UNCERTAINTY ANALYSIS OF BUILDING DESIGN EVALUATIONS

Sten de Wit[1,2] and Godfried Augenbroe[3]
1. Delft University of Technology, Subfaculty of Civil Engineering
Delft, The Netherlands
2. TNO Building and Construction Research
Delft, The Netherlands
3. Georgia Institute of Technology, College of Architecture, Doctoral Program
Atlanta, U.S.A.

ABSTRACT

This paper summarizes the recently concluded PhD study by the first author. The study addressed uncertainties in building performance evaluations and their potential impact on design decisions. Design evolution involves a chain of design decisions. Each decision is supported by input supplied by the various domain experts to the design team at large. The research has focused on the domain expertise of the building physics expert, responsible for those inputs that sustain rational decisions with respect to energy use, thermal comfort, HVAC system sizing etc. Prime attention has been given to thermal comfort.

KEYWORDS

Building design, uncertainty, expert judgment, thermal comfort, building simulation.

1. INTRODUCTION

In current building design practice, design evaluations may be the result of an advanced building simulation or simplified design guide lines, or expert advice based on personal judgment alone. They all have in common that they do rarely convey insight into the uncertainties of the evaluation results or advice. In fact, most design evaluations are offered to the design team as deterministic values. Our study and other recent studies have shown that the uncertainties in design evaluations can be quite substantial, which makes it imperative to convey these uncertainties to the decision maker.

It should be recognized that there is very limited data available with respect to the statistical distribution of building simulation parameters. The paper gives a brief overview of sources and techniques to determine the uncertainties in material properties and (more importantly) the uncertainties stemming from model simplifications, i.e. from the approximation of the complex physical processes that govern the relevant characteristics of building behavior. The paper reports on a statistical screening technique to determine which of these sources of uncertainty will have dominant effects on the outcome of the simulation. Two dominant effects were identified: (1) the uncertainty in ventilation rates of building spaces, attributable to uncertainty in wind pressure coefficients, and (2) uncertainty in room air temperature distribution. The uncertainties in both effects were assessed by means of expert judgment . To measure the uncertainty in a variable through expert judgment, this variable is presented to a number of reputed experts as the outcome of a hypothetical experiment. The experts are asked to state their uncertainty over the outcome of the experiment. The experts' assessments are combined to obtain the requested uncertainty.

This paper presents a brief outline of the expert judgment study on wind pressure coefficients. Furthermore, it will be shown how the identified uncertainties propagate through the design evaluation (using simulation) into the performance evaluations and quantifications of design performance. A Bayesian decision analysis may then be used to ascertain the impact of the resulting performance uncertainties on a design decision. The design decision whether to install mechanical cooling in an office building is used as an example. The final remarks project the findings of the research on the implications for current and future applications of building simulation in the support of design evolution.

2. APPROACHES TO UNCERTAINTY

In the building simulation research field, several studies have been dedicated to uncertainty in the output of simulations and building performance indicators derived from these outputs through post-processing. A good overview can be found in Clarke et al. (1990), Fürbringer (1994), Lomas (1993), Jensen (1994), Wijsman (1994), De Wit (1997). Adequate data on the various uncertainties that may contribute to the uncertainty in building performance is limited. Among these, uncertainties related to natural variability, which can sensibly be quantified on the basis of statistical analysis such as spread in e.g. material properties and building dimensions, are relatively well covered. Modeling uncertainties, though, and other uncertainties that cannot be comprehensively derived from observed relative frequencies, have received only limited attention, and usually only on an ad-hoc basis. Although several of the studies have focused on a comparison of techniques for model sensitivity analysis and propagation of uncertainty these techniques have hardly pervaded the mainstream tools for building simulation. All analyses restrict their focus to a given model structure, often suggested by a particular simulation tool. The issue how explicit information about uncertainty can be used to selectively simplify or refine (part of) the model has been studied by Fürbringer (1994) for ventilation models, but has not been addressed for thermal building models. Virtually no concern is given to the question how quantitative uncertainty can be used to better inform a design decision.

3. PERFORMANCE ASSESSMENT

All quantitative results that will be presented relate to a particular case study: a top floor corner space in a naturally ventilated four-story office building in the Netherlands. The case is a fully documented real office building in an urban setting. A full description can be found in (de Wit, 2001).

In this paper all uncertainty analysis will be limited to thermal comfort performance. Moreover, a specific indicator was chosen for that purpose, i.e. the TO. This indicator is commonly used in The Netherlands to rate buildings with respect to indoor climate. It reflects the number of hours per year that more than 10% of the occupants are dissatisfied with the climatic conditions in the building. Simulation is the most used technique to quantify the performance indicator. First, the indoor climate is simulated dynamically with a thermal building model. This model is developed on the basis of the design specifications of the building. The inputs to the model, collectively referred to as the scenario, specify the ‘external’ conditions as a function of time. These conditions include among other things a time series of the outdoor climatic conditions, heat gains from people, lighting and equipment in the building and the control of solar shadings and windows. Subsequently, the building performance is assessed and in our case study quantified with the TO performance indicator.

A variety of methods and tools exist for performing the building simulation. In this study a ‘consensus approach’ based on approaches by Clarke (1985), Augenbroe (1986), and reflected in many mainstream tools (DOE website) has been chosen. A recent trend analysis of building simulation techniques can be found in (Augenbroe, 2000). The consensus approach is based on a nodal space discretization (e.f. based on the finite element or finite difference technique) of all physical processes in the building. The spatial nodes contain the discrete values of the state variables. The modeling technique leads to a space discretized system of ode’s in the state variables, which are subsequently solved by numerical time integration. The actual simulations in the case study have been executed with two thermal building modeling tools, ESP-r (ESRU, 1995a) and BFEP (Augenbroe, 1986).

A crucial part of the proper execution of a building simulation is the judicious choice and quantification of model parameters. It has been reported earlier (de Wit, 1997) that the following heat flows deserve the most attention from an uncertainty standpoint: ventilation heat flows, internal convective heat transfer, distribution of incoming solar heat loads, loads from internal heat sources, radiant heat exchange between internal wall surfaces and external convective heat transfer. These provide a sample of the physical phenomena that to some extent are inherently impossible to describe in an exact manner or predict deterministically, and thus provide sources of uncertainty in the simulation. The next section will assess these uncertainties and perform a crude analysis.

4. CRUDE UNCERTAINTY ANALYSIS

A first step in a crude uncertainty analysis the assessment of plausible ranges for the model parameters, globally expressing the uncertainty in their values. Parameter uncertainty arising from two sources has been considered in this study, viz. specification uncertainty and modeling uncertainty. The specification uncertainty relates to a lack of information on the exact properties of the building. In the case at hand, this mainly concerns the building geometry and the properties of the various materials and (prefabricated) components. Modeling uncertainty arises from simplifications and assumptions that have been introduced in the development of the model. As a result, the building model contains several (semi-) empirical parameters, for which a range of values can be found in the literature. The first phase of the research has been reported in (De Wit, 1997a): total of 89 independent parameters were identified and subjected to a crude uncertainty analysis to assess their relative importance on the uncertainty in the resulting thermal comfort indicator. The building performance indicator was calculated by propagating the parameter uncertainties through the model. For this propagation, a Monte Carlo simulation technique was used, i.e. Latin Hypercube Sampling, based on the algorithm from UNCSAM (Janssen et al., 1992). For lack of explicit information on the parameter distributions, normal distributions were assumed for all parameters from which samples were drawn. The established parameter ranges were interpreted as central 95% confidence intervals. Where necessary, the normal distributions were truncated to avoid physically infeasible values.

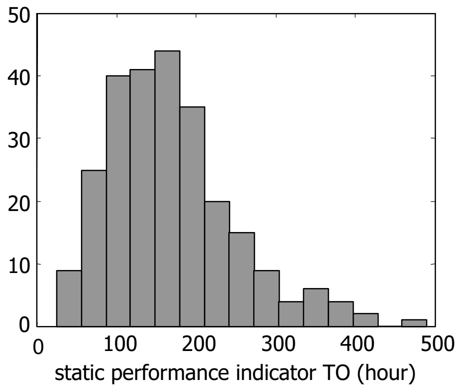

Figure 1 Histogram of the thermal comfort performance indicator, obtained from the propagation of the Latin Hypercube sample of size 250. A common target value for TO is 100 hours.

Figure 1 shows the observed histogram for the thermal comfort performance indicator (TO). The variability in the indicator is significant. The coefficient of variation, i.e. the standard deviation divided by the mean value, is about 0.5.A sensitivity analysis was performed to find the limited set of parameters, which accounts for most of the uncertainty in the model output. The analysis started with a screening technique based on the factorial sampling technique as proposed by Morris (1991). In an earlier analysis (De Wit, 1997b) this technique was found to be suitable for application with building models. It is economical for models with a large number of parameters, it does not depend on any assumptions about the relation between parameters and model output (such as linearity) and the results are easily interpreted in a lucid, graphical way. An elementary effect of a parameter is the change in the model output as a result of a change Δ in that parameter, while all other parameters are kept at a fixed value. By choosing the variation Δ for each parameter as a fixed fraction of its central 95% confidence interval, the elementary effects become a measure of parameter importance. If the model is non-linear in the parameters or if the parameters interact, the value of the elementary effect of a parameter may vary with the point in the parameter space where it is calculated. By calculating the elementary effect of a parameter at a number of randomly selected points in the parameter space, a sample of elementary effects is obtained. A large mean value or a large standard deviation of this sample indicates importance of the corresponding parameter. For each parameter 5 independent samples (r = 5) of the elementary effects on the comfort performance indicator TO were assessed in 450 simulation runs. The mean values of TO over these runs was 170 hours.

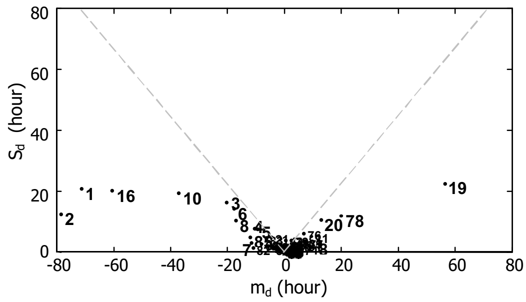

Figure 2 Sample mean m_d and standard deviation S_d of the elementary effects on the static comfort performance indicator TO obtained in the parameter screening

The figure shows for each parameter the sample mean m_d and the standard deviation S_d of the observed elementary effects on the performance TO. The numbers in the plot are the parameter indices (see Table 1). The dotted lines constituting the wedge are described by $m_d = \pm 2\ S_d/\sqrt{r}$. Points above this wedge indicate significant non-linear effects or parameter interactions.

Table 1 Parameters, which emerge from the parameter screening as most important. The ranking is in decreasing order of importance.

index	Description
2	wind pressure difference coefficients
1	wind reduction factor
16	temperature stratification
19	local outdoor temperature
10	external heat transfer coefficients
3,4,5,6	discharge coefficients of windows and vents
8	internal heat transfer coefficients in space under study
11	albedo
78	solar transmission of windows
20	solar transmission of sunblinds

Table 1 shows the 13 most important parameters found in the screening process in decreasing order of importance. Three immediate conclusions can be drawn. First, the set of top 5 parameters in Table 1, i.e. the wind pressure difference coefficients, the wind reduction factor, temperature stratification, local outdoor temperature and the model for the external heat transfer coefficients are the parameters, which account for the majority of the uncertainty in the model output. Secondly, the variability in the comfort performance, observed in the Monte Carlo propagation exercise is significant. This is expressed by the coefficient of variation of 0.5 and the histogram in Figure 1. In current practice the simulated value of the performance indicator is commonly compared with a maximum value between 100 - 200 hours to evaluate if the design is satisfactory or not under the selected scenario. Indeed, deterministic simulation results may depict the design as highly satisfactory or as quite the contrary by just changing the values of the model parameters over plausible ranges. It should be kept in mind though that the observed spread in the comfort performance values is based on crudely assessed 95% confidence intervals for the model parameters. An improved quantification of the uncertainty in the building performance could be obtained via a more thorough assessment of the parameter uncertainties. Clearly, those parameters, which have been ranked as the most important ones, deserve primary focus. The research has therefore focused on a more accurate assessment of uncertainties in those model parameters that were identified as most important, i.e. wind pressure difference coefficients, air temperature distribution and internal heat transfer coefficients. Because of space limitations only a short summary of the approach is given of in the next section, applied to the most important set of parameters, i.e. the wind pressure coefficients. The full treatment can be found in (de Wit, 2001).

5. UNCERTAINTY IN WIND PRESSURE

The simulation of the natural ventilation flows in buildings requires accurate knowledge of the wind pressure distribution over the building envelope. In the design of low-rise buildings, wind tunnel experiments are scarcely employed to measure these wind pressures. Instead, techniques are used, which predominantly rely on inter- or extrapolation of generic knowledge and data, e.g. wind pressure coefficients, measured in prior wind tunnel and full-scale experiments. Due to the complexity of the underlying physics, this is a process, which may introduce considerable uncertainty. None of the existing techniques, however, accounts for this uncertainty. The previous section showed that the effect of the uncertainty in wind pressure coefficients on the output of a building simulation model was large compared to the effect of other uncertainties. One of the aims of the overall study was therefore to evaluate the uncertainty in wind pressure coefficients in a more rigorous way.

To quantify this uncertainty, structured elicitation of expert judgment was used. A method to acquire and process the experts' assessments was selected, which has a solid methodological and mathematical foundation. It has been developed in the framework of the joint CEC/USNRC Consequence Code Uncertainty Analysis (Cooke and Goossens, 2000). In an expert judgment study, uncertainty in a variable is considered as an observable quantity. Measurement of this quantity is carried out through the elicitation of experts, viz. people with expertise in the field and context to which the variable belongs. These experts are best suited to filter and synthesize the body of existing knowledge and to appreciate the effects of incomplete or even contradictory experimental data.

The uncertain variables are presented to the experts as outcomes of (hypothetical) experiments, preferably of a type the experts are familiar with. They are asked to give their assessments for the variables in terms of subjective probability distributions, expressing their uncertainty with respect to the outcome of the experiment. Combination of the experts' assessments aims to obtain a joint probability distribution over the variables for a (hypothetical) decision-maker (DM), who could use the result in his/her decision problem. This resulting distribution, which is referred to as the DM, can be interpreted as a 'snapshot' of the state-of-the-knowledge, expressing both what is known and what is not known. Cooke and Goossens (2000) present a procedure for structured elicitation and processing of expert judgment, which ensures accountability, traceability and empirical calibration among other things.

This procedure was closely followed involving six experts, renowned for their expertise in the field of wind pressure measurements on low-rise buildings. De Wit (2001) reports on the successful expert judgment study to quantify the uncertainty in wind pressure difference coefficients for the case study building. The observed uncertainty proved to be large, both compared to the median values of the coefficients, and compared to the (estimated) uncertainty in wind tunnel results. This suggests that point estimates on the basis of existing data do not give useful information. Instead, probability distributions for the coefficients as obtained from an expert judgment study, might be valuable for certain applications. In the form it was implemented in this study, elicitation and processing of expert judgments is much more expensive than a wind tunnel experiment. Further study is required to investigate to which extent the costs (and possibly the uncertainties) would be reduced if experts would become more familiar with and skilled in the assessment of subjective probabilities.

6. PROPAGATION AND IMPLICATIONS OF UNCERTAINTY

The uncertainties that have been identified, augmented by the more refined outcomes of the expert judgment exercises, are propagated through the model to assess the resulting uncertainty in the building performance aspect of interest.

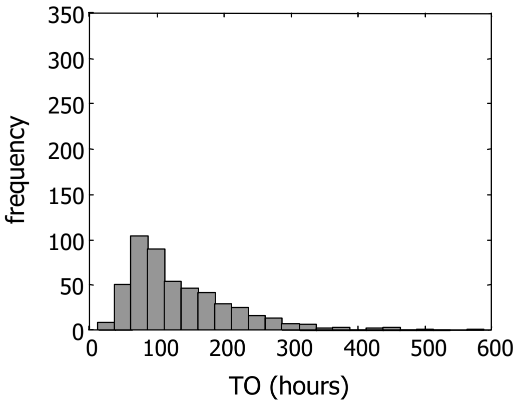

Figure 3 Frequency distributions of the comfort performance indicator TO on the basis of 500 samples. The uncertainty in all parameters is propagated. The left figure shows a histogram of the propagation results, whereas the right figure shows the cumulative relative frequency.

Figure 3 shows the results of the propagation of the uncertainty in all parameters. The figures are based on 500 random samples and a fixed scenario (specifying weather data and occupant behavior).

The results in the figure once more confirm that the uncertainty in the indicators for thermal comfort performance is quite pronounced. Compared to the results from the initial crude analysis (Section 4), the uncertainty is even somewhat larger. This finds expression in an increase of the coefficient of variation (standard deviation divided by the sample mean) from 0.5 to 0.6. The implications of this uncertainty are the subject of the next section.An evaluation of this uncertainty on its own merits may give an intuitive idea of its significance and the relevance to account for it in design decisions. The only way, however, to fully appreciate these issues is by evaluation of the impact of uncertainty information on, or rather its contribution to a design decision analysis.

7. DESIGN DECISIONS UNDER UNCERTAINTY

To ascertain the relevance of uncertainty information, imagine a decision-maker, who is faced with the choice whether or not to integrate a cooling system in the design of the building case. In the particular context, he prefers to implement the cooling-system if the TO-performance value of the building (without cooling) will exceed, say, 150 hours. To assess the performance, he requests a performance study. The building physics consultant performing the study uses a mainstream simulation approach, which (we hypothesize) happens to turn out a value for TO close to the most likely value according to Figure 3, i.e. 100 hours. This value is well below the threshold value of 150 hours and the decision-maker comfortably decides not to implement the cooling system. Suppose now that the consultant had not just provided a point estimate, but the full information in Figure 3 Then the decision-maker should have concluded that the performance is not at all *well below* the threshold of 150 hours. In fact, the probability of getting a building with TO in excess of 150 hours is about 1 in 3. In other words, his perception of the decision problem would have been quite different in the light of the extra information. This in itself is a clear indication that the uncertainty information is relevant for the decision analysis. Hence, the advice should convey this uncertainty in some form.

However, it may not be clear to the decision-maker how to decide in the presence of this extra information. It is no longer sufficient to simply compare the outcome of the performance assessment with a threshold value. To use the information constructively in his decision analysis, the decision maker needs to weigh his preferences over the possible outcomes (performance values) against the probability of their occurrence. This requires a more sophisticated approach.

Here, an approach is illustrated, which is based on Bayesian decision theory. Bayesian decision theory is a normative theory; of which a comprehensive introduction and bibliography can be found in e.g. French (1993). It describes how a decision-maker *should* decide if he wishes to be consistent with certain axioms encoding rationalism. It is not a prescriptive tool, but rather an instrument to analyze and model the decision problem. The theory embeds rationality in a set of axioms, ensuring consistency. We will assume that the decision-makers considered here in principle wish their choice behavior to display the rationality embodied in these axioms. If not, a decision analysis on Bayesian grounds is not useful: it will not bring more understanding. Moreover, we assume that decisions are made by a single decision-maker. Choice behavior by groups with members of multiform beliefs and or preferences can not be rational in a sense similar to that embedded in the axioms mentioned before.

Suppose a decision-maker is concerned with the quality of the working environment in the office building under design. He may consider several alternative *actions*: leave the design as it is, integrate a cooling system in the design, reduce the glass-area in the façade, improve the lighting system, etc. We shall not dwell on the process in which such a list of alternative actions is generated, we just assume that it exists. Parallel studies are looking to derive process scenarios that make these design analysis interactions explicit (de Wilde et. al., this proceedings).

In this stage of the decision analysis, an assessment of the consequences of each action under consideration is carried out. These consequences are expressed as performance levels. It is important to note, though, that our earlier choice to represent uncertainty in terms of subjective probability has been based on the fact that this representation is one of the cornerstones of Bayesian decision theory.

Modeling of preferences

In complex decision problems involving multiple attributes with uncertainty in their values, Bayesian decision theory offers an approach to rank the various actions in order of preference. The crux of this theory is that if a decision maker adopts the rationality encoded in its axioms, it can be proven that the preferences of the decision maker can be numerically represented in terms of a function over the attribute levels, the *utility* function. In a case that each action leads to a set of attribute levels without uncertainty, the actions can be associated with a single value of the utility function, and the action with the highest utility is preferred. Moreover, if the attribute levels resulting from the actions are uncertain, an action with higher *expected* utility is preferred over one with a lower expected utility. Hence, the *optimal* action is the one with the highest expected utility. The practical importance of the utility function as a quantitative model for the decision-maker's preference is that it can be assessed by observing the decision-maker's choice behavior in a number of simple reference decision problems. After this assessment, he can use the function to rank the actions in the actual decision problem in the order of expected utility. He may directly use this ranking as the basis for his decision or explore the problem further e.g. by doing a sensitivity analysis for assumptions made in the elicitation of either uncertainty or utility, or by a comparison of the expected utility ranking with an intuitive ranking he had made on beforehand. Moreover, a systematic assessment of the utility functions helps the decision maker to clarify and straighten out his own preferences, including the elimination of possible inconsistencies.

In our research the following case was introduced as a demonstration of the technique. It deals with the situation that only two actions are of concern to the decision-maker, i.e. he either leaves the design as it is or he integrates a mechanical cooling system in the design. The two objectives X and Y that are considered are: (X) minimizing investment costs and (Y) maximizing occupant satisfaction (measured by the TO) through an investment (cost: 400 10^3 monetary units) in mechanical cooling.

A first step in the actual elicitation of the utility function is the assessment of the (in)dependence structure of this function. The dependence structure indicates in which way the decision-maker's preferences on one attribute depend on the levels of the other attributes. Here we will assume that the decision-maker holds the attributes *additively independent*, which implies that his utility function can be written as:

$$U(x,y) = b_2 U_X(x) + b_1 U_Y(y) + b_0 \tag{1}$$

U_X and U_Y are called *marginal* utilities over X and Y. French (1993) briefly addresses the elicitation of (in)dependency structures and gives references. We will not go into that subject here: less strong assumptions about independence lead to similar lines of reasoning as we will follow here although more elaborate. Elicitation of the marginal utility functions U_X and U_Y in a number of simple thought experiments and substitution into (1) could result in the decision maker's utility function (details are given in De Wit (2001)):

$$U(x,y) = -8.3\,10^{-4}x - 2.2\,10^{-3}y + 1 \tag{2}$$

His expected utility is then:

$$E\{U(x,y)\} = -8.3\,10^{-4}x - 2.2\,10^{-3}E\{y\} + 1 \tag{3}$$

We used E(x) = x here, as the investment cost x is considered to be known without uncertainty. As a result of the linearity of the utility function of this specific decision-maker, we need only limited information on the probability distribution over y, i.e. only the expected value, to calculate the decision-maker's expected utility. We can now calculate the expected utilities for both actions a_1 and a_2:

Table 2 Expected utilities for the example decision maker

Action	Expected utility
a_1 (zero investment)	0.70
a_2 (maximize comfort)	0.67

Note that E(y) is the mean value of TO calculated from Figure 3 (=137). These results suggest that action 1 is the most preferred action of this decision-maker, barring the result of any further analysis the decision-maker might consider.

It is interesting to investigate the result of the analysis for another (imaginary) decision-maker. We assume for the sake of the argument that he differs from decision maker 1 only in his marginal utility for attribute *Y* (TO-indicator). Unlike his colleague, he prefers action 1. His line of reasoning might be that buildings with a value of the TO-indicator of 100 hours or less are reputedly good buildings with respect to thermal comfort and he is not willing to take much risk that he would end up with a building with TO = 300 hours. This decision-maker is *risk averse*. Further elicitation of his marginal utilities might yield the function shown in Figure 4.

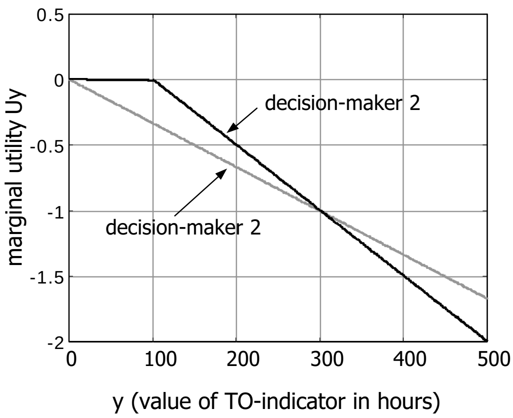

Figure 4 Marginal utility function of the two decision-makers over the level of attribute Y (value of TO – indicator in hours).

Following the same approach as for the first decision maker we arrive at the expected utilities:

Table 3 Expected utilities for decision maker 2

Action	Expected utility
a_1 (zero investment)	0.47
a_2 (maximize comfort)	0.50

Hence this decision-maker would prefer action 2, whereas his colleague tends to prefer action 1. In itself it is not surprising that two decision-makers with different preferences make different choices in the same situation. However, the two decision-makers in this example would have preferred the same decision in the absence of uncertainty. It is solely as a result of the introduction of uncertainty into the problem that they tend towards different choices.

8. FINAL REMARKS

Evaluation of thermal building performance at a time that the building is still under design, implicates uncertainty. In current design practice, uncertainties in performance assessments are not explicitly quantified. It has been argued that quantitative appraisal of this uncertainty can contribute to more rational design decisions. Moreover, it gives guidance in the development and selection of methods to assess building performance. It has been acknowledged that many of the uncertainties cannot be estimated by straightforward statistical analysis of available data. This raises the question by which method these uncertainties could be assessed. Would such a method be applicable in design practice? Although earlier efforts have given intuitive arguments to emphasize the relevance of quantitative uncertainty information for design decisions, no attempts have been made to show *how* a decision maker could use this information to improve his decision. In the research reported here, an approach to uncertainty analysis is presented for a specific performance aspect. The emphasis was on quantifying modeling uncertainties. The uncertainty analysis revealed various model parameters for which the uncertainty had to be quantified on an ad-hoc basis. For these parameters insufficient data could be found, the available data were conflicting, or their validity and relevance could not be established. The uncertainties in two sets of these parameters were further analyzed. These parameter sets were identified as significantly contributing to the uncertainty in building performance. Expert judgment was used to quantify uncertainty that cannot be estimated on a statistical basis. The expert judgment study proved to be successful and a statistical comparison showed that the experts' combined assessments are well-calibrated, i.e. they are suitable measures of the uncertainty in predictions of the wind pressure difference coefficients. The uncertainties in all model parameters, including those obtained from the expert judgment studies, were propagated to find the resulting uncertainty in the thermal comfort performance. A coefficient of variation of 0.6 was obtained, a moderate increase compared to the value of 0.5, which was obtained in the initial crude analysis. The integration of quantitative uncertainty assessment in a design decision analysis was illustrated in the context of Bayesian decision theory. It was illustrated how uncertainty in building performance assessments can be used in, and is essential to rational design decisions.

Recommendations

The bottom line of this work is that uncertainty in building performance should be taken into account. Hence, if 'crude' uncertainty analyses, in which the building physics consultant assesses all uncertainties, would become more common in building design practice, this could be a significant step forward. In this approach, a consultant may directly profit from the material that was collected on building model parameters in this study, both from the literature and the two expert judgment studies. A necessary requirement for the adoption of uncertainty analysis in practice would be the enhancement of the functionality of most building simulation tools to facilitate uncertainty and sensitivity analyses. A consultant's uncertainty assessments could gradually improve if he would occasionally be scored in a similar way as the experts were scored in this study: by statistical comparison of his assessments with measured data. Hence it would be useful that libraries with suitable seed variables would be developed, e.g. by branch-organizations.

Finally, if in future research more expert judgment studies would be carried out on building model components, experts in the associated domains would become more involved in building simulation, and their domain expertise would become more readily available to the building simulation community. Moreover, the information about the uncertainties that would result could be used to review whether the level of refinement in the current mainstream modeling approach, which is implemented in most building simulation tools, is in accordance with the level of uncertainty.

REFERENCES

Augenbroe, G.L.M., Research-oriented tools for temperature calculations in buildings, *Proc. 2nd Int. Conf. on System Simulation in Buildings, Liege, 1986.*

Augenbroe, Godfried, (2000), The role of ICT tools in Building Performance Analysis. *IBPC 2000 Conference, Eindhoven, September 2000, pp 37-54.*

Clarke, J., Yaneske, P., Pinney, A., *The harmonisation of thermal properties of building materials,* Report CR59/90 of the Building Research Establishment, Watford, UK, 1990.

Clarke J A. 1985. *Energy simulation in building design*, Adam Hilger, Bristol and Boston.

Cooke, R.M., Goossens, L.H.J., *Procedures guide for structured expert judgment,* Report EUR 18820 EN prepared under contract FI4P-CT95-0006 for the European Commission, Directorate general for Research, 2000.

DOE, US Department of Energy Building Energy Software Tools Directory. URL:
http://www.eren.doe.gov/buildings/tools_directory/

ESRU, *ESP-r, A building energy simulation environment,* User Guide Version 8 Series, ESRU Manual U95/1, 1995a.

French, S., *Decision theory – an introduction to the mathematics of rationality*, Ellis Horwood, London, 1993.

Fürbringer, J.-M., *Sensibilité de modèles et de mesures en aéraulique du bâtiment à l'aide de plans d'expériences*, Ph. D. thesis nr. 1217. École Polytechnique Fédérale de Lausanne, Switzerland, 1994.

Janssen, P.H.M., Heuberger, P.S.C., Sanders, R., *UNCSAM 1.1: a Software Package for Sensitivity and Uncertainty Analysis; Manual*, Report 959101004 of the Rijksinstituut voor volksgezondheid en milieuhygiene (RIVM), Bilthoven, The Netherlands, 1992.

Jensen, S.∅. (ed.), *The PASSYS Project phase II Subgroup model Validation and Development,* Final report EUR 15115 EN for the Commission of the European Communities, DG XII, Brussels, 1994.

Lomas, K.J., *Applicability study 1 – Executive summary*, Report for the Energy Technology Support Unit, contract ETSU S 1213, School of the Built Environment, De Montfort University, Leicester, UK, 1993.

Morris, M.D., *Factorial sampling plans for preliminary computational experiments,* Technometrics v33 n2 pp161-174, 1991.

Wijsman, A.J.Th.M., Building Thermal Performance Programs: Influence of the Use of a PAM, BEP '94 Conference, York, UK, April 5-8 1994.

Wilde, P. de, G Augenbroe, M. van der Voorden, A Strategy to Provide Computational Support for the Selection of Energy Saving Components, *This proceedings*

De Wit, S.: *Uncertainty in predictions of thermal comfort in buildings*. Doctoral Dissertation, TU Delft, June 2001.

Wit, M.S. de, Influence of modeling uncertainties on the simulation of building thermal comfort performance, *Proc. Building Simulation '97, 5th International IBPSA Conference*, September 8-10, Prague, Czech Republic, 1997a.

Wit, M.S. de, *Identification of the important parameters in thermal building simulation models*, J. Statistical Computation and Simulation v57 n1-4 pp305-320, 1997b.