BRI Building Research & Information, 2014
Vol. 42, No. 1, 47–61, http://dx.doi.org/10.1080/09613218.2013.814746

Routledge Taylor & Francis Group

RESEARCH PAPER

Improved benchmarking comparability for energy consumption in schools

Sung-Min Hong[1], Greig Paterson[2], Dejan Mumovic[2] and Philip Steadman[1]

[1]UCL Energy Institute, University College London, Central House, 14 Upper Woburn Place, London WC1H 0NN, UK
E-mails: s.hong@ucl.ac.uk and j.p.steadman@ucl.ac.uk

[2]Bartlett School of Graduate Studies, University College London, Gower Street, London WC1E 6BT, UK
E-mails: greig.paterson.10@ucl.ac.uk and d.mumovic@ucl.ac.uk

The method behind the UK Display Energy Certificate (DEC) improves the comparability of benchmarking by accounting for variations in weather and occupancy. To improve the comparability further, the incorporation of other features that are intrinsic to buildings (*e.g.* built form and building services) deserve exploration. This study investigates the impact of these features and explores ways to improve further comparability in benchmarking the energy performance of schools. Statistical analyses of approximately 7700 schools were performed, followed by analyses of causal factors in 465 schools in greater detail using artificial neural networks (ANNs), each designed to understand and identify the factors that have significant impact on the pattern of energy use of schools. Changes in the pattern of energy use of schools have occurred over the past four years. This fact highlights issues associated with static benchmarks. A significant difference in energy performance between primary and secondary schools meant that it was necessary to re-examine the way non-domestic buildings are classified. Factors were identified as having significant impact on the pattern of energy use. The characteristics raise new possibilities for developing sector-specific methods and improving comparability.

Keywords: benchmarks, building stock, CO_2 emissions, Display Energy Certificate (DEC), energy performance, energy use, schools

Introduction

Finite resources, energy security and climate change are some of the most prominent drivers for improving energy efficiency and reducing anthropogenic carbon emissions. In response to these critical issues, the UK government has set a legally binding target to reduce net CO_2 emissions in 2050 by more than 80% from the 1990 baseline (HM Government, 2008). CO_2 emissions from non-domestic buildings account for approximately 18% of national total emissions. Therefore, an imperative exists to reduce the emissions from these buildings, including schools, to achieve the 2050 target (Carbon Trust, 2009).

In the built environment, benchmarking is often used to evaluate the energy performance of buildings. The technique not only raises awareness of how much energy is being used, but the public display of benchmarked ratings can also provide motivation to improve the efficiency of operation. Benchmarking, therefore, is a crucial step towards reducing emissions from buildings.

In the UK, implementation of the Display Energy Certificate (DEC) scheme under the European Energy Performance of Buildings Directive (EPBD) in 2008 has greatly increased interest in benchmarking the energy performance of buildings (Chartered Institution of Building Services Engineers (CIBSE), 2009; Department for Communities and Local Government (DCLG), 2008). The scheme produces ratings of how well a building is being operated, based on a benchmarking methodology developed by CIBSE (2009). Under the scheme, it is currently mandatory for all public buildings with floor areas greater than 1000 m^2 to produce DECs, with the threshold being reduced to 500 m^2 as of January 2013 (CIBSE, 2011).

A vital element to the success of a benchmarking system is the level of comparability of an individual building with the buildings that form the basis of the benchmarks. It is important that the building and benchmarks have similar construction, operational and other characteristics that determine the energy demand, so that a comparison of the performances yields an accurate indication of how well the building is being operated. Under the current DEC scheme, the level of comparability is determined by a combination of a classification system and a set of adjustment procedures. There are 29 activity-based benchmark categories that broadly group buildings together. These categories have similar requirements for use, environment and equipment (Bruhns, Jones, & Cohen, 2011). The comparability is further improved via procedures that adjust benchmarks to account for variations in weather and the occupancy of individual buildings (CIBSE, 2009). An option to discount 'separable' energy uses[1] further reduces the difference. Compared with the historical UK benchmarks, this method which adjusts benchmarks according to the circumstances of individual buildings is a significant improvement. Nevertheless, there is a plethora of features intrinsic to buildings, such as the built form or the efficiency of building services, which contribute towards energy efficiency. Consideration of these features has the potential to improve further the benchmarking comparability (CIBSE, 2012).

Godoy-Shimizu, Armitage, Steemers, & Chenvidyakarn (2011) showed possibilities for applying various statistical techniques to characterize the energy use of schools using DEC data. In the United States, Sharp (1996, 1998) has used multiple linear regression models to assess the impacts of various building and operational characteristics on the energy use of offices and schools as part of a benchmarking process. Levels of energy performance were normalized for the characteristics identified as strong determinants of energy use, specifically for offices and schools, considerably improving comparability. Similar methods were used in Hong Kong (Chung, Hui, & Lam, 2006) and Taiwan (Lee, 2008; Lee & Lee, 2009) to benchmark energy performances of supermarkets and government office buildings. A comparison by Yalcintas & Ozturk (2007) of the accuracy of predicting the energy use intensity (EUI) of commercial buildings using, respectively, multiple linear regression models and artificial neural networks (ANNs) found that the ANN method made more accurate predictions. ANNs were also found to be suitable for assessing determinants of energy use in university buildings (Hawkins, Hong, Raslan, Mumovic, & Hanna, 2012).

The aim of the current study is to provide a better understanding of the ways in which the intrinsic features of buildings affect energy use. Using schools as a demonstration case, the work also explores ways to improve further the comparability of benchmarking energy performance of non-domestic buildings beyond current methods.

The paper is structured as follows. Data are presented on changes in the pattern of energy use in primary and secondary schools in England, based on information from DEC records. Statistical analyses of the top-level energy consumption figures are then carried out to observe trends of energy use, and to identify factors that significantly affect the energy use of schools. A database is developed comprising building characteristics and patterns of energy consumption in 465 primary and secondary schools. This database is analysed using ANN to assess the impact of each building characteristic and to identify the parameters that have significant effects. Finally, consideration is given to how these characteristics could be used to improve comparability in benchmarking the energy use of schools.

Methods

Data collection and adjustments

The DEC and EduBase databases

In the UK, information on energy consumption and building characteristics used to produce DECs are stored in the non-domestic energy performance register maintained by Landmark.[2] In late 2012, a database containing 120 253 DEC records lodged until June 2012 was acquired by the project team from CIBSE.

The DEC method provides 29 benchmark categories, within which there are a further 237 building types. These building types are differentiated through the activities occurring within the building. DEC records from primary and secondary schools are found under the 'Schools and seasonal public buildings' category, which contains 26 building-type classifications. For the present study, DEC records with building types 'Primary school', 'Secondary school', 'State primary school' and 'State secondary school' formed the chosen subsets.

Prior to the analyses, uncertain and erroneous records were cleaned and filtered from the raw dataset. The list below sets out the criteria, a refined version of the criteria used by Bruhns *et al.* (2011). These were used to select records which were deemed valid, as follows:

- the operational rating[3] is not 200 or 9999[4]
- the operational rating is greater than 5 and less than 1000
- the total useful floor area is greater than 50 m^2
- the total annual CO_2 emissions are less than 100 000 tonne CO_2/year

- the electric area energy use intensity (EUI) is not 0 kWh/m^2
- the building is not electrically heated
- the fossil-thermal EUI is not 0 kWh/m^2
- the DEC is not based on a 'composite methodology'[5]

Further steps were taken to clean the dataset of duplicate records and 'pro-rata DECs',[6] the inclusion of which would adversely affect the results. Lastly, the latest DEC record from each building was extracted for the analyses. Once the DEC database was cleaned, those schools listed as operating extended hours were discounted from the analyses, so that distributions and trends in energy use are not affected by these differences in operating characteristics. However, this exclusion is limited to the cross-sectional analyses outlined below.

Table 1 Summary of changes in the number of Display Energy Certificate (DEC) records in the database

Number	Data processing steps	Number of DEC records after each step		
		Primary	Secondary	Total
1	Raw DEC data	–	–	120 520
2	Cleaned and filtered records	–	–	73 160
3	Subset of school records	30 625	5610	36 235
4	Latest DEC record from each building	12 488	3051	15 539
5	Joined with pupil information	8625	1519	10 144
6	Extended operating hours removed	6686	1045	7731

The DEC dataset was supplemented with information on the number of students in each school, acquired in January 2013 from the Department for Education's EduBase Public portal.[7] This contained 39 604 records. These were merged into a subset of schools each of which has lodged only one DEC in a specific postcode. Once joined, each combination was manually inspected to ensure a correct match between the two datasets. The scope of the study was narrowed down to schools located in England due to insufficient information on the number of pupils in Wales.

For the statistical analyses of the school stock, the fossil-thermal consumption of all schools was adjusted to account for the variation in heating demand due to regional and seasonal differences in climate (CIBSE, 2006). Based on the literature and comments from experts, 80% rather than 55% of the fossil-thermal energy use was assumed to be used for space heating, and was adjusted to 2021 heating degree-days (Building Research Energy Conservation Support Unit (BRECSU), 1996). Monthly average heating and cooling degree-days were acquired from the Central Information Point (CIP).[8]

As shown in Table 1, the final dataset comprised 7731 schools. These represent approximately 39% and 31% of the primary and secondary school stock in England, respectively.

Building characteristics

Information describing the built form of school buildings was collected to assess the impact of various geometrical and constructional characteristics on energy use. A database comprising a subset of DEC data, numbers of pupils, degree-days and the building characteristics information was developed for a causal factor study using ANNs. The information was collected via a desk-based approach using online resources including Bing Maps[9] and Google Street View.[10]

Schools for building characteristic analysis were randomly selected from a list of those primary and secondary schools in England that have lodged a DEC to ensure the availability of actual energy consumption figures. Criteria were developed to ensure that the impact of building characteristics was assessed on a building-by-building basis (not by sites), in line with DEC methodology. These were:

- the school has a valid DEC
- the school has one main building
- building characteristics are consistent throughout
- the facades of the school can be observed using Bing Map's Bird's Eye View function or Google Street View

The building characteristics for which data were collected are shown in Table 2.

Once the raw data were collected, a set of variables (Table 2) that numerically describe the built form was derived (*e.g.* height, facade length). For information on the heights of buildings, there was an initial attempt at using geographical information system (GIS) data from Landmap.[11] However, the approach proved inaccurate, and therefore the next best dataset available was for the average floor-to-floor height of schools in England and Wales from

Table 2 Collected building characteristics

Building characteristic	Description
Phase of education	Primary or secondary school
Construction year	Year a school was built
Site exposure	Exposed, semi-exposed or sheltered from the wind
Orientation (degrees)	Angle at which the external walls differ from due north
Building perimeter (m)	Total and exposed
Building footprint (m^2)	–
Number of storeys	–
Height of the building (m)	–
Building shape	Singular, courtyard, crescent, bend or branch
Facade lengths (m)	N, S, E, W
Facade adjacency	Obstruction of the sun by neighbouring objects (*e.g.* buildings or trees). Collected for each facade orientation (N, S, E, W)
Glazed area (%)	N, S, E, W
Glazing type	Single or double
Roof shape	Flat, sloped or inverted
Principal roofing material	Polymer, ceramic, slate, etc.
Principal external wall material	Brick, masonry, render, etc.
External shading	Yes or no
Presence of an atrium	Yes or no
Presence of wind-catchers	Yes or no

Table 3 Derived variables and their descriptions

Variable	Description
Exposure ratio	Volume divided by the exposed surface area
Depth ratio	Volume divided by the external wall area
Compactness ratio	Perimeter of the building footprint divided by the perimeter of a circle with the same area
Glazing ratio	Total glazed wall area of a building divided by the total floor area

the Non-Domestic Building Stock project (Steadman, Bruhns, & Rickaby, 2000). The overall height was derived by multiplying the average number of storeys by 3.62 m, rather than making assumptions about the heights of buildings based on visual inspection. The volume was derived by multiplying the height by the building footprint area, measured from an online mapping source Digimap.[12]

The complete building dataset comprised detailed information on 502 schools scattered throughout England. It should be noted that inferences were made about the nature of some of the characteristics such as the types of window, based on an evaluation of the available data on age and appearance.

To prevent extreme values from affecting results during the training process of the ANN study, input and output values that were more than 1.5 interquartile ranges away from the upper and lower quartile figures were removed. The final cleaned dataset comprised 465 schools.

Statistical analyses of the school stock

A series of statistical analyses were carried out to assess the energy performance of the school stock of England using a further dataset comprising information from the DEC database and EduBase. The analyses were carried out using SAS Statistical Analysis Software 9.3.[13]

Longitudinal analyses

Year-on-year changes in the energy performance of the school stock in England from 2008 to 2011 were assessed using the assessment end dates from the DEC database. These indicate when the energy consumption figures for each school were collected. In addition, the median of the ratio between the actual energy consumption and the adjusted benchmarks was used as an indicator of how the stock performed in each year in order to ensure that the effects on energy use of weather and variation in occupancy hours were excluded from the trends.

Cross-sectional analyses

Trends in the energy consumption of primary and secondary schools were plotted by means of cumulative frequency distributions by floor area and number of pupils. Descriptive statistics were used to assess and compare trends between the school types. Kolmogorov–Smirnov (K-S) tests were also carried out, prior to conducting hypothesis tests, in order to assess the adequacy of the parametric tests. Due to the skewed distribution, non-parametric Wilcoxon–Mann–Whitney tests and Kruskal–Wallis tests were used, rather than Student's *t*-tests and analysis of variance (ANOVA), in order to assess the statistical significance of the difference in trends of energy use between primary and secondary schools, as well as differences between schools with varying heating, ventilation and air-conditioning (HVAC) system types. A Bonferroni correction was used to reduce the level of significance at which results are reported to prevent the Type 1 error rate from increasing due to multiple Wilcoxon two-sample tests (Field & Miles, 2010).

Causal factor study

Artificial neural network (ANN)

A non-linear multivariate analysis of the dataset described above was carried out using an ANN method to assess the relative importance that these characteristics have on energy use of schools. The ANNs were modelled using the Neural Network Toolbox[14] in Matlab R2012a.[15]

A multilayer perceptron network was used for the study, comprised of an input layer, a hidden layer and an output layer. Figure 1 shows the conceptual structure of this ANN. Each neuron in the input and output layer took continuous, categorical or binary values, as listed in Tables 4 and 5. Two ANN models were constructed: one with heating energy consumption as an output and one with electrical energy consumption as an output. Both ANN models included all the input parameters (Table 4). Each neuron in the input layer represents a variable in the dataset, and the single neuron in the output layer represents the unadjusted heating or electrical energy consumption figure from the DECs.

The layer of hidden neurons was specified to enable the model to learn non-linear and complex relationships between the inputs and outputs (Haykin, 1999). A bias was included to the networks by adding a neuron to the input and hidden layers that always has an activation value of 1, in order to improve the learning capabilities of the ANN (Sarle, 2002). Prior to the training of the network, all input data were normalized to values between −1 and 1 so that the calculation process could be generalized. The value of each continuous input neuron was a floating number between −1 and 1. Binary input neurons were 1 when activated and −1 when not activated. Categorical input neurons were 1 when activated, 0 when partially activated and −1 when not activated.

Each neuron is connected to every neuron in the adjacent layer by synaptic weights. These weights take random values at the beginning of the training process (Beale, Hagan, & Demuth, 2012). During this process the synaptic weights are modified to attain a response from the network that closely matches the actual outputs after a number of iterations (Haykin, 1999). A Levenberg–Marquardt back-propagation, a supervised training technique, was used to train the feed-forward network to recognize the patterns that exist in the dataset.

A random selection from the cleaned dataset of 465 schools was subdivided into three datasets, where 80% of the records were used for training the network, 10% for the testing process and the remaining 10% for stopping training to prevent the network from 'over-learning'. It was deemed important for the network not to 'over-learn' the training data so that the trained network could make useful generalizations when presented with new input data. An indication of whether the network was 'over-learning' was based on the mean-squared error (MSE) from the network, processing the stopping dataset after each iteration with the training dataset. The network was considered to have 'over-learnt' if the error in the stopping dataset increased for six consecutive training iterations.

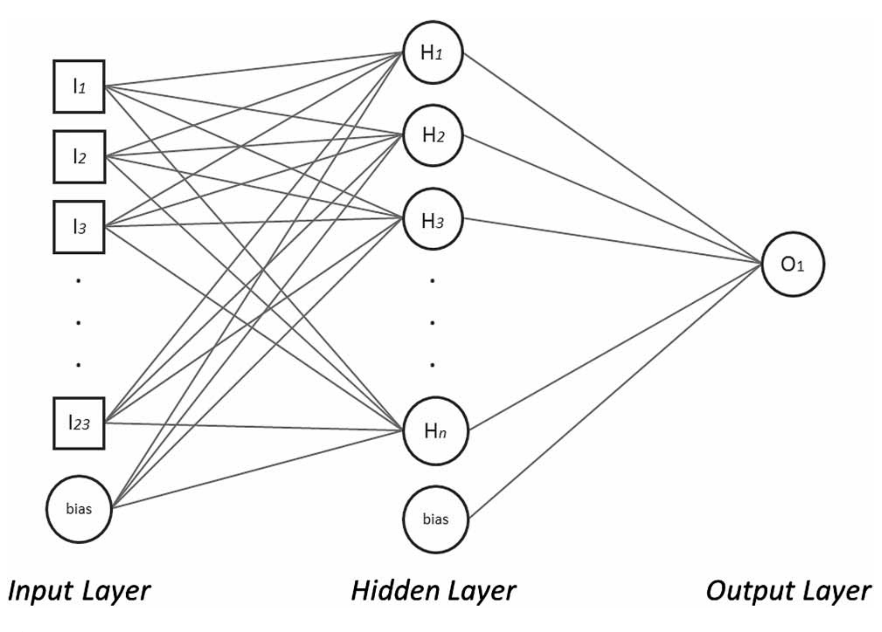

Figure 1 Structure of the multilayer perceptron

Table 4 Input parameters

Input parameter	Input neuron type	Data range/binary activation criteria
Construction year	Continuous	1860–2010
Phase of education	Binary	(−1) Primary, (1) secondary
Number of pupils	Continuous	44–2013
Internal environmental conditioning	Categorical	(−1) Natural ventilation, (0) mixed mode, (1) mechanical ventilation
Site exposure	Categorical	(−1) Exposed, (0) semi-sheltered, (1) sheltered
Orientation	Continuous	−45° to 45°
North facade adjacency	Binary	(−1) Open, (1) obstructed
South facade adjacency	Binary	(−1) Open, (1) obstructed
East facade adjacency	Binary	(−1) Open, (1) obstructed
West facade adjacency	Binary	(−1) Open, (1) obstructed
Floor area	Continuous	861–15 396 m^2
Building depth ratio	Continuous	2.50–16.60
Compactness ratio	Continuous	1.01–4.59
Surface exposure ratio	Continuous	1.71–5.67
North glazing ratio	Continuous	0.00–0.13
South glazing ratio	Continuous	0.00–0.15
East glazing ratio	Continuous	0.00–0.11
West glazing ratio	Continuous	0.00–0.14
Glazing type	Binary	(−1) Single, (1) double
Roof shape	Binary	(−1) Pitched, (1) flat or sloped
Roof glazing	Binary	(−1) None, (1) glazing
Heating degree-days	Continuous	1635.6–2843.3
Cooling degree-days	Continuous	73.9–425.2

Table 5 Output parameters

Output	Output neuron type	Data range (kWh/m^2)
Fossil fuel (heat) use (unadjusted)	Continuous	7–272
Electricity use (unadjusted)	Continuous	7–95

Different network configurations were tested during the training and validation phases to find the optimum specification for the given data. The number of neurons in the hidden layer was altered in exponential steps from two to 32 and the errors were compared.

Due to the initial synaptic weight values being random, the results of the same network configuration varied with each training computation. For this reason each network configuration was trained 500 times and the mean generalization errors of the best performing 1% were averaged and compared.

The errors used to assess the performance of the network were of three types:

$$\text{Root} - \text{mean} - \text{squared error (RMSE)} = \sqrt{\frac{\sum_i^n \left(\hat{Y}_i - Y_i\right)^2}{n}} \text{(same unit as output)} \tag{1}$$

$$\text{Coefficient of variance of RMSE(1) (CV−RMSE)} = \frac{RMSE}{\bar{Y}} (\%) \tag{2}$$

$$\text{Mean absolute percentage error (MAPE)} = \frac{\sum_i^n \frac{\left|\hat{Y}_i - Y_i\right|}{Y_i}}{n} (\%) \tag{3}$$

where Y_i and $\hat{Y}_i$ are the target and predicted outputs, respectively, for the training, testing or stopping configuration I; $\bar{Y}$ is the mean target output over each configuration; and n is the total number of configurations in the training, testing or stopping dataset.

Sensitivity analysis

In order to understand the influence that each input parameter has on the predicted output, a study was conducted to test the change in output as the inputs were altered.

The process was as follows:

- Across the 465 input patterns, the mean values of all continuous inputs and the modal values for all binary and categorical inputs were set to form a base-case ANN configuration.
- For one input at a time, the normalized values of the input were set to their extremes across their range, −1 then 1, and the two outputs calculated. All other inputs remained in their base-case condition as each individual input was altered.
- The change in output across the range in each input was recorded and compared against the base-case ANN outputs.

This process was carried out on the best-performing ANN configurations (according to the number of hidden neurons). The final results were an average of the results from the best-performing 1% of 500 ANN simulations.

Results

Statistical analyses

Figures 2 and 3 show year-on-year changes in the energy use of schools. Medians of the ratios between the actual energy uses and adjusted benchmarks in each year were used instead of raw consumption figures, so that the trends were not affected by variations in weather and the operating hours of individual buildings.

As shown in Figure 2, increases are observed in the electricity consumption of primary and secondary schools from 2008 to 2011, where the ratios have changed by approximately 9%. The changes suggest that schools have continued their uptake of information and communication technology (ICT) and electrical equipment, a trend that has continued up to the present (Global Action Plan, 2006). Moreover, it can be seen that secondary schools are notably more intensive in electricity use which is likely to be due to the widespread use of electrical equipment in ICT at secondary level (Carbon Trust, 2012).

In contrast to the trends in electricity consumption, heating consumption has decreased over the past four years. This trend is probably due in part to the increased internal heat gains from electrical equipment use that was observed in Figure 2. In addition, continued increases in the price of fossil fuels in recent years may have encouraged schools to manage their energy use better to reduce their fuel bills.

The contrasting changes in the use of electricity and fossil fuels by schools were also found by Godoy-Shimizu *et al.* (2011) in whose work similar trends were traced back to 1999. This shows how schools

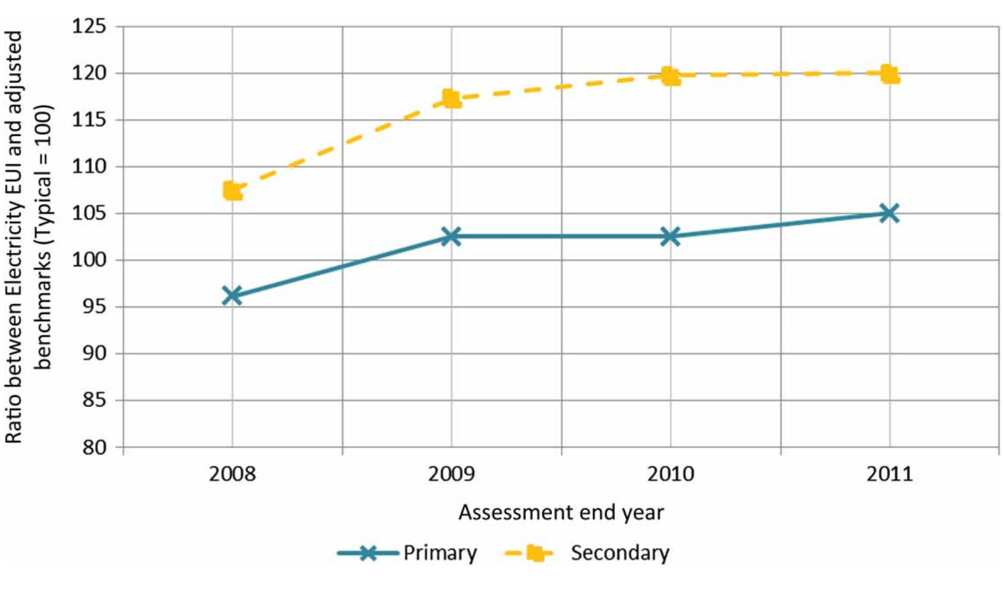

Figure 2 Year-on-year changes in the electricity use of schools

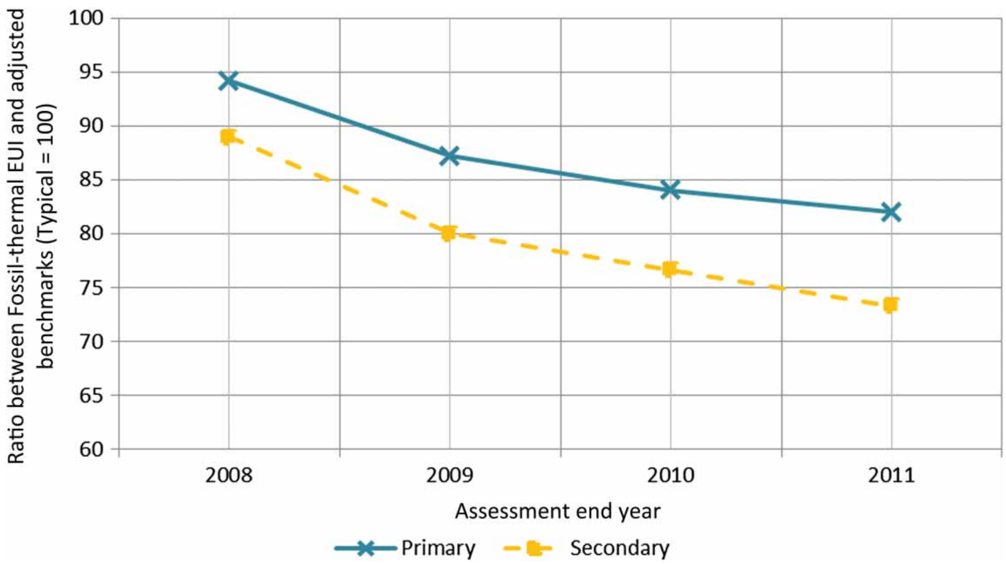

Figure 3 Year-on-year changes in the fossil-thermal energy use of schools

continue to change in their use of energy and that, therefore, there is a need to identify the factors that cause such changes, particularly those affecting fossil-thermal energy use, to understand the trends fully.

The performance figures from DECs lodged in 2012 were not presented in Figures 2 and 3, since records for the complete year were not available. Moreover, the trends were derived from a sample of all schools that lodged DECs by the ends of specific years. These are not necessarily the same schools and therefore do not provide like-for-like comparisons. A further investigation into changes in energy performance of the same schools over some given period would provide a clearer picture.

Figure 4 shows differences in the trends for electricity and fossil-thermal energy use in different types of school. Significant differences in electricity use were observed (Kruskal–Wallis, $p < 0.0001$). Primary schools were less intensive in electricity use than secondary schools, at 44 and 51 kWh/m^2, respectively. This is probably due to teaching facilities in secondary schools requiring greater use of electrical equipment, including ICT, hence higher electricity consumption (Carbon Trust, 2012; Global Action Plan, 2006). In contrast to electricity, there was no significant difference in fossil-thermal energy use between primary and secondary schools, where median values were 122 and 121 kWh/m^2, respectively (Wilcoxon–Mann–Whitney, $p > 0.0167$).

Figure 5 shows different levels of energy use per pupil in different types of school. Primary schools were found to use significantly less electricity per pupil than secondary schools, with median values of 270 and 430 kWh per pupil, respectively (Wilcoxon–Mann–Whitney, $p < 0.0001$).

A comparison of the trends in fossil-thermal energy use per pupil shows that the energy used for heating per pupil is significantly lower in primary schools than secondary schools, with median values of 744 and 965 kWh per pupil in each case (Wilcoxon–Mann–Whitney, $p < 0.0001$). The difference is probably due to variations in the density of pupils per unit floor area. Comparison of energy use per floor area and per pupil shows that approximately 6 m^2 are used per pupil in primary and 8 m^2 per pupil in secondary schools. This is attributable to the additional teaching facilities such as computer rooms, laboratories and libraries provided in secondary schools, which in turn lead to higher heating demand.

Scatter plots of floor areas and numbers of pupils against the annual electricity and fossil-thermal energy use show varying levels of correlation.

As seen in Figures 6 and 7, the differences in coefficient of determination (R^2) values indicate that floor areas account for a much greater proportion of the variation in annual electricity use than do numbers of pupils, reconfirming that floor area is a key driver of energy use in schools (Isaacs, Donn, & Baird, 1990; Isaacs & Donn, 1996). This suggests that using floor area as the denominator in the EUI metric, expressed as kWh/m^2, is more appropriate than using the number of pupils.

Figure 6 also shows the differences in sizes of the types of school, where the majority of primary schools can be

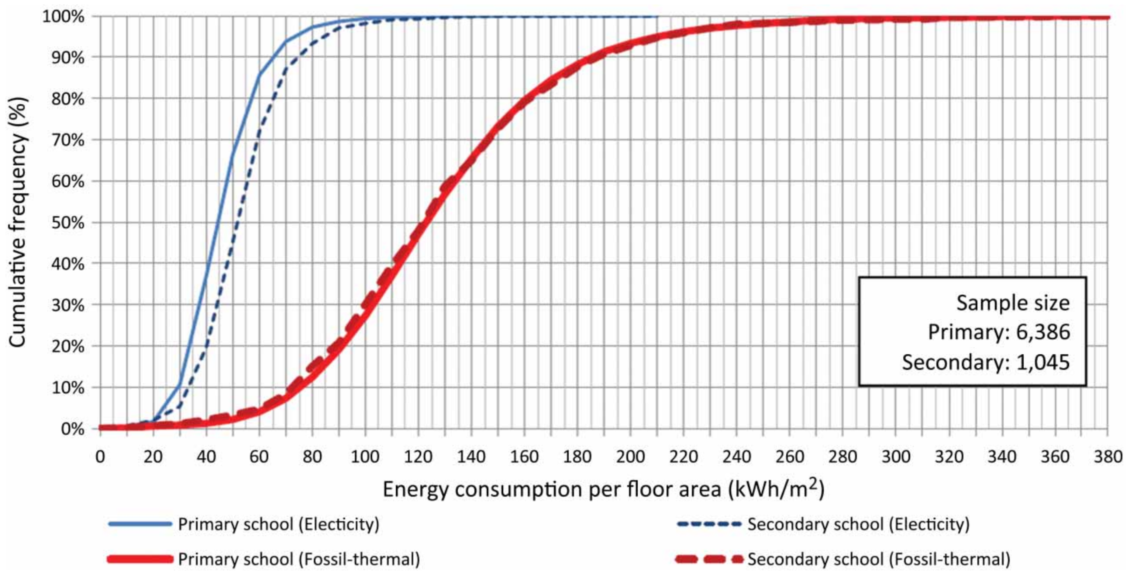

Figure 4 Cumulative frequency distribution of energy use index by school type

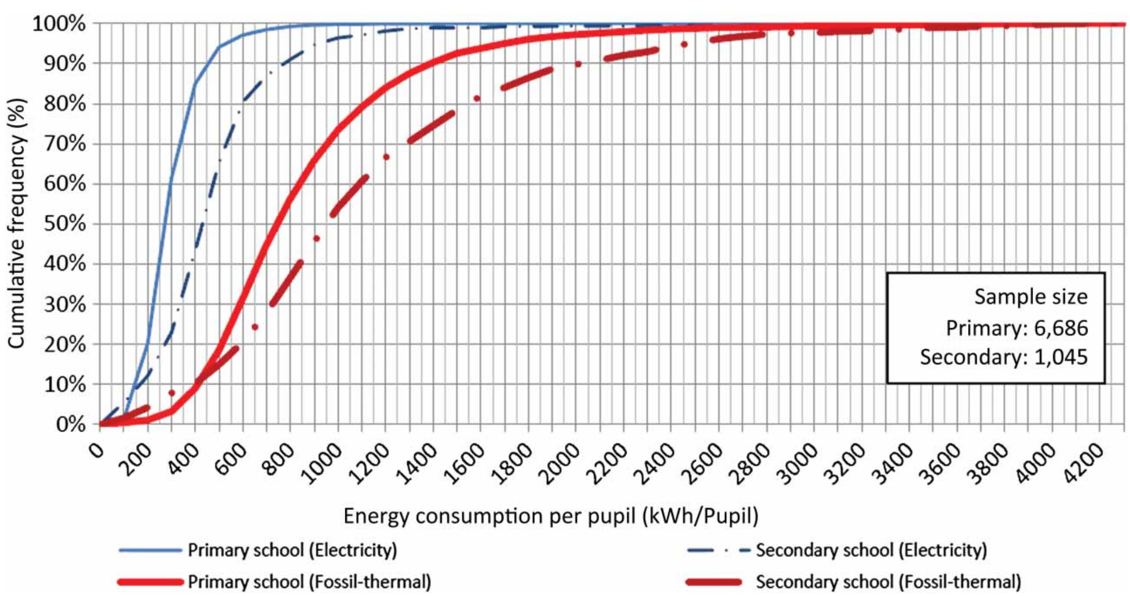

Figure 5 Cumulative frequency distribution of energy use per pupil by school type

found near the lower end of the size spectrum, around 3000 m^2, where secondary schools vary across a much wider spectrum, going up to 15 000 m^2 and greater. This supports the findings of Figure 5

Table 6 shows statistics for electricity and fossil-thermal energy use of schools by types of ventilation and heating in schools. The statistics show that electricity consumption is notably higher in mechanically ventilated schools while heating consumption is lower. This is likely to be due to the increased electrical load from components of the HVAC system such as fans and pumps in mechanically ventilated buildings, which generally use more electricity than their naturally ventilated counterparts (Bordass, Cohen, Standeven, & Leaman, 2001). On the other hand the differences in the fossil-thermal energy use by schools are negligible.

Initial hypothesis tests also indicated that there are significant differences between the school types with different ventilation strategies in the use of

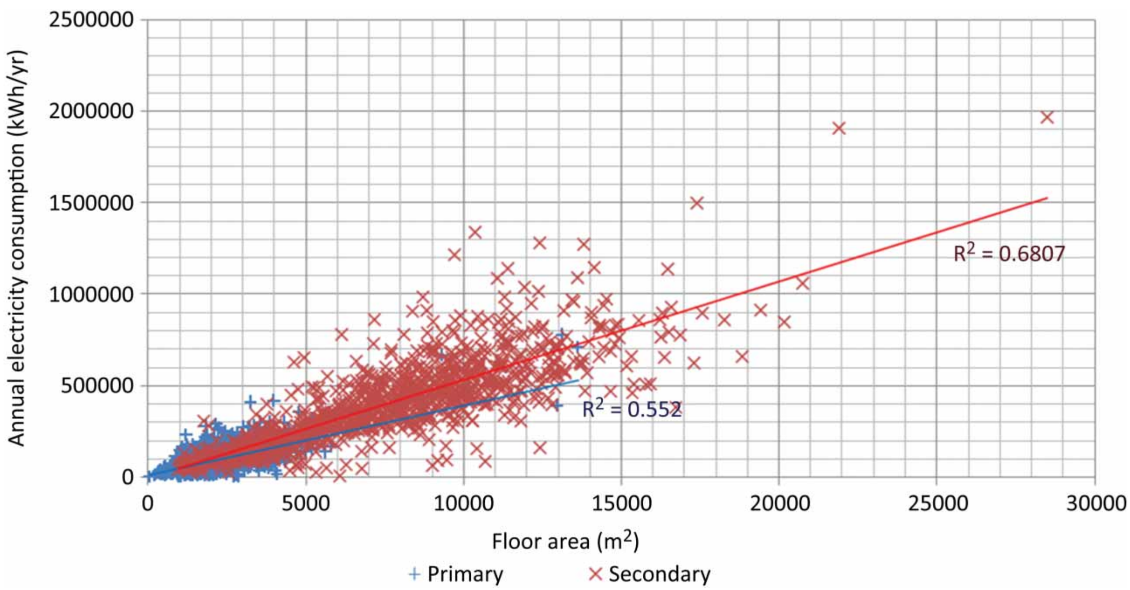

Figure 6 Scatter plot of annual electricity use and floor area by school type

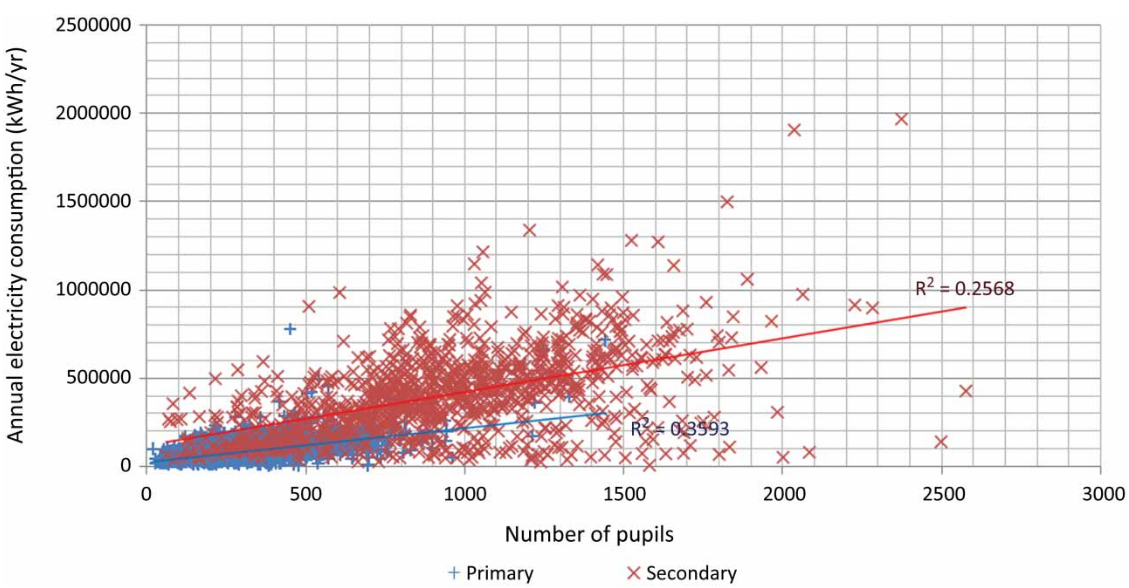

Figure 7 Scatter plot of annual electricity use and number of pupils by school type

electricity (Kruskal–Wallis, $p < 0.0001$) but not in the use of fossil-thermal energy (Kruskal–Wallis, $p > 0.05$).

Table 7 shows the results from a series of Wilcoxon–Mann–Whitney tests carried out to identify the differences.

A significant difference in electricity use of schools with natural ventilation and mechanical ventilation has been found (Wilcoxon–Mann–Whitney tests, $p < 0.0001$). However, no significant differences were found between schools with ventilation strategies involving mechanical systems (Wilcoxon–Mann–Whitney test, $p > 0.0125$). This suggests that the subtle differences between the classifications of ventilation strategies, illustrated in CIBSE TM46, may not be related to the differences in energy use (CIBSE, 2008). This raises the possibility of revising the classification system so that categories with no significant differences in energy use can be grouped together, particularly the ‘Mixed-mode with natural ventilation’ and ‘Mixed-mode with mechanical ventilation’ types.

Table 6 Distribution of energy use by internal environment

Internal environment	Primary			Secondary		
	N	Electricity EUI	Fossil-thermal EUI	*N*	Electricity EUI	Fossil-thermal EUI
		Median (kWh/m^2)			Median (kWh/m^2)	
Natural ventilation only	4	49	147	.	.	.
Heating and natural ventilation	6396	43	122	914	51	122
Mixed-mode with natural ventilation	114	48	119	67	53	122
Mixed-mode with mechanical ventilation	21	50	106	9	66	95
Heating and mechanical ventilation	140	50	118	48	57	112
Air-conditioning	11	47	99	7	49	97

Note: EUI = energy use intensity.

Table 7 Summary of the results from Wilcoxon–Mann–Whitney tests on electricity use by schools with different internal environment types

Internal environment type	Phase of education	
	Primary	Secondary
	p-value	
Heating and natural ventilation versus heating and mechanical ventilation	< 0.0001	< 0.0125
Heating and mechanical ventilation versus mixed-mode with mechanical ventilation	> 0.0125	> 0.0125
Mixed-mode with natural ventilation versus mixed-mode with mechanical ventilation	> 0.0125	> 0.0125
Mixed-mode with mechanical ventilation versus air-conditioning	> 0.0125	> 0.0125

However, it should be noted that the majority of the schools in the dataset were naturally ventilated and, therefore, the samples of schools with air-conditioning and mechanical ventilation were considerably smaller. Further studies with a well-distributed sample and a larger number of schools with air-conditioning and mechanical ventilation are necessary to test the findings reported here.

Causal factor study

This section reports results from ANN analyses in which the impact of various building characteristics was assessed on energy use in 465 schools.

ANN configurations with two and eight neurons in the hidden layer were found to produce the smallest generalization errors for fossil-thermal and electricity use, respectively. Table 8 summarizes the mean errors for each configuration. Electricity use was predicted with very similar accuracy to fossil-thermal energy use: the electricity output was predicted with mean errors of 23.5% (CV-RMSE) and 20.6% (MAPE), and the heating output was predicted with mean errors of 24.0% (CV-RMSE) and 22.0% (MAPE).

Figures 8 and 9 show the changes in output values across the range of each input when compared with the base-case output values. Larger changes in output indicate greater influence of the input on the output.

Figure 8 shows the changes in predicted fossil-thermal energy across each input range. The degree of compactness of a building was found to have the greatest impact on heating energy use of schools. This shows that schools with a longer perimeter relative to their floor area have greater heat loss through external walls, and therefore use more fossil-thermal energy. In addition, the year at which the building was built was found to have a considerable impact on fossil-thermal energy use. The energy efficiency requirements of building regulations, which have become gradually more stringent over recent decades, are likely to have

Table 8 Summary of the artificial neural network (ANN) mean errors

Output	Root-mean-squared error (RMSE) (kWh/m^2)	Coefficient of variance of RMSE (CV-RMSE) (%)	Mean absolute percentage error (MAPE) (%)
Fossil-thermal energy use (heating)	32.0	24.0	22.0
Electricity use	11.6	23.5	20.6

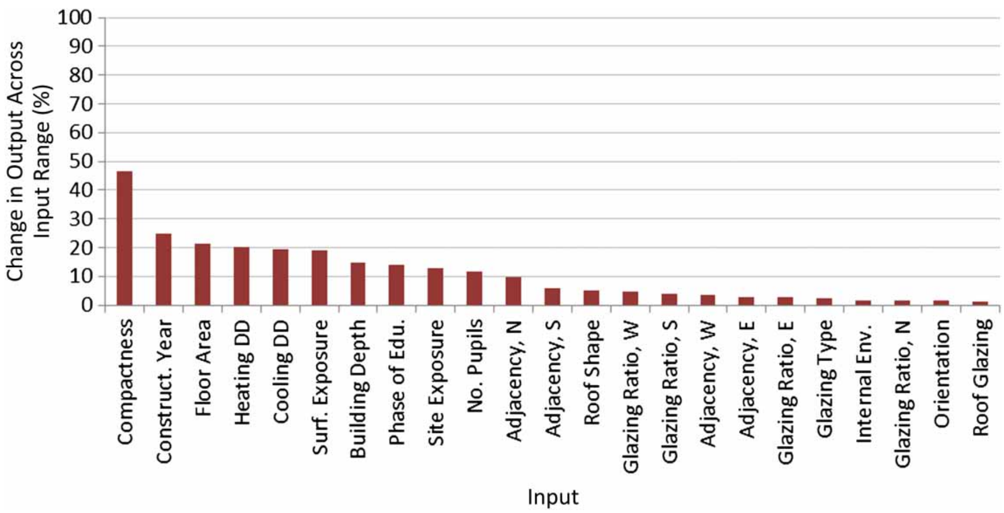

Figure 8 Change in output across input range for fossil-thermal energy use

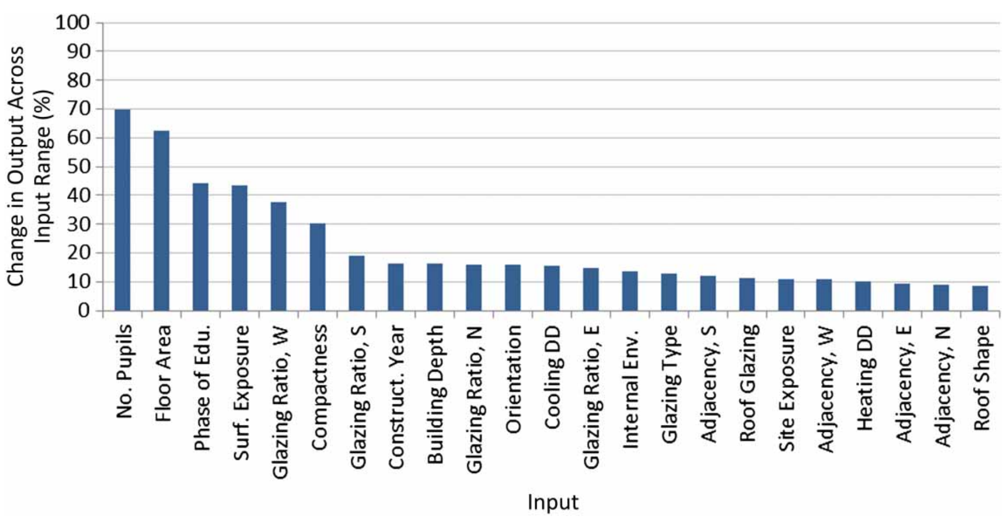

Figure 9 Change in output across the input range for electricity use

reduced the demand for heating in buildings which were erected more recently.

The results also indicate a correlation between the sizes of schools and heating intensity. This is perhaps due to larger schools having more spaces for other uses than teaching such as wide corridors and sports facilities, requiring less heating, hence the reduced intensity. Heating degree-days were found to have a noticeable impact on the use of fossil-thermal energy, because of the changes in heating demand dependent on the external temperature. It should be noted that the cooling degree-days had a similar impact on heating intensity. However, this may be due to a correlation between the heating and cooling degree-days.

Figure 9 shows the changes in predicted electricity energy across each input range. Changes in the number of pupils, hence the occupancy density, was found to have the most influence on electricity use. This impact indicates a strong correlation between the number of pupils and the electrical equipment used in schools, resulting in greater energy use. The analysis also found the size of schools (floor area) to be a parameter having considerable impact on energy use. The larger school buildings are mostly secondary schools which make greater use of information technology (IT) and electrical equipment in laboratories. They therefore have higher electricity consumption. The phase of education was found to have a significant impact on electricity use, as already discussed. The proportion of glazing on western facades was also found to have a strong influence on electrical energy use. This may be because the low afternoon sun on western orientations causes glare, resulting in the blinds or curtains being used and the lights being switched on for longer.

Discussion

Changes in the pattern of energy use

An assessment of the changes in pattern of energy use of schools from DEC records lodged from 2008 until June 2012 has shown a gradual increase in the intensity of electricity consumption and a decrease in fossil-thermal energy use. The contrasting trends observed over the past decade have indicated that the pattern of use of energy by schools continues to change in relation to developments in technology and other factors. This prompts the need to revise the way benchmarks are set in the UK. Currently, benchmarks in CIBSE TM46 are static, in the sense that there is no schedule for updating the performance figures. They are therefore not able to keep up with the changes in the way schools use energy. Such issues were raised in the revision of the benchmarks by Bruhns *et al.* (2011), which found that the benchmarks in several categories were generally lower for electricity and higher for fossil-thermal energy compared with the trends found in DECs. It is therefore important to explore ways of keeping the benchmarks up to date so that they accurately reflect how energy is used by the school stock. However, such an approach should take into consideration the implications of variable benchmarks, since those would 'move the goal posts', making it more difficult for building owners or operators to achieve better grades.

Activity classification for schools

Analyses of energy use by the UK school stock have shown that there are significant differences in electricity use between different school types, where secondary schools were significantly more intensive than primary schools. (The difference in fossil-thermal energy use was insignificant.) An assessment of the distribution of electricity use by floor area and the number of pupils suggested that the difference is probably due to intrinsic differences in occupancy and in requirements for space and equipment. This conclusion is supported by the results from the ANN study that indicate that phase of education, along with floor area and numbers of pupils, has a stronger impact on the electrical energy use of schools than other characteristics. These findings suggest that it would be desirable to revise the current classification system, which requires both school types, primary and secondary, to be compared against a single benchmark.

Internal environment and the pattern of energy use of schools

The analyses of the patterns of energy use in schools with different internal environments have shown that there is a significantly different pattern of electricity use between naturally and mechanically ventilated school buildings. On the other hand, results from the ANN indicated that the impact of the ventilation strategies was much smaller than that of other building characteristics. This is likely to be due to the fact that having a mechanical ventilation system does not necessarily mean high energy use, and that mechanically ventilated buildings have the potential to perform as well in energy terms as their naturally ventilated counterparts (Bordass *et al.*, 2001). The results thus indicate that there is insufficient evidence of intrinsic differences in demand for energy between school buildings with varying types of mechanical services. This confirms the rationale behind the CIBSE TM46 methodology, which does not include internal environment as part of the benchmarking process, in order to avoid bias in favour of the use of mechanical systems (Bruhns *et al.*, 2011).

Determinants of energy use and benchmarking

Floor areas were found to account for considerable variation in energy use of schools, hence confirming the rationale for using floor area as a standard denominator of the EUI. The number of pupils was also found to account for considerable variation in electricity and fossil-thermal energy use of schools, indicating that this is an important factor in assessing energy performance. In addition, the multivariate (ANN) analyses of building and occupant characteristics found compactness of built form to have the largest influence on fossil-thermal energy use in schools. The year in which the building was constructed and the number of heating degree-days were also found to have relatively high impact on heating energy consumption. In addition to the number of pupils, floor area and phase of education, surface exposure and the proportion of west facing glazing were found to be the strongest determinants for electrical energy consumption.

The results indicate possibilities for expanding the list of parameters by which the benchmarks or actual performances could be normalized. However, the development of a method to incorporate the new parameters will require further analyses. Due to the nature of numerical adjustments to the benchmarks, expanding the existing adjustment procedures may lead to over-manipulation of the benchmarks, so distorting their values. It is therefore necessary not only to conduct further research to identify ways to utilize the existing methodology, but also to consider other methods that allow the normalization of performance for large numbers of parameters, as in the use of multiple regression models in the United States (US Environmental Protection Agency (USEPA), 2011).

Conclusions

This study aimed to improve the comparability of benchmarking energy performance of English schools by assessing the impact of intrinsic features of their buildings such as built form and occupancy. The energy performance of the school stock was analysed statistically using a combination of the latest DEC records, lodged up to June 2012, and EduBase. Multivariate analyses of approximately 470 schools were also carried out using ANNs to assess the impact of various building characteristics on energy use.

Four-year trends in the energy use of schools, from 2008 to 2011, showed a gradual increase in electricity consumption and a decrease in heating consumption in both primary and secondary schools. Secondary schools were found to be significantly more intensive in electricity consumption than primary schools. Electricity consumption of schools with natural ventilation was found to be significantly different from that it mechanically ventilated schools. However, results from ANNs indicated that there are stronger determinants than the ventilation strategy. Statistical and ANN analyses identified floor area and number of pupils to be strong determinants of schools' energy use. Parameters that describe the built form such as compactness and exposure ratios were also found to be prominent determinants of energy use.

The findings from the study indicated possibilities for improving the comparability of benchmarking energy performance of schools. The continued changes in the pattern of energy use of schools over recent years highlighted a need to explore the implications of keeping the benchmarks up to date by making an evaluation based on benchmarks that reflect the most recent trends in energy use of the stock. The intrinsic differences in the pattern of energy use between primary and secondary schools indicated that there is a need to revise and explore the way buildings are classified and benchmarked. The varying impact of various determinants of energy use and identification of variables with stronger impacts opened possibilities for improving benchmarking comparability for schools. In a broader context, the study raises more general issues about the way that the energy performance of other non-domestic buildings, not just schools, are benchmarked.

This was a preliminary study using a combination of statistical techniques and ANNs to explore the impact that building characteristics have on the energy performance of buildings. Although data on various building characteristics were collected for a considerable number of schools, the adoption of a desk-top approach meant that data were not collected on characteristics that could not be seen from the exterior, such as boiler efficiencies and installed lighting capacity. Further studies are therefore currently being carried out to collect information on building services and equipment as well as operational characteristics.

Acknowledgements

This study was undertaken as part of a doctoral programme "Benchmarking and assessing energy consumption for the UK non-domestic stock" which is partially funded by CIBSE via UCL. The study was also partially supported by EPSRC funded RCUK Centre for Energy Epidemiology (CEE): the study of energy demand in a population (EP/K011839/1).

References

Beale, M. H., Hagan, M. T., & Demuth, H. B. (2012). *Matlab Neural Network Toolbox user's guide*. Retrieved from http://www.mathworks.com/help/pdf_doc/nnet/nnet_ug.pdf/. Accessed December 14, 2012.

Bordass, B., Cohen, R., Standeven, M., & Leaman, A. (2001). Assessing building performance in use 3: energy performance of the Probe buildings. *Building Research & Information*, *29*(2), 114–128. doi:10.1080/09613210010008036.

Bruhns, H., Jones, P., & Cohen, R. (2011). *CIBSE review of energy benchmarks for display energy certificates – Analysis of DEC results to date*. Retrieved from http://www.cibse.org/content/Technical_Resources/Technical_Reports/TechnicalReport_CIBSEReporton45000DECs.pdf/. Accessed June 11, 2011.

Building Research Energy Conservation Support Unit (BRECSU). (1996). *Energy Consumption Guide 73: Saving energy in schools*. Watford: BRECSU.

Carbon Trust. (2009). *Building the future today – Transforming the economic and carbon performance of the buildings we work in (CTC765)*. London: Carbon Trust.

Carbon Trust. (2012). *Schools sector overview (CTV019): Learning to improve energy efficiency*. *United Kingdom*. Retrieved

January 17, 2013, from http://www.carbontrust.com/media/39232/ctv019_schools.pdf
Chartered Institution of Building Services Engineers (CIBSE). (2006). *CIBSE TM41: Degree-days: theory and application*. London: CIBSE Publ.
Chartered Institution of Building Services Engineers (CIBSE). (2008). *CIBSE TM46 Energy benchmarks*. London: CIBSE Publ.
Chartered Institution of Building Services Engineers (CIBSE). (2009). *CIBSE TM47 Operational ratings and display energy certificates*. London: CIBSE Publ.
Chartered Institution of Building Services Engineers (CIBSE). (2011). *CIBSE Briefing: The recast energy performance of buildings directive*. Retrieved from http://www.cibse.org/index.cfmgo=page.view&item=721/. Accessed July 3, 2011.
Chartered Institution of Building Services Engineers (CIBSE). (2012). *CIBSE Guide F: Energy efficiency in buildings* (3rd ed.). CIBSE Publ.
Chung, W., Hui, Y., & Lam, Y. (2006). Benchmarking the energy efficiency of commercial buildings. *Applied Energy*, *83*(1), 1–14. doi:10.1016/j.apenergy.2004.11.003.
Department for Communities and Local Govenment (DCLG). (2008). *Improving the energy efficiency of our buildings: A guide to Display Energy Certificates and advisory reports for public buildings*. Retrieved May 24, 2011, from http://www.communities.gov.uk/documents/planningandbuilding/pdf/20.pdf
Field, A., & Miles, J. (2010). *Discovering statistics using SAS*. London: Sage.
Global Action Plan. (2006). *UK schools carbon footprint scoping study*. Stockholm: Stockholm Environment Institute.
Godoy-Shimizu, D., Armitage, P., Steemers, K., & Chenvidyakarn, T. (2011). Using Display Energy Certificates to quantify schools energy consumption. *Building Research & Information*, *39*(6), 535–552. doi:10.1080/09613218.2011.628457.
Hawkins, D., Hong, S. M., Raslan, R., Mumovic, D., & Hanna, S. (2012). Determinants of energy use in UK higher education buildings using statistical and artificial neural network methods. *International Journal of Sustainable Built Environment*, *1*(1), 50–63. doi:10.1016/j.ijsbe.2012.05.002.
Haykin, S. (1999). Neural networks: a comprehensive foundation. *Knowledge Engineering Review*, *13*, 409–412. doi:10.1017/S0269888998214044.
HM Government. (2008). *Climate Change Act 2008*. London: Stationery Office.
Isaacs, N., & Donn, M. (1996). Evaluating energy management. In G. Baird (Ed.), *Building Evaluation Techniques* (pp. 119–123). New York, NY: McGraw Hill.
Isaacs, N., Donn, M., & Baird, G. (1990). Energy audits and their effect on improving energy management. *Building Research and Practice*, *18*(5), 279–283.
Lee, W. (2008). Benchmarking the energy efficiency of government buildings with data envelopment analysis. *Energy and Buildings*, *40*(5), 891–895. doi:10.1016/j.enbuild.2007.07.001.
Lee, W.-S., & Lee, K.-P. (2009). Benchmarking the performance of building energy management using data envelopment analysis. *Applied Thermal Engineering*, *29*(16), 3269–3273. doi:10.1016/j.applthermaleng.2008.02.034.
Sarle, W. S. (2002). *Neural network FAQ, part 2 of 7: Learning*. Retrieved from ftp://ftp.sas.com/pub/neural/FAQ2.html/. Accessed September 9, 2011.
Sharp, T. (1996). Energy benchmarking in commercial office buildings. In *Proceedings of the American Council for an Energy Efficient Economy (ACEEE) 1996 Summer Study on Energy Efficiency in Buildings,* Vol. 4, pp. 321–329.
Sharp, T. (1998). Benchmarking energy use in schools. In *Proceedings of the American Council for an Energy Efficient Economy (ACEEE) 1998 Summer Study on Energy Efficiency in Buildings,* pp. 305–316.
Steadman, P., Bruhns, H., & Rickaby, P. (2000). An introduction to the national Non-Domestic Building Stock database. *Environment and Planning B: Planning and Design*, *27*(1), 3–10. doi:10.1068/bst2.
US Environmental Protection Agency (USEPA). (2011). Methodology. In *ENERGY STAR® performance ratings technical methodology*. Retrieved from http://www.energystar.gov/ia/business/evaluate_performance/General_Overview_tech_methodology.pdf/. Accessed June 8, 2011.
Yalcintas, M., & Ozturk, U. A. (2007). An energy benchmarking model based on artificial neural network method utilizing US Commercial Buildings Energy Consumption Survey (CBECS) database (April 2005). *International Journal of Energy Research*, 412–421. doi:10.1002/er.

Endnotes

[1]Separable energy uses are end uses that do not usually occur in a specific activity type (*e.g.* regional server rooms in offices); therefore, a separable is not allowed for by the benchmark.

[2]Non-domestic Energy Performance Register (see https://www.ndepcregister.com).

[3]The operational rating is used in DECs in the UK as a basis for grading building performance. The rating is derived by dividing the actual energy consumption by adjusted benchmarks and multiplying the ratio by 100.

[4]An operational rating of 200 is a default rating given when there is insufficient information about energy consumption figures. Such cases are therefore not suitable for the analyses. The default rating was later changed to 9999 in 2010.

[5]A composite methodology is used for benchmarking the energy performance of buildings which comprise mixtures of activities that belong to more than one benchmark category.

[6]Pro rata DECs relate to sites with multiple buildings where consumption is known only for the entire site, and this is apportioned between buildings in proportion to floor area.

[7]For the EduBase Public portal, see: http://www.education.gov.uk/edubase/home.xhtml/.

[8]For CIP, see: http://www.landmark.co.uk/solutions/registers/nondomestic/cip/.

[9]For Bing Maps, see: http://www.bing.com/maps/?FORM=Z9LH3/.

[10]For Google Street View, see: http://maps.google.com/.

[11]For Landmap, see: http://www.landmap.ac.uk/.

[12]For Digimap, see: http://digimap.edina.ac.uk/digimap/home/.

[13]For Statistical Analysis Software (SAS), see: http://www.sas.com/software/sas9/.

[14]For the Matlab Neural Network Toolbox, see: http://www.mathworks.co.uk/products/neural-network/index.html/.

[15]For MathWorks Matlab, see: http://www.mathworks.co.uk/products/matlab/.