Assessing the implications of socioeconomic diversity for low carbon technology uptake in electrical distribution networks

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Russell Mckenna
ETH Zurich

Jann Michael Weinand
Forschungszentrum Jülich

Wolf Fichtner
Karlsruhe Institute of Technology

G. Strbac
Imperial College London

Assessing the implications of socioeconomic diversity for low carbon technology uptake in electrical distribution networks

McKenna, R.[1]*, Djapic, P.[#], Weinand, J.*, Fichtner, W.*, Strbac, G.[#]

*Chair of Energy Economics, Karlsruhe Institute for Technology (KIT), Karlsruhe, Germany

[#] Control and Power Group, Department of Electrical and Electronic Engineering, Imperial College London, UK

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. This paper combines dwelling/household archetypes (DHAs) combined with a mixed integer linear program to generate optimal (minimum cost) technology configurations and operation schedules for individual dwellings. These DHAs are scaled up to three socioeconomically differentiated neighbourhood clusters at the Output Area level in the UK. A synthetic distribution network generation and simulation assesses the required network upgrade costs for these clusters with different LCT penetration scenarios. Whilst the application here is to the United Kingdom (UK) setting, the method is largely based on freely available data and is therefore highly transferable to other contexts. The results show significant differences between the upgrade costs of the three analysed network types, and especially the semi-rural cluster has much higher costs. The employment of heat pumps together with photovoltaics (PV) has strong synergy effects, which can considerably reduce the network upgrade and carbon abatement costs if deployed in parallel. The determined CO_2-abatement costs also suggest that decarbonisation measures with these two technologies should focus on semi-urban neighbourhoods due to the lower cost in comparison to the semi-rural case. This shows that such a socioeconomically differentiated approach to distribution network modelling can provide useful energy policy insights.

Keywords

Low voltage distribution network; network upgrade; households; residential buildings; neighbourhoods, socioeconomic factors; low carbon technologies

[1] Corresponding author, email: mckenna@kit.edu, Tel. +49 721 6084 4582, Address: Building 06.33, Hertzstr. 16, 76187 Karlsruhe, Germany

1. Introduction

Residential buildings account for a major component of final energy demand and CO_2 emissions in many countries. 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). This paper focuses on a case study for the United Kingdom (UK), where the energy supply of households accounts for around 29% and 25% of final energy demand and CO_2 emissions respectively (Palmer & Cooper 2013).

Low carbon technologies (LCTs), such as micro-Combined Heat and Power (mCHP), heat pumps, and photovoltaics (PV) are especially promising in this context (OECD/IEA 2011). They enable efficient, decentralised low-carbon heat and/or electricity supply at the level of individual buildings or neighbourhoods. Their operation at the interface of heat and electricity systems means that these LCTs interact with local electricity infrastructure. Whilst these measures have significant technical and economic potential in residential buildings, the diversity within the building stock (i.e. between individual dwellings) as well as between individual households suggests a differentiated approach is required in order to assess their implications. Only by considering the effects of this diversity on residential energy consumption at the building and neighbourhood level, can meaningful insights into the potential impacts of these technologies be obtained.

In a previous study, a novel approach to analyse the possible effects of a diffusion of LCTs in residential buildings on electrical load profiles at dwelling/household and neighbourhood levels was presented (McKenna et al. 2016a). The approach includes the generation of socioeconomic dwelling/household archetypes (DHAs), which serve as the basis for an optimisation of supply-side LCTs in individual buildings. These DHAs are then scaled up to the neighbourhood level through a cluster analysis based on relevant socioeconomic variables at the Output Area (OA) level 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 at the low voltage distribution network level.

One shortcoming of the presented approach in McKenna et al. (2016a) is that it overlooks the distribution network infrastructure within neighbourhood clusters and instead analyses aggregated results by assuming a “copper plate” with no network constraints. However, previous studies have demonstrated the significant impacts that decentralised LCTs can have on low voltage distribution grids (e.g. Protopapadaki & Saelens 2017). Hence the current paper extends the approach from McKenna et al. (2016a) to analyse the implications for the low voltage (LV) distribution network in these neighbourhood clusters. The purpose of the distribution network modelling is to understand and quantify the impact of future load growth, including the impact of electrification of the heating sector, on necessary distribution network reinforcements. The approach to distribution network modelling is based on statistically representative networks rather than actual networks. This is motivated by the fact that the reinforcement cost in distribution networks tends to be driven by the network length, which can be expressed as a function of customer density, as well as the fact that detailed network topologies and characteristics are not widely available. The method allows the formulation of computationally feasible analytical models with only a minor sacrifice in terms of the accuracy when estimating reinforcement costs.

The literature review in section 2 demonstrates the research gap filled by this study. In particular, the paper presents a highly transferable approach to analyse the implications of technical and socioeconomic diversity at the dwelling/household level on the implications of decentralised LCTs at the neighbourhood level. The key novelties over existing contributions lie, firstly, in the combination of two discrete research areas, namely those relating to technical and economic factors of residential energy use and modelling of the impact of LCTs in low voltage distribution networks. Secondly, the approach is based on publicly available data and does not require proprietary network data, and is therefore in principle transferable to other areas. Thirdly, the case study in this paper is in the UK, whereas previous studies have only analysed other regions. The research question thereby posed is whether there are significant differences between the required network strengthening measures in these socioeconomic neighbourhood clusters and LCT penetration scenarios. This research question is explored in this paper in order to derive insights into cost-effective decarbonisation strategies for residential buildings at the local level.

The paper is structured as follows. The subsequent section gives a literature review relating to the modelling of LV distribution networks, with a particular focus on approaches that do not require detailed network data, followed by a discussion of socioeconomic influencing factors surrounding residential energy use. Section 3 then presents the methodology, with a particular focus on the derivation of DHAs and neighbourhood clusters, as well as the developed LCT penetration scenarios and the electricity network modelling. Section 4 presents the results and discussion, and section 5 closes the paper with a summary and conclusions.

2. Literature review

a. Low voltage network modelling in the absence of specific network data

Whilst there are some datasets available for singular instances (openmod 2016), distribution grid data is not widely available and in some cases even the distribution system operators themselves do not have detailed inventories. Instead, most applications in this area employ proprietary data and/or stylised representative grid topologies. For example, De Conick et al. (2014) and Baetens et al. (2012) apply similar approaches to the modelling of small neighbourhoods consisting of 33 households of four types, each of which is a Zero Energy Building (ZEB) through adequate sizing of heat pumps and PV systems, for which they employ the IEEE model distribution network. The focus in Baetens et al. (2012) is on the effects on the local distribution network of having a significant number of ZEBs in one neighbourhood. De Conick et al. (2014) employ a similar approach to analyse the potential for demand side management with heat pumps. In addition, Protopapadaki & Saelens (2017) extend these approaches to assess the impacts of PV and heat pumps on low voltage distribution networks as a function of building and district properties. Their contribution is similar to the present one, but with the following key differences: they focus on a statistically representative simulation of typical Flemish feeders, which limits the transferability of the approach; they do not asses the network reinforcement required to accommodate additional capacities of PV and heat pumps; and they analyse random combinations of parameters such as building types that do not (necessarily) correspond to actual residential areas.

Others have attempted to generate a distribution network automatically based on open data from Open Street Map (OSM). For example, Lüscher et al. (2012) discuss the problem and associated effort of continuously updating cadastral and electrical network maps, but acknowledge that the purpose of their paper is to "…open up a discussion about possible solutions rather than to present one". In addition, Mateo et al.'s (2011) contribution extends beyond this by presenting a method to generate a Reference Network Model (RNM) with OSM data. Based on the location of buildings within OSM the authors determine the location of distribution transformers and substations, and then plan and size the electrical lines, by using branch exchange algorithms. Electrical lines are constrained by an automatically calculated street map obtained using an algorithm based on a Delaunay triangulation, so that their paths resemble the street map of a city. In a subsequent contribution, the algorithms to address the problem of transformer substation placement within a greenfield RNM (Gonzalez-Sotres et al. 2013) are described.

Another thread of research in this area is concerned with the optimal sizing and siting of different LCTs within distribution networks. Within this field a central planner perspective is generally taken, which entails for example minimising the total system costs or CO_2 emissions for a given distribution network. Examples include those given by Torrent-Fontbona & Lopez (2016), who present a novel approach to optimise the number, size and type of LCTs within the network, and reviews of similar related work are given in Georgilakis & Hatziargyriou (2013) and Zubo (2016). The problem with such approaches is their adoption of a centralised planner perspective. Whilst this perspective principally offers a solution to the integration of many decentralised ICTs, it requires both the hardware (i.e. smart meters) and the customer willingness to be flexible. In the UK context of this paper, it seems reasonable to argue that neither of these are given. Instead, households individually adapt their energy supply differently and the network operator has to ensure network stability – in other words, he cannot control where, which and how many LCTs are installed, which is largely determined by the socioeconomic factors turned to in the following section.

b. Socioeconomic aspects of residential energy use

The discussion in McKenna et al. (2016a) demonstrated that socioeconomic factors have a strong impact on the energy use in residential buildings, including both the total annual consumption and its short term temporal profile. For example, 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). 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 accounts for 51%, 37%, and 11% respectively of the variance in heat, electricity and water consumption.

Additional socioeconomic, dwelling- and appliance-related factors which have a significant impact on electricity consumption in residential buildings include household and disposable income, number of occupants, and the age of the household representative person (HRP) (Jones et al. 2015a). Amongst the dwelling factors, 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. In addition, 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 (Jones et al. 2015b).

In terms of electrical load profiles, 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. Torriti (2014) points out that data relating to income, number of occupants, homeowner age and education are variously employed in residential electricity demand models (e.g. Richardson et al. 2010, 2012, Widen et al. 2009, Wilke et al. 2013). A similar approach to these models of residential energy demand based on time-use data is presented by Aerts et al. (2014) based on Belgian time-use data from 2005. They employ a clustering method to group similar time-use patterns according to day of the week and three socioeconomic criteria (age, employment and income), and identify seven distinct occupancy patterns for Belgium. Many other approaches to the statistical analysis of residential load profiles also employ socioeconomic criteria (e.g. Anderson et al. 2016, Boßmann et al. 2015, Rhodes et al. 2014).

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. However, the foregoing discussion illustrates that the precise energy consumption and its temporal profile of a particular building between these two extremes heavily depend on the socioeconomic characteristics of occupants and their behaviour.

3. Methodology

The discussion in the preceding section highlights the background for this study. Its original contribution lies in the combination of several methods in order to analyse the effects socioeconomic diversity at household and neighbourhood levels on LCTs in distribution networks. This section therefore gives an overview of the developed and applied methodology, as shown in Figure 2 and Table 1, which highlights the main data sources. The first subsection (3.a) presents the general approach to the derivation of household/dwelling and neighbourhood clusters developed in McKenna et al. (2016a). The subsequent subsection (3.b) presents the method for the generation and simulation of representative LV distribution networks for these neighbourhood clusters.

a. Dwelling and Household Archetypes (DHAs)

Figure 2 gives an overview of the employed methodology to derive DHAs and neighbourhood archetypes. For extensive details of the method the reader is referred to McKenna et al. (2016a) and for the models within the dashed rectangles in the figure to the given source, i.e. Hofmann et al. (2016) and Merkel et al. (2014, 2015) for the CHAP[2] and microtechnology optimisation models respectively. The CHAP model is a stochastic bottom-up electricity, space heating (SH) and domestic hot water (DHW) load profile simulation, which was extended beyond the original electricity-based model (Richardson et al. 2010) to include heating applications using a lumped-parameter thermal model (for SH) and occupancy profiles (DHW) by Hofmann et al. (2016). As input, it takes the geometric and thermal specification of buildings, the target annual demands for heat and electricity, as well as the number of occupants. CHAP is employed to generate electric and heat demand profiles in one minute resolution for the DHAs. These profiles serve as input to the microtechnology optimisation, which determines the optimal capacity and dispatch of pre-defined technology configurations. This microtechnology optimisation is a Mixed Integer Linear Program (MILP) that minimises the total system cost for these energy supply systems under key constraints such as demand fulfilment, generation and storage capacities and techno-economic technology specifications (Merkel et al. 2014, 2015). Subsequently, the residual load profiles for the DHAs are scaled up to the neighbourhood level based on a cluster analysis of Output Area statistics in the UK.

Seven DHAs are used in this analysis, based on Element Energy (2013). The assumption is thereby made that the archetypes with lower social grades have a very low or null propensity to invest in low carbon technologies, therefore only five of the archetypes are optimised (cf. Table 2). The number of occupants is derived from the source, except in the case of the Practical Considerations cluster where it is increased to five (from four) in order to give a wider range of occupancies from one to five. 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 types are present.

[2] CHAP: CREST Heat And Power, as the original model was developed by the CREST group at Loughborough University (Richardson et al. 2010).

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 2 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 the Household Energy Use Study (HEUS, Element Energy 2013) and the Cambridge Housing Model (CHM, CAR 2013) 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. The complete process of data retrieval from the CHM is explained in greater detail in Hofmann et al. (2016).

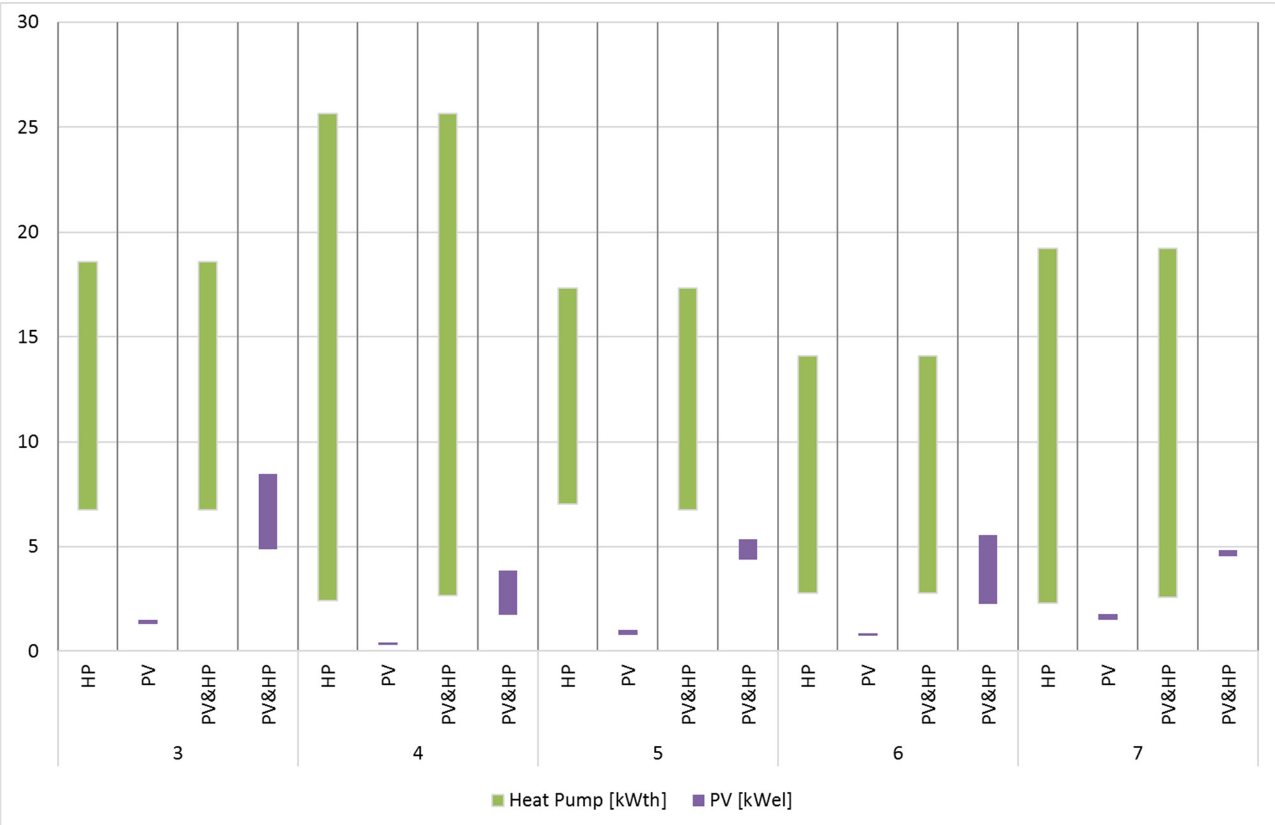


Figure 1: Ranges of installed PV and HP capacities for the five optimised DHAs in Table 2

Figure 1 gives an overview of the installed capacities of PV and HP systems for the 5 optimised DHAs from Table 2. It is clear from this table that the installed capacity of the PV systems is significantly higher when used in combination with heat pumps, whereas the installed heat pump capacity seems to be unaffected by the presence of PV. This observation is returned to in the discussion section.

Table 1: Overview of employed datasets and sources

Stage of method (cf. Figure 2)	Data input	Source
2. CHAP Model	Building configuration, including metabolic rates, heat emission rates, ventilation rates, heating system limitations, maximum shading factor, temperature data series etc.	Cambridge Housing Model (CHM, CAR 2013)
	Building type, occupancy, annual heat and electricity demand	Household Energy Use Study (Element Energy 2013)
3. Microtechnology optimisation	Techno-economic specification of micro-technologies	Manufacturers' specifications, industry literature, field tests (cf. Merkel et al. 2015)
	Energy-political framework conditions (i.e. feed-in tariffs), energy carrier price developments	Official documentation (e.g. from DECC) and assumptions documented in Merkel et al. (2015)
4. Cluster analysis of Output Areas	Socio-economic data relating to the composition, inhabitants and building stock in Output Areas of England and Wales	CSE (2015)
5. Network simulation	Cost assumptions for cables and transformers	OFGEM (2009)
	Empirical parameters for network configuration	Based on other steps of methodology, especially cluster analysis in step 4 (cf. Table 5)

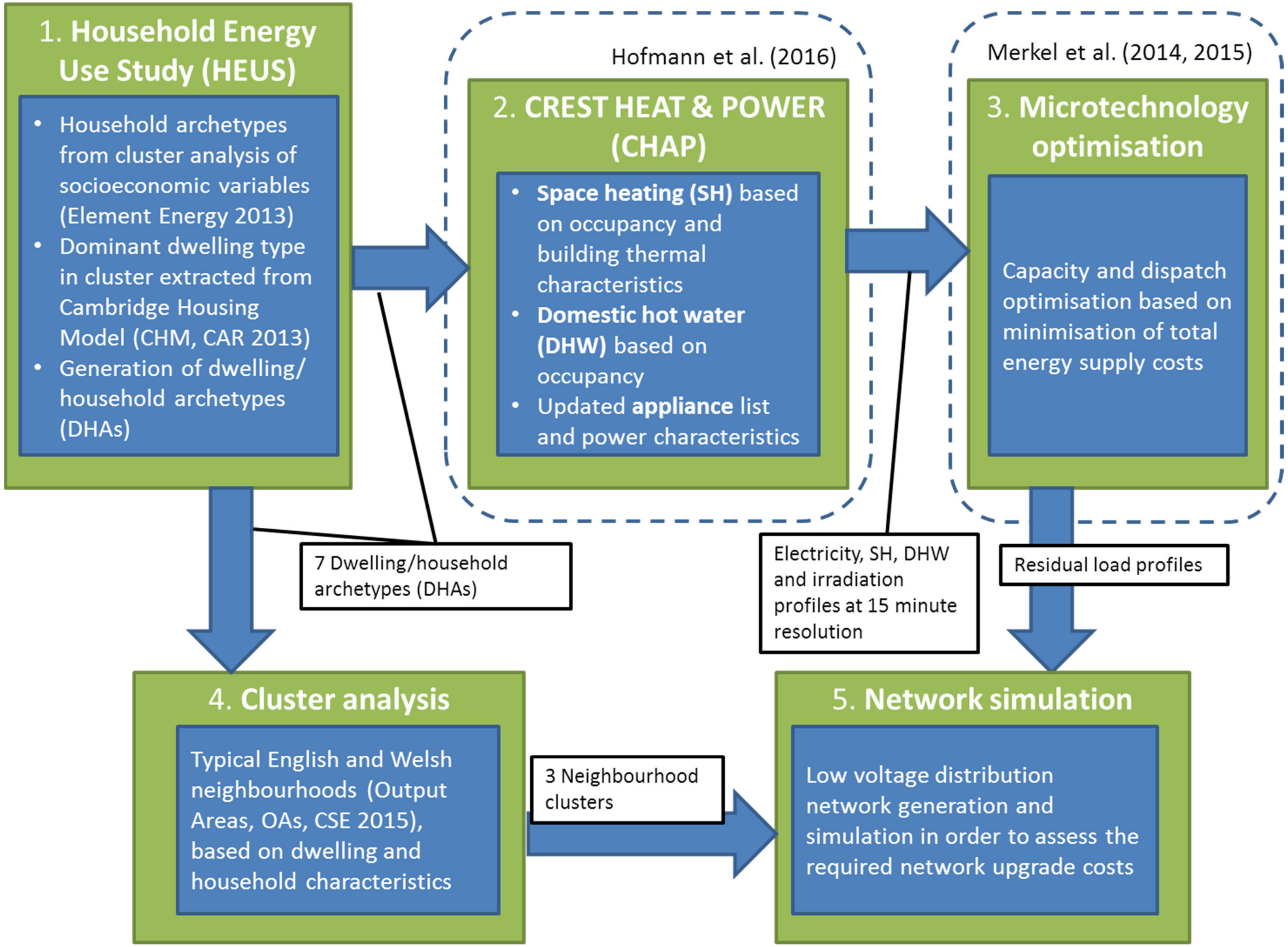


Figure 2: Overview of the employed methodology from McKenna et al. (2016a). Parts within dashed boxes are documented in detail in the given sources, so are not the focus of this paper.

Table 2: Overview of dwelling/household archetypes (DHAs), adapted from Element Energy (2013)

HEUS Archetype	No. of occupants	No. of electrical appliances	Average social grade[3]	Dominant building type	Internal floor area (m^2)	Existing technology	Future technology	Electricity demand (kWh/year)	SH demand (kWh/year)	DHW demand (kWh/year)
1. Profligate Potential (PP)	3	53	Low	Semi-detached	112	Boiler and grid	Boiler and grid	7,839	11,496	4,017
2. Thrifty Values (TV)	2	27	Low	Terrace	78	Boiler and grid	Boiler and grid	2,254	7,272	3,443
3. Lavish Lifestyles (LL)	3	53	High	Detached	169	Boiler and grid	Optimised	5,567	14,634	3,763
4. Modern Living (ML)	1	31	High-medium	Semi-detached	77	Boiler and grid	Optimised	1,868	5,882	2,750
5. Practical Considerations (PC)	5[4]	43	High-medium	Semi-detached	107	Boiler and grid	Optimised	4,084	9,868	4,424
6. Off-Peak Users (OP)	2	48	Medium	Detached	111	Boiler and grid	Optimised	3,491	12,175	3,828
7. Peak-time Users (PU)	3	47	Medium	Detached	97	Boiler and grid	Optimised	5,871	8,505	3,865

[3] National Readership Survey (NRS) categories
[4] In order to ensure a wide spread in the number of occupants across the employed archetypes, the number of occupants in the Practical Considerations archetype was increased from 4 to 5.

b. Simulation of statistically representative networks

The general approach for the network simulation involves determining the required investment to reinforce the network, under different penetration levels of LCTs.

In order to deal with overloads of feeders and transformers and inadequate network voltages caused by the uptake of heat demand, a like-for-like reinforcement strategy is investigated in this paper. It is based on reinforcing feeders with inadequate voltage profiles or feeder sections with thermal overloads where constraints are violated, while maintaining the original structure of the network. The associated upgrade cost for a given scenario and control strategy (resulting in a given level of peak demand) is used to build reinforcement cost characteristics.

The LV network model is based on representative fractal networks (see next section) with the parameters that represent the key characteristics of typical LV networks supplied from individual distribution transformers. The approach consists of two major steps, namely: fractal network creation, and analysis and network sizing. The details of the steps are as follows:

1) In the first step, at the LV level, different customer settlements (e.g., urban, rural, semi-urban, etc.) based on the concept of fractal dimensions are created. Many statistically similar networks (in terms of network topological characteristics) can thus be generated to resemble actual towns, cities, etc.
2) Starting from the network topology from step 1) as an input, in the second step alternating current (AC) load flow simulations are performed. These are aimed at calculating relevant variables such as branch currents, losses, voltage drops, and so on. These variables are then used to size the network circuits based on an assumed capacity margin of 15%, in order to allow for future supply and load developments. In addition, based on the topology and assumed capacity margin, an optimal siting and sizing of transformer substations is carried out.

The model also optimises the location of substations, transformer sizes, and conductor sizes, and evaluates the maximum voltage drop and re-optimises the selection, if necessary, to mitigate voltage excursion and excessive fault levels in critical operating conditions.

The customer distribution pattern varies greatly from one area to another. An inner city area will have very different customer distribution patterns than a rural area. Furthermore, the customers are typically not uniformly distributed along the feeder. The conventional geometric model, which assumes equal spacing between the customers, is therefore not adequate to represent the customer distribution adequately. In order to capture the customer position and hence the network length more realistically, the statistically similar network models based on fractal science are used; see Green et al. (1999).

The key element of the distribution network analysis is the Fractal Distribution Networks Model that can create representative LV distribution networks that capture statistical properties of typical network topologies that range from high-load density urban networks to low-density rural networks. The design parameters of the representative networks reflect those of real distribution networks of similar topologies, e.g. the number and type of customers and load density, ratings of feeders and transformers used, associated network lengths and costs, etc.

Due to the lack of detailed information and the large degree of diversity in distribution network planning and design, it is not feasible to perform a detailed assessment of the existing distribution networks in different countries or regions within a relatively short timeframe. Nevertheless, experience has shown that it is possible to represent real networks through a limited number of typical networks with statistically similar network configurations. This approach allows for a number of design policies to be tested on a network with the same statistical properties as the network of interest, with only a minor sacrifice in terms of accuracy of reinforcement cost estimates. Moreover, any conclusions reached are applicable to other areas with similar characteristics.

The procedure of generating representative networks consists of the following steps: (i) creation of customer layouts, (ii) generation of supply networks, and (iii) supply network design.

i. Customer point generation

Customers' positions play the most critical role in terms of network design, as together with the specific demand load patterns they affect the design and the length of the network. In this respect, previous research has shown that typical customer location characteristics for different areas, such as urban or rural, can be modelled through spatial distributions of fractal dimensions (FD) (Barnsley et al. 1988). Fractal dimensions relate to the extent to which a shape (fractal) fills its space. In this context the fractal dimension relates to the form and spatial extend of the generated distribution networks. The Fractal Dimension D is related to the expected network length l as defined in Equation (1). Thereby l_0 is an empirical constant and n is the number of connected customers (Green et al. 1999).

$$l = l_0 n^{\left(\frac{D-1}{D}\right)} \tag{1}$$

The number of customer points in a given area and the area itself are inputs to the developed tool, which are created by specifying the desired FD, which varies from 1.9 for urban areas to 1.4 for rural ones. If all customers were located along a single line, the FD of this layout would be equal to one (minimum value), while if the customers fill the space uniformly, the FD would be two (maximum value).The statistically similar networks can be generated by manipulating the input parameter seed. With a different seed number, a completely new set of random numbers (representing customer load points) can be generated. These random numbers generate a new set of realistic customer positions, which have similar network characteristics (customer distribution, load density, substation density, etc.). This occurs under the continued influence of fractal and economic interaction with other points driven by the high cost of land in crowded areas and high cost of supply in sparsely populated areas. The capability to generate many statistically similar network sets allows a number of design policies to be tested on a network with the same specific characteristics.

ii. Generation of supply networks

The capital cost of the network depends on the total length of the network. Prim's (1957) minimum spanning tree algorithm, starting from a single node, generates a set of links that connects all given customers along the way by ensuring that the generated network has the shortest possible length.

Once the customer points are generated, they are connected with a number of connections that can be identified by using the concept of the branching rate (BR), i.e. the ratio of the number of T-points to the total number of customers' nodes of the generated network. A T-point is a place on a network section between two customers where the network is branching out. In practice, a lower BR indicates that the network tends to follow the customer base as normally encountered in the LV network. On the other hand, a medium voltage (MV) network path is influenced more by other factors such as avoiding lakes and parks, which in turn leads to a higher network BR. The developed tool combines two algorithms for connecting customers to the network:

- In the first algorithm, the next customer to be dynamically connected to the network is chosen randomly. This algorithm leads to networks with a higher BR.
- In the second algorithm, the next customer to be connected is always the nearest one to the previous one connected to the existing network. This approach produces a much lower BR than the previous algorithm.

By combining these two approaches, it is possible to control the branching rate (that is an input to the model) and to generate networks with BR in the range 0.2-0.6. Typical branching rates for different areas have been estimated through empirical calculations as shown in Green et al. (1999). Despite the same customer layout, the resulting network topologies are visibly diverse for different branching rates.

iii. Supply network design

Once a network of viable paths has been determined, the supply network is designed based on optimal locations and ratings of distribution transformers (MV/LV), their supply area and selected conductors. The heuristic approach, which uses direct search, is used to solve the problem of distribution transformers' location by dividing the network area into smaller regions and finding local density maxima. The network areas are covered with circles of the same size so that there is a minimum of blank spaces and minimum overlap, with the centre point of each circle representing the ideal location of each distribution transformer. Circle diameters are derived from the desired number of distribution transformers and the total circle area is equal to the total network area. Each circle represents a region and the first distribution transformer is located in the centre of the region with the greatest load density. All customers in that region are excluded and the location of the next distribution transformer is then determined iteratively using the same principle.

The obtained network is meshed and some of the sections have to be opened to obtain a radial network where each customer is supplied from only one distribution transformer by applying so-called null-point load flow (Willis et al. 1996). A load flow calculation (Peterson and Meyer 1971) is carried out using the typical network resistivity and reactivity and an average expected load for each customer.A backward-forward sweep method of calculating load flow in radial network (Shirmohammadi et al. 1988) is used in network design in the base case and upgrade for different future scenarios. In the first step, for each customer an annual load profile is input. For a period, a customer current is defined in Equation (2)

$$I_i^k = \left(\frac{S_i}{V_i^{k-1}}\right)^* \tag{2}$$

where I_i^k is the current of customer i in power flow iteration k, S_i is the customer load during the specified period and V_i^{k-1} is the voltage at the connection point of customer i during iteration k-1. The initial voltage is equal to the voltage specified at the supply node.

In the backward sweep step, starting from each customer node, the calculated customer supply current is added to each section flow on the path from customer node to the source node. This is repeated for each customer. Hence, the flow F through section j in iteration k is given by Equation (3)

$$F_j^k = \sum_{i \in G_j} I_i^k \tag{3}$$

where G_j is the set of customers which are supplied through line j.

In the forward sweep step, starting from the source node, the voltage at the other node of each supplied adjacent line is calculated as in Equation (4)

$$V_{j2}^k = V_{j1}^k - Z_j F_j^k \tag{4}$$

where V_{j2}^k and V_{j1}^k are voltages at supplied node from branch j and node supplying branch j, respectively in iteration k, and Z_j is impedance of line j.

These steps are repeated until convergence is achieved, i.e. maximum active and reactive power mismatches are less than or equal to desired values. The calculation is repeated for all periods and results used in the calculation of the optimal capacity of assets, as described below, or for asset upgrade, in order to keep maximum flow within asset capacity and voltage within statutory limits.

Segments in which the power flow between distribution transformers is minimal are opened, resulting in separate radial networks, one per each distribution transformer. In each of the separate radial networks, a local load density maximum is found using the same circle approach but with a smaller diameter. Each distribution transformer is repositioned at the point of maximum local load density.

The optimal capacity of cables and overhead lines for the pure transport of electricity is determined by trading off the annual cost of losses and annuitised capital cost and satisfying security criteria (Melovic & Strbac 2003). A similar approach is used for choosing the optimal rating of a transformer, the only difference being that the transformer has greater no-load losses that occur in the transformer core. The cost function is defined in Equation 5, with the total cost C_{TN}, the specific cable cost C_l, the number of transformers N_t and the specific transformer cost C_t.

$$C_{TN} = l \times C_l + N_t \times C_t \quad (5)$$

4. Results and discussion

a. Neighbourhood clusters, LCT penetration scenarios and network configurations

Three neighbourhood clusters are employed based on Census 2011 data at the OA level (CSE, 2015). These were pre-filtered to exclude all of the OAs in England and Wales that either contain mostly flats (including private rented and social housing) and/or are characterised as having a high proportion of the population in lower socioeconomic groups. This process relies on the OA Classification from 2011, which categorises OAs into 8 supergroups, 26 groups and 76 subgroups based on various socioeconomic criteria (as documented in the "pen portraits", ONS 2015). The only subgroups that were retained were those that contained at least 60% of owner-occupied, non-flat type buildings, which reduces the total number of OAs from 181,409 to 79,962. A two-stage cluster analysis was performed using SPSS, via the log-likelihood distance measure and the Bayesian Information Criteria (BIC) quality measure (Zelterman 2015). This resulted in three OA clusters, with a cluster quality of 0.55, with 0 being poor and 1 excellent[5] as defined in Table 3. Further details can be found in McKenna et al. (2016a).

Table 3: Overview of neighbourhood clusters at the Output Area level (for derivation see McKenna et al. 2016a)

	C1	C2	C3
Dwelling/hectare (ha^{-1})	3.17	2.60	0.43
Mean weighted floor area per dwelling (m^2)	86.3	81.3	94.0
Mean area of Output Areas in cluster (hectares)	39.8	50.7	294.3
Mean no. of Households in cluster	126	132	127
No. of semi-detached dwellings	86	45	29
No. of detached dwellings	29	29	88
No. of terraced dwellings	11	58	10

[5] For the sake of these clusters, it is assumed that one household inhabits one dwelling.

Initially five LCT penetration scenarios for these neighbourhoods were considered in McKenna et al. (2016a), namely a reference case without any LCTs, cases with 25% and 50% of DHAs with heat pumps and CHP systems respectively, and two final cases with 100% HPs and CHP systems respectively. For the current case, these scenarios have been revised in order to provide richer insights into the effects of LCT penetration on network upgrade costs. The exception is the baseline scenario, which remains the same; it is assumed in this case that all of the DHAs have a gas boiler (the dominant heating source in the UK) for their existing heat supply alongside electricity from the network. The baseline scenario containing no LCTs is justified because 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).

Table 4: Allocation of DHAs to neighbourhood clusters and number of CHAP load profiles generated per LCT system and DHA (for abbreviations see Table 1 and for details of the clusters see McKenna et al. 2016a)

DHA / Cluster	1 (PP)	2 (TV)	3 (LL)	4 (ML)	5 (PC)	6 (OP)	7 (PU)	Total
C1	19	11	5	42	25	9	15	126
C2	4	58	3	32	9	5	21	132
C3	11	10	21	9	9	29	38	127
No. of load profiles per LCT system	5	15	5	11	6	7	10	59

The additionally defined scenarios focus on the impacts of various penetration levels, from 0% to 100%, of PV systems and heat pumps. The analysis of mCHP systems was excluded in the present case, as initial modelling showed that they have only a very marginal effect on network upgrade costs. MCHP systems are typically heat driven, which is during the winter period when demand is typically greater. Hence, the majority of electricity produced by micro-CHP is consumed locally. PV systems also have a marginal effect, but these systems are retained in order to analyse their interaction effects with heat pumps. Hence, we consider a total of 35 scenarios as shown in Table 5 below. The scenarios are distinguished by the fraction of each LCT, from HP, HP+PV and PV only, which are randomly allocated to the households within the cluster.

Table 5: Definition of LCT technology penetration scenarios for the neighbourhood clusters

Index	LCT penetration (%)			Index	LCT penetration (%)			Index	LCT penetration (%)		
	HP	HP + PV	PV		HP	HP + PV	PV		HP	HP + PV	PV
1	0	0	0	**13**	0	0	100	**25**	25	0	50
2	25	0	0	**14**	25	25	25	**26**	0	25	50
3	50	0	0	**15**	25	25	0	**27**	75	25	0
4	75	0	0	**16**	25	0	25	**28**	75	0	25
5	100	0	0	**17**	0	25	25	**29**	25	75	0
6	0	25	0	**18**	50	25	25	**30**	0	75	25
7	0	50	0	**19**	25	50	25	**31**	25	0	75
8	0	75	0	**20**	25	25	50	**32**	0	25	75
9	0	100	0	**21**	50	25	0	**33**	50	50	00
10	0	0	25	**22**	50	0	25	**34**	50	0	50
11	0	0	50	**23**	25	50	0	**35**	0	50	50
12	0	0	75	**24**	0	50	25				

Table 6 gives an overview of the network parameters for each of the neighbourhood clusters. In order to obtain networks that are more realistic, the number of customers per type as shown in Table 4 and the area size shown in Table 3 are multiplied by 12. Table 6 shows the length, branching rate and fractal dimension of resulting networks, depicted in Figure 3. The blue squares represent customers and red cubes represent distribution transformers. The networks of clusters 1 and 2 have similar fractal dimensions and slightly different branching rates, resulting in similar ratios of network length and network areas. The random number seed is the same and therefore these networks look overall similar. The network of cluster 3 has a lower fractal dimension resulting in more 'white spaces'. It should be noted that network graphs are shown at different scales in order to include the whole area specified in Table 6.

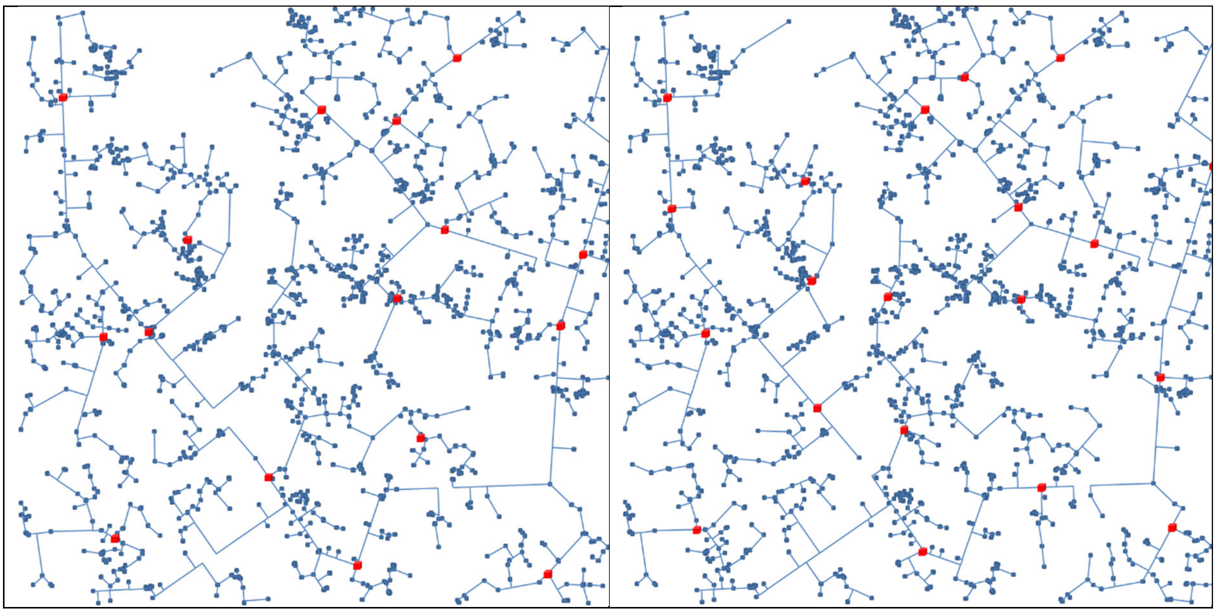
Table 6: Overview of selected network configuration parameters (for abbreviations see Table 2)

Cluster	Number of customers per type (PP, TV, LL, ML, PLL, DP, PU)	Network length (km)	Network area (km^2)	No. of transformers	Branching rate (%)	Fractal dimension
1	228,132,60,504,300,108,180	48	4.8	16	44	1.7
2	48,696,36,384,108,60,252	56	6.1	20	48	1.7
3	132,120,252,108,108,348,456	111	35.3	36	45	1.6

b. Network upgrade and CO_2-abatement costs

The network upgrade costs per customer in the three clusters and 35 scenarios are shown in Figure 4. These costs represent the difference between the total upfront investments for the networks shown in Figure 3 without any LCT penetration (not shown in Figure 4 as zero) and the total costs in the respective scenarios. For this study, cost assumptions for the 0.4 kV underground cables and transformers are taken from OFGEM (2009). Hence, these costs represent the additional costs incurred due to the penetration of LCTs. As they are the total upfront costs, they neither include maintenance of the network nor the required interest for the DSO over its 25-40 year lifetime.

Whilst the general trend in the costs is similar for the three clusters, the costs per customer are significantly higher in cluster 3. In this cluster, the costs reach around £3000 per customer, compared to about £1200 in cluster 1 and £900 in cluster 2. An approximate conversion of these costs to the nominal annual costs per household can be achieved by assuming this 40 year lifetime and a 3.5 % (social time preference) discount rate (HM Treasury 2003), with a corresponding annuity factor of 0.05. This results in maximum annual costs (annuities) of £60, £45 and £150 per customer in clusters 1, 2 and 3 respectively.



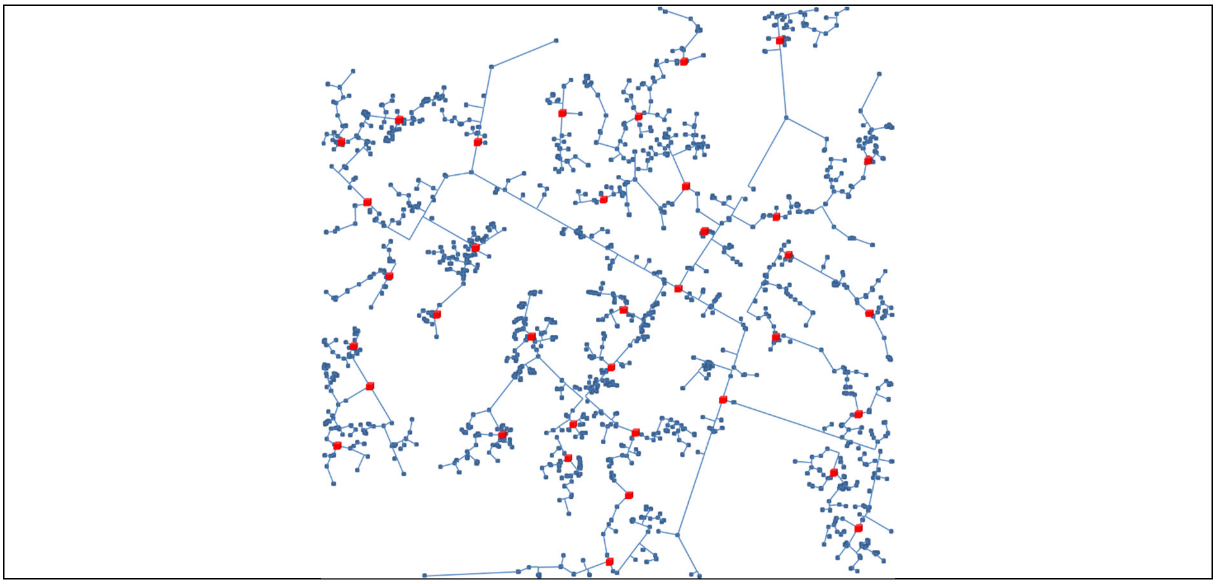


Figure 3: Network configurations of clusters 1 (top left), 2 (top right) and 3 (bottom) (blue squares are customers and red cubes are distribution transformers)

The main reason for the higher costs in cluster 3 is the much lower housing density and the resulting longer network length and larger area (Figure 3, Table 4 and Table 6). In addition, cluster 3 is dominated by larger, detached dwellings, which have higher overall energy demands and therefore larger technology capacities than in the other two cases. Cluster 2 is dominated by smaller, terraced and semi-detached dwellings. It has a smaller area and lower housing density than cluster 1 (40 vs. 51 and 2.6 vs. 3.2 ha^{-1} respectively). Hence, cluster 2 has a lower overall capacity installation and therefore lower specific network upgrade costs.

Figure 4 also allows a comparison of the network upgrade costs across different LCT penetration scenarios. It is clear that the heat pumps are the strongest driver of the upgrade costs, whereas PV systems alone result in no upgrade costs (not shown in the figure). Interestingly, the combination of heat pumps with PV systems can lead to lower overall upgrade costs than for the heat pumps in isolation. This is especially the case at lower levels of LCT penetration for clusters 1 and 2. For example, compare the scenarios with 25% of HP and HP/PV systems respectively, to those with 50% HP. The upgrade cost is about 10-20% lower with the combination of technologies than that of HPs alone, which is due to the synergy effects of these technologies, whereby the electricity produced by PV is partly used to power the heat pump.

Another interesting insight from Figure 4 relates to the breakdown in LV network upgrade costs between thermal, stability and voltage components. Thermal driven network reinforcement occurs when the maximum power flow through an asset is greater than the thermal rating of the asset. Voltage stability driven network reinforcement occurs when the flow through an asset would be significantly high enough that voltage collapse could occur. It is assumed in this study, that if the voltage on any node is below 0.85 p.u. (i.e. 340 V on the 400 V network modelled here) the system is close to voltage collapse and only network reinforcement could alleviate the condition. Some of the line sections on the supply path to the node with abnormally low voltage are reinforced to improve voltage. Voltage driven network reinforcement is carried out when voltage on any node is below or above the statutory limits and above 0.85 p.u. Similarly to the voltage stability approach, some of the line sections on the supply path are upgraded to improve voltage. However, there might be other less expensive solutions to the voltage driven reinforcement like the installation of on-load tap changing distribution transformers or in-line voltage regulators. In general, Figure 4 shows that, with increased penetration of HPs, the thermal and voltage stability driven network reinforcement increases. Concerning the voltage driven reinforcement, an increase of HP penetration leads to two effects. First, more sections would need upgrading due to voltage drop/rise. Second, some of those sections would need upgrade anyway due to thermal or voltage driven reinforcement. Hence, this component reduces at very high LCT penetrations. However, the overall LV reinforcement cost increases with the penetration. It can also be seen that up to some level of PV penetration, reinforcement costs reduce, as PV alleviates network constraints. With further increases of PV penetration, the reinforcement cost starts to increase due to a voltage rise effect. This is not clearly visible in all cases due to the fact that, in this study, the same customers might not have the same devices from one scenario to another (see next section).

The thermal driven distribution transformer replacement costs are also shown in Figure 4. For clusters 1 and 2, with the relatively higher customer density, ground mounted distribution transformers are assumed and unit cost includes replacement of the distribution transformer (£13.2k) and ring main unit (£13k). For cluster 3, with relatively lower customer density, pole mounted transformers are assumed and the unit cost only includes the transformer (£2.9k). All of these assumptions are taken from OFGEM (2009). Given the unit costs of distribution transformer replacement and the value of the LV network replacement cost per cluster, distribution transformer replacement costs for clusters 1 and 2 are more pronounced than for cluster 3, even though more distribution transformers supply customers in cluster 3. The overall distribution transformer replacement cost trend is similar to the trend of LV network replacement cost.

Fehler! Verweisquelle konnte nicht gefunden werden. shows the CO_2-abatement costs for the 3 clusters and the 35 scenarios. These are calculated based on the sum of the total network upgrade cost according to Equation 5, plus the total costs for the technologies (investment and running costs, assuming a 20 year lifetime, C_{LCT}), divided by the reduction in CO_2 emissions as given in Equation 6.

$$C_{CO2} = \frac{C_{TN} + C_{LCT}}{\Delta CO_2} \tag{6}$$

Thereby the term ΔCO_2 is determined as the difference between the energy supply in the reference case (i.e. scenario 1 in Table 5) and the respective scenario. The emissions resulting from residential electricity feed in from PV systems receive a credit equal to the average CO_2-intensity of the UK mix. For further details of the CO2 and cost assumptions the reader is referred to McKenna et al. 2016b. The figure shows that with PV systems alone, the CO_2-abatement costs are moderate in all scenarios and clusters. Only with HP systems do these costs rise significantly due to much more electricity being required from the network. In fact, the figure highlights the disproportionately of high carbon abatement costs for cluster 3, which largely results from the high network upgrade costs at low LCT penetrations. For example, even with just 25% HP, cluster 3 incurs around £1760 per customer, compared to just £435 and £620 in clusters 2 and 1 respectively (Figure 4). The picture is similar with 25% HP+PV, where cluster 3 incurs costs of £1500 per customer, compared to only £270-480 in the other two clusters. These effects are due to the nature of the networks: whereas clusters 1 and 2 represent semi-urban contexts, cluster 3 is a semi-rural network. Hence in terms of CO_2-abatement cost at least, it seems favourable to focus on clusters 1 and 2. In addition, **Fehler! Verweisquelle konnte nicht gefunden werden.** reinforces the statement already made, that the combination of PV and HP systems is economically and environmentally favourable compared to employing these systems independently.

Figure 4: Network upgrade costs per customer in clusters 1 (top), 2 (middle), and 3 (bottom) for all 35 scenarios (cf. Table 3 for definitions of scenarios: baseline and "PV only" scenarios are not shown for clarity, as upgrade costs are all nil for these cases)

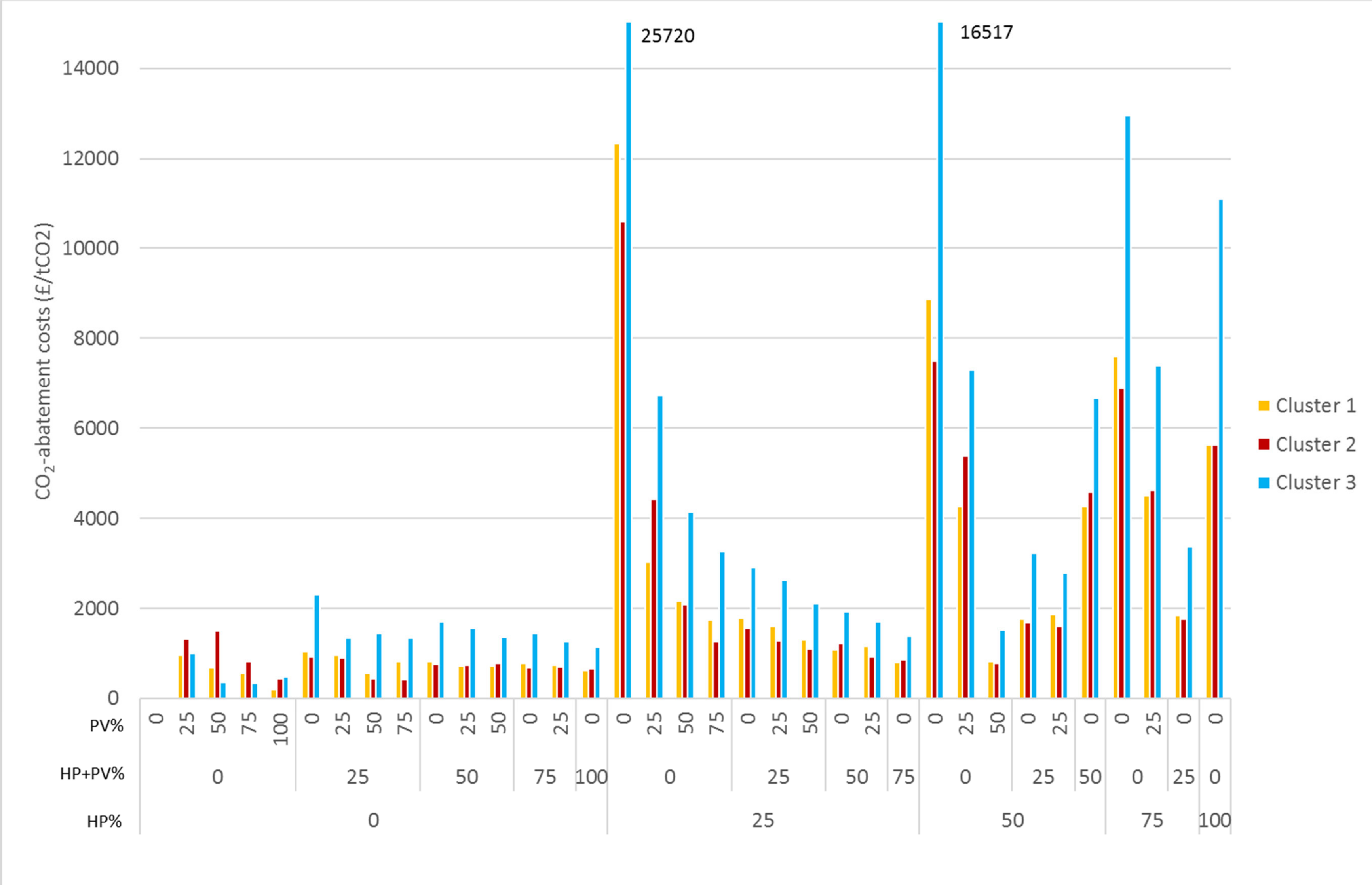


Figure 5: CO_2-abatement costs for the 3 clusters and 35 scenarios

One of the few studies in the literature to explore related research questions with a similar methodology is that of Protopapadaki & Saelens (2017), so a comparison of the results seems appropriate. They found that heat pump penetration rates above about 20-30% would result in overloading and voltage stability problems, especially in rural areas. This finding broadly relates to ours, which suggests a network upgrade requirement at HP penetrations of 25% and above, especially in rural areas. The fact that the PV effect (i.e. network upgrade impacts) is significantly smaller is also confirmed in the present case, but the interaction effects of PV and HP systems were not encountered by Protopapadaki & Saelens (2017). But it is not clear from their method how the PV and HP systems are distributed across the network, which makes a direct comparison with the present study difficult.

c. Simultaneity and residual load

A central consideration for the design and operation of low voltage distribution networks is the simultaneity of loads. As networks are typically dimensioned according to the maximum simultaneously occurring load, the simultaneity of load within the network plays an important role. Whilst on the one hand the aggregation of consumers tends to reduce the simultaneous peak load per consumer, due to smoothing effects, the integration of LCTs such as PV and heat pumps can strongly impact these simultaneity effects. Hence, in this section the results are analysed with respect to these aspects. Due to the large number of scenarios employed in this work (Table 5), this analysis only considers seven central ones that differ in the respective penetration of HP and PV.

A useful and commonly employed indicator to assess the simultaneity of loads in distributions networks is the Diversity Factor (DF). This is defined as the ratio of the maximum non-concurrent load to the maximum concurrent load within the network. Whilst the former relates to the sum of the maximum load in each household over the year, the latter is the maximum load that occurs in one 15 minute time slot. A higher DF indicates a higher degree of diversity and allows a smaller network dimensioning (in terms of distribution capacity and number of transformers) than in the case of a lower DF. The DF for several of the analysed scenarios is shown in Figure 6 below. It is clear that in the reference scenario 1 (i.e. without any LCTs) the DF is around 4. In scenarios 11 and 12, with additional PV capacity, the DF is only slightly reduced, which is due to the relatively small capacities of PV systems installed (cf. Figure 1). The scenarios with heat pumps (3 and 4) and heat pumps and PV (7 and 8), exhibit substantially lower DFs, however. The presence of these LCTs, especially heat pumps, contribute to more frequent and higher simultaneous loads within the network. The differences between the DFs for the three clusters are due to the different cluster composition and hence the number of households that are optimised – for example, in cluster 2 62/132 households are not optimised due to being households of type 1 and 2 (Table 4).

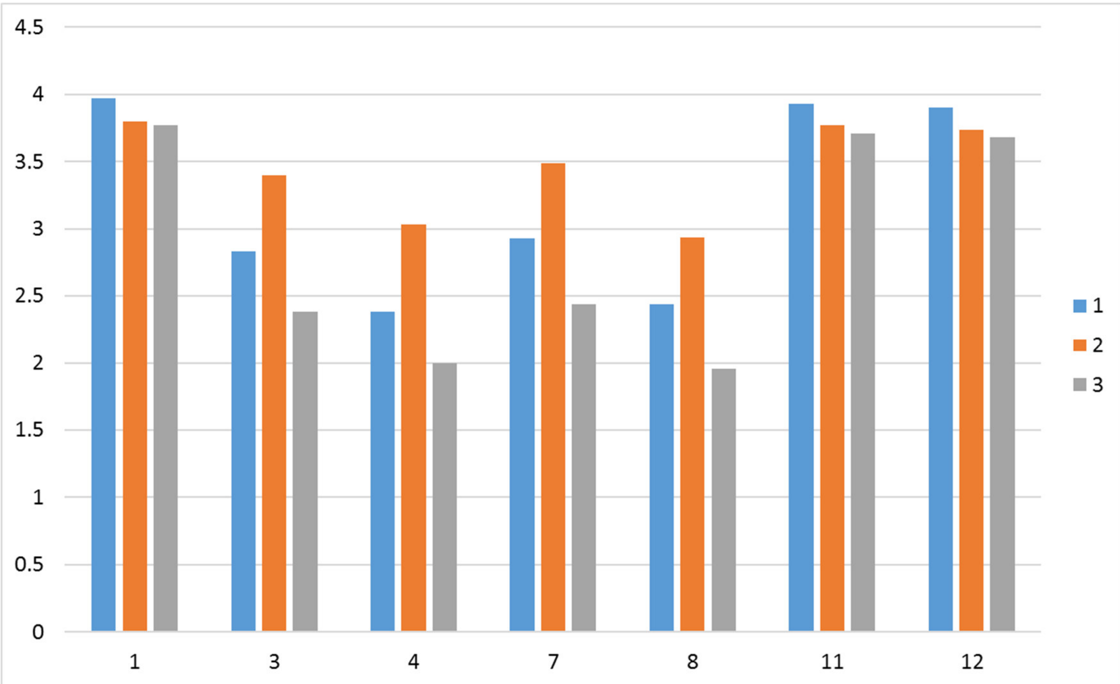


Figure 6: Diversity Factor (DF) for selected scenarios and all three network configurations (for scenario definitions see Table 5)

Furthermore, Figure 7 shows the so called After Diversity Maximum Demand (ADMD), for the same 7 scenarios. This is determined by randomly selecting the specified number of households from the cluster (without replacement). The ADMD is then determined by the ratio of the maximum concurrent load over this number of households divided by the number of households. The error bars in the figure show the 95% confidence interval of a normal distribution fitted to the data. The figure shows both of the abovementioned effects, namely the smoothing through aggregation of households and the impact of LCTs on the diversity. As in Figure 5, the strongest effect on the ADMD comes in the scenarios with heat pumps; with 75% heat pump penetration the ADMD is almost 3 kW over 20 households, compared to about 1.5 kW without.

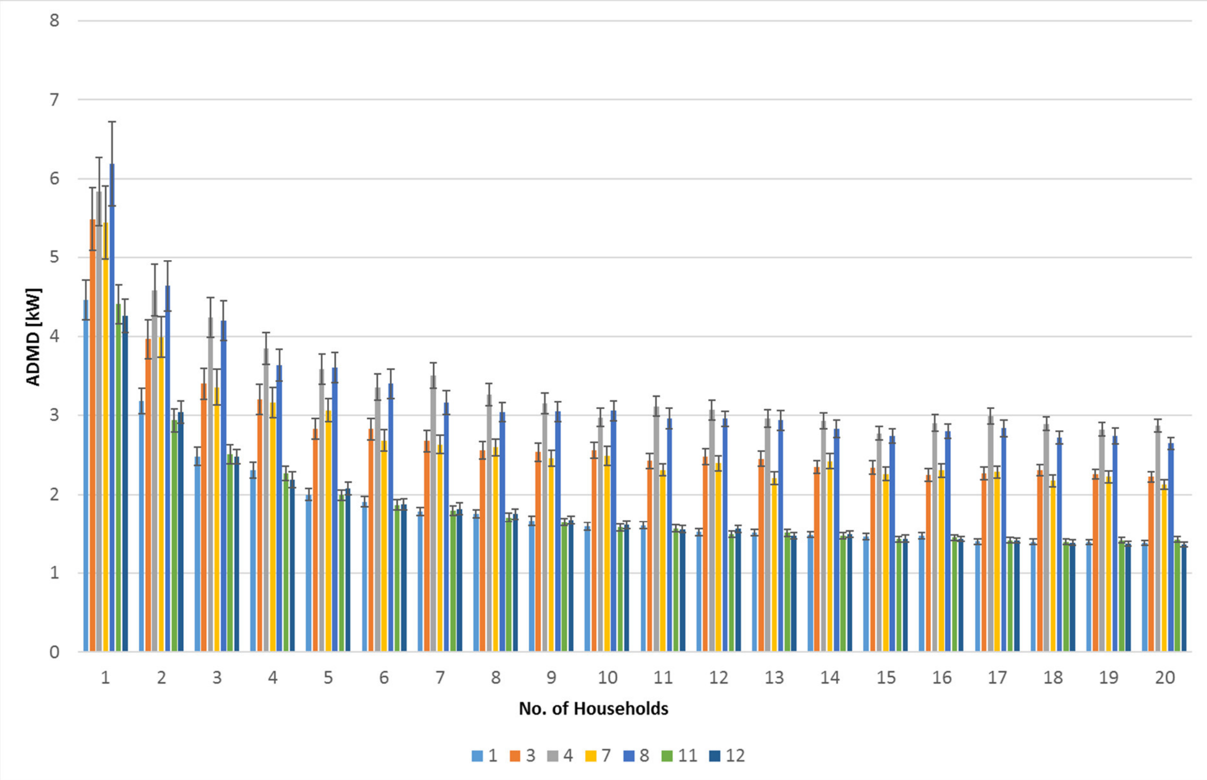


Figure 7: After Diversity Maximum Demand (ADMD) for seven scenarios and number of households

Finally, Figure 8 shows the sorted residual load curve for the same seven scenarios and neighbourhood cluster 1. Here again the impact of the heat pumps as the strongest influencing factor on the load profiles is clear. The increasing penetration of heat pumps results in many more hours of the year with peak loads up to 300 kW, compared to 141 kW in the case without LCTs. In addition, the scenarios with HP and PV systems have around 1000 hours per year of negative residual load, which reaches -146 kW in the case of 75% HP and PV. Despite the widespread PV installations in 50% and 75% of optimised households respectively (scenarios 11 and 12), this barely leads to a net negative residual load. Instead, the relatively small system capacities of 1-2 kW implies any PV electricity fed into the grid is balanced by the network load and not transformed to higher voltage levels.

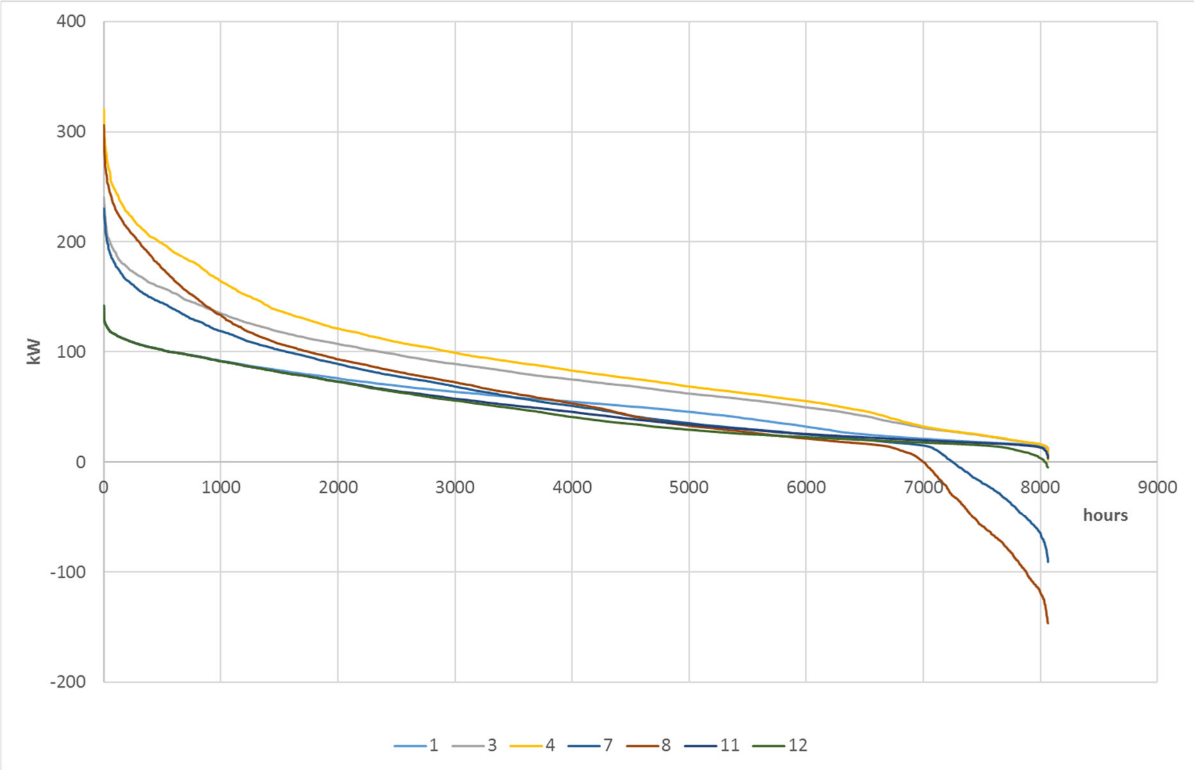


Figure 8: **S**orted annual residual load curve for **Cluster 1 and seven scenarios**

d. Critical discussion and further work

This section briefly discusses the method and highlights areas for further work. The focus is thereby placed on the combination of socioeconomically-differentiated neighbourhood clusters with an electrical network simulation. The method employed to generate these clusters is discussed at length in McKenna et al. (2016a). One counter-intuitive insight from Figure 4 is the effect on the network upgrade costs that PV alone has in combination with HP and HP/PV systems. For example, with either 25% HP or 25% HP/PV, increasing levels of PV penetration from 0% to 25% results primarily in a reduction in the network upgrade cost. The subsequent increase in PV penetration, from 25% to 50%, however, results in an increase in the upgrade costs. This is either due to the synergy effects mentioned above or the random selection of DHAs within the cluster for a given LCT configuration, whereby the latter is more likely. There is no guarantee that those DHAs having PV in the “25% PV” scenario would also have this technology in the “50% PV” scenario. This means that their location within the network could change between scenarios and thus also change the distance from other customers and the transformer. Further work should ensure that the same DHAs receive the same technology across increasing penetrations, which would enable the further analysis of this effect that is considered beyond the scope here.

In addition, there are many uncertainties relating to the employed input data. These include assumptions relating to costs of the LCTs and the network upgrade as well as the network structure itself. Sensitivities of the microtechnology optimisation model results to different cost assumptions have been discussed at length in Merkel et al. (2015) and McKenna et al. (2016). Several assumptions relating to the network development should be critically assessed here, though. For example, we only considered the LV network and not the interaction with the medium and high(er) voltage networks. This could mean that the analysis of upgrade costs for the LV network does not capture the "full picture" and neglects overarching requirements for upgrades. However, it is expected that the greatest proportion of such cost is related to the upgrade of LV networks. Furthermore, the network cables are considered all underground, which has a strong impact on the cost (by a factor of about three) compared to overhead lines. The cost of these cables can vary significantly by region (Parsons Brinckerhoff 2013), which means that these results are only indicative and almost certainly will not be precise for specific neighbourhoods. Especially in cluster 3, the employment of overhead lines might be partly more appropriate due to the higher spacing between dwellings and the longer overall network length. In addition, the CO2-abatement costs were determined based on the total investment required for heat and power technologies and network upgrade, but in the reference case (scenario 1) no initial investment in the technologies would be required. Hence all of these factors would tend to reduce the overall upgrade and CO2 abatement. One way of addressing these uncertainties would be to do a sensitivity analysis based on Monte-Carlo generation of about 100 networks to obtain statistics for the reinforcement cost. But it should be emphasised that the presented approach is not intended for detailed network planning in specific neighbourhoods. Instead, it is a highly transferable approach that requires only minimal information about a municipality and therefore can be easily scaled and applied to other contexts. The attention should therefore be drawn to the relationship between the results rather than the absolute numbers.

Hence, despite the shortcomings mentioned above, the transferability of the presented method as well as its real world applications should be highlighted. Given the correct input data and assumptions, the method is applicable to arbitrary areas worldwide. Based on different assumptions related to the penetration of different LCTs and the structure of the distribution networks, the method could be used to provide local investors and policymakers with invaluable insights relating to the reinforcement and CO_2-abatment costs under different future technology scenarios. These insights could in turn be employed to inform decision makers at the local and – given an appropriate neighbourhood/distribution network typology – national levels.

5. Summary and conclusions

This paper has analysed the impact of LCTs, especially heat pumps and PV systems, on the upgrade costs of LV distribution networks. It employs a combination of methods, including a detailed thermal and electrical load profile model for individual households, cluster analyses at the household and neighbourhood levels and a synthetic LV network generation and simulation model. The unique contribution lies in the combination of socioeconomically differentiated households and neighbourhood clusters with this network model. Whilst the application here is to the UK setting, the method is largely based on freely available data and is therefore highly transferable to other contexts.

Whilst it is clear that the heat pumps drive the network upgrade costs compared to the effect of PV system, the results show significant differences between the upgrade costs of the three analysed network types, and especially the semi-rural cluster 3 that has much higher costs. In addition, the employment of heat pumps together with PV seems to have strong synergy effects, which can considerably reduce the network upgrade and CO_2-abatement costs if they are deployed in parallel. The determined CO_2-abatement costs also suggest that decarbonisation strategies with these two technologies should focus on semi-urban neighbourhoods due to the lower cost than in the semi-rural case. That these costs reduce with increasing penetrations of these two technologies for all clusters would tend to support a higher level of LCT deployment in terms of economic efficiency.

Uncertainties in the input data mean that the results are only indicative, however, and the focus should be on a relative comparison rather than their absolute values. In addition, some aspects of the method involve simplifying assumptions, like for example the binary decision of whether or not a specific household invests in LCT and neglecting flexibility on the demand side which could be exploited by the centralised control of the network operator. Further work should therefore focus on quantifying these uncertainties and extending the method, especially with regard to the investment decision, the synergy effects between technologies and the medium voltage network, and the effects of decentralised flexibility.

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References

Aerts, D. et al. (2014): A method for the identification and modelling of realistic domestic occupancy sequences for building energy demand simulations and peer comparison, Building and Environment, 75, 67-78.

Anderson, B., Lin, S., Newing, A., Bahaj, A., James, P. (2016): Electricity consumption and household characteristics: Implications for census-taking in a smart metered future, Computers, Environment and Urban Systems, 63, 58-67.

Baetens, R., De Coninck, R., Van Roy, J., Verbruggen, B., Driesen, J., Helsen, L., Saelens, D., 2012. Assessing electrical bottlenecks at feeder level for residential net zero-energy buildings by integrated system simulation. Applied Energy, 96, 74-83. Doi: 10.1016/j.apenergy.2011.12.098.

Barnsley, M. F. (1988), Fractals Everywhere, Academic Press, San Diego.

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.

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

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.

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

De Coninck, R., Baetens, R., Saelens, D., Woyte, A., Helsen, L., 2014. Rule-based demand-side management of domestic hot water production with heat pumps in zero energy neighbourhoods. Journal of Building Performance Simulation, 7(4). DOI: 10.1080/19401493.2013.801518.

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.

Georgilakis, P. S., Hatziargyriou, N. D. (2013): Optimal Distributed Generation Placement in Power Distribution Networks: Models, Methods, and Future Research, in IEEE Transactions on Power Systems, vol. 28, no. 3, pp. 3420-3428.

Gonzalez-Sotres, L. (2013): Large-Scale MV/LV Transformer Substation Planning Considering Network Costs and Flexible Area Decomposition, IEEE Transactions on Power Delivery, Vol. 28, No. 4, October 2013. DOI: 10.1109/TPWRD.2013.2258944.

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.

Green, J.P, S.A. Smith and G. Strbac (1999): Evaluation of electricity distribution system design strategies, IEE Proc. Generation, Transmission and Distribution, vol.146, no.1, pp.53-60, Jan 1999.

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.

HM Treasury (2003): The Green Book, TSO, London, https://www.gov.uk/government/uploads/system/uploads/attachment_data/file/220541/green_book_complete.pdf, checked 17.04.03.

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.

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.

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.

Lüscher, P. et al. (2012): Automatic generation of network schematics from cadastral databases: Applications for an electric utility company, Paper at the 15th ICA Generalisation Workshop, Istanbul, Turkey, 2012. Weblink: http://generalisation.icaci.org/images/files/workshop/submissions2012/genemr2012_session3_sub2.pdf, checked on 08.02.2017.

Mateo, C. D. et al. (2011): A Reference Network Model for Large-Scale Distribution Planning with Automatic Street Map Generation, IEEE Transactions on Power Systems, Vol. 26, No. 1, February 2011. DOI: 10.1109/TPWRS.2010.2052077.

McKenna, R., Hofmann, L., Merkel, E., Fichtner, W., Strachan, N. (2016a): Analysing socioeconomic diversity and scaling effects on residential electricity load profiles in the context of low carbon technology uptake, Energy Policy, 97, pp. 13-26 DOI: 10.1016/j.enpol.2016.06.042.

McKenna, R., Merkel, E., Fichtner, W. (2016b): Energy autonomy in residential buildings: a techno-economic model-based analysis of the scale effects, Applied Energy, 189, 800-815, http://dx.doi.org/10.1016/j.apenergy.2016.03.062.

Melovic, D., Strbac, G. (2003): Statistical Model for Design of Distribution Network, IEEE Power Tech Conference, Bologna, Italy, June 2003.

Merkel, E., Fehrenbach, D., McKenna, R., Fichtner, W. (2014): Modelling decentralised heat supply: An application and methodological extension in TIMES, Energy 73, 592-605, doi: http://dx.doi.org/10.1016/j.energy.2014.06.060.

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.

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

OFGEM (2009): Electricity Distribution Price Control Review Final Proposals - Allowed revenue – Cost assessment appendix, Ref. 146a/09, Appendices, OFGEM, London.

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

openmod (2016): Distribution network datasets, http://wiki.openmod-initiative.org/wiki/Distribution_network_datasets, accessed on 26.01.2017.

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

Parsons Brinckerhoff (2013): Review of WPD Unit Costs, Project no: 3512700A, Prepared for Western Power Distribution, June 2013.

Peterson, N. M. and Meyer, W. S. (1971): Automatic Adjustment of Transformer and Phase-Shifter Taps in the Newton Power Flow, in IEEE Transactions on Power Apparatus and Systems, vol. PAS-90, no. 1, pp. 103-108, Jan. 1971.

Prim, R. C. (1957), Shortest connection networks and some generalizations, Bell System Technical Journal, 36 (6): 1389–1401.

Protopapadaki, C. Saelens, D. (2017): Heat pump and PV impact on residential low-voltage distribution grids as a function of building and district properties, Applied Energy, 192, 268-281.

Rhodes et al. (2014): Clustering analysis of residential electricity demand profiles, Applied Energy, 135, 461-471.

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.

Shirmohammadi, D., et al. (1988) A compensation-based power flow method for weakly meshed distribution and transmission networks, IEEE Transactions on Power Systems, Vol. 3, No. 2, 753-762.

Torrent-Fontbona, F., Lopez, B. (2016): Decision support for grid-connected renewable energy planning, Energy, 115, 577-590.

Torriti, J. (2014): A review of time use models of electricity demand, Ren. Sust. En. Rev., 37, 265-272.Widen et al. (2009): Constructing load profiles for household electricity and hot water from time-use data – Modelling approach and validation, Energy and Buildings, 41, 753-768.

Wilke, U., Haldi, F., Scartezzini, J.-L., Robinson, D. (2013): A bottom-up stochastic model to predict building occupants' time-dependent activities, Building and Environment, 60, 254-264.

Willis, H.L., Tram, H., Engel, M.V., Finley L. (1996), Selecting and Applying Distribution Optimisation Methods, in IEEE Computer Applications in Power, Vol. 9, Issue 1, p. 12-17, Jan 1996

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

Zubo, R. H. A., Mokryani, G., Rajamani, H.-S., Aghaei, J., Niknam, T., Pillai, P. (2016): Operation and planning of distribution networks with integration of renewable distributed generators considering uncertainties: A review, Renewable and Sustainable Energy Reviews, in press.