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Abstract

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

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

1. Introduction

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

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

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

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

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

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

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

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

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

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

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

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

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

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

2. Methodology

The proposed methodology to integrate occupant thermal comfort in the design of energy-efficient buildings comprises six main steps, as discussed in the following sections. Figure 1 illustrates the framework of the proposed method.

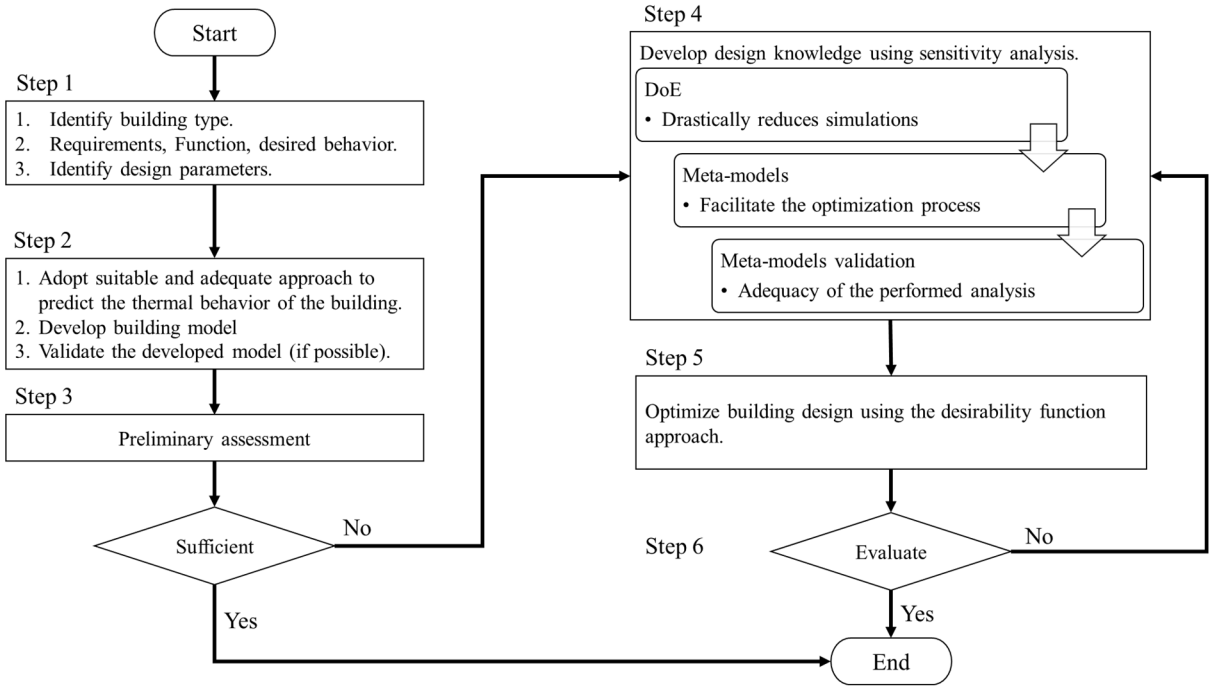


Figure 1 : The framework of the proposed method.

2.1 Identifying building type, desired behavior and design parameters

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

2.3 Preliminary assessment

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

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

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

2.4 Developing design knowledge using sensitivity analysis

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

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

2.5 Optimization

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

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

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

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

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

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

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

2.6 Final evaluation

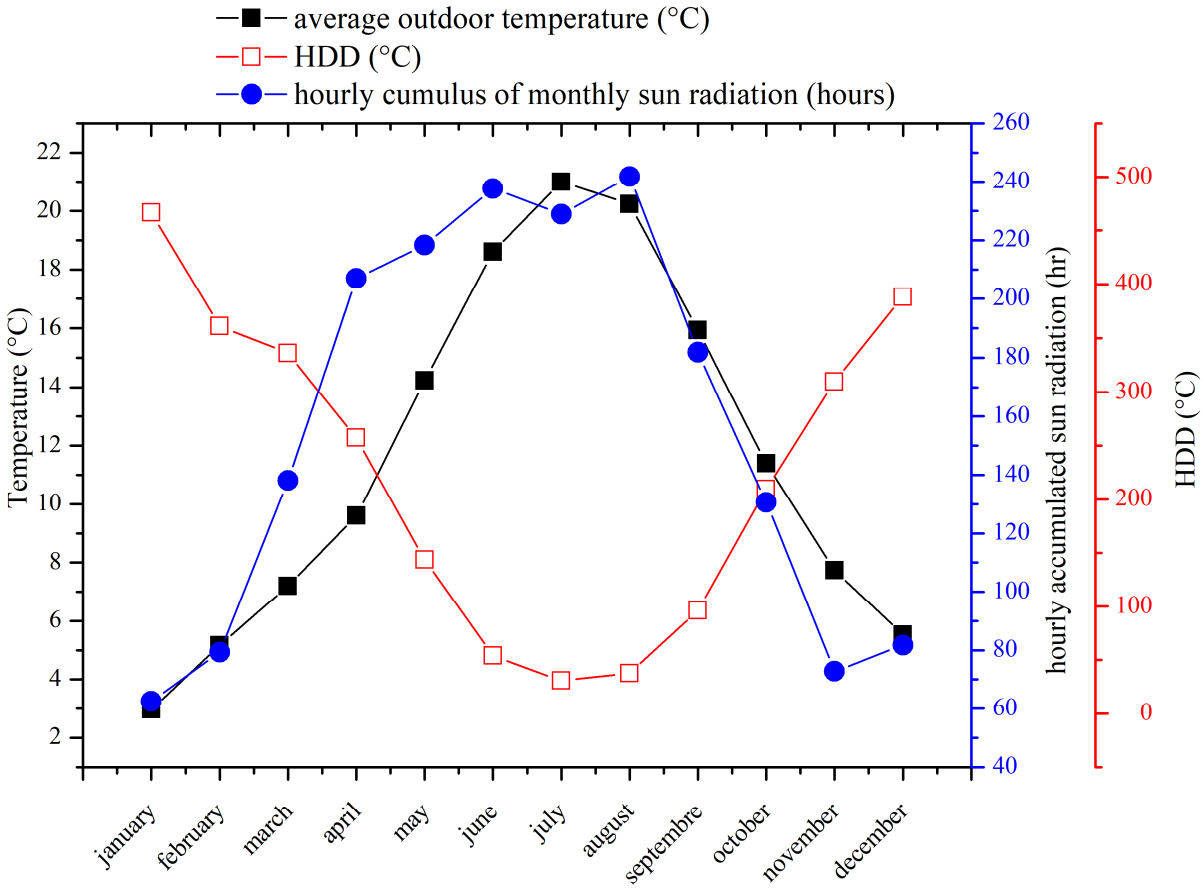
Indeed, after identifying the values of design parameters, a final evaluation step must be performed. Here the evaluation process follows the same approach as indicated in step 3, section 2.3. If the evaluation process is satisfying, then the values of design parameters are set to those obtained from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

3. Case study

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

280

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



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

Despite all the efficient measures and innovative solutions to reduce emissions and total energy consumption of the building, students occupying the Foyer (Figure 2b), a public room for doing different activities, reported dissatisfaction in thermal comfort conditions. In this regards, both subjective and objective investigations were performed to assess the thermal comfort level in that space [25,31], a brief description of the space characteristics is summarized in Table 2. For this purpose, a multifunctional sensor (Figure 4) was utilized to monitor the environmental parameters and to calculate the indices of thermal comfort. The metabolic rate and clothing level were assumed to be 70 $W.m^{-2}$ (1.2 met) and 0.155 $K.m^2.W^{-1}$ (1 clo), respectively, representing sedentary activity and typical winter clothing. The characteristics of the used sensor and the conducted measuring cycles are reported in Table 3. In addition, survey questionnaires were prepared and collected from 41 students during the investigations. It is worth noting that the 41 students represent a sample of 90% confidence interval and a 12% margin of error compared to the total number of 281 students and staff members occupying the building. Bearing in mind that not all the students attend the Foyer and the total number includes the staff member, it is assumed that the sample size is statistically significant. The obtained PPD values form both the measured data and the survey were above the recommended comfort range of 10% (Figure 5). The results show a good agreement between the obtained results and students assumptions regarding the thermal environment conditions within the Foyer. Therefore, further investigations to improve the thermal comfort conditions in the Foyer are required. For this purpose, a numerical model using Modelica is developed, the model is comprehensively explained in [25,26]. It is worth noting that, during the experimentation and the survey the students were occupying different locations inside the Foyer. The responses, however, were almost similar or slightly different and in a good agreement with the experimental results even though only one measuring point 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	58.0m²
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

Figure 4 : Multifunctional sensor

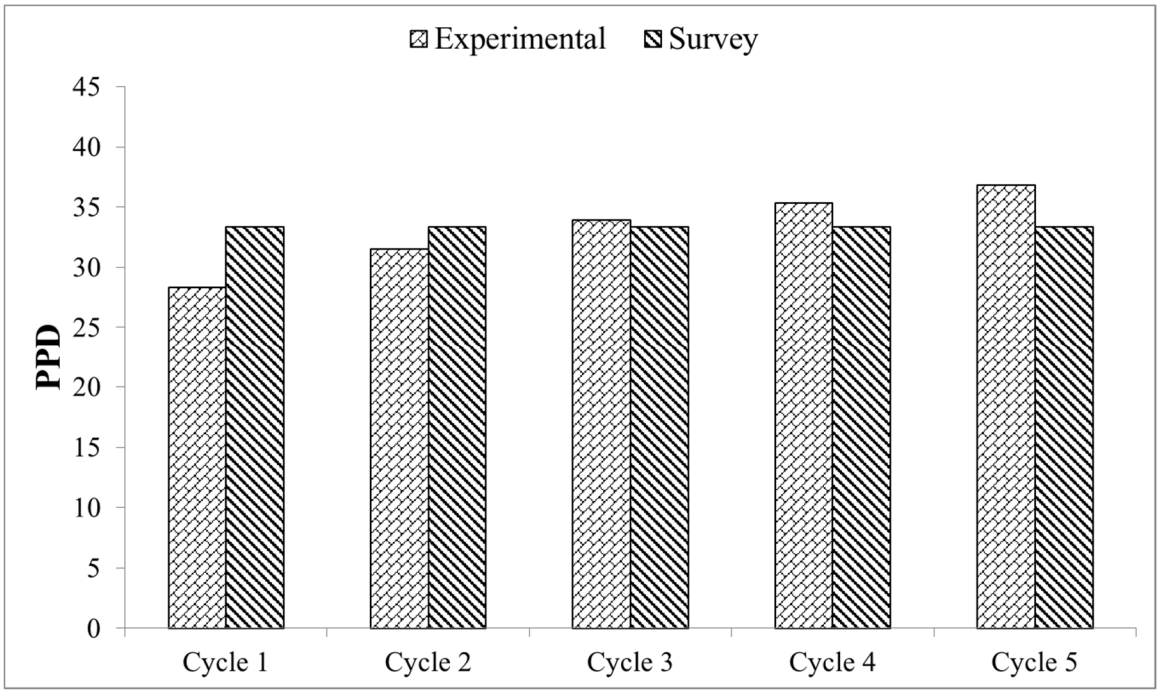


Figure 5 : Average values of PPD for the various cycles [24].

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].

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

Experimental cycles	12th November		13th	14th 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

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

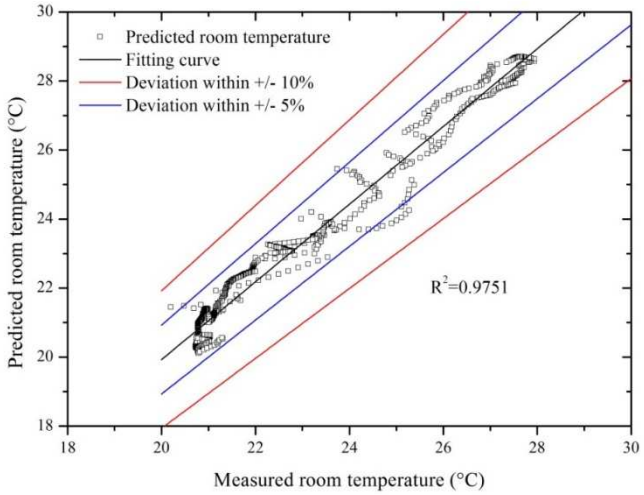
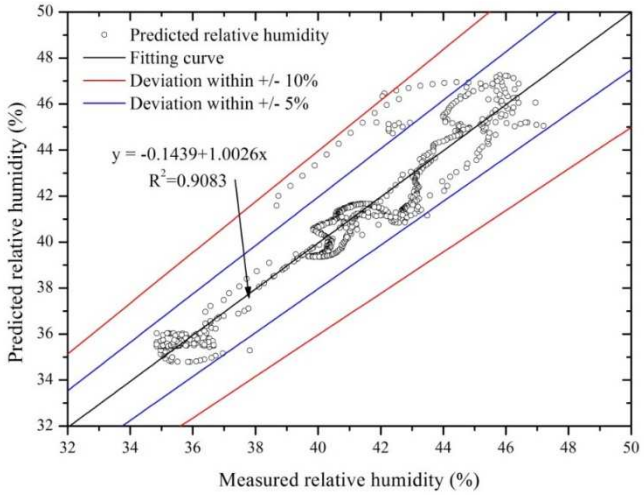


Figure 6 : Coefficient of determination of the room temperature for the five cycles and the relative deviation of the model prediction.



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.

4. Results and discussion

The existing thermal comfort standards, such as ISO 7730, ASHRAE standard 55, and EN 15251 provide thermal comfort ranges for four categories of mechanically conditioned spaces (Table 5). Educational buildings are considered in the second category with a normal level of expectations. Besides, energy consumption in educational buildings is usually high. In recent studies, the annual heating energy consumption for some European educational buildings is reported to be in the range of 67 kWh/m^2 and 192 kWh/m^2 [32]. However, the thermal regulation in France sets a benchmark of 50 kWh/m^2 for annual heating energy consumption in new and renovated educational buildings. Therefore, the desired behavior in the deemed case study is to maintain the PMV values within the range of [-0.5, 0.5] and to reduce the annual heating energy consumption to less than 50 kWh/m^2.

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

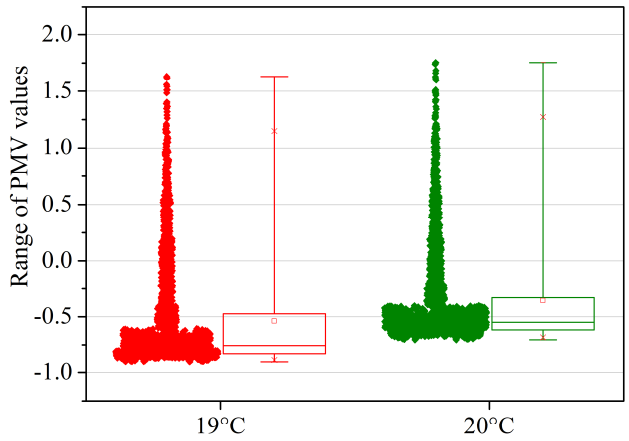
392 Moreover, the total heating energy consumption and the EQI for the two cases are
393 illustrated in Figure 9. The results show that the case of set-point 19°C consumes the least
394 heating energy consumption, while the case of set-point 20°C offers better thermal comfort
395 conditions. These results 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



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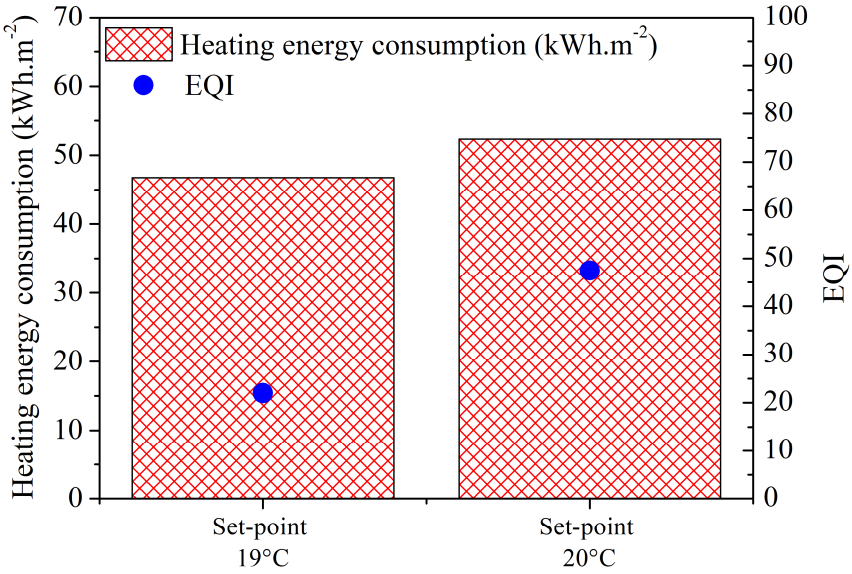
415 Figure 8: Box plots of hourly PMV index values. *(The quartiles represent the 25%-75%*
416 *interval, and the intermediate line the median.)*



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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
Set-point temperature	*A*	°C	19	21
Sol-air temperature	*B*	°C	-2.2	17.2
glazing type (U-value)	*C*	$W.m^{-2}.K^{-1}$	0.7	2.8
(g-value)		-	0.3	0.77
WFR	*D*	%	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

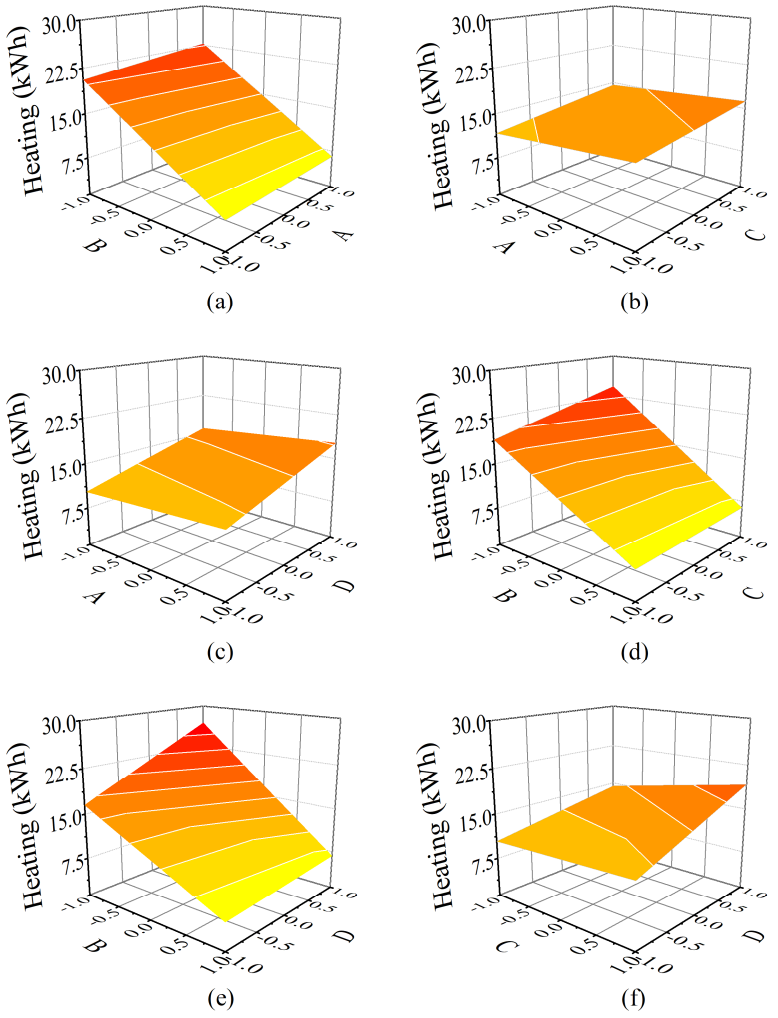
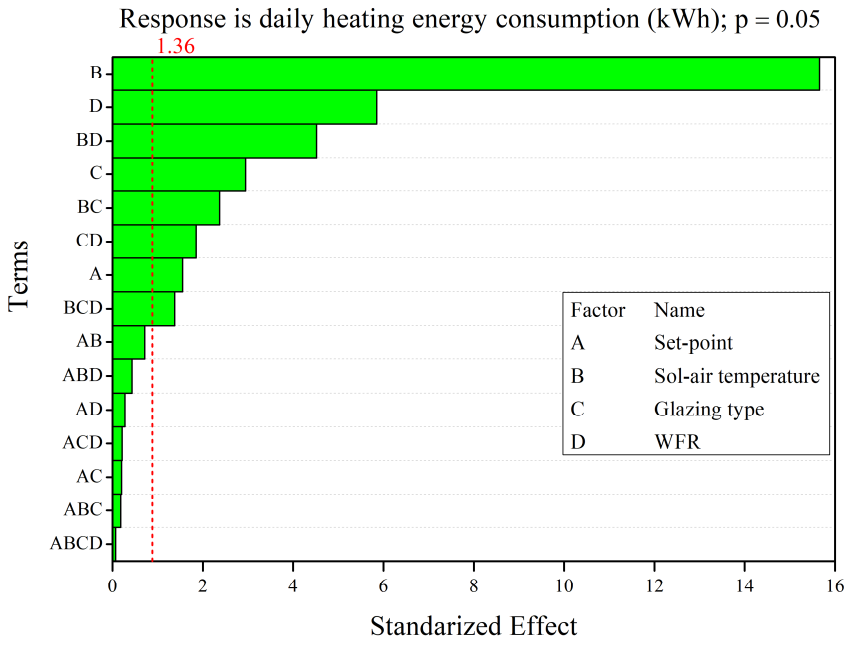


Figure 10: 3D response surface interactive effects of varied: (a) sol-air temperature and set-point temperature, (b) set-point temperature and glazing type, (c) set-point temperature and glazing area, (d) sol-air temperature and glazing type, (e) sol-air temperature and glazing area, and (f) glazing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

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

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

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



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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
497 expected values if the factor does not affect the response variable. Figure 12 illustrates the
498 normal probability plot of standardized effects at p=0.05 for the daily heating energy
499 consumption. Sol-air temperature (B) and the interactions between sol-air temperature and
500 glazing area (BD) and glazing type (BC) are the factors having a negative influence on the
501 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
504 type, interaction between glazing area and glazing type, and set-point temperature, which
505 means that the response variables increase with increasing level.

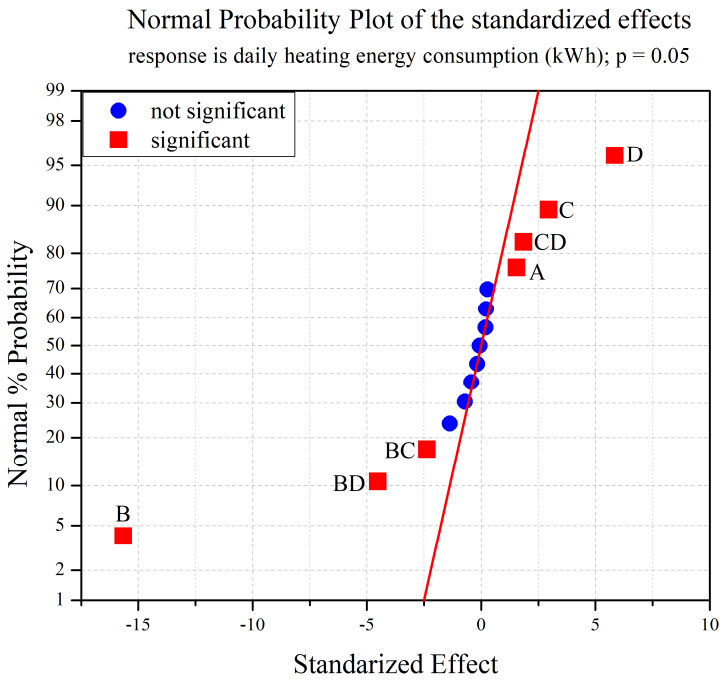


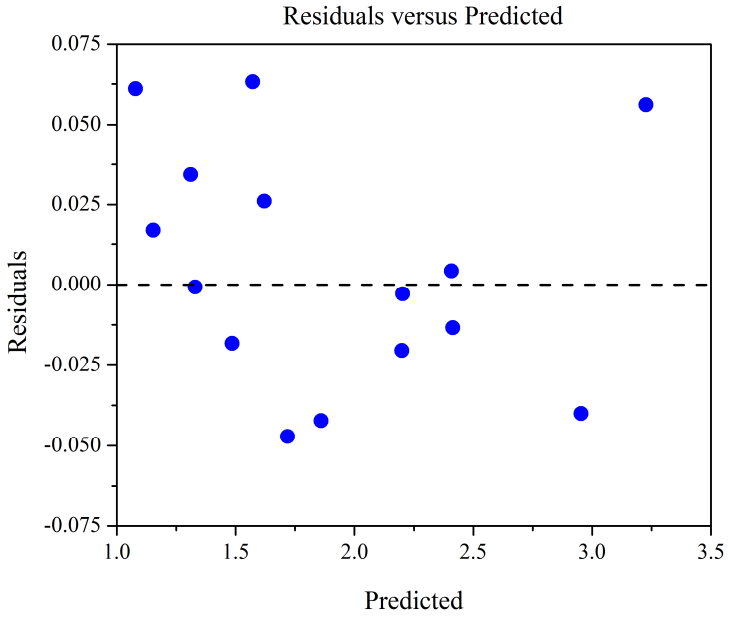
Figure 12: Normal probability plot of the standardized effects.

4.2.4. ANOVA and Development of meta-models

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-value < 0.05). The non-significant factors (p-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.

519 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				



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

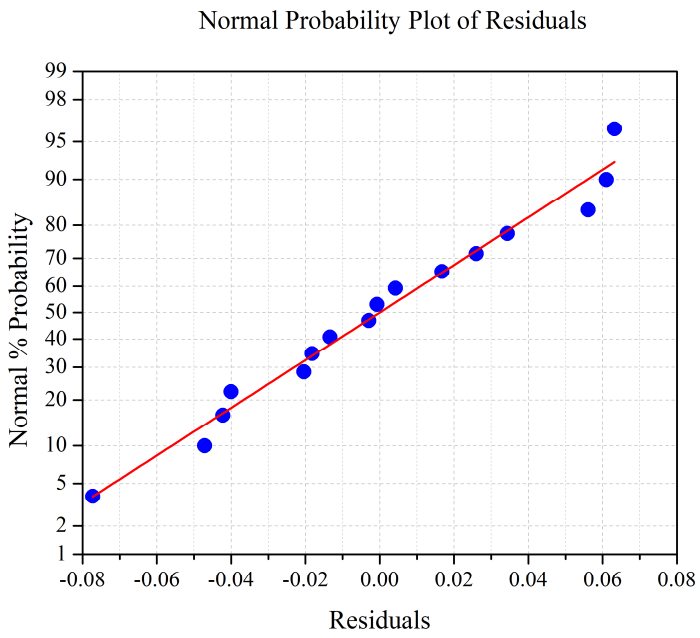


Figure 14 : Normal probability plot of residuals for daily heating energy consumption.

4.2.5. Determination and analysis of optimal solutions

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

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

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

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

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

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

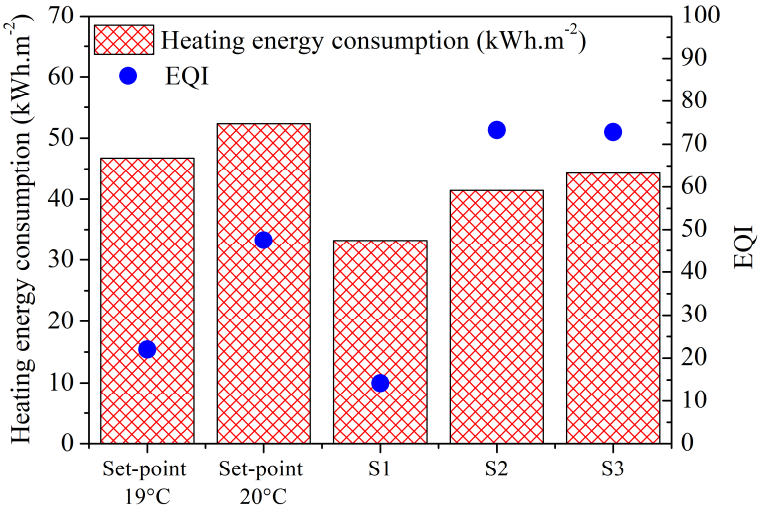
563 indicates that a simultaneous optimization, here S2, is the best scenario. Considering both
564 parameters allows for energy-saving, as well as maintaining acceptable thermal comfort
565 conditions.

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.

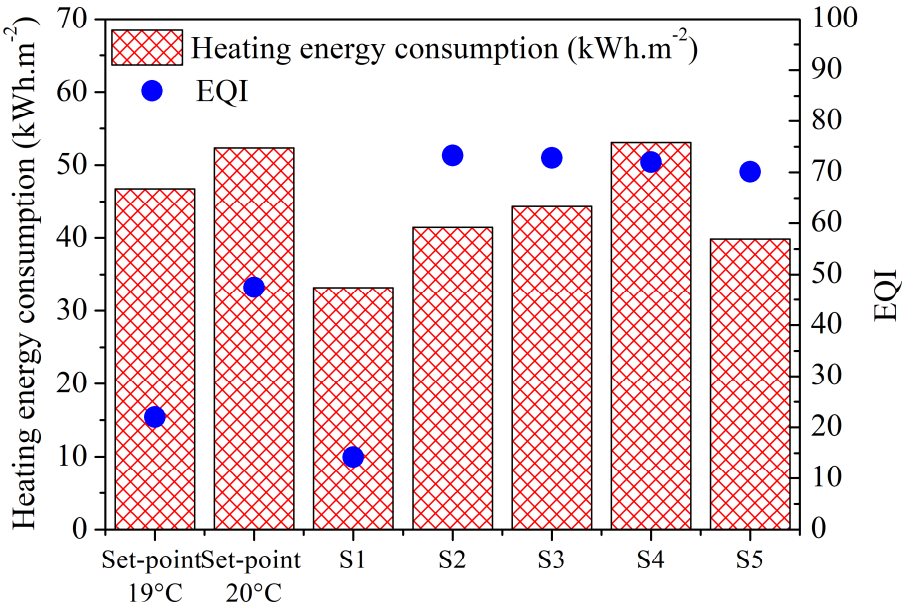
576 **4.3. Comparison with thermal comfort based control**

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

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

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

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

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References

[1] F. Amirifard, S.A. Sharif, F. Nasiri, Application of passive measures for energy 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.jobe.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. Arahal, 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/matecconf/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