ON SUPPORTING DESIGN DECISIONS IN CONCEPTUAL DESIGN ADDRESSING SPECIFICATION UNCERTAINTIES USING PERFORMANCE SIMULATION

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ABSTRACT

Building performance simulation (BPS) is a powerful technique to predict the performance of a design proposal. It is extensively used towards the end of the design process to, for example, prove code compliance. However, its potential to provide design guidance early in the design process is rarely exploited. That is although decisions taken during conceptual design have a disproportionate impact on the final building performance, relative to time and effort consumed (Domeschek et al, 1994). To intensify the use of BPS early is to extend its capabilities. One issue to be addressed is the building performance uncertainty due to a wide range of plausible (uncertain) design decisions.
A case study was conducted to evaluate the use and potential of uncertainty and sensitivity analysis techniques in BPS to support conceptual design. It was found that the techniques can be implemented with little effort. The results are promising for making explicit design decisions and for improving inter-design team communication.

KEYWORDS

Uncertainty & sensitivity analysis; Sample distribution; Conceptual building design; Building performance simulation; Design decision guidance

INTRODUCTION

Design decisions are often based on experience and intuition, rather than on quantitative prediction of performance indicators such as running costs, thermal comfort and CO_2 emissions. This could potentially be facilitated with BPS. However, BPS is merely used towards the end of the design process, mostly, to demonstrate code compliance.

Self-explanatory, early design decisions have greater impact than later decisions. So the aim of the work underlying this paper is to investigate how BPS can be used for decision support in earlier design phases. More in particular, the current objective is to assess the potential of uncertainty and sensitivity analysis in this context.

Earlier efforts (Hopfe et al 2005) indicate that only few BPS tools are suitable to support practitioners during the conceptual design stage. LEA, prerelease v0.9.1, is one example of a conceptual design analysis tools (CDAT). It is specifically developed for Dutch professionals to predict instantaneous peak loads and annual energy demands, already, during the early design stages.

Because it is meant to support early phase design, LEA reduces the representation of a building and its operation to the most crucial input variables. For example, the building is modeled as one thermal zone and walls are defined as thermal resistances only.

UNCERTAINTIES IN BPS - TOOLS

Building performance prediction is subject to uncertainties as; numerical-, modeling-, scenario-, and specification uncertainties (De Wit 2001). The latter two types, scenario and specification uncertainties are of particular importance during concept design. Specification uncertainties can be subdivided into physical uncertainties and design uncertainties (Figure 1).

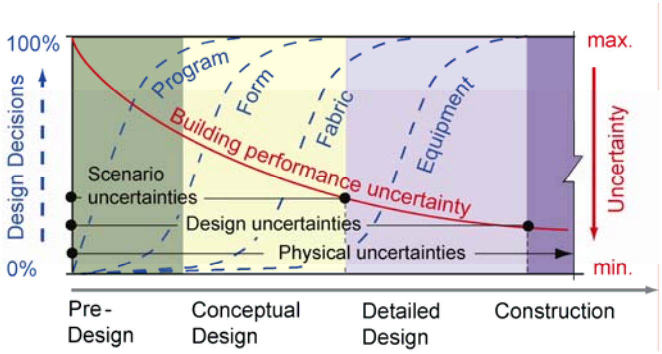

Figure 1, Traditional decision making process in building design adapted from Torcellini and Ellis (2006)

Scenario uncertainties are imposed on a building by dynamic effects as occupancy pattern or external weather conditions. The assessment of scenario uncertainties provides information about the design robustness. Variables representing scenario uncertainties are the infiltration rate, internal gains and weather data. Scenario uncertainties have been excluded from the presented analysis.

Design parameter uncertainties (i.e. window to wall ratio) represent a range of possible design values (i.e. 0.5 – 1.0) with uniform probability distribution.

Their consideration enables practitioners to rank the variables impact based on their sensitivities.

Physical uncertainties relate to physical properties of building materials. They are caused by differences between the materials thermal on site and laboratory performance. Variables influencing the differences are temperature, moisture content and aging processes. The consideration of physical uncertainties is useful to estimate the prediction error. Uncertainties in physical input variables are typically normally distributed around a mean value.

METHODOLOGY

A case study based investigation into the use of two techniques for sensitivity analysis, Morris- and Monte Carlo analysis, was conducted. The case study was based on the Bestest Case 600 (Judkoff and Neymark 1995). The analysis techniques were used to derive uncertainties and sensitivities, for both physical and design variables. Deviating from their occurrence in practice for this study they have been considered separately. The BPS tool, LEA was used as simulation model. For the purpose of the investigation the annual energy demand for cooling was chosen as performance indicator.

Uncertainty and sensitivity analysis

Two techniques were considered, the method of Morris and Monte Carlo analysis.

The two methods are applicable to epistemic uncertainties, which result from inaccurate or incomplete information about building related model parameter (Helton et al 2006).

The method of Morris is a local method. It describes the individual variable importance on a performance indicator. The impact of each variable on the performance indicator is expressed by its associated mean value and standard deviation.

The Monte Carlo analysis (MCA) is a global method. It provides total uncertainties of performance indicators and variable sensitivities. The variable importance is derived from the strength of correlation between the variable and performance indicator. The stronger the correlation the more sensitive the variable is assessed.

To facilitate the analysis, design variables are distributed across their likely range of occurrence. The variables range of occurrence can be determined by expert review or the use of published data. Due to the character of the study published and assumed values were used.

For the MCA, the latin hypercube sampling method was chosen, Its advantage over other sampling methods is that large amounts of uncertainties and sensitivities can be represented with relatively small sample sizes.

The computational expense depends on the number of samples to process with the building BPS tool. The sample size for the Morris analysis depends on the number of input variables and quantiles chosen to represent their distribution. 80 samples were processed for the Morris analysis. The minimum number of samples for the MCA is determined by the accuracy of the output standard deviation.

Lomas and Eppel (1992) state that independent of the number of variables, only marginal improvements in accuracy can be achieved after 60 to 80 simulations. A test analysis did show that the limits defined can be confidently applied to the problem at hand.

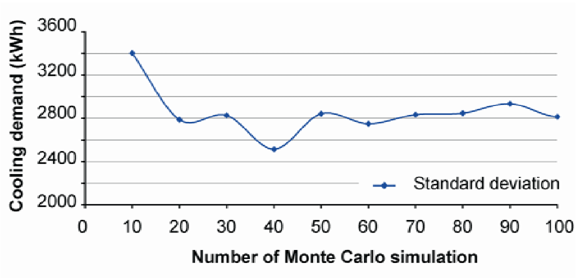

Figure 2, Accuracy assessment - Relationship between standard deviation and number of Monte Carlo simulations

Figure 2, shows that the standard deviation for the annual cooling demand fluctuates between 10 and 50 and stabilizes after 50 simulations. The percentage difference between the standard deviation calculated for 60 and 100 simulation is below 5%. Based on the test analysis the number of samples used with MCA was limited to 100.

Prototyping

In order facilitate the uncertainty and sensitivity analysis a prototype was developed using Matlab R2006a as platform by integrating LEA and Simlab 3.0. Simlab acts as statistical pre- and post processor, whilst LEA represents the calculation model to predict the annual cooling demand.

Physical input variables and associated uncertainties

The input variables have been selected reflecting the definition and purpose of the Bestest Case 600 as well as the limits of LEA.

Using LEA the building definition is limited to the definition of the thermal resistance to describe the thermal performance of opaque-, and U-value, g-value and the light transmittance for transparent building elements.

Subsequently, seven variables have been selected representing uncertainties related to the thermal performance of walls, roof and glazing construction. The floor construction has been excluded as its definition is not realistic. Its high thermal resistance aims to decouple the space from the influence of the ground.

The variables have been normally distributed around their mean value. Negative values were excluded by truncation, where necessary (see table 1).

Design parameter as window to wall ratio, floor area and building mass are fixed to 0.5, 48m^2 and 125kg/m^2 respectively.

Table 1, Physical variables

VARIABLE	MEAN VALUE	STAND. DEV.	SAMPLE DISTRIB.
Conductivity of insulation, Wall (W/mK)	0.04	0.016[(a)]	Truncated normal
Thickness of insulation, Wall (m)	0.066	0.0118 (20%)	Normal
Conductivity of insulation, Roof (W/mK)	0.04	0.016[(a)]	Truncated normal
Thickness of insulation, Roof (m)	0.112	0.02 (20%)	Normal
Glazing, U-value (W/m2K)	3.0	0.3 (10%)	Normal
Glazing, g-value	0.78	0.078 (10%)	Normal
Glazing, light transmittance	0.6	0.06 (10%)	Normal

Note: Percentage values of standard deviation indicate assumption made based on percentage of mean value.
[(a)] derived from Clarke et al (1991)

Input variables related to design and associated uncertainties

The input variables represent example design problems occurring during the conceptual design stage. They relate to single design parameter and systems. Systems such as glazing types i.e. are represented by fixed U-values, g-values and light transmittances.

Building mass is by nature no design variable. However, it is regarded as design variable as it is nowadays consciously integrated into innovative spatial conditioning strategies.

The glazing system as well as standard of wall and roof insulation has been included to demonstrate that their uncertainties differ looking from the physical or design point of view.

The design variables have been distributed uniformly as their likelihood of occurrence is equally possible. The same applies for the glazing systems. However, their representation by integers, 1 to 5, required discrete sampling.

Table 2, Design variables

VARIABLE	VALUE RANGE	SAMPLE DISTRIB.
Window to wall ratio	0.5 – 1,0 [(a)]	Uniform
Floor area	48 m2 – 72m2 [(b)]	Uniform
Building mass	105kg/m2-295 kg/m2 [(c)]	Uniform
Glazing system (1-5)	Low to high thermal performance [(d)]	Discrete
Wall insulation standard	Minimum to high [(e)]	Uniform
Roof insulation standard	Minimum to high [(e)]	Uniform

[(a)] One window in south facing wall.
[(b)] Internal gains raise proportional to floor area.
[(c)] Light weight to medium weight constructions (i.e. wood frame structures, steel skeleton and hollow core constructions).
[(d)] Clear double glazed, air filled, units (6-12-6 built up); U-value, g-value & Light transmittance according to manufacturers catalogue (Saint-Gobain Glass 2000)
[(e)] The insulation standard is represented by the thermal resistance of the building element; value range 2.5 – 4 m2K/W. (NPR2917:2005)

RESULTS

Physical and design uncertainties

The MCA analysis allows calculating the total uncertainty of the annual cooling demand caused by the input uncertainties. The standard deviation is used as uncertainty indicator.

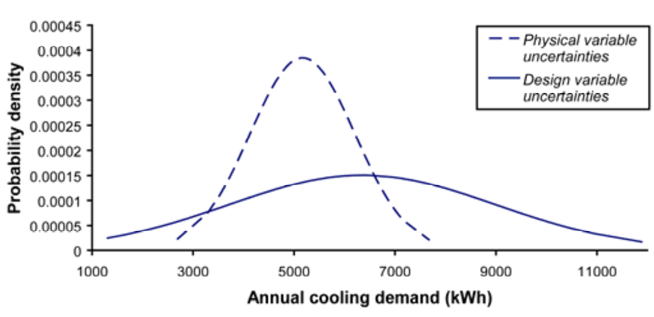

Figure 3, Probability distribution of annual cooling demand due to uncertainties in physical and design variables.

Figure 3 shows the normally distributed annual cooling demand for both types of variables. Specific for the case study and variable selection, the standard deviation, is larger for design variables than for physical variables by a factor of 2.5 (see table 3).

Table 3, MCA – Total uncertainties due to physical and design uncertainties

INPUT:	OUTPUT: ANNUAL COOLING DEMAND	
	Mean value (kWh)	Standard deviation (kWh)
Physical variables	5166.96	1037.28
Design variables	6352.23	2650.04

Individual sensitivities of design variables

The method of Morris uses the variable specific mean value and standard deviation of the performance indicator as a measure of individual variable importance (see Figure 4).

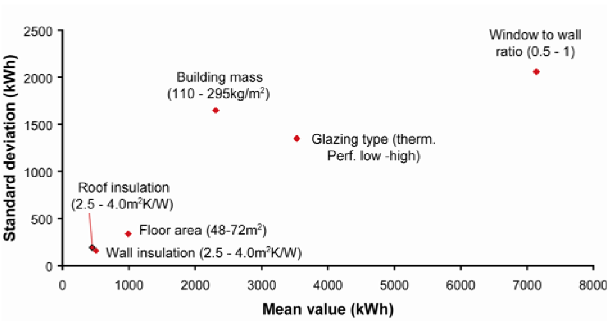

Figure 4, Individual sensitivity of design variables for annual cooling demand (Morris analysis)

The data points in the upper right corner indicate highly sensitive variables, window to wall ratio i.e. Data points in the lower left corner indicate variables with negligible small sensitivity, roof insulation wall insulation standard and floor area i.e. The variables glazing types and building mass show an intermediate sensitivity. The glazing type compared to building mass has a higher mean values but smaller standard deviation.

Total sensitivities of design variables

The MCA uses the strength of correlation between variable and performance indicator as measure of variable importance. However, prior correlation analysis scatter plots are useful to assess their relationship. Figure 5 shows the correlation of two variables ,window to wall ratio and roof insulation standard, to the annual cooling demand.

To derive more quantitative information about the correlation, multiple approaches can be found in literature.

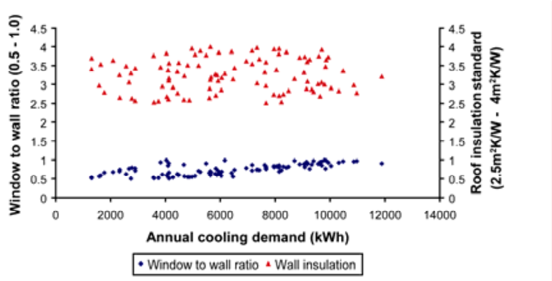

Figure 5, Scatter plot indicating relationship of two variables, window to wall ratio & roof insulation standard, to annual cooling demand.

Such methods are i.e. correlation-, partial correlation- and regression analysis. Whilst the raw data can be used if linearity exists, rank transformed data are typically used in case of non-linearity. Helton et al (2006) propose regression analysis to determine model sensitivities. The standardized regression coefficient (SRC) was selected due to the linearity of the model. One advantage of the SRC over simple regression coefficients is that the influence of the variable units is eliminated.

In MCA the coefficients themselves provide the measure of variable importance. The higher the absolute value of the coefficient associated to a variable the more sensitive the variable is assessed. The prefix corresponds to the direction of impact (see figure 6).

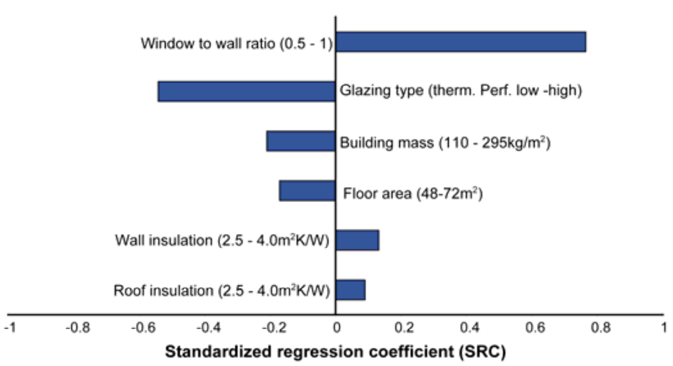

Figure 6, Total sensitivity of design variables for annual cooling demand (MCA)

Figure 6 shows the window to wall ratio as variable having the biggest importance on the uncertainty of the output. The positive prefix of its coefficient indicates its positive impact on the increase of the annual cooling demand. The roof insulation standard is the least sensitive variable.

DISCUSSION

Both types of analysis considered, MCA and method of Morris, have the potential to add value to the conceptual design stage. The choice of the type of sensitivity analysis is governed by the design problem.

Early experiences did show problems conveying results about individual and total sensitivities to practitioners. The communication failed as no obvious relationship could be exists between sensitivity indicators SRC and variable specific mean values and standard deviations.

It is anticipated that the communication can be enhanced by presenting both sets of results in one graph. It is proposed to replace the standardized regression coefficients with regression lines and using error bars around the mean value (see figure 7 and 8).

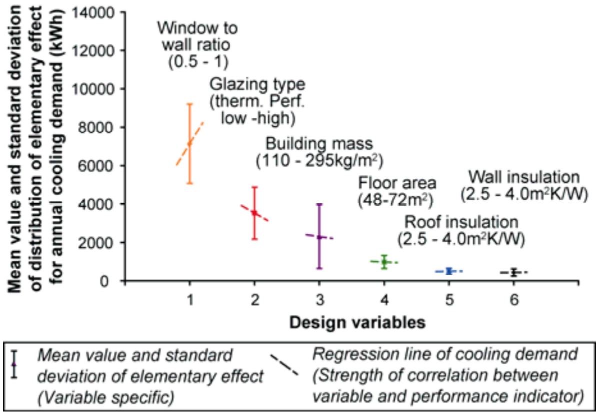

Figure 7, Design variables - Proposed combined presentation of individual and total sensitivities for annual cooling demand

The angle of the regression line presents the strength of correlation. The bigger the angle relative to the horizontal the stronger the correlation is appraised. The inclination of the regression line relative to the vertical is an indicator for the direction of impact on the raise of the performance indicator.

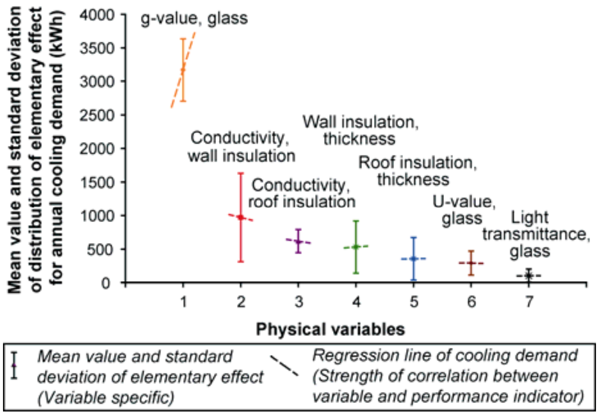

Figure 8, Physical variables - Proposed combined presentation of individual and total sensitivities for annual cooling demand

CONCLUSIONS AND FUTURE WORK

A case study based comparison was conducted to evaluate the potential of using uncertainty and sensitivity analysis techniques coupled with BPS tools to support the conceptual design stage.

Uncertainty and sensitivity analysis is not limited to single parameters but can be used to evaluate sensitivities associated to architectural or building services systems represented by a number of discrete values.

The sample distribution techniques for design and physical variables are different. Design variables are typically distributed uniformly and physical variables normally.

It was found that both methods considered Morris and Monte Carlo analysis are with little effort to implement and use.

The method of Morris provides qualitative results of the individual variable importance based on mean value and standard deviation of the performance indicator. However, it is not possible to determine the combined impact of the input variable uncertainty on the uncertainty of the performance indicator.

The quantitative Monte Carlo analysis does allow determining the combined impact of input uncertainties on the uncertainty of the performance indicator. Furthermore, it provides total uncertainties of the performance indicator. However, individual sensitivities can not be derived.

An operational drawback is the need to choose a correlation coefficient based on the linearity of the model. However, guidance on the subject can be found in literature. Here the standardized correlation coefficient was applied as suggested by Helton et al (2006).

Due to the lack of a technique providing both individual and total sensitivities they were separately calculated and combined for presentation.

The case study did show that the techniques used could potentially be useful to make implicit design knowledge explicit for communicative purposes.

Future work will be dedicated to identify how practitioners assess the value of sensitivity analysis in design practice. Therefore, the case study will be expanded to a more realistic design problem and different types of uncertainties assessed to provide design guidance. Furthermore, attention will be given to the order in which the types of uncertainties need to be considered.

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