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Abstract

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

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

Nomenclature

CI	Clothing Insulation
D	Global desirability function
IQR	Inter Quartile Range
MR	Metabolic Rate
MRT	Mean Radiant Temperature
PMV	Predicted Mean Vote
PPD	Percentage of Persons Dissatisfied
Q	Quartile
SHGC	Solar Heat Gain Coefficient
TS	Thermal Sensation

TSV	Thermal Sensation Vote
WFR	Window-Floor-Ratio
WWR	Window-Wall-Ratio
C_i	Regression coefficients
d_i	Individual desirability function
e_i	Residual
r_i	Weighting parameter
R^2	Coefficient of determination
X_i	Independent coded factor
y_i	Actual observation
$\hat{y}_i$	Fitted value
Y_i	Predicted response variable
ε	Random error term

1. Introduction

Over the last decade, the buildings sector was responsible for 40% of the European Union (EU28) final energy consumption in front of transport (33.2%) and industry (25%) [1]. This concern has led the Energy Performance of Buildings Directive (EBPD) to state that the energy efficiency of existing buildings must be improved, and all new buildings must be close to zero energy in 2020 [2]. However, the primary objective of buildings must be to provide a comfortable environment for the people, since they spend 80-90% of the day indoors [3]. Additionally, inappropriate indoor thermal comfort leads to lower work efficiency, higher 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 between energy-saving and occupants' thermal comfort [5]. Thermal comfort is defined as "*that condition of mind which expresses satisfaction with the thermal environment*"[6,7]. Among all the standard thermal comfort indices [8], Fanger's [9] Predicted Mean Vote (PMV) and Percentage of Persons Dissatisfied (PPD) are the most applicable indices that can be used to evaluate the thermal comfort within an air conditioned space and to quantify its value [10].

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 because of users' requirement of higher light transmittance and better view [11]. However, poorly designed glass facades vastly affect occupants' thermal comfort, because of the large hot surfaces resulting from dissipated solar radiation [12]. For instance, a high intensity of solar radiation leads to an increase in the interior surface temperature of the glass facade, which leads to an increase in the mean radiant temperature (MRT) and ultimately affecting occupants' thermal comfort [13].

Numerous studies have been conducted to investigate the influence of glass facade design on building energy consumption [14–18], thermal comfort [19–22] and visual comfort [18,22–26]. The vastly investigated parameters are Window-Wall-Ratio (WWR), glazing properties (U-value, solar heat gain coefficient (SHGC) and visible transmittance), and shading device. Thalfeldt *et al.* [14] investigated several facade designs in nearly zero energy building; the study indicated that the performance improved significantly when improving the thermal properties of the window. Poirazis *et al.* [15] carried out building energy simulations for extensive amount of scenarios combining different glazing types and shading solutions for an office building with fully glazed facades, the study concluded that the buildings with fully glazed facades are likely to have higher energy consumption than those with conventional facades. Jin and overend [16] carried out a comparative study on 13 glazing types on the facade of a typical cellular office, the study indicated that high-performance glazing technologies, such as photovoltaic integrated glazing, offer significant improvements over opaque insulated walls and conventional insulated glazing windows, even for extensive glazed envelope, in terms of both energy consumption and indoor environmental quality. Lee *et al.* [17] investigated the effect of window systems on the energy consumption of buildings in five typical Asian climates using regression analysis; the main finding of the investigation is that the WWR must be minimized except for the north facing opaque wall, and the placement of window depends hugely on the climatic conditions. Cheong *et al.* [26] performed comparative simulation study to evaluate the effect of glazing system type on both thermal comfort and daylighting in a highly glazed residential building. The study indicated that improving the glazing type reduces the cooling load and electricity cost. Stavrakakis *et al.* [21] presented a novel computational method to optimize window design for thermal comfort in naturally ventilated buildings. They found that as one of the openings' height increases, thermal sensation is improved. Zomorodian and Tahsildoost [22] assessed the effect of window design on thermal and visual comfort using dynamic simulations in an educational building. The results of the study suggested that solar-control coated glazing with low SHGC and high visual transmission could be an alternative solution to solar shadings. Tzempelikos *et al.* [19] investigated the effect of changing glazing type and shading device on indoor thermal comfort and energy consumption in an office building with extensive glazing area. The study concluded that both thermal resistance and solar transmittance have a huge effect 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].

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

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

2. Case Study

The considered case study is a highly glazed room, called the foyer, which includes café and seating space. It is a communal place of life in which students meet to eat, rest, and do activities. It is situated in the south-eastern part of the ground floor of a low energy consumption building located in Troyes, France, and designed to meet the French standard requirement RT2012 (Figure 1). The Foyer has a floor area of $58m^2$ and south- and east-oriented glass facades. It is heated by radiators and a dual-flow ventilation system that contains three Air Handler Units integrating heating coils to enable heating and ventilation. Dimensions as well as the physical parameters of the Foyer are summarized in Table 1.

Students occupying the Foyer reported a significant difference in temperature from that in other parts of the building and indicated dissatisfaction in the thermal conditions. In order to confirm this allegation, subjective thermal comfort was assessed using survey questionnaire by asking the students to express their thermal sensation, preference and satisfaction. Thermal sensation vote (TSV) was evaluated using the ISO seven-level scale [6,34]. Thermal preference was assessed using a seven-point scale: 'a lot more cooler', 'more cooler', 'a bit more cooler', 'no change', 'a bit more warmer', 'more warmer' and 'a lot more warmer'. Thermal satisfaction was evaluated using two levels: 'satisfied' and 'dissatisfied'. In addition, students' activity level was determined using a five-point scale: 'seated quiet', 'standing relaxed', 'light activity', 'medium activity' and 'high activity'. The survey questionnaire, entitled "Current Thermal comfort in the Foyer", was constructed using the *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 noting that the building was occupied by 281 students and staff members in 2016 [33]. Thus, the collected questionnaires represent a sample of 90% confidence interval and 10% margin of error.

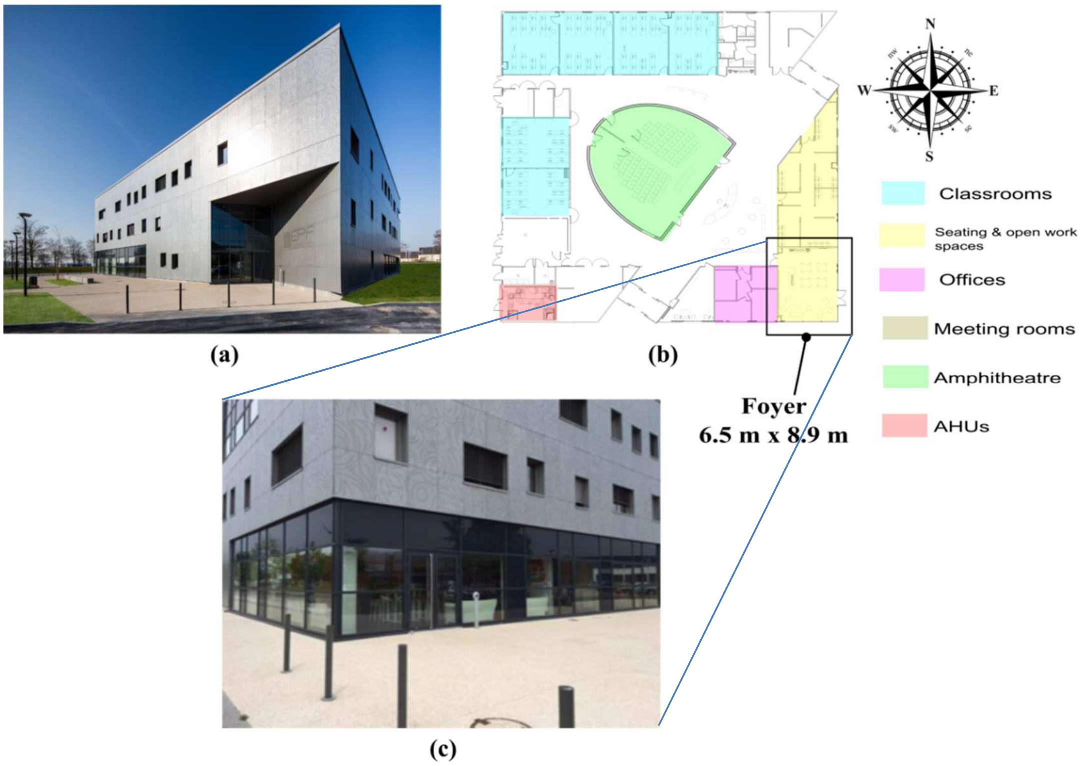


Figure 1: Engineering school building overview (a), ground floor map (b) and the Foyer (c).

Table 1 : 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}

3. Methodology

3.1. Design of Experiments

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

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

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

4. Choice of experimental design
5. Performing the experiment
6. Statistical analysis of the data
7. Conclusions and recommendations

The Analysis of Variance (ANOVA) in combination with Fisher's statistical test (p-value < 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.

3.2. Meta-modeling and regression coefficients

One of the main objectives of the DoE technique is to pursue a suitable mathematical model, called "meta-model", which approximates the response variable as a function of predefined factors. 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, successively expressed as follows [36]:

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

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

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

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

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:

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

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].

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$(\hat{y}_i)$:

$$e_i = y_i - \hat{y}_i \quad (6)$$

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].

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 desirability function approach, represents a useful approach to optimization of multiple responses. The desirability function approach proposed by Harrington [41] and then modified and popularized by Derringer and Suich [42] aims to simultaneously optimize multiple equations. Its basic idea is to convert a multiple response problem into a single one by converting each response y_i into an individual desirability function d_i that ranges from zero, if the response is outside the limits, to one if the response is at its target. The individual desirability functions have different formulations depending on the desired objective. If the objective is a maximum, a minimum or a target value, the desirability functions are described, respectively, by the following equations:

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

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

$$d_i^{target} = \begin{cases} 0 & if \quad y_i < L \\ \left(\frac{y_i - L}{T - L}\right)^{r_1} & if \quad L \le y_i \le T \\ \left(\frac{U - y_i}{U - T}\right)^{r_2} & if \quad T \le y_i \le U \\ 1 & if \quad y_i > U \end{cases} \tag{9}$$

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):

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

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

4. Results and discussion

4.1. Subjective assessment of thermal comfort

4.1.1. TSV and thermal preference

Using the comfort survey questionnaire, TSV and thermal preference of the students were assessed using the questions “How do you feel inside the foyer?” and “How would you prefer the indoor condition of the foyer to be?” respectively. The distribution of collected subjects’ responses is shown in Figure 2. The results show that the distribution of students’ thermal sensations was skewed toward the warm side. The most frequently selected vote was “Warm”. More accurately, about 30 % of the students selected this option. In addition, 24.5% of the votes were for the “slightly warm” option. Further, the frequency for "cold" TSV is very small. To test the statistical significance of this response and the possibility to be considered an outlier, numerous types of possible statistical methods can be used [45,46]. In this study, two different methodologies, known as Tukey’s method and Grubbs' test, were employed to detect outliers in the data. Tukey’s method is based on box plots that identify the first (Q1) and third (Q3) quartiles of the data [45]. The difference between these values is known as the interquartile range (IQR). The range for outlier detection is then established by identifying the inner and upper fences, located at a distance 1.5 IQR below Q1 and above Q3. If the value is less than the lower fence or higher than the upper fence, these values are considered as outliers. The Grubbs' test is a method that uses the approximate normal distribution to detect a single outlier in the dataset [46]. It detects outliers in the dataset through an established hypothesis with two statements – no outlier found or an outlier found in dataset. In our case, the box plot of the TSV (Figure 2b) shows that the “cold” vote lays on the upper fence of the box plot, and the performed Grubbs’ test indicated that the “cold” vote is far from the rest, but is not a significant outlier. Based on these results, the response is not considered as an outlier.

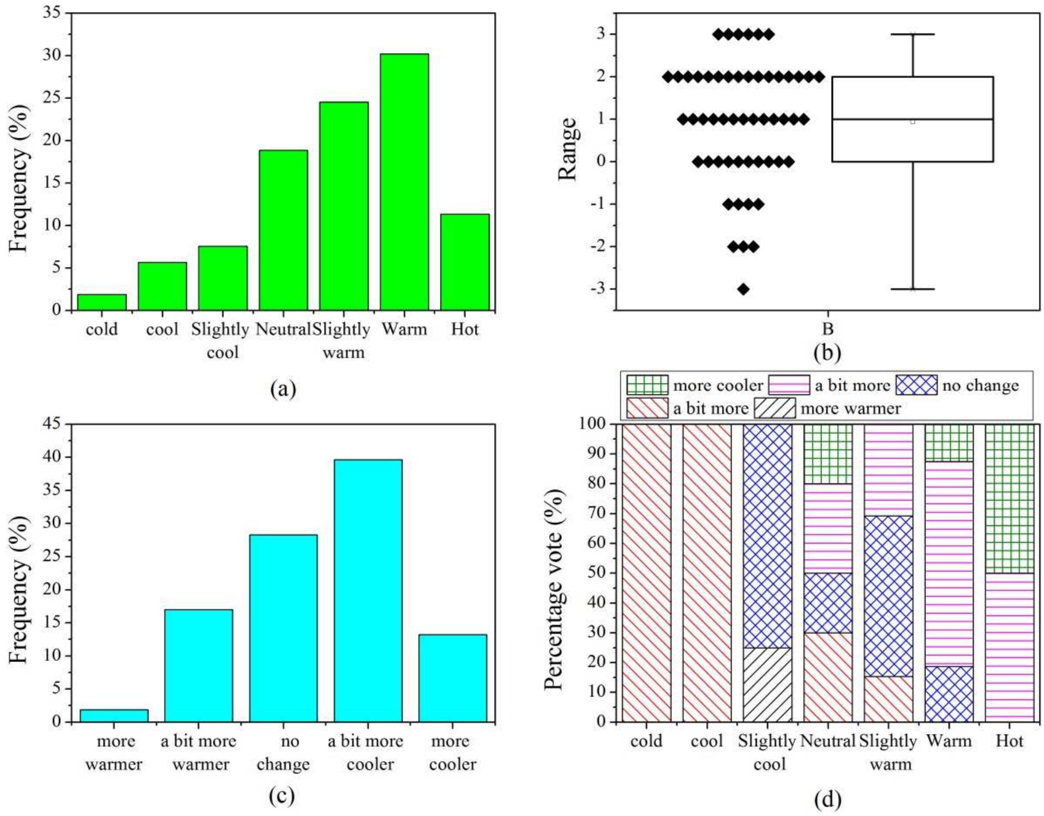


Figure 2: Statistical summary of survey questions: (a) TSV, (b) box plot of TSV, (c) thermal preference and (d) relationship between thermal sensation and thermal preference.

The distribution of thermal preference was broadly distributed, but was mainly concentrated on the “a bit cooler” option. More specifically, about 39% of the students selected the option “a bit cooler” and about 28% selected the “no change” option. Figure 2d shows the detailed relationship between thermal preference and thermal sensation. The first important inference is that the neutral thermal sensation was not preferred by the majority of 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 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 warm' did not vote to change the thermal conditions, and 56.25 % of the students who felt 'warm' preferred a bit cooler thermal conditions.

4.1.2. TSV and Satisfaction

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

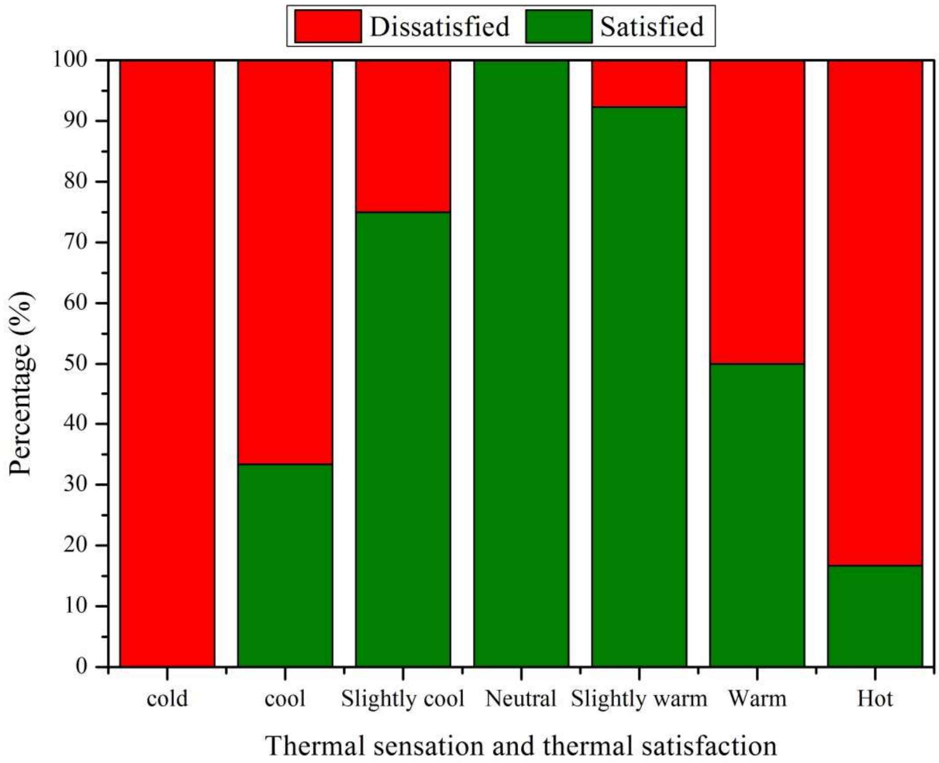


Figure 3: Relationship between thermal sensation and thermal satisfaction.

4.1.3. TSV and climate

In order to examine the relationship between thermal sensation and outdoor climatic conditions, the students were asked to answer the question "How would you describe the weather outside today?" and the three options were: "overcast", "partially cloudy", and "Sunny". These three options were based on weather data collected by a weather station in Barberey located 11.5km from the considered case study and are displayed online [48]. Figure 4 shows the distribution of collected responses and the detailed relationship between TSV and outdoor climate. The results show that the majority of the students, nearly 70%, answered the survey questionnaire during a winter day with sunny sky. In addition, slightly warm, warm and hot were voted by the overwhelming majority of the respondent, nearly 80%, who answered sunny. On the other hand, the results show that during a partially cloud day, about 70% of the respondent voted between "slightly cool" and "slightly warm". Moreover, the "cold" and "hot" votes appeared only during "overcast" and "sunny" days, respectively. These results show a wide variation in thermal sensation during different climatic conditions. These results could be correlated to the presence of fully glazed facades because frequent changes in the outdoor climate affect the MRT, and eventually students' thermal comfort.

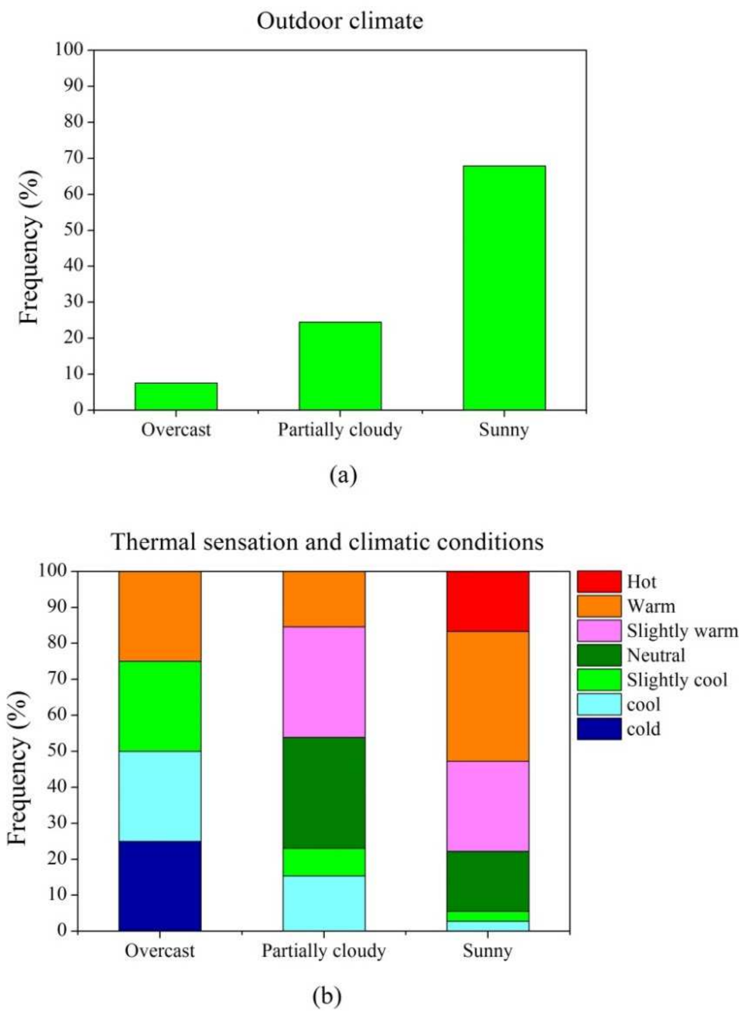


Figure 4: Statistical summary of survey questions: (a) outdoor climatic conditions during the questionnaire time and (b) relationship between thermal sensation and climatic conditions.

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.

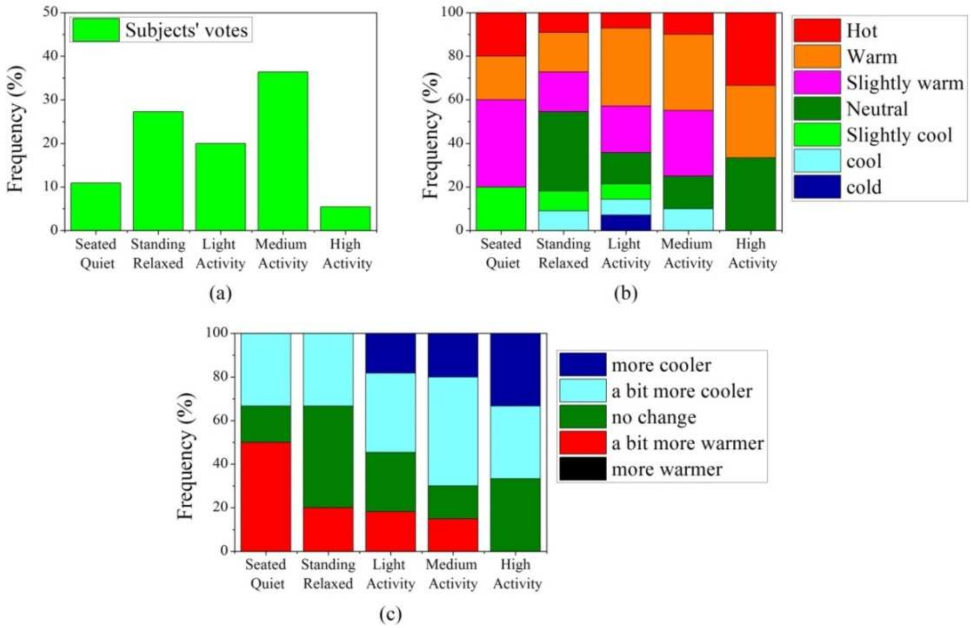


Figure 5: Statistical summary of survey questions: (a) students' activity level, (b) relationship between thermal sensation and activity level and (c) relationship between thermal preference and activity level.

4.2. Thermal comfort assessment using numerical simulations

In order to evaluate and analyze the thermal comfort features of the foyer, a previously 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 simulation environment used to translate a Modelica model into an executable program. The thermal performance simulations highlighted the evolution of the PMV index and the MRT on four winter days corresponding to bright overcast, partly cloudy, dark overcast and sunny skies, noted as cases A, B, C and D, respectively. Outdoor temperatures, global solar radiations and solar altitude angles are illustrated in Figure 6. Case A represents a typical winter day with no direct solar radiation due to overcast sky. Case B signifies a winter day with relatively high outdoor temperature and solar radiation. Case C designates a winter day with low outdoor temperature and weak solar radiation. Case D denotes a winter day with relatively high outdoor temperature and intense solar radiation.

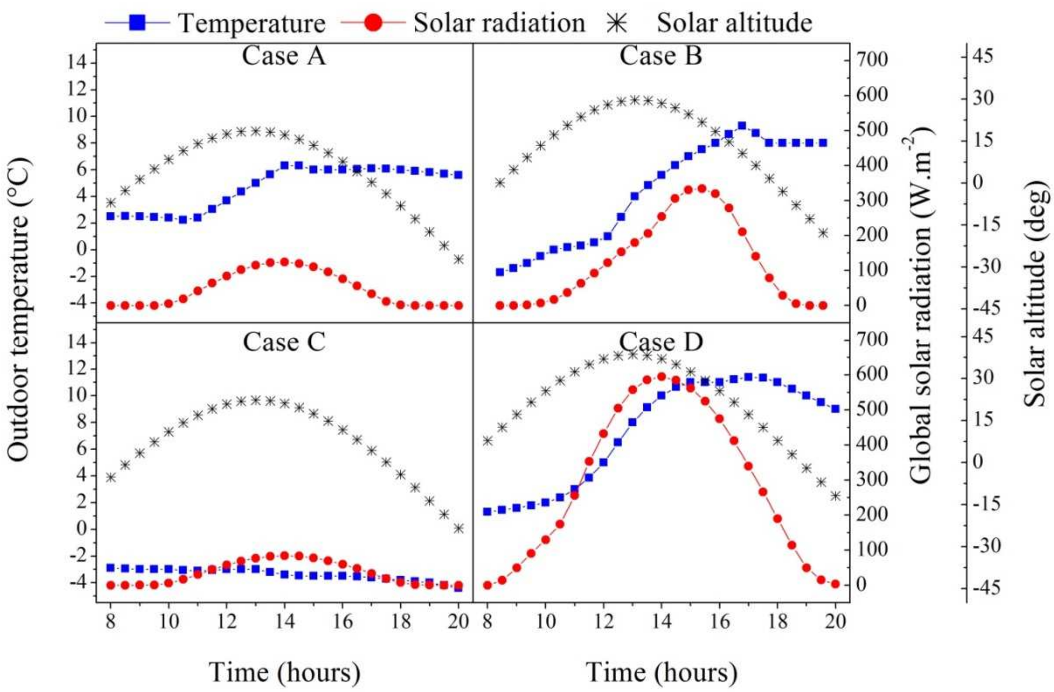


Figure 6: Outdoor climatic conditions of the four studied days.

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.

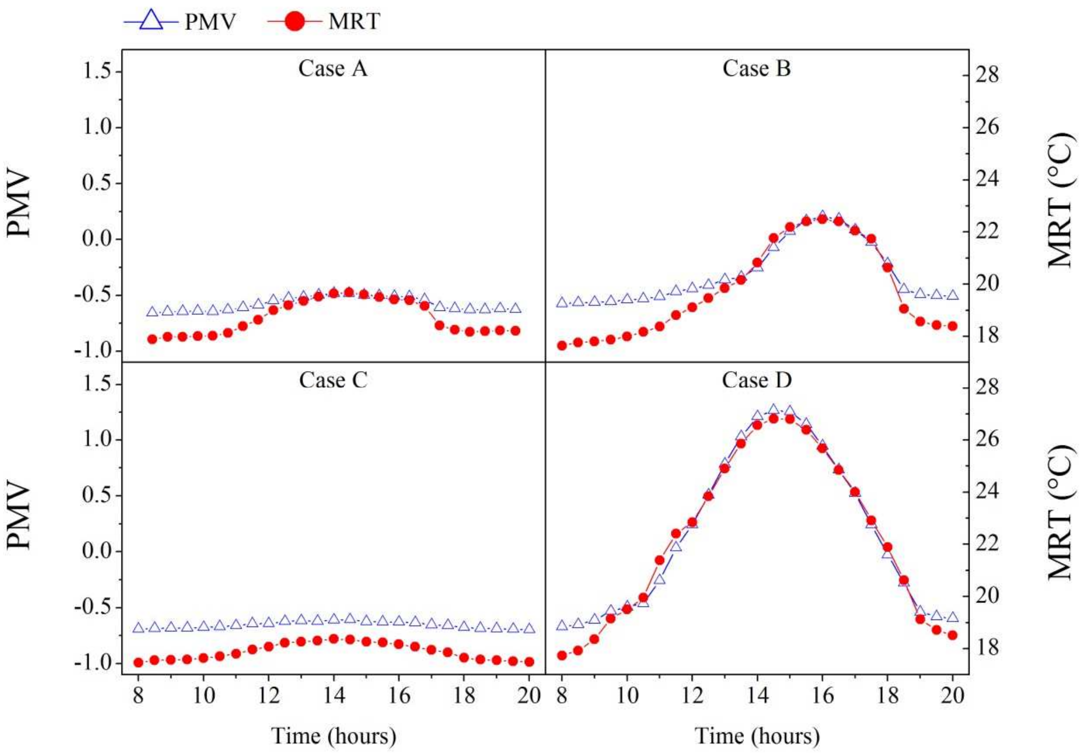


Figure 7 : PMV and MRT of the four studied days

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.

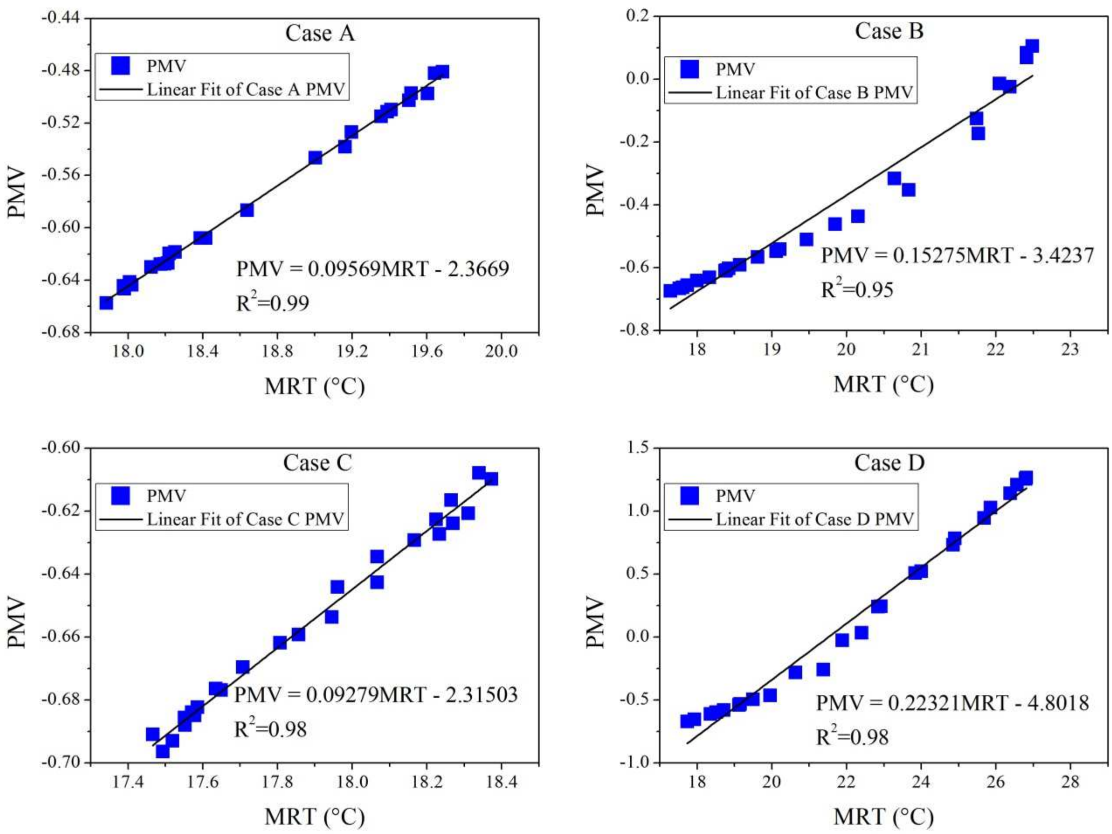


Figure 8 : Correlation between PMV and MRT.

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 limit for high activity level. Additionally, on the day with intense solar radiation, PMV exceeded the upper comfort limit for all activity levels during the presence of the solar radiation. These results explain the appearance of different votes and confirm the high variability of students' thermal sensation during the same period. For example, a student with low activity level present in the Foyer during the lack of solar radiation may experience a thermal sensation between "slightly cool" and "cold". However, a student with the same activity level present in the Foyer during the occurrence of intense solar radiation may experience a "slightly warm", "warm" or "hot" thermal sensation depending on other factors.

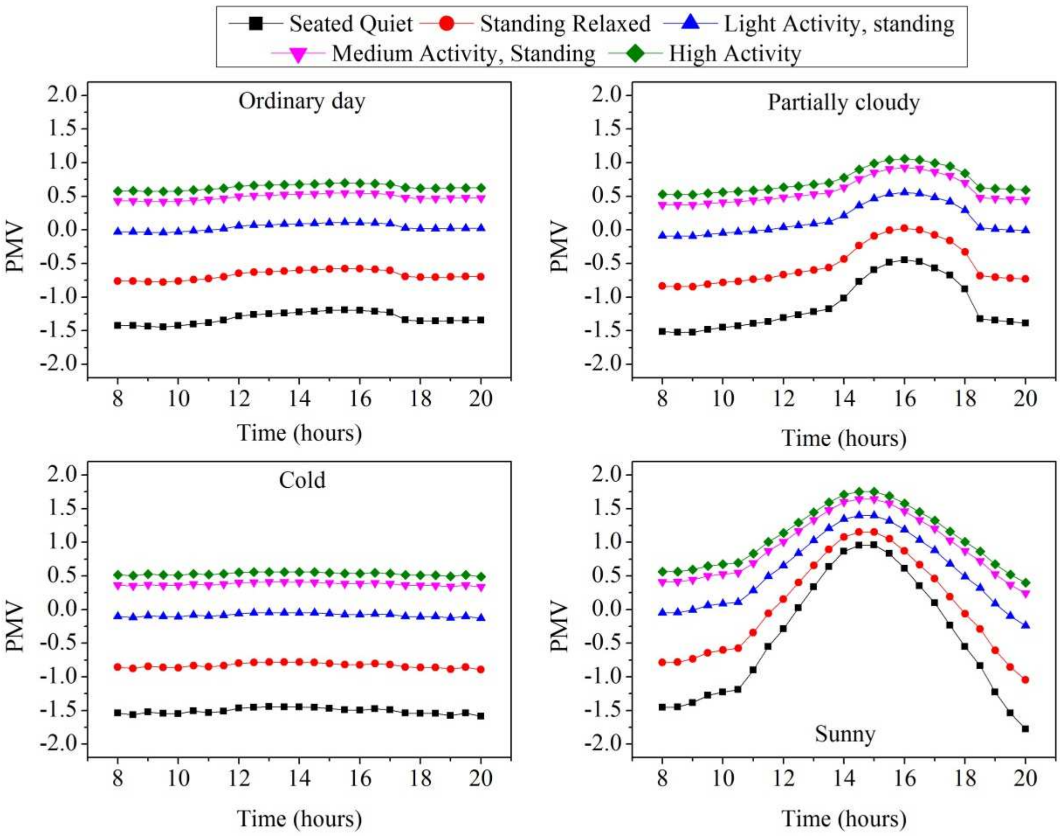


Figure 9: Effect of activity level on the PMV index in the four studied days

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 conditions. On the other hand, PMV index is directly and indirectly influenced by other factors, e.g. clothing insulation. In this consequence, the proposed approach is applied to the Foyer in order to determine the most critical parameters affecting the PMV value, then to optimize the glass facades configuration for thermal comfort.

4.3. **Sensitivity study**

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.

PMV is influenced by room temperature, MRT, relative humidity, air velocity, metabolic rate, and clothing insulation. Relative humidity and air velocity were excluded from the sensitivity study, since PMV was found to be less sensitive for both parameters compared to the four other parameters [49,50]. Besides, since MRT is highly influenced by the outdoor climatic condition, as previously discussed, it was replaced by the sol-air temperature. This last is a parameter defined as "the outside air temperature which, in the absence of solar radiation, would give the same temperature distribution and rate of heat transfer through a wall/roof as exists due to the combined effects of the actual outdoor temperature distribution plus the incident solar radiation" [51]. The sol-air temperature was found to be a good illustration of the weather conditions [52]; its mathematical formulation is presented in [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 factors influencing the response variable.

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 = 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 values that are recommended by the French and the European standards [54,55]. The daily average sol-air temperature was calculated and the minimum and maximum values were chosen to represent the lower and higher levels. While, the levels of the remaining factors were selected based on the questionnaire results and the recommended values by the standards [54,55]. Table 2 reports the considered parameters and their corresponding codes and levels.

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

Factor	Code	Unit	Level	
			-1	+1
Clothing insulation	*A*	clo	0.8	1.2
Metabolic rate	*B*	$W.m^{-2}$	58	125
Room temperature	*C*	°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

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 factors and their interactions. Additionally, center points were added to the design to examine the adequacy of the model for capturing the curvature expressed in the response. Figure 10 shows the design matrix (64 runs) and the response variables resulting from the simulation results (numerical results are reported in Table A of the supplementary information). Minitab® software, a statistical computer package, was used to analyze the data of Figure 10.

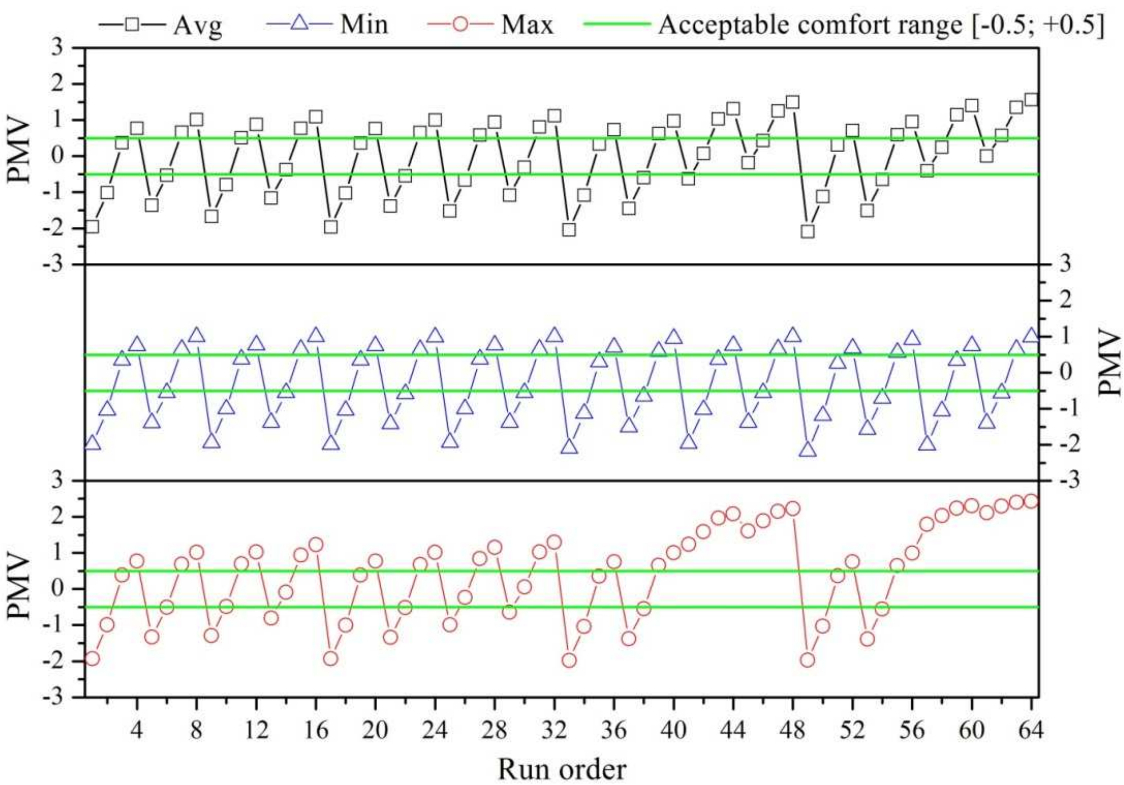


Figure 10: DoE simulation results (each run represnts a unique combination of factors levels)

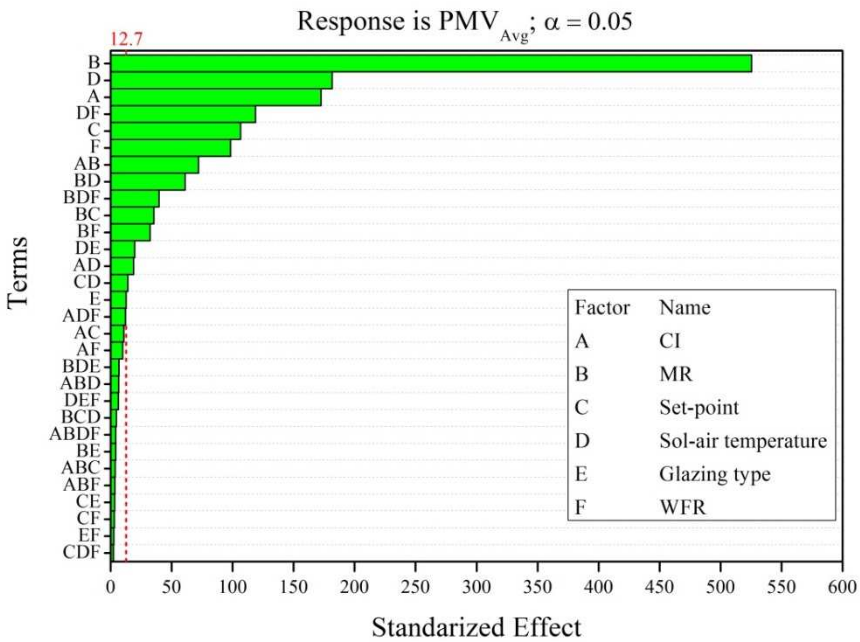
4.3.3. Statistical analysis of the data

ANOVA was carried out in order to identify the significant factors. The results of ANOVA reported in Table 3, (complete ANOVA tables are reported in Tables B, D and F in the supplementary information), indicate that the linear and 2-way interactions between factors are significant, while the remaining interactions and the curvature are not. As a result, the relationship between the investigated parameters and the response variable is deemed to follow a linear equation.

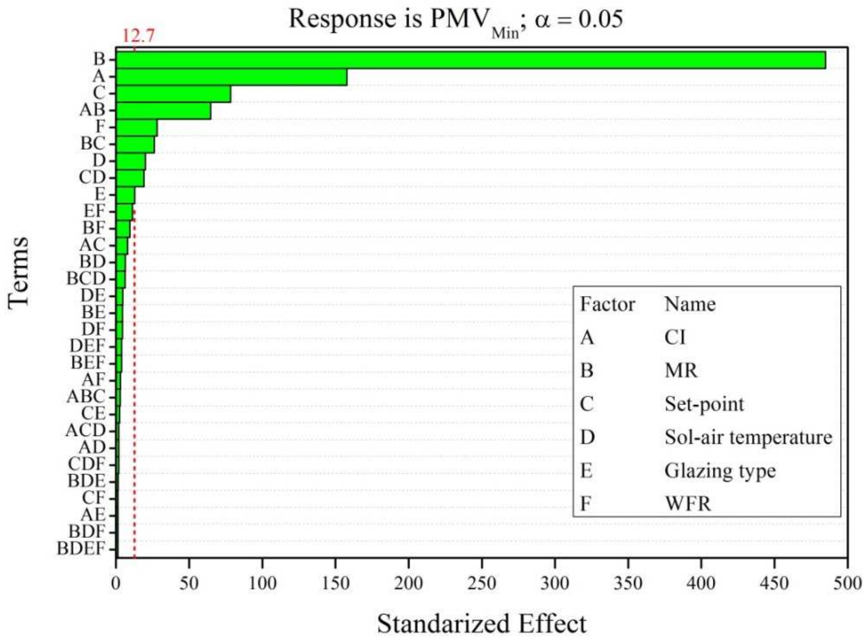
Table 3: ANOVA results for average, minimum and maximum PMV values.

Source	DF	Seq SS	Adj SS	Adj MS	F-Value	P-Value
Average PMV						
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			

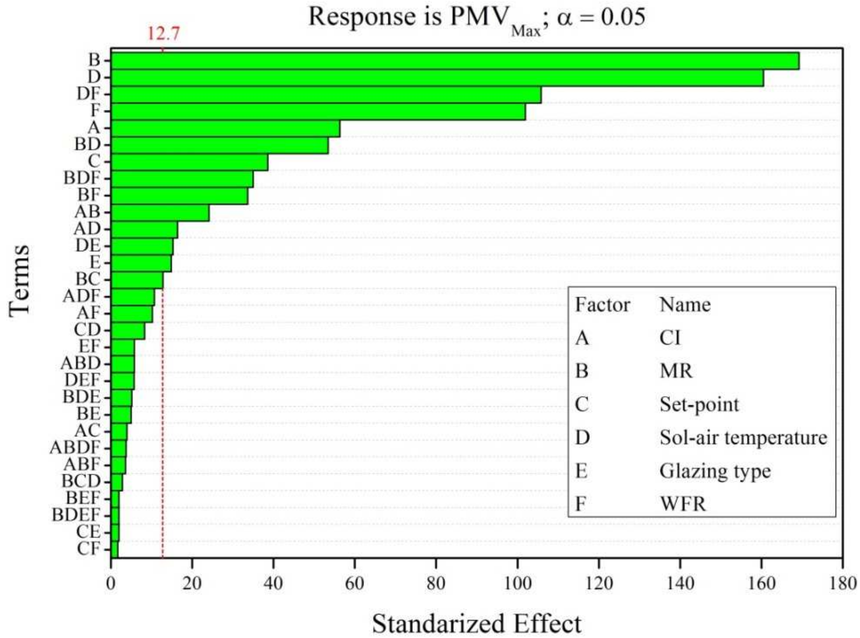
The Pareto charts for standardized effects for the average daily, minimum and maximum PMV values are shown in Figure 11. The bars display the variables and their interactions, where all the bars that exceed the vertical dashed line are considered significant. The results reported in Figure 11 show that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



(a)



(b)

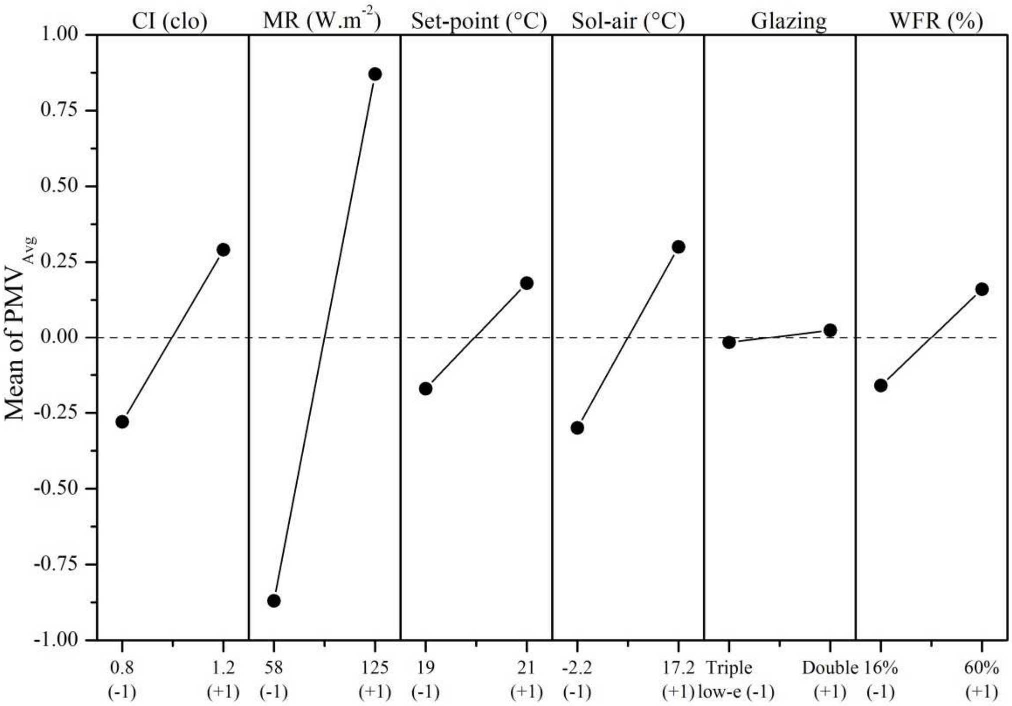


(c)

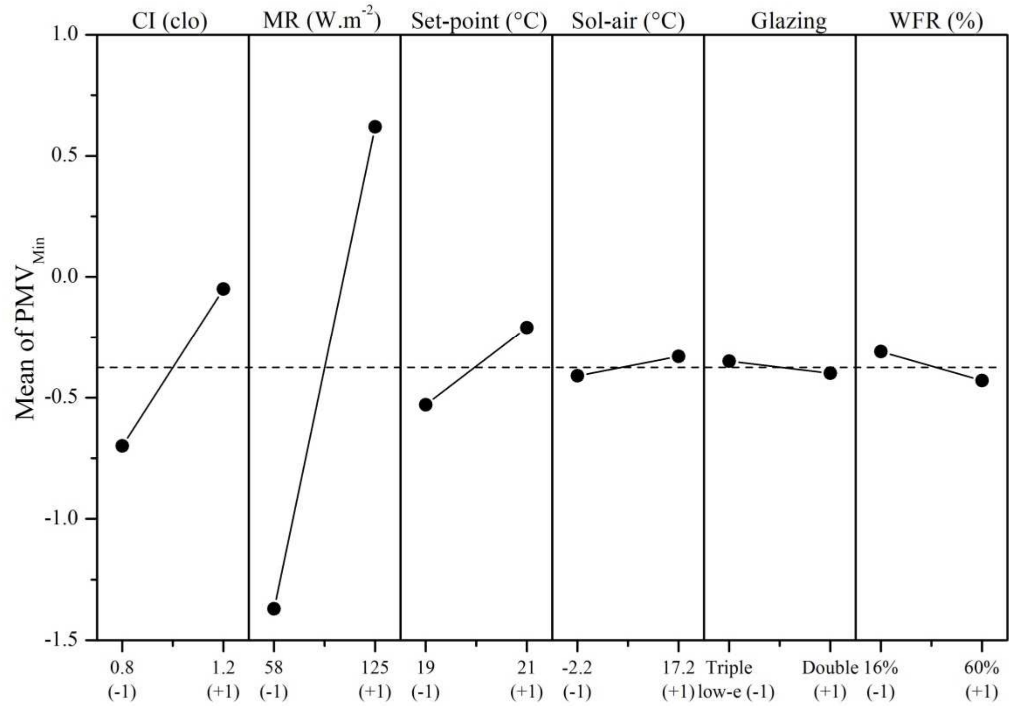
Figure 11 : Pareto plots of standardized effects at p = 0.05 for: (a) daily average PMV, (b) minimum PMV and (c) maximum PMV.

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

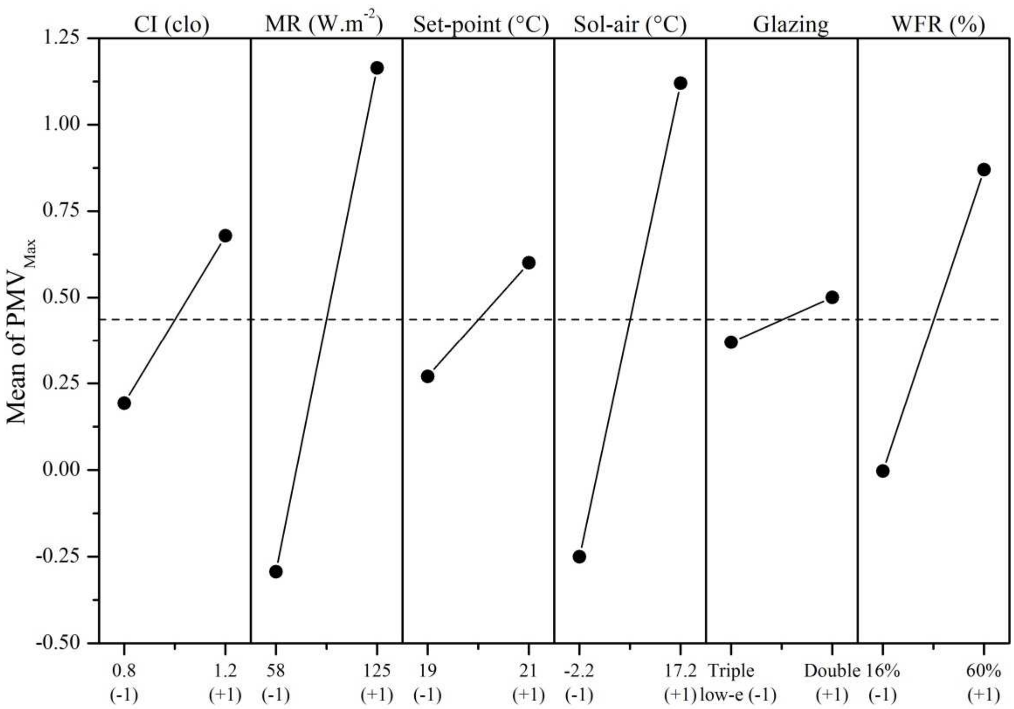
After identifying the main effects, it is important to study the interactions between them, since this was found to be significant using the Pareto charts, as described in Figure 11. Interactions occur when the effect of a factor is dependent on the level of another one. Figure 13 shows the interaction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


CI (clo)
MR (W.m^{-2})
Set-point (°C)
Sol-air (°C)
Glazing
WFR (%)
Mean of PMV_{Avg}
1.00
0.75
0.50
0.25
0.00
-0.25
-0.50
-0.75
-1.00
0.8 (-1)
1.2 (+1)
58 (-1)
125 (+1)
19 (-1)
21 (+1)
-2.2 (-1)
17.2 (+1)
Triple low-e (-1)
Double (+1)
16% (-1)
60% (+1)

(a)

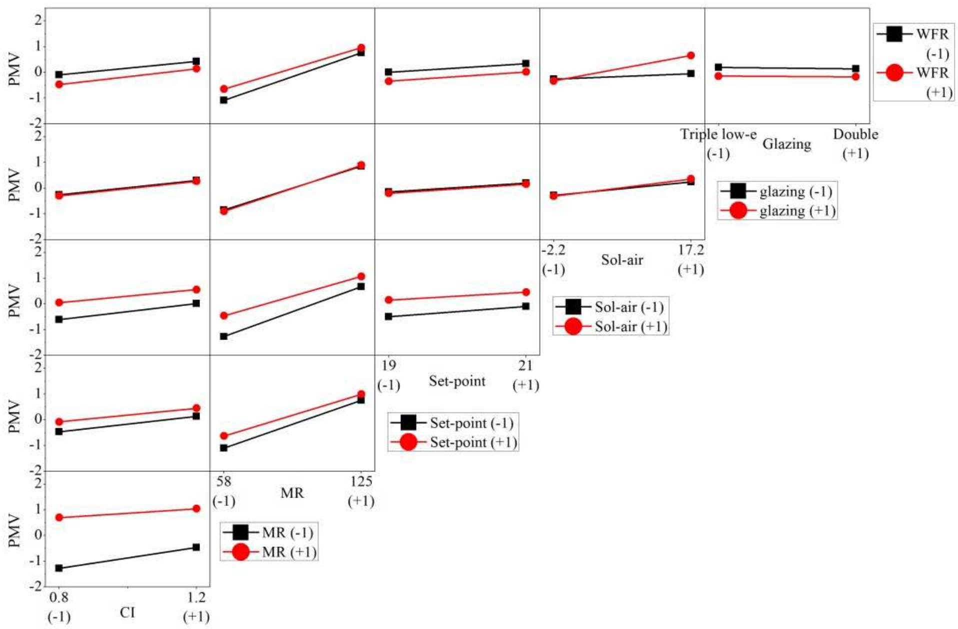

CI (clo)
MR (W.m^{-2})
Set-point (°C)
Sol-air (°C)
Glazing
WFR (%)
Mean of PMV_{Min}
1.0
0.5
0.0
-0.5
-1.0
-1.5
0.8 (-1)
1.2 (+1)
58 (-1)
125 (+1)
19 (-1)
21 (+1)
-2.2 (-1)
17.2 (+1)
Triple low-e (-1)
Double (+1)
16% (-1)
60% (+1)

(b)

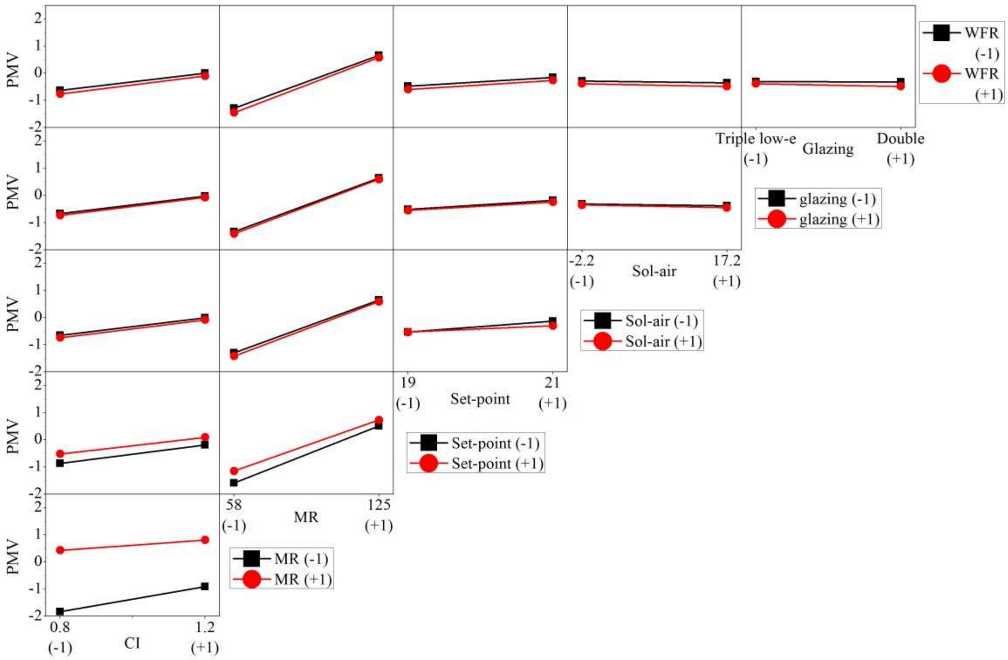


(c)

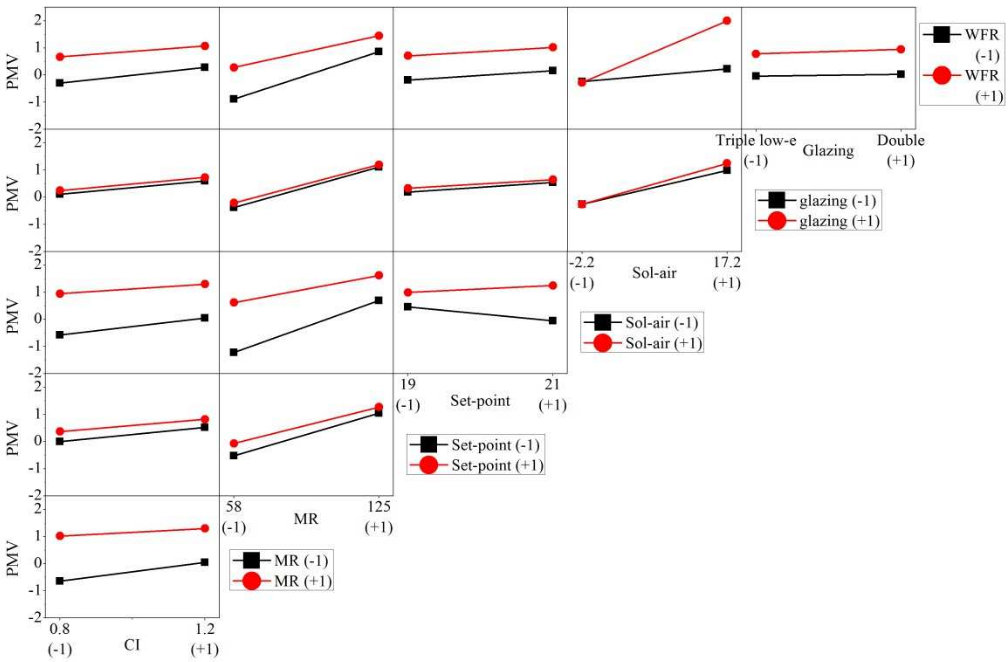
Figure 12: Main effect plot for: (a) daily average PMV, (b) minimum PMV and (c) maximum PMV.



(a)



(b)



(c)

Figure 13: interaction plots for: (a) daily average PMV, (b) minimum PMV and (c) maximum PMV

4.3.4 Development of meta-models for the prediction of the PMV values

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.

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

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

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

The ANOVA results of the models indicate good performance with R^2 (> 0.98) and adjusted-R^2 (0.97). The value of adjusted-R^2 indicates that more than 97% of the total factors associated with the PMV are attributed to the selected parameters of the model. The Predicted 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 proposed models are adequate. In addition, the normal probability plots shown in Figure 14 designate that the residuals followed a straight line, thus confirming the validity of the models.

Furthermore, 50 additional simulations were performed with different factors' levels 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 of 0.99, meaning that 99% of variance is explained by the obtained meta-model. Therefore, the meta-models are considered to be valid and adequate. These meta-models can be used instead of the numerical model as a fast and simple way to predict the thermal comfort condition within an indoor environment. However, the reliability of these meta-models is limited to a similar case study and the considered range of variation of the investigated factors.

4.3.5. Determination and analysis of optimal solutions

Finally, an optimization is carried out using the obtained meta-models. The response variables are the average, minimum and maximum PMV values. The objective is to maintain these values within the recommended acceptable thermal comfort range of [-0.5;+0.5] [6]. 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 ranges of [66.5;73.5] and [0.95;1.05], respectively, representing sedentary activity and typical winter clothing with 5% variation [56].The sol-air temperature parameter was excluded from the optimization because it is an uncontrollable parameter. The objectives and constraints of the optimization are summarized in Table 4.

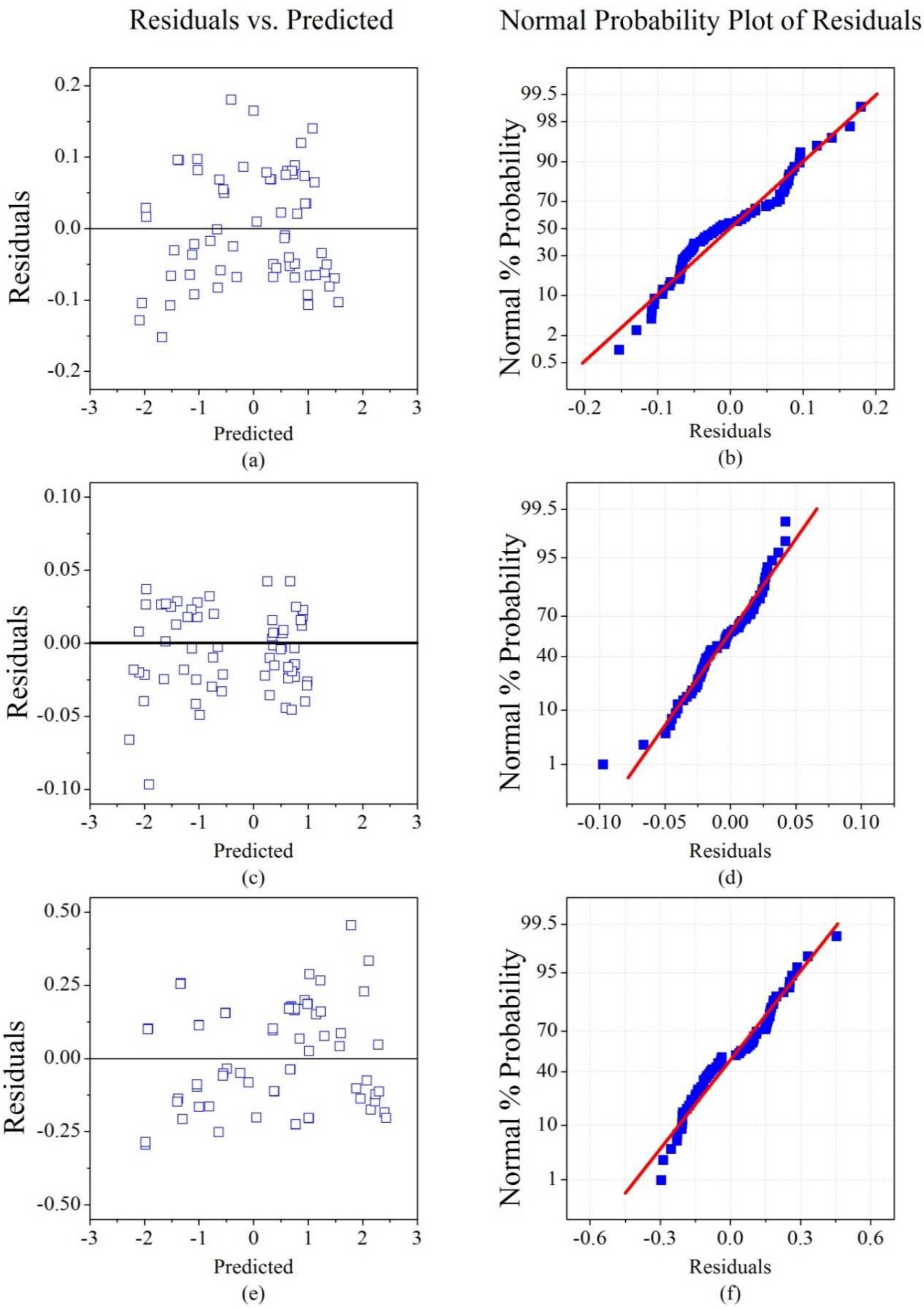


Figure 14: Residuals versus fitted values, (a), (c) and (e), and Normal probability of residuals, (b), (d) and (f), for average, minimum and maximum PMV values, respectively.

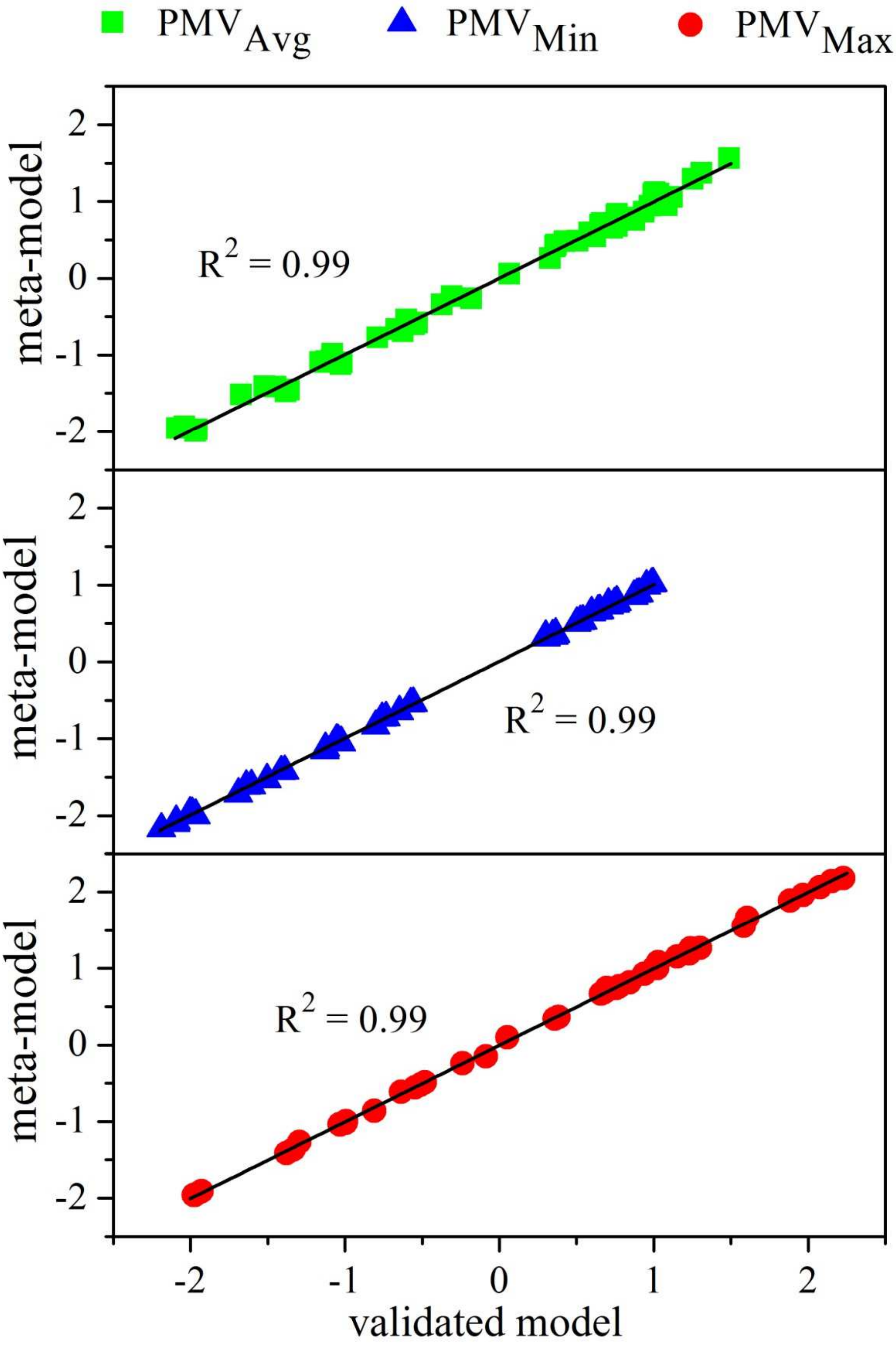


Figure 15: Coefficient of determination between simulation results and the meta-model predictions.

Table 4: objectives and constraints of the optimization

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

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

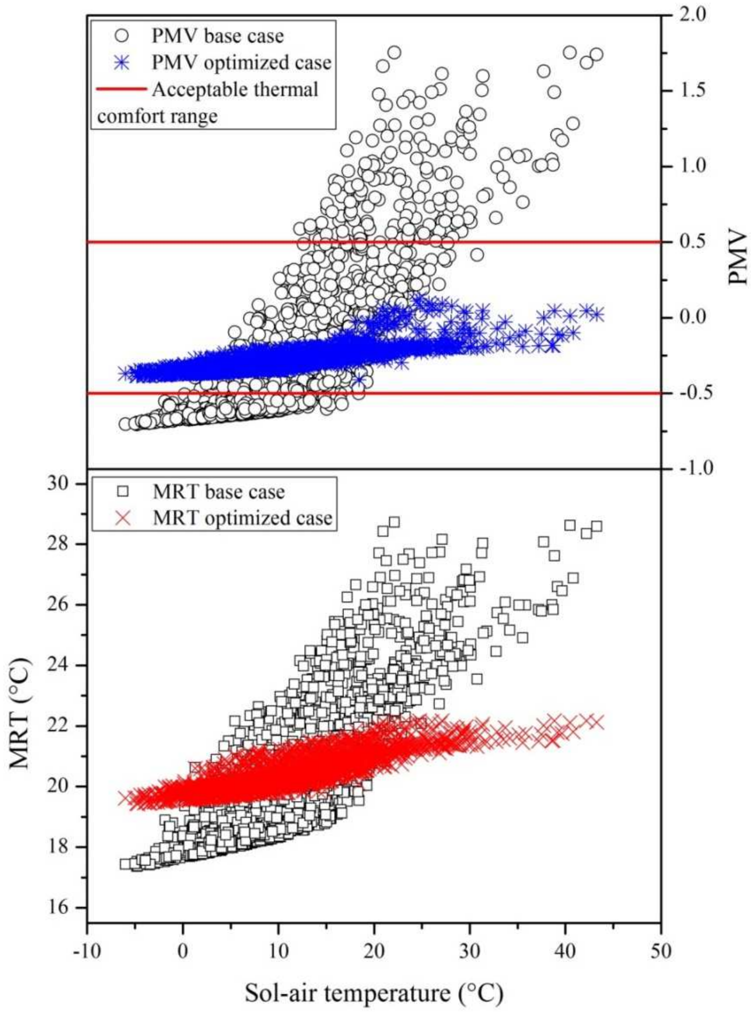


Figure 16: Numerical hourly values of (a) PMV index and (b) MRT of the base-case and the optimized-case designs.

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.

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

This study demonstrated that optimizing building design for thermal comfort can be achieved by adequate treatment of building envelope design, i.e. glass facades configuration in our case. Although the proposed approach outcomes robust and credible results, its limitation is that few parameters and response variables were considered in the analysis. In addition, both u-value and SHGC of the glazing were considered simultaneously. Future work 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 typologies.

Acknowledgment

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