

Combined use of dynamic building simulation and metamodeling to optimize glass facades for thermal comfort

Abed Al-Waheed Hawila, Abdelatif Merabtine, Nadège Troussier, Rachid Bennacer

▶ To cite this version:

Abed Al-Waheed Hawila, Abdelatif Merabtine, Nadège Troussier, Rachid Bennacer. Combined use of dynamic building simulation and metamodeling to optimize glass facades for thermal comfort. Building and Environment, 2019, 157, pp.47-63. 10.1016/j.buildenv.2019.04.027. hal-02270883

HAL Id: hal-02270883 https://utt.hal.science/hal-02270883

Submitted on 22 Oct 2021

HAL is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers. L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.



Distributed under a Creative Commons Attribution - NonCommercial 4.0 International License

Version of Record: https://www.sciencedirect.com/science/article/pii/S0360132319302719 Manuscript_32c7701a12cba5289c68983982721b66

1 Combined use of dynamic building simulation and metamodeling

2 to optimize glass facades for thermal comfort

- 3 Abed Al-Waheed Hawila^{1,*}, Abdelatif Merabtine^{1, 2, 3}, Nadège Troussier¹,
- 4 Rachid Bennacer^{4, 5, 6}
- 5 ¹ICD-CREIDD, STMR CNRS 6281, University of Technology of Troyes, 12 rue Marie Curie,
- 6 CS 42060, 10004, Troyes Cedex, France
- 7 ²EPF School of Engineering, 2 rue Fernand Sastre, 10430, Rosières-Prés-Troyes, France
- 8 ³Laboratory of Thermo-mechanics, GRESPI, SFR Condorcet FR CNRS 341, Université de
- 9 Reims Champagne-Ardenne, Campus Moulin de la Housse, 51687 Reims Cedex, France
- 10 ⁴ENS-Cachan, LMT, CNRS, Université Paris Saclay, 61 Avenue du Président Wilson, 94235,
- 11 France
- ⁵*Tianjin Key Lab of Refrigeration, Tianjin University of Commerce, 300134, P.R.C.*
- 13 ⁶ECAM EPMI, 13 Boulevard de l'Hautil, 95000 Cergy, France
- 14 * Corresponding author. E-mail address: abed_al_waheed.hawila@utt.fr; Phone number: +33
- 15 (0) 6 01432838
- 16
- 17 **Declarations of interest: none**
- 18
- 19
- 20

21 Combined use of dynamic building simulation and metamodeling

22 to optimize glass facades for thermal comfort

23 Abstract

24 The primary objective of buildings must be to provide a comfortable environment for people. 25 Recently, glass facades have gained popularity due to their aesthetic appearance. However, Low 26 performance facades often allow substantial heat exchange between the indoor and outdoor 27 environment that increases building energy consumption and rapid change in indoor thermal 28 environment near the glass facade. Thus, adequate design of building envelope, namely glass facades, 29 is essential to ensure a trade-off between several aspects, such as aesthetic appearance of the building, 30 occupants' thermal and visual comfort and energy consumption. The main purpose of this study is to 31 quantify the interactions and optimize building design, particularly glass facades, for thermal comfort 32 based on the combined use of numerical simulations, Design of Experiments (DoE) technique and an 33 optimization method. The proposed approach is applied to a real case study, characterized by two glass 34 facades, after subjectively assessing thermal comfort using survey questionnaire. For the analysis, a 35 previously developed and validated dynamic simulation model is used. The combined use of 36 numerical simulations and DoE aims to determine the critical parameters affecting thermal comfort, 37 and to develop meta-modeling relationships between design factors and response variables. The 38 developed meta-models are then used to determine a set of optimal solutions by performing a 39 simultaneous optimization of building design based on the desirability function approach. The results 40 indicate that the optimized design improve thermal comfort conditions as well as energy-savings. 41 Finally, the results show the added value of the proposed methodology towards enhanced thermal 42 comfort conditions.

Keywords: PMV, design of experiments, meta-models, sensitivity analysis, numerical
 simulations, desirability function

45 Nomenclature

46	CI	Clothing Insulation
47	D	Global desirability function
48	IQR	Inter Quartile Range
49	MR	Metabolic Rate
50	MRT	Mean Radiant Temperature
51	PMV	Predicted Mean Vote
52	PPD	Percentage of Persons Dissatisfied
53	Q	Quartile
54	SHGC	Solar Heat Gain Coefficient
55	TS	Thermal Sensation

56	TSV	Thermal Sensation Vote
57	WFR	Window-Floor-Ratio
58	WWR	Window-Wall-Ratio
59	C_i	Regression coefficients
60		•
60	d_i	Individual desirability function
61	e_i	Residual
62	r_i	Weighting parameter
63	<i>R</i> ²	Coefficient of determination
64	X _i	Independent coded factor
65	\mathcal{Y}_i	Actual observation
66	\hat{y}_i	Fitted value
67	Y _i	Predicted response variable
68	ε	Random error term

69 1. Introduction

70 Over the last decade, the buildings sector was responsible for 40% of the European 71 Union (EU28) final energy consumption in front of transport (33.2%) and industry (25%) [1]. 72 This concern has led the Energy Performance of Buildings Directive (EBPD) to state that the 73 energy efficiency of existing buildings must be improved, and all new buildings must be close 74 to zero energy in 2020 [2]. However, the primary objective of buildings must be to provide a 75 comfortable environment for the people, since they spend 80-90% of the day indoors [3]. 76 Additionally, inappropriate indoor thermal comfort leads to lower work efficiency, higher 77 possibility of personnel errors, and indirect effect on the energy consumption of the buildings [4]. Therefore, it is necessary to design low energy buildings in order to fulfil a trade-off 78 79 between energy-saving and occupants' thermal comfort [5]. Thermal comfort is defined as

80 "that condition of mind which expresses satisfaction with the thermal environment"[6,7].
81 Among all the standard thermal comfort indices [8], Fanger's [9] Predicted Mean Vote
82 (PMV) and Percentage of Persons Dissatisfied (PPD) are the most applicable indices that can
83 be used to evaluate the thermal comfort within an air conditioned space and to quantify its
84 value [10].

85 In recent years, glass facades and extensive glazing areas are becoming more popular for office, public and educational buildings due to their aesthetic appearance as well as 86 87 because of users' requirement of higher light transmittance and better view [11]. However, 88 poorly designed glass facades vastly affect occupants' thermal comfort, because of the large 89 hot surfaces resulting from dissipated solar radiation [12]. For instance, a high intensity of 90 solar radiation leads to an increase in the interior surface temperature of the glass facade, 91 which leads to an increase in the mean radiant temperature (MRT) and ultimately affecting 92 occupants' thermal comfort [13].

93 Numerous studies have been conducted to investigate the influence of glass facade 94 design on building energy consumption [14–18], thermal comfort [19–22] and visual comfort 95 [18,22–26]. The vastly investigated parameters are Window-Wall-Ratio (WWR), glazing 96 properties (U-value, solar heat gain coefficient (SHGC) and visible transmittance), and 97 shading device. Thalfeldt et al. [14] investigated several facade designs in nearly zero energy 98 building; the study indicated that the performance improved significantly when improving the 99 thermal properties of the window. Poirazis et al. [15] carried out building energy simulations 100 for extensive amount of scenarios combining different glazing types and shading solutions for 101 an office building with fully glazed facades, the study concluded that the buildings with fully 102 glazed facades are likely to have higher energy consumption than those with conventional 103 facades. Jin and overend [16] carried out a comparative study on 13 glazing types on the 104 facade of a typical cellular office, the study indicated that high-performance glazing

105 technologies, such as photovoltaic integrated glazing, offer significant improvements over 106 opaque insulated walls and conventional insulated glazing windows, even for extensive 107 glazed envelope, in terms of both energy consumption and indoor environmental quality. Lee 108 et al. [17] investigated the effect of window systems on the energy consumption of buildings 109 in five typical Asian climates using regression analysis; the main finding of the investigation 110 is that the WWR must be minimized except for the north facing opaque wall, and the 111 placement of window depends hugely on the climatic conditions. Cheong et al. [26] 112 performed comparative simulation study to evaluate the effect of glazing system type on both 113 thermal comfort and daylighting in a highly glazed residential building. The study indicated 114 that improving the glazing type reduces the cooling load and electricity cost. Stavrakakis *et al.* 115 [21] presented a novel computational method to optimize window design for thermal comfort 116 in naturally ventilated buildings. They found that as one of the openings' height increases, 117 thermal sensation is improved. Zomorodian and Tahsildoost [22] assessed the effect of 118 window design on thermal and visual comfort using dynamic simulations in an educational 119 building. The results of the study suggested that solar-control coated glazing with low SHGC 120 and high visual transmission could be an alternative solution to solar shadings. Tzempelikos 121 et al. [19] investigated the effect of changing glazing type and shading device on indoor 122 thermal comfort and energy consumption in an office building with extensive glazing area. 123 The study concluded that both thermal resistance and solar transmittance have a huge effect 124 on thermal comfort.

The overwhelming majority of the aforementioned studies were performed using building simulation tools, since on one hand, the performed investigations require extensive amount of scenarios to outcome robust results and experimentation could be extensive and time consuming, and on the other hand, building simulation tools have been recognized as a broadly approved method for assessing indoor air quality and energy consumption [27–29].

130 In addition, parametric studies have been used to investigate the proposed scenarios. 131 Although parametric studies provide solid outcomes regarding the influential parameters 132 affecting the studied response, it is of limited accuracy in terms of achieving optimal solutions 133 because it is not continuous and it is hard to identify the interactions between parameters 134 unless a huge number of simulations are performed. In order to overcome this limitation, the 135 numerical results could be used to form a database allocated for meta-modeling process 136 [21,30]. Mathematical meta-models can convert the discretized domain into a continuous one, 137 thus serving as a practical tool, which improves the accuracy of the near-optimal solution 138 without the need of excessive computational power [21]. In recent years, Design of 139 Experiments (DoE) technique has been used with success in the building domain to develop 140 meta-modeling relationships between design factors and response variables [30,31]. Static 141 indoor air temperature was assumed in these studies, even though thermal comfort is more 142 than just an air temperature [32]. To the authors' best knowledge, no previous study deals 143 with the coupling of numerical simulation, DoE and optimization approach to predict thermal 144 comfort as a function of glass facade configuration and other environmental parameters in 145 order to optimize glass facades design for thermal comfort.

146 In this consequence, the objective of this study is to optimize building design, 147 particularly glass facades, for thermal comfort based on the combined use of numerical 148 simulations, DoE technique and desirability function approach. A single room representing a 149 part of an academic low energy building is selected for the investigations. Additionally, a 150 previously developed and validated dynamic simulation model is used for the analysis 151 [13,33]. Afterwards, the DoE is employed for several objectives. At first, it helps analyze the 152 sensitivity of the PMV index to different parameters. In addition, it allows developing meta-153 modeling relationship between the PMV index and the investigated parameters. Finally, the

developed meta-models are validated using several approaches and then utilized to optimizeglass facades design for thermal comfort.

156 **2. Case Study**

157 The considered case study is a highly glazed room, called the foyer, which includes 158 café and seating space. It is a communal place of life in which students meet to eat, rest, and 159 do activities. It is situated in the south-eastern part of the ground floor of a low energy 160 consumption building located in Troyes, France, and designed to meet the French standard requirement RT2012 (Figure 1). The Foyer has a floor area of 58m² and south- and east-161 162 oriented glass facades. It is heated by radiators and a dual-flow ventilation system that 163 contains three Air Handler Units integrating heating coils to enable heating and ventilation. 164 Dimensions as well as the physical parameters of the Foyer are summarized in Table 1.

165 Students occupying the Foyer reported a significant difference in temperature from 166 that in other parts of the building and indicated dissatisfaction in the thermal conditions. In 167 order to confirm this allegation, subjective thermal comfort was assessed using survey 168 questionnaire by asking the students to express their thermal sensation, preference and 169 satisfaction. Thermal sensation vote (TSV) was evaluated using the ISO seven-level scale 170 [6,34]. Thermal preference was assessed using a seven-point scale: 'a lot more cooler', 'more 171 cooler', 'a bit more cooler', 'no change', 'a bit more warmer', 'more warmer' and 'a lot more 172 warmer'. Thermal satisfaction was evaluated using two levels: 'satisfied' and 'dissatisfied'. In 173 addition, students' activity level was determined using a five-point scale: 'seated quiet', 174 'standing relaxed', 'light activity', 'medium activity' and 'high activity'. The survey 175 questionnaire, entitled "Current Thermal comfort in the Foyer", was constructed using the 176 surveyplant website [35]. In total, 54 questionnaires were collected and analyzed from students between the ages of 17-22 during December 2016 (From 1st until 12th). It is worth 177

- 178 noting that the building was occupied by 281 students and staff members in 2016 [33]. Thus,
- 179 the collected questionnaires represent a sample of 90% confidence interval and 10% margin
- 180 of error.
- 181



- 183 Figure 1: Engineering school building overview (a), ground floor map (b) and the Foyer (c).
- 184 Table 1 : 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 = 0.4 W .m ⁻² .K ⁻¹
Internal wall	U-value = 4.1 W .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

185 **3. Methodology**

186 **3.1. Design of Experiments**

187 An Experiment is defined as test in which purposeful changes are made to the input 188 parameters of a system/process so that the experimenter may observe and identify the reasons 189 for changes in the response variable [36]. Poorly designed experiments can often lead to 190 ineffective use of valuable resources and inconclusive results. Hence, experiments should be 191 well-designed. One-factor-at-a-time is a popular approach, in which the influence of the tested 192 parameters is measured by changing the level of one parameter while maintaining other 193 parameters at their levels [37]. The major disadvantage of this method is that it fails to 194 consider any possible interaction between the parameters [37]. Contrarily, in the DoE 195 approach, the influence of each parameter on the studied process is measured simultaneously on several levels of all other parameters, thus taking into consideration all the occurring 196 197 interactions between parameters [36].

198 The DoE technique is a statistical method used to approximate the mathematical 199 relationship between different factors affecting several response variables, and most often one 200 response variable. It can be used to simplify parametric studies by significantly reducing by 201 the required number of experiments or simulations [30]. The obtained mathematical models, 202 also known as meta-models, can be used instead of numerical simulation tools to simplify and 203 accelerate the parametric studies to find optimal solutions. It is also utilized to analyze the 204 effect of each factor on the response variable and the interaction between factors. To 205 implement DoE technique, the following steps should be followed [36,38]:

- 206
- 1. Recognition and statement of the problem.
- 207 2. Selection of the response variable
- 208 3. Choice of factors, levels, and ranges

209 4. Cho	pice of experimental	design
------------	----------------------	--------

- 210 5. Performing the experiment
- 211 6. Statistical analysis of the data
- 212 7. Conclusions and recommendations

The Analysis of Variance (ANOVA) in combination with Fisher's statistical test (pvalue < 0.05) can be used to test the significance of the model along with model terms. The significance of a factor or its effect is determined based on its P-value. If the P-value of a factor is less than 0.05, it is considered as significant [39]. Additionally, graphical illustrations, such as the Pareto charts and the normal plots of standardized effects, can be utilized to identify the significant terms.

219 **3.2. Meta-modeling and regression coefficients**

220 One of the main objectives of the DoE technique is to pursue a suitable mathematical 221 model, called "meta-model", which approximates the response variable as a function of 222 predefined factors. The most common meta-models are the first-order linear model, the linear 223 model with interaction terms, the pure quadratic model, and the complete quadratic model, 224 successively expressed as follows [36]:

$$Y_i = C_0 + \sum_{i=1}^n C_i X_i + \varepsilon \tag{1}$$

225

$$Y_i = C_0 + \sum_{i=1}^n C_i X_i + \sum_{i=1}^{n-1} \sum_{j=1+1}^n C_{ij} X_i X_j + \varepsilon$$
(2)

226

$$Y_i = C_0 + \sum_{i=1}^n C_{ii} X_i^2 + \varepsilon$$
⁽³⁾

$$Y_i = C_0 + \sum_{i=1}^n C_i X_i + \sum_{i=1}^{n-1} \sum_{j=1+1}^n C_{ij} X_i X_j + \sum_{i=1}^n C_{ii} X_i^2 + \varepsilon$$
(4)

where Y_i is the predicted response variable, X_i , X_j and X_iX_j are the independent coded factors and the two-factors interaction, C_0 , C_i , C_{ii} , and C_{ij} represent the regression coefficients for intercept, linear, quadratic and interaction terms, respectively, and ε is a random error term that accounts for the experimental error. Indeed, the transition from dimensional to coded factors must be made by applying the following formulation:

$$X_{i} = \frac{x_{i} - (x_{i,high} + x_{i,low})/2}{(x_{i,high} - x_{i,low})/2}$$
(5)

where X_i is the coded value of the variable x_i ranging between -1 and +1, and $x_{i,low}$ and $x_{i,high}$ are the values of the variable at low and high levels, respectively. Simple matrix multiplication is then used to determine the coefficients of the meta-model using the least square method [30].

237 **3.3. Meta-models validation**

The adequacy of the model, and as a result the performed analysis, can be done by graphical analysis of residuals [36]. The residual (e_i) is defined as the difference between the actual observation (y_i) and the corresponding fitted value (\hat{y}_i) :

$$e_i = y_i - \hat{y}_i \tag{6}$$

If the model is accurate, the residuals should be "structure-less"; in particular, they should be unrelated to any other variable including the predicted response [36]. A simple check is to plot the residuals versus the fitted values. This plot should not reveal any obvious pattern [36].

In addition, a very useful method is "The Normality Assumption", which is to construct a normal probability plot of the residuals. If the underlying error distribution is normal, this plot resembles a straight line, and thus confirming the validity of the model [36]. Moreover, computer programs for supporting DoE display some other useful information. The coefficient of determination (R^2) is loosely interpreted as the proportion of the variability in the data "explained" by the ANOVA model. The "adjusted- R^2 " is a variation of the ordinary R^2 that reflects the number of factors in the model. It can be a useful statistic for more complex experiments with several design factors when evaluating the impact of increasing or decreasing the number of model terms is desired.

The obtained meta-model is used to find desirable results, such as maximizing or minimizing the response variable. However, in many cases the term "desirable" is a function of more than one response. Therefore, a simultaneous optimization procedure is needed to find a compromise solution [40].

258 **3.4. Optimization method**

Simultaneous consideration of multiple-responses involves first building an appropriate mathematical model for each response and then trying to find a set of operating conditions, design factors, which in some sense optimizes all responses or at least keeps them in desired ranges.

In this consequence, the simultaneous optimization technique, known as the 263 264 desirability function approach, represents a useful approach to optimization of multiple 265 responses. The desirability function approach proposed by Harrington [41] and then modified 266 and popularized by Derringer and Suich [42] aims to simultaneously optimize multiple 267 equations. Its basic idea is to convert a multiple response problem into a single one by 268 converting each response y_i into an individual desirability function d_i that ranges from zero, 269 if the response is outside the limits, to one if the response is at its target. The individual 270 desirability functions have different formulations depending on the desired objective. If the

- 271 objective is a maximum, a minimum or a target value, the desirability functions are described,
- 272 respectively, by the following equations:

$$d_{i}^{max} = \begin{cases} 0 & if \quad y_{i} < L \\ \left(\frac{y_{i} - L}{T - L}\right)^{r} & if \quad L \le y_{i} \le T \\ 1 & if \quad y_{i} > T \end{cases}$$
(7)

$$d_{i}^{min} = \begin{cases} 0 & if \quad y_{i} > U \\ \left(\frac{U - y_{i}}{U - T}\right)^{r} & if \quad T \le y_{i} \le U \\ 1 & if \quad y_{i} < T \end{cases}$$
(8)

$$d_{i}^{target} = \begin{cases} 0 & if \quad y_{i} < L \\ \left(\frac{y_{i} - L}{T - L}\right)^{r_{1}} & if \quad L \le y_{i} \le T \\ \left(\frac{U - y_{i}}{U - T}\right)^{r_{2}} & if \quad T \le y_{i} \le U \\ 1 & if \quad y_{i} > U \end{cases}$$
(9)

where L, T and U are successively the lower, the target and the upper limits, and r_i is a weighting parameter used to assess the importance for the response to be close to the desired objective. The individual desirability functions are then combined in the so-called global desirability function (D) as expressed in Equation (10):

$$D = (d_1 \times d_2 \times \dots \times d_n)^{1/n} = \left(\prod_{i=1}^n d_i\right)^{1/n}.$$
 (10)

Lastly, the algorithm searches for the set of input factors to maximize the overall desirabilityfunction D [43] using the Nelder-Mead simplex method [44].

279 **4. Results and discussion**

4.1. Subjective assessment of thermal comfort

281 *4.1.1. TSV and thermal preference*

282 Using the comfort survey questionnaire, TSV and thermal preference of the students 283 were assessed using the questions "How do you feel inside the foyer?" and "How would you 284 prefer the indoor condition of the foyer to be?" respectively. The distribution of collected 285 subjects' responses is shown in Figure 2. The results show that the distribution of students' 286 thermal sensations was skewed toward the warm side. The most frequently selected vote was 287 "Warm". More accurately, about 30 % of the students selected this option. In addition, 24.5% 288 of the votes were for the "slightly warm" option. Further, the frequency for "cold" TSV is 289 very small. To test the statistical significance of this response and the possibility to be 290 considered an outlier, numerous types of possible statistical methods can be used [45,46]. In 291 this study, two different methodologies, known as Tukey's method and Grubbs' test, were 292 employed to detect outliers in the data. Tukey's method is based on box plots that identify the 293 first (Q1) and third (Q3) quartiles of the data [45]. The difference between these values is 294 known as the interquartile range (IQR). The range for outlier detection is then established by 295 identifying the inner and upper fences, located at a distance 1.5 IQR below Q1 and above Q3. 296 If the value is less than the lower fence or higher than the upper fence, these values are 297 considered as outliers. The Grubbs' test is a method that uses the approximate normal 298 distribution to detect a single outlier in the dataset [46]. It detects outliers in the dataset 299 through an established hypothesis with two statements - no outlier found or an outlier found 300 in dataset. In our case, the box plot of the TSV (Figure 2b) shows that the "cold" vote lays on 301 the upper fence of the box plot, and the performed Grubbs' test indicated that the "cold" vote





Figure 2: Statistical summary of survey questions: (a) TSV, (b) box plot of TSV, (c) thermal
 preference and (d) relationship between thermal sensation and thermal preference.

304

The distribution of thermal preference was broadly distributed, but was mainly 307 308 concentrated on the "a bit cooler" option. More specifically, about 39% of the students 309 selected the option "a bit cooler" and about 28% selected the "no change" option. Figure 2d 310 shows the detailed relationship between thermal preference and thermal sensation. The first 311 important inference is that the neutral thermal sensation was not preferred by the majority of 312 students. About 80 % of the students who voted for 'Neutral' thermal sensation expressed an expectation to change the thermal conditions in the Foyer, by voting 'a bit warmer', 'a bit 313 314 cooler', and 'more cooler'. The second important inference is that students tended to be more receptive to 'slightly warm' conditions. With about 50% of the students who voted 'slightly 315

warm' did not vote to change the thermal conditions, and 56.25 % of the students who felt'warm' preferred a bit cooler thermal conditions.

318 4.1.2. TSV and Satisfaction

319 Thermal satisfaction of the students was evaluated using the question "Are you satisfied with the indoor conditions of the foyer?" it was noted that 37% of the students' 320 321 responses were dissatisfied. This value is above standards recommendations for the three 322 different levels of acceptable classes of thermal comfort [6,47]. This means that the thermal 323 comfort in the studied room is below expectations. Figure 3 illustrates the thermal satisfaction 324 of the students as a function of TSV. One can observe that a neutral thermal sensation 325 corresponds to the most satisfaction assessment, although 80% of students voted to change the 326 thermal conditions (Figure 2d). These results show that, occupants may ask for cooler or 327 warmer conditions even though they are satisfied with the indoor environment. In addition, 328 when thermal sensation moves from neutral, more votes for dissatisfaction appear in the 329 results. Another important inference is that the students expressed the least dissatisfaction 330 when they felt slightly warm, while more dissatisfaction was expressed when they felt slightly 331 cool. This may have occurred because the students became acclimatized to neutral or slightly 332 warm thermal conditions in winter owing to the wide use of heating systems.





Figure 3: Relationship between thermal sensation and thermal satisfaction.

335 *4.1.3. TSV and climate*

336 In order to examine the relationship between thermal sensation and outdoor climatic 337 conditions, the students were asked to answer the question "How would you describe the 338 weather outside today?" and the three options were: "overcast", "partially cloudy", and 339 "Sunny". These three options were based on weather data collected by a weather station in 340 Barberey located 11.5km from the considered case study and are displayed online [48]. Figure 341 4 shows the distribution of collected responses and the detailed relationship between TSV and 342 outdoor climate. The results show that the majority of the students, nearly 70%, answered the 343 survey questionnaire during a winter day with sunny sky. In addition, slightly warm, warm 344 and hot were voted by the overwhelming majority of the respondent, nearly 80%, who 345 answered sunny. On the other hand, the results show that during a partially cloud day, about 346 70% of the respondent voted between "slightly cool" and "slightly warm". Moreover, the

347 "cold" and "hot" votes appeared only during "overcast" and "sunny" days, respectively.
348 These results show a wide variation in thermal sensation during different climatic conditions.
349 These results could be correlated to the presence of fully glazed facades because frequent
350 changes in the outdoor climate affect the MRT, and eventually students' thermal comfort.





351



354 4.1.4. Effect of activity level on thermal sensation and preference

Activity level of the students attending the Foyer was evaluated using the question "How would you describe your activity level in the foyer?" Figure 5 shows the distribution of collected responses, the relationship between activity level and TSV, and the detailed relationship between activity level and thermal preference. The statistical results show that students' activity level was broadly distributed, but was centered around the three options 'standing relaxed', 'light activity' and 'medium activity'. The results show that about 60% of the students' respond with an activity level higher than 'standing relaxed', the assumed activity level during the design phase. This justifies why the 'warm' option appeared the most in the TSV.

Another important inference driven from the results is that neutral sensation appeared mainly with the standing relaxed votes and continued in descending order as we move away. Moreover, 46.6% of the respondents voted 'standing relaxed' preferred no change in the thermal conditions. Furthermore, the majority of thermal preference for cooler thermal environment is distributed among the activity levels above the design value, while warmer thermal preference is concentrated mainly on the seated quiet option.



Figure 5: Statistical summary of survey questions: (a) students' activity level, (b) relationship
between thermal sensation and activity level and (c) relationship between thermal preference
and activity level.

4.2. Thermal comfort assessment using numerical simulations

375 In order to evaluate and analyze the thermal comfort features of the foyer, a previously 376 developed and validated numerical simulation model, for the considered case study, was used [13,33]. The model was developed using Dymola[®] (Dynamic Modeling Laboratory), a 377 378 simulation environment used to translate a Modelica model into an executable program. The 379 thermal performance simulations highlighted the evolution of the PMV index and the MRT on 380 four winter days corresponding to bright overcast, partly cloudy, dark overcast and sunny 381 skies, noted as cases A, B, C and D, respectively. Outdoor temperatures, global solar 382 radiations and solar altitude angles are illustrated in Figure 6. Case A represents a typical 383 winter day with no direct solar radiation due to overcast sky. Case B signifies a winter day 384 with relatively high outdoor temperature and solar radiation. Case C designates a winter day 385 with low outdoor temperature and weak solar radiation. Case D denotes a winter day with 386 relatively high outdoor temperature and intense solar radiation.



387

Figure 6: Outdoor climatic conditions of the four studied days.

PMV index and the MRT of the four studied days are illustrated in Figure 7. For cases A and B, the PMV index was stable until 10:00; it then started to increase to reach its maximum when the outdoor temperature and solar radiation reached their maximum at 14:30. The PMV index then decreased and maintained a stable value. For case C, the PMV index was below the acceptable comfort range throughout the entire occupied time. However, for case D, the PMV index exceeded the acceptable upper limit of PMV +0.5.



395



Figure 7 : PMV and MRT of the four studied days

Figure 7 shows that PMV followed the same trend as the MRT, which also followed the same trend as the solar radiations. The obtained values of PMV were then correlated with MRT values to quantify the correlation between both parameters, as shown in Figure 8. A good correlation is observed showing R^2 values greater than or equal to 0.95, meaning that more than 95% of variance is explained by the variation of MRT. This indicates that PMV variations are correlated to the MRT variations due to the presence of extensive glass areas.



- 403
- 404

Figure 8 : Correlation between PMV and MRT.

Moreover, simulation results are in a good agreement with the survey results, and the obtained results justify why 75% of the votes in an overcast day were between "slightly cool" and "cold". In addition, PMV index results of a day with relatively high outdoor temperature and strong solar radiation confirm the 80% appearance of the three votes, "slightly warm", "warm" and "hot".

Furthermore, students' votes show a different activity level while spending time at the Foyer. In this regards, an investigation using the validated model was carried out to evaluate the effect of activity level on the PMV index during the four studied days. Figure 9 shows the PMV index for the different activity levels. The results show that, for an ordinary or cold winter day, the PMV index falls below the acceptable comfort limits for a student with seated quiet or standing relaxed activity level. However, the PMV index was maintained within the acceptable comfort range for a Light or Medium activity levels, and around the upper comfort 417 limit for high activity level. Additionally, on the day with intense solar radiation, PMV 418 exceeded the upper comfort limit for all activity levels during the presence of the solar 419 radiation. These results explain the appearance of different votes and confirm the high 420 variability of students' thermal sensation during the same period. For example, a student with 421 low activity level present in the Foyer during the lack of solar radiation may experience a 422 thermal sensation between "slightly cool" and "cold". However, a student with the same 423 activity level present in the Foyer during the occurrence of intense solar radiation may 424 experience a "slightly warm", "warm" or "hot" thermal sensation depending on other factors.





425

To sum up, the subjective assessment of students' thermal comfort in the Foyer show that less than 65% of the students were satisfied with the thermal environment. The results show that the variations in thermal sensation are related to several factors, e.g. students' activity level and climatic conditions, as well as acclimatization to specific thermal 431 conditions. On the other hand, PMV index is directly and indirectly influenced by other
432 factors, e.g. clothing insulation. In this consequence, the proposed approach is applied to the
433 Foyer in order to determine the most critical parameters affecting the PMV value, then to
434 optimize the glass facades configuration for thermal comfort.

435 *4.3.* Sensitivity study

436 *4.3.1. Response variables and choice of factors and levels*

The response variables are the average daily, maximum, and minimum PMV values. The reason behind the average daily value is that it makes no sense to have a weekly, monthly or yearly PMV value because it can frequently change during the day; in addition the average can be considered as a representative value to replace the hourly values. However, the average value alone, in the case of occupants' feeling, is not meaningful if not complemented by the maximum and minimum values. This helps in determining if the PMV value exceeded the upper or lower acceptable comfort limit.

444 PMV is influenced by room temperature, MRT, relative humidity, air velocity, 445 metabolic rate, and clothing insulation. Relative humidity and air velocity were excluded from 446 the sensitivity study, since PMV was found to be less sensitive for both parameters compared 447 to the four other parameters [49,50]. Besides, since MRT is highly influenced by the outdoor 448 climatic condition, as previously discussed, it was replaced by the sol-air temperature. This 449 last is a parameter defined as "the outside air temperature which, in the absence of solar 450 radiation, would give the same temperature distribution and rate of heat transfer through a 451 wall/roof as exists due to the combined effects of the actual outdoor temperature distribution 452 plus the incident solar radiation" [51]. The sol-air temperature was found to be a good 453 illustration of the weather conditions [52]; its mathematical formulation is presented in 454 [51,53]. Lastly, the effect of the external glass facades on the PMV index was considered using both Window-to-Floor-Ratio (WFR) and glazing type as two independent factorsinfluencing the response variable.

457 Each considered parameter has a lower (-1) and higher (+1) level. The high level of the WFR (60%) and glazing type (double glazing with u-value = 2.8 W.m^{-2} .K⁻¹ and SHGC = 458 459 0.77) represents the base case study, and the low level, 16% WFR and triple low-emissivity glazing (u-value = 0.7 W.m^{-2} .K⁻¹ and SHGC = 0.3), has been selected with respect to the 460 461 values that are recommended by the French and the European standards [54,55]. The daily 462 average sol-air temperature was calculated and the minimum and maximum values were 463 chosen to represent the lower and higher levels. While, the levels of the remaining factors 464 were selected based on the questionnaire results and the recommended values by the standards 465 [54,55]. Table 2 reports the considered parameters and their corresponding codes and levels.

Factor	Code	Unit	Level	
			-1	+1
Clothing insulation	A	clo	0.8	1.2
Metabolic rate	В	$W.m^{-2}$	58	125
Room temperature	С	°C	19	21
Sol-air temperature	D	°C	-2.2	17.2
glazing type (u-value)	E	$W.m^{-2}.K^{-1}$	0.7	2.8
(g-value)			0.3	0.77
WFR	F	%	16	60

466 Table 2: Investigated factors and their corresponding codes and levels.

467 *4.3.2.* Choice of experimental design and performing the experiments

DoE was performed using a two-level full factorial design. This design considers all possible factors combination. The full factorial design aims to identify the significant variables that influence the response variable. In addition, it helps to analyze the interaction between these factors, and also it offers more precise results compared to fractional factorial design and avoids specious conclusions [36]. The number of experiments is 2^k, where k is the number of factors. This design results in 64 experiments to investigate the main effect of 474 factors and their interactions. Additionally, center points were added to the design to examine 475 the adequacy of the model for capturing the curvature expressed in the response. Figure 10 476 shows the design matrix (64 runs) and the response variables resulting from the simulation 477 results (numerical results are reported in Table A of the supplementary information). 478 Minitab[®] software, a statistical computer package, was used to analyze the data of Figure 10.



480 Figure 10: DoE simulation results (each run represents a unique combination of factors levels)

481 *4.3.3. Statistical analysis of the data*

479

482 ANOVA was carried out in order to identify the significant factors. The results of 483 ANOVA reported in Table 3, (complete ANOVA tables are reported in Tables B, D and F in 484 the supplementary information), indicate that the linear and 2-way interactions between 485 factors are significant, while the remaining interactions and the curvature are not. As a result,

- 486 the relationship between the investigated parameters and the response variable is deemed to
- 487 follow a linear equation.

Source	DF	Sea SS	Adi SS	Adi MS	F-Value	P-Value
Average PMV			<u>_</u>			
Model	63	68,4953	68,4953	1,0872	6166,54	0,01
Linear	6	63,4854	63,4854	10,5809	60012,77	0,003
2-Way Interactions	15	4,67	4,67	0,3113	1765,81	0,019
3-Way Interactions	20	0,3354	0,3354	0,0168	95,13	0,081
4-Way Interactions	14	0,0045	0,0045	0,0003	1,8	0,531
5-Way Interactions	6	0	0	0	0,03	0,999
6-Way Interactions	1	0	0	0	0	0,977
Curvature	1	0	0	0	3,29	0,321
Error	1	0,0002	0,0002	0,0002		
Total	64	68,4955	68,4955			
Minimum PMV						
Model	63	74,2413	74,2413	1,1784	4337,36	0,012
Linear	6	72,6844	72,6844	12,1141	44587,27	0,004
2-Way Interactions	15	1,5306	1,5306	0,102	375,56	0,04
3-Way Interactions	20	0,0255	0,0255	0,0013	4,69	0,351
4-Way Interactions	14	0,0008	0,0008	0,0001	0,2	0,957
5-Way Interactions	6	0	0	0	0,02	0,999
6-Way Interactions	1	0	0	0	0	0,982
Curvature	1	0	0	0	0,13	0,777
Error	1	0,0003	0,0003	0,0003		
Total	64	74,2416	74,2416			
Maximum PMV						
Model	63	104,256	104,256	1,6549	1394,38	0,021
Linear	6	82,704	82,704	13,784	11614,36	0,007
2-Way Interactions	15	19,791	19,791	1,3194	1111,74	0,024
3-Way Interactions	20	1,738	1,738	0,0869	73,2	0,092
4-Way Interactions	14	0,023	0,023	0,0016	1,37	0,593
5-Way Interactions	6	0	0	0	0,03	0,999
6-Way Interactions	1	0	0	0	0	0,978
Curvature	1	0	0	0	0,02	0,908
Error	1	0,001	0,001	0,0012		
Total	64	104,257	104,257			

Table 3: ANOVA results for average, minimum and maximum PMV values.

489

490

The Pareto charts for standardized effects for the average daily, minimum and maximum PMV values are shown in Figure 11. The bars display the variables and their

. .

491 interactions, where all the bars that exceed the vertical dashed line are considered significant. 492 The results reported in Figure 11 show that the metabolic rate (B) has the highest effect on all 493 the response variables. In addition, the daily average and maximum values were significantly 494 influenced by the daily average sol-air temperature (D), clothing insulation (A), interaction 495 between sol-air temperature and WFR (DF), set-point temperature (C) and WFR (F). 496 However, the minimum PMV value was significantly influenced by clothing insulation (A), 497 set-point temperature (C), interaction between clothing insulation and metabolic rate (AB) 498 and WFR (F), respectively. Effects of other factors and their interactions are in descending 499 order as shown in Figure 11. These results are in a good agreement with the previously 500 discussed results regarding the effect of activity level and outdoor climates on the thermal 501 sensation of the students.



502

503

(a)











Figure 11 : Pareto plots of standardized effects at p = 0.05 for: (a) daily average PMV, (b)
minimum PMV and (c) maximum PMV.

510 Figure 12 illustrates the main effect plot of each of the studied factors. The effect of a 511 factor is defined as the change in the response due to the change in the level of the factor. It 512 can be clearly seen that the metabolic rate was the most significant parameter affecting the 513 PMV values, while glazing type was the least significant. These results confirm that in the 514 investigated Foyer, students' thermal comfort is highly affected by their activity and clothing 515 levels. Furthermore, maximum PMV values are sensitive to climatic conditions and glazing 516 area more than the set-point temperature, which confirms the effect of glass facades on the 517 variations of PMV.

518 After identifying the main effects, it is important to study the interactions between 519 them, since this was found to be significant using the Pareto charts, as described in Figure 11. 520 Interactions occur when the effect of a factor is dependent on the level of another one. Figure 521 13 shows the interaction plot for the daily average, maximum and minimum PMV values. The interaction plot allows to easily identifying interactions between two factors. It plots the mean 522 523 response of two factors for all occurring combinations. Non-parallel intersecting lines indicate 524 that an interaction between factors occurs, while parallel lines signify no interaction between 525 them. The results reported in Figure 13 show that several lines are not parallel but the 526 interaction between the sol-air temperature and the WFR has the most significant impact on 527 the daily average and maximum PMV values. This interaction effect indicates that the 528 relationship between PMV value and the outdoor climatic conditions depends on the external 529 glazed surface. As the external glazed surface area decreases, the effect of outdoor climatic 530 conditions become less important. Hence, decreasing glazing area results in more consistent 531 thermal comfort conditions. The results also show that the interaction between metabolic rate 532 and clothing insulation has the most significant impact on the minimum PMV value.











Figure 12: Main effect plot for: (a) daily average PMV, (b) minimum PMV and (c) maximumPMV.



(a)

541







(b)



546

545



Tables C, E and G of the supplementary information report the coefficients (column 3) of fitting polynomials to the simulation results by linear regression analysis. The ANOVA test shows that the meta-models for PMV values predictions are statistically significant at a 95% confidence level (p < 0.05). The obtained meta-models can be simplified by eliminating the non-significant factors (p > 0.05). The best fit meta-model equations that describe the average, the minimum and the maximum PMV values are given by Equations (11), (12) and (13), respectively.

$$PMV_{avg} = 0.00372 + 0.28635 \times A + 0.87226 \times B + 0.17675 \times C + 0.30146 \times D + 0.02108 \times E + 0.16296 \times F - 0.11939 \times AB - 0.03119 \times AD - 0.05882 \times BC - 0.10105 \times BD - 0.05360 \times BF - 0.02331 \times CD + 0.03271 \times DE + 0.19716 \times DF$$
(11)

$$PMV_{Min} = -0.37557 + 0.32530 \times A + 0.99898 \times B + 0.16164 \times C - 0.04150 \times D - 0.02642 \times E - 0.05801 \times F - 0.13309 \times AB - 0.05402 \times BC - 0.03939 \times CD$$
(12)

$$PMV_{Max} = 0.43566 + 0.24247 \times A + 0.72880 \times B + 0.16611 \times C + 0.69132 \times D + 0.06404 \times E + 0.43896 \times F - 0.10397 \times AB - 0.07044 \times AD - 0.05513 \times BC - 0.22996 \times BD - 0.14480 \times BF + 0.06577 \times DE + 0.45554 \times DF$$
(13)

557 The ANOVA results of the models indicate good performance with R^2 (> 0.98) and 558 adjusted- R^2 (0.97). The value of adjusted- R^2 indicates that more than 97% of the total factors 559 associated with the PMV are attributed to the selected parameters of the model. The Predicted 560 R^2 is in reasonable agreement with the Adjusted- R^2 ; i.e. the difference is less than 0.2.

Moreover, residuals versus predicted values plot and normal probability plot of residuals are two graphical approaches that are used to check the validity of a regression model [39]. The residual versus predicted response plots illustrated in Figure 14 show that less patterned structures are observed for the three deemed responses indicating that the 565 proposed models are adequate. In addition, the normal probability plots shown in Figure 14 566 designate that the residuals followed a straight line, thus confirming the validity of the 567 models.

568 Furthermore, 50 additional simulations were performed with different factors' levels 569 using the numerical model and the results were compared to the meta-model predictions. The obtained results are shown in Figure 15. A good correlation is observed showing a R^2 value 570 571 of 0.99, meaning that 99% of variance is explained by the obtained meta-model. Therefore, 572 the meta-models are considered to be valid and adequate. These meta-models can be used 573 instead of the numerical model as a fast and simple way to predict the thermal comfort 574 condition within an indoor environment. However, the reliability of these meta-models is 575 limited to a similar case study and the considered range of variation of the investigated 576 factors.

577 4.3.5. Determination and analysis of optimal solutions

578 Finally, an optimization is carried out using the obtained meta-models. The response 579 variables are the average, minimum and maximum PMV values. The objective is to maintain 580 these values within the recommended acceptable thermal comfort range of [-0.5;+0.5] [6]. 581 The range of variation of the set-point temperature, glazing type and WFR is kept as indicated in Table 2, while the metabolic rate and clothing insulation were assumed to vary in the 582 583 ranges of [66.5;73.5] and [0.95;1.05], respectively, representing sedentary activity and typical 584 winter clothing with 5% variation [56]. The sol-air temperature parameter was excluded from 585 the optimization because it is an uncontrollable parameter. The objectives and constraints of 586 the optimization are summarized in Table 4.



588 Figure 14: Residuals versus fitted values, (a), (c) and (e), and Normal probability of residuals, 589 (b), (d) and (f), for average, minimum and maximum PMV values, respectively.



591 Figure 15: Coefficient of determination between simulation results and the meta-model
592 predictions.

Name	Objective	Lower limit	Upper limit
PMV	Is maintained in a	-0.5	+0.5
Minimum PMV	range		
Maximum PMV			
	Constraints		
CI	Is maintained in a	0.95	1.05
MR	range	66.5	73.5
Set-point		19	21
Glazing type		Triple low-e	double
WFR		0.16	0.6

594 The numerical optimizations show that the maximum D value, D=1, is provided when 595 the set-point temperature, the glazing type and the WFR are 21°C, double glazing, and 16%, 596 respectively. The optimization results suggest that using this combination of parameters yields 597 average, minimum and maximum PMV values of -0.381, -0.5 and 0.107, respectively. This 598 same combination of parameters is then simulated using the Dymola model; the obtained 599 average, minimum and maximum PMV are -0.284, -0.41 and 0.124, respectively. These 600 results are in a good agreement with the outcomes predicted by optimizing the meta-models, 601 thus confirming the validity and adequacy of the obtained results.

In addition, the optimized case is compared to the base case and the obtained hourly numerical values of PMV and MRT are presented in Figure 16. The results show that the optimized design yields better thermal comfort condition within the studied room. More specifically, it leads to alleviate the high MRT values during high sol-air temperatures, thus preventing the PMV values from exceeding the upper acceptable limit. On the other hand, it reduces the heat loss through building envelope thus leading to increasing MRT during cold times, which means improved PMV values during low sol-air temperature values.

Furthermore, although the optimized case allows an increase in the set-point temperature to maintain acceptable thermal comfort condition, it results in reducing the heating energy consumption. An energy audit for the whole building comprising the Foyer is performed in [33]. One can refer to this study for a detailed description about the total number of days requiring heating and the outdoor climatic conditions. The total heating energy consumption of the base case, set-point 20°C, was 3034 kWh per year, while that of the optimized case was 2566 kWh per year. These results are correlated to the optimized glazing area that results in improved thermal resistance of the external walls, allowing the reduced transmission heat loss under low sol-air temperature, thus improving the heating energy consumption.



Figure 16: Numerical hourly values of (a) PMV index and (b) MRT of the base-case and theoptimized-case designs.

622 **5. Conclusion**

Adequate design of building envelope is essential to ensure a trade-off between several aspects, such as aesthetic appearance of the building, occupants' thermal and visual comfort and energy consumption. The aim of this study was to optimize building design for thermal comfort. The proposed method is based on the combined use of numerical simulations, DoE technique and the desirability function approach.

Firstly, a real case study characterized by two glass facades was selected for the investigations. Subjective thermal comfort was assessed using questionnaire survey. The collected responses indicated that 37% of the respondents were dissatisfied with the thermal environmental conditions. Next, a previously developed and validated model was used to run simulations, and the obtained results were in agreement with the collected responses.

633 Then, a sensitivity analysis based on the combined use of numerical simulation and 634 DoE technique was performed. From this analysis, the most significant parameters and 635 interactions affecting the response variables (average, minimum and maximum PMV value) 636 were determined, as well as mathematical relationships, referred as meta-models, which 637 approximate the response variables as a function of predefined factors were developed. The 638 meta-models were validated using graphical analysis of residuals and the coefficient of 639 determination \mathbb{R}^2 . The residual versus predicted response plots demonstrated less patterned 640 structures; the normal probability plots indicated that the residuals followed a straight line and 641 the coefficient of determination was greater than 0.98, thus confirming the validity of the 642 meta-models.

Lastly, an optimization procedure using the desirability function approach was carried out. The objective of the optimization was to maintain the PMV values within the acceptable comfort range of [-0.5; 0.5]. The results indicated that the optimized design yields better thermal comfort conditions, PMV values ranged from -0.381 to 0.107. In addition, it reduces heating energy consumption, even though it requires increased heating set-point. This
indicates that an optimized design of building envelope is vital to achieve energy-saving and
thermal comfort, rather than just reducing the set-point temperature.

650 This study demonstrated that optimizing building design for thermal comfort can be 651 achieved by adequate treatment of building envelope design, i.e. glass facades configuration 652 in our case. Although the proposed approach outcomes robust and credible results, its 653 limitation is that few parameters and response variables were considered in the analysis. In 654 addition, both u-value and SHGC of the glazing were considered simultaneously. Future work 655 will focus on increasing the number of parameters and response variables by simultaneously considering several issues, as well as applying the proposed approach to other buildings 656 657 typologies.

658 Acknowledgment

This work was supported by the Conseil régional de Champagne-Ardenne (CRCA)
and the Fonds européen de développement économique et régional (FEDER).

661 **References**

662 [1] Statistical pocketbook 2018 - European Commission, (n.d.).

https://ec.europa.eu/transport/facts-fundings/statistics/pocketbook-2018_en (accessed
December 20, 2018).

European Parliament, Directive 2010/31/EU of the European Parliament and of the
Council of 19 May 2010 on the energy performance of buildings, Off. J. Eur. Union.
(2010) 13–35. doi:10.3000/17252555.L_2010.153.eng.

668 [3] Z. Deng, Q. Chen, Artificial neural network models using thermal sensations and
669 occupants' behavior for predicting thermal comfort, Energy Build. 174 (2018) 587–

670

602. doi:10.1016/J.ENBUILD.2018.06.060.

- 671 [4] D. Kolokotsa, D. Tsiavos, G.S. Stavrakakis, K. Kalaitzakis, E. Antonidakis, Advanced
 672 fuzzy logic controllers design and evaluation for buildings' occupants thermal-visual
- 673 comfort and indoor air quality satisfaction, Energy Build. 33 (2001) 531–543.
- 674 doi:10.1016/S0378-7788(00)00098-0.
- M. Castilla, J.D. Álvarez, M.G. Ortega, M.R. Arahal, Neural network and polynomial
 approximated thermal comfort models for HVAC systems, Build. Environ. 59 (2013)
 107–115. doi:10.1016/j.buildenv.2012.08.012.
- [6] ISO, ISO 7730: Ergonomics of the thermal environment Analytical determination and
 interpretation of thermal comfort using calculation of the PMV and PPD indices and
- local thermal comfort criteria, Management. 3 (2005) 605–615.
- 681 doi:10.1016/j.soildyn.2004.11.005.
- 682 [7] R.A. Hoovestol, T.R. Mikuls, Environmental Exposures and Rheumatoid Arthritis
- 683 Risk, Curr. Rheumatol. Rep. 13 (2011) 431–439. doi:10.1007/s11926-011-0203-9.
- M. Taleghani, M. Tenpierik, S. Kurvers, A. Van Den Dobbelsteen, A review into
 thermal comfort in buildings, Renew. Sustain. Energy Rev. 26 (2013) 201–215.
 doi:10.1016/j.rser.2013.05.050.
- 687 [9] P.O. Fanger, Thermal comfort: Analysis and applications in environmental688 engineering, 1970.
- 689 [10] D. Enescu, A review of thermal comfort models and indicators for indoor
- 690 environments, Renew. Sustain. Energy Rev. 79 (2017) 1353–1379.
- 691 doi:10.1016/j.rser.2017.05.175.

- 692 [11] B. Bueno, J.M. Cejudo-López, A. Katsifaraki, H.R. Wilson, A systematic workflow for
 693 retrofitting office façades with large window-to-wall ratios based on automatic control
 694 and building simulations, Build. Environ. 132 (2018) 104–113.
- 695 doi:10.1016/J.BUILDENV.2018.01.031.
- 696 [12] D.H. Kang, P.H. Mo, D.H. Choi, S.Y. Song, M.S. Yeo, K.W. Kim, Effect of MRT
- 697 variation on the energy consumption in a PMV-controlled office, Build. Environ. 45
 698 (2010) 1914–1922. doi:10.1016/j.buildenv.2010.02.020.
- 699 [13] A.A.W. Hawila, A. Merabtine, M. Chemkhi, R. Bennacer, N. Troussier, An analysis of

the impact of PMV-based thermal comfort control during heating period: A case study

- 701 of highly glazed room, J. Build. Eng. 20 (2018) 353–366.
- 702 doi:10.1016/j.jobe.2018.08.010.

- M. Thalfeldt, E. Pikas, J. Kurnitski, H. Voll, Facade design principles for nearly zero
 energy buildings in a cold climate, Energy Build. 67 (2013) 309–321.
- 705 doi:10.1016/j.enbuild.2013.08.027.
- 706 [15] H. Poirazis, Å. Blomsterberg, M. Wall, Energy simulations for glazed office buildings
 707 in Sweden, Energy Build. 40 (2008) 1161–1170. doi:10.1016/j.enbuild.2007.10.011.
- [16] Q. Jin, M. Overend, A comparative study on high-performance glazing for office
 buildings, Intell. Build. Int. 9 (2017) 181–203. doi:10.1080/17508975.2015.1130681.
- 710 [17] J.W. Lee, H.J. Jung, J.Y. Park, J.B. Lee, Y. Yoon, Optimization of building window
- 711 system in Asian regions by analyzing solar heat gain and daylighting elements, Renew.
- 712 Energy. 50 (2013) 522–531. doi:10.1016/j.renene.2012.07.029.
- 713 [18] L. Vanhoutteghem, G.C.J. Skarning, C.A. Hviid, S. Svendsen, Impact of façade

714		window design on energy, daylighting and thermal comfort in nearly zero-energy
715		houses, Energy Build. 102 (2015) 149–156. doi:10.1016/j.enbuild.2015.05.018.
716	[19]	A. Tzempelikos, M. Bessoudo, A.K. Athienitis, R. Zmeureanu, Indoor thermal
717		environmental conditions near glazed facades with shading devices - Part II: Thermal
718		comfort simulation and impact of glazing and shading properties, Build. Environ. 45
719		(2010) 2517–2525. doi:10.1016/j.buildenv.2010.05.014.
720	[20]	T. Anderson, M. Luther, Designing for thermal comfort near a glazed exterior wall,
721		Archit. Sci. Rev. 55 (2012) 186–195. doi:10.1080/00038628.2012.697863.
722	[21]	G.M. Stavrakakis, P.L. Zervas, H. Sarimveis, N.C. Markatos, Optimization of window-
723		openings design for thermal comfort in naturally ventilated buildings, Appl. Math.
724		Model. 36 (2012) 193–211. doi:10.1016/j.apm.2011.05.052.
725	[22]	Z.S. Zomorodian, M. Tahsildoost, Assessment of window performance in classrooms
726		by long term spatial comfort metrics, Energy Build. 134 (2017) 80-93.
727		doi:10.1016/j.enbuild.2016.10.018.
728	[23]	R.A. Mangkuto, M. Rohmah, A.D. Asri, Design optimisation for window size,
729		orientation, and wall reflectance with regard to various daylight metrics and lighting
730		energy demand: A case study of buildings in the tropics, Appl. Energy. 164 (2016)
731		211-219. doi:10.1016/j.apenergy.2015.11.046.
732	[24]	W.J. Hee, M.A. Alghoul, B. Bakhtyar, O. Elayeb, M.A. Shameri, M.S. Alrubaih, K.
733		Sopian, The role of window glazing on daylighting and energy saving in buildings,
		Barrow, Sustain Energy, Bay, 12 (2015) 222, 242, dai:10.1016/j.man.2014.00.020
734		Renew. Sustain. Energy Rev. 42 (2015) 323–343. doi:10.1010/j.rser.2014.09.020.

- 736 windows for dynamic daylight and solar energy control in buildings: A state-of-the-art
- 737 review, Sol. Energy Mater. Sol. Cells. 94 (2010) 87–105.

738 doi:10.1016/j.solmat.2009.08.021.

- 739 [26] C.H. Cheong, T. Kim, S.B. Leigh, Thermal and daylighting performance of energy-
- refficient windows in highly glazed residential buildings: Case study in Korea, Sustain.
- 741 6 (2014) 7311–7333. doi:10.3390/su6107311.
- 742 [27] J.A. Clarke, J.L.M. Hensen, Integrated building performance simulation: Progress,
- prospects and requirements, Build. Environ. 91 (2015) 294–306.
- 744 doi:10.1016/J.BUILDENV.2015.04.002.
- 745 [28] T. Hoyt, E. Arens, H. Zhang, Extending air temperature setpoints: Simulated energy
 746 savings and design considerations for new and retrofit buildings, Build. Environ. 88
 747 (2015) 89–96. doi:10.1016/J.BUILDENV.2014.09.010.
- 748 [29] H.X. Zhao, F. Magoulès, A review on the prediction of building energy consumption,
- 749 Renew. Sustain. Energy Rev. 16 (2012) 3586–3592. doi:10.1016/j.rser.2012.02.049.
- 750 [30] F. Chlela, A. Husaunndee, C. Inard, P. Riederer, A new methodology for the design of
 751 low energy buildings, Energy Build. 41 (2009) 982–990.
- 752 doi:10.1016/j.enbuild.2009.05.001.
- [31] I. Jaffal, C. Inard, C. Ghiaus, Fast method to predict building heating demand based on
 the design of experiments, Energy Build. 41 (2009) 669–677.
- 755 doi:10.1016/j.enbuild.2009.01.006.
- Z.A. Al-Absi, N.F. Abas, Subjective assessment of thermal comfort for residents in
 naturally ventilated residential building in Malaysia, in: IOP Conf. Ser. Mater. Sci.

758 Eng., 2018. doi:10.1088/1757-899X/401/1/012009.

- 759 [33] A. Merabtine, C. Maalouf, A.A.W. Hawila, N. Martaj, G. Polidori, Building energy
- audit, thermal comfort, and IAQ assessment of a school building: A case study, Build.
- 761 Environ. 145 (2018) 62–76. doi:10.1016/j.buildenv.2018.09.015.
- 762 [34] ANSI/ ASHRAE Standard 55-2010, Thermal environmental conditions for human
 763 occupancy, 2010. doi:ISSN 1041-2336.
- 764 [35] SurveyPlanet, (n.d.). https://surveyplanet.com/ (accessed November 29, 2018).
- 765 [36] D.C. Montgomery, Design and analysis of experiments, ninth, 2017.
- 766 https://www.wiley.com/en-
- 767 us/Design+and+Analysis+of+Experiments%2C+9th+Edition-p-9781119113478.
- W. Tian, A review of sensitivity analysis methods in building energy analysis, Renew.
 Sustain. Energy Rev. 20 (2013) 411–419. doi:10.1016/j.rser.2012.12.014.
- 770 [38] D.E. Coleman, D.C. Montgomery, A Systematic Approach to Planning for a Designed
- 771 Industrial Experiment, Technometrics. 35 (1993) 1–12.
- doi:10.1080/00401706.1993.10484984.
- 773 [39] D. Montgomery, Introduction to statistical quality control, 2009. doi:10.1002/1521-
- 774 3773(20010316)40:6<9823::AID-ANIE9823>3.3.CO;2-C.
- 775 [40] R.H. Myers, D.C. Montgomery, C.M. Anderson-Cook, Response Surface
- 776 Methodology : Process and Product Optimization Using Designed Experiments.,
- Fourth edi, Wiley, 2016. https://www.wiley.com/en-
- vs/Response+Surface+Methodology%3A+Process+and+Product+Optimization+Using
- +Designed+Experiments%2C+4th+Edition-p-9781118916032 (accessed December 11,

780 2018).

- 781 [41] E.C. Harrington, Desirability Function, Ind. Qual. Control. (1965).
- 782 [42] G. Derringer, R. Suich, Simultaneous Optimization of Several Response Variables, J.
- 783 Qual. Technol. 12 (1980) 214–219. doi:10.1080/00224065.1980.11980968.
- [43] G. Zhou, L. Fu, X. Li, Optimisation of ultrasound-assisted extraction conditions for
 maximal recovery of active monacolins and removal of toxic citrinin from red yeast
 rice by a full factorial design coupled with response surface methodology, Food Chem.
- 787 170 (2015) 186–192. doi:10.1016/j.foodchem.2014.08.080.
- [44] J.A. Nelder, R. Mead, A Simplex Method for Function Minimization, Comput. J. 7
 (1965) 308–313. doi:10.1093/comjnl/7.4.308.
- [45] S. Seo, P.D. Gary M. Marsh, A review and comparison of methods for detecting
 outliers in univariate data sets, Grad. Sch. Public Heal. Univ. Pittsburgh. (2006).
 doi:10.1016/j.arth.2008.03.010.
- [46] H. Do, K.S. Cetin, Evaluation of the causes and impact of outliers on residential
 building energy use prediction using inverse modeling, Build. Environ. 138 (2018)
 194–206. doi:10.1016/j.buildenv.2018.04.039.
- 796 [47] J. Van Hoof, Forty years of Fanger's model of thermal comfort: Comfort for all?,
 797 Indoor Air. 18 (2008) 182–201. doi:10.1111/j.1600-0668.2007.00516.x.
- 798 [48] Climatologie mensuelle en décembre 2016 à Troyes-Barberey | climatologie depuis
 799 1900 Infoclimat, (n.d.). https://www.infoclimat.fr/climatologie-
- 800 mensuelle/07168/decembre/2016/troyes-barberey.html (accessed March 1, 2019).

- [49] M.H. Hasan, F. Alsaleem, M. Rafaie, Sensitivity study for the PMV thermal comfort
 model and the use of wearable devices biometric data for metabolic rate estimation,
 Build. Environ. 110 (2016) 173–183. doi:10.1016/j.buildenv.2016.10.007.
- [50] F.R. d'Ambrosio Alfano, B.I. Palella, G. Riccio, The role of measurement accuracy on
 the thermal environment assessment by means of PMV index, Build. Environ. 46
 (2011) 1361–1369. doi:10.1016/j.buildenv.2011.01.001.
- 807 [51] P.W. O'Callaghan, S.D. Probert, Sol-air temperature, Appl. Energy. 3 (1977) 307–311.
 808 doi:10.1016/0306-2619(77)90017-4.
- 809 [52] T. Catalina, V. Iordache, B. Caracaleanu, Multiple regression model for fast prediction
 810 of the heating energy demand, Energy Build. 57 (2013) 302–312.
- 811 doi:10.1016/j.enbuild.2012.11.010.
- 812 [53] T. Catalina, V. Iordache, IEQ assessment on schools in the design stage, Build.
 813 Environ. 49 (2012) 129–140. doi:10.1016/j.buildenv.2011.09.014.
- 814 [54] MEDDE, Réglementation thermique 2012 : un saut énergétique pour les bâtiments
 815 neufs, 2011.
- 816 [55] Cen, EN 15251: Indoor environmental input parameters for design and assessment of
- 817 energy performance of buildings- addressing indoor air quality, thermal environment,
- 818 lighting and acoustics, Eur. Comm. Stand. 3 (2007) 1–52. doi:10.1520/E2019-
- 819 03R13.Copyright.
- 820 [56] Ashrae, ASHRAE Handbook Fundamentals (SI Edition), 2009.