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Estimating the impact of climate change and local operational procedures on the energy use in several supermarkets throughout Great Britain

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ABSTRACT

Possible changes in gas and electricity consumption in supermarkets throughout Great Britain have been investigated for the 2030s in order to assist decision makers with choices relating to energy use. In addition to this, two operational procedures, which vary between supermarkets, were investigated to see if a link between them and differences in energy consumption could be established. To achieve these aims, seven similar supermarkets were identified and their data analysed to derive their energy signatures through simple and change point regression analysis. These models were then combined with data from climate change prediction project UKCP09 for different probabilities (10%, 50% and 90%) of temperature increase in order to calculate changes in future energy use. In addition it was investigated if a linear regression model between the selected operational procedures and electricity use could be established.

The results showed that, compared with the base period 1961–1990, the mean values of the annual average temperature for these seven supermarkets was predicted to rise by 2.0 °C or 20% for the central estimate. This led to an estimate of an increase in average electricity consumption of 2% and an average drop in the gas usage of 10%. The result also showed that differences in operational practices seem to have little impact on the in-store energy use. Differences in gas use models between stores can be more credibly explained by the building volume.

1. Introduction

The main purpose of a supermarket is the sale of goods and services from suppliers to end users for their personal use [1]. While engaging in this activity a supermarket interacts with other organisations, the natural environment and the community it is located in. One example of this interaction is the use of energy supplied by utility companies; the UK sector that supermarkets belong to accounting for approximately 3% of total electricity use [2]. Through this energy usage and other emissions, supermarkets have an impact on the environment, e.g., the emission of greenhouse gases (GHG). Tassou et al. [2] reported that UK supermarkets and similar organisations are responsible for 1% of the total UK GHG emissions. The bilateral interaction with the community not only includes employing people, but also their staff influencing how the supermarket is operated, thus having an impact on its energy consumption.

In addition to the atmospheric interaction described in the previous paragraph, there is also a possible feedback loop through the changing climate affecting supermarkets. Therefore this paper investigates how climate change may alter the energy use in this type of building, especially as supermarkets are considered buildings with a high energy use intensity (EUI) [2]. As this research covers a number of supermarkets the possible effect of differences in operational procedures is also considered.

The literature review section of this paper establishes that, although the effect of climate change on energy use in different building types has been investigated for different locations in the UK and around the world, no such investigation has been performed for supermarkets located in the climatic regions in Great Britain. Therefore this paper remedies this situation by using the seven research steps described in Section 3. These steps cover the identification of seven similar grocery supermarkets throughout Great Britain and follow on with a description of how the energy consumption and temperature data were prepared to arrive at statistical models for future gas and electricity use prediction. This section also comments on the examined operational procedures.

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The next section showing the results of the model development and application explains that for four out of the seven identified supermarkets electricity consumption could be model as change point models, whereas for gas data only linear regression models were required. These models were then used together with data from the climate change predation project UKCP09 to estimate future gas and electricity use. Section 5 shows that the spread of predictions for various locations in Great Britain was comparable to that of other types of building. The final section summarises the overall conclusions for the two research questions regarding dependency of energy use on climate change and local operational procedures.

2. Literature review

Probably one of the earliest works which described an investigation into the effects of climate change on energy use in buildings is the report to the US Congress by Loveland and Brown in 1989 [3] in which they detailed their research into five building types located in six US cities. They used computer programme based one hourly transient thermal network simulations and a climate change scenario for which the atmospheric CO_2 had doubled. The researchers found that, regardless of whether the building was internal load dominated or skin load dominated, the cooling demands would rise greatly. Although the authors reported a drop in heating loads, they concluded that this would not compensate for the increase in cooling, so an overall increase in energy use could be expected. That this interest has been sustained can be seen by a paper by Wang and Chen [4] from 2014 in which the authors essentially updated the research introduced in [3]. These researchers simulated nine types of building with EnergyPlus, a building simulation software package based on the heat balance approach [5], for fifteen cities located in all seven US climate zones. Their research, which used morphed weather data based on the atmospheric-ocean general circulation model HadCM3, showed that the magnitude of the impact would be more dependent on the building type than on location. Regarding spatial dependency the authors reported that for the warmer climate zones the energy use would increase, whereas for the colder zones the energy demand would drop. Another example of this continued interest is the review of a significant number of climate change impact studies by Li et al. [6]. Their paper reported that the degree day method and building simulation approach were the most popular study methods and that whether the reduction in heating demand would outweigh the increase in required cooling depended on the climate under consideration.

Although all of the works referred to above reported on a number of building types, none of them included supermarkets. This seems to be the general situation with climate change impact assessments on building energy use. However, Tassou et al. [2] reported that the UK sector that supermarkets belonged to accounted for approximately 3% of total electricity use and 1% of total GHG emissions. These statistics show that the question of how changing climate may alter the energy consumption in supermarkets deserves attention, especially because they can be classed as high energy intensity buildings due to their peculiar refrigeration systems and lighting requirements [2].

An exception to the situation described in the previous paragraph is the work by Braun et al. [7] in which the researchers investigated the impact of the changing climate on the gas and electricity requirements of a single UK supermarket by means of multiple regression models. The expected energy consumption for the 2040s was based on the climate change prediction UKCP09 [8] and reported a significantly larger drop in heating demand than increase in cooling load. However, work on an office building involving five cities throughout Great Britain [9] and residential dwellings in four cities in the UK [10] suggests that the change in energy use may well be location dependent and therefore studying only one supermarket may have been insufficient to draw conclusions for the whole of the UK.

To remedy the deficiency shown above this study primarily aims at exploring the change in supermarket energy use owing to climate change at various locations in the UK. As it has been shown that occupant behaviour should be included in building energy models [11], this work also investigates if a statistically significant relationship between two operational procedures, which may vary between supermarkets, and energy use can be established. To do this, it is more advantageous to analyse actual buildings rather than use software building models as the human factor is implicitly included. To be relevant to decision makers in supermarkets, the time horizon is relatively short (the 2030s).

3. Study method

Potential modelling methods which may be employed to achieve the aims of this research are highlighted in, e.g., [6] and can be divided into data-driven and deterministic tools [12,13]. The most popular approaches according to [6], the degree day method and using building simulation software, were deemed unsuitable for this research. The main reason for rejecting building simulation software packages based on the heat balance equation was that they are unsuitable for large volumes [14]. In addition, it was judged that the calibration effort was considerable [15] without using the software package's main strength namely evaluating of different design options (for instance, Leach et al. [16] evaluated 78,000 software models with different design options in their case study). CFD based software tools are capable of solving the equations for fluid flow thus providing estimates of the spatial distribution of airflow, pressure, temperature etc. more accurately. This being the case, they have been used for building simulations to compare, for example, the thermal comfort provided by diverse HVAC. However, CFD tools by themselves are unable to calculate the energy consumption of buildings as they are unable to calculate the heat transfer through opaque structures [17]. The other popular deterministic tool mentioned in [6], the degree day method, was also considered inappropriate as these make use of what is called the balance point temperature, which is the outside temperature at which the inside heat gain and the thermal losses cancel each other out for a specific set-point temperature and therefore for this temperature no heating is required [12]. However, the supermarkets investigated here require heating all year round because of the cold aisle phenomenon [18] and therefore no balance point temperature could be established.

In contrast with deterministic tools, data driven methods employ input and output data to generate an energy signature model relating these two [19,20]. For a pilot study multiple linear regression analysis was used [7], but the correlation between the predictors was a cause for concern [21]. During this case study, it was noted that the coefficient of determination for a simple linear regression model for the gas data was reasonably high. However, the electricity data showed non-linear behaviour with a section relatively independent of temperature. This type of electricity usage pattern had been successfully modelled by change point regression models [22,23]. In order to develop time efficient yet useful models it was decided to utilise a simple regression model where possible and a change point regression model where necessary.

As shown in Fig. 1 the study method ultimately chosen was divided into seven steps of which the first two were concerned with the selection of comparable supermarkets. When this search began the sponsoring company reported a chain of 766 stores in the UK (of which 243 were franchised) [24] and divided them into different categories. The store format which had the highest

Table 1
Supermarket data.

Location	Glasgow	Gateshead	Washington	Hull	Leicester	Newbury	Exeter
Latitude	55.905	54.923	54.900	53.748	52.684	51.385	50.902
Longitude	−4.378	−1.620	−1.532	−0.425	−1.088	−1.318	−3.485
Weekly trading hours (h)	81	80	78	75	80.5	77	78
Total area (m^2)	1550	1730	1320	1820	1640	1650	1440
Sales area (m^2)	1030	1210	743	1250	1000	1190	929
Volume (m^3)	12,000	7800	7090	13,700	9210	8270	10,400
Volume/total area (m)	7.74	4.51	5.37	7.55	5.61	5.01	7.22
Lobby (yes/no)	Yes	No	Yes	Yes	Yes	No	Yes
Installed lighting (kW)	17.5	21.4	15.1	19.1	18.6	21.8	16.9
Installed heating (kW)	277	232	227	191.5	215	256	227
Installed A/C cooling (kW)	50.1	65.7	12.9	59.5	23.1	83.4	29.5
Total length of ref. shelves (m)	97	89	71.4	94.4	90.1	88.2	102
Refrigeration plants (kW)	80 + 60	100	100	80 + 60	100	100	100

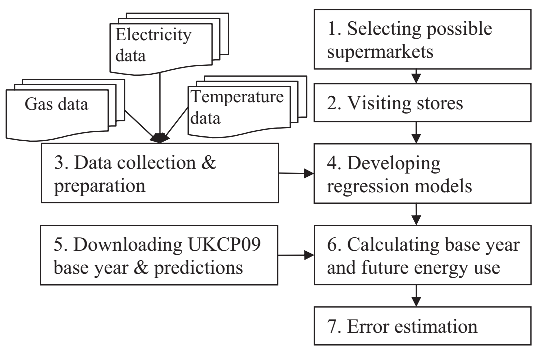

Fig. 1. Research flow for the whole supermarket investigation.

number of supermarkets contained an inhomogeneous building stock and, as the building type can have a significant impact on energy demand [25], it was considered unsuitable for this study. In addition to this, the same report indicated that, comparatively speaking, more supermarkets were added to a different store format. This type of store can be described as grocery supermarkets with a relatively large amount of refrigerated display cases. The sponsoring company divided those 176 grocery supermarkets into small and large stores. The category containing the larger sized stores had about 100 entries with sales areas ranging from approximately 535 m^2 to 1925 m^2 and averaging around 950 m^2. These approximately 100 stores were investigated as to building location and building type as well as to the presence of an in-store café and bakery. For this, the company's on-line store guide was used as it not only gave the address, but also indicated if a particular store had the required café and bakery. When investigating the supermarket location the Street View [26] and satellite option on Google Maps [27] were used and it was found that 45 of these large grocery supermarkets were located in retail parks of which 18 had both a café and bakery. As a final step it was ensured that all supermarkets had an R404/R744 type of refrigeration system. This led to the selection of seven supermarkets which had all these features in common.

As Table 1, which lists the supermarket data along a north–south axis, indicates, the supermarket locations were well spaced throughout Great Britain, two towards the west, two inland and three to the east. It was hoped to also include Wales, but no suitable supermarket could be located. Although the UK climate can be classified as being of only one type according to Köppen there are different climate regions caused by air masses with different origins [28]. One way to separate the climate regions is to divide Great Britain into four roughly equal quarters [29]. Following this type of division the supermarket in Glasgow is located in the mild-winter-cool–summer region, whereas the Gateshead and Washington supermarkets are situated in the cold-winter-cold summer climate. The three supermarkets in Hull, Leicester and Newbury are all in a region characterised by cold winters and warm summer, leaving the Exeter supermarket in the mild-winter–warm-summer climate.

Table 1 also shows that the sales areas of the selected stores tend to be larger than the average. However, this was not considered significant as their sales areas were still considerably smaller than that of the largest store in this category.

3.1. Site visits

In order to verify the degree to which the selected supermarkets were actually comparable, site visits were conducted. Prior to these visits, a site visit protocol detailing the number of major energy consuming devices was devised. This was based on HVAC layout plans, lighting layout plans (if available) and other architectural drawings.

Six of these seven supermarkets were visited between early May 2014 and early July 2014, the store in Hull having been visited before for a pilot study (see [7]). During the visits the following tasks were performed:

- The actual numbers of installed energy consumers were compared with the number on the site visit protocol. This included documenting the installed refrigerated display cases.
- The building timer settings were documented. (These timers were centrally controlled.)
- The times the night covers for the refrigerated display cases and freezers are removed and put back were recorded.
- The times the main baking started and finished were noted down.
- If possible informal discussions were held with the store manager, the operations manager and the Plan A champion (see [30] for a description of the role of the Plan A champion).

The operational timings which may have an impact on energy consumption are listed in Table 2 and are based on the estimates given by store personnel. This means that these values may be only approximate. Nonetheless it can be seen that some stores (i.e. Hull, Leicester and Newbury) put the night covers on the refrigerated display cases immediately after the store closes for the day whereas others allow for stocking during after store hours which may be in addition to the preopening stocking time. One example of this is the Gateshead store which also has different opening hours; thus the notation "Shut + 45 min" was used to indicate that after the supermarket was closed to the public, stocking continued for approximately 45 min. Based on these estimates an average of approximately 14 h (standard deviation: approximately 0.5 h) for the length of time that the display cases where without night cover was calculated. The table also records the times for the main bake of bread and cakes in the morning. This may be significant because

Table 2
Operational timings.

Location	Glasgow	Gateshead	Washington	Hull	Leicester	Newbury	Exeter
Night cover							
Off	7:00	6:00	6:30–7:00	6:30	6–7:00	6:00	6–7:00
On	20:50	Shut + 45 min	20:30–20:45	20:00	20:00	20:00	20:45
Total (h:min)	13:50	≈15:00	≈13:50	13:30	≈13:30	14:00	≈14:15
Main bake							
On	6:00	6:00	6:30	6:00	6:00	6:00	6:00
Off	11:00	10:00	9:30	10:00	10:00	9:30–10	10:00
Total (h:min)	5:00	4:00	3:00	4:00	4:00	3:45	4:00

the ovens, which are in constant operation during this time, have a combined power consumption of 15 kW. Almost all stores start baking as early as possible and continue well after the supermarket has opened. The majority of stores suggested four hours for their main bake, with Glasgow and Washington being the outliers. As the baking time varies so little, performing a regression analysis was not considered to be meaningful.

After the visits the site visit protocols were updated, the main energy consumers were aggregated and recorded in Table 1. The volume-area ratio in this table shows whether or not a mezzanine floor is installed. For instance, this ratio shows that the supermarkets in Glasgow, Hull and Exeter have only one level whereas the other stores have a mezzanine floor. This table also records the nominal size of the refrigeration plants. If two figures are given, then the supermarket has two plants, otherwise only one has been installed.

Although these seven supermarkets have a number of features in common, they are not identical. These differences include the installed lighting intensity, which ranges from approximately 10 W/m^2 to just over 13 W/m^2. The spread of installed heating capacity density (between 105 W/m^2 and 178 W/m^2) may be partly due to the absence of precise data for the under-case heating modules for the refrigerated display cases and partly due to different cold aisle heating system designs. Table 1 also indicates that the installed comfort cooling density, ranging between 9.8 W/m^2 and 50.5 W/m^2, is considerably smaller than the installed heating density. The reason for this may be the open refrigerated display cases, which also remove room heat so that, normally, no additional cooling is required for the sales floor, but heating is. Despite these variations the supermarkets were considered sufficiently similar and, therefore, they were used for the investigation here to achieve the research aims.

3.2. Collection and preparation of data

The data collection phase is shown as step three in Fig. 1 and comprised the acquisition of data for electricity and gas consumption as well as for site temperature. To this end the weekly consumption was downloaded from the supermarkets' energy logger for the time interval from the week commencing (w/c) 1 July 13 to w/c 8 September 14. The period from w/c 1 July 13 to w/c 23 July 14 was then used for the actual data analysis and the rest for error estimation. During the download it was discovered that the gas data for the Washington store could not be retrieved and therefore only the electricity data for that location were analysed. When comparing the coefficients of variation (CVs) of all weekly consumption data it was found that those for the Hull store were significantly higher. An investigation showed that the boiler was out of order for 3 months during the period of interest. Therefore the data for 2012, which was utilised for the case study in [7], was substituted for the analysis here, and data from the w/c 30 June 14 to w/c 8 September 14 was used for error estimation. The electricity consumption for 25 and 26 December 2013 was considered the base load as all the stores were closed for these two days due to the Christmas holiday (for values see Table 3).

The site temperature sensors (tolerance of sensor: 0.5%, accuracy of sensor: ±0.5 °C [31]) were remotely accessed in order to download data in 15-min intervals for the same period as mentioned above. However, this was not possible for the supermarkets in Newbury and Exeter and hourly data from a nearby MET Office weather station were substituted. The temperature data for each supermarket were then averaged for each week.

To prepare data for analysis, potential outliers and inconsistencies were identified with box plots, energy use vs time line graphs and scatter plots for energy consumption over temperature. This led to the exclusion of weekly data points owing to:

- The Christmas period (all stores): here the supermarket restocked during the nights prior to Christmas (higher than normal energy use) and then closed for Christmas (lower than normal consumption of energy).
- The addition of refrigerated display cases (Glasgow).
- A faulty repair resulting in higher energy consumption (Gateshead).
- The building timers for heating being incorrectly set (Newbury).

The overall result of the data preparation phase was a reduction in data points of between 3.85% and 28.9%. Hence, even in the extreme case, more than 70% of the data points could still be included in the analysis. Therefore it could be concluded that, for all supermarkets, useful data sets existed (the only exception being the missing gas data for the Washington store).

3.3. Regression analysis

Regression analysis, employed for analysing the data prepared as described in the previous section, is a statistical tool exploring the possibility of a relationship between one response variable and one or more predictor variable(s). As mentioned above, the data analysis phase used here employed the simple linear regression and change point regression model as efficient data analysis methods, both of which utilised the ordinary least square method (discussed in, e.g., [32]). If a simple regression equation was considered to be inadequate because of an apparent non-linear data set, a change point model was considered. To decide when to apply a change point regression model, a second order polynomial regression model was evaluated and, if the coefficient of determination improved over a simple regression model by more than 10%, a change point regression model was used. This decision also took the shape of the scatter plot and the likely behaviour outside the data range into consideration. Fig. 2 shows a four-parameter regression model where the dependent variable, $\hat{y}$, is the energy consumption and the independent variable is the outside temperature ϑ. The two straight line equations $\hat{y}^* = b_0^* + b_1^*\vartheta$ and $\hat{y}' = b_0' + b_1'\vartheta$ join at the change point ϑ_{cp}.

Table 3
Energy consumption data of supermarkets.

Location	Glasgow	Gateshead	Washington	Hull	Leicester	Newbury	Exeter
Electricity							
Annual (kW h)	646,800	594,733	541, 940	581,200	555,660	592,956	552,189
Base load (kW)	35.0	31.6	28.6	31.6	33.5	42.7	34.7
EUI_{pa} (W/m^2)	5150	4300	5260	4260	4210	4670	4920
Av EUI_{wkly} (W/m^2)	99.0	82.7	101	81.9	81.0	89.8	94.6
CV (%)	6.26	6.62	7.15	6.26	6.08	5.50	5.05
Gas							
Annual (kW h)	394,000	328,000	N/A	408,000	254,000	242,000	210,000
EUI_{pa} (W/m^2)	3140	2370		2990	2000	1910	1870
Av EUI_{wkly} (W/m^2)	60.4	45.6		57.5	38.5	36.7	36.0
CV (%)	31.3	26.8		35.1	38.1	35.4	42.0

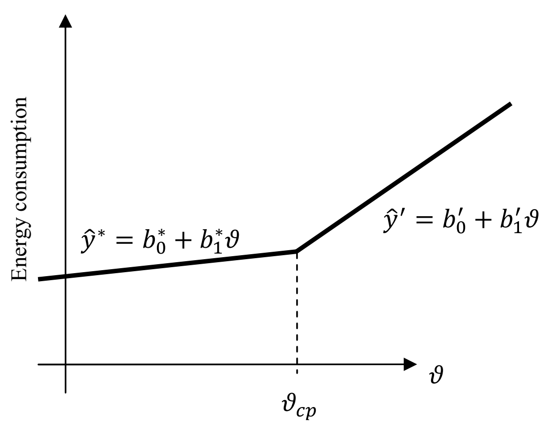

Fig. 2. Four parameter change point regression models.

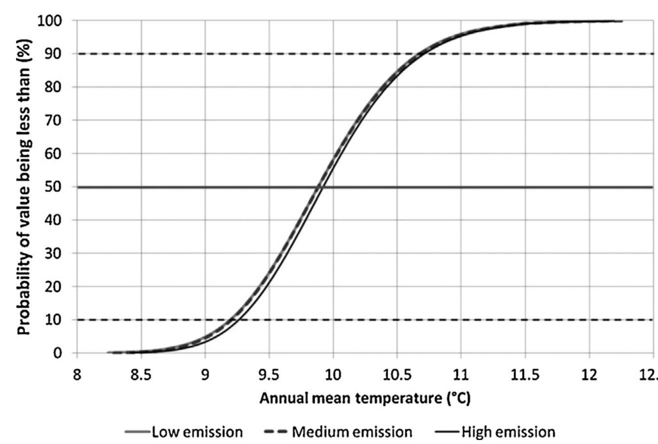

Fig. 3. Cumulative distribution function of the mean annual temperature for Glasgow (cell ID: 764) for the 2030s.

To calculate the coefficients the Matlab function ‘lsqcurvefit’ was used implementing Eq. (1). The initial estimates for b_0^*, b_1^*, b_1' and ϑ_{cp} required by Matlab were derived using Excel.

$$\hat{y} = \begin{cases} b_0^* + b_1^*\vartheta, & \vartheta < \vartheta_{cp} \\ b_0^* + (b_1^* - b_1')\vartheta_{cp} + b_1'\vartheta, & \vartheta_{cp} \le \vartheta \end{cases} \quad (1)$$

In order to indicate to which degree the model explains variation within a data set the coefficient of determination, r^2, is frequently used [32,33]. However, this coefficient does not support any conclusion about a statistically significant relationship between the dependent and independent variable [33]. This can be established by, for instance, the *F*-test, which was also used here to establish the overall statistical significance of either type of model. For regression models with one predictor this statistic can be calculated with the following equation [33].

$$F = \frac{\sum(\hat{y}_i - \bar{y}_i)^2}{\sum(y_i - \hat{y}_i)^2/(n-2)} \quad (2)$$

3.4. Climate change prediction UKCP09

The fifth step of the research method employed here (see Fig. 1) was concerned with data from the climate change predictions for the UK, UKCP09. As each stage of generating useable climate predictions (namely future emissions predictions, global climate modelling, downscaling and preparing for computer use [34–36]) introduces uncertainties and inaccuracies, UKCP09 does not state a single value, but uses a different method for their predictions. UKCP09 selected three anthropogenic greenhouse gas emission scenarios out of the over 40 possible scenarios suggested in [37] and refers to theses as high, medium and low emissions in their literature [38,39]. The uncertainties introduced during the stages of modelling the global climate system and formulating a regional climate model for downscaling were combined into a probabilistic forecast [36,38]. When using UKCP09 data it is worth bearing in mind that the total amount of model uncertainties is likely to be underestimated [40].

One way UKCP09 expresses predictions is by a cumulative distribution function which shows what the likelihood is that a climate variable stays below a certain value [38]. Fig. 3 displays the cumulative distribution function of the annual mean temperature for the high, medium and low emission scenarios for the time period from 2020 to 2049 for the UKCP09 grid cell ID: 1240 (Glasgow). In this figure the lowest, dashed line refers to the 10% likelihood that the value will be below this line. Similarly ‘50%’ denotes the central estimate and ‘90%’ indicates a 90% likelihood of the temperature not exceeding this value. The same figure also shows that the results for emission scenarios differ only slightly compared with the differences between the 10% and 90% values.

For this research monthly temperature data for the base period from 1961 to 1990 (the ‘1970s’) and for the ‘2030s’ running from 2020 to 2049 were downloaded from the UKCP09 website [41] for the relevant grid cells for each supermarket and the values for the 10%, 50% and 90% probabilities for the medium emission scenario were extracted. The reason why only the medium scenario values were used can be illustrated by Fig. 3, which shows that the differences between the emission scenarios were small, especially when compared with the three probability values chosen. The recommendation by Baltazar and Claridge [42] to use simple linear interpolation for small data sets, rather than more advanced techniques, was followed to generate the weekly predictions.

3.5. Error estimation associated with the regression models

When constructing and using the regression models, three different sets of verification checks were employed. The first set of tests was concerned with checking the regression models against the underlying assumptions mentioned in [32]. In particular, the assumption of normal distribution of the residuals was verified, as this influences the validly of the *F*-test.

During the second, the individual prediction intervals for the estimated values, $\Delta\hat{y}_i$, were calculated [33] and then combined with Eq. (3) to compute the total propagated error $\Delta\hat{y}_{\text{tot}}$ [43]. This was then compared against the predicted change to see if detection seemed to be reasonable.

$$\Delta\hat{y}_{\text{tot}} = \sqrt{\sum_i \Delta\hat{y}_i^2} \quad (3)$$

For the last set of tests the mean bias error (MBE), root mean square error (RMSE) and its coefficient of variation (CV (RMSE)) were calculated based on data from w/c 30 June 14 to w/c 8 Sept 14. These statistics have been used for data-driven energy models and in deterministic models to indicate how well the model performs [15,44]. The MBE is a measure of the overall bias of the model and was calculated as shown in Eq. (4).

$$\text{MBE} = \frac{\sum_n (\hat{y}_i - y_i)}{n} \quad (4)$$

The RMSE, which was computed according to Eq. (5), calculates by how much the estimated values deviate from the measured values. The annual average consumption was preferred to the average of the period from w/c 30 June 14 to w/c 8 Sept 14 to calculate CV (RMSE), because this approach avoided seasonal bias. [15] lists a small number of acceptance criteria for the MBE (e.g., 5% for monthly data) and the CV (RMSE) (e.g., 15% for monthly data) when used in calibrating building simulation models.

$$\text{RMSE} = \sqrt{\frac{\sum_n (\hat{y}_i - y_i)^2}{n}} \quad (5)$$

4. Results of model development and application

This section makes frequent use of energy use intensity figures which are given in W/m^2. The annualised EUI, EUI_{pa}, was calculated by dividing the annual consumption by the total supermarket area and the weekly trading hours. Weekly trading hours were used as only inter-supermarket differences had to be eliminated in order to investigate the possible effect of the variation in operation procedures. The EUI_{wkly}, which is the average energy use intensity of a given week, was chosen because of the weekly operating cycles of the supermarkets, the average of which is listed as 'Av EUI_{wkly}' in Table 3.

The energy use data in Table 3 is listed from north (i.e. Glasgow) to south (i.e. Exeter). The average EUI_{wkly} for electricity has an average of 90 W/m^2 and exhibits a linear relationship with the total supermarket area ($r = -0.854$). The CVs have been calculated after the exclusion of data inconsistencies, such as outliers, to avoid a false impression of the magnitude of data spread and show relatively little variation amongst the supermarkets. Apart from the outlier at Newbury (the 2013 value for this supermarket was 24% higher than the one for 2012) the base consumption figures are also consistent with each other with low correlation to building area and volume.

The gas data in Table 3 has a distinct north-south divide with Glasgow, Gateshead and Hull making up the northern cluster and the other three supermarkets the southern cluster. This can also be seen by the strong linear relationship ($r = 0.877$) between a supermarket's latitude and its average EUI_{wkly}. The relationship between annual average temperature and average EUI_{wkly} is much weaker ($r = 0.612$). The CV, also excluding inconstancies, has a relationship with latitude ($r = -0.829$) that is similarly strong to that of the average EUI_{wkly}, and which may be related to the fact that daylight is also a function of latitude.

The scatter plots in Figs. 4 and 5 are for one supermarket with a change-point model and one with a purely linear regression model for electricity use. The data clouds for the supermarket in Glasgow in Fig. 4 are discussed first as they illustrate all the pertinent points for data preparation for all seven supermarkets. The panels in Fig. 4 divide these data clouds into included and removed data points. The excluded data in the left-hand panel are outliers in the true sense of the word. For instance, the excluded data points for the Christmas and New Year period include two points which have a lower than expected consumption (because of shorter opening hours) and one with a higher than average consumption (due to overnight stocking). Another example is the increase in electricity demand after the installation of new refrigerated display cabinets marked as 'New display case outliers'. When examining the included data, it can be noted that the non-linear relationship in the electricity data is well captured by a change point regression model, represented by the solid black line, resulting in a high coefficient of determination (for r^2 see Table 4).

The scatter plot displayed in the right hand panel in Fig. 4 shows that the excluded gas data are much closer to the expected value, indicated by the straight solid black line, than the electricity outliers. The included data points exhibit a relatively linear relationship and therefore a simple linear regression model portrays this behaviour well (for r^2 see Table 5). Interestingly, after the additional open refrigerated display cases were installed, the gas use was generally lower than the expected value. This seems counterintuitive as it is to be expected that more heat is removed from the sales area because of the additional shelves and therefore one would assume a higher heating demand and, in turn, an increase in gas use.

The left hand panel in Fig. 5 shows the electricity data cloud for the supermarket in Newbury. The positive trend of the included data is captured by the simple regression model, but because of the spread of the data cloud, the coefficient of determination is smaller than for the change point regression model for Glasgow in Fig. 4. An investigation into the cause of this spread proved to be inconclusive. The gas model for Newbury has a higher r^2 than the electricity model. The gas consumption data seems to taper off towards higher temperatures for this supermarket as all data points above 20 °C are above the regression line which may be due to the absence of a lobby which isolates the outside and inside temperatures from each other.

The headings 'r^2 (Linear)' and 'r^2 (Square)' in Tables 4 and 5 refer to the coefficients of determination for a linear regression model and for a quadratic polynomial regression model respectively. The row entitled 'Improvement: Square (%)' was included to make the decision process regarding which model was used clearer. These improvements are correlated with the volume with a correlation factor of 0.891 for electricity and −0.767 for gas. If a change-point model, rather than a simple regression model, was used b_0 is the intercept and b_1 the gradient before the change-point temperature ϑ_{cp} and b'_0 and b'_1 are the intercept and gradient respectively after this temperature. All *F*-tests for the selected models show that statistically significant regression models were selected.

The results relating to the electricity consumption given in Table 4 show that for four supermarkets a change-point regression model improved the predictive power by between 13.3% and 32.5%. For other stores r^2 (Linear) is relatively small, but could not be significantly improved by a change point model. Unidentified technical problems were suggested by the relevant energy manager as a

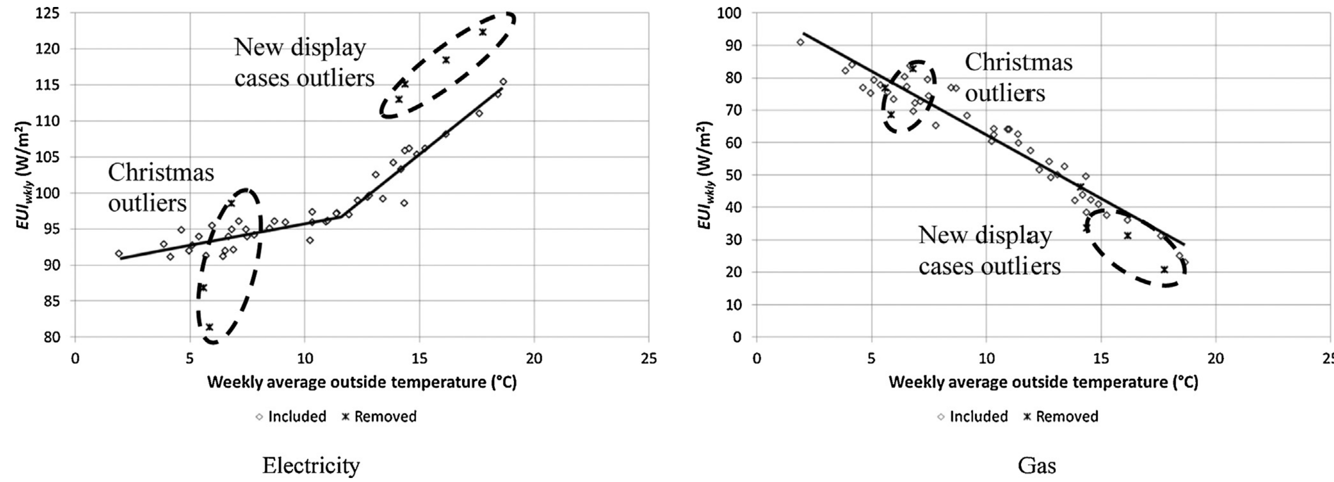

Fig. 4. Scatter plots of gas and electricity consumption vs outside temperature for the supermarket in Glasgow along with the model of this supermarket (black line).

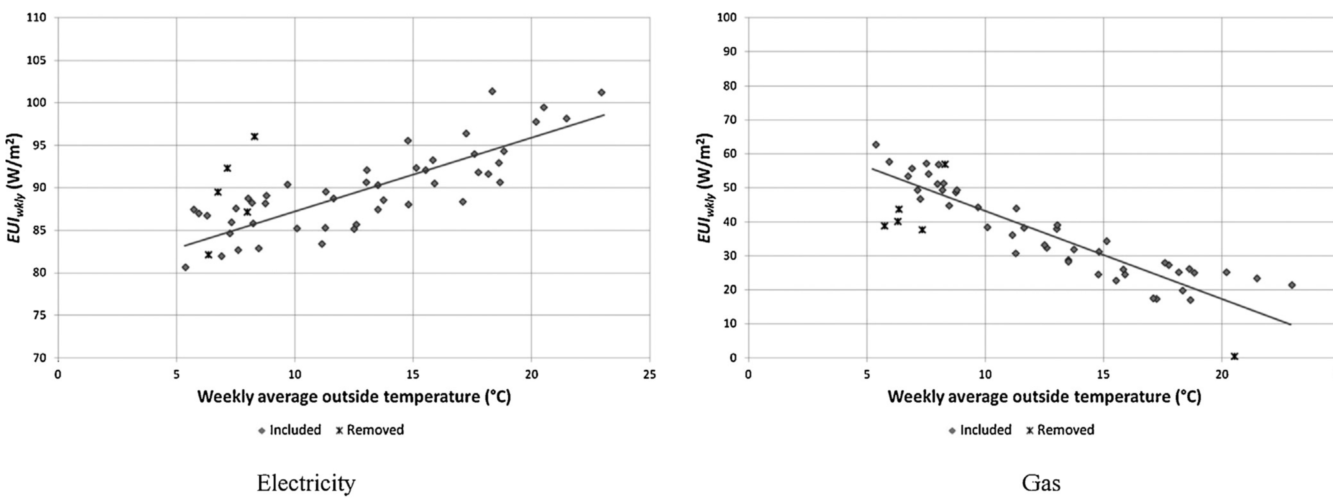

Fig. 5. Scatter plots of gas and electricity consumption vs outside temperature for the supermarket in Newbury along with the model of this supermarket (black line).

Table 4
Models of electricity consumption in supermarkets.

Location	Glasgow	Gateshead	Washington	Hull	Leicester	Newbury	Exeter
r^2 (Linear)	0.826	0.859	0.945	0.676	0.563	0.674	0.642
r^2 (Square)	0.934	0.956	0.954	0.878	0.607	0.705	0.743
Improvement: Square (%)	13.1	11.2	1.03	29.8	7.77	4.73	15.7
r^2 (Change point)	0.950	0.973		0.896			0.766
Improvement: change point (%)	15.0	13.3		32.5			19.3
b_0 (W/m^2)	90.0	73.9	82.3	78.0	71.4	78.9	88.0
b_1 (W/m^2/°C)	0.578	0.582	1.55	0.0875	0.739	0.840	0.452
ϑ_{cp} (°C)	11.6	16.0		15.0			14.5
b_0' (W/m^2)	67.5	39.2		39.2			58.6
b_1' (W/m^2/°C)	2.52	2.75		2.68			2.48
F-test	714	1250	803	407	60.75	92.9	154
MBE (W/m^2)	−11.8	−5.11	2.45	−1.90	−6.35	0.56	−6.01
RMSE (W/m^2)	12.0	5.29	6.60	2.43	7.38	2.04	6.82
CV (RMSE) (W/m^2) (%)	12.2	6.50	6.49	2.96	9.07	2.27	7.19

reason for the limited predictive power. The MBEs suggest that for the chosen period the models tend to underpredict electricity use and that the CV (RMSE) is below 10%, except for Glasgow where the larger spread is due to the installation of more refrigerated display cases.

The values of r^2 (Linear) for the gas consumption models listed in Table 5 have an average of 0.879 and a much smaller spread than for the linear electricity models. Therefore only linear models were used for gas data. The two supermarkets for which the second order regression would have offered the greatest improvement were both without a lobby. The MBEs indicate that for the chosen interval all models overpredict gas use. The CV (RMSE) for all locations is above 10%, and for the three southern supermarkets it is greater than 25% due to the low annual consumption.

Fig. 6 displays the results for the consumption models and thus visually represents the model parameters listed in Tables 4 and 5.

Table 5
Models of gas consumption in supermarkets.

Location	Glasgow	Gateshead	Washington	Hull	Leicester	Newbury	Exeter
r^2 (Linear)	0.933	0.833	N/A	0.843	0.930	0.846	0.886
r^2 (Square)	0.951	0.893		0.846	0.939	0.912	0.888
Improvement (%)	1.94	6.67		0.391	0.975	7.19	0.154
b_0(W/m^2)	103	70.1		110	76.0	69.4	77.7
b_1 (W/m^2/°C)	−4.11	−2.27		−4.15	−2.85	−2.56	−3.54
F-test	651	239		263	653	242	366
MBE (W/m^2)	9.02	5.53		6.15	9.13	9.16	8.80
RMSE (W/m^2)	9.28	6.91		6.81	11.17	10.72	9.27
CV (RMSE) (W/m^2) (%)	15.6	15.6		11.72	28.65	29.2	26.3

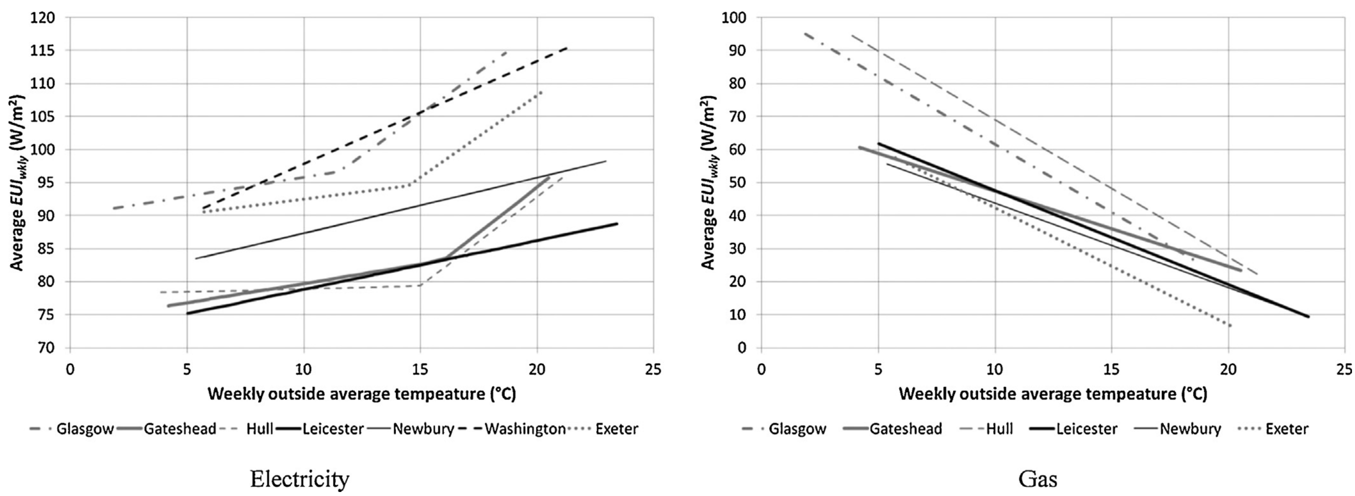

Fig. 6. Summary graphs of all models for electricity and gas usage.

In this figure the change point models are grey whereas the linear models are black. The reason for these differences in the graphs for electricity consumption (shown on the left-hand side) is likely to be the control algorithm of temperature sensitive electric equipment (if it were owing to the building fabric, a linear relationship would be expected). This equipment may be the air conditioning units, but it is more likely that it is the refrigeration system, because the air conditioning units are standard products which should behave in an identical manner and the analysis showed that three supermarkets can be adequately represented by linear models. Further investigation should confirm if this change point is related to the point where the minimum head pressure of the refrigeration system is insufficient. The right hand panel in Fig. 6 also shows two groups of models. The graphs for the supermarkets without a mezzanine floor at Glasgow, Hull and Exeter (shown as non-solid lines) are virtually parallel lines, whereas the other three (shown as solid lines) are not. The intercepts of all of these models have a strong correlation with the building volume ($r = 0.959$). The slope is also closely correlated to the building volume ($r = 0.968$), but the relationship with the volume-to-total-area ratio is even stronger ($r = 0.977$). Based on this Eqs. (6) and (7) can be suggested to compute the coefficients in the models for gas consumption, $\widehat{\mathrm{EUI}}_{\mathrm{wkly}} = b_0 + b_1 \vartheta_{\mathrm{outside}}$.

$$b_0 = 14.2\ \mathrm{W/m^2} + 0.00694\,\mathrm{W/m^5}\ \ \mathrm{Volume} \tag{6}$$

$$b_1 = 0.0100\,\mathrm{W/m^2\,°C} - 0.526\,\mathrm{W/m^3\,°C}\ \frac{\mathrm{Volume}}{\mathrm{Total\ area}} \tag{7}$$

4.1. Application of models

The models developed so far were used to estimate the changes in energy use and these values are shown in Table 6 and Fig. 7. The table also includes average weekly temperature data including projected changes relative to the base period showing that the current temperature rises from Glasgow to Leicester and then drops towards Exeter. Generally speaking, these average temperatures used for developing the models are at least as high as the central future estimate. For Hull and Leicester, these temperatures are even higher than the 90% future estimate.

The changes in electricity and gas consumption displayed in Fig. 7 are also given as changes relative to the base period of the relevant parameter for each respective location. A bar graph was chosen to emphasise that the estimates include values up to the maximum value, but are not necessarily equal to this maximum. For instance, the estimate for Glasgow labelled '90%' in the left-hand panel in this figure is 3.78%, which means that the likelihood that the estimated increase does not exceed 3.78% is 90% and, therefore, may be less than that. The error bars, shown as whiskers on the bars in these graphs, indicate the propagation error, which means that only uncertainties introduced through the modelling process were taken into account. These error bars show that, for the central estimates and the 90% estimates, changes in energy consumption should be detectable. However, for the 10% estimate the detection is more doubtful. The predicted changes in electricity demand, displayed in the left hand graph in Fig. 7, are smaller than for gas, which is plausible because of the larger temperature independent load (for instance lighting) so that an overall reduction in energy demand can be expected.

5. Discussion

The analysis of the seven selected UK supermarkets indicated that the geographical spread of the predicted changes in energy usage (see Table 3) was larger for electricity than for gas. These findings are moderately similar to results from work done on different types of dwelling in four locations in Great Britain [10]. This research suggests a drop in gas consumption for three of the four

Table 6
Changes in energy use and temperature as percentage of the respective base years.

Location	Glasgow	Gateshead	Washington	Hull	Leicester	Newbury	Exeter
Electricity							
Change 10% (%)	0.722	0.559	1.23	0.554	0.598	0.638	0.628
Change 50% (%)	2.11	1.40	2.92	1.68	1.61	1.72	2.00
Change 90% (%)	3.78	2.84	4.73	3.32	2.76	2.94	3.71
Gas							
Change 10% (%)	−3.37	−3.34	N/A	−4.45	−3.54	−3.71	−5.41
Change 50% (%)	−8.90	−7.92		−10.6	−9.55	−9.98	−14.2
Change 90% (%)	−15.0	−12.82		−17.7	−16.3	−17.1	−24.1
Av temperature							
Base (°C)	8.15	8.24	8.24	9.22	8.88	9.36	9.86
Current (°C)	10.3	11.1	12.2	12.5	13.1	12.4	11.8
Change 10% (%)	7.44	9.16	9.16	8.40	7.11	7.04	6.72
Change 50% (%)	19.7	21.7	21.7	20.1	19.2	18.9	17.7
Change 90% (%)	33.2	35.1	35.1	33.3	32.8	32.4	30.0

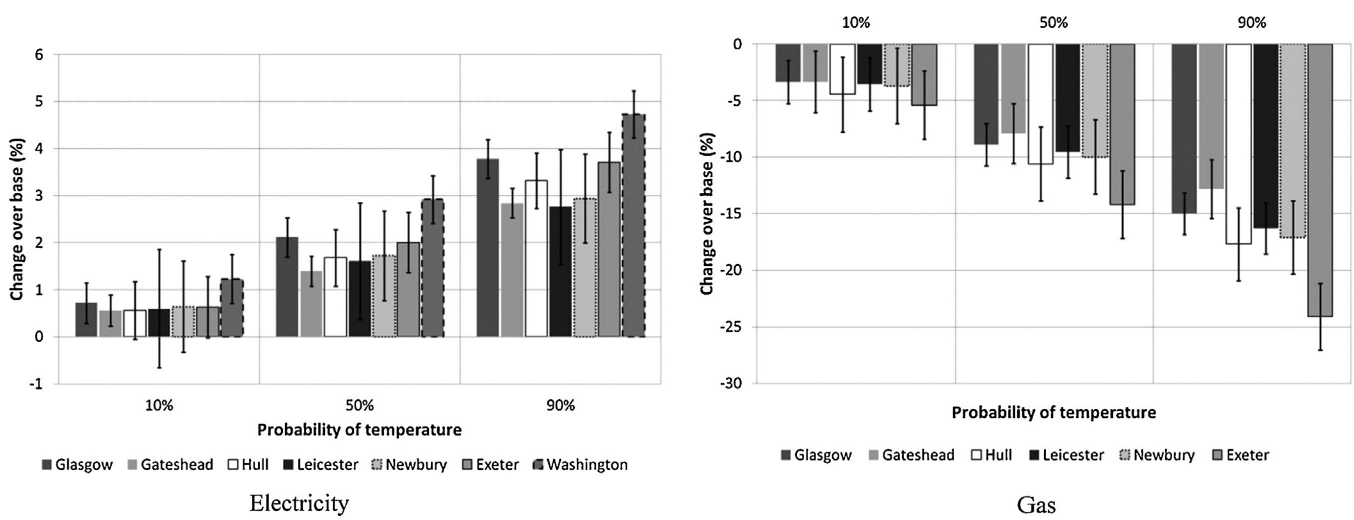

Fig. 7. Summary of energy change predictions with error bar.

locations of 26%, and of 32% for the remaining one. However, the percentage increase in electricity use reported in [10] owing to a rise in cooling load, is higher both in magnitude and in spread than for the investigated supermarkets, this being due to low initial figures for the current demand. The location dependant energy change in Great Britain reported for an office building in [9] also agrees with the results for gas here both in magnitude (average: −10.7%) and spread (average: 9.6%). Again, the increase in electricity use suggested in this paper (average magnitude: 31.6%, average spread: 14.6%) is considerably higher, probably owing to the fact that supermarkets have a higher electricity EUI because of the process cooling from the refrigeration system and a higher lighting density.

Four of out of the seven consumption models for electricity are change point regression models. All supermarkets have a temperature insensitive electricity load, in particular lighting, but these change point models show this more clearly as these models show a flatter slope up to the change point temperature. At what temperature and by what factor the slope changes may be due to the control algorithms for such temperature sensitive equipment such as the A/C units for comfort cooling and the refrigeration system for process cooling. The correlation coefficient between the annual average temperature during the study period and the annual EUI is 0.552 and therefore not as strong as between the installed lighting and the annual EUI ($r = 0.649$). This could lead to the suggestion that a modest amount of decrease in lighting consumption (such as through daylight dimming) may compensate any temperature related increase.

In contrast to the electricity consumption the variation in all the gas use data sets could be represented with simple linear regression models (minimum $r = 0.913$). These models were adequately explained by thermodynamic principles and building dimensions. Part of this reasoning is that air behaves similarly to a perfect gas. This means that, for a given temperature rise, the required amount of heat is proportional to the volume of the thermodynamic system, everything else being equal. However, for Gateshead and Newbury, this model seems to start to break down as the second order model improves the fit by over 5%. This behaviour may be due to the absence of a lobby resulting in the outside temperature having a more direct influence.

The results of the primary research question were based on the climate change data from UKCP09, which predicted an increase in annual average temperature of approximately 20% for the central estimate for the 2030s over the base period (the 1970s) with little spread among the supermarkets (CoV = 7.38%). This translates into a predicted average rise in the average electricity use of 1.92% for all seven supermarkets (CoV = 26.1%), and an average drop in average gas consumption of 10.2% (CoV = 21.3%) for these temperatures and, therefore, into a reduction in the overall energy demand. The electricity estimate for the temperatures at 10% and 90% probabilities gives an average deviation from the central estimate of −1.2 percentage points for the 10% temperature values and +1.5 percentage points for the 90% temperature values. For the same temperatures the gas consumption deviated from the central estimate by +6.2 percentage points for the 10% temperature values and

−7.0 percentage points for the 90% temperature values on average. As climate change predictions have a large margin for error, these estimates should be treated more as indicative rather than as absolute values.

These predictions suggest a year on year average increase in electricity use of 0.033% (central estimate), which may be considered very small compared with other changes to the electricity use in supermarkets, of which the addition of refrigerated display cases as encountered in the Glasgow supermarket, or incorrectly set timers detected in the store in Newbury are but two examples. The year on year drop in average gas consumption estimated at 0.16% (central estimate) is greater than the electricity use change, but may not be considered significant for the purpose of supermarket decision makers.

The findings here regarding changes in energy use agree with earlier research [3,4,6] as they suggest an increase in cooling load and a decrease in heating demand for a warming climate. In the supermarkets investigated above gas is the sole fuel for heating and, therefore, the predicted drop in gas use is related to the expected reduction in heating demand. Conversely, the rise in electricity use relates to the increase in cooling demand including comfort cooling and refrigerating of foodstuff.

Another question investigated was the possible influence of the different ways the supermarkets are operated. When visiting the stores it was noticed that most large energy consumers, such as lighting or gas boilers, were centrally controlled, and hence differences were minor. Furthermore the data were normalised by the opening hours to exclude this variable over which the local staff may have no control. The two operational practices investigated were the main baking time and the times the night covers were removed and replaced. The main baking time estimated by the baking staff was approximately 4 h for five of the seven supermarkets. Therefore establishing a relationship between a supermarket's EUI and the baking times was not possible. The reported practice regarding refrigeration night covers varied from supermarket to supermarket, but a linear regression model indicated that a store's EUI was not relegated to the period these covers were removed ($r \approx 0$). Another indication that the differences in local operation procedures seem to have only a small overall effect is that the differences in gas use models can be explained with thermodynamic principles.

The research here could be expanded by investigating how model parameters for both electricity and gas models can be estimated reliably and in a time effective manner. The research indicated that, for gas consumption, the building volume alone may suffice. However, the sample size of this building type needs to be increased and then broadened to include other types of building (including buildings without a lobby). For the electricity model it has been found that three supermarkets can be modelled with a simple regression equation and the other four with a change point model. The need for two different types of model should be investigated further. The result of this investigation could then serve as a base line against which actual consumption could be compared in order to detect energy inefficiencies.

6. Conclusions

The investigation into how the gas and electricity use may change with respect to the change in temperature from the 1970s to 2030s showed a total maximum increase for the 90% probability temperature of 4.73% (for the supermarket at Washington). This translates into a yearly increase of 0.077% when using the compound interest formula. The largest predicted drop in gas use of 24.1% for the 90% probability temperature is expected to occur at the Exeter supermarket, which is a year on year decrease of approximately 0.36%. Because other changes to supermarkets (e.g. addition of display cases) or problems at supermarkets (e.g. faulty equipment) may have a larger impact on energy use, supermarket decision makers should benefit more directly from energy saving measures.

When researching if local operational procedures have an impact on the energy usage, it was found that major energy consumers, such as lighting or heating, are centrally controlled. Furthermore a significant relationship between the two investigated procedures (main baking time and refrigerated displays without night covers) and the yearly EUI could be established. This leads to the conclusion that the impact of the local differences in procedures on the energy use that were investigated can be considered small.

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