Metamodelling of Summer Thermal Comfort in a Non-Air-Conditioned Building

Issa Jaffal1,2, Christian Inard3, Nesreen Ghaddar2, Kamel Ghali2
1Laboratoire du Froid des Systèmes Énergétiques et Thermiques (Lafset), Cnam, HESAM
Université, Paris, France
2Mechanical Engineering Department, American University of Beirut, Beirut, Lebanon
3Laboratory of Engineering Sciences for the Environment (LaSIE), UMR CNRS 7356, La Rochelle
University, La Rochelle, France

Abstract
Providing a comfortable indoor thermal environment is a primary objective of building design. In this work, we present a new flexible metamodel for evaluating the long-term thermal comfort in non-air-conditioned buildings. The metamodel was used to study the adaptive thermal comfort in an office during summer for two typical cold and hot European climates using four indices. The metamodel was fitted by multiple regression analysis with a low number of dynamic simulations using the design of experiments. Moreover, the nonlinearities in the metamodel were calculated. High accuracy was obtained for indices where the lower and upper limits were not frequently encountered such as maximum indoor temperature. However, alternative metamodels should be developed for the remaining indices such as overheating degree-hours.

Introduction
Thermal comfort has a significant impact on occupants’ health, satisfaction, and productivity. Many European buildings are not-air-conditioned during summer. They are in free-running mode where the indoor temperatures are dependent on the outdoor conditions.

The indoor conditions in these buildings are of increasing concern throughout Europe, where serious overheating problems have been reported (Sameni et al., 2015; Morgan et al., 2016). Furthermore, overheating is exacerbated by urban heat islands (Demanuele et al., 2012) and climate change (Jenkins et al., 2011). Thus, these buildings would face extreme overheating in the future and mechanical cooling systems would be needed to ensure acceptable indoor conditions (Santamouris, 2016).

Consequently, the development of methods to assess the thermal conditions in non-air-conditioned buildings has attracted attention in the recent years. Long-term thermal comfort indices summarize in a single value the thermal comfort in a building evaluated over a long period (year, season, etc.). They provide an overall picture of the thermal performance of a building and as such they are suitable for solving optimization problems (Carlucci et al., 2014).

Dynamic simulations can be used to assess the thermal conditions in non-air-conditioned buildings with relatively high fidelity. However, their use would become very time consuming when conducting detailed studies, e.g. for optimizing building design, forecasting the impact of climate change on overheating or studies at the urban level. Moreover, these simulations require a large amount of data which limits their use in the early design stages where the most important design decisions are taken.

Metamodels are constructed to replace expensive simulation models in order to reduce the simulation cost and to better understand model behavior (Kleijnen, 1987). Several approximation strategies have been developed to construct metamodels. The most common and simplest metamodels are polynomial regressions. They can be fitted with low computational effort and are suitable to provide insight into model behavior. The number of simulations needed for their fit can be drastically reduced using the design of experiments (Montgomery, 2017).

More advanced metamodeling methods such as artificial neural networks, support vector regression and kriging can be also used to approximate models (Li et al., 2010). Generally, these methods provide better approximations than the polynomials. However, they can be computationally expensive and may be difficult to interpret.

Several metamodels have recently been developed to study thermal comfort in non-air-conditioned buildings. Breesch et al. (2010) developed a linear regression metamodel for long-term thermal comfort using weighted temperature excess hours as an index (Linden et al., 2002). They used the standardized coefficients of the metamodel in order to identify the most important parameters that were causing uncertainty on thermal comfort.

van Gelder et al. (2014) compared polynomial regression, Multivariate Adaptive Regression Splines (MARS), kriging, radial basis function networks and neural networks when predicting the number of hours of overheating and the energy demand for heating as a function of probabilistic building parameters. MARS was preferred because of its simplicity, although kriging and neural networks performed slightly better.

Moreover, metamodels based on artificial neural networks were found by Symonds et al. (2015) to perform better than those based on radial basis functions when studying the number of overheating hours and air pollution versus building parameters.

Maderspacher et al. (2015) used neural network and support vector machine metamodels to forecast the number of overheating hours and the future energy...
demand for heating with respect to weather variables. They found that both metamodels were reliable for the period 2000–2030 but the errors increased for the period 2060–2090. Neural networks were ten times faster and support vector machines more than one hundred and fifty times faster than the detailed building model.

Rackes et al. (2016) developed a support vector regression metamodel that assesses the fraction of hours in which the comfort limit is exceeded as a function of building and weather parameters. They recommended the metamodel for labeling of naturally ventilated commercial buildings in Brazil.

MARS also improved the accuracy of linear regression metamodels when predicting the proportion of time with acceptable thermal comfort versus building passive design parameters (Chen et al., 2017).

In addition, metamodels have been extensively used to study the energy performance of air-conditioned buildings (Tian et al., 2015; Hester et al., 2017). They have also been used to study building components (Capozzoli et al., 2013; del Coz Diaz et al., 2014).

However, the metamodels for non-air-conditioned buildings concerned specific cases. In addition, the number of thermal comfort indices was limited. Moreover, the ability of the metamodels to provide insight into building thermal behavior in free-running mode was not investigated. Furthermore, the accuracy was lower than when studying the energy performance of air-conditioned buildings. These studies highlight the need for metamodels to accurately assess thermal comfort in non-air-conditioned buildings in a flexible way and using various indices.

To address this issue, this work presents a new flexible metamodel for evaluating thermal comfort in non-air-conditioned buildings following the general metamodel developed for the energy performance of air-conditioned buildings (Jaffal and Inard, 2017). This metamodel is designed to be adaptable to various case studies in order to rapidly assess thermal comfort as a function of building characteristics and based on several indices.

The metamodel was used to study thermal comfort in an office during summer for two typical cold and hot European climates. To this end, the adaptive comfort model of the prEN 16798-1 standard was used (CEN/TR, 2015). Thermal comfort was assessed with four of the most commonly used indices including maximum indoor temperature and degree-hours of discomfort.

The metamodel was fitted from dynamic simulations by multiple regression analysis. The design of experiments was used to reduce the number of dynamic simulations needed to fit the metamodel, and the metamodel fit was tested by comparing the results with those of dynamic simulations. Moreover, the non-linearity in the metamodel was calculated based on the analysis of its coefficients.

Methods

Metamodeling

The metamodel for a given long-term thermal comfort index \( I_c \) is expressed as

\[
I_c = a_0 + \sum_{i=1}^{n} a_i X_i + \sum_{i=1}^{m} \sum_{j=i+1}^{m} a_{ij} X_i X_j + e
\]

where \( X_i \) and \( X_j \) are two influencing factors, \( a_0, a_i, a_{ij} \) and \( e \) are the metamodel coefficients to be determined and \( e \) is the error term.

For heat transfer by transmission or ventilation, \( X_i \) is equal to a coefficient of heat transfer \( H_t \). For internal or solar heat gain \( X_i \) is equal to a seasonal heat quantity \( Q_s \).

The metamodel coefficients are assumed to depend mainly on climate, the thermal mass of the building and its use, occupants' behavior and control scenarios.

A transmission heat transfer coefficient is calculated from

\[
H_{tr} = U A
\]

where \( U \) (W m\(^{-2}\) K\(^{-1}\)) and \( A \) (m\(^2\)) are the U-value and the area of a wall, respectively.

A ventilation heat transfer coefficient is given by

\[
H_v = \rho_a c_p q_v
\]

where \( q_v \) is the design airflow rate (m\(^3\) s\(^{-1}\)), \( \rho_a \) and \( c_p \) are the air density (kg m\(^{-3}\)) and specific heat capacity (J kg\(^{-1}\) K\(^{-1}\)), respectively.

A heat quantity due to internal gains can be calculated from

\[
Q_{ig} = \sum p_{ig} A_f \Delta t
\]

where \( p_{ig} \) are the internal heat gains (W m\(^2\)), \( A_f \) is the floor area (m\(^2\)) and \( \Delta t \) is the time step (h).

A solar heat gain through a window can be expressed as

\[
Q_{so} = \sum F_{ish} F_{cob} SHGC_o I_w A_w \Delta t
\]

where \( SHGC_o \) and \( A_w \) are the solar heat gain coefficient and the area of the window (m\(^2\)), respectively, \( I_w \) is the solar irradiance in the direction of the window (W m\(^2\)) and \( F_{ish} \) and \( F_{cob} \) are the reduction factors of the internal and external shading devices, respectively.

**Comfort temperatures**

The adaptive comfort temperature in non-air-conditioned buildings is related to the outdoor temperature. The outdoor temperature is an exponentially weighted running mean of the daily mean air temperature (CEN, 2007; CEN/TR, 2015). This temperature for a given day is calculated from

\[
\theta_{rm} = (1 - \alpha)(\theta_{ed-1} + \alpha \theta_{ed-2} + \alpha^2 \theta_{ed-3} ...)
\]

where \( \theta_{ed} \) is the daily mean air temperature for the previous day, \( \theta_{ed-2} \) is the daily mean air temperature for the day before and so on, \( \alpha \) is a constant between 0 and 1 with a recommended value of 0.8.

The optimal comfort temperature \( \theta_{comp} \) is correlated to the weighted running mean temperature using the following linear relationship:
\[ \theta_{\text{conf}} = 0.33\theta_{\text{rm}} + 18.8 \quad (7) \]

The allowable difference from the optimal comfort temperature depends on the type of building (CEN, 2007; CEN/TR, 2015). In this work, we considered a building of category II (normal expectation). The corresponding acceptable temperature range in the prEN 16798-1 standard is \( \theta_{\text{conf}} = -4 \text{ K} \) to \( \theta_{\text{conf}} = +3 \text{ K} \).

**Case study**

The metamodel was used to study the thermal conditions in an office (Figure 1). The office was a concrete structure. It was occupied from Monday to Friday from 8h to 18h.

The thermal comfort was assessed for the cold climate of Helsinki, Finland, and the hot climate of Athens, Greece from the beginning of June until the end of September. The mean outdoor air temperatures during the studied period were 14.1 °C in Helsinki and 25.3 °C in Athens. Four typical indices were considered to assess the long-term thermal comfort.

The maximum indoor temperature \( \theta_{\text{i,max}} \) (°C),

- The mean seasonal value of the likelihood of overheating \( L_{\text{o},m} \) (%),

- The degree-hours of overheating \( DH_{o} \) (°C h).

- The percentage of time with acceptable thermal comfort \( PT_{a} \) (%), which has the particularity of including both overheating (when the indoor operative temperature \( \theta_{i} > \theta_{\text{conf}} + 3 \text{ K} \)) and overcooling (when \( \theta_{i} < \theta_{\text{conf}} - 4 \text{ K} \)).

The likelihood of overheating gives the percentage of subjects indicating ‘warm’ or ‘hot’ on the ASHRAE comfort scale, which is expressed as (Nicol et al., 2009)

\[ L_{o} = \frac{(0.4734569-2.607)\theta_{i}+4.0743489-2.607}{100} \quad (9) \]

The degree-hours of overheating is calculated as follows:

\[ DH_{o} = \sum w f \Delta t \quad (10) \]

where \( w f \) is the weighting factor and \( \Delta t \) is the time step.

The weighting factor \( w f \) is given by

\[ \{ \begin{align*} \theta_{i} & \leq \theta_{i,max} \Rightarrow w f = 0 \quad (11) \\ \theta_{i} & > \theta_{i,max} \Rightarrow w f = \theta_{i} - \theta_{i,max} \end{align*} \]

where \( \theta_{i} \) is the indoor operative temperature and \( \theta_{i,max} \) is the upper comfort limit (here equal to the optimal comfort temperature + 3 °C).

Next, the nonlinearities in the metamodel were calculated based on the metamodel coefficients. The ratio of quadratic to linear effects is given by

\[ Q L = \frac{\sum_{l} |a_{l}|}{\sum_{l} |b_{l}|} \quad (12) \]

where \( a_{l} \) is the effect of a linear term, \( a_{l} \) is the effect of a quadratic term and \( n \) is the number of linear terms equal to the number of the quadratic terms (here \( n = 7 \)).

The ratio of interaction to linear effects is calculated from

\[ I L = \frac{\sum_{l} \sum_{ij} |a_{ij}|}{\sum_{l} |a_{l}|} \quad (13) \]

where \( a_{ij} \) is the effect of an interaction term and \( n_{ij} = n_{ij}(n_{ij} - 1)/2 \) is the number of interaction terms (here \( n_{ij} = 21 \)).

\[ \text{Figure 1: View of the office.} \]

**Table 1: Influencing factors on thermal comfort and corresponding physical parameters with their lower and upper levels.**

<table>
<thead>
<tr>
<th>No</th>
<th>Influencing factor</th>
<th>Parameter</th>
<th>Lower level</th>
<th>Upper level</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>( H_{\text{d},\text{ow}} )</td>
<td>( U_{\text{ow}} ) (W m(^{-2}) K(^{-1}))</td>
<td>0.1</td>
<td>0.5</td>
</tr>
<tr>
<td>2</td>
<td>( H_{\text{d},\text{w}} )</td>
<td>( U_{\text{w}} ) (W m(^{-2}) K(^{-1}))</td>
<td>0.7</td>
<td>2.7</td>
</tr>
<tr>
<td>3</td>
<td>( H_{\text{e},\text{ont}} )</td>
<td>( q_{\text{e},\text{ont}} ) (m(^{2}) h(^{-1}))</td>
<td>100</td>
<td>250</td>
</tr>
<tr>
<td>4</td>
<td>( H_{\text{e},\text{vent}} )</td>
<td>( q_{\text{e},\text{vent}} ) (vol h(^{-1}))</td>
<td>0</td>
<td>5</td>
</tr>
<tr>
<td>5</td>
<td>( Q_{\text{ig}} )</td>
<td>( p_{\text{ig,ow}} ) (W m(^2))</td>
<td>15</td>
<td>40</td>
</tr>
<tr>
<td>6</td>
<td>( Q_{\text{ao,ws}} )</td>
<td>SHGC(_{\text{ws}})</td>
<td>0.4</td>
<td>0.7</td>
</tr>
<tr>
<td>7</td>
<td>( Q_{\text{ao,ww}} )</td>
<td>SHGC(_{\text{ww}})</td>
<td>0.4</td>
<td>0.7</td>
</tr>
</tbody>
</table>
The metamodel was fitted by multiple regression analysis from detailed dynamic simulations performed with TRNSYS software (Klein and al., 2004). In particular, TRNSYS uses the response factor method proposed by Stephenson and Mitalas (1971) to calculate heat transfer through walls.

To this end, the influencing factors were varied by considering three levels of the following physical parameters:

- U-values of the opaque walls $U_{ow}$ and windows $U_w$ for $H_{o,w}$ and $H_{w}$, respectively.
- Airflow rates of ventilation $q_{o,vent}$ and night ventilation $q_{o,night}$ for $H_{o,night}$ and $H_{night}$, respectively.
- Solar heat gain coefficients of the south window $SHGC_{ws}$ and the west window $SHGC_{ww}$ for $Q_{o,ws}$ and $Q_{o,ww}$, respectively.
- Internal heat gains during occupation $p_{ig,occ}$ for $Q_{ig}$ (with a value of 0.1$p_{ig,occ}$ when unoccupied).

The influencing factors, the corresponding physical parameters with their lower and upper levels, are summarised in Table 1.

Furthermore, a Box-Behnken experimental design was used to plan the simulations (Box and Behnken, 1960). Consequently, 57 dynamic simulations were needed to fit the metamodel instead of 3$^7$ = 2187 when using a full factorial design.

The metamodel fit was tested by comparing the results with those of the dynamic simulation using TRNSYS with 100 additional dynamic simulations and a random combination of the physical parameters shown in Table 1.

Results and discussion

Metamodel coefficients

The metamodel coefficients obtained by multiple regression analysis are given for Helsinki in Tables 2 and 3, for lightweight and heavy thermal masses, respectively. These coefficients were calculated using coded variables of the influencing factors ranging from -1 to +1.

The coefficient $a_0$ corresponds to the thermal comfort level when all the coded values of the influencing factors are null, i.e. when their real values are at their mean levels. In this situation, highly acceptable thermal conditions were encountered with a heavy thermal mass, in contrast to those with a lightweight thermal mass. For instance, the mean likelihood of overheating $L_{o,m}$ was equal to 38.4% and 8.1% with lightweight and heavy thermal masses, respectively. The corresponding percentages of hours with acceptable thermal comfort $PT_c$ were equal to 39.8% and 99.2%, respectively.

Moreover, the coefficients $a_1$-$a_4$ were all negative for all the studied indices except $PT_c$, highlighting that higher coefficients of heat transfer $H$ improved thermal comfort. The highest values were for the coefficient $a_2$ indicating that the heat transfer by ventilation was the most effective in enhancing the thermal comfort in the office.

The coefficients $a_5$-$a_7$ corresponding to heat gains were, as expected, of opposite signs of $a_1$-$a_4$ with higher absolute values for $a_6$ indicating that the effect of the internal heat gains was more important than those of heat gains through the windows.

The same coefficients for Athens are presented in Tables 4 and 5, for lightweight and heavy thermal masses, respectively. The values of the coefficient $a_5$ revealed that the indoor conditions were very uncomfortable when the influencing factors were at their mean values especially with a lightweight thermal mass (e.g. mean likelihoods of overheating of 76.4% and 43.1% with lightweight and heavy thermal masses, respectively).

All the coefficients have the same signs as those for Helsinki. Therefore, high levels of coefficient of heat transfer $H$ and low levels of heat gain $Q$ would be necessary to provide acceptable indoor conditions in this hot climate.

In addition, the absolute values of $a_5$ were much higher for both climates with a heavy thermal mass, highlighting the key role of the association of night ventilation with heavy thermal mass for improving thermal comfort in non-air-conditioned buildings.
Metamodel nonlinearities

The nonlinearities in the metamodel are given by the ratio of quadratic to linear effects \( QL \) (Eq.12) and the ratio of interaction to linear effects \( IL \) (Eq.13). Their values for each index are presented in Tables 6 and 7, respectively. The results revealed that these nonlinearities were significant suggesting that linear metamodels would not provide good approximations of the dynamic model. In addition, \( QL \) and \( IL \) vary significantly with respect to index, climate and thermal mass. High nonlinearities were obtained for \( DHo \) and \( PTc \) for Helsinki and a heavy thermal mass which would be associated to values of these indices equal or close to zero that can be frequently encountered in these conditions.

Metamodel testing

The metamodel fit was tested by comparing the results with those of TRNSYS dynamic simulation for each index studied (Figures 2-5 and Tables 8-11). For maximum indoor temperature \( \theta_{i,max} \) (Figure 2 and Table 8), the metamodel gave results very close to those of TRNSYS for both climates and both thermal masses. The errors were less than 0.5 °C for Helsinki and less than 0.3 °C for Athens. In addition, the coefficients of determinations \( R^2 \) were higher than 0.992.

A high level of agreement between the results of the metamodel and those of TRNSYS was also obtained for the mean likelihood of overheating (Figure 3 and Table 9). However, lower accuracy was obtained for Helsinki with a heavy thermal mass which might be associated to the fact that \( L_{o,m} \) had several values close to zero which was not well approximated by the metamodel based on a polynomial assumption.

In addition, the accuracy for both climates was generally lower than that of \( \theta_{i,max} \). This may be attributed to the fact that Eq. (9), which incorporates subjects’ voting, was approximated by the metamodel for \( L_{o,m} \) in addition to the heat transfer equations. It should be also noted that \( L_{o,m} \) expresses a seasonal mean value, in contrast to the instantaneous value for \( \theta_{i,max} \).

Concerning the degree-hours of overheating \( DHo \) (Figure 4 and Table 10), the accuracy for Athens was high and comparable to that for \( L_{o,m} \). However, for Helsinki, the accuracy was lower especially with a heavy thermal mass. This might be associated to many values of \( DHo \) equal to zero.

The lowest agreement was obtained for the percentage of time with acceptable thermal comfort \( PTc \), which varies between zero and 100% (Figure 5 and Table 11).

### Table 5: Coefficients of the metamodel for Athens and heavy thermal mass.

<table>
<thead>
<tr>
<th>Index</th>
<th>( \theta_{i,max} ) (°C)</th>
<th>( L_{o,m} ) (%)</th>
<th>( DHo ) (°C h)</th>
<th>( PTc ) (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>( a_0 )</td>
<td>35.39</td>
<td>43.1</td>
<td>1648.0</td>
<td>12.2</td>
</tr>
<tr>
<td>( a_1 )</td>
<td>-0.18</td>
<td>-2.62</td>
<td>-212.64</td>
<td>2.78</td>
</tr>
<tr>
<td>( a_2 )</td>
<td>-0.59</td>
<td>-7.73</td>
<td>-610.77</td>
<td>6.32</td>
</tr>
<tr>
<td>( a_3 )</td>
<td>-0.90</td>
<td>-11.80</td>
<td>-960.41</td>
<td>10.20</td>
</tr>
<tr>
<td>( a_4 )</td>
<td>-1.35</td>
<td>-15.54</td>
<td>-1276.74</td>
<td>12.80</td>
</tr>
<tr>
<td>( a_5 )</td>
<td>1.72</td>
<td>17.24</td>
<td>1311.49</td>
<td>-17.74</td>
</tr>
<tr>
<td>( a_6 )</td>
<td>0.63</td>
<td>6.47</td>
<td>493.88</td>
<td>-7.58</td>
</tr>
<tr>
<td>( a_7 )</td>
<td>0.37</td>
<td>3.35</td>
<td>266.26</td>
<td>-3.76</td>
</tr>
</tbody>
</table>

### Table 6: Ratios of quadratic to linear effects for lightweight L and heavy H thermal masses.

<table>
<thead>
<tr>
<th>Location</th>
<th>Helsinki</th>
<th>Athens</th>
</tr>
</thead>
<tbody>
<tr>
<td>Thermal mass</td>
<td>L</td>
<td>H</td>
</tr>
<tr>
<td>( \theta_{i,max} ) (°C)</td>
<td>14%</td>
<td>15%</td>
</tr>
<tr>
<td>( L_{o,m} ) (%)</td>
<td>11%</td>
<td>33%</td>
</tr>
<tr>
<td>( DHo ) (°C h)</td>
<td>21%</td>
<td>58%</td>
</tr>
<tr>
<td>( PTc ) (%)</td>
<td>14%</td>
<td>61%</td>
</tr>
</tbody>
</table>

### Table 7: Ratios of interaction to linear effects for lightweight L and heavy H thermal masses.

<table>
<thead>
<tr>
<th>Location</th>
<th>Helsinki</th>
<th>Athens</th>
</tr>
</thead>
<tbody>
<tr>
<td>Thermal mass</td>
<td>L</td>
<td>H</td>
</tr>
<tr>
<td>( \theta_{i,max} ) (°C)</td>
<td>15%</td>
<td>18%</td>
</tr>
<tr>
<td>( L_{o,m} ) (%)</td>
<td>10%</td>
<td>42%</td>
</tr>
<tr>
<td>( DHo ) (°C h)</td>
<td>25%</td>
<td>73%</td>
</tr>
<tr>
<td>( PTc ) (%)</td>
<td>8%</td>
<td>59%</td>
</tr>
</tbody>
</table>

**Figure 2:** Maximum indoor temperature during summer computed by dynamic simulation and the metamodel for: (a) Helsinki and (b) Athens.
Table 8: Errors (°C) and coefficients of determination $R^2$ of the metamodels for maximum indoor temperature for lightweight L and heavy H thermal masses.

<table>
<thead>
<tr>
<th>Location</th>
<th>Helsinki</th>
<th>Athens</th>
</tr>
</thead>
<tbody>
<tr>
<td>Thermal mass</td>
<td></td>
<td></td>
</tr>
<tr>
<td>L</td>
<td>H</td>
<td>L</td>
</tr>
<tr>
<td>RMSE</td>
<td>0.18</td>
<td>0.11</td>
</tr>
<tr>
<td>Maximum error</td>
<td>0.43</td>
<td>0.26</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.9955</td>
<td>0.9966</td>
</tr>
</tbody>
</table>

The lowest accuracy ($R^2 = 0.8931$) for $PTc$ was also obtained for Helsinki and heavy thermal mass where many of its values were 100%, which again was not accurately approximated by the metamodel. On the other hand, the accuracy for Athens was acceptable but lower than that for the other indices, which might be also related to some values of $PTc$ that are equal or close to zero.

Furthermore, the level of agreement with dynamic simulation results was lower than that obtained for the energy performance of air-conditioned buildings (Jaffal and Inard, 2017). However, the difference was low for $\theta_{i,max}$ and $Lo,m$ and high for $DHo$ and $PTc$. Therefore, the metamodel can accurately approximate the heat transfer in a free-running building which has high indoor temperature variation.

However, in some conditions, the metamodel is not suitable for indices with lower or upper limits which can be frequently encountered. Alternative metamodels (artificial neural networks, support vector machines, MARS…) should be developed to accurately assess thermal comfort with these indices.

Table 9: Errors and coefficients of determination $R^2$ of the metamodels for mean likelihood of overheating for lightweight L and heavy H thermal masses.

<table>
<thead>
<tr>
<th>Location</th>
<th>Helsinki</th>
<th>Athens</th>
</tr>
</thead>
<tbody>
<tr>
<td>Thermal mass</td>
<td></td>
<td></td>
</tr>
<tr>
<td>L</td>
<td>H</td>
<td>L</td>
</tr>
<tr>
<td>RMSE</td>
<td>1.1%</td>
<td>1.9%</td>
</tr>
<tr>
<td>Maximum error</td>
<td>3.9%</td>
<td>7.2%</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.9943</td>
<td>0.9645</td>
</tr>
</tbody>
</table>

Figure 4: Degree-hours of overheating during summer computed by dynamic simulation and the metamodel for: (a) Helsinki and (b) Athens.

Table 10: Errors (°C h) and coefficients of determination $R^2$ of the metamodels for degree-hours of overheating for lightweight L and heavy H thermal masses.

<table>
<thead>
<tr>
<th>Location</th>
<th>Helsinki</th>
<th>Athens</th>
</tr>
</thead>
<tbody>
<tr>
<td>Thermal mass</td>
<td></td>
<td></td>
</tr>
<tr>
<td>L</td>
<td>H</td>
<td>L</td>
</tr>
<tr>
<td>RMSE</td>
<td>98.5</td>
<td>176.0</td>
</tr>
<tr>
<td>Maximum error</td>
<td>294.1</td>
<td>723.5</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.9951</td>
<td>0.8272</td>
</tr>
</tbody>
</table>
as a surrogate for dynamic models to rapidly assess building performance and to formulate optimization problems.

The metamodel was used to assess thermal comfort in a non-air-conditioned office during summer for cold and hot European climates with lightweight and heavy thermal masses and four thermal comfort indices. The design of experiments was used to reduce the number of dynamic simulations needed to fit the metamodel.

The accuracy of the metamodel was found to be dependent on the thermal comfort index. Two categories of indices could be distinguished. The first, in which the lower and upper limits of the indices were not frequently encountered, were in this study maximum indoor temperature and mean likelihood of overheating. For this category, the metamodel was highly accurate.

For the second category, with lower or upper limits that can be frequently encountered, the metamodel based on polynomial assumptions did not give satisfactory results in some conditions. In this study, this was the case for degree-hours of overheating, for which values of zero were common in a cold climate, and for percentage of time with acceptable thermal comfort, where values of 100% were often encountered for a cold climate and zero for a hot climate.

These results revealed that the metamodel is capable of accurately approximating the long-term thermal behavior of free-running buildings. However, it might not be able to capture the nature of the response of some indices. Alternative metamodels (artificial neural networks, support vector machines, MARS…) should be developed for these indices to obtain accurate results. In addition, their metamodels may be derived from those of the first category.

It should be noted that the nonlinearities in the metamodel where found high when its accuracy was low. However, understanding these nonlinearities and the possible use of nonlinear metamodels for future energy regulations necessitate further investigation.

Finally, to develop new metamodels to study building energy performance, a compromise should be found between accuracy, flexibility, reasonable computational cost and ability to provide insight. To this end, the incorporation of a knowledge of building models into metamodels would be very beneficial.

**References**


Carlucci, S., Pagliano, L., & Sangalli, A. (2014). Statistical analysis of the ranking capability of long-

---

**Figure 5:** Percentage of time with acceptable thermal comfort computed by dynamic simulation and the metamodel for: (a) Helsinki and (b) Athens.

**Table 11:** Errors and coefficients of determination $R^2$ of the metamodels for percentage of time with acceptable thermal comfort for lightweight L and heavy H thermal masses.

<table>
<thead>
<tr>
<th>Location</th>
<th>Helsinki</th>
<th>Athens</th>
</tr>
</thead>
<tbody>
<tr>
<td>Thermal mass</td>
<td>L</td>
<td>H</td>
</tr>
<tr>
<td><strong>RMSE</strong></td>
<td>1.6%</td>
<td>6.7%</td>
</tr>
<tr>
<td><strong>Maximum error</strong></td>
<td>10.5%</td>
<td>24.1%</td>
</tr>
<tr>
<td><strong>$R^2$</strong></td>
<td>0.9900</td>
<td>0.8931</td>
</tr>
</tbody>
</table>

Finally, the lowest accuracy and the highest nonlinearities were both obtained with $DHL$ and $PT_c$ for Helsinki and heavy thermal mass. However, the association between the metamodel accuracy and its nonlinearity needs further research.

**Conclusions**

This work presented a new metamodel for evaluating the long-term thermal comfort in non-air-conditioned buildings. The metamodel can be used in a flexible way to study the impact of the building characteristics on indoor conditions based on several indices. It can be used as a surrogate for dynamic models to rapidly assess building performance and to formulate optimization problems.

The metamodel was used to assess thermal comfort in a non-air-conditioned office during summer for cold and hot European climates with lightweight and heavy thermal masses and four thermal comfort indices. The design of experiments was used to reduce the number of dynamic simulations needed to fit the metamodel.

The accuracy of the metamodel was found to be dependent on the thermal comfort index. Two categories of indices could be distinguished. The first, in which the lower and upper limits of the indices were not frequently encountered, were in this study maximum indoor temperature and mean likelihood of overheating. For this category, the metamodel was highly accurate.

For the second category, with lower or upper limits that can be frequently encountered, the metamodel based on polynomial assumptions did not give satisfactory results in some conditions. In this study, this was the case for degree-hours of overheating, for which values of zero were common in a cold climate, and for percentage of time with acceptable thermal comfort, where values of 100% were often encountered for a cold climate and zero for a hot climate.

These results revealed that the metamodel is capable of accurately approximating the long-term thermal behavior of free-running buildings. However, it might not be able to capture the nature of the response of some indices. Alternative metamodels (artificial neural networks, support vector machines, MARS…) should be developed for these indices to obtain accurate results. In addition, their metamodels may be derived from those of the first category.

It should be noted that the nonlinearities in the metamodel where found high when its accuracy was low. However, understanding these nonlinearities and the possible use of nonlinear metamodels for future energy regulations necessitate further investigation.

Finally, to develop new metamodels to study building energy performance, a compromise should be found between accuracy, flexibility, reasonable computational cost and ability to provide insight. To this end, the incorporation of a knowledge of building models into metamodels would be very beneficial.

**References**


Carlucci, S., Pagliano, L., & Sangalli, A. (2014). Statistical analysis of the ranking capability of long-

CEN (European Committee for Standardization) (2007). Indoor environmental input parameters for design and assessment of energy performance of buildings addressing indoor air quality, thermal environment, lighting and acoustics (EN 15251).


