ON KEY PARAMETERS INFLUENCING BUILDING ENERGY PERFORMANCE

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ABSTRACT

This paper describes the methodology used for selecting the most influential parameters on the energy performance of a building, using limited computing power.

Detailed building energy performance models development and their manual calibration are depicted. Novel interfaces for the connection of a detailed building simulation software with advanced analytics are then presented. After a first screening of the parameters by domain experts, two techniques are deployed on the models to reduce the number of parameters to be considered in an automatic calibration process: boundaries check and Morris method. The methodology is applied on two non-residential buildings.

Finally, the study results are presented, providing deep insight on the buildings energy performance and thus setting the basis for automatic model calibration and faults detection.

INTRODUCTION

Detailed Building Energy Performance Simulation (BEPS) models are increasingly being used as methods for information management along the entire lifecycle of buildings. Over the last 50 years, many BEPS programs have been developed and enhanced to integrate the latest researches in the field, including novel HVAC systems and controllers. These models, if used throughout the buildings commissioning phase, might become powerful means in helping building operators and facility managers to assess building energy performance, detect anomalies and suggest management improvement. Today, the numerous available tools may differ in several ways: thermodynamical models, graphical user interfaces, purpose, life-cycle capabilities, transparency and ability to communicate with other programs (Crawley, 2008).

Despite the increasing reliability of these programs, one of the major limits to their wide adoption is the number of parameters required for model development. In fact, each model requires hundreds of configuration parameters, which are generally difficult and costly to obtain and which can be responsible for large variance of the model output if not estimated with sufficient accuracy (New, 2012). For this reason, it is important to select a subset of parameters, which are most likely to explain the model deviation from reality and should thus be determined more carefully for calibrating the model.

In the frame of the European project Tribute (http://www.tribute-fp7.eu) the authors have collaborated to develop a new version of BEPS tools. This new-generation software aims at minimizing the gap between computed and measured energy consumption, thus improving the predictive capability of the tool. In order to achieve this goal, advanced algorithm connecting measured and simulated data for automatic calibration of the buildings parameters will be developed. In order to limit the cost of sensors deployment and the complexity of the optimization algorithm to be implemented, the number of parameters considered for calibration should be limited. For this reason, it is important to select the most influential parameters to be optimized and discard the others.

The method chosen for the parameters screening, as well as the insight provided by the results on the buildings under analysis, will be described in the following sections.

SIMULATION ENVIRONMENT

Building modelling

Two existing public buildings were modelled. One library located in Torino, Italy and one office building located in La Rochelle, France. The software used was IDA Indoor Climate and Energy (IDA-ICE), developed by EQUA. IDA-ICE is a whole building simulation tool, based on dynamic multi-zone calculations, and providing results on thermal indoor climate and energy consumption. Simulations are made on variable time steps.

The IDA-ICE models were developed by energy simulation experts according to available data on building geometry, construction materials and HVAC systems (Diallo, 2015).

It should be noted that the development of a building model consists of different phases, with continuous refinement of subsystems and increasing results accuracy.

The first phase is the development of the "as-built" model, which is designed from commissioning and audit data. The sensitivity study on this model can help to identify the meters and sensors to be installed and detect the priorities of the calibration phase. Secondly, the model can be manually calibrated according to available measurements data. During this phase, the model is refined at subsystem level, resulting in higher accuracy of the complete model. The model is then periodically re-tuned to be able to represent the building ageing and usage modifications. The sensitivity study can then be again performed on this fully calibrated model to provide on-line analytics and help in the identification of retrofit options.

In this paper we focus on the analysis of the "as-built" models, on which a first manual calibration was done according to real building energy consumptions as obtained from the energy audit.

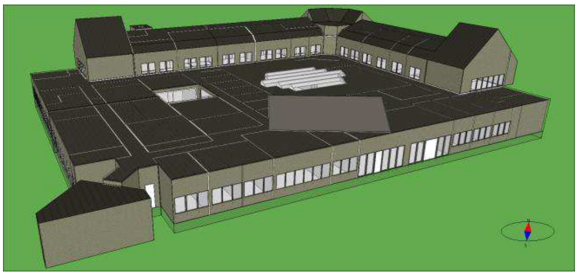

Figure 1: La Rochelle building, IDA-ICE 3D view

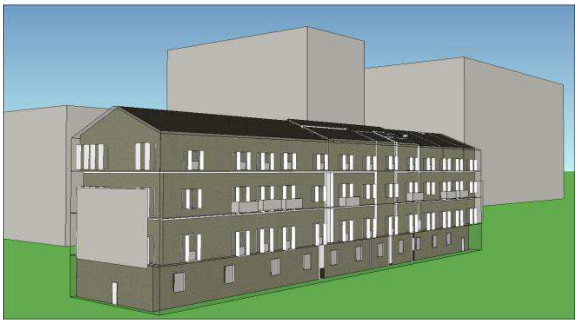

Figure 2: Torino library, IDA-ICE 3D view

The first calibration step was done to validate the parameters configuration in the simulation model, including the hypothesis made by the experts on unknown parameters, with respect to data obtained from audit, site managers and equipments' manufacturers.

This first calibration step provides higher confidence on the sensitivity analysis results, since the model is more likely to perform as the real building and thus to reflect its behaviour concerning the impact of parameters variation on the energy performance.

For Vaucanson building in La Rochelle (*Figure 1*), the simulated annual consumption after this first calibration step was of 382 MWh, 7.3% far from the total measured consumption. The energy splits obtained from the detailed model (*Figure 3*) reflected the results of the audit, showing a good match between the behaviour of the simulated and the real building.

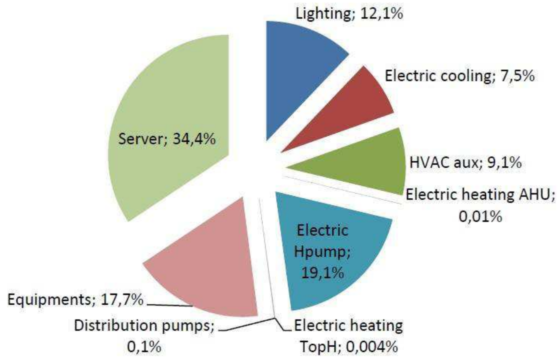

Figure 3: Energy consumption repartition per usage for IDA-ICE simulation model of La Rochelle office building – pie chart.

First manual calibration on Torino building (*Figure 2*) was harder to perform, due to lack of information on HVAC system controls (such as the humidification process in AHU, which constitutes a significant part of the energy consumption) and on building envelope (such as glazing heat conductivity). Furthermore, there were not any detailed energy consumption measures or estimates available. Comparison was, thus, made with Italian standard building consumption. Eventually, the simulated total energy consumption differed from 25%, but further calibration being meaningless, it was decided to use the simulation model "as it was" (*Figure 4*) for the sensitivity analysis.

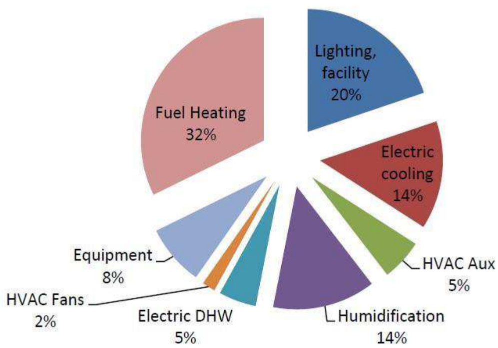

Figure 4: Energy consumption repartition per usage for IDA-ICE simulation model of Torino library, pie chart.

Interfaces development

For simple simulations, "what if" analysis or simple, predefined sensitivity studies, IDA-ICE software can be used as a standalone software. However, for more complex studies, there is a need to couple the simulation tool with another software platform that will execute the analytic algorithms required for sensitivity analysis, calibration, fault detection and diagnostic or even advanced control.

An example of such a coupling is proposed by the MOBO tool[1], which uses a set of search algorithms to solve multi-objective optimization problems on the building model. MOBO allows the user to define investment cost and simulations to estimate energy consumption cost. Despite being interesting for design and retrofit optimization, MOBO is not a sufficiently open environment for some of the analytic development targeted in this paper the Tribute project.

Matlab is a software commonly used by engineers in research and development. Mentions of its coupling with various simulation platforms (Energy+, TRNSys, etc) have been reported in a number of studies (Nouiduia, 2014)(Riederer, 2009)(Wetter, 2010). High level coupling (e.g. co-simulation) will be described in (Azar, 2015).

In this paper, we present a low-level coupling in which Matlab is used to set configuration parameters, run simulations and analyse results of IDA-ICE models in an iterative search process.

To achieve this objective, a set of functions relating IDA-ICE to Matlab were developed. These functions allow the user to:

- Import IDA-ICE model data in Matlab.
- Allow modification of specific parameters within the model.
- Write and save models.
- Start (multiple) simulations using parallel computation feature.
- Import results in Matlab for post-treatment analysis.

In IDA-ICE, all the configuration parameters of a building simulation model are stored in a file with *.idm extension. *.idm files can be opened with a text editor and contain all the information needed by IDA-ICE to build the model, organized in a specific manner. These files might be quite long (3505 lines for La Rochelle building, 2760 for Torino library), depending on the complexity of the building, and cumbersome to read.

A function was then developed to gather the model's information from the *.idm file and store it in a Matlab structure. This structure reproduces the *.idm architecture. It can easily be converted into xml format for exchange with other software. One limitation comes from the fact that default value are normally not stored in the *.idm files. A specific script was developed by EQUA to force IDA-ICE to save all values, but this remove some of the links in the data structure.

Model modifications were then performed through changes in the configuration parameters stored in the Matlab structure.

For each parameter listed in *Table 1*, a "Set_Param" function was developed to retrieve the initial value of the parameter from the structure and modify it according to the selected criteria (percentage variation, fixed value variation, fixed value setting). The "Set_Param" functions were designed to be as much as possible building independent. Unfortunately, this was not always possible as some parameters have to be modified in different ways depending on the building system structure. For example, setting the emitters capacity (i.e. the nominal power of the heating or cooling unit in the zone) is done in very different ways depending on the type of emitter.

Another function was developed to write the modified model from the Matlab structure back into an *.idm file. The new model could then be interpreted and simulated using IDA-ICE.

Finally, a function was developed to start several IDA simulations using Matlab, thus enabling the user to run automatically and in parallel (depending on the performance and number of core of the computer) a set of specified simulations. If the number of models to simulate is higher than the number of cores (k), up to k simulation can be started in parallel. Moreover, each time a simulation is finished a new one can be automatically started.

The resulting Matlab toolbox can be easily used to run the sensitivity analysis simulation reported in this paper. The user only has to specify the parameters to be modified and the range to be considered in an excel file. The same toolbox will also be used in future calibration and fault detection and diagnostic algorithms development. As it is based on the *.idm file structure, there is no guarantee that this toolbox will continue to work in future version of IDA-ICE. However, it is planned by EQUA to propose an official API between Matlab and IDA-ICE.

METHODS

There have been many studies in the energy modelling literature using different sensitivity analysis approaches. These include screening methods, local methods and global sensitivity studies.

Screening methods are generally used to determine a subset of parameters really influencing the output. They are qualitative methods and imply lower computing power compared to other methods. For this reason, they are often applied prior to a more detailed sensitivity study. For instance, Monari et al applied Morris method to screen input factors before performing MonteCarlo analysis (Monari, 2013).

Local sensitivity analysis evaluates the sensitivity at one point in the parameters hyperspace (Griensven, 2006) while global sensitivity studies evaluate the influence of the parameters over their whole range of variation and take into account their mutual interactions.

[1] - MOBO: http://ibpsa-nordic.org/tools.html.

Table 1

List and range of variation of the parameters selected for the sensitivity study on Torino and La Rochelle buildings

Parameter's name	Range of variation	Building concerned
Outdoor Temperature	+/- 2 °C from nominal value	Torino and La Rochelle
Global irradiance	+/- 10% from nominal value	Torino and La Rochelle
Albedo	0.1 to 0.3	Torino and La Rochelle
Glazing	+/- 15% from nominal value	Torino and La Rochelle
External walls U-value	+/- 15% from nominal value	Torino and La Rochelle
Roof U-value	+/- 20% from nominal value	Torino and La Rochelle
Materials inertia	+/- 30% from nominal value	Torino and La Rochelle
Infiltration	0.3 to 0.6 ACH	Torino and La Rochelle
Thermal bridges	+/- 50% from nominal value	Torino and La Rochelle
Occupants density	+/- 10 % from nominal value	Torino and La Rochelle
Temperature setpoint of the AHU	+/- 1 °C from nominal value	Torino and La Rochelle
Emitters auxiliaries	+/- 20% from nominal value	Torino
Emitters capacity	+/- 20% from nominal value	Torino
Light power density	+/- 20% from nominal value	Torino and La Rochelle
Equipment power density	+/- 50% from nominal value	Torino and La Rochelle
AHU rated air flow rate	+/- 20% from nominal value	Torino and La Rochelle
Air duct losses	0.2 to 6.5 W/m^2	Torino
Fan efficiency	0.7 to 0.9	Torino
Boiler efficiency	0.45 to 0.5	Torino and La Rochelle
Boiler temperature setpoint	+/- 3 °C from nominal value	Torino
Heat pipe losses	2 to 7 W/m^2	Torino and La Rochelle
Chiller efficiency	+/- 10% from nominal value	Torino
Chiller temperature setpoint	+/- 2 °C from nominal value	Torino
Cool pipe losses	0.2 to 1 W/m^2	Torino
Zone cooling temperature setpoint	+/- 1 °C from nominal value	Torino
Zone heating temperature setpoint	+/- 1 °C from nominal value	Torino and La Rochelle
AHU humidification setpoint	45 to 55 %	Torino
Pumps efficiency	+/- 20% from nominal value	La Rochelle

Global methods are those providing most information on the model but are also the most time consuming. Among these, quasi Monte Carlo analysis (O'Neill, 2013), Markov models (New, 2012), global derivatives (Eisenhower, 2011) and variance analysis (Li, 2002) were already applied to building simulations models, often requiring thousands of simulations on super-computers (Sanyal, 2013).

In this study, access to supercomputers was not possible and given the computing time needed to run each model (around 8 hours for La Rochelle building, 3 hours for Torino building on a standard laptop) and the memory space needed to store the results, the number of simulations that could be run for the study was limited.

Memory space required by the model depends on the number of results needed, the length of simulation period and the accuracy required. More detailed results, longer simulation and smaller time step require more memory space. In the presented case, 1.21 GB was needed to store the model and the simulation's results for La Rochelle building, while 200 MB were needed for Torino building.

Given these constraints, the authors decided to limit the study to screening methods. These would provide enough information for the selection of most influential parameters at a low computing cost.

Starting from the available literature results (Spitz, 2012, McDonald, 2002, Bailey, 2011) on this topic and taking into account the specificities of the building considered, building simulation and building management experts selected a subset of parameters to be used for the study. The proposed list included the parameters that, according to experts opinion, were the ones more likely of being responsible for the model variance on global energy consumption. The list of parameters used for each building and their relative uncertainty are reported in *Table 1*.

A first screening of the potential key parameters identified by expert knowledge was performed using a One-Factor-At-A-Time (OFAT) algorithm, in which at every iteration one parameter was set to one of its limit values, i.e.maximum or minimum of its uncertainty range. This method required $2k+1$ simulation runs, where k is the number of parameters considered. On one side, the main advantages of this technique are its simplicity of implementation and easiness of interpretation. On the other side, the main drawback is that interactions between parameters are not taken into account.

In order to take into account these interactions and gain more knowledge on parameters effect while keeping the number of required simulations low, Morris elementary effects method (Morris, 1991) was implemented.

The algorithm was structured as follows:

- Initialize path and choose target building;
- Declare the parameters to be considered in the study and their range of variation;
- Initialize the sampling matrix. Every column of the matrix represents one of the parameters to be modified, while every row represents a simulation configuration;
- Load IDA-ICE building base model as a Matlab structure
- Generate copies of the base model
- For each model, modify the selected parameter according to the sampling matrix and the allowed variation range defined in the parameters structure
- Save the modified model
- Run the batch of simulations in parallel
- Compute the elementary effects and their mean and standard deviation.
- Plot results.

The sampling matrix cited encloses the design of an experimental plan consisting of individually randomized set of parameters. The configuration parameters of two subsequent simulations, stored in two subsequent rows of the sampling matrix, differ by only one parameter value. Therefore, the effect of every parameter on the output can unambiguously be determined.

The parameter to be varied between each simulation is chosen in a pseudo-random way. The experimental plan implemented insures that, for every input, the same number of elementary effects can be computed, i.e. that all the parameters are "randomly" selected the same number of times (Saltelli, 2004).

The elementary effects attributable to each input are defined as the difference in output between two following experiments, divided by the variation of the corresponding input.

The elementary effect of the ith input (or parameter) is then defined as follows:

$$ee_i(\boldsymbol{x}) = \frac{y(x_1, x_2, \dots, x_i + \Delta, \dots x_k) - y(\boldsymbol{x})}{\Delta} \qquad (1)$$

These elementary effects can be regarded as partial approximations of the partial derivatives of the model.

In our case, the elementary effects of every parameter defined in *Table 1* were computed considering as output the total yearly energy consumption of the building. For every parameter, we chose to compute 4 elementary effects, 4 being the minimum suggested number to be used in order to obtain reliable results. Hence, every parameter is varied 4 times in the experimental plan, allowing the elementary effect computation in 4 different points of the chosen sampling space.

The resulting computational effort is given by

$$N=r*(k+1) \qquad (2)$$

Where N is the number of simulations required, k is the number of parameters used for the screening and r is the number of elementary effects considered for every parameter.

Finally, the mean μ^* of the absolute values of the elementary effects associated with each parameter and the standard deviation σ are computed. μ^* provides a measure of the input relevance, while σ can be used to detect factors involved in interactions or whose effects are non-linear.

The use of μ^* for parameters discrimination was proposed by an enhanced version of Morris method proposed by Campolongo et al (Campolongo, 2003).

RESULTS

Boundaries check

The results of the first screening showed that the parameters can be classified in four major groups:

- Parameters having a large impact (>3%) on the energy performance: these should be accurately tracked for calibration and should be monitored for Fault Detection and Diagnostic (FDD).
- Parameters having low impact: these should be fixed to their initially selected value and not considered any further.
- Parameters having different impact on the two buildings: these should be considered for calibration in further studies on other buildings.
- Parameters that are not included in previous groups and which have a limited impact on energy consumption.

In *Figure 5* and *Figure 6* the impact of the eight most influential parameters for the two buildings is displayed.

Each parameter is reported with its range of variation and the results are normalized with respect to the results of the first calibrated model. In the figures, light blue bars represent an increase in the parameters values while dark blue bars represent a decrease in parameters values.

As expected, a constant variation of outdoor temperature of two degrees over the year has a major impact on both buildings.

For La Rochelle building, the effect of temperature variation is reflected on the heating consumption, which varies proportionally.

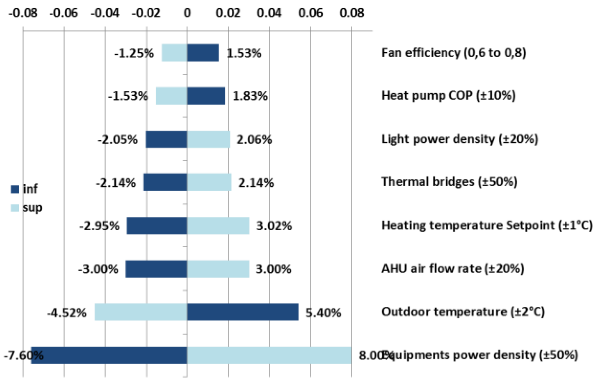

Figure 5: Impact of the most influential parameters on the total energy consumption of La Rochelle building model.

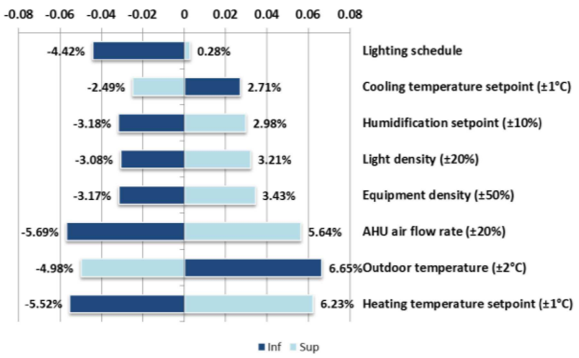

Figure 6: Impact of the most influential parameters on the total energy consumption of Torino building model.

On the other hand, for Torino building, the outdoor temperature not only impacts the heating consumption, but also the cooling consumption and the humidifier one. In fact, a change in temperature of 2 °C implies a change of about 10% of the humidity ratio (kg$H_2$0/kgAir) to keep a constant relative humidity in the building.

The equipment power density affects both the electrical power consumption directly related to the usage of the equipment and the temperature of the zones in which they are stored. Therefore, in Torino the equipment has a direct impact on the cooling power, as well as the fan coils and humidifier consumption. On Vaucanson, since there is no cooling system, the impact is mainly seen on the direct electrical consumption and on the heating pump consumption.

Thermal bridges are defined as heat transfer between the interior (or conditioned space) and exterior environment of a building shell, due to the penetration of the insulation layer by a conductive material. This parameter should have similar impact to that of the building envelope U-value or the air infiltration rate. Despite the large uncertainty, this parameter has a low effect on Torino building. This can be explained both by the limited part of thermal bridges in the global envelope losses in the reference model (5%) and by the inverse impact on heating and cooling. Besides, the large part of thermal bridges (21% of total envelope losses) and impact on heating only make thermal bridges one of the most influent parameter on the La Rochelle building.

Finally, parameters such as humidification setpoint and heat pumps COP are specific to respectively Torino and Vaucanson, since the two buildings do not have the same systems.

Morris method

The results of Morris screening algorithm results are shown in *Figure 7* and *Figure 8*. The most influential parameters are the ones with high values of μ*, meaning large overall impact, and/or large σ, meaning high correlation with other parameters or non-linearity.

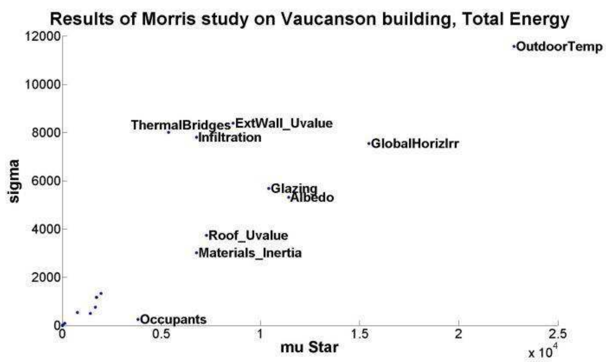

Figure 7: Results of Morris study on Vaucanson building, considering the total energy consumption as output. The figure shows the absolute mean and the standard deviation of the computed elementary effects.

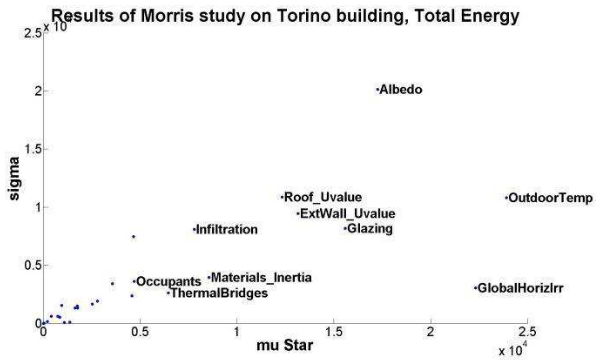

Figure 8: Results of Morris study on Torino building, considering the total energy consumption as output. The figure shows the absolute mean and the standard deviation of the computed elementary effects.

The graphs show that few parameters have a significant impact on the yearly consumption, while the others form a cluster with low mean and variance. These have limited influence and low interaction and should then be discarded in further studies for the considered buildings.

The nine most influential parameters are summarized in *Table 2*. It should be noted that some parameters (in bold) have a high impact on both buildings.

Table 2:

List of parameters in order of importance according to Morris method results

Order of importance	Output of Morris study	Output of screening
1	**AHU Rated air flow rate**	**Outdoor Temperature**
2	**Outdoor Temperature**	**AHU Rated air flow rate**
3	AHU_Tsetpoint_Torino	**Light power density**
4	**Light power density**	Thermal Bridges
5	**Equipment power density**	Zone heating temperature setpoint
6	Zone heating temperature setpoint	**Boiler Efficiency**
7	Zone cooling temperature setpoint	Fan Efficiency
8	AHU Humidification Setpoint	**Equipment power density**
9	**Boiler Efficiency**	Roof U-value

Nevertheless, some parameters are specifically important for one determined building while being non-influent on another, revealing some peculiarity of the buildings. It is thus important to avoid generalization and estimate carefully the important parameters for each building separately.

CONCLUSION

The main benefit of this study was to provide a methodology for the selection of a building's critical parameters for energy performance estimation, starting from the "as-built" model of the edifice. The subset of parameters can then be used to guide manual or automatic calibration and provide support for faults detection applications.

As opposed to a number of similar studies that have been focusing on building design optimization, the sensitivity study presented in this paper is targeting the impact of parameters on the on-line use of the Building Energy Simulation model for performance follow-up.

In this context, parameters and variables used in the study were classified in different groups:

- External signals that cannot be controlled. They act as unpredicted perturbations on the performance and should be measured and directly provided to simulation. Signals related to weather and occupancy belong to this group. These would be monitored by dedicated sensor and connected as real-time inputs to the simulation model.
- Controls variables implemented in building control units. They will be available through connection of the model with the Building Management System (BMS). Additional measurements might be considered to check that these are correctly applied.
- Key parameters. They are the building physical constants selected by the sensitivity study, on which calibration and fault detection algorithms might be applied to reduce the gap between expected and real performances.

Attention should be brought to the fact that the results presented in this study reflect the state of knowledge on the two buildings at the beginning of the study. Further information on building usage and performance – especially the analysis of newly installed sensors – will probably require a redefinition of the as-built models and in particular of the sub-systems. The sensitivity study might then be run again to assess the influence of parameters in the new configuration.

Nevertheless, before this model refinement, there are some open questions that might be considered as next steps:

- The Morris method has been run considering only 4 elementary effects for every input. It might be interesting to increase this number to check that the information gathered by the study is not biased by the low number of simulations considered.
- One of the problems faced during the study was the long time needed for running the simulations on laptops. In the future, access to advanced computing solutions might be provided. As of today, having to rely on common laptops, the best solution to reduce simulation time is to simplify the model, for example reducing the number of zones considered or increasing the output tolerance. These simplifications should also be considered for commercial approach, since the number of sensors considered for later calibration should be limited.

Finally, it should also be noted that the presented results are specific to the considered buildings and cannot be generalized. Therefore, the study should be performed systematically on each building model to determine its influent parameters, prior to apply automatic calibration method (O'Neill, 2013)(Heo, 2015).

Nevertheless, after a first selection of the parameters to be included in the study, the Matlab toolbox described in this paper could be used. The process would then be mostly automatic.

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