Journal of Building Performance Simulation
Vol. 5, No. 3, May 2012, 171–184

Uncertainty and sensitivity decomposition of building energy models

Bryan Eisenhower[a]*, Zheng O'Neill[b], Vladimir A. Fonoberov[c] and Igor Mezić[a,d]

[a]*Center for Energy Efficient Design, University of California, Santa Barbara, CA, USA;* [b]*United Technologies Research Center, Hartford, CT, USA;* [c]*Aimdyn, Inc., Santa Barbara, CA, USA;* [d]*Department of Mechanical and Environmental Engineering, University of California, Santa Barbara, CA, USA*

(*Received 10 August 2010; final version received 17 December 2010*)

As building energy modelling becomes more sophisticated, the amount of user input and the number of parameters used to define the models continue to grow. There are numerous sources of uncertainty in these parameters, especially when the modelling process is being performed before construction and commissioning. Past efforts to perform sensitivity and uncertainty analysis have focused on tens of parameters, while in this work, we increase the size of analysis by two orders of magnitude (by studying the influence of about 1000 parameters). We extend traditional sensitivity analysis in order to decompose the pathway as uncertainty flows through the dynamics, which identifies which internal or intermediate processes transmit the most uncertainty to the final output. We present these results as a method that is applicable to many different modelling tools, and demonstrate its applicability on an example EnergyPlus model.

Keywords: uncertainty analysis; sensitivity analysis; decomposition methods; EnergyPlus

1. Introduction

For the past 30–40 years, tools for energy simulation have evolved into a suite of detailed physical relations, both differential and algebraic, that describe the way various disturbances (from weather, humans, control systems, etc.) influence the thermodynamic behaviour of the building itself. Within these equations, thousands of parameters exist, which are often assigned by best-educated guesses. Due to this, even though each component of the tool may be empirically validated, its simulation output of a building design may be far from the performance of the actual building. It is ironic that the time when the building simulation is most useful (e.g. the initial design phase), the parameters of the simulation may be the least certain, which limits the confidence of the simulation results.

To overcome these issues, uncertainty analysis (UA) is used to quantify how uncertainties in these parameters influence the conclusions that are made from the model and quantify confidence intervals of the output. In the case of building simulation, UA is a method to resolve the dependability of model predictions due to uncertain user input (Moon 2005). To do this, a distribution is chosen for a number of inputs and numerous models are generated or realized (model realizations) and simulated to determine statistics of important outputs.

Depending on the range of uncertainty in each parameter, the number of parameters, and the required accuracy, numerous simulations are needed to determine the statistics. Whether 10, 100 or 1000 samples are desired within the range, it is important to decide exactly where to choose these samples (an equidistant grid is often not the most efficient approach). Another consideration is whether or not all parameters change individually (one at a time), or all at once (which happens to be more efficient computationally). One of the ways the effectiveness of these samples is determined is to observe how statistics of the output vary or converge as the number of samples increases. We present this convergence information for the output variables that we analyse by displaying these trends as a function of the number of samples.

When choosing samples, there is a balance between computation time and accuracy, and there have been many methods developed to create samples as efficiently as possible. The Monte Carlo (MC) method is an approach which randomly samples the parameter space, but often leads to *clumps* of samples in certain regions. The Latin hypercube sampling (LHS) approach initially partitions the space into equally probable areas prior to taking random samples to avoid this problem. Both of these approaches obtain convergence rates that are no better than $1/\sqrt{N}$, where N is the number of samples. This type of parameter

*Corresponding author. Email: bryane@engr.ucsb.edu

ISSN 1940-1493 print/ISSN 1940-1507 online

http://dx.doi.org/10.1080/19401493.2010.549964
http://www.tandfonline.com

sampling has been performed in building simulation in (Macdonald 2009) where the performance of numerous MC sampling approaches were compared. In this study, it was concluded by studying a model with two uncertain parameters, only 100 samples are typically needed to obtain convergence. We find that in a model with approximately 1000 uncertain parameters, after 100 samples we are within 15% of the statistics that would be calculated after 5000 samples (this convergence is discussed further below). The accuracy at 100 samples may be sufficient for some conceptual studies while more samples may be needed for greater accuracy. LHS was also performed by Struck *et al.* (2009) to compare the performance of conceptual and detailed building models during uncertainty and sensitivity analysis (SA) (discussed further below).

A more recent approach is to use a quasi-random sampling method (Saltelli *et al.* 2000), which obtains a faster convergence rate bound of $1/N$. This faster convergence rate means that fewer simulations are needed to obtain the same accuracy that other methods offer, and because of this, more uncertain parameters can be handled in the same amount of time. In our work, we use quasi-random sampling, and we are unaware of any previous use of quasi-random sampling in the building simulation community.

The choice of parameter range and distribution type both influence the sampled behaviour of the building model which is to be studied. There have been many studies to determine the type of distribution (normal, uniform, log-uniform, etc.) for typical parameter values in building models (see (Dominguez-Munoz *et al.* 2009) where statistical properties of the thermal conductivity of different materials were empirically identified, or (Cóstola *et al.* 2010) where uncertainty in airflow rates were calculated, or the comprehensive report (Clarke *et al.* 1990), or thesis (Macdonald 2002) for other information). When the exact distribution is not known, a large range is chosen and a uniform distribution is typically used.

In this study, since we are varying over 1000 parameters, we have not yet paired each of these parameters with distribution types from literature (because it would be too time consuming). We apply a uniform distribution to all nonzero parameters, and for those with zero nominal value, we apply an exponential distribution so that the samples are centered closer to the nominal value of zero. The most important parameters of the particular EnergyPlus building model are then identified and this information will allow us to go back and associate physically-based distributions for these important parameters in future work (if they are different from the assumed type). In Struck *et al.* (2009), there is a discussion between the different aspects of UA and SA in the detailed vs. conceptual design phase. It was found that during the conceptual phase of building design, detailed tools are best suited for UA and SA. In this article, we are using a detailed design tool that has only rudimentary parameter information. In a sense, a portion of our approach is conceptual (parameters), and a portion is detailed (modelling code and equations). Once one round of analysis is performed, further detail could be gathered for the parameters that have been identified to be more important for further analysis.

At times, UA is the sole statistical study in building system modelling (Soratana and Marriott 2010), while in most cases, SA is also performed in conjunction with UA. SA is a method which identifies how uncertainty in an output can be allocated to uncertainty in the input parameters of a process or model. There are three basic approaches to SA which differ in their complexity and accuracy; screening methods, local sensitivity methods and global methods. Parameter screening is a coarse one parameter at a time (OAT) approach that investigates extreme values of the parameters and quickly identifies how they influence the output by ranking them in order of importance. This method is good for studying models with a few uncertain parameters and have been used in building systems studies including (Rahni *et al.* 1997) where 23 parameters were selected from an original set of 390 using 136 simulations, and in Brohus *et al.* (2009b) which used pre-screening techniques to reduce the number of uncertain parameters in a model from 13 to 7 prior to detailed SA. Similarly, in Brohus *et al.* (2009a), a screening method was used to reduce a parameter set from 57 down to 10, upon which an Analysis of Variance (ANOVA) based analysis (described below) was performed to identify the most sensitive parameters of a single-family home simulation model.

Local methods use numerical approximations of local derivatives between the output and input to estimate parameter sensitivity. There are a few different approaches to calculate this derivative (finite difference, direct methods, using Green functions, etc.), but each method typically requires OAT sampling. Again, this method is good for studying a small number of uncertain parameters, and has been used extensively in the building system community where Spitler *et al.* (1989) studied family housing with five uncertain parameters, and in Struck *et al.* (2009) where 10 parameters were studied using 200 simulations, and in Lomas and Eppel (1992) which used various local methods on a model containing 70 uncertain parameters. In the article (Lam *et al.* 2008), 10 parameters were studied using OAT (43 realizations each) for 10 different building types, and Firth *et al.* (2010) who studied 27 parameters in a household model using local methods as well.

As the name implies, local methods obtain only approximate sensitivity results at different locations in the sampled space. As illustrated in Figure 1, outputs of building system models may be multi-modal, which implies that local methods may not be the best way to analyse this data. To account for this, global methods calculate how the variance of the output varies due to the entire sampled range of the parameter space. Unlike local methods, the global approach does not assume linearity or monotonicity in the data or the process which produces it. The Morris method is one example of a global SA approach wherein randomized matrices are constructed with one parameter varying at a time. The Morris method has been used in SA for many building simulations models as in de Wit and Augenbroe (2002) where 100 realizations for 89 uncertain parameters was performed on room air distribution, or Corrado and Mechri (2009) where 10 parameters were found to be significant out of the 129 which were varied using LHS and the Morris method. In Heiselberg *et al.* (2009), the Morris method was used to calculate the elementary effects for a building model with 21 parameters (88 realizations were performed).

ANOVA is a global method that decomposes the variance of an output into variance that is based on single parameters and variance that is due to uncertainty in combinations of parameters. Sobol' illustrated that a square-integrable function can be decomposed into a sum of functions (see (Sobol' 2001) and references within)

$$f(x) = f_0 + \sum_{i=1}^{k} f_i(x_i) + \sum_{j>i}^{k} f_{ij}(x_i, x_j) + \cdots + f_{12\ldots k}(x_1, \ldots, x_k), \tag{1}$$

where $f(x)$ is an arbitrary function (e.g. a building system simulation), and x_i are the k uncertain parameters of this model. If the samples are generated in an orthogonal way, the Sobol' decomposition of a sampled function is then unique. Because of this, the variance of a complicated function can be represented as a sum of variances of first order and higher order functions (by first order we mean it is a function of one parameter, second order means a function of two parameters, and so on). The variance of the output (D) can then be decomposed as

$$D = \sum_{i=1}^{k} D_i + \sum_{j>i}^{k} D_{ij} + \cdots + D_{12\cdots k}, \tag{2}$$

where D_i are first order, and $D_{12\ldots k}$ are higher order variances. A sensitivity index is then calculated from this expansion by dividing by the total variance. The first order sensitivity indices are $S_i = D_i/D$, the second order sensitivity indices are $S_{ij} = D_{ij}/D$ and so on (there are $2^k - 1$ terms in the decomposition). The magnitude of the sensitivity index for a particular parameter quantifies how sensitive a particular output is to variation of that parameter.

The total sensitivity index S_{T_m} is the sum of the all sensitivity indices for a particular parameter. The m^{th} total sensitivity index for parameter x_m is

$$S_{T_m} = S_m + \sum_{\substack{j>i \\ i \text{ or } j=m}}^{k} S_{ij} + \sum_{\substack{l>j>i \\ i \text{ or } j \text{ or } l=m}}^{k} S_{ijl} + \cdots + S_{1\cdots m\cdots k}. \tag{3}$$

When the model is additive, and the higher order contributions are negligible, the total sensitivity is approximately equal to the first-order sensitivity. If the total sensitivity for a parameter m is zero, it can be concluded that uncertainty in that parameter has no influence on the uncertainty in the output. In this article we present the total sensitivities (we have found that building system models are primarily additive). Other ANOVA-based studies have been performed with building simulation, for example in Mara and Tarantola (2008), ANOVA was used on a model of a test cell using 35 parameters to classify the most important parameters for subsequent model calibration, as well as in Brohus *et al.* (2009a) which was

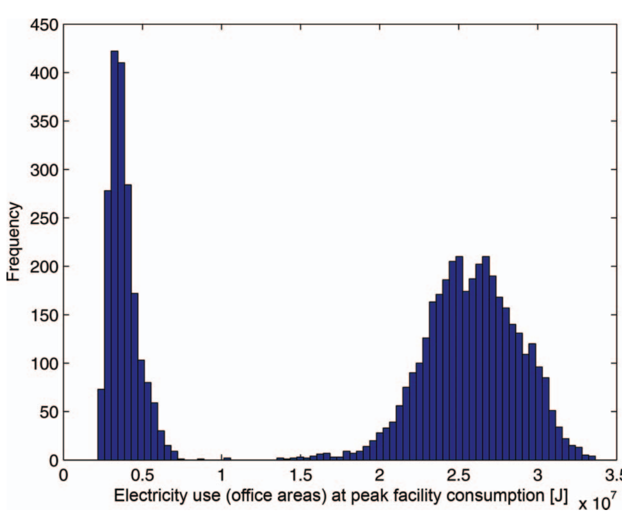

Figure 1. Output distribution of office electricity consumption at peak load for 5000 parameter realizations (simulations details in Section 2). The two peaks illustrate that local variance may not be the best way to characterize this distribution.

described above. In Capozzoli *et al.* (2009) LHS and ANOVA was used to calculate sensitivity indices for six architectural parameters using 100 realizations for five different buildings in Italy.

The drawbacks to ANOVA analysis is its computational cost and that it is based on variance of the output alone. When the output of the simulation is not normally distributed, a variance-based approach may not characterize the sensitivities well. As illustrated in Figure 1, it is not uncommon that output from building simulation tools are not normally distributed. This can be explained because the inputs are not always identically distributed and because of nonlinearities in the model. Due to this, not only will there be issues with the ANOVA analysis, but convergence is no longer guaranteed even after many simulations. To account for this, we use a meta-model based sensitivity analysis, and present data of the output statistics as the number of samples increases to illustrate convergence in our data.

Response surface (also known as a meta-model among other names) methods are often used to generate approximate information in the place of full data. High dimensional model realization (HDMR) (Li *et al.* 2002) is an approach that approximates the output surface in this way. In this approach, a series of weighted orthonormal polynomials are used to approximate the component functions of Equation (1). With this method, not only can you analyse the variance of the output, the model response at parameter locations that differ from the sampling points can also be identified.

The generation of a meta-model provides a means for additional sensitivity tools including global derivative-based methods. As we mentioned above, screening-type methods approximate local derivatives by simple finite difference type techniques. On the other hand, if an analytical meta-model is developed, *global derivatives* can be calculated (Campolongo *et al.* 2007). Derivative-based global sensitivity can be calculated from functions such as (Sobol and Kucherenko 2009)

$$\mu_m = \int \left|\frac{\partial f}{\partial x_m}\right| d\boldsymbol{x} \quad \text{or} \quad v_m = \int \left(\frac{\partial f}{\partial x_m}\right)^2 d\boldsymbol{x}, \qquad (4)$$

where the integration is performed over all dimensions of the sampling points. Both of these estimates are norms of the output of the derivative of the meta-model (f), where μ_m is an L^1 norm and v_m is an L^2 norm of the derivative of f.

Wrapper applications have been created to facilitate numerous, or even parallel simulations in building system software, such as EnergyPlus (Zhang 2009). In addition to this, there are numerous existing UA/SA software packages that are available either for purchase or under open license agreements (e.g. Simlab (Simlab 2010)). There are even some HDMR software packages available, for instance Ziehn and Tomlin (2009) which provides a GUI-based software tool, but is limited to the use of polynomials up to 10th order (see (Saltelli *et al.* 2010) for other algorithms that can be implemented). Many studies that perform SA use polynomials for the response surface (e.g. (Li and Rabitz 2006, Mara and Tarantola 2008)).

We have developed our own approach that best addresses the unique dynamics found in building system simulation. As we mentioned above, we use quasi-random sampling to generate the samples and subsequent models to be simulated. To calculate the response surface, instead of using polynomials, we use support vector regression as described by Smola and Scholkopf (2004) using Gaussian kernels. In this work, we calculate both ANOVA and L^2 norm derivative-based sensitivities, while for brevity we only present L^1 norm (μ_m) derivative-based sensitivities. The software we use to compute the samples and calculate sensitivities is available at Aimdyn GoSUM Software (2010).

1.1. Sensitivity decomposition

All literature that we are aware of relating to both UA and SA investigates the behaviour of a system from an input–output viewpoint alone. For example, envelope parameters of a building may be varied to investigate how they influence the total energy used in a building. For output variables, heating and cooling consumption has been studied by Capozzoli *et al.* (2009), Brohus *et al.* (2009a,b), and Heiselberg *et al.* (2009). In Spitler *et al.* (1989) energy performance was studied. Energy rating was studied by Corrado and Mechri (2009), while other efforts investigate other environmental variables, such as CO_2 concentrations in Firth *et al.* (2010) or room air temperature (Mara and Tarantola 2008).

Studying the input–output behaviour of building system models is insightful, but more information can be gained by decomposing the path in which uncertainty passes through the dynamics of the model. For example, the energy consumed by a building may be derived from a combination of many different HVAC subsystems. It is insightful to identify which of these subsystems contribute most to the uncertainty at the building level. In particular, it is useful to have this type of information when trying to calibrate the model to better fit data, or to design optimizing controllers. We present this sensitivity decomposition in Section 5.

1.2. Outline

The remainder of this article describes analysis performed on an example EnergyPlus model. Section 2 describes the test building and the EnergyPlus model of it. Within this description, we describe the parameters which are varied and the outputs that we analyse. In Section 3, we present how uncertainty in a few key outputs of the model is influenced by different levels of uncertainty in the input. After this, we perform SA in Section 4, and present the decomposition in Section 5. The article concludes with a summary of the findings and the methods.

2. Modelling and simulations

2.1. Simulation platform

A whole-building EnergyPlus simulation model representing the performance of the envelope, HVAC, lighting, water and control systems was developed in EnergyPlus (Crawley *et al.* 2000), which is a whole-building simulation program developed by the US Department of Energy. It models heating, cooling, lighting and ventilating processes, as well as water usage in buildings, and includes many simulation capabilities, such as time steps of less than 1 h modular systems, multizone airflow, thermal comfort, water use and natural ventilation. An EnergyPlus model takes as input a description of the building (e.g. geometry, materials, roof type, window type, shading geometry, location, orientation), its usage and internal heat loads (as a scheduled function of time) and the HVAC equipment and system description (e.g. chiller performance, air and water loop specifications), and then computes the energy flows, zonal temperatures, airflows and comfort levels on subhourly intervals for periods of days to years. There are other similar simulation packages, and the methods in this article can be applied to most of them.

2.2. Building specifics

For this study, we chose building number 7230 (the Atlantic Fleet Drill Hall) at the Naval Station Great Lakes, Great Lakes, Illinois which is owned by the US Department of Defense. The EnergyPlus model is being used as the reference model for automated commissioning of this building and at the time of this study, it was being calibrated with realtime data (ESTCP 2010). The drill hall is a two-storey facility with a gymnasium-like drill deck, offices and administrative rooms. The gross area of this building is approximately 6430 m^2 (69 K ft^2).

The drill hall HVAC system consists of four airside subsystems and two separate waterside subsystems. The drill deck is supplied by two variable-air volume (VAV) air handling units (AHU) with heating and cooling capability, and a classroom on the second floor is served by one VAV air handling unit. Operation of these units depends on the occupancy of the drill deck space. Double-walled sheet metal ductwork with a perforated liner and drum louvers distribute the air throughout the space. The office and administrative area is served by one VAV air handling unit with VAV terminal units (with hot water reheat). The chilled water system consists of two 110-ton air-cooled rotary-screw type chillers with fixed-speed primary pumping and variable-speed secondary pumping. Heating is supplied from the existing campus-wide steam system through a steam-to-water heat exchanger. The hot water serves unit heaters, VAV box reheating coils and air handling unit heating coils. There is an instantaneous steam-to-domestic hot water generator for domestic hot water service. The server room and communication service room are served by dedicated duct free split systems. Table 1 lists major HVAC equipment used in building 7230.

A distributed Direct Digital Control (DDC) control system is installed in this building which monitors all major environmental systems. Building electric and water meters are also read by the DDC system. Operator workstations provide graphics with real-time status for all DDC input and output connections.

2.3. EnergyPlus model

The EnergyPlus geometry interface used for this analysis is DesignBuilder (DesignBuilder 2010) which allows for a graphical display of all the three-dimensional geometry. After the geometry is entered into DesignBuilder, an IDF file (the file in which EnergyPlus uses) with all geometry information is exported, and then the IDF editor is used to create the HVAC system model.

The EnergyPlus model used in this study is version 4.0 (build 4.0.0.024), and the weather file used in this simulation is the TMY3 (typical meteorological year) data for Chicago, O'Hare airport. The structure of the HVAC system in the EnergyPlus model is a series of

Table 1. Major equipment used in building 7230.

Equipment	Number
Duct free split system	2
Air cooled screw chiller	2
Variable volume air andler unit	4
Suspended unit heater	7
Cabinet unit heater	9
VAV box with hot water reheat coil	8
Pumps	7

modules connected by air and water fluid loops that are divided into a supply and a demand side. EnergyPlus assumes ideal controls for all the subsystems and components. Within the HVAC system capacity, the demand side is always balanced with the supply side. If due to the limited capacity, the supply side cannot provide enough output, EnergyPlus will correct the zone temperature based on the actual output from supply side.

In order to keep the size of the model and computation time manageable, zoning simplifications were made when entering the building geometry. The building model consists of 30 conditioned zones (12, 12 and 6 zones for the drill deck, first, and second floors, respectively). Some zones represent a physical room in the building while other zones represent adjacent multiple rooms operating under similar energy usage/requirements. Each zone includes an "internal mass" that represents the thermal storage capacity of the room(s) (e.g. interior walls, furnishings, books, etc.).

2.4. *Parameter variation and simulation*

Almost all numeric parameters in the EnergyPlus input file were selected as uncertain, a few of the parameters were chosen to be held constant in the analysis like architectural parameters (size, shape and orientation of the building), as well as parameters related to equipment performance curve coefficients. Categorial, or text-based parameters (e.g. whether certain equipment is auto-sized, or other calculation methods), as well as the weather data were also not changed. The nominal values for parameters are chosen from (1) as-built architectural, mechanical and control drawings (e.g. thermal properties of envelope and windows); (2) actual building operation (e.g. lighting and AHU operation schedules); (3) manufacturer's catalog data (e.g. chiller coefficient of performance (COP)).

The resulting 1009 parameters were varied $\pm 20\%$ of their nominal value (we also include data illustrating how uncertainty is influenced when this range is only $\pm 10\%$). For non-zero parameters, a uniform distribution was imposed, while for parameters with zero nominal value (and which are constrained to be positive), an exponential distribution was used to keep the mean of the sampled values closer to nominal. Many of the parameters were constrained; for instance, fractional parameters with a nominal of 0.9 would be varied between 0.72 and 1.0. The heating and cooling setpoints had to be limited to 6.5% variation because otherwise they would overlap, which created conflict in the dual-setpoint management. All parameters were varied concurrently using a quasi-random approach. In this way, 5000 model realizations were created which were ultimately parallelized and simulated on a 184-CPU Linux cluster.

From the numerous outputs that are available, 10 different outputs were chosen for analysis as listed in Table 2. These outputs are related to building energy consumption, including electricity and steam (i.e. district heating) from the facility level, to subsystems such as pumps, fans, equipment, and lights. Annual total energy consumption and peak demand (hourly peak in one year or season) were two metrics used in this study. We chose these outputs because they best reflect the drill hall building performance and energy end-use pattern. In Section 5, we limit our analysis to two outputs; output Facility Electricity and District Heating. These two outputs characterize all of the energy consumed by the building.

The convergence behaviour of these 10 consumption outputs is presented in Figure 2 (when parameters were varied by $\pm 20\%$). The trends in this figure were obtained by calculating the per cent difference between

Table 2. Consumption outputs chosen for the analysis.

Number	Name
1	DistrictHeating:Domestic Hot Water Energy [J]
2	DistrictHeating:HVAC [J]
3	Electricity:Facility [J]
4	DistrictHeating:Facility [J]
5	InteriorEquipment:Electricity [J]
6	InteriorLights:Electricity [J]
7	Cooling:Electricity [J]
8	Pumps:Electricity [J]
9	Fans:Electricity [J]
10	Chillers:EnergyTransfer

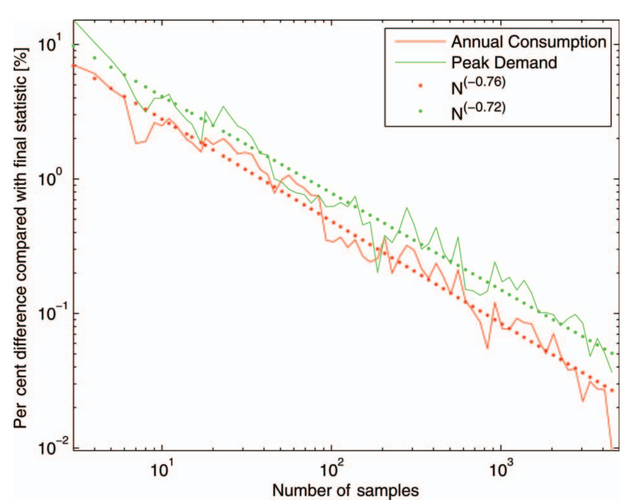

Figure 2. Convergence properties of the averaged relative error in mean of 10 outputs. The averaged relative error in mean (with respect to the values after 5000 simulations) is presented for both peak demand and annual consumption.

the mean at the ith simulation and the mean after 5000 simulations. The percentage of absolute value of the error for each of the 10 annual consumption and peak demand outputs were then averaged to create two convergence response curves. In this figure, the slope at which the error converges is calculated using a least squares fit and included in the legend. Note that the exponent of the line fit for the annual consumption and peak demand variables is on the order of -0.7 (using the quasi-MC approach). This same exponent for a $\frac{1}{\sqrt{N}}$ convergence rate, which is common for standard MC methods, would be -0.5.

3. Uncertainty analysis

In this section, we present the uncertainty (both in actual and normalized units) for 10 output variables (Figures 3 and 4) and the actual distributions of two consumption variables (Figure 5) for both annual consumption and peak demand.

As illustrated in Figures 3, 4 and 5, the variance and coefficient of variation (standard deviation divided by the mean) increases by increasing the uncertainty in the input parameters. Specifically, in most cases, the increase in a factor of two on the input parameter standard deviation amplifies the uncertainty in the output by a factor of two as well, indicating linearity in the dynamics.

The way in which the model either amplifies or attenuates the uncertainty in the input is also evident in Figures 3 and 4. The coefficient of variation (in per cent) for a uniform distribution with a range of 10% of its mean is about 6.0 and about 11.0 for a range of 20%. We find that cooling electricity is always amplified the most (whether considering the peak or sum from the year). The uncertainty in the peak pump usage is significantly amplified as well. The uncertainty in energy consumption from both interior equipment and interior lights is attenuated by about a factor of two in both the peak and sum usages. All other output variables have uncertainty which is similar to the input uncertainty.

4. Traditional sensitivity calculation: input–output results

After gaining insight into how uncertainty in input parameters influences the uncertainty in the outputs,

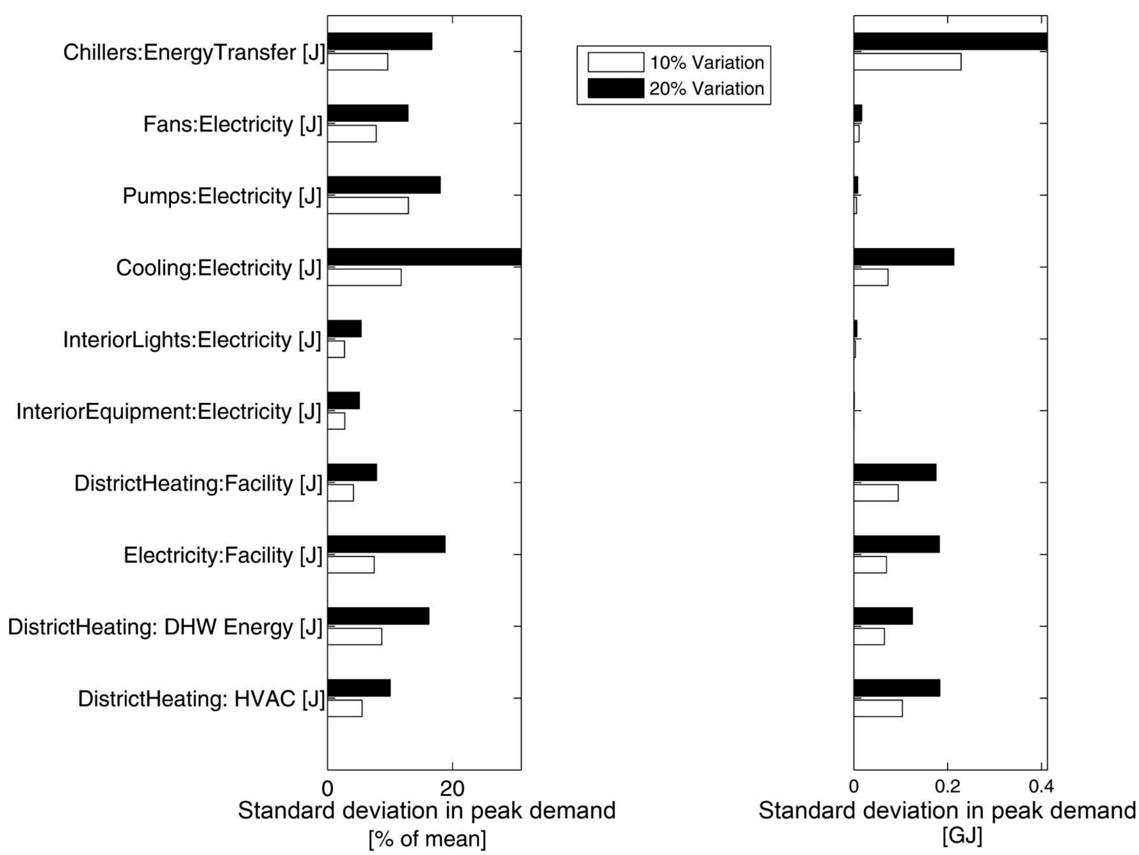

Figure 3. Uncertainty in the 10 consumption variables (peak demand) when varying the input parameters by either 10% or 20%.

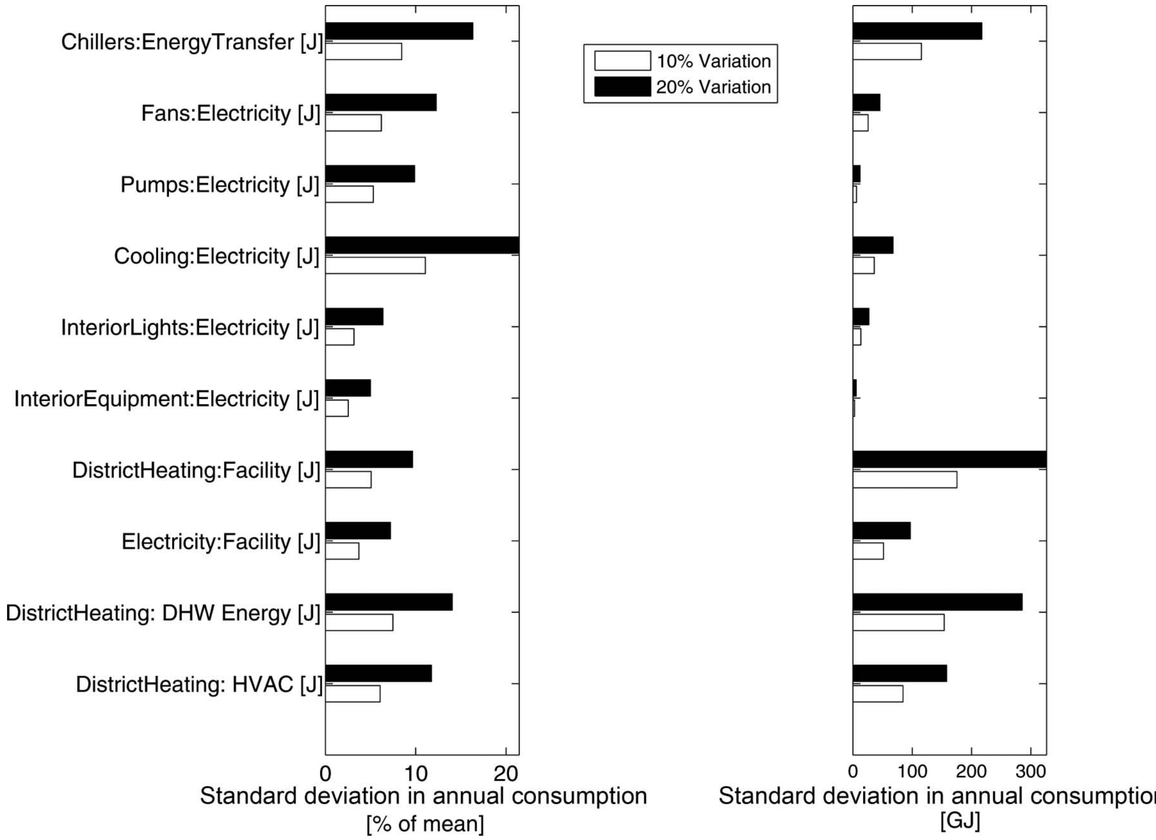

Figure 4. Uncertainty in the 10 consumption variables (annual consumption) when varying the input parameters by either 10% or 20%.

we now proceed to calculate the sensitivity indices. We first calculate the sensitivity indices for the two main seasonal outputs of the model; the district hot water consumption in winter (October 15 to April 14), and the facility electricity in summer (April 15 to October 14). In the next section, we will also calculate sensitivity of these outputs along with intermediate sensitivities for variables throughout the energy consumption process. Figure 6 illustrates the aggregated total sensitivity indices for the 10 parameter types described in Table 3.

To generate these numbers, the total sensitivity (calculated from μ_m in Equation 4) for each of the 1009 parameters was calculated. If the sensitivity index was less than 0.08, it was considered negligible and ignored (138 of the 1009 parameters remained after this selection). We came up with this number by observing a cutoff in the number of influential parameters vs. the sensitivity index amplitude. All parameters with an sensitivity index greater than this were then collected and labeled with respect to their parameter type (as in Table 3). Once collected, the total sensitivities for each parameter type were then added to generate a single number for the aggregated total sensitivity between a parameter type and an output type. It should be noted that since we are using derivative based sensitivities (Equation 4), the summation may be larger than 1.0.

Starting from the bottom of Figure 6, we highlight the parameters which contribute most to the parameter type for those outputs.

(1) For the *Heating Source* parameter type, two parameters are influential, but one parameter stands out as dominant: HW loop max temperature (hot water loop maximum temperature).
(2) For the *Cooling Source* parameter type, out of nine total, two parameters stand out the most: Chiller on at OAT (chiller is on when outside temperature reaches a threshold) and CW loop temp schedule (chilled supply water temperature setpoint schedule).
(3) The *Air Handling Unit* parameter type is comprised of 22 parameters in this case, but is predominately defined by Min OA schedule fraction (minimal outside air fraction) and SAT reset temp (AHU supply air temperature setpoint).
(4) The *Primary Mover: Air Loop* parameter type contains 20 parameters which are dominated

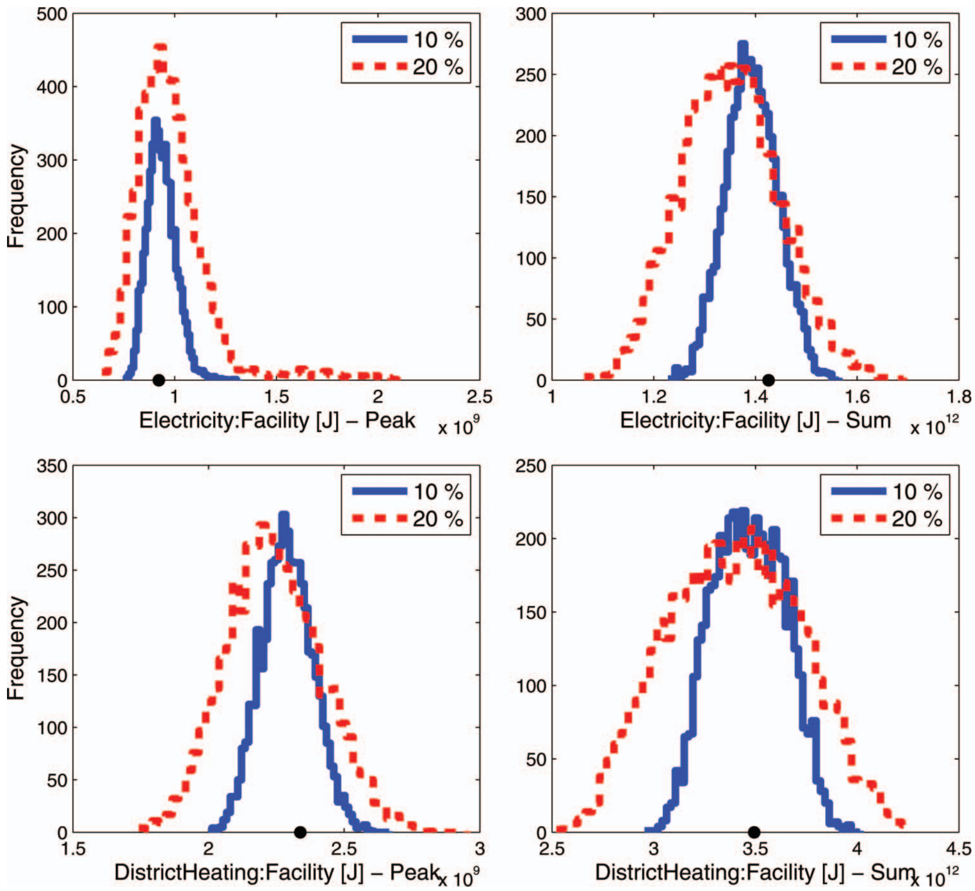

Figure 5. Example distributions for cooling (top) and heating (bottom) when varying the input parameters by either 10% or 20%. The black dot is the nominal simulation results.

by AHUS1 and AHUS2 fan parameters (fan efficiency and pressure rise).

(5) The *Primary Mover: Water Loop* parameter type only has five significant parameters in it. The most dominant of these parameters are the Rated pump consumption parameters, while one pump efficiency, from the primary chilled water pump does play a small role.

(6) The *Terminal Unit* parameter type is comprised of nine parameters, with approximately equal contributions from Zone max flow rate (drill deck) and VAV max flow rate (office area) parameters.

(7) The *Zone external* parameter type has 14 significant parameters in it. There is no small set of parameters which stand out in this set. The contributions come from material types in building construction as well as ground surface temperature and ground reflectance.

(8) The parameter type *Zone internal* contains 48 significant parameters, with People schedule (fraction of number of people) and Lighting Schedule (fraction of lighting load) parameters dominating this group.

(9) The *Zone setpoint* parameter type has 3 significant parameters. These are associated with high-use time periods of the Zone cooling setpoint and one Zone heating setpoint schedules. They influence the facility electricity and district hot water respectively.

(10) The *Domestic hot water* parameter type has 6 significant parameters. The Water equipment target temperature is a large contributor, followed closely by four parameters that define the domestic hot water use fraction.

Figure 6 also shows that (1) summer electricity peak demand is mainly influenced by cooling source (i.e. chiller); (2) summer electricity consumption is mainly influenced by the air loop primary mover (i.e. supply and return fans); (3) winter district heating peak demand is mainly influenced by the AHU (i.e. AHU heating coils, and the AHU supply air temperature setpoints) and (4) winter district heating consumption is mainly influenced by domestic hot water (i.e. water

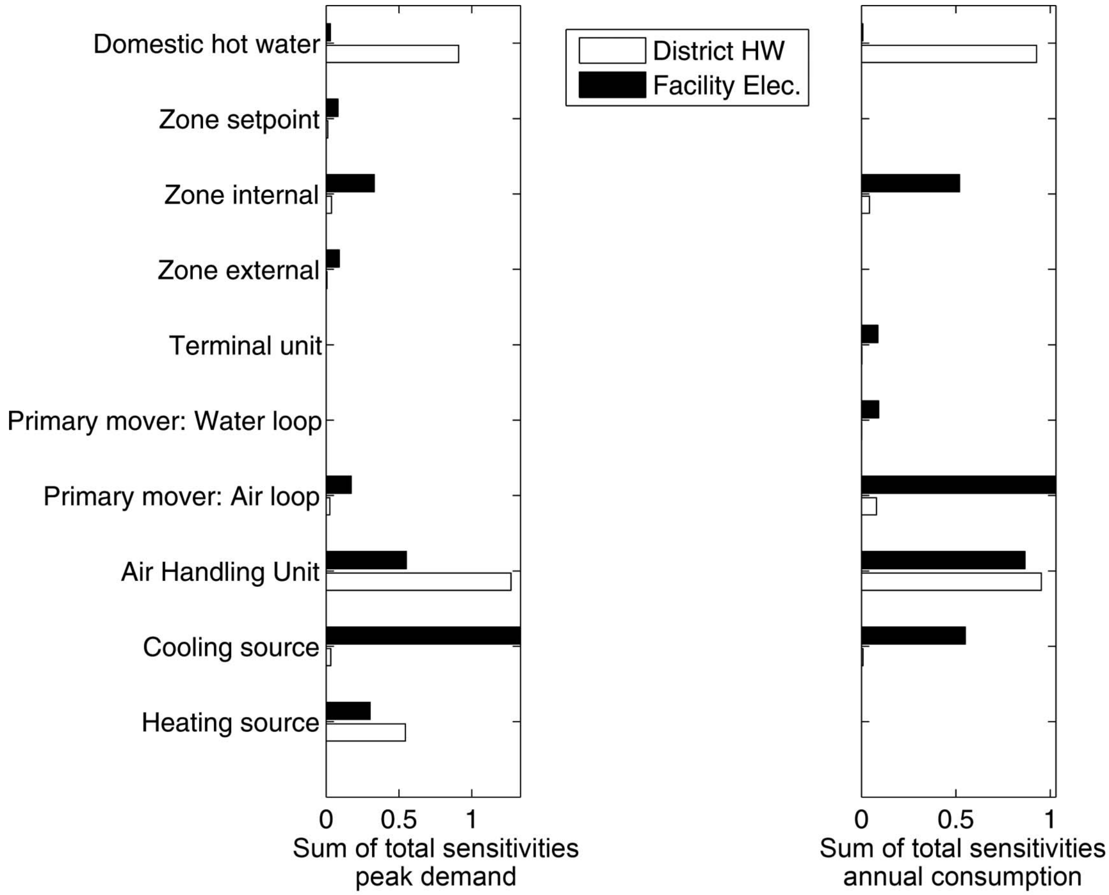

Figure 6. Sensitivity indices for two facility consumption variables.

usage) and the AHU (i.e. AHU heating coils, and the AHU supply air temperature setpoints).

5. Sensitivity decomposition

The standard input–output SA described above is useful to identify which parameter type influences the two facility-wide consumption variables the most. In this section, we further break this down to illustrate how uncertainty in the input parameters influences intermediate consumption variables which eventually make up the total consumption (either district hot water, or building electricity).

In Figure 7, the sensitivity decomposition for facility electricity is presented. In this plot, the nodes are subsystem energy variables, which are described in Table A1, and the connecting wires are sensitivity indices. For instance, in Figure 7 the right most node is the electricity use at the building level. The 5 nodes to the left of this are the 5 major electrical subsystems in the building (lighting, interior equipment, fan total, pump total, and cooling). To the left of this, an even greater decomposition is presented for electrical consumers (individual fans and pumps, etc.). The left-most axis contains the input parameter types which influence the entire dynamics of the model (as in Table 3). For each node, a circle is drawn around it which represents the coefficient of variation. There is no appropriate scale for these circles, they are intended to be viewed relative to other circles in the figure.

The thickness of the wires corresponds to the magnitude of the sensitivity index. Where there is no wire, the sensitivity index is negligible, and the thickest wires represent the strongest influence between the variables. The decomposition was only performed for seasonal consumption as the peaks for each consumption variable at the subsystem and component level did not always occur at the same time of year.

As seen in the decomposition of facility electricity consumption, the uncertainty in facility electricity is driven mostly by uncertainty in fan and cooling source (chillers) electricity consumption. These in turn are influenced mostly by AHU1S and AHU2S fan consumption, and CHILLER1 electricity consumption, respectively. This makes sense because (1) AHU1 and AHU2 are serving all the zones in the drill deck

Table 3. Parameter types.

Number	Type	Note: examples in this drill hall system 1
1	Heating source	District heating system (normal capacity, maximum hot water system temperature, loop flow rate, etc.)
2	Cooling source	Air cooled chiller (chiller reference capacity, reference COP, reference leaving chilled water temperature, etc.)
3	AHU	AHU (supply air temperature setpoint, cooling coil design flow rate, design inlet water temperature, design inlet air temperature, etc.)
4	Primary mover: air loop	Fans (efficiency, pressure rise, etc.)
5	Primary mover: water loop	Pumps (rated flow rate, rated head, rated power consumption, etc.)
6	Terminal unit	VAV boxes (maximum air flow rate, minimum air flow fraction, etc.), maximum zonal flow rates
7	Zone external	Building envelope (material thermal properties such as conductivity,density, and specific heat, window thermal and optic properties, etc.), outdoor conditions (ground temperature, ground reflectance, etc.)
8	Zone internal	Internal heat gains design level (lighting load, number of people, people activity level, etc.), schedules
9	Zone setpoint	Zone temperature setpoint (space cooling and heating setpoints)
10	Domestic hot water	Domestic hot water usage (peak flow rate, target temperature, etc.)

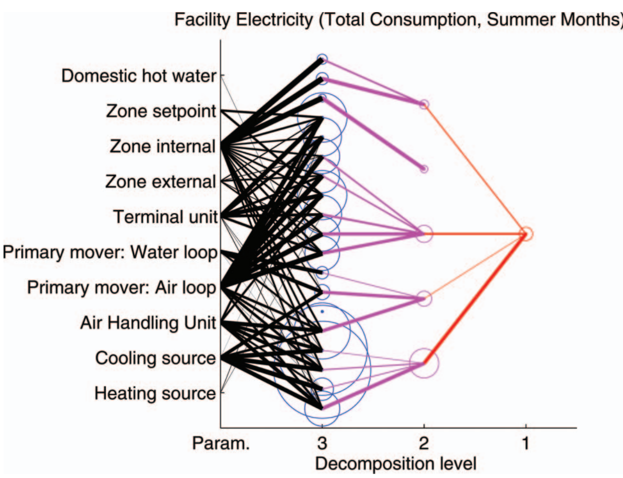

Figure 7. Sensitivity decomposition of the electricity consumed by the facility (total consumption over the summer months). The labels on the vertical axis describe the parameter types, while the other node/levels of this plot are tabulated in Table A1 (Appendix A).

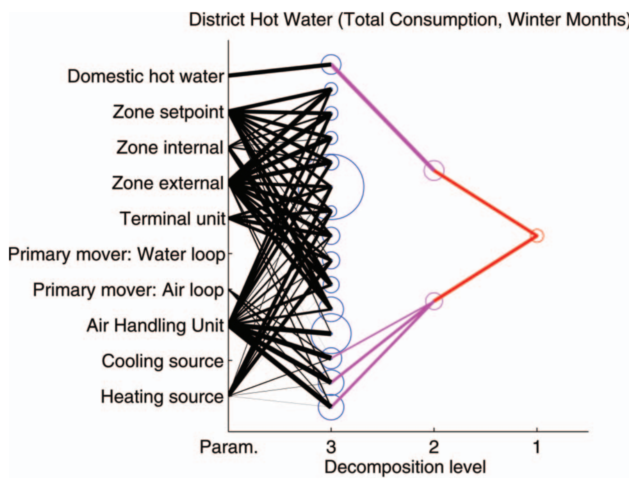

Figure 8. Sensitivity decomposition of the district hot water consumed by the facility (total consumption over the winter months). The labels on the vertical axis describe the parameter types, while the other node/levels of this plot are tabulated in Table A2 (Appendix A).

which is the largest area in the building (80%) and (2) CHILLER1 was set as the primary chiller in the model.

Similar analysis has been performed on the district water consumption (Figure 8). In this figure, we find that uncertainty in the total hot water consumed is spread relatively evenly between domestic and HVAC consumption. Beyond this, we find that uncertainty in the domestic hot water is driven by only one variable (the domestic water equipment usage variable), while for the HVAC hot water usage, uncertainty is driven by three large heating coils in AHU1, AHU2 and AHU3.

We would like to highlight that the SA in no way quantifies the amount of consumption at each node. That is, the data in Figure 7 or 8 does not imply that the nodes on the third level which have no wires leading to level two do not contribute significant portion to the total consumption. It specifically identifies when *uncertainty* in these variables influences *uncertainty* in variables on other levels.

This decomposition process highlights which subcomponents of the model need the most engineering attention when deriving design specifications for building construction, or in model calibration (if the building has been built and the model needs to be tuned). Based on the results from this study, we were able to better calibrate the drill hall EnergyPlus model to match acquired data.

6. Summary

In this article we presented UA of an EnergyPlus model with a large number of uncertain parameters. In addition to this we presented input–output SA which illustrates which parameter type influences the uncertainty in the two main outputs of the building model. Taking this a step further, we performed a decomposition to quantify which intermediate processes were contributing the most to this uncertainty. This type of analysis, including the decomposition, is valuable for identifying which subcomponents of a model need more attention during building design or model calibration. In addition to this, this method highlights subsystems within a building that would have the most impact on energy reduction when optimizing building operation (e.g. for diagnostics and control).

Acknowledgements

The authors would like to thank Dr. Sophie Loire for generating some of the scripting for the simulations on the computer cluster. This work was partially supported under the contract W912HQ-09-C-0054 (Project Number: SI-1709) administered by SERDP technology program of the Department of Defense. The authors also thank the project leader Dr. Satish Narayanan (UTRC) for technical guidance.

References

Aimdyn GoSUM Software, 2010. *Global optimization, sensitivity and uncertainty in models (GoSUM)* [online]. Santa Barbara, CA: Aimdyn Inc. Available from: http://aimdyn.com [Accessed 11 August 2010].

Brohus, H., *et al.*, 2009a. Application of partial safety factors in building energy performance assessment. *In*: *Building Performance Simulation Association (IBPSA) conference*, 27–30 July 2009, Glasgow, UK, 1014–1021.

Brohus, H., *et al.*, 2009b. Uncertainty of energy consumption assessment of domestic buildings. *In*: *Building Performance Simulation Association (IBPSA) conference*, 27–30 July 2009, Glasgow, UK, 1022–1029.

Campolongo, F., Cariboni, J., and Saltelli, A., 2007. An effective screening design for sensitivity analysis of large models. *Environmental Modelling and Software*, 22, 1509–1518.

Capozzoli, A., Mechri, H., and Corrado, V., 2009. Impacts of architectural design choices on building energy performance, applications of uncertainty and sensitivity analysis. *In*: *Building Performance Simulation Association (IBPSA) conference*, 27–30 July 2009, Glasgow, UK, 1000–1007.

Clarke, J., Yeneske, P., and Pinney, A., 1990. *The harmonization of thermal properties of building materials, 1990*. Technical report, Building Environmental performance analysis club. Watford, UK: Building research Establishment.

Corrado, V. and Mechri, H., 2009. Uncertainty and sensitivity analysis for building energy rating. *Journal of building physics*, 33 (2), 125–156.

Cóstola, D., *et al.*, 2010. Uncertainty in airflow rate calculations due to the use of surface-averaged pressure coefficients. *Energy and Buildings*, 42, 881–888.

Crawley, D.B., *et al.*, 2000. EnergyPlus: energy simulation program. *ASHRAE Journal*, 42, 49–56.

de Wit, S. and Augenbroe, G., 2002. Analysis of uncertainty in building design evaluations and its implications. *Energy and Buildings*, 34, 951–958.

DesignBuilder, 2010. *Design builder building simulation* [online]. Gloucestershire, UK: DesignBuilder Software Ltd. Available from: http://www.designbuilder.co.uk/ [Accessed 19 July 2010].

Dominguez-Munoz, F., *et al.*, 2009. Uncertainty in the thermal conductivity of insulation materials. *In*: *Building Performance Simulation Association (IBPSA) conference*, 27–30 July 2009, Glasgow, UK, 1008–1013.

ESTCP, 2010. *Automated continuous commissoning of commercial buildings*. Department of Defense Environmental Security Technology Certification Program Project SI-0929.

Firth, S., Lomas, K., and Wright, A., 2010. Targeted household energy-efficiency measures using sensitivity analysis. *Building Research and Information*, 38 (1), 25–41.

Heiselberg, P., *et al.*, 2009. Application of sensitivity analysis in design of sustainable buildings. *Renewable Energy*, 34, 2030–2036.

Lam, J., Wan, K., and Yang, L., 2008. Sensitivity analysis and energy conservation measures implications. *Energy Conversion and Management*, 49, 3170–3177.

Li, G. and Rabitz, H., 2006. Ratio control variate method for efficiently determining high-dimensional model representations. *Journal of Computational Chemistry*, 27, 1112–1118.

Li, G., *et al.*, 2002. Global uncertainty assessments by high dimensional model representations (HDMR). *Chemical Engineering Science*, 57, 4445–4460.

Lomas, K.J. and Eppel, H., 1992. Sensitivity analysis techniques for building thermal simulation programs. *Energy and Buildings*, 19, 21–44.

Macdonald, I., 2002. *Quantifying the effects of uncertainty in building simulation*. Thesis (PhD). University of Strathclyde, Department of Mechanical Engineering.

Macdonald, I., 2009. Comparison of sampling techniques on the performance of Monte Carlo based sensitivity analysis. *In*: *Building Performance Simulation Association (IBPSA) conference*, 27–30 July 2009, Glasgow, UK, 992–999.

Mara, T. and Tarantola, S., 2008. Application of global sensitivity analysis of model output to building thermal simulations. *Building Simulation*, 1, 290–302.

Moon, H., 2005. *Assessing mold risks in buildings under uncertainty*. Thesis (PhD). Georgia Institute of Technology.

Rahni, N., *et al.*, 1997. Application of group screening to dynamic building energy simulation models. *Journal of Statistical Computation and Simulation*, 57 (1), 285–304.

Saltelli, A., Chan, K., and Scott, E.M., 2000. *Sensitivity analysis*. New York: Wiley.

Saltelli, A., *et al.*, 2010. *Global sensitivity analysis – the primer*. Wiley.

Simlab, 2010. *Simlab: a professional tool for model developers, scientists and professionals, to learn, use and exploit uncertainty and sensitivity analysis techniques* [online]. European Commission: Unit of Econometrics and Applied Statistics of the Joint Research Centre. Available from: http://simlab.jrc.ec.europa.eu/ [Accessed 4 May 2010].

Smola, A. and Scholkopf, B., 2004. A tutorial on support vector regression. *Statistics and Computing*, 14, 199–222.

Sobol', I., 2001. Global sensitivity indices for nonlinear mathematical models and their Monte Carlo estimates. *Mathematics and Computers in Simulation*, 55, 271–280.

Sobol, I. and Kucherenko, S., 2009. Derivative based global sensitivity measures and their link with global sensitivity indices. *Mathematics and Computers in Simulation*, 79, 3009–3017.

Soratana, K. and Marriott, J., 2010. Increasing innovation in home energy efficiency: Monte Carlo simulation of potential improvements. *Energy and Buildings*, 42 (6), 828–833.

Spitler, J., Fisher, D., and Zietlow, D., 1989. A primer on the use of influence coefficients in building simulation. *In: Building Performance Simulation Association (IBPSA) conference*, 23–24 June 1989, Vancouver, British Columbia, Canada, 299–304.

Struck, C., Hensen, J., and Kotek, P., 2009. On the application of uncertainty and sensitivity analysis with abstract building performance simulation tools. *Journal of Building Physics*, 33 (1), 5–27.

Zhang, Y., 2009. ''Parallel'' EnergyPlus and the development of a parametric analysis tool. *In*: *Building Performance Simulation Association (IBPSA) conference*, 27–30 July 2009, Glasgow, UK, 1383–1388.

Ziehn, T. and Tomlin, A.S., 2009. GUI-HDMR – a software tool for global sensitivity analysis of complex models. *Environmental Modelling and Software*, 24, 775–785.

Appendix A. Variables captured in the nodes of Figure 7 and Figure 8

Table A1. Variables for the nodes of the sensitivity decomposition of facility electricity (Figure 7).

Level 3	Level 2	Level 1
Equipment: Office area [J]		
Equipment: Drill deck [J]		
Lights: Office area [J]		
AHU4RFAN:Fan Elec. Cons. [J]		
AHU3RFAN:Fan Elec. Cons. [J]		
AHU2RFAN:Fan Elec. Cons. [J]	InteriorLights:Elec. [J]	
AHU1RFAN:Fan Elec. Cons. [J]		
AHU4SFAN:Fan Elec. Cons. [J]	Int.Equip.:Elec. [J]	
AHU3SFAN:Fan Elec. Cons. [J]		
AHU2SFAN:Fan Elec. Cons. [J]	Fans:Elec. [J]	Facility Elec. [J]
AHU1SFAN:Fan Elec. Cons. [J]		
DHWPUMP:Pump Elec. Cons. [J]	Pumps:Elec. [J]	
PRIMARYPUMP:Pump Elec. Cons. [J]		
HWPUMP:Pump Elec. Cons. [J]	Cooling:Elec. [J]	
SECONDARYPUMP:Pump Elec. Cons. [J]		
CHILLER2:Chiller Cond Fan Elec. Cons. [J]		
CHILLER2:Chiller Elec. Cons. [J]		
CHILLER1:Chiller Cond Fan Elec. Cons. [J]		
CHILLER1:Chiller Elec. Cons. [J]		

Table A2. Variables for the nodes of the sensitivity decomposition of district heating (Figure 8).

Level 3	Level 2	Level 1
Water use equipment heating energy		
Baseboard10 HW Consumption [J]		
Baseboard9 HW Consumption [J]		
Baseboard8 HW Consumption [J]		
Baseboard7 HW Consumption [J]	DHW Energy [J]	
Baseboard6 HW Consumption [J]		
Baseboard5 HW Consumption [J]		DistrictHeating:Facility [J]
Baseboard4 HW Consumption [J]		
Baseboard3 HW Consumption [J]	HVAC [J]	
Baseboard2 HW Consumption [J]		
Baseboard1 HW Consumption [J]		
Water Heating Coil4 HW Cons. [J]		
Water Heating Coil3 HW Cons. [J]		
Water Heating Coil2 HW Cons. [J]		
Water Heating Coil1 HW Cons. [J]		