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Original Research

Degree-day based non-domestic building energy analytics and modelling should use building and type specific base temperatures

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ABSTRACT

A deeper understanding of building performance is essential to reduce their energy consumption and corresponding greenhouse gas emissions. Heating degree-days (HDD) encapsulates the severity and duration of cold weather, which is routinely used for weather related analysis of fuel consumption, performance benchmarking, and compliance. The accuracy of HDD-based prediction largely depends on the correct base temperature, which varies depending on building thermal characteristics, and their operation and occupancy. We analysed four years' (2012–2016) half-hourly metered gas consumption from 119 non-domestic buildings representing seven types, to: (a) identify their base temperature using a three-parameter change point (3pH) regression model, and (b) their relationships with intrinsic building parameters. The highest mean base temperature, 17.7 °C was found for clubs and community centres, and the lowest, 12.8 °C was for storage buildings. The average of all base temperatures is 16.7 °C, which is 1.2 °C higher and 1.6 °C lower than the British (15.5 °C) and American (18.3 °C) standards respectively. The current practice of a fixed base temperature degree-days for all buildings has been found to be unrealistic. Building type specific base temperatures must be developed, agreed upon and published for increasing accuracy in energy analytics and legislative compliance, as well as for developing effective standards and policies.

1. Introduction

Globally, buildings account for over 33% of all energy use and greenhouse gas (GHG) emissions, and 50% of all electricity consumption [1]. Given the improvements in living standards and rapid economic development in developing countries, as well as projected increases in global population, energy use and associated GHG emissions from buildings are estimated to rise significantly [2]. Increasingly stringent legislations and tighter building regulations in recent years have resulted in improved energy and environmental performance of buildings. Energy conservation goals are now pursued aggressively during design stages, with increased focus on maintaining the designed performance over the life of the building [3].

In the UK, buildings account for 34% of total GHG emissions. Non-domestic buildings represent 36% of all direct and indirect emissions from buildings, and 12% of total UK emissions [4]. Non-domestic buildings are thus an ideal candidate for a significant reduction in energy use and corresponding emissions. The largest energy uses in UK non-domestic buildings include space and water heating, accounting for 46% of total energy use [5]. Natural gas is used to generate about 60% of non-domestic heat in the UK [6], the use of which is highly correlated with weather conditions. The analysis of natural gas consumption for heating in buildings against the weather is, therefore, crucial [7] for energy-efficient design, operation, and refurbishment.

Heating degree-day (HDD) is a versatile climatic indicator that encapsulates the severity and duration of cold weather in one index [8], enabling weather related analysis of the consumption of fuel such as natural gas [9] and coal [10]. The versatility of HDD is due to its simplicity in reducing the dimensions required to characterise a given weather. HDDs are essentially the summation of temperature differences between the ambient air temperature and a *reference* or *base* temperature. The *base* or *balance point* temperature is the ambient air temperature below which a building requires heating to maintain desirable indoor environmental conditions. During a steady-state period, the heating load of a building is proportional to the HDD of that period [9]. HDD-based energy calculations are simpler than dynamic thermal simulations or hourly calculation methods but they are particularly effective in energy management. Their widespread use is due to their simplicity in capturing weather

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Nomenclature

HDD	Heating degree-days (°C.day)
R^2	Coefficient of determination (–)
RMSE	Root mean square error (–)
CV-RMSE	Coefficient of variation of root mean square error (%)
NMBE	Normalised mean bias error (%)
T_a	Ambient dry-bulb temperature (°C)
T_b	Base temperature (°C)
G	Gas consumption (kWh)

characteristics reasonably well, and the reduced resource requirements for preparing and collecting inputs, and computation [11]. HDDs are routinely used in benchmarking and compliance checking as part of legislative requirements. Degree-day based methods[2] are used to estimate building energy consumption, and to determine energy performance rating for certification to comply with the overarching European legislation, Energy Performance of Buildings Directive (EPBD) [12]. Besides, base temperatures can also be used for setting a suitable controller set-point [13].

The accuracy of HDD-based calculations depends on the identification and selection of an appropriate base temperature. Apart from local climatic conditions, a building's usage type and pattern, and thermal characteristics influence the base temperature [8] and corresponding energy consumption. On the other hand, the thermal response of the building is a factor of heating regime[3] and thermal properties of the construction [14], which are often similar for building types and construction periods. Base temperatures of all buildings are not constant, even in a climatically homogenous location. Appropriate base temperatures help derive a realistic representation of building energy consumption and efficiency, while an inappropriate one can lead to misleading results [15]. The official publications of degree-days are often based on a single base temperature—15.5 °C in the UK [9] and 18.3 °C USA [16] by the Chartered Institution of Building Services Engineers (CIBSE) and American Society of Heating, Refrigerating, and Air-Conditioning Engineers (ASHRAE) respectively. Previous studies acknowledged the need for variable base temperatures [17] and some have published degree-days data for various locations [18], yet studies on how degree-days base temperatures vary depending on building type are scarce.

Base temperatures are generally determined either by applying the energy signature method or the performance line method [19]—the former requires greater sampling frequency (e.g. daily) than the latter (e.g. monthly). Previous works have used both approaches [18,20], as well as made improvements over classical methods [21,22]. The use of energy signature method is growing because of the increased availability of detailed utility bills, historical weather, and high-resolution smart meter data. Most previous studies used simulated data, and a few have used monitored data. Moreover, case buildings often lacked diversity. Therefore, generalisation of findings and conclusions were not robust.

Considering the discussed gap in the literature and their importance in HDD-based energy calculation and analytics, the base temperatures of 119 UK non-domestic buildings of seven different types were determined in this research, by employing a three-parameter heating (3pH) change point model on half-hourly

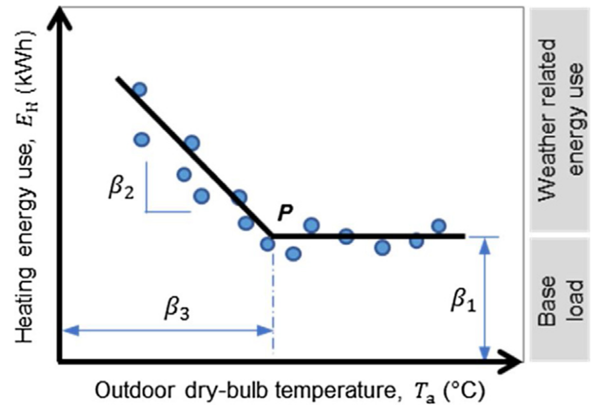

Fig. 1. 3pH regression model.

four-year (2012–2016) metered gas consumption data. Second, the variance of base temperatures, as well as their base and mean gas consumptions were identified and critiqued. This work is one of the most comprehensive studies to date on the estimation of base temperatures of non-domestic buildings—not only because of the use of multi-year sub-hourly consumption data but also because of the diversity and coverage of buildings types.

The rest of the paper is organised as follows. Section 2 provides theoretical discussions on the energy signature method and adopted methodology, as well as data sources and pre-processing of weather and gas consumption data. Results are discussed in Section 3, followed by conclusions and directions for future research.

2. Theory and related work

2.1. Energy signature model

Change-point (CP) model [23] is an energy signature method for analysing historical energy use data. CP detects when the probability distribution of a time series changes; i.e. identifies the sudden change of the regression slope (β_2) at a given point P, as illustrated in Fig. 1. The benefits of CP-based energy analytics arise from the ability to detect both the weather and non-weather dependent (i.e. baseline or base load) energy use. CP methods are also comparatively effective in predicting energy demand. In a recent study, Zhang et al. [24] compared four different approaches: change-point (CP), Gaussian process regression (GPR), Gaussian Mixture Regression (GMR) and Artificial Neural Network (ANN) models for predicting building HVAC and hot water energy consumptions. GMR had slightly better statistical performance, compared to the other three. However, all differences were small. Because of its simplicity, the change-point (CP) model is the most effective in terms of accuracy vs. effort spent for predicting energy consumption in buildings. CP model is, therefore, used in this paper to investigate the relationship between building energy consumption and ambient air temperature.

The best-fit change-point model, described in the American Society of Heating, Refrigerating, and Air-conditioning Engineers (ASHRAE) Inverse Modeling Toolkit (IMT) [25] is adopted in this research to derive regression models of building energy use. The functional forms for best-fit three-parameter change-point models for heating (3pH), is given in Eq. (1).

$$Y_h = \beta_1 + \beta_2 \left(\beta_3 - X_1\right)^+ \tag{1}$$

where, Y_h is energy use (here, gas consumption in kWh), X_1 is ambient dry-bulb temperature (°C), β_1 is baseline energy consumption or base load, and β_3 is base temperature (°C). The ($^+$) notation indicates that values of the parenthetic term shall be set to zero when

[2] Standard Assessment Procedure (SAP) and its derivative Reduced data SAP (RdSAP) in the UK use degree-days as weather indicator [32].

[3] Whether a building is continuously or intermittently heated, as well as whether the heating is thermostatically controlled.

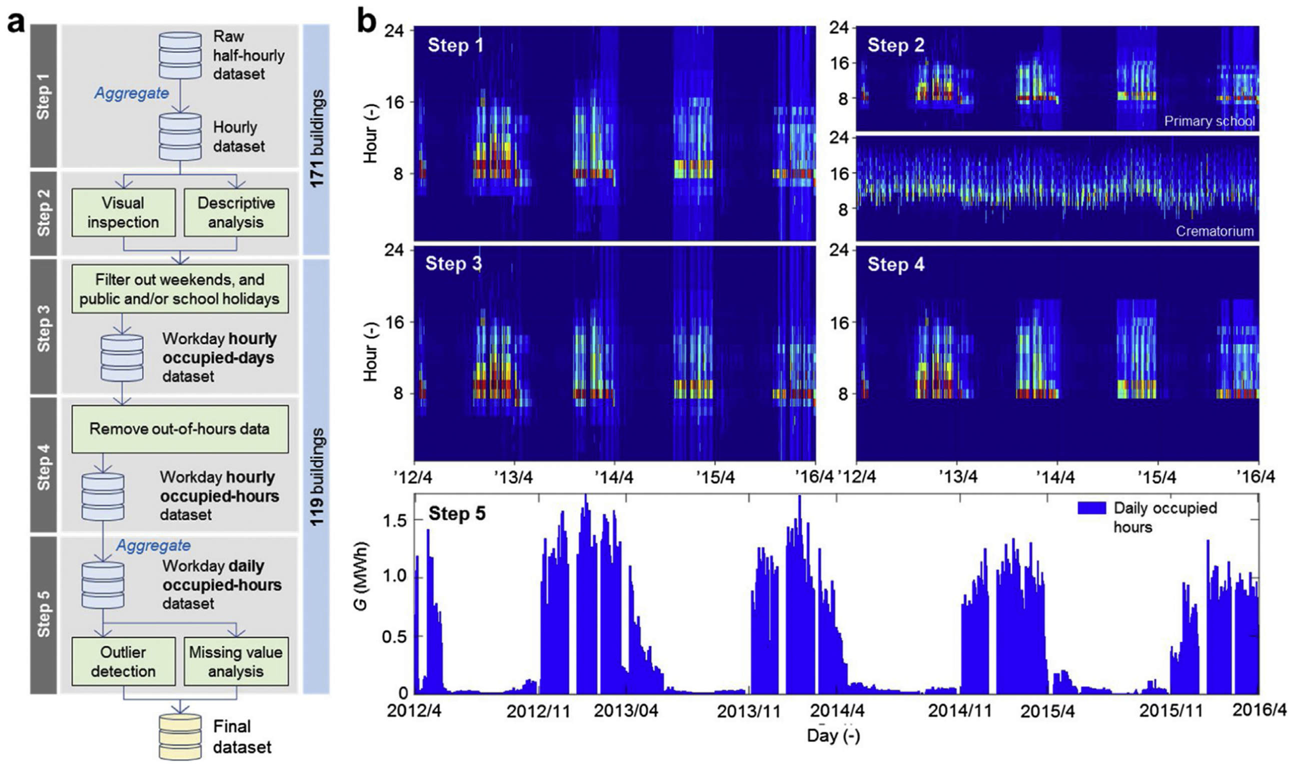

Fig. 2. Data processing steps. (a) Flow chart. (b) Illustration of the data processing stages.

it is negative. The 3pH model, shown in Fig. 1, is appropriate for modelling building energy use that varies linearly with an independent variable over part of its range and remains constant over the remainder. For example, space-heating consumption in a building increases as ambient air temperature decreases below a certain balance-point temperature, which is defined as the base temperature of the building. When ambient air temperature is above the base temperature, no energy use is required for thermal comfort related space heating. However, energy use may also be needed for hot water and cooking. This energy use is often defined as base load or baseline energy consumption of the building.

2.2. Annual heating degree-days (HDD)

Different approaches are taken to calculate heating degree-days depending on the availability of ambient air temperature data [9]. Due to the availability of hourly ambient air dry-bulb temperature, the hourly method in [8] was used to calculate annual HDD. The difference between the base and hourly dry-bulb temperatures are summed up to estimate degree-hours in a specified period. The cumulative degree-hours of a day is divided by the number of hours in a day (=24) to get the daily degree-days, HDD_d, as shown in Eq. (2).

$$HDD_\mathrm{d} = \sum_{i=1}^{24} \frac{(T_\mathrm{b} - T_i)^+}{24} \tag{2}$$

where, T_b and T_i are base and ambient air temperatures (°C) at the i-th hour of the day respectively. The plus symbol ($^+$) has the same meaning as in Eq. (1).

Annual degree-days, HDD_a, is calculated by summing up daily, HDD_d over a year, as shown in Eq. (3).

$$HDD_\mathrm{a} = \sum_{j=1}^{N} HDD_{\mathrm{d},j} \tag{3}$$

where, $HDD_{d,j}$ is daily HDD of the j-th day of the year and N is number of days in a year; i.e. 366 in a leap year, and 365 in others.

3. Data and methodology

3.1. Data collection and pre-processing

3.1.1. Buildings and gas consumption

Data for this research are obtained from the City of Cardiff Council,[4] who monitor gas and electricity consumption of 330 non-domestic buildings and facilities they own and manage, as part of their sustainable development strategy. The 330 monitored buildings cover a wide range of building types: primary schools (n = 95), community facilities (n = 54), care facilities (n = 39), city services (n = 37), parks buildings (n = 33), high schools (n = 24), leisure & sports buildings (n = 17), workshops & depots (n = 12), offices (n = 11), and key & cultural buildings (n = 8). Energy consumption is measured every half hour and sent to the central server via the Internet. Part of this data is also publicly available in Carbon Culture,[5] a community platform for promoting the efficient use of resources.

Of the 330 monitored non-domestic buildings, not all buildings reported gas consumption. In addition, the monitoring did not start and end at the same date for all buildings. To maintain consistency, buildings with significant missing data at the beginning and at the end of the analysis period are removed from the dataset. At this stage, 171 buildings are selected for further processing and analysis. The selected gas consumption data covers four whole years, between 1 April 2012 and 31 March 2016. Data pre-processing is conducted in five stages, the flow chart of which is given in Fig. 2a.

[4] The governing body for Cardiff, the capital of Wales. https://www.cardiff.gov.uk.
[5] Carbon Culture. https://platform.carbonculture.net/communities/cardiff-council/19/.

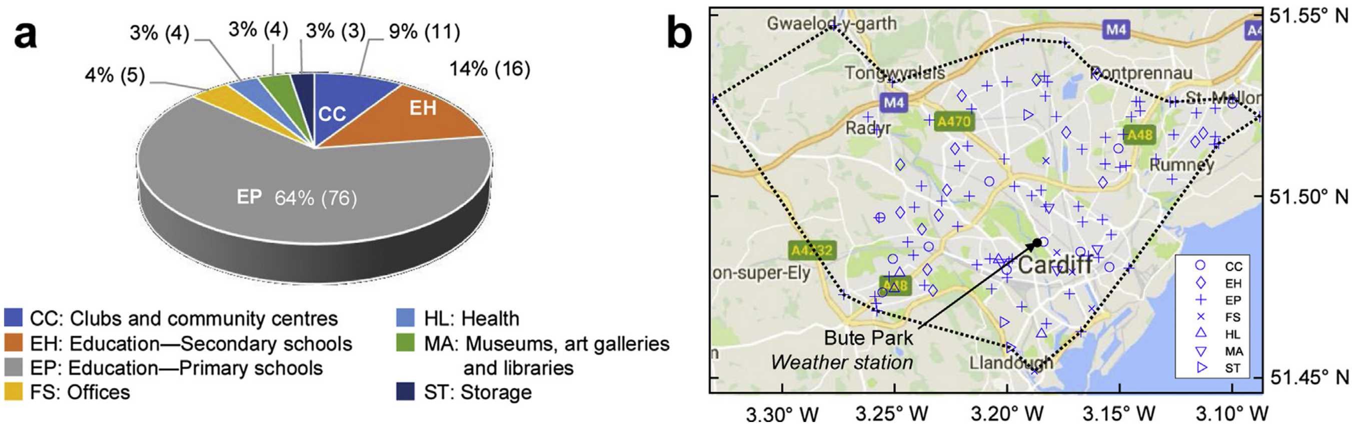

Fig. 3. Location and type of 119 selected buildings. (a) Location of selected buildings and the weather station. (b) Distribution of buildings according to building type.

The steps are illustrated and explained with an example in and Fig. 2b, and described as follows.

First, half-hourly data are aggregated to produce the hourly dataset.

Second, the hourly dataset is visualised with scaled colours and analysed descriptively to identify patterns of energy consumption. Buildings and facilities without seasonal and diurnal variations are excluded as their gas consumption is not entirely dependent on heating energy requirement. An example of visual inspection and subsequent exclusion of a building is shown in Fig. 2b (Step 2) in which gas consumption of one primary school and a crematorium are analysed. Gas consumption in the crematorium is fairly constant throughout the year, compared to the primary school, which has distinct seasonal and weekday vs. weekend trends, and visual correlates with the variations in temperature in Fig. 4. Higher gas consumption in the primary school is for the heating season, from late October to early April, between 08:00 and 17:00 h. Peak heating consumption occurs at around 08:00 h, which coincides with the pre-heating of the building at the start of the day. Lower heating consumption occurs before 07:00 h and after 15:00 h. There is almost no gas consumption during the unoccupied periods, including weekend and holidays. Buildings without a seasonal trend; e.g. care facilities, are excluded from the dataset. After this step, 119 buildings are retained for further processing. The distribution of the selected buildings according to typology and their locations are illustrated in Fig. 3a and b respectively.

Third, records corresponding to weekends, and public and school holidays are removed from the dataset to produce the *workday hourly occupied-period* dataset. Occupied days are 970 and 1032 days for school and other building types respectively, out of a total 1461 days in the original data.

Fourth, the *workday hourly occupied-period* dataset is filtered further to remove out-of-hours data as heating energy consumption in non-domestic buildings are significantly associated with occupancy hours in a day. Occupancy schedules, including pre-heating times are used to filter out non-occupied hours. Occupied hours for most buildings were 08:00–18:00 h, except some leisure centres, for which the occupied hours were 10:00–22:00 h.

Fifth, the *workday hourly occupied-hours* dataset is aggregated to produce the *workday daily occupied-hours* dataset. Outlier detection and missing value analysis were conducted to produce the final dataset. Descriptive statistics of the final dataset, in terms of building type, and count, mean and standard deviation (SD) of floor area are given in Table 1.

3.1.2. Weather

There are three nearby meteorological stations for Cardiff: Bute Park (WMO: 037170), Rhoose (WMO: 037150) and St Athan (WMO: 037160). Average distance of all 119 selected buildings from the three weather stations are 3.83 km (Bute Park), 15.82 km (Rhoose), and 20.17 km (St Athan). Bute Park is an urban weather station, located at the heart of Cardiff city. Rhoose and St Athan are located in nearby airports, and are far from the city. Their surrounding landscape, built-up area, and exposure are different from that of the investigated buildings. Therefore, Bute Park's weather data,[6] sourced from the Centre for the Environmental Data Analysis (CEDA),[7] are utilised in this research. CEDA's Web Processing Service (WPS) combines data from several sources, often resulting in duplicates and missing data fields. Pre-processing for duplicates and missing observations were conducted on the downloaded data. There were six missing values for dry-bulb temperature, which were interpolated from the neighbouring time-steps. Fig. 4 illustrates hourly dry-bulb temperature; i.e. ambient air temperature for Bute Park from 1 April 2012–31 March 2016. Air temperature varies between −5 °C and 30 °C during the study period. Minimum temperatures occur at around 05:00 h and the maximum at around 15:00 h. Coinciding with the heating season, lower ambient temperature is prevalent between late October and early April.

Since daily gas consumption is used in the 3pH model for base temperature estimation, daily mean temperature during workdays, $\bar{T}_d$, is calculated using Equation (8) and used in the analysis. Previous research [8] indicated strong relationship between mean temperature of a location and degree-days, demonstrating the reliability of the indicator in energy analytics.

$$\bar{T}_d = \frac{1}{|h_e - h_b| + 1} \sum_{i=h_b}^{h_e} T_i \tag{8}$$

where, h_b is the hour of day when pre-heating or work begins depending on building type, and h_e is the hour when workday ends. T_i represents ambient air temperature at the i-th hour of the day.

3.2. Model development and evaluation

3.2.1. pH regression model

A fast-explicit solution for determining the coefficients a three-parameter cooling (3PC) model proposed by Paulus [26] was adopted and modified in this research for estimating the coefficients of the three-parameter heating (3pH) model. The regression process is illustrated using the gas consumption data of a primary

[6] Bute Park is an AWSHRLY (Automatic Weather Station HouRLY) station that automatically logs weather parameters and reports hourly.

[7] CEDA archives data from the UK Met Office's network of weather stations as part of the Met Office Integrated Data Archive System (MIDAS) Land and Marine Stations dataset. http://badc.nerc.ac.uk/data/ukmo-midas.

Table 1
Descriptive statistics of 119 selected buildings.

Code	Building type	Count (–)	Floor area (m^2)			
			Maximum	Minimum	Mean	SD[1]
CC	Clubs and community centres	11	1805	240	890	407
EH	Secondary school	16	12924	1188	9023	3612
EP	Primary school	76	4373	736	2036	749
FS	Offices	5	25087	521	8754	10710
HL	Health	4	330	182	267	69
MA	Museums, art galleries and libraries	4	3889	540	1422	1645
ST	Storage	3	3962	1130	2692	1439
All buildings		119	25087	182	3088	3700

Note: [1]SD: Standard deviation

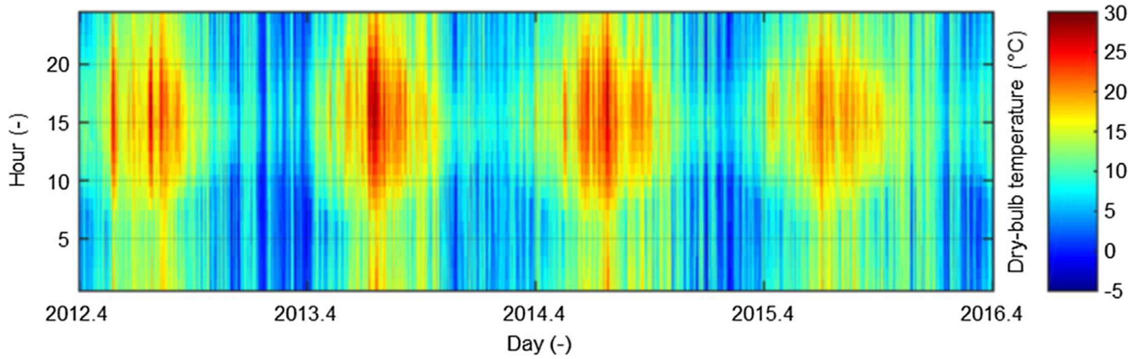

Fig. 4. Dry-bulb temperature in Bute Park, Cardiff between 1 April 2012 and 31 March 2016.

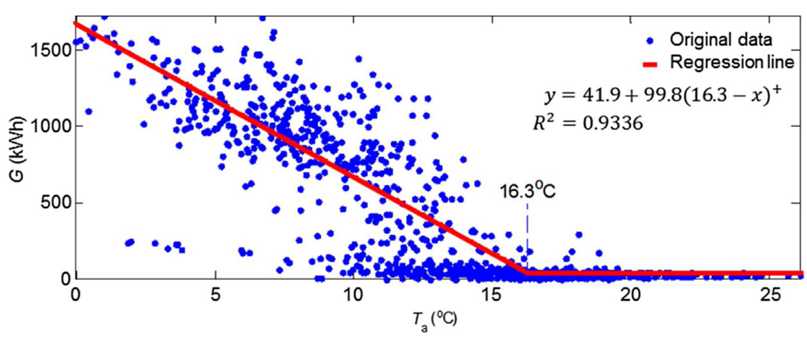

Fig. 5. Three-parameter heating (3pH) regression model of gas consumption, G vs ambient temperature, T_a of an example primary school.

school in Fig. 5. 3pH model is accomplished in two steps. First, a regression is conducted to obtain the initial base temperature and base load. Gas consumptions more or less than half the values predicted by the initial regression model are considered to be outliers and are, therefore, excluded for the next step. Further, distances greater than 1σ (standard deviation) from the mean are also considered as outliers.[8] Next, the second regression is then applied to obtain the final base temperature and base load. Fig. 5 shows the final regression of gas consumption (G) vs ambient temperature (T_a) between April 1, 2012 and March 31, 2016. There are two regions divided by the base temperature, 16.3 °C: a non-weather related horizontal component corresponding to the base load of 41.9 kWh to the right, and a weather-related component to the left with a slope of 99.8 kWh/°C. R^2 and CV-RMSE of the best-fit regression model are 0.9336 and 22.5% respectively, which meet the model evaluation requirement discussed in the following section.

[8] Mathworks. Removing outliers programmatically. https://www.mathworks.com/examples/curvefitting/mw/curvefit-ex00591249-remove-outliers-programmatically.

3.2.2. Model evaluation

Three statistical indices: coefficient of determination; i.e. R-squared (R^2), coefficient of variation of root mean square error (CV-RMSE) and normalised mean bias error (NMBE), are used to evaluate the 3pH model performance of goodness-of-fit of the predicted values against the measured values, and to describe the statistical characteristics of the model. The three indices are calculated using Eqs. (4)–(7), as per ASHRAE Guideline 14 [27].

$$R^2 = 1 - \frac{\sum_{i=1}^{n}\left(Y_i - \hat{Y}_i\right)^2}{\sum_{i=1}^{n}\left(Y_i - \bar{Y}_i\right)^2} \tag{4}$$

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{i=1}^{n}\left(Y_i - \hat{Y}_i\right)^2}{n}} \tag{5}$$

$$\mathrm{CV-RMSE} = \frac{RMSE}{\bar{Y}} \times 100 \tag{6}$$

$$\mathrm{NMBE} = \frac{\sum_{i=1}^{n}\left(Y_i - \hat{Y}_i\right)}{n\bar{Y}} \times 100 \tag{7}$$

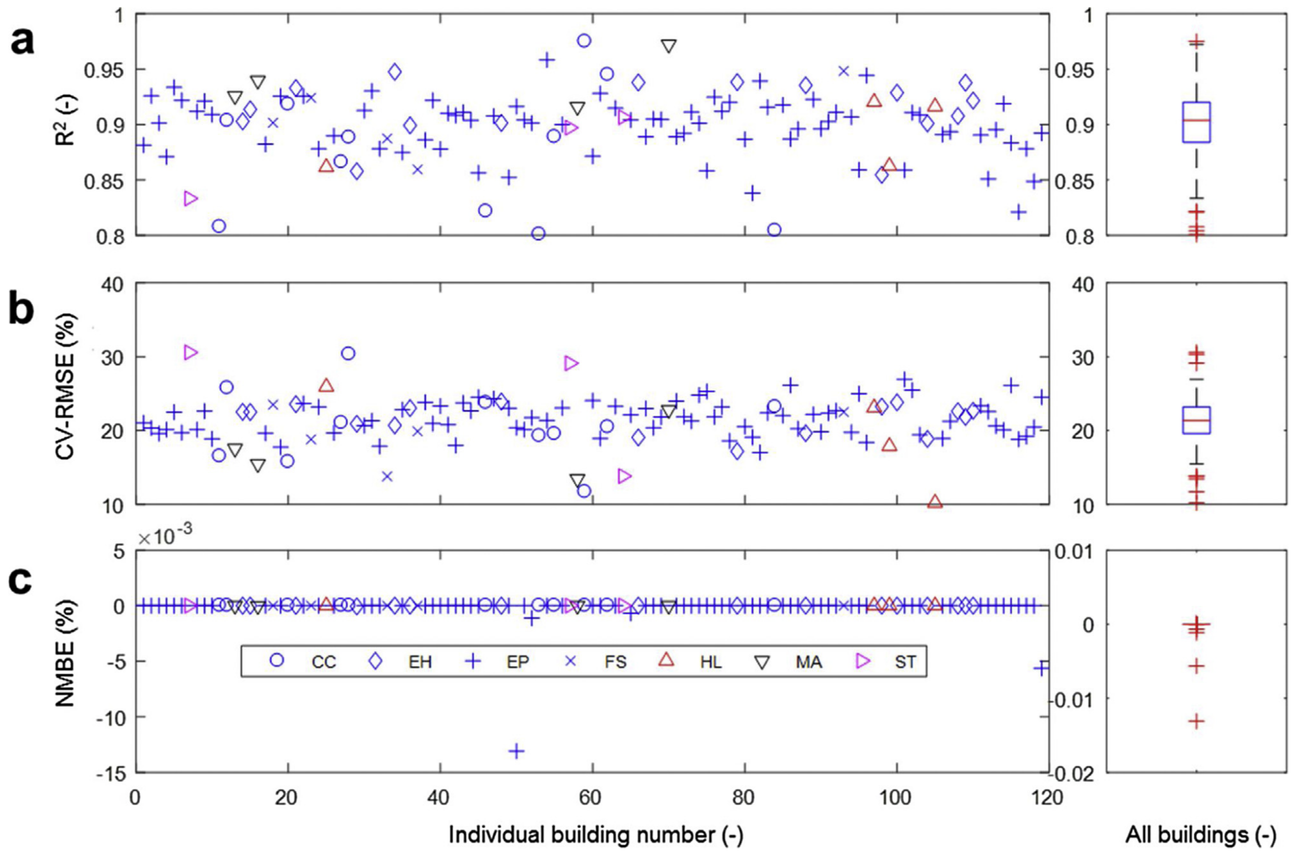

Fig. 6. 3pH regression statistical indices for all 119 buildings. (a) R-squared (R^2). (b) Coefficient of variation of root mean square error (CV-RMSE). (c) Normalised mean bias error (NMBE).

Table 2
Acceptable range for CV-RMSE and MBE.

Data resolution	Acceptable range (%)	
	NMBE	CV-RMSE
Monthly	±5	15
Daily	±7.5	22.5
Hourly	±10	30

where, Y_i is the i-th measured heating energy use (kWh), $\hat{Y}_i$ is the corresponding i-th heating energy use predicted by the model (kWh), n is total number of data points, and $\bar{Y}$ is the mean of the measured heating energy use over the analysis period (kWh).

The greater the R^2, and the smaller the CV-RMSE and NMBE, the closer the predicted values are to the actual values. Generally, $R^2 > 0.7$ is considered acceptable, indicating confidence in the relationship. ASHRAE [27] provides recommended values of CV-RMSE and NMBE for evaluating monthly and hourly baseline models, from which the required values for the daily 3pH model are interpolated, as listed in Table 2.

4. Results and discussion

4.1. Model accuracy

Statistical indices from all change-point regression runs are illustrated in Fig. 6. Further details such as maximum, minimum, mean, and standard deviation of all three indices are given in Table 3. R^2 index (Fig. 6a) varies between 0.8 and 0.975. Mean R^2 is 0.9, which can be considered very good given the multi-year data of many building types. Lower R^2 is found for clubs and community centres. The intermittent nature of their use may explain the relatively lower goodness of fit, compared to the rest of the building types. Greater use of natural gas for hot water may also be responsible for their intermittent gas consumption. CV-RMSE (Fig. 6b) varies between 10.2% and 30.6%. Mean CV-RMSE is 21.3%, which is less than the upper limit of 22.5% as per ASHRAE Guideline 14 [27]. The lower standard deviations (SD) of CV-RMSE are found to be 2% and 2.2% for secondary and primary schools respectively. The highest SD of CV-RMSE of 9.3% is found for storage buildings, indicating the differences in their operation. Both school building types, primary and secondary, are the two largest sub-samples, which may also explain the lower SD. NMBE (Fig. 6c) for all buildings are low and very close to zero, except for two primary schools which has a negative bias. All three statistical indices satisfied the requirements given in Table 2, with the conclusion that the models are reliable.

4.2. Base temperature

Estimated HDD base temperature, T_b for all 119 buildings are given in Fig. 7 and further statistics are provided in Table 4. Base temperatures range from 11.6 °C to 20.5 °C while the mean is 16.7 °C. However, T_b of most buildings lie between 15.7 °C and 17.5 °C, corresponding to the quantiles for the cumulative probabilities of 0.25 and 0.75 respectively. Standard deviation of T_b for all buildings is 1.43 °C, which is visually represented in Fig. 7a. Low T_b, ranging between 11.6 °C and 14 °C (SD: 1.2 °C) is found for the three storage buildings in the dataset. Low temperature set points and less priority for maintaining a close range of temperature for human thermal comfort are the reason for a lower base temperature for storage buildings. On the other hand, base temperatures greater than 1σ, although in relatively small numbers, are mostly

Table 3
Summary statistics of error analysis.

Code	Building Type	Count	R^2				CV-RMSE				NMBE			
			Max	Min	Mean	SD[1]	Max	Min	Mean	SD[1]	Max	Min	Mean	SD[1]
CC	Clubs and community centres	11	0.98	0.8	0.87	0.06	30.3	11.7	20.7	5.1	0	0	0	0
EH	Secondary school	16	0.95	0.85	0.91	0.03	23.9	17.2	21.6	2	0	−0.00007	−0.00001	0.00002
EP	Primary school	76	0.96	0.82	0.9	0.03	26.9	17	21.6	2.2	0	−0.01309	−0.00027	0.00163
FS	Offices	5	0.95	0.86	0.9	0.03	23.5	13.8	19.7	3.8	0	0	0	0
HL	Health	4	0.92	0.86	0.89	0.03	25.9	10.2	19.3	6.9	0	0	0	0
MA	Museums, art galleries and libraries	4	0.97	0.92	0.94	0.02	22.8	13.4	17.3	4	0	−0.00003	−0.00001	0.00001
ST	Storage	3	0.91	0.83	0.88	0.04	30.6	13.8	24.5	9.3	0	0	0	0
All buildings		119	0.98	0.8	0.9	0.03	30.6	10.2	21.3	3.3	0	0	−0.00017	0.00131

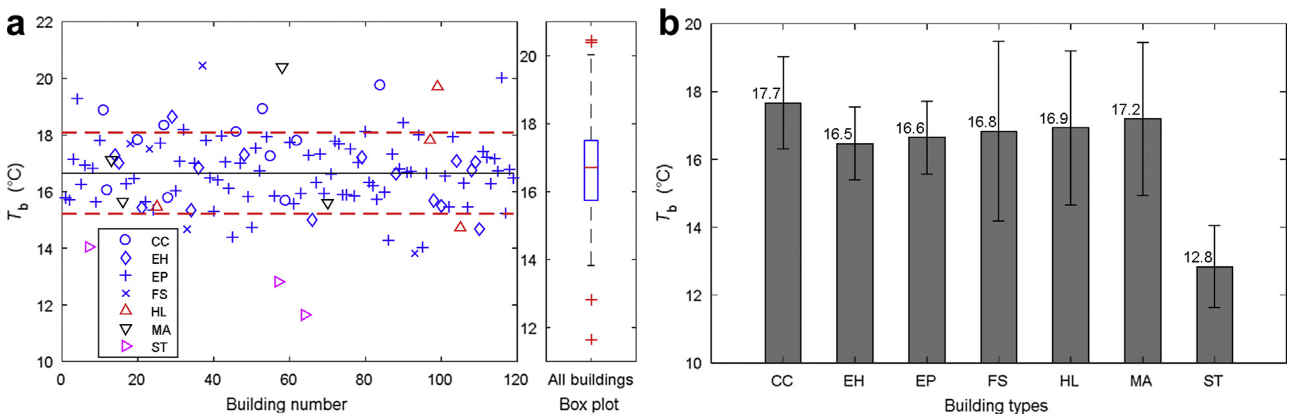

Fig. 7. Estimated heating degree-day base temperature, T_b of all case study buildings. (a) Base temperature of individual building, and (b) Mean base temperature by building type. T_b is comparatively lower in storage buildings, while offices have the largest SD.

Table 4
Estimated base temperature of all buildings.

Code	Building Type	Count	Base temperature, T_b (°C)				
			Max	Min	Mean	SD[1]	CI (95%)[2]
CC	Clubs and community centres	11	19.7	15.7	17.7	1.36	0.91
EH	Secondary school	16	18.6	14.7	16.5	1.07	0.57
EP	Primary school	76	20	14	16.6	1.08	0.25
FS	Offices	5	20.5	13.8	16.8	2.65	3.29
HL	Health	4	19.7	14.7	16.9	2.28	3.62
MA	Museums, art galleries and libraries	4	20.4	15.6	17.2	2.25	3.58
ST	Storage	3	14	11.6	12.8	1.2	2.98
All		119	20.5	11.6	16.7	1.43	0.26

Notes: [1]SD: Standard deviation. [2]CI: Confidence interval

prevalent in care and community centres; and museums, art galleries and libraries. Their atypical operating patterns and special requirements for a narrow temperature range for human thermal comfort may be the reason for the higher base temperature. Age of the building can be another factor for higher base temperature, as it can be seen for four primary schools having T_b greater than 1σ from the mean, as illustrated in Fig. 7b.

A comparison of mean T_b and corresponding standard errors for building type are shown in Fig. 7b. Despite the climatically similar conditions the buildings were exposed to, each building type had a different base temperature. Clubs and community centres (CC), and museums, art galleries and libraries (MA) has the highest mean T_b at 17.7 °C and 17.2 °C respectively. Higher average base temperatures are found for buildings that are classed as category I building in comfort standards such as ISO EN 15251 [28]. They are characterized with a high level of expectation of thermal comfort. Relatively greater standard errors are found for offices (FS), health (HL) and museums, art galleries and libraries (MA).

Each building, because of its type (i.e. purpose), location, and construction, is unique. Their construction year, variations in energy use and operational behaviour, as well as the heating, ventilation, and air-conditioning (HVAC) system types and characteristics are likely to have an impact on the base temperature. Attention should, therefore, be given on the intrinsic building characteristics while making use of base temperature in building energy applications. Researchers have also argued that the observed anomalies of T_b can be indicative of specific building faults [29].

4.3. Relationship between base temperature and physical characteristics

Fig. 8 illustrates the relationship between base temperature and physical characteristics such as total treated floor area and the number of occupants. The floor area ranges from 182 m^2 to 25,087 m^2 while the mean and SD are 3088 m^2 and 3700 m^2 respectively. The distribution of total floor area is given in Fig. 8a, which shows there are more small and medium sized buildings than the very large ones—typical of UK non-domestic building stock. Estimates suggest that small premises are far more common in terms of frequency; 92 per cent of non-domestic premises in the UK are smaller than 1000 m^2 [30]. Only one building in our dataset has a

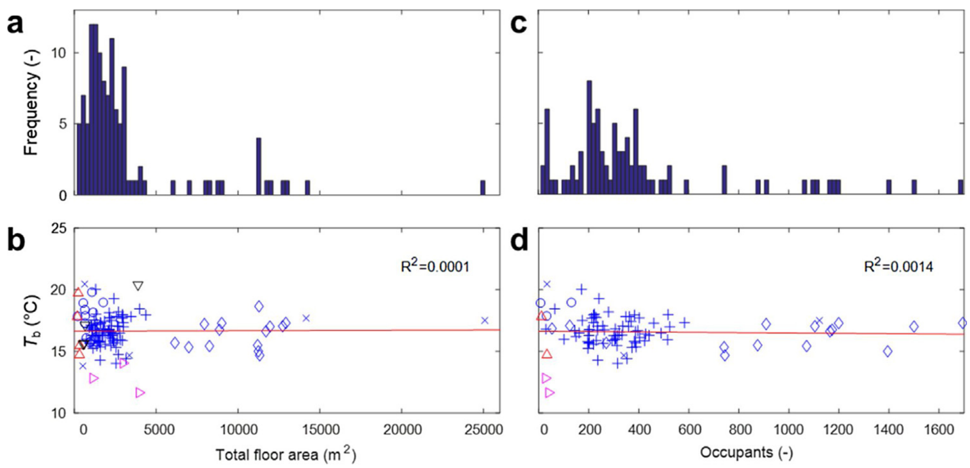

Fig. 8. Relationship between building intrinsic parameters and base temperature. (a) The distribution of building floor area in the dataset, (b) T_b vs. floor area, (c) The distribution of the number of building occupants in the dataset, (g) T_b vs. occupants.

total floor area of 25,000 m^2. T_b vs. floor area is given in Fig. 8b. Base temperatures does not have a discernible relationship with floor area, as the linearly fitted line has an R^2 estimate of almost zero. The literature lacks further information on the relationship between T_b and floor area; however, the Department for Business, Energy & Industrial Strategy (DBEIS) conducted a survey of non-domestic building stock between 2014 and 2015. Their findings suggest that mean energy intensity; i.e. energy consumption per unit floor area are higher for both the small and large buildings. The lowest annual energy intensity (<100 kWh/m^2) has been found for buildings with a floor area between 1000 and 2499 m^2 [30]. Probability of factors other than floor area having an impact on T_b and energy intensity is, therefore, high.

The frequency distribution of occupants is shown in Fig. 8c. Most buildings have around 200–400 occupants but some premises have many occupants. The relationship between floor area and occupants is not always straightforward. Some buildings, especially educational facilities such as primary and secondary schools often have a high density of occupants [30]. In keeping with the relationship between T_b and floor area there is not a discernible relationship between T_b and occupants.

4.4. Limitations

Our investigation of base temperature in non-domestic buildings included a wide range of buildings in terms of type, size, and number of occupants. Sub-hourly metered data for four full years enabled the consideration of year to year weather variations. Conclusions drawn from the research are, therefore, representative, especially for buildings with large sample size. The limitation of this research is that the sample sizes for health; offices; and museums, art galleries and libraries are smaller than we hoped for. Each of these building types have distinct sub-types with variations in building size, construction, and operating patterns; i.e. time of use and comfort requirements. Their standard errors are also relatively greater than other building types. Contextual interpretation of results for these buildings is, therefore, recommended.

4.5. Implications for building energy management and design

The main findings of this research are twofold. First, the average base or balance point temperature for all case study buildings in this research is 1.2 °C higher than the UK standard of 15.5 °C and 1.6 °C lower than the American standard of 18.3 °C. The widespread use of heating degree-days based on T_b = 15.5 °C for energy performance rating, calculations and monitoring will, therefore, underestimate heating energy demand and consumption in UK non-domestic buildings. Second, significant variations in base temperature exist between building types, ranging from the minimum of 11.6 °C for a storage building to the maximum of 20.5 °C for an office building. While previous research indicated that such variations are likely to exist [29] but the scale of the variation was not known prior to this research. Considering both findings, it is imperative that national calculation methodologies are updated to account for the variations in balance point temperature so that the energy performance is measured and monitored more accurately. The selection of an appropriate base temperature according to building types can also help in reducing the gap between predicted and measured energy performance of buildings, as discussed in the review by de Wilde [31]. Building characteristics, on the other hand, are subject to change.

Thermal performance of buildings is improving because of progressively stringent building regulations. The improvement is likely to influence base temperatures in new and retrofitted buildings alike. Innovation in tools and techniques for continuous monitoring and benchmarking of energy performance of buildings are, therefore, essential. In addition, the objectives for monitoring and underlying techniques for comparison should be consistent with the evaluation and simulation methods used during design so that the design strategies can be reliably validated, lessons are learned, if any, and corrective measures are adopted. An appropriately selected base temperature can ensure that predicted and actual performance benchmarking have the same criteria.

4.6. Directions of future work

While statistical regression method can successfully extract reasonably accurate relationships between investigated parameters, future work can focus on increasing the estimation accuracy. Because of the existence of change point relationships in the data, conditional quantile functions may also work well. One advantage of quantile regression is that the method's estimates are more robust than the ordinary least squares regression, especially when outliers in the response measurements are considered. The other direction of future work relates to weather variables. The consideration of solar radiation, with or without base temperature can offer insights into building energy consumption. The third direction relates to how energy consumption data are filtered. For single building energy use data, the filtering method can over-filter (filtering out valuable data) or under-filter (reserving outlier data).

More reliable filter method can be developed to tackle this issue. On the other hand, standardising variable base temperatures for the whole of a country (e.g. UK) will require further characterisation by increasing the geographical spread and number of buildings in the sample. From an application[9] perspective, further research needs to be carried out to investigate the reasons for the community's reluctance to adopt variable base temperatures.

5. Conclusion

Differences in intrinsic thermal characteristics, space usage, occupancy pattern, operational schedule and performance of installed equipment, and miscellaneous loads can significantly impact energy performance of buildings—with corresponding effects on their base temperature. This research conducted one of the most comprehensive investigations of base temperatures by using four years sub-hourly data from 119 UK non-domestic buildings covering a wider range of building type, size, and number of occupants.

There are two headline contributions from this work, with significant implications for the energy-efficient design and operation of buildings. First, the average base temperature of all investigated buildings found to be 1.2 °C higher than the widely adopted base temperature of 15.5 °C in the UK. The existing use of the lower base temperature in building energy calculations, benchmarking, and certifications results in underestimation of energy demand and consumption, giving an inaccurate picture of energy performance. Second, base temperatures vary from one building to another, and from one building type to another. The variations in base temperature between building types in this research ranged from 11.6 °C for a storage building to 20.5 °C for an office building. Health and clubs and community buildings have higher base temperatures because of their specialised use and possibly higher and intermittent demand for hot water. These specialised buildings also require the maintenance of a narrow range of thermal comfort and operate for longer hours.

Building regulations and policies would be less effective if they are based on the inaccurate assumption about the base temperature, which is an intrinsic thermal property of a building. The current practice of a fixed base temperature degree-days for all buildings has been found to be unrealistic in this research, even within a smaller geography of Cardiff city. It is imperative that building type specific base temperatures are developed, agreed upon and published for increasing accuracy in energy analytics and legislative compliance, as well as for developing effective standards and policies.

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[9] The application of degree-days has not changed much since its origin in the United States with the American Gas Association in the 1920s where 18.3 °C was adopted as the base temperature because of the empirical relationship between fuel consumption in dwellings and the degree-days to a base temperature of 65 °F (18.3 °C). The use of 60 °F (15.5 °C) as the base temperature in the UK has similar roots to the USA as was suggested by Dufton in 1934, despite calls to adopt building specific base temperatures in the recent years [9].

References

[1] IEA, Key World Energy Statistics, International Energy Agency, Paris, France, 2014.
[2] IEA, Transition to Sustainable Buildings: Strategies and Opportunities to 2050, International Energy Agency, Paris, France, 2013.
[3] G.P. Henze, S. Pless, A. Petersen, N. Long, A.T. Scambos, Control limits for building energy end use based on frequency analysis and quantile regression, Energy Effic. 8 (6) (2015) 1077–1092.
[4] CCC, Reducing Emissions and Preparing for Climate Change: 2015 Progress Report to Parliament, The Committee on Climate Change, London, UK, 2013.
[5] DBEIS, Heat in Buildings: The Future of Heat: Non-domestic Buildings, The Department for Business, Energy & Industrial Strategy, London, UK, 2016.
[6] DBEIS, Energy Consumption in the UK, Department for Business, Energy & Industrial Strategy, London, UK, 2016.
[7] E. Moreci, G. Ciulla, V. Lo Brano, Annual heating energy requirements of office buildings in a European climate, Sustain. Cities Soc. 20 (2016) 81–95.
[8] M. Mourshed, Relationship between annual mean temperature and degree-days, Energy Build. 54 (12) (2012) 418–425.
[9] CIBSE, Degree Days: Theory & Application, Chartered Institution of Building Services Engineers, London, UK, 2016.
[10] X. Shen, B. Liu, Changes in the timing, length and heating degree days of the heating season in central heating zone of China, Scientific Reports, Sci. Rep. 6 (2016) 33384.
[11] M.M. Mourshed, D. Kelliher, M. Keane, Integrating building energy simulation in the design process, IBPSA News 13 (1) (2003) 21–26.
[12] EP, Directive 2010/31/EU of the European Parliament and of the Council on the Energy Performance of Buildings, European Parliament, Brussels, Belgium, 2016.
[13] A. Day, T. Karayiannis, Identification of the uncertainties in degree-day-based energy estimates, Build. Serv. Eng. Res. Technol. 20 (4) (1999) 165–172.
[14] R.M. Dowd, M. Mourshed, Low carbon buildings: sensitivity of thermal properties of opaque envelope construction and glazing, Energy Procedia 75 (2015) 1284–1289.
[15] Z. Verbai, Á. Lakatos and F. Kalmár, Prediction of energy demand for heating of residential buildings using variable degree day, Energy 76 (2014) 780–787.
[16] ASHRAE, ASHRAE Handbook: Fundamentals, American Society of Heating, Refrigerating and Air-Conditioning Engineers, Atlanta, GA, 2016.
[17] D.N. Wortman, C.B. Christensen, Variable-Base Degree-Day Correction Factors for Energy Savings Calculations, Solar Energy Research Institute, Golden, CO, 1985.
[18] K. Lee, H.-J. Baek, C. Cho, The estimation of base temperature for heating and cooling degree-days for South Korea, J. Appl. Meteorol. Climatol. 53 (2014) 300–309.
[19] CIBSE, Degree-days: Theory and Application (TM41), The Chartered Institution of Building Services Engineers, London, UK, 2016.
[20] M. Shin, S.L. Do, Prediction of cooling energy use in buildings using an enthalpy-based cooling degree days method in a hot and humid climate, Energy Build. 110 (2016) 57–70.
[21] C. Ghiaus, Experimental estimation of building energy performance by robust regression, Energy Build. 38 (6) (2006) 582–587.
[22] D. Lindelöf, Bayesian estimation of a building's base temperature for the calculation of heating degree-days, Energy Build. 134 (2017) 154–161.
[23] U. Jensen, C. Lütkebohmert, Change-Point Models. Encyclopedia of Statistics in Quality and Reliability, John Wiley, Chichester, UK, 2007.
[24] Y. Zhang, Z. O'Neil, B. Dong, G. Augenbroe, Comparisons of inverse modeling approaches for predicting building energy performance, Build. Environ. 86 (2015) 177–190.
[25] J. Kissock, J. Haberl, D. Claridge, Inverse modeling toolkit (1050RP): numerical algorithms for best-fit variable-base degree-day and change-point models, ASHRAE Transactions, ASHRAE Trans. 109 (Part 2) (2003) 425–434.
[26] M.T. Paulus, Algorithm for explicit solution to the three parameter linear change point regression model, Sci. Technol. Built Environ. (2017) 1–10.
[27] ASHRAE, Measurement of Energy and Demand Savings (Guideline 14), American Society of Heating Refrigerating and Air-Conditioning Engineers, Atlanta, GA, 2002.
[28] ISO, Indoor Environmental Input Parameters for Design and Assessment of Energy Performance of Buildings Addressing Indoor Air Quality, Thermal Environment, Lighting and Acoustics, International Organization for Standardization, Geneva, Switzerland, 2007.
[29] A.R. Day, I. Knight, G. Dunn, R. Gaddas, Improved methods for evaluating base temperature for use in building energy performance lines, Build. Serv. Eng. Res. Technol. 24 (4) (2003) 221–228.
[30] DBEIS, Building Energy Efficiency Survey, 2014-15: Overarching Report, Department for Business, Energy & Industrial Strategy (DBEIS), London, UK, 2016.
[31] P. de Wilde, The gap between predicted and measured energy performance of buildings: a framework for investigation, Autom. Constr. 41 (2014) 40–49.
[32] BRE, Guide to the Government's Standard Assessment Procedure for Energy Rating of Dwellings (SAP), Building Research Establishment, Watford, UK, 2016.