ASSESSING THE SIGNIFICANCE OF DESIGN CHANGES WHEN SIMULATING BUILDING PERFORMANCE INCLUDING THE AFFECTS OF UNCERTAIN INPUT DATA.

Iain A Macdonald
Energy Systems Research Group
University of Strathclyde
Glasgow, Scotland
iain@esru.strath.ac.uk
http://www.esru.strath.ac.uk

ABSTRACT

Computer simulation of buildings is currently used to predict their performance and the effect of design changes. The effect on predictions caused by uncertainties in the input data is rarely assessed. However, if it is quantified the performance of the simulated building can be described as a range of possibilities given the inherent uncertainty in the input data.

This paper takes the process further, assessing the effect of uncertainty for an initial model and a model incorporating a design change. It then describes how to use statistical tests to quantify the significance of the change in performance: i.e. has the design change produced a real difference to the buildings performance, or is the change in performance lost in the error band of the predictions.

In this paper the method of quantifying the overall effect of uncertainties on predictions and how to differentiate between a significant and insignificant change is described. This is then applied to two case studies to exemplify the importance of quantifying the effect of uncertainties.

INTRODUCTION

During the design process practitioners usually go through an iterative process to improve a building's performance as the design progresses. Data used for simulation work is often unknown or subject to a degree of error, and this could impact on the accuracy of the predictions made by the simulation tool.

When quantifying the effects of uncertainties, a confidence band can be generated for the resulting predictions. This is usually presented as a standard deviation of the performance metric being examined (heating energy use, peak temperatures, PPD *etc*). This information can then be used directly to quantify, for example, energy use at specific confidence levels.

The quantification of uncertainty in the design process is therefore necessary when applying simulation in practice to assess the risk in design decision making. Uncertainty effects all aspects of simulation: from algorithm choice to data input for a tool. This paper is focussed on the latter example.

At all design stages the input data to a simulation tool is subject to uncertainty. This is especially true at earlier design stages, where decisions made on building form have the largest effect on energy consumption [DETR 1994]. Therefore, it is desirable to be able to effectively employ simulation as early as possible to assist the design process. This has been achieved through the use of assumed standard databases and profiles [Morbitzer 2003]. However, these standard assumptions rarely match the building being analysed. A more effective approach is to embrace the uncertainty in the design and quantify its effect. By adopting this approach the simulation tool is modelling the building as closely as possible at all stages but has the ability to assess the effects and causes of variability in the predictions.

This paper shows how the decision making process can be assisted by quantifying the overall uncertainty in predictions. In doing so the difference between design variants can be fully quantified and the likelihood of correct design decisions being made is increased.

UNCERTAINTY ASSESSMENT

Several statistical uncertainty analysis techniques have been developed [Hamby 1994]. They can be categorised as structured and non-structured methods. Structured methods are derived from experimental techniques, whereby a series of experiments would be designed to analyse the outcome for predetermined models. Non-structured methods are stochastic in nature. In the former category, the most popular method for application to building thermal simulation is Differential Sensitivity Analysis (DSA); in the latter category Monte Carlo Analysis (MCA) has been used.

It should be noted that it is also possible with deterministic solution techniques to carry the uncertainty information through the calculation procedure [Macdonald 2003]. These techniques rely on altering the underlying arithmetical functions as all operations are carried out on ranges rather than individual numbers.

Statistical techniques

Both DSA and MCA have the advantage of being relatively easy to apply to existing software because the simulation is treated as a black box, and the only parameters which can be influenced are contained in the data model describing the problem. The basis of the methods is described in Lomas and Eppel (1992). However, the main problem with the use of structured techniques such as DSA is that they were devised for practical experiments with relatively few (typically less than a dozen) measured (and controllable) inputs. When applied to simulations where there are typically hundreds of input parameters the technique can become cumbersome and time consuming.

The DSA method "is the backbone of nearly all other sensitivity analysis techniques" [Hamby 1994] and requires a base case simulation in which input parameters are set with the best estimates of the parameters under consideration. Then the simulation is repeated with one input parameter changed from P to $P + \delta P$ and the effect on the output parameter(s) of interest noted. This is done for each parameter in turn, giving a total of $N + 1$ simulations to analyse the effects of N uncertain parameters. An underlying assumption of this analysis is that the effect of an uncertainty is linear over the perturbation. This assumption can be tested to a limited degree by carrying out further simulations with the parameter values set to $P - \delta P$. If the effect on output parameters is the same (but in opposite directions) then linearity is assumed. The DSA method is not optimised for the number of simulations required and does not identify any parameter interactions. However, it does inform the user which of the analysed parameters have most influence on the output parameter(s).

To measure the interactions between parameters factorial designs can be used. In these designs any number of parameters can be altered at one time (a structured design is created and followed so as the results can be decomposed after the simulations have been carried out). The number of simulations required for a full factorial analysis is 2^N and is only practical for a few parameters. However it is possible to only analyse a fraction of all the combinations by assuming that certain interactions will have a negligible effect. Fractional factorial designs for up to 12 parameters have been published (Box *et al* 1978). The main advantage of these methods is that the interactions between parameters can be quantified directly.

MCA is the most commonly used non-structured method. It relies on the central limit theorem to provide an overall assessment of the uncertainty in the predictions being made. The Monte Carlo technique generates an estimate of the overall uncertainty in the predictions due to all the uncertainties in the input parameters, regardless of interactions and quantity of parameters. In operation, a probability distribution is firstly assigned to each input parameter under consideration. For all parameters, values from within their probability distribution are randomly selected and a simulation undertaken. Simulations are undertaken repeatedly with new values randomly selected. Given a large number of simulations, the uncertainty in the output parameter of interest will have a Gaussian distribution, irrespective of the input parameter probability distributions. It has been shown [Lomas and Eppel 1992] that the number of simulations required by this technique is 60-80, after which only marginal gains in accuracy are obtained. Figure 1 shows the 95% confidence bands in the calculated standard deviation (normalised by the standard deviation) as a function of the number of simulations. As can be seen there is initially (after only a few simulations) a lack of confidence in the calculated standard deviation, although this quickly improves with marginal improvements after 60-80 simulations. It should be noted that this result is true for any number of uncertain parameters, thus the Monte Carlo method is appropriate for calculating the overall uncertainty in predictions when there are many uncertain inputs.

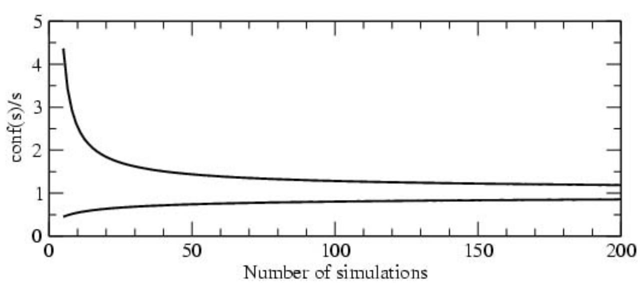

Figure 1: Confidence in Monte Carlo results.

The main difficulty in employing this method is in identifying the distributions that the input parameters are likely to have. In practice it is usual to assume that most parameters will have a Gaussian distribution although any distribution is possible. A major disadvantage is that the method does not distinguish individual parameter sensitivities.

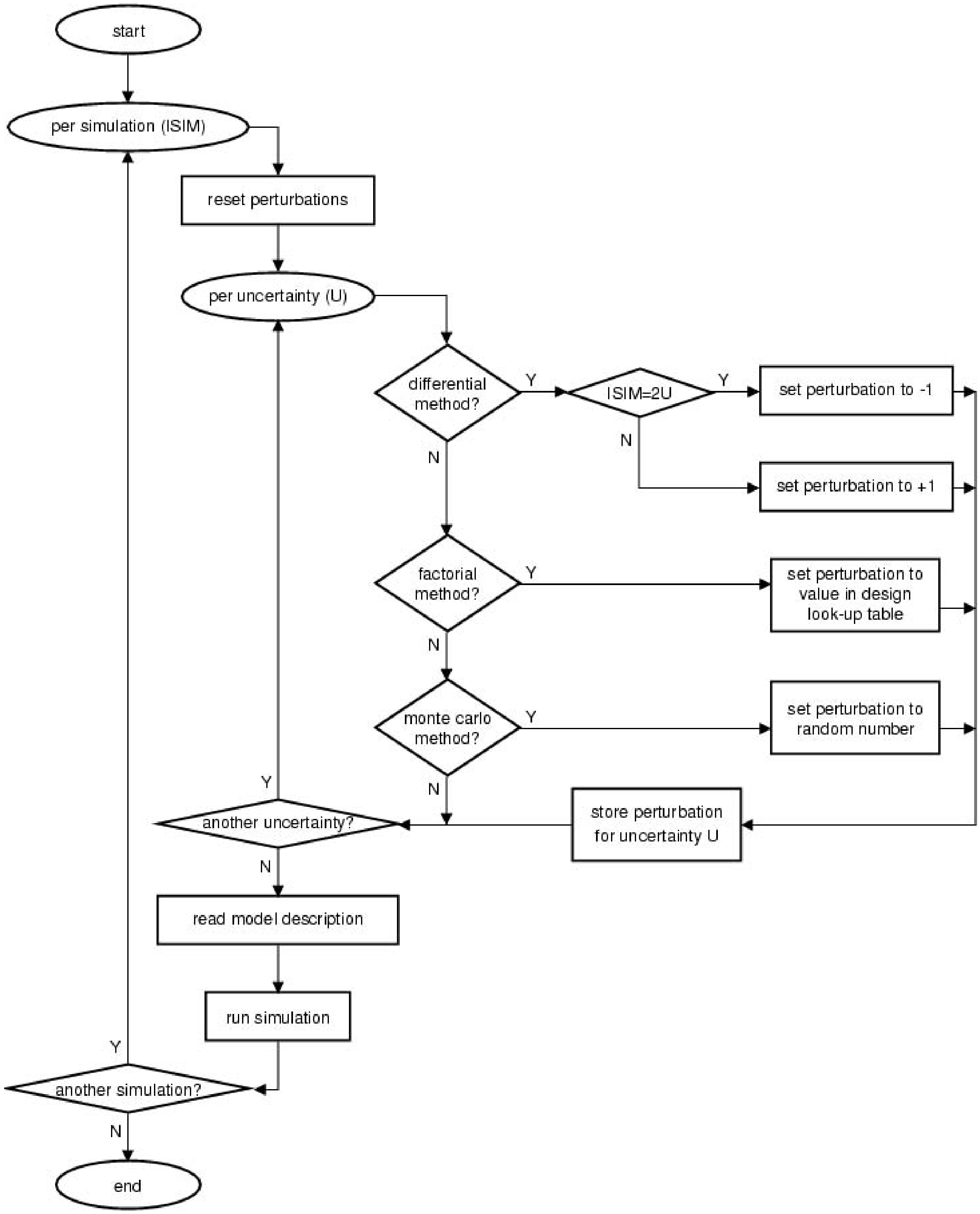

Figure 2: Simulating with uncertainties defined.

The ESP-r system has been equipped with these methods to quantify the effects of uncertainty [Macdonald and Strachan 2001]. Figure 2 shows the updated simulation process. As can be seen for each necessary simulation a set of perturbations are created, depending on the selected assessment method. The data model is then adjusted while the model files are being read into the simulation engine, with the simulation engine being unaltered by these methods and is effectively treated as a black box, *i.e.* they are external to the core equation sets. Statistical inferences are then used to quantify the effects of uncertainties.

Thus to undertake an analysis of the effects of uncertainty using these external methods requires multiple simulations of the deliberately perturbed data model. Furthermore, to calculate individual effects and the overall effect of uncertainty necessitates using different analysis methods: differential, factorial and Monte Carlo techniques.

To calculate the overall uncertainty in predictions the Monte Carlo technique is the most appropriate method to use. The average prediction and standard deviation can then be easily calculated. The results of such an analysis can then be used to assess the difference between two design options.

SIGNIFICANCE TESTING

The difference between two simulation results can be assessed in two ways [Reschenhofer 2001]:

1. the difference between the two results is assessed for practical importance, and

2. a formal rule, *significance testing*, may be employed.

The latter option is of interest where design options provide similar improvements in building performance and further quantification of the improvement is required. In fact it could be argued that a formal test should be used in all cases so that the significance of the change can be quantified. This would reduce the possibility of making the wrong design decision, which is possible with a single simulation approach, ignoring uncertainty.

Currently users of building simulation use the terms ‘significance’ and ‘insignificance’ informally when describing the difference that a design change makes to the building’s performance. With the ability to quantify the overall uncertainty in the output (*via* a Monte Carlo analysis), the significance of a design change can be formally quantified using a standard test [Gardiner and Gettinby 1998]. This statistical approach enables the practitioner to differentiate between an apparently significant difference and a truly significant one.

For a statistical test a hypothesis is required, for example $x_1 = x_2$. The statistical test is then performed to discover whether the hypothesis is true or false.

The hypothesis is referred to as the null hypothesis. This gives rise to a counter assumption or alternate hypothesis which is often easier to test. For example if the hypothesis is $x_1 = x_2$ then alternatives would be:

$$x_1 > x_2 \tag{1}$$

$$x_1 < x_2 \tag{2}$$

$$x_1 \neq x_2 \tag{3}$$

The statistical test requires a significance level. The significance level determines the probability of coming to the wrong conclusion. For example, if the significance level is 5% then one in twenty tests would be rejected even though it was true: this is equal to a 95% confidence level in the alternate hypothesis being true. Clearly, the lower the significance level the lower the risk of making the wrong decision.

Various statistical tests exist depending upon the information available and what is to be tested [Kreyszig 1993, Reschenhofer 2001]. In the case of comparing two means of normal distributions (as is the case with results of a Monte Carlo analysis) the following formula can be used:

$$t_0 = \sqrt{R}\frac{\mu_x - \mu_y}{\sqrt{s_x^2 + s_y^2}}, \tag{4}$$

where t_0 is the test statistic given that there were R simulations for each of the two Monte Carlo analyses (x and y), with μ the average result and s the standard deviation. The critical value for this test is read from a table of the *t*-distribution for R degrees of freedom at the required significance level, but the larger the value the more probably that the two results are not different.

Another test is as follows for a 95% confidence interval:

$$\{min, max\} = (\mu_x - \mu_y) + / - 1.96\sqrt{\frac{s_x^2}{R} + \frac{s_y^2}{R}}, \tag{5}$$

If zero is inside the interval then there is a 95% probability that the two means are not different (or a 5% probability that they are equal). For different confidence levels the factor 1.96 can be increased or decreased for more or less confidence in the result.

To illustrate the application of this theory a case study will be elaborated.

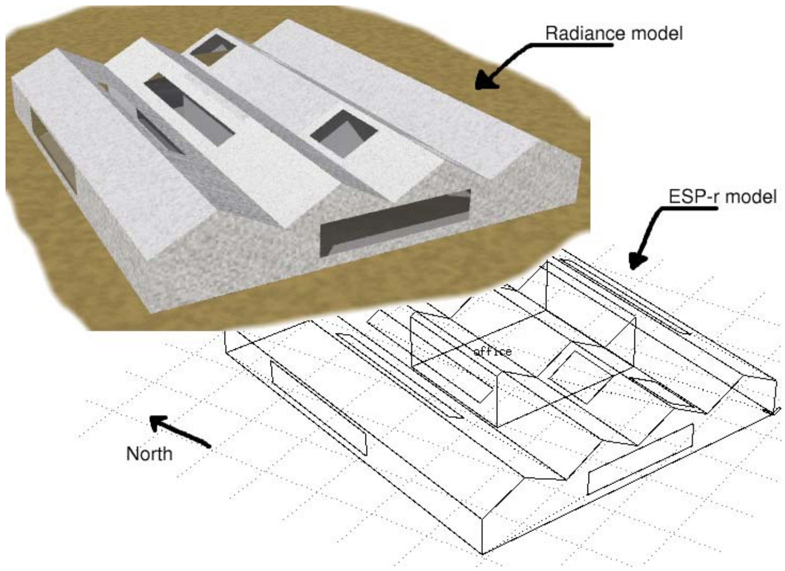

Figure 3: Model of top floor.

CASE STUDY

A 100 year old factory building in Scotland was converted into office space in 2000. The top floor of this building had ample opportunity for use of daylight although this had to be offset against possible overheating, due to solar and other gains.

The purpose of the analysis was to examine the level of space overheating and what measures could be applied to mitigate the overheating. For this analysis overheating was defined as a dry bulb temperature above 26°C.

Model

A model of the top floor of the building was created, as shown in figure 3. The glazed area represents 15% of the external surface area of the space. The construction of the building is typical of Scottish building stock of this age - solid stone external walls finished with a plaster lining on the inside. To comply with building regulations insulation was added to the inside faces of the exterior walls, with the finish being plaster board. The windows in the vertical walls and the roof are standard double glazing.

Key aspects of the model are now described.

Occupancy The top floor area was occupied from 8am until 6pm, by up to 50 adults. To account for people being absent/ out of the office the heat gain was defined on the basis of 45 occupants.

Lighting Provision is assumed to be $2.5W/m^2$ between 8am and 6pm. This figure includes an assumption for lighting control (automatic and user controlled task lighting).

Equipment An allowance was made for IT equipment and other miscellaneous heat sources of $8kW$ (50 computers, $160W$/computer) during occupied hours. Overnight and at weekends the gain was reduced to $3kW$ to represent the effect of equipment left on stand by.

Ventilation The office space was naturally ventilated at 4 air changes per hour. This rate was assumed to cover occupied hours only. The supplied air is not cooled, *i.e.* it will be at ambient temperature. Outside occupied hours an infiltration rate of 0.25 air changes per hour was assumed.

Uncertainties

The data used to create the model was subject to considerable uncertainty: construction materials are typically 100 years old, occupancy and space use is not well defined and the natural ventilation scheme will not deliver a constant fresh air supply. The following assumptions were made as to the extents of uncertainty and were applied to all design variants analysed as the design changes would not effect the sources of the uncertainty.

Material properties The thermophysical properties of the construction materials were assumed to have a standard deviation of 10% of the database values.

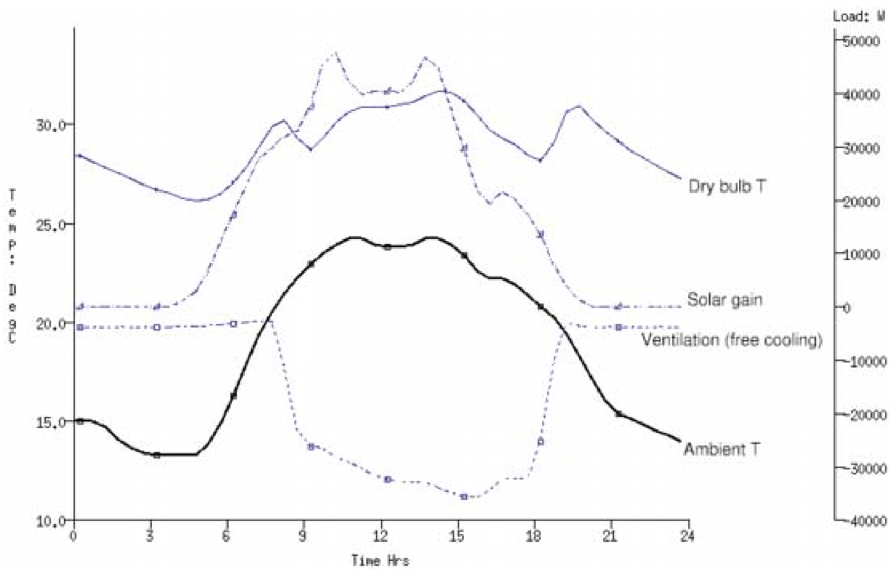

Figure 4: Typical building performance.

Occupancy Due to the variation in use of the space (occupants are often away from their desks) the uncertainty was defined as anywhere between 50% and 100%, although typically 90%.

Lighting In line with the assumptions regarding occupancy the uncertainty was defined as anywhere between 50% and 100%, although typically 90%.

Equipment Again the heat gains from equipment are subject to several sources of uncertainty: occupant behaviour (switching items on/ off), device characteristics (power saving modes, discrepancies between actual and name plate power consumption). Again due to the multiple sources of uncertainty the overall effect was assumed to be a 25% uncertainty of the defined gain.

Ventilation The natural ventilation system is subject to several sources of uncertainty: occupant behaviour and climate conditions being the main sources, but others include build quality. As such the uncertainty was defined as 25% of the specified air change rate.

Climate To account for possible changes in climate over the use of the building a 3°C ambient temperature and 15% solar radiation uncertainties were defined.

Simulations

Simulations were undertaken for a summer period and the number of hours over 26°C calculated.

Base case results

The initial, base case, simulation showed that overheating occurred for 48.5 occupied hours during the simulation period. Figure 4 shows results for a typical summer day. For this day the temperature in the space is about $30^{\circ}C$, approximately $6^{\circ}C$ above ambient temperature. The solar gain entering the space and the heat removed via natural ventilation are also shown. In both cases these are significant energy flows.

Design changes

After analysis of the base case results two design variants were tested:

1. due to the large solar gains the use of a reflective solar film to the roof glazing was proposed, and
2. as there was still a significant temperature difference between the internal and ambient air temperature increased ventilation to remove heat from the space was an alternative proposal.

Models were created for both cases.

Reference case 1

The solar film used reduced the solar transmittance by 90% and was applied to the roof glazing. The aim of this modification was to reduce the heat gain to the space without adversely affecting the luminous environment, although it was appreciated that there would be a reduction in daylight levels.

Table 1: Overheating hours from single simulation.

Case	Number of overheating hours
Base case	48.5
Reference 1	43.5
Reference 2	45.5

Reference case 2

The increase in ventilation was to be achieved by increasing window openable areas. The aim of this modification was to preserve the luminous environment in the space and to remove the excess heat through increased air flow.

Reference case results

Table 1 shows the number of overheating hours for all models simulated. As can be seen both of the reference cases improve the building's performance by reducing the overheating problem. The reference 1 case, solar film, has the greatest effect.

In a traditional design there would have been an easy choice to make here: the solar film reduced the overheating by the most number of hours, therefore it should be applied to the building.

Results including the effects of uncertainty

The simulations were undertaken again to measure the effect of uncertainty on the overheating hours. In this case overheating occurred for only 45.1 of occupied hours, showing that the initial base case simulation overestimated the overheating hours. This is not due to an inbuilt safety margin and the adverse result could easily have been generated.

The Monte Carlo analysis results for all cases are displayed in table 2 and graphically in figure 5. Comparing these with the results in table 1 it can be seen that the number of overheating hours were overestimated in all cases. It can also be seen that, due to the uncertainty in the predictions, there is an overlap in possible building performance between the base case and reference cases.

Now there is no obvious difference between the two reference cases: they both improve the building performance by about 7%. In this case a formal test can be employed to attempt to differentiate between the two results: to quantify the significance in performance.

Table 2: Mean overheating hours, with uncertainty.

Case	Number of overheating hours	Standard deviation
Base case	45.1	9.0
Reference 1	41.9	12.2
Reference 2	41.8	11.6

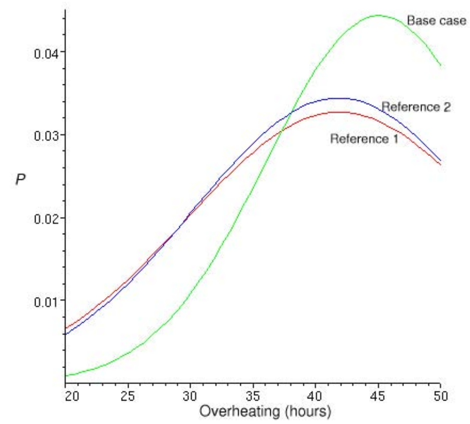

Figure 5: Probability distribution of overheating.

Significance quantification

Using equation 4 the t_0 statistic was calculated as 1.9 and 2.0 for the change from base case to reference 1 and base case to reference 2 respectively. This statistic is calculated based on the null hypothesis that there is no difference between the base case and reference results. Therefore, the larger the value of t_0 the greater the probability that the simulation results are different. This would indicate that reference 2 is a more significant design change.

Typically the significance in the result is calculated for a known confidence level, *e.g.* 95%. By using equation 5 this can be calculated. For reference 1 the result of this calculation is the range $\{-0.15, 6.51\}$, indicating that at this significance level there is no difference between the base case and reference case 1 results (as zero is in the calculated range). For reference 2 the range is $\{0.07, 6.51\}$, indicating that there is a difference between the base case and reference case 2 results.

Discussion

This case study has shown how by quantifying the uncertainty in simulation predictions further statistical tests can be applied to differentiate between the simulated building performance and potentially change design decisions.

Initial simulations, made with best estimates, showed that overheating was a problem in the modelled space. Two proposals were made to address the problem, with the solar control film (reference 1) being a more effective solution.

The second set of simulations, with uncertainty defined, showed that:

- All of the initial simulations had predicted more than the average number of overheating hours,
- Both of the reference models reduced the overheating by the same amount.

The change in performance for both reference cases was analysed further, to quantify the difference using statistical testing. Using the null hypothesis that there was no change and a significance level of 5% (*i.e.* a 1 in 20 chance that the wrong conclusion will be made) showed that only the second option (increased ventilation) resulted in a significant reduction in overheating hours. The uncertainty in the results for the solar control film (reference 1) was large enough that the two results (base case and reference 1) could not be separated, *i.e.* the null hypothesis was true.

This is of interest in this building as the design team used the first option, the solar control film on the glazing. There were subsequently complaints from the occupants about the space overheating, despite the building being cooler than predicted. Further measures have been applied to reduce the likelihood of further overheating.

CONCLUSIONS

Uncertainty affects all aspects of building simulation and its effects must be assessed. This paper has described how uncertainty can be assessed and has then gone further to show how this assessment can inform the decision making process. The case study demonstrated that:

- the initial single simulation analysis produced different results compared with the analysis including the effects of uncertainties, and
- despite the two design changes producing similar performance benefits (when the effects of uncertainty are included) only one of these was significantly different from the base case performance.

Furthermore, the design change recommended from the initial solution was different from that selected from the analysis including uncertainties.

Overall, it can be concluded that uncertainty assessment should be undertaken as a matter of course during simulation studies as it not only quantified the average prediction and the variability therein, but the results can then be used to quantify the significance of design changes.

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