Technical Overview: Real-time Energy Use Predictions at the Early Architectural Design Stages with Machine Learning

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Studies have shown that the actual energy consumption of buildings once built and in operation is often far greater than the energy consumption predictions made during design – leading to the term: 'performance gap'. An alternative to traditional simulation methods is an approach based on real-world data, where bahaviour is learned through observation. Display Energy Certificates (DECs) are a source of observed building 'behaviour' in the UK, and machine learning, a subset of artificial intelligence, can predict global behaviour in complex systems, such as buildings. In view of this, artificial neural networks, a machine learning technique, were trained to predict thermal (gas) and electrical energy use of building designs based on a range of collected design and briefing parameters. As a demonstrative case, the research focused on school design in England. Mean absolute percentage errors of 22.9% and 22.5% for thermal and electricity energy use predictions respectively were achieved. This is an improvement of 9.1% for the prediction of thermal energy use and 24.5% for the prediction of electricity energy use when compared to sources evidencing the current performance gap.

Introduction

Building Energy Use

Background

In the UK, the Climate Change Act 2008 (DECC 2008) sets legally binding targets to reduce UK carbon emissions by 80% by 2050 against a 1990 baseline. The built environment contributes significantly to the anthropogenic environmental impact, with buildings consuming over 40% of all of the UK's energy use (Carbon Trust 2009). It is the responsibility of the design team to take the appropriate sustainable actions to reduce energy consumption and meet our sustainability aspirations (CIBSE 2004). As such, the prediction of energy use during the design stages is undertaken.

Performance Gap

Studies, such as that carried out by the UCL Energy Institute (2013), provide evidence that the actual energy use of buildings, once built and in operation, regularly exceeds design calculations. Table 1 shows the comparison of design and actual energy use figures for office and educational buildings in the CarbonBuzz (2014) database: an online crowdsourcing building data collection platform. The design data in Table 1 came from simplified building energy models (SBEMs) (30%), energy performance certificates (EPCs) (40%) and 'full energy models' (30%). Underestimation of electricity energy use during design seems to be greater than underestimation of thermal energy (including space heating, hot water and other non-electric fuel uses). UCL Energy Institute (2013) claimed that there was no marked difference in the performance gap between those buildings with design data emanating from SBEM and those where it comes from a full energy model.

Table 1. Energy use performance gap as evidenced in the CarbonBuzz database – adapted from UCL Energy Institute (2013)

Fuel Type and Sector	Mean Design Total Energy Consumption (kWh/m^2/yr)	Mean Actual Total Energy Consumption (kWh/m^2/yr)	Design Prediction Error (%): 'Performance Gap'
Thermal			
Offices	46	73	37
Education	57	84	32
Electricity			
Offices	71	121	41
Education	56	106	47

Data-driven Approach

"A major hindrance in modelling real problems is the lack of understanding of their underlying mechanisms because of complex and nonlinear interactions among various aspects of the problem [...] in many cases, the best solution is to learn system behaviour through observations" (Samarasinghe 2007, p.1-2). In view of this, an alternative approach at predicting energy consumption to mathematical models based on building physics (traditional building energy simulation) is to collect large amounts of actual energy and design data and learn the patterns between the two. This is in line with Big Data methods which have arisen in recent years due to the abundant availability of data in the modern world (Harvard Magazine 2014). A source of actual energy data in the UK are Display Energy Certificates (DECs), introduced in Section 'Display Energy Certificates' below, and a method of learning the complex relationships between energy consumption and design and briefing data are artificial neural networks (ANNs), introduced in Section 'Artificial Neural Networks' below.

Display Energy Certificates

In the UK, it is mandatory for some public buildings to publicly display how energy efficient they are with a Display Energy Certificate (DEC). The DEC scheme, under the European Energy Performance of Buildings Directive (EPBD) in 2008, 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 1000m^2 (DCLG 2007) to produce DECs, with the threshold reduced to 500m^2 in 2013 and 250m^2 in 2015 (DCLG 2012 2015). The publicly available data collected in the scheme includes thermal and electrical energy use intensity (kWh/m^2/yr). The DEC scheme provides a rich source of raw data; as of June 2012, there were 120,253 DEC records, relating to 46,441 different buildings (or sites).

Artificial Neural Networks

Artificial neural networks (ANNs) are machine learning algorithms which are a subset of artificial intelligence. They are inspired by biological neural processes that take place within the brain (Haykin 1999). There are many variations of ANNs, which represent the different ways to abstract inspiration from neuroscience. Their ability to learn, and therefore generalise, allows the models to produce predicted outputs for inputs not encountered during their training (learning) process (Haykin 1999). A number of studies have been carried out using ANNs for building energy use analysis. These include analysing the determinants of energy use in university buildings (Hawkins et al. 2012), predicting building heating demand (Ekici and Aksoy 2009) and the development of energy benchmarks (Yalcintas and Ozturk 2007).

Research Carried Out

Using school buildings in England as a test case, work was carried out to gather data to train ANNs to predict the energy use of building designs as an exploration of an alternative prediction method to traditional physics based building energy simulation models. The gathered training dataset included actual energy use and measured building characteristics for 502 existing schools across England. The data was collected from the DEC scheme and a range of other database and digital map resources. The building characteristics included geometry, services, glazing, activity, site, construction year and weather data.

The accuracy of the ANNs were fine-tuned by altering the architecture of the ANN models, including the number of input building characteristic parameters. Finally, four case studies were carried out, evaluating the prediction accuracy of the ANN method using recently constructed school buildings.

As part of the wider doctoral research, a user-friendly design tool interface (see Appendix) was created which makes energy use predictions in real-time as design and briefing paramaters are altered. The software was named the SEED Tool (School Early Environmental Design Tool). The full doctoral research is outined by Paterson (2017).

Methodology

Building Characteristics Dataset

Display Energy Certificates

The annual energy use intensity (EUI) (kWh/m^2/yr) figures for fossil-thermal and electrical energy consumption from the DEC records were used in this research. ‘Fossil-thermal’ relates to combustion fuel for all purposes, such as space heating, water heating and cooking – from here on, 'thermal' will be used in place of 'fossil-thermal'. ‘Electrical’ includes electricity used for all purposes, including lighting, equipment and mechanical systems. It should be noted that buildings that use electricity for space heating were disregarded in this research, as outlined in the following section. The prediction of annual thermal and electrical energy use of new school buildings is the aim of the ANN method. As such, the thermal and electrical energy use intensity data collected from the DECs formed the training output data for the ANNs, as outlined in Section ‘Building Characteristics’ below. Some of the non-energy data in the DEC dataset were utilised in the building characteristics dataset for ANN inputs, which is also outlined in Section ‘Building Characteristics’.

Data Cleaning

Analysis of DEC records by Bruhns, H., Jones, P., & Cohen (2011) highlighted that preparation work is required ahead of any analysis, in order to identify and eliminate invalid, erroneous or uncertain records from the raw dataset. The criteria from Bruhns, H., Jones, P., & Cohen (2011) were developed and refined further in this research with assistance from members of the CIBSE Energy Benchmarks Steering Group[1] and in collaboration with Dr Sung Min Hong. The process to select records that were deemed valid was as follows:

- Remove records with operational ratings that are 200 or 9999
- Remove records with operational ratings that are less than 5 or greater than 1000
- Remove cancelled DECs
- Remove records with a total useful floor area that is less than 50m^2
- Remove records where the total annual CO_2 emissions are greater than 100,000 tonnes of CO_2/year
- Remove records where the electric energy use intensity (EUI) is 0 kWh/m^2/yr
- Remove records where the building is electrically heated
- Remove records where the thermal EUI is 0 kWh/m^2/yr
- Remove records where more than one DEC is lodged within 6 months of each other

[1] The CIBSE Energy Benchmarks Steering Group was set up by CIBSE to oversee the development of the energy benchmarks in CIBSE TM46 (CIBSE 2008) that underpin the DEC scheme.

Further steps were taken to clean the dataset by amending typing errors and removing duplicate, 'pro-rated'[2] and 'composite'[3] DECs. Lastly, the latest DEC record from each building was extracted. The DEC building types 'Primary school', 'Secondary school', 'State primary school' and 'State secondary school' were used for this resaerch.

Building Characteristics

The data collection process adopted a desktop approach over site surveys in order to maximise the number of buildings in the dataset. Sources of data included the DEC database, digital map software, satalite images, publically available databases and school websites. A geographical spread of schools across England was sought. In order to achieve this, schools in the cleaned DEC dataset were randonmly ordered to ensure no bias was given to a particular location. In order to reduce factors that may cause uncertainties and ensure all required data may be collected, a set of collection criteria was created. As such, schools were chosen from the cleaned DEC dataset if they adhered to the following criteria:

- The school has one main building.
- Building features are consistent throughout (e.g. age and main construction materials).
- The facades of the school can be observed using Bing Map's Bird's Eye View (Microsoft 2012) function or Google Street View (Google 2012b).
- The school has pupil number data from the Department for Education's (DfE) database.

Final Dataset

Upon the completion of the data collection process, energy use outliers were removed. Machine learning algorithms are sensitive to the range and distribution of the training data. Outliers in the training data can

[2] Pro-rated 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.
[3] A composite methodology is used for mixed use buildings which comprise of different activities that belong to more than one benchmark category; the process involves dividing the usable floor area of a building between the different activities and applying different benchmarks to those areas

'mislead' the training process of a neural network and can result in less accurate models (Brownlee 2013). Therefore, a process to remove outliers was undertaken on the energy use figures. Energy use data 1.5 times the interquartile range below the lower quartile and above the upper quartile were used as a boundary for identifying outliers. Outliers were identified from the data using interquartile ranges to account for the possibility of skewed distributions. The outlier removal procedure was carried out on the thermal and electricity energy use figures separately.

The final building characteristics dataset consited of 502 school buildings across England. All parameters (ANN inputs), their envisaged impact on energy use and data sources are given in Table 2. The annual energy use range of these schools are given in Table 3.

Table 2. Building characteristic parameters (ANN inputs) and their envisioned impact on energy use

Parameter	Description Summary	Envisioned impact on energy use	Data Type	Data Range/ Categories	Data Source
Floor Area	Gross internal area (GIA)	Occupancy density – thermal/electricity: use of equipment and services (such as ICT) (Godoy-Shimizu et al., 2011)	Continuous	861-15396m^2	DEC
Surface Exposure Ratio	Exposed surface area / building volume	Space heating: fabric heat transfer (Steadman et al., 2009)	Continuous	0.1725 - 0.8457	EDINA (2012b); Microsoft (2012)
Building Depth Ratio	Building volume / exposed external wall area	Space heating/electricity: ventilation strategy (see 'Ventilation Strategy' below); electricity: daylight (Steadman et al., 2009)	Continuous	2.1145 - 11.4932	EDINA (2012b); Microsoft (2012)
Orientation Correction	Angle at which the external walls differ from absolute north, south, east and west. Positive angle for clockwise orientations	Space heating: solar gain (Ratti et al., 2005)	Continuous	-45 - +45^o	(Google, 2012a)
Number of Pupils	Part-time pupils divided by 2, plus the number of full-time pupils	Occupancy density – thermal/electricity: use of equipment and services (such as ICT) (Godoy-Shimizu et al., 2011)	Continuous	54 - 2013	DfE (2011)
Year of Construction	Year the school was built	Space heating: fabric thermal performance; Electricity: ICT equipment, efficiencies of building services; space	Continuous	1828 - 2010	School website; EDINA (2012a)

		heating/electricity: ventilation strategy (see 'Ventilation Strategy' below) (Godoy-Shimizu et al., 2011; Global Action Plan, 2006)			
Glazing Ratio on Northern Facades	Glazed area on the northern facades / total floor area	Space heating: fabric heat transfer; electricity: daylight (Yang et al., 2008)	Continuous	0.0014 - 0.1313	Bespoke Processing (2014) code; Microsoft (2012)
Glazing Ratio on Southern Facades	Glazed area on the southern facades / total floor area	Space heating: fabric heat transfer, solar heat gain; electricity: daylight (Yang et al., 2008)	Continuous	0 - 0.1734	Bespoke Processing (2014) code; Microsoft (2012)
Glazing Ratio on Eastern Facades	Glazed area on the eastern facades / total floor area	Space heating: fabric heat transfer, solar heat gain; electricity: daylight (Yang et al., 2008)	Continuous	0 - 0.1349	Bespoke Processing (2014) code; Microsoft (2012)
Glazing Ratio on Western Facades	Glazed area on the western facades/total floor area	Space heating: fabric heat transfer, solar heat gain; electricity: daylight (Yang et al., 2008)	Continuous	0 - 0.1341	Bespoke Processing (2014) code; Microsoft (2012)
Heating Degree Days[4]	Heating degree days during the DEC monitoring period	Space heating: fabric heat transfer (CIBSE, 2006)	Continuous	1519.9 - 2843.3	Department for Communities and Local Government (2008)
Cooling Degree Days[5]	Cooling degree days during the DEC monitoring period	Cooling: fabric heat transfer (CIBSE, 2006)	Continuous	73.9 - 457.1	Department for Communities and Local Government (2008)
Phase of Education	Primary schools or secondary schools/sixth form colleges	Electricity: use of equipment (such as ICT) (Global Action Plan, 2006)	Categorical	[Primary], [Secondary]	DEC
Ventilation Strategy	Does mechanical ventilation exist?	Space heating: ventilation heat loss; electricity: mechanical systems (Thomas, 2006)	Categorical	[Full nat. vent], [Mech. vent]	DEC
Adjacency of Northern Facades	Obstructed if a building or tree is within 1 x the height of the building from the majority of the facade orientation	Electricity: daylight (Ratti et al., 2005)	Categorical	[Not obstructed], [Obstructed]	Microsoft (2012)
Adjacency of Southern Facade	See adjacency of northern facades	Space heating: insolation on facade, solar gain; electricity: daylight (Ratti et al., 2005)	Categorical	[Not obstructed], [Obstructed]	Microsoft (2012)

[4] Heating degree days were utilised within the thermal ANNs only
[5] Cooling degree days were utilised within the electrical ANNs only

Adjacency of Eastern Facades	See adjacency of northern facades	Space heating: insolation on facade, solar gain; electricity: daylight (Ratti et al., 2005)	Categorical	[Not obstructed], [Obstructed]	Microsoft (2012)
Adjacency of Western Facade	See adjacency of northern facades	Space heating: insolation on facade, solar gain; electricity: daylight (Ratti et al., 2005)	Categorical	[Not obstructed], [Obstructed]	Microsoft (2012)
Hours of Operation	Standard or extended occupant hours	Space heating/electricity: extra hours use of systems and services (BRE, 1998)	Categorical	[Standard], [Extended]	DEC

Table 3. Annual energy use ranges for the collected building characteristics dataset (ANN outputs)

Fuel Type	**Data Range (kWh/m^2/yr)**
Thermal Energy Use	47-246
Electricity Energy Use	13-91

Artificial Neural Network Approach

Overview

MATLAB (Mathworks 2013) was used to create the ANNs in this research. Feedforward multilayer perceptron networks were used, each comprised of an input layer, hidden layer and output layer. Two ANN models were constructed: one with thermal energy consumption as an output and one with electrical energy consumption as an output. The number of potential input neurons was eighteen and the number of output neurons was one. The final number of input and hidden neurons were determined as a result of the analysis outlined in Section ‘Training’ below. Each neuron in the input layer represents a variable in the building characteristics dataset (Table 2), and the single neuron in the output layer represents energy consumption (Table 3): one model predicting thermal energy use and another predicting electrical energy use. Figure 1 shows a simplified example of the structure of an ANN predicting thermal energy consumption.

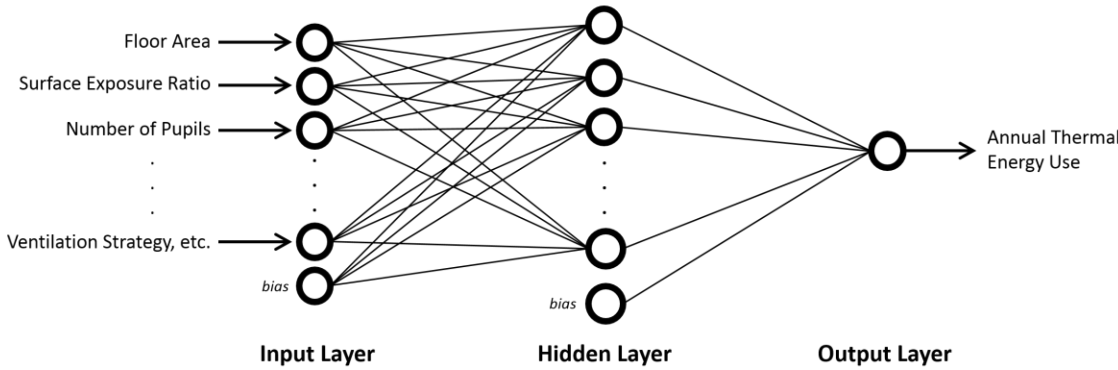

Figure 1. : Simplified example of an ANN predicting thermal energy consumption

Each neuron in the input layer is comprised of continuous or categorical data, as listed in Table 2. The input data was normalised to values between -1 and 1 to generalise the calculation processes. Continuous input neurons were a floating number between -1 and 1 and categorical (binary) input neurons were either 1 or -1. The middle layer is referred to as the 'hidden layer' as it is never exposed to the external environment (data) (Samarasinghe 2007). The hidden layer enables the system to generate nonlinear and complex relationships by intervening between the input and the output layers (Haykin 1999). A single hidden layer was deemed sufficient for this application (Fausett 1994). Each neuron is connected to each neuron in the next layer by synaptic weights. These weights hold a random value at the beginning of the training process (Beale et al. 2013).

Training

During the training process, the synaptic weights of the network were modified to attain a prediction from the network that closely matched the actual energy outputs after a number of iterations (Haykin 1999). The building characteristics dataset was split into three groups: training (80% of the dataset), validation (10% of the dataset) and testing (10% of the dataset). A Levenberg-Marquardt backpropagation process (Beale et al. 2013), a supervised training technique, with early stopping, was used to train the network. K-folding and committee machine teqniques were adpoted to improve the performance of the ANNs (Mitchell, T. 1997; Haykin 1999). K-folding involved splitting the dataset into ten parts, or ‘folds’. One fold was used for testing, one for validation (which relates to early stopping as described below), and the remaining eight for training. This process was repeated 10 times, each time using a different fold for testing, the adjacent fold for validation and the remaining folds for training. The best performing ANN from each of the 10 folds were utilised in a committee machine, whereby multiple ANNs make predictions and their results are combined. In the final committee machine, the 10 ANNs in the thermal energy model and 10 ANNs in the electricity energy model all receive the same inputs and make individual predictions. Through the process of ensemble averaging (Haykin 1999), the mean of the 10 ANN predictions for thermal energy use formed the first committee output and the mean of the 10 ANN predictions for electricity energy use formed the second committee output. For each of the individual ANNs, the number of hidden layer neurons were altered from 2, 4, 8, 16, 32 and 64. 100 runs were performed for each hidden neuron configuration, with the initial synaptic weights randomised each time. For each fold, the ANN with the lowest mean squared error (MSE) (Equation 1) for the testing dataset was saved and the generalisation errors determined retrospectively. The generalisation errors of the ANN were evaluated in terms of the root-mean squared error (RMSE) (Equation 2) and the mean absolute percentage error (MAPE) (Equation 3) for the testing dataset. The overall ANN performance was established as the average of the minimum generalisation errors achieved for all 10 folds.

$$\text{Mean square error (MSE)} = \frac{1}{n}\sum_{n}^{1}(\hat{Y}_i - Y_i)^2 \tag{1}$$

$$\text{Root-mean square error (RMSE)} = \sqrt{\sum_{n}^{i}\frac{(\hat{Y}_i - Y_i)^2}{n}}\ (\text{kWh/m}^2\text{/yr}) \tag{2}$$

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

Where Y and $\hat{Y}$ are the target and predicted outputs respectively for the training, validation or testing data configuration i, and n is the total number of configurations in the training, validation or testing datasets.

After each iteration, the MSE (Equation 1) of the validation set was recorded. The training was stopped when the validation error increased for six iterations, the default indication of divergence within MATLAB (Mathworks 2013). This early stopping technique ensures the algorithm will not overlearn and will be able to best generalise when presented with new inputs it has not experienced.

Addition Analysis

In order to assess the correct number and type of building characteristic inputs to include in the ANN analysis, that is, which inputs produce the least generalisation errors, input sets were cumulatively added to the network and the mean minimum generalisation errors across all 10 folds were calculated. The ordering of the input sets were based on statistical analyses of the building characteristics dataset, outlined in Paterson (2017).

Case Studies

As part of the ANN training process, the accuracy of the energy predictions were tested on schools that made up the building characteristics dataset. A proportion of the differences in, for example, fabric quality and building systems between newer schools and older schools are likely to be picked up in the construction year input neuron. However, in order to verify the accuracy of the tool at predicting energy use in new school designs, the ANN method was used to predict the energy consumption of four case studies (see Figure 2): all of which had actual energy consumption data to compare the ANN predictions against. Two of the case studies, Loxford School of Science and Technology and Petchey Academy, were designed by the industrial sponsor of this research, AHR, therefore the author was granted access to the schools' design team, engineering reports and architectural drawings which enabled the collection of energy and building characteristics data. The data from the remaining two schools were sourced from DfES (2006). Tables 4 and 5 show the collected building characteristics (ANN inputs) and energy use data (ANN output targets) respectively. In addition to actual energy consumption, the ANN predictions were compared to the original design calculations, where available.

Loxford School of Science and Technology
London, UK
Secondary School and Sixth Form

Notes:
Concrete frame with flat slab construction
Natural ventilation + mechanical ventilation

Petchey Academy
London, UK
Secondary School

Notes:
Materials include curtain walling and blockwork
Fully air conditioned

Kingsmead Primary School
Northwich, UK
Primary School

Notes:
Glulam timber frame and timber clad facades
Fully naturally ventilated

The Academy of St Francis of Assisi
Liverpool, UK
Secondary School

Notes:
Materials include brick, copper and timber
Natural ventilation + mechanical ventilation

Figure 2. Overview of case study buildings

Table 4. Case study un-normalised building characteristics data (ANN inputs)

ANN Inputs	Loxford	Petchey	Kingsmead	St Francis of Assisi
Building depth ratio	6.63923	9.58161	5.86039	6.12633
Surface exposure ratio	0.24087	0.19641	0.42146	0.34439
Floor area	14610m^2	10490m^2	1296m^2	7704m^2
Orientation correction	-5º	-38º	10º	16º
Construction year	2010	2007	2004	2006
Ventilation strategy	[1] Mech. Vent.	[1] Mech. Vent.	[-1] Full nat. vent.	[1] Mech. vent.
Glaz. ratio on northern facades	0.01757	0.03641	0.05478	0.03731
Glaz. ratio on southern facades	0.02024	0.03200	0.01698	0,07509
Glaz. ratio on eastern facades	0.04477	0.03434	0.02469	0.00669
Glaz. ratio on western facades	0.04960	0.01108	0.00463	0.00572
Occupancy hours	[-1] Standard	[-1] Standard	[1] Extended	[1] Extended
Phase of education	[1] Secondary	[1] Secondary	[-1] Primary	[1] Secondary
Number of pupils 2000	2000	1200	250	900

Table 5. Case study annual energy consumption figures

	Loxford	Petchey	Kingsmead	St Francis of Assisi
Thermal (kWh/m^2/yr)				
Actual Energy Use (ANN output targets)	105	157	103	138
Original Design Calculations	43.3	20.48	NA	16
Electricity (kWh/m^2/yr)				
Actual Energy Use (ANN output targets)	75	146	72	73
Original Design Calculations	15.8	30.26	NA	22

Results

Artificial Neural Network Addition Analysis

Tables 6 and 7 give the generalisation errors by input sets for the thermal and electricity energy consumption ANN models respectively. As more inputs were cumulatively added, the ANN prediction errors tended to decrease. This is in line with the building physics principles and environmental studies outlined in Table 2. The errors did, however, increase when site (building adjacency) and weather (heating/cooling degree days) inputs were added. For both the thermal and electricity ANN models, the lowest errors were achieved with the 5th input sets, which both contained inputs relating to geometry, construction year, services, glazing and activity. These ANNs were therfore selected for all further analysis.

Table 6. Thermal energy use ANNs – number of input neurons and ANN mean minimum errors for each input set

Input Set	**Input Set 1**	**Input Set 2**	**Input Set 3**	**Input Set 4**	**Input Set 5**	**Input Set 6**	**Input Set 7**
Geometry	4	4	4	4	4	4	4
Construction year		1	1	1	1	1	1
Services			1	1	1	1	1
Glazing				4	4	4	4
Activity					3	3	3
Site						4	4
Weather							1
Total Input Neurons	4	5	6	10	13	17	18
RMSE (kWh/m^2)	37.1	37.0	36.7	36.3	36.1	36.3	37.0
MAPE (%)	24.2	23.9	23.9	23.2	22.9	23.8	24.1

Table 7. Electricity energy use ANNs – number of input neurons and ANN mean minimum errors for each input set

Input Set	**Input Set 1**	**Input Set 2**	**Input Set 3**	**Input Set 4**	**Input Set 5**	**Input Set 6**	**Input Set 7**
Construction Year	1	1	1	1	1	1	1
Activity		3	3	3	3	3	3
Glazing			4	4	4	4	4
Geometry				4	4	4	4
Services					1	1	1
Site						4	4
Weather							1
Total Input Neurons	1	4	8	12	13	17	18
RMSE (kWh/m^2)	13.3	13.1	13.1	12.5	12.1	12.7	12.8
MAPE (%)	25.4	25.5	24.9	23.5	22.5	23.5	23.6

Table 8 shows the comparison between the performance gap, as determined by an audit on the CarbonBuzz data (Table 1), and the ANN mean absolute percentage errors (MAPEs). The results show that that the ANN models are an improvement of 9.1% for the prediction of thermal energy use and 24.5% for the prediction of electricity energy use when compared to the performance gap evidenced in the CarbonBuzz database.

Table 8. Comparison of MAPEs of original design calculations and ANN predictions for all case studies

	Difference Between Predicted and Actual Energy Use (%)	
	Thermal Energy Use	Electricity Energy Use
CarbonBuzz data[6]	32	47
ANN MAPE	22.9	22.5
Improvement	*9.1*	*55.1*

Case Studies

Table 9 shows the ANN predictions against the actual thermal and electrical energy consumption figures for the case studies. Figure 3 shows the ANN predictions against actual energy use and original design calculations. These results are summarised in Table 10 where the mean absolute percentage errors (MAPEs) between the original design predictions and the ANN predictions are compared. The ANN MAPEs are 18.4% for the prediction of thermal energy use and 20.9% for the prediction of electricity energy use. These errors are less than the lowest MAPEs recorded when testing the ANN during the training process (Tables 6 and 7). The case study ANNs are also more accurate than the original design calculations, with an improvement of 59.6% for thermal energy predictions and 55.1% for electricity energy predictions (Table 10). It was shown that the ANN method's greatest errors were in the prediction of the fully air-conditioned building, Petchey Academy.

Table 9. Case study ANN predictions and errors

	Loxford	**Petchey**	**Kingsmead**	**St Francis of Assisi**
Thermal				
Actual ($kWh/m^2/yr$)	105	157	103	138
ANN Prediction ($kWh/m^2/yr$)	115	114	129	122
RMSE ($kWh/m^2/yr$)	10	43	26	16
Percentage error (%)	9.5	27.4	25.2	11.6
Electricity				
Actual ($kWh/m^2/yr$)	75	146	72	73
ANN Prediction ($kWh/m^2/yr$)	115	68	56	69
RMSE ($kWh/m^2/yr$)	10	78	16	4
Percentage error (%)	9.5	53	22.2	5.5

[6] CarbonBuzz Educational data (see Table 1)

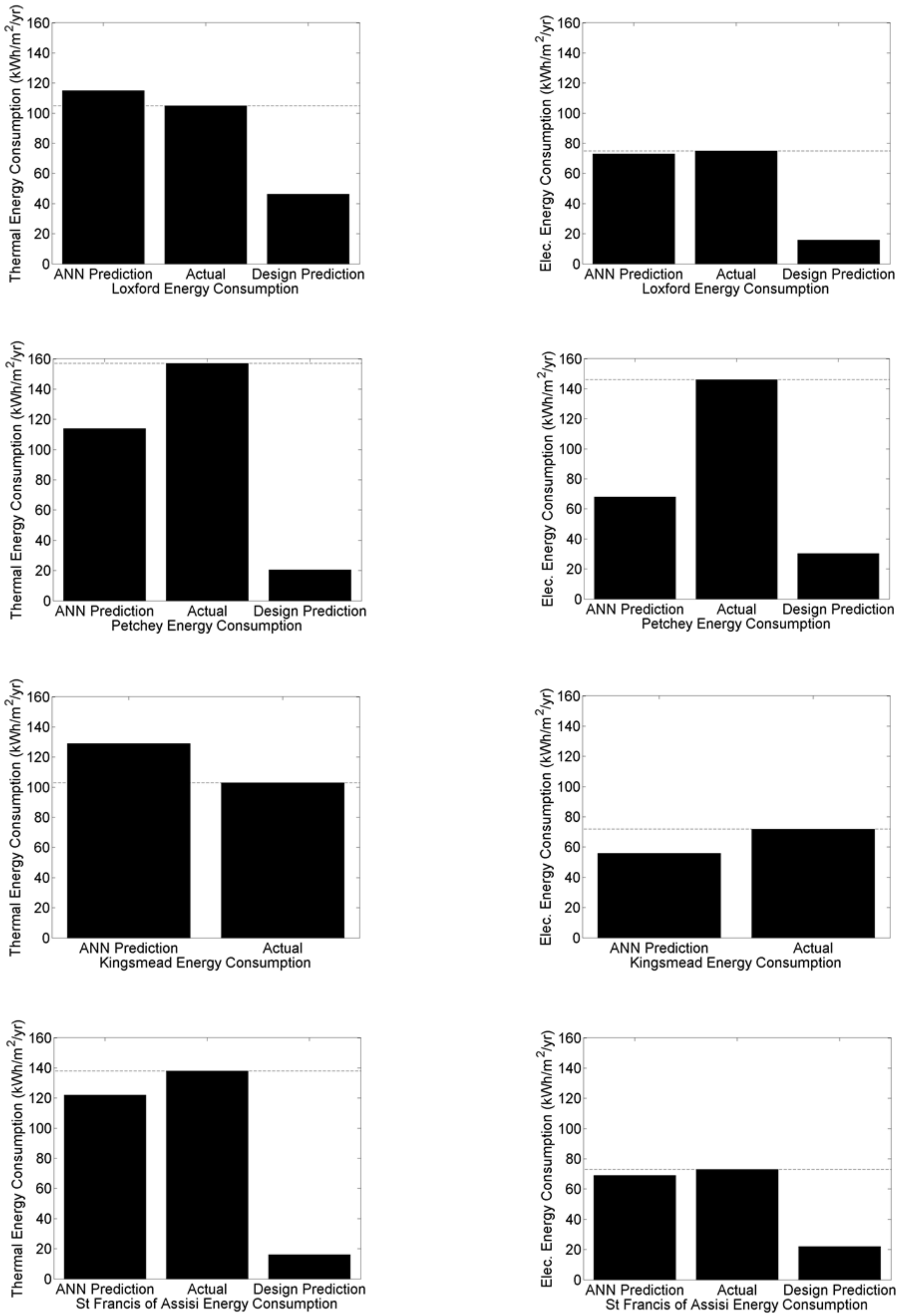

Figure 3. Case study energy consumption comparisons between ANN predictions, actual energy use and original design calculations

Table 10. Comparison of MAPEs of original design calculations and ANN predictions for all case studies

	Mean Absolute Percentage error (%)	
	Thermal Energy Use	Electricity Energy Use
Original Design Calculations	78	76
ANN Predictions	18.4	20.9
Improvement	*59.6*	*55.1*

Discussion

Data Collection Process

This research has shown that the availability of suitable data is necessary in adopting a machine learning approach. The challenge is in the difficulty obtaining such data in sufficient quantity. Despite the fact that the desktop data collection approach allowed data on more buildings to be collected, compared to site based surveys, the process was timely. Also, the availability of building characteristics data was limited by the fact that the desktop approach, which included the utilisation of digital maps, could not collect all desirable information, such as construction details. Furthernmore, energy data and additional building characteristic data, obtained from the DEC scheme, is only available for public buildings in the UK that are frequently visited by the public. Therefore, data from private sector buildings, such as retail and commercial offices, tend not to be collected through the scheme. Moreover, the information in the DEC database, gathered in order to produce a DEC, is not sufficient by itself – requiring the aforementioned desktop approach for the collection of additional building charateristics. A framework which supplies sufficient building characteristics data for future expansion of this research would require a more comprehensive database similar to the Commercial Building Energy Consumption Survey (CBECS) (US Department of Energy 2015) in the USA. CarbonBuzz, as introduced in Section 'Performance Gap', has the potential to crowdsource such data on a large scale. However, the platform was growing and at the time of carrying out this research, and there was not sufficient building characteristics information in the database to carry out this study. This highlights the need to support and maximise the potential of existing database frameworks, such as the DEC scheme and CarbonBuzz.

Artificial Neural Network

The addition analysis showed that as more inputs were added, the ANN prediction errors tended to decrease, which is in line with the building physics principles and environmental studies outlined in Table 2. The errors did, however, increase when site (building adjacency) and weather (heating/cooling degree days) inputs were added. The building adjacency inputs were expected to affect space heating and electricity use, in that overshadowing from adjacent buildings, or other obstructions, reduce solar gain and daylight (Ratti et al. 2005). However, when adjacency was statistically analysed in the collected building characteristics dataset (Paterson 2017), it largely did not influence thermal or electrical energy use, and therefore these ANN results are representative of the wider building stock's behaviour. Building adjacency may not have affected thermal energy use that greatly because of related aspects such as cloud cover or the fact that other building characteristics are more dominant. Cooling degree days would be expected to affect electricity use of schools with mechanical cooling. However, unsuprisingly, as no schools in the collected building characteristics dataset were air-conditioned, this parameter did not improve the performance of the ANN model. Heating degree days were expected to affect space heating because of their relationship with fabric heat loss. However, when the collected heating degree days were statistically analysed (Paterson 2017), they were shown not to influence thermal energy use, and therefore these ANN results are representative of the wider building stock's behaviour. The fact that heating degree day inputs did not affect thermal energy use is likely due to the poor control of heating systems (Hong 2014) and also because of the relative similarity of external temperatures in England – if the study expanded to Scotland, with typically lower external temperatures, or indeed internationally, it would be expected that heating degree days would be more influential on thermal energy use. This highlights a difference between a building physics model, such as traditional building simulation, and a data-driven model, such as an ANN method. Physics based models will indicate the effect of design and briefing variables on energy use under a controlled virtual environment, whereas the importance of variables in ANN models are assessed under 'messy', real-world conditions, which may suggest some variables are less, or more, influential in practice than in theory.

Overall, the best performing ANNs showed success in terms of predicting energy use with greater accuracy than the current 'performance gap' evidenced in the CarbonBuzz database (Table 8). The ANN prediction (generalisation) errors contain a number of component errors and uncertainties. The following is a breakdown of these components:

- Systematic errors of the ANN model
- Observatioinal errors within real-world conditions

The systematic errors are the errors associated with the architecture of the ANN. The process to reduce this error within this research involved altering the number of input and hidden neurons during the ANN training process. The systematic errors may be reduced further by exploring alternative ANN architectures, such as increasing the number of hidden layers and including new inputs parameters. The observational error is the difference between a measured parameter and its true value (Dodge 2003), which includes natural variability, such as material properties and building dimensions; occupancy behaviour; and climate. These uncertainties can be substantial (Wit and Augenbroe 2002). Research carried out by Clevenger and Haymaker (2006) estimates that occupancy behaviour alone can affect the outcome of energy predictions by 10-40%. The difficulty of simulating real-world systems, such as buildings, is the lack of understanding of the complex, non-linear and random interactions that take place (Samarasinghe 2007). This is in part due to the involvement of people, whose behaviour is difficult to predict. As outlined in Section 'Data-driven Approach', Samarasinghe (2007) lays the argument to predict the behaviour of real-world systems through the study of observed data of these systems in operation, rather than modelling each individual relationship in theory. The ANN method follows this approach by using observed energy and building characteristics data under real-world conditions to make global energy use predictions. This method accounts for the some of complex and random interactions of, for example, occupancy behaviour. Nonetheless, Clevenger and Haymaker's conclusions (2006) highlight the difficulty in producing prediction models, of any type, with very small errors. The observational errors may be reduced by utilising measured data which more closely match their true value, such as site survey measurements over digital map measurements – a process which would be more timely unless the data is crowdsourced as discussed in Section 'Data Collection Process'.

Case Studies

The ANN case study MAPEs are less than the MAPEs recorded when training and testing the ANN method with the building characteristics dataset. This provides evidence that the ANN method predicts new school buildings with no less accuracy than older buildings. Furthermore, the ANNs were more accurate than the original design calculations. This highlights the success of the ANN method in being able to more accurately predict energy consumption than the original design calculations. During the case study analysis, it was shown that the ANN method's greatest error was in the prediction of electricity energy use for Petchey Academy. Petchey Academy was the only fully air-conditioned case study building. The ANN's error at predicting electrical energy use in this school was 53.4%. This figure, however, was an improvement of 25.9% on the prediction of the original design calculation which had an error of 79.3%. Nonetheless, the ANN error may still be viewed as excessive. As previously mentioned, no buildings collected in this research had air-conditioning – therefore the ANN training dataset did not include air-conditioned buildings. Due to the extra electricity consumed by the systems in these buildings, it is deemed that the energy use of fully air-conditioned buildings cannot be accurately predicted by the ANN method in this research as it did not have this type of data to learn from. This applies to continuous data also. An inherent limitation in ANN models is their inability to extrapolate beyond the training data range (Beale et al. 2013). Building physics based models (traditional building energy simulation) do have the ability to extrapolate, which is a benefit over an ANN based prediction method. This issue highlights the necessity of having a design within the range of parameters in the ANN training data to ensure a more accurate prediction when using an ANN based method. As such, any ANN based prediction tool made available to the building design community must make it clear what these boundary conditions are.

Conclusion

This paper presents research carried out to develop a method of predicting a building's energy consumption using a machine learning approach as an alternative to traditional building simulation at the early design stages. Artificial neural networks (ANNs) were trained to predict the energy consumption of school designs by linking actual thermal (gas) and electrical energy consumption data from Display Energy Certificate (DEC) data to a range of collected design and briefing parameters. The ANN mean absolute percentage errors (MAPEs) were 22.9% and 22.5% for thermal and electricity energy use predictions respectively. This is an improvement of 9.1% for the prediction of thermal energy use and 24.5% for the prediction of electricity energy use when compared to the performance gap evidenced in the CarbonBuzz database. The case study MAPEs were 18.8% and 20.9% for themal and electricity energy use predictions respectively, which is an improvement of 59.6% and 55.1% for the prediction of thermal and electrical energy use respectively when compared to the original design calculations.

The research provides evidence that an ANN method may form a viable addition to the range of environmental analysis methods utilised by design teams.

This research is part of a wider doctoral research project, which includes the development of a user-friendly design tool which makes energy use predictions in real-time as early design and briefing paramaters are altered (see Appendix). This research is detailed in full by Paterson (2017).

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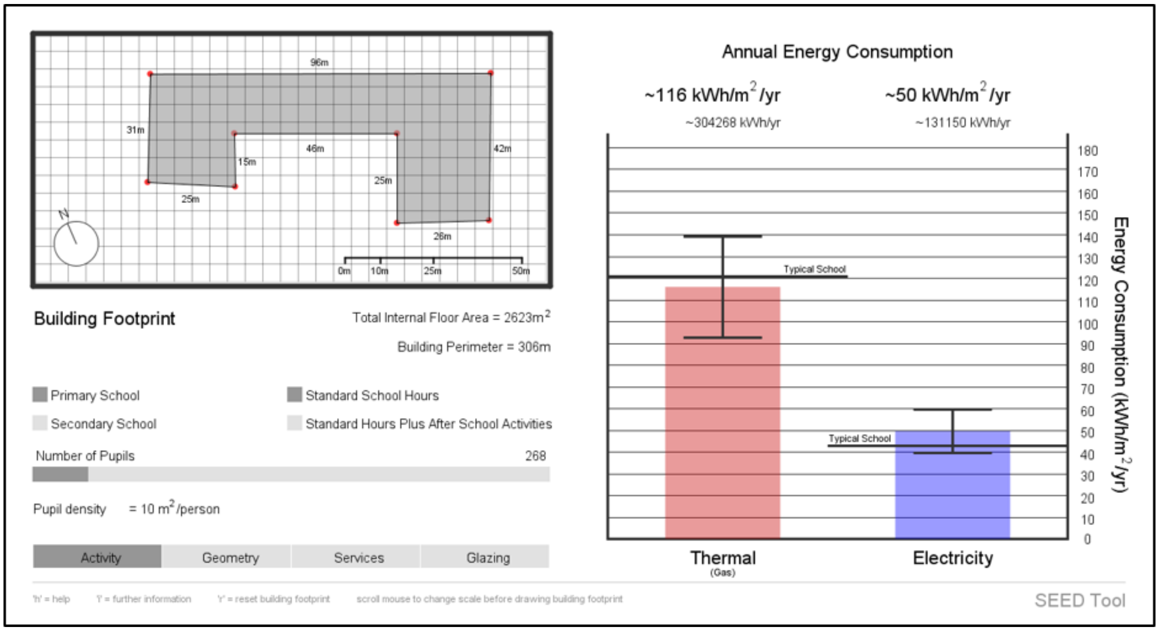
Appendix

SEED Tool Interface



References

TO BE COMPLETED