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User behavior in whole building simulation

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Abstract

Energy use in buildings is closely linked to their operational and space utilization characteristics and the behavior of their occupants. The occupant has influence due to his presence and activities in the building and due to his control actions that aim to improve indoor environmental conditions (thermal, air quality, light, noise). Due to the demand of sustainable buildings more passive buildings will be built.

Consequently the weight of the user behavior on the energy balance of a building increases. In the design phase, e.g. via building performance simulation, this effect has only recently been recognized. In this study the effect of user behavior on building performance has been evaluated further to assess requirements for design solutions to arrive at buildings that are more robust to the influence of user behavior. In the research two recent developments with respect to user presence and user interactions in a building have been combined. The results indicate that for specific buildings user behavior should be assessed in more detail, to allow the building design to be optimized for the actual user and its peculiarities. A guideline supports the decision process.

Keywords

User Behavior, Building Simulation, Performance Indicator, Guideline, Robustness

Introduction

Energy use in the built environment in the Netherlands takes up approximately 35% of the total energy use [1]. Energy reduction in the built environment therefore is an important contributor to a sustainable environment. An improved design of buildings may lead to significant energy reduction [2]. Especially early design decisions will contribute to this. Performance assessment of different design solutions, e.g.

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building concepts, in the early design phase therefore is important. Conventional solutions will be preferred if assessment options are not available. These design solutions may not be optimal towards the requirements for the building and its users, impacting the energy use negatively.

Building performance simulation has become an accepted method of assessment during the design process. With increasing complexity of building designs and higher performance requirements on sustainability, use of building simulation will become inevitable. Requirements with respect to such tools and the input parameters will increase as well. Various model input parameters may introduce uncertainties. For a standard type of office building the internal heat gain was found to be an important and sensitive input parameter when applying a building performance simulation tool to assess the building performance (e.g. energy use; [3]). The internal heat gain has a direct relation with user behavior. Therefore it is assumed that user behavior is one of the most important input parameters influencing the results of building performance simulations. Unreliable assumptions regarding user behavior may have large implications for such assessments. This effect will become more important when the design under investigation contains improved passive energy-efficiency measures. Soebarto en Williamson [4] state that difference in assumed and actual energy use can be large (positive and negative).

Degelman [5] notes that over the last forty years thermal processes in building energy performance simulation have been brought to perfection. However, user behavior has a much larger influence on the energy performance of a building than the thermal process within the building façade. Yet, it did not get much attention in the simulation models. User behavior in this respect may be defined as the presence of people in the building, but also as the actions users take (or not) to influence the indoor environment. Degelman states that building simulation is only capable of accurate predictions if the use of a building is predictable and routine. This generally will be the case for buildings where user influence is minimized or not possible at all.

The buildings that Degelman [5] refers to for accurate predictions, however, are not the buildings that adhere to current ideas about buildings and their relation with the users. Occupant perception of so-called

‘sealed, centrally air-conditioned buildings with open plan floor layouts that provide minimal adaptive opportunity’, with no option for opening windows, is negative [6]. User influence is a prerequisite for the correct functioning of the human body. Modern building designs will have to take this into account. This is supported further by the requirement to build sustainable buildings and should result in a shift from buildings with a fully air-conditioned indoor environment, to buildings that mainly rely on passive (sustainable) systems, at least under suitable climatic conditions. This shift should also affect the role of the user of a building, becoming more active and therefore the influence of the user on the building will increase even further [7]. Rijal et al. [8] state that the application of user behavior models with higher resolution and higher complexity will improve the understanding of the relation between building, user and building performance. Eventually this should result in better building designs.

Robustness is another indicator that may explain the mentioned differences found between design and practice [9]. Robustness is defined as the sensitivity of identified performance indicators of a building design for errors in the design assumptions. This may also relate to user behavior and the change of that behavior over the life-time of a building. In this respect and given the discussion above, integrating a more precise user behavior model in whole building simulations will be important.

In current building performance simulation tools user behavior generally is mimicked in a very static way. General assumptions are applied to describe user presence in a building or room. This also relates to the user actions in the building. User profiles represent the presence and user actions, e.g., describing the use of lighting from 8 o’clock in the morning till 18 o’clock in the afternoon. In reality user behavior is much more complex. For example, it depends on building design or climate [8]. Furthermore, as averaged values are used, optimization for, e.g., sustainable solutions is less sensible.

In recent years some models have been developed to include the interaction of an average user of an office space with his environment in building simulation [8;10;11;12]. Generally these are empirical models based on measurements in practice. These algorithms focus on the manual opening of windows and lighting control (light and sun shading devices). Bourgeois [13] developed the Sub-Hourly Occupancy Control (SHOCC) model that includes improved versions of the algorithms of Nicol [11] and

Reinhart [12] and deals with the use of lighting, sun shading, opening of windows and use of equipment. It also has a stochastic presence predictor included as developed by Reinhart. The SHOCC model has been integrated in the whole building simulation program ESP-r [2]. Example results for a simulated office model indicate that a realistic treatment of the manual control of lighting and a sun shading device can result in significant reductions (in the order of 50%) in energy use [13]. This is for an ‘active’ user that strives for optimal use of daylight in comparison to a ‘passive’ user that is not interested in efficient use of daylight. In the example the energy reduction in lighting (79%) also reduces the use of cooling, but increases the energy use for heating as a result of lower internal gains and less direct solar irradiation.

The presence prediction in the SHOCC-model requires several assumptions with respect to the occupation degree and the behavior of users. This is useful for a two-person office, but results in less reliable predictions for an open office plan with less strict time schemes for the individual occupants. For such situations and other more complex occupant presence predictions the User Simulation of Space Utilization (USSU) model as developed by Tabak [14] may be used. This model simulates the use of space and the movements between spaces in a building using detailed information regarding the actual user (i.e. roles of occupants in the organization) and the floor plan (i.e. functions of spaces). The model allows for an optimization of the space use as a function of the organization that is using the building. The model provides, amongst others, information on the use of walking routes and the use and occupancy rate of facilities and spaces. The USSU model however has not been applied yet in connection with a building performance simulation model.

The above overview indicates that developments are ongoing to allow for a better assessment of user behavior in building performance simulations. The significance of this is acknowledged. Improvements of behavior models still are possible. This will result in more complex models. However, there is no guideline that supports the efficient use of this type of higher resolution models for user behavior in building simulation. Therefore, the results of the research presented in this paper focus on the question: When is it useful to include user behavior (presence and user interaction with the building) in the building simulation process in more detail? In addition to this, the question is answered how different building designs respond to differences in user behavior, i.e. how robust are they.

Methods

In order to answer the research questions a tool was developed that included the above described advanced models for user behavior. For this the USSU model (presence) was coupled to the SHOCC model (interaction + presence) as shown in Figure 1. ESP-r was used as the whole building simulation program for performing the dynamic simulations of a building model. The coupling between ESP-r and SHOCC model was developed by Bourgeois [13].

Figure 1. Coupling procedure for the advanced user behavior USSU and SHOCC model and the coupling with the whole building simulation program ESP-r.

Similar to the Coupling Procedure Decision Methodology (CPDM) as developed by Djuneady [15] a decision methodology was developed to allow for an objective assessment of required user behavior modeling resolution and complexity. Next, analogue to Djuneady, sensitivity analysis has been used to determine the minimal required resolution. For the sensitivity analysis different techniques have been investigated. A comparison has been made between Monte Carlo analysis with regression analysis [16] and Morris- and FAST-analysis [17]. From this comparison Monte Carlo analysis was rated most suitable in terms of results and simulation requirements [3].

In contrast to the work of Djuneady the sensitivity analysis did not only relate to identified performance indicators, but also to building related parameters. This includes the function of the building and the type of users, the building system concept that is used, the relation between the user and the building and the user-outdoor climate relation in the building.

Finally, with the decision methodology the robustness of a number of building concepts (passive system) were investigated for different representations of user profiles. In the results and the discussion the decision methodology and robustness are described separately. Case studies are applied to support the development.

Decision methodology

Concept

The available user behavior models can be ranked according to increasing resolution level and complexity. In Table 1 these levels are defined based on the available models in literature and the new combined model.

(Table 1)

In a building simulation model a decision has to be made to model user behavior. It is tempting to choose the most sophisticated and detailed method. However, given the required input constraints for such models a less detailed model may perform just as well. Figure 2 presents a flow chart of the decision methodology that has been designed to decide on the use of a specific user behavior model for a building simulation. It uses the in Table 1 identified resolution levels. The developed methodology takes the same line of thought as that of Djuneady (2005).

Figure 2. Flow chart of the decision methodology for making the appropriate choice between resolution levels.

The question marks in Figure 2 represent the position where a decision is made to apply a more complex model or not. This decision should be based on the functional and performance requirements that have been set for a design. These requirements translate in performance indicators and target values that can be evaluated through the application of building simulation.

The sensitivity of performance indicators for less complex user behavior model should be checked. This sensitivity will not be similar for individual performance indicators. E.g., maximum and minimum indoor temperature may be determined applying relative simple user profiles (with extreme values). Total energy use may require a more detailed modeling of user behavior. Similar to Djuneady [15] therefore starting resolution levels may be proposed for different performance indicators [3]. This proposal is summarized in Table 2 and answers the left upper question mark in Figure 2.

(Table 2)

The performance indicators requiring an advanced user behavior modeling assume a larger sensitivity of the user behavior on the indicator value. As an example, the cooling load is affected directly by internal heat loads and the ventilation and infiltration in the building, in combination with the solar load through windows. For the maximum cooling load a worst case predefined user profile may be used.

In addition to the performance indicator resolution level, design related parameters may also be sensitive to user behavior modeling resolution level. In Table 3 some of these design related parameters have been identified. They will be discussed below.

(Table 3)

A building function generally relates to a specific type of user. Therefore, for specific building functions, the sensitivity to user behavior modeling may be low. Furthermore, the importance of the two parts of user behavior modeling (presence and interaction) may differ. Offices, museums and schools are examples of building functions where large changes in presence can be expected, while interaction of the user with the environment may be assumed for, e.g., offices and dwellings. For schools and museums, presence may be predicted relatively well, which would assume the application of standard user profiles. The starting resolution levels as indicated in Table 2 are useful for user functions that have a less predictable motion pattern in buildings and where interaction of the user is possible. As an example, the above would refer to an office with flexible working schedules.

The building concept mainly refers to the response of a building to changes in indoor climate requirements. In buildings with a slow response the effect of user behavior generally will lag behind. This makes a correct prediction of the behavior (presence) important in order to arrive at an optimal situation (i.e. the building should anticipate on the future arrival of occupants). Changes in behavior on the other hand do not affect the environment directly. Examples of buildings with such a response generally will rely on the thermal mass in the heating and cooling concept for the building. Buildings with the opposite characteristic will respond directly to changes in presence. In that case, the interaction will also affect the indoor climate more directly. Examples of this type of building concept relate to high temperature heating systems, air conditioning and low thermal mass.

In addition to the above, the building concept may allow for a close interaction of the user with the building or not, i.e., changing the (local) temperature or opening a window. This will also affect the type of user behavior modeling applied. Furthermore, the presence of other internal heat sources may outweigh the effect of a detailed knowledge of user presence. Advanced user behavior modeling (presence) is more important when active daylighting control systems are present in the building.

Buildings with a high façade/floor-ratio will result in a stronger relation of the user with the outdoor climate. Changing outdoor conditions will affect user behavior, specifically for daylight. In combination

with different orientations within a building, high resolution user behavior modeling may be required. For a climate with generally stable weather conditions user behavior may be predicted with user profiles.

Case study sensitivity analysis user behavior

The sensitivity of the in Table 2 indicated performance indicators and the in Table 3 indicated design parameters for user behavior modeling was investigated in a case study for a simple office room. The room geometry is shown in Figure 3. The geometry and conditions for the model are included in Appendix A. The first two types of user behavior modeling methods in Table 1 have been used (i.e. Simple user behavior and Advanced user behavior I). The whole building simulation program ESP-r was used to simulate the office room.

Figure 3. Room geometry used in the case study.

The starting user behavior resolution level for evaluating the performance indicators has been assessed by performing a Monte Carlo analysis. 150 different cases for the office space have been evaluated with random variations of several design related parameters. In Appendix A the applied mean and standard deviation values for these parameters have been summarized. Note that it is not possible to quantify all parameters as some represent a design decision (e.g. manual or automated lighting). For these parameters a decision should be made. In this case study, the lighting and indoor air temperature were controlled automatically and the sun shading device was controlled manually. The office room was situated in a temperate climate.

The results of the analysis for the case study are shown in Table 4. In this table averaged values (μ) and the standard deviation (σ) for a number of performance indicators for the investigated cases are given. These results indicate the sensitivity of the investigated performance indicators for user behavior modeling and provide information on the starting resolution level. When the difference in averaged value and the standard deviation for the two user behavior modeling methods is small, it is assumed that the indicator is not sensitive for the difference in user behavior modeling for this case study.

(Table 4)

The results show that for this case (and buildings similar to the case study) some of the investigated performance indicators are sensitive to the applied user behavior modeling. The heating and cooling energy demand are most sensitive and require an advanced user model (Type I). The primary energy for this case study does not show a high sensitivity but will generally be related to the heating and cooling demand. PMV is very sensitive, but in absolute values the difference is small.

A further regression analysis of the data reveals the important design related parameters (Appendix A; parameter 3 to 12) that result in a difference in sensitivity for the user behavior models. For this assessment the sensitivity of these parameters has been ranked for each performance indicator individually and summed over all indicators. This analysis shows that some parameters have a strong influence on the minimal required user model resolution level. Other parameters have a relatively small influence. For the investigated performance indicators shown in Table 4, the influence of the design parameters is shown in Table 5. From this overview the following design parameters were rated most influential: U-value glass, power of apparatus, lighting power, G-value glass, percentage of transparency of the façade.

(Table 5)

Guideline

From the above introduced concept and the case study a general guideline has been derived for the decision methodology for user behavior resolution level modeling (Figure 4).

Figure 4. Guideline to determine the appropriate user behavior resolution level modeling.

In other words, the guideline in Figure 4 translates to:

1. Determine the performance indicator and the minimal starting resolution belonging to the performance indicator. (see Table 2 and 3)
2. Determine the parameters that require a design decision and determine the starting resolution belonging to the identified choices. (see Table 3 and Table A.1 – parameter 13 to 16)
3. If the highest resolution is not yet required, execute a sensitivity analysis from the in point 2 derived minimum resolution level, e.g. to internal heat load. Perform the simulations and evaluate if the result for the performance indicator corresponds with the required target values. If this is not the case, a higher resolution level should be applied. If the highest resolution is reached, then the design should be altered to meet the required targets.

Robustness of building concepts to user behavior

The robustness of a building to user behavior can be tested by assessing the design performance indicators for different user types. The performance of a robust building will show less variation due to the difference in user types than a less robust building. Therefore the deviation in the results of the simulated performance indicators can be used as a measure of robustness.

In order to assess robustness, it is necessary to define the behavior of the (office) user. An average office user can be characterized as follows:

- Occupancy presence in the room has a constant or an irregular pattern [12];
- Occupants make passive or active use of sun blinds and/or lighting [12];
- Occupants use relates to different sizes of internal heating loads (low, medium, high) [18].

Combining these characteristics, twenty-four user types can be defined. All these user types have been simulated with the Advanced user behavior II modeling method (ESP-r + SHOCC + USSU).

The robustness has been investigated for several cases. These cases are based on the above described office space (Appendix A). The above derived results from the sensitivity analysis for the investigated design parameters for this office space have been used to define five variants (Figure 5) with assumed differences in sensitivity for the user behavior. Table 6 summarizes the design parameters that have been used to distinguish within building type variants. Case 1 represents a design with average values for these parameters. The other cases are based on the extreme values of these parameters. For the other design parameters from Table A.1 average values are used.

Figure 5. Five cases for the investigated office space. 1: Average values for design parameters, 2: Low thermal mass and closed façade, 3: Low thermal mass and open façade, 4: Heavy thermal mass and closed façade, 5: Heavy thermal mass and open façade.

(Table 6)

The results for the cases are assessed through the Relative Standard Deviation (RSD). The RSD has been calculated from the average value (μ) and standard deviation (σ) for a number of performance indicators. A small RSD indicates a performance indicator which is less sensitive to the user behavior. Table 7 and Figure 6 present the results for the five case studies.

(Table 7)

Figure 6. Relative Standard Deviation (RSD) for a number of performance indicators for the investigated variants.

Comparing the five cases it is evident that case study 3 (low thermal mass and transparent façade) is most robust to user behavior. The large glass façade and the low thermal mass of the building increase the influence of outdoor climate on the performance indicators. In contrast, for case study 4 (heavy thermal mass and closed façade) the outdoor climate has almost no influence on the performance indicators. For this case a strong influence towards user behavior is found.

From the RSD, Case 3 is assessed most robust to user behavior, given the heating and cooling load constraints. However the absolute values for the maximum room temperature indicate a very uncomfortable building (values up to 48°C). If minimum performance criteria would have been set for this case, this design would have been discarded. As the other cases indicate a high sensitivity, Figure 6 therefore shows that user behavior is an important aspect in the design of the building. Adequate

assessment of (future) behavior can significantly and positively influence the final design result. Optimization to a certain known (future) user behavior therefore may be beneficial.

Conclusion

The research has shown that user behavior is an important aspect in building performance assessment. The simple approach used nowadays for design assessments applying numerical tools are found inadequate for buildings that have a known close interaction of the user with the building. The proposed decision methodology for the user behavior resolution level modeling gives guidance for an improved representation of user behavior in building performance assessment. Higher resolution level modeling is available and the presented coupling and examples show its added value.

The robustness study has shown that there is no realistic general design concept, without applying extensive oversized active systems, that minimizes the effect of different types of user behavior and with that shows robustness to this parameter. Intended and future user behavior therefore should be assessed carefully. Improved modeling of user behavior in numerical simulation can optimize overall building performance.

Appendix A

Geometry case study + investigated ranges for the parameters.

The geometry represents an office room (3m×5m×3m [L×W×H]) with south wall representing a façade facing the outdoor environment. Other walls are assumed adiabatic. The façade contains a window (2.0m×1.3m) at 0.95m height above the floor, centrally positioned. Indoor air temperature and lighting is controlled automatically. The sun shading device is controlled manually. The room is located in a temperate climate zone.

(Table A.1)

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Figure captions

Figure 1. Coupling procedure for the advanced user behavior USSU and SHOCC model and the coupling with the whole building simulation program ESP-r.

Figure 2. Flow chart of the decision methodology for making the appropriate choice between resolution levels.

Figure 3. Room geometry used in the case study.

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Figure 6. Relative Standard Deviation (RSD) for a number of performance indicators for the investigated variants.

Tables

Table 1. Overview of increasing resolution and complexity of user behavior modeling.

Resolution / complexity ↑ Low ↓ High	Simple user behavior
	Standard user profiles (averaged values or minimum and maximum values)
	Advanced user behavior I
	SHOCC (simulation of the interaction between the user and its environment)
	Advanced user behavior II
	SHOCC (simulation of the interaction between the user and its environment) + USSU (complex mobility prediction)

Table 2. Proposed starting resolution level for different performance indicators: S (simplified user behavior), AI (advanced user behavior I), AII (advanced user behavior II).

Energy related	
Heating energy demand	AI
Cooling energy demand	AI
Primary energy use	AI
Load related	
Maximum heating load	S
Maximum cooling load	S
Comfort related	
PMV	AI
Maximum room air temperature	S
Minimum room air temperature	S

Table 3. Design related parameters sensitive to user behavior modeling.

Design parameter
- Building function and type of user
- Building concept (passive and active systems)
- Relation between user and building
- Relation between user and the outdoor environment

Table 4. Averaged values (μ) and standard deviation (σ) for various performance indicators for the case study. Simulations have been performed with ESP-r and ESP-r + SHOCC (in this table named as SHOCC).

Performance indicator	Unit	ESP-r		SHOCC		Δ ESP-r and SHOCC	
		μ	σ	μ	σ	μ	σ
Heating energy demand	[kWh/m ² .y]	15.11	4.19	16.43	5.27	9%	26%
Cooling energy demand	[kWh/m ² .y]	34.65	9.31	26.3	7.35	-24%	-21%
Primary energy use	[kWh/m ² .y]	251.02	45.77	249.18	45.48	-1%	-1%
PMV	[-]	0.23	0.06	0.17	0.06	-26%	0%
Max. room temperature	[°C]	27.71	1.42	27.34	1.23	-1%	-13%
Min. room temperature	[°C]	15.31	0.63	15.45	0.65	1%	3%

Table 5. Difference in the influence of the design parameters between simulations with ESP-r and ESP-r + SHOCC. The most important parameters as shown by the regression analysis are printed bold. A dash in the table indicates that the parameters did not have significant regression coefficients; as a result a comparison cannot be made.

Design parameters	Performance indicator					
	Heating energy demand	Cooling energy demand	Primary energy use	PMV	Maximum room air temperature	Minimum room air temperature
Specific active mass	-36%	5%	-7%	-	-12%	1%
Transparency façade	20%	-65%	-54%	-229%	-15%	1%
G-value glass	-66%	-91%	-	-80%	-	-
U-value glass	-19%	-	98%	-25%	26%	-5%
Thermal resistance façade	-	-	-	-	-	-
Light transmittance glass	-	-	-	-7%	-	-
Heat gains lighting	-14%	18%	-6%	5%	4%	4%
Heat gains apparatus	2%	20%	5%	16%	10%	55%
Maximum heating load	-	-60%	-	-25%	-	-10%
Maximum cooling load	-	-	-	-39%	-3%	-

Table 6. Values of design parameters that affect the robustness of the investigated cases through the variation in user behavior.

Design parameters		1	2	3	4	5
		Average	Low mass and closed	Low mass and open	Heavy mass and closed	Heavy mass and open
U-factor glass	[W/m ² K]	2.1	3.0	3.0	1.2	1.2
G-value	[-]	0.6	0.8	0.8	0.4	0.4
Transparency facade	[%]	35	10	90	10	90
Specific thermal mass	[kg/m ²]	50	5	5	100	100
R-value	[m ² K/W]	2.5	4.0	4.0	1.3	1.3

Table 7. Average value (μ) and standard deviation (σ) for a number of performance indicators, representative for the robustness with regard to the user behavior in the building.

	Heating energy demand [kWh/m ² .y]	Cooling energy demand [kWh/m ² .y]	Maximum room air temperature [°C]	Primary energy use [kWh/m ² .y]
Case 1 – Average				
μ	22.26	-30.83	27.7	284.82
σ	12.86	28.65	2.1	166.29
Case 2 – Low thermal mass and closed				
μ	23.04	-38.79	29.4	296.95
σ	7.89	35.15	4.4	179.24
Case 3 – Low thermal mass and open				
μ	51.14	-56.23	48.3	337.37
σ	12.13	22.40	7.9	158.95
Case 4 – Heavy thermal mass and closed				
μ	15.95	-29.83	26.3	280.89
σ	12.11	31.44	1.4	171.36
Case 5 – Heavy thermal mass and open				
μ	22.21	-37.78	28.2	290.00
σ	12.19	28.50	2.2	165.36

Table A.1: Overview of sensitive factors, of which factor 1 to 12 can be quantified and the remaining factors assume a choice. Averaged values in the table are based on values that generally are applied in practice (Hoes, 2007).

Building function and type of user

	Sensitive parameter	Simulation values				Unit
		Min	Mean	Max	SD	
1	occupants per floorarea	4.3	11.1	22.8	3.1	m ² /occupant
2	occupant mobility	1	4	8	1.2	room changes per hour

Building concept (passive and active systems)

	Sensitive parameter	Simulation values				Unit
		Min	Mean	Max	SD	
3	building response time specific active mass	5	50	100	15.8	kg/m ²
4	active systems response time maximum heating load maximum cooling load	200 300	500 650	800 1250	100.0 150.0	W W
5	window size in façade percentage of transparency total façade	6	35	100	15.7	%
6	influence of outdoor environment on indoor environment heat transport through transparent construction - solar heat gain (G-value) - size transparent surfaces [5] - heat transfer coefficient (U-value)	0.4	0.6	0.85	0.1	-
7		-	-	-	-	m ²
8		1.2	2.1	3	0.3	W/m ² K
9	heat transport through opaque construction - thermal resistance (R-value)	1.3	2.5	4	0.5	m ² K/W
10	daylight gains - light transmittance	0.7	0.75	0.8	0.0	-
11	heat gains lighting	6.2	12.7	33.9	4.6	W/m ²
12	heat gains apparatus	5.7	17.5	34	4.7	W/m ²

Relation between user and building

	Sensitive parameter	Design decision	Unit
13	lighting control	constant / manual / automatic	-
14	climate control	constant / manual / automatic	-
15	blinds control	constant / manual / automatic	-

Outdoor environment

	Sensitive parameter	Design decision	Unit
17	outdoor environment	temperate/extreme	-