Calibration of a Multi-Residential Building Energy Model – Part I: Cluster-Based Sensitivity Analysis

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Abstract
In the field of building models, sensitivity analyses are used to identify parameters that most influence buildings energy consumption. Most sensitivity analyses are applied to tertiary or industrial buildings. Few publications deal with sensitivity analyses applied to multi-residential buildings. The specific challenges of multi-residential buildings, such as the many apartments involved, each one having its physical characteristics (orientation, area, etc.), its specific equipment and energy use habits, are tackled with the new cluster-based method described here and applied at various levels (multi-scale analyses), to the case of a white-box model of a multi-residential building, having from 1 to 3 bedrooms, equipped with a centralised gas boiler. Results show that while the boiler characteristics and the building envelop parameters have the most influence on the energy consumption at building scale, the parameters related to customers’ behaviours have the most influence on the energy consumption at apartment scale and building scale. Those important parameters are then calibrated based on measured data and surrogate models (the calibration work is presented in a separate paper: Part II - Calibration Using Surrogate-Based Optimisation).

Key Innovations
- Cluster-based method applied to the apartments of a multi-residential building
- Multi-scale sensitivity analysis

Practical Implications
The sensitivity analysis method described in this paper strongly depends on the clusters and the building characteristics. Be aware that various clustering methods can be used, with different criteria, depending on what should be highlighted from the study.

Introduction
Designing and operating energy efficient buildings is a key solution to meet the European targets regarding the reduction of building impacts on greenhouse gases emissions. The technical advances and the growing interest for buildings digitalisation allow to monitor and precisely control their energy consumption and their energy systems. To take advantage of these new technologies and maximise the energy efficiency in the design and operational phases of new buildings, it is necessary to use building energy models.

In the framework of the TPEE project, co-financed by Thomas&Piron Bâtiment and the ERDF (European Structural and Investment Funds Regulations) 2014-2020, an energy toolbox is developed for multi-residential buildings which are both simulated with EnergyPlus (opensource energy simulation engine) and IoT equipped, to forecast their energy needs and detect and diagnose faults in their energy systems. To do so, the building energy model must be calibrated accordingly (the calibration work is presented in a separate paper: Part II - Calibration Using Surrogate-Based Optimisation).

However, as the building energy model is based on more than 1200 parameters, a preliminary step consists in applying a sensitivity analysis, to identify the most influential parameters on which the calibration should focus.

The present paper details this sensitivity analysis step.

State-of-the-art
When it comes to building models, sensitivity analyses (SAs) are used to identify the main parameters whose variations have the highest impact on the studied model response (i.e building energy consumption or thermal comfort in the case of energy models). In literature, few publications are about SAs on detailed dynamic building energy models for multi-residential buildings. Most sensitivity and uncertainty analyses are performed using simplified energy models, due to high computation time and difficulties in coupling building simulation tools and SA tools (Monetti et al., 2015). Whereas publications dealing with SAs are available for tertiary or industrial buildings, very few publications tackle multi-residential buildings.

Goldwasser et al. (2018) modelled and simulated an office building in OpenStudio, then used the Morris method and expert knowledge (to define the parameters space boundaries), to calculate the sensitivity of the variables and identify the ones that should be calibrated. Sun et al. (2016) state the importance of selecting parameters to be calibrated, considering that “model calibration is an over-parameterized process with an immense amount of inter-dependent input parameters that represent the complexity of building systems”. To select the parameters to be calibrated, they applied a SA using EnergyPlus and expert advice. The priority list of parameter selection was established, by simulating a reference medium office building as a baseline model under different conditions.
The building case study described, then the results of the clustering methods and building case study, the methodology applied is In the following sections, after the introduction of the building case study, the methodology applied is described, then the results of the clustering methods and the sensitivity analyses are presented and discussed. The building case study The building studied in this paper is a new multi-residential building, located in Belgium, composed of 41 apartments (including one triplex), having from 1 to 3 bedrooms, and organised in three different blocks. The heat production for space heating and domestic hot water (DHW) preparation is ensured by a central gas boiler of 160kW. Two storage tanks with a total capacity of 1.5m³ are used as buffers between production and consumption of DHW. Each building apartment has been equipped with an individual double flow controlled mechanical ventilation system. As illustrated in Figure 1, Most apartments have their own specific physical characteristics, in terms of size, orientation, architecture, etc. but also specific characteristics related to occupants, such as the number of occupants, the type of equipment and electrical appliances, the energy consumption habits, etc.

Figure 1: 3D sketch of the studied building.

After creating the 3D geometry from scratch in SketchUp, based on 2D architect plans, the building energy model is developed using the OpenStudio software, based on technical data, typical values, etc. EnergyPlus calculation engine is used through OpenStudio to simulate the energy behaviour of the building.

The present paper describes a new cluster-based SA method. First, the apartments are grouped into clusters defined by a combination between a Self-Organising Maps clustering and an artificial intelligence method (Affinity Propagation method from Scikit-Learn machine learning package) available in Cenaeor’s in-house design space exploration and multi-disciplinary optimization platform, called Minamo. Then two SA methods, ANOVA (Sobol based) and Morris methods, are carried out with different simulated periods and scales.

Methodology

The general methodology of the building model calibration is illustrated by Figure 2. The complete building model consists in about 1200 parameters. Considering that within the duration of the TPEE project, the calibration step will be iterated regularly (to perform fault detection and diagnosis algorithms on a regular basis), it is important to reduce the computation time, and so the number of parameters to be calibrated. The first step is the clustering of the 41 apartments into categories with similarities. Two methods are applied (Self -Organising Maps (SOMs) method (from Minamo) and the Affinity Propagation method (from Scikit-learn package)), and the final clustering is a combination of both results. One apartment is selected in each cluster (called representative apartment in the rest of the paper) for the next step of SA.

(climate types, and with different heating/cooling systems). Although this local sensitivity analysis is simple and has low computational costs, it does not consider interactions between inputs. Only few studies are published on residential buildings, for example: Wang (2020) presents a study at district scale for residential buildings, however, to perform a sensitivity analysis, using the Morris method, he considers construction parameters and geometrical parameters of only one reference building as a whole (without considering individual apartments).

In Fabrizio and Monetti (2015), the authors made a literature review on sensitivity analyses commonly used. They describe the Morris method as the most common and one of the most effective method, also known as the method of “Elementary Effects”. The method using the Sobol indices, also named ANalyse Of Variance (ANOVA) technique is described together with the FAST method as the most precise and used variance-based methods for SAs. Other publications, (such as Pang, and O’Neill, 2019; Gan et al., 2014) present the Morris method as one of the most recommended for its performances, without requiring a high computational cost and leading to a quick convergence.

The particularities of residential buildings might not be easy to grasp, but it is important to understand in which ways residential buildings are different from tertiary and industrial buildings when energy consumption is considered, so SAs can be adapted accordingly. To avoid a lack of representativeness of the other apartments in the analysis, SAs should not be performed on a specific apartment. Indeed, this method could be relevant in the past, considering the homogeneous block-architecture of the old buildings, however with the modern tendency to design buildings with different types and shapes of apartments, it is not possible anymore to study one apartment and generalize the results. Additionally, it is important to consider building usage, insofar as different occupants’ behaviours can lead to significant differences in energy consumption. The specific challenges of residential buildings, such as the many apartments involved, most of them having its physical characteristics, its specific equipment and energy use habits, cannot be addressed appropriately with the same methodology used for other types of buildings. That is the reason why within the TPEE project, in the calibration process of the detailed EnergyPlus white-box model of a multi-residential building, a SA is carried out after a new cluster-based method is developed and applied at various levels (multi-scale analyses).

In the following sections, after the introduction of the building case study, the methodology applied is described, then the results of the clustering methods and the sensitivity analyses are presented and discussed.
To ensure the consistency and the relevance of the clusters, several analyses are carried out to check the results within the clusters. The SA step is then performed to identify the parameters that have the highest influence at both apartment and building scales on the energy consumption. The ANOVA method and the Morris method are chosen as SA methods and the results obtained are compared. With this methodology, it is possible to focus on a reduced number of important parameters for the calibration of the whole building energy model.

Instead of the initial 1200 parameters, the methodology results in 230 parameters. Each step of the methodology is described in the next sections.

The clustering tool (Self-Organising Maps) and the SA tool based on the ANOVA method as well as the optimizer used for the calibration of the building energy model are available in the Minamo (Sainvitu et al., 2010). For the description of the Minamo tool and the calibration step, see the second part of this paper.

Description of the clustering criteria

The objective of the clustering step of the methodology is to group apartments with similar characteristics into categories, to reduce the number of simulations for the SA process (by reducing the number of apartments to be studied) and therefore reduce the calculation time and simplify the sensitivity analysis. The criteria to cluster the apartments, after discussion with modellers, are:

- The number of bedrooms: integer parameter \( \in \{1 \, ; \, 3\} \)
- The number of adjacent apartments: integer parameter \( \in \{2 \, ; \, 7\} \)
- The architecture: the category parameters [‘no contact with the ground’, ‘contact with the ground’, ‘overhanging’, ‘last floor’] correspond to the integer parameters \( \in \{0 \, ; \, 3\} \)
- The orientation: handled through a mapping with two integer parameters as presented in Table 1 (attic is used to characterize an apartment at the very top of a block, with all orientations).

Description of the ANOVA method

This is a method of parameters selection. The variability of the inputs on their whole variation range is considered. The general theory is based on the decomposition of the variance of a function, (Jacques, 2011; Saltelli, et al., 2008). The first-order indices, as calculated by (1), the

Description of the SOMs method

A Self-Organising Map (SOM) (Kohonen, 1995; Vesanto et al., 2000) is a type of artificial neural network trained through unsupervised learning. The idea is to project high-dimensional data onto a low-dimensional (usually 2D) map. The SOM uses a neighbourhood function to keep the topology properties of the input space, so elements with similar data will be positioned at nearby locations on the map. Like most artificial neural networks, SOMs operate in two phases training and mapping. Training builds the map using input examples, and mapping automatically classifies a new input vector.

Description of the Affinity Propagation clustering method

The Affinity Propagation identifies clusters by sending messages between pairs of samples (messages represent the suitability for one sample to be the exemplar, i.e. the most representative, of the other): A dataset is described using a small number of exemplars. The messages sent between pairs are updated, considering the values from other pairs, iteratively until convergence, where the final exemplars and so the final clusters are chosen. Clusters have been identified based on the Affinity Propagation method derived from the Python package Scikit-Learn, described in Pedregosa (2011).

The final cluster distribution is a combination of the results from the SOMs and the Affinity Propagation methods. Clusters’ consistency is validated in the SA step, by several analyses.

Table 1: Corresponding integer parameters to handle the category orientation parameters (N: North; E: East; S: South; W: West; A: Attic).

<table>
<thead>
<tr>
<th>N</th>
<th>NE</th>
<th>E</th>
<th>SE</th>
<th>S</th>
<th>SW</th>
<th>W</th>
<th>NW</th>
<th>A</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>-1</td>
<td>-1</td>
<td>-1</td>
<td>0</td>
</tr>
<tr>
<td>1</td>
<td>1</td>
<td>0</td>
<td>-1</td>
<td>-1</td>
<td>-1</td>
<td>0</td>
<td>1</td>
<td>0</td>
</tr>
</tbody>
</table>

Figure 2: Calibration Methodology for the Building Energy Model.
least expensive to compute, give an idea of the sensitivity of each variable on the output(s) of the model.

\[ S_i = \frac{V[\epsilon(Y|X_i)]}{V(Y)} \]  

(1)

With \( V[Y] \), the variance of the output \( Y \) and \( V[E(Y|X_i)] \), the variance of the expectation of \( Y \) conditionally to \( X \). In the case of interactions between variables, the first order indices can be insufficient and the estimation of second-order indices, or even higher orders, is required to refine the knowledge of the model. Unfortunately, their cost of calculation is often prohibitive. Total indices help to overcome this problem since they consider the total influence of the variable (sensitivity to the variable alone as well as to all possible interactions). They also have the advantage that they can be estimated for a cost equivalent to those of order 1. In Practice, the total indice \( S_{Ti} \) relative to the variable \( i \) is the sum of the indices involving \( i \), as described in (2) for instance, considering a model with 3 inputs and the sum of all indices is 1, as shown in (3).

\[ S_{Ti} = S_1 + S_{12} + S_{13} + S_{123} \]  

(2)

\[ S_1 + S_2 + S_3 + S_{12} + S_{13} + S_{23} + S_{123} = 1 \]  

(3)

The interpretation of the Sobol indices can be easily understood: the higher the indice, the greater the influence the variable. Monte Carlo (MC) approach is used here to calculate the Sobol indices. This approach assumes that the input parameters are independent. Given the cost calculation that MC point evaluations could take with the TPEE simulation, a Radial Basis Function (RBF) surrogate model of the evaluated function is used (Sainvitu et al., 2010). The use of this surrogate model allows reducing the computational cost while keeping a very good precision, more details on the surrogate models used can be found in the second part of this paper.

**Description of the Morris method**

The Morris method (Campolongo et al., 2007; Iooss, 2010; Morris, 1991; Saltelli et al., 2000) used is the one implemented in the SALib package for Python (Herman, 2017). It consists in repeating \( r \) times (\( r = 5 \) to10) a design of experiments (DOE) “One at a time” (OAT), randomly in the inputs space, discretizing each input by a suitable number of levels (depending on the number \( r \)). “Randomly” means that the starting point of the OAT experiment is randomly drawn as well as the sequence of directions in which new experiences are sequentially evaluated. Thus, the Morris method makes it possible to overcome the restrictive assumptions of the OAT plan by classifying the inputs into three categories:

- **Inputs with negligible effects**
- **Inputs with linear effects and without interactions**
- **Inputs with non-linear effects and/or with interactions** (no differentiation between these two effects)

Each repetition \( i(i = 1 \ldots r) \) allows to evaluate an elementary effect \( E_i \) on the input \( X_i \). The whole DOE (\( r \) repetitions) give a sampling of the effects for each input \( X_i \), the sensitivity indices can be calculated:

- Average of the absolute values of the effects, given by (4):

\[ \mu_j = \sum_{i=1}^{r} |E_i| \]  

(4)

- Standard deviation of effects: \( \sigma_j \)

The higher \( \mu_j \), the more the input \( X_j \) contributes to the dispersion of the output. \( \sigma_j \) measures the model linearity, the higher \( \sigma_j \) (relatively to \( \mu_j \)), the more non-linear the effects or the higher the interactions, as illustrated on Figure 3 on the analytic test case of Ishigami.

![Figure 3: Interpretation of effects depending on the \( \sigma/\mu \) ratio.](https://doi.org/10.26868/25222708.2021.30621)

As for the ANOVA method, for the evaluations of the DOEs with the Morris method, a RBF surrogate model from Minamo is used.

**Multi-scale sensitivity analyses**

Different types of sensitivity analyses are carried out at various scales, as described in the Table 2. For each type of SA, the ANOVA and the Morris methods are performed and compared, to evaluate the influence of the variation of each input parameter on the model outputs, (heating and electric energy consumption) and identify the most important parameters. For these SAs, the whole building is simulated, (with 15 and 190 varying parameters for the SA at apartment scale and the SA building scale, respectively) but focus is put on the studied parameters, as described in Table 2.

A first set of SAs at apartment scale is performed with two objectives: 1- to validate the consistency of the clustering and the choice of the cluster’s representative apartment. Several SAs are run, and the clusters are validated if the results for different apartments of the same cluster are similar. 2- to identify the most important parameters for energy consumption, for each cluster representative and so for each apartment of the building (if the clusters are validated). For each cluster, the following SAs are carried out, to evaluate the influence of the parameters of the studied apartment on its own energy consumption:

- **1st vs 2nd representative for a winter week,**
- **2 apartments with identical characteristics within the same cluster**

The parameters used in the SAs at apartment scale are related to the use of the apartment by the occupants (Figure 5). For instance, the infiltration rate corresponds to the opening of windows and all the ventilation
parameters are dependent from the way the occupants are using the ventilation system.

After this step of validation and analysis at apartment scale, two sensitivity analyses are carried out at building scale, on a winter week period, to identify the most influencing parameters of the HVAC system and of the building envelop.

Table 2: Description of the different sensitivity analyses performed.

<table>
<thead>
<tr>
<th>Type of SA</th>
<th>SA on apartment use param.</th>
<th>SA on heat production param.</th>
<th>SA on building envelope param.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Objective: to identify param.</td>
<td>That most influence energy consumption of apartments</td>
<td>That most influence global energy consumption</td>
<td>That most influence global energy consumption</td>
</tr>
<tr>
<td>Param. studied</td>
<td>15 param. /apt (one apt/cluster); 19 param. for triplex</td>
<td>19 param. from boiler room</td>
<td>171 building envelop param.</td>
</tr>
<tr>
<td>Examples of param.</td>
<td>Infiltration rate, number of people, power of appliances, ventilation rate</td>
<td>Boiler efficiency, nominal capacity, storage volume</td>
<td>Windows and wall param.</td>
</tr>
</tbody>
</table>

Results

The results obtained in the different parts of the methodology are presented here.

Clustering step

The final clustering, presented in Table 3 and Figure 4, is defined as a combination of the results from the SOMs and the Affinity Propagation methods and expert knowledge (used when the two methods do not give similar results or when an apartment clearly fits to a specific cluster like the C31 and C32). The apartments on the attic (A41, B41) are grouped in a cluster (cluster 5) because of their physical and architectural specificities. Additionally, as it is modelled in a different way than the rest of the apartments, it seems relevant to create an independent cluster (cluster 1) for the triplex (D01).

Sensitivity analyses step

The following graphs, for SAs at apartment scale, represent with one histogram per parameter, the influences of the first order and total order obtained by the ANOVA as well as the expression $D^*$ obtained with the Morris method, given by (5).

$$D^* = \sqrt{\mu^2 + \sigma^2} \tag{5}$$

As the results obtained from the different SAs at apartment scale were highly similar, (no matter the apartment chosen within a cluster nor the cluster), with both the SA methods, the histograms are shown only for one apartment.

Table 3: Results of clustering methods and final clusters. In bold, the apartments from the methods 'results selected to be in Final clusters (based on expert knowledge).

<table>
<thead>
<tr>
<th>Cluster</th>
<th>Affinity Pr.</th>
<th>SOM</th>
<th>Final</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>A32, C31, A14, C21</td>
<td>A32, C31, C24</td>
<td>A32, C02, C14, C24, C32</td>
</tr>
<tr>
<td>2</td>
<td>A01, A11, A21, A31, A24, A25, C14, A33, B11, B21, B13, B01, B12, B22, B23, B32, C22</td>
<td>A01, A11, A21, A31, C12, B01, B12, B22, B32, C22</td>
<td>A01, A11, A21, A31, C12, C31, B01, B12, B22, B32, C22</td>
</tr>
<tr>
<td>3</td>
<td>A15, C02, C12</td>
<td>A14, A15, A24, A25, A33, B11, B21, B13</td>
<td>A14, A15, A24, A25, A33, B11, B21, B31</td>
</tr>
<tr>
<td>4</td>
<td>A41, B41, C32</td>
<td>A41, B41, C32, C02, C14</td>
<td>A41, B41</td>
</tr>
<tr>
<td>5</td>
<td>A02, A22, B02, A13, C13, C23</td>
<td>A02, A22, B02, A01, A21</td>
<td>A02, A22, B02, C01, C11, C21</td>
</tr>
<tr>
<td>6</td>
<td>A12, A23, B13, B33</td>
<td>A12, A23, B13, B23, B33, C11</td>
<td>A12, A23, B13, B23, B33</td>
</tr>
<tr>
<td>7</td>
<td>C01, C11, C24, D01</td>
<td>A13, C13, C23</td>
<td>A13, C13, C23</td>
</tr>
</tbody>
</table>

Figure 5 illustrates the SA results of a representative apartment from cluster 2 for a winter week, with the heating and electric energy consumption as studied model outputs. As described in Table 2, for this SA only parameters related to building usage are considered. The graphs clearly show that the infiltration rate (describing the opening of windows and doors, which create heat losses to the outside) and the setpoint temperature are the two most influencing parameters on the heat consumption. These parameters only depend on the occupant’s behaviour and so, can strongly fluctuate. Then, to a small extent, the ventilation rate is the next parameter with influence on the heat consumption. In the same way, the power from the cooking trays and the lighting are the most influencing parameters on the electrical consumption at apartment scale. This can be explained because of the consumption patterns associated, which make the use of these equipment more energy consuming than the rest of the appliances. Indeed, in the model, the energy needed for the functioning of electrical appliances is calculated based on the nominal power and the time schedule defining its usage. Then, to a small extent, the power of plugs, television, dishwasher, dryer, fridge and washing machine.

These results allow to validate the clustering of the 41 apartments and to identify the most influencing parameters on the heating and electrical consumption at apartment scale.
Figure 4: 3D visualization of the clusters.

Figure 5: SA results of a representative apartment from cluster 2 for a winter week (on x axis: 1: infiltration rate; 2: ventilation rate; 3: number of occupants; 4: lighting power; 5: fridge power; 6: washing machine power; 7: Dishwasher power; 8: cooking trays power; 9: plugs power; 10: radiator power; 11: dryer power; 12: tv power; 13: ventilation efficiency IN; 14: ventilation efficiency OUT; 15: setpoint temperature).

For the SAs at building scale, the results are illustrated by pie charts, for the ANOVA, only showing the most influencing parameters (>3%) and Morris graphs, as explained in Figure 3, that shows the different types of influences depending on the values of \( \mu \) and \( \sigma \). For readability reasons, parameter codes are used in the Figure 6 and Figure 7. Considering the huge number of parameters, not all parameters are described. The two methods (ANOVA from Minamo and Morris method) give consistent results for all SAs.

The results from the SA on heat production parameters, illustrated on Figure 6, show that the most influencing parameters (from the heat production system) on the heat consumption of the whole building are the boiler efficiency (X172), the boiler nominal flow rate (X174) and the upper limit of outlet temperature of the boiler (X175). The most influencing parameters (from the heat production system) on the electricity consumption of the whole building are the upper limit of outlet temperature of the boiler (X175), pump efficiency (X179) and the inlet temperature to the radiators inside the apartments (X188) (which is also depending on the boiler outlet temperature). These results highlight that the thermal performance characteristics of the boiler and the radiators influence the electricity consumption of the whole building. Indeed, the heat production system must adapt the pump operation and the system temperatures to meet the requirements from the apartments, and this impacts the electricity consumption of the HVAC system.

The results from the SA on building envelop parameters, illustrated by Figure 7, show that the most influencing parameters among the constructive parameters on the heat consumption of the whole building are: the U coefficient of windows (describing the insulation level) (X169), the solar thermal transfer coefficient of windows (heat
transferred by sunrays through windows) (X170), the conductivity and the thickness of wall insulation (describing the U coefficient of material Sto Iso PSE Top32 016) (X47, X23), the conductivity and the thickness of wall insulation (describing the U coefficient of material Recticel Isu Eurothane Bi4A 014) (X45, X21).

Discussion

The clustering method gives 8 clusters which are easily understandable but hard to manually define. When looking at the apartments in each cluster (Figure 4) one can find out some similarities, but regarding the clustering itself, considering the 504 combinations of 4 criteria, it would not have been possible to create these clusters without using specific algorithms. The multi-residential building studied is a challenging test case for the clustering method. Indeed, almost each apartment has its specificities (orientation, number of rooms, etc.). For this study, the clustering criteria are chosen, but more criteria or different criteria can be used (i.e. ratio windows to wall, area, etc.) depending on the question to be answered, which would probably results in different clusters. The study shows that even if the apartments considered are all different, it is possible to group them into clusters and analyse only one representative apartment per cluster, from which the results can be extrapolated to all others in the cluster. The clustering method is used here in a larger building model calibration process, but could eventually be used for other purposes, such as quick energy diagnosis, pre-feasibility studies, etc.

For the sensitivity analyses, two of the most common methods are compared (ANOVA and Morris) and give consistent results. The most influencing parameters on energy consumption at both apartment and building scales are identified. SA is a useful tool to understand the inputs/outputs relationship and diagnose modelling errors. The results of the SAs carried out during this study, are relevant and prove that the building energy model used is working properly.

To further test and improve this cluster-based sensitivity analysis methodology, it would be interesting to apply it on other multi-residential building cases or on a set of individual residential houses and test other clustering criteria.

Conclusion

In the TPEE project, to improve the energy performance of a new-built multi-residential building in Belgium, through energy prediction and fault detection and diagnosis of the energy systems, a building energy model is created from scratch with the tool Openstudio/EnergyPlus and must be calibrated before being used with real measured data. This paper presents the general calibration methodology and explains why it is necessary to reduce the number of parameters to be calibrated. To do so, a new cluster-based multi-scale sensitivity analysis method is proposed to identify the most influent parameters for heating and electric energy consumption. From an initial complex building model with 1200 parameters, the sensitivity analysis process...
highlighted around 230 important parameters to focus on for the model calibration.

The developed methodology is applied on a multi-residential building of 40 apartments and a triplex. In the clustering step, a combination of clustering methods, applied with 4 architectural characteristics, identifies 8 clusters of apartments. The interest of clustering is double: 1) for time computing purpose (to avoid studying all the 41 apartments); 2) for scaling up the results, indeed for this building, it is not trivial, because most apartments have their own physical characteristics (building architecture, height, orientation, etc.) that influence internal thermal gains and so the energy consumption. After validation of the clusters, it is possible to scale up the results for one apartment to all others in his cluster.

In the sensitivity analysis step, for individual apartments, results show that the infiltration rate, the temperature setpoint and the nominal power of electric appliances (cooking range, lights, plugs) have the most impact on the heating and electricity consumption. At building scale, the boiler characteristics (efficiency, mass flow rate, maximum setpoint outdoor temperature) the circulating pump efficiency (distribution side), the radiators inlet temperature (from the apartments side) and the parameters characterizing the physical elements (insulation and thermal parameters of the walls and windows) have the highest influence on the gas and electricity consumption in the building energy system.

The next step is the calibration with a reduced number of parameters to focus on (identified in the SA step), which is presented in a second paper (Part II - Calibration Using Surrogate-Based Optimisation).

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