COMPARING THE ROBUSTNESS OF BUILDING REGULATION AND LOW ENERGY DESIGN PHILOSOPHIES

Stephen Simm¹, David Coley², and Pieter de Wilde³

¹Centre for Energy and the Environment, Physics Building, University of Exeter

²Corresponding Author: Department of Architecture and Civil Engineering, University of

Bath

³School of Architecture, Design and Environment, University of Plymouth

ABSTRACT

The sensitivity of a real (under construction) UK school building's energy consumption to input parameters was investigated using IES Virtual Environment. Differential sensitivity analysis and Monte Carlo analysis were conducted for two base models, one set at 2006 Building Regulation standards and one at Passivhaus certification level. Heated temperature and envelope specification were the dominant factors governing energy consumption for the Building Regulation model, while for the Passivhaus model occupancy parameters and class equipment load were most important. In addition, the range of final energy consumption was far smaller for the Passivhaus base case than for the Building Regulation equivalent.

INTRODUCTION

Whether in response to concerns about future energy security (Bang, 2010; Bäckstrand, 2010) or damaging climate change (Solomon et al, 2007), there is an increasing trend in national policies towards both energy efficiency (Dixon et al, 2010) and developing or diversifying current energy supplies.

Buildings in use account for $\sim 25\%$ of the world's total energy consumption; this percentage is greater in more developed countries. For example, the USA and Britain consume 40% and 39% of their total energy budget supplying buildings respectively (Pérez-Lombard et al, 2007). The International Energy Agency (IEA) predicts that energy use in the built environment will grow by ~30% in the next twenty-five years, primarily fuelled by developing nations increasing and replacing their current building stock (IEA, 2009). It is evident that buildings' energy consumption in use must necessarily be one of the primary foci for national energy policy.

In the construction industry, there is a trend towards increasingly stringent building regulations. In England and Wales, Part L of the 2010 Building Regulations (which refer to energy consumption for non-domestic buildings) require a reduction in associated CO₂ emissions of 25% relative to the 2006 building regulations (UK Government, 2010). This reflects a similar pattern of increasingly stringent energy use targets for buildings across the EU, driven by the Energy Performance of Buildings Directive and the Energy End-Use Efficiency and Energy Services Directive (Ekins & Lees, 2008). In addition. voluntary certification schemes guaranteeing a level of energy efficiency or CO2 emissions (such as Passivhaus (PH) (PHI, 2011) or LEED (USGBC, 2011)) are growing in popularity internationally.

A concern for some time in the UK has been the clear discrepancy between the predicted performances at design stage of buildings in comparison to real data (Bordass et al, 2004). This worry is not unique to the UK, as buildings in other countries have had similar issues (Branco, 2004; Torcellini et al, 2004). This can have a significant impact on the goal of energy efficiency in buildings by giving the design team an incorrect impression of the energy their building will consume in practice. This performance gap has been attributed to many causes, but the commonly cited reasons include poor assumptions during modelling (Raslan et al, 2009) and/or occupant behaviour (Masoso, 2009; Torcellini et al, 2004).

Whether poor modelling assumptions, occupant behaviour or failure to meet the expected standards on site are responsible, there is evidence that there is an element of variability in the energy performance of buildings. Most likely, this is the result of several of the above factors acting in combination.

Classically, energy efficient building design employs two types of approach – the use of passive and active measures. Passive measures are features of the building that contribute to energy efficient performance with no direct energy input, such as insulation within walls. Active measures require some energy input to operate – for example, the use of heat pumps. In the recent past, it has been popular to focus on passive measures, such as optimising building orientation and improving the fabric of the building, from simply improving the U-value of glazing to trying to minimise thermal bridges and utilise thermal mass. As building regulations tighten and the uptake of certification methods such as Passivhaus rises, an important consideration is what aspects of a building's design, construction and use need to be controlled to minimise energy use as its basic design parameters improve. Perhaps it is the case that improving the fabric further is of the most value, however this is not self-evident and it might be better to control unregulated power use or other aspects of occupant behaviour (the term unregulated power is used here to refer to the appliances installed in the building post-handover).

BACKGROUND

A building's energy performance is dependent on a large number of factors. The form and construction techniques used have a major effect on the physical performance. Building form can affect factors such as wind shielding and solar gain, whilst not forgetting the impact of surface area to volume ratio. Construction methods and materials directly affect the U-value, available thermal storage, daylighting, acoustics and a variety of other input parameters. Construction techniques such as off-site manufacture can improve the match between initial design and final achieved building parameter value (Blismas & Wakefield, 2009).

Occupant behaviour can also have a large effect on the energy consumption of a building. Occupants can have many effects, including thermal gain, control of unregulated power devices, door and window opening or using the building in a way that counteracts the designed ventilation or lighting strategy.

Finally, other variables that may affect a building's energy performance exist which are not under human control. These factors are related to weather and climate. Examples include external air temperature, wind speed and insolation.

There have been a variety of sensitivity analysis techniques developed which allow investigation of how a building's final performance is affected by the state of a set of input factors, whether architectural features. construction specifics or occupant The primary sensitivity analysis behaviour. techniques used with building thermal simulation programs are differential sensitivity analysis (DSA), Monte Carlo analysis (MCA) and stochastic sensitivity analysis (Lomas & Eppel, 1992). The purposes of each vary considerably and a short discussion follows of each method.

In DSA, a base case model is created with a set of typical values assigned to all input parameters. Each

parameter is then varied independently of the others to extract a direct relationship between the input variable and the performance indicator (PI) of interest.

MCA is used in analysis of systems in several scientific fields. In MCA, all the input variables are assigned a definite distribution. Individual simulations are then run with these variables being determined probabilistically according to their distribution. This process is repeated a suitably large number of times (in this work, 80), ensuring that the PI distribution is likely to be normally distributed according to the Central Limit Theorem (Fisz, 1963). Once this process is complete, a mean and standard deviation for the PI distribution are calculated, which represent an estimate of the realistic range of outcomes for that PI in the completed building.

Lastly, stochastic sensitivity analysis works almost as a combination of the two previously discussed methods. A single stochastic sensitivity analysis run varies all inputs simultaneously much as in the MCA method. This process needs to be repeated a number of times (typically fewer than for MCA) to avoid skewing results. However, through use of regression techniques it is then possible to extract the sensitivity of the PI to any single input variable. Stochastic sensitivity analysis does not lend itself to using graphical and dialogue box based software such as IES VE because it relies on programming the simulation to take account of variation in inputs, although it is possible to create a program 'shell' to allow this (Struck et al, 2007). Due to this conflict with the chosen building modelling tool, SSA was not used in this work.

DSA will allow investigation of the relationship between input variables and PIs to be answered in a simple way. It was also decided that MCA would be used to get an understanding of the possible ranges for the PIs in both the basic building regulation case and the energy efficient case.

A complication in building modelling is that buildings vary widely in their purpose and this in turn strongly influences the design and patterns of use. As mentioned above, the building being investigated in this case is a recently designed school in the UK. Schools have relatively different occupancy patterns and hours of use to other non-domestic buildings. However, there are a large number of schools in most countries. As public buildings are at the centres of many communities, they are buildings that governments may feel it is important to improve early on in the drive to improve building efficiency, as has been argued for in the UK (Sustainable Development Commission, 2009).

There has been some previous work done on the subject of variability of performance in schools. Pegg et al. (2007) found that predicted CO₂ savings were not consistently achieved real UK schools,

while Demanuele et al. (2010) concluded that variables related to occupancy have a major influence on the energy performance of schools, using DSA in a similar way to this study.

Research Goal

In this work, the change in the response of a building to changes in specific input variables, both in terms of direct relationship and in terms of the potential range of final performance, is measured. This has been termed the 'robustness' of the building (Leyten & Kurvers, 2006). Variables studied include those related to building fabric, such as U-value, and others related to design and occupancy. To investigate how changes in the input variables influence final energy consumption, DSA and MCA techniques were used.

It was desirable to use a dynamic thermal modelling program to run the simulations for several reasons. Dynamic thermal modelling allows the effects of hourly weather data and occupancy schedules to be taken into account, as well as modelling airflow within the building. The latter was deemed important for accurate simulation of door and window opening as well as the performance of mechanical ventilation systems. Finally, dynamic thermal modelling allows extraction of further PIs, such as overheating hours.

The school building used in this experiment is a real building being constructed in Exeter at the time of writing. The actual building is designed to Passivhaus standards and thus incorporates some of the passive energy efficiency measures discussed earlier. In addition, the design team have made all design data available for this research, and there is an intention to monitor the building's performance for five years after completion. This will be valuable data for comparison with this study.

<u>METHOD</u>

The Model

The school chosen was modelled using Integrated Environmental Solutions Virtual Environment (IES VE), which is industry standard software. The geometry and surrounding geography of the building were recreated as they are in the physical case.



Figure 1: An image of an IES VE model of the school.

Once the geometrical structure was completed, two 'base case' buildings were created by setting a group of input parameters. The parameters and the values for each base case are shown in Table 1. No weather-related variables were changed; the Plymouth Test Reference Year was used for all model runs.

One base case building took values matching those specified as the minimum acceptable in 2006 Part L England & Wales BRs, while the other took input values equivalent to those required as a minimum by the PH certification scheme. This scheme was chosen as a base case for three reasons. Firstly, the scheme has a pedigree of measured performance, in energy terms as well as occupant satisfaction (Schnieders & Hermelink, 2006). Additionally, there has been growing interest in the PH method of construction in the UK, as evidenced by the national PH conferences held in the UK in 2010. Finally, the real building is designed to achieve PH certification. The values that vary between base cases are primarily those relating to envelope standards, although some others (such as heated temperature) are also different. They are shown in Table 1.

The input parameters have been divided into three groups. Envelope standards incorporate the parameters that are decided at design stage but are subject to changeable standards on site. Design variables includes of those parameters which are decided at design stage but are somewhat subject to occupant behaviour. Occupancy includes variables that may be controlled by a building management system but are essentially under the occupants' control.

The BR base case building was calibrated to real UK school data (DfES, 2003; DfES 2007) by iterative model design. The annual energy consumption was calculated to be approximately 130 kWh/m²; this is close to the 25^{th} percentile of mean energy consumption for UK schools. While low, this value was deemed reasonable given the energy efficient nature of the building design. The PH base case was simply a modified version of this building to match PH criteria – the annual energy consumption for the PH base case was approximately 65 kWh/m².

The wall, roof and glazing U-values were taken from building regulation and Passivhaus literature. The floor U-value was calculated by taking the specified value and then applying the appropriate correction for potential edge losses etc. (CIBSE, 2006).

Thermal bridging was calculated by applying typical Ψ -values (BRE, 2010) to the geometry of the building model and summing estimated thermal losses from this approach. This effect was then averaged over the wall area. Heated temperature describes the realised set point. In typical naturally ventilated schools, this is frequently higher than the design set point as it is rare that all rooms have a way

of maintaining a given set point via any controls. This is less of a problem with designs such as the PH one where each room has controlled heat delivery.

Table 1: Base case inputs for Building Regulation and Passivhaus case base models.

		Building Regulation	Passivhaus
Envelope Standards	Wall U-value (W/m ² K)	0.35	0.15
	Glazing U-value (W/m ² K)	2.2	0.8
	Roof U-value (W/m ² K)	0.2497	0.15
	Floor U-value (W/m ² K)	0.168	0.1134
	Infiltration Rate (Ach/h)	0.326	0.042
	Thermal Bridging (W/K)	181.7	181.7
Design Variables	Ventilation Rate (l/s/person)	5	5
	Heated Temperature (°C)	21	19
	Lighting Load (W/m ²)	12	12
	Class Equipment Load (W/m ²)	7.3	7.3
	Office Equipment Load (W/m ²)	4.7	4.7
	Heat Recovery Efficiency	n/a	0.85
Occupancy	Door Opening (Minutes)	95	95
	Lighting Schedule (Minutes)	540	540
	Equipment Schedule (Minutes)	900	900
	Occupancy Hours (Minutes)	315	315

All Occupancy variables and most of the Design Variables were kept constant between the PH and BR models, as the assumption is that occupants' requirements and activities would remain approximately similar between different buildings. It is of course possible that this would not be the case, and the occupants of an energy efficient building would behave more carefully. With no evidence to support this, the alternative assumption was considered reasonable. The PI studied in this work is final energy consumption, although in the future it is anticipated that additional PIs will also be investigated.

DSA Method

Differential sensitivity analysis is one of the simplest methods of determining the direct relationship between input parameters and output PIs. In conducting a DSA process, one input parameter is varied while all the others remain fixed. This method assumes linearity of response; in many cases, this is a reasonable assumption but some variables may be non-linear. To ameliorate the effect of this, both higher and lower values for each input variable were simulated. The relationship was then considered as an 'average sensitivity' over the range measured. The upper and lower values for each parameter were chosen to be within a realistic range of the mean value.

The results of the DSA analysis are initially expressed as an 'influence coefficient'. This is equal to the change in the PI divided by the change in the input variable. As discussed in Lomas & Eppel (1992), the value of the influence coefficient is an estimate. They recommend calculating the change in PI due to a relatively large change in input variable and then using interpolation to estimate the effect of smaller changes.

The main output of the DSA is the normalised influence coefficient (NIC). This is a modified influence coefficient, adjusted to represent the ratio of the percentage change in the PI to the percentage change in the input variable. While this is one of the most useful outputs from the DSA process, it must be remembered that each input variable has a different range of realistic variation. Using the normalised influence coefficient without considering this will not give a full picture of how the relationship might play out in reality.

MCA Method

All input variables used in the DSA were considered for the MCA. Where the NIC was found to be very low (<0.05), that variable was held static at its base case for all iterations. In these cases, the PI would change by less than 1% in response to a 20% change in the input variable. As such, the sensitivity of the PI to these variables was deemed negligible. The exception to this was that the most responsive inputs from the three sections (Envelope Standards, Design Variables and Occupancy), which were always This was done to get a general included. understanding of how important each subdivision of factors might be as a whole. The mean and value of 2.33 standard deviations for each variable included in the MCA analysis is shown in Table 2.

	Units	Building Regulation Base Case		Passivhaus Base Case	
Variable		Mean	2.33 Standard Deviations	Mean	2.33 Standard Deviations
Wall U-value	W/m ² K	0.35	0.2	N/A	N/A
Roof U-value	W/m ² K	0.25	0.1	N/A	N/A
Floor U-value	W/m ² K	N/A	N/A	N/A	N/A
Glazing U-value	W/m ² K	2.2	1.2	0.8	0.015
Infiltration Rate	Ach/h	0.326	0.094	N/A	N/A
Ventilation Rate	l/s/person	5	2	5	2
Lighting Load	W/m ²	N/A	N/A	12	6
Class Equipment Load	W/m ²	N/A	N/A	7.3	5.4
Office Equipment Load	W/m ²	N/A	N/A	N/A	N/A
Heated Temperature	°C	21	3	19	2
Heat Recovery Efficiency	%	-	-	0.85	0.1s
Door Opening	Minutes	95	47.5	95	47.5
Lighting Schedule	Minutes	N/A	N/A	540	120
Equipment Schedule	Minutes	N/A	N/A	900	180
Classroom Occupancy	Minutes	315	60	315	60

Table 2: Values used in the MCA analysis for each variable. N/A denotes a variable that had an NIC of < 0.05 and thus was kept fixed for all simulation runs.

These values were typically estimates. Where possible, values were related to research by Demanuele (2010) into real school buildings.

Ideally, distributions for the variables would be assigned distributions from research. As such research was not available, each variable was assigned a normal distribution, as has been done previously for work of this type by de Wit and Augenbroe (2002). The normal distribution is generally the most appropriate for measured physical data (MacDonald, 2002). In some cases, the variable was dependent on another that was more likely to have a normal distribution. For example, wall Uvalue is unlikely to vary as a normal distribution, whereas it is much more reasonable to assume that the variation of insulation thickness would. In such cases, the independent variable was assigned the distribution, and then the dependent variable of interest was derived from this.

RESULTS

DSA Results

The NICs for the BR and PH base case are shown in Figure 2. The NICs are grouped by general input variable type as done in Table 1. It can be seen that there are significant differences in the coefficients for the BR case as compared to the PH case. In envelope terms, the BR base case is more sensitive to changes in all inputs except for floor U-value; for this coefficient, the reverse is true.

The designed variables section shows the BR case to be particularly sensitive to heated temperature in comparison to the PH case. This is as might be expected; the BR case has a lower level of fabric



Figure 2: NICs for the Building Regulation and Passivhaus base case models, split into input parameter groups.

performance and so will lose more heat energy than the PH case.

In comparison, the PH design is far more sensitive to changes in the class equipment load. In occupancy terms, it can be seen that door opening has a nonnegligible effect for both models. Class occupancy (in the form of hours of operation in this case) is also highly relevant to the PH design due to their increased proportion of total energy use.

It can be seen that the primary factors to which final energy consumption is sensitive for the BR case are the heated temperature and envelope parameters. This is logical as the BR base case has a lower level of envelope performance. As such, small changes in the envelope parameters can have a significant impact on the building's energy performance. The high sensitivity of the heated temperature follows from this; with a lower level of envelope performance, raising the heated temperature will have the two-pronged impact of requiring more energy to raise the temperature of the building and more energy to maintain that temperature. The reverse is true of dropping the heated temperature. For the PH case, it can be seen that the envelope is of far less importance; the total energy consumption of the building is not very sensitive to the envelope Rather, due to the lower total parameters. consumption of the base building, small power

becomes a much more important variable. This is evident by the relatively high sensitivity coefficients to class equipment load and equipment schedule. The energy consumption of the PH building is also shown to be far more sensitive to occupancy parameters than the BR case.



Figure 3: Box-whisker plot of the results from the MCA analysis. The box shows the 25th and 75th percentiles while the whiskers extend to the 5th and 95th percentiles.

MCA Results

A box-whisker plot showing the form of the MCA data is shown in Figure 3. In each case, 80 iterations of the base model were run. This number was deemed sufficient to ensure accuracy (i.e. bring the normalised confidence interval down to a reasonable number).

It can be seen that the BR base case has a higher mean (as is to be expected) and a larger standard deviation than the PH Base Case. In practical terms, this means that the range of possible final energy consumptions of the BR base case is larger than that for the PH base case.

CONCLUSION

Bearing in mind that this is a single case study, it is possible to draw some interesting conclusions from this work.

As the industry move towards designing and constructing more energy efficient buildings, the pivotal design features and parameters in the design stage are likely to change. Where once reducing energy consumption required that designers focus on ensuring the building fabric and thermal performance of a building were as good as possible, when designing to higher standards of energy efficiency other factors have been shown in the case discussed in this paper to be of more relevance. With a better building fabric, incremental changes in thermal performance of the building are shown to have a reduced impact on energy consumption.

Instead, occupant behaviour and equipment load have been shown to be of much greater importance in these energy efficient designs. This matches up relatively well with the popularly held belief that occupant behaviour is crucial when it comes to the energy consumption of a building; however it may be the case that it is the evolution of building standards that have brought occupant behaviour towards a greater dominance as an input variable.

In terms of variability of energy consumption in the final design, it has been shown that for this school building that the energy consumption of the 2006 BR design is almost double that of a building designed to Passivhaus certification. The standard deviation of the BR model's energy use is over double that of the PH model when put through the MCA process, although it must be borne in mind that the range of the input variables was lower. We can say that the PH model is a more robust design in the sense that the final energy consumption of the building model is less responsive to realistic variations in the input variables. This implies that with a greater level of performance targeted, the variation in possible outcomes is reduced, which will be reassuring for designers aiming at achieving such buildings as any predictions made at design stage have an associated increase in accuracy. In future design work, as

building regulations tighten, it will be of increased value to focus on occupant effects and unregulated power usage.

The next step in this project is an extension of the experimental process used in this paper to further school buildings in the UK. By using buildings of varied architecture, it will be possible to investigate how case-specific the NIC and variability demonstrated there truly is. In addition, it would be interesting to extend the study to other PIs – in particular a comfort indicator such as overheating hours.

The production of statistical information on the likely energy consumption of a building has potential to be used effectively in the design process. It can be envisioned that by varying the input variables, risk in terms of energy cost is quantifiable. With the application of appropriate probability distributions, it would then be possible to assign an 'energy risk' to a project as design data becomes known to greater certainty. It would be useful if thermal modelling software could do this automatically. For example, it could vary the infiltration rate between predefined limits and output a range of possible performances with associated likelihoods.

Once the building is constructed, its performance will be monitored over five years. The resultant data will be used in a comparative study with the modelling work reported on here and completed in the interim.

REFERENCES

- Bäckstrand, K. (2010), Climate change and energy security in the European Union: from rhetoric to practice?. In: C. Lever-Tracy, ed. *Routledge Handbook of Climate Change and Society*. Routledge: New York, pp. 353.
- Bang, G. (2010), Energy security and climate change concerns: Triggers for energy policy change in the United States?. *Energy Policy* 38, pp. 1645-1653.
- Bordass, W., Cohen, R. & Field, J. (2004), Energy Performance of Non-Domestic Buildings: Closing the Credibility Gap. In: Building Performance Congress, *IEECB '04*. Frankfurt, Germany, 19-22 April 2004.
- Branco, G., Lachal, B., Gallinelli, P. & Weber, W. (2004), 'Predicted versus observed heat consumption of a low energy multifamily complex in Switzerland based on long-term experimental data. *Energy and Buildings* 36, pp. 543-555.
- Blismas, N. & Wakefield, R. (2009), Engineering sustainable solutions through off-site manufacture. In: P. Newton, K. Hampson & R. Drogemuller, eds. *Technology, Design and*

Process Innovation in the Built Environment. Taylor & Francis: New York, pp. 355-370.

- BRE (Building Research Establishment) (2010), National Calculation Methodology (NCM) modelling guide (for buildings other than dwellings in England and Wales) Online at: http://www.2010ncm.bre.co.uk/ [Accessed 02/05/2011]
- CIBSE (The Chartered Institution of Building Services Engineers) (2006), *CIBSE Guide A: Environmental Design*, CIBSE: London.
- Demanuele, C., Tweddell, T. & Davies, M. (2010), Bridging the gap between predicted and actual energy performance in schools. In: World Renewable Energy Congress, WREC XI. Abu Dhabi, UAE, 25-30 September 2010.
- de Wit, S. & Augenbroe, G. (2002), Analysis of uncertainty in building design evaluations and its implication. *Energy and Buildings* **34**, pp. 951-958.
- Dixon, R., McGowan, E., Onysko, G. & Scheer, R. (2010), US energy conservation and efficiency policies: Challenges and opportunities. *Energy Policy* 38, pp. 6398-6408.
- Ekins, P. & Lees, E. (2008), The impact of EU policies on energy use in and the evolution of the UK built environment. *Energy Policy* 36, pp. 4580-4583.
- Fisz, M. (1963), *Probability Theory and Mathematical Statistics*, 3rd edition, John Wiley & Sons, Inc.: New York.
- IEA (2009) Total World Delivered Energy Consumption by End-Use Sector and Fuel, US Department of Energy. Online (08/12/2009) at: http://www.eia.doe.gov/

Lomas, K. & Eppel, H. (1992), Sensitivity analysis techniques for building thermal simulation programs, *Energy and Buildings* 19, 21-44.

- MacDonald, I. (2002), 'Quantifying the Effects of Uncertainty in Building Simulation', PhD thesis, Department of Mechanical Engineering, University of Strathclyde.
- Pegg, I.M., Cripps, A. & Kolokotroni, M. (2007) Post-Occupancy Performance of Five Low-

Energy Schools in the UK, *ASHRAE Transactions*, **113(2)**

- Pérez-Lombard, L., et al. (2007) A review on buildings energy consumption information, *Energy and Buildings*, **40**, pp. 394-398.
- PHI (Passivhaus Institut) (2011) Online at: <u>http://www.passiv.de/07_eng/index_e.html</u> [Accessed 06/05/2011]
- Raslan, R., Davies, M. & Doylend, N. (2009), An analysis of results variability in energy performance compliance verification tool. In: IBPSA, IBPSA Conference '09. Glasgow, Scotland, 27-30 July 2009.
- Schnieders, J. & Hermelink, A. (2006), CEPHEUS results: measurements and occupants' satisfaction provide evidence for Passive Houses being an option for sustainable building. *Energy Policy* 34, pp. 151-171.
- Solomon, S., D. et al.: Technical Summary. In: Climate Change 2007: The Physical Science Basis. Contribution of Working Group I to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA.
- Struck, C., Kotek, P. & Hense, J. (2007), On incorporating uncertainty analysis in abstract building performance simulation tools.
 'Proceedings of the 12th Symposium for Building Physics', pp. 193-205.
- Sustainable Development Commission (2009) *Towards a Schools Carbon Management Plan.* Department for Children, Schools and Families. Online at: <u>http://www.sd-commission.org.uk/</u> [Accessed 07/05/2011]
- Torcellini, P., Deru, M., Griffith, B., Long, N., Pless, S. & Judkoff, R. (2004), Lessons learned from field evaluation of six high performance buildings. ACEEE, ACEEE Summer Study on Energy Efficiency in Buildings 2004. Pacific Grove, California, USA, 22-27 August 2004.
- UK Government (2010), *Approved Document L2A*, NBS, London.
- USGBC (2011), Leadership in Energy and Environmental Design. Online at: <u>http://www.usgbc.org/</u> [Accessed 02/05/2011]