Seasonal effects of input parameters in urban-scale building energy simulation

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Abstract

Urban Building Energy Models are powerful tools for estimating future states of energy consumption and energy generation in buildings. Due to the complexity of these systems, large amounts of data are required, which are often incomplete or unavailable. Through the implementation of building archetypes, models such as the City Energy Analyst minimize the amount of input data. However, these simplifications inherently increase the uncertainty of the expected results.

This paper presents a sensitivity analysis of architectural properties (window-to-wall ratio, occupant density and envelope leakiness), thermal properties (U-values, G-values, thermal mass and emissivity of building surfaces), operating parameters (set point temperatures and ventilation rates) and internal loads (heat gains due to occupancy, appliance use and lighting). For this, the study combines a two-step process of sensitivity analysis with Saltelli’s extension of the Sobol method and the City Energy Analyst. The methodology is applied to a case study area in central Zurich, Switzerland, comprising 284 buildings with predominantly educational, hospital and residential uses.

The results showed that the cooling demand in the area was very strongly influenced by the set point temperature, with other variables having a relatively minor influence. For the heating case a larger number of variables were needed in order to explain variations in demand, primarily the thermal properties of the envelope and air exchange rates of the buildings. This was generally true for all occupancy types, shapes, sizes and locations, showing the importance of accurate estimates of these parameters in urban building energy modeling. On a broader sense, the results contribute to the development of urban energy simulations that are both practical and accurate.

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1. Introduction

Urban Building Energy Models (UBEM) are expected to become a key planning tool for public utilities, municipalities, urban planners and architects. Currently, the two major obstacles UBEM must tackle are input data availability...
and input uncertainty [1]. Input data uncertainty is a key aspect of UBEM and as such, UBEM inputs hold a fundamental role for accurate model predictions. Computational models such as the City Energy Analyst (CEA) [2,3] are powerful tools to estimate future states of energy consumption and energy generation in districts accounting for hourly exchanges of energy among buildings, users and the environment. Such a level of detail requires a vast number of user inputs, including information about 3D geometry, materials, occupancy and HVAC components of buildings. However, these input data are often incomplete or unavailable. Through a wide database of building properties or archetypes, UBEM such as the CEA aim to minimize these inputs. However, these simplifications in input parameters inherently increase the uncertainty of the expected results.

Sensitivity analysis studies how the uncertainty of input parameters is assigned to different output parameters. Sensitivity methods are classified into local and global methods. While local methods evaluate the effect of one input on one output, global sensitivity methods sample the complete input space and are therefore able to calculate overarching sensitivities [4]. Global sensitivity analysis is a generic term referring to various sensitivity methods. The Morris method is a one-at-a-time method widely used to rank a set of input variables according to their qualitative influence on the output of a computational model [5,6]. In contrast to the Morris method, the Sobol method is a variance-based method that furthermore estimates the percentage of variance caused by the variability of a certain input [7,8]. It is useful to determine, in a quantitative way, the effects of an input variable on the output of a computational model.

The objective of this paper is to analyze the seasonal effects (heating and cooling season) of architectural properties (window-to-wall ratio, occupant density, envelope leakiness), thermal properties (U-values, G-values, thermal mass and emissivity of building surfaces), operating parameters (set point temperatures and ventilation rates) and internal loads (heat gains due to occupancy, appliance use and lighting) on the demand for heating and cooling of urban areas. For this, the study combines a two-step process of sensitivity analysis using the Sobol method and the UBEM City Energy Analyst [9]. The method is applied to an area in central Zurich, known as the Hochschulquartier. The area hosts 284 buildings in the residential, educational, services and healthcare sectors.

2. Method

2.1. Data collection

The CEA demand is based on a resistance-capacitance model of the buildings in a district and on the application of construction archetypes to minimize the amount of input data required. The necessary information about 3D geometry, materials, occupancy and mechanical components was obtained from GIS data, owner information and the archetype database. Data on energy-relevant retrofits for the main building components was scarce and thus estimated.

Table 1 presents the probability density functions of input variables and their references. Twenty-three different variables and their corresponding probability density functions were selected to cover different sources in uncertainty, including the effects of buildings’ architectural and thermal properties, operating parameters and internal loads. The means and standard deviations shown in the table were calculated assuming a triangular distribution from published minimum and maximum values.

2.2. Sensitivity analysis

The Saltelli series [7] was used to create stratified samples out of the probability distributions in Table 1 with a sample size $N$ of 1000. CEA was executed on every sample to determine yearly heating and cooling needs for each building. The Sobol method was applied on the data with the computational implementation of SALib [16].

The number of simulations needed for this methodology depends strongly on the number of variables sampled, however, with $N \cdot (2k + 2)$ simulations required for $k$ variables and a sample size $N$. Thus, in order to reduce the computational time required, pre-screening was used to select the most sensitive variables to the yearly consumption of heating and cooling in buildings. First, a reduced case study was created that consisted of ten representative buildings covering the main usage types in the area, construction years and building sizes. CEA was then executed on 48’000 samples to determine yearly heating and cooling needs of these ten representative buildings. The parameters that caused 90% of the observed effects on the demand were selected. Through pre-screening, the number of variables...
Table 1: Probability density function parameters for key input variables.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Symbol</th>
<th>Unit</th>
<th>Distribution</th>
<th>Ref.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Window-to-wall ratio</td>
<td>( \text{win} - \text{wall} )</td>
<td>[-]</td>
<td>0.36</td>
<td>0.20</td>
</tr>
<tr>
<td>Occupant density</td>
<td>( \text{Occ} )</td>
<td>([\text{m}^2/\text{p}])</td>
<td>14</td>
<td>8</td>
</tr>
<tr>
<td>Air change rate at 50 Pa</td>
<td>( n_{50} )</td>
<td>([\text{h}^{-1}])</td>
<td>3.17</td>
<td>1</td>
</tr>
<tr>
<td>Overall thermal transmittance coefficient of basement ceiling</td>
<td>( U_{\text{base}} )</td>
<td>([\text{W}/\text{m}^2\cdot\text{K}])</td>
<td>0.62</td>
<td>0.15</td>
</tr>
<tr>
<td>Overall thermal transmittance coefficient of exterior walls</td>
<td>( U_{\text{wall}} )</td>
<td>([\text{W}/\text{m}^2\cdot\text{K}])</td>
<td>0.35</td>
<td>0.11</td>
</tr>
<tr>
<td>Overall thermal transmittance coefficient of roof</td>
<td>( U_{\text{roof}} )</td>
<td>([\text{W}/\text{m}^2\cdot\text{K}])</td>
<td>0.29</td>
<td>0.09</td>
</tr>
<tr>
<td>Overall thermal transmittance coefficient of windows</td>
<td>( U_{\text{win}} )</td>
<td>([\text{W}/\text{m}^2\cdot\text{K}])</td>
<td>1.78</td>
<td>0.90</td>
</tr>
<tr>
<td>Solar energy transmittance of window glazing</td>
<td>( G_{\text{win}} )</td>
<td>[-]</td>
<td>0.70</td>
<td>0.50</td>
</tr>
<tr>
<td>Internal heat capacity of building</td>
<td>( C_{\text{m}} )</td>
<td>([\text{Wh}/\text{m}^2\cdot\text{K}])</td>
<td>55</td>
<td>22</td>
</tr>
<tr>
<td>Emissivity of external walls</td>
<td>( \varepsilon_{\text{wall}} )</td>
<td>[-]</td>
<td>0.91</td>
<td>0.84</td>
</tr>
<tr>
<td>Emissivity of windows</td>
<td>( \varepsilon_{\text{win}} )</td>
<td>[-]</td>
<td>0.60</td>
<td>0.02</td>
</tr>
<tr>
<td>Emissivity of roofs</td>
<td>( \varepsilon_{\text{roof}} )</td>
<td>[-]</td>
<td>0.78</td>
<td>0.09</td>
</tr>
<tr>
<td>Solar absorption coefficient of external walls</td>
<td>( a_{\text{wall}} )</td>
<td>[-]</td>
<td>0.62</td>
<td>0.3</td>
</tr>
<tr>
<td>Solar absorption coefficient of roof</td>
<td>( a_{\text{roof}} )</td>
<td>[-]</td>
<td>0.52</td>
<td>0.3</td>
</tr>
<tr>
<td>Ratio of gross floor area that is heated or cooled</td>
<td>( H_s )</td>
<td>[-]</td>
<td>0.80</td>
<td>0.75</td>
</tr>
<tr>
<td>Set-point temperature for space cooling</td>
<td>( T_{\text{cs, set}} )</td>
<td>([\circ\text{C}])</td>
<td>26</td>
<td>22</td>
</tr>
<tr>
<td>Set-point temperature for space heating</td>
<td>( T_{\text{hs, set}} )</td>
<td>([\circ\text{C}])</td>
<td>21</td>
<td>20</td>
</tr>
<tr>
<td>Set-back temperature for space cooling</td>
<td>( T_{\text{cs, setback}} )</td>
<td>([\circ\text{C}])</td>
<td>28</td>
<td>22</td>
</tr>
<tr>
<td>Set-back temperature for space heating</td>
<td>( T_{\text{hs, setback}} )</td>
<td>([\circ\text{C}])</td>
<td>12</td>
<td>12</td>
</tr>
<tr>
<td>Minimum air ventilation rate per person</td>
<td>( V_e )</td>
<td>([\text{L}/\text{s}])</td>
<td>10</td>
<td>8</td>
</tr>
<tr>
<td>Sensible heat gain due to occupancy</td>
<td>( Q_s )</td>
<td>([\text{W}/\text{p}])</td>
<td>70</td>
<td>60</td>
</tr>
<tr>
<td>Maximum electrical consumption due to appliances</td>
<td>( E_a )</td>
<td>([\text{W}/\text{m}^2])</td>
<td>7</td>
<td>3</td>
</tr>
<tr>
<td>Maximum electrical consumption due to lighting</td>
<td>( E_l )</td>
<td>([\text{W}/\text{m}^2])</td>
<td>15.9</td>
<td>11.6</td>
</tr>
</tbody>
</table>

\( a \) Includes linear transmittance losses (10% more of standard value).

\( b \) Calculated for different typical building materials.

to be sampled was reduced from 23 parameters to 11. The Saltelli series was then used again to create 24,000 samples out of the probability distributions of these variables and CEA was again executed for the 284 buildings in the area.

For each variable \( i \), the Sobol method generates an associated sensitivity measure \( S_i \) (first order sensitivity coefficient) and a total effect index \( S_{Ti} \), which measures the total (i.e., first and higher order) effects. In order to analyze not only the direct effects of a variable on the model results but also indirect interactions, in the following results section the total effect index \( S_{Ti} \) is used to quantify the primary and secondary effects of each of these variables on the demand of each building in the area.

3. Results

3.1. Effect of occupancy

Building archetypes such as the ones used by CEA assume different thermal and architectural properties, system set points and controls, and internal gains for different occupancy types. Thus, the sensitivity of each of these parameters was analyzed for the various occupancy types found in the case study. For this, the following generalized building occupancy types were defined: educational (including classrooms, libraries and laboratories), hospital (including hospital laboratories), office (including both private and university office spaces) and residential (including multi-dwelling units and hotels). Other usages found in the area, such as exhibition and retail spaces, were scarce and thus not included in this analysis. Figures 1 and 2 present a comparison of seasonal effects (winter and summer) on heating and cooling consumption for the area of study. The results are categorized by the type of occupancy.

For the heating case, the building envelope’s thermal properties are responsible for more than half of the variation, while the air exchange rate is responsible for about a quarter and the rest of the parameters have a much smaller influence. Hospital buildings were found to be particularly sensitive to the air exchange rate, whereas window U-
values had a much greater influence on residential buildings. Set point temperatures were generally less influential, while setback temperatures only had an effect in educational and office buildings.

For the cooling case, the set point temperature was responsible for the vast majority of the variation, especially in hospital buildings. The window-to-wall ratio and window U-values showed a relatively high effect, in particular in educational and office buildings. All other variables had a rather small impact.

3.2. Effect of building shape

The case study area also presented a variety of building scales and typologies. Thus, the correlations to building shape were also analyzed. The buildings were then categorized by their envelope factor [17] as compact (envelope factor less than 0.8), medium (0.8 – 1.4) and non-compact (greater than 1.4). Of all the heated buildings in the area, 15% are compact, 48% medium, and 36% are non-compact.

The results in Figures 3 and 4 show a strong correlation of seasonal effects to building compactness, with less compact buildings showing a greater effect of building envelope parameters such as U-values and window-to-wall ratios. Compact buildings, on the other hand, showed a greater influence of the set point temperatures and air exchange rates. For the cooling season, however, the set point temperature was again most influential in all cases.
A similar effect was seen when analyzing the correlation of building heating and cooling energy demand to buildings’ heated floor area. In particular, building envelope properties had a stronger effect on smaller buildings than larger ones due to their higher surface to volume ratio.

3.3. Spatial effects

The spatial distribution on the sensitivity results are represented in Figure 5. For the heating case, the top variable for each building is represented. Large buildings tend to have a stronger influence from air exchange rate in the heating case, while buildings with a higher exposure to sunshine such as those on the top left and in the center of the area show a stronger influence from the window U-values. For the cooling case, since the set point temperature had the greatest effect on all buildings, the second most impactful variable is represented, with the majority of the remaining effects relating to the window properties.

4. Discussion and conclusion

Sensitivity analysis using Saltelli’s extension of the Sobol method was carried out on an urban area comprising 284 buildings in central Zurich, Switzerland, using the City Energy Analyst urban building energy model. The analysis considered variations in seasons, occupancy type, building shape and size, and spatial distribution.

The results showed that the cooling demand in the area was very strongly influenced by the set point temperature, with other variables having a relatively minor influence. For the heating case a larger number of variables were needed.
in order to explain variations in demand, with an especially strong influence of the thermal properties of the building envelope and air exchange rates. This was generally the case for all occupancy types, even though variations could be observed for different activities, stressing the importance of these input parameters on the models capability to provide more accurate predictions. It is worth noting that due to the very different of use types within hospital buildings (e.g. operating room, laboratory, bedroom), the sensitivity results presented here might not be representative of each of these uses. In terms of shape and size, small and non-compact buildings generally showed a greater influence of the thermal envelope due to their relatively larger exposed surfaces, while compact and large buildings showed a stronger influence of air exchange rates and set point temperatures. The effects due to spatial distribution were relatively minor.

The methodology shown in this paper provides insight into the parameters most relevant for CEA models with different building typologies and occupancy types. The results show which parameters are most sensitive in this scale and thus provide key variables that need to be calibrated in order to accurately predict the demands of urban areas. Further work will be carried out on calibrating these parameters using measured energy demand data for the case study area.

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References