EFFECTS OF AGGRESSIVE ENERGY EFFICIENCY REGULATIONS ON AN UNPREPARED BUILDING SECTOR USING UNCERTAINTY ANALYSIS

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 developing nations because of under-policed construction sector. To address this, our work analyses uncertainty in a typical air-conditioned multi-storey residential 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 and 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 internal gains; cooling setpoints and infiltration. The variation in cooling demand and discomfort hours is more than double between the best and worst case.

INTRODUCTION

Anthropogenic activities in the last decades have altered climatic stability, water cycles and natural habitats. At the time of writing, atmospheric CO2 concentration is 399 ppm (Tans & Keeling, 2014) (Mauna Loa Observatory); 37% more than the highest concentrations in 8,00,000 years (EPICA DATA) (Lüthi, D., et al., 2008). The annual mean surface temperatures are rising due to greenhouse gasses (GHG) concentration increase. 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. Indian meteorological data shows a 0.4°C increase in the mean annual air temperature in the past 50 years (INCCA, 2010). Also, intensity and frequency of extreme weathers like heat waves, dry spells and heavy rainfall have increased (INCCA, 2010). Data assessments indicate warmer climates in India, with temperatures rising by 2-4oC by 2050 (INCCA, 2010).

Buildings have a significant impact on the environment. Infrastructural development of cities leads to rapid growths in construction, causing 25% of India's current carbon emissions (Parikha, et al., 2009). Buildings are responsible for 40% of energy use and 33% of GHG emissions globally (UNEP, 2009). The 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) (Chris Scheuer, 2003). 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 a national level in India (PC : IEP, 2006). Building assessment tools (BATs) are widely used for detail assessment of energy use in buildings.

Buildings are complex systems and their energy use assessments dependent on many parameters. However, in most cases, these parameters are variable and 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 building design input parameters, which are regulated by energy saving related 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 residential building in Delhi, including the effects of construction processes used. The paper focuses on uncertainties in the fabric (i.e. 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

Use of Building Assessment Tools (BATs) for code compliance to reduce energy use in buildings

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-Gonzáleza, et al., 2013). This results in simulations that are fundamentally unrealistic and have shown to have errors exceeding 100% (Brohus, et al., 2009) (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 (ECBC) (BEE, 2009) has a performance based compliance criterion (BEE, 2009). ECBC is partly mandatory and does not include residential buildings. Experience in other countries suggests that voluntary codes eventually make the transition to mandatory codes (National Action Plan for Energy Efficiency, 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.

Uncertainty and applicability of BATs

Most BATs use deterministic algorithms to predict a single value for the building performance. Actual prediction is more complex. 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:

- Environmental: Uncertainty in weather data because of use of nearest weather station's synthetic weather file and uncertainty in prediction of changing climate.
- Workmanship and quality of building elements: Differences amid the design and the real building: Conductivity of insulation and thermal bridges, infiltration amount or U-values of walls and windows.
- Behavioural: Actual building occupant 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. Aleatory uncertainties represent the randomness nature of some variables. Epistemic uncertainties are due to lack of knowledge (Sandia Lab, n.d.). Uncertainties make it impossible to find, for some inputs, a value that is actually true; observed by Newton when building 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 and evaluate designs, there is a significant risk (could be financial or of occupant comfort) if the real and predicted performance vary. Additional information about the uncertainty (like confidence intervals) would facilitate a more informed decision by the designer. Therefore, the argument of this paper is to prove how BATs should not be relied upon in a deterministic manner but in a probabilistic way, to provide the designers with stochastic indicators of the future performance or demand of the building. In this paper, we have used these indicators to verify the impact of uncertainties in workmanship and operations in the final energy performance of buildings.

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 studies the variation of energy use in dwellings, which was about 15%.

There is little literature showing the impact of uncertainties in specific inputs. De Wit studies the effect of uncertainty as well as relative importance of non-linear effects and parameter interactions on thermal comfort, using factorial sampling (de Wit, 1997) (de Wit & Augenbroe, 2002). He also explores effect of assumptions in measurement and simplification in calculations. Domínguez-Munoz studies the impact 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 et al. have also worked on uncertainty and sensitivity analysis for thermal comfort prediction to help in design decision making and optimisation (Hopfe, et al., 2007). Another paper written by Hopfe and Hensen (Hopfe & Hensen, 2011), covers the implication of uncertainties on energy consumption and thermal comfort using a theoretical case study and studying various building performance parameters using as inputs physical, design based, and scenario variables with their standard deviation.

Several works of MacDonald have focused on quantifications and application of uncertainty on the predictions of demand using building simulation software (MacDonald, et al., 1999), (Macdonald & Strachan, 2001), (MacDonald, 2002).His thesis (MacDonald, 2002) shows two ways of achieving this: The first way altered the input variables, requiring multiple simulations of systematically altered models and the subsequent analysis of the changes, with differential, factorial and Monte Carlo sampling; The second way altered the algorithm of BAT to include uncertainty at all computational stages. Applying these changes, the predicted uncertainty in thermo-physical properties, casual heat gains and infiltration rates was quantified and was compared with MCA and differential analysis. Further, the issue of non-convergence building simulations was discussed (MacDonald & Clarke, 2007). The non-convergence was caused by introduction of new uncertainty terms that were uncorrelated to existing terms.

In other recent works, Wang examines uncertainties in energy consumption due to annual weather variation and building operations using MCA (Wang, et al., 2012). Eisenhower enlarged uncertainty and sensitivity analysis to take into account the influence of 1000+ parameters (Eisenhower, et al., n.d.).

Uncertainties in India Context

The uncertainties in building input parameters are particularly relevant in the Indian context because of the techniques of construction used. Indian standards, codes and practices for construction allow significant tolerances and deviations in the fabric (IS: 2212: 2005 (BIS, 1991)), (IS4021: 1995 (BIS, 1995)), (IS: 4913-1968 (BIS, 2001)), (IS: 1948: 1961 (BIS, 2006)). General construction practice shows that most of the construction procedures are not consistent. From mixing of concrete by rough estimation to fabrication of wood framed doors and windows, all the work is done on-site. The quality is mainly dependent on the skills of the professionals. The doors and windows, constructed on site have gaps created at the time of installation which are filled with plaster (IS: 4913-1968 (BIS, 2001)) (IS: 3935: 1966 (BIS, 1986)). This technique compromises the U-value of the construction and airtightness and it might lead to thermal bridging because of the improper sealing and frame effects.

The bricks used for construction also have variation in their properties due to the variation in 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 in the walls (SP20 (BIS, 1991)), (IS: 2212: 2005 (BIS, 1991)). This reduces the wall's thermal effective thickness, affecting the overall U-value. These inconsistencies in the fabric can create variation in the actual energy use. We show here a method to quantify this effect. We think it is a powerful tool for policymakers, as it will enable them to understand the fruitless and somewhat detrimental impact of stringent energy policies on an un-prepared industry. In other words the building sector, at present, is not prepared for incorporating energy policies unless the functioning of the whole sector is modified. 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.

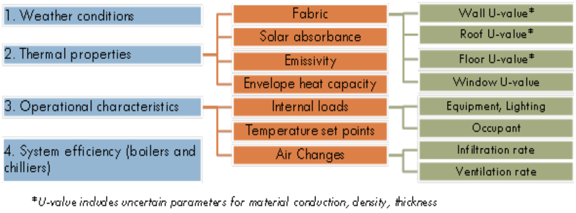


Figure 1 Uncertanity Parameters included in existing studies

In order to estimate the overall effect, uncertainties due to variation in inputs, discussed earlier, have to be combined with the impact of construction procedures in India on the building fabric. 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) on uncertainty (Figure 1) and assuming the uncertainties because of local factors, uncertainties in various parameters are estimated. A more accurate finding of the distributions is suggested for further work. For this paper, we have used generic distributions that could be changed for each region to obtain more accurate results.

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 in this study, 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, six major uncertainty factors were selected and the calculations of their 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 (MLR) is done to asess the sensitivity of variables - sensitivity analysis (SA).
5. A mean and peak variation for each output is calculated to assess the uncertainty - uncertainty analysis (UA).

SIMULATION

Building Plan

The reference building is a three story residential building in New Delhi based on normal practice. The floor area is 75 m2 (total built up area of 225 m2). The floor-to-floor height is 3 meters. The building has longer axis along E-W direction. The Living (4.275m*4.8m – with toilet)/Dining (2.915m*2.8m) room is in North and the bedrooms are located on in SE (3.915m*4.21m) and SW (3.235m*4.21m – with toilet) corner; the kitchen faces West (2.8m*1.885m). Each room is taken as a separate zone.

Construction and operation

The building has a mixed mode running system with natural ventilation happening between heating and cooling setpoints. 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; Openable, and air filled clear double glazed (6-12-6)		
Roofs	0.40 W/m2K; Insulation covered RCC slabs		
Setpoints	Heating -19°C; Cooling - 24°C		
Room type	**Occupancy schedule**		**Internal gains**
Bedroom	Weekdays Weekends	2200-0600 2200-0600; 1400-1600	2 people, 1 TV, 1 tube light, 1 fan
Kitchen	Daily	0600-0800; 1200-1400; 1900-2100	1 person, 1 tube light, 1 fan, 1frige
Living/dining room	Weekdays Weekends	0600-1000 0600-0200; 1600-2200	4 people, 1 TV, 8 tube lights, 4 fans

Outputs considered

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

Variable inputs and their distributions

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

Internal loads

Internal loads are one of the most significant aspects governing the building performance. Internal loads cannot be negative, thus, a normal distribution is not ideal to represent the variation in internal loads. In previous studies (Schnieders & Hermelink, 2006) internal loads have been assumed to vary in a symmetric distribution. However, in actual measurements done on accumulated electricity use in the UK (Carbon Trust, 2011) it has been seen 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 heating and cooling set points is assumed to follow a normal distribution as these variables are far from zero, therefore could be assume 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

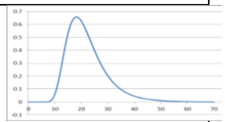
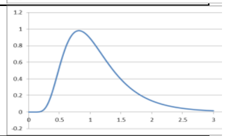
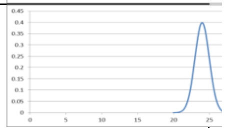
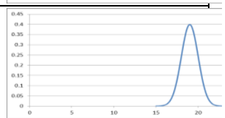
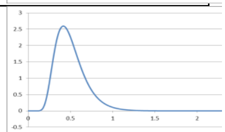
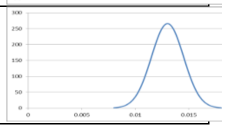
Wall U-Value has a large impact on energy calculations. Standard deviation in U-values because of measurement techniques is 5 % (MacDonald, 2002). Moreover, due to construction techniques, detailing and material manufacturing processes, the variation is more. It is more likely that errors in manufacturing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

Window U-value

The in-situ construction of windows will affect the overall U-Values. The variation in the overall U-Values is mimicked by changing in thickness of the cavity as we consider it is the parameter of the window more likely to vary in a production process with poor quality control.

Table 2 Uncertain parameters chosen and their distribution

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
Window U-Value	Air Gap	mm	0.013	0.01	0.016

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	$\mu = 0.5$; $\lambda = 4$	
Window U-Value	normal	$\lambda = 0.013$; $\sigma^2 = 0.0015$	

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 3427-simulation runs are analysed to propagate the uncertainty and to perform a SA and UA.

Uncertainty propagation

The histograms in Figure 3 show variation in heating and cooling energy use and non-comfortable hours (minimum, average and maximum of all zones). Being a cooling dominated climate the cooling energy use is in GJ and heating energy use is in MJ. The cooling energy use in the building varies between 150 GJ and 385 GJ with the peak frequency at 225 GJ. Heating energy use shows a very large variation with values ranging from zero to 17GJ. The peak frequency is at 100 MJ of energy with the average use of 446 MJ. The graph is presented in logarithmic scale. For the non-comfortable hours the values vary from 0 to 2180, 0 to 3110 and 0 to 4960 for minimum, average and maximum for all the rooms respectively.

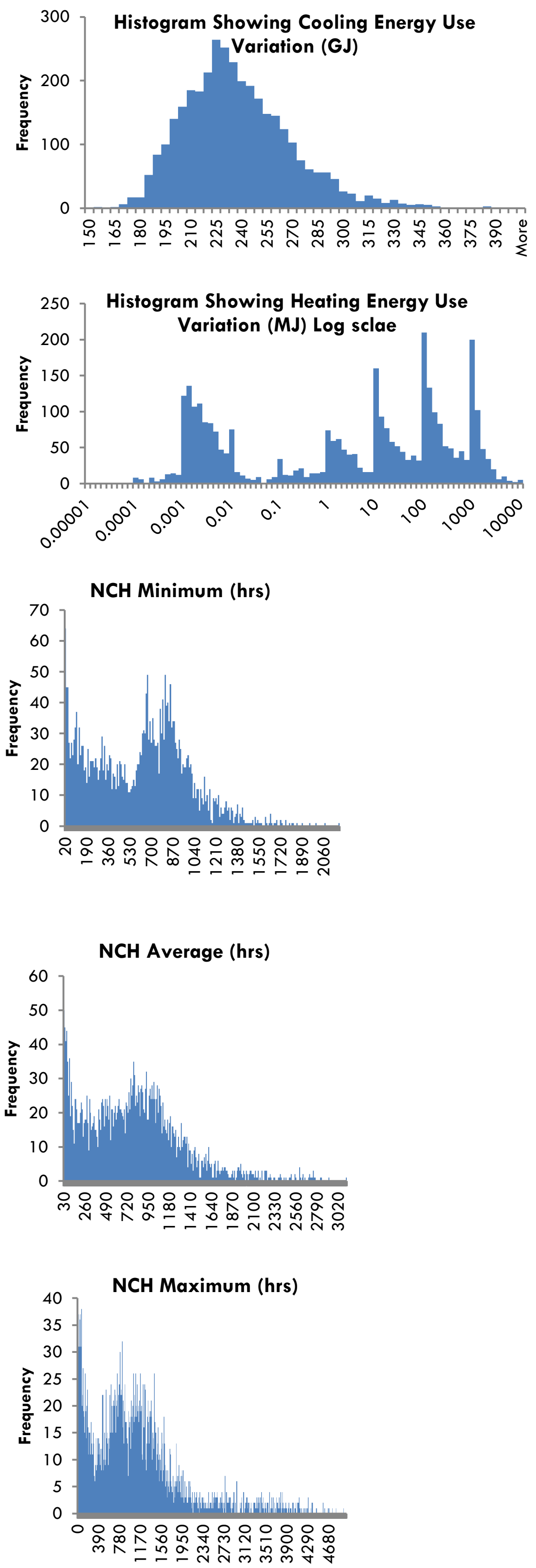


Figure 3 Histograms showing spread of output results

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.

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

Output Variable	adj R sq	F	Remarks
Cooling Energy Use	0.986	0	Regression model fits the outputs very well. Coefficient values are significant.
Heating Energy Use	0.546	0	There are more factors which affect the output. Coefficient values are significant
NCH Min	0.863	0	Regression model fits the outputs very well. Coefficient values are significant.
NCH Avg	0.818	0	Regression model fits the outputs very well. Coefficient values are significant.
NCH Max	0.721	0	There are some factors more affecting the output. Coefficient values are significant

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. 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.

Table 4 P-value (significance) of inputs for the different outputs

	Insulation Conductivity	Window Air Gap	Internal Loads	Cooling Set points	Heating Set points	Infilteration Rate
Cooling Energy	0	0.79	0	0	0.13	0
Heating Energy	0.00003	0.48	0.000001	0.0001	0	0
NCH Min	0.0003	0.59	0	0	0.34	0
NCH Avg	0.023	0.29	0	0	0.29	0
NCH Max	0.23	0.21	0	0	0.33	0

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.

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 use are internal loads and cooling set points with infiltration and wall U-value next. Window air gap does not have any big impact on the output but does change is a little. Similarly, for heating energy use infiltration and heating set points are factors that are more dominant. For the NCH hours Infiltration, internal loads and cooling set point affect the outputs the most.

It can be seen that occupant behaviour is the most important aspect as in most cases; they determine the internal loads and cooling set points. A conservative approach in estimating the internal loads can be quite detrimental when calculating building's cooling energy needs and comfort. Infiltration and U-value of the fabric also show that construction and proper airtightness is required.

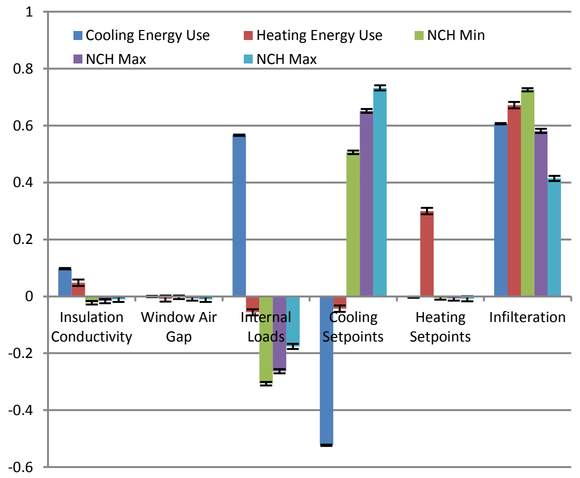


Figure 5 Standardized regression coefficient comparing the relative influence of the explanatory variables on the dependent variables

Uncertainty Analysis

The values in all outputs show substantial variation. Table 5 below shows the upper value, lower value, mean value, 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)	384.97	152.36	234.94	31.76 (13%)
Heating Energy (MJ)	17305.56	0.00	441.30	1150.85 (260%)
NCH Min (hrs.)	2177.75	0.00	495.17	411.92 (83%)
NCH Avg (hrs.)	3107.14	0.00	711.02	454.58 (63%)
NCH Max (hrs.)	4955.50	0.00	1108.89	888.76 (80%)

It can be seen from the results that the variation is very big and outputs have very 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 assuming building's cooling energy needs. Infiltration and U-value of the fabric also show that construction and proper airtightness is also required.

CONCLUSION

Through this study, it has been shown that there could 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 could produce variations over the mean of about 13% with the variation in maximum and minimum values of more than 150%. Similarly, non-comfortable hours in the year could have a variation of whole year comfortable to more than half a year uncomfortable. While, the sensitivity analysis it is seen that the most influential variables in regarding the increase the cooling loads and decrease in comfort are internal gains and cooling set points, both factors primarily governed by occupants. Infiltration and U-value of the walls are similar on importance; both are primarily governed by quality of construction. 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 when making the assessment.

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.

REFERENCES

BECP: US DoE. (1991). *Building Energy Codes Program*. Retrieved December 02, 2013, from http://www.energycodes.gov/

BEE. (2009). *Bureau of Energy Efficiency, Energy Conservation Building Code User Guide*. New Delhi: Ministery of Power, Government of India.

BIS. (1986). *CODE OF PRACTICE FOR COMPOSITE CONSTRUCTION* . New Delhi: Bureau of Indian Standard.

BIS. (1991). *Brick Works - Code of Practice*. New Delhi: Bureau of Indian Standards.

BIS. (1991). *Handbook on Masonry Design and Construction SP20 (S&T)*. New Delhi: Bureau of Indian Standard.

BIS. (1995). *Timber door, window and ventilator frames-specifications.* New Delhi: Bureau of Indian Standards.

BIS. (2001). *Code of Practice for Selection installation and maintenance of Timber Doors and Windows.* New Delhi: Bureau of Indian Standards.

BIS. (2003). *CODE OF PRACTICE FOR COMPOSITE CONSTRUCTION.* New Delhi: Bureau of Indian Standard.

BIS. (2006). *Specification for Aluminum doors, windows and ventilators.* New Delhi: Bureau of Indian Standards.

Blight, T. S., & Coley, D. A. (2013). Sensitivity analysis of the effect of occupant behaviour on the energy consumption of passive house dwellings. *Energy and Buildings, 66*, 183-192.

Blight, T., & Coley, D. (2013). THE IMPACT OF OCCUPANT BEHAVIOUR ON THE ENERGY CONSUMPTION OF LOW ENERGY DEWELLINGS.

Brohus, H., Heiselberg, P., Simonsen, A., & Sørensen, K. (2009). Uncertanity of Energy Consumption Assessment of Domentic Buildings. Glasgow: Eleventh International IBPSA Conference.

Carbon Trust. (2011). *The Micro-CHP Accelerator Report.* London: The Carbon Trust.

Chris Scheuer, G. A. (2003). Lifecycleenergy and environmentalperformance of anewuniversitybuilding: modeling challenges and design implications. *Energy and Buildings, 35*(10), 1049–1064.

Clarke, J. A. (2001). *Energy Simulation in Building Design.* Oxford: Butterworth-Heinemann.

de Wilde, P., & Tian, W. (2009). Identification of key factors for uncertainty in the prediction of the thermal performance of an office building under climate change. *Building Simulation, 2*(3), 157-174.

de Wit, S. (1997). Influence of modeling uncertainties on the simulation of building thermal comfort performance. Prague: Proceedings of Building Simulation ’97, 5th International IBPSA Conference.

de Wit, S., & Augenbroe, G. (2002). Analysis of uncertainty in building design evaluations and its implications. *Energy and Buildings, 34*(9), 951-958.

Demanuele, C., Tweddell, T., & Davies, M. (2010). Bridging the gap between predicted and actual energy performance in schools. Abu Dhabi: World Renewable Energy Congress XI.

Domínguez-Munoz, F., Cejudo-López, J., & Carrillo-Andrés, A. (2010). Uncertainty in peak cooling load calculations. *Energy and Buildings, 42*(7), 1010-1018.

Eisenhower, B., O’Neill, Z., Fonoberov, V. A., & Mezic, I. (n.d.). Uncertainty and Sensitivity Decomposition of Building Energy Models. *Journal of Building Performance Simulation*, Accepted Paper.

Gregory A. Keoleian, S. B. (2008). Life-cycle energy, costs, and strategies for improving a single-family house. *Journal of Industrial Ecology, 4*(2), 136-156.

Haldia, F., & Robinson, D. (2011). The impact of occupants' behaviour on building energy demand. *Journal of Building Performance Simulation, 4*(4), 323-338.

Heo, Y., Choudhary, R., & Augenbroe, G. (2012). Calibration of building energy models for retrofit analysis under uncertainty. *Energy and Buildings, 47*, 550-560.

Hopfe, C., & Hensen, J. (2011). Uncertainty analysis in building performance simulation for design support. *Energy and Buildings, 43*(10), 2798-2805.

Hopfe, C., Hensen, J., Plokker, W., & Wijsman, A. (2007). Model uncertainty and sensitivity analysis for thermal comfort prediction. In *Proceedings of the 12th Symposium for Building Physics* (pp. 103-112). Dresden: Technische Universitat Dresden.

INCCA. (2010). *India: Greenhouse Gas Emissions 2007.* New Delhi: Ministry of Environment and Forests.

IPCC. (2013). *Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change.* Cambridge, United Kingdom and New York, NY, USA: Cambridge University Press.

IPCC. (2014). *Climate Change 2014: Mitigation of climate change, Contribution of Working Group III to The Fifth Assessment Report of The Intergovernmental Panel on Climate Change.* Cambridge, U.K. and New York, U.S.A: Cambridge University Press.

Lingbawan, S. G. (2009). *Thermal Properties of Fly Ash Bricks; Thesis Report.* University of New South Wales at the Australian Defence Force Academy.

Liu, F., Meyer, A. S., & Hogan, J. F. (2010). *Mainstreaming Building Energy Efficiency Codes in Developing Countries: Global Experiences and Lessons from Early Adopters.* Washington DC: The World Bank.

Lüthi, D., et al. (2008). *EPICA Dome C Ice Core 800KYr Carbon Dioxide Data.* Boulder, CO, USA: IGBP PAGES/World Data Center for Paleoclimatology Data Contribution Series # 2008-055. NOAA/NCDC Paleoclimatology Program.

MacDonald, I. (2002). Quantifying the effects of uncertainty in building simulation - PHD Thesis. Scotland: University of Strathclyde.

MacDonald, I., & Clarke, J. (2007). Applying uncertainty considerations to energy conservation equations. *Energy and Buildings, 39*(9), 1019-1026.

Macdonald, I., & Strachan, P. (2001). Practical application of uncertainty analysis. *Energy and Buildings, 33*(3), 219-227.

MacDonald, I., Clarke, J., & and Strachan, P. (1999). Assessing uncertainty in building simulation. Kyoto: Proceedings of Building Simulation, ’99.

National Action Plan for Energy Efficiency. (2009). *Energy Efficiency Program Administrators and Building Energy Codes.* <www.epa.gov/eeactionplan>.

Newton, D., James, R., & Bartholomew, D. (1988). Building energy simulation-a user's perspective. *Energy and Buildings, 10*, 241-247.

Page, J., Robinson, D., & Scartezzini, J.-L. (2007). Stochastic Simulation of Occupant Presence and Behaviour in Buildings. *Proceedings: Building Simulation 2007* (pp. 757-754). Lausanne, Switzerland : Solar Energy and Building Physics Laboratory (LESO-PB), Ecole Polytechnique Fédérale de .

Parikha, J., Panda, M., Ganesh-Kumar, A., & Singh, V. (2009). CO2 emissions structure of Indian economy. *Energy, 34*(8), 1024-1031.

Pettersen, T. D. (1994). Variation of energy consumption in dwellings due to climate, building and inhabitants. *Energy and Buildings, 21*, 209-218.

Planning Commission : Integrated Energy Policy. (2006). *Integrated Energy Policy - Report of the Expert Committee.* New Delhi: Planning Comission, Government of India.

Ramallo-González, A. P. (2013). *PhD thesis: Modelling, Simulation and Optimisation Methods for Low-energy Buildings.* Exeter: University of Exeter.

Ramallo-Gonzáleza, A. P., Eamesa, M. E., & Coley, D. A. (2013). Lumped parameter models for building thermal modelling: An analytic approach to simplifying complex multi-layered constructions. *Energy and Buildings, 60*, 174-184.

Sandia Lab. (n.d.). *Epistemic Uncertainty Project Home*. Retrieved December 02, 2013, from http://www.sandia.gov/epistemic/

Sarangapani, G., Reddy, B. V., & Jagadish, K. S. (2002). Structural characteristics of bricks, mortars and masonry. *Journal of Structural Engineering, 29*(2), 101-107.

Schnieders, J., & Hermelink, A. (2006). CEPHEUS results: measurements and occupants' satisfaction provide evidence of Passive House Bbeing an option for sustainable building. *Energy Policy*, 151-71.

Tans, D. P., & Keeling, D. R. (2014, May 04). Trends in Atmospheric Carbon Dioxide. NOAA/ESRL; Scripps Institution of Oceanography . Retrieved from www.esrl.noaa.gov/gmd/ccgg/trends/, scrippsco2.ucsd.edu/

The European Parliament and The Council of European Union. (2003). Directive 2002/91/EC of the European Parliament and of the Council of 16 December 2002 on the energy performance of buildings. *Official Journal of the European Communities*, L1/65-L1/71.

UNEP. (2009). *Buildings and Climate Change:Summary for Decision-Makers.* Paris: UNEP DTIE, Sustainable Consumption & Production Branch.

Wang, L., Mathew, P., & Pang, X. (2012). Uncertainties in energy consumption introduced by building operations and weather for a medium-size office building. *Energy and Buildings, 53*, 152-158.