 3,
262 section 2.3. If the evaluation process is satisfying, then the values of design parameters are set
263 to those obtained from the optimization process. Otherwise, repeat *Step 4*, with a different
264 range of variation of the considered design parameters.

265 **3. Case study**

266 The selected case study for evaluating the proposed method is a highly glazed room
267 situated in the south-east part of the ground floor of a low energy consumption educational
268 building (Figure 2). Addressing this type of building is important because the energy issues
269 and indoor environmental quality are of great concern and require greater attention due to
270 their specific nature in comparison with other buildings. For instance, educational buildings
271 have a specific pattern of occupation and different levels of freedom for adaptive activities.
272 Located in the southern part of Troyes, France, the building was designed to meet the RT2012
273 and committed to reducing its overall energy consumption by 20% and greenhouse gas
274 emissions by 50% by 2025 and enhancing the indoor air quality of its occupants. Figure 3
275 illustrates the monthly average outdoor temperature, the heating degree days (HDDs), and the
276 hourly accumulation of monthly global solar radiation at the considered location. HDDs
277 designate the sum of the average daily differences between outdoor temperature and 18 °C by
278 considering that when the outdoor temperature is 18 °C, heating is not required.

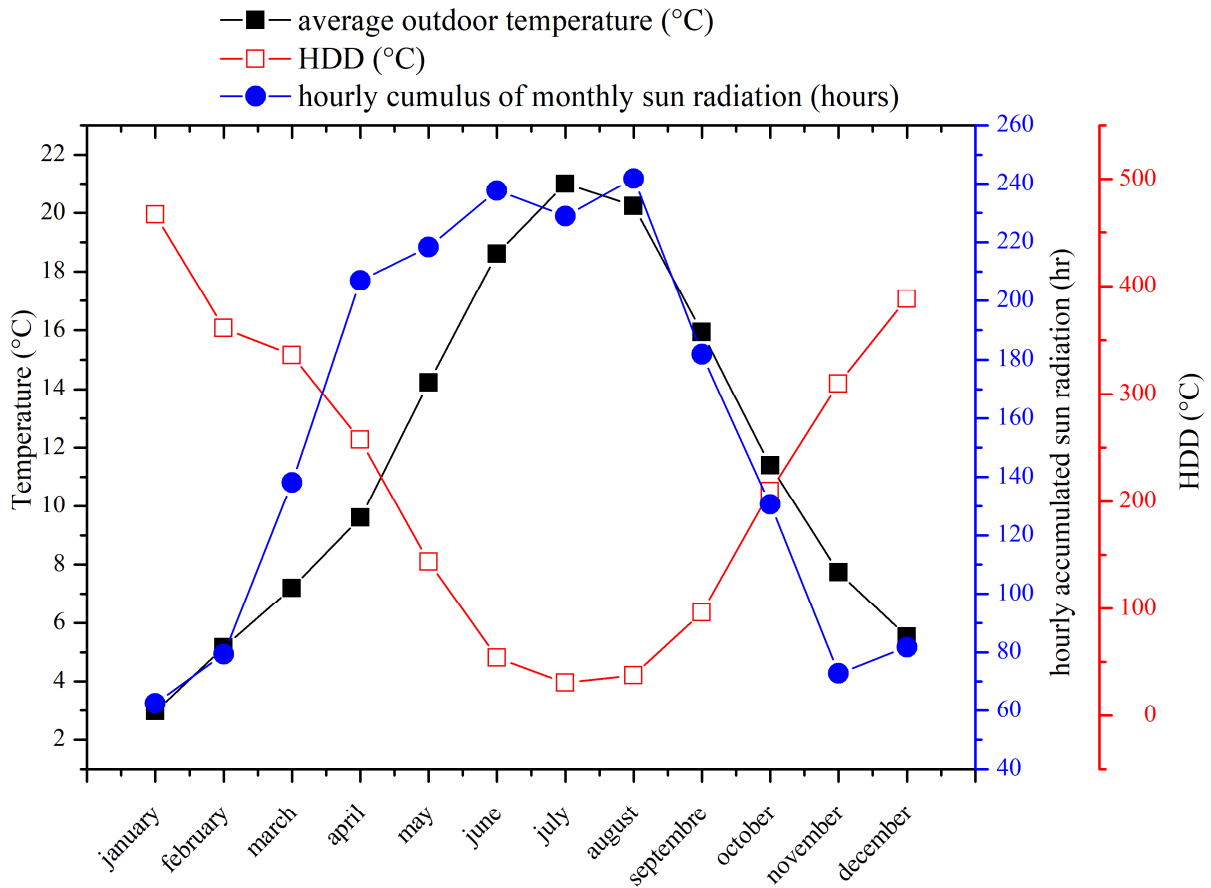
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Figure 2: considered case study: (a) outdoor view, and (b) indoor view.



282

283 Figure 3: Averaged outdoor temperature, HDD, and hourly accumulation of monthly sun
 284 radiation in Troyes, France.

285 Despite all the efficient measures and innovative solutions to reduce emissions and
286 total energy consumption of the building, students occupying the Foyer (Figure 2b), a public
287 room for doing different activities, reported dissatisfaction in thermal comfort conditions. In
288 this regards, both subjective and objective investigations were performed to assess the thermal
289 comfort level in that space [25,31], a brief description of the space characteristics is
290 summarized in Table 2. For this purpose, a multifunctional sensor (Figure 4) was utilized to
291 monitor the environmental parameters and to calculate the indices of thermal comfort. The
292 metabolic rate and clothing level were assumed to be 70 W.m^{-2} (1.2 met) and $0.155 \text{ K.m}^2.\text{W}^{-1}$
293 (1 clo), respectively, representing sedentary activity and typical winter clothing. The
294 characteristics of the used sensor and the conducted measuring cycles are reported in Table 3.
295 In addition, survey questionnaires were prepared and collected from 41 students during the
296 investigations. It is worth noting that the 41 students represent a sample of 90% confidence
297 interval and a 12% margin of error compared to the total number of 281 students and staff
298 members occupying the building. Bearing in mind that not all the students attend the Foyer
299 and the total number includes the staff member, it is assumed that the sample size is
300 statistically significant. The obtained PPD values from both the measured data and the survey
301 were above the recommended comfort range of 10% (Figure 5). The results show a good
302 agreement between the obtained results and students assumptions regarding the thermal
303 environment conditions within the Foyer. Therefore, further investigations to improve the
304 thermal comfort conditions in the Foyer are required. For this purpose, a numerical model
305 using Modelica is developed, the model is comprehensively explained in [25,26]. It is worth
306 noting that, during the experimentation and the survey the students were occupying different
307 locations inside the Foyer. The responses, however, were almost similar or slightly different
308 and in a good agreement with the experimental results even though only one measuring point
309 was considered in the investigations. Thus, the transients in the Foyer are deemed

310 insignificant and it is assumed that the PMV index can satisfactorily represent the thermal
 311 comfort condition in further investigations.

312 Table 2 : Brief description of the Foyer's characteristics

Location	Troyes, France (latitude 48.2°N, longitude 4.07°E)
Net area	58.0m ²
Dimensions	6.525m x 8.9m
Ceiling height	2.54m
Orientation	South and east facing glass facades
Roof	U-value = 0.4W.m ⁻² .K ⁻¹
Internal wall	U-value = 4.1W.m ⁻² .K ⁻¹
Glass facade	Window Floor ratio = 0.6; double glazing with U=2.8W.m ⁻² .K ⁻¹ and SHGC=0.6; equipped with internal shading.
Internal gains	Light=3.6W.m ⁻² , occupancy=0.2person.m ⁻² , appliance=2W.m ⁻²
Operating hours	All days: 8am–8pm
HVAC	
(a)Ventilation	Supply air temperature 20°C, heat recovery system efficiency 66% Air volume flow rate 208m ³ .h ⁻¹
(b)Radiators	Supply water temperature function of outdoor temperature Maximum water volume flow rate 0.1m ³ .h ⁻¹

313 Table 3 : Multifunctional sensor characteristics and experimental cycles

Parameters	Range of variation			Accuracy	
Ambient temperature (°C)	[-40.0, 123.8]			± 0.4	
Mean radiant temperature (°C)	[0, 100]			± 0.4	
Relative humidity (%)	[0, 100]			± 3	
Air velocity (m.s ⁻¹)	[0.05, 5.00]			± 0.05 for [0.05, 1.00] ± 0.15 for [1.00, 5.00]	
Experimental cycles					
	12/11		13/11	14/11	
	Cycle 1	Cycle 2	Cycle 3	Cycle 4	Cycle 5
Start hour	10:47 am	2:46 pm	8:21 am	10:01 am	2:31 pm
End hour	11:29 am	6:36 pm	8 :55 am (+1 day)	11:49 am	5:31 pm

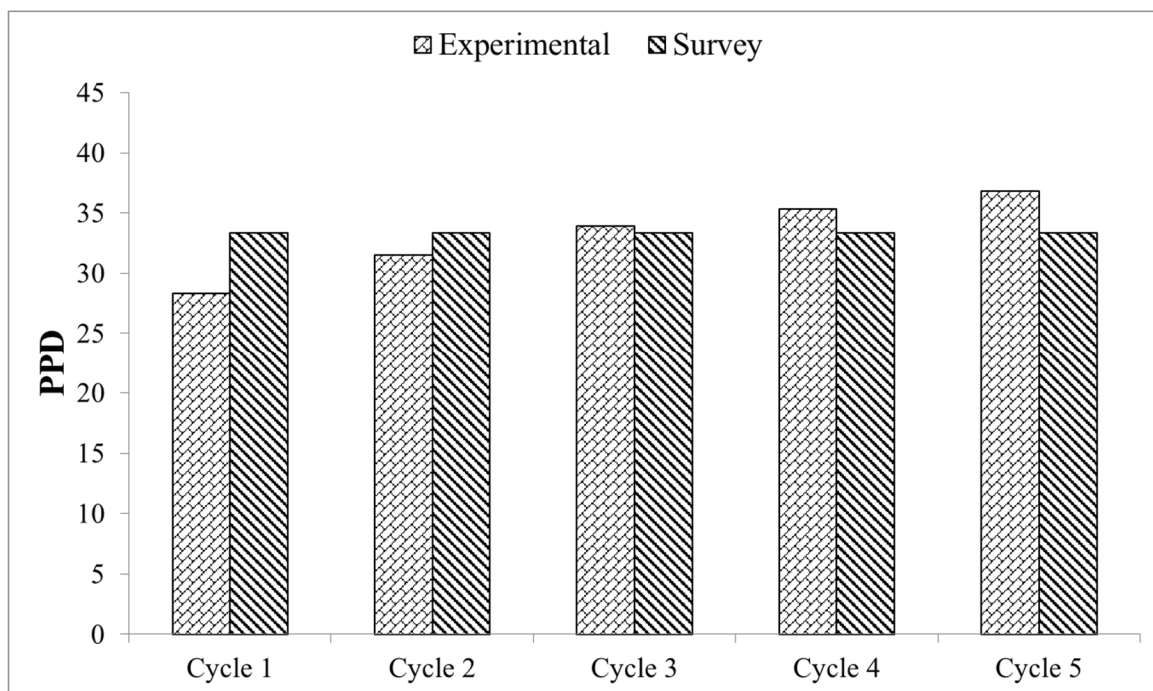
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Figure 4 : Multifunctional sensor



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Figure 5 : Average values of PPD for the various cycles [24].

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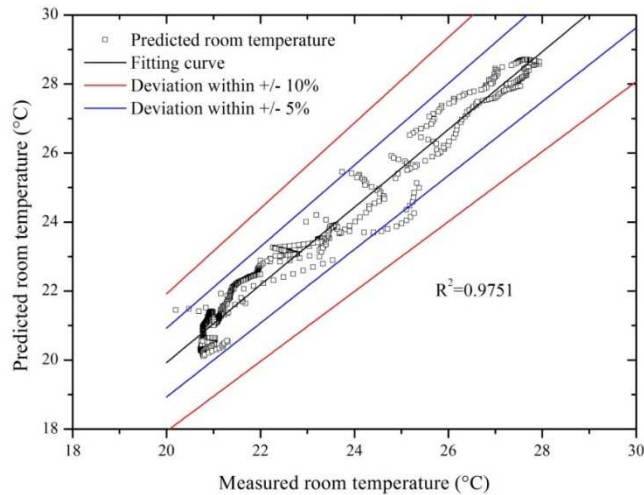
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To validate the model, the predicted room temperature and relative humidity are compared with measured data. NMBE, CVRMSE and the coefficient of determination (R^2) were used to quantify the deviations between predicted and measured values. The NMBE and CVRMSE of both the room temperature and the relative humidity for the five measuring cycles are calculated and reported in Table 4. The obtained values of both NMBE and CVRMSE are within the acceptable limits of $\pm 10\%$ and $\pm 30\%$, respectively [28].

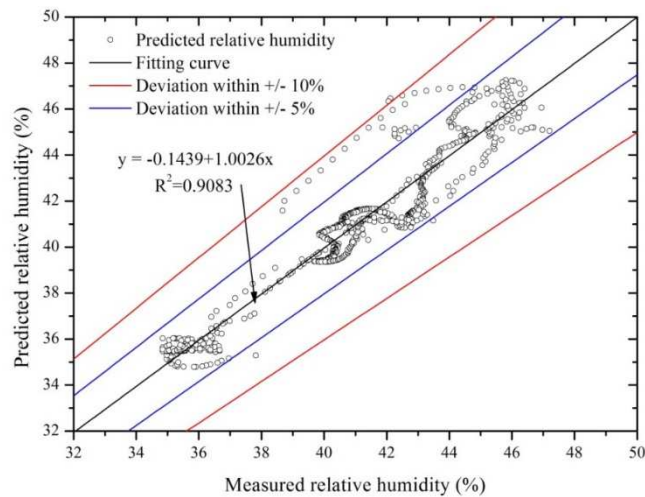
325 Table 4: NMBE and CVRMSE of the room temperature and relative humidity for the five
 326 cycles.

Experimental cycles	12 th November		13 th	14 th November	
	Cycle 1	Cycle 2	Cycle 3	Cycle 4	Cycle 5
Start hour	10:47 a.m.	2:46 p.m.	8:21 a.m.	10:01 a.m.	2:31 p.m.
End hour	11:29 a.m.	6:36 p.m.	8:55 a.m.(+1 day)	11:49 a.m.	5:31 p.m.
NMBE (%)					
Room Temperature	-2.12	-2.60	-0.29	-1.25	-4.68
Relative humidity	-2.21	1.55	-1.13	1.85	-3.10
CVRMSE (%)					
Room Temperature	2.20	5.00	6.38	2.40	4.73
Relative humidity	2.23	3.09	3.43	2.56	2.89

327 Moreover, the coefficient of determination that indicates how the predicted values fit
 328 the measured data is obtained by plotting the predicted values on a scatter graph as a function
 329 of measured values as demonstrated in Figure 6 and Figure 7. A good correlation is observed
 330 showing an R^2 of 0.9751 and 0.9083 for the room temperature and the relative humidity,
 331 respectively, meaning that 97.51% and 90.83% of the variance is explained by the model.
 332 Also, the results show that the deviation of all the data is within a 10% deviation of the model.



333
 334 Figure 6 : Coefficient of determination of the room temperature for the five cycles and the
 335 relative deviation of the model prediction.



336

337 Figure 7 : Coefficient of determination of relative humidity for the five cycles and the relative
 338 deviation of the model prediction.

339 The obtained results indicate that the model prediction is in good agreement with the
 340 measured data, although some discrepancies were noticed. These discrepancies could be
 341 attributed to experimental errors which are a function of the accuracy of the sensor. As well as
 342 the lack of exact occupancy profile at the time of experimentations and some weather data
 343 parameters. On the other hand, the discrepancies can be reduced by monitoring occupancy
 344 profiles and matching simulation schedules with real data; however, this could result in
 345 increasing modeling time and complexity and outcomes robust results for specified periods.

346 Therefore, based on all these aforementioned discussions and bearing in mind that the
 347 main intention is to obtain a model that can represent the real building in general terms rather
 348 than out coming exact results for a specified time, the model is considered to be validated and
 349 deems it useful for further evaluations and investigations.

350 **4. Results and discussion**

351 The existing thermal comfort standards, such as ISO 7730, ASHRAE standard 55, and
352 EN 15251 provide thermal comfort ranges for four categories of mechanically conditioned
353 spaces (Table 5). Educational buildings are considered in the second category with a normal
354 level of expectations. Besides, energy consumption in educational buildings is usually high. In
355 recent studies, the annual heating energy consumption for some European educational
356 buildings is reported to be in the range of 67 kWh/m² and 192 kWh/m² [32]. However, the
357 thermal regulation in France sets a benchmark of 50 kWh/m² for annual heating energy
358 consumption in new and renovated educational buildings. Therefore, the desired behavior in
359 the deemed case study is to maintain the PMV values within the range of [-0.5, 0.5] and to
360 reduce the annual heating energy consumption to less than 50 kWh/m².

361 Heating energy consumption and occupants' thermal comfort are considered in the
362 preliminary assessment and throughout the remaining parts of the paper. The thermal
363 environment of the building meets the criteria of a specific category when the PMV values are
364 outside the category limits no more than 3% of occupied hours. For instance, to meet the
365 criteria for class II, 97% of the PMV values must be in the range of [-0.5, 0.5]. The obtained
366 occurrence frequencies can be used to calculate a single index, known as the Environmental
367 Quality Index (EQI), using Equation (8) [33], where $f_{PMV,j}$ is the occurrence frequency
368 defined as the fraction of time during which the values of the PMV outcome within the range
369 limits defining the j^{th} category of quality. The EQI is an index utilized for the long term
370 assessment of the indoor environment and varies between 0 when all PMV values fall in
371 category IV, and 100 when they fall in category I. A value of 70 indicates that all the PMV
372 values fall in category II. Hence, it facilitates the long term assessment of the considered
373 environment while implicitly demonstrating the PMV value variations.

$$EQI = 100 \times f_{PMV,I} + 70 \times f_{PMV,II} + 35 \times f_{PMV,III} . \quad (8)$$

374

375 Table 5 : Recommended categories and PPD-PMV for mechanically conditioned buildings
 376 [9,34].

Category	Thermal state of the body as a whole	
	PPD %	Predicted mean vote
I	<6	-0.2 < PMV < +0.2
II	<10	-0.5 < PMV < +0.5
III	<15	-0.7 < PMV < +0.7
IV	>15	PMV < -0.7; or PMV > +0.7

377

378 **4.1. Preliminary assessment**

379 Two different cases are considered for the preliminary assessment step:

- 380 1. A set-point room temperature of 20°C representing the base case scenario.
- 381 2. A set-point room temperature of 19°C as recommended by RT2012.

382 The PMV values for each case are calculated using the validated numerical model. The
 383 measure of central tendency and dispersion and the Box plots of the obtained hourly PMV
 384 values are reported in Table 6 and Figure 8. Box plots represent a useful way to compare
 385 different data sets. They summarize sets of data by showing the shape of the data distribution,
 386 their central value, and variability. The mean PMV increases by about 0.18 by increasing the
 387 set-point temperature from 19°C to 20°C. The median values of both cases indicate that at
 388 least 50% of the time the PMV values fall outside the acceptable thermal comfort limits. High
 389 values of the standard deviation indicate that the PMV is spread out over a wide range of
 390 values, which can be visually noticed using the Box plots. The standard errors' values,
 391 however, signify less variability around the mean values.

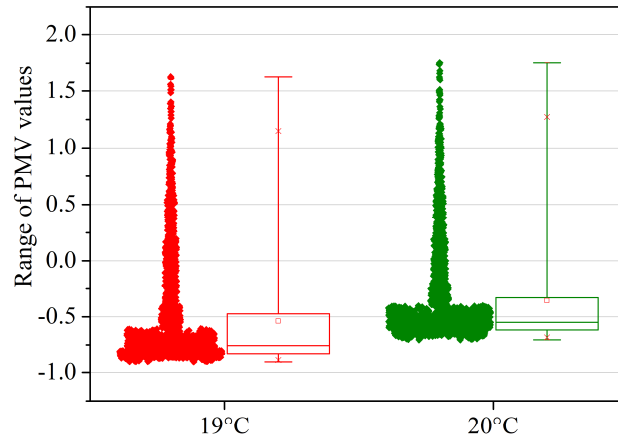
392 Moreover, the total heating energy consumption and the EQI for the two cases are
 393 illustrated in Figure 9. The results show that the case of set-point 19°C consumes the least
 394 heating energy consumption, while the case of set-point 20°C offers better thermal comfort
 395 conditions. These results indicate that both cases fail to maintain the desired thermal comfort
 396 levels under the current design and no significant improvements in energy-savings are
 397 achieved by shifting the set-point temperature to 19°C as recommended by the French thermal
 398 regulation standard RT2012. Also, bearing in mind that, in practice, due to the variation of
 399 actual indoor temperature, a 1°C change in the set-point temperature could be insignificant to
 400 allow for much change in energy-savings and occupant thermal comfort. It can be concluded
 401 that these recommendations must be aligned with an improvement in the thermal performance
 402 of building envelope to achieve the desired objectives.

403 These results indicate that both cases fail to maintain the desired thermal comfort
 404 levels under the current design. Besides, the overwhelming majority of the obtained values are
 405 below -0.5, and hence an increase in the set-point temperature may lead to better thermal
 406 comfort conditions. However, this may lead to more heating energy consumption. In addition,
 407 the dispersion of the obtained PMV values can be correlated to the presence of fully glazed
 408 facades, which leads to fluctuations in the radiant temperature under different and extreme
 409 weather conditions. So reducing the area of the glass facades could lead to better thermal
 410 comfort conditions, yet this may lead to an increase in heating energy consumption as it
 411 reduces the solar heat gain. Therefore, both desired objectives compete with each other and a
 412 sensitivity analysis is required to simultaneously optimize both variables.

413 Table 6: Descriptive statistics of obtained PMV values.

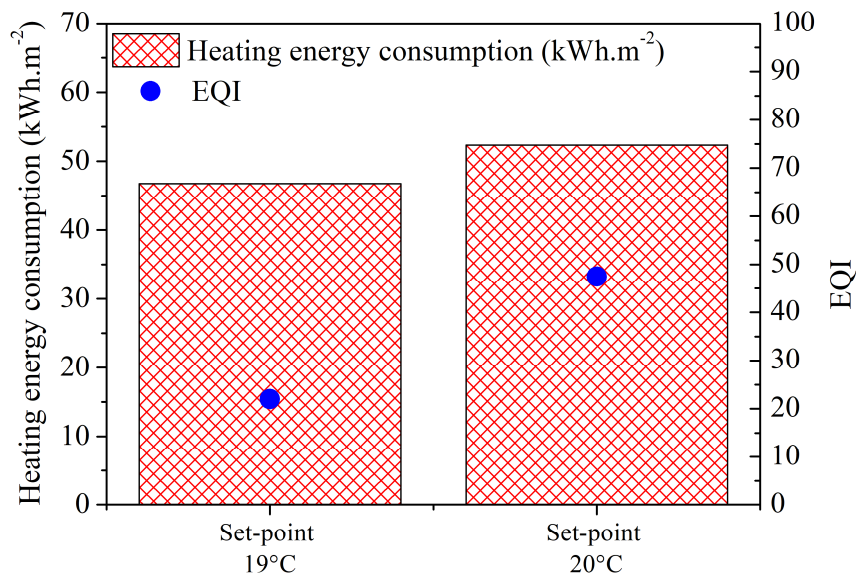
	19°C	20°C
Measure of central tendency		
Mean	-0.53909	-0.35592
Median	-0.75609	-0.54912
Mode	-0.84031	-0.59025

Measure of variability		
Standard deviation	0.477445	0.44433
Standard Error	0.009816	0.009135
Min	-0.90701	-0.70526
Max	1.6325	1.75418



414

415 Figure 8: Box plots of hourly PMV index values. (The quartiles represent the 25%-75%
 416 interval, and the intermediate line the median.)



417

418 Figure 9: Total heating energy consumption and the EQI for the two cases, set-point of 19°C
 419 and 20°C.

420 **4.2. Development of design knowledge using sensitivity analysis**

421 *4.2.1. Response variables and choice of factors and levels*

422 As previously discussed, this study focuses on heating energy consumption and
423 occupants' thermal comfort. The considered response variables are thus the daily heating
424 energy consumption, the average, the maximum, and the minimum PMV values. The reason
425 for choosing a daily bases is to facilitate the integration of outdoor climatic conditions in the
426 sensitivity study, as it will be indicated later.

427 The considered factors for investigations are room temperature, sol-air temperature,
428 WFR, and glazing type. Sol-air temperature is defined as “*the outside air temperature which,
429 in the absence of solar radiation, would give the same temperature distribution and rate of
430 heat transfer through a wall (or roof) as exists due to the combined effects of the actual
431 outdoor temperature distribution plus the incident solar radiation*” [35]. It represents a good
432 demonstration of the weather conditions. The mathematical formulation of the sol-air
433 temperature is presented in [26]. The selection criteria of the considered factors are further
434 explained in [31]. Each factor has two levels, the high level (+1) of the Window-Floor-Ratio
435 (WFR) and glazing type represents the base case study, and the low level (-1) has been
436 selected based on the values recommended by the French and the European standards [12,34].
437 The daily average sol-air temperature was calculated and the minimum and maximum values
438 were chosen to represent the lower and higher levels. Table 7 reports the considered factors
439 and their corresponding codes and levels.

440 Table 7: Investigated factors and their corresponding codes and levels.

Factor	Code	Unit	Level	
			-1	+1
<i>Set-point temperature</i>	<i>A</i>	°C	19	21
<i>Sol-air temperature</i>	<i>B</i>	°C	-2.2	17.2
<i>glazing type (U-value)</i>	<i>C</i>	W.m ⁻² .K ⁻¹	0.7	2.8
<i>(g-value)</i>		-	0.3	0.77
<i>WFR</i>	<i>D</i>	%	16	60

441 *4.2.2. Performing the simulations*

442 In this study, the two-level full factorial design is adopted because few factors are
 443 considered and it considers all the possible combinations of factors. Once the experimental
 444 plan was obtained, the experiments were carried out by running the simulation model for
 445 different combinations of factors levels. The design matrix considering the further tests and
 446 the simulation results of the considered response variables are reported in Table 8. The full
 447 factorial design considering four factors, each at two levels results in 16 runs. Design-Expert®
 448 Software version 11 (Stat-Ease Inc., Minneapolis, MN, USA) was used to analyze the data.

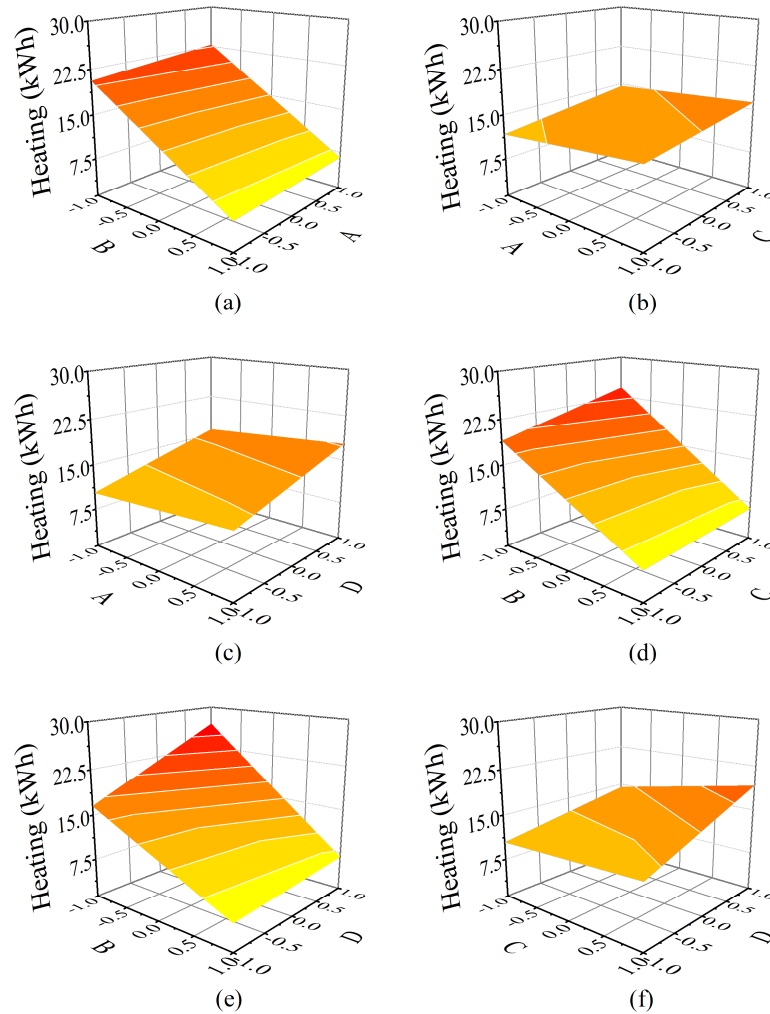
449 *4.2.3. Statistical analysis of the data*

450 It worth noting that the statistical analysis focused only on heating energy
 451 consumption because those related to the PMV are presented and discussed in detail in [31].
 452 The results of the daily heating energy consumption were analyzed with ANOVA and for the
 453 response surface plots. Figure 10 shows the effect of the considered factors on the response
 454 variables using 3D graphs. These graphs are obtained by the combination of the different
 455 design parameters and the resulting daily heating energy consumption.

456 Table 8: Design matrix and the obtained results.

Run order	Standard order	Set-point	sol-air temperature	Glazing type	Glazing Area	Daily heating	PMV _{avg}	PMV _{Min}	PMV _{Max}
1	1	-1	-1	-1	-1	14.80	-1.02	-1.04	-0.99
2	7	-1	1	1	-1	5.00	-0.55	-0.57	-0.51
3	3	-1	1	-1	-1	4.80	-0.66	-1.02	-0.23
4	2	1	-1	-1	-1	16.22	-0.30	-0.76	0.05
5	9	-1	-1	-1	1	21.50	-1.01	-1.05	-0.99
6	13	-1	-1	1	1	29.40	-0.53	-0.55	-0.50
7	15	-1	1	1	1	6.80	-0.78	-1.02	-0.48
8	11	-1	1	-1	1	5.94	-0.37	-0.73	-0.08
9	5	-1	-1	1	-1	16.75	-1.12	-1.20	-1.03
10	6	1	-1	1	-1	18.40	-0.65	-0.72	-0.55
11	10	1	-1	-1	1	23.79	0.24	-1.27	2.03
12	4	1	1	-1	-1	5.91	0.57	-0.98	2.29
13	12	1	1	-1	1	6.46	-1.08	-1.12	-1.03
14	8	1	1	1	-1	5.88	-0.60	-0.64	-0.54

15	16	1	1	1	1	7.67	0.07	-1.12	1.58
16	14	1	-1	1	1	32.98	0.42	-0.80	1.88



457

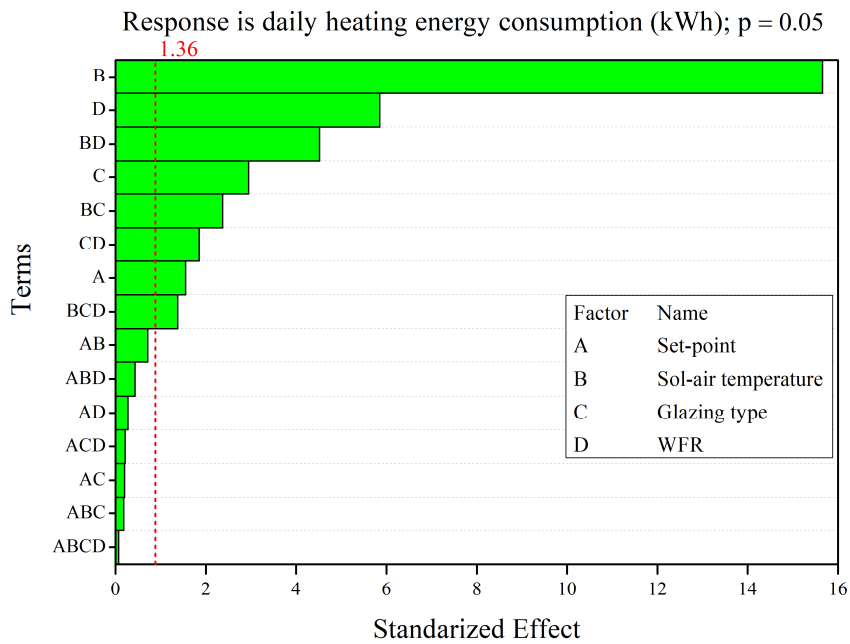
458 Figure 10: 3D response surface interactive effects of varied: (a) sol-air temperature and set-
 459 point temperature, (b) set-point temperature and glazing type, (c) set-point temperature and
 460 glazing area, (d) sol-air temperature and glazing type, (e) sol-air temperature and glazing area,
 461 and (f) glazing type and glazing area, on heating energy consumption.

462

463 Figure 10 (a) and (d) show the interactions between sol-air temperature and set-point
 464 temperature and glazing type, respectively, and it is observed that the lowest heating energy
 465 consumption values are located in the region defined by the higher sol-air temperatures. This
 466 evident observation is correlated to the fact that at higher sol-air temperatures, more heat is
 467 transmitted into the indoor environment of the room. However, the interactions between sol-

468 air temperature and glazing area Figure 10(e) indicates that the heating energy consumption
469 decreases as the glazing area decreases alongside the increase in sol-air temperature. This
470 indicates that the sensitivity of heating energy consumption to outdoor climatic conditions is
471 highly dependent on the glazing area. On the other hand, the interactions between set-point
472 temperature and both glazing type and glazing area, and the interactions between glazing area
473 and glazing type demonstrates that the heating energy consumption values decrease while all
474 the parameters decrease (Figure 10(b), (c) and (f)). This can be correlated to the following: i)
475 decreasing the set-point temperature implies less energy consumption, ii) improving glazing
476 properties implies less heat loss to the external, and iii) less glazing area implies more
477 insulated envelope.

478 Figure 10 demonstrates the behavior of the studied parameters on the daily heating
479 energy consumption; however, it is not possible to understand which interactions were more
480 important. For this purpose, Pareto Charts have been presented and analyzed. The Pareto chart
481 for standardized effects at $p = 0.05$ for the daily heating energy consumption is shown in
482 Figure 11. Each bar represents a factor or an interaction between factors. The effect of a factor
483 or interaction between factors is significant if its corresponding bar exceeds the vertical
484 dashed line. This means that the response variable is influenced by the factor or interaction at
485 a minimum statistically significant level of 95% confidence. The results reported in Figure 11
486 designate that the most significant factors influencing the energy consumption are (in
487 descending order): Sol-air temperature (B), Glazing area (D), the interaction between Sol-air
488 temperature and Glazing area (BD), Glazing type (C), interaction between Sol-air temperature
489 and glazing type (BC), interaction between glazing type and glazing area (CD), and set-point
490 temperature (A).



491

492

Figure 11: Pareto chart of the standardized effects.

493

The Pareto chart helps in determining the significant factors and interactions.

494

However, the normal probability plot is important to complement the analysis. It assists in

495

determining if the significant effects have a negative, positioned to the left, or positive,

496

positioned to the right of the fit line, impact on the response variable. The fit line identifies the

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expected values if the factor does not affect the response variable. Figure 12 illustrates the

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normal probability plot of standardized effects at $p=0.05$ for the daily heating energy

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consumption. Sol-air temperature (B) and the interactions between sol-air temperature and

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glazing area (BD) and glazing type (BC) are the factors having a negative influence on the

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daily heating energy consumption, which means that an increase in their levels leads to a

502

decrease in the heating energy consumption. On the other hand, the factors with positive

503

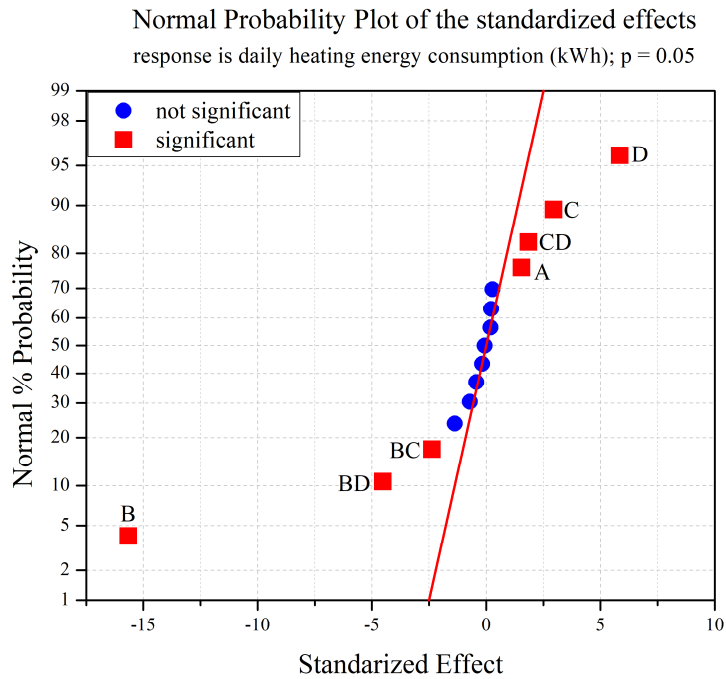
influence on the considered response variable are, in descending order, glazing area, glazing

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type, interaction between glazing area and glazing type, and set-point temperature, which

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means that the response variables increase with increasing level.



506

507

Figure 12: Normal probability plot of the standardized effects.

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4.2.4. ANOVA and Development of meta-models

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The Analysis of Variance (ANOVA) approach is used to identify the significant factors. The results of ANOVA reported in Table 9 indicate that the obtained model is significant ($p\text{-value} < 0.05$). The non-significant factors ($p\text{-value} > 0.05$) could be eliminated in the aim to simplify the obtained meta-models. The ANOVA results showed good performance with $R^2 (> 0.99)$ and adjusted $R^2 (0.98)$, the residuals versus fit values plots demonstrates less patterned structure (Figure 13), and the normal probability plot of residuals illustrated in Figure 14 show that the residuals followed a straight line. This indicates that the obtained meta-model is appropriate, and can be used to predict the set of design parameters that lead to the desired objective.

Table 9: ANOVA results for daily heating energy consumption.

Source	DF	Seq SS	Adj SS	Adj MS	F-Value	P-Value
Model	14	1290.82	1290.82	92.201	4779.13	0.011
Linear	4	1161.84	1161.84	290.459	15055.54	0.006
A	1	9.64	9.64	9.637	499.53	0.028
B	1	980.69	980.69	980.687	50832.49	0.003
C	1	34.71	34.71	34.711	1799.17	0.015
D	1	136.8	136.8	136.803	7090.97	0.008
2-Way Interactions	6	120.41	120.41	20.068	1040.19	0.024
A*B	1	2.03	2.03	2.025	104.98	0.062
A*C	1	0.16	0.16	0.156	8.07	0.215
A*D	1	0.3	0.3	0.3	15.57	0.158
B*C	1	22.51	22.51	22.509	1166.71	0.019
B*D	1	81.68	81.68	81.681	4233.8	0.01
C*D	1	13.74	13.74	13.737	712.02	0.024
3-Way Interactions	4	8.58	8.58	2.144	111.13	0.071
A*B*C	1	0.13	0.13	0.129	6.68	0.235
A*B*D	1	0.75	0.75	0.75	38.87	0.101
A*C*D	1	0.18	0.18	0.178	9.21	0.203
B*C*D	1	7.52	7.52	7.52	389.77	0.032
Error	1	0.02	0.02	0.019		
Total	15	1290.84				

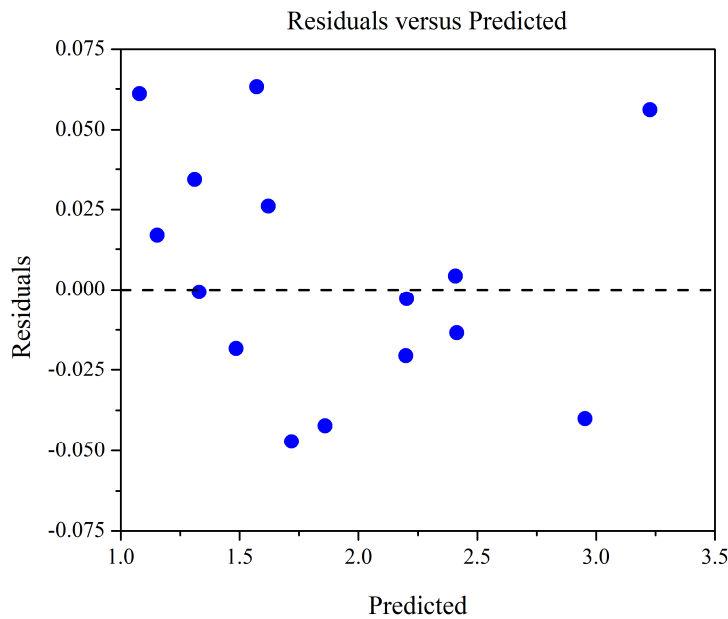
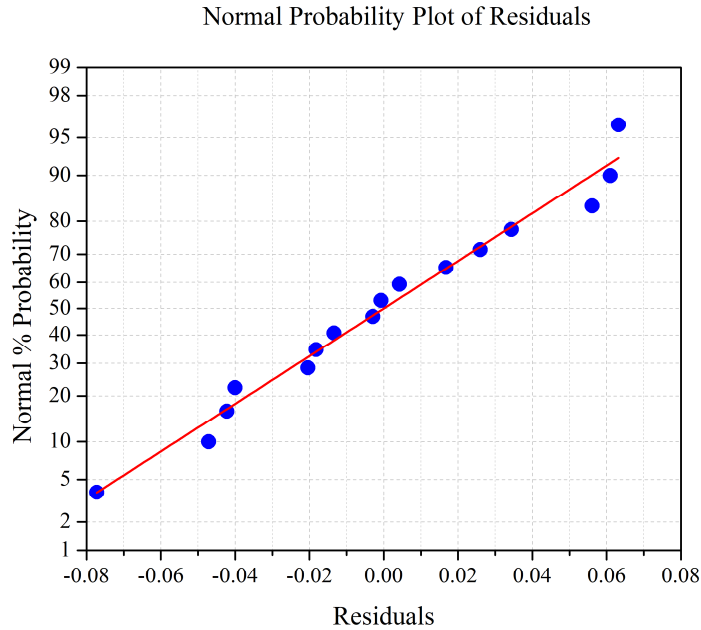


Figure 13 : Residuals versus fitted values for daily heating energy consumption.



522

523 Figure 14 : Normal probability plot of residuals for daily heating energy consumption.

524 *4.2.5. Determination and analysis of optimal solutions*

525 Finally, and after developing and validating the meta-models, an optimization process
 526 is needed to identify the values of the considered design-parameters to achieve the desired
 527 objectives. The optimization process considers three different scenarios:

- 528 • First scenario (S1): Optimizing building design for energy-savings. In this case, the
 529 obtained meta-model is used to minimize the daily heating energy consumption.
- 530 • Second scenario (S2): Optimizing building design for both thermal comfort and
 531 energy-savings. Here, the obtained meta-model and the meta-models of PMV values,
 532 developed in [31], are used to achieve a building optimized design for a trade-off
 533 between heating energy consumption and thermal comfort.
- 534 • Third Scenario (S3): Optimizing building design for thermal comfort. This scenario
 535 represents the one demonstrated in [31], where the authors optimized the design for
 536 thermal comfort without considering the heating energy consumption.

537

538 The range of variation of the factors is the same as indicated in Table 7. In the first
539 scenario (S1) the numerical optimizations indicated that the maximum GDF value is provided
540 when the set-point temperature is 19°C, the glazing type is triple low-e (u-value = 0.7, g-value
541 = 0.3), and the WFR is 16%. The optimization results suggest that using this combination of
542 parameters will outcome an average daily heating energy consumption of 8.705 kWh and an
543 average, minimum, and maximum PMV values of -0.808, -1.044, and -0.518, respectively.

544 In the second scenario, the numerical optimizations indicated that the maximum GDF
545 value is provided when the set-point temperature is 21°C, the glazing type is triple low-e (u-
546 value = 0.7, g-value = 0.3), and the WFR is 16%. The optimization results suggest that using
547 this combination of parameters will outcome an average daily heating energy consumption of
548 10.170 kWh and an average, minimum, and maximum PMV values of -0.404, -0.5, and -
549 0.086, respectively.

550 After determining the combination of parameters for each proposed scenario, a
551 comparative study is performed. The comparative study considers the hourly PMV values,
552 EQI, and heating energy consumption throughout the whole winter season. The measure of
553 central tendency and dispersion of the obtained hourly PMV values for all the considered
554 scenarios are reported in Table 10. The results show that the distribution, the central values,
555 and the variability of the PMV values for both S2 and S3 lies within the recommended
556 acceptable thermal comfort levels, but not those of S1. An important inference that can be
557 noticed is the low values of the standard deviations for the three scenarios (S1, S2, and S3),
558 which implies less dispersion of the obtained PMV values.

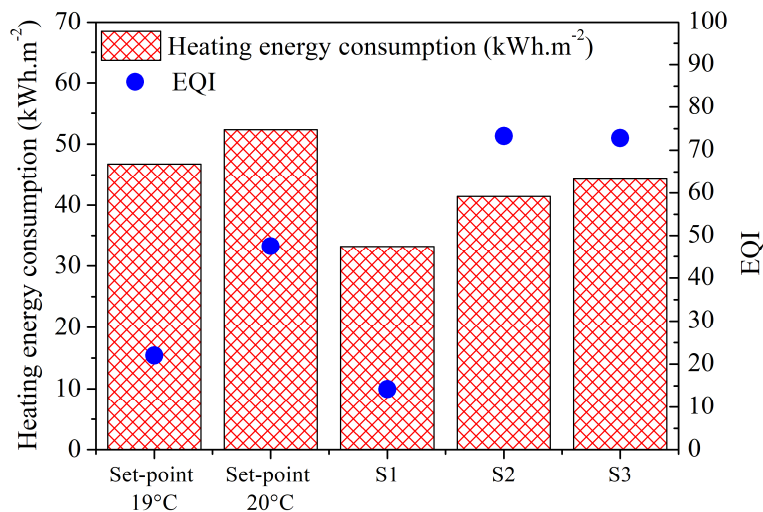
559 On the other hand, the heating energy consumption is the lowest for S1 compared to all other
560 scenarios, however, the EQI is very low and lies below the recommended acceptable range
561 (Figure 15). These results indicate that optimizing for heating energy consumption alone is
562 not enough to ensure acceptable thermal comfort conditions. Further, comparing S2 and S3

563 indicates that a simultaneous optimization, here S2, is the best scenario. Considering both
 564 parameters allows for energy-saving, as well as maintaining acceptable thermal comfort
 565 conditions.

566 Table 10: Descriptive statistics of obtained PMV values.

	19°C	20°C	S1	S2	S3
Measure of central tendency					
Mean	-0.53909	-0.35592	-0.69191	-0.26796	-0.28435
Median	-0.75609	-0.54912	-0.72082	-0.28677	-0.30586
Mode	-0.84031	-0.59025	-0.74445	-0.30502	-0.31499
Measure of variability					
Standard deviation	0.477445	0.44433	0.083469	0.059749	0.068324
Standard Error	0.009816	0.009135	0.001716	0.001228	0.001405
Min	-0.90701	-0.70526	-0.78578	-0.37774	-0.40989
Max	1.6325	1.75418	-0.2079	0.08962	0.12456

567
 568 Furthermore, although the optimized case allows an increase in the set-point
 569 temperature, it results in reducing the heating energy consumption (S2 compared to the cases
 570 of set-point temperature of 19°C and 20°C). This can be correlated to the optimized design of
 571 the glazed envelope, which leads to enhanced thermal resistance by reducing the glazing area.
 572 This results in reducing the transmission heat loss under low outdoor temperatures, and as a
 573 consequence reduced heating energy consumption.



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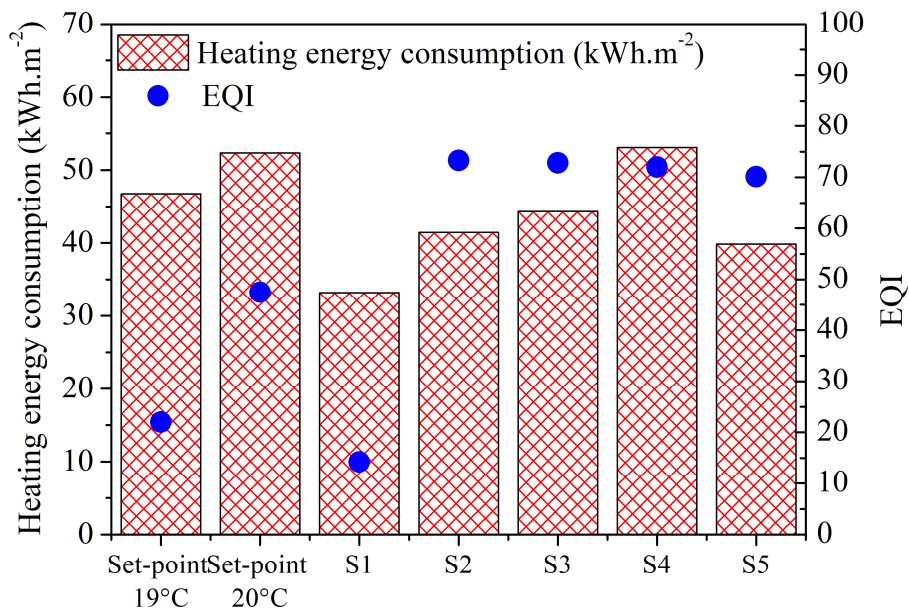
575 Figure 15: Total heating energy consumption and the EQI for the five simulated scenarios.

576 **4.3. Comparison with thermal comfort based control**

577 After identifying the best scenario to simultaneously optimize both energy-saving and
578 thermal comfort, it is important to compare with another approach to highlight the added
579 value of the proposed approach. In this consequence, a comparative study with two other
580 scenarios is performed. The fourth and fifth considered scenarios are:

- 581 • Fourth Scenario (S4): Using a PMV-based thermal comfort control without
582 altering the current design.
- 583 • Fifth Scenario (S5): Using a PMV-based thermal control in the case of
584 optimized design.

585 The EQI index and total heating energy consumption are shown in Figure 16. The
586 obtained results show that the optimized thermostatic cases, S2 and S3, allowed about 22%
587 and 16.5%, respectively, reduction of heating energy consumption compared to the comfort
588 controlled case (S4), and consumed about 4% and 11% more than that of S5. In addition,
589 scenarios S1 to S4 offered equivalent thermal comfort levels, almost equal EQI values, and
590 better than all the studied cases using the base design. These results indicate that i) thermal
591 comfort control is a reasonable solution to neutralize the trade-off between thermal comfort
592 and energy savings under poorly designed building, ii) integrating occupants thermal comfort
593 in the design process leads to an optimized design for both thermal comfort and energy
594 consumption, and iii) by considering S2 and S5, one can observe that it could be possible to
595 suppress the need for an advanced control strategy, which could require additional devices
596 installations to keep continuous monitoring of the indoor environment, thus leading to
597 additional installation and functional costs.



598

599 Figure 16: Total heating energy consumption and EQI for the considered scenarios in this
 600 study.

601 5. Conclusion

602 In this paper, we proposed that integrating occupants' thermal comfort in the design of
 603 energy-efficient buildings leads to a trade-off between energy-savings and thermal comfort.
 604 This act alongside the shift towards designing and constructing energy-efficient buildings,
 605 which leads to further requirements of performance and sustainability, causes the design
 606 process of buildings to be more complex. Adopting a method that is capable of, firstly
 607 integrating occupants' thermal comfort simply and efficiently, and secondly providing
 608 accurate predictions, is thus an essential need for building designers.

609 For this reason, a method for integrating occupant thermal comfort in the design process
 610 was proposed. The method, comprising six main steps, was evaluated by applying it in the
 611 design of a reference case study, particularly a highly glazed room, to investigate the impact
 612 of integrating occupant thermal comfort in the design of energy-efficient buildings. A

613 previously developed numerical model was utilized. The DoE technique was then used to
614 perform sensitivity analysis and to develop meta-models that approximate the response
615 variables as a function of design parameters. Using the desirability function approach the
616 meta-models were then used in the optimization process of building design. The results
617 indicated that integrating occupants' thermal comfort in the design of energy-efficient
618 buildings leads to optimized building design for both thermal comfort and heating energy
619 consumption.

620 A comparative study between the proposed approach and a comfort controlled
621 approach was then performed. The results indicate that in the case of extensive glazing areas,
622 before optimizing building design, PMV-based thermal comfort-control is a reasonable
623 solution to neutralize the trade-off between thermal comfort and energy-savings. However,
624 the results show that optimizing building design using the proposed method could lead to
625 suppress the need for an advanced control strategy, which could require additional device
626 installations to keep continuous monitoring of the indoor environment, thus leading to
627 additional installation and functional costs.

628 Finally, developing a tool that allows the combined use of dynamic simulation, DoE
629 and desirability function approach would make the application of the proposed method very
630 useful for designers and decision-makers of building construction projects.

631 **Acknowledgment**

632 This work was supported by the Grand Est region, France, and the European Regional
633 Development Fund.

634 **References**

- 635 [1] F. Amirifard, S.A. Sharif, F. Nasiri, Application of passive measures for energy
636 conservation in buildings – a review, *Adv. Build. Energy Res.* 13 (2019) 282–315.

- 637 doi:10.1080/17512549.2018.1488617.
- 638 [2] D. Ürge-Vorsatz, L.F. Cabeza, S. Serrano, C. Barreneche, K. Petrichenko, Heating and
639 cooling energy trends and drivers in buildings, *Renew. Sustain. Energy Rev.* 41 (2015)
640 85–98. doi:10.1016/j.rser.2014.08.039.
- 641 [3] L. De Boeck, S. Verbeke, A. Audenaert, L. De Mesmaeker, Improving the energy
642 performance of residential buildings: A literature review, *Renew. Sustain. Energy Rev.*
643 52 (2015) 960–975. doi:10.1016/j.rser.2015.07.037.
- 644 [4] A.J. Marszal, P. Heiselberg, J.S. Bourrelle, E. Musall, K. Voss, I. Sartori, A.
645 Napolitano, Zero Energy Building – A review of definitions and calculation
646 methodologies, *Energy Build.* 43 (2011) 971–979.
647 doi:10.1016/J.ENBUILD.2010.12.022.
- 648 [5] J. Williams, R. Mitchell, V. Raicic, M. Vellei, G. Mustard, A. Wismayer, X. Yin, S.
649 Davey, M. Shakil, Y. Yang, A. Parkin, D. Coley, Less is more: A review of low energy
650 standards and the urgent need for an international universal zero energy standard, *J.*
651 *Build. Eng.* 6 (2016) 65–74. doi:10.1016/j.jobbe.2016.02.007.
- 652 [6] M.C. Katafygiotou, D.K. Serghides, Thermal comfort of a typical secondary school
653 building in Cyprus, *Sustain. Cities Soc.* 13 (2014) 303–312.
654 doi:10.1016/j.scs.2014.03.004.
- 655 [7] ANSI/ASHRAE, Thermal Environmental Conditions for Human Occupancy Standard
656 55-2013, Ashrae. (2013). doi:ISSN 1041-2336.
- 657 [8] D. Enescu, A review of thermal comfort models and indicators for indoor
658 environments, *Renew. Sustain. Energy Rev.* 79 (2017) 1353–1379.
659 doi:10.1016/j.rser.2017.05.175.
- 660 [9] ISO, ISO 7730: Ergonomics of the thermal environment Analytical determination and
661 interpretation of thermal comfort using calculation of the PMV and PPD indices and

- 662 local thermal comfort criteria, *Management*. 3 (2005) 605–615.
663 doi:10.1016/j.soildyn.2004.11.005.
- 664 [10] ASHRAE, Thermal environmental conditions for human occupancy, *ASHRAE Stand.*
665 (2010) 1–44. doi:1041-2336.
- 666 [11] J. Van Hoof, Forty years of Fanger’s model of thermal comfort: Comfort for all?,
667 *Indoor Air*. 18 (2008) 182–201. doi:10.1111/j.1600-0668.2007.00516.x.
- 668 [12] MEDDE, Réglementation thermique 2012 : un saut énergétique pour les bâtiments
669 neufs, 2011.
- 670 [13] M.W. Ahmad, M. Mourshed, B. Yuce, Y. Rezgui, Computational intelligence
671 techniques for HVAC systems: A review, *Build. Simul.* 9 (2016) 359–398.
672 doi:10.1007/s12273-016-0285-4.
- 673 [14] Jian Liang, Ruxu Du, Thermal comfort control based on neural network for HVAC
674 application, in: *Proc. 2005 IEEE Conf. Control Appl. 2005. CCA 2005.*, IEEE, 2005:
675 pp. 819–824. doi:10.1109/CCA.2005.1507230.
- 676 [15] P.M. Ferreira, A.E. Ruano, S. Silva, E.Z.E. Conceição, Neural networks based
677 predictive control for thermal comfort and energy savings in public buildings, *Energy*
678 *Build.* 55 (2012) 238–251. doi:10.1016/j.enbuild.2012.08.002.
- 679 [16] M. Castilla, J.D. Álvarez, M.G. Ortega, M.R. Arahál, Neural network and polynomial
680 approximated thermal comfort models for HVAC systems, *Build. Environ.* 59 (2013)
681 107–115. doi:10.1016/j.buildenv.2012.08.012.
- 682 [17] S. Hussain, H.A. Gabbar, D. Bondarenko, F. Musharavati, S. Pokharel, Comfort-based
683 fuzzy control optimization for energy conservation in HVAC systems, *Control Eng.*
684 *Pract.* 32 (2014) 172–182. doi:10.1016/j.conengprac.2014.08.007.
- 685 [18] A. Garnier, J. Eynard, M. Caussanel, S. Grieu, Predictive control of multizone heating,
686 ventilation and air-conditioning systems in non-residential buildings, *Appl. Soft*

- 687 Comput. 37 (2015) 847–862. doi:10.1016/j.asoc.2015.09.022.
- 688 [19] A. Ruano, S. Pesteh, S. Silva, H. Duarte, G. Mestre, P.M. Ferreira, H. Khosravani, R.
689 Horta, PVM-based intelligent predictive control of HVAC systems, IFAC-
690 PapersOnLine. 49 (2016) 371–376. doi:10.1016/j.ifacol.2016.07.141.
- 691 [20] Z. Xu, G. Hu, C.J. Spanos, S. Schiavon, PMV-based event-triggered mechanism for
692 building energy management under uncertainties, Energy Build. 152 (2017) 73–85.
693 doi:10.1016/j.enbuild.2017.07.008.
- 694 [21] Y.R. Yoon, H.J. Moon, Performance based thermal comfort control (PTCC) using deep
695 reinforcement learning for space cooling, Energy Build. 203 (2019) 109420.
696 doi:10.1016/j.enbuild.2019.109420.
- 697 [22] J. Ngarambe, G.Y. Yun, M. Santamouris, The use of artificial intelligence (AI)
698 methods in the prediction of thermal comfort in buildings: energy implications of AI-
699 based thermal comfort controls, Energy Build. 211 (2020) 109807.
700 doi:10.1016/j.enbuild.2020.109807.
- 701 [23] R.L. Hwang, S.Y. Shu, Building envelope regulations on thermal comfort in glass
702 facade buildings and energy-saving potential for PMV-based comfort control, Build.
703 Environ. 46 (2011) 824–834. doi:10.1016/j.buildenv.2010.10.009.
- 704 [24] A. Merabtine, C. Maalouf, A.A.W. Hawila, N. Martaj, G. Polidori, Building energy
705 audit, thermal comfort, and IAQ assessment of a school building: A case study, Build.
706 Environ. 145 (2018) 62–76. doi:10.1016/j.buildenv.2018.09.015.
- 707 [25] A.A.W. Hawila, A. Merabtine, N. Troussier, Numerical and experimental investigation
708 on the thermal behaviour of the building integrating occupant thermal comfort,
709 MATEC Web Conf. 307 (2020) 6. doi:10.1051/mateconf/202030701025.
- 710 [26] A.A.W. Hawila, A. Merabtine, M. Chemkhi, R. Bennacer, N. Troussier, An analysis of
711 the impact of PMV-based thermal comfort control during heating period: A case study

- 712 of highly glazed room, *J. Build. Eng.* 20 (2018) 353–366.
713 doi:10.1016/j.jobe.2018.08.010.
- 714 [27] H.X. Zhao, F. Magoulès, A review on the prediction of building energy consumption,
715 *Renew. Sustain. Energy Rev.* 16 (2012) 3586–3592. doi:10.1016/j.rser.2012.02.049.
- 716 [28] ANSI/ASHRAE, Measurement of Energy and Demand Savings, in: *ASHRAE Guidel.*
717 14-2002, 2002. doi:10.1016/j.nima.2012.12.050.
- 718 [29] W. Tian, A review of sensitivity analysis methods in building energy analysis, *Renew.*
719 *Sustain. Energy Rev.* 20 (2013) 411–419. doi:10.1016/j.rser.2012.12.014.
- 720 [30] J.A. Nelder, R. Mead, A Simplex Method for Function Minimization, *Comput. J.* 7
721 (1965) 308–313. doi:10.1093/comjnl/7.4.308.
- 722 [31] A.A.-W. Hawila, A. Merabtine, N. Troussier, R. Bennacer, Combined use of dynamic
723 building simulation and metamodeling to optimize glass facades for thermal comfort,
724 *Build. Environ.* 157 (2019) 47–63. doi:10.1016/j.buildenv.2019.04.027.
- 725 [32] T. Sekki, M. Airaksinen, A. Saari, Measured energy consumption of educational
726 buildings in a Finnish city, *Energy Build.* 87 (2015) 105–115.
727 doi:10.1016/j.enbuild.2014.11.032.
- 728 [33] C. Marino, A. Nucara, M. Pietrafesa, Proposal of comfort classification indexes
729 suitable for both single environments and whole buildings, *Build. Environ.* 57 (2012)
730 58–67. doi:10.1016/j.buildenv.2012.04.012.
- 731 [34] Cen, EN 15251: Indoor environmental input parameters for design and assessment of
732 energy performance of buildings- addressing indoor air quality, thermal environment,
733 lighting and acoustics, *Eur. Comm. Stand.* 3 (2007) 1–52. doi:10.1520/E2019-
734 03R13.Copyright.
- 735 [35] P.W. O’Callaghan, S.D. Probert, Sol-air temperature, *Appl. Energy.* 3 (1977) 307–311.
736 doi:10.1016/0306-2619(77)90017-4.

Graphical abstract

