

## INTRODUCING UNCERTAINTY AND SENSITIVITY ANALYSIS IN NON-MODIFIABLE BUILDING PERFORMANCE SOFTWARE

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### ABSTRACT

If using simulation tools for predicting the overall building performance, important decisions concerning the input of those tools need to be taken. The input is based on experience but also assumptions. It is obvious that this introduces uncertainties on which the quality of the simulation output is dependent. It is self-explanatory that there is a demand for analyzing and quantifying those uncertainties regarding their impact on the building design.

Therefore a case study is described to evaluate the necessity to use uncertainty analysis (UA) and sensitivity analysis (SA) in building performance simulation (BPS) especially during the detailed design. The experimental set-up using an UA and SA performing tool called Simlab coupled with a commercial and in the Netherlands commonly-used simulation tool VA114 is described. Furthermore, some results indicating the impact of UA and SA for detailed design decision support are presented.

Finally, future steps are discussed in terms of how this research will be accomplished.

### INTRODUCTION

Currently, BPS is used only for code compliance in the detailed design, neither to make informed choices between different design options nor for building and/ or system optimization [Wilde, 2004]. The more efficient use of BPS in the design process could be very beneficial [Hopfe et al., 2005]. In order to enhance the use of BPS especially during the detailed design, it leads to a need of decision support tools, appropriate optimization tools and user-oriented design analysis facilities among others. Moreover, one important aspect is dealing with uncertainties, to provide solutions which are insensitive to fluctuations of parameters [Poloni, 2005]. In this respect, UA and SA gain more and more importance. Although closely related, UA and SA are two different disciplines. UA assesses the uncertainty in model outputs that derives from uncertainty in inputs. SA assesses the contributions of the inputs to the total uncertainty in analysis outcomes. There are several possible procedures to perform uncertainty and

sensitivity analysis. The most common SA is sampling-based, in which the model is executed repeatedly for combinations of values sampled from the distribution (assumed known) of the input factors. In general, UA and SA are performed jointly by executing the model repeatedly for combination of factor values sampled with some probability distribution.

In the near future, the impact of uncertainties on a certain tool will be analyzed; results from the same approach accomplished with different simulation tools will be compared. Different considered tools will be for instance IES, henk and Hambase; they differ e.g. in the complexity and the amount of input, their numerical approximation scheme (e.g. explicit, implicit methods) among others.

### METHODOLOGY

For the simulation, a standard in the Netherlands well-known simulation tool VA114 is chosen. Due to the fact that the source code is non-accessible and the research methodology is rapid prototyping, the experimental set-up using an UA and SA performing tool called Simlab is coupled with VA114. Input parameters are for instance construction boundaries, material properties and room conditions. The output of interest is energy consumption as well as heating and cooling peak loads. By reason of limiting the given results, only the outcomes of peak heating are demonstrated. For the analysis of the uncertainty/sensitivity the Monte Carlo analysis (MCA) is selected. The MCA is one of the most commonly used methods to analyze the approximate distribution of possible results on the basis of probabilistic inputs. The MCA is a black box approach- there is no code modification necessary; thus it is easy to implement to any desired tool [Lomas et al. 1991].

Starting point for this analysis is the BESTEST case 600, which is executed by a sample matrix with 200 simulations. The outcomes of both analyses are discussed in the chapter results.

In this research the following steps can be listed in general:

1. Description of a target function and consideration of the essential input.

2. Assignment of a normal distribution to the selected variables.
3. Generation of a matrix of inputs with the normal distribution through a suitable design.
4. Evaluation of the model and computation of the distribution.
5. Selection of (a) method/s for assessing the influence or relative importance/ sensitivity of each input factor based on the target function.

First focus of interest was to analyze the amount on uncertainties regarding peak heating loads. The input parameters varied under normal distribution and deviations of 5 percent are listed in the table 1. The 5 percent is chosen with the intention to compare easily the outcomes with other tools. Totally 48 input parameters are considered.

For UA and SA the MCA was selected which is an external global analyses method. Global methods are used to check how much the uncertainty in an input influences the uncertainty of the output. Thus, all 48 parameters were varied simultaneously.

*Table 1  
 Input parameter*

| Variable                   | Varied on...  |
|----------------------------|---------------|
| Specific Heat Capacity     | every surface |
| Conductivity               | every surface |
| Density                    | every surface |
| Thickness                  | every surface |
| Inside Solar Absorptivity  | every surface |
| Outside Solar Absorptivity | every surface |
| Inside Emissivity          | every surface |
| Outside Emissivity         | every surface |
| Internal Heat Gains        | entire case   |
| Infiltration AC Rate       | entire case   |

Two aspects can be examined with MCA: first, what the uncertainty in the output as a consequence from the uncertainty in the input is; secondly, how big the contingent of each input parameter to the uncertainties of the output is. For generating the sample matrix, the latin hypercube sampling (LHS) was picked out. There are several methods for generating sample matrix. The chosen one is a particular case of stratified sampling which is meant to achieve a better coverage of the sample space of the chosen input parameters [Saltelli et al., 2005].

Altogether 200 simulations are executed. From those 48 variables 3 different input files necessary for one simulation were generated, one with all the material properties, one for internal heat gains and one for air change rate. This procedure was done 200 times via one macro in Excel.

There are a number of different techniques in Simlab available, for instance PEAR (Pearson product

moment correlation coefficient), SPEA (Spearman coefficient), SRC (standardized regression coefficient), PCC (partial correlation coefficient) among others. With the help of those techniques the various types of sensitivity can be examined.

The analysis techniques differ for example in their linear or a non-linear relation between the input parameter and the output assumptions.

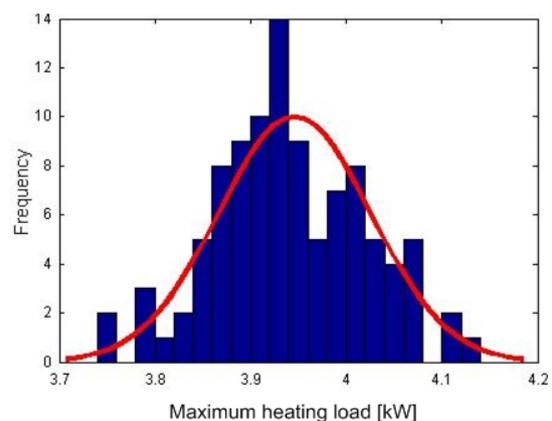
The correlation coefficients describe the mass, the input and output parameters are related to each other. PEAR is used to define the linear correlation coefficient. In the case of non-linear relations the correlation coefficient is computed by SPEA. More quantitative measures of sensitivity are based on regression analysis (SRC for linear, SRRC for non-linear). Another type of sensitivity analysis based on correlation of the data are partial correlation coefficients (PCC for non-linear, PRCC for linear). Further information can be found in [Saltelli et al., 2005].

The simulation of the chosen tool VA114 can be easily started by a batch file whilst providing the different material files.

## RESULTS

### Uncertainty Analysis

In the UA the spread of the output values can be demonstrated, which is caused by the uncertainties in the input. Representative results are given for maximum heating loads and shown in following histograms. The line shows a normal curve of distribution.



*Figure 1 Histogram- peak heating load*

The second graph indicates how far this normal distribution matches the assumption by illustrating a normality plot.

Due to the fact that the results follow the line, it can be noticed that the output of the simulations is normal distributed.

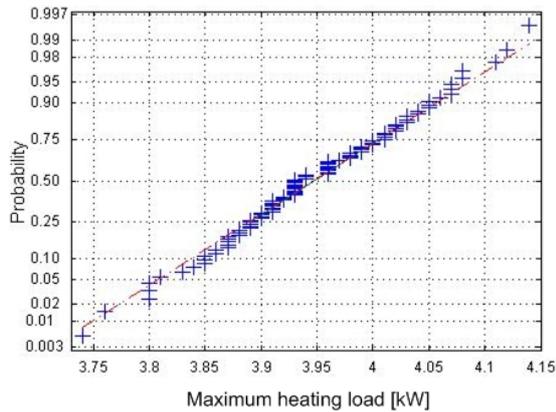


Figure 2 Normality plot- peak heating load

### Sensitivity Analysis

As stated before, in Simlab different techniques can be displayed, for instance, PEAR, SPEA, PCC etc. Simlab calculates those coefficients for each given variable. The higher the value of a variable, the more sensitive it is.

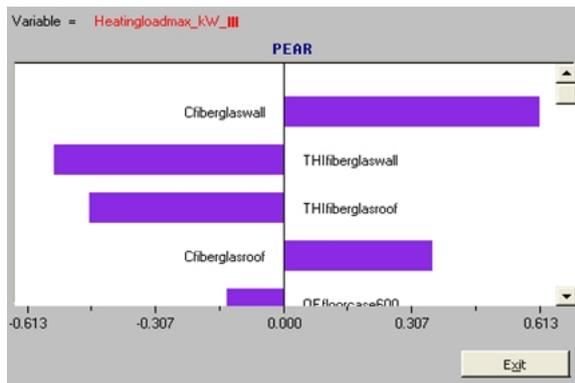


Figure 3 Visual Output Sensitivity analysis of peak heating

In this case considering peak heating with the PEAR technique, the conductivity of the fiberglass layer of the wall is the most sensitive one, followed by thickness of the fiberglass layer, thickness of the fiberglass layer of the roof and conductivity of the fiberglass layer.

### CONCLUSION

The BESTEST 600 is simulated in VA114 200 times via external input files. Parameters with possible effect on uncertainty are identified. This approach is currently being applied to other tools in order to lead to more general conclusions. Up till now, a number of preliminary conclusions can be summarized: First of all the amount of 5 percent for the distribution is not realistic and is only chosen in order to receive better comparable results by conducting the same case study with other tools. Secondly, the amount of simulations seems to be sufficient to draw conclusions. In literature two different upper limitations of 80 and 1.5 times the

number of parameters can be found; which even means less in this case [Wit, 2001].

The results given by the different techniques like SPEA, PEAR etc. coincide. This is further evidence therefore that the number of executed simulations is enough. All specified parameters have the same order of sensitivity.

### FUTURE WORK

As mentioned before, the underlying research project focuses on comparing different tools in UA/SA. In future also another sensitive analysis method called Morris will be applied, which is in contrast to MCA an internal local method.

The ultimate goal of this research will be giving design decision support in the detailed design.

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