Energy and Buildings 94 (2015) 109–120

Contents lists available at ScienceDirect

Energy and Buildings

journal homepage: www.elsevier.com/locate/enbuild

Building model calibration using energy and environmental data

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ARTICLE INFO

Article history:
Received 1 December 2014
Received in revised form 18 February 2015
Accepted 21 February 2015
Available online 28 February 2015

Keywords:
Model calibration
Measured energy data
Local weather data
Building performance simulation
Energy Plus
Hourly data
Sensor deployment
Case study building

ABSTRACT

A large number of randomly interacting variables combine to dictate the energy performance of a building. Building energy simulation models attempt to capture these perturbations as accurately as possible. The prediction accuracy of building energy models can now be better examined given the widespread availability of environmental and energy monitoring equipment and reduced data storage costs. In this paper a set of two calibrated environmental sensors together with a weather station are deployed in a 5-storey office building to examine the accuracy of an EnergyPlus virtual building model. Using American Society of Heating, Refrigerating and Air-Conditioning Engineers (ASHRAE) Guide 14 indices the model was calibrated to achieve Mean Bias Error (MBE) values within ±5% and Cumulative Variation of Root Mean Square Error (CV(RMSE)) values below 10%. The calibrated EnergyPlus model was able to predict annual hourly space air temperatures with an accuracy of ±1.5 °C for 99.5% and an accuracy of ±1 °C for 93.2% of the time.

1. Introduction

The origins of building energy modelling can be traced back as early as 1920s with the development of response factor method for transient heat flow calculations [1]. The availability of computers in the 60s heralded a new dawn when, especially from early 80s the HVAC companies developed energy models for heating and cooling load calculations [2,3]. This trend accelerated as the 70s oil crises raised building energy standards, leading to greater energy efficiency and modelling methods that continue to this day [4]. Whilst initially a design phase tool, increasingly building energy simulation (BES) models of existing buildings are developed to aid research into model-based controls, optimisation, energy conservation measures (ECM) and financial appraisals [5–7]. The creation, maintenance and updating of virtual building models therefore increasingly require greater levels of accuracy to enable more meaningful studies.

In the last few years the widespread deployment of multifunctional environmental sensors, mandatory sub-metering of building energy consumptions, longitudinal data collection and the internet of things have all led to substantial amounts of building and energy related data being made available. The richness of digital infrastructure output has grown to an extent comparable to biological ecosystems in all their complexity [8]. Within building related applications, the availability of both simulated and measured energy and comfort data gives the issue of model calibration greater potency. Building model calibration is a measure of model accuracy, which despite increasing sophistication still suffers vast under-determined parameter space [9].

The aim of this paper is to conduct an energy calibration using an EnergyPlus model before examining the match between simulated and actual space air temperatures. This two-tiered objective is perused through the following steps:

1 Using an office building as a platform, a first stage energy calibration of the model is performed using 2012 hourly-metered values.
2 Space air temperature is collected for the same period using environmental sensors to enable an assessment of zone temperature prediction accuracy of the calibrated EnergyPlus model.

The calibration process follows ASHRAE guideline 14 recommendations. This guideline was originally developed to quantify energy saving potentials of proposed retrofit schemes, and is among

Abbreviations: AHU, air handling units; BES, building energy simulation; BIM, building information modelling; BWM, Box whisker mean; CV(RMSE), cumulative variation of root mean square error; ECM, energy conservation measures; EPW, EnergyPlus weather (file); HAM, heat, air and moisture (Modelling); HVAC, heating, ventilation, air-conditioning and cooling; MBE, mean bias error; PIR, passive infra-red.

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http://dx.doi.org/10.1016/j.enbuild.2015.02.050

Fig. 1. The building's heavily glazed front aspect faces +34° from due south.

three current guides that define virtual model acceptance criteria [10–12].

1.1. Case-study building

A modern 5-storey sandstone office inaugurated in 2010 is the platform for the work undertaken here (located 54°58′N, 1°36′W). At north, east, south and west orientations solar control glazing cover 54%, 29%, 87% and 42% of the facades respectively (hence overall the building's external facade is 53% glazed). The south aspect is partially shaded by extruded aluminium brise soleil (Fig. 1).

The building fabric *U*-value exceeded the statutory UK building requirements of the time by an average of 29%. Internally the complex architecture includes two large southerly and westerly voids, two internal atria facilitating displacement ventilation and a blend of cellular and open plan offices over 8365 m^2 of gross area (housing around 500 staff). Thermally induced displacement ventilation and exposed concrete surfaces are among two carbon reduction philosophies that guided the original design (Fig. 2).

A Gill's MetPak Pro weather station combined with a SPN1 pyranometer were mounted on the rooftop of this building (Appendix A) to provide the following outputs (accuracy noted in brackets):

1 Global solar radiation (±5%).
2 Diffused radiation (±5%).
3 Wind speed (±2% at 12 m/s).
4 Wind direction (±3°).
5 Air temperature (±0.1 °C).
6 Relative humidity (± 0.8% at 23 °C).
7 Dew point (±0.15 °C at 23 °C with a dew point of 20 °C).
8 Barometric pressure (±0.5 hpa).

Except for solar radiation, all measurements are instantaneous values sampled at 10-minute intervals. Global and diffused solar components are however 10 min averages which are further rounded to form hourly figures to construct EPW (EnergyPlus weather) files.

1.2. HVAC services

Three equally sized condensing boilers provide a total heating output of 744 kW which are delivered to the zones via a combination of radiators, trench and perimeter heaters, under floor heating and tempered air. Two central air handling units (AHUs) with 2-stage heat recovery facilitate displacement ventilation at a total rate of 11.32 m^3/s with 90% of the supplied volume being recirculated. The design attempted to eradicate any need for refrigerant-driven cooling yet a small degree of back-up cooling capacity is provided first by adiabatic evaporative coils acting directly on the summertime air intake, followed by direct expansion vapour compression coils (which have a relatively small capacity of 100 kW). Because of extensive IT use in the building, power factor correction and surge suppression facilities are incorporated into electrical supply to guarantee a power factor quality of 0.96 at all times. Lighting is operated by presence detection and is equipped with daylight compensation sensors.

Table 1
Comparison of energy benchmarks for existing UK open-plan office buildings (KWh/m^2 of treated floor area).

Category	Case study building	Best practice	Typical
Electricity	137	128	226
Fossil Fuel	51	97	178

1.3. Energy data

Box whisker mean (BWM) plots are used to present 2012 metered energy use of the building (Figs. 3 and 4). This allows quick and efficient communication of many aspects of building energy demand, namely peaks, medians, extreme values (outliers) and seasonal variations [13]. The building has a rather consistent electricity demand throughout the year (Fig. 3) where on average, working-hour electrical loads float at around 180 kWh (with peaks of around 200 kWh) before falling to a base-load of about 50 kWh at night.

Night purge ventilation strategy raises the night time base-load to around 60 kWh in mid and late summer months. Daylight-linked lighting conversely reduces the summer months' electricity demand during office hours.

The building annual heating demand is more variable given that it is a function of climatic conditions. Except in January, loads above 100 kWh fall above the upper quartile range indicating the building's well-insulated fabric (Fig. 4). Building heating requirements are well below CIBSE best practice recommendations (Table 1) [14].

1.4. Software description

EnergyPlus is a first principle based tool and the official building simulation programme of the United States Department of Energy. It is extensively used and examined by the international research community to model heating, cooling, ventilation, lighting and also water consumption using a state-space method (the thermal load of the building is simulated using a heat balance method) [15,16]. Energyplus is primarily a simulation engine (with no interface) and as such DesignBuilder version 3.2.0.067 was used as the graphical interface (front-ending EnergyPlus Version 7.2.0)[17]. Several formatting steps were required to allow weather files to be used in EnergyPlus models, including generating '.stat' files using EnergyPlus weather statistics and conversions program.

2. Literature review

2.1. Modelling limitations

Building models capture an arbitrary and limited part of what essentially is a multiplicity of dynamic (fabric properties and HVAC), stochastic (occupant) and probabilistic (weather) elements, resulting in both inaccuracy [18,19] and uncertainty [9,20]. Software limitations, input parameter and weather data inaccuracy compounded by difficulties in capturing how exactly a building

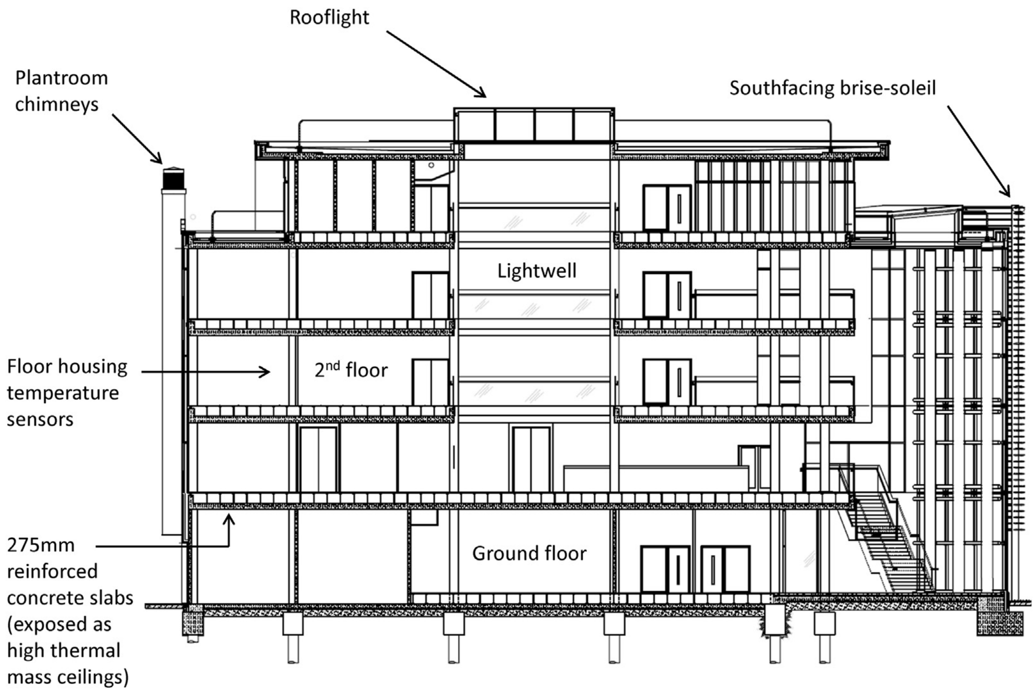


Fig. 2. Section drawing of the case study building.

is operated are the major causes of virtual model errors [21]. The behaviour of heat in a space, and the 'coupled' sorption and desorption of moisture into and out of building fabric (and furniture) are phenomena of great dynamic complexity and quite understandably only partially described by building models [22] despite having significant building energy implications [23]. Several computational methods exist that quantitatively evaluate heat and moisture transfer by solving the governing differential equations. These are concisely captured in the introductory notes of Chen, Y. and S. Wang [24]. Limitations of hygrothermal modelling are due (but not limited) to:

1 The properties of building material are assumed constant in most analytical and numerical models proposed to solve heat and moisture balance problems [25]. In reality the predominantly porous and hygroscopic building fabric properties change with changing temperature and moisture content, impacting heavily on HVAC loads particularly in humid climates [22].

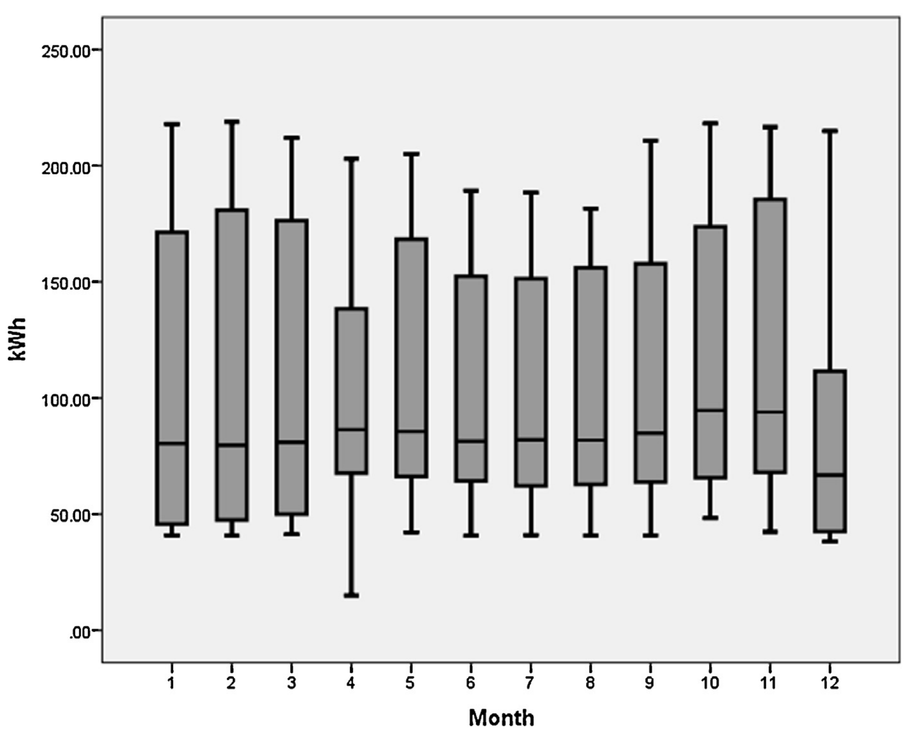


Fig. 3. BWM plot of metered hourly electricity consumption (2012).

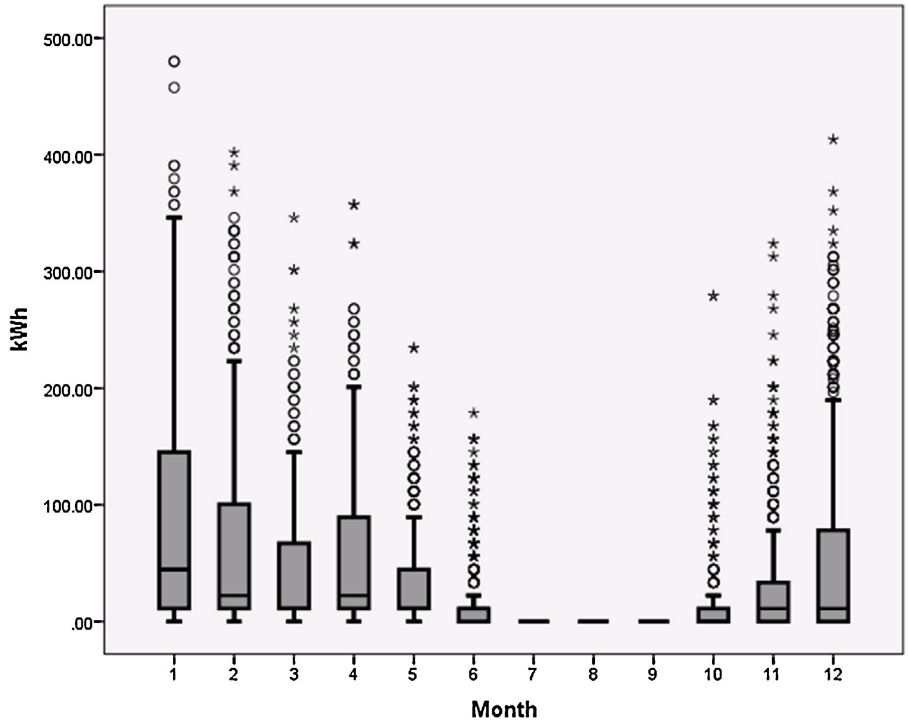


Fig. 4. BWM plot of metered hourly gas consumption (2012).

2 The boundary conditions are difficult to define, and current knowledge of climatic excitation of building hygrothermal behaviour requires further refinement [26].
3 The highly nonlinear governing equations are computationally difficult, time-consuming [27] and prone to errors.

Natural ventilation and infiltration also heavily impact on hygrothermal building properties [28]. Air flow related elements are also among the most notable sources of uncertainty in building simulation [29]. Overall these shortcomings in simultaneous modelling of heat, air and moisture (HAM) form a catalogue of inquiries that are the subject of ongoing scientific work [30].

2.2. Work on calibration

Until recently calibration efforts primarily focused on how closely simulated results match the metered energy data [10,31,32], and also allowed for the personal judgement of the analyst [33], although a pattern of common consensus is emerging towards the application (and further refinement) of ASHRAE guide 14 method [9,34–37]. A comprehensive coverage of historical and current calibration techniques and their merits is available from Coakley, D. et al. [34]. In most instances current guidelines that set out criteria on building calibration make allowances for calibrating against actual data at either monthly or hourly intervals [10–12]. However, calls have now been made to use hourly values of sub-metered services over annual cycles to calibrate a model [9,38]. Calibration work has mostly been performed manually [39] although a few methods have been proposed for the automation of the process using input parameter optimisation as well as uncertainty and sensitivity analysis [40]. Reddy identifies three calibration methods: first manual iterative, second automated and finally graphical and statistical methods [38]. Most efforts examined during this work centred around the manual iterative method which also allows trending the improvements made as a result of input adjustments. Mustafaraj, G., D. Marini, et al. [41] offer one of the most lucid efforts that is an extension of previous works [35,38,42]. In its comprehensive form this entails a two stage version control parameter input (and screening) approach that begins by populating the model with as-built fabric, HVAC and occupancy values. In the second stage the model is further refined by identifying the most influential input parameters and using field measurement data in a reiterative process of adjustment to eventually establish the final calibrated version. This method informs the work conducted here.

2.3. Accounting for uncertainty

When reconciling measured and simulated values, two overall sources of error exist. Measurement error contained in the actual data and model error emanating from the simulation process. Measurement errors can be identified with reference to equipment manufacturer literature or by conducting equipment calibration. Underpinning model errors are however more convoluted due to the intrinsic uncertainties involved. Several examples exists that attempt to capture source and magnitudes of uncertainty in building simulation modelling [43–46]. The essence of most of these efforts are captured by De Wit [47] who classifies the sources of uncertainty into the following:

- Specification related: arising when the building fabric and systems are described partially or inaccurately.
- Modelling related: the virtual model governing principles are fundamentally a simplified description of reality.
- Scenario related: external (e.g. climate) and internal (e.g. occupant) parameters within the model are often different from reality.

Inevitably the vast volume of information that is required to describe a building model generally leads to simplification and parameter reduction [48–51]. Despite this inevitability, recommendations are made to attempt to identify the magnitude of model uncertainties so that predictions of ECM studies could be presented with greater levels of confidence [52–54]. Several methods had been provided to automatically calibrate a building model while imposing certain constraints on relevant input parameters; including (but not limited to) objective and penalty function techniques [55,56], which can estimate critical parameters and then quantify the magnitude of uncertainty [52,54]. More recently Bayesian techniques were also proposed but these tend to be more application-specific [57–59]. An increasing body of research has come to recognise that occupancy related issues act as a more prominent source of uncertainty in model predictions than previously assumed, leading to efforts to develop mostly case-specific stochastic models of occupancy [60–67].

3. Method

The two-stage method [35,41] referred to in Section 1.2 informed the calibration process undertaken for this study. A succession of 19 models each with incremental adjustments paved the way to arrive at the final version containing local 2012 weather files. Against actual hourly data, ASHRAE Guideline 14-2002 was followed to calibrate the building model [10]. This entails determining two dimensionless indicators of errors, MBE and CV(RMSE) values using formulae (1) and (2):

$$\mathrm{MBE} = \frac{\sum_{i=1}^{N_i}(M_i - S_i)}{\sum_{i=1}^{N_i} M_i} \tag{1}$$

$$\mathrm{CV(RMSE)} = \frac{\sqrt{\sum_{i=1}^{N_i}\left[\frac{[(M_i - S_i)]^2}{N_i}\right]}}{\frac{1}{N_i}\sum_{i=1}^{N_i} M_i} \tag{2}$$

Where M_i and S_i are respective measured and simulated data at instance i, and N_i is the count of the number of values used in the calculation. ASHRAE Guide 14 considers a building model calibrated if hourly MBE values fall within ±10% and hourly CV(RMSE) values fall below 30%. MBE and CV(RMSE) indices were constructed over monthly intervals in order to study monthly variations too. MBE figures provide an indication of errors averaged to the mean of measured values but suffer from the cancellation effect. CV(RMSE) index however is a measure of accumulated error normalised to the mean of the measured values. As such CV(RMSE) more closely reflects the accumulated magnitude of error and therefore is a better measure of the overall prediction accuracy of the model.

Conventionally when simulating complex phenomena, error is defined as reference value (observed) subtracted from the model forecast (simulated) [68]. Error values were constructed for the three streams of data under analysis using equation (3):

$$\varepsilon_i = M_i - S_i \tag{3}$$

3.1. Parameter input and calibration

Prior to the handover of the building, a complete building log-book was compiled by the architectural firm which outlines detailed descriptions of as-built fabric properties, electrical and HVAC service distribution and control strategies. This enabled a complete description of the building (summarised in Table 2). The estate facilities managements and building users were also consulted for operational details.

The results of an infiltration smoke test (carried out at 50 Pa) provided the infiltration input. A point particularly noteworthy is the conversion of measured building's air change rates (expressed at 50 Pa) to normalised air leakage at atmospheric pressure. This was achieved using formula (4):

$$\mathrm{ACH}_{\mathrm{Atmospheric}} \approx \frac{\mathrm{ACH}_{50}}{F} \tag{4}$$

Table 2
Summary of parameter input.

Input parameters	Value
Heating	LTHW radiators + underfloor heating
Heating setpoint/setback temperatures	22 °C (12 °C)
Ventilation	Displacement with heat recovery
Heating system seasonal CoP	0.8
Natural ventilation rate (per person)	8 l/s
Cooling setpoint/setback temperatures	24 °C (28 °C)
Lighting (daylight linked with linear control)	9 W/m^2 (to achieve 300 Lux)
Occupants (from head count)	490 (peak time)
Total office equipment gains[a,b]	10 W/m^2
Occupied hours	8 am–5 pm
Fabric *U*-values	
Glazing (with low emissivity coating)	6 mm double pane solar control glazing with 20 mm air gap (*U*-value 1.772 W/m^{2}K)
Glazing G value (solar transmittance)	0.38
External walls (W/m^{2}K)	0.292
Roof (W/m^{2}K)	0.25
Floor (W/m^{2}K)	0.13
Infiltration (ac/h)[c]	0.33

[a] Computers: 6 W/m^2 (derived from agent-based power monitoring system deployed by the university IT department).
[b] Office equipment: 4 W/m^2 (derived from 12 electricity sub-meters at the building).
[c] Constant rate of infiltration expressed at atmospheric pressure.

Where F is a factor used to relate the air exchange rates under typical conditions ($\mathrm{ACH}_{\mathrm{atmospheric}}$) to the air exchange rate at 50 Pascal (ACH_{50}) [69]. An average F-value of 20 was used as given by Sherman, M. [70].

3.2. Room sensors

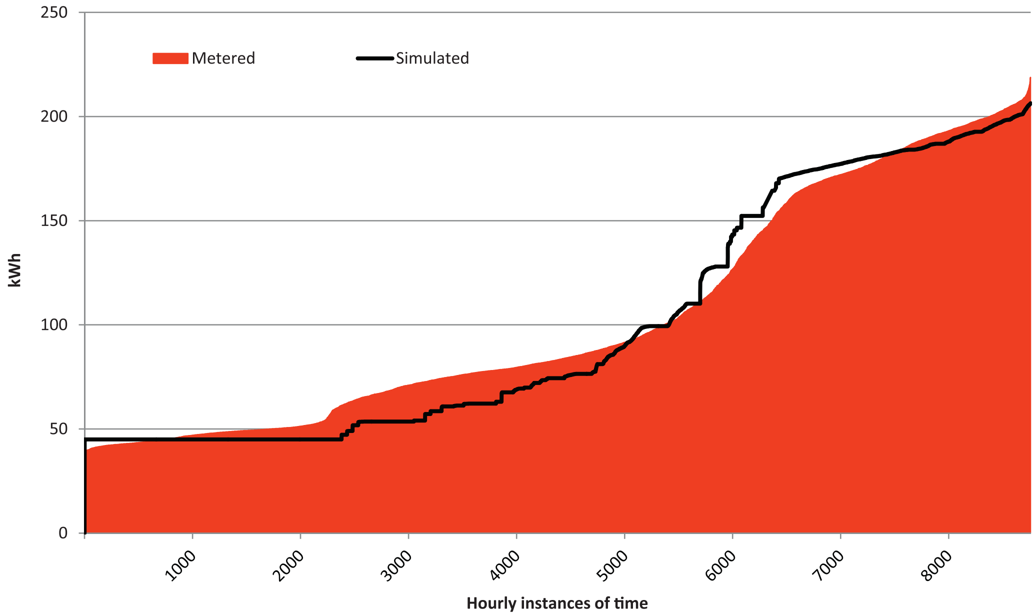
As part of this project a first generation prototype wireless sensor units were developed and a set of two of these sensors were positioned 1.5 m above floor level and away from direct sunlight rays within the 2nd floor open plan office (Appendix B). Prior to deployment the sensors were calibrated within a variety of locations with both stable and changing thermal conditions. Measurement results of the two units were within ±0.3 °C of each other and within ±0.5 °C of a TESTO 435 audit device. The response time of the two individual sensors were also below 1 min (Appendix C) which is adequate for measuring highly damped building zone temperatures. The readings from the two sensors were averaged to construct the actual zone air temperature of the target space (Fig. 11).

4. Results

4.1. Electricity

Statistically, electrical power measurement is a continuous quantitative data type. Fig. 5 enables a quick visual inspection of measured and simulated values and their statistical variations by arranging paired data points in ascending order.

The building's 2012 annual electricity consumption is 910,926 kWh. The final calibrated model produced a sum of 901,059 kWh (i.e. a deviation of 1.08%). Electricity carries the biggest CV(RMSE) in among the other two calibrated streams of data since electrical consumption is more closely related to occupant activity that deviates (in a random manner) from the deterministic occupancy templates used in Energyplus model. Hourly MRE and CV(RMSE) indices for individual months show that December carries the biggest monthly accumulation of errors



Measured			Simulated		
i	8760	hrs	i	8760	hrs
min	40.7	kWh	min	45.0	kWh
Max	218.8	kWh	Max	206.2	kWh
Ave	105.6	kWh	Ave	101.5	kWh
∑	910,926	kWh	∑	901,059	kWh
σ	54.2	kWh	σ	58.2	kWh

Fig. 5. Hourly-based measured and simulated building electricity consumption in ascending order (kWh).

(Fig. 6). The facilities manager in the target building also takes a very proactive role and the set points within the space are regularly updated in response to occupant's comments. This adds a greater probabilistic pattern to actual building performance as opposed to the static and template-driven nature of simulation results. Lighting, small power and HVAC plant electrical consumption are sub-metered but available on monthly intervals only and the final model MBE and CV(RMSE) values for monthly data were within ASHRAE recommended monthly values (Table 3).

HVAC energy consumption carries the biggest error in the three categories for which monthly sub-metered values were available.

Table 3
Sub-categorised CV(RMSE) and MBE values (monthly data).

Category	BE* (monthly)	V (RMSE)** (monthly)	V (RMSE)*** (hourly)
HVAC	4.69	13.1	–
Lighting	−2.62	9.1	–
Small power	−1.6	6.3	
Overall electricity consumption	0.50	9.7	9.9

* Acceptance limit: −5% ≤ MBE (monthly) ≤+5%.
** Acceptance limit: CV (RMSE) (monthly) ≤+15%.
*** Acceptance limit: CV (RMSE) (hourly) ≤+30%.

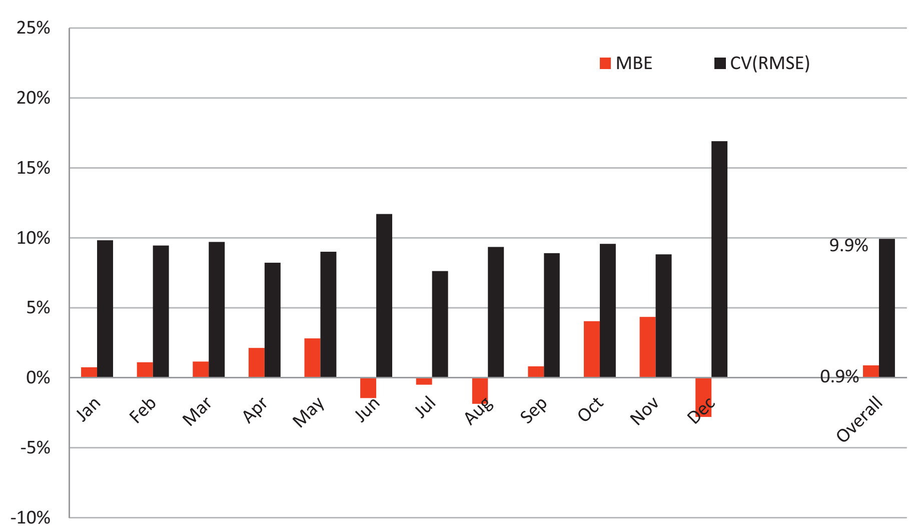


Fig. 6. MBE and CV(RMSE) analysis for building electrical consumption (hourly data).

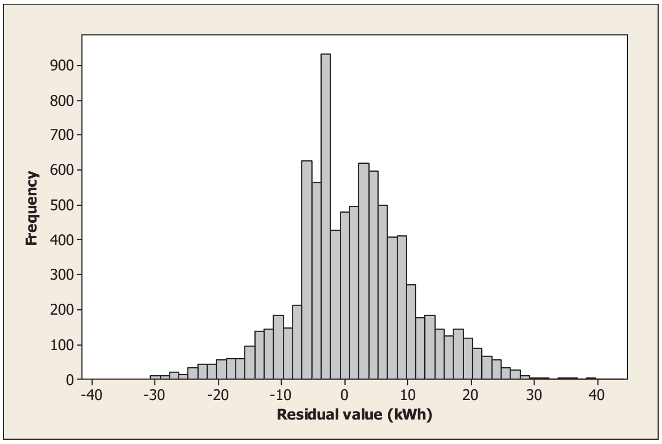


Fig. 7. Histogram of hourly electricity residuals (kWh).

Lighting and small power were both slightly over-predicted by the model whereas HVAC was under-predicted. Note that consistent manufacturer seasonal efficiencies for HVAC plants were used and no adjustments were made to achieve closer results.

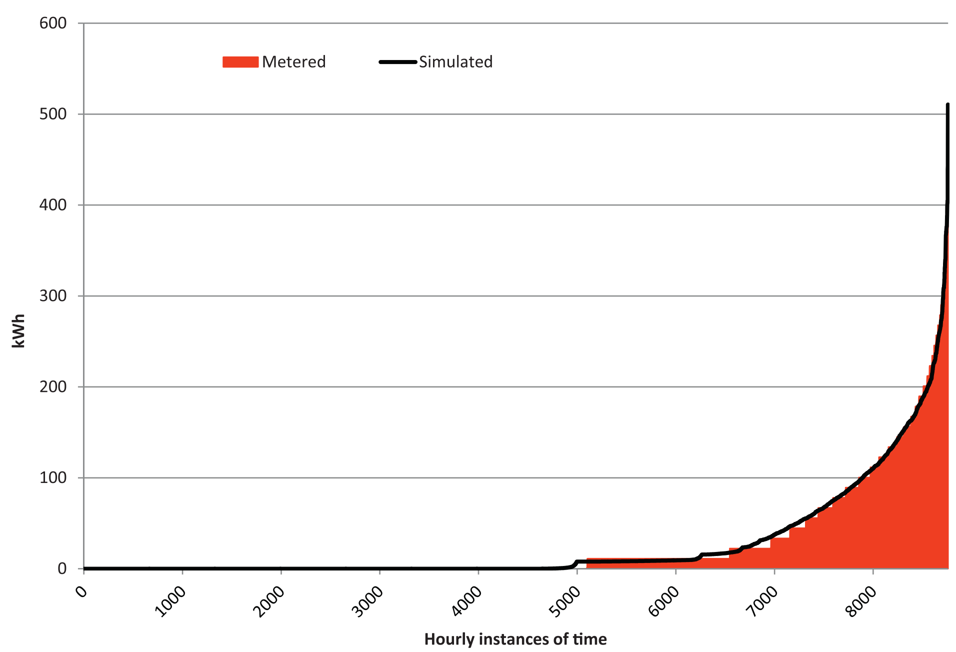
Quite clearly EnergyPlus electricity prediction surpasses the calibration criteria set by the ASHREA guide 14. However the cancelling effect of MBE values are evident given that for instance the overall $\text{MBE}_{\text{hourly}}$ figure of 0.9% is much smaller than $\text{CV(RMSE)}_{\text{houlry}}$ value of 9.9 (Fig. 6).

The histogram of hourly residuals provides a quantified illustration of the magnitude and spread of model electrical errors (Fig. 7). Hourly electrical errors (or residuals) form a bi-modal chart with overall characteristic of normal distribution centring on zero. Expressed in relative terms, 94% of errors have a magnitude falling within ±10% of daily peak electricity consumption (i.e. ±20 kW). The extreme incidents of negative errors (i.e. model over-predicting) have a similar magnitude to positive errors and the frequency of both instances are low (only 1.1% of errors are larger than ±30 kWh).

4.2. Gas

Space heating in the case study building only occurs when the average daily outdoor temperature is below 11.5 °C, confirming the well-insulated nature of the building fabric. The heating system (for the year under examination) was also entirely shut down from mid-June to early October. The paired instances of measured and simulated gas consumption, again another continuous quantitative data type, are arranged in ascending order in Fig. 8.

A building's heating-related gas consumption is a direct function of outdoor temperatures. As the weather data used in the simulation process was generated using the building's rooftop weather station, the simulated and measured data predictably bear a very close resemblance. A Pearson correlation figure of 99.7% indicates that measured and simulated gas consumption values vary closely in magnitude and direction. The measured energy consumption in Fig. 8 has a stepped pattern due to the fact that the three boilers serving the building cannot modulate infinitely, so there is repetition of specific part/full load capacity outputs at times of similar heat demand. The simulated values however result from mathematical load calculation, which would by definition have an infinitely variable nature. Fig. 9 outlines the MBE and CV(RMSE) calibration results. As well as monthly and annual values, the overall



Measured		
i	8760	hrs
min	0.0	kWh
Max	480	kWh
Ave	41.4	kWh
∑	362,443	kWh
σ	62.6	kWh

Simulated		
i	8760	hrs
min	0.0	kWh
Max	511	kWh
Ave	43.1	kWh
∑	376,426	kWh
σ	61.3	kWh

Fig. 8. Hourly-based measured and simulated building gas consumption in ascending order (kWh).

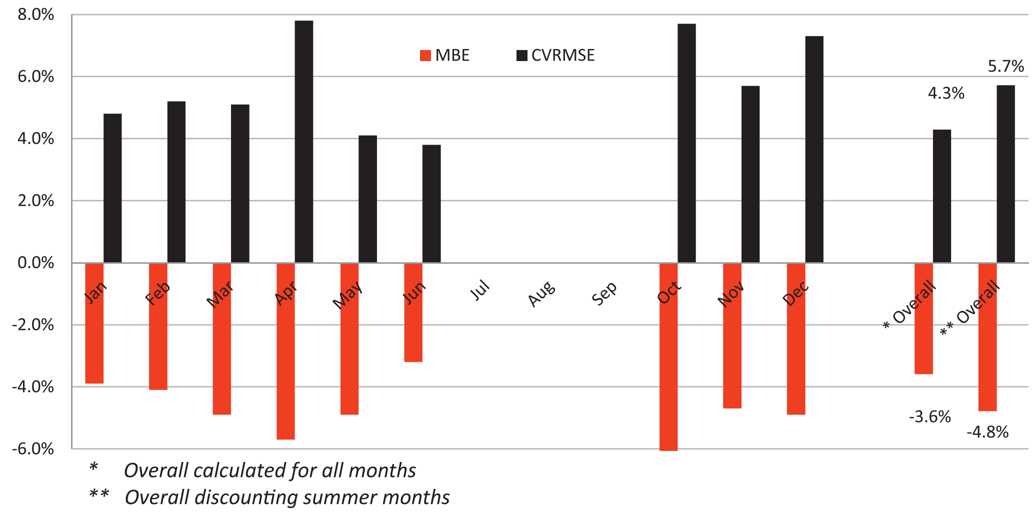


Fig. 9. MBE and CV(RMSE) analysis for building gas consumption (hourly data).

results are calculated discounting the summer months to demonstrate the moderating effect that 3 months of no heating load (i.e. zero gas prediction errors) can have on the overall result. The largest errors belong to October season when the building was also used at the weekends for organisational purposes.

The MBE and CV(RMSE) values fall within the respective ASHREA acceptance limits of within ± 10% and below + 30%. Equally 91.1% of the residual values fall within ±10kWh (Fig. 10). The simulated model displays a slight tendency to over-predict gas consumption (hence greater incidents of negative residuals). The frequency of both over and under predicted values are however insignificant. Note that the large incidents of values binned at the bar centring on zero (Fig. 10) is due to three months of no loads (hence residual value of zero) as well as incidents of no boiler operation during heating season.

4.3. Space temperature

Actual recorded air temperature over a full annual cycle were used to examine the ability of EnergyPlus model to accurately predict zone temperature. This also acts as a stage 2 calibration. Fig. 11 allows a quick visual comparison of the BWM plots of annual hourly space air temperatures for both measured and simulated data sets. Fig. 12 outlines the MBE and CV(RMSE) error checks of temperature results. It was noted earlier that MBE and CV(RMSE) indices are statistical gauges of normalised 'relative' and normalised 'accumulated' errors and as such they can offer insights into deviations of EnergyPlus space temperature prediction from corresponding actual values. 99.5% of the errors (as defined by formula 3) fall within ±1.5 °C and 93.2% are within ±1 °C. Overall actual space temperatures are warmer by an average of 0.47 °C over the full annual cycle, and this is evident by the greater instances of positive errors on Figs. 13 and 14. The histogram in Fig. 13 has a bimodal spread with its centre at around 0.25 °C, indicating that the EnergyPlus model in this case study tends to marginally under-predict the temperature in the space. Errors however have an equal distribution on both sides of the peak. The scatterplot on Fig. 14 shows a constant spread of errors with increasing simulated temperatures, which demonstrates that Energyplus model maintains a constant level of accuracy across the full range of predicted temperatures.

The summer period (with the heating system idle) observes a small reduction in the magnitude of MBE and CV(RMSE) values (Fig. 12). Conversely all winter months have slightly larger error magnitudes. This trend suggests a more accurate temperature prediction by the model in the absence of heating system input (When AHUs are only delivering displacement ventilation). HVAC heating operation therefore introduces a larger element of error in model temperature predictions in this study. Recall from sub-metered electrical calibration results that HVAC category had the largest magnitude of error (Table 3).

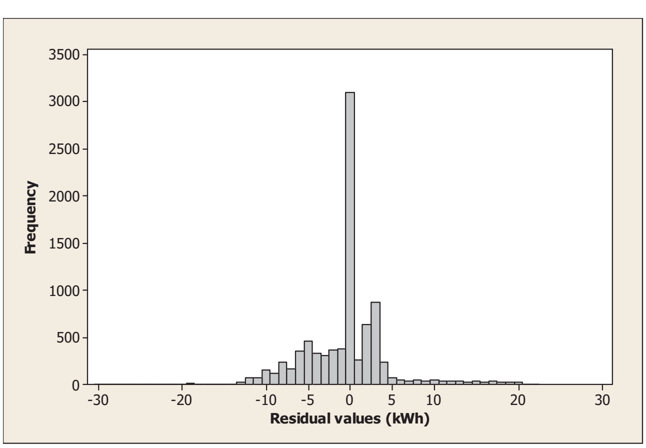


Fig. 10. Histogram of hourly gas residuals (kWh).

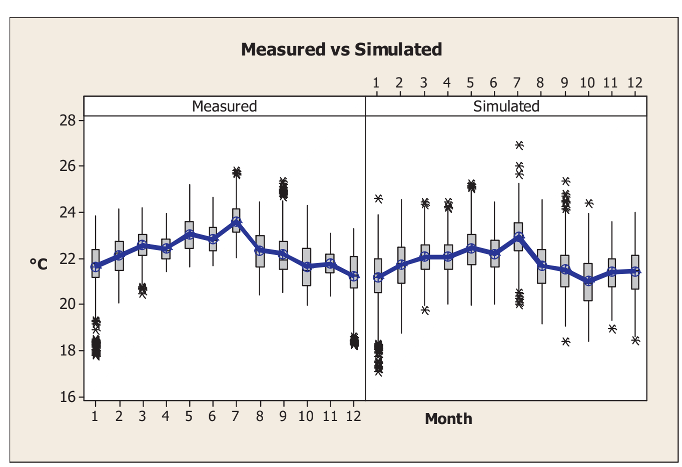


Fig. 11. Hourly-based BWM plots of measured vs. simulated space temperature.

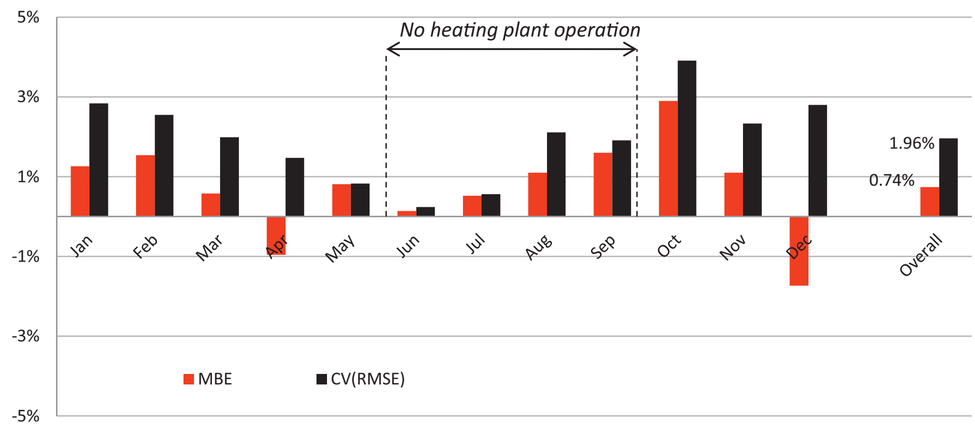


Fig. 12. MBE and CV(RMSE) analysis of office temperature (hourly data).

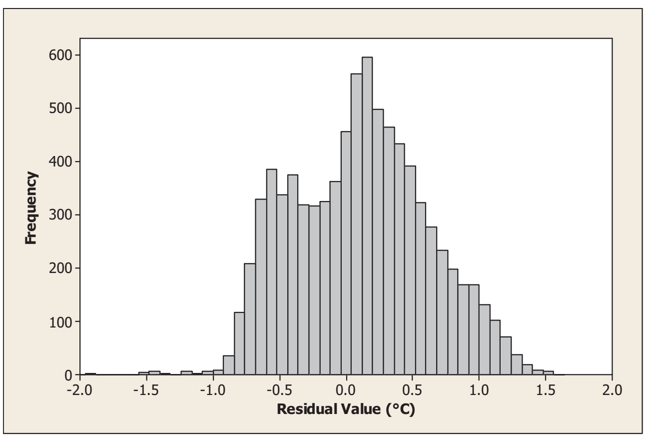


Fig. 13. Histogram of hourly temperature residuals.

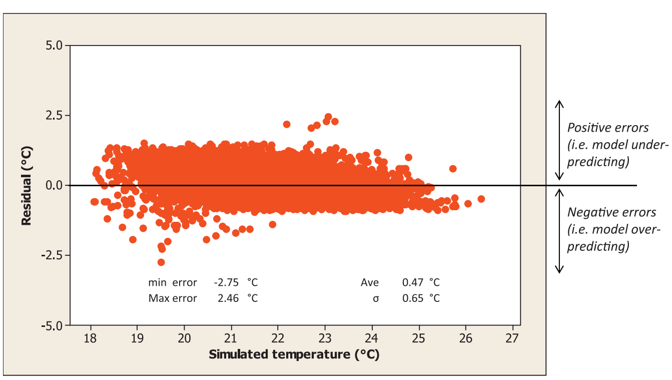


Fig. 14. Hourly-based scatterplot of residual versus simulated values (°C).

5. Discussions

Given the diverse and varied nature of underlying uncertainties in simulation attempts, building performance results can at best rest within a small allowable error margin. In the first stage of the calibration, a detailed EnergyPlus building model containing local weather data achieved respective hourly MBE and CV(RMSE) values of ±5% and below +10% for gas and electricity load prediction. In the second stage the calibrated model demonstrated air temperature prediction accuracies of ±1.5 °C for nearly 99.5% and an accuracy of ±1 °C for nearly 93.2% of hourly instances over the full annual cycle. MBE and CV(RMSE) values each provide a different set of insights. MBE values have the drawback of cancellation and hence might under-report the magnitude of seasonal errors, as observed for instance in electrical calibration where the overall MBE value of 0.9 concealed much larger monthly MBE errors (Fig. 6). Therefore, if the analyst seeks to highlight instance of under or over prediction, monthly intervals of MBE index can prove more instrumental. This therefore allows the analyst the opportunity to account for seasonal variations and reasons behind them. In contrast CV(RMSE) values provide a better indication if a single index demonstrating the 'accumulated magnitude' of error is sought. Within this work the HVAC energy consumption carried the largest error and was the greatest source of uncertainty in the model energy prediction, affecting mostly the simulated electricity value. In contrast model gas consumption prediction (being a direct function of weather data) achieved greater levels of accuracy. Interestingly actual gas consumption was smaller than simulated (Fig. 8), yet the actual HVAC electricity consumption was bigger than simulated (from Table 3, Electricity MBE_{Mothly} value for HVAC consumption has a positive magnitude of 4.69 which points to larger actual HVAC electricity consumption). Since less gas consumption should lead to smaller heating related pumping duties (hence smaller HVAC electricity), this discrepancy could arise form:

1 The two large AHUs and the cold water booster pump sets.
2 Natural ventilation and infiltration values which could lead to larger summer-time cooling load. Air flows in buildings continue to remain very difficult to measure and quantify despite their significant energy and comfort implications.

Deriving more definite conclusions in the absence of sub-metered water and hourly AHU figures would however not carry much scientific rigor. Another notable point is that in order to account for the measurement error within this calibration exercise, authors have made the assumption that the gas and electricity meter's accuracy within target building complies with SI 684 (1983) and IEC 62053 respectively as extensive attempts to obtain meter compound error margins from manufacturers failed to produce any results. These guidelines allow +2.5% or −3.5% of compound instantaneous deviations.

Overall Energyplus engine provided a very accurate evaluation of building energy and environmental performance whereby annual simulated electricity load was under-predicted by only 1.08%, that of gas was over-predicted by 3.8% and annual temperature within the space was under-predicted by 0.47 °C. It is hoped that this attempt can offer insight to further refinement of the calibration process where currently clarifications are particularly needed for instances when measured data is limited or of a coarse nature. It could be argued that the bulk of existing building stock in the UK, EU and beyond have very limited data on details of design and construction. At the same time such buildings frequently happen to be the most suitable vehicles for ECM and renewable integration studies. Therefore further development of calibration protocols should seek not to penalise buildings with limited primary data, and stricter calibration acceptance criteria should only inform leading scientific work. A tiered method for instance could be developed to accommodate progressing levels of model accuracy and primary data granularity.

6. Conclusion

Simulation remains an indispensable tool for performance analysis of buildings both pre and post construction [71]. Insights offered by mathematical building models also remain statistically much more significant than model error margins so long as attempts are made to account for the source and magnitude of errors. Pervasive sensing technologies and digitally logged sub-metered information offer the re-focusing the post occupancy studies to the exploitation of actual values that within a calibrated model can facilitate ECM and optimisation studies with increasing accuracy. The following summarises the main findings of this work that offers a set of recommendation if further development of ASHRAE method of building energy model calibration was to be undertaken:

1 Where possible calibration should be conducted over an annual cycle using hourly energy data. Where impractical; hourly primary data could be collected for shorter cycles (weekly or monthly) to 'validate' simulation results.
2 Local weather files should be obtained and used for a model to be considered calibrated. Any other weather file type may assist a virtual model to be validated.
3 MBE and CV(RMSE) calibration results (as those inferred by ASHRAE Guide 14) when presented in monthly intervals will allow an assessment of seasonal variations.
4 Residual histograms or scatterplots can also shed further light on the tendency of the model to under/over predict across the full range of simulated values.
5 The levels of tolerated error of a model should be dictated by the function of the virtual model and primary data availability. There is scope for further work to define the required levels of model accuracy for efforts such as optimisation and control studies, ECM and technology appraisals, renewable integration, etc. To that end, further refinement of calibration guidelines should first reflect the model purpose.

Fig. A1. Case study building's rooftop weather station (inset left: two main dashboard desktop interfaces providing live readings).

In their concluding remarks, Raftery, P et al. recommend narrowing ASHREA acceptance criteria hourly MBE and CV(RMSE) values to ±5% and ≤+20% respectively [72]. As demonstrated within this work, models calibrated to these limits can more confidently predict actual prevailing temperatures within the building. The findings of this paper supports this proposition particularly for scientific work conducted using actual hourly data over annual cycles. This would ensure greater confidence in the accuracy of model based studies and brings about a unified approach to model calibration. The existing MBE and CV(RMSE) values of ±10% and ±30% can still be adhered to when complete annual hourly data is not available to the analyst and such a model can be considered 'validated'.

In a follow-up paper the calibrated model is used to examine the potentials of adaptive comfort as defined by EN 15251 2007 in the target office building within current and passive house envelope.

Acknowledgements

The authors would like to thank Engineering and Physical Sciences Research Council (EPSRC) for their financial support which enabled the undertaking of this research work (EPSRC grant reference EP/I000755/1).

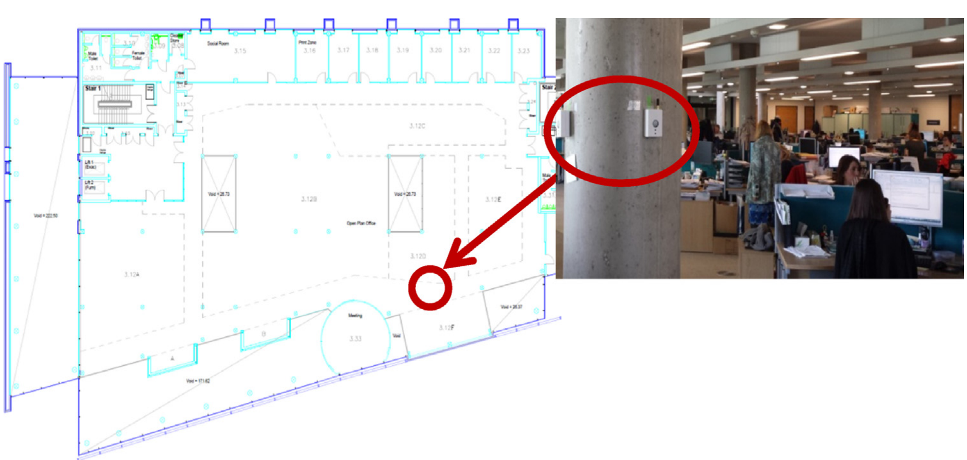


Fig. B1. Thermal sensors within the 2nd floor open plan office.

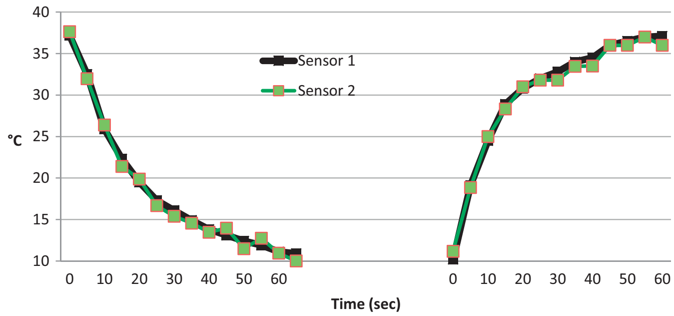


Fig. C1. Sensor response time curves over full room temperature ranges.

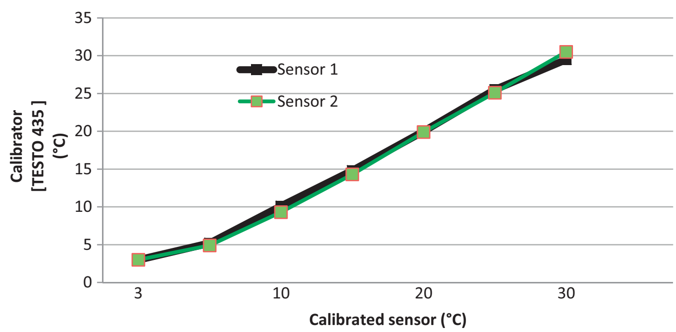


Fig. C2. Accuracy graph produced against TESTO 435 measurements.

Appendix A. Weather station

Fig. A1

Appendix B. Sensor positions

Fig. B1

Appendix C. Sensor calibration results

Figs. C1 and C2.

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