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Practical application of uncertainty analysis and sensitivity analysis on an experimental house

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ABSTRACT

Today, simulation tools are widely used to design buildings because their energy performance is increasing. Simulation is used at different stages to predict the building's energy performance and to improve the thermal comfort of its occupants, but also to reduce the environmental impact of the building over its whole life cycle and lower the cost of construction and operation. Simulation has become an essential decision support tool, but its reliability should not be overlooked. It is important to evaluate the reliability of simulation and measurement as well as uncertainty so as to improve building design. This work aimed to evaluate and order the uncertainty of the simulation results during the design process. A three-step methodology was developed to determine influential parameters in the building's energy performance and to identify the influence of parameter uncertainty on the building performance. This methodology was applied at the INCAS experimental platform of the French National Institute of Solar Energy (INES) in Le-Bourget-du-Lac to identify and measure the uncertainty in a simulation hypothesis. The method can be used during the entire design process of a building, from preliminary sketches to operating phase.

1. Introduction

Today, increasingly energy-efficient buildings are being built and energy performance simulation is widely used in the design process. Simulation is used to predict the building's energy performance and to improve the thermal comfort of its occupants, but also to reduce the environmental impact of the building over its whole life cycle and to lower the cost of construction and operation. The energy performance of buildings is increasing rapidly due to thermal regulations instituted by several countries. Today an efficient building needs almost no energy for heating, whereas 10 years ago energy consumption was around 200 kWh/(m^2 year).

To check the building performance that was defined during the project's design phase, sensors are installed and measured data are compared with simulation results, and usually a difference between the two is found. Won-Jun et al. [1] compared simulation results with measurements for a campus library building in Suwon City, South Korea. Differences were observed that may have been the result of errors in, for example, input parameters, occupation scenarios, or weather data. To improve the simulation results and the building design process, some studies focused on assessing uncertainty in simulation output (e.g., [2–5]). Many other studies focused on checking the model validity by comparing predictions with measured data (e.g., [6–8]). It is important to explain the difference between measured and predicted data and to try to minimize it.

This paper presents a method applied to an experimental low-energy building located in an experimental platform at the French National Institute of Solar Energy near Chambéry, France. The aim of this work was to provide a comparison between predictions and the first available measurements. The studied house was recently built for a research program and much attention was focused on the construction details. However, there is always uncertainty; for example, there is a difference between the theoretical flow ventilation and the one measured. We wanted to evaluate the effects of the input parameter uncertainty on the predicted air temperature. For this reason, the most influential parameters were first determined by means of local sensitivity analysis and global sensitivity analysis. Uncertainty analysis was then performed using a Monte Carlo method to predict air temperature within uncertainty bands.

2. Literature review

Saltelli et al. [9] defined sensitivity analysis as: "the study of how uncertainty in the output of a model (numerical or otherwise) can be apportioned to different sources of uncertainty in

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the model input." Sensitivity analysis is used in many fields, and Saltelli [10,11] presents a few examples for the ecological, chemical, semiconductor material, and economics fields.

Sensitivity analysis is useful to determine:

- Parameters with a real influence on the output model. This information is useful to know whether the physical model is correct. If the sensitivity analysis determines a parameter whose value is attested as influential, the simulation does not represent correctly the model and needs to be changed.
- Parameters that are influential on simulation output. If the parameter uncertainty is reduced, the output error will be minimized.
- Parameters that are not influential on simulation output. A default value will be chosen for this parameter.
- Correlation between parameters. A better knowledge interaction between parameter will be useful to have a better understanding of the modeled phenomenon, providing useful information on groups of parameters as well as individual parameters.

There are several sensitivity analysis methods available [10]:

- Screening methods identify the most important factors among a large group with only a small number of model evaluations. These methods are essentially qualitative. Sensitivity analysis has often been used in the building sector. Rahni et al. [12] used the group screening method suggested by Watson [21]. This method was applied on the ETNA model with the CLIM2000 tool developed by the research team of the French electricity company (EDF). The input parameter number was 390; they selected 23 parameters that were influential and the simulation number was equal to 136. The results of this study confirm that the screening method can be used in the building sector.
- Uncertainty analysis determines a confidence limit for the model output. Macdonald et al. [13] presented an uncertainty analysis that has been included in the ESP-r tool.
- Calibration makes a comparison between result simulations with data from experiments to determine optimal values.
- Local and global sensitivity analyses determine the effect of parameters on the model output. Global sensitivity analysis is the study of how uncertainty in the output of a model can be apportioned to different sources of uncertainty in the model input. Global sensitivity analysis can evaluate the interaction effect but the time require for this method is expensive. The most widely used methods are Sobol, FAST, Random Balance Design, and the Monte Carlo method.

Global sensitivity analysis has been used often. Burhenne et al. [14] used the Monte Carlo method in the case of a German building in which the input/output relationship was examined. A drawback of the method is that only one graphic is obtained for each parameter. If the number of the parameters is high, the treatment time is long. Macdonald [13] used the Monte Carlo method on a simulation building for his PhD thesis. Domínguez-Munóz et al. [15] determined the standardized regression coefficient (SRC) parameters in the peak cooling load. Breesch et al. [16] used the Monte Carlo method to predict the performance of natural night ventilation using building energy simulation, taking into account the uncertainty in the input. These authors also determined the SRC in their study. De Wilde et al. [17] used the Monte Carlo method to study the impact of climate change on a theoretical office building in the UK. The Monte Carlo method is often used because both the sensitivity and uncertainty analyses can be done with the same simulation number. Other global sensitivity analyses are also available.

Sobol and FAST methods are used to decompose the variance of the output of the algorithm. From variance analysis, the most influential uncertainty factor is found as well as the contribution of the interaction between the uncertain factors. Several sensitivity indices may determine:

- First-order indices, S_i, which measure the effect of the input parameter X_i on output y.
- Second-order indices, S_{ij}, which measure the effect of the input interaction parameters X_i and X_j on output y without considering the effect parameters alone.
- Upper-two-order indices can also be determined, and they measure the effect of the input interaction parameters on output y without considering the effect parameters alone.
- Total effect indices, S_{Ti}, measure the effect parameter alone and the sensitivity of the interaction parameter with all other parameters: $ST_i = S_i + S_{ij} + S_{ik} + \cdots + S_{ijk} + \cdots$

The sensitivity index values are always between [0;1], and the higher the indices, the more influential the parameters.

Mara et al. [18] developed a method to identify the most influential parameter, and this method has a lot in common with the FAST methods. These authors also [19] used a sampling-based method (Monte Carlo) with iterated one-dimensional fittings to determine the influential parameter for the test case, which was set at the University of Reunion Island.

3. Methodology

In this study we applied successively local sensitivity analysis, correlation analysis, uncertainty analysis, and global sensitivity analysis.

Local sensitivity analysis is based on derivatives and is the most popular in the literature. This method classifies the impact of parameters in a model that contains many factors (n) with a relatively small number of simulations ($n+1$). The method is ideal for reducing a large number of input factors before applying global sensitivity analysis. The parameter perturbation method was implemented. Local sensitivity indices are defined as follows: consider a model with k independent inputs $X_i = 1, \ldots, k$. For a given value of X, local sensitivity indices of the ith input factor are defined as:

$$S_i(t) = X_i \frac{\partial y_k(t)}{\partial X_i} \tag{1}$$

The numerical approximation is:

$$S_i(t) = X_i \frac{\Delta y_k(t)}{\Delta X_i} \tag{2}$$

$$S_i(t) = X_i \frac{[Y(X_1, X_2, \ldots, X_{i+\Delta_i}, \ldots, X_k) - Y(X_1, X_2, \ldots, X_i, \ldots, X_k)]}{\Delta X_i} \tag{3}$$

where X_i is the nominal value of parameter i, and ΔX_i is a small perturbation around its nominal value. This method is easy to use because there are no complex mathematical calculations; however, the parameter interaction is not taken into account, and if the parameter number is large the simulation time may be long.

For a time-dependent series, correlation analysis allows one to group parameters with the same effect and thus to reduce the parameter number that needs to be considered. The degree of correlation between two parameters X_i and X_j is:

$$r_{i,j} = \frac{(1/N)\sum(S_i(t) - S_{i,m})(S_j(t) - S_{j,m})}{S_{i,std}S_{j,std}} \tag{4}$$

Local sensitivity analysis and correlation analysis allow one to select the most influential parameter (around 10 parameters). For each parameter, an uncertainty and a distribution value must be chosen, and then uncertainty analysis is performed. Uncertainty analysis focuses on quantifying the uncertainty in the model