Building and Environment 219 (2022) 109101

Contents lists available at ScienceDirect

Building and Environment

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

The influence of weather on heat demand profiles in UK social housing tower blocks

Victoria Aragon [a,*], Patrick A.B. James [a], Stephanie Gauthier [a]

[a] University of Southampton, Faculty of Engineering & Physical Sciences, Boldrewood Innovation Campus, Southampton, SO16 7QF, United Kingdom

ARTICLE INFO

Keywords:
Social housing
Heat demand
Energy signature
Regression
Seasonality
Baseline energy model

ABSTRACT

Prediction of heat demand is of distinct importance for policy planning in social housing, where residents are in higher danger of falling into fuel poverty. Understanding the behavioural response of fuel vulnerable households against weather allows generating accurate baseline energy models and estimations of energy savings. This paper evaluates weekly heat demand profiles of 462 social housing dwellings in five tower blocks in the South of the UK, monitored over two years. Linear and segmented regressions are fitted through the 'segmented' package in R Studio to explore the relationship between heat demand (including Domestic Hot Water and space heating) and Outdoor Temperature, generating energy signature models for each flat. Three distinct heat demand profiles are found: (i) households that do not use space heating (11%), (ii) irregular consumers, where the transition towards the heating season is not identifiable (33%), and (iii) households with marked seasonal thresholds (56%). Consumption trends as well as the effect of extremely weather events such as the 2018 storm 'The Beast from the East' on the heat demand are evaluated. Low consuming households show little to no variation in their demand patterns during extreme weather events, whereas higher consumers seem to reach a plateau in their demand even at extremely low temperatures. The variability of heat demand in dwellings which have identical physical properties, and are exposed to the same weather conditions, is attributed to occupant behaviour. This study highlights the heterogeneity of heat demand in social housing and the need to move away from national averages.

1. Introduction

In 2019, the UK extended its commitment to reduce its carbon emissions from 80% to 100% by 2050, relative to 1990 levels [1]. As a result, a ten-point plan to accelerate the pathway to net zero was published in 2020, underlining buildings as one of the pivotal areas to focus on [2]. Within the UK's domestic buildings sector, space heating demand amounts to 60% of the energy consumption and Domestic Hot Water to 18%, and both are usually provided through the same system [3]. Given the relevance of heat demand, many studies aim to identify what the main drivers of domestic heat are, and to develop methods to accurately predict it at both local and national levels [4–9]. Forecasting heat demand is of distinct importance for policy planning related to social housing, where residents are in higher danger of falling into fuel poverty, due to their low level of income [10]. Social housing represents 17% of the UK's building stock and holds distinct building features as well as hosting residents with specific socioeconomic characteristics [11]. Hence energy consumption in this sector is expected to differ from national averages [12].

At a first glance, heat demand in buildings is defined the three aspects: local climate, building characteristics such as thermal performance and type of systems, and user behaviour -their comfort needs and socioeconomic characteristics-. The convergence of these aspects leads to unique heat consumption patterns, which makes forecasting and replicability difficult. The more is understood about what triggers and limits heat demand the better it can be predicted. This helps to diminish the performance gap, meaning the difference between predicted and observed energy performance in buildings.

Moreover, evidence on the potential energy impact of large-scale retrofits and or technology deployment is needed to support policy development regarding heat demand in domestic buildings. This type of analysis should consider the heterogeneity of households. By disaggregating data in heat demand modelling, policies can be tailored to different types of consumers. In social housing, for example, financial restrictions mean that some households may adapt to living under lower temperatures to save on their heating bills [13], reinforcing the threat of

* Corresponding author.
E-mail addresses: V.Aragon@soton.ac.uk (V. Aragon), P.A.James@soton.ac.uk (P.A.B. James), S.Gauthier@soton.ac.uk (S. Gauthier).

https://doi.org/10.1016/j.buildenv.2022.109101
Received 6 September 2021; Received in revised form 7 April 2022; Accepted 13 April 2022
Available online 26 April 2022

the rebound effect after building retrofits [7,12,14,15]. Given that social housing is an ideal target for future retrofits, it is paramount to understand the heat demand in this sector.

This paper extends on the analysis presented at the 2018 Building Performance Analysis Conference and SimBuild co-organized by ASHRAE and IBPSA-USA, where the seasonal variation of monthly heat demand, including space heating and Domestic Hot Water (DHW), was evaluated for a group of social housing dwellings [16]. This preliminary analysis showed an overall low heat demand and a changing correlation between heat demand and outdoor temperature. Building on this work, this study aims to increase the understanding of heat demand, including both Domestic Hot Water and space heating, in social housing in the UK. In particular, it seeks to identify characteristics of behavioural response to weather. The objectives of the analysis are: (a) to discover heat demand profiles in social housing dwellings, (b) to examine the transition between the periods when there is no space heating demand, and when there is, and (b) to evaluate the impact of weather-related factors, such as outdoor temperature, wind, and an extreme weather events on space heating demand. A bottom-up statistical regression method was applied to study the relationship between heat demand and outdoor temperature using heat billing records from five social housing tower blocks over two years.

The paper is structured as follows. First a review of UK residential space heating demand and building energy models is presented in Section 2. This is followed by an introduction to the Case Study buildings in Section 3. Section 4 presents the dataset and methodology used to develop heat demand regression models and evaluate their main characteristics. Finally, results are presented and discussed in Section 5.

2. Background

2.1. Seasonality of space heating demand

Space heating demand can be analysed at different scales. Numerous studies focus on social housing indoor temperatures and daily patterns [5,7,17,18] as well as affordability of heat and sociodemographic determinants of demand [9,19,20]. However, to the authors knowledge, there is very little research on seasonality of space heating.

The largest UK survey on space heating in English households is The Energy Follow-up Survey [21], which presents an analysis of energy usage and seasonality derived from a combination of surveys and indoor temperature monitoring. The reported mean length of the heating season is of 5.6 months, with most household heating regularly from October to March or April, and 85% of households starting to use their heating in September and November. A small number of households (2%) reported heating their homes throughout the whole year, and a similar percentage of households reported not using any heating at all. Regarding dwelling characteristics, detached or semi-detached houses showed significantly longer heating periods than flats. Additionally, the Energy Follow-up Survey highlights the difficulty of determining an exact start and end of a heating season, as demand varies within each month.

The majority of UK building physics models are based on the methodology defined in the British Research Establishments Domestic Energy Model (BREDEM), with some modifications [22]. BREDEM details calculations methods for domestic monthly energy consumption based on characteristics of buildings and standardised temperature setpoints, daily occupancy and heating patterns. The heating season is defined on a monthly basis and is considered specific to each building and location. For each month, heating requirement is calculated based on the number of days that a certain temperature threshold is surpassed. This threshold, knowns as base temperature, is determined by the building's thermal gains and losses [23]. The validity of BREDEM assumptions has been questioned by various authors [7,12,20,21] with a predominant focus on temperature setpoints and daily profiles. In particular Kane et al. [9] evaluated the duration of the heating season as well as threshold temperatures, indicating that socio demographic variables such age and employment had an impact on a household's threshold temperature, and highlighting as well, the difficulty of determining the start and end of heating periods.

2.2. Building energy modelling

Building Energy models are developed to understand and predict the energy demand of buildings at different scales, from a single building to district or national levels. Depending on the level of aggregation of the data analysed, models can be classified into two methods: 'top-down' or 'bottom-up'. Swan & Ugursal [24] appraised modelling techniques for regional and national residential energy modelling, highlighting the main characteristics of these two methodologies. The first, top-down, perform regression on historical energy usage data of a sector or region and aim to identify what macroeconomic indicators explain the characteristics of the demand. Bottom-up models, in contrast, estimate energy consumption of specific buildings or groups of, and aim to serve as an input for large scale quantification of energy demand. These last are useful for discovering typical usage patterns and rely on simple data.

Bottom-up models can be further divided into statistical or engineering models, based on how end-use energy is estimated [25]. Statistical methods perform different types of regression analysis looking for correlations between historical energy consumption records and a variety of parameters, to forecast future energy demand. Engineering, or building-physics methods, use systems and building physical properties as well as occupant information to generate energy usage profiles. These last have greater flexibility and allow evaluating the impact of new technologies. However, the same level of disaggregation that gives them flexibility, requires detailed quantitative information, and results are heavily impacted by the assumptions on occupant behaviour [26]. Kavgic et al. [22] performed a review of residential bottom-up models, highlighting that the main benefit of statistical models is the ease of using billing data, in contrast with the detailed information required by building physics models. However, statistical modelling requires a large sample of historical records to be accurate.

Statistical models can use a variety of regression techniques, from simple linear regression to multivariate regression, such as Conditional Demand Analysis (CDA), and the use of Artificial Intelligence (AI) algorithms. These last are the most advanced and are used to evaluate non-linear relationships between energy demand and multiple parameters [25]. Machine learning is a type of AI method, where the models learn and improve with data input [27]. Support Vector Machine (SVM) and Artificial Neural Networks (ANN) are amongst the most used machine learning algorithms. These are very useful when little information is known about the building, but they rely heavily on the quality of the data used to train the model [28,29].

2.3. Application of simple regression models

The need to update current standards and assumptions calls for more data driven modelling approaches. These type of models are used in Measurement & Verification protocols to generate baseline energy models and evaluate building performance and the impact of technology deployment, and [30]. Zhang et al. [31] compared different approaches to generate baseline energy models in an office building, suggesting that regression models, in particular change point or piece-wise models, present a good balance of accuracy and amount of work needed to develop the model. ASHRAE Guideline 14 [30] suggests different types of regression models that can be fitted to whole-building energy demand records of different temporal resolutions. For UK buildings, The Chartered Institution of Building Services Engineers - CIBSE-presents two methodologies to generate baseline energy models: performance lines and energy signatures [32]. The first are linear models between space heating demand and Heating Degree Days at a monthly resolution. In contrast, the energy signature method evaluates total energy demand against outdoor temperature at high resolution, daily or hourly.

Energy signature models have multiple uses. They can be used to predict building physics parameters, such a building's heat loss coefficient and or base temperature [32,33], to identify problems in a building's thermal performance [34] and characteristics of their heating systems [35], to evaluate the impact of retrofits in energy demand [36, 37], and to identify energy consumption patterns. Overall, their simplicity in both the data needed and the type of analysis, as well as their multiple applications, make them an attractive tool to assess energy demand in residential buildings [38].

3. Case study

The case study analysed in this paper is a social housing building complex located in the city of Southampton, in the Southeast of the United Kingdom. The climate in the region is classified as temperate and oceanic (Köppen-Geiger Cfb), showing average Heating Degree Days of 1937 HDD/yr and average yearly minimum and maximum temperatures of 8.2 °C and 14.5 °C respectively [39]. The complex consists of five high-rise 13 storeys towers, each with 104 living units (N = 520). All five are identical in construction, layout, heating system, and orientation. The layout of the buildings, as depicted in Fig. 1, is the same across floors and consists of one- and two-bedroom properties of 50 m^2 and 70 m^2 respectively, oriented West to East. The towers are located on the waterfront, directly exposed to weather elements without any shielding from adjacent buildings.

Built in the late 60's, the fiver tower blocks were retrofitted in 2012 meeting BREEAM excellent certification standards. This included the improvement of the building fabric and the installation of a high temperature water-based heat network supplied by gas boilers. The resulting envelope shows U-Values of 0.30 W/m^2K for the external walls and 1.2 W/m^2K for the windows. The heat network supplies heat to metered heat exchangers in each flat, which are used for both space heating and hot water. Inside the flats the controls to regulate their heating and hot water are the same as in most UK households: on/off switch, thermostats, and TRVs (Thermostatic Radiator Valves) in the radiators [40]. An important characteristic of the heat exchangers is that they operate through a prepaid metering system, meaning that heat consumption is limited by the credit available on the customer's account. The case study (520 flats) was monitored from 2017 through 2019 as part of the Thermoss project [41] to evaluate the energy demand in the buildings. As part of the same project, indoor temperatures and thermal comfort were monitored in 10 flats from one tower during the same period.

4. Study design

4.1. Heat demand records

The analysis presented in this paper originates from the examination of weekly heat billing records from all the dwellings in the case study (N = 520) from October 2017 to October 2019 (104 weeks). This period includes an extreme weather event which took place during February–March 2018; a storm known as "The Beast from the East" which resulted in daily maximum temperatures of 2.5 °C and snowfall across the UK [42]. The billing records derive from the heat metering units in each flat and include heat consumed for space heating and Domestic Hot Water together as one value. Regarding the characteristics of the flats, the only information available included: flat number, floor number, floor area, orientation, and number of bedrooms.

The first step of data cleaning involved eliminating incomplete and null records. Metering interruptions and incorrect readings may be the result of malfunctioning of the metering units, communication problems and or changes in the metering when resetting or replacing equipment. The remaining dataset (N = 505) was re formatted to fit the ISO week calendar [43]. The second step was to identify and eliminate outliers, following the work of Chambers & Oreszczyn [44] on processing domestic energy demand records. As the heat demand data was non-normally distributed, a modified Z-score test was used, which evaluates the deviation of each data point in comparison with the median instead of the mean. Finally, long term occupancy was evaluated for each flat. If the heat demand of a flat was of 4 kWh or less for four continuous weeks or more, the flat was considered unoccupied for that period. This was done to identify long periods of absence to eliminate empty properties from the dataset and identify possible changes of tenancy. Periods of low demand (equal or less than 4 kWh) of three weeks or less were classified as occupied. As a result, 10 empty properties were eliminated from the dataset (N = 495).

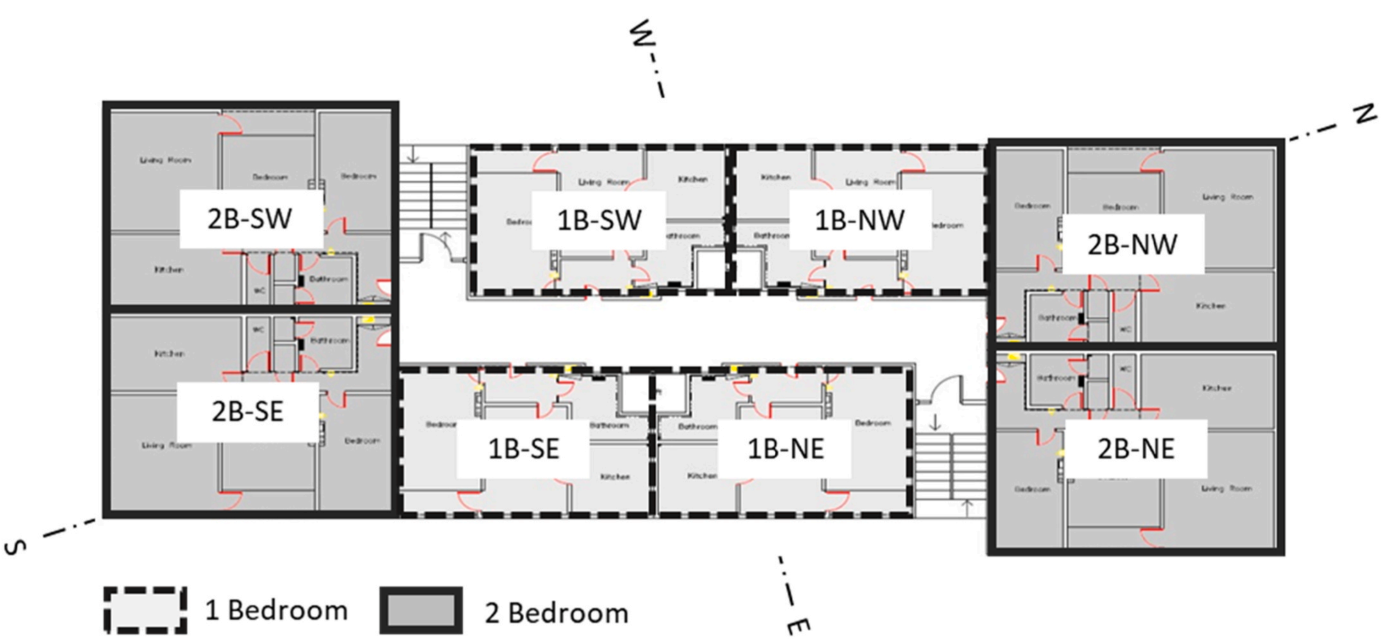

Fig. 1. – Typical floor layout within tower block. Each tower block has 13 stories with the same layout, composed of one- and two-bedroom flats, oriented West to East.

4.2. Indoor temperature records

Indoor temperature was monitored in 10 flats of one of the towers from February 2018 to October 2019 at 15-min intervals. Additionally, two thermal comfort and occupant behaviour surveys were performed in each flat: one during the winter of 2018 and the other at the end of the summer of the same year. The quality of the indoor monitoring dataset is very poor, given recurrent problems with the remote monitoring system. Additionally, the number of flats monitored is not enough to generalise aspects the indoor quality in the building. However, these records are still of interest as examples of comfort preferences in the flats of the case study. After eliminating faulty readings and outliers, mean temperatures during winter months were obtained for each of the 10 flats.

4.3. Weather

Weather records were obtained from a weather station [45] installed on the rooftop of one of the towers as part of the Thermoss project [41]. The resolution was 5 min, and the quality of the dataset was very good. Within the two years of data, 93% of all hours had complete readings (12 readings per hour), and only 5% of readings (1064 h) were missing intermittently. The only continuous period of missing data was in November 2017. The weather dataset includes the following variables: Outdoor Temperature (°C), Relative Humidity (%), Wind Speed (m/s), Wind Direction (DEG), Air pressure (hPa) and Solar Irradiance (W/m^2). These were aggregated per week, to match the resolution of the main dataset. The frequencies of mean weekly Outdoor Temperatures were evaluated to identify weeks of extreme low and high temperatures, as shown in Fig. 2. Weeks with a mean Outdoor Temperature lower than the 5th percentile (5 °C) or higher than the 95th (21.5 °C), were classified as 'extreme'. Four weeks were identified as extreme lows and one as extreme high. Out of the low temperature weeks, three of them correspond to the period of time when the storm 'The Beast from the East' took place, February and March of 2018.

4.4. Regression models

The relationship between heat demand (including space heating and Domestic Hot Water) and weather was evaluated by generating heat demand models for each flat by plotting weekly Heat Demand (kWh/m^2) against mean weekly Outdoor Temperature (°C) and fitting a regression model. The choice of this model, which is an adaptation of the energy signature, was defined by the type of data available and the objectives of this study. The energy signature method evaluates total energy demand

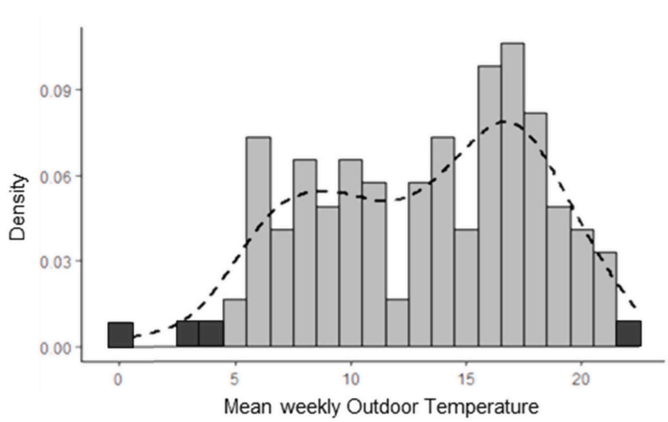

Fig. 2. Distribution of mean weekly Outdoor Temperature for the period of analysis, October 2017 to October 2019. Low and high extremes are identified using the 5th (5 °C) and 95th (21.5 °C) percentiles of the distribution. Weeks below or above those limits are classified as 'extreme' and highlighted in dark grey.

against outdoor temperature at high resolution, daily or hourly, and can be used to identify a building's base temperature [32]. The heat dataset used in this study includes total heat demand but has a weekly resolution. However, the large number of datapoints (104 weeks) is enough to perform a linear regression and generate a baseline energy model (ASHRAE Guideline 14 suggests a minimum of 12 months of data [30]). Hence, the energy signature method, but with a weekly resolution, was chosen for this analysis. Additionally, the metric kWh/m^2 was selected to allow a direct comparison across one- and two-bedroom flats.

The techniques used to generate the models were linear regression and change-point linear regression, with Heat Demand (kWh/m^2) being the dependant variable, and mean weekly Outdoor Temperature (°C) the independent variable. Using the software R Studio, and the 'Segmented' package for change point regression models [46], both a linear – Equation (1) [47]- and a segmented or piece-wise model -Equation (2) [47]- were fitted to the dataset of each flat. R Studio is an open-source software which uses R programming language for statistical analysis. The 'Segmented' package performs iterations of the linear model described in Equation (2) to find the changepoint or changepoints that result in the best fit for the data; if no changepoint is found it returns a linear model [47].

$$\text{Linear model}: \quad \gamma = \beta_1 + \beta_2 X_i \tag{1}$$

$$\text{Piece} - \text{wise model}: \quad \gamma = \beta_1 X_i + \beta_2 (X_i - \varphi)_+ \tag{2}$$

$(X_i - \varphi)_+ = (X_i - \varphi) \times I\ (\ X_i > \ \varphi)\ \ I()$ *equals* 1 *when statement is true*

γ = dependent variable (Heat Demand)
X_i = independent variable (Outdoor Temperature)
β_1 = slope of curve before the change point
β_2 = slope of curve after the change point
φ = change-point temperature

For each flat, the choice of a linear or a segmented or piece-wise model was done by evaluating the coefficient of determination (R^2) of each model; the one with the highest R^2 was assigned to the flat. Fig. 3 shows an example of the resulting demand models and their characteristics. ASHRAE [30] suggests using R^2 and CV(RMSE) - Coefficient of the Variation of the Root Mean Square Error-as measurements of a model's goodness of fit for baseline energy models. These are calculated using equations (3)–(5) [30].

$$R^2 = 1 - \frac{\sum_i (y_i - \widehat{y}_i)^2}{(y_i - \overline{y}_i)^2} \tag{3}$$

$$RMSE = \sqrt{\frac{\sum_i (y_i - \widehat{y}_i)^2}{n}} \tag{4}$$

$$CV(RMSE) = \frac{RMSE}{\overline{y}} \times 100 \tag{5}$$

The complete dataset of occupied flats (N = 495) was evaluated for a model fit. Similarly to the work of Bruce-Konuah et al. (2019), a minimum period of occupancy was set, excluding from the analysis flats that were occupied for less than 24 continuous weeks (6 months). This resulted in a sample of 482 flats where a model was fitted. Out of this sample, 20 did not show a discernible pattern and it was not possible to fit any model. Models were successfully assigned to 462 flats. All models excluded the weeks classified as 'extreme' (mean weekly Outdoor Temperature of less than 5 °C or higher than 21.5 °C); these data points were analysed separately.

4.5. Grouping

In order to group the models, the first characteristic evaluated was

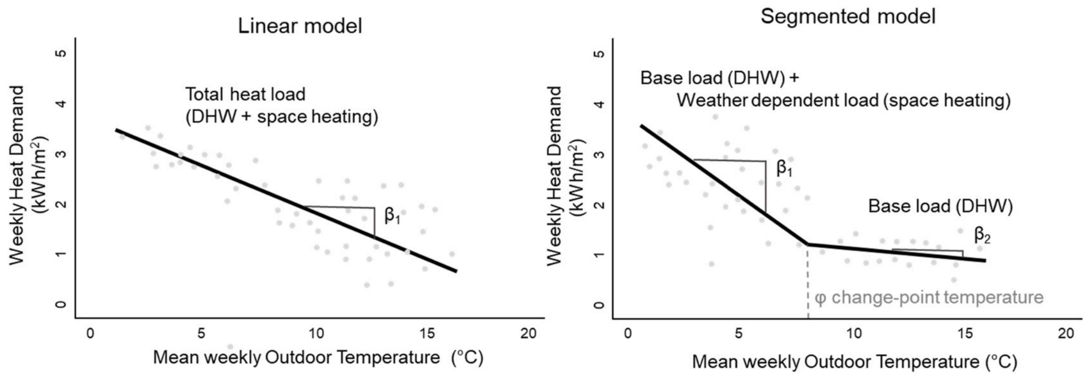

Fig. 3. Example of flat Heat Demand profiles. The models show the relationship between weekly Heat Demand in kWh/m^2 and mean weekly Outdoor Temperature. (a) Linear models do not exhibit a breakpoint, hence the transition between base loads and weather dependent loads is not defined. (b) Segmented models show a defined transition between base loads only (Domestic Hot Water) and the addition of weather dependent heat loads (space heating). The threshold represents the value of Outdoor Temperature at which space heating usage commences, which can be defined as a building's base temperature.

the presence of a breakpoint. Models which did not exhibit breakpoint were classified as 'Linear' (N = 201) and those which did, as 'Segmented' (N = 261). For each of these two groups the main characteristics of each model were summarized. The variables assessed were R^2, CVRMSE, MSE of entire model, MSE of each segment separately (for segmented models only), slope of linear segment(s), maximum, minimum, and mean weekly heat demand. Pairwise comparison plots suggested MSE (Mean Square Error) of the entire model, CVRMSE and mean weekly heat demand as potential grouping variables. After performing spearman correlation tests, MSE showed the most significant correlation for both types of models (Linear models: $S = 4.4\ 10^{+11}$, p-value $< 2.2\ 10^{-16}$; Segmented models: $S = 1.3\ 10^{+12}$, p-value $< 2.2\ 10^{-16}$).

In summary, the heat demand models were grouped according to two characteristics: (i) presence of a breakpoint, meaning whether the model was either linear or segmented, and (ii) dispersion of datapoints measured through the Mean Squared Error (MSE) of the data. The upper and lower quartiles of the MSE were identified as limits to classify the models into groups of low, medium and high dispersion resulting in six groups, three Linear and three Segmented. Fig. 4 shows the distribution of the MSE for each type of model, Linear and Segmented.

The resulting six groups were tested for differences, and the main characteristics of each were evaluated. The annual Heat Demand was estimated using the only complete year of monitoring, 2018, following the method described in CIBSE TM 41 [32] which differentiates non-weather related base loads from weather related ones. The first are considered constant and the second are normalized to represent the consumption of a standard year. Based on this procedure, it was assumed that Heat Demand between the months of June and August is non-weather related and includes only Domestic Hot Water. For each flat, the mean Heat Demand in these months was used as a base load and the difference between this base load and the actual Heat Demand was considered as space heating. Space heating was scaled by the Standard Heating Degree Days for the region of the case study (1937 HDD/year). This differentiation between Domestic Hot Water and space heating loads was only done with the purpose of normalizing the annual energy consumption of each flat. The remaining analysis presented in this paper analyses total Heat Demand, including both Domestic Hot Water and space heating.

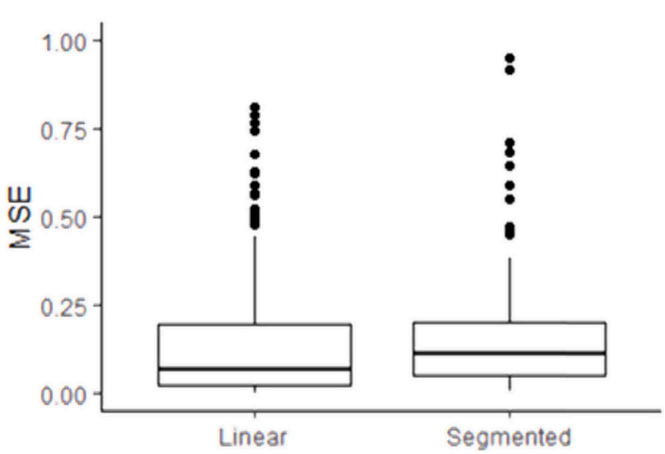

Fig. 4. Mean Squared Error (MSE) by model type. Heat Demand models of 462 flats (201 Linear and 261 Segmented) were classified into low, medium and high dispersion using the upper (Q3) and lower (Q1) quartiles of the MSE of the corresponding model type as limits. Segmented models exhibited Q1 and Q3 of 0.05 and 0.20. Linear models exhibited a Q1 and Q3 of 0.02 and 0.19.

Finally, the distribution of breakpoints in segmented models was analysed to look for differences across groups, following the works of Meng et al. [48] and Kane et al. [9]. The breakpoint in the model curve was identified as the threshold between the heating and non-heating periods, meaning the base temperature of the flat.

4.6. *Impact of extreme weather*

Firstly, the relationship between Heat Demand and weather factors was evaluated through Spearman correlation tests to identify how each factor affects the different groups. In relation to extreme weather events, the data points corresponding to weeks identified as extreme lows, were compared against the trend of the fitted model to evaluate possible changes in the demand in each group. Additionally, the impact of wind speed on Heat Demand was evaluated by analysing the patterns of demand on the weeks with the 95th percentile winds.

5. Results & discussion

5.1. *Fit of regression models*

In the 462 flats where a model was fitted, heat demand was non normally distributed. Hence, the non-parametric test, Kruskal-Wallis, was used to test for differences across the six groups, at 0.05 level of significance. Results indicated a significant difference ($X^2 = 7076$, df = 5, $p = 2.2\ 10^{-16}$) across all groups. Post hoc pairwise comparisons were performed using Wilcoxon Rank test, showing that the distribution of Heat Demand was not significantly different across groups with the same dispersion category (low, medium, or high) and different model type (Linear or Segmented). This indicates that flats in the same dispersion category show similar levels of Heat Demand. However, this test does not evaluate she shape of the model, which is an indication of how the demand occurs. Consequently, the type of model, Linear or Segmented, was still used as a grouping variable, to reflect the shape of the Heat Demand profile.

As a result, six groups were defined: three Linear, '*L1-low dispersion*' (N = 50, MSE≤0.02), '*L2 – medium dispersion*' (N = 101, MSE >0.02 & <0.19) and '*L3 – high dispersion*' (N = 50, MSE≥0.19); and three Segmented, *'S1-low dispersion'* (N = 22, MSE≤0.05), *'S2-medium dispersion* (N = 166, MSE >0.05 & <0.20)' and *'S3 -high dispersion'* (N = 73, MSE≥0.20). A summary of the groups characteristics is shown in Table 1. The datapoints and average demand profile of each are shown in Fig. 5.

Firstly, R^2 and CV(RMSE) were used as measurements of goodness of fit. R^2 indicates how much of the variation in the dependent variable (Heat Demand) is explained by the independent variable (Outdoor Temperature) [32]. The higher the value of R^2, the better the fit. The ranges of R^2 exhibited in Table 1 are considerably low across all groups, between 0.08 and 0.68. Despite the low granularity (weekly resolution) there is high scatter in the data. This is not attributed to problems with data quality, given the reliability of the data collection method used (metering readings). Furthermore, the Coefficient of Variation of the Root mean Square Error CV(RMSE) is also an indicator of uncertainty in a regression model; lower values signal lower uncertainty. An acceptable range of CV(RMSE) for baseline energy models based on 12–60 months of monitoring, is 25%–35% [49]. Low dispersion groups - L1 and S- showed adequate values of CV(RMSE). About a quarter of medium dispersion groups -L2 and S2-, and half of high dispersion groups – L3 and S3- showed values above 35%. This is reasonable, as the higher the spread of the data, the higher the uncertainty of the model.

Given these results, it can be assumed that Heat Demand in the flats is not fully driven by Outdoor Temperature, and further investigation is needed. The datapoints represents individual behaviour, which leads to greater variation of Heat Demand, and uncertainty in the models. As a comparison, a regression analysis was performed at building level for each of the five tower blocks. The fit of the resulting five models (one for each tower), measured through R^2 and CV(RMSE), showed values ranging from 0.73 to 0.76 and CV(RMSE) from 17% to 20%. At building level, the large number of flats in each tower (104) is enough to balance the variability of the individual demand.

Looking further into the regression models fitted, two types can be observed in Fig. 5: linear and segmented. The first consists of flats where the trend of the Heat Demand does not change with Outdoor Temperature. The second are flats where the trend of Heat Demand varies, resulting in a break point in the curve. Additionally, the Outdoor Temperature range observed during mid-season months – March to May and September to November –is highlighted in grey. Values above the maximum range are expected to be weeks where there is no need for space heating, whereas values below correspond to weeks where there is. The recorded mean weekly temperature during those months ranged from 8.5 °C to 17.5 °C. As a comparison, a Test Reference Year weather file for the same location (Southampton, UK) showed mean weekly temperatures during mid-season months from 3 °C to 15.1 °C [50].

Table 1
Summary of group characteristics. R^2 and CVRMSE are used as measurements of goodness of fit of the models as per ASHRAE Guideline 14 [49].

Group		L1	L2	L3	S1	S2	S3
Model type			Linear	Segmented			
Number of flats		50	101	50	22	166	73
Weekly Heat Demand (kWh/m^2)	Q3	0.66	1.05	2.01	0.64	1.15	2.10
	Median	0.47	0.78	1.26	0.46	0.74	1.20
	Q1	0.31	0.54	0.73	0.34	0.47	0.65
R^2	Q3	0.26	0.34	0.47	0.48	0.62	0.68
	Median	0.17	0.23	0.30	0.39	0.51	0.59
	Q1	0.08	0.08	0.20	0.29	0.38	0.43
CV (RMSE)	Q3	24	43	55	33	42	46
	Median	20	33	44	25	34	39
	Q1	16	25	37	22	29	33

Furthermore, the shape of the segment is an indication of the type of demand. Flat or shallow segments with low variability correspond to a type of demand that is not dependent from outdoor temperature and hence can be interpreted as Domestic Hot Water demand. In contrast, steep segments show a high correlation between Heat Demand and Outdoor Temperature and can be interpreted as periods that include space heating in addition to Domestic Hot Water. A study by Lomas & Kane [51] showed that the majority of UK households turn their heating off during summer months, but a small proportion, mostly elderly individuals, still use some form of space heating. Summer heating was also reported in the Energy Follow Up Survey [21]. Consequently, at high outdoor temperatures, it is most likely to see flat segments, but steep segments are possible as well.

5.2. Group characteristics

One of the main characteristic analyzed for each group, was the normalized annual Heat Demand, in kWh/m^2yr. This was estimated following the method described in CIBSE TM 41 [32] which differetiates Domestic Hot Water and space heating demand, as explained in the Study Section . Results were summarized by group, resulting in the distributions shown in Fig. 6. The group with the lowest heat demand is 'L1 – low dispersion' (N = 50). Households in this group do not manifest a correlation between Heat Demand and Outdoor Temperature and show a median heat consumption of 21 kWh/m^2 year (Table 1). Considering that the average Domestic Hot Water demand in UK households is of 55 kWh/m^2 [52] it can be assumed these flats do not use heat for space heating, only DHW. Differences in DHW demand across flats may be related to the number of occupants [53], as this group includes both one and two bedroom flats. Group '*L1'* comprises 11% of the household sample analysed, which is five times higher than the average percentage of non-heating English households (2%) reported in the Energy Follow up Survey [21]. A high percentage of no heating households could be a reflection of the towers being highly insulated.

As an example, out of the 10 flats where indoor monitoring took place, one belonged to group L1. This one-bedroom flat showed a Heat Demand of 12 kWh/m^2 year and mean indoor temperatures during winter months of 17.6 °C and 18.8 °C in the lounge and bedroom, which are below or just in the limit of what is considerable healthy (18.5 °C–21 °C). In this case, the resident reported to not opening windows during winter months and not using space heating because they liked cold temperatures. However, this is not necessarily the case for all residents. If a lack of space heating demand is caused by occupant's financial constraints, it could be a worrying sign for the City Council who manages the properties and needs to assure affordable living conditions for its residents. Unfortunately, with the limited information available, it is not possible to identify the cause of such a high number of non-heating properties in the site.

In contrast to group 'L1', all other groups show an increase of Heat Demand with lower Outdoor Temperature, suggesting that these households do use space heating. Linear groups 'L2-medium dispersion'(N = 101) and 'L3-high dispersion'(N = 50) represent 33% of flats and show median Heat Demands of 37 kWh/m^2yr and 69 kWh/m^2yr. These are households with 'irregular demand' meaning that there is no identifiable change in the correlation between Heat Demand and Outdoor Temperature. As a comparison, the Energy Follow up Survey [21] reports that 27% of houses in England use heating in a non-regular manner. Of the 10 flats with indoor monitoring, 2 correspond to group L2 and two to group L3. The mean indoor temperatures during winter

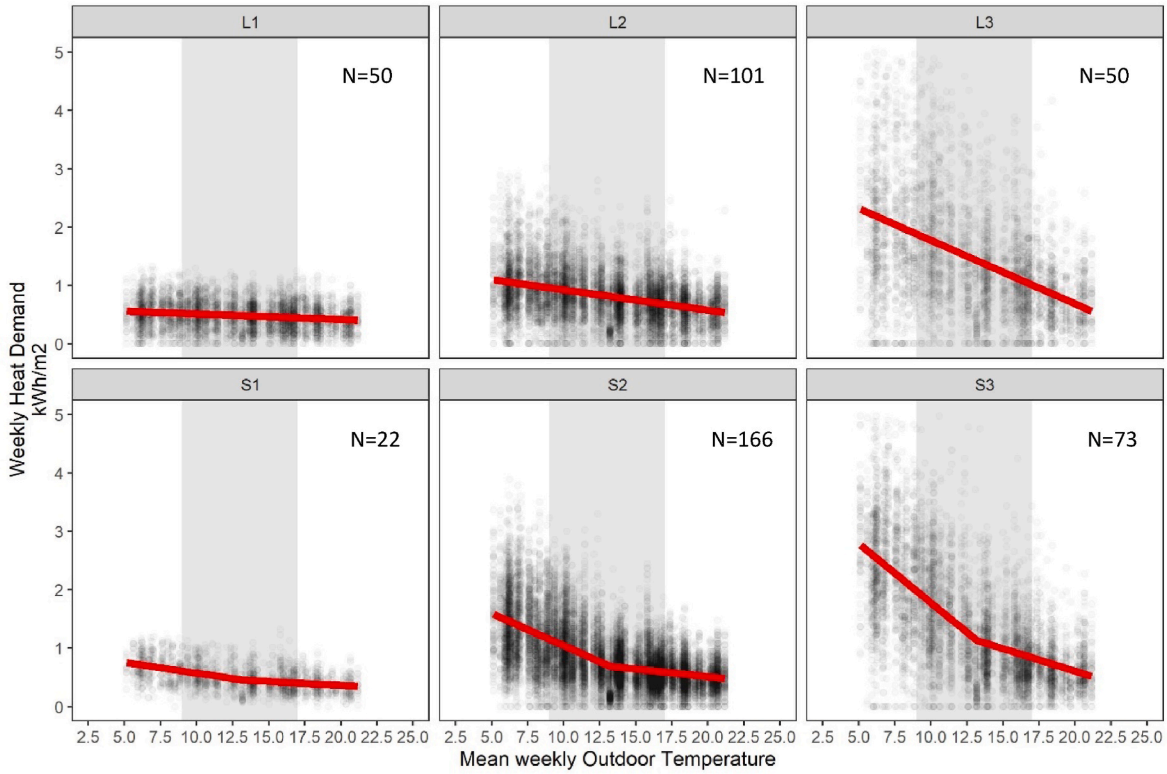

Fig. 5. Heat demand profiles by group. Each plot shows the mean shape of the models in red and the datapoints of all the flats in each group. The area highlighted in grey represents the Outdoor Temperature range observed during mid-season months, March to May and September to November. Group L1-low dispersion': Heat Demand is uniform across Outdoor Temperature, there is no breakpoint. Groups 'L2-medium dispersion' and "L3-high dispersion": linear models where heat demand increases as Outdoor Temperature decreases and there is no breakpoint. Groups 'S1 -low dispersion', 'S2 - medium dispersion' and 'S3 - high dispersion': segmented models with different degrees of dispersion. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

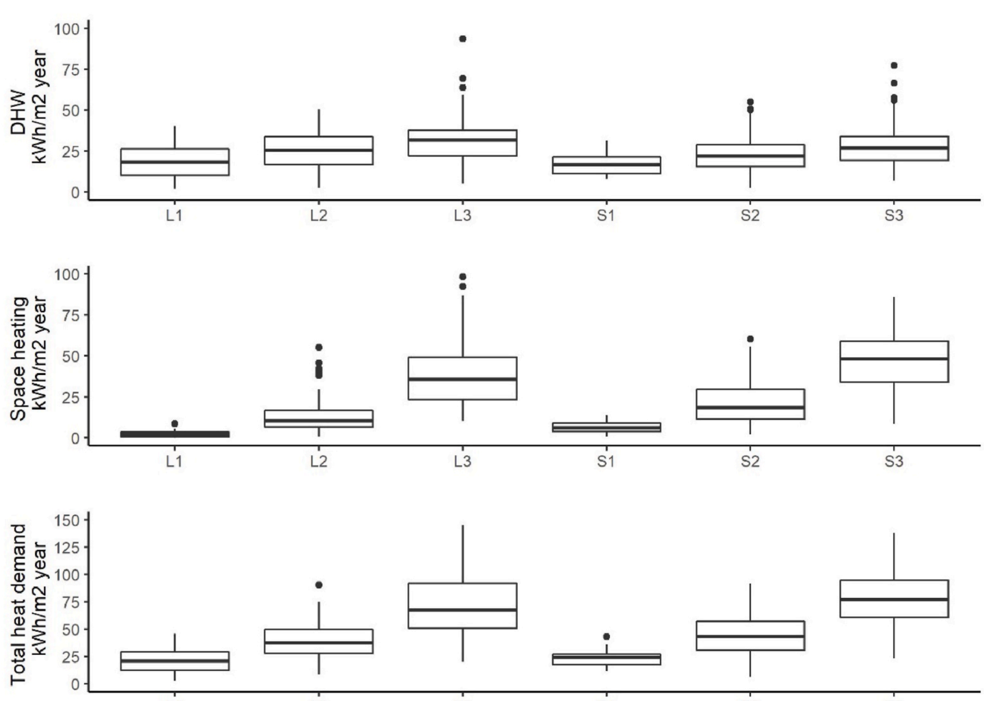

Fig. 6. – Normalized Annual Heat demand by group. DHW is considered non-weather related and constant throughout the year. It was estimated for each flat considering that **H**eat Demand during summer months (June to August) includes DHW loads only. Space heating is considered weather dependent and was normalized for a typical weather year (Heating Degree Days = 1937 HDD). Total Head Demand includes the sum of annual DHW and normalized space hating loads as described in CIBSE TM 41 [32].

months in flats from group L2 were of 18.8 °C and 20.9 °C for the lounge and main bedroom, and of 22.2 °C and 24.9 °C for lounge and main bedroom in group L3. These results suggest that comfortable indoor temperatures in winter are achievable with a very low space heating demand, indicating that the thermal performance of the building is very good.

The remaining 56% (N = 261) corresponds to segmented groups 'S1-low dispersion', 'S2-medium dispersion' and 'S3-high dispersion', which exhibit changes in both the trend and dispersion of data points at a certain range of Outdoor Temperature, and can hence be classified as 'regular consumers' (The Energy Follow up Survey [21] reports that 71% of houses in England use heating in a regular manner). The largest segmented group,'S2-medium dispersion' (N = 166), shows a median of 43 kWh/m^{2}yr. In contrast, the smallest group is 'S1-low dispersion' (N = 22), where the median Heat Demand is of 25 kWh/m^{2}yr. Finally, group 'S3-high dispersion' (N = 73) has the highest median Heat Demand amongst all groups −77 kWh/m^{2}yr-. One of the monitored flats corresponded to group S1 and another to S2. The flat in S1 showed median ambient temperatures of 18 °C and 18.8 °C in the lounge and main bedroom, and the flat in group S2, of 20.4 °C and 22 °C respectively.

As a whole, Heat Demand was very low across all groups, with medians between 20 and 80 kWh/m^2 yr. As a comparison, new buildings that are compliant with UK Building Regulations are expected to have a total Heat Demand between 115 and 135 kWh/m^2 yr [52]. In terms of the length of the heating season, this was only estimated for groups that exhibit a segmented model, 'S1', 'S2'and 'S3'. Space heating was considered 'ON' only in weeks in the second segment of the curve, and if Heat Demand was higher than the median of the first segment (median Domestic Hot Water demand). It should be noted that this calculation did not consider continuity, but the overall sum of weeks where the heating was on. After normalizing the sums for an average year (HDD = 1937), the resulting lengths of the heating season were of 17.3 (group S1), 23.7 (group S2) and 27.7 (group S3) weeks per year. The Energy Follow up Survey [21] estimates that the length of the heating for households with central heating is of 5.6 months (22.4 weeks).

The low heat demand and the variability of the heating season length observed could be the result of multiple factors: building envelope, flat orientation, household characteristics such as number of inhabitants and level of income, and occupant's behaviour, household occupancy and thermal preferences [17]. Regarding building characteristics, social housing dwellings rank high in energy efficiency when compared to other UK households [40], and the towers analysed meet strict performance standards. Consequently, a low heat demand seems reasonable for the case study (see Fig. 6).

Concerning orientation and layout, the only information available for all flats is their location within the building. As indicated in Fig. 1, there are eight types of flats based on their configuration (one or two bedroom) and orientation (South-East, South-West, North-East and North-West). A chi-square test of independence was used to evaluate the relationship between group and type of flat. At a 0.05 level of significance, there was not enough evidence to confirm a significant relationship ($X^2 = 28.4$, df = 35, p = 0.8), meaning that flat type cannot not be used as a predictor for group type. However, the distribution of flat types across groups is still of interest to evaluate the building's performance. Fig. 7 displays the type of heat demand profile group (L1, L2, L3, S1, S2 and S3) for each flat type (8 types as depicted in Fig. 1). As expected, the flats with the lowest number of *'No heating'* flats (group L1) are North corner flats, two-bedroom Northwest & Northeast, which have the least solar gains and larger exposed surface.

5.3. Seasonal behaviour

In order to understand the transition from the 'heating off' to 'heating on' periods, two characteristics of the models were evaluated: dispersion and location of the breakpoint (if present). In this study, the

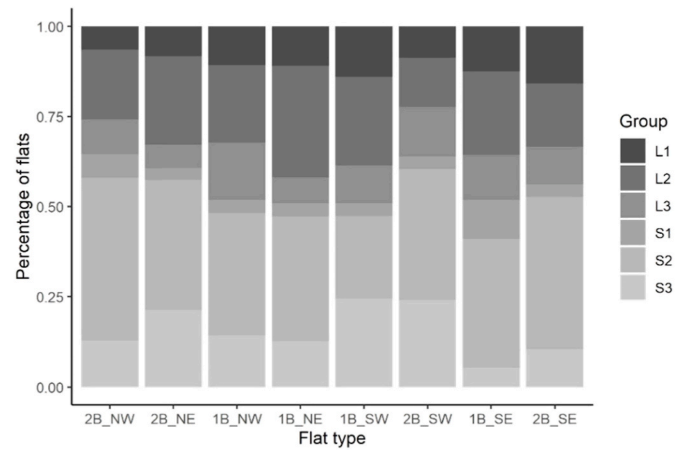

Fig. 7. Profile group for each type of flat. Flats are classified by type, one or two bedrooms, and orientation. The flats with the lowest proportion of 'No heating' flats are two-bedroom flats oriented North.

Mean Square Error -MSE-is used to evaluate of the spread of the datapoints in each model. The MSE of each model was binned for every 2 °C, resulting in the profiles observed in Fig. 8. All groups but 'L1-low dispersion' show a variation of MSE across Outdoor Temperature, exhibiting lower dispersion at higher values of Outdoor Temperature where space heating demand is unlikely. The highest heat consumers -groups S3, and L3 - show a higher spread of heat demand both at the start of the mid-season – 17 to 13 °C - and at extreme values– less than 6 °C. This could suggest that some models should include an additional breakpoint. In contrast, the lowest and medium heat consumers – groups S1, L2 and S2- show a lower spread at lower Outdoor Temperature, suggesting that Heat Demand reaches a plateau and stops being reactive to outdoor temperature.

Regarding the transition between the non-heating and heating periods, the impact of both group and flat type on the change-point was evaluated for segmented groups 'S1-low dispersion', 'S2-medium dispersion' and 'S3- high dispersion'. There were significant differences in the breakpoints across groups at 0.05 level of significance ($X^2 = 19.1$, df = 2, p = 7.1 10^{-5}). Additionally, post hoc comparisons showed that the distribution of breakpoints was significantly different across all group combinations. In an energy signature model, the breakpoint can be interpreted as the base temperature of a building and serves as an indication of its thermal performance. In this analysis, the breakpoint temperature was obtained for each flat individually, and at building level. Fig. 9 shows the distribution of flat breakpoints across the three segmented groups, all of which resulted non-normal.

The first characteristic observed in the distributions is that in all groups, most breakpoints lie within the mid-season area marked in grey. Additionally, in almost 50% of flats, breakpoints fall in the range of 12 °C–14 °C. The main difference across the groups is the shape of the distribution. Groups 'S1 and 'S2', show a left skewed curve with around 70% of breakpoints below 14 °C. These are 'late heaters' with a second peak around 10 °C. In contrast, group 'S3' shows a more normal distribution, with 50% of breakpoints between 12 °C and 15 °C. Group S3 consists of high consumers which can be classified as 'early heaters'.

At building level, a regression analysis for each of the five towers yielded a mean breakpoint temperature of 13.3 °C, which coincides with the findings for half of the flat sample. The standard base temperature used in the UK for Degree Days calculations is of 15.5 °C [32]; using standard assumptions would lead to overestimating the heating demand in these buildings. Literature suggests that using building specific base temperatures is a better approach for building energy modelling [32, 48].

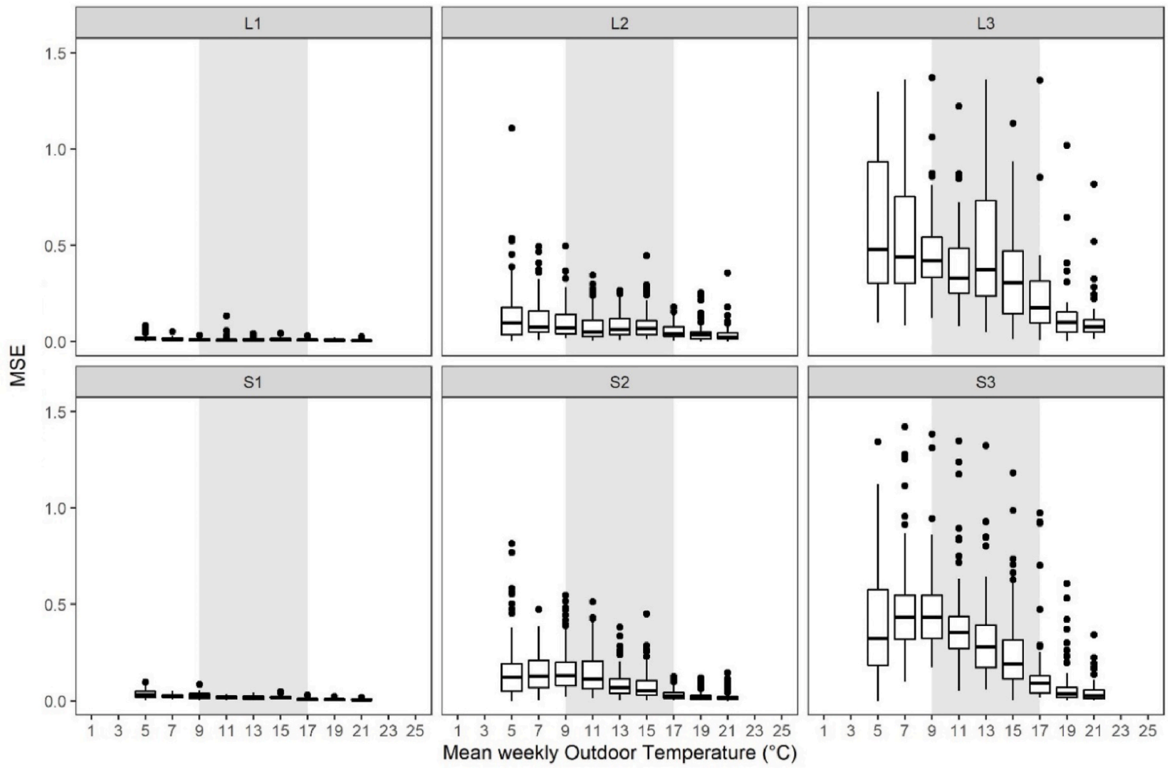

Fig. 8. Heat Demand dispersion by group. Distribution of Mean Square Error (MSE) at different ranges of Outdoor Temperature by group. Mid-season temperatures ranges– 8.5 to 17.5 °C - are marked in grey. 'L 1': heat demand is uniform across Outdoor Temperature. 'S1','L2 and "S2': the spread of heat demand grows as Outdoor Temperature decreases. 'L3' and 'S3′ and 'S3' show a higher variability during mid-season temperatures and at lower Outdoor Temperature.

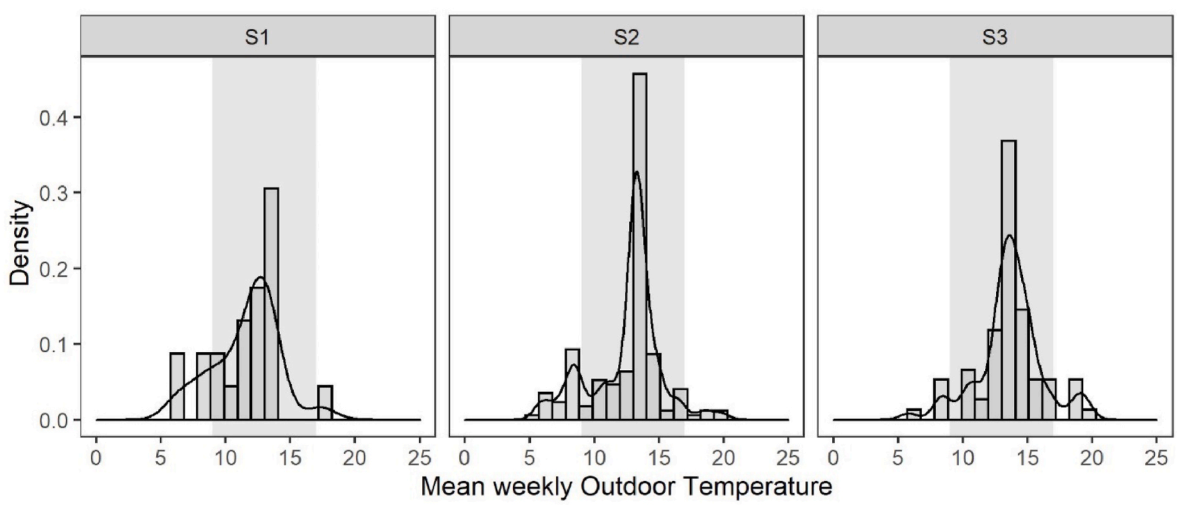

Fig. 9. Distribution of breakpoints in segmented models, *'S1-Low dispersion', 'S2-Medium dispersion', 'S3-High dispersion'*. Mid-season temperatures – 8.5 to 17.5 °C - are marked in grey. In all groups, almost 50% of flats show a breakpoint peak between 12 °C and 14 °C.

5.4. *Effect of extreme weather*

The relationship between heat demand and three weather factors, outdoor temperature, solar radiation, and wind speed, was first evaluated for all the flats (N = 462) for the entire period of monitoring (October 2017 to October 2019). The results from Spearman correlation tests between the observed Heat Demand of each flat in the six groups, and weather factors are shown in Fig. 10. The distributions of the correlation factors were very similar for outdoor temperature and solar radiation indicating that both have an impact on Heat Demand. As expected, group 'L1-low dispersion' exhibited the smallest correlation factors. The largest segmented group, 'S3-high dispersion' was the most' reactive' to outdoor temperature and solar radiation. Furthermore, linear groups 'L2-medium dispersion' and 'L3-high dispersion' exhibited a higher spread of correlation factors than all the other groups. Finally, regarding wind speed, correlation factors were low or close to null across all groups. This is surprising given the intensity of wind speed on site and the level of exposure of the facades, but suggests that heat loss through thermal bridges and ventilation losses in the building is low.

Furthermore, the effect of extreme weather conditions was evaluated by analysing the heat demand for both weeks with high winds, and for the four weeks classified as 'extreme low' temperatures, which include

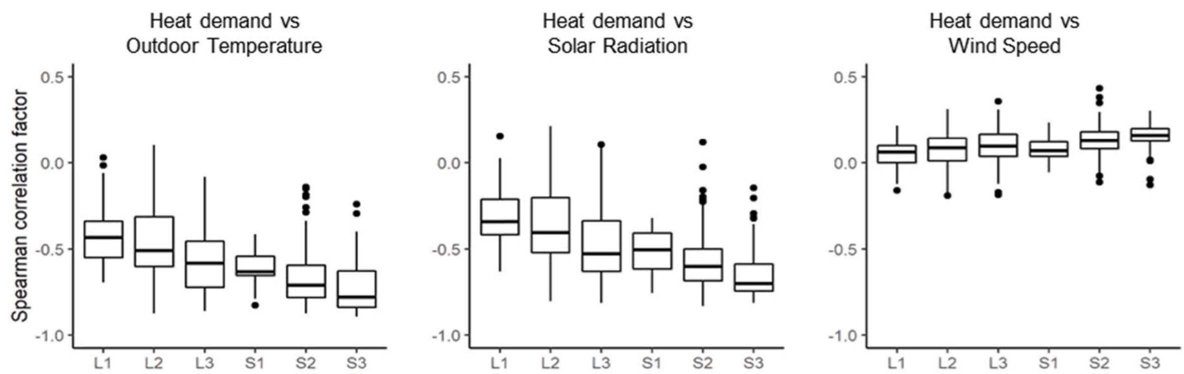

Fig. 10. Spearman correlations for weather factors and heat demand from October 2017 to October 2019. Distribution of correlation factors between weekly means of outdoor temperature, solar radiation and wind speed, and heat demand per group.

three weeks during the 2018 storm "The Beast from the East". Concerning winds speeds, Heat Demand during weeks with speeds above the 95th percentile - 3.8 m/s-were evaluated, but no correlation was found. Regarding the 'extreme low' weeks, the observed Heat Demand of each flat was compared to that predicted by each model for each week. When evaluating Heat Demand during these weeks, it is important to consider that the 2018 storm not only involved lower temperatures, but also the amount of snowfall meant that most people stayed inside their homes. Hence, in some households, the change in demand could be a result of outdoor conditions as well as the change in household occupancy.

The distributions of observed and fitted values of each group were tested for differences through a Wilcoxon Signed-Rank Test, which results are shown in Table 2. Groups 'L1-low dispersion', 'L2-medium dispersion' and 'S1-low dispersion' did not show significant difference between observed and predicted Heat Demand (p value > 0.05). This suggests that the household heating behaviour remained as per previous weeks, which doesn't mean that there was not an increase in the heat demand, but that the ratio of Heat Demand against Outdoor Temperature remained the same. This is reasonable for flats in groups L1 and S1 which are the lowest consumers, and least reactive to Outdoor Temperature. Groups 'L3-high dispersion', 'S2-medium dispersion' and 'S3-high dispersion' did show a significant difference between observed and predicted heat demand (p value < 0.05) and the median of observed Heat Demand was lower than the predicted in all groups. None of the groups showed a significant increase in Heat Demand during extreme low temperature weeks.

Looking further into the deviation between observed demand and predicted, Fig. 11 shows the distribution of the differences between the distributions of these two values. A difference of zero means that the demand was as predicted, a positive value means that observed Heat Demand was higher than predicted for that Outdoor Temperature, and a negative less. Firstly, in groups 'L1' and 'S1' most flats did not show a change in their Heat Demand, meaning that they continued to not use their heating or use very little. It is possible that the one-bedroom flats in this group benefit from 'parasitic heat' from adjacent flats. Heat usage and transmission from other flats would be particularly high during a week with high occupancy and low temperatures. Regarding the flats in group S1 which did show a change, they increased their weekly heat demand by less than 0.30 kWh/m^2, almost doubling their normal heat usage.

Table 2
Results of Wilcoxon Rank Sum tests for differences between observed and predicted Heat Demand during four extreme low temperature weeks identified in Section 3.2. At a 0.05 level of significance, p values lowers than this limit are an indicator of a significant difference between the actual demand and that predicted by the model.

	Median Heat Demand kWh/m^2 week		V (test statistic)	p value
	Observed	Predicted		
L1	0.53	0.52	12050	0.105
L2	0.98	0.98	39581	0.166
L3	1.95	2.12	12888	**0.0201**
S1	0.67	0.74	1224	0.160
S2	1.27	1.50	134516	**1.50e^{-14}** *
S3	2.46	2.90	38435	**4.54e^{-12}** *

*p value < 0.05.

Moreover, in group 'L2-medium dispersion' 50% of flats exhibited little or no change – 0.30 kWh/m^2 or less-, 25% a decrease of up to 1 kWh/m^2, and 25% an increase of up to 1 kWh/m^2. Finally, all three groups that showed a significant difference between observed and predicted demand, exhibit a left skewed distribution, meaning that most flats consumed less than predicted by the model. This could be an indication that Heat Demand has reached a plateau and another breakpoint is needed in the models. It is very unlikely that this plateau or maximum Heat Demand is caused by the system reaching its maximum capacity. The heat exchangers in the flat have a capacity of 31 kW, which if run at full capacity during a week would result in a demand almost 40 times higher than the observed in the flats. Possible reasons behind the plateau could be indoor temperature reaching a comfort level or that residents maximizing their credit; but without more information it is not possible to pinpoint the cause.

6. Conclusion

In this study, a bottom-up approach was applied to explore the relationship between Heat Demand (including Domestic Hot Water and space heating) and weather, in the context of a social housing complex in the United Kingdom. The case study consisted of a highly controlled environment; five identical tower blocks monitored for two years. Linear and segmented regression models were fitted to 462 flats and the overall heat demand, as well as the transition between the heating and non-heating periods, were evaluated.

The regression analysis discovers six distinct types of heat demand profiles and differences against standard assumptions, such as the low level of heat demand (between 20 and 80 kWh/m^{2}yr), the high proportion of households that do not use space heating at all (11% of the analysed flats) and a base temperature that varies across the type of profile. Considering that all the building of the case study analysed are in the same location and have identical physical properties, it is surprising to find such variability. The type of flat, determined by area and orientation, was not found to be significant. Consequently, the authors attribute the heterogeneity of the heat demand to occupant behaviour.

These results support the need to have a more diversified approach to energy modelling and consider different types of consumers. In view of Net zero policies and targets, it is paramount to accurately predict building's energy demand, and avoid over estimation which is of common occurrence for social housing properties.

Furthermore, the analysis of the demand during weeks of extremely

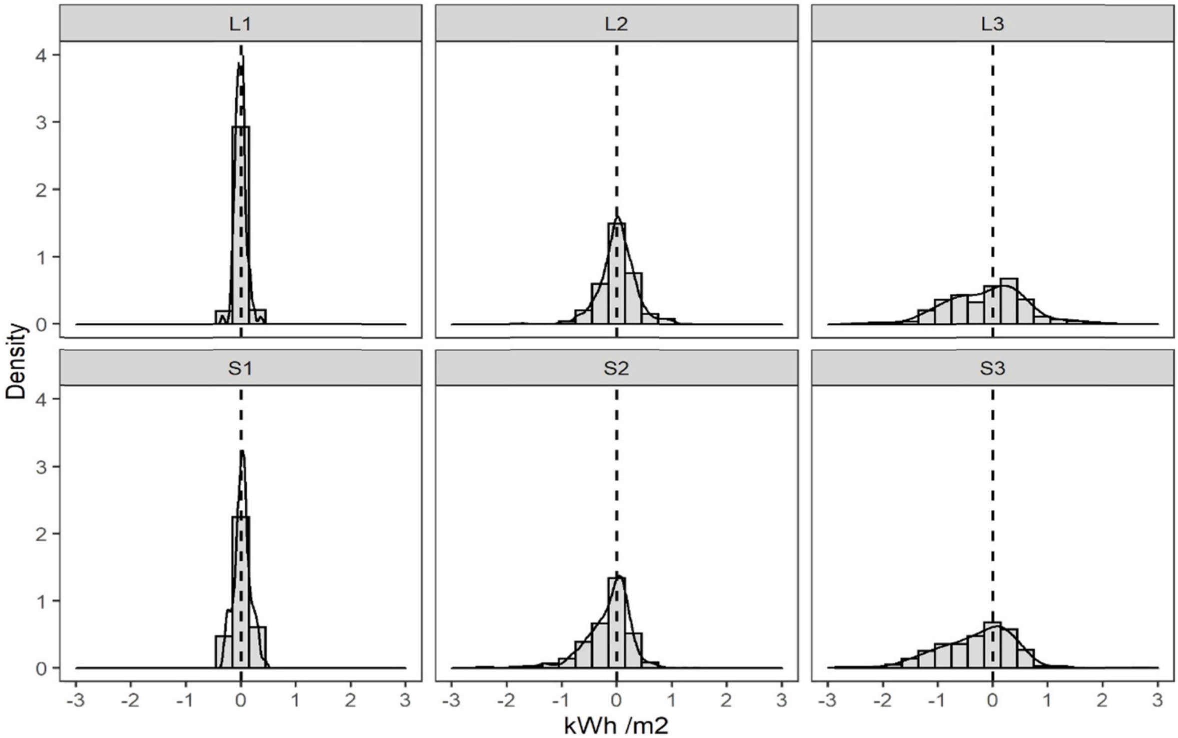

Fig. 11. Distribution of models' residuals during weeks of extreme low temperature. Residuals are the difference between observed and predicted Heat Demand by the model of each flat. Positive values indicate that the heat demand was larger than predicted; negative values that it was lower. The weeks classified as extreme low temperature include the episode of the storm 'the Beast from the East' in February–March 2018.

low temperatures showed that lowest consuming flats did not change their heat demand behaviour, whereas the highest consumers used less energy than expected, meaning that the demand reached a plateau. Trying to understand the behavioural response of fuel vulnerable households to changes in ambient temperature has important implications for policy makers and health in the social housing sector. By disaggregating data in heat demand modelling, we can evaluate different types of consumer behaviour and tailor policies.

Overall, this study highlights the heterogeneity in the heat demand in five social housing tower blocks and the need to move away from averages, looking at population distributions in terms of their behaviour instead. In the current context of rising fuel and energy prices, understanding the behaviour of low-income households is of utmost importance to reduce the risk of fuel poverty.

7. Limitations & future research

The analysis presented is limited by the data available. Firstly, the weekly resolution of the heating dataset does restrict the accuracy of the models and in particular the determination of the curve breakpoint for segmented models. Additionally, the lack of information on occupant behaviour and thermal comfort constraints the analysis. Future research should focus on collecting this information from a representative sample, including monitoring of indoor temperature and ventilation patters as well as occupants' sociodemographic characteristics.

CRediT authorship contribution statement

Victoria Aragon: Conceptualization, Data curation, Formal analysis, Methodology, Writing – original draft. **Patrick A.B. James:** Supervision. **Stephanie Gauthier:** Supervision.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

This work was supported by the H2020-EEB-2016 European project [grant number 723562 (THERMOSS)]. Additionally, this work was done in partnership with Southampton City Council.

References

[1] Department for Business Energy and Industrial Strategy, The climate change act 2008 (2050 target amendment) order 2019, statut. INSTRUMENTS 2019 No. 1056. https://www.legislation.gov.uk/uksi/2019/1056/made, 2019. (Accessed 6 October 2021).
[2] HM Government, The ten point plan for a green industrial revolution. https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/936567/10_POINT_PLAN_BOOKLET.pdf, 2020.
[3] J. Palmer, I. Cooper, United Kingdom housing energy fact file 2013. https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/345141/uk_housing_fact_file_2013.pdf, 2013.
[4] R. Burzynski, M. Crane, R. Yao, V.M. Becerra, Space heating and hot water demand analysis of dwellings connected to district heating scheme in UK, J. Cent. South Univ. 19 (2012) 1629–1638, https://doi.org/10.1007/s11771-012-1186-z.
[5] G.M. Huebner, M. McMichael, D. Shipworth, M. Shipworth, M. Durand-Daubin, A. Summerfield, Heating patterns in English homes: comparing results from a national survey against common model assumptions, Build. Environ. 70 (2013) 298–305, https://doi.org/10.1016/j.buildenv.2013.08.028.
[6] G.M. Huebner, Z. Chalabi, I. Hamilton, T. Oreszczyn, Determinants of winter indoor temperatures below the threshold for healthy living in England, Energy Build. 202 (2019), 109399, https://doi.org/10.1016/j.enbuild.2019.109399.
[7] C. Hanmer, M. Shipworth, D. Shipworth, E. Carter, How household thermal routines shape UK home heating demand patterns, Energy Effic 12 (2019) 5–17, https://doi.org/10.1007/s12053-018-9632-x.
[8] S. Karatasou, M. Laskari, M. Santamouris, Determinants of high electricity use and high energy consumption for space and water heating in European social housing: socio-demographic and building characteristics, Energy Build. 170 (2018) 107–114, https://doi.org/10.1016/j.enbuild.2018.04.019.

[9] T. Kane, S.K. Firth, K.J. Lomas, How are UK homes heated? A city-wide, socio-technical survey and implications for energy modelling, Energy Build. 86 (2015) 817–832, https://doi.org/10.1016/j.enbuild.2014.10.011.
[10] BEIS, Annual fuel poverty statistics 2019 (2017 data), 2019, https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/829006/Annual_Fuel_Poverty_Statistics_Report_2019_2017_data_.pdf, 2019, 1-70.
[11] HM Department for Communities and Local Government, English Housing Survey, Headline Report, 2017. https://www.gov.uk/government/collections/english-housing-survey.
[12] A. Druckman, T. Jackson, Household energy consumption in the UK: a highly geographically and socio-economically disaggregated model, Energy Pol. 36 (2008) 3177–3192, https://doi.org/10.1016/j.enpol.2008.03.021.
[13] D. Teli, T. Dimitriou, P. James, A. Bahaj, L. Ellison, A. Waggott, Fuel poverty-induced 'prebound effect in achieving the anticipated carbon savings from social housing retrofit, Build. Serv. Eng. Technol. (2015), 0143624415621028, https://doi.org/10.1177/0143624415621028.
[14] V. Cheng, K. Steemers, Modelling domestic energy consumption at district scale: a tool to support national and local energy policies, Environ. Model. Software 26 (2011) 1186–1198, https://doi.org/10.1016/j.envsoft.2011.04.005.
[15] G.M. Huebner, M. McMichael, D. Shipworth, M. Shipworth, M. Durand-Daubin, A. Summerfield, The reality of English living rooms - a comparison of internal temperatures against common model assumptions, Energy Build. 66 (2013) 688–696, https://doi.org/10.1016/j.enbuild.2013.07.025.
[16] V. Aragon, J.D. Quintero, S. Gauthier, P.A. James, A. Bahaj, Unpacking mid-season heating demand IN social housing, in: 2018 Build. Perform. Anal. Conf. SimBuild Co-organized by ASHRAE IBPSA-USA Chicago, Sept. 26-28, 2018, 2018. https://www.ashrae.com/File Library/Conferences/Specialty Conferences/2018 Building Performance Analysis Conference and SimBuild/Papers/C104.pdf. (Accessed 23 November 2020).
[17] G.M. Huebner, M. McMichael, D. Shipworth, M. Shipworth, M. Durand-Daubin, A. J. Summerfield, The shape of warmth: temperature profiles in living rooms, Build. Res. Inf. 43 (2015) 185–196, https://doi.org/10.1080/09613218.2014.922339.
[18] M. Shipworth, S.K. Firth, M.I. Gentry, A.J. Wright, D.T. Shipworth, K.J. Lomas, Central Heating Thermostat Settings and Timing: Building Demographics, 2010, https://doi.org/10.1080/09613210903263007.
[19] R. V Jones, A. Fuertes, C. Boomsma, S. Pahl, Space heating preferences in UK social housing: a socio-technical household survey combined with building audits, Energy Build. 127 (2016) 382–398, https://doi.org/10.1016/j.enbuild.2016.06.006.
[20] A. Bruce-Konuah, R. V Jones, A. Fuertes, P. de Wilde, Central heating settings and heating energy demand in low energy social housing in the United Kingdom, Energy Proc. 158 (2019) 3658–3663, https://doi.org/10.1016/j.egypro.2019.01.895.
[21] J. Hulme, A. Beaumont, C. Summers, Energy Follow-Up Survey 2011 Report 4 : Main Heating Systems, 2013, pp. 1–77. https://www.gov.uk/government/uploads/system/uploads/attachment_data/file/274772/4_Main_heating_systems.pdf.
[22] M. Kavgic, A. Mavrogianni, D. Mumovic, A. Summerfield, Z. Stevanovic, M. Djurovic-Petrovic, A review of bottom-up building stock models for energy consumption in the residential sector, Build. Environ. 45 (2010) 1683–1697, https://doi.org/10.1016/J.BUILDENV.2010.01.021.
[23] B. Anderson, P.F. Chapman, N.G. Cutland, C.M. Dickson, S.M. Doran, G. Henderson, J. Henderson, L. Kosmina, L.D. Shorrock, BREDEM-12 Model Description 2001 Update, 2008.
[24] L.G. Swan, V.I. Ugursal, Modeling of end-use energy consumption in the residential sector: a review of modeling techniques, Renew. Sustain. Energy Rev. 13 (2009) 1819–1835, https://doi.org/10.1016/j.rser.2008.09.033.
[25] H.X. Zhao, F. Magoulès, A review on the prediction of building energy consumption, Renew. Sustain. Energy Rev. 16 (2012) 3586–3592, https://doi.org/10.1016/J.RSER.2012.02.049.
[26] C. Deb, A. Schlueter, Review of data-driven energy modelling techniques for building retrofit, Renew. Sustain. Energy Rev. 144 (2021), 110990, https://doi.org/10.1016/J.RSER.2021.110990.
[27] S. Fathi, R. Srinivasan, A. Fenner, S. Fathi, Machine learning applications in urban building energy performance forecasting: a systematic review, Renew. Sustain. Energy Rev. 133 (2020), 110287, https://doi.org/10.1016/J.RSER.2020.110287.
[28] A. Foucquier, S. Robert, F. Suard, L. Stéphan, A. Jay, State of the art in building modelling and energy performances prediction: a review, Renew. Sustain. Energy Rev. 23 (2013) 272–288, https://doi.org/10.1016/J.RSER.2013.03.004.
[29] M. Labiadh, Methodology for Construction of Adaptive Models for the Simulation of Energy Consumption in Buildings. Modeling and Simulation, Université de Lyon, 2021. English. ffNNT : 2021LYSE1158f, n.d.
[30] ASHRAE, ASHRAE Guideline 1 4-2014, Measurement of energy, demand, and water savings, 2014. www.ashrae.org%0Awww.ashrae.org/technology.
[31] Y. Zhang, Z. O'Neill, B. Dong, G. Augenbroe, Comparisons of inverse modeling approaches for predicting building energy performance, Build. Environ. 86 (2015) 177–190, https://doi.org/10.1016/j.buildenv.2014.12.023.
[32] CIBSE, Degree-days: Theory and Application (TM 41), The Chartered Institution of Building Services Engineers, 2006.
[33] C. Ghiaus, Experimental estimation of building energy performance by robust regression, Energy Build. 38 (2006) 582–587, https://doi.org/10.1016/J.ENBUILD.2005.08.014.
[34] L. Belussi, L. Danza, Method for the prediction of malfunctions of buildings through real energy consumption analysis: holistic and multidisciplinary approach of Energy Signature, Energy Build. 55 (2012) 715–720, https://doi.org/10.1016/J.ENBUILD.2012.09.003.
[35] P. Westermann, C. Deb, A. Schlueter, R. Evins, Unsupervised learning of energy signatures to identify the heating system and building type using smart meter data, Appl. Energy 264 (2020), 114715, https://doi.org/10.1016/J.APENERGY.2020.114715.
[36] J. Rose, J. Kragh, K.F. Nielsen, Passive house renovation of a block of flats - measured performance and energy signature analysis, Energy Build. 256 (2022), 111679, https://doi.org/10.1016/J.ENBUILD.2021.111679.
[37] M. Eriksson, J. Akander, B. Moshfegh, Development and validation of energy signature method - case study on a multi-family building in Sweden before and after deep renovation, Energy Build. 210 (2020), 109756, https://doi.org/10.1016/J.ENBUILD.2020.109756.
[38] Y. Ding, D. Ivanko, G. Cao, H. Brattebø, N. Nord, Analysis of electricity use and economic impacts for buildings with electric heating under lockdown conditions: examples for educational buildings and residential buildings in Norway, Sustain. Cities Soc. 74 (2021), 103253, https://doi.org/10.1016/J.SCS.2021.103253.
[39] Met Office, Southern England: climate. https://www.metoffice.gov.uk/binaries/content/assets/metofficegovuk/pdf/weather/learn-about/uk-past-events/regional-climates/southern-england_-climate—met-office.pdf, 2016.
[40] Ministry of Housing Communities & Local Government, English housing Survey, Energy efficiency, 2018-19. https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/898344/Energy_Report.pdf, 2015.
[41] European Comission, Building and district thermal retrofit and management solutions. https://cordis.europa.eu/project/id/723562, 2020.
[42] K. Greening, A. Hodgson, Atmospheric analysis of the cold late February and early March 2018 over the UK, Weather 74 (2019) 79–85, https://doi.org/10.1002/wea.3643.
[43] ISO, ISO 8601-1:2019, Date and Time — Representations for Information Interchange — Part 5: Date and Time Representations, 2019.
[44] J.D. Chambers, T. Oreszczyn, Deconstruct: a scalable method of as-built heat power loss coefficient inference for UK dwellings using smart meter data, Energy Build. 183 (2019) 443–453, https://doi.org/10.1016/j.enbuild.2018.11.016.
[45] Met Office, International way (n.d.), https://wow.metoffice.gov.uk/observations/details?site_id=89af247c-29ed-e611-93ff-0003ff599b64.
[46] V.M.R. Muggeo, Regression models with break-points/change-points estimation. R package version 1.3-0. https://cran.r-project.org/web/packages/segmented/segmented.pdf, 2020.
[47] V. Muggeo, Segmented: an R package to fit regression models with broken-line relationships, R. News 8 (2008) 20–25.
[48] Q. Meng, M. Mourshed, Degree-day based non-domestic building energy analytics and modelling should use building and type specific base temperatures, Energy Build. 155 (2017) 260–268, https://doi.org/10.1016/j.enbuild.2017.09.034.
[49] ANSI/ASHRAE, ASHRAE guideline 14-2002 measurement of energy and demand savings, Ashrae 8400 (2002) 170. http://www.eeperformance.org/uploads/8/6/5/0/8650231/ashrae_guideline_14-2002_measurement_of_energy_and_demand_saving.pdf.
[50] University of Exeter, Southampton Test Reference Year, 2016, Version 1.
[51] K.J. Lomas, T. Kane, Summertime temperatures and thermal comfort in UK homes, Build. Res. Inf. 41 (2013) 259–280, https://doi.org/10.1080/09613218.2013.757886.
[52] S. Pelsmakers, The Environmental Design Pocketbook, RIBA Publishing, London, 2012.
[53] Energy Savings Trust, Measurement of Domestic Hot Water Consumption in Dwellings, Energy Savings Trust, 2008, pp. 1–62. https://www.gov.uk/government/uploads/system/uploads/attachment_data/file/48188/3147-measure-domestic-hot-water-consump.pdf.