IMPACTS OF UNCERTAINTY IN ENERGY MODELLING WIDELY USED IN AGGRESSIVE ENERGY EFFICIENCY REGULATIONS

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ABSTRACT

Building Assessment Tools (BATs) are widely used to estimate the performance of building and to assist designers in making decisions. As building codes and rating systems move from prescriptive to performance-based metrics, BATs are increasingly used to show compliance. BATs use computational methods and the results are mostly in a single annualised metric. However, the scientific community has shown that aleatory factors such as occupant behaviour and weather make the potential energy use of a building far from being a single deterministic value. Also, it is known that there is a significant deviation between predicted (at design stage) and actual energy use in buildings. These variations reduce the credibility of the predictions, questioning the acceptance of BATs results without considering underlying errors. This problem is amplified in under-policed construction sectors. India is one such example, where the adoption of Energy Conservation Building Code is becoming mandatory and one of its compliance method is based on BATs. Our work, therefore looks at the uncertainty in a typical multi-storey commercial office building's performance in Delhi and shows implications of variable inputs in the results.

The paper first reviews the use of BATs and existing studies on simulation uncertainty. Then uncertainty is evaluated in energy simulation of a sample building, including effects of inconsistent construction practices. EnergyPlus is then fed values sampled (by Monte-Carlo method) from probability distribution functions of inputs (building fabric and operational parameters). Further sensitivity and uncertainty analysis of the results is performed. From the 3500+ simulations, the most sensitive inputs found were Wall U-values, cooling setpoints and infiltration. The variation in cooling demand and discomfort hours is more than three times between best and worst cases.

INTRODUCTION

Anthropogenic activities in the last decades have altered the natural climatic cycles due to the large CO2 emissions. At the time of writing, atmospheric CO2 concentration is 399 ppm (Tans & Keeling, 2014) (Mauna Loa Observatory); 33% more than the highest concentrations found in earth polar ice cores dating back to 650,000 years (IPCC Working Group Science, 2007) and 37% more than the highest concentrations in 8,00,000 years (EPICA DATA) (Lüthi, D., et al., 2008). Large concentration of CO_2 and greenhouse gases (GHG) is resulting in rising average temperature of the biosphere. It is estimated to rise by 0.3 to 4.8 in next 100 years (IPCC, 2013).

Governments around the world are evaluating the impacts of climate change on their economies. The Indian economy could be considered as climate sensitive as many sectors are wholly or partially dependent on seasonal weather cycles. Meteorological data shows that in past 50 years there have been an increase in the mean annual surface air temperature by 0.4°C (INCCA, 2010). In addition, intensity and frequency of extreme weathers like heat waves, dry spells and heavy rainfall have increased (INCCA, 2010). Further, data assessments indicate a warmer climate in future over India, with temperature rising by 2-4°C by 2050 (INCCA, 2010).

Buildings have substantial impact on environment. In a developing country like India the demand for infrastructural development of cities has led to a rapid grown in construction, which contributes a 1/4 of India's current carbon emissions (Parikha, et al., 2009). Buildings are responsible for >40% of energy use and third of GHG emissions globally (UNEP, 2009). Energy use in buildings includes operational and embodied energy and 80% of building's life cycle energy is by the former (Gregory A. Keoleian, 2008). Also, the building sector has the highest and most cost-effective potential for providing long-term, energy and GHG emission savings globally (IPCC, 2014). This has also been observed at national level in India (PC : IEP, 2006). Building assessment tools (BATs) are widely used for estimating of energy use in buildings.

Buildings by themselves are very complex systems when their energy use is considered. When assessing their energy demands, many parameters have to be considered, and in most cases, those parameters are not certain (Pettersen, 1994). These uncertainties arise due to lack of knowledge in simulation inputs, improper construction methods, approximate weather data and unpredictable occupant behaviour.

Statistical analysis of energy simulations has been seen as a powerful tool in predicting this variability (MacDonald, et al., 1999) (Blight & Coley, 2013). In this paper, we assess the effect in outputs by the variation of some design input parameters, which are, or should be regulated by building energy polices.

This paper begins with a background section reviewing: (1) the use of BATs for design decision making; and (2) existing studies that analyse uncertainty in simulation results. This is followed by assessing variations in input parameters in energy simulations of a typical commercial office building in Delhi. The paper focuses on uncertainties in fabric (thermal properties) and operational parameters. It concludes by performing uncertainty and sensitivity analysis of the input variables for the output of cooling and heating energy use and discomfort hours.

BACKGROUND

Building Assessment Tools and energy codes

BATs are widely used to estimate energy performance of building designs. These tools assist designers in the decision making process by providing comparative and detailed assessments of building performance under various design conditions and strategies. Due to their capabilities to model building systems and physical phenomena in detail, they are used make predictions about the performance of a building under a wide range of scenarios. But, in most cases, these tools rely on input parameters that are either assumed or averaged to provide deterministic outputs, i.e. predict future scenarios that are known to be uncertain (Haldia & Robinson, 2011) (de Wilde & Tian, 2009) (Blight & Coley, 2013) (Ramallo-González, et al., 2013). This results in simulations that are fundamentally unrealistic and have shown errors exceeding 100% (Demanuele, et al., 2010).

In the context of the move from prescriptive to performance-based building regulations (e.g. US building energy performance assessments (BECP:US DoE, 1991); and Energy Performance of Buildings Directive in Europe (The European Parliament and The Council of European Union, 2003)), deterministic outputs seem to be ill-suited to provide realistic estimates of future performance due to the well demonstrated stochastic nature of energy use in buildings (Page, Robinson, & Scartezzini, 2007) (Blight & Coley, 2013). Similarly, India’s Energy Conservation Building Code has performance based compliance criterion, based on Appendix G and ECB chapter of ASHRAE user manual (BEE, 2009). Experience in other countries suggests that voluntary codes eventually make the transition to mandatory (NPACC, 2009) (Liu, et al., 2010).

Apart from the issues of uncertain results due to deterministic nature BATs’ results, construction techniques that are widely used in India might result in underperforming fabrics even when conforming to ECBC specifications. Uncertainty analysis (with the inclusion of construction process deficiencies) could provide a contextual picture, with a more robust understanding of the likely outcomes of measures in the ECBC.

Energy Conservation Building Code (ECBC)

Developed by Bureau of Energy Efficiency, Govt. of India, ECBC is the first stand-alone standard for energy efficiency of buildings in India, prescribing a minimum standard for energy use in new buildings and major retrofits. It is applicable to commercial buildings with conditioned areas >1000 m^2. It targets baseline energy consumption reduction by adoption and implementation of minimum standards in construction and design practices.

Among the two compliance options, in the presctive compliance, it lays specifications (mostly tangible) on key design features of (1) Building Envelopes, (2) Mechanical systems and HVAC, (3) Hot Water, (4) Lighting and, (5) Electrical power and motors. ECBC’s ‘Prescriptive Method’ requires adoption of these minimum requirements whereas another performance-based path requires whole building to prove efficiency over base building defined by the code. In both the cases, BATs are used, doing simulations and generating the required numbers. Simulations have to be done in the performance approach and specifications of in the prescriptive approach have been developed after simulations.

Uncertainty and applicability of BATs

Most building simulation software packages use deterministic algorithms to predict the building energy use and provide a single figure of demand, the prediction of energy use in the real world is a much more complicated task. Not knowing the confidence in the result obtained in a deterministic fashion could be a substantial risk. Uncertainty in building simulations arise due simplifications in computation process and building complexity to reduce computing time; or because of unknown and erroneous input parameters (Clarke, 2001). Simplification generally occurs in inputs like weather data, material properties (like U-values), geometry etc. There, only the mean or most probabilistic values are used. This provides an unrealistic picture as value of each input can vary within a range of data. This theoretical simplification gives a range for the value calculated but not a credible result (especially when results depend on many such inputs). Adapted from Ramallo-González’s PhD thesis (Ramallo-González, 2013) and other similar works, we classify the types of uncertainty into three groups:

1. Environmental: Uncertainty in weather as nearest weather station’s data is used and uncertainty in prediction of climate change.
2. Workmanship and quality of building elements: Differences amid the design and the real building: Conductivity of insulation, infiltration, thermal bridges, U-value of walls and windows.

3. Behavioural: Building occupant's behaviour and usage patterns.

Additionally there is divergence in computation i.e. the approximation and uncertainty in computational formulas in the simulation tools. Above groups, describe the broad areas of uncertainty. Based on the reasons of existence they can also be divided in two types, aleatory and epistemic. While, aleatory uncertainties represent randomness and probabilistic uncertainties within the actual measured values, the epistemic uncertainties are due to lack of knowledge and extensive appropriate data in the inputs (Sandia Lab, n.d.). Uncertainties make it impossible to find, for some inputs, a value that is actually true; observed by Newton when energy simulations were in their infancy (Newton, et al., 1988):

"…the choices of climatological data and occupancy patterns are not easy and, in many cases, there is no single correct value."

Assessment of uncertainties at all levels is required to get results with confidence intervals. It is the only way to have realistic assessments and a better understanding of energy simulation results. In this study, aleatory and epistemic uncertainties in groups 2 and 3 would only be considered.

Areas where consideration of uncertainty can play a major role are in energy-savings performance contracts and in certification and code compliance for green and ultra-energy efficient buildings (e.g. LEED Ratings, or codes like EPBD in Europe or ECBC in India.). Since BATs are used to inform the design and evaluation of a building, there is a significant risk (that could be regarding financial or occupant comfort) because of the variation of the real and predicted performance of a proposed strategy. The additional information about the measure of the uncertainty like confidence intervals, if provided, would help in taking a much better and optimum decision by the designer leading to an increasing likelihood good outcome (with respect to the building performance). Therefore the argument is that BATs should not be relied upon in a deterministic manner but in a probabilistic way. In this paper, we have used these indicators to see impact of workmanship and operations in energy performance of buildings.

The lack of focus on uncertainty when energy assessment is performed in practical scenarios is understandable because of logistics required in its incorporation. Also, even in scientific publications, it is a new topic shows that how these methods are still immature. However, from a conceptual point of view, this lack of concern in uncertainty is surprising. While commercially available tools do not provide suitable methods to explore the influence of uncertainties in assessments despite their importance; it is surprising that performance assessments using BATs is incorporated in building codes

Most of the studies discussed in the next section take the variation in input parameters as a normal distribution. These variations when seen practically do not necessary apply. E.g. actual measurements of accumulated electricity use in the UK (Carbon Trust, 2011) show a non-normal distribution. For that reason, in this paper, probability distributions that are more representative have been used. They represent more closely what seen in reality. This point will be further developed in later sections.

Existing studies on uncertainty in building energy design

There have been many studies in the last two decades vis-à-vis uncertainties influencing the results of BATs. However, the studies are mainly theoretical and have not been applied in real world problems. Pettersen's work is one of the first studies that looked at the effects of climate variability, building characteristics and occupants (Pettersen, 1994). Using a statistical simulation method, based on Monte Carlo Analysis (MCA) Pettersen studied the variation of energy use in dwellings. It showed that occupant behaviour variation results in around 15% deviations of outputs.

The impact of uncertainties in specific inputs of BATs has been evaluated in depth. De Wit studied the impact of uncertainty as well as the relative importance of non-linear effects and parameter interactions on thermal comfort performance, using a factorial sampling technique (de Wit, 1997) (de Wit & Augenbroe, 2002). De Wit explored the parameters like, physical assumptions in measurements and simplifications in calculations. Domínguez-Munoz on the other hand studied the impacts of uncertainties on the peak-cooling loads using MCA with a global sensitivity analysis to identify the most important uncertainties (Domínguez-Munoz, et al., 2010).

Hopfe also worked on uncertainty and sensitivity analysis for thermal comfort prediction to help in design decision making and optimisation (Hopfe, et al., 2007). In her 2011 paper (Hopfe & Hensen, 2011) it was extended to showing the implication of uncertainties on energy consumption and thermal comfort with respect to various building performance parameters having physical, design based, and scenario uncertainties with their standard deviation.

Several works of MacDonald have been focused on quantifications and application of uncertainty on the predictions of the building simulation software (Macdonald & Strachan, 2001), (MacDonald, 2002).In his thesis (MacDonald, 2002) he described two ways of achieving this: The first method was based on altering the input variables, requiring multiple simulations of systematically altered models and the subsequent analysis of the differences, with differential, factorial and Monte Carlo sampling, the second method consisted on altering the underlying algorithms of the simulation tool so that uncertainty is included at all computational stages and a single simulation provides the results. Applying these changes in simulation tools, the predicted uncertainty in thermo-physical properties, casual heat gains and infiltration rates was quantified and was compared with Monte Carlo and differential analysis. Following it further, (MacDonald & Clarke, 2007) discussed the issue of non-convergence building simulations. The non-convergence was caused by introduction of new terms that were uncorrelated to existing terms.

Other recent works in UA in simulation include (Wang, et al., 2012) (Eisenhower, et al., n.d.). While, Wang examines uncertainties in energy use due to annual weather variation and building operations using Monte Carlo method to analyse, Eisenhower elaborates the existing UA and SA techniques to take into account the influence of 1000+ parameters.

Uncertainties in India Context

The uncertainties in input parameters are even more important in the Indian context because of the present techniques of construction used; most of the construction is in-situ. Indian standards of codes and practices for construction allow significant tolerances and deviations in the fabric (IS:2212:2005 (BIS, 1991)), (IS:4913-1968 (BIS, 2001)), (IS :1948:1961 (BIS, 2006)). General construction practice in New Delhi shows that most of the construction procedures are not consistent. The quality is primarily dependent on the skills of the professionals. The doors and windows have gaps created at the time of installation that are filled with plaster (IS:4913-1968 (BIS, 2001)). This compromises the U-value, airtightness and it might lead to thermal bridging.

The bricks used for construction also have variation in their properties due to the composition of clay used and non-consistency of the firing process (Sarangapani, Reddy, & Jagadish, 2002). Small ducts for building services (plumbing pipes and electric conduits) are also embedded within walls (SP20 (BIS, 1991)), (IS:2212:2005 (BIS, 1991)). This reduces the wall's thermal effective thickness. Therefore U-value of walls is uncertain. These inconsistencies in the building fabric can create much larger variation in the actual energy use of the building. We show here a method to quantify this effect. We think it is a powerful tool for policy makers, as it enables them to understand the fruitless and somewhat detrimental impact of stringent energy policies on an un-prepared industry. The building components used should be quality controlled, ensuring consistency in performance then only the energy polices can be implemented. Such recommendations are incorporated in ECBC, e.g. supply-chain improvements to ensure availability of certified products, but are not exercised in practice.

In order to estimate the overall effect, uncertainties because of simulation tool's approximations and inaccuracy in testing of materials have to be combined with the effects of on-site construction procedures on the building fabric thermally. Studies exploring the latter issue were not found. Based on past studies (Heo, et al., 2012), (de Wilde & Tian, 2009), (Hopfe, et al., 2007), (MacDonald, 2002), (Wang, et al., 2012), (Pettersen, 1994) which address the uncertainty issue in different context (Figure 1) (regarding technique of construction) and with assuming the one's generating because of local constructions (calculated from professional guides and observation) uncertainties in various parameters are estimated. A more accurate finding of the distributions is suggested for further work. We have used generic distributions that could be changed for each region to obtain more accurate results.

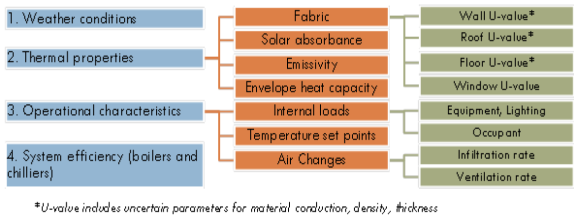


Figure 1 Uncertanity Parameters included in existing studies

In this paper, a methodology for uncertainties related to thermal properties, temperature set points, internal loads and ventilation is presented. Weather, system efficiencies and other operation parameters have not been considered but the method can be extrapolated to include these too.

METHODOLOGY

Uncertainty propagation, sensitivity analysis (SA) and uncertainty analysis (UA) has been carried out in this paper in the following manner (It has been assumed in this study that the input variables are not dependent):

1. A baseline building with fabric based on ECBC specifications was created as refernce point.
2. Based on existing studies, five uncertain factors were selected and the calculations of variability with probabilistic distributions defined.
3. The deviation in conditioning loads and occupant comfort in relation to the input variables was explored. Random MCA sampling is used for input variables based on their determined probability distributions. Those samples are used for multiple EnergyPlus runs for Propogation of uncertanity.
4. Multiple Linear Regression is done to assess the sensitivity of variables -sensitivity analysis (SA).
5. A mean and peak variation is calculated to assess the uncertainty - uncertainty analysis (UA).

SIMULATION

Building Details

The reference building is an eight story commercial office building in New Delhi based on normal practice. The floor area is 1020 m2 (total built up area of 8160 m2). The floor-to-floor height is 4m.

The building has longer axis along N-S direction. Each floor is taken as a separate zone.

The building is fully air conditioned with a window to wall area ratio of 40%. Table 1 below shows the input parameters for the initial base case.

Table 1 Table showing the input parameters taken for the baseline building model

Criteria	**Remarks**		
Structure	RCC and brick infill panel walls		
Walls	0.44 W/m2K ; Insulated brick cavity walls		
Windows	3.3 W/m2K; air filled clear double glazed (6-12-6) SHGC=0.25		
Roofs	0.40 W/m2K; Insulation covered RCC slabs		
Setpoints	Heating -19°C; Cooling - 24°C		
Room type	**Occupancy schedule**		**Internal gains**
Office Space	Weekdays	0800-2200	People (10m2/person), Lighting:10 W/m2 Equipment: 20W/m2
	Weekends	Off	

Outputs considered

Two outputs were obtained from the simulations: (1) the total heating and cooling energy use; and (2) the non-comfortable hours (NCH). The standard ASHRAE 55-2004 Predicted Mean Vote (PMV) was used to define NCH (integrated in EnergyPlus).

Variable inputs and their distributions

As described earlier, the uncertain factors taken are fabric thermal properties, temperature set points, and ventilation. The section below shows input variables and Table 2 and 3 show the base case, upper and lower values, distributions and their variation graphs.

Internal loads

Internal loads a very significant aspect governing the building performance. Internal loads cannot be negative, thus, a normal distribution is not ideal to represent the variation. In earlier studies (Schnieders & Hermelink, 2006) internal loads have been assumed to vary in symmetric distribution. However, actual measurements done on accumulated electricity use in the UK (Carbon Trust, 2011) shows that the electricity use has been an asymmetric distribution.

Infiltration rate

Infiltration is primarily due to construction defects, gaps and cracks. Onsite fabrication of windows and high tolerances in construction of fenestration increase infiltration drastically.

Temperature set points

Set points depend on personal preferences. Variation in set points is assumed to be in a normal distribution as these variables are far from zero, therefore could be assumed symmetric. During sampling, if the heating set point is less than 2 degrees below the cooling set point, the sample is rejected and another one calculated as this is considered the width of comfort (ASHRAE, 2009).

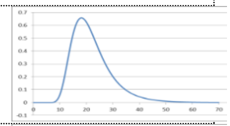
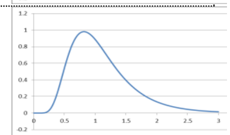
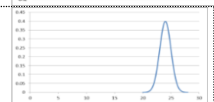
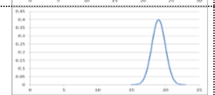
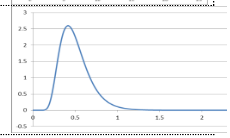
Wall U-value

Wall U-Value has a large impact on energy calculations. Standard deviation in U-values because of measurement techniques is 5 % (MacDonald, 2002). Moreover, due to construction techniques, detailing and material manufacturing processes, the variation is more. It is more likely that errors in manufacturing processes and workmanship lead to a larger U-Value (lower quality).

Table 2 Uncertain parameters chosen and their range values

Parameter	**Element changed**	**Units**	**Base**	**LB**	**UB**
Internal Loads	Equipment Loads	W/m^2	20	10	50
Infiltration Rate	Space Infiltration Design Flow Rate	Ach/h	0.75	0.25	2
Cooling Set points	Thermostat	°C	24	22	26
Heating Set points	Thermostat	°C	19	17	21
Wall U-Value	Insulation Cond.	W/mK	0.03	0.02	0.11

Table 3 Uncertain parameters chosen and their distribution

Parameter	**Distribution Name**	**Distribution details**	**Graph**
Internal Loads	Scaled inverse chi-squared	$\mu = 20$; $\tau^2 = 2$	
Infiltration Rate	Log Normal Distribution	$\sigma = 0.45$; $\mu = 0$	
Cooling Set points	normal	$\mu = 24$; $\sigma^2 = 1$	
Heating Set points	normal	$\mu = 19$; $\sigma^2 = 1$	
Wall U-Value	inverse gaussian	$\mu = 0.5$; $\lambda = 4$	

SIMULATION RESULTS ANALYSIS

Based on the values ranges and the PDFs, values between the upper and lower bounds are selected by random monte-carlo sampling for multiple simulation runs. Results of all 3500-simulation runs are analysed to propagate the uncertainty and to perform a Sensitivity Analysis and Uncertainty Analysis.

Uncertainty propagation

The histograms in Figure 3 show variation in heating and cooling energy use and non-comfortable hours. Being a cooling dominated climate the cooling energy use >> heating energy use. The cooling energy use in the building varies between 4000 GJ and 13500 GJ with the peak frequency at 7400 GJ. Heating energy use shows a very large variation with values ranging from zero to 330 GJ. The peak frequency is at 0GJ and then 5GJ of energy with the average use of 11GJ. For the non-comfortable hours the values vary from 0 to 3700.

Sensitivity Analysis (SA)

Sensitivity of each input, for the outputs is gauged through regression. The analysis is similar to one in (Blight & Coley, 2013). Table 3 shows adjusted R Square value and Significance F for regression.

It can be seen that adjusted R square values are high (except heating energy use) showing high accuracy of the data. Significance F value is 0. This shows that the variables are still important and relevant enough and that the results are not by chance.

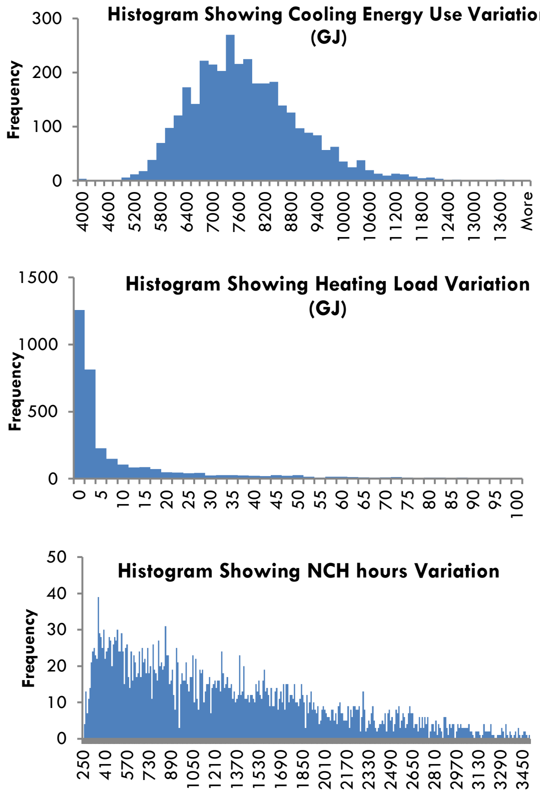


Figure 3 Histograms showing spread of output results

Table 3 Results of regression analysis showing adjuster R square value and significance F

Output Variable	adj R sq	F	Remarks
Cooling Energy	0.99	0	Regression model fits the outputs very well. Coefficient values are significant.
Heating Energy	0.63	0	There are more factors which affect the output. Coefficient values are significant
NCH	0.83	0	Regression model fits the outputs very well. Coefficient values are significant.

The regression analysis is done at 95% confidence interval and P-value <0.05 in Table 4 shows that those input variables are significant for the output. Green means significant and red means insignificant.

Residuals for each output also show randomness and equal distribution about the x-axis thus showing homogeneity and linearity and verifying the credibility of the regression.

Table 4 P-value of inputs for the different outputs

	Insulation Conductivity	Internal Loads	Cooling Set points	Heating Set points	Infilteration Rate
Cooling Energy	0	0	0	0.02	0
Heating Energy	0.20	0	0.007	0	0
NCH	0.35	0	0	0.001	0

The standardised coefficients are found by dividing the 'distance from the mean' by the standard deviation of each variable, and can be used to directly compare the relative contributions from independent factors. The taller the bar, more influential is the input on the output. Positive means a direct relation between the change and vice-versa.

The most influential variables for cooling energy are cooling set points, infiltration and wall U-value. Similarly, for heating energy, wall U-value, infiltration and heating set points are factors that are more dominant. For NCH hours, infiltration, wall U-value and cooling set point affect the most.

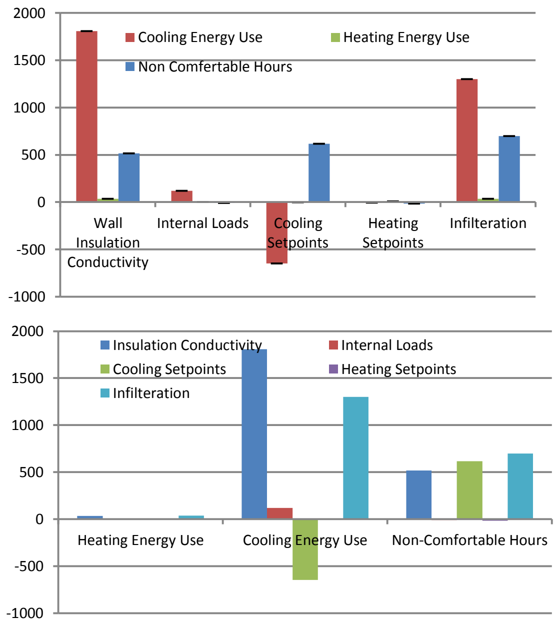


Figure 5 Standardized regression coefficient comparing the dependent variables and explanatory variables with each other

Uncertainty Analysis

The values in all outputs show substantial variation. Table 5 below shows the upper value, lower value, mean and standard deviation of the various outputs.

Table 5 Spread of the outputs because of variations in the input values

Outputs	Maximum Value	Minimum Value	Mean	Std. Dev.
Cooling Energy (GJ)	13564.74	4176.86	7663.06	1264.15 (16%)
Heating Energy (GJ)	332.24	0.00	11.34	24.82 (218%)
NCH (hrs.)	3700.83	190.5	1258.27	754.54 (60%)

It can be seen from the results that there is large variation and outputs have high percentage of uncertainty. Through the results, it can be seen that occupant behaviour is the most important aspect as in most cases; the occupants determine the internal loads and cooling set points. A conservative approach in estimating the internal loads can be quite detrimental in estimating building's cooling energy. Infiltration and U-value of the fabric also show that construction and proper airtightness is also required.

CONCLUSION

There can be a significant variation in the simulation result output because of the variation in the inputs. Cooling energy use because of occupant usage and construction quality alone produced variations over the mean of about 16% with the variation in maximum and minimum values of more than 200%. Similarly, NCH in the year has a variation from the whole year being comfortable to more than half a year being uncomfortable. The most influential variables in regarding the increase the cooling loads and decrease in comfort are infiltration and U-value of the walls; both are mainly governed by quality of construction. Internal gains and cooling set points are also important, they are governed by occupants. Therefore, owing to these persistent uncertainties, simulation results should be taken in a more probabilistic manner to ensure that the risk associated with the uncertainties in the inputs is also calculated.

Another important issue that needs to be addressed when performing uncertainty analysis is that the type probability distribution of input variables should be based on realistic factors and measured data. The use of normal distributions might not represent the actual variation in some cases as it has been shown here. Fail to use the right distribution could render the methodology misleading.

It is of prime importance that the uncertainty on input variables is considered when performing energy assessment. Obtaining stochastic results encourage constructor and designers to take the adequate measurements to minimise this variation when it has a large impact in the final energy use of the building. This has even more importance in buildings in which low-demands are the aim.

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