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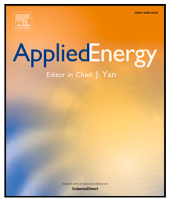

Electrified heat and transport: Energy demand futures, their impacts on power networks and what it means for system flexibility☆

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ABSTRACT

Demand electrification, system flexibility and energy demand reduction (EDR) are three central tenets of most energy system decarbonisation pathways in the UK and other high-income countries. However, their combined impacts on local energy systems remain understudied. Here, we investigate the impact of different UK energy demand future scenarios on the loading of local electricity networks, and the ability of electrified demand to act flexibly in (i) mitigating the need for network reinforcement and (ii) shifting demand around according to variable tariffs reflecting wider system needs. These scenarios are used to drive spatially- and temporally-explicit technology uptake and energy demand modelling for heating and transport in a localised context, for application to a local electricity network. A particular case study energy network in Scotland, representative of many networks in the UK and Northern Europe, is selected to demonstrate the method. On the basis of the presented case study, which considered a typical winter demand day, energy futures based on EDR policies were found on average to reduce evening transformer loading by up to 16%. Further reductions of up to 43% were achieved with flexible smart charging and up to 69% with the use of vehicle-to-grid. Therefore, we find that policies focused on EDR can mitigate the need for reinforcement of electricity networks against the backdrop of demand electrification. However, flexibility in electricity demand contributes a larger difference to a network's ability to host electrified heat and transport than relying solely on EDR. When used in tandem, policies that simultaneously pursue EDR and electricity system flexibility are shown to have the greatest benefits. Despite these benefits, peak electricity demand is very likely to increase significantly relative to the current baseline. Therefore, widespread reinforcement is required to local electricity networks in the net-zero transition and, accordingly, urgent investment is required to support the realisation of the UK's legally-binding climate goals.

1. Introduction

Whilst several independently developed pathways have been proposed to meet the UK's legally-binding net-zero greenhouse gas emissions target (e.g. [1–4]), they are generally in agreement on three points. Firstly, that mass electrification of heating and transport demand is the most cost-effective way to shift demand away from fossil fuel use. Secondly, that reducing energy demand – by improving conversion efficiencies and managing the proliferation of high-consumption activities, e.g. flying – will reduce the scale of investment needed for net-zero and de-risk our reliance on technologies

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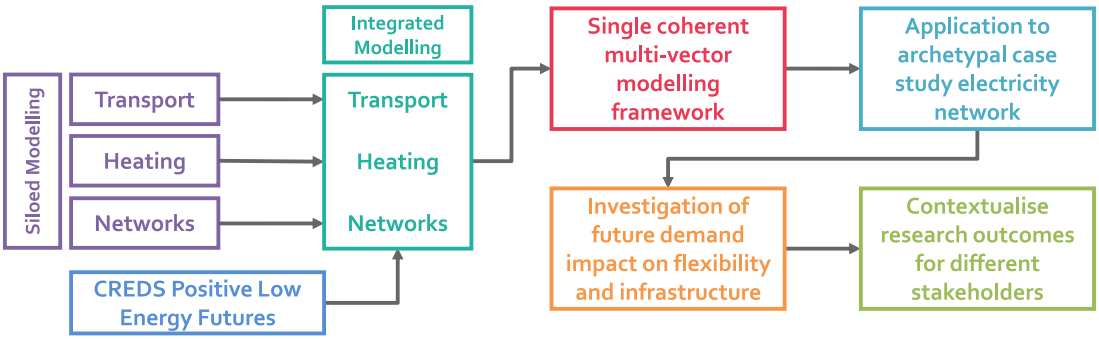

Fig. 1. High-level overview of the methodology developed to investigate the impact of future demand scenarios on flexibility and infrastructure.

that remain to be demonstrated at scale [5]. Thirdly, that time- and space-based flexibility in the electricity demand can avoid or defer the need for network reinforcement and is key to supporting the variable renewables-dominated electricity system needed for decarbonisation [6].

In high-income countries like the UK, energy demand reduction (EDR) can help to mitigate climate change by reducing the amount of fossil fuels burned [7] whilst simultaneously leading to positive improvements in well-being [8]. These demand reductions can arise from *avoiding* unwanted or unnecessary sources of demand, such as having to drive long distances to access basic services or having to heat poorly-insulated homes; *shifting* demand to a more effective means of energy delivery, such as mode shift from private car to public transport or replacement of a gas boiler by a heat pump (HP); or by *improving* the efficiency of the devices that convert final energy into its useful form, such as the substitution of internal combustion engine-powered cars for electric cars or an improvement in boiler efficiency. This *Avoid-Shift-Improve* hierarchy of EDR, as detailed in [9], can be used to quantify routes to EDR as a means of climate change mitigation and well-being improvement.

Whilst recognising that there has been a wealth of research on quantifying the impacts of demand electrification on electricity systems, as evidenced through the literature review in Section 2, there remains a knowledge gap in how different futures regarding demand for energy services will impact network infrastructure and subsequently, inform the value proposition for local flexibility.

This paper aims to fill this gap by addressing the question of what impact does different future energy demand narratives have on local electricity systems and demand flexibility? via the following contributions (as summarised by Fig. 1):

1. Existing demand scenarios, as developed by the Centre for Research in Energy Demand Solutions (CREDS) in their Positive Low Energy Futures (PLEFs) [7], are used to drive (i) *spatially* explicit modelling of the uptake of electrified transport and heating; and (ii) *temporally* explicit modelling of the electricity demand of these technologies for a local geography.
2. A model of a real electricity distribution network that serves households in the given local geography is used as the basis to examine the impacts of varying demand scenarios on electricity system infrastructure. An optimal power flow (OPF) model of a three-phase electricity network with realistic distributions of loading among the three phases is used to investigate the impact of these demand scenarios on the potential of flexibility in electricity demand.
3. Results are reported in terms of loading of that network under the different scenarios, with and without flexible demand (from electric vehicles). These results are used as evidence of the potential benefits of policies that support EDR and flexibility.

The remainder of the paper is organised as follows. Section 2 provides a review of the related literature; Section 3 describes the PLEFs; Section 4 describes the spatial uptake modelling for both heat and transport; Section 5 describes the temporal modelling for both heat and transport; Section 6 describes the distribution network and domestic demand modelling; Section 7 describes the unbalanced OPF and flexibility modelling; Section 8 describes the case study area, the case studies and their modelling methods; Section 9 presents the results from the study; Section 10 discusses the results in the context of future implications for energy infrastructure and policy; Section 11 presents conclusions from the research and recommendations for further work.

2. Literature review

Two observable trends on energy demand are that:

1. **Growth in wealth leads to growth in demand for energy services**: over the time period 1971–2018, each percentage point of growth in global gross domestic product (GDP) led to an increase in 0.68% of energy demand [10];
2. **Improvements in conversion efficiencies alone do not lead to reductions in energy consumption**: the evidence for this has been consistently revisited in the literature as an application of the Jevons paradox [11–13].

There is a growing body of literature on the potential for EDR to contribute towards climate ambitions, and this is generally presented not only as a vital part of climate mitigation strategies. Grubler et al. present a global energy consumption scenario whereby total demand is reduced by 40% by 2050 relative to today's levels [14]. The International Energy Agency's pathway to global net-zero emissions by 2050 stresses the importance of measures to limit energy demand, including behavioural changes and resource efficiency, stating that global energy demand can be reduced by approx. 90% versus the counterfactual baseline by 2050 [15]. Van Vuuren et al. use integrated assessment models to construct alternative models to meeting the 1.5 °C target of the Paris Agreement and, in doing so, support wide-ranging reductions in energy demand from switches in mobility to improvements in building thermal efficiency [16].

Increasingly, studies frame the contribution of EDR in meeting climate targets at the national – rather than international – level. In a UK context, Barrett et al. use a suite of whole energy systems models and scenario development through expert stakeholder engagement to investigate the potential role of EDR in supporting and 'de-risking' pathways to net-zero emissions [7]. By examining trade-offs between varying levels of technology adoption and behavioural change, they conclude that energy demand can be reduced by up to 52% by 2050, compared to 2020 levels, without compromising on citizens' quality of life. The Climate Change Committee (CCC), the UK government's independent statutory advisor on climate and energy policy, has a significant focus on EDR in their analysis of possible pathways to the

UK meeting its net-zero target [2]. In the CCC's 'balanced' pathway to net-zero, which represents the mid-point between technology change and behaviour change, there is significant focus on the contribution of EDR both through efficiency improvements (e.g. increased rates of retrofitting leading to a 12% reduction in domestic heating energy demand) and behaviour change (e.g. reductions in per-capita car kilometres by 17% and per-capita meat consumption by 34%). Brand et al. [17] explored the roles of lifestyle change and socio-cultural norms vs. electrification and phasing out of conventional fossil fuel vehicles, suggesting that lifestyle change alone can have a comparable and earlier effect on transport carbon and air quality emissions than a transition to electric vehicles (EVs) with no lifestyle change. Yet, both strategies have limits to meeting legislated carbon budgets, which may only be achieved with a combined strategy of radical change in travel patterns, mode and vehicle choice, vehicle occupancy and on-road driving behaviour with high electrification and earlier-than-planned phasing out of conventional fossil fuel vehicles. However, while the study in [17] was carried out at a national level with zero spatial detail, these measures can vary significantly by local area and so there is a need to examine the effects of these policies at finer geographical and political boundaries.

There is a largely separate body of literature that has looked to quantify the impacts of the electrification of heat and transport on electricity system infrastructure. These studies typically generate temporal demand profiles based on the electrification of energy services such as heat and transport and superimpose these profiles onto a model of a distribution network.[1] These profiles are usually derived either from data captured from real EV chargers or HPs, typically from government-sponsored trials, as in [19–23], or from data collected from incumbent technologies, such as internal combustion vehicles (ICVs) or gas-fired boilers, to understand energy service demand and extrapolate to the electricity demand of meeting these same services, as in [24–27].

Whereas [19–27] focus on the electrification of one particular energy service (generally heat or transport), studies that focus on the aggregate effects of combined heat and transport electrification on network infrastructure are less commonplace. One study is provided by Navarro-Espinosa et al. [28], who employ a Monte Carlo technique to sample from HP and EV demand profiles, generated from heating demand data and EV trial data respectively, assigning them to UK distribution feeder models in assessing the voltage and thermal impacts of the uptake of these technologies.

The potential for both EVs and HPs to act as providers of system flexibility in the context of a high-renewables power system with embedded communications has been well-researched. Edmunds et al. [29] present a study on the potential for controlled EV charging to maximise the available capacity in allowing maximal HP penetration for a given level of network reinforcement. Venegas et al. [30] identify and analyse potential frameworks for the active integration of EVs to the power system at various temporal and spatial scales, concluding that there is significant value in flexibility of distributed demand at the scale of distribution systems. Backe et al. [31] present a local ('community') energy system model to assess the potential to use HP and EV flexibility to manage variance in demand and supply in the Norwegian power system. The authors estimate that by using HPs and EVs as providers of flexibility, the average European electricity cost could reduce by 3% and the expansion rate of the transmission network could reduce by 0.4%. Salpakari et al. [32] present a similar study to that in [31], but rather than the objective function of the optimisation being over a wide area, a control model is presented to optimise the provision of flexibility from EVs and HPs at the scale of a microgrid. On the basis of a single house, the study suggests that a consumer can save 33% on energy costs through the optimal coordination of flexibility, given their energy demand requirements. Aside from saving costs and quantifying the level of network reinforcement required, studies have shown that flexibility can reduce the emissions intensity of electricity delivered in a region, as demand can be scheduled for periods of high renewable availability. For instance, Gunkel et al. [33] present a modelling framework to compare the total carbon emissions resulting from a power system spanning much of Northern and Central Europe before and after the introduction of flexibility from EVs. They estimate that between 2020 and 2050, the addition of flexibility from EVs can save up to 23 $MtCO_2e$ without any changes to the generation mix: in context, that is around 4% of the UK's current economy-wide emissions.

Whilst there is demonstrably a considerable body of literature on the impacts of electrification on electricity system infrastructure and potential of demand flexibility, none of the above cited studies consider the future evolution of energy service demand as a result of shifting societies, evolving technologies and policies that actively support EDR in the name of climate change mitigation and promotion of human well-being. This is identified as a considerable research gap; to the authors' knowledge, there has been no work on linking pathways in energy demand futures – such as those presented in [7] – to the potential impacts on infrastructure and the value proposition of flexibility. Thus, the work of this paper will translate narratives on energy demand futures in heating and transport to impacts on local electricity systems, enabling quantification of the stress placed on key infrastructure and the ability of those demands to act 'flexibly' in supporting the renewables-dominated generation mix necessary to achieve energy system decarbonisation at pace.

3. Energy demand futures: re-introducing the CREDS positive low energy futures

CREDS was established as part of the UK Research and Innovation's Energy Programme in April 2018, to "*make the UK a leader in understanding the changes in energy demand needed for the transition to a secure and affordable, net-zero society*" [34]. This was based on the premise that the ongoing displacement of fossil fuels is not proceeding at a rate that aligns with the UK's 2035 emission reduction goal. Therefore, in order to ensure that reductions in fossil fuel usage occur at the necessary pace to achieve the UK's climate objectives, there is a need for both an acceleration in the deployment of renewable energy sources and for rapid substantial reductions in energy demand. With this, the CREDS PLEFs (shown in Table 1) that represent detailed energy demand scenarios were developed as part of a significant programme of research aimed at quantifying the potential of demand reduction policies to assist the realisation of the net-zero GHG emissions target in the UK. Unlike other future scenarios, the PLEFs are unique in that they are solely focused on the potential contribution of EDR, this makes the PLEFs the most comprehensive set of scenarios currently available that informs on the future of energy demand in the UK.

The PLEFs were developed by compiling narratives written by various experts across a range of fields in industry, academia, policy and civil society. These narratives are underpinned by seven observable underlying trends in wider society that have impacted energy demand to date, and/or are likely to do so in the time horizon under consideration (to 2050). The seven observable trends are (i) digitalisation, (ii) sharing and circular economies, (iii) energy efficiency, (iv) healthy societies, (v) environmental awareness, (vi) globalisation and (vii) work and automation. A full description of the scenario development process and full details of the sectoral implications of the scenarios are available in the 2021 CREDS report [34]. In this paper, the PLEFs are taken as a starting point and used to develop scenarios for technology uptake (Section 4) and energy service demand (Section 5) for both heating and transport.

[1] The literature tends to focus on the impact of electrification of heat and transport on distribution networks. Indeed, Crozier et al. [18] present analyses of the impacts on distribution and transmission infrastructure using a common analysis method and find that distribution networks are at higher risk of having their operational limits compromised as a result of demand growth.

Table 1
Summaries of CREDS positive low energy futures.
Source: Reproduced from [7].

Scenario	Description
Ignore	Identifies levels of energy demand up to 2050 assuming only existing UK government climate policy instruments are implemented (as of 2018). This includes existing policy for delivery of emission reductions but not climate targets or ambition.
Steer	Adopts the more ambitious legislated target of net-zero GHG emissions by 2050 but falls just short of meeting it. Uses the same energy service-demand projections as the Ignore scenario but implements a wide range of energy efficiency options.
Shift	Adopts the net-zero greenhouse gas (GHG) emissions target. Significant shift in the attention given to energy demand strategies providing an ambitious programme of interventions across the whole economy describing what could possibly be achieved with currently available technologies under current social and political framings.
Transform	Adopts the net-zero GHG emissions target. Considers transformative change in technologies, social practices, infrastructure and institutions to deliver both reductions in energy but also numerous co-benefits such as health, improved local environments, improved work practices, reduced investment needs, and lower cumulative GHG emissions.

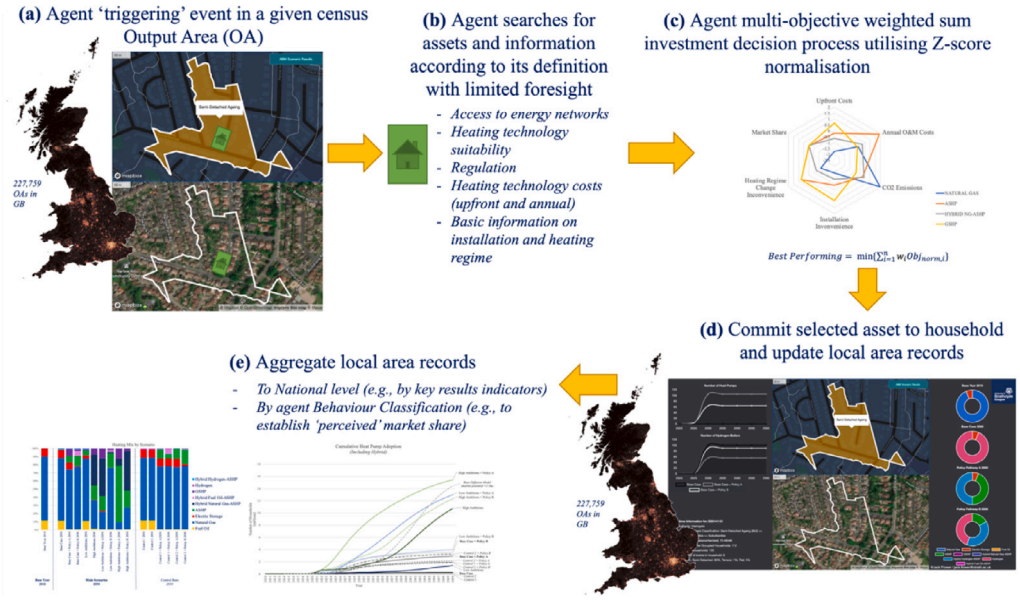

Fig. 2. Schematic highlighting agent-based heating technology uptake model workflow.

4. Spatial technology uptake modelling in heat and transport

This section describes the uptake modelling for both heat and transport and how, from this, future technology penetration levels for heating and transport are obtained for each of the PLEFs.

4.1. Heat technology uptake model and application of PLEFs

Prevalent options for exploring energy transitions have limited treatment of societal actors and socio-political dynamics, and are typically poor at representing the co-evolving nature of society and technology, tending to overlook spatial and within-sector detail [35,36]. Therefore, a spatially explicit, place-based, agent-based[2] heating technology diffusion modelling approach was used in this study to address these concerns. Whilst detailed descriptions of the modelling approach are provided in [37,38], a brief overview is presented here. The high-level agent investment decision process, and thus the abstract modelling workflow, is illustrated in Fig. 2. The modelling workflow repeats on an annual basis over the modelling period for all households that are 'triggered' to undergo the investment process.

The agent-based model (ABM) considers the point at which existing owner-occupied households choose between either upgrading their existing heating system to the same technology with modern performance parameters or retrofitting a low-carbon heating option. A heterogeneous set of agents are modelled with bounded rationality, and a high degree of spatial and within-sector detail is obtained while having national coverage. This allows both the impact of different incentives and regulations on heating technology investment decisions to be explored at local, regional and national scales, and also allows for strategic last-mile energy infrastructure planning activities to capture projected heat system change. The model is calibrated and validated against actual heating technology uptake statistics. For this study, the PLEFs (Table 1) were input into the heating technology uptake model as detailed in Fig. 3.

4.2. Transport technology uptake modelling and application of PLEFs

This work presents the development of a high-resolution EV uptake model and describes the application of the PLEFs to this model. The model combines an adaptation of the vehicle stock model (VSM) car module in the Transport Energy Air pollution Model (TEAM), an existing transport-energy systems model originally presented in [39], with

[2] In agent-based modelling, a collection of autonomous decision making entities called agents are used to model a system. These entities follow a predefined set of rules, interacting with each other and their dynamic environment [37]. For this work, the 'agents' depict households that have the following attributes: output area, residential area-based classification, tenure type, behaviour classification, heating system size, annual heat demand, existing heating option, ground-source heat pump availability and hydrogen heating availability. The reader is referred to [37] for further information on these attributes.

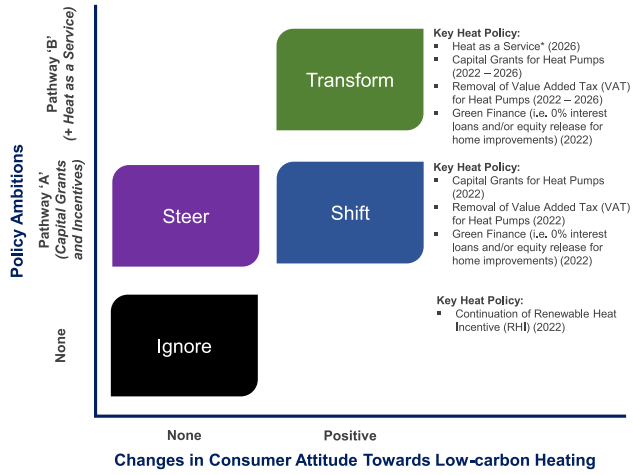

Fig. 3. Scenario matrix showing changes in consumer attitudes (horizontal axis) and policy ambitions (vertical axis).

a car ownership prediction model based on artificial neural networks originally presented in [40].

TEAM is a strategic transport, energy, emissions and environmental impacts systems model, covering a range of transport-energy-environment issues from socio-economic and policy influences on EDR through to lifecycle carbon and local air pollutant emissions and external costs.

Based on its precursor model, the UK Transport Carbon Model (UKTCM) [41], TEAM has been developed over the last decade to undertake policy analysis (e.g. [42], which examined the implications of the EU 'Dieselgate' scandal in the UK by exploring unaccounted and future air pollutant emissions and energy use for Britain's cars, and [43], which explored the energy and emissions implications of the UK Government's 2018 Road to Zero strategy [44]) and exploration of possible future transport pathways [17].

TEAM was used for the mobility sector level modelling in developing the PLEFs. Therefore, for consistency with the CREDS scenario development framework, TEAM is considered to be more applicable for use in this work in comparison with other alternative transport-energy-environment models which are also typically proprietary and lack the detail to simulate policy decisions against a backdrop of contextual changes. The part of TEAM used for this study was the car choice module of the VSM, which projects the disaggregation of the car market (for both private and company/fleet owners) by technology and by year, taking into account established scrappage rates, vehicle buyer behaviour, consumer segmentation as well as market response to vehicles attributes, price signals and incentives (financial and otherwise). It is beyond the scope of this paper to describe the VSM in detail; the reader is referred to [39,45] for full details. The car module of the TEAM VSM was translated into the Python for use in the modelling framework developed in this study [46].

The *Spatial-Temporal Engine for Vehicle fleet Evolution* (STEVE) combines the car stock model of TEAM (as described above) with a spatial car ownership prediction model as a way of providing insights on the spatial variation in electricity demand from EVs. The car ownership prediction model was developed based on artificial neural networks that use historical car registration data and projections of key socio-economic indicators available at the local level, including household disposable income, economic activity, demographic and population density. The model is described in detail in [40].

In this work, for application of the PLEFs to the EV uptake modelling, STEVE was used to simulate possible futures for transport electrification at a local level. Firstly, the spatial regression approach described previously was used to characterise the business-as-usual evolution of the UK car fleet by lower super output area, UK Census geographies containing on average 300–700 households, based on forecasted changes in independent variables that have been consistently shown to influence car ownership [47]. This business-as-usual trajectory is then taken to represent the Ignore and Steer scenarios; they are altered to produce UK car fleet trajectories for the Shift and Transform scenarios using the uptake scenario results in the PLEFs [34]. Secondly, the set of new cars – driven by an increasing 'demand' for private cars, as well as the scrappage of old ones – is disaggregated into a set of technologies (covering size, powertrain, fuel, engine type and capacity) according to a discrete choice modelling framework (within the VSM), in which vehicle technology uptake is modelled amongst a heterogeneous consumer market represented by four private and two fleet UK market segments. For full details on the discrete choice model used in STEVE, the reader is referred to [39]. The PLEFs are then input as a set of modellable levers into STEVE which covers, amongst other things, consumer awareness, access to charging, subsidies of technologies, sale bans of certain technologies (e.g. the ban of sale of internal combustion vehicles after a certain date), and fuel taxation. For full details on the levers as applied to STEVE, the reader is referred to [34]. From this, the rate of EV uptake for different local areas is obtained which supports a more representative network impact assessment in comparison with using simple fixed uptake assumptions that fail to consider local attributes.

5. Temporal energy demand modelling in heat and transport

This section describes the temporal demand modelling approaches for both heat and transport, and where applicable describes how the influence of the different PLEF scenarios are captured in the modelling. From this, daily temporal demand profiles for the heating and transport technologies are obtained.

5.1. Heat modelling

5.1.1. Electricity demand from heat pumps

The method developed in [48] is used to model household HP demand. In [48], the relationship between the Scottish Index of Multiple Deprivation (SIMD) and gas consumption is explored and from this, representative gas consumption cumulative distribution functions (CDFs) for each individual SIMD decile are derived. Two established approaches of converting gas demand to equivalent electrical heat demand are then employed, the *Heat Demand Magnitude Localisation Model* and the *Electrical Heat Demand Shape Model* developed in [49]. 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 brief description of each model component is provided in the following subsections. For detailed descriptions the reader is referred to [49,50].

The *Heat Demand Magnitude Localisation Model* transforms the CDF sampled gas demand into a daily demand magnitude that is reflective of the local factors influencing heat demand e.g. local building, climate, and behavioural parameters. Firstly, a gas conversion efficiency (η_{gas}) is applied to convert the raw annual gas demand (D_G^{annual}) into an equivalent annual direct heat demand (D_H^{annual}) through (1). For this study, a fixed gas boiler efficiency of 80% was used, which was obtained by averaging over 2000 different mains gas boiler models with efficiencies ranging from 55% to 90.3% [51]. D_H^{annual} is then transformed into a daily heat demand (D_H^{daily}) through (2) and (3), assuming that heat demand follows a sinusoidal pattern throughout the year that corresponds to seasonal temperature variation. D_H^{annual} provides the area under the sinusoid, which defines the amplitude and offset parameters and, as a result, the daily demand variation throughout the year and x corresponds to day of year.

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

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

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

$$D_E^{daily} = \frac{D_H^{daily}}{COP} \quad (4)$$

The default amplitude (D_{amp}) and offset (D_{off}) parameters have been used for this work. These fit parameters were evaluated using the 30-min interval monitored gas meter data collected in 2010 as part of the Energy Demand Research Project (EDRP) [52] and monitored HP heat and electrical demand data from the Renewable Heat Premium Payment (RHPP) dataset [53]. The daily heat demand is then converted into a daily electrical demand (D_E^{daily}) via a coefficient of performance (COP) through (4). HP COPs in the RHPP dataset typically range from 2 to 4 [53], which is consistent with the air and ground source HP COPs presented in [54]. However, as with gas boiler efficiency, COP is temperature-sensitive and varies based on the specific installation and manufacturer's model. From the typical COP range, a fixed COP of 3 was used for this paper [54].

The *Electrical Heat Demand Shape Model*, developed in [49], is used to transform daily electrical demand into a set of half-hourly values that are sensitive to local temperature. The model includes HP data from the RHPP dataset and is verified using demand data from the Low Carbon London (LCL) HP trials [55]. The research in [49] identified common recurring electrical heat demand patterns in the RHPP dataset, despite variations in the underlying geographical and demographic conditions. These use-patterns were normalised for a 0 °C ambient temperature.[3] The normalised patterns are then used to form HP daily load profiles and are sampled accordingly.

5.1.2. Electricity demand from electric storage heaters

As identified in [29], the smart meter data recorded during the LCL trial contained households that had a high overnight demand which can be attributed to storage heating. These households tend to have a large spike in demand at midnight which is consistent with storage heater operation on an Economy 7 tariff [56]. These profiles have been used to represent electric storage heaters (ESHs) where a similar process is used as with domestic demand (described in Section 6.2) to create a bank of half-hourly daily profiles representing households that have an ESH in addition to generic domestic demand. These profiles are separated from those with no ESH demand to prevent heat demand being added twice if and when adding HPs. Note that any household demand profile with a spike in demand greater than 6 kW at midnight and lasting longer than one hour was considered to have an ESH. Standard household appliances as represented in the CREST demand model [57] are typically lower than 6 kW with the exception of a 9 kW electric shower, though it is assumed that average shower duration would typically be less than one hour.

5.1.3. Application of PLEFs to annual heat demand

Work by Canet et al. [58] is used to arrive at plausible percentage reductions in annual household heat demands that align with the PLEF narratives. More specifically, Canet et al. conduct statistical analysis using Energy Performance Certificates (EPCs) for England and Wales, where they generate annual heat demand reduction potentials given the measures listed on EPCs and other factors, which are well aligned to the drivers of heat demand reductions in [34]. The dataset in [58] is first filtered to obtain the same classification of dwellings as that found in the area of interest, and the range of heat demand reduction potentials for the remaining dwellings are then characterised. Given that the potential reductions as in [58] are based on meeting the UK's 2050 net-zero target, they are scaled back to 2030 based on the same rates of progress in the National Household Model (NHM)[4] as used in the CREDS work [34].

5.2. Transport modelling

5.2.1. Electric vehicle charging model

Opportunities for EV owners to plug in their vehicles for charging depend on when they start and finish their journeys and what the destinations are. These journeys also dictate what the minimum amount of energy in each charge will be. This then determines the temporal and spatial pattern of demand for electricity for EV charging, necessary for the modelling of future electricity demand. Therefore, to account for EV utilisation by domestic consumers as part of this work, an EV charge event model originally presented in [60] is used. The model, a heuristic used to generate EV charge events from trip data (such as those from the UK National Travel Survey (NTS)), has been used in a number of studies [24,61,62]. This paper uses trip data from the 2019 UK NTS, which contains 210,717 car-based trips split between 13,863 cars. Accordingly, this study assumes that future EV drivers – at a baseline, before the application of the PLEFs – will use their cars in the same way as combustion engine car drivers, before the Covid-19 pandemic.

5.2.2. Application of PLEFs to electric vehicle charging

The EV charging schedules resulting from the heuristic described above are modified by a stochastic process of adjustment according to a consolidated set of changes in the number of trips and the trip distance for each relevant PLEF scenario in Table 2.[5] This applies specifically to the Shift and Transform scenarios, which unlike Ignore and Steer, consider policies focused on changes in behaviour in addition to policies focused on technology uptake. These consolidated changes are the net changes for each scenario where there are several factors that influence – both positively and negatively – each trip type. For example, four trends impacting the number of commuting trips for each person are identified as: reduction due to more people in retirement; reduction due to increased teleworking; increase due to gig and service economy; reduction due to 4-day working week. Table 2 represents the consolidation of the impacts of these trends for each trip type. The full details for which are available in [34].

To apply these consolidated changes to the NTS travel diaries, the following steps were taken.

- For the **number of trips**:
    1. The set of car-based NTS travel diaries were split into 'high-travel' and 'low-travel' diaries according to whether they took a car-based trip on all 7 days ('high-travel') or not ('low-travel'). This was to allow duplicate trips to be added in a way that did not result in overlapping trips (by adding them on days where there were no trips taken, to the 'low-travel' diaries).

[3] Due to the limited availability of data for the operating region below 0 °C in existing monitored datasets the model cannot reliably capture the effects of HP demand below 0 °C. Furthermore, as conversion efficiency is reduced in-line with a reduction in the COP in this operating region it would not be uncommon for secondary resistive heating to be installed to support HP output during colder conditions. This could further increase temperature dependent electrified heating demand and would require additional modelling to capture the demand characteristics of this behaviour.

[4] The National Household Model is an open-source analytical tool that was developed to project the effects of policy and other legislative changes on the energy and emissions of the UK domestic housing stock [59].

[5] Local leisure = social entertainment; sports; visiting friends and relatives elsewhere. Distance leisure = visiting friends and relatives at home; holiday; day-trip.

Table 2
Change in number of trips and trip distance in 2030 and 2050 for Shift and Transform scenarios relative to 2019 baseline (1.0 = no change).

Trip type	Shift				Transform			
	No. trips		Trip dist.		No. trips		Trip dist.	
	2030	2050	2030	2050	2030	2050	2030	2050
Commuting	1.01	1.03	0.92	0.75	0.88	0.815	0.85	0.65
Business	0.9	0.75	0.95	0.85	0.85	0.65	0.9	0.83
School travel	0.95	0.95	0.9	0.85	0.95	0.95	0.85	0.75
Shopping	0.8	0.7	0.9	0.9	0.7	0.6	0.8	0.85
Personal business	0.95	0.95	0.95	0.9	0.9	0.9	0.9	0.85
Local leisure	1.15	1.25	0.95	0.9	1.15	1.3	0.9	0.85
Distance leisure	1.1	1.2	0.95	0.9	1.15	1.22	0.95	0.9

2. If the number of trips of a certain type (e.g. school travel) were to be *increased*, then a random set (of size corresponding to that proportional increase) of trips of that type would be duplicated (including return trips) on days where travel did not take place. This would be done for the 'low-travel' diaries.
3. If the number of trips of a certain type were to be *decreased*, then a random set (of size corresponding to that proportional decrease) of trips of that type would be removed (including their corresponding return trip, if it existed). This would be done for the 'high-travel' diaries.

- For the **trip distance**, if the distance of a trip of a certain type is to be changed, then all trips of that type have their distance (and thus energy expenditure) adjusted accordingly.

The resulting modified NTS travel diaries were then processed through the aforementioned heuristic to produce charging schedules for use in the EV demand flexibility modelling (Section 7.2).

6. Distribution network and domestic demand modelling

6.1. Distribution network modelling

The methodology used in this study to model 'real' electricity networks for a given area (e.g. the case study described in Section 8.1) is extensively described in [63]. This methodology makes use of network geographic information system (GIS) data made available to the authors by the distribution network operator (DNO) for the north of Scotland. This datum includes both spatial and technical information pertaining to key network infrastructure installed across the entire licence area.

The method allows for place-based modelling by integrating the network GIS data with external spatially linked datasets. These datasets can provide valuable insight into the characteristics of specific areas and support detailed modelling of both electricity networks and local energy demand [63]. The method has been developed in Python with use of the GeoPandas package [64] and the electrical network models are developed in OpenDSS [65] using the Python COM-interface.

6.2. Domestic demand modelling

Smart meter data from the LCL project collected between 2011 and 2014 is used to model the domestic demand [66]. Following a similar approach as adopted in [29], over 1800 daily profiles for each day in a winter period between 01/12/2013 and 27/02/2014 are considered to represent a winter demand scenario (under which heating-related electricity demand would be at its highest). For the LCL project, consumers were divided into three groups based on their socio-economic status, as determined by the CACI Acorn Group classification [67]. This classification grouped consumers into 'Affluent', 'Comfortable' and 'Adversity' categories. For this work, the CACI Acorn groups are matched to a decile scale of the SIMD, to ensure that the variations in energy consumption among different groups of consumers are captured. This considers consumers for SIMD decile 9–10 to be 'Affluent', 4–8 to be 'Comfortable' and 1–3 to be 'Adversity' where boundaries are defined based on parallels between the Acorn classification and SIMD. From this, a bank of half-hourly daily winter profiles for each Acorn category is created allowing for stochastic iterative sampling and assignment to individual consumers. Reiterating that the profiles in this bank are purely domestic demand and separate from the profiles also containing ESH demand.

7. Optimal power flow and flexibility modelling

In distribution networks, power or current flows need to be kept within asset thermal ratings and the voltages at customers' points of connection need to be within defined limits. In order to know that, a mathematical model – a power flow – needs to be used to calculate what the power flows and voltages would be under different circumstances. Whilst conventional power flow analysis is necessary for understanding basic steady-state behaviour, an OPF is used to determine the optimal operating conditions of a network while adhering to various operational constraints and objectives e.g. minimising network losses in consideration of thermal and voltages limits. The open-source python-based package with a three-phase unbalanced OPF model developed in [68] is used as the base model for this work. The equations used to form the OPF model are derived from the current mismatch method presented in [69]. This model is advantageous compared with those used in studies which assume that loads on the three phases are balanced, as it allows for consideration of the practicalities of real distribution networks which typically have asymmetrical phase distribution.

This section describes the key expressions used to define the OPF model in the open-source optimisation modelling language, Pyomo, according to [68]. It also describes the formulation of the smart charging and parametrised vehicle-to-grid (V2G) model originally published in [61] which allows for multi-period optimisation of automated EV charging in response to time-of-use pricing signals and the approach taken for contingency load shedding. The application of these models relative to the case studies considered in this work is described in the proceeding section.

7.1. Base OPF formulation

7.1.1. Definition of nodal current injections

Derived from [69], the current mismatch equations are defined by (5)–(9). These are used to relate the nodal voltage phasors with the active and reactive power injections from each load and generating asset in the network.

$$\Delta I_k^s = I_{calc_k}^s - I_{sp_k}^s \tag{5}$$

$$P_{sp_k}^s = \Re(V_k^s)\Re(I_{sp_k}^s) + \Im(V_k^s)\Im(I_{sp_k}^s) \tag{6}$$

$$Q_{sp_k}^s = \Im(V_k^s)\Re(I_{sp_k}^s) - \Re(V_k^s)\Im(I_{sp_k}^s) \tag{7}$$

$$\Re(I_{calc_k}^s) = \sum_{i\in\Omega}\sum_{j\in\sigma_p}[G_{ki}^{sj}\Re(V_i^j) - B_{ki}^{sj}\Im(V_i^j)] \tag{8}$$

$$\Im(I_{calc_k}^s) = \sum_{i\in\Omega}\sum_{j\in\sigma_p}[G_{ki}^{sj}\Im(V_i^j) + B_{ki}^{sj}\Re(V_i^j)] \tag{9}$$

where

Ω set of network buses[6]

[6] A bus in electrical terms is short for 'busbar' and refers to a junction or common electrical point to which multiple electrical devices e.g. generators, transformers, and loads are connected.

$k, i \in \Omega$
σ_p set of phases {a,b,c}
$s, j \in \sigma_p$
$I^s_{calc_k}$ calculated ($calc$) current injections
$I^s_{sp_k}$ specified (sp) current injections
V^s_k, V^a_i phase voltage at bus k
G^{sa}_{ki}, B^{sa}_{ki} conductance and susceptance from nodal admittance matrix

In [68], load profiles are represented by a load composition in terms of constant impedance (Z), constant current (I) and constant power (P) i.e. a ZIP model. For this work, as only constant power information is available from the demand modelling previously carried out, Eqs. (10) and (11), used to calculate the specified active and reactive power injections, $P^s_{sp_k}$ and $Q^s_{sp_k}$ respectively, are simplified to represent a constant power load model.

$$P^s_{sp_k} = P^s_{g_k} - P^s_{P_k} \tag{10}$$

$$Q^s_{sp_k} = Q^s_{g_k} - Q^s_{P_k} \tag{11}$$

where $P^s_{g_k}, Q^s_{g_k}$ are the active and reactive power generation[7] at bus k and phase s respectively, and $P^s_{P_k}, Q^s_{P_k}$ are the active and reactive power demand at bus k and phase s, respectively. For reactive power, this work assumes a constant power factor of 0.95 (inductive/lagging) for the domestic demand as in [70], and similarly, though conservatively, for the HP and EV demand as used in [28].

7.1.2. Equality constraints

There are two equality constraints that are enforced within this OPF formulation, the current mismatch constraint defined by (12) and slack bus constraint defined by (13).

$$\Delta I^s_k = 0 \tag{12}$$

$$V^s_{slack} = V^s_{sp_{slack}} \tag{13}$$

The current mismatch constraint is used to force current deviations ΔI^s_k in (5) to zero and the slack bus constraint is used to force the slack bus voltage V^s_{slack} to equal the specified value $V^s_{sp_{slack}}$.

7.1.3. Inequality constraints (network operational limits)

There are three inequality constraints that form part of this OPF formulation, the voltage limits constraint (14), the line thermal limits constraint (15) and the transformer rating limits constraint (16).

In (14), the magnitude of the steady-state voltage V^s_k at bus k must conform to the respective upper and lower statutory limits, V_{max_k} and V_{min_k} according to the distribution network code. In the UK, the upper and lower statutory voltage limits are set at +10% and −6% respectively.

$$V_{min_k} \leq V^s_k \leq V_{max_k} \tag{14}$$

In (15), the current flow I^s_l at each phase s on line l must not exceed the rated current capacity $I_{l_{max}}$ of the respective line as specified by the manufacturer.

$$I^s_l \leq I_{l_{max}} \tag{15}$$

In (16), the total apparent power flow S^{trans}_n across each transformer n must not exceed its maximum rating S^{trans}_{max} as specified by the manufacturer.

$$\sum_{n \in \Psi} S^{trans}_n \leq S^{trans}_{max} \tag{16}$$

where Ψ is a set containing all transformers.

[7] Generation in this context does not explicitly refer to generating technologies such as solar PV, rather the injection of power to the network at any given bus and phase.

7.2. Smart charging and parametrised vehicle-to-grid model

As EV charging and subsequent energy consumption is time-coupled, $E_{e,t}$, which is the energy storage content of an EV during charge event e at time t, is dependent on the energy storage content of the EV at the previous time step and the change in energy, either gained or lost, during Δt as represented by (17).

$$E_{e,t} = (\eta_{ev} p^{\text{imp}}_{e,t} - \frac{1}{\eta_{ev}} p^{\text{exp}}_{e,t})\Delta t + E_{e,t-1} \tag{17}$$

where η_{ev} represents a fixed charging and discharging efficiency of 90% (this is in line with typical home charging efficiency values observed in the literature [71,72]) and $p^{\text{imp}}_{e,t}$, $p^{\text{exp}}_{e,t}$ represent the power imported or exported by an EV during charge event e at time t.

The EV's battery energy content upon plug-out must be greater than or equal to what it would have received under an uncontrolled charging event (18). The EV driver may not necessarily need this amount of energy content to complete their travel plans, and they may be able to manage with a lower amount without any significant impact on their schedule. Therefore, a relaxation of this constraint could bring further benefits to the driver, such as increased revenue resulting from greater flexibility potential. The EV's energy content for each charge event e is constrained by the capacity limits, i.e. between 0 and the battery's maximum capacity $E^{\max}_e$, $\forall\, t \in \mathcal{T}$ (19).

$$E_{e,\mathrm{t}^{\text{out}}_e} \geq \mathrm{E}^{\text{end}}_e \tag{18}$$

$$0 \leq E_{e,t} \leq \mathrm{E}^{\max}_e \tag{19}$$

where $\mathcal{T}$ is the time horizon set comprised of half-hourly timesteps, indexed by t, $\mathrm{E}^{\text{end}}_e$ is the energy storage content of EV at end of charge event e and $\mathrm{t}^{\text{out}}_e$ is the plug-out time of EV for charge event e.

A typical constant current–constant voltage (CC–CV) charging profile for lithium-ion batteries is used to constrain EV charging power [73,74], where the maximum charging power equals the rated power $P^{\max}_e$ for a battery state of charge up to γ (set at 0.8 [75]), after which it linearly decreases to zero until a state of charge of 1 is achieved. The charging power constraint is stated formally in (20), $\forall\, t \in \mathcal{T}$.

$$p^{\text{imp}}_{e,t} \leq \begin{cases} \mathrm{P}^{\max}_e, & \sigma_{e,t} \leq \gamma \\ \left(\dfrac{1-\sigma_{e,t}}{1-\gamma}\right) \mathrm{P}^{\max}_e, & \sigma_{e,t} > \gamma \end{cases} \tag{20}$$

During an EV charge event e at time step t, the battery's state of charge, $\sigma_{e,t}$, is obtained from (21).

$$\sigma_{e,t} = \frac{E_{e,t}}{E^{\max}_e} \tag{21}$$

For each EV, the active power discharged is constrained by (22).

$$p^{\text{exp}}_{e,t} \leq \mathrm{P}^{\max}_e \tag{22}$$

With V2G capability, it is necessary to constrain the battery such that only either charging (power import) or discharging (power export) can occur at any single time step i.e. if an EV's import power at a given time step is greater than zero, then its export power is zero (and vice versa). This is achieved through the constraint (23).

$$p^{\text{imp}}_{e,t} \times p^{\text{exp}}_{e,t} \leq 0 \tag{23}$$

7.3. Load shedding method

To ensure network physical limits are satisfied within the OPF, load shedding is introduced. Load shedding is typically a last resort measure taken in extreme circumstances to maintain system operability e.g. use of under frequency load shedding schemes [76]. In this work, load shedding is modelled in terms of dynamic load curtailment, this ensures that the OPF will always satisfy the defined network constraints and that the OPF *should* always return a result, allowing for validation

Table 3
Key attributes of study area versus Scotland mean values.
Source: Data from [77,78].

Attribute	Insch	Scotland (mean)
Gross disposable household income (£/year)	20,220	16,160
Cars per household	1.78	1.1
Proportion residents who report driving to work	67.6	49.3
Proportion of households with gas-fired heating	5.59	74.2
Proportion of households with electric heating	18.1	13.4
Proportion of households with oil heating	62.25	5.70
Proportion of households with solid fuel heating	4.42	1.10
Proportion of households with other heating	1.70	0.70

and testing. In practice, DNOs do not typically have the capability or communications infrastructure to dynamically curtail demand connected to existing low voltage (LV) networks. At LV, conventional overcurrent protection in the form of fuses would typically be used to disconnect overloaded parts of the network. Therefore, the idealised load curtailment modelled in the OPF is a proxy for such action.

Should load curtailment be necessary, the value of lost load (VOLL) is used as an associated cost within the optimisation and any curtailment is constrained by (24) and (25) such that demand can only be reduced and not increased

$$p^{H}_{h,t} \leq P^{H}_{h,t} \tag{24}$$

$$p^{D}_{d,t} \leq P^{D}_{d,t} \tag{25}$$

where $p^{H}_{h,t}$, $p^{D}_{d,t}$ is the active power drawn by heat pump h and by household base demand d at time period $[t, t+1]$, $P^{H}_{h,t}$, $P^{D}_{d,t}$ is the unconstrained active power drawn by heat pump h and by household base demand d at time period $[t, t+1]$. Note that base demand refers to all other non-EV and HP demand.

8. Case studies and modelling methods

The following subsections outline the selected case study area and the case studies used to inform the analysis carried out in this work. Each of the case studies require separate modelling methods which are also described.

8.1. Case study area

To demonstrate the developed framework, as described in the previous sections, a data zone was selected that covers the settlement of Insch, Aberdeenshire, in northeast Scotland. This area was chosen as it has several characteristics that would be likely to aid the uptake of EVs and HPs: a high gross disposable household income (GDHI), a high number of cars per household, a low proportion of gas-fired central heating systems, ubiquitous driveway parking, and a high proportion of residents reporting that they drive to work (Table 3).

Applying the heating technology uptake model (Fig. 2) as described in Section 4.1, the resulting heating mix for each PLEF scenario (Table 1) for the case study area is shown in Fig. 4. This figure shows that in 2030, for Ignore, Steer and Shift, the majority of households use legacy oil fired heating and ESHs with only moderate uptake of HPs. However, in the Transform scenario, HPs are the dominant technology with significant uptake by comparison. In 2050, for Shift and Transform, HP uptake dominates and all legacy heating is fully displaced. For Steer, there remains a small portion of households with oil fired heating and ESHs. In the Ignore scenario, there is no change in heating technology between 2030 and 2050. The technology uptake figures in Fig. 4 provide the respective technology penetrations necessary to simulate the different future demand scenarios in the case studies outlined in the following sections.

The comparative reductions in annual heating demand for the PLEF scenarios in 2030 and 2050 for the case study area are shown in Fig. 5.

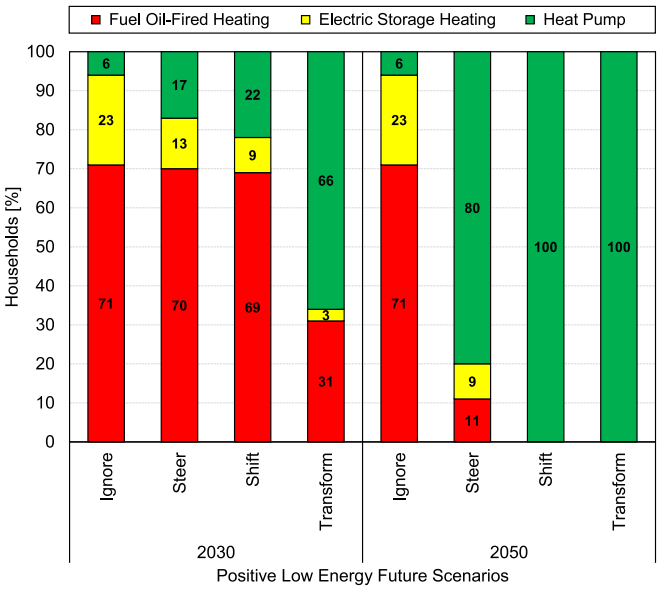

Fig. 4. Breakdown of the heating mix for each year and positive low energy future scenario for the case study area.

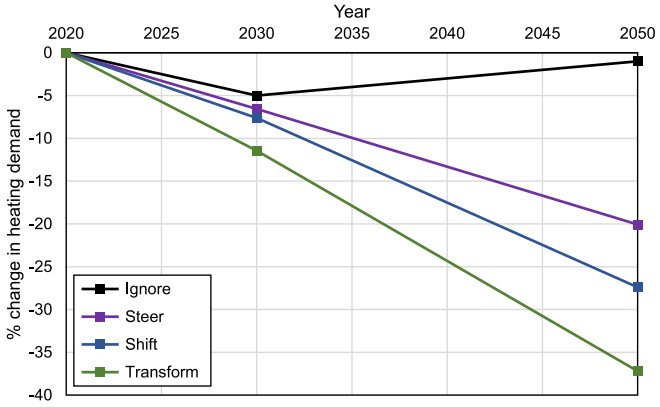

Fig. 5. Heating demand reductions for each year and positive low energy future scenario for the case study area.

These are used to simulate improvements in building efficiency (e.g. improvements in building fabric) and improvements in heating system efficiency under the different future scenarios. The figure shows that under the Transform scenario greater reductions in heating demand are achieved than in Ignore, Steer and Shift. For the Ignore scenario, the observed reductions are lower in 2050 than in 2030, this aligns with the CREDS report [34] for EDR in the residential sector. In the CREDS narratives, changes in the long term can act against efficiency improvements.

In terms of transport, the results of applying the PLEFs to the car stock model STEVE (as described in Section 4.2) for the case study are shown in Fig. 6. This figure shows the total cars and proportion of EVs by scenario for the study area. The figure highlights that a reduction in the total number of cars is observed for both the Shift and Transform scenarios up to 2050 whilst the total number of cars for Ignore and Steer increases in the same period (these overlap in Fig. 6 as the Steer scenario uses the same energy service-demand projections as the Ignore scenario). For Shift and Transform, the proportion of these cars that are EVs increases significantly from 2025 and begins to plateau around 2045. For Steer, the proportion of cars that are EVs also increases significantly, though slightly less than both Shift and Transform in 2030, Steer has a greater proportion of cars that are EVs

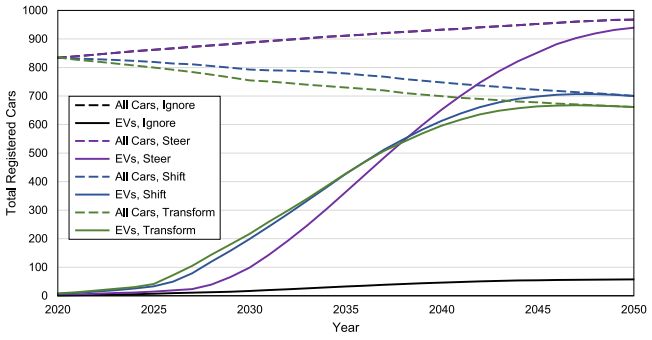

Fig. 6. Total cars and proportion of battery electric vehicles by scenario for study area as output by STEVE.

Algorithm 1 Statistical Impact Assessment

```
for year ∈ years do
    Transport spatial modelling: p_ev for year
    Transport temporal modelling: profiles for year
    Heat spatial modelling: p_hp & p_esh for year
    Heat temporal modelling: profiles for year
    while i < min iterations do
        Sample ESH profiles based on p_esh
        Sample DD profiles based on remaining houses
        Sample EV charging profiles based on p_ev
        Sample HP profiles based on p_hp
        Stochastically distribute on the network
        Add to demand base load per household
        Execute daily load flow
        Store results for every sampling iteration i
        i = i + 1
    return the distribution of results for year
```

in 2050 by comparison. For the Ignore scenario, the proportion of cars that are EVs remains much lower in comparison with only a marginal increase across the same period. EV uptake for each of the scenarios for the case study area as shown in Fig. 6 is then used to determine the proportion of EVs connected to the LV distribution network that is modelled within the study area. Fig. 7 presents a detailed visualisation of this network which has been modelled using the method presented in [63].

8.2. Case study 1: no flexibility (base case)

This case study represents the base case where there is no optimisation or incentivisation driving flexibility modelling (i.e. the charging and discharging actions associated with the EVs). As a result, in this scenario, the EVs are essentially modelled as 'dumb' where the charge obtained for each charge interval is the battery's maximum capacity relative to the charge constraints. With no flexibility, the focus of this case study is solely concerned with the network impact of the different future energy demand narratives. Algorithm 1, demonstrates at a high-level, the approach taken to carry out a statistical power flow impact assessment of the existing LV network infrastructure for this case study, where p_{ev}, p_{hp} and p_{esh} represent the penetration of EVs, HPs and ESHs, respectively.

For each year modelled, spatially explicit uptake penetrations informed by the PLEFs are obtained for EVs, HPs and ESHs using the modelling approaches described in Section 4. The bank of smart meter profiles containing both ESH and generic domestic demand are first sampled and distributed relative to the ESH penetration. The secondary bank of smart meter profiles solely containing generic domestic demand (DD in Algorithm 1) are then sampled and assigned to each of the remaining households. Following this, a series of daily demand profiles with half-hourly temporal granularity are obtained for both HPs and EVs relative to their penetration. These are stochastically distributed across the network (with the constraint that households with an ESH should not also have a HP and that there should only be one ESH or HP for each household, there can be multiple EVs connected at each household with the ability to charge simultaneously) and combined with the base demand on a household basis. A statistical assessment with a number of sampling iterations is then carried out to ascertain the distribution of impact stemming from the uptake of these technologies.

8.3. Case study 2 and 3: smart charging and vehicle-to-grid

The smart charging and V2G case studies are semi-related and are therefore described together in this section. Both the modelling method and the objective function are also described.

8.3.1. Modelling method

For these case studies, EV travel diaries that represent travel behaviour (i.e. plug-in time and stay duration) are used as time-coupled constraint windows within the optimisation that inform when charge and discharge events take place. From the smart charging and parametrised V2G model described in Section 7.2, for case study 2 (smart charging), only the charging portion of the formulation is considered. For case study 3 (smart charging and V2G) the full formulation as presented is applied. This distinction is also applied to the objective function.

Linearisation of non-linear AC power flow equations to model voltages and reactive power has become common in recent years [79–81]. However, this paper takes a traditional approach to non-linear ACOPF to account for the high line impedances and voltage variations typically observed in distribution networks [82]. However, with the time-coupled modelling of EV charging, this results in a significantly large-scale optimisation problem. Further complexity is introduced with the introduction of the V2G and discharging element in case study 3 as a complementarity constraint is used to ensure that only either charging or discharging can occur at any single instance. Problems with these types of constraints are inherently difficult to solve. Therefore Knitro, a specialised solver for solving large scale non-linear mathematical optimisation problems (primarily using interior-point methods and active-set methods) with built-in techniques for handling such constraints, is used in this work [83]. Despite using Knitro to handle this complexity it is difficult to guarantee a global optimal solution, particularly when there are high penetrations of EVs. As such, case study 2 and 3 are only demonstrated at a feeder level to reduce the problem scale and complexity.

A high-level overview of the developed method for these case studies is presented in Fig. 8. The figure highlights that contextual knowledge pertaining to the historical evolution of distribution network planning practices and standards in GB as summarised in the network headroom, engineering upgrades and public acceptance (NEUPA) project [84,85], is paired with the distribution network modelling method described in Section 6.1. Whilst the NEUPA knowledge provides context for the case study area that is the focus of this work, the LV network modelling method captures spatial and technical information pertaining to the network infrastructure.

The figure then highlights the approach taken to model future spatial and temporal demand for heating and transport as described in Sections 4 and 5, and domestic demand as described in Section 6.2. A similar stochastic sampling approach to the method described in Section 8.2 is then undertaken based on technology penetration for each future energy scenario and year simulated. The outputs along with the network model then become the primary inputs to the OPF model described in Section 7.

Fig. 7. Satellite visualisation of the low voltage distribution network under study using Bing Aerial showing which households are connected to which of the four network feeders in the area that are connected to the substation shown.

$$\min \sum_{t\in\mathcal{T}} \Bigg(\underbrace{\sum_{e\in E}(p^{ch}_{e,t}\times c^{buy}_{e,t}) - \sum_{e\in E}(p^{dch}_{e,t}\times c^{sell}_{e,t})}_{\text{Cost of charging and discharging all EVs}} + \underbrace{\sum_{h\in H}(P^{H}_{h,t}-p^{H}_{h,t})Voll^{H}_{h} + \sum_{d\in D}(P^{D}_{d,t}-p^{D}_{d,t})Voll^{D}_{d}}_{\text{Cost of shedding HP and base demand}} \Bigg)\Delta t \tag{26}$$

Box I.

8.3.2. Objective function

In this work, an optimisation is used to show an idealised utilisation of the available network capacity and demand flexibility to show the upper limit of what might be achieved by the latter. In acknowledgement of this, two distinct objective functions have been created, with one specifically for case study 2 and the other for case study 3. For case study 2 the objective function is to minimise the total cost of charging all EVs and the cost associated with any necessary load shedding whilst satisfying network constraints and asset physical limits. For case study 3, the total cost of discharging all EVs is also introduced and is given by (26), where E is a set of electric vehicles, indexed by e, H is a set of heat pumps, indexed by h, D is a set of base demands, indexed by d, $p^{ch}_{e,t}$, $p^{dch}_{e,t}$ are the active power charged and discharged by EV e at time period $[t, t+1]$, $c^{buy}_{e,t}$, $c^{sell}_{e,t}$ are the buy and sell price for EV e at time period $[t, t+1]$ and $Voll^{H}_{h}$, $Voll^{D}_{d}$ are the VOLLs for heat pump h and base demand d.

In case study 2, for $c^{buy}_{e,t}$, a flat price profile is used across the time-horizon (effectively minimising losses) whereas in case study 3, for $c^{buy}_{e,t}$, $c^{sell}_{e,t}$, the use case import (buy) and export (sell) Octopus Agile time-varying electricity tariffs (half-hourly price changes based on day-ahead wholesale rates) shown in Fig. 9 are used as a price differential to demonstrate V2G functionality [86–88]. For load shedding, it is assumed that V^{H}_{h}, V^{D}_{d} are fixed at a penalty price of £16,940/MWh [89] such that the optimiser would only consider curtailment as a last resort measure.

9. Case study results

The PLEFs are modelled using the full assessment methodology developed in this work for 2030 and 2050 (these are key milestones in the net-zero time frame) for each of the case studies. For case study 1, results are presented by considering both transport and heat separately, and then combined. For case studies 2 and 3 only the combined scenarios are considered.

9.1. Case study 1: no flexibility (base case)

The results for case study 1 are presented in Figs. 10 and 11 where the impact of the PLEF scenarios on transformer loading across two days (a 0 °C winter Tuesday and Wednesday) is shown for 2030 and 2050, respectively. These results are reported in terms of the average transformer loading for the sample and also show the interquartile range variance. In each figure, electricity demand from other domestic devices is included. The top plot shows additional demand from transport only (i.e. no heat demand or supply technologies are modelled); the middle plot shows additional demand from heat only (i.e. no transport demand or supply technologies are modelled); the bottom plot shows the combined impacts from heat and transport (i.e. both are modelled). Note that to show impact over the two day period, it is assumed that domestic demand and heat demand are similar each day i.e. a standard two day working period in winter where the average temperature is 0 °C.

Considering transport demand, it is demonstrated that the uptake of EVs in all scenarios has a significant impact on the traditional evening peak. From Fig. 10, the impact of EV uptake is much less pronounced than in Fig. 11, emphasising that penetration is the key determinant of impact in terms of magnitude. This is further evidenced when comparing between the different PLEF scenarios in each of the figures. In Fig. 10, the Shift and Transform scenarios are similar with only marginal difference from Steer. However, in Fig. 11, the

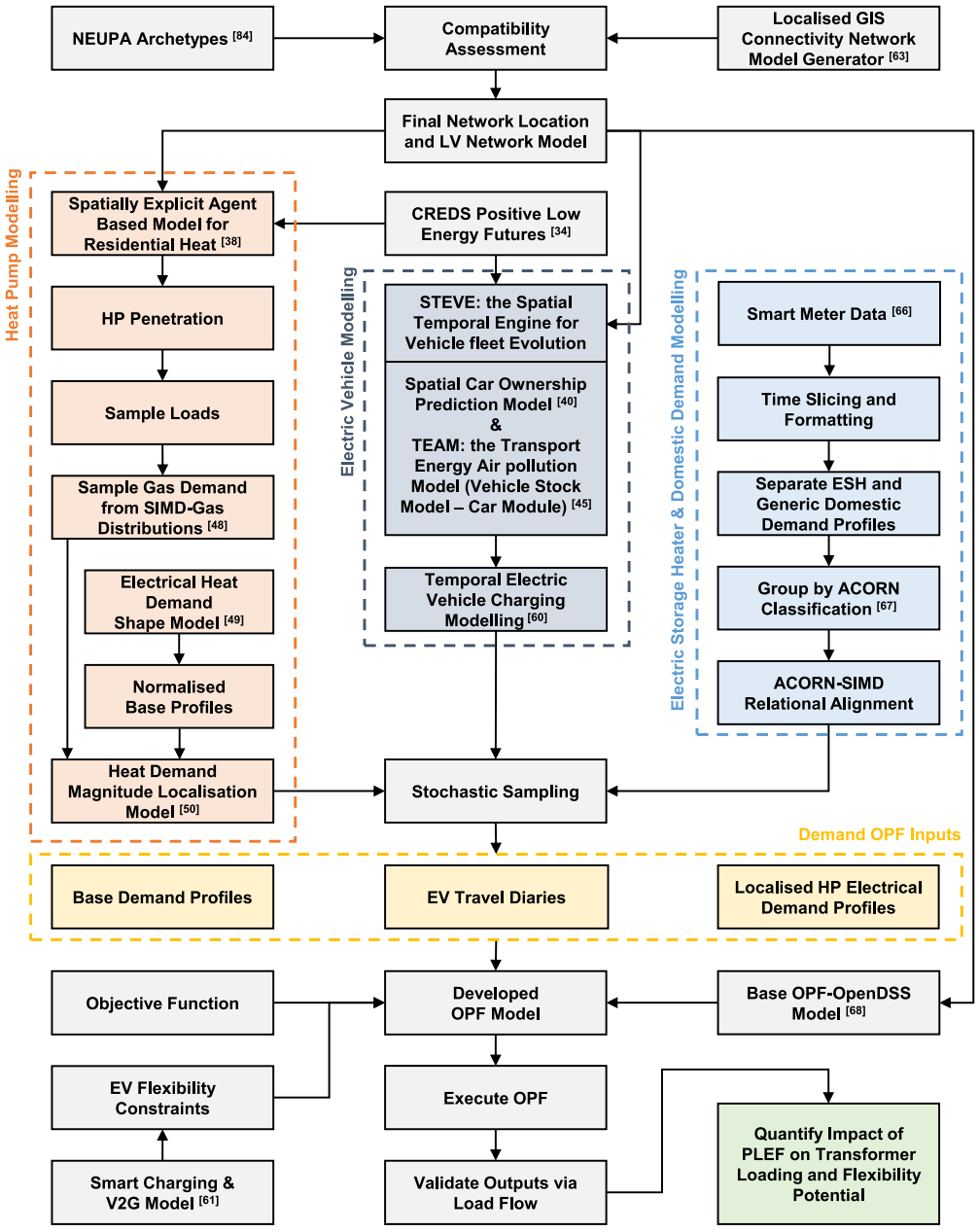

Fig. 8. High-level flow chart of the entire methodology and integration of the various modelling techniques.

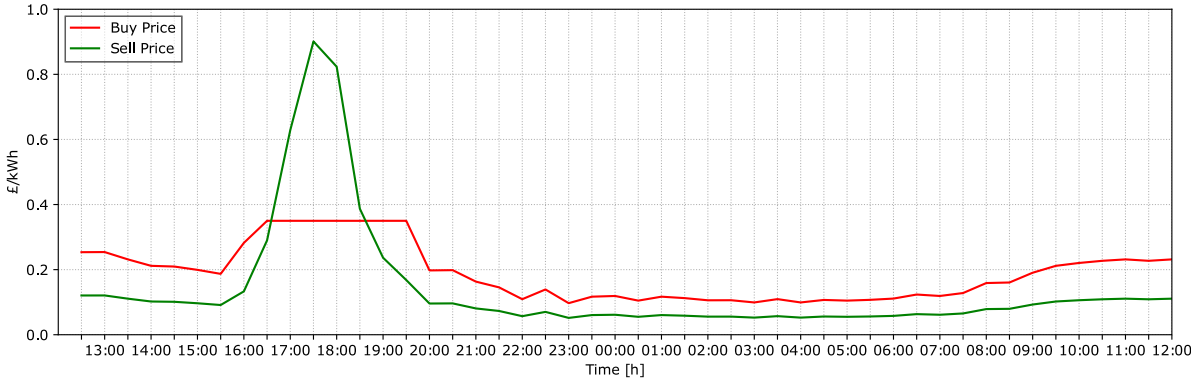

Fig. 9. Use case Agile tariff price profiles with price differential for demonstration of V2G functionality.

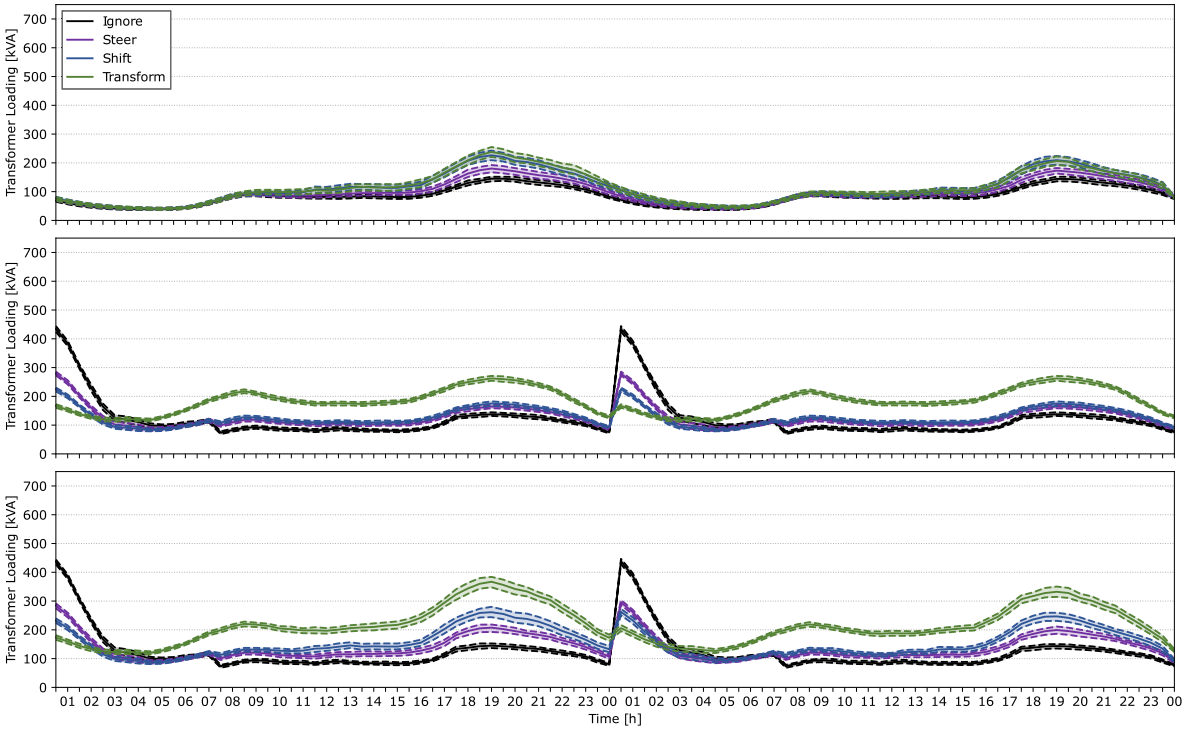

Fig. 10. Impact on transformer loading for 2030: (top) transport demand, (middle) heat demand, (bottom) combined demand.

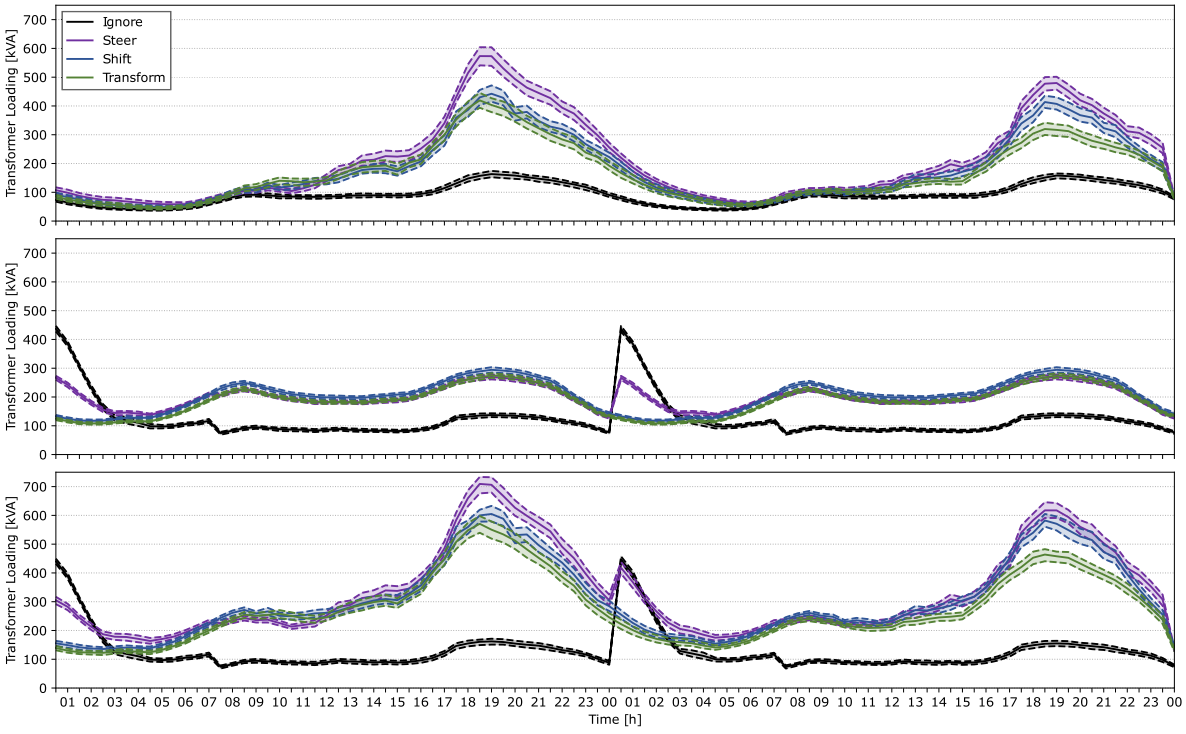

Fig. 11. Impact on transformer loading for 2050: (top) transport demand, (middle) heat demand, (bottom) combined demand.

difference between the Steer scenario and both the Transform and Shift scenarios is more prominent around the traditional evening peaks. The observed difference between Shift and Transform is primarily due to the changes in number of trips and trip distance between 2030 and 2050 as presented in Table 2. An additional observation is the difference in scenario impact around the traditional evening peak on each individual day in Fig. 11, with the difference between the scenarios typically more pronounced on the Wednesday showing the Transform scenario to have a lower impact than in the Shift scenario and a reduction in the peak for Steer. This relates to the prevalence of certain trip types in certain

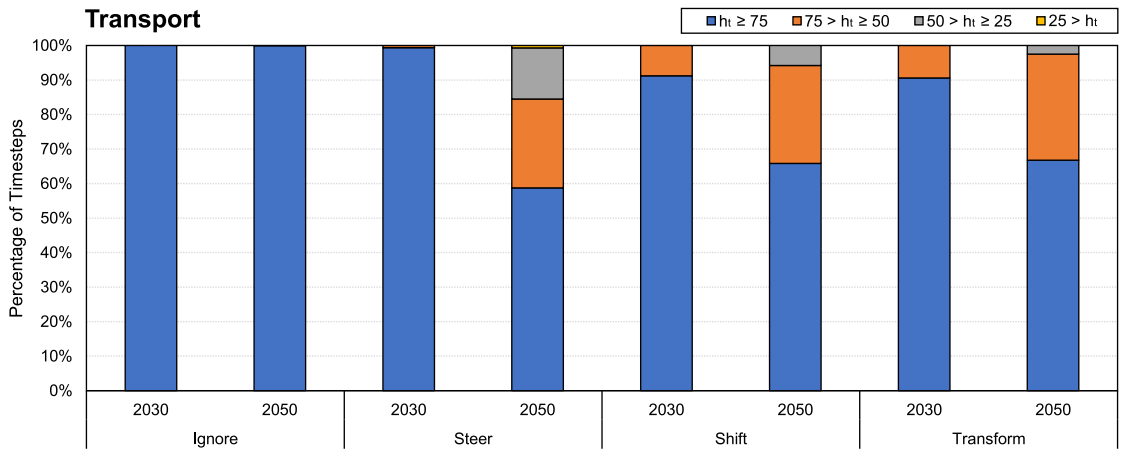

Fig. 12. PLEF scenario comparison by year considering only transport demand, showing the transformer headroom as a percentage of the time spent in each classification band across all simulations in the sample.

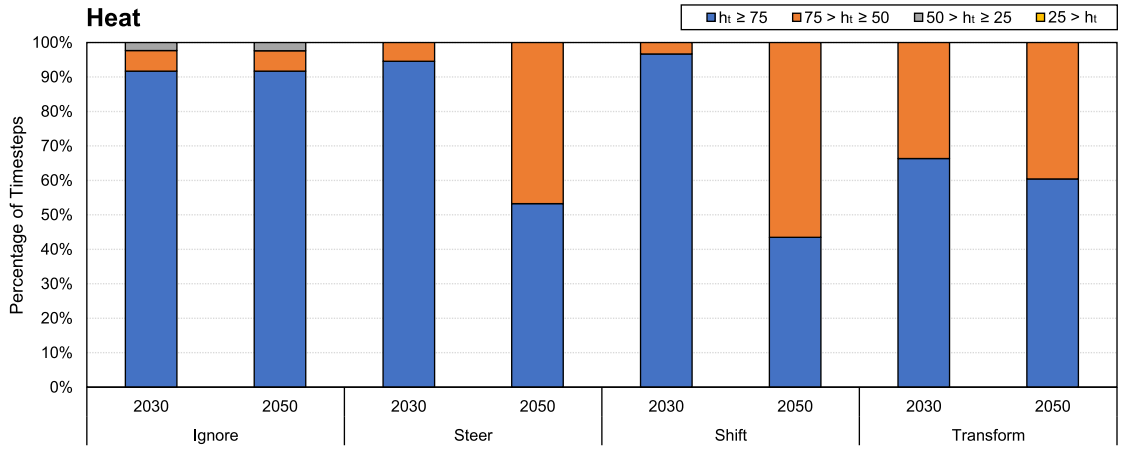

Fig. 13. PLEF scenario comparison by year considering only heating demand, showing the transformer headroom as a percentage of the time spent in each classification band across all simulations in the sample.

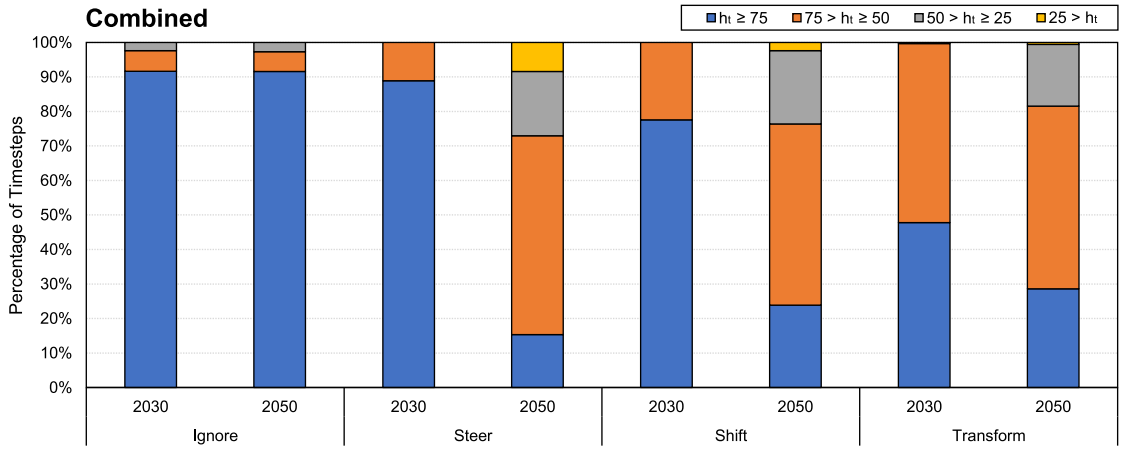

Fig. 14. PLEF scenario comparison by year considering both transport and heating demand, showing the transformer headroom as a percentage of the time spent in each classification band across all simulations in the sample.

weekdays, and is reflective of wider variation in travel habits as per the UK NTS [90].

Considering heating demand, in both Figs. 10 and 11, there is an observed increase in demand during the early morning hours that can be attributed to the ESHs. This noticeably decreases in the Shift and Transform scenarios in comparison with the Ignore and Steer scenario as the ESHs are replaced with HPs. Also, for Shift and Transform, a second morning increase in demand that can be attributed to HP usage for space heating demand is observed. In Fig. 10, as similar with EVs, penetration dominates impact in terms of magnitude and there is a

distinct difference between Transform and the other scenarios (Transform has a higher percentage penetration of HPs in 2030 as in Fig. 4). In Fig. 11, where both Shift and Transform HP penetrations are 100%, the marginal difference in impact can be attributed to the representative heat demand reductions used in each scenario. Additionally, despite Transform having a greater number of HPs than Steer, due to the comparative difference in heat demand reductions this results in a fairly similar profile in terms of magnitude.

Considering the combined effects of heating and transport, the extent of the impact is evident in comparison of Figs. 10 and 11. In Fig. 11, the traditional evening peak is significantly increased for the Steer, Shift and Transform scenarios in comparison with the Ignore scenario, increasing from an approximate loading of 200 kVA in the Ignore scenario to 500–750 kVA in the Steer, Shift and Transform scenarios. Note that the rating of this transformer is 800 kVA and would likely have initially been sized to accommodate the large increase in demand at midnight stemming from the ESHs. However, consider that the case study represents a location that, today, predominantly uses gas heating but otherwise is the same as the case study area. The ESH related loading would only be present for any household that adopts them in place of gas heating. With the policies present in the Shift and Transform scenarios the agent-based model indicates that all households would adopt HPs. For Steer, it is likely that the majority would also adopt HPs with a smaller portion continuing to use gas. In Ignore, they would continue using gas. Therefore, in a network that was not designed to accommodate ESHs, the substation would likely have a lower kVA rating unless oversized for a particular reason in the planning process. As such, given transformer headroom is significantly eroded in the combined scenarios, it raises concerns with existing transformers that have lower levels of headroom currently available. Also, as HPs are constrained to one at each household and EVs can have multiple connections that charge simultaneously, EV impact tends to dominate.

Ultimately, a network operator's decision to invest in network reinforcement is based on its peak loading. As such, transformer headroom is considered next. The headroom for a particular time interval (h_t) is a measure of how much spare capacity is available in a transformer at a specific instance in time, expressed as a percentage of maximum capacity. It is calculated by comparing the apparent power observed at that specific time interval (S_t) to the transformer's rated capacity. For this analysis, a simple classification is used to split the daily headroom into four percentage bands: $h_t \geq 75$, $75 > h_t \geq 50$, $50 > h_t \geq 25$ and $25 > h_t$. Using this classification, Figs. 12–14 present a comparison of each PLEF scenario by year, considering in turn demand from transport, heating and combined impacts, showing the transformer headroom as a percentage of the time spent in each classification band across all simulations in the sample. These figures are used to complement Figs. 10 and 11 and the accompanying analysis.

9.2. Case study 2 and 3: smart charging and vehicle-to-grid

For case study 2, Fig. 15 shows the impact on transformer loading (with only feeder 1 modelled) for the Steer, Shift and Transform scenarios in 2030 and 2050 comparing generic 'dumb' EV charging with smart EV charging for combined heating and transport demand. In this figure, whilst the optimisation is performed over the same two day period, the results are presented over a period that spans from 12:30 to 12:00 the following day to emphasise the impact of smart charging on the evening peak and overnight (typically when it would be expected that the bulk of charging would be carried out). The figure demonstrates that flexible smart charging can be used to reduce peak demand in each of the PLEF scenarios, both in 2030 and 2050.

For case study 3, Fig. 16 shows the impact on transformer loading (with only feeder 1 modelled) for the Steer, Shift and Transform scenarios in 2030 and 2050 comparing dumb charging with use of smart charging that includes V2G. As before, electricity demand from both transport and heating is considered. In the V2G scenarios, with the use case Agile price profiles, the evening peak loading as seen at the transformer is further reduced in all scenarios. The extent of this reduction is accentuated in 2050, primarily as there are a greater number of EVs connected. Whilst the traditional evening peak is significantly reduced, there is a substantial increase in overnight charging in each of the scenarios. This emphasises that although the V2G scenarios have an impact that exceeds that of the smart charging with respect to the traditional evening peak demand reduction, the overnight demand increase from charging is greater in comparison. This would be expected as the EVs operating as V2G during the traditional evening peak would have a reduced capacity and thus require additional demand than in the smart only scenario to satisfy the charging constraints.

Ultimately, Fig. 16 shows the increase in the potential for EV charging demand to act more flexibly under the more ambitious PLEF scenarios. This results from the assets having a lower duty cycle, being available more with a lower requirement for energy. Whilst under-used private vehicles are a persistent symptom of modern transportation systems, their use as distributed electricity storage providers has the potential to offer benefits to the wider energy system.

On the basis of the presented case studies, which considered a typical winter demand day, energy futures based on EDR policies were found to reduce evening transformer loading significantly. The transformer loading between 16:00 and 21:00 in 2050 was found to reduce on average by 11.55% and 16.10% for the Shift and Transform scenarios relative to the Steer scenario. In addition to EDR based policies, introduction of flexible smart charging achieved reductions on average of 39.26% and 43.29% for the Shift and Transform scenarios relative to the Steer scenario. The achievable reductions increased to 56.64% and 69.07% for the Shift and Transform scenarios relative to the Steer scenario with the use of V2G (driven by the use case import and export Octopus Agile tariffs).

10. Discussion

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

10.1. Electricity system operators

The method presented in this work describes an approach that has the ability to postulate what electric heating and EV charging demand would be for a particular local area under particular future scenarios. The approach then has the capability to assess whether a particular electricity distribution network could accommodate those demands and the extent to which optimal utilisation of smart charging can avoid or defer network reinforcement. The findings emphasise that 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. This extends beyond use of simplistic network planning metrics such as ADMD – the highest point of electricity consumption that is expected to occur after accounting for consumer diversity – which looks at individual instances of peak demand separately and therefore does not account for coincidence of maximum demand peaks, potentially leading to an underestimation of the actual network requirements during critical periods.

Areas with higher flexibility potential can be identified using the presented method. However, to fully capitalise on this, several questions remain: how would the necessary flexibility actions for a particular day be identified, and who would be responsible for carrying them out? Does the DSO have a role? Will this depend on householders responding to price signals as modelled in this work (with some uncertainty as to whether they will)? Or is there a role for a third

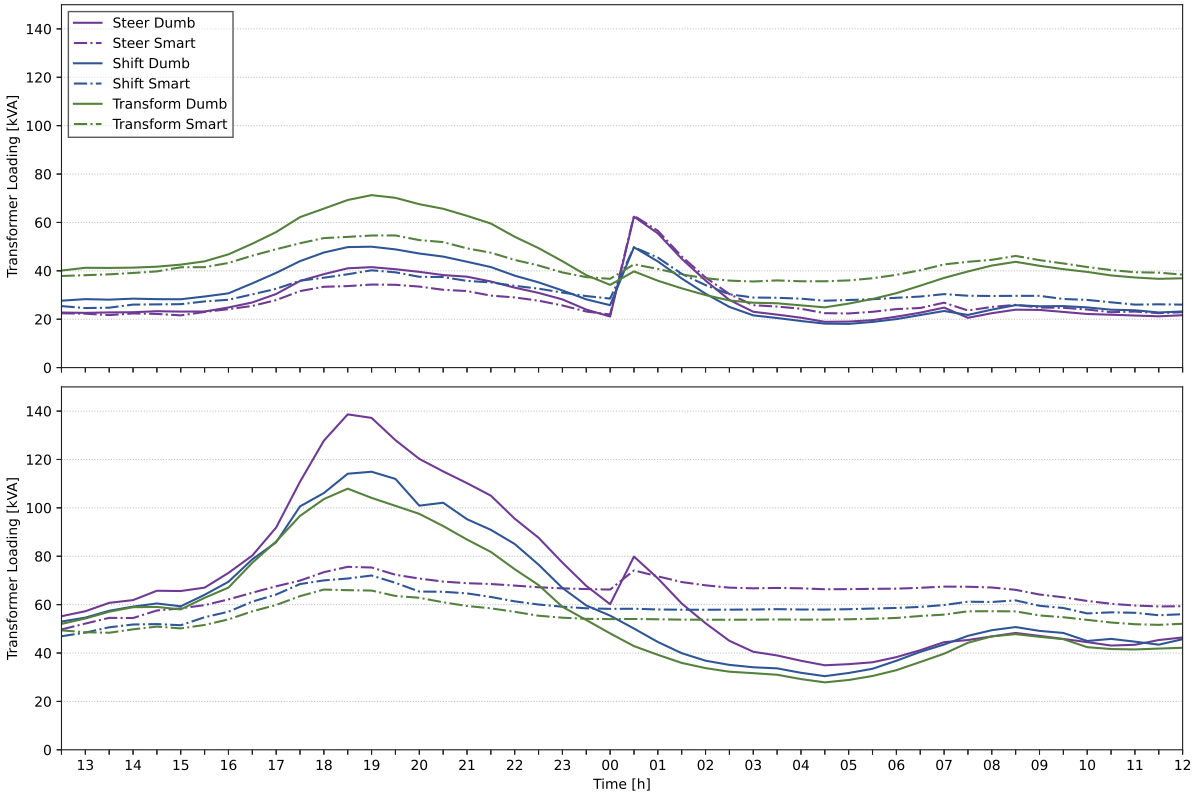

Fig. 15. Impact on transformer loading with only feeder 1 modelled for Steer, Shift and Transform scenarios in 2030 (top) and 2050 (bottom) comparing smart charging with dumb charging — both heating and transport demand.

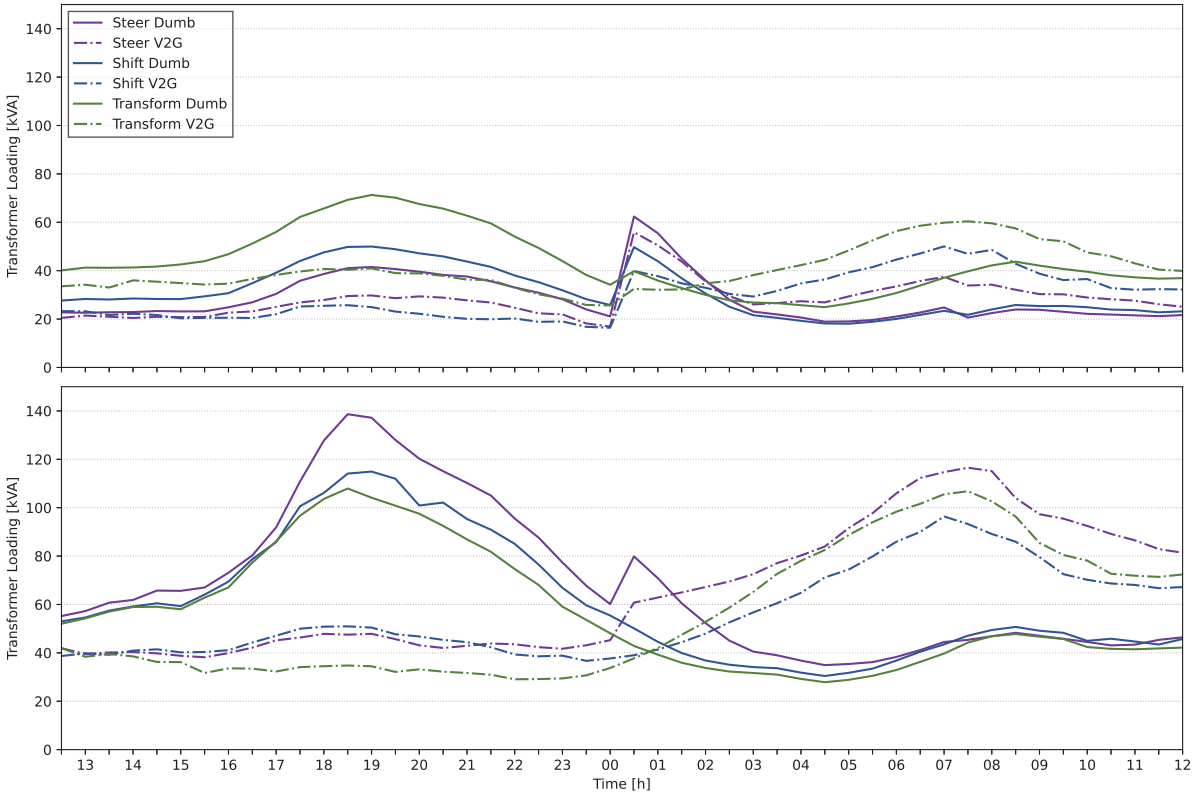

Fig. 16. Impact on transformer loading with only feeder 1 modelled for Steer, Shift and Transform scenarios in 2030 (top) and 2050 (bottom) comparing V2G with dumb charging — both heating and transport demand.

party to do the work for energy users (using automation, i.e. adopting technology as an enabler of behavioural change)? A challenge in the case of using price signals, is that price signals articulated only at a wholesale/national system level may fail to reflect the times at which local network constraints arise.

The case study area described in this work has been used to demonstrate the presented method's high-resolution applicability at the 'local' level. However, it also must be recognised that this is a single local area with one ground mounted secondary transformer. Therefore, it is also important to acknowledge the wider implications in the context of aggregated impacts at the national and sub-national level, i.e. as seen by the transmission and wider distribution networks. The methods presented for estimating future energy demand and the likely time series of power demand are generally scalable for use at less granular resolutions. The main challenge is around mapping this to detailed network models. The network modelling methodology used is highly transferable in that different LV networks for alternative case study areas can be easily modelled. Simplifications such as use of a single phase model and relaxation of constraints e.g. voltage or thermal can be made to improve scalability.

10.2. National policymakers, regulators and local authorities

Local authorities have the potential to influence and guide locally-specific decarbonisation pathways [91]. This requires high-level planning and a significant understanding of local requirements. It is also recognised that the feasibility of interventions from such parties are highly dependent on future network capability and headroom e.g. works including [92], 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 require an understanding of network capability and future flexibility potential based on the unique characteristics of specific localities. They also require a broader understanding of different types of emerging heating technologies including heat networks (and for those heat networks to access low carbon sources of heat, which might be large electric HPs) and for use of low carbon hydrogen. This would allow for investment to be optimised with better foresight of regional economic plans and local area energy infrastructure. The method presented in this work can be used to inform on the impacts of local development strategies and the proposed interventions in this regard.

For policymakers the presented method can be used to inform on the impacts of decision making in this space e.g. as evidenced through the presented findings and analysis, the policy options and narratives (described in detail in [34]) that underpin the modelled future scenarios yield different network impacts at varying timescales. As evidenced by the results in this paper (see in particular Fig. 14), EDR policies have the potential to mitigate the need for reinforcement of energy networks. This chimes with existing decarbonisation strategies presented for the UK: for example, the CCC's Sixth Carbon Budget recommendation (2020) details varying pathways to reaching the 2050 Net Zero target [2]. The pathways are presented as a trade-off between technological intervention and behaviour change; scenarios with more onus on energy demand reduction (through reduced car use, reduced meat consumption, etc.) require fewer engineering interventions (including technologies that are as yet unproven at scale, including direct air carbon capture).

Furthermore, policies aimed at enabling the use of smart functionality to unlock the flexibilities offered by electrified technologies is likely to have significant impacts on networks. The findings evidence that greater peak demand reductions can be achieved when these are applied in combination with policies focused on consumer behavioural aspects of demand reduction.

11. Conclusion & further work

This paper presents a methodology to translate narratives on energy demand futures in heating and transport to impacts on distribution networks. Previously developed low-energy future demand scenarios are used to drive spatially explicit modelling of the uptake of electrified transport and heating; and temporally explicit modelling of the electricity demand of these technologies for local geography. The methodology is demonstrated on a model of a real electricity distribution network that serves households within the local geography and is used as the basis to examine the impacts of the varying demand scenarios on key network infrastructure. An OPF formulation that enables smart EV charging and V2G also forms part of the methodology and is used to investigate the impact of these future demand scenarios on the potential of flexibility in electricity demand.

Electrification of heat and transport enables more efficient use of primary energy than use of fossil fuels. However, as a consequence, the electricity demand will significantly increase, challenging existing electricity system infrastructure. On the basis of the reported findings, we conclude that:

1. Energy demand futures with policies focused on EDR using the *Avoid-Shift-Improve* framework [9] are shown to mitigate the need for reinforcement of electricity networks. For the case study considered a reduction in evening transformer loading of up to 16% can be achieved.
2. However, flexibility in electricity demand contributes a larger difference to a network's ability to host electrified heat and transport than relying solely on EDR.
3. Energy futures that combine policies that pursue EDR and simultaneously enable electricity system flexibility present the greatest benefits, both to the mitigation of reinforcement and to system operability in the context of growing penetrations of variable renewable generation. For the case studies considered a reduction in evening transformer loading of up to 69% can be achieved.
4. Despite these benefits, it has been shown that electricity demand is still likely to increase significantly relative to the current baseline. Therefore, widespread reinforcement of the electricity system will still be necessary in the transition to net-zero and, accordingly, urgent investment is required to support the realisation of the UK's legally-binding climate goals.

We recommend several pieces of further work based on this research. Firstly, we recommend that the impact and role of flexible heating demand in parallel with flexible transport demand be investigated. Secondly, as the assumptions used for future reductions in heating demand in the CREDS PLEFs are relatively vague, this limited the derivation of quantitative demand reduction values in this work. Therefore, although plausible future reductions in heating demand are used to capture improvements in building fabric and the evolution of heating technologies. We recommend future research surrounding derivation of future heating demand and the role of policies aimed at demand reduction, and energy efficiency improvement. We note that there are contradicting assumptions/evidence in the existing literature in this respect. More broadly, there are further opportunities to explore the impacts of changes in heating and domestic demand usage patterns under different future demand scenarios with a need to explore whether much greater sensitivity of demand to time of use tariffs might have adverse effects due to the erosion of diversity. There is also scope to conduct further research to account for different heating technologies and the respective impacts on network infrastructure.

CRediT authorship contribution statement

Connor McGarry: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Resources, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **James Dixon:** Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Resources, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Jack Flower:** Writing – original draft, Methodology, Investigation, Data curation, Conceptualization. **Waqquas Bukhsh:** Writing – review & editing, Validation, Supervision, Resources, Methodology. **Christian Brand:** Writing – review & editing, Supervision, Resources, Conceptualization,. **Keith Bell:** Writing – review & editing, Supervision, Resources, Funding acquisition, Conceptualization. **Stuart Galloway:** Writing – review & editing, Supervision, Resources, Funding acquisition, Conceptualization.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Connor McGarry reports that the development of this research is supported by the Centre for Research into Energy Demand Solutions (CREDS), UK Research & Innovation grant number [EP/R035288/1], the UK Energy Research Centre (UKERC), [EP/S029575/1], and by the UK Engineering and Physical Sciences Research Council (EPSRC) through the Centre for Doctoral Training in Future Power Networks and Smart Grids [EP/L015471/1].

Data availability

The authors do not have permission to share data.

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