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

R. McKenna[a,*], L. Hofmann[a], E. Merkel[a], W. Fichtner[a], N. Strachan[b]

[a] Chair of Energy Economics, Karlsruhe Institute for Technology (KIT), Karlsruhe, Germany
[b] UCL Energy Institute, London, UK

HIGHLIGHTS

- Low carbon technologies (LCTs) for heat/electricity in residential buildings.
- Socioeconomic effects and interactions with overarching energy system.
- Building thermal/electrical model combined with optimisation.
- Significant differences between neighbourhood load profiles.
- Policy implications: support for LCTs and investment in infrastructure.

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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) to generate optimum (minimum cost) technology configurations and operation schedules. Even in the baseline case, 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, including heat pumps, micro-CHP and photovoltaic (PV), 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, including transmission and distribution infrastructure, and centralised generation plant. Further work should focus on attaining a superior socioeconomic differentiation between households.

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 and 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

Abbreviations: ADMD, After Diversity Maximum Demand; BIC, Bayesian Information Criteria; CHAP, CREST Combined Heat and Power (model); CHM, Cambridge Housing Model; CHP, Combined Heat and Power; CSE, Centre for Sustainable Energy; DDM, Dynamic Dispatch Model; DF, Diversity Factor; DHAs, dwelling/household archetypes; DHW, Domestic Hot Water; EFUS, Energy Follow Up Survey; HEUS, Household Energy Use Study; HP, Heat Pump; HRP, Household Representative Person; LCTs, Low Carbon Technologies; mCHP, micro-Combined Heat and Power; MILP, Mixed Integer Linear Program; NHM, National Household Model; NRS, National Readership Survey; OA, Output Areas; PV, Photovoltaics; RC, (thermal) Resistance-Capacitance (model); SH, Space Heating; SLP, Standard Load Profile; WholeSEM, Whole Systems Energy Modelling

* Corresponding author.
E-mail address: mckenna@kit.edu (R. McKenna).

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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 and 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, 2016) 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 this differentiation. 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., 2015; for a spatial analysis for the UK see Druckman and Jackson (2008)). Haldi and 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 accounts for 51%, 37%, and 11% of the variance in heat, electricity and water consumption respectively. Despite these findings, some studies that have attempted to explain the variance in internal temperatures (Kelly et al., 2013) and energy demand (Hüebner et al., 2015) have been unable to fully do so. Kelly et al. (2013) are able to explain just 45% of the variation in internal temperatures using panel methods, and Hüebner 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. (2015) 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 and Lomas (2015) 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 and Lomas, 2015) confirms the above findings (Jones et al., 2015), 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