Analysing socioeconomic diversity and scaling effects on residential electricity load profiles in the context of low carbon technology uptake

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Abstract

Adequately accounting for interactions between Low Carbon Technologies (LCTs) at the building level and the overarching energy system means capturing the granularity associated with decentralised heat and power supply in residential buildings. The approach presented here adds novelty in terms of a realistic socioeconomic differentiation by employing dwelling/household archetypes (DHAs) and neighbourhood clusters at the Output Area (OA) level. These archetypes are combined with a mixed integer linear program (MILP), which is used to generate optimum (minimum cost) technology configurations and operation schedules. Even in the baseline case, i.e. without any LCT penetration, a substantial deviation from the standard load profile (SLP) is encountered, suggesting that for some neighbourhoods this profile is not appropriate. With the application of LCTs this effect is much stronger, including more negative residual load, more variability, and higher ramps with increased LCT penetration, and crucially different between neighbourhood clusters. The main policy implication of the study is the importance of understanding electrical load profiles at the neighbourhood level, because of the consequences they have for investment in the overarching energy system (e.g. transmission and distribution infrastructure, centralised generation plant etc.). Further work should focus on attaining a superior socioeconomic differentiation between households.

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Keywords

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1. Introduction

In many countries, residential buildings account for a major component of final energy demand and CO_2 emissions. Particularly in regions with a temperate or continental climate (across America, Europe and Asia) the heat supply of buildings, for space heating and hot water, are key energy service demands (Lucon et al. 2014). In this paper's representative case study of the United Kingdom (UK), the energy supply of households accounts for around 29 % and 25% of the UK's final energy demand and CO_2 emissions respectively (Palmer & Cooper 2013).

Hence low carbon technologies (LCTs) at the interface between electricity and heat systems, such as micro-Combined Heat and Power (mCHP) and heat pumps, are especially promising in this context (OECD/IEA 2011). Furthermore, several other renewable technologies, such as photovoltaics (PV) and solar thermal, tend to be exploited decentrally, on the individual building scale. So individual residential buildings and neighbourhoods are therefore a prime target for renewable energy and energy efficiency measures (collectively referred to here as low carbon technologies, LCTs).

Whilst these measures have significant technical potential in residential buildings, the diversity within the building stock as well as between individual households means that a differentiated approach is necessary in order to assess their potential uptake (as discussed in section 2). Indeed, the UK research community has called for more detailed modelling of the residential sector in a whole systems framework. For example, Kannan & Strachan (2009) stress the necessary compromise between depicting the residential sector in detail and the whole energy system on an aggregated level in the context of the government's target of 60% CO_2 reduction by 2050 (since superseded by an 80% target). This has been taken up by the UK government in the development of the National

Household Model (NHM, CSE 2015) as a key component in their long-term energy modelling suite, in addition to the UK TIMES energy systems model, the National Transport Model and the electricity dynamic dispatch model (DDM).

In the context of modelling LCTs in residential buildings, the discussion in section 2 illustrates the necessity to differentiate between dwelling and household types, and demonstrates the lack of attention given to differentiation between household types. Only if the effects that this diversity has on both the patterns in, and the overall total household energy consumption, are considered, can meaningful insights into the potential applications and impacts of these technologies be gained. Hence this paper presents a novel approach to analyse the possible effects on the electrical load profiles of a diffusion of LCTs in residential buildings. This includes an examination of these effects at the individual household and neighbourhood levels. The method explicitly considers the diversity inherent in heating patterns and set temperatures, as well as paying attention to appliance-related factors. The objective is thereby to analyse scale effects on residential load profiles at the neighbourhood level, by considering decentralised LCTs for heat and electricity supply as well as some important socioeconomic aspects. The approach includes the generation of dwelling/household and neighbourhood archetypes, which serve as the basis for an optimisation of supply-side LCTs in individual buildings. These dwelling/household archetypes (DHAs) are then scaled up to the neighbourhood level and through the derived archetypes are mapped to the Output Areas (OA) in England and Wales. In a final step the potential effects on the aggregated (residual) load profiles of these neighbourhoods are analysed through recourse to different technology penetration scenarios.

The paper is structured as follows. The following section gives a literature review relating to socioeconomic influencing factors surrounding residential energy use, thus providing the motivation for and demonstrating the added value of this work. Section 3 then presents the methodology used, with particular focus on the derivation of dwelling/household archetypes (DHAs) and neighbourhood clusters, as well as the developed LCT penetration scenarios. Section 4 presents the results and section 5 discusses them as well as the methodology more generally. Finally, section 6 closes with conclusions and policy implications.

2. Literature review

In general there is evidence that the overall energy demand of a household is closely correlated with its income, although other factors also play a significant role (e.g. Jones et al. 2015a; for a spatial analysis for the UK see Druckman & Jackson 2008). Haldi & Robinson (2011) suggest that behavioural factors alone can account for a doubling of building energy demand and the diversity between occupants may have an even stronger effect. In the context of low-energy dwellings Gill et al. (2010) find that occupants behaviour account for the 51%, 37%, and 11% respectively of the variance in heat, electricity and water consumption. Despite these findings, some studies that have attempted to explain the variance in internal temperatures (Kelly et al. 2013) and energy demand (Hübner et al. 2015) have been unable to fully do so. Whilst Kelly et al. (2013) are able to explain 45% of the variation in internal temperatures using panel methods, Hübner et al. (2015) are only able to account for 44% of variability in residential energy consumption. Whilst both of these studies clearly suggest that further work is required to fully understand the dwelling and household factors that determine internal temperature and overall energy demands, they do highlight at least some of the key factors that should be considered if variability between households is at least partly to be accounted for.

Jones et al. (2015a) review the socioeconomic, dwelling- and appliance related factors affecting electricity consumption in residential buildings, concluding that several household factors, including household and disposable income, number of occupants, age of the household representative person (HRP), have a positive effect on the electricity consumption. Other factors also have an effect but the nature of this effect is less conclusive in the literature. Amongst the dwelling factors, there is a more conclusive picture, showing for example that dwelling type, size and age, and electric space and water heating have been examined most in the literature and shown to have a positive effect. For individual appliances, the study highlights the lack of attention paid in the literature to appliance-related factors, including ownership, use and power demand.

In addition, Jones et al. (2015b) analyse the determinants of particularly high electrical demands in UK homes, finding that the presence of teenagers, electric space heating as primary heating, portable electric heating and electric water heating are all key drivers for high electricity demand. Interestingly, this study (Jones et al. 2015b) confirms the above findings (Jones et al. 2015a), except for the following factors, which are shown to have no statistically significant effect on above-average electricity consumption in UK dwellings: the employment status and education of the HRP, the number of floors in the dwelling, the presence of fixed electric (space) heating and the proportion of low-energy lighting.

There is also strong evidence that socioeconomic differences between households affect the temporal profiles of electricity demand, i.e. the load profiles. There is an extensive literature on residential electrical load profile modelling; for a review of these models the reader is referred to Grandjean et al. (2012), and for a review of the time-use data that often underpins them to Torriti (2014). Whilst the latter points out that data relating to income, number of occupants, homeowner age and education are variously employed in residential electricity demand models, it does not analyse their use in combination. In addition, whilst arguing for a differentiated treatment of residential electricity load profiles in Europe, Hayn et al. (2014) identify four distinct but interrelated influencing characteristics: lifestyles, socio-demographic characteristics, electric appliances and new residential heat and electricity generation technologies. Hayn et al. confirm the above findings that household size, income, and employment status are the key socio-demographic factors. They also recommend that future work also considers the effects of LCTs such as PV, mCHP, heat pumps and batteries, due to their effect on the peak load, as well as linking socio-demographic factors with the ownership of appliances and technologies. However, only a few of the residential electricity demand models based on time-use data enable a detailed socioeconomic differentiation between households. One of these is presented by Fischer et al. (2015), who develop a stochastic bottom-up model and apply it to German households, where the main novelty seems to be the level of socioeconomic differentiation achieved. Households are characterized by the number of people, the structure, the age, the dwelling type and the working pattern. Results are validated with empirically-measured load curves and show a high level of accuracy.

In the context of analyzing residential heat demand, Hübner et al. (2013a, 2013b) compare internal temperature settings in English dwellings with common model assumptions as employed in widely used assessment methodologies and building stock models. They conclude (Hübner et al. 2013a) that the commonly-used assumptions in these models, especially those relating to the internal temperature and heating patterns do not accurately reflect behaviour in these dwellings. Instead, the internal temperature is consistently found to be below the assumed value of 21°C, the heating durations were shorter than assumed, and a large degree of variability between dwellings was encountered. In addition, they find (Hübner et al. 2013b) that weekdays and weekends are far more similar than commonly supposed and homes are frequently heated outside assumed heating hours. The authors suggest that further work should focus on explicitly addressing heating load patterns and set temperatures, as well as linking socioeconomic and building variables to the heating patterns and internal temperatures, with a view to identifying sub-segments of the population with similar behaviour.

In addition to the demand side, several contributions have analysed the potentials for and likely impacts of different supply-side LCTs at the individual building and neighbourhood level. Most of these studies employ optimisation and/or simulation approaches that depict the building's physical and thermal characteristics in detail yet do not differentiate between (types of) households. For a detailed discussion the reader is referred to McKenna et al. (2016).

In summary, the upper and lower bounds for the annual energy consumption of a residential building are largely determined by the building's thermal characteristics (including geometry and insulation standard), the type of heating system, the climate, the number of persons and the number/type of appliances. But the foregoing discussion illustrates that the precise energy consumption of a particular building between these two extremes depends heavily on the occupants and their behaviour. The temporal patterns of energy consumption are also strongly affected by certain socioeconomic characteristics. Hence why several important socioeconomic factors that determine residential energy consumption are employed in the subsequent section.

3. Methodology

This section gives an overview of the developed and applied methodology as shown in Figure 1. The areas enclosed within a dashed rectangle in the figure are not presented here in detail due to space restrictions; instead the reader is referred to the given source. The first subsection (3.a) presents the employed CREST electrical load profile tool and the further developments made to consider space heating and hot water. The second subsection (3.b) presents the dwelling and household archetypes (DHAs) employed in this study. The third subsection (3.c) describes the derivation of representative neighbourhoods at the Output Area level with a cluster analysis. The household/dwelling archetypes are then allocated to these neighbourhoods in order to scale up the results to selected neighbourhoods in the UK. The final subsection (3.d) briefly presents the methodology for employing a preexisting optimisation model in order to derive optimal technology combinations, capacities and dispatch profiles.

a. CREST model

The CREST (henceforth “CREST 1.0”) tool by Richardson et al. (2010) and Richardson & Thomson (2012) simulates residential electricity load profiles in 1-minute resolution. A first-order Markov-chain approach is used to stochastically generate a 24-hour occupancy pattern, which defines the occupancy state during every minute of the day. Based on this occupancy pattern, the model generates electricity load curves for every electric appliance present in the simulated household. Electric appliances that do not depend on active occupancy follow a static consumption pattern.

Appliances that require active occupancy are mapped to activity profiles, which incorporate varying appliance use over the day. Activity profiles and transition probability matrices for generation of occupancy patterns are obtained by evaluation of time-of-use survey data. The tool is further extended by Richardson & Thomson (2012) through the integration of stochastic generation of irradiation profiles and simulation of on-site photovoltaic power generation.

In the scope of this work, the following five extensions to the CREST tool have been implemented (referred to in the following and in Figure 1 as "CREST Heat And Power (CHAP)"):

1. The two-state occupancy model has been replaced by a four-state occupancy model developed by McKenna et al. (2015). This allows for a more detailed simulation of internal heat gains and losses.
2. A domestic hot water (DHW) module has been integrated. It incorporates six DHW service demands and relies on the same approach already used by Richardson et al. (2010) to simulate electricity demand. DHW service demands do not feature stand-by power consumption and restart delay but mean delivery temperature. Flow and temperature meter data surveyed by EST (2008) has been used to obtain DHW appliance parameters and to validate the model.
3. A space heating (SH) model has been implemented, which is based on the lumped-parameter model by Nielsen (2005). The two-node thermal RC-model allows for estimation of thermal indoor temperature and residential SH demand under consideration of building structure, irradiation and heating load. Construction parameters are taken from the Cambridge Housing Model (CAR, 2013) and data on realistic heating regimes and internal set temperatures are extracted from the Energy Follow Up Survey (EFUS: DECC 2011).
4. Consumption parameters of electric appliances have been updated based on the studies of Armstrong et al. (2009) and Stamminger (2008). Further electric appliances monitored in the scope of the Household Electricity Usage Study (Element Energy 2013) have been added to the electricity model.

5. The CREST CHAP model allows for calibration of appliance use frequencies so that the simulated dwelling energy demand matches an ex-ante defined yearly target value. A similar calibration mechanism has been developed for DHW by deriving mean active occupancy and mean activity values depending on the number of residents occupying the simulated dwelling.

There are two types of climate data processed by the CHAP simulation. Firstly, irradiation data is required by the SH model and by the electricity model (in case of PV power production). A data series with location set to Loughborough (UK) is generated by the irradiation model developed in Richardson & Thomson (2012). Secondly, outdoor temperature data is required by the SH model. A UK temperature data series representing an average of UK's prevalent climatic zones is obtained by averaging 2006 temperature data for London, Birmingham, Newcastle Upon Tyne and Glasgow (Met Office, 2012). Both irradiation and temperature data series are seasonal.

The CHAP model will be presented and validated in detail in a forthcoming contribution. The main limitations of the model are discussed in section 5.b. For further details of the CHAP model, the reader is referred to Hofmann et al. (2016).

b. Definition of dwelling/household archetypes (DHAs)

A quite recent study to analyse trends of energy use in a residential building context was carried out by Element Energy (2013). This study, based on somewhat older data from the Household Energy Usage Survey (HEUS) of 250 mainly owner-occupied dwellings between 2010 and 2011 (Zimmermann et al. 2012), analysed how socioeconomic occupant characteristics influence their electricity consumption. A hierarchical (with Ward's method) and subsequent k-means cluster analysis in SPSS resulted in the identification of seven household archetypes based on the "elbow criterion" on the Scree plot. These 7 HEUS Archetypes are employed as the basis for the dwelling/household archetypes (DHAs) used in this analysis; for more details, the reader is referred to the original report (Element Energy 2013).

The assumption is thereby made that the clusters with lower social grades have a very low or null propensity to invest in low carbon technologies, hence why only five of the archetypes are optimised. The number of occupants is taken from the source, except in the case of the Practical Considerations cluster where it is increased to 5 (from 4) in order to give a wider range of occupancies from 1 to 5. The dominant dwelling type for the household is taken from the source and in cases where no one building type is dominant an attempt is made to ensure that a balanced selection of buildings is present. It is further assumed that all of the DHAs have a gas boiler (the most dominant type of heating in the UK) as their existing heat and electricity supply technologies in combination with electricity from the network. This assumption is justified due to the fact that only 0.06% of dwellings have heat pumps (CAR 2013), an average of 120 residential PV installations are installed per 10,000 households, and the existing installed mCHP capacity is also very low at a maximum of 19 kW_{el} amongst 70,000 households (DECC 2015).

The last stage in specifying the DHAs is to define the building characteristics, which are taken from the Cambridge Housing Model 2012 (CHM: CAR 2013). For each dwelling type given in Table 1 a typical building configuration is taken from the model, including metabolic rates, heat emission rates, ventilation rates, heating system limitations, maximum shading factor, temperature data series etc. Certain attributes are defined by both HEUS and CHM archetypes (1. number of occupants, 2. dominant building type, 3. floor area, 4. building age). A link between HEUS and CHM archetypes was established by filtering the list of CHM archetypes for the four above attributes. Building parameters required by CHAP model were then obtained by calculating the mean or mode value of the remaining CHM archetypes. Heating regime data (daily heating periods, set point temperature and heating months) was generated by the help of EFUS data (DECC 2011). Further parameters required by the SH model not provided by the CHM (e.g. differentiated metabolic rates, heat emission rates, ventilation rates, heating system limitations, maximum shading factors, temperature data series etc.) were obtained by consulting different sources. The complete process of data retrieval is explained in greater detail in Hofmann et al. (2016).

c. Derivation of neigbourhood archetypes

In this section the method for clustering neighbourhoods at the Output Area (OA) level is presented. Census 2011 data relating to dwelling type, tenure and household structure at the Output Area level have been used as assembled and published by the Centre for Sustainable Energy (CSE, 2015). The first step in using these data involves pre-filtering all of the OAs in England and Wales that either contain mostly flats (including private rented and social housing) and/or are characterized as having a high proportion of the population in lower socioeconomic groups[2]. This process relies on the 2011 Output Area Classification, which categorizes OAs into 8 supergroups, 26 groups and 76 subgroups based on various socioeconomic criteria (as documented in the "pen portraits", ONS 2015). Only those subgroups were retained that contained at least 60% of owner-occupied, non-flat type buildings, resulting in reducing the total number of OAs from 181,409 to 79,962 (cf. footnote 2).

Based on the remaining 79,962 OAs a two-stage cluster analysis was performed using SPSS, using the log-likelihood distance measure and the Bayesian Information Criteria (BIC) quality measure (Zelterman 2015). The cases were randomly sorted prior to clustering in order to avoid order effects and the number of clusters determined automatically based on the above criteria. This analysis was carried out with many combinations of variables contained in the OA data and the best results were obtained with the following variables: households per unit of area, percentage of detached, semi-detached and terraced dwellings respectively, and weighted average floor area per dwelling. The latter variable was determined as the weighted average of the product of the percentage of a given dwelling type and the national average floor area for this type in the English Housing Survey 2012 (DCLG 2014). With these configurations the cluster analysis identified three OA clusters as defined in Table 2 below with a cluster quality of 0.55, with 0 being poor and 1 excellent[3]. An additional, fourth cluster C0, is defined as the average (mean) over all 79,962 OAs.

[2] It should be noted here that also social housing organisations and energy cooperatives could decide to invest in and install LCTs in their buildings. Such initiatives are not considered in this analysis.
[3] For the sake of these clusters, it is assumed that one household inhabits one dwelling.

Finally, the DHAs are allocated to the three clusters based on the required number of dwellings of a given type and the weighted average floor area per dwelling, as defined in Table 3 below.

d. Optimisation of dwelling energy supply systems

The final stage in the employed methodology is the optimisation of the energy supply systems for the individual DHAs (cf. Figure 1 above). The employed model is a mixed integer linear program which minimizes the total system costs for energy supply and thus optimises the capacity and dispatch of the following decentralised LCTs: mCHP (gas internal combustion engine), heat pumps, PV panels, thermal storage tank, battery storage, gas boiler and grid electricity. The model methodology is documented in detail and applied to case studies of UK buildings in Merkel et al. (2015) and is therefore not described in any detail here. The main extension beyond the model version presented in this source relates to the inclusion of PV and battery storage systems as documented in McKenna et al. (2016). The basic techno-economic assumptions employed in the model for the present case are the same as in this source. Hereby the load and irradiation profiles from the CHAP model are provided as a crucial input to this optimisation model (Figure 1), as the model functions on the basis of demand fulfillment.

Finally, it should be noted that, whilst the model optimises the energy supply system for a given object/building, it does this for pre-defined technology configurations. That is, the selection of individual LCTs is only optimised insofar as these technologies are available in the first place. Hence while the system setup in terms of capacity and dispatch is optimal for any given configuration, it is not necessarily the most economic configuration. For the purposes of the current study, where the focus lies on thermal and electrical LCTs with a strong interaction with the local electricity network, the following technology configurations (“systems”) are defined based on sensible combinations of technologies[4]:

1. **REF:** Boiler + thermal storage + grid electricity

[4] E.g. a combination of heat pumps and CHP units is not considered practical.

2. **CHP:** CHP + boiler + thermal storage + grid electricity + PV + battery storage
3. **HP:** Heat pump + boiler + thermal storage + grid electricity + PV + battery storage

Also note that, for reasons of limited space in residential buildings, the thermal storage size is capped at 500 l. As already noted, only the five of the seven DHAs are optimised, as shown in Table 1 above.

Hence by employing the CHAP model described above, a set of electrical and heat profiles for each DHA is generated as input to the optimisation model. The total number of profiles is chosen so that any one profile, i.e. with the same load profiles and heating pattern/temperature, appears in a cluster a maximum number of four times. This results in the number of profiles per DHA and LCT system shown in Table 3.

Figure 2 below shows the optimised capacity dimensions and total annual costs for DHAs 3-7, averaged over the number of profiles given in Table 3. System 3 with heat pumps is consistently around 50% more expensive than system 2 with mCHP. The thermal storage is typically dimensioned as large as possible and does not differ significantly in size between these two cases. In addition, the respective size of the main heat supply unit (CHP or heat pump), peak load boiler and thermal storage depends on the overall thermal heat demand (Table 1).

The final stage in the methodology relates to the definition of scenarios for technology penetration. These scenarios are defined in Table 4, whereby for scenarios 2-5 those households to be optimised are randomly selected from the set of similar households (i.e. DHAs).

4. Results

Figure 3 shows the electrical load profiles in the baseline scenario for the three clusters C1-C3 as well as C0 and the Domestic Unrestricted standard load profile (SLP) (Elexon 1997), for three days in summer (top) and winter (bottom) respectively. In general there is a good agreement between the simulated load profiles for the clusters and the SLP. On average, the profile of C3 is up to about 0.2 kW higher than the SLP, whereas that for C2 is up to about 0.2 kW lower. The timing of the morning and evening peaks is correct, but their magnitude differs between clusters as discussed in the following section.

Figure 4 below shows the electric load profiles for the 25% scenario in the three neighbourhood clusters, for three weekdays in summer (top) and winter (bottom) respectively. The standard load profile is also shown for reference. Only this one scenario is shown for clarity as well as because, of all the scenarios, this seems to be the most realistic one (also returned to in section 4). The three profiles are significantly different from those in the baseline case. In summer, the lower residual load profiles due to PV generation during the middle of the day are clearly visible, whereby this is highest for cluster C3. The differences between clusters is more pronounced in winter, when especially for C2 and C3 the morning and evening peaks lie above the SLP, in the latter case by about 50%. For example, the peak load of C3 is around 1.4 kW compared to 1.2 kW and 0.9 kW for C1 and C2 respectively, and the mean load also exhibits the same trend (cf. Figure 6). Again, during the midday hours, all three clusters lie below the SLP, but do not exhibit the diversity seen in summer.

The residual load profile for individual households is defined here as positive in the case of a load on the network and negative for feed-in. The aggregated residual load profile is determined by summing up the individual residual load profiles and normalizing the result based on the number of households in the respective cluster. Figure 5 shows the sorted load duration curves thus determined for all C1 and 25% scenarios for one year.

The increasing LCT penetration results in a steepening of the residual load curve and a higher number of hours in the year with peak and negative values. The curves shown in Figure 5 show a reasonable agreement with the SLP for low LCT penetrations (scenarios C1_B and C1_25) but above 50% there are significant deviations. In general, these higher LCT penetrations tend to shift the residual load curve downwards for most hours of the year (except the several hours of peak load). The lower three curves in the right hand bottom corner of Figure 5 represent the penetrations of 50%, 100% HP and 100% CHP respectively. The number of hours with negative residual load is roughly the same for these three scenarios, at about 1,500. Significant differences between the three scenarios are also clear from the figure, namely that C3 exhibits the most extremes in peak and minimum hours, whereas C1 and C2 are very similar in low load hours, only diverging somewhat in the peak hours. Finally, the 100% HP scenario results in the greatest increase in peak loads (top left of the figure, with the intercept being at about 2 kW compared to 1 kW for the SLP), whereas the 100% CHP scenario results in the largest negative residual loads (down to about -1.1 kW, bottom right).

Figure 6 depicts some key statistical parameters, namely mean, minimum, maximum and standard deviation, for all scenarios and SLP. Whilst there is a general trend towards lower minimum (i.e. higher feed-in) and higher maximum loads with increasing LCT penetration, this is not wholly the case. For example, for C1 and C2 the minimum load is significantly lower with 100% CHP compared to 100% HP, which is not the case for C3. Instead, the latter has closer minimum and maximum values across the three scenarios 50%, 100% CHP and 100% HP. Generally speaking the LCT penetration results in a lower mean load as well as a higher standard deviation.

An important criterion for dimensioning electrical distribution networks is the peak load per household. In this context it is helpful to distinguish between the maximum concurrent and non-concurrent loads, whereby the ratio of the two is known as the Diversity Factor (DF). Hence Figure 7 shows the maximum non-concurrent and concurrent loads per household as well as the corresponding diversity factor for all the scenarios listed in Table 4, both normalized with the number of households in the neighbourhood. Whilst the former is determined by summing up the maximum individual household loads within the cluster, regardless of their temporal correlation, the latter relates to the simultaneous maximum load occurring within the cluster/neighbourhood.

The Diversity Factors are in the range from 2.7 to 4.2, with the average (mean) of 3.5. The trends across the three clusters are somewhat similar, i.e. the lowest diversity factors are encountered with the highest (100%) penetration of HP or CHP devices. With LCT penetrations up to and including the 50% scenario, the DF is substantially lowered in clusters C1 and C3, whereas the effect in C2 is actually to slightly increase the DF. Whereas the lowest DF is encountered with 100% CHP in clusters C1 and C2 (at 2.7 and 2.9 respectively), for C3 the lowest value of 2.7 corresponds to the 100% HP scenario.

In addition, Figure 8 below shows the maximum concurrent total load per household for all of the scenarios relating to selected clusters and LCT penetrations. This is determined by picking the number of households shown at random from the cluster for 100 iterations, and building the minimum, mean and maximum values, which are shown with error bars in the chart. The maximum concurrent load, known as the After Diversity Maximum Demand (ADMD), reduces rapidly with the number of households, and in general there is also a marked reduction in the range of peaks encountered. In addition, the technology penetration scenario has a strong effect on the encountered peak load. Especially those scenarios with a high penetration of HP seem to influence the maximum concurrent load, such that with 50% HP and above, the asymptote seems to be higher than 2 kW. In comparison the asymptote is somewhat below this, at around 1.4 kW, in the reference scenario (C1_B). In addition, the difference between the clusters in terms of the diversified peak load in the 25% scenario can be seen at 20 households, where clusters 1-3 have ADMD values of 1.7, 1.3, and 1.8 kW respectively.

5. Discussion

a. Discussion of results

Whilst the cluster load profiles exhibit some agreement with the SLP, there are some key differences. Firstly, the cluster profiles have a lot more "noise" (i.e. are less smooth) than the SLP, which is due to the averaging of only about 130 households to determine them. This phenomenon has also been encountered in other studies with a similar number (230) of households (e.g. Jenkins et al. 2014). Wherever individual, (partly) stochastic profiles are aggregated, this characteristic is expected, whereby the larger the population, the smoother the resulting profiles.

The differences between the load profiles of the individual clusters can be explained as follows. C3 is dominated by larger, detached dwellings containing DHAs 3 (Lavish Lifestyles), 6 (Off-Peak Users) and 7 (Peak-time Users) (cf. Table 1 and Table 2). These households have a medium or high occupancy, building floor area, and social grade, as well as number of electrical appliances, resulting in a higher than average annual electricity consumption. It is therefore not surprising that the load profile for this cluster tends to be above both the standard and C0 profiles. On the other hand, C2 is dominated by terraced dwellings containing smaller than average households in terms of occupancy, floor area, number of appliances and total annual electricity consumption (i.e. mainly DHAs 2, Thrifty Values, and 4, Modern Living). Generalizing across this cluster is difficult, though, due to the substantial presence of DHAs 4 (Modern Living) and 7 (Peak-time Users), whereby especially the latter has a relatively higher number of appliances and annual consumption. Finally both C1 and C0 are very close to the standard load profile and therefore each other, both in terms of the statistics and the profile shape (although C1 has a higher peak). This is due to the fact that the latter is an average over all employed OAs and the former also represents an average amongst the clusters in terms of dwelling type, size, and household combinations (cf. Table 2). This would seem to support the selection of these three clusters, as the extreme cases C3 and C2 tend to cancel each other out, so that on average a good agreement between C1 and C0 is given. In addition, all of the generated clusters seem to exhibit a higher peak in the evening hours compared to the standard profile, especially in summer. This is likely to be due to the lack of seasonal differentiation in the UK time-use data, and therefore also in the occupancy profiles employed in the CREST 1.0 model (Richardson et al. 2010), returned to in section 5.b.

It is also noteworthy that the same technology penetrations have quite different effects on the three clusters. If one considers the 25% scenario as the most realistic for the near term future, due to the proportion of dwellings affected and the fact that all dwellings will most likely not install LCTs, it can provide some useful insights. The greatest effect on the neighbourhood load curve and the Diversity Factors is encountered for clusters C1 and C3 in this scenario. This is thought to be due to the nature of this cluster, containing generally larger, higher-consumption houses, which means the LCTs installed can be dimensioned larger. Cluster C3 is also the only cluster which exhibits significant negative loads on a neigbourhood level in this 25% scenario, as well as substantially higher peaks compared to the SLP. Whilst the former is strongest in summer, the latter is more pronounced in the winter months, when heating is relevant.

In general the largest impact on the load profile characteristics is encountered with 100% respectively of HP or CHP. Cluster C3 is marginally more sensitive to CHP, whilst having similar statistical characteristics in the three scenarios 50%, 100% CHP and 100% HP, whereas the load profiles of C1 and C2 react more strongly to CHP units (cf. Figure 6). This is particularly the case for cluster C2, in which the 50% scenario has a much smaller relative impact on the overall load profile compared to the same scenario for the other two clusters (especially in terms of negative loads). This is thought to be due to the fact that C2 contains predominantly smaller, terraced dwellings, and a smaller proportion of optimised heat supply systems – around 50% of dwellings compared to about 80% in the clusters C1 and C3 (cf. Table 3). The high negative loads in the case of HP scenarios result solely from PV systems feeding into the grid, whereas in the case of CHP scenarios they can result from both PV and CHP feed-in. However, the two are unlikely to be superposed due to their diurnal profiles, such that the large negative loads as seen in scenarios C1_100_CHP and C3_100HP are thought to be due to the larger-dimensioned PV systems due to larger roofs (cf. Figure 2).

Given that two of the three clusters (i.e. C1 and C3) already differ from the SLP in the baseline scenario, it also makes sense to compare the technology penetration profiles with these baseline cases. The shift to the 25% scenario can be interpreted in this context as moderate in both of these clusters, especially in terms of the increase in mean and peak loads. The associated increase in negative feed-in is moderate compared to stronger LCT penetrations. In addition, given that a higher Diversity Factor is attractive from a network planning perspective, these results seem to suggest that a maximum level of penetration of 25% each of HP and CHP (i.e. 50% in total) is feasible to maintain the DFs at the level of the baseline clusters. But it would be impossible to assess the capability of the network to absorb these power flows without a detailed power flow analysis (considered beyond the scope of this paper). Also, whilst the actual asymptote in the 100% HP scenario does not seem much higher than in the baseline scenario (cf. Figure 8), the variation in the maximum concurrent peak load is noticeable: in all scenarios other than C0 and C1_B this variation is very high.[5] Hence from a network perspective this would therefore suggest a degree of diversity in supply would be advantageous in terms of enabling these technologies to be integrated.

b. Discussion of methodology and further work

The guiding principle behind the developed methodology is to achieve a superior socioeconomic differentiation between dwellings and neighbourhoods in terms of their demand for heat and electricity. This section highlights some of the weaknesses associated with the employed methodology and suggests possible improvements. Other than to mention that the economic optimization does not necessarily determine the most environmentally optimum configuration, other related weaknesses are not included here. Instead the reader is referred to Merkel et al. (2015) and McKenna et al. (2016), in which they are discussed at length.

As well as differentiating between the number of occupants (and day type and season) as in the original CREST 1.0 model, the CHAP model developed here considers several additional aspects. Firstly, based on the DHAs, the number and type of appliances, as well as the building type and floor area are considered. Secondly, the CHAP model differentiates between heating patterns and internal set temperatures based on the EFUS study (BRE 2013). Whilst there is a strong link between these first variables and the HEUS study, the second variables relating to heating behaviour had to be inferred. This means that the actual heating behaviour of individual households was not captured. Whilst for individual households the assumed heating behaviour will most likely be incorrect, on an aggregated neighbourhood level the diversity in heating behaviour should be well represented. An

[5] Incidentally, the reason for the asymptote in **Error! Reference source not found.** being somewhat below the 2 kW typically employed for UK context is thought to be due to the updating of appliance ownership and characteristics for the DHAs, as documented in Hofmann et al. (2016).

alternative approach, which would also ensure accuracy for individual buildings, would be to employ the raw data from the EFUS (DECC 2011) in order to develop DHAs, but this data was not available at the time of carrying out this work.

It should also be noted here that the building type employed for the DHAs represents an average and/or dominant building type within the individual HEUS Archetypes (cf. section 3). In practice, households clearly inhabit different building types, such that an average across a cluster of households is not very meaningful. The use of a single set of average building characteristics (dimensions, u-values, etc.) for multiple simulated dwellings leads to a lower variety in generated SH demand profiles. But the link between households and dwellings is not trivial. The English Housing Survey (DCLG, 2014) gives some general insights into the types of households that inhabit different types of buildings, but it is difficult to generalize across variables such as employment status and income level etc. Hence further research is required to better understand the link between households and dwellings in the context of residential and neighbourhood heat and electricity modelling.

The CHAP simulation does not consider several important aspects of residential electricity and heat use. Firstly, seasonal variations in occupancy effects are not considered due to a lack of granularity[6] in the original time-use data employed to derive transition probability matrices between occupancy levels and appliance activity profiles (Richardson et al. 2010). This results in the seasonal effects of energy use, whereby households tend to spend more time indoors in the colder, darker winter months than in the summer, being underestimated in the winter and overestimated in the summer. The effect relates solely to electricity and DHW use, however, as the SH demand only occurs during the defined household-specific heating season. An amelioration of this effect would require more detailed time of use data and/or a higher granularity in other areas, such as the number of people

[6] Granularity is used here to refer to the spatial and temporal resolution as well as the level of detail employed to capture households/dwellings and LCTs.

per household or the type of day, both of which are currently not readily available and are thus considered beyond the scope of this work.

Secondly, the appliance use frequency is defined in the model according to the total number and types of appliances, as well as their cycle characteristics. The frequency of use of appliances, in terms of the number of cycles for which they operate over the year, is then calibrated to match the overall target annual electricity demand. Hence explicit use frequencies of appliances, which are differentiated by households are not considered. In addition, the correlation of appliance use is not considered by the model. For example, adding a second TV to a dwelling does not only reduce the use frequency of the first TV but of all other electric appliances. This is obviously mainly due to the lack of data at this level of detail; even with smart meter data at the level of the household, it is very challenging to determine the load profiles of individual appliances. But initial research in this area has obtained some valuable insights and may have opened up a new avenue for further research (Boßmann et al. 2015).

Thirdly, the link between the heat and electricity models does not extend to electrical heating technologies and showers. This means that, for example, whilst a boiler circulation pump is typically present in the appliance configuration of the analysed dwellings, the use of this appliance is not correlated with the use of the heating system. In addition, where an electric shower is present its use is not correlated with the DHW runoff profiles for the shower. In both cases, the total electricity use of the appliance over the course of the year, as well as the cycle specifications (length and average power) are thought to be accurate, and their time and duration of operation is determined by appropriate activity profiles. Hence the effect of this discrepancy is thought to be insignificant.

Fourthly, the model focusses on the supply side and thus does not consider the potential to modify the thermal characteristics of the building through renovation/insulation measures. Such measures might in practice be more economical than supply-side measures, but might not be realized because of barriers such as split incentives or lack of/imperfect information. The effect would be to reduce the overall annual heat demand of the building and thus decrease the optimal size of a heat supply technology for the building. Whilst excluded from the scope here, such measures could be included in future work by including standardized insulation measures in the optimisation model, which vary according to the cost per saved unit of heating energy.

The socioeconomic grade of the households is captured through the use of the HEUS Archetypes, which differentiates between National Readership Survey (NRS) classes. This is reflected in the specification of the DHAs in terms of appliances ownership and use, as well as their propensity to invest in LCTs. The latter represents a binary variable in the present case, with five of seven archetypes being likely to invest in these technologies. In practice, actual households would be expected to have a willingness to invest which is continuous and varies between 0 and 1, and an investment in the context of social housing organizations and/or energy cooperatives would be feasible. This might be reflected by their expected (discounted) payback period and/or discount rate employed with respect to LCT investments, both of which would differ between households. Some progress in this area has been made by Cayla et al. (2011) Cayla & Maizi (2015), who have analysed these distinctions based on survey in the French context and partly implemented them in the French TIMES model. Interestingly, they found that, whilst the willingness to invest in new space heating equipment actually increases with household income, the required rate of return also increases, in contrast to the results for vehicles and refrigerators. Such a differentiation in the present case would be feasible in terms of the discount rate, but was not employed due to the requirement of limiting the number of combinations (between DHA, technology system, and load profiles) to a manageable level. It thus remains an area for further work, to be explored in the context of coupling the approach presented here with larger energy system models.

In addition, the representativeness of the DHAs of the UK/English residential sector should also be questioned. The 250 households included in the survey were mainly owner-occupiers, which would explain the tendency to somewhat larger detached, semi-detached and bungalow type dwellings. The compromise of this bias in the input data was accepted in the present case because of the richness it provides for individual households. Because of the focus on OAs with owner-occupiers in this study, the effect of employing this input data is not thought to be significant.

One final aspect, which could not be addressed in the present case, is the interaction between individual dwellings through the local electrical distribution network. In determining residual profiles for individual dwellings and summing these to an aggregated neighbourhood profile, the implicit assumption is made that the distribution grid is able to manage these power flows. Without a detailed depiction of this electricity network and a dynamic modelling of these power flows it is impossible to critically assess the validity of this assumption. Hence such a detailed network simulation remains an area for further work.

6. Conclusions and policy implications

Whilst Low Carbon Technologies (LCT) at the heat/electricity interface have significant potential to reduce CO_2 emissions in residential buildings, their adoption is strongly dependent on non-technical factors (especially socioeconomic grade, as considered here) and they have significant interactions with the overarching energy system. Two types of these interactions are addressed in this paper. The first is at the level of the distribution network, where the combination of households, dwellings and neighbourhoods affect the exploitation of LCTs and thus the aggregated load profiles in these networks. This has implications for the design and operation of distribution networks. The second is the interaction between the distribution grid and the overarching energy system, for example through the dimensioning and operation of transformers to/from higher voltage levels as well as in terms of the respective environmental attractiveness of different LCT measures (e.g. the electricity mix from a centralised system strongly affects the attractiveness of heat pumps). Hence decisions made at the household and dwelling level, as well as the characteristics of the neighbourhood itself, can impact the ability of the distribution and transmission networks to accommodate increased capacities of LCTs in the future. These interactions between household/dwelling, neighbourhood and whole energy system levels require a detailed understanding of both electricity and heat loads in modelling of technology deployment, if investments in distribution and transmission network infrastructure are to be appropriately made.

In order to adequately account for these interactions it is necessary to capture the granularity associated with decentralised heat and power supply in residential buildings. On the one hand, this relates to purely technical factors, such as the number, type, age etc. of buildings and the associated technology characteristics. On the other hand, it means considering the socioeconomic diversity between dwellings and within neighbourhoods. At the local level this technical and socioeconomic diversity has strong implications for aggregated/residual electrical load profiles in distribution networks. The approach presented here adds novelty in terms of this socioeconomic differentiation by employing dwelling/household archetypes (DHAs) and neighbourhood clusters at the Output Area (OA) level. It thus allows a realistic level socioeconomic diversity at the dwelling/household level to be captured at the neighbourhood and national levels. Hence the modelling approach captures both types of interactions reasonably well: the effects of this diversity, both within the distribution network on the After Diversity Maximum Demand (ADMD) and from the perspective of the transmission network (overarching energy system) on the aggregated neighbourhood load profiles (as compared to the Standard Load Profile), are quantified. Whilst the four parts of the developed approach have each been validated to different degrees (cf. Figure 1 for sources), the detailed presentation and validation of the CHAP model will be the subject of a forthcoming contribution.

Even in the baseline case, i.e. without any LCT penetration, a substantial deviation from the SLP is encountered, suggesting that for some neighbourhoods this profile is not appropriate. Whilst there is a good agreement between the phase of the simulated load profiles for the clusters and the SLP, on average, the profile of C3 is up to about 0.2 kW higher than the SLP, whereas that for C2 is up to about 0.2 kW lower. These differences are due to the predominance of one type of DHAs within these clusters, i.e. larger, detached dwellings in C3 and smaller, terraced dwellings in C2, whereas C1 is most similar to the average C0. This deviation also supports the distinction between neighbourhood clusters rather than adopting an average neighbourhood across all OAs (as, apart from having a lower minimum load, the average is closely aligned with the SLP). With the application of LCTs, as quantified here, this effect is much stronger, including more negative residual load, higher maxima, more variability, and higher ramps with increasing LCT penetration. Such effects are already encountered with only moderate levels of LCT penetration and, significantly, differ between neighbourhood clusters. Whilst a 25% penetration of HP and CHP respectively would be expected to modify the neighbourhood load profile substantially, the effect on the Diversity Factor is demonstrably moderate. This implies that a mix of different LCTs, especially heat pumps, mCHP units and PV systems, is better than just one and suggests that the electrical distribution network in these neighbourhoods might be able to manage the additional and modified power flows. But the analysis of the exact implications for the distribution network of an increased LCT penetration requires a detailed power flow simulation.

The primary policy implication of the study is the importance of understanding electrical load profiles at the neighbourhood level, because of the consequences they have for investment in the distribution infrastructure. Secondary policy implications relate to the consequences of socioeconomically diverse neighbourhood loud profiles for the overarching energy system, especially transmission infrastructure and centralised generation plant. This understanding relates especially to the temporal variability and higher or lower peak loads at the neighbourhood level, both of which are strongly influenced by socioeconomic characteristics. Households' socioeconomic grade has a large impact on the dwellings and neighbourhoods they live in as well as their predisposition to invest in LCTs. Even without LCTs, this leads to different neigbourhood peak loads, mostly due to differently-sized dwellings, numbers and types of electrical appliances. With the addition of LCTs such as heat pumps and mCHP units, not only the individual and neighbourhood peak loads are further affected, but also their temporal occurrence, which is strongly dependent on the LCT employed. Temporal variability and peak loads influence both the best deployment of technologies and the need for interlinkage and grid back-up of distributed LCT solutions. It could be that a more differentiated support system for LCTs is more economically efficient than the current one. Instead of remunerating solely based on technology and capacity, such a scheme would also consider the location and/or type of neighbourhood in which the technology is deployed. But it would be speculative to draw this conclusion from this work, which only represents a first step in this direction. As such, there are several areas where future work should focus. These include a better socio-economic differentiation between households, beyond the socioeconomic grade, size of household and dwelling employed in this paper, to also consider, for example, household structure, age and employment status. Hence future work should especially focus on the following aspects:

a. Their willingness or intention to invest in technologies, as manifested for example in the households specific discount rate or expected rate of return (Cayla et al. 2011, Cayla & Maizi 2015),
b. The link between dwellings and households: this is not important for individual buildings, what is required is an adequate representation of (socioeconomic/household and technical/building) diversity at the neighbourhood level, and
c. Understanding individual appliance use and correlation effects. In particular this relates to the heat and electrical appliance characteristics included in the CHAP model. Their cycle characteristics, including average power and mean cycle duration, are not distinguished between households, instead being calibrated to an annual heat and electricity demand. In addition, interaction effects between multiple similar appliances (e.g. television) as well as heat and electricity systems (e.g. boiler circulation pump) are not well depicted.

In order to test the hypothesis that a regionally- and/or socioeconomically-differentiated support scheme might be economically more efficient than the current one, an interlinked analytical framework is required. This probably means a coupling of the approach presented here, including a linked electrical/heat load profile model, DHAs and neighbourhood clusters, with a national energy system model to understand how to meet very low levels of buildings emissions on a national level. In order to account for more vulnerable households and neighbourhoods, the presented approach could also be extended to cover neighbourhoods in lower socioeconomic groups. In such a model coupling the DHAs and neighbourhood clusters developed here would serve as demand classes in the national model, and iterations could involve the exchange of mutually dependent variables such as the electricity mix, fuel prices and the penetration of decentralised LCTs. The main contributions of this work towards this end are to augment existing studies on heat/electricity LCTs in residential buildings by socioeconomic factors, as well as providing a spatial differentiation enabling a scale-up and coupling with national models.

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References

Armstrong, M.M., Swinton, M.C., Ribberink, H., Beausoleil-Morrison, I. Millette, J. (2009): Synthetically derived profiles for representing occupant-driven electric loads in Canadian housing. – Journal of Building Performance Simulation 2, 1, 15–30.

Boßmann, T., Schurk, R., Schleich, J. (2015): Unravelling load patterns of residential end-uses from smart meter data, Proceedings of the ECEEE Summer Study on Energy Efficiency, 1–6 June 2015 Club Belambra Les Criques, Presqu'île de Giens, Toulon/Hyères, France

BRE (2013): Energy Follow-Up Survey 2011, Report by BRE on behalf of DECC.

Cambridge Architectural Research (CAR, 2013): The Cambridge Housing Model 2012, Cambridge, UK.

Cayla, J.-M., Maizi, N., Marchand, C. (2011): The role of income in energy consumption behaviour: Evidence from French households data, Energy Policy, 39, 7874-7883

Cayla, J.-M., Maizi, N. (2015): Integrating household behaviour and heterogeneity into the TIMES-Households model, Applied Energy, 139, 56-67

Centre for Sustainable Energy (CSE, 2015): Heating and housing census data (at smallest output area level), data from the ONS Census 2011, prepared and supplied by CSE, https://www.cse.org.uk/projects/view/1259#Lower_Super_Output_Area_data, checked 02.10.15.

Centre for Sustainable Energy (CSE, 2016): The National Household Model: DECC's new computer model of the whole GB housing stock, project overview, https://www.cse.org.uk/projects/view/1233, checked 01.02.16.

Department for Communities and Local Government (DCLG, 2014): English Housing Survey 2012-2013, London.

DECC (2011): Energy Follow Up Survey, 2011 (survey data). London: Department of Energy and Climate Change and Building Research Establishment. http://doi.org/10.5255/UKDA-SN-7471-2

DECC (2015): Sub-national Feed-in Tariff Statistics, Q2 2015, Excel Table, checked 16.12.15. https://www.gov.uk/government/statistical-data-sets/sub-regional-feed-in-tariffs-confirmed-on-the-cfr-statistics

Druckman, A., Jackson, T. (2008): Household energy consumption in the UK: a highly geographically and socio-economically disaggregated model, Energy Policy, 36, 3177-3192

Element Energy (2013): Further Analysis of Data from the Household Electricity Usage Study: Consumer Archetypes, Final report for Department of Energy and Climate Change and Department for the Environment Food and Rural Affairs, 29 November 2013.

Elexon (Electricity Association) (1997): Electricity Demand User Profile Data, Nov-97, Ref: LR 1/6/1 (provided to UKERC courtesy of Elexon Ltd.), retrieved from UKERC Energy Data Centre, http://data.ukedc.rl.ac.uk/simplebrowse/edc/efficiency/residential/LoadProfile, checked 02.02.16, see also: https://www.elexon.co.uk/reference/technical-operations/profiling/, checked 02.02.16

Energy Saving Trust (EST, 2008): “Measurement of Domestic Hot Water Consumption in Dwellings”, DEFRA, London.

Fischer, D., Härtl, A. & Wille-Haussmann, B. (2015): Model for Electric Load Profiles With High Time Resolution for German Households, Energy and Buildings, 92, 170-179.

Gill, Z.M., Tierney, M.J., Pegg, I.M., Allan, N. (2010): Low-energy dwellings: the contribution of behaviours to actual performance, BRI, 38(5), 491-508

Grandjean, A., Adnot, J. & Binet, G. (2012): A review and an analysis of the residential electric load curve models, Renewable and Sustainable Energy Reviews 16, 9, 6539–6565.

Haldi, F., Robinson, D. (2011): The impact of occupants' behaviour on building energy demand, Journal of Building Performance Simulation, 4, 4, 323-338

Hayn. M., Bertsch, V. Fichtner, W. (2014): Electricity load profiles in Europe: The importance of household segmentation, Energy Research & Social Science, 3, 30-45

Hofmann, L., McKenna, R., Fichtner, W. (2016): Development of a multi-energy residential service demand model for evaluation of prosumers' effects on current and future residential load profiles for heat and electricity, Working Paper Series in Production and Energy, No. 11, February, IIP, KIT, http://www.iip.kit.edu/img/Hofmannetal_WP_Feb2016.pdf, checked 16.02.16

Hübner, G. M., McMichel, M., Shipworth, D., Shipworth, M., Durand-Daubin, M., & Summerfield, A. (2013a): The reality of English living rooms - a comparison of internal temperatures against common model assumptions, Energy & Buildings. doi:10.1016/j.enbuild.2013.07.025

Hübner, G. M., McMichael, M., Shipworth, D., Shipworth, M., Durand-Daubin, M., & Summerfield, A. (2013b): Heating patterns in English homes: Comparing results from a national survey against common model assumptions, Building and Environment, 688-696.

Huebner, G., Hamilton, I., Chalabi, Z., Shipworth, D., Oreszczyn, T. (2015) Explaining domestic energy consumption – The comparative contribution of building factors, socio-demographics, behaviours and attitudes, Applied Energy, 159, 589-600

Jenkins et al. (2014): Synthesising electrical demand profiles for UK dwellings, Energy and Buildings, 76, 605-614.

Jones, R.V., Fuertes, A., Lomas, K. (2015a): The socio-economic, dwelling and appliance related factors affecting electricity consumption in domestic buildings, Renewable and Sustainable Energy Reviews, 43, 901-917

Jones, R.V., Lomas, K.J. (2015b): Determinants of high electrical demand in UK homes: Socio-economic and dwelling characteristics, Energy and Buildings, 101, 24-34

Kannan, R. and Strachan, N. (2009): Modelling the UK residential energy sector under long-term decarbonisation scenarios: Comparison between energy systems and sectoral modelling approaches, Applied Energy 86(4): 416-428.

Kelly, S., Shipworth, M., Shipworth, D., Gentry, M., Wright, A., Pollitt, M.,…. Lomas, K. (2013): Predicting the diversity of internal temperatures from the English residential sector using panel methods, Applied Energy, 102, 601-621. doi:10.1016/j.apenergy.2012.08.015.

Lucon O., D. Ürge-Vorsatz, A. Zain Ahmed, H. Akbari, P. Bertoldi, L., F. Cabeza, N. Eyre, A. Gadgil, L. D., D. Harvey, Y. Jiang, E., Liphoto, S. Mirasgedis, S. Murakami, J. Parikh, C. Pyke, and M. V. Vilariño, 2014: Buildings. In: Climate Change 2014: Mitigation of Climate Change. Contribution of Working Group III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change

[Edenhofer, O., R. Pichs-Madruga, Y. Sokona, E. Farahani, S. Kadner, K. Seyboth, A. Adler, I. Baum, S. Brunner, P. Eickemeier, B. Kriemann, J. Savolainen, S. Schlömer, C. von Stechow, T. Zwickel and J.C. Minx (eds.)]. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA.

McKenna, E., Krawczynski, M., Thomson, M. (2015): Four-state domestic building occupancy model for energy demand simulations, Energy and Buildings, 96, 30-39.

McKenna, R., Merkel, E., Fichtner, W. (2016): Energy autonomy in residential buildings: a techno-economic model-based analysis of the scale effects, Applied Energy, article in press.

Merkel, E., McKenna, R., Fichtner, W. (2015): Optimisation of the capacity and the dispatch of decentralised micro-CHP systems: a case study for the UK, Applied Energy, 140, 120-134.

Nielsen, T. R. (2005): "Simple tool to evaluate energy demand and indoor environment in the early stages of building design", Solar Energy, 78, 73-83.

OECD/IEA 2011: Technology Roadmap: Energy-efficient buildings: Heating and Cooling Equipment, IEA, Paris.

ONS (2015): Pen Portraits for the 2011 Area Classification for Output Areas, Office for National Statistics, Newport, Wales.

Palmer, J. Cooper, I. (2013): United Kingdom housing energy fact file, DECC, London.

Richardson, I., Thomson, M., Infield, D. & Clifford, C. (2010): Domestic electricity use: A high-resolution energy demand model, Energy and Buildings 42, 10, 1878–1887.

Richardson, I., & Thomson, M. (2012). Integrated simulation of photovoltaic micro-generation and domestic electricity demand: a one-minute resolution open-source model. Proceedings of the Institution of Mechanical Engineers, Part A: Journal of Power and Energy, 227(1), 73–81. http://doi.org/10.1177/0957650912454989

Stamminger, R. (2008): Synergy Potential of Smart Appliances: D2.3 of WP 2 from the Smart-A project, Bonn.

Torriti, J. (2014): A review of time use models of electricity demand, Ren. Sust. En. Rev., 37, 265-272

Zelterman, D. (2015): Applied Multivariate Statistics with R, Springer, Switzerland.

Zimmermann et al. (2012): Household Electricity Survey: A study of domestic electrical product usage, Final Report Issue 4, Intertek Report R66141, Milton Keynes