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Evaluation of the impact of weather variability on a Net Zero Energy Building: advantage of sensitivity analysis for performance guarantee

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ABSTRACT

Global sensitivity analysis associated with uncertainty analysis evaluates the robustness of a physical system and prioritises measurement and/or modelling efforts. The uncertainty analysis evaluates a confidence interval, whereas the sensitivity analysis quantifies the accountability of each uncertain input on the dispersion of the output.

These statistical methods are usually used to account for the variability of the static inputs, which are constant regarding the evolution of the system, for example the physical properties of the materials modelled. Dynamic inputs however, i.e. parameters that are variable over time, are rarely taken into account in the statistical analyses because of the difficulty managing correlations between the inputs in stochastic methods. Yet, the system's boundary conditions, such as meteorological input, are decisive for the evaluation of the behaviour of the building system.

This paper aims at quantifying the influence of six meteorological variables as well as 39 static inputs on the dynamic thermal behaviour of a net zero energy building. To do so, a method that stochastically generates consistent meteorological data is used and is adapted to the purpose of global sensitivity analysis. The results show a high dispersion of the cooling requirements, for which the direct solar radiation, the albedo and the window solar factor can be held accountable. Thus the variability of solar resources and their interaction with the building have the greatest impact on the performance of the building.

The variability of meteorological data needs to be considered to evaluate confidence intervals on energy performance. Furthermore, the impact of static parameters should not be overlooked, because their influence may remain significant. The considerable influence of the albedo and solar factor on the results of the present case study also shed light on the importance of assessing its value on site.

KEYWORDS

Global sensitivity analysis, Uncertainty analysis, Weather data, NZEB, solar gain

INTRODUCTION

Performance guarantee is a major issue in the context of the Net Zero Energy Building design. It consists of assigning a confidence bound to the building performance in order to guarantee a consumption level during the building's operation stage. The main concern is the strong variability of energy consumption due to the variation of weather and occupancy (Wang et al. 2012). Studies emphasise that an adjustment variable must be developed from the building's actual operating condition (weather, occupants, system settings) (Ligier et al. 2017). This makes dynamic thermal simulation combined with statistical methods essential tools. Uncertainty analysis and sensitivity analysis (UASA) occur at different stages of the energy performance guarantee process. By disturbing uncertain inputs, uncertainty analysis evaluates the confidence interval on the building performance so as to control the margin of error on the guarantee. In addition, sensitivity analysis identifies the most influential parameters on the variability in performance of the building modelled (Saltelli et al. 2008). This quest for the most influential parameter guides and/or warrants setting up a protocol for specific priority measures on the building delivered and/or the definition of the measurement and verification plan during the operation phase. This also allows one to identify the key elements in the pursuit of performance optimisation, while still in the design phase.

These statistical methods usually take into account the variability of the static inputs, which are constant regarding the evolution of the system, for example the physical properties of the materials modelled. Dynamic inputs, i.e. parameters that are variable over time, are rarely taken into account in the statistical analyses however, because of the difficulty managing correlations between the inputs in stochastic methods (Tian, 2013). Yet, the system's boundary conditions such as meteorological input, are decisive in evaluating the behaviour of the building system and therefore are one of the most important operating conditions for adjustment processes in the performance guarantee.

The purpose of the present study was to perform a UASA with dynamic and static inputs to illustrate the capabilities of this approach for the performance guarantee. The aim is to assign confidence bounds to model predictions by accounting for the natural variability of the weather inputs from year to year. This results in the characterisation of the robustness of the building performance, i.e. the stability of the performance predicted in an uncertain environment. Then we estimate the most influent input lead to measure and/or strategy to gain, respectively, confidence and/or performance. The study illustrates this on the cooling needs for July of a net zero energy single-family house with 39 static inputs and six weather variables.

METHODS

The building model

The detached house studied was built as part of the COMEPOS project, a French national program for the design, building, monitoring and feedback on 20 net zero energy single-family houses. The houses are occupied and located throughout France. The case study, in Figure 1, is situated in Strasbourg, which has a continental climate with hot summers and cold winters. The house is 137 m² on two levels. The airtightness is 0.4 m^3/(h.m²) and the thermal resistance of the insulated exterior walls is 6 m². K/W. Annual energy needs are 43.6 kWh/m² for heating and 11.5 kWh/m² for cooling with, respectively, set points at 19 °C and 25 °C. Details and validation of the EnergyPlus model are available in (Josse, 2017).

Figure 1: 3D representation of the case study house, west-south façade, east-south façade.

The input variation for the UASA

To perform sensitivity and uncertainty analyses, a set of samples is generated based on the input variation defined. The variability definition of the input conditioned the results of the analysis. In this study the static and dynamic input uncertainty corresponds to the partial knowledge at the design stage.

A sampling-based method generates stochastic meteorological time series according to the typical meteorological EnergyPlus file. In this case study the Strasbourg IWEC (International Weather for Energy Calculations) is used and the generations are made for the month of July. The weather data set for UASA is built to be representative of the natural year-to-year variability of a summer month of July for Strasbourg. The sampling-based method is based on the procedure of Iman and Conover and maintains the statistical features of the meteorological time series (auto- and cross-correlations) (Goffart et al. 2017). The weather data sample generated allows the estimation of Sobol's indices (Sobol, 2001) of the first-order effect on the energy needs. The influence of each weather variable on the output variability can be quantified. The weather data set for the UASA is composed of six inputs: the dry bulb temperature, the relative humidity, the direct normal solar radiation, the diffuse horizontal solar radiation and the wind velocity and direction.

In the case of static inputs, the variability on the thermophysical properties of materials and windows are taken into account in the study as specific heat, conductivity, density in the case of materials and conductance and the solar factor for triple-glazing windows. Also considered in the study are airtightness, orientation, internal load of occupants for activity (90 W) and sleep (63 W), ventilation and ground reflectance. The variation of ground reflectance (albedo) is between 0.2 and 0.4, default values for asphalt and concrete, respectively. Both are potential exterior ground coating at the design phase. All variations are defined by uniform law and the range for each input is reported in Table 1.

Table 1: Variability of the static inputs

Input	Number of parameters	Range of the uniform law
Material properties (density, specific heat, conductivity)	31	± 10%
Window properties (conductance, solar factor)	2	± 10%
Orientation	1	± 5 °
Air-tightness	1	± 20%
Ventilation	1	± 10%
Internal load (occupants: activity and sleep)	2	± 20 W
Albedo (ground reflectance)	1	± 0.1 (33%)

Study protocol

According to the variability defined in Table 1 and the sampling-based method for weather data, coherent with natural weather variability for the month of July in Strasbourg, a set of 2000 values of the 39 static inputs and 2000 sequences of the six weather data variables was built and propagated into the EnergyPlus model of the single-family house. The 2000 simulations result in 2000 cooling need values, which are studied according to the 45-input variability in the next section.

RESULTS

Uncertainty analysis

First, we studied the output dispersion due to the propagation of the 45 uncertain inputs through the 2000 simulations. The cooling needs predicted for the month of July ranged from

1.30 to 5.31 kWh/m² with a mean of 3.07 kWh/m². The 95 % confidence interval of the energy need in July was 3.07 ± 1.31 kWh/m², *i.e.* 43%. To extract the elements responsible for this variability from the 45 inputs, the sensitivity indices were computed.

Sensitivity analysis

The Sobol sensitivity indices of the most influential inputs are gathered in Table 2. They represent the variance part of each influential uncertain input on the output variance. The sum of the indices is close to 1, indicating that interactions between inputs do not influence the overall output dispersion. Its variability is bound to the effect of each input separately.

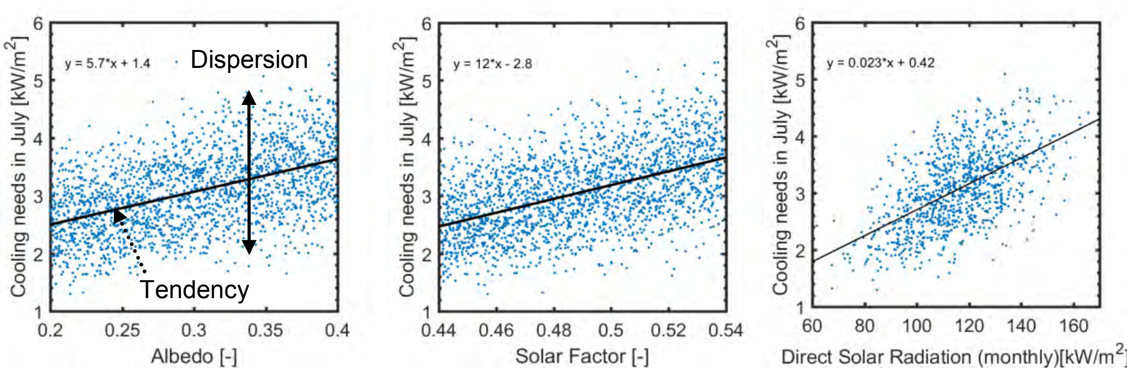
This result underscores the importance of the solar aspects on the cooling needs and especially the impact of the natural variability of direct solar radiation (34%). Then the second and third most influential inputs are the albedo (24%) and the solar factor (22%), respectively, with the same order of magnitude. Finally, the outside temperature and the conductivity of the exterior wall insulation explain the rest of the output dispersion.

Table 2. Sensitivity indices of the most influential inputs.

Input	Nature	Sensitivity index
Direct solar radiation	Dynamic	34%
Albedo	Static	24%
Solar factor	Static	22%
Dry bulb temperature	Dynamic	10%
Ext. wall insulation conductivity	Static	8%

Tendencies

It is possible to extract more information from the uncertainty and sensitivity analysis with the evolution of the output dispersion according to the variability of the most influential inputs. Figure 2 represents these tendencies for the albedo (a), the solar factor (b) and the monthly sum of the direct solar radiation (c). The shift of the average performance and the output uncertainty according to the value of an influential input can be visualised directly. For example, in Figure 2a), raising the albedo value to 0.2 from 0.4 results in a mean 45% increase in cooling needs. The same increase is observed in Figure 2b) with an increase in the solar factor to 0.44 from 0.54. The output dispersion in Figure 2a) and b) seems stable through the different albedo values and the solar factor.



a) b) c)

Figure 2. Evolution of the 2000 output values according to a) the albedo, b) the solar factor, c) the sum of direct solar radiation for each sequence generated for UASA. The tendency is represented by a black line.

The direct solar radiation is a time series and because of this dynamic characteristic, the dependence between output variability and weather data variability is more difficult to characterise. Figure 2c) represents the behaviour of the building performance according to the sum of direct solar radiation of each sequence. The sum variability is about 45%. This may help to better understand the variability in the solar impact on the cooling behaviour of the house.

DISCUSSION

The building performance uncertainty due to the natural variability in weather data and partial knowledge of the physical parameters of the building simulation is significant, with a variation of 43% at a 95% confidence bound. The sensitivity analysis quantifies the proportion of the influence of each input variability on the output variability: almost half of the output uncertainty is due to the variability of static parameters that determine solar radiation in the building: the ground reflectance and the window solar factor. The other part of output variability is explained by the natural weather variability of direct solar radiation (35%) and dry bulb air temperature (10%).

The interpretation takes into account the fact that the analysis results are conditioned by input variability: the solar radiation sum variability over stochastic sequences is about 45%, which explains 35% of the output dispersion; the albedo has 33% variability, which explains 24% of the output dispersion; and the solar factor has 10% variability, explaining 22% of the output dispersion. Thus, with variability at one-third of the variability of the albedo, the solar factor impacts the output variability equally, which must be the priority in characterising both the range of uncertainty and its nominal value.

The natural variability of direct solar radiation over the year cannot be reduced and is part of the operating uncertainty. More accurate in situ quantification of this entity might produce less bias in evaluating performance dependency in the guarantee process. Some of the input uncertainties may be reduced by expert knowledge by measuring the actual materials used and by the manufacturers' specifications. However, reducing uncertainties does not imply leaving them out. Indeed, the present study shows that ignoring uncertainty might result in underestimating the building performance variability and so may compromise the performance guaranteed.

CONCLUSIONS

This case study illustrates the capability of the sensitivity and uncertainty analysis for building performance. It focuses on the necessity of taking into account the natural variability of weather data and especially direct solar radiation when evaluating the interval bounds of cooling needs. Identification of the most influential static parameter prioritises in situ measurements of the solar aspects and thus increases confidence in the building's predicted energy performance. Uncertainty must be characterised so that it can be taken into account in the performance guarantee procedure and the accurate confidence bound assessed.

The building performance simulation coupled with uncertainty and sensitivity analyses makes it possible to test a large number of configurations on the model to evaluate the response of the building and thus extract the dependencies of the most influential variables on consumption. The UASA with natural variability assigns more realistic confidence bounds to the building performance and characterises the building's behaviour according to the weather data input from year to year. This might contribute to the adjustment process.

Because of the importance of a building's solar characteristics, one should focus on the sun management components such as opening and closing the shutters. Optimal management can be carried out by the occupant or using an automatic strategy and may decrease the cooling needs significantly. However, the occupants' behaviour is complex and highly uncertain. With in-situ sociological studies and measurements, it should be possible to characterise and include the building's specific occupancy in the UASA statistical approach.

REFERENCES

Goffart J., Mara T. and Wurtz E. 2017. Generation of stochastic weather data for uncertainty and sensitivity analysis of a low-energy building. Journal of Building Physics 41(1): 41-57.

Josse R. 2017. Méthode et outils pour l'identification de défauts des bâtiments connectés perfromants. Thesis. School of Genie Electrique of University of Grenoble Alpes. 227 pages. In French.

Ligier S., Robillart M., Schalbart P. and Peuportier B. 2017. Energy Performance Contracting Methodology Based upon Simulation and Measurement. Proceedings of the International Building Performance Simulation Association – BS2017, San Francisco

Saltelli A., Ratto M., Andres T., Campolongo F., Cariboni J., Gatelli D., Saisana M., and Tarantola S. 2008. Introduction to Sensitivity Analysis. In Global Sensitivity Analysis. The Primer, 1–51. John Wiley & Sons, Ltd. https://doi.org/10.1002/9780470725184.ch1.

Sobol', I. M. 2001. Global Sensitivity Indices for Nonlinear Mathematical Models and Their Monte Carlo Estimates. Mathematics and Computers in Simulation 55 (1–3): 271–80. https://doi.org/10.1016/S0378-4754(00)00270-6.

Tian W. 2013. A review of sensitivity analysis methods in building energy analysis. Renewable & Sustainable Energy Reviews 20: 411–419.

Wang L., Paul M. and Xiufeng P. 2012. Uncertainties in Energy Consumption Introduced by Building Operations and Weather for a Medium-Size Office Building. Energy and Buildings, 53, 152-58. doi:10.1016/j.enbuild.2012.06.017