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Investigating an adequate level of modelling for retrofit decision-making: A case study of a British semi-detached house

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Abstract

This paper investigates what level of modelling (zoning or internal load scheduling) is required to support heating related retrofit decision-making. First, this paper tests the effect of thermal zoning by incrementally reducing the number of thermal zones from modelling every room as a separate zone to modelling the house as a single zone. Second, this paper examines the influence of internal load schedules (occupancy, lighting and equipment schedules) on prediction accuracy. Actual internal load schedules were derived from the smart meter data of 666 households collected by the Customer-Led Network Revolution project. Cluster analysis was applied to extract a set of prototypical schedules to capture major variations across all households. Last, this paper evaluates the effects of the zoning and internal load scheduling modelling assumptions in the context of thermal retrofit decision-making.

For the specific parameters studied and the specific building design, the use of different zoning strategies and different internal load schedules yielded the same ranking of top retrofit options. For the specific climate and the baseline assumptions for the retrofits, different cluster schedules resulted in different magnitudes of energy savings, but the ranking of top retrofit options was not impacted by the choice of household internal load schedules. However, the actual internal load schedules affected the energy-saving potentials achievable by the same set of retrofit options. The case study highlights that the optimal set of retrofit options selected given the specific physical characteristics of a house is the same regardless of differences in the input of internal load schedules. However, it was found that energy-

saving potentials achievable by the same retrofit option substantially vary according to the actual internal load schedules. This finding implies that energy retrofit policies can be tailored to target certain groups of households selected by clustering their actual energy use profiles to cost-effectively maximise energy savings from the domestic sector.

1. Introduction

The Paris Agreement marks a significant positive step in global action to tackle climate change. In line with the Paris Agreement, the UK Government has set a target for reducing carbon emissions to net zero by 2050 (Committee on Climate Change, 2018). In 2017, the domestic sector occupied 28% of the total final energy consumption in the UK (Department for Business Energy and Industrial Strategy, 2017). Thus, it is urgent to improve energy efficiency in the UK domestic sector. Streicher et al. (2017) suggested that large-scale energy retrofits of residential buildings could have an energy saving potential of up to 84% in comparison to the current energy demand. Therefore, the appropriate level of energy retrofit of existing residential buildings could help to achieve the net-zero goal by 2050. The UK Environmental Audit Committee reported that most old housing stock in the UK is poorly insulated, and, in 2010, domestic buildings obtained an average Standard Assessment Procedure (SAP) rating of 53, much lower than the recommended baseline level which ranges between 65 and 81 (Power and Lane, 2010). The 2008 Climate Change Act sets the legal energy-saving target of improving the energy efficiency of existing homes through deep retrofit to achieve the net-zero goal (Institution of Engineering and Technology, 2018). The Green Deal was launched in 2013 and provided retrofit funding for 14,000 properties during the policy's operating period of January 2013 to March 2016 (Department of Energy and Climate Change, 2016). However, in practice, when considering the large amount of government funding provided, this scheme failed to achieve a notable result as planned and resulted in substantially lower carbon savings when compared to previous policies (Gooding and Gul 2017). Thus, it is urgent for policy makers to find a way to maximise the cost-effectiveness of retrofit programs.

Several studies have developed methods based on building energy simulation to support large-scale retrofit analysis. Caputo, Costa and Ferrari (2013) created 56 representative buildings as a combination of 2 building functions, 4 archetypes, and 7 construction ages to evaluate energy saving strategies at the city-scale. Each representative building was modelled as a multiple-zone model, and hourly occupancy-related schedules were defined based on the Swiss Technical Worksheet collected by SIA Merkblatt 2024 (2006). In order to create actual occupancy-related profiles, Shimoda et al. (2003) used the National Time Use Survey collected by the Broadcasting Culture Research Institute (2000) for computing schedules associated with occupants' activities as inputs to multiple-zone models of 460 dwelling types. They applied a bottom-up approach to modelling every building of the building stock to predict building end-use energy demand at a large-scale, accounting for variations in building geometries, thermal properties, and system types. Tian et al. (2015) developed an automated programming code for extracting building geometric information from GIS and creating EnergyPlus models of individual buildings. They applied the zoning strategy of modelling one single zone for parts of a building with similar functions, and highlighted the necessity of an appropriate modelling strategy (multiple-zone vs one-zone) for large-scale energy analysis.

The predictive performance of the simulation model depends greatly on assumptions and simplifications made in the model and the reliability of the model input parameters (Ghiassi et al., 2017). Indeed, a modelling process often involves subjective judgement to efficiently create the simulation model that reasonably represents the actual situation. The simplifications often made in the simulation process include reducing the number of thermal zones and using typical occupancy-related schedules specified in national standards. The common practice for thermal zoning is combining rooms with similar activities into one zone, but further simplications of modelling a building as a single-zone have been observed in urban-scale energy studies to facilitate modelling a large number of buildings (Tian et al., 2015; Heo et al., 2015; Booth and Choudhary, 2013). In general, many building-scale studies use the typical occupancy-related schedules specified in national standards for energy performance simulation (Heiple and Sailor, 2008; Dascalaki et al., 2011; Ballarini et al., 2014). These simplifications, however, unavoidably affect the accuracy of model outputs, which may possibly bias retrofit decision-making.

Several studies have investigated the effect of modelling simplications on the accuracy of energy predictions. Korolija and Zhang (2013) compared the prediction accuracy of detailed simulation models for domestic buildings in which every room is modelled as a separate zone and simplified simulation models in which each floor is modelled as a single zone. The comparative study indicated that the simplified thermal zoning strategy reduced the simulation time by 30% on average and resulted in the mean absolute relative error of 10.6% for predicting annual heating demands. Harrou et al. (2016) also investigated the effect of thermal zoning strategies on heating demand predictions. The simulation results indicate that single-zone simulation yields roughly half the annual heating demand prediction of multiple-zone simulation. However, limited research has been done on evaluating the effect of modelling simplications on selecting appropriate target groups and retrofit options.

This paper aims to investigate the role of major modelling assumptions in model-based retrofit analysis through a case study of a semi-detached house in the UK. Section 2 will present the details of this case study, including building components, locations and occupants, as well as the assumptions made in the simulations. Section 3 will test what level of thermal zoning is sufficient to support the energy analysis of domestic buildings. To answer this question, we reduce the number of thermal zones incrementally in the case study and compare the simulation results predicted by different levels of thermal zoning strategies. Section 4 will examine the use of actual internal load profiles for the energy analysis of domestic buildings. The details of the smart meter data and how it is representative for this case study building will also be discussed in section 2. Section 4 will compare simulation results predicted with four different methods for specifying an internal load schedule: (a) typical schedule in standards according to the National Calculation Method (BRE, 2015), (b) average schedule derived from the dataset, (c) a set of cluster centroids derived from the actual internal load profiles, and (d) all schedules from the dataset. Section 5 will evaluate the effect of modelling assumptions in the context of retrofit decision-making, in which the energy saving potentials of different retrofit options are evaluated and rankings of retrofit options are compared for the case study. The following five retrofit options are considered for analysis: (A) added wall insulation, (B) added roof insulation, (C) infiltration treatment, (D) energy-efficient light, and (E) window replacement. These five retrofit measures were selected on the basis of recent papers on the retrofit analysis of British houses (Ben and Steemers, 2017; Booth and Choudhary, 2013).

2. Introduction of the case study

The semi-detached house was selected as a case study because it is the second most prevalent dwelling type in 2015, occupying 26% of the UK housing stock (Department for Communities and Local Government, 2017). Based on Hamilton et al. (2013), the average gas demand per household was 17,533 kWh per year for a semi-detached house, 22,823 kWh per year for a detached house, 16,004 kWh per year for a terrace house, and 11,557 kWh per year for a flat. Trotta (2018) indicated that couples with independent child(ren) living in detached or semi-detached houses built before 1990 and with a length of residence higher than one year are more likely to invest in retrofit measures.

The case house consists of a lounge, dining room, kitchen and bathroom on the ground floor and bedrooms and a bathroom on the first floor, with the total floor area of 98 square metres. Figure 2 in section 3 shows the original layout of the house (the kitchen faces North). It was assumed that the representative house is occupied by a working couple with two children. The case study location was selected in the suburban area of London, thus the weather data of London Gatwick was used in the simulation. In this climate region, radiators and boilers provide heating for the vast majority of houses. The construction materials were assumed based on BRE National Calculation Method (BRE, 2015), as shown in Table 1.

Table 1 Assumption of building materials based on the case study

Components	U-value
Wall	0.37 W/m^2K
Roof	0.26 W/m^2K
Window	1.96 W/m^2K

To specify internal heat gains and indoor temperature settings in this case study, we used standard schedules specified in the National Calculation Method (NCM) in the simulation, downloaded from the Building Research Establishment (BRE) website (BRE, 2015). Internal load density values from occupants, lighting, and equipment and heating temperature setpoints during occupied and unoccupied hours are presented in Table 2. In addition, Figure 1 shows the standard hourly heat gain schedules from occupants, lighting, and equipment for each room type, which were derived by multiplying its internal load density value with associated hourly diversity profile values. Across all room types, the magnitude of heat gains from occupants is negligible in comparison to that from lighting and equipment. The kitchen has much higher lighting and equipment power densities than other rooms, which have relatively similar power density values. Particularly, peak equipment heat gains in the kitchen are predominantly much higher (roughly 10 times higher) than those in the other rooms. As British domestic houses are typically equipped with a boiler for heating and rely on natural ventilation for cooling, this study considers only heating setpoint temperatures that impact the energy consumption. In the NCM, the lounge has a higher heating setpoint temperature (21°C) during occupied hours than the other rooms, which are set at 18°C. All the rooms are set back to 12°C during non-occupied hours. In addition, the heating schedule varies per room type; heating is provided to the bedroom during the night time (from 20:00 to 8:00), to the lounge during the afternoon and evening (from 14:00 to 22:00), and to the other rooms during the morning and evening.

Table 2 Standard internal load density values and heating set-point temperatures

Room	Occupancy (m^2/person)	Light (W/m^2)	Equipment (W/m^2)	T_heating_occ (°C)	T_heating_unocc (°C)
Lounge	53.3	7.5	3.9	21	12
Dining	59.1	7.5	3.1	18	12
Bathroom	53.4	7.5	1.7	18	12
Kitchen	42.2	15.0	30.3	18	12
Bedroom	43.6	5.0	3.6	18	12
Corridor	64.5	5.0	1.6	18	12

(Source: BRE, 2015)

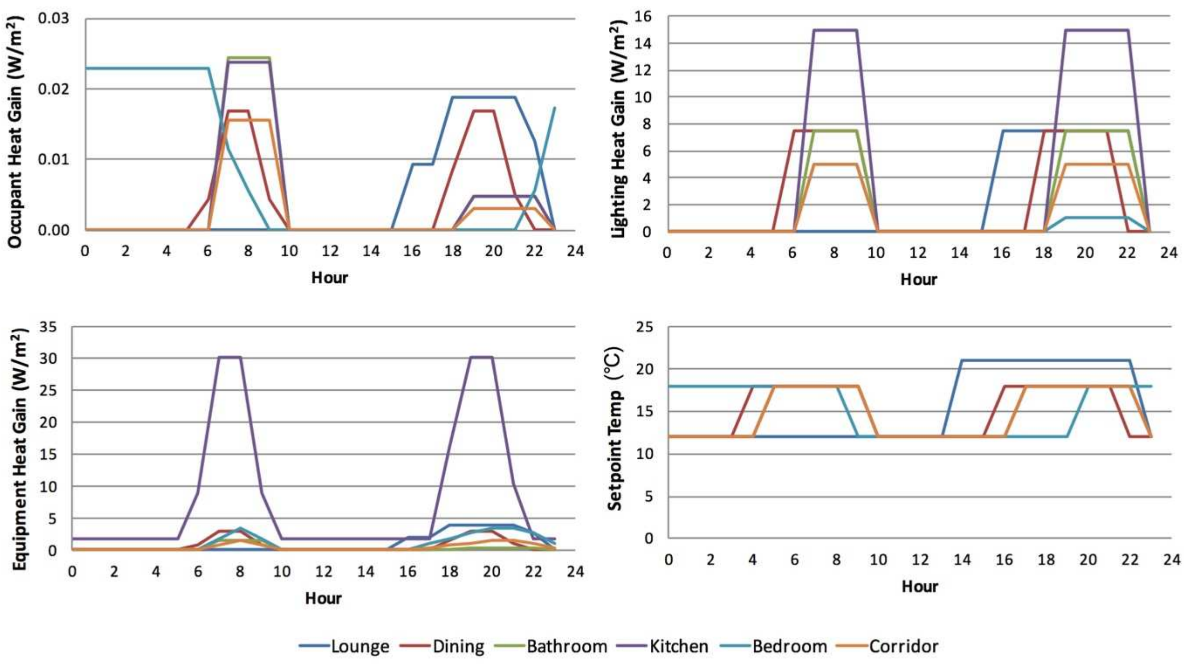

Figure 1 Standard hourly heat gains and heating setpoint temperature schedules

In section 4, we use selected smart meter data to derive average internal load schedules and a set of cluster centroids that are representative of all actual profiles within each cluster. The domestic electricity use dataset was collected by the Customer-Led Network Revolution (CLNR, 2015) during the period between May 2011 and September 2013. Information regarding household characteristics (such as number of residents, family composition, employment status, level of earnings) was not provided by the report, but the report grouped all households into 15 mosaic types based on Experian (2018). By considering the selected location of this case study, we selected the mosaic Group F "Suburban Mindsets" for further analysis, which is defined as "*maturing families on mid-range incomes living a moderate lifestyle in suburban semis*" (Experian, 2018). According to Experian (2018), Suburban Mindsets are mostly married people of middle age, living together with their children in family houses built between the 1930s and the 1960s. Typically, these homes conform to one of a limited number of designs for semi-detached houses which were popular during the inter-war years or during the period between 1945 and 1960. This group of people are typically middle class and skilled working class families looking for a comfortable house in which to bring up a family. The Suburban Mindsets group properly matches the households of representative buildings as the case study occupants were assumed to be maturing families on mid-range incomes living a moderate lifestyle, including a working couple with one or two child(ren).

3. Thermal zoning

This section examines the effect of thermal zoning on prediction accuracy through a case study. Figure 2 presents the original plan and three steps in which the thermal zoning of the house is incrementally simplified. First, every room of the house is modelled as a single zone to represent the actual house layout. Then, Step 1 combines rooms with similar space types into one thermal zone. This step represents a common thermal zoning strategy in practice in which rooms with similar characteristics (e.g., same use and operation schedules, orientation, and perimeter vs core areas) are grouped into a single thermal zone. The bathrooms on the ground floor and on the first floor are combined with circulation areas into a new thermal zone, as the floor area of bathrooms and circulation areas are small and the use of electrical appliances in these two types of zone is very low. Then, Step 2 combines all rooms on the same floor into one thermal zone, and Step 3 models the entire house as one single zone. These two steps (Steps 2–3) are often used in large-scale energy analysis where the cost-effectiveness of the modelling process is key to modelling every building of the building stock.

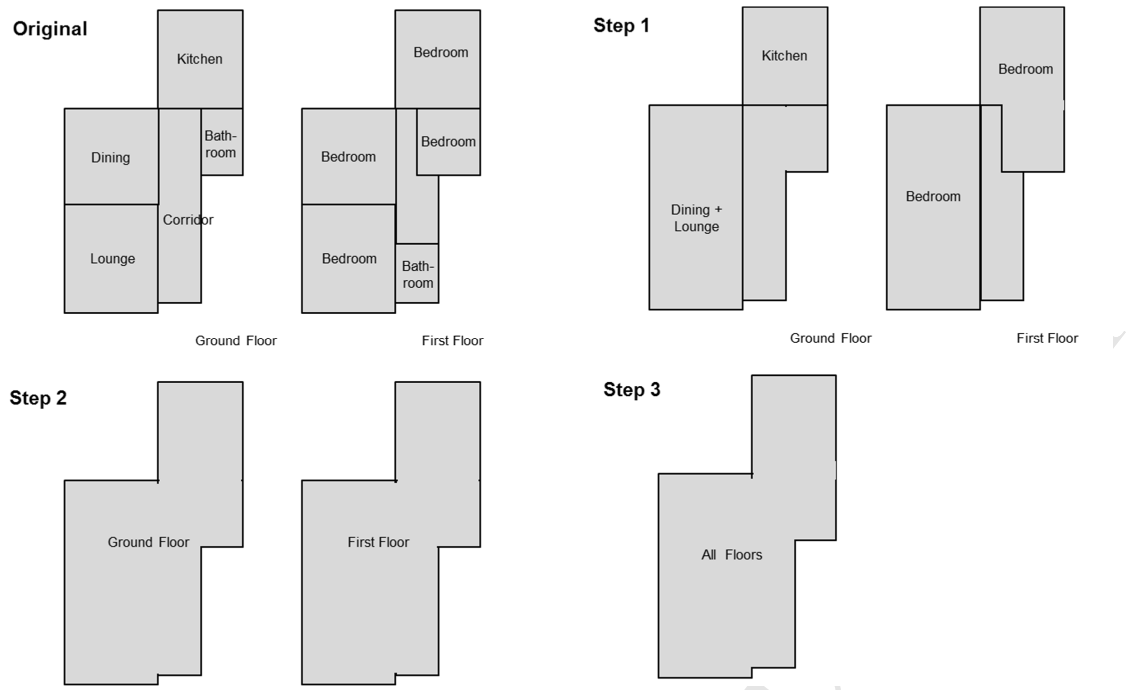

Figure 2 Incremental simplications in thermal zoning

We selected EnergyPlus to create the energy simulation models of the studied house with four levels of zoning strategies for three reasons: first, EnergyPlus is a reliable simulation tool for building performance simulation; second, the idf profiles generated by EnergyPlus could be modified in Matlab for multiple simulation runs in section 4; third, EnergyPlus has the function of group simulation which could automatically run thousands times of simulations by one click. In simulation, the occupancy schedules, as well as lighting and appliance schedules were revised in EnergyPlus for each thermal zone by area-weighted averaging of all density values and diversity profiles of rooms that fell into the same zone, respectively. For instance, for Step 1, the dining room and lounge were combined into one thermal zone, thus the density values were computed as:

$$average\ density\ value = \frac{dining\ room\ density\ value \times floor\ area + lounge\ density\ value \times floor\ area}{dining\ room\ floor\ area + lounge\ floor\ area}$$

After multiple simulation runs in EnergyPlus, Table 3 summarises the annual electricity and heating demand predictions with different numbers of thermal zones in comparison to modelling every room as a zone based on the actual house layout. Overall, the simplified zoning strategies have a minor effect on the lighting electricity use prediction, but they result in much larger differences in the prediction of equipment electricity use. This disparity occurs in Step 2 due to large differences in the equipment diversity profile between the kitchen and the other rooms. The kitchen with the small floor area has the highest equipment power density value with only a two-hour peak period and quite low diversity values for the non-peak period, whereas the other rooms have a longer period of peak hours. In Step 2, the average diversity profile for a thermal zone of the ground floor is calculated from all diversity profiles of different rooms with area weighting and, consequently, has higher hourly diversity values than the original one for the kitchen. The percentage values in the second part of Table 3 were calculated by first subtracting the annual demand prediction of each step from the original annual demand prediction, and then the differences were divided by the original demand. As the result, for the specific parameters studied and the specific building design, Steps 2 and 3 over-predict the annual equipment electricity demand by roughly 21%, and the total electricity demand by 11% and 8%, respectively.

Table 3 Comparison of annual demand predictions in thermal zoning

	Lighting (kWh)	Equipment (kWh)	Electricity (kWh)	Heating (kWh)
Original	1567	1388	2955	6199
Step 1	1572	1382	2954	5774
Step 2	1604	1688	3292	5143
Step 3	1505	1679	3184	4581
	Lighting (%)	Equipment (%)	Electricity (%)	Heating (%)

Step 1	0.3%	-0.4%	0.0%	-6.9%
Step 2	2.4%	21.6%	11.4%	-17.0%
Step 3	-4.0%	21.0%	7.7%	-26.1%

(Note: Electricity [kWh] = Lighting [kWh] + Equipment [kWh])

4. Internal load scheduling

This section examines whether using actual internal load profiles is necessary to provide accurate energy predictions by comparing energy predictions with actual internal load schedules against those with assumptions from national standards. The standard schedules used in this section are the average density values and associated diversity profiles computed by area-weighted averaging of standard density values and diversity profiles of rooms based on the National Calculation Method (BRE, 2015). We note that the standard heating set-point profiles in Figure 1 were used without adjustment based on the smart meter data, as information about the temperature settings was not available in the dataset used for analysis.

In this section, we tested the single-zone simulation with the internal load data collected by the Customer-Led Network Revolution (CLNR, 2015) project. Based on the reasons explained in section 2, the group F “Suburban Mindsets” was chosen for further analysis, and 666 out of the total 9200 recorded households (7.24%) were finally selected. Figure 3 presents the profiles of average hourly electricity consumption at each hour of the day of weekdays and weekends that fall under the group F classification. Overall, a similar trend is observed across individual household schedules although substantial variation exists. In the weekday schedule, peaks occur sharply around 8am for a short period, the curve is relatively smooth during 8am and 6pm, and another peak occurs for a longer period between 5pm–10pm. The weekend profile also shows two peak periods, one in the morning and the other in the evening, but the trend is smoother than the weekday one. As noticeable differences between weekday and weekend schedules are observed, we generated separate average internal load schedules of individual households for weekdays and weekends for further analysis.

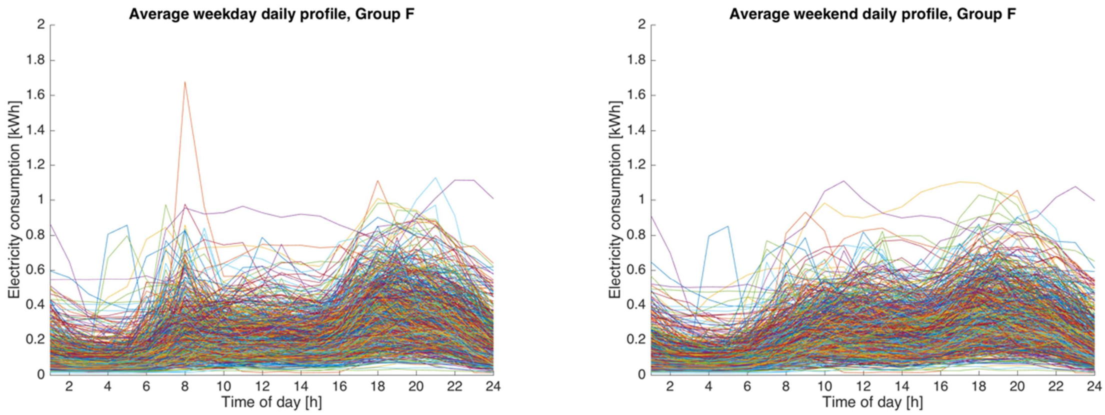

Figure 3 Average hourly electricity consumption at weekday (left) and weekend (right)

The average hourly electricity consumption at each hour of the day was calculated for each household as internal load schedules, and examples are shown in Figure 3. The internal load schedules derived from the electricity data were used as the model input for hourly internal loads for lighting and equipment. However, this simulation method may result in a simulation gap between the actual consumption and predicted results. For instance, fridges may consume a different amount of energy than they dispose as heat gain in the space, or at least they may have a time lag between the time electricity is consumed and the time heat is dissipated in the kitchen. Those discrepancies are acceptable, as the electricity consumed by the fridge is relatively small when compared with other domestic appliances.

Cluster analysis is a convenient method used to deal with thousands of electricity daily profiles, to effectively capture variability in the actual internal load profile and extract the representative profile for each household. We performed K-means cluster analysis to effectively capture major variability in the actual internal load schedule with a small set of schedules. K-means uses an iterative process that assigns customers into groups based on the distance between themselves and a cluster centre (Mcloughlin, 2013). K-means clustering aims to partition n observations into K subsets so as to minimize the within-cluster sum of squares, and where μ_j is the geometric centroid of the data points in S_j in order to achieve a global minimum for J. Figure 4 shows the prediction accuracy of using different numbers of cluster centroids used as representative schedules for all household schedules falling under each cluster, in comparison to using all individual household schedules. The prediction accuracy is quantified in terms of the coefficients of variation of the root mean square error (CVRMSE) that is obtained by computing the square root of the mean square error between actual profiles and the corresponding cluster centroid and normalising it by the mean of the actual profiles. When the number of clusters increases from 1 to 5, the CVRMSE value drops dramatically from 0.50 to 0.30, and further drops to 0.27 when the number of clusters increases to 10. As the number increases from 10 to 30 clusters, the CVRMSE value gradually decreases from 0.27 to 0.24. Based on these results, we selected 10 clusters that sufficiently capture the variability in the actual schedule. One thing to note is that the possible number of clusters can be also determined by using statistical methods such as gap statistics (Tibshirani et al., 2001) and the Davies-Bouldin index (Mcloughlin, 2013).

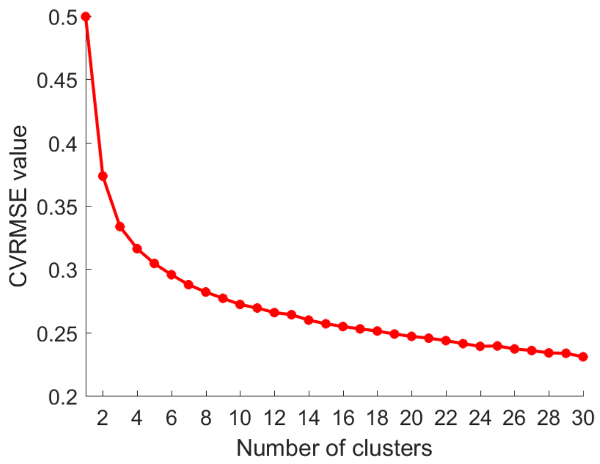

Figure 4 CVRMSE values for different numbers of clusters

Figure 5 presents 10 cluster centroids of hourly weekday and weekend schedules in comparison to the average hourly schedule of the entire dataset. Overall, all the centroid schedules indicate a similar pattern of internal loads; internal loads rise from 5am, continuously increase until 8am, and gradually decrease or remain constant until 3pm. Then, they increase again until reaching the peak load around 6pm and gradually decrease until midnight. However, the trend is slightly different between the weekday and weekend profiles. From 8am to 4pm, the average profiles (red dotted line) for the weekend are higher than for the weekday as the house is more likely to be occupied during the weekends. There are differences between clusters, as some clusters (such as Clusters 4, 5 and 10) have peaks during 12am and 4pm, but some clusters (such as Clusters 1 and 5) have a constant value but are slightly higher than the equivalent value on weekdays.

Although the timing of changes in the internal load is similar across the clusters, the cluster centroids show distinct differences in the magnitude of base loads and peak loads. Clusters 1 and 6 show consistently lower base loads with smaller peak loads than the average schedule. Clusters 3, 7, and 8 show a relatively similar trend to the average schedule, with slight differences in the peak shape. Clusters 4 and 10, on the other hand, show spiky peaks with much higher magnitudes whereas Cluster 5 shows constantly higher base and peak loads. In order to test whether the centroid schedules well reflect all household schedules included in each cluster, all the household schedules for selected clusters are plotted in Figure 6 and visually inspected in terms of the similarity among individual schedules. Individual schedules within each cluster show variation, and some spikes in individual schedules were smoothed by the cluster analysis and not represented in the cluster centroids. Nevertheless, the cluster centroids capture the major trend of changes in the internal load pattern observed across the households under each cluster.

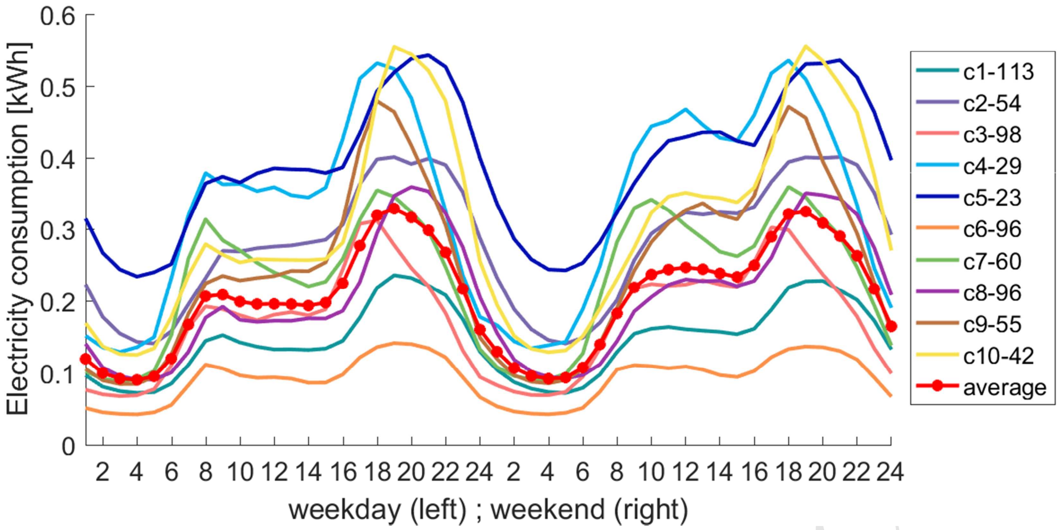

Figure 5 Ten cluster centroids of weekday and weekend schedules (legend indicates the cluster number and the number of households falling in each cluster)

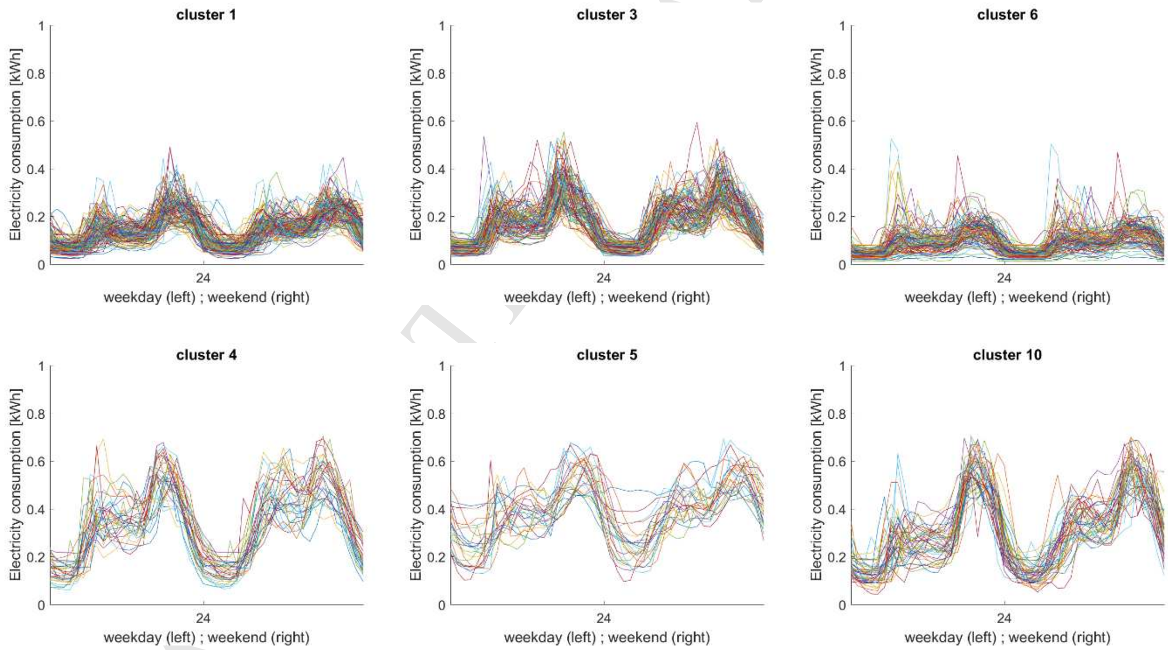

Figure 6 All household schedules falling under each cluster for selected clusters

In order to evaluate the effect of internal load schedules on the prediction, we compared the simulation results with different internal load schedules derived from the electricity dataset against those with the standard schedules for each room specified in the NCM. The single-zone model of the two-storey house (Step 3 model) was used to analyse the effect of internal load schedules on electricity and heating demand predictions. The internal load schedules derived from the electricity data were used as the model input for hourly internal loads from lighting and equipment. As the electricity data does not provide information about occupant heat gains, this simulation study uses the standard occupant heat gain schedule derived from NCM and, hence, does not account for variation in the actual occupant heat gains for heating demand predictions. However, as occupant heat gains are negligible in comparison to those from lighting and equipment (shown in Figure 1), model outcomes which consider variability only in lighting and equipment heat gains are sufficiently reliable to draw valid modelling recommendations related to internal load scheduling.

Figure 7 presents the annual electricity and heating demand predictions computed using the input schedules of 1) the average density values and diversity profiles computed by area-weighted averaging of standard schedules for each room specified in NCM, 2) the average profiles derived from the actual profiles of 666 households, 3) the 10 cluster centroid schedules derived from the profiles of the 666 households, and 4) the individual internal load profiles of the 666 households. For the specific parameters studied and the specific building design, the standard schedule produces electricity and heating demand predictions that closely match those predicted by the average schedule. The annual electricity and heating demand predictions with different centroid schedules vary significantly between 1,600–6,800 kWh and between 3,200–5,400 kWh, respectively.

This large variation suggests that, for this specific case study, obtaining actual internal load schedules of specific households substantially improves the accuracy of the building energy prediction. The simulation results using 10 cluster schedules effectively cover the majority of variation in the predictions computed using the entire set of actual schedules, which shows the potential value of developing a small set of occupancy-related schedules to predict a plausible range of energy predictions in an efficient manner.

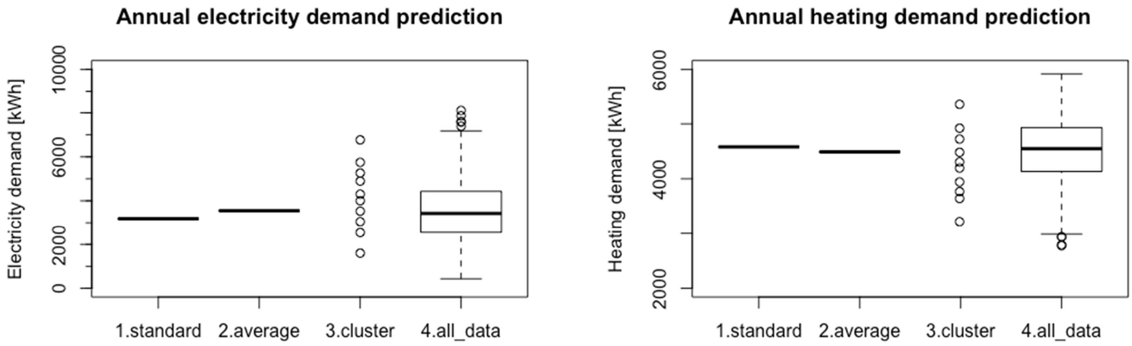

Figure 7 Annual electricity demand (left) and heating demand (right) predictions using different internal load schedules

In addition to annual predictions, we further evaluate the effect of using different internal load schedules on average hourly heating demand predictions in January. Figure 8 presents the simulation results of the average hourly heating demand predicted in EnergyPlus. Overall, the results predicted with the standard schedule from the National Calculation Method (green line) align well with the average profiles of all 666 actual internal load schedules (red line). This comparison indicates that, for the specific parameters studied and the specific building design, the standard schedule derived from the NCM is sufficient to reliably predict the average energy behaviour of domestic buildings on an hourly time scale. Additionally, hourly demand predictions with different centroid schedules resulted in almost the same pattern of hourly predictions with variation mainly in the load magnitude.

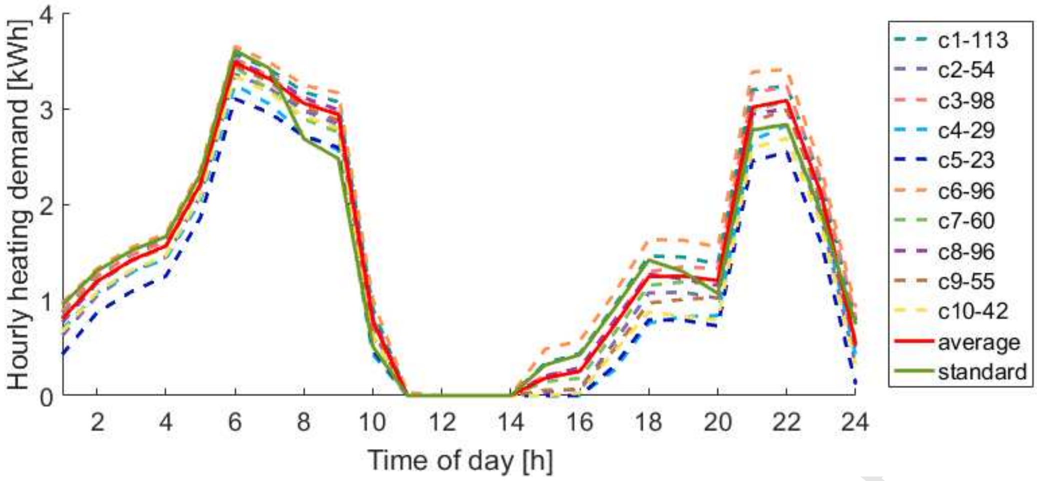

Figure 8 Average hourly heating demands for January

5. Retrofit analysis

The effect of various retrofit options on the energy performance of UK houses has been tested in recent research papers. Hardy et al. (2018) tested the effect of internal and external solid wall insulation, using the recorded data of electricity, gas and temperature readings before and after the retrofit. It was found that 8 of the 14 houses presented a significant decrease in daily gas use and 6 of the 14 houses showed a decrease in daily electricity use. Ben and Steemers (2017) compared the energy saving potential from eight retrofit measures (the insulation of external walls, ground floor, loft, ceiling, window, and tank/pipes, with boiler upgrade and smart control) across five household behavioural patterns (active spender, conscious occupier, average user, conserver, and inactive user), by simulation of a mid-terraced house.

This section investigates the effect of thermal zoning and internal load scheduling on retrofit decisions. Table 4 presents five retrofit options considered for the case building: (A) added wall insulation, (B) added roof insulation, (C) infiltration treatment, (D) energy-efficient light, and (E) window replacement. The effectiveness of these retrofit options was evaluated in terms of the annual energy saving from space heating demand. These five retrofit measures were selected on the basis of recent papers on the retrofit analysis of British houses (Ben and Steemers 2017; Booth and Choudhary 2013; Hall et al. 2013).

Table 4 List of different retrofit options

	Retrofit options	Detail
(A)	Wall insulation	Improve the wall U-value from 0.37 W/m^2K to 0.19 W/m^2K by adding an extra extruded polystyrene layer with air cavity.
(B)	Roof insulation	Improve the roof U-value from 0.26 W/m^2K to 0.13 W/m^2K by adding an extra glass wool layer
(C)	Infiltration treatment	Reduce infiltration rate from 1 ACH to 0.5 ACH through improved draught proofing
(D)	Energy-efficient light	Improve lighting efficiency by 20%, from 5 W/m^2-100 lux to 4 W/m^2-100 lux
(E)	Window replacement	Replace double glazing with triple glazing and improve U-value from 1.96 W/m^2K to 1.40 W/m^2K, Visible Transmittance from 0.74 to 0.68, and Solar Heat Gain Coefficient (SHGC) from 0.69 to 0.63

First, we evaluated the effect of different thermal zoning strategies on predicting relative percentage energy saving estimates of retrofit options and resulting retrofit decisions. Table 5 presents the relative percentages of annual energy saving estimates of five retrofit options predicted with the four different levels of thermal zoning strategies as described in Section 3. Although the different thermal zoning strategies resulted in a discrepancy of up to 26% in baseline energy predictions (in Table 3), they result in the similar ranking of retrofit options (in Table 5); infiltration treatment (option C) is the most preferred option, followed by wall insulation (option A). For the specific climate and the baseline assumptions for the retrofits, not only do all zoning strategies identify the same set of two retrofit options as the most effective measures that far outperform the others, but they produce similar energy saving estimates for all retrofit options.

Table 5 Relative percentage in annual energy saving estimates of retrofit options predicted with different thermal zoning strategies

Retrofit Option	Original	Step 1	Step 2	Step 3
(A)	14.5%	14.3%	13.5%	14.1%
(B)	2.9%	3.0%	2.9%	2.9%
(C)	20.7%	17.0%	20.9%	21.9%
(D)	2.9%	3.6%	3.8%	3.9%
(E)	1.7%	1.8%	1.8%	1.9%

Second, we evaluated the relative percentage energy saving estimates of using single-zone simulation with actual internal load profiles. Figure 9 presents the mean and standard deviation of relative percentage energy saving estimates of the five retrofit options predicted with individual profiles of the 666 households. In terms of the average performance, option C was selected as the best choice, but possible energy saving predictions ranged from about 13% to 30% for different households. Among the five retrofit options, retrofit options A and C showed much higher energy-saving potential than the other three options, but also showed a high variation in the annual energy saving prediction. This suggests that, in this case study, for the specific climate and the baseline assumptions for the retrofits, retrofit options A and C were highly impacted by the energy-use behaviour of occupants. It is admitted that there are constant-on internal loads that are not linked with the occupants, such as the electricity use by a fridge, but the differences are acceptable as the electricity use by a fridge is relatively small when compared with other domestic appliances used during the two peak periods.

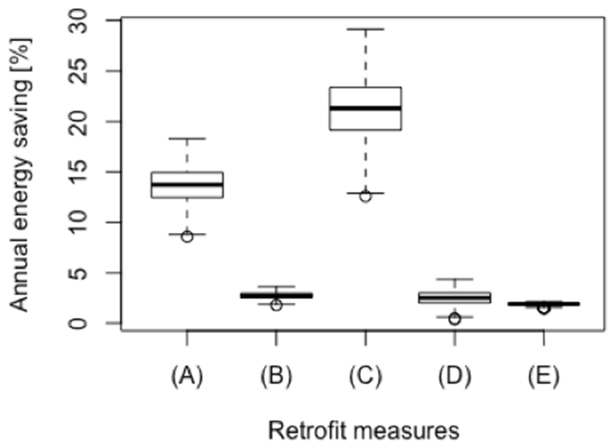

Figure 9 Boxplot of annual energy saving estimates from the five retrofit options predicted with individual profiles of the 666 households

Table 6 presents the annual energy saving estimates of the five retrofit options predicted using the standard schedule derived from the National Calculation Method and using each of the 10 cluster centroid schedules. Similar to retrofit decisions derived using different thermal zoning strategies (shown in Table 5), Table 6 shows that option C is selected as the best choice regardless of the internal load schedules, followed by option A. It highlights that the optimal set of retrofit options selected in this case study remains the same regardless of differences in energy-use behaviour. However, differences in the energy-use behaviour result in substantially different energy saving estimates. For instance, in Table 6, the Cluster 5 schedule yields the smallest magnitude of annual energy savings from the top two options: 10% and 15% from options A and C, respectively. In contrast, the Cluster 6 schedule produces the highest magnitude of energy savings, 16% and 26% from the same options in the same order. This difference indicates that certain groups of households have larger energy saving potential depending on the internal load pattern that is highly related to occupant lifestyle.

Table 6 Annual energy saving estimates (%) of retrofit options predicted by the standard schedules and 10 cluster schedules

	Standard	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10
(A)	14.1	14.9	11.9	14.2	11.0	9.9	16.4	13.0	13.6	12.6	11.5
(B)	2.9	3.0	2.4	2.9	2.2	2.0	3.3	2.6	2.7	2.5	2.3
(C)	21.9	23.4	18.2	22.2	16.7	14.8	25.8	20.1	21.1	19.4	17.5
(D)	3.9	2.0	3.3	2.3	3.6	4.0	1.4	2.8	2.6	3.0	3.4
(E)	1.9	2.0	1.7	1.9	1.7	1.6	2.1	1.8	1.9	1.8	1.7

In addition, we investigated whether the cluster centroid profiles are representative of the households within each cluster. Particularly we looked into the retrofit options A and C as they were identified as the top choices and their performance was substantially impacted by internal load schedules. Figure 10 illustrates the ranges of annual energy saving potential of retrofit options A and C, predicted with the 666 actual internal load profiles grouped by 10 clusters (left-side) and with the 10 cluster centroid profiles (right-side). The average prediction with individual household profiles in each cluster is very similar to the single prediction with the corresponding cluster centroid profile. This comparison indicates that the cluster centroid profiles could be used to predict the overall energy-saving performance of retrofit options for different clusters.

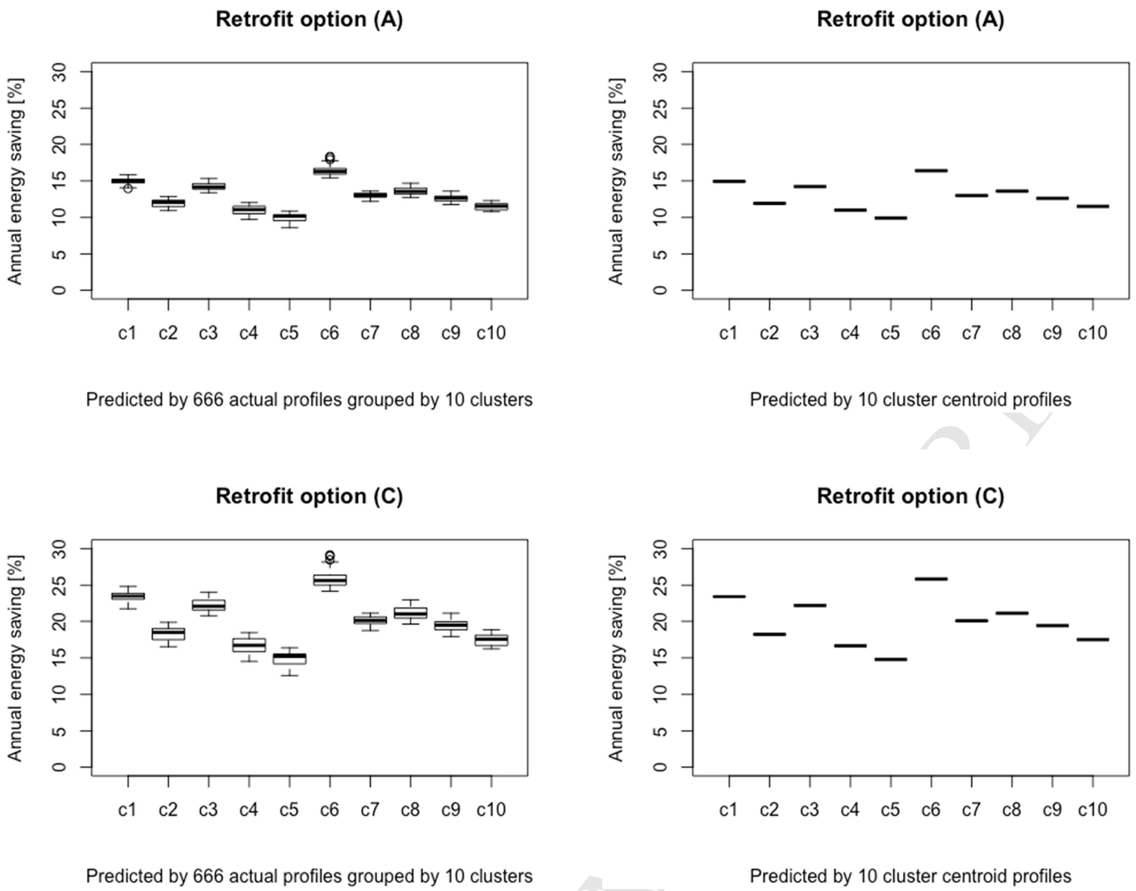

Figure 10 Prediction of annual energy savings of retrofit options A and C with the 666 actual profiles grouped by 10 clusters (left) and the 10 cluster centroid profiles (right)

For the specific climate and the baseline assumptions for the retrofits, the analysis results from this specific case suggest that the optimal set of retrofit options is not impacted by the household internal load schedules, but higher energy-saving potentials achievable by the set of retrofit options is substantially impacted by the internal load schedules. The results from this study are consistent with existing research findings. Marshall et al. (2016) investigated the effectiveness of three retrofit measures (boiler upgrade, roof insulation, wall insulation) for three occupancy patterns (working family, working couple, day-time present couple) and concluded that the energy saving depends on the occupancy patterns of the household. Similar to these findings, this study showed that the energy saving estimates are impacted by occupancy-related internal load schedules. However, unlike this case study, Ben and Steemers (2017) concluded that the optimal ranking of energy efficiency measures varied across five behavioural patterns. The difference might be because the household energy-use behaviour considered in this study is limited to adjusting the simulation assumptions of internal load schedules, but not considering the actual temperature setting for each single room of each household. However, the aim of this study is to analyse the retrofit options at the large scale, and it is not possible to obtain their temperature setpoint in the real case.

6. Conclusion

This paper investigated the effect of zoning and internal load scheduling assumptions on the large-scale retrofit analysis of domestic buildings. Through the case study of the British semi-detached house, the effect of simplications commonly made in thermal zoning and internal load scheduling was examined in terms of the baseline prediction accuracy and retrofit decisions. For the specific parameters studied and the specific building design, the common thermal zoning strategy of combining rooms with similar thermal characteristics into a zone underestimates the annual heating demand by 7% in comparison to modelling every room as a separate zone, and modelling a single zone model for the entire house underestimates the annual heating demand by 24%.

In order to evaluate the value of using actual internal load schedules, cluster analysis was applied to the electricity interval data of 666 homes to generate a set of prototypical schedules that effectively capture variability across households. For this specific case, the EnergyPlus simulation results using the National Calculation Method standard schedule show a good agreement with predictions made using the average schedule derived from the electricity use data. However, different schedules derived by the cluster analysis result in large variation in the prediction, which suggests that using the actual internal load schedules of specific households could substantially improve the accuracy of the building energy prediction.

The effect of different zoning and internal load scheduling strategies was examined in the context of large-scale retrofit decision-making. The use of different zoning strategies and different internal load schedules all selected the retrofit option C (infiltration treatment) as the best choice, which suggests that, for the specific climate and the baseline assumptions for the retrofits, the most simplified thermal zoning strategy (modelling the entire house as a single zone) is sufficient to reliably evaluate the performance of different retrofit options. In this case study, options A and C (wall insulation, and infiltration treatment) are the top two retrofit options, but the variations in the energy saving potential are large for these top retrofit options. It was also found that the level of energy saving potential achievable by the same set of retrofit options substantially depends on the internal load schedules of each household. In addition, the case study demonstrated that the internal load schedules derived on the basis of the cluster analysis effectively predict the average energy saving prediction of retrofit options for all clusters. It may appear that the comparative result analysis is more likely a validation to the simulation results, as different zoning and internal load scheduling strategies all result in selecting the same retrofit options. In the retrofit analysis, the energy saving potential of different clusters is diverse, which implies that the information of household internal load schedules can be valuable for urban-planners for the decision-making between retrofitting scenarios. For instance, simulations with smart meter data could help to identify the target retrofit groups with higher energy-saving potential. Cluster analysis of the electricity data from smart meters is a useful method to understand occupancy-related schedules of households and cost-effectively maximise the energy saving potential of the limited retrofit funding provided by the government.

There is a need to note that the heating set-point temperature is not included under the scope of this paper due to lack of data, and neither is socio-economic analysis within the scope of research. This paper only explored the use of actual internal load profiles used for the simulation of electricity scheduling strategies. This paper is not aimed at generalising the findings and conclusions from a single case study. Similar studies should be expanded to address more building designs in different climate conditions. Overall, this study has contributed to the understanding of how occupancy patterns affect the energy savings achievable using different retrofit measures, and aims to propose an effective method that could be used for urban-planners, modellers, and policy-makers for large-scale retrofit analysis and retrofit policy design.

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Highlights

- Single-zone simulation with smart meter data to improve simulation efficiency
- Retrofit energy saving potential is impacted by occupants' energy use patterns
- Cluster centroid profiles to capture variations in occupancy-related schedules
- Use cluster method to select priority group for house thermal retrofit