A high-resolution geospatial and socio-technical methodology for assessing the impact of electrified heat and transport on distribution network infrastructure☆

Connor McGarry [a],*, James Dixon [a,b], Ian Elders [a], Stuart Galloway [a]

[a] *Department of Electronic and Electrical Engineering, University of Strathclyde, Glasgow, UK*
[b] *Environmental Change Institute, University of Oxford, Oxford, UK*

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ABSTRACT

There is an increasing need to decarbonise both heating and transport sectors in the UK, and the uptake of low carbon technologies (LCTs) will be central to this. The impact of LCTs on electricity network infrastructure varies both spatially and temporally, and is driven by the diversity in technology type, consumer behaviour, variable weather patterns, variation of the building stock and the incumbent network assets. In recognition of this diversity and household energy variability, LCT adoption and utilisation will be influenced by the distribution of socio-economic factors within a local area. This has the potential to impact network decision-making across different regions. As such, there is a requirement to consider socio-technical and socio-spatial dimensions when modelling LCT impact on network infrastructure. This research, presented within a UK context, demonstrates a novel high-resolution methodology that enables assessment of electrified heat and transport impact on transformer headroom using socio-economic indicators to inform the application of LCT consumption. This includes mapping of spatially linked datasets to identify relationships between consumption and social deprivation. These relationships are used as inputs to a heat pump modelling methodology that converts gas demand to equivalent electrical heat demand. This approach is compared with a generalised trial data approach to ascertain the impact of incorporating socio-economic elements. Electric vehicles are then introduced, where charging is based on socially disaggregated behaviour in the form of travel diaries showing the combined impact of different LCTs. Findings are considered from the perspective of the distribution network operator and other key stakeholders.

1. Introduction

Distribution Network Operators (DNOs) face the challenge of ensuring appropriate investment in infrastructure and the development of new management solutions in response to increased electrification from the decarbonisation of heat and transport [1]. This is strongly influenced by the UK energy regulator, Ofgem, who promote competition in the energy markets and regulate networks. Diversity in technology type, consumer behaviour, increasingly variable weather patterns, variation of the building stock and the network assets is expected to have a significant impact on the extent of this electrification, particularly as certain areas are likely to engage in radically different decarbonisation pathways at varying rates [2,3].

The displacement of internal combustion engine vehicles with electric vehicles (EVs) and conventional gas boilers with heat pumps (HPs) is expected to be at the forefront of this electrification with up to 913,000 EVs and up to 564,000 HPs anticipated in the north of Scotland by 2045 [4]. Unlike other low carbon technologies (LCTs) e.g., solar PV which is predominately resource-driven, LCTs such as EVs and HPs are in part consumer-driven. This manifests in a distinct set of locally sensitive demand profiles that are inherently driven by consumer lifestyle and comfort or by wider societal rhythms such as work patterns and affordability [5]. Therefore, in recognition of consumer diversity and household energy variability [6–10], the way that LCTs are adopted and used will be influenced by the distribution of socio-economic factors within a local area. This, in turn, has the potential to impact network decision-making across different regions.

DNOs in Great Britain (GB) and other actors in this space, specifically policy makers and local authorities are aware of these

* Corresponding author.
E-mail address: connor.mcgarry@strath.ac.uk (C. McGarry).

challenges [11,12]. However, at present, although there exists recognition of the issues pertaining to socio-economic factors and their impact on LCT demand and subsequent electricity network infrastructure, there remains a need for an enhanced modelling capability that can capture key elements of socio-technical and socio-spatial diversity to inform LCT demand consumption in different areas. There is also a growing requirement to reduce the uncertainty surrounding the impact LCTs of different types will have on existing infrastructure, [4]. These insights will support place-based DNO decision making by informing the network planning requirements of infrastructure in various locations.

Such strategic 'intelligent decision-making' of infrastructure can help to minimise network interventions (reduce regular re-inforcement of legacy assets), minimise customer minutes lost and customer interruptions which incur heavy financial penalties, maximise profits, maintain (improve) network resiliency as the network evolves in the transition to net zero and as the penetration of intermittent technologies increases, to operate assets more efficiently improving longevity, reducing losses and increasing life-cycle value. Ultimately the intention of this work is to improve network planning in business as usual operations and while DNOs are regulated, that does not mean that the regulator makes investment decisions for them: the DNOs are expected to use best-practice techniques to determine what investment is needed, and where other methods should be used to defer or avoid investment. Intelligent decision-making of network infrastructure investment also has the potential to inform wider decarbonisation pathways and can support timely deployment of cost-effective decarbonisation solutions.

Therefore, this motivates the focus of this work to investigate – through high-resolution geospatial and socio-technical modelling – the combined impact of electrified residential heat and transport on key network infrastructure and the influence of socio-technical and socio-spatial dimensions.

2. Literature review

2.1. The influence of socio-economic factors on household energy consumption and LCT uptake

It is well understood that energy consumption and resulting emissions are unequally distributed [13]. Research has been undertaken at national levels to describe this problem in more detailed contexts; studies focusing on energy use and resultant emissions in the UK have been many. For instance, Druckman and Jackson [14] explore patterns of household energy use in the UK at high levels of socio-economic disaggregation on variables including household type, index of multiple deprivation (IMD) and employment type, supporting the hypothesis that different segments have very different patterns of consumption. The areas of focus in [14] are the very least deprived (top 1%) and most deprived (bottom 1%) of households in terms of the IMD; it is found that energy consumption in the top 1% is approaching twice that of the bottom 1%. Generally, there is a wealth of research on the topic which is in strong agreement: household energy use increases with income (e.g., [6–10]) and is also heavily influenced by household composition (including household size and number of children) (e.g., [9,15,16]).

Where the research differs on this matter is often what conclusions are drawn from the analyses carried out. Chatterton et al. [17] use a Multiple Analysis of Variance (MANOVA) technique to explore the dependency of energy demand in the UK – including direct gas, electricity and petroleum consumption – on a set of proposed explanatory variables covering demographics, socio-economics and the built environment. The analysis in [17] then focuses on the subset of these variables that are likely to set the degree of control a household has of their energy consumption, and how that relates to the level of energy consumed. It is concluded that those who are the largest consumers of energy have the highest incomes and the lowest levels of social deprivation, but also that they tend to be those who have the greatest opportunity to reduce their energy consumption, as also recognised in [18].

Research published on sector-specific analysis has been important for understanding the influence of socio-economic indicators on demand across different energy services. For example, Büchs and Schnepf [19] examine the associations between socio-economic factors and UK household energy consumption by sector (the three sectors are: home energy use from electricity and gas consumption; transport energy use from motor fuel, flights and public transport; and indirect emissions from food, clothing, etc.). It is reported that whilst all energy use is positively correlated with income, home energy use (i.e., gas and electricity consumption) is less sensitive to changes in these factors than transport and indirect consumption. Brand et al. [20] apply multivariate linear and logistic regression analyses to survey data from over 3000 UK adults to examine the distribution of energy and emissions resulting from motorised passenger travel. Whilst income, education and tenure were found to be predictors of energy and emissions, the strongest independent predictors are listed as owning at least one car, being in full-time employment and having a home-work distance of greater than 10 km. Priessner et al. [21] conduct a multinomial logistic regression analysis of EV adoption and a set of socio-economic and psychological factors. They find that whilst a subset of the socio-economic factors do serve as predictors (gender, household size, number of cars), stronger prediction is afforded by psychological factors, including (as they term it) 'cultural worldview': respondents who rate their own worldview as less egalitarian and more individualistic are less likely to want to adopt EVs than their culturally opposing counterparts.

2.2. Evaluation of impacts from LCTs on electricity system infrastructure

Concerns from DNOs [22], regulators [23] and policy makers [24,25] that the capacity of distribution networks may not cope with the increase in electricity demand from their adoption have contributed to the motivation in the academic literature to produce methods to characterise the likely impact of LCTs on electrical infrastructure. Sometimes referred to as spatial load forecasting (SLF), these methods have become an increasingly important tool for actors involved in planning and investment of power networks [26,27].

This field of study is generally broken down into three parts:

1. Plausible levels of uptake of LCTs are modelled, which are generally returned as time-bound levels of penetration (e.g. $X\%$ of cars will be EVs by year Y);
2. Energy demand, or temporal demand profiles, of those corresponding LCTs are simulated, sampled or assumed;
3. Those demand profiles are assigned to nodes in a network that represent served customers (households) of an electricity network. Specific network analysis is not always present; rather, some studies seek to return the quantity of energy demand for a particular area.

Methods used for modelling technology uptake varies significantly between studies, and includes statistical methods such as Bayesian models [28], regression analysis [29–31], agent-based modelling [32–34] and scenario development [35,36]. Some studies draw upon the significant impacts of socio-economic indicators on energy demand in modelling LCT uptake.

For example, Van der Kam et al. [30] use a non-linear regression method to examine the influence of several socio-economic indicators, including age, education level, income, and even level of allegiance to green left-wing political parties on EV and solar PV uptake; using this model, the authors construct 'S-curve' technology uptake analysis based on projected changes in these socio-economic indicators over time. Other studies focus their uptake modelling on spatial influences. For example, Rodrigues et al. [31] present an autoregression approach to examine the effects of peerage – including the neighbourhood effect, a.k.a. 'keeping up with the Joneses' – on EV uptake; this is paired with a logistic regression model to forecast EV uptake into the future given these spatial influences.

Demand profiles of LCTs can be derived using one of three methods: (i) simple, fixed assumptions can be used, such as 'assume all EV drivers plug in at 18:00' as in [37,38]; (ii) data from real EV chargers or HPs can be used, usually from government-sponsored trials, as in [39–43]; (iii) usage data of incumbent 'high carbon technologies', such as internal combustion vehicles or gas-fired boilers, can be used to understand energy service demand and serve as a basis for simulation of LCT demand, as in [44–47].

The first method is commonly seen in older literature, and has since fallen out of favour: for the EV example, while the 'arrives in the evening, leaves in the morning' model of driver behaviour as used in [37,38] is a fairly common assumption in the literature, it is shown through analysis of UK National Travel Survey (NTS) data by Mattioli et al. [48] that under half of UK cars are driven according to this daily commuter stereotype.

The second method does have one distinct advantage, in that it can capture the fundamentally different operation of LCTs compared with the technologies they are replacing: EV adoption has been shown to change driver behaviour [49,50] and HP operation is fundamentally different to gas boiler operation due to their comparatively lower output temperature. However, there are two key drawbacks to using trial data. Firstly, they are inherently tied to a particular set of technologies. This is particularly clear for the EV example, as trial data can date quickly as battery sizes and charging power increase [44]. Secondly, trials are often descriptive of – or only open to – a particular subset of energy consumers. For example, in the 2021/2022 Electric Nation Vehicle to Grid trial, participants not only had to already own a compatible EV (and hence, by definition, be an early adopter of the technology), they also had to be homeowners with access to their own off-street parking [51].

The main advantage of the third method is that it circumvents these problems. In using consumption data from incumbent technologies to derive energy service demand, or by simulating energy service demands themselves, analyses of LCT demand cannot only be made independent of particular technologies but can also encompass a wider range of energy consumer types. For example, in [44], NTS data (that naturally covers a much wider set of energy consumption behaviours than an EV trial) is used to derive potential EV charging schedules for different battery sizes, charger power levels and levels of access to charging at different locations.

Whereas research on the impacts of individual LCTs (i.e., either EVs or HPs) on distribution networks is plentiful, the literature on the combined effects of EVs and HPs on network infrastructure is comparatively scarce. Edmunds et al. [52] present a study on the potential for smart EV charging to maximise the available demand capacity ('headroom') for HP penetration in GB distribution networks. They conclude that smart EV charging could significantly increase the headroom for EVs, but only marginally increase the headroom for HPs (this is due to the significantly lower levels of flexibility assumed for heating demand than EV charging). Navarro-Espinosa et al. [53] assess the voltage and

thermal impacts of these technologies for a set of LCT penetration scenarios by employing a Monte Carlo assessment technique to sample from HP and EV demand profiles, generated from heating demand data and EV trial data respectively, and randomly assign them to models of 128 UK distribution feeders. Neither of these studies use socio-economic indicators in forming their analyses, which as previously discussed, has been established as a major driver of household energy consumption and as such a key determinant in influencing the necessary network investment.

The spatial mapping of these demands onto electricity networks specifically is the final part of the studies in this area.

The use of socio-economic indicators to assign LCT demand profiles in distribution network models is relatively rare in the literature. Kelly et al. [45] analyse the impact of a simulated fleet of plug-in hybrid EVs on a distribution network; in doing so, disaggregation of travel behaviour via analysis of the US National Household Travel Survey is carried out to present differences in driving habits – and expected charging load – from a fleet of plug-in hybrid vehicles on the basis of age, income and location (urban/rural). Dixon and Bell [44] present a model of EV charging impact on a Scottish distribution network that uses a set of socio-economic indicators, including employment type and means of travel to work (which, as aforementioned, were found in [20] to be amongst the main drivers of household vehicle energy consumption), to assign disaggregated travel diaries and simulated charging schedules to a distribution network based on the socio-economic characteristics of the neighbourhood it serves. However, in both [44,45], only EVs are considered and HPs are not included. McKenna et al. [54] present a model to investigate the impact of HPs on distribution networks by developing three archetypal socio-economically differentiated neighbourhood clusters, based on analysis of UK Census data, thus linking socio-economic indicators with HP demand. However, in [54], only HPs are considered and EVs are not included. Agbonaye et al. [55] present a tool for mapping the impact of EVs, HPs and other LCTs on electricity network infrastructure. However, the analysis in [55] is carried out at the resolution of primary substations; while this is useful for high-level analysis, it misses the challenges of incorporating LCTs in distribution networks at the local level.

To the authors' knowledge, there is no work in the literature that has sought to simulate the combination of EV and HP demand on distribution network infrastructure, at a higher resolution than primary substations, using socio-economic indicators to inform the application of LCT consumption data.

3. Contribution

From the related scholarship it is evident that although works have probed elements within this research space, gaps remain within the collective knowledge and this paper therefore addresses them as follows:

- The work carries out mapping of spatially linked gas demand and socio-economic datasets and then through analysis identifies relationships between gas consumption and social deprivation/affluence. The relationships support generalised socio-technical analysis in the absence of sufficiently granular metadata and are used to support novel spatial and socio-sensitive LCT modelling.
- A localised HP modelling methodology that couples two established methods of converting gas demand to equivalent electrical heat demand is incorporated where the developed relationships between gas demand and social deprivation are used as inputs to the modelling. The benefits of this approach are shown by comparison with a generalised HP
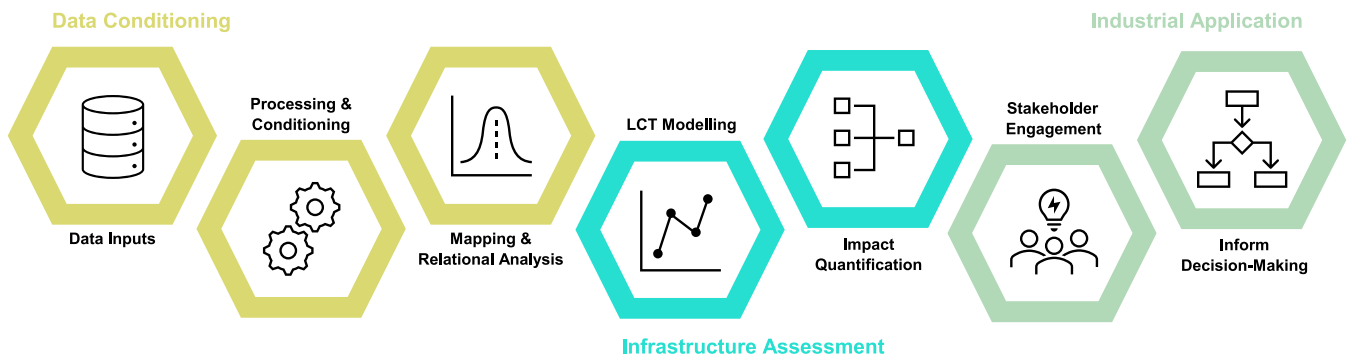
Fig. 1. High-level step-by-step overview of the developed methodology and its application.

modelling approach that uses raw trial data as used in [42]. Findings from this analysis provide novel insights into the value of localised modelling with respect to socio-technical analysis.

- In addition to the localised HP modelling, the work incorporates modelling of EVs where EV charging schedules are based on socially disaggregated charging behaviour in the form of charging diaries synthesised from UK NTS data [56, 57]. This allows for a combined infrastructure assessment that accounts for both the electrification of heat and transport in consideration of socio-economic indicators.

The core contributions are formalised through a novel high-resolution assessment methodology that enables assessment of electrified heat and transport impact on transformer headroom at scale using socio-economic indicators to inform the application of LCT consumption data. The methodology is applied to a fleet of over 4000 secondary transformers (typically 11/6.6 kV − 400 V in the UK) distributed across the north of Scotland and a subset are used to inform the analysis. Findings are then analysed primarily from the perspective of the incumbent DNO but the implications and value of such modelling capabilities for other stakeholders e.g., policy makers and local authorities are also discussed.

The remainder of the paper is organised as follows. Section 4 describes the datasets used and their mapping, in addition to the relational analysis undertaken. Section 5 describes the developed methodology and the LCT modelling techniques used to underpin the approach, also describing the assessment mechanism. Section 6 provides the results with accompanying analysis. Section 7 takes a wider contextual view of the presented findings and Section 8 concludes the work whilst making a recommendation for future research.

4. Mapping and relational analysis

This section provides a brief description of the external data used to inform place-based LCT modelling and its conditioning, it also describes the relational modelling between datasets. Outputs from the mapping and relational analysis then feed into an infrastructure assessment that consists of LCT modelling and impact quantification as highlighted in the high-level step-by-step overview of the methodology shown in Fig. 1. The figure also highlights the industrial application of this research where the developed method is used to support engagement between different stakeholders and to inform interrelated decision-making. Mapping of the datasets and analysis was carried out in Python and the GeoPandas package [58] was used to manage all geospatial data.

4.1. Description and mapping of data

The data concerned includes: GIS data for Scottish Hydro Electric Power Distribution's (SHEPD's) network, the Scottish Index of Multiple Deprivation (SIMD) published by the Scottish Government [59], gas demand data published by the Department for Business, Energy & Industrial Strategy (BEIS) [60], Monitored HP data from the Renewable Heat Premium Payment (RHPP) scheme [61] and smart meter energy consumption data from the Low Carbon London (LCL) project [62]. These are described as follows.

4.1.1. SHEPD network GIS data

DNOs in GB typically record GIS data for their network assets to assist with network management and planning [63]. In support of this research, GIS data for SHEPD was made available to the authors in the form of shapefiles, which is a geospatial vector data format developed by the Environmental Systems Research Institute (ESRI) [64]. This includes spatial and technical information for their entire licence area which supplies the north of Scotland. The spatial and technical information associated with their secondary transformers is of specific relevance to this work. However, although SHEPD's GIS data is used, the hierarchical methodology developed could be applied to any GIS transformer dataset.

There are approximately 56,000 active secondary/distribution transformers in the shapefile dataset provided by SHEPD. This is comprised of approximately 47,000 pole mounted transformers and around 9000 ground mounted transformers. 4000 ground mounted transformers, for which technical and customer data are available, are selected for use here.

4.1.2. Scottish index of multiple deprivation

The SIMD is the Scottish Government's standard approach to identifying areas of multiple deprivation [59]. It is an area-based measure of relative deprivation over 6976 discrete data zones, which are ranked from most deprived to least deprived [59]. The 2020 SIMD data zones [65] are ranked into 10 deciles. Geospatial data is used to correlate SIMD data zones with transformer location and to classify transformers by SIMD decile.

4.1.3. Gas demand data

BEIS records annual gas consumption information for every postcode in the UK [60]. The mean consumption (kWh) is used for this work. The 2020 gas information is first mapped to a shapefile containing geospatial digital postcode boundaries for Scotland [66]. Through this mapping, the spatial diversity in gas demand for each postcode in Scotland is obtained. Most importantly, the digital postcode boundaries also identify which data zone each postcode corresponds to. Note that the dataset is only intended to consider domestic consumers and therefore excludes

industrial and commercial dominated postcodes. However, it can include postcodes dominated by smaller commercial premises which only marginally fail to meet the classification threshold, such postcodes are typically outliers within the observed dataset.

4.1.4. RHPP: Monitored HP data

The RHPP scheme provided subsidies for households and communities to install renewable heat options in residential properties [67]. An extensive monitoring campaign was carried out on 700 of these installations between October 2013 and March 2015. The output dataset contains physical monitoring data including 2-minute resolution electrical demand data, and metadata describing the features of the HP installations and the dwellings in which they were installed. A subset of this dataset [61] which contains electrical demand data for both air and ground source HPs was used for the generalised modelling approach in this work, as also used in [42]. The raw daily HP demand profiles are re-sampled from the 2-minute resolution to 30-minutes and a winter period between 01/12/2013–26/02/2014 is considered.

4.1.5. LCL: Smart meter energy consumption data

As smart meter data or transformer SCADA data is unavailable to the authors for the areas concerned in this work, the domestic demand is modelled from smart meter data recorded during the LCL project from 2011–2014 [62]. The smart meter readings were taken at half hourly intervals and the consumer sample was based on the Greater London population. During the project these consumers were classified into three categories based on CACI Acorn Group [68]; 'Affluent', 'Comfortable' and 'Adversity'. Following a similar approach as adopted in [52], more than 1800 daily profiles for each day in a winter period between 01/12/2013–27/02/2014 are considered to represent a winter demand scenario. Therefore, for each CACI Acorn classification, a bank of smart meter demand profiles for a shared winter period are available for sampling.

4.1.6. Summary

The network GIS data is regularly updated and maintained by the DNO and both the SIMD and Gas demand data are published annually by government-bodies. The LCL smart meter data and the RHPP monitored data are the most recent publicly available monitored datasets for this demand type in the UK. Whilst society has evolved since these trials were conducted, accurately capturing the behavioural changes at the resolutions and scales concerned in this work, in terms of demand e.g., post COVID societal changes to working routines, volatility in energy prices and technological modal shifts without monitored data remains an ongoing challenge. Studies such as [69], have highlighted the challenges with representative HP demand modelling given the lack of trial data and that alternatives to using monitored data are limited by availability of household information at a granular level (to develop building physics modelling approaches that can be validated). The confidence of modelling such granularities at scale across a diverse housing stock (in consideration of occupant diversity) is also a significant limitation. As such, the datasets used are considered to be largely representative of both current domestic and HP demand behaviour. Though fundamentally, the developed methodology would be able to take any HP and smart meter monitored data as an input. Should new trial data become available, the method could be used to investigate to what extent consumer end-use demand has changed and the subsequent impact on electricity networks which could inform modelling of future demand scenarios.
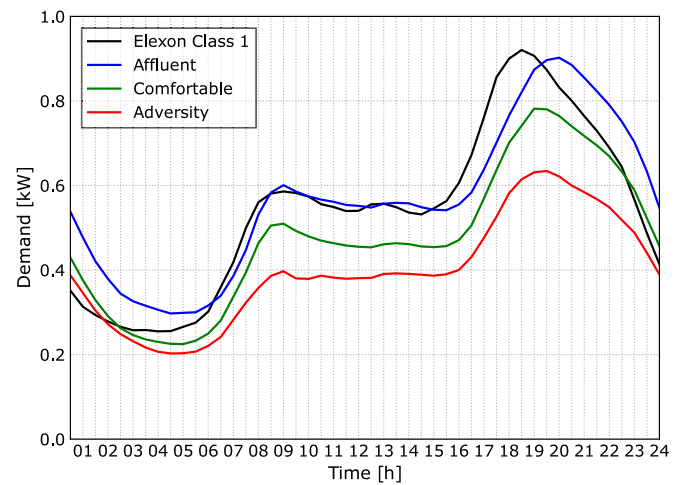

Fig. 2. Base winter weekday demand profile for each Acorn category compared with generic Elexon winter weekday profile.

4.2. SIMD - demand relationship

This section provides a breakdown of the relational modelling between the SIMD and both the LCL smart meter data and the gas demand data. First, describing how the diversity in conventional household demand is modelled with respect to the SIMD. Then exploring the relationship between the SIMD and gas consumption by describing the derivation of representative gas consumption Cumulative Distribution Functions (CDFs) for each SIMD decile.

4.2.1. SIMD and LCL domestic demand

From the smart meter daily profiles, an average daily winter load profile for each Acorn category is obtained. Fig. 2 compares these with the generic class 1 Elexon profile [70]. The figure shows that for the smart meter data the daily demand shape is similar between the Acorn categories. However, variation in magnitude is observed indicating that 'Affluent' consumers have the highest consumption and 'Adversity' the lowest, further confirming that socio-economic factors have an influence on household energy consumption as described in Section 2.1. The figure also highlights that smart meter peak demand occurs later in the evening than the generic Elexon Class 1.

To account for heterogeneity in consumer demographic across the areas concerned in this work, each transformer is classified based on its location with respect to the SIMD e.g., each transformer located in a geographic area where the SIMD is 10 would be classified accordingly. To relate the Acorn classified smart meter profiles with the SIMD classified transformers, a simple distribution alignment is considered based on the assumption that all consumers connected to a secondary transformer are of the category corresponding to the transformer's assigned SIMD decile (the average number of consumers for each secondary is typically much lower than the SIMD data zone resolution which on average contains 340 households). For transformers classified with SIMD decile 9–10, connected consumers are considered to be 'Affluent' according to the Acorn classification, 4–8 to be 'Comfortable' and 1–3 to be 'Adversity' where boundaries are defined based on parallels between the Acorn classification and SIMD.

4.2.2. SIMD and gas demand

The relationship between SIMD decile and annual mean gas demand is presented in Fig. 3. The interquartile range (IQR) method was used to clean the dataset to remove any outliers [32].

(a)

(b)
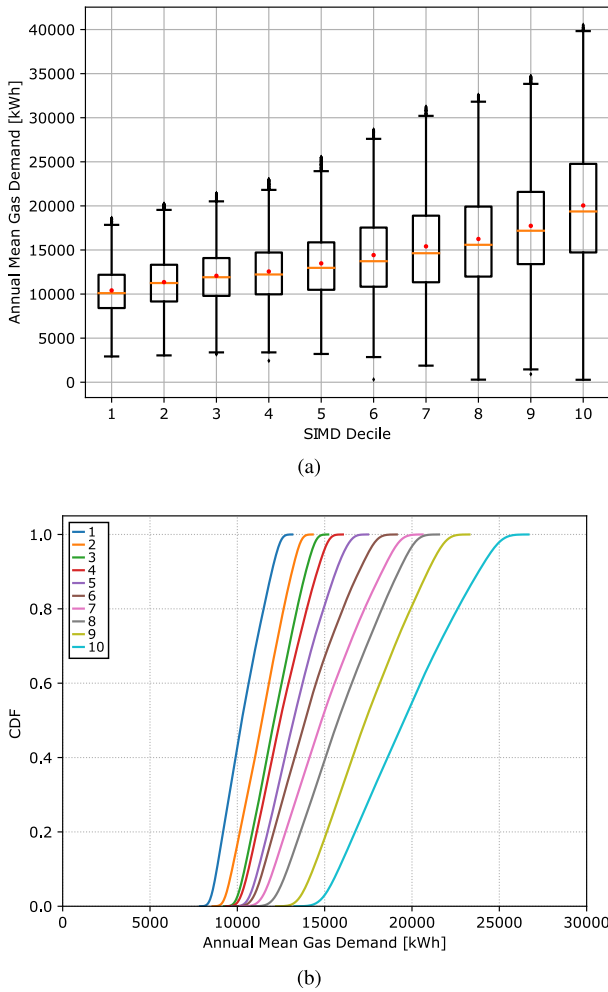
Fig. 3. Relationship between SIMD deciles and annual mean gas demand. (a) Box plot distributions of gas demand for each decile. (b) Cumulative Distribution Function of central 50% gas demand for each decile.

Fig. 3(a) highlights that mean and variance increase with respect to SIMD decile. This suggests that although there is correlation between social deprivation and gas demand, other factors such as building characteristics e.g., building fabric, floor space and construction type also have an effect on consumption.

As the dataset includes postcodes dominated by smaller commercial premises which only marginally fail to meet the classification threshold, these can be attributed to the higher portion of the gas demand spread, whereas postcodes that are comprised of both gas and other heating solutions or dominated by properties not in continuous occupation can be attributed to the lower portion. As a result, the CDFs shown in Fig. 3(b) are created purely from the central 50% portion of each box plot distribution for each decile in Fig. 3(a). This is considered to be representative of typical residential household gas consumption across each of the deciles whilst accounting for variation in building stock characteristics internally within each SIMD data zone.

5. Transformer assessment methodology

This section provides a detailed description of the developed assessment methodology and the modelling techniques used to underpin the approach. This includes details on both HP and EV modelling and the mechanism used to evaluate the results.

Algorithm 1 Monte Carlo Assessment Approach

1: **for** $si \in SIMD$ **do**
2:     **for** $T \in Transformers$ **do**
3:         Use (5) to calculate P_{dem}
4:         **for** $p \in Penetrations$ **do**
5:             **while** $i < 100$ **do**
6:                 Use (6) to calculate C^{HP}
7:                 Use method in Fig. 5 and (1)–(4) to create localised socio-technical electrical heat demand profiles based on si then sample according to C^{HP}
8:                 Use (7) to calculate P_{dem}^{HP}
9:                 Use (8) to calculate C^{EV}
10:               Sample EV charging diaries based on C^{EV}
11:               Use (9) to calculate P_{dem}^{EV}
12:               Use (10) to calculate daily headroom h
13:               **Store** h for every iteration
14:               $i = i + 1$
15:             **end while**
16:             **return** average of h for each p
17:         **end for**
18:     **end for**
19: **end for**

5.1. Methodology overview

The methodology is adaptable subject to the assessment scenario under consideration. This work considers four scenarios: the uptake of HPs in isolation modelled by using either the localised method which accounts for social dimensions or the generalised RHPP trial data method, the uptake of EVs in isolation and the combined uptake of both EVs and HPs (using the localised HP modelling method). A high-level flowchart of the developed methodology for the combined assessment scenario is presented in Fig. 4. The flowchart demonstrates how mapping of external data is used to support relational analysis which feeds into socio-technical and socio-spatial LCT modelling and then into infrastructure assessment. A Monte Carlo assessment technique is used with multiple iterations to account for variations in the distribution of gas demand according to the CDFs for each SIMD decile, HP usage profiles and EV charging profiles as similarly used in [53]. Algorithm 1 provides a summary of the iterative process for the combined scenario. For the HP only scenarios steps 9–11 in Algorithm 1 are excluded and for the EV only scenario steps 6–8 are excluded. For the generalised HP modelling approach scenario, step 7 is replaced with the raw re-sampled daily HP profiles which are stochastically sampled according to HP penetration levels.

5.2. Localised heat pump modelling

A household's electrical heat load is directly proportional to its heat demand [69]. In turn, domestic heat demand is a complex interdependent function of several components combining building physical parameters as well as the behavioural habits of the occupants. This complexity is further compounded by the specific HP parameters of a household, such as power rating, heat source, and efficiency [69], as this governs the relationship between heat output and electrical demand.

Note that whilst some 'large' heat loads such as commercial and industrial loads may be decarbonised via electrification e.g., industrial sized HPs or district heating/heat networks. They may also follow alternative pathways e.g., use of hydrogen, and other evolving technologies in this space. As this work is focused at the secondary transformer resolution (by extension the LV
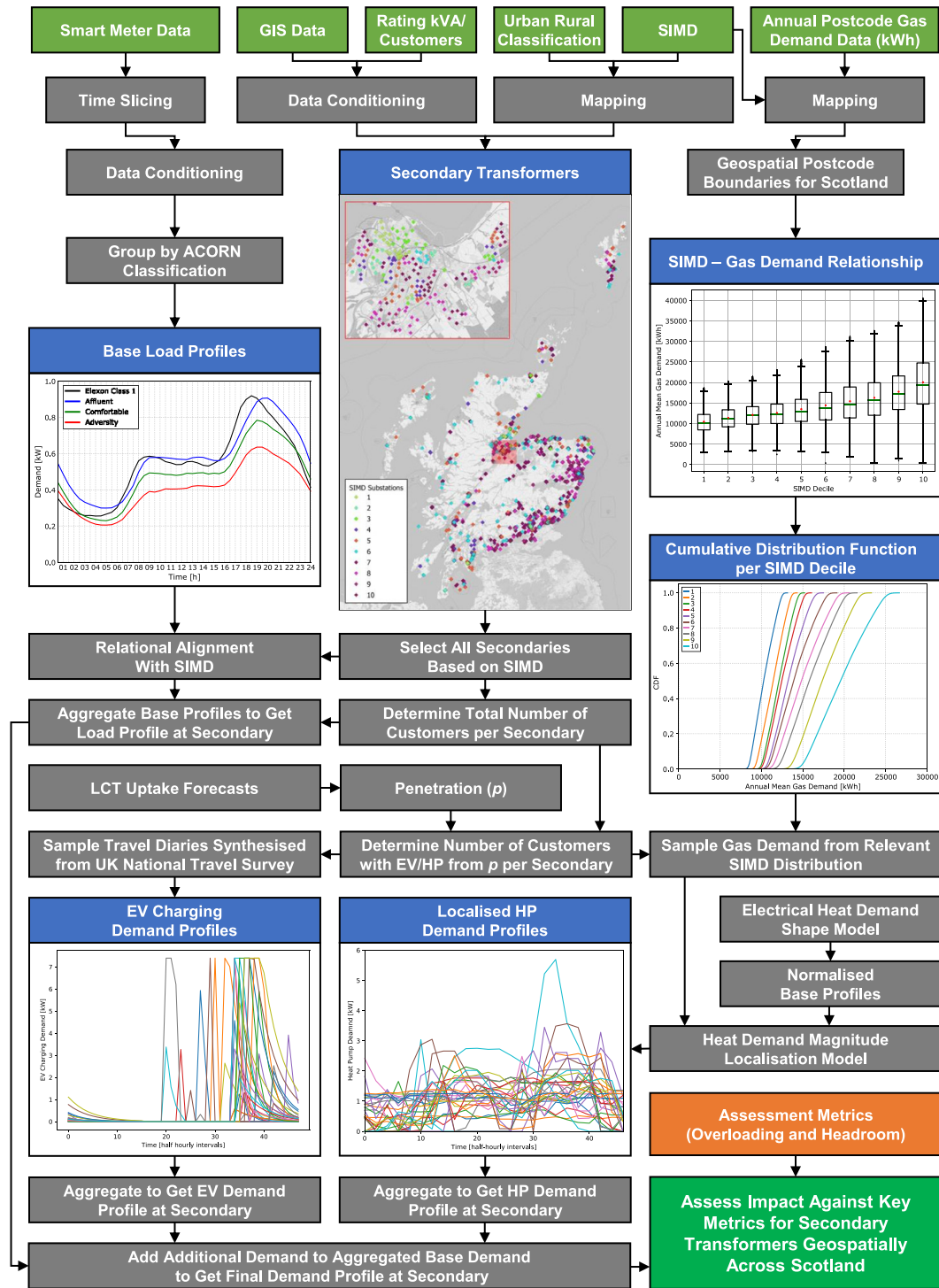
Fig. 4. High-level representation of the developed assessment methodology.

level) and primarily on space heating demand (the amount of heat required to heat a building and to maintain a particular heating profile), 'large' commercial and industrial modelling of demand is excluded as it is considered that the bulk of this heating demand, at least in the UK, will be connected above the secondary transformers i.e., at 11/6.6 kV and above. There may be scope in future work to include small-scale commercial and industrial HP demand, though at the time of writing no trials have been conducted yet to obtain monitored data in the UK for these premises.

For the studies considered in this paper, in the absence of sufficiently granular technical information surrounding household physical and behavioural parameters, two established approaches of converting gas demand to equivalent electrical heat demand are employed, the *Heat Demand Magnitude Localisation Model* and the *Electrical Heat Demand Shape Model* developed in [69]. These are combined to construct locally sensitive half hourly electrical heat demand profiles where the developed relationships between gas demand and social deprivation are used as inputs to the modelling. A summary of the combined modelling
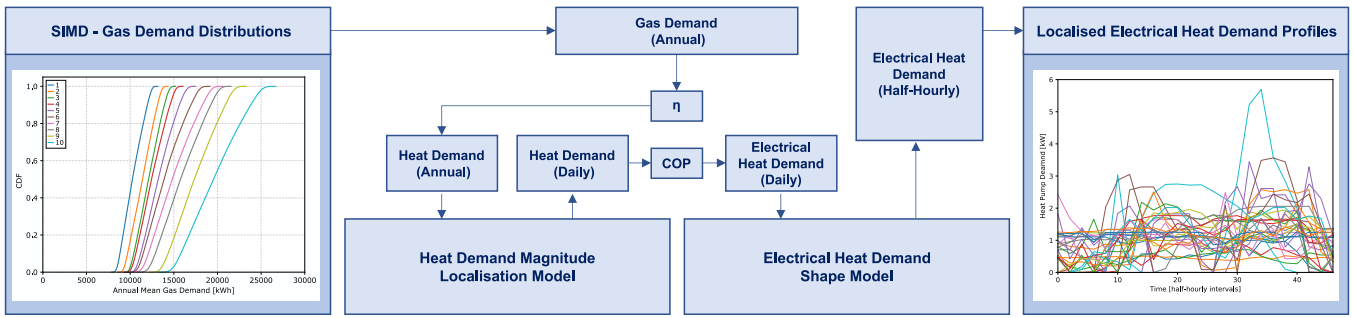
Fig. 5. Methodology used to convert annual gas demand to localised electrical heat demand profiles.

approach is outlined by Fig. 5 and a brief description of each model component is provided as follows.

5.2.1. Heat demand magnitude localisation model

The *Heat Demand Magnitude Localisation Model* is used to transform the CDF sampled gas demand into a daily demand magnitude that is proportionally scaled to local physical and behavioural components that influence heat demand. This gas demand serves as a proxy for local building, climate and behavioural parameters. Firstly, a gas conversion efficiency (η) is used to transform the raw annual gas demand (D_G^{annual}) into an equivalent annual direct heat demand (D_H^{annual}) as shown in (1). For this work, a fixed gas boiler efficiency of 80% has been used. This has been obtained by taking an average of over 2000 different mains gas boiler models with efficiencies ranging from 55% to 90.3%. The recorded efficiencies are based on the Seasonal Efficiency of Domestic Boilers in the UK (SEDBUK) rating scheme and are stored in a database that is used to support UK building energy performance assessments [71]. D_H^{annual} is then converted into a daily heat demand (D_H^{daily}) through (2) and (3) by assuming that heat demand varies sinusoidally throughout the year in accordance with temperature variation, D_H^{annual} provides the area under the sinusoid which defines the amplitude and offset parameters and subsequently the daily demand variation throughout the year and x corresponds to day of year.

$$D_H^{annual} = \frac{D_G^{annual}}{\eta} \tag{1}$$

$$D_H^{annual} = \int f(x)\,dx = \int_0^{365} D_{amp} \times \sin(\frac{2\pi}{365}x + \phi) + D_{off}\,dx \tag{2}$$

$$D_H^{daily} = f(x) = D_{amp} \times \sin\left(\frac{2\pi}{365}x + \phi\right) + D_{off} \tag{3}$$

$$D_E^{daily} = \frac{D_H^{daily}}{COP} \tag{4}$$

The default amplitude (D_{amp}) and offset (D_{off}) parameters have been applied. These fit parameters were tested versus monitored gas meter data collected at 30-minute intervals for several thousands of customers in 2010 as part of the Energy Demand Research Project (EDRP) [72] and monitored HP heat and electrical demand data obtained from the RHPP dataset [61]. The daily heat demand is transformed into a daily electrical demand (D_E^{daily}) via a coefficient of performance (COP) through (4). From the RHPP dataset HP COP typically ranges from 2 to 4 [61] which is comparable to the air and ground source HP COPs presented in [73]. A fixed COP of 3 is used for the studies considered in this paper.

5.2.2. Electrical heat demand shape model

The *Electrical Heat Demand Shape Model* developed in [69] is then used to transform the daily electrical demand into a set of half hourly demand figures sensitive to local temperature conditions. The modelling approach incorporates monitored HP data from the RHPP dataset and is validated against operational demand data collected during the LCL HP trials [74]. Fundamentally, the work in [69] identified common recurring electrical heat demand profiles that repeat within the RHPP dataset, despite the disparate geographical and demographic conditions. These have been normalised for an ambient temperature of 0°Celsius which is used to simulate winter cold conditions. The normalised profiles are then used as the basis for HP daily load shape forming and are sampled accordingly.

5.3. Electric vehicle modelling

In addition to traditional power rating and capacity challenges, a significantly challenging aspect of EV modelling is the uncertainty surrounding consumer behaviour. External factors are expected to influence consumer travel routines and as a consequence EV charging patterns. In this work, residential EV charging schedules synthesised from the UK NTS [75] are used to capture elements of the significant variation in energy demand for car usage across society. This method was previously developed in [56,57] and used in other works including [52].

EV modelling in this work follows the government-lead assumption that the majority charging in the UK will take place at home [25]. The area modelled also has high instances of off-street parking. Additionally, from the perspective of the DNO, modelling at-home charging only is more conservative, as it is reasonable to expect they will have to deal with scenarios where all vehicle chargers in a given area are home-chargers rather than work-chargers or a combination of (particularly in purely residential areas where HPs are more likely to be installed). Also, it is considered that fast charging stations or charging hubs are more likely to attract specific attention and study from DNOs and would typically fall within the remit of the local authority planning system. Therefore, there would be scope for DNOs to anticipate their connection and to influence their location to ensure compatibility with network capacity.

As in [57], EV modelling considers routine charging schedules to be the primary charging scenario. These charging schedules consider the principle of 'least inconvenience' to the consumer where charging behaviour has become routine and reflective of social behaviour. EVs are connected when consumers arrive at their households irrespective of the vehicle's state of charge seeking the maximum feasible state of charge gain during the parked duration and by the charging constraints. These charging patterns are essentially 'dumb' in that there is no incentivisation for scheduling or optimisation that facilitates demand-side management. In addition, this work assumes all households have

the necessary EV charging infrastructure at each residence and assumes that a maximum of one EV can be charged at each residence at any given interval. A set of 10,000 winter weekday charging schedules have been derived with a fixed 7.4 kW rating (high power 'fast' home charging, typically a single phase 32 A, 230 V connection) across a range of 'typical' vehicle battery sizes: 24, 30, 40, 60 and 75 kWh. An inverter efficiency of 88% [76] has been used for the heuristic which is further described in [56,57].

5.4. Transformer headroom

Transformer headroom is one of the key indicators as to when DNO intervention may be necessary. Headroom relates to the remaining capacity after the downstream demand has been met. As in [52], headroom is used analogous to hosting capacity (HC). Whilst DNOs in the UK may carry outing HC assessments of their infrastructure, they often use 'headroom' and 'footroom' as the metrics for doing so. Note that 'headroom' is used to distinguish from 'footroom' which could also fall under the HC bracket, where in the presence of certain LCTs 'footroom' would be the possible increase (or decrease) in injection by e.g., vehicle-to-grid or solar PV within export limits.

Network planners historically adopted a 'fit and forget' philosophy, oversizing transformers by building in additional headroom to accommodate marginal demand growth. The demand growth associated with the uptake of LCTs is expected to significantly erode existing headroom. Across the distribution network this may lead to overloading and eventual degradation of assets as they operate closer to their physical limits.

To determine the daily headroom profile for each individual transformer, the aggregated demand, $P_{dem,t}$ at time t, where $t = 1, 2, 3, \ldots, 48$ for all consumers ($i = 1, 2, 3, \ldots, TC$, where TC is the total number of consumers), is first calculated as follows:

$$P_{dem,t} = \sum_{i=1}^{TC} lp_{i,t} \tag{5}$$

where $lp_{i,t}$ is the measurement of the ith consumer load profile at the tth interval. The aggregated HP demand, $P_{dem,t}^{HP}$, at the tth interval, is then calculated as follows:

$$C^{HP} = TC \times HP_{pen} \tag{6}$$

$$P_{dem,t}^{HP} = \sum_{i=1}^{C^{HP}} HP_{i,t} \tag{7}$$

where C^{HP} is the number of customers with a HP based on TC, HP_{pen} is the HP penetration percentage and $HP_{i,t}$ is the measurement of the ith HP profile at the tth interval. The aggregated EV demand $P_{dem,t}^{EV}$, at the tth interval, is similarly calculated:

$$C^{EV} = TC \times EV_{pen} \tag{8}$$

$$P_{dem,t}^{EV} = \sum_{i=1}^{C^{EV}} EV_{i,t} \tag{9}$$

where C^{EV} is the number of customers with an EV based on TC, EV_{pen} is the EV penetration percentage and $EV_{i,t}$ is the measurement of the ith EV profile at the tth interval. The headroom, h_t, at the tth interval, is then obtained from:

$$h_t = \frac{P_{max} - (P_{dem,t} + P_{dem,t}^{HP} + P_{dem,t}^{EV})}{P_{max}} \times 100 \tag{10}$$

where P_{max} is the transformer rating.

To visualise the results geospatially the daily headroom is split into four bands as shown in Fig. 6. These bands are based on
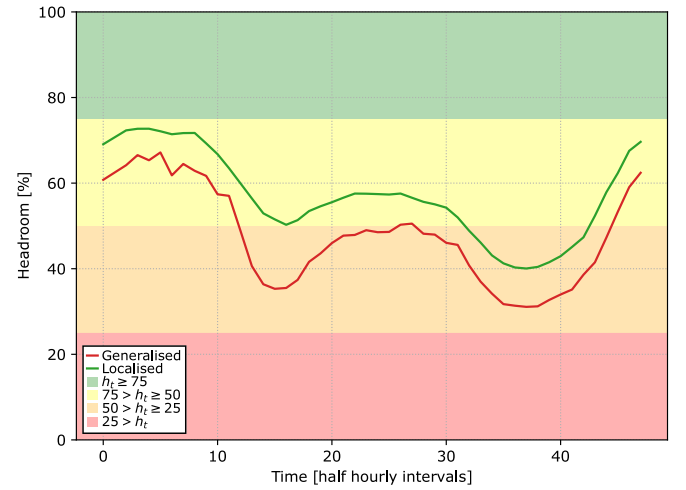

Fig. 6. Example of daily headroom profiles for both the localised and generalised HP modelling approaches with associated constraint banding.

the constraints in (11) and are primarily used to determine the priority state of the transformer.

$$h_x = \begin{cases} L, & h_t \geq 75 \\ M, & 75 > h_t \geq 50 \\ H, & 50 > h_t \geq 25 \\ C, & 25 > h_t \end{cases} \tag{11}$$

where h_x is a set containing the priority classification of h_t, L is Low-priority, M is Medium-priority, H is High-priority and C is Critical-priority. The final priority state S is that in which the transformer spends most time over the 48 daily time periods. For example, in Fig. 6, for the generalised approach, as the transformer spends the most time in $75 > h_t \geq 50$, the transformer's S would be Medium-priority. For the localised approach, as the transformer spends the most time in $50 > h_t \geq 25$, the transformer's S would be High-priority. This provides a means of classifying all transformers in terms of their criticality with respect to the urgency of a network management intervention.

6. Results and analysis

The results section is split into two subsections; firstly, a comparative analysis between the localised socio-technical approach to HP modelling and the generalised RHPP approach is presented. Then EVs are introduced, independently and in combination with the localised HP modelling approach which enables combined impact assessment analysis.

6.1. Comparative analysis between localised socio-technical and generalised HP modelling

To determine the spread of social deprivation impact, analysis is focused on transformers classified by SIMD deciles 1, 5 and 10. A subset of the relevant transformers are used to demonstrate the impacts of both the localised and generalised HP modelling approaches. The subset and examples presented are selected to capture variation in both transformer rating and the number of connected consumers to provide an indication of the expected variance and impact across the asset base. A larger subset is then used to support geospatial analysis which demonstrates scalability of the methodology. The larger subset is also selected to allow for cross-comparison between areas with differing levels of social deprivation.

Fig. 7 provides the daily headroom profile of two different transformers at varying HP penetrations (25%/50%/75%/100%) for SIMD decile 1. Figs. 8 and 9 show the profiles for SIMD deciles 5 and 10, respectively. From the two examples provided in Fig. 7, the headroom for the socio-technical localised HP modelling approach varies compared with the generalised approach. Variation is also observed in Fig. 9. In Fig. 8 the headroom under both approaches is similar with marginal variation. The figures highlight that the generalised model tends to underestimate headroom in the most socially deprived areas and to over-estimate it in the least socially deprived. This infers that the localised model provides an improved assessment of the true headroom in comparison with the generalised approach. Note that although daily HP demand profile shape is sensitive to temperature variation [69], as winter scenario is considered for both approaches, the impact of temperature variation is negated and due to the numbers of consumers concerned, diversity in consumer behaviour is also negated [42]. This explains why similar daily headroom shapes are observed for both approaches. It is considered that with the variation in magnitude observed the similar-but-scaled curves are sufficiently modelling local diversity for the purpose of this study. Fig. 10 further demonstrates this by highlighting the daily transformer headroom for multiple different transformers at 100% penetration each with related SIMD deciles 1, 5 and 10, respectively. Fig. 10 also confirms that headroom is highly dependent on transformer rating and number of connected customers. More importantly, Fig. 10(c) specifically highlights that in taking a generalised approach to modelling HP demand, in certain instances, the headroom would be underestimated to the extent that it fails to capture an overloading scenario that would otherwise be identified by taking a localised HP modelling approach. Conversely, in Fig. 10(a), by taking a generalised approach, a network management intervention may be triggered before necessary due to an overestimation of the headroom. Fig. 10 highlights that inaccurate estimation of headroom does not apply for all transformers and as such, the proposed classification method allows for prioritisation in terms of their criticality. In general terms, the localised HP modelling approach can capture generic demand variation. However, by directly linking demand to socio-technical characteristics, the headroom can be better quantified with respect to socio-spatial diversity.

The variation in headroom at each transformer as demonstrated in Fig. 10 is geospatially represented in both Figs. 11 and 12. A geospatial snapshot of daily transformer headroom at the four levels of HP penetration studied using the generalised HP modelling approach and constraint bands is presented in Fig. 11. The figure demonstrates the spatial diversity in secondary transformer headroom across a region in Scotland encapsulating a portion of the 4000 transformers considered. The figure provides a visualisation of the impact HP uptake has on transformer headroom in different areas of network. The available headroom noticeably declines as HP penetrations are increased. Fig. 12 presents a snapshot of the same area using the localised HP modelling approach and constraint bands. The impact of the localised approach in comparison with the generalised is visually evident.

Figs. 13 and 14 show the effect of localised modelling in relation to relative affluence. Fig. 13 provides an area snapshot with emphasis specifically on areas with lower social deprivation (SIMD deciles 9 and 10). The figure compares the generalised approach (top) with the localised approach (bottom). As these areas have lower social deprivation, HP demand is likely to have a greater impact on headroom in these regions. Fig. 14 provides an area snapshot with emphasis specifically on areas that have higher social deprivation in terms of SIMD (deciles 1, 2 and 3). The opposite effect can be observed, where the impact of HP uptake

is less prominent for the localised modelling approach compared with the generalised (as also demonstrated in the presented examples in both Figs. 7 and 10(a)).

Using the classification defined by (11), each transformer is classified in terms of S as determined by the modelled 'worst-case' daily headroom scenario. Figs. 15(a) and 15(b) compare transformer intervention priority for each SIMD decile and modelling approach, respectively. In Fig. 15(a), the proportion of High-priority transformers, particularly for 100% HP penetration, are relatively consistent across the SIMD deciles with only minor variation. However, in Fig. 15(b) there is a trending increase from decile 1 to 10 and a reduction in the number of transformers classified as Low-priority is observed. This reduction trend is present but less pronounced in Fig. 15(a). This is likely a consequence of the variation in domestic demand from the diversified base load profiles shown in Fig. 2. In broad terms, the figures emphasise the impact socio-technical and socio-spatial diversity may have in influencing network decision-making. They highlight that failing to consider socio-economic diversity may lead to an over/underestimation of transformer headroom in different locations which may feed into reinforcement and flexibility planning. This confirms the need for consideration of socio-economic indicators in the decision-making process. Also noting that this diversity may have an impact on rate of LCT uptake which has the potential to influence decision-making further.

6.2. Combined LCT assessment

In this section the combined impact of electrified heat and transport is investigated. Both HPs and EVs are initially considered independently, then they are integrated, as shown in Fig. 4, to assess the cumulative impact. Fig. 16 shows the average daily transformer headroom for the localised HPs only, EVs only and combined scenarios for two transformers with varying penetrations of each (0%/25%/50%/75%/100%). It is noted that HP and EV uptake are assumed to be the same here, though the developed methodology can account for independent variation. As previously, the transformers have been selected to highlight the general impact of LCT uptake on the daily headroom profile shape and magnitude. The figure highlights that for both transformers under the HP only scenario there is a noticeable reduction in headroom in the early morning and early evening. This can be attributed to space heating requirements which generally align with standard daily social rhythms. As penetrations increase, the headroom is significantly reduced, although the extent varies between the examples presented. In the EV only scenario, a noticeable evening peak can be observed, this is a consequence of the 'least inconvenience' consumer charging behaviour as described in Section 5.3. Both scenarios in isolation have remaining headroom at 100% penetration. However, in the combined scenario for both cases, when penetrations exceed 75%, the headroom becomes negative during the evening peak which indicates that overloading has occurred. In the combined scenario, due to HP early morning demand and combined HP/EV evening demand, the daily headroom is significantly reduced across the day which may have negative consequences for their long-term health and serviceability [77]. Fig. 17 presents the geospatial visualisation of daily transformer headroom for the combined HP and EV uptake scenario based on the defined constraint bands. In comparison with the HP only scenario using the localised modelling approach shown in Fig. 12, the headroom is significantly more challenged across the asset base, particularly at higher penetrations.

This analysis emphasises the extent of the cumulative challenge with both the decarbonisation of heat and transport via electrification. The combination of both HPs and EVs, and the changes in headroom indicates that demand-side management techniques such as peak shaving through EV charge scheduling must consider the mix of LCTs and their relative demand.
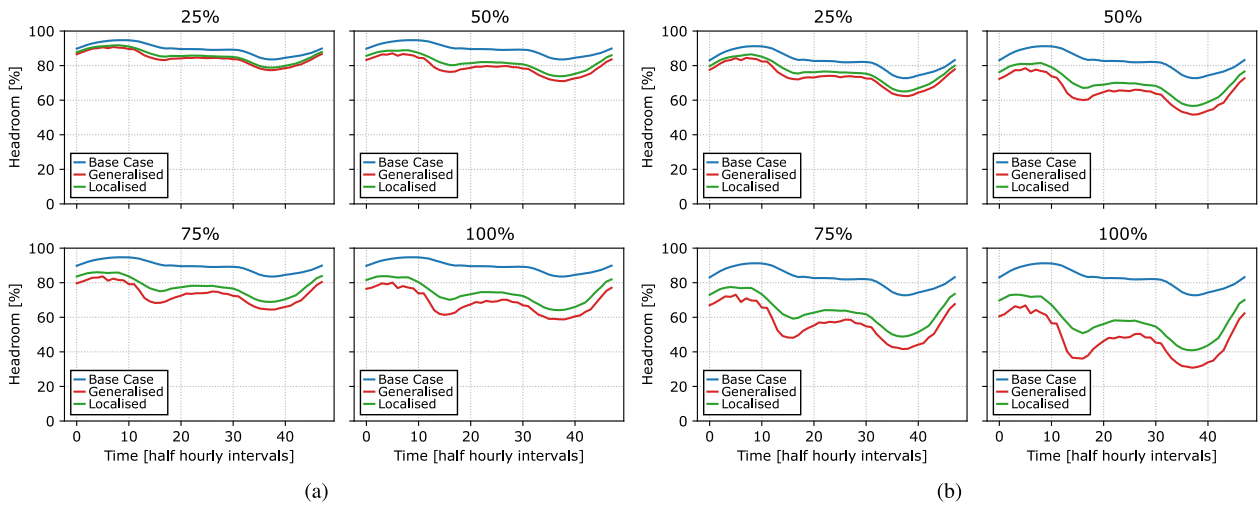
Fig. 7. Daily transformer headroom at different penetrations for SIMD decile 1. (a) Example 1. (b) Example 2.
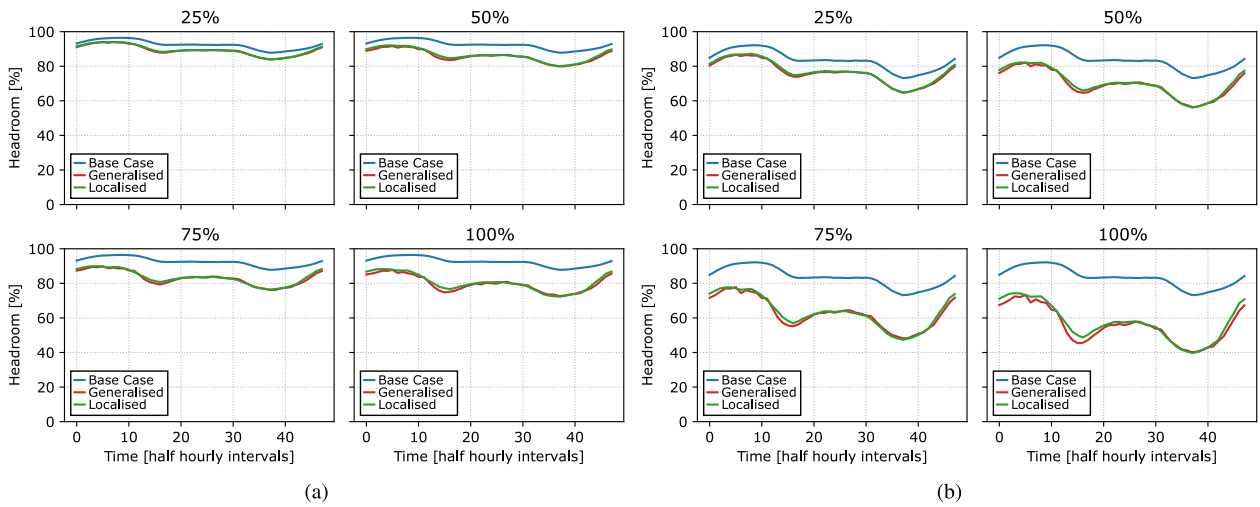

Fig. 8. Daily transformer headroom at different penetrations for SIMD decile 5. (a) Example 1. (b) Example 2.
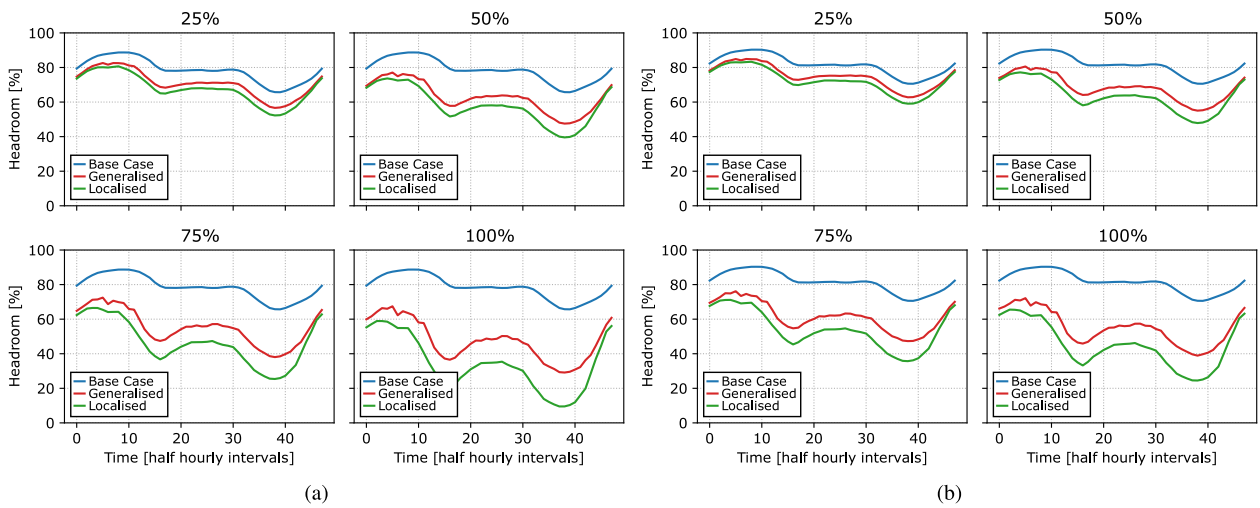

Fig. 9. Daily transformer headroom at different penetrations for SIMD decile 10. (a) Example 1. (b) Example 2.
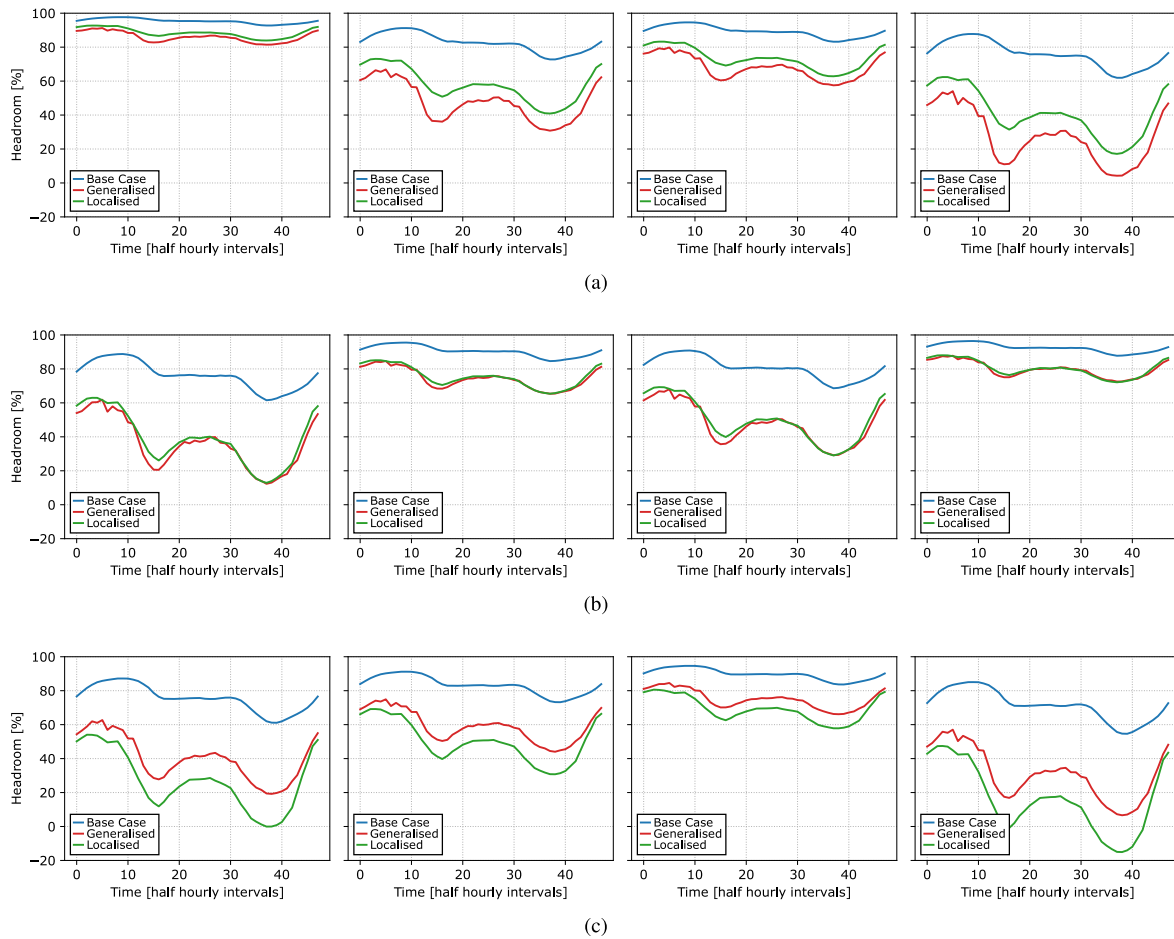
Fig. 10. Daily transformer headroom for multiple different transformers at 100% penetration. (a) SIMD 1. (b) SIMD 5. (c) SIMD 10.

7. Discussion

The discussion presented in this section takes a wider contextual view of the described findings and considers the broader implications. The value of the developed methodology is also established with respect to key parties that are actively involved in the energy transition.

7.1. Distribution network operators

The developed methodology allows for broad infrastructure assessments at a local level whilst accounting for socio-technical and socio-spatial diversity. This is attractive for DNOs due to the high uncertainty associated with LCT uptake and impact across different regions [4]. Having a better understanding of LCT demand allows for improved quantification and understanding of the associated impact. This is necessary when considering local flexibility options; there is a need to understand how much flexibility is available and when [52]. By having better foresight into the impact of local diversity on LCT usage, the value in adopting flexible solutions can be better quantified in comparison with conventional reinforcement.

The findings presented in this work demonstrate the impact of place-based socio-technical analysis in this regard, emphasising that whilst a non-localised modelling approach may still be considered an improvement to conventional simplistic load modelling techniques for headroom quantification, such approaches can risk misallocation of planning resources and failure to reinforce in time in certain areas. The findings also indicate that as the network evolves, local level challenges will emerge as to when and where investment in infrastructure and management solutions should be focused, emphasising the challenge with both heat and transport electrification and the extent that this may impact existing infrastructure.

Historically, due to the relatively predictable nature of domestic demand there was a lack technical need for extensive monitoring and modelling of LV networks. As such, the vast majority of system wide demand related studies are conducted at a primary level [55] given the volume of secondary transformers and the data related challenges. However, with the uptake of locally sensitive LCTs, this work takes a higher resolution approach and is targeted at the secondary level. The findings are generalised indicators of the true headroom (downstream voltage limit breaches and low voltage cable overloads are not considered) and are used predominantly to reveal the impact of localisation and the need to consider socio-technical and socio-spatial dimensions in detailed technical studies. The final decision between adopting a flexible solution or reinforcement to manage the electrification of heat and transport as part of a development plan would ultimately require detailed technical analysis, but the developed method, through the prioritisation criteria, can help identify where such detailed targeted assessment studies should be performed.

In terms of validation, as it was common for DNOs to only install monitoring equipment at the primary level as a business as usual practice, monitored data for secondary transformers is relatively scarce. As part of RIIO-ED2, there is ongoing work being carried out by the DNOs to increase visibility and automation of the distribution networks, this includes installing LV on-load tap changing transformers and monitoring equipment at
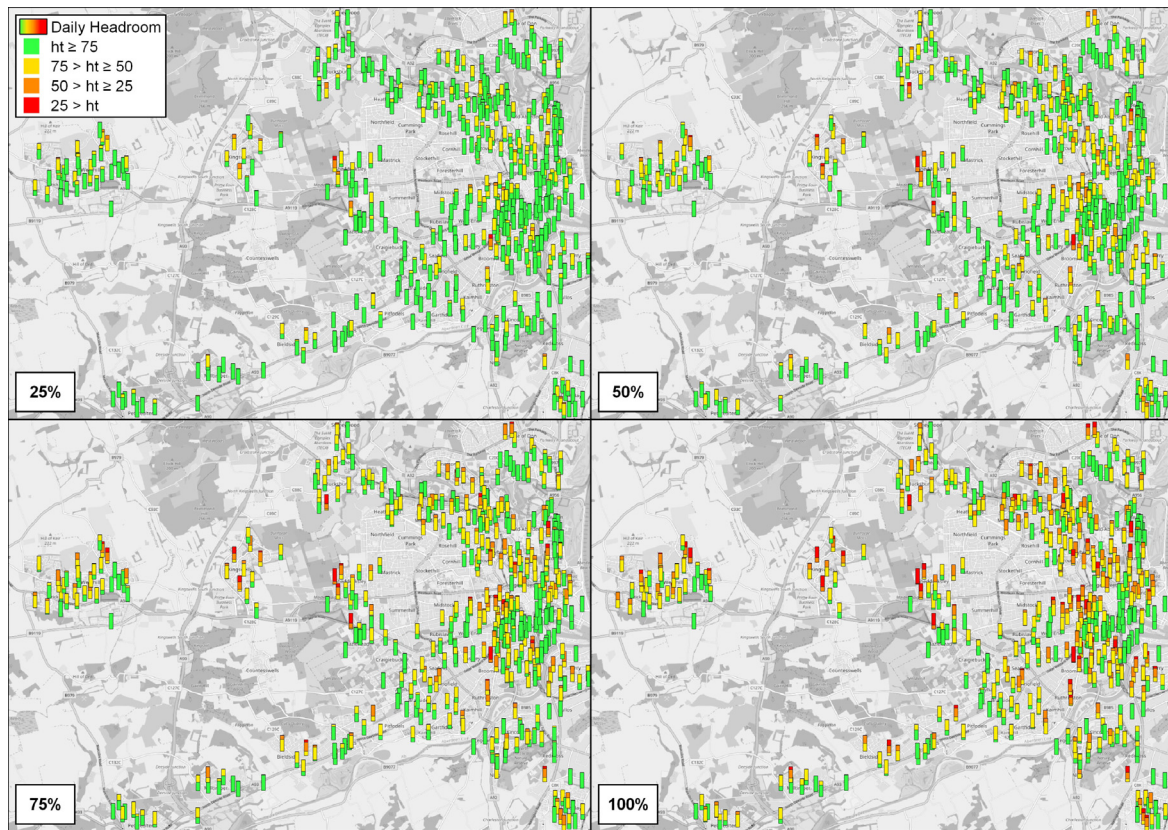
Fig. 11. Visualisation of daily transformer headroom for each penetration using the generalised HP modelling approach and constraint bands.
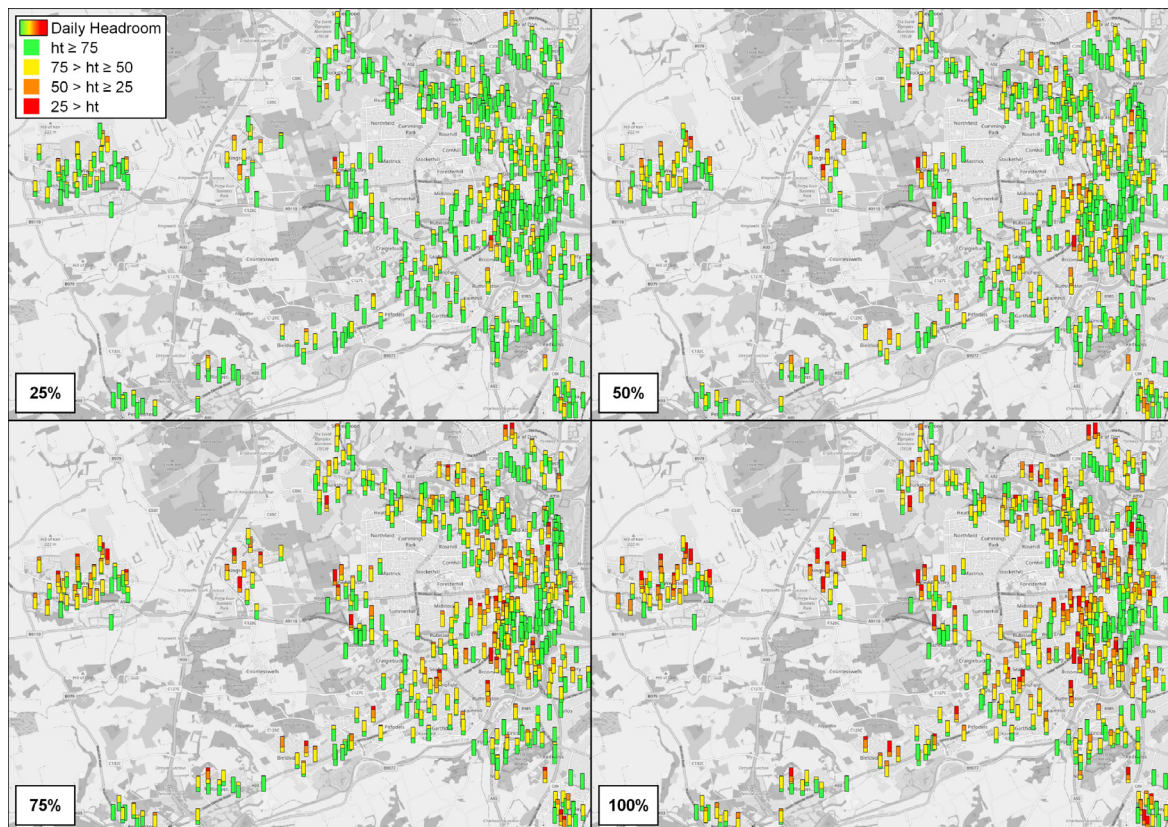

Fig. 12. Visualisation of daily transformer headroom for each penetration using the localised HP modelling approach and constraint bands.
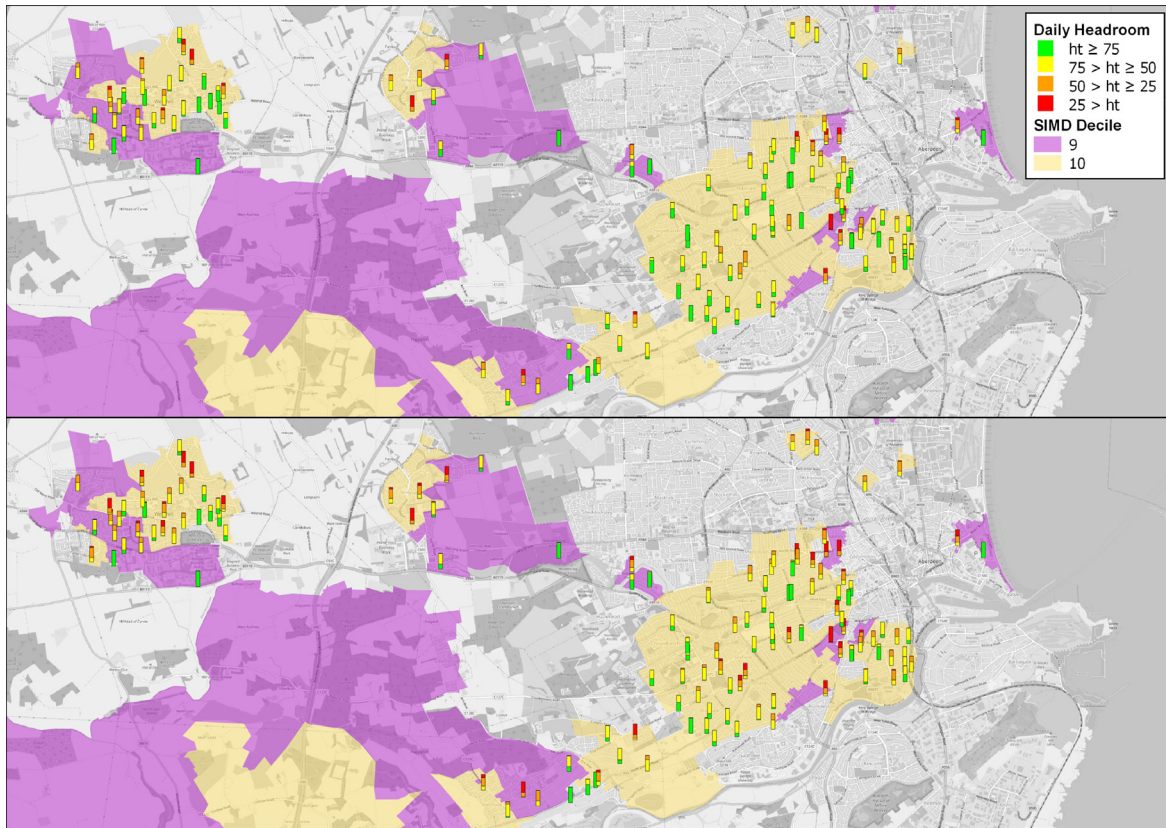
Fig. 13. Comparison of the generalised approach (top) and the localised (bottom) in less deprived areas (SIMD deciles 9 and 10) at 100% penetration.

Fig. 14. Comparison of the generalised approach (top) and the localised (bottom) in more deprived areas (SIMD deciles 1, 2 and 3) at 100% penetration.
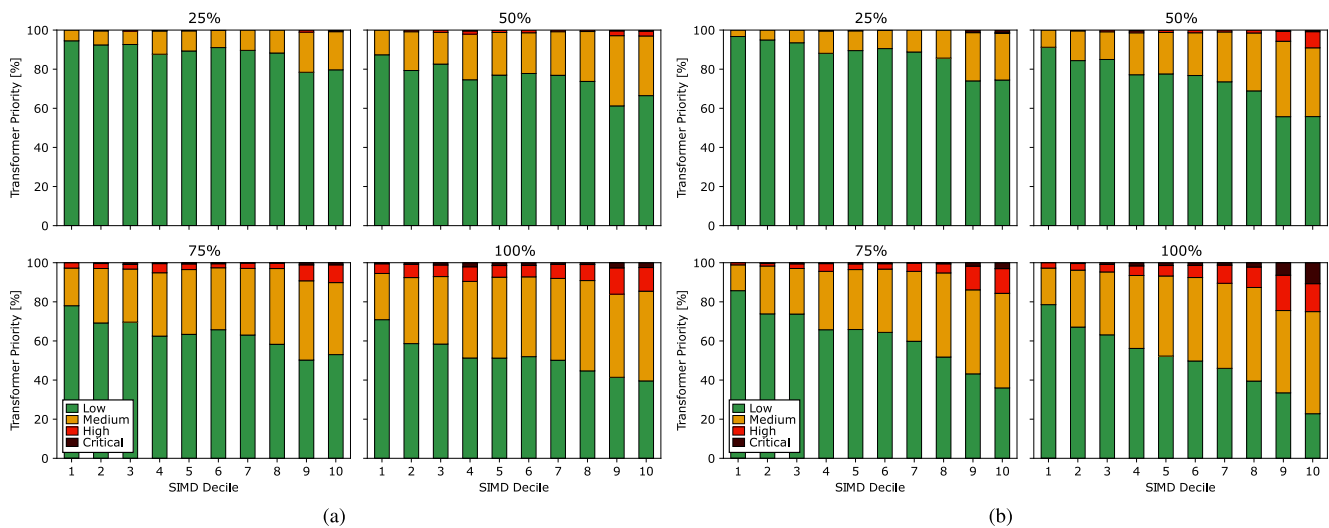
Fig. 15. Transformer intervention priority for each SIMD decile. (a) Generalised HP modelling approach. (b) Localised HP modelling approach.
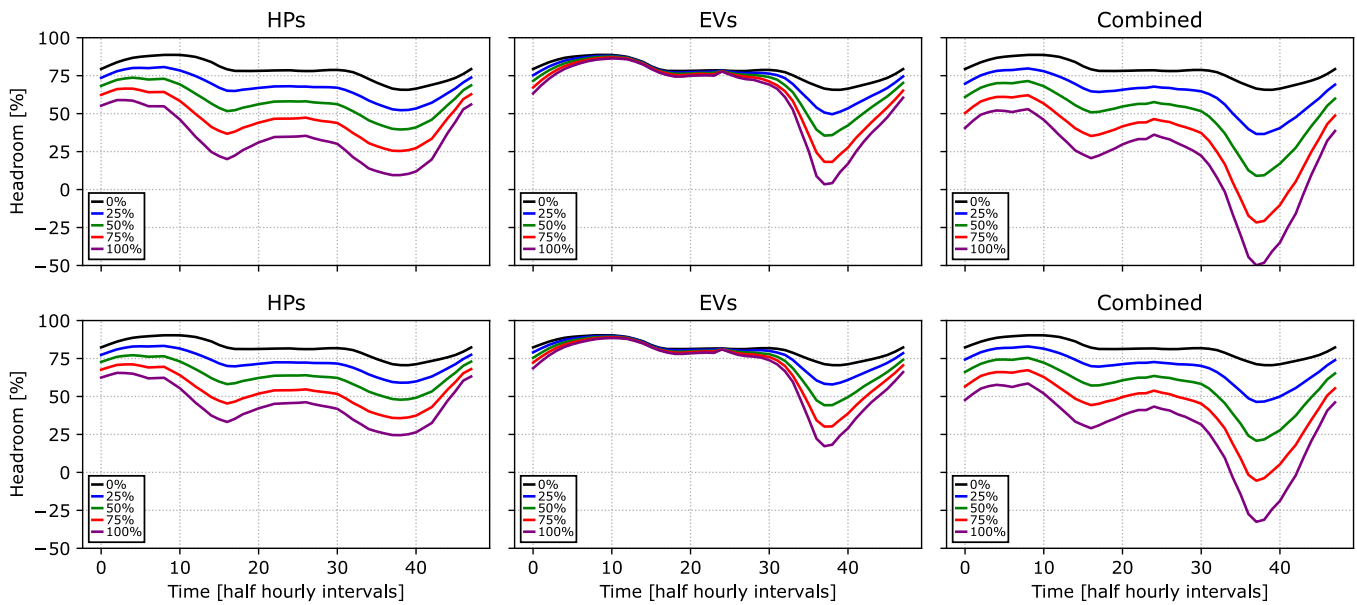

Fig. 16. Average daily transformer headroom for HP, EV and combined uptake scenarios for each penetration. Example 1 (top) Example 2 (bottom).

the secondary level (with ground mounted transformers more of a priority than pole mounted) [78]. Whilst this is a positive step, representative data for comparative statistical analysis and validation of the presented method for the areas concerned in this work may not be available for some time. Any monitored data that currently exists is limited for validation purposes as the penetrations of EVs/HPs simulated in this analysis are not yet seen on distribution networks. Therefore, any existing monitored data would not allow for direct statistical comparison, as the power flows and voltages would be reflective of the existing demand and not representative of high EV and HP penetration scenarios. Additionally, whilst field trial datasets for different areas with monitored data have been made publicly available over the years, these typically do not capture the demographic and geospatial information that is relevant to this analysis limiting the ability to carry out sufficiently detailed 'equivalent analysis'. Furthermore, these trials tend to be limited to either HPs or EVs and data for combined trials is extremely limited. Therefore, to validate the analysis, it is recommended that a bespoke field trial be carried out to obtain actual field data that the modelling methodology

could be compared and benchmarked against using various statistical metrics e.g., mean absolute percentage error or coefficient of determination to robustly validate modelling accuracy and confidence. Analysis of detailed simulations and field trial data has been carried out in the likes of [79,80] emphasising that similar techniques could be used when representative monitored data becomes available in the future.

7.2. Local authorities and policy makers

The presented analysis takes the perspective of the DNO focusing primarily on distribution transformers. However, the benefits and implications of such modelling for external stakeholders is also considered of value.

Local authorities and policy makers are partly responsible for ensuring decarbonisation targets are met [81]. They have the potential to influence and guide specific decarbonisation pathways as there are various means of achieving these targets, particularly in terms of heat decarbonisation. This could include subsidies for retrofitting building stock with energy efficiency improvements
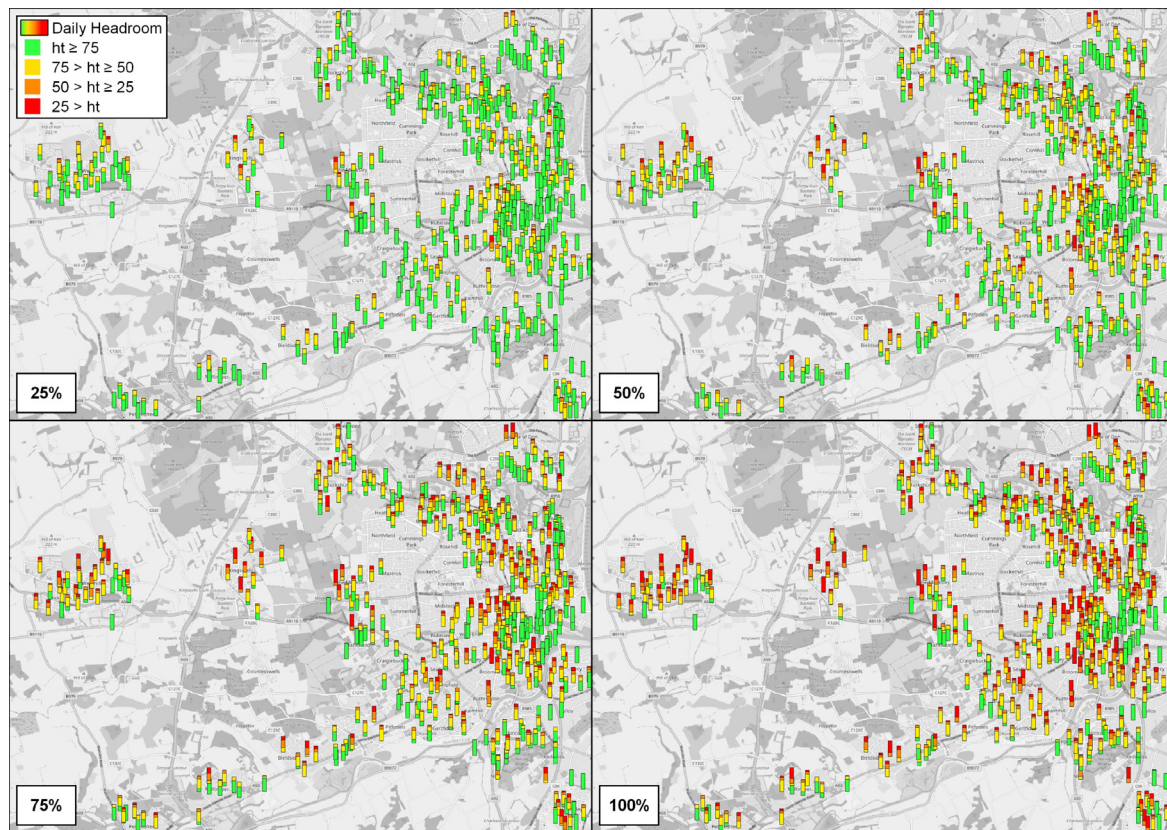
Fig. 17. Visualisation of daily transformer headroom for each penetration for combined HP and EV uptake based on the constraint bands.

in areas of high social deprivation to support specific technology uptake or subsides for the technologies and installation costs. This requires high-level planning and a significant understanding of local requirements. The Scottish Government's Local Heat and Energy Efficiency Strategies (LHEES) aim to establish local authority area-wide plans and priorities for improving the energy efficiency of buildings and decarbonising heat [82]. However, it is recognised that the feasibility of interventions from such parties are highly dependent on future network capability and headroom. As such, works including [83], are recommending that local government should have a statutory role in guiding the future development of local energy infrastructure, including investment decision-making. To do so effectively, whilst also addressing social objectives, they need an understanding of the capability of the network and future flexibility potential based on a localised understanding of consumer behaviour. This would allow for network investment to be optimised with better foresight of regional economic plans and local area energy plans.

The development of this methodology and the findings presented demonstrate the influence local sensitivities may have in relation to electrical infrastructure impact and subsequent investment requirements. As such, the analysis presented in this work has the ability to support a 'just transition' which is a key component of many national government-strategies [11], by enabling policy makers and local authorities to better understand the wider impacts of place-based electrification i.e., by having a better understanding of HP uptake impact in a specific region thus enabling co-developed plans with the DNO to be determined. This then allows for planning and funding allocation to be optimised with respect to 2030 targets in the Net Zero transition. This is particularly valuable when considering social welfare and fuel poverty [84]. It is highlighted in [83], that English regions with the highest fuel poverty and coldest winter climates are not

receiving the most heat funding. This reiterates that the social imbalance of wealth may inadvertently have an influence on network investment as early adopters and 'able-to-pay NOW' consumers are typical located in areas with lower social deprivation. The methodology and findings presented can therefore provide the Government and local authorities with insight into the implications of their strategies and frameworks with respect to the consequential impacts on electrical network infrastructure and the associated costs. Additionally, a more direct application of the method may see social investors support increased uptake of HPs in less affluent areas as there is likely to be more headroom for them to do so without reinforcement. Equally funders may (through participation in the regulatory process) promote and potentially contribute financially to support reinforcement in more affluent areas so that those who can afford to install HPs have the ability to do so unimpeded by network capacity and lengthy reinforcement times.

More broadly, although the work focuses on the decarbonisaton of heat and transport with an emphasise on EVs and HPs, the developed method has the ability to support wider decarbonsiation analysis and assessment of diverse technological impacts on electricity infrastructure e.g., to investigate trade-offs between multi-carrier decarbonisation pathways. For example, by identifying areas where electricity infrastructure is particularly challenged by electrification, alternative methods of decarbonisation can be explored and the full ramifications and costs associated with deploying these solutions assessed. With limited knowledge into the impacts of decarbonisation pathways on electrical network infrastructure, local authorities and policy makers may inadvertently make decisions that would see decarbonisation become significantly more expensive than necessary. Exactly how to perform this multi-carrier analysis at sufficiently localised resolutions and at scale with consideration for socioeconomic factors and existing infrastructure is a challenge many

stakeholders in the energy transition are struggling to overcome. The developed method has the potential to feed into wider multi-disciplinary collaborative works that are seeking to tackle this problem.

8. Conclusions and future work

This work has presented a novel assessment methodology that enables quantification of electrified heat and transport impact on transformer headroom at scale using socio-economic indicators to inform the application of LCT consumption data. The value of this quantification has been demonstrated on an existing physical transformer dataset and findings have been contextualised for different actors involved in the energy transition.

Findings from the analysis provide novel insights into the value of localised modelling with respect to socio-technical and socio-spatial analysis. In particular, they indicate that the broad link between social diversity and heat demand variation has the potential to influence decision-making. This is of particular concern in the near-term where affordability and access to LCTs is expected to be a barrier for those in areas with higher social deprivation. The findings also highlight an increasing need to consider the combined uptake of different LCTs with respect to the electrification of heat and transport. In particular, they emphasise the cumulative severity of this combined impact and confirm that demand-side management services will be required to avoid significant evening peak demands. This may include scheduling of EV charging, adoption of time-of-use tariffs and changes in consumer energy awareness and behaviour.

Future work would expand on this research through use of detailed localised forecasting of LCT uptake, this would provide enhanced insight into the challenges which social diversity presents for local network infrastructure investment planning. Additionally, in recognition that this work focuses primarily on EVs and HPs, there would be scope to investigate a wide array of diverse LCTs e.g., solar PV, thermal storage and combined heat and power (CHP), to ascertain the combinatorial impacts of electrification on key infrastructure.

The future of decarbonised domestic heating is highly uncertain with numerous different technological options available and that different areas may take radically different decarbonisation pathways e.g., use of HPs, CHP, district heating and hydrogen. This is expected to have varying impacts on electricity network infrastructure and how consumers interact with heating systems in different locations. Whilst this work has in part captured the impact of place-based localisation and diversity in relation to HPs there is scope to conduct further research to include different heating technologies. Supporting analysis is also required of the behavioural and economic triggers for switching to EVs and HPs which will influence to what extent changes in transport and heating will be clustered in space and time (this may be affected by local affluence and could lead to local changes in load shape). Future research would also further demonstrate how such modelling techniques can directly support decision-making with respect to fuel poverty beyond the current understanding and demonstrate the value of local flexible demand-side management options with consideration for socio-economic indicators for informing ahead of need investment decision-making.

CRediT authorship contribution statement

Connor McGarry: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Data curation, Writing – original draft, Writing – review & editing , Visualization, Project administration. **James Dixon:** Conceptualization, Resources, Writing – original draft, Writing – review & editing. **Ian Elders:** Conceptualization, Resources, Supervision, Writing – review & editing. **Stuart Galloway:** Conceptualization, Resources, Supervision, Writing – review & editing.

Declaration of competing interest

Data availability

The authors do not have permission to share data.

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