

A COMPARATIVE STUDY ON UNCERTAINTY PROPAGATION IN HIGH PERFORMANCE BUILDING DESIGN

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ABSTRACT

In this paper, analysis is performed on the uncertainty in energy consumption calculated from whole-building energy models of two different building designs; a typical code compliant building, and the same building redesigned with high performance elements. We perform sensitivity analysis which reveals which parameters (out of approximately 900) influence the uncertainty in the consumption of energy in the building model the most. We conclude that the most sensitive parameters of the model relate to building operation (i.e. scheduling), and also find that a low energy building design is more robust to parameter variations than the conventional design.

INTRODUCTION

Building energy modeling has been pursued for the past few decades and has resulted in various modeling tools that predict energy use with reasonable accuracy. As building design focuses on low energy concepts, new technologies are being introduced into building design, and new component models are needed for these modeling packages to analyze their performance. New component models not only bring new dynamics and behavior to the model, they also bring new sources of uncertainty in its output, and the need to analyze this uncertainty.

Uncertainty analysis (UA) in this context, is the process of predicting how uncertain inputs (typically constant-in-time parameters) influences the output of the model (e.g. energy consumption or comfort variables). To perform this quantitative analysis, the model is usually parsed into many different realizations, each with a different set of parameter values within a given range. The outputs of these realizations are then computed and statistical analysis is performed on these output distributions (see (Moon, 2005) for a general discussion of UA in building modeling). There are many benefits of performing UA which include quantifying confidence bounds on outputs of a building energy simulation.

In some cases, UA is insightful enough to make conclusions from (as in (Soratana and Marriott, 2010)), while typically, once this data is generated, sensitivity analysis is then performed. Sensitivity analysis (SA) is a method that calculates the uncertain parameters which have most influence on the outputs. There

are many obvious benefits to this type of analysis because once the most influential parameters are identified, more engineering attention can be placed on them (e.g. for model calibration (see (O'Neill et al., 2011)), building or control design, and for online diagnostic algorithms).

Parameter range and distribution type of the samples influences the sampled behavior 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 parameters in building models (see (Dominguez-Munoz et al., 2009) where statistical properties of the thermal conductivity of different materials was empirically identified, or (Cóstola et al., 2010) where uncertainty in airflow rates were calculated, or the report (Clarke et al., 1990), or thesis (Macdonald, 2002)). Without specific information, a uniform distribution is typically used with a large parameter range.

In this work, 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 tools in this paper identify the most important parameters of the building model, 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 uniform type). In a sense, the analysis in this paper is associated with conceptual design analysis while the same process can be repeated for detailed design analysis (Struck et al., 2009).

There are multiple ways to calculate the samples once the distribution type and range is defined. One traditional method is the Monte Carlo (MC) approach and an updated version of this method called Latin Hypercube Sampling (LHS) which creates samples with less clumps than the MC approach. In this work, we use a quasi-MC approach which has faster convergence rates than the MC or LHS method and samples that fill the volume more uniformly (Saltelli et al., 2000). A more detailed discussion of convergence as well as a typical convergence plot for this type of analysis can be found in (Eisenhower et al., 2011).

There have been many studies in the energy modeling literature using different SA approaches (screening methods, local methods, and global analysis) to study

building energy models. For example, (Venancio and Pedrini, 2009) studied the impact on energy in three different architectural options, and in (Pollack et al., 2009), five different design options were studied using sensitivity analysis.

The screening method method is good for studying models with a few uncertain parameters and has 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) where pre-screening techniques were used to reduce the number of uncertain parameters in a model from 13 to 7 prior to detailed sensitivity analysis. Similarly, in (Brohus et al., 2009a), a screening method was used to reduce a parameter set from 57 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. This is useful for a conceptual understanding of how one parameter influences the output of a model, but is time intensive when there are a large number of parameters. In addition to this, combinatorial influences (when the perturbation of two or more parameters at the same time has more influence than individual perturbations) are not captured in this approach.

Local methods are another approach that 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 5 uncertain parameters, and in (Struck et al., 2009) where 10 parameters were studied using 200 simulations, and (Lomas and Eppel, 1992) which used various local methods on a model containing 70 uncertain parameters. In the paper (Lam et al., 2008), 10 parameters were studied using OAT (43 realisations each) for 10 different building types, and (Firth et al., 2010) who studied 27 parameters in a household model using local methods as well.

Global methods, including the Morris method have been used in sensitivity analysis for many building simulations models as in (de Wit and Augenbroe, 2002) where 100 realisations 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 (a type of sensitivity analysis screening method) for a building model with 21 parameters (88 realisations were performed). Another global approach is the Analysis of Variance method (ANOVA), which calculates individual and combinatorial variance contributions in the output variables. In (Capozzoli et al., 2009) LHS and ANOVA was used to calculate sensitivity indices for 6 architectural parameters using 100 realizations for 5 different buildings in Italy.

In some cases, output distributions from energy models are not fully described by their variance alone (Eisenhower et al., 2011). Due to this, we use a global derivative-based approach which uses the function (Sobol and Kucherenko, 2009)

$$\mu_m = \int \left| \frac{\partial f}{\partial x_m} \right| dx, \quad (1)$$

where f is a meta-model of the energy simulation (described below) and x_m is the m^{th} uncertain parameter in the model. The integration is performed over all dimensions of the sampling points.

The sensitivity calculations we perform are all based on a model of the EnergyPlus model (a meta-model) which allows analytic operations to be performed (among other things, see (Chlela et al., 2009)). Meta-modeling, including the high dimensional model realization (HDMR) (Li et al., 2002) has been performed in other sensitivity analysis studies (Mara and Tarranto, 2008). This approach fits either polynomial, or other analytic functions through the data points. This approach works well in many cases, but is also very susceptible to either noise or outliers in the data. Another approach uses support vector regression (SVR) as described in (Smola and Scholkopf, 2004). We have found that this SVR approach (using Gaussian kernels) works the best for the type of data produced by energy models. The software we use to compute the samples and calculate sensitivities is available at (Aimdyn GOSUM Software, 2010).

Models

The two models that are compared in this study originate from the United States Department of Energy (DOE) EnergyPlus Benchmark Model Suite (Deru et al., 2009). The DOE benchmark model suite contains 15 models that represent approximately 70% of commercial building stock in the United States. The models are then organized so that each one of them can be simulated at one of 16 different locations in the US (using typical meteorological year (TMY) weather data for each of these locations). Each model is also organized by construction type; new construction, existing construction - post 1980, and existing construction - pre 1980.

The model studied in this paper is a new construction medium office building located in Las Vegas, Nevada. This location is subject to hot and dry summers and cool winters (relatively extreme in both the summer and winter). This medium office building has three floors and approximately 5000 m² (54,000 ft²) of floor area. The entire building is conditioned and the total energy per total building area is about 467 [MJ/m²]. The building is a rectangular cube (aspect ratio 1.5), with 33% window to wall ratio, and is zoned with 5 zones per floor (one central zone and one zone for each perimeter side of the building). Throughout this paper we will call the model of this building the *nominal model*.

The building has one boiler which serves variable air volume (VAV) reheat coils for each of the 15 occupied zones, and heating in the air handling units (AHUs) is provided by a gas furnace. Cooling is supplied by direct expansion (DX) coils in the AHUs, one for each floor. Load and usage schedules are based on ASHRAE guidelines (e.g., ASHRAE Standard 90.1-2004).

A high performance version of this building was also constructed using design information from a technical report from the Pacific Northwest National Lab (Thornton et al., 2009). Building performance was enhanced by improvements to both the envelope as well as equipment within the building (including scheduling).

For the envelope, the insulation was enhanced in both the walls (R13 to R20.5) and in the roof (R15 to R25) without changing its thermal capacity. To reduce the impact of solar radiation, the solar reflectance of the roof was increased from 0.23 to 0.69. Since the nominal building was designed based on standards for Las Vegas, high efficiency windows were already specified, and so there was no change between the nominal and high performance models. However, in the high performance model, overhang shading was added with a projection factor of 0.5.

To reduce the amount of energy consumed by the heating and cooling equipment, a ground source heat pump (GSHP) was incorporated into the design. This GSHP supplies hot water for radiant floor heating and cold water for active chilled beam cooling. In the high performance building, a dedicated outside air system for ventilation was also implemented.

The electrical loads were also decreased in the high performance building. The interior lighting power density was reduced from 10.8 W/m² to 8.1 W/m². Interior lighting schedules (usage fraction) were changed to consider occupancy-sensor based control. For the perimeter zones, lighting is dimmed based on sensed natural daylight. Exterior lighting power allowances were reduced by 37.5% and the exterior lights were turned off between 12am and 12pm. In addition to the lighting changes, the plug load density was also decreased from 8.07 to 5.92 W/m².

With the performance enhancements to both the envelope and equipment, the annual energy intensity of the building was reduced by about 41% (from 467 to 273 [MJ/m²]). In addition to the reduction of energy, the building was more comfortable as modeled. The zone hours not comfortable in either winter or summer clothes as calculated by EnergyPlus was reduced by 73% in the high performance model. Table 1 presents annual usage comparison for subsystems in the nominal and high performance models.

Parameter Variation and Simulation

In each model, almost every numeric parameter was varied to capture how this variation quantitatively in-

Table 1: Electricity usage comparison, nominal vs. high performance model (all units in GJ).

Electricity Type	Nominal	High Performance Case
Heating	0	32.69
Cooling	318.93	216.32
Interior Lighting	552.57	260.6
Exterior Lighting	42.89	9.00
Interior Equipment	806.04	554.47
Fans	119.51	56.61
Pumps	0.82	77.73
Annual Total	1840.76	1207.42

fluences building energy use. The exceptions were in the parameters related to equipment performance curves, and parameters that describe solution methods (e.g. autosizing, or method of calculating infiltration). Because of differences in the building designs, the models had a different number of parameters (746 for the nominal model, while the high performance building had 947). We have selected 10 different groups as shown in Table 2 to characterize all of these parameters.

All of the parameters were varied by $\pm 25\%$ of their nominal value, although many of the parameters were constrained; for instance, fractional parameters with a nominal of 0.9 would be varied between 0.675 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. To obtain the output distributions, 5000 model realizations were created which were ultimately parallelized and simulated on a 184-CPU Linux cluster using EnergyPlus build 3.1.0.027. It was found that 5000 realizations (EnergyPlus models with different input files) were more than enough to gain good convergence results on the statistics of the output variables.

EnergyPlus has the ability to output many different metered variables from the energy simulation. From the outputs that are available, 7 different outputs were chosen for analysis: Facility Gas, Facility Electricity, Heating, Cooling, Pump Electricity, Interior Lights, and Interior Equipment (all units in Joules). Total annual consumption and peak demand (hourly peak in one year) were two metrics used in this study. We chose these outputs because the profiles of these outputs clearly reflect the building performance and energy end-use pattern. The gas and electricity outputs are facility-wide consumption variables, and because of this, more attention will be paid to these two quantities in this paper.

Uncertainty Analysis

Simulations were performed on numerous realizations of both models and the statistics of the outputs were

Table 2: Examples of parameters in each group type (partial list).

Number	Type	Examples of specific parameters captured in the parameter group
1	Heating source	Gas fired furnace (efficiency), boiler (capacity, efficiency), ground source heat pump (rated heating capacity, rated heating power consumption, rated load/source side flow rate), ground heat exchanger (depth, number of boreholes, etc.)
2	Cooling source	DX coil (COP, sensible heat ratio), ground source heat pump (rated cooling capacity, rated cooling power consumption, rated load/source side flow rate, etc.)
3	AHU	AHU SAT setpoint, outside air fraction schedule, 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.), radiant heating floor (hydraulic tube inside diameter, heating control throttle range etc.), chilled beam (supply air flow rate, maximum total chilled water flow rate, beam length, number of beam etc.)
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	Sizing parameter	Size factor, design parameters for zones, system and plant (zone cooling design supply air temperature, loop design temperature difference, etc.)

calculated. In Figure 1, standard deviation for each output is presented for both the nominal model and the high performance model.

It is evident that the energy efficient design is more robust to uncertainty. We also find that the uncertainty in peak demand (the simulated hour with highest magnitude consumption) is much less than in the annual consumption. This can be explained by the idealized control systems within the model, which attempt to keep process variables within a controlled range.

It should be noted that the total consumption of the high performance building is less than the nominal building, and this should be accounted for when considering the uncertainty. To accommodate for this difference, the coefficient of variation (CV) for each of the outputs of both models is presented. The CV is the standard deviation divided by the mean, which allows a comparison of distributions from dissimilar sources (which consume drastically different amounts of energy). The plot of the CV for each of the outputs of both models is presented in Figure 2.

For brevity, the entire distributions for only two of the outputs are illustrated in Figure 3. The distributions for all of the other outputs look fairly similar to these

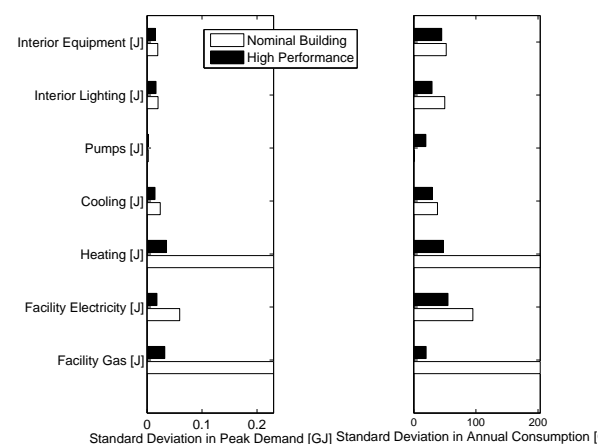


Figure 1: Standard deviation for the seven outputs of the two models (nominal model and high performance design).

two plots. Figure 3 shows that a low energy building design with well integrated envelope and equipment is more robust to parameter variations than a conventional design that does not explicitly address subsystem interactions. In addition to this, the CV's are

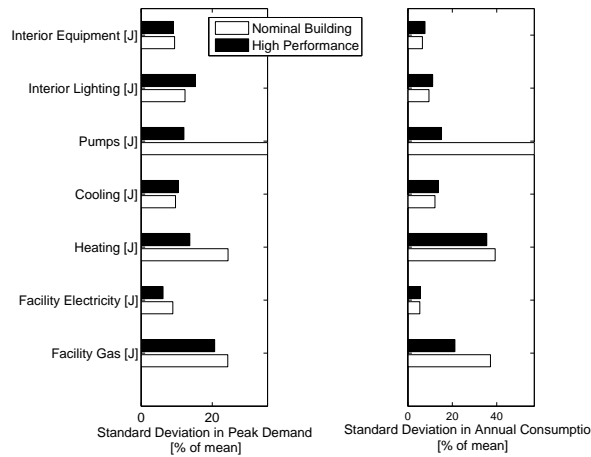


Figure 2: Coefficient of variation (standard deviation as % of Mean) for the seven outputs of the two models (nominal model and high performance design).

most different between nominal and high performance building in heating and facility gas, which also suggests the role of the good envelope design (which affects heating energy consumption the most).

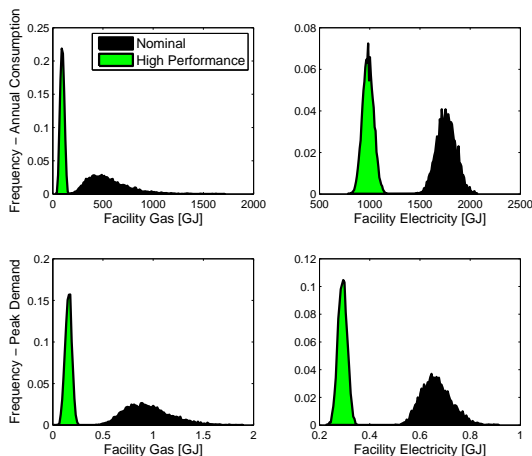


Figure 3: Example histograms of the two main facility wide outputs.

Parameter Sensitivity

After gaining insight into how uncertainty in parameter inputs influences the uncertainty in the outputs, we now proceed to calculate the sensitivity indices which identify which parameters influence the variance of the output the most. Figures 4 and 5 illustrate the aggregated total sensitivity indices for the 10 parameter groups described in Table 2. The total sensitivity (calculated from μ_m in Equation 1) for each of the parameters was calculated. If the influence coefficient was less than 0.08, it was considered negligible and ignored. We came up with this number by observing a cutoff in the number of influential parameters versus the sensitivity index amplitude. All parameters with an index greater than this threshold were then collected

into their respective parameter type (as in Table 2). For the nominal model, 55 of 746 (7.4%) were found to be important, while 63 of the 947 (6.7%) were found to be important for the high performance model. 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 group type and an output type. It should be noted that since we are using derivative based sensitivities (Equation 1), the summation may be larger than 1.0.

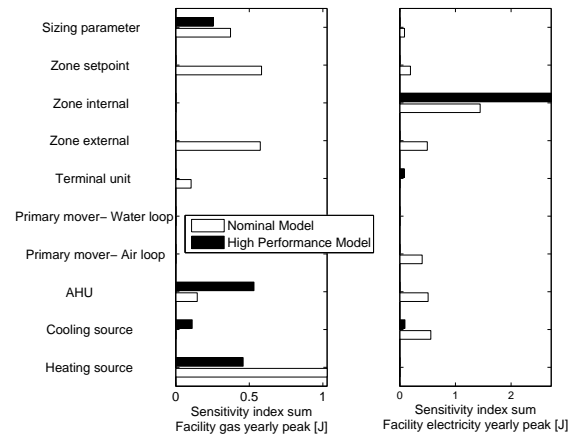


Figure 4: Aggregated influence coefficients for yearly peak energy consumption (nominal and high performance models)

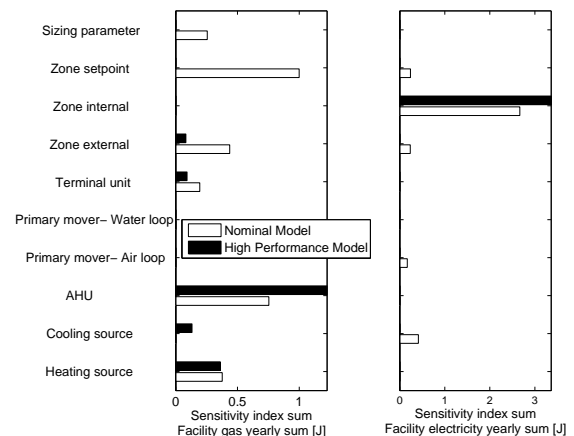


Figure 5: Aggregated influence coefficients for annual energy consumption (nominal and high performance models)

It is clear from Figures 4 and 5 that the high performance model has different parameter sensitivities compared to the nominal design. Below we go through each parameter type and describe which specific parameters are most influential.

- Parameter type 1 - Heating Source: The most significant parameters in this group are related to the efficiency of the boiler (in the nominal model) and the gas burner efficiency for each air handling unit (in the high performance model). In nominal

model, a boiler is used to provide hot water to re-heat coils in VAV boxes. On the other hand, in the high performance model, the only heating source is the gas burner in the AHU for the DOAS (dedicated outside air system).

- Parameter type 2 - Cooling Source: The sensitivity due to cooling source parameters arises predominately from the coefficient of performance (COP) ratings for the three AHUs and the gas consumption (both sum and peak) in the high performance model. This may occur because in the high performance model, chilled beams are used in the cooling season and there is humidity control to avoid condensation on the chilled beam surface.

There is also a large connection between cooling source parameters and electricity usage in the nominal model. The specific parameter that comes into play is the COP of the DX system because all of the cooling is handled by DX coils. In the high performance model, only the dedicated outdoor air system (DOAS) system use DX coil, most of cooling is handled by GSHP and chilled beams.

- Parameter type 3 - Air Handling Unit: The seasonal reset supply air temperature supply setpoints for the three AHUs are the only set of parameters from the air handling unit that influences the variance in the consumption variables. The Supply air temp setpoints have a big impact on the gas burner energy usage in both cases. The gas burner in the AHU is the only HVAC equipment using gas in the high performance case, while there is a gas boiler in the nominal case for providing hot water to the reheat coil in terminal VAV boxes. For both cases, HVAC equipment consumes most of the gas. However, HVAC equipment only consumes less than 35% electricity in both cases (nominal - 24%, high performance - 32%). This can explain why gas consumption is more sensitive than electricity consumption.
- Parameter type 4 - Primary Mover - Air Loop: The efficiencies and pressure rise for the fans is the most influential parameters in the air loop. In the high performance model, the size of fan in AHU is smaller since the AHU is only handling ventilation (DOAS), fan energy consumption is a very small portion of total energy consumption.
- Parameter type 5 - Primary Mover - Water Loop: The parameters that influence uncertainty in the water loop do not influence the uncertainty in the facility outputs very much and this may be due to the relatively low energy consumption on the primary water loop. For instance, the pump usage is only 0.045% of total facility electricity in the nominal model and 6.45% for the high per-

formance model. A few parameters in the water loop for the high performance model (hot water pump rated head, condenser pump rated head and motor efficiency) are still small but may be due to the increased pumping due to the chilled beams.

- Parameter type 6 - Terminal Unit: In the nominal model, outdoor air flow per zone was found to be most significant parameters affecting gas consumption (both yearly sum and peak). The high performance model has very small influences from both the induction coefficient for one of the chilled beams as well as the radiant floor heating setpoint.
- Parameter type 7 - Zone External: The maximum dry-bulb temperature for the heating design day is the most significant parameter for the nominal model (this shows up in all four consumption cases). Followed closely behind this is the ground temperatures for January, June, and July (since ground temperatures have significant impact on building loads, and building loads in these three months are relatively large). In the high performance model, these design day conditions do not have any influence. In the high performance model, the building envelope is very good, and therefore outside air temperature will not have significant impact on the system performance. In addition to this, there is only a slight contribution from some of the envelope parameters like the roof insulation, dirt correction factor on the windows, and water temperature of the water main.
- Parameter type 8 - Zone Internal: The parameters that influence the electrical consumption in the nominal model are the lighting schedules, the receptacle schedules and the elevator schedules (in EnergyPlus a maximum power/load level is defined and then a fraction of this level is set up in the time schedule). For the high performance model, the same schedules were found to be the most influential. Due to high performance envelope, uncertainty in the energy consumption is dominated by the internal load more than in the nominal design case.
- Parameter type 9 - Zone Setpoint: The zone heating and cooling setpoint schedules have an almost equal contribution to the variance in both the peak and sum gas usage for the nominal building. These schedules do not show up in the high performance building which may be because radiation heat transfer is dominant in the high performance model.
- Parameter type 10 - Sizing Parameter: The nominal model has significant influence in its variance from zone design supply air temperatures which affects the gas consumption. This is also the case for the high performance model, but to a lesser degree. This is because in the high performance

model, most of load is handled by a hydronic system (e.g. radiant heating floor in heating mode, chilled beam in cooling mode), and the air system (e.g. DOAS) affects the overall system performance to a lesser extent.

CONCLUSION

In this paper we performed large scale uncertainty and sensitivity analysis on two similar building designs using recently developed rapid sensitivity and uncertainty analysis tools. The first design was a standard medium sized office building and the second design is the same building with high performance features substituted (better envelope and more efficient equipment). In both models, almost all parameters were considered uncertain (700-900), and thousands of simulations were performed to quantify how this uncertainty influences the predicted energy consumption. It was found that the high performance building is more robust to parameter uncertainty due to better specification of the envelope and the equipment, while considering their interactions carefully during design. It was also found that internal zonal loads (lighting, plug loads, etc.) are dominant parameters for propagating uncertainty to the output, particularly for cooling energy consumption. This is more noticeable in the high performance model due to the energy efficient envelope that manages external loads very well and leaves the system more sensitive to internal loads. This type of analysis is useful not only for building design, but for its operation as well as it identifies which control parameters or schedules influence energy consumption the most.

There is an ongoing effort to make this process more manageable with respect to the actual building design process. In this paper we studied on the order of 1000 uncertain parameters. This analysis is being performed on other models of different building types. There is an effort to collect all of these results into a database that summarizes the top 10% most influential parameters in each building type. Knowing this information would give the designer a list of the most important parameters in their design model and accelerate the analysis, making it more manageable and scalable.

ACKNOWLEDGEMENTS

This work was performed under the contract W912HQ-09-C-0054 (Project Number: EW-1709) administered by SERDP technology program of the United States Department of Defense under program manager Dr. Jim Galvin.

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