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A geographically disaggregated approach to integrate low-carbon technologies across local electricity networks

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Meeting climate targets requires widespread deployment of low-carbon technologies such as distributed photovoltaics, heat pumps and electric vehicles. Without mitigating actions, changing power flows associated with these technologies would adversely impact some local networks. The extent of these impacts, and the optimal means of avoiding them, remains unclear. Here we use local-level data and network simulation to estimate variation in future network upgrade costs in over 40,000 geographical regions comprising all of Great Britain. We find that costs vary substantially between localities, and are typically highest in urban areas, and areas with highest deployment of heat pumps and electric vehicles. We estimate reductions in required upgrades associated with local flexibility, which vary substantially between localities. We show that using geographically disaggregated data to inform flexibility deployment across the country could reduce network upgrade costs by hundreds of millions of pounds relative to an approach that treats localities as homogeneous.

Globally, increased deployment of low-carbon technologies in the form of distributed photovoltaics (PVs), heat pumps (HPs) and electric vehicles (EVs) is required to meet climate targets[1]. These technologies are central to Great Britain (GB)'s decarbonization strategy[2,3]. Without network upgrades or increased system flexibility, higher distributed generation and loads associated with these technologies would adversely impact some local networks[4,5].

Deployment of low-carbon technologies can cause multiple impacts, which depend on context and particularly on rurality[4,6–8], on local networks. Increased load from EVs and HPs can overload transformers and cables and cause falling voltages[9]. High levels of PVs can overload cables and cause voltage rises when insolation is high[10–14]. In urban areas, long feeders serve many households through a single transformer, making them more susceptible to overloading and voltage issues[4]. Additionally, transformers are typically ground mounted and cables run underground in urban areas, making them more expensive to replace than pole-mounted transformers and overhead cables in rural areas[15]. Further, levels of technology deployment vary between rurality contexts. In GB, PV deployment is higher in rural areas, where there is more space and a higher proportion of owner-occupied houses[10].

The electricity distribution system in GB is organized across a range of spatial scales associated with different voltage levels[16–18]. Medium-voltage networks, referred to here as regional, distribute voltage from transmission networks to low-voltage networks. Low-voltage distribution networks, referred to here as local, serve individual households and small commercial electricity users (typically at 230–400 V). A distribution substation transforms electricity from medium to low voltage to serve each section of local network, connecting up to around 500 households through cables known as feeders.

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Local networks have received little attention in national planning owing to their geographically disaggregated nature. However, they could be subject to substantial adverse impacts with increasing deployment of low-carbon technologies[19], and account for approximately half of the total length of the distribution network[20]. Upgrading them could incur substantial costs[20,21]. These local networks represent the focus of this paper.

Appropriate mechanisms to avoid network impacts depend on local context. Conventionally, overloads and voltage rise have been avoided by upgrading cables and transformers[22]. Impacts can also be reduced or eliminated with flexibility through deployment of distributed storage[17,23–25] and/or demand-side response[26–29] to reduce local electricity consumption at times of peak load, and/or increase consumption at peak PV generation[23,25,30]. GB distribution system operators (DSOs) are beginning to tender for these flexibility services to alleviate stresses on particular regions of distribution networks[31,32].

The importance of local network characteristics and technology deployment levels in determining stresses on particular networks is well established. Reports produced by GB DSOs indicate few grid impacts of low-carbon technologies across GB regions at present, but anticipate more such problems with increased deployment of distributed PVs[33–36]. Across GB contexts, modelling studies predict problematic levels of voltage rise when PVs are deployed at 5% (ref. 14), 30% (ref. 13) and 30–100% (ref. 12) of urban and semi-urban households. On a GB local network, ref. 14 finds that transformers operate close to their limits during cold periods for 20% penetration of HPs. Across Belgian networks, ref. 6 finds voltage rise associated with HP deployment in rural areas to be the main driver of upgrade costs, with integration costs in urban areas. This case study includes a longer feeder in the rural than the urban area, which is untypical in the UK. An international review finds PV penetration limits of between 2.5% and 500% of minimum load across local networks, attributable to differences in load profiles, generation profiles and network configuration[37].

Few studies address the impact of low-carbon technology deployment across local networks at a country level. Reference [10] maps local impacts of one technology, solar PVs, through the development of the United Kingdom Photovoltaic Database (UKPVD) framework. This comprises a database that geographically maps PV deployment, domestic and non-domestic demand and network assets across GB, and is used to assess local imbalances of PV generation and electricity demand[38] and the potential for storage to mitigate these[25]. References [4,39] build on this work by simulating local network impacts and costs associated with demand growth, PV deployment and flexibility in networks representative of city, town and village contexts. In parallel efforts, refs. 7,40 map estimated PV hosting capacity in local areas across the UK, Sweden and Germany, and calculated impacts of EV charging across Sweden.

Both ref. 4 and ref. 7 generate useful insights on the integration of low-carbon technologies across local contexts. Both studies suggest that network impacts will be more severe, and upgrade costs higher, in cities and towns than in villages. Reference [7] points out substantial differences in grid capacity between Sweden, where heating is electrified, and the UK and Germany, where it is not. However, neither study maps the impact of decarbonization scenarios including widespread deployment of PVs, EVs and HPs together across local networks.

In this Article, we build upon a methodology developed in ref. 4, but with a substantial expansion of scope. The present study explicitly calculates the local network impacts associated with low-carbon technology deployment across over 40,000 local areas in GB using geographically disaggregated data to inform local characteristics of each of them (as opposed to three representative contexts in our previous study[4]). This is achieved by constructing a UK Low-Carbon Technology Database (UKLCTD), which updates and expands the UKPVD[4,10] to include current data and future scenarios for EV and HP deployment up to 2050 across each local area. The UKLCTD is used alongside a network modelling tool[41] to develop a meta-model that can calculate local impacts of low-carbon technologies across each local area. This meta-model is used to address two questions. First, how might costs of avoiding local network impacts through local network upgrades vary with local context? Second, where would local flexibility measures be most effective in reducing network upgrade requirements? The meta-model's ability to answer these questions is necessarily limited by data available at a national level, and it cannot match the local realism of studies focused on a smaller subset of networks[12–14]. The key contribution arises instead from a methodology to bridge local and national analyses, and an initial application of this methodology.

Diversity of local contexts across GB

To assess context-dependent local impacts of low-carbon technology deployment, variation in network upgrade costs associated with their integration, and cost-effective measures to avoid these upgrades, it is necessary to build up a picture of relevant local characteristics. The UKPVD[10,25,38] represents a starting point for this, and includes geographically disaggregated data from a range of sources on domestic and non-domestic electricity demand[42], density of domestic and non-domestic meters[43,44], PV deployment[45] and local network infrastructure[4]. The UKPVD is updated and expanded to the UKLCTD by (1) revising the base year to 2020, (2) adding data on EV and HP deployment, (3) adding data on rurality, broken down into major urban conurbations (referred to as 'urban' henceforth), cities, towns and villages following the UK Government Statistical Service's classifications[39,46,47], (4) expanding to include Scotland and (5) extrapolating available data on network infrastructure to approximate network data in other regions. These data are disaggregated across Lower Layer Super Output Areas (LSOAs) in England and Wales and Data Zones in Scotland, geographical units that contains approximately 700 and 400 households, respectively. The local characteristics considered in this study, alongside data sources and ranges across GB, are summarized in Table 1.

The distribution of present-day local characteristics across GB is shown in Fig. 1a–c. Urban regions typically have a higher density of meters and more meters per substation than more rural areas, and major urban centres are clearly visible in Fig. 1b,c ref. 4.

Local deployment scenarios for PV, EVs and HPs are developed in ten-year intervals up to 2050, on the basis of regional Distribution Future Energy Scenarios (DFESs) produced by regional DSOs where sufficient data are available[48–50], and Future Energy Scenarios (FESs) produced by the national electricity system operator in other locations[51], curated in the UKLCTD dataset[52]. The GB distribution network is broken down into regions owned and operated by six regional DSO groups. For each region, DSO groups produce DFESs including higher or lower levels of low-carbon technology deployment with a more regional focus than the national FESs. For three of these six regions, DFES data were available at an appropriate geographical resolution to allow their inclusion at an LSOA level in scenarios presented here. In others, national scenarios were used to inform future technology deployment (Methods). Each of these scenarios is designed to be consistent with UK climate targets.

The approach of combining geographically disaggregated DSO data where available, and national level data in other regions, has benefits and drawbacks. It allows for a more detailed representation of local areas on the basis of local characteristics, increasing the realism of results, and fulfilling the objective of connection national plans with local data. However, it also risks producing spurious differences across DSO boundaries, particularly where different DSOs make different assumptions about the future development of the electricity system. By presenting scenarios together, this Article helps to clarify where these assumptions diverge across regions.

Projected 2050 deployment of low-carbon technologies across GB is shown in Fig. 1d–f. In line with present-day deployment

Table 1 | Characteristics used to define local contexts across GB at an LSOA level

Characteristic	Range of values across LSOAs (5th to 95th percentile/discrete values)	Data source(s)
Basic LSOA characteristics		UK Office for National Statistics[39,43], Scottish Government[44,46]
Area (km^2)	0.11–27	
Population density (people/km^2)	56–13,000	
Rurality[a]	Urban, city, town, village	
Electricity demand		UK Department for Business Energy and Industrial Strategy[6]
Number of domestic meters[b]	320–1,050	
Number of non-domestic meters	9.0–140	
Domestic electricity demand per household (kWh)	380–1,400	
Non-domestic electricity demand per meter (kWh)	9,400–23,000	
Network infrastructure[c]		Western Power Distribution[4]
Number of distribution substations	2.6–48	
Proportion of substations that are ground mounted	0.11–1	
Number of ground-mounted substations	2.4–9.1	
Number of pole-mounted substations	0–42	
Present technology deployment[d]		UK Energy Regulator, Ofgem[6]
Domestic PV deployment (installations per meter)	0–0.09	
Non-domestic PV deployment (installations per meter)	0–0.08	
Domestic PV deployment (kW in LSOA)	1.4–220	
Non-domestic PV deployment (kW in LSOA)	0–150	
Future technology deployment[e]		National Grid ESO[37], UK Power Networks[6], Northern Powergrid[6], Western Power Distribution[6]
Domestic PV installations per meter in 2030	0.0–0.20	
Domestic PV installations per meter in 2040	0.01–0.41	
Domestic PV installations per meter in 2050	0.01–0.53	
Non-domestic PV installations per meter in 2030	0.0–0.25	
Non-domestic PV installations per meter in 2040	0.0–0.54	
Non-domestic PV installations per meter in 2050	0.0–0.67	
HP installations per meter in 2030	0.03–0.24	
HP installations per meter in 2040	0.26–0.61	
HP installations per meter in 2050	0.37–1.2	
EVs per meter in 2030	0.26–0.70	
EVs per meter in 2040	0.61–1.8	
EVs per meter in 2050	0.6–2.0	
Flexibility		N/A
Flexibility (proportion of peak demand reduction)[f]	0, 0.1	

[a]Rurality categories referred to in this paper are merged from subcategories defined by the UK Office for National Statistics for England and Wales: urban ('A1', 'B1'), cities ('C1'), towns ('D1', 'D2') and villages ('E1', 'E2')[39]. Data Zones in Scotland are assigned rurality categories on the basis of the population density that they match most closely amongst LSOAs in each category in England and Wales. [b]This range is extended substantially by the inclusion of Data Zones in Scotland, which are somewhat smaller than LSOAs in the rest of GB. Excluding Scotland, this range is 511–1,090 meters. [c]Actual data are available only for South West England and are derived for other regions on the basis of meter density (Supplementary Note 7). [d]Present-day levels of HP and EV deployment are assumed to be negligible. [e]Due to differences in data availability, scenarios for future technology deployment are developed using different approaches in different regions (described in main text). [f]No reference is provided for flexibility scenarios. These are used to illustrate the potential role of flexibility in reducing network upgrade costs rather than to explore specific flexibility scenarios.

patterns[10], PV deployment is higher in more rural areas (Fig. 1d). There is no strong correlation between projected EV or HP deployment and rurality (Fig. 1e,f), but projected HP deployment is higher in regions where spatially resolved data were available from DSOs (the South East, Midlands, South West and North East England)[48–50] when compared with other regions, where uniform distribution is assumed on the basis of National Grid scenarios[51]. This may suggest that these DSOs are more optimistic about low-carbon technology deployment than the National Grid, particularly in the South East, where almost two EVs per meter are projected by 2050 (although values are markedly lower in London, perhaps due to its well developed public transport network).

Estimating local network upgrade costs and flexibility savings

Local network impacts and variation in costs of upgrading them to avoid these are calculated across GB on the basis of data assembled in the UKLCTD. To do this, a statistical network design and investment model developed by Gan et al. is used[41]. This model simulates representative network configurations across rurality contexts, simulates

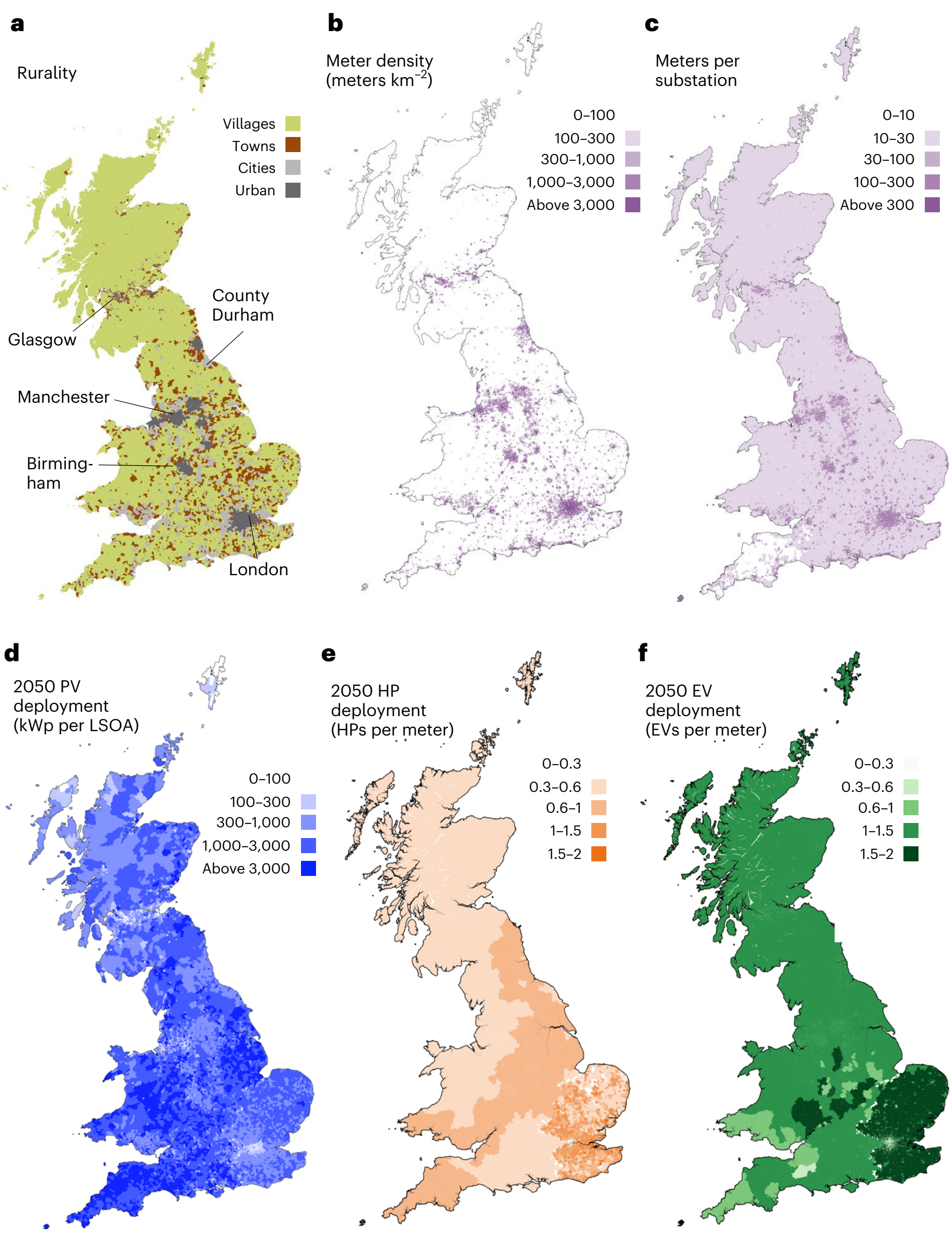

Fig. 1 | UKLCTD data on local characteristics and projected 2050 low-carbon technology deployment. a–**f**, LSOA-level maps of GB showing rurality category (**a**), meter density (**b**), domestic meters per distribution substation (**c**), 2050 PV deployment (**d**), 2050 HP deployment (**e**) and 2050 EV deployment (**f**). Data from ref. 52.

power flows through these networks under conditions of peak demand and generation and derives implications for capacity and voltage constraints across the network.

Whilst this model is necessarily limited by availability of data on actual network configurations across LSOAs, it nonetheless represents the state of the art in network modelling and calculating upgrade costs. Simulated networks have been validated against real UK networks in rural and urban areas[41,53], and the model has been used extensively to provide evidence on network upgrade costs and requirements associated with deployment of low-carbon technologies, including in research commissioned by the former UK Department for Energy and Climate Change[54], by the UK government's advisory body the Climate Change Committee[7] and by the European Commission[55], and published in range of peer-reviewed journal articles[4,56–60].

Here, the statistical network design and investment model of Gan et al.[41] is used to (1) simulate distribution networks representative of a range of GB contexts on the basis of data available at an LSOA level, (2) calculate the impact of deployment of low-carbon technologies on these networks, (3) estimate the costs associated with conventional network upgrades to avoid these impacts on the basis of the local balance of generation and demand and (4) estimate the reduction in costs and impacts associated with a reduction in peak demand associated with local flexibility. Additional details of this model and assumptions around demand evolution within it are provided in Methods.

Having defined local contexts' characteristics as well as future scenarios for low-carbon technology deployment across GB LSOAs, it is desirable to assess impacts of deployment on local networks in each LSOA. The large number of LSOAs (>40,000 for GB) makes explicit simulation of networks to represent each LSOA using the model of Gan et al. computationally intractable. Instead, a neural network technique is used to develop a meta-model that can reproduce results of the model of Gan et al. using less computational resource. This process is schematized in Fig. 2.

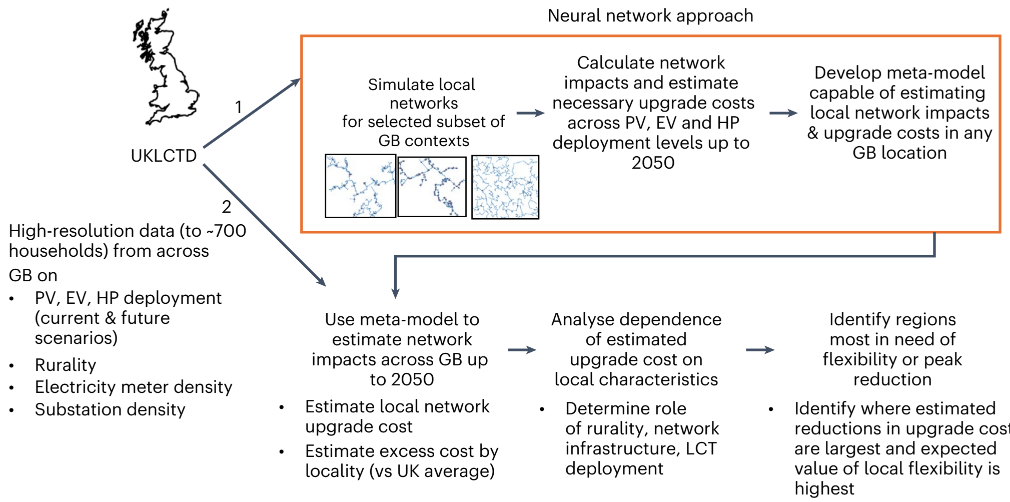

Fig. 2 | Schematic of methodology underlying this study. Geographically disaggregated data from across GB on local conditions and future technology deployment are fed into a neural network approach, which is used to develop a meta-model. This meta-model is used to estimate network impacts and upgrade costs in local areas across GB, explore the dependence on local conditions and identify areas where flexibility can bring the greatest savings.

This meta-model is developed through a number of steps. A self-organizing map is used to cluster LSOAs in each group on the basis of the LSOA-level characteristics using a neural network classification tool implemented in MATLAB[61,62]. This neural network approach selects a set of LSOAs that are representative of the whole dataset of local conditions across GB. LSOA areas are divided into groups on the basis of transformer mounting (ground mounted or pole mounted) and rurality. In total, 362 clusters are obtained. The statistical network design and investment tool of Gan et al.[4,41] is used to simulate representative networks associated with each of these clusters and to calculate local network impacts and network upgrade costs to avoid impacts across levels of PV, EV and HP deployment. The neural network approach uses these results for specific representative networks to build a meta-model capable of calculating impacts and upgrade costs in any LSOA across low-carbon technology deployment levels using relatively little computational resource.

This meta-model is used to calculate local network impacts and upgrade costs for every LSOA in GB across scenarios of simultaneous deployment of HPs, EVs and PVs up to 2050 in ten-year intervals.

Regions in which the deployment of local flexibility may be expected to bring the largest reduction in local network upgrade cost (referred to henceforth as 'local savings') are identified. This is achieved by calculating the reduction in network upgrade cost associated with a small reduction (10%) in peak electricity demand across local regions and highlighting regions where this reduction is highest. The form this flexibility takes is not prescribed, but could represent deployment of distributed storage or demand.

To develop a methodology that provides insight across national and local levels, it is necessary to make a range of assumptions beyond what would be typical of an analysis focusing solely on the local or the national level. These assumptions are made chiefly to address limitations in data availability, but also to simplify the computational process of estimating network impacts across such a large number of contexts. The limitations associated with these are discussed in more detail in Discussion and conclusions.

Diversity of network upgrade costs across local contexts

The distribution of estimates for local network upgrade cost in all GB LSOAs across dates and rurality contexts is presented in Fig. 3a. Whilst emphasis is on relative rather than absolute costs in this analysis, this figure provides an indication of the extent to which costs vary between dates and across rurality contexts. For 2030, 2040 and 2050 levels of technology deployment, estimated network upgrade costs are highest in cities, lower in towns and lower again in villages (Fig. 3a). This is due to longer feeders and higher unit costs for infrastructure replacement in urban areas, in line with previous findings for individual networks[4,15]. However, there is substantial spread of estimated costs across all years and rurality contexts, indicating that rurality is not the only factor determining costs across local areas.

Localized costs are presented as relative to an average UK LSOA rather than in absolute terms. Costs are presented as 'estimated excess local network upgrade costs', defined as the difference between the estimated cost in each LSOA and the mean estimated cost across all LSOAs in GB. This presentation emphasizes how upgrade costs would change and be influenced by local context rather than indicating the total investment costs needed. Selected absolute costs are presented in Supplementary Note 1 to validate the approach against other studies.

The spatial distribution of estimated excess local network upgrade costs to accommodate 2050 levels of technology deployment is shown in Fig. 3b. This represents the difference between the estimated cost per LSOA and the average across all GB LSOAs. The value is positive (red in Fig. 3b) for LSOAs in which network upgrade costs are expected to be higher than average, and negative (blue in Fig. 3b) for LSOAs in which costs are expected to be lower than average. Higher estimated costs in urban when compared with rural areas are clearly visible in Fig. 3b.

Estimated upgrade costs are higher in the southeastern that the southcentral region of England (Fig. 3b). This may be due to higher levels of HP and EV deployment in future scenarios developed by the DSO for the southeastern region when compared with the national average (Fig. 1e,f), and the division between these regions may be less stark in practice. Interestingly, this division is less stark than the difference between rural and urban regions, implying that rurality could be more important in determining network upgrade cost than level of technology deployment.

To demonstrate the potential for this framework to provide insights across geographical scales, a closer analysis is conducted of results in three locations. These are Greater London, the largest urban centre in GB; Yorkshire and the Humber, a region containing major urban centres in the west, rural areas, and heavy industry in the east, making it a focus area for decarbonization, and County Durham, a predominantly rural region, which has received less national policy attention. Insets in Fig. 3b show estimated excess local network upgrade costs associated with 2050 deployment of EVs, HPs, and PVs

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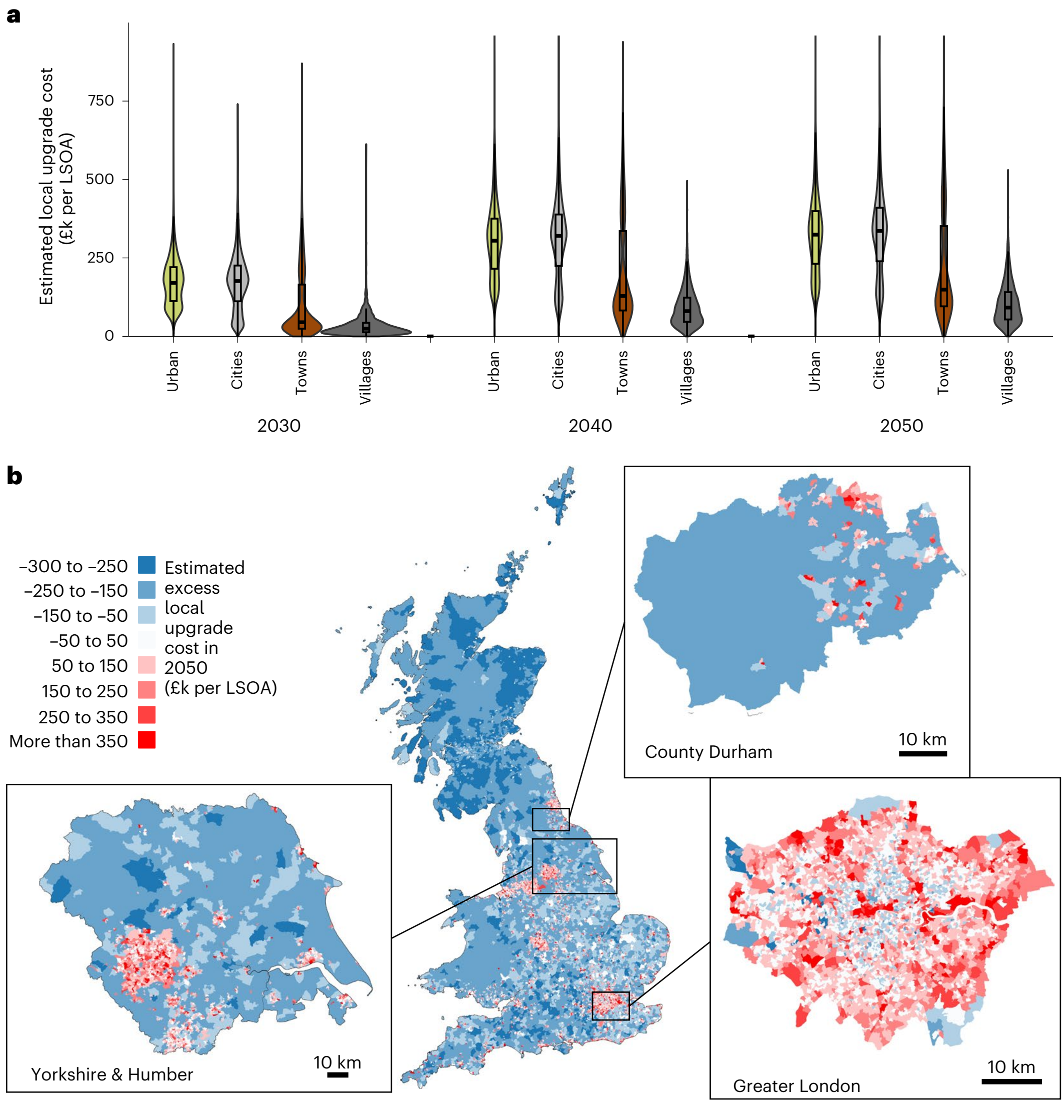

Fig. 3 | Local context dependence of estimated costs to accommodate distributed PVs, EVs and HPs across GB in local networks. a, Violin plots showing distribution of local network upgrade cost for 2030, 2040 and 2050 levels of PV, EV, and HP deployment in LSOAs in major urban conurbations, cities, towns and villages across GB. The central line, upper and lower bounds of the box and edges of the whiskers represent the median, one s.d. and extreme values, respectively (n = 14,662, 19,429, 3,968 and 3,642 for major urban conurbations, cities, towns and villages respectively). The widths of the violin plots represent the distribution of upgrade costs amongst LSOAs within each rurality category. **b**, Map showing LSOA-level local network upgrade costs associated with deployment of 2050 levels of PVs, EVs and HPs across GB, in an urban area (Greater London), a mixed area (Yorkshire & Humber) and a more rural area (County Durham).

in these three regions. In line with Fig. 3a, estimated costs are typically higher in urban areas. This includes the majority of Greater London, the largely urbanized West Yorkshire, York, Sheffield and Hull, and to a lesser extent the northeastern part of County Durham. Estimated costs are lower in more rural areas, indicated by larger, more sparsely populated LSOAs. This includes other parts of Yorkshire and the Humber, County Durham and the outer edges of Greater London. A cluster of LSOAs with lower costs are also visible in some densely populated regions in central London.

Further analysis is conducted to disentangle the main drivers behind variations in estimated network upgrade cost across and within ruralities identified above. Figure 4a–c indicates how, respectively and separately, the deployment of EVs, HPs and PVs impact estimated excess local network upgrade cost within each rurality. Figure 4d indicates how local network characteristics impact on the same. This analysis reinforces national trends across rurality contexts in Fig. 3, and also demonstrates the relative importance of technology deployment and rurality in determining local network upgrade costs. Figure 4 shows substantially higher estimated costs in urban areas, reinforcing the importance of rurality in determining local network upgrade cost. Across ruralities, Fig. 4a,b indicates that estimated costs rise substantially only for high or very high levels of EV or HP deployment (above 75th or 90th percentile). No strong trend in estimated cost is found for low and medium levels of deployment of either technology (up to 1.3 EVs per household, and HPs in 80% of households). Figure 4c indicates no clear correlation between excess local network upgrade cost and PV deployment.

Present-day network infrastructure is a key determinant of estimated local network upgrade costs to meet 2050 requirements. Across villages, towns and cities, estimated costs are higher where there are more meters per substation (Fig. 4d). Interestingly, this trend reverses in the densest rurality category, 'urban' (apparent in the densest parts of London in Fig. 3b). This may be linked to a reduction in feeder length associated with closely clustered households in the densest LSOAs,

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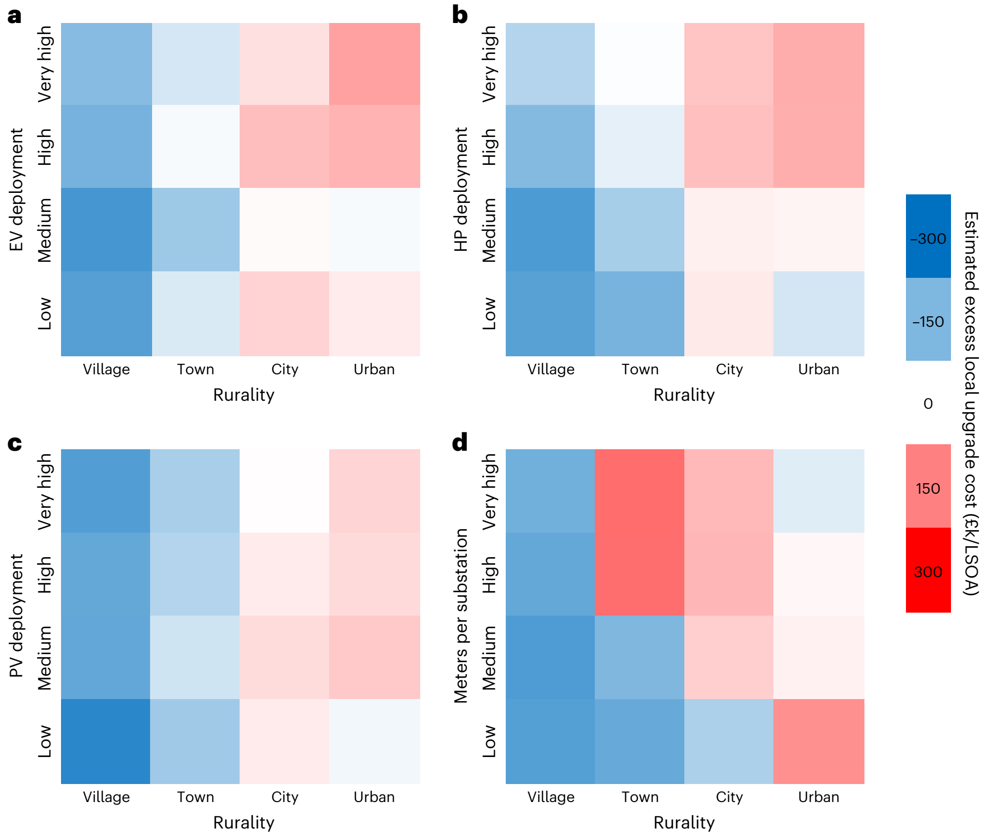

Fig. 4 | Combined impact of rurality, technology deployment and network infrastructure on estimated excess local network upgrade cost. a–d, Heat maps showing mean estimated excess local network upgrade cost amongst LSOAs with low (below 25th percentile), medium (25th to 75th percentile), high (above 75th percentile) and very high (above 90th percentile) 2050 deployment of EVs (**a**), HPs (**b**) and PV (**c**) and number of meters per substation (**d**). In **a**–**c** these percentiles are derived from the entire distribution across GB, whilst in **d** they are only considered across LSOAs of the same rurality (as numbers of meters per substation is highly dependent on rurality). Percentile values are provided in Supplementary Note 5.

leading to a lower susceptibility to voltage issues, and shorter cable lengths to upgrade per LSOA. Lower deployment of EVs in this region, associated with London's well developed public transport network, may also reduce upgrade requirements.

Diversity of flexibility savings across local contexts

This section considers where flexibility measures (represented by a 10% reduction in peak demand) can be most cost-effectively deployed to reduce local network impacts and estimated local network upgrade costs to overcome these. As with network upgrade costs, these savings are presented in relative rather than absolute terms as 'estimated excess local network upgrade savings', defined as the difference between the estimated savings in any given LSOA and the mean estimated cost across all LSOAs in GB. This allows the identification of LSOAs in which local flexibility is expected to be most effective in reducing upgrade cost. Figure 5a shows a marginal excess flexibility savings curve, indicating the estimated excess local savings associated with deploying local flexibility in each LSOA, arranged in descending order. This figure demonstrates the wide distribution of estimated excess local savings, spanning a range of over £100,000.

These geographically resolved data on estimated local savings could be used to develop a targeted approach for deployment of local network flexibility that could increase estimated local savings substantially when compared with an approach that deploys flexibility across localities as if they were homogeneous. This is demonstrated in the green shaded area of Fig. 5a, which indicates estimated excess local savings of £200 million if flexibility is deployed in only LSOAs bringing greater than average savings (relative to a scenario in which the same amount of flexibility is deployed in LSOAs bringing average savings). Whilst caution is required in translating localized comparisons to aggregated values across GB, this indicates the potential magnitude of savings that a geographically disaggregated approach to flexibility deployment could bring.

Local savings within case study areas vary substantially, but a clear dependence on local characteristics remains elusive. Figure 5b–d shows local savings associated with flexibility across selected regions. These figures demonstrate substantial savings in the densely populated centre of London, but no overall trend is identified between local savings associated with flexibility and rurality or low-carbon technology deployment across GB as a whole (Supplementary Note 2). This may be partly due to the 'lumpy' nature of network infrastructure investments, which makes it challenging to establish what level of flexibility will allow particular large units of infrastructure replacement to be avoided.

Discussion and conclusions

This paper demonstrates a methodology to estimate and map the relative cost of upgrading local networks to accommodate low-carbon technology across local regions, and to inform cost-effective approaches to flexibility deployment. This framework can help policymakers and network planners to plan for future needs of the electricity system at a local level, and inform cost-effective deployment strategies for local flexibility through distributed storage or demand reduction.

Estimates of excess local network upgrade costs vary substantially between local areas of each rurality, but are typically higher in urban areas, owing to longer feeders serving larger numbers of meters.

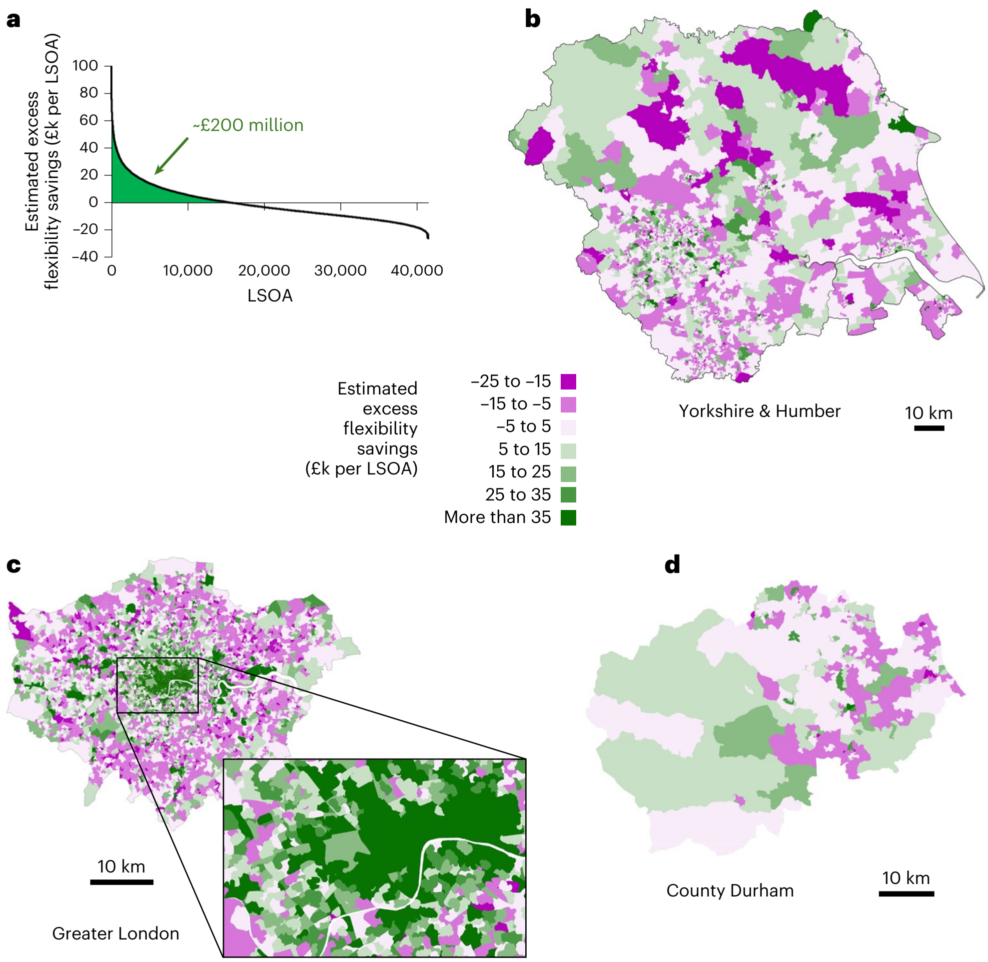

Fig. 5 | Estimated excess local savings associated with local flexibility deployment across regions. a, Marginal excess flexibility savings curve showing the distribution of estimated excess savings associated with reducing peak load by 10% in each LSOA, relative to the estimated average savings across all LSOAs. The green shaded area indicates excess savings associated with deploying flexibility in only LSOAs bringing greater than average savings relative to a deployment approach treating all areas as homogeneous. **b**–**d**, Local savings in Yorkshire and the Humber (**b**), urban Greater London (**c**), Central London (**c**, inset) and more rural County Durham (**d**).

This analysis suggests that differences in local network characteristics are more important in determining network upgrade costs than level of technology deployment, with exceptionally high costs estimated only in LSOAs with more than 1.3 EVs per household, or HPs in more than 80% of households.

Estimates of reduction in local network upgrade cost associated with local flexibility vary substantially between local areas, but with no clear relationship with rurality context. Nonetheless, analysis here suggests that a targeted approach to flexibility deployment enabled by the use of geographically disaggregated data could lead to substantial reductions in network upgrade cost when compared with an approach where flexibility is deployed in an untargeted manner.

The methodology and insights developed in this work can help to design incentives and regulations around deployment of low-carbon technologies and flexibility across GB. For example, national policies to support technology deployment could be designed to target higher levels of EV and HP deployment in rural areas where estimated impacts on local networks are less severe. Similar considerations apply to flexibility, where the methodology could be used to inform regulation and incentives for storage deployment and demand-side management targeted in areas where local networks are identified as more constrained. In implementing these policies, the broader context in which localities are situated should be taken to account, including regional network impacts, other value streams for flexibility, and socioeconomic conditions not considered here[63].

The high geographical resolution of the approach developed here could support local and regional authorities in developing local net-zero plans[64]. This approach could be used to develop technology deployment trajectories at local level that would minimize required local network upgrades and associated costs. It could also be used to identify promising locations for new sources of intensive electricity demand, such as EV charging stations. Conversely, the framework could be used to identify local areas in which network infrastructure may be less capable of accommodating additional electrical demand and other technologies may be more appropriate (for example, where a heat network may be more appropriate than HPs). In each case, we envisage the framework playing an exploratory role, before a network study incorporating more detailed local datasets.

To develop a tractable methodology that uses geographically disaggregated data to bridge national scenarios and local network challenges, it has been necessary to make challenging assumptions around data and modelling. This limits the reliability of outputs relative to studies focusing exclusively on one locality or conducted solely at the national level. Analysis is necessarily limited by data that are available at a national level. Data on network infrastructure are particularly limited. Use of different scenarios developed by different

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stakeholders in different geographical regions leads to a lack of consistency of approach across DSO boundaries.

The model also has limitations. The model of Gan et al.[41] is used to simulate network capacity, topology and configuration of this infrastructure based only on dwelling density, rurality, historical electricity demand across GB and substation density for one UK region. Whilst this model is verified against real UK networks, it cannot capture the full range of network characteristics across these regions. Further, a single approach to flexibility is examined, and a single operational profile is assumed for PVs, EVs and HPs, which are subject to uncertainty and variation across regions. The use of a meta-model that replicates the model of Gan et al. leads to a loss of fidelity relative to a power flow analysis of real distribution networks.

The large number of DSOs worldwide (>190 in Europe alone), the confidential nature of information they collect and the lack of a consistent high-resolution geographical data system used for reporting internationally[65], as well the heterogeneity of electricity distribution systems, makes analysing differences in local impacts of low-carbon technologies in an international context challenging[18,66]. Therefore, detailed analysis in this paper is limited to the case of GB. Distribution network characteristics in GB fall broadly within the range of those in other European countries[4,18], implying that trends identified in GB are likely to be comparable to those in many other countries.

One response to limitations is to reduce uncertainty associated with inputs. This could be informed by improved access to data. Access to more detailed data on present network infrastructure and future energy scenarios, connected between local, national and international levels and on a consistent geographical basis (ideally at LSOA level in the UK in line with other national statistics) would improve analyses building upon the approach presented here. Ideally, these would be accessible through a single portal and in a consistent format (administered by, for example, the European Commission in the EU and the UK Government in GB). However, there is also a value in making best use of publicly available data in support of independent analysis. It is hoped that through the demonstration of the value of analysis using open data, and of how this analysis could be improved with greater data availability, this Article may help facilitate further sharing of relevant data.

An alternative response to limitations is to develop different approaches to handling uncertainty. This could involve a shift in focus from reducing uncertainty to identifying actions that perform well enough across conceivable outcomes[67]. Exploration of (in)consistencies in future energy scenarios developed by different stakeholders (for example in FESs produced by the GB electricity system operator (National Grid ESO), DFESs produced by DSOs and local energy plans under development by local authorities[64]) through the framework presented in this Article could be a promising approach here.

Methods

Data on local network infrastructure

Data on local network infrastructure are not available across GB as a whole, but are estimated on the basis of data available for South West England. Within this region, data are available on the number of substations by type (ground mounted or pole mounted) per LSOA[4,68], both of which are found to correlate strongly with meter density (as demonstrated in Supplementary Note 3). Data from this region are used to generate an approximate function for number of ground- and pole-mounted substations by meter density on the basis of a locally weighted polynomial regression[69,70]. This regression is used to estimate the number of ground-mounted and pole-mounted substations for each LSOA in GB, assuming a similar relationship between network infrastructure and meter density across the country. Whilst this maximizes the utility of available network infrastructure to predict network characteristics across GB, meter density is only a partial predictor of network characteristics, and this represents a limitation in this study. Improved public data on network infrastructure from across the UK would help to inform future analysis.

Low-carbon technology deployment scenarios

As described in the main text, low-carbon technology deployment scenarios are based upon regional DSO scenarios where available, and national scenarios in other regions.

For regions covered by three of GB's six DNO groups, UK Power Networks[48], Northern Powergrid[49] and Western Power Distribution[50], DFESs are available at a level of geographical disaggregation that allows their inclusion in this analysis. For the UK Power Networks region, deployment of PVs, EVs and HPs are specified at an LSOA level up to 2050 in three scenarios, informed by local characteristics of each region, including building stock, vehicle stock and historical PV uptake at a geographically disaggregated level. For Northern Powergrid and Western Power Distribution regions, low-carbon technology deployment is specified at the level of a local authority, a geographical area that typically contains between 100 and 500 LSOAs. These data are also used in this analysis, on the basis of an assumption that low-carbon technology deployment per household is identical across LSOAs within each local authority in the region[71].

For regions covered by GB's other three DSO groups, usable local-level low-carbon technology deployment scenarios are not available. This includes regions served by Scottish and Southern Electricity Networks, who had not released geographically disaggregated data associated with their DFES when this analysis was conducted[72], and Electricity North West and Scottish Power, who have produced DFESs in geographical units that cannot be directly mapped to LSOAs[73,74].

For each region where geographically disaggregated data are not available, PV, HP and EV deployment scenarios are developed on the basis of the most ambitious FES published by National Grid ESO in terms of distributed generation and electrification of demand ('Community Renewables')[51]. A geographically disaggregated scenario for PV deployment across GB in 2030, 2040 and 2050 is developed by multiplying the national growth rate in microgeneration specified in National Grid ESO's scenario by the actual number of domestic and non-domestic PV installations recorded in each LSOA in 2020[45]. This scenario reaches a ninefold increase in PV deployment by 2050, although PV deployment is capped at 100% of meters in a small number of LSOAs, which would otherwise exceed this limit (around 2%). A geographically disaggregated scenario for HP and EV deployment is developed on the basis of an assumption that each LSOA has the same average number of HPs and EVs per household as the national average in National Grid ESO's scenario (0.37 pure electric HPs, 0.25 hybrid HPs and 1.3 EVs per household by 2050).

By 2050, this approach implies 1.3 EVs per household and HPs installed in 63% of households. This is broadly consistent with the net-zero strategy for GB, which includes a ban on non-zero-emission cars, and aims for HPs installed in 24–37% of households by 2035[2].

Selected results from an additional scenario considering deployment of PVs alone is presented in Supplementary Note 4, but impacts of PVs are found to be negligible when compared with those of EVs and HPs.

Electricity network modelling

Local network impacts of PVs, EVs and HPs are calculated on the basis of a power flow analysis of simulated networks before and after these technologies are added. This power flow analysis identifies sections of the network where cables and transformers become overloaded and/or voltage rises/falls to levels outside regulatory boundaries. Costs of avoiding these impacts through conventional network upgrades are calculated on the basis of component replacement costs specified by the UK energy regulator[15]. Local low-voltage networks represent the primary focus of this paper. However, selected impacts on regional network infrastructure at medium voltage and above are presented in Supplementary Note 5.

This power analysis is performed on the basis of current electricity demand characteristics, and estimated characteristics of newly deployed technologies. Diversified peak demand is assumed to reach 0.93 kW per domestic meter and 8.0 kW per non-domestic meter before the addition of low-carbon technologies. These values are calculated on the basis of UK electricity consumption data[75,76], alongside demand profiles and diversity across households informed by UK smart meter data[77] (further details in Supplementary Note 6). HPs and EVs are assumed to contribute 4 kW and 7 kW to peak demand, respectively. These are associated with coincidence factors of 0.425 and 0.1, respectively, to account for variability in times of heating and EV charging across households (implying a diversified peak of 1.7 kW per HP and 0.7 kW per EV). These values are informed by data from field trials of HPs and EVs in the UK[78,79]. Hybrid vehicles and hybrid gas HPs are excluded from this analysis on the basis that they are unlikely to use electricity at peak times when local networks could be impacted.

Domestic and non-domestic PVs are assumed to cause reverse power flow peaking at 4 kW and 63 kW per unit, respectively. A coincidence factor of 1 is assumed in both cases to reflect the simultaneity of peak output across PV panels on a network (on a sunny day). PV is assumed not to reduce peak demand on networks, since peak electricity demand in the UK occurs during winter evenings when there is little sunlight[80].

Data availability

The UKLCTD LSOA-level data on current and future technology deployment, electricity demand characteristics, rurality and network infrastructure are freely available at https://doi.org/10.5281/zenodo.10948931 (ref. 52). Datasets on estimated costs and savings are not available due to commercial sensitivity.

Code availability

Code used in generating the UKLCTD and future scenarios from original datasets are freely available at https://doi.org/10.5281/zenodo.10948931 (ref. 52). Code used in network modelling is not available due to commercial sensitivity.

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Author contributions

S.F., C.C., and J.N. conceptualized and co-ordinated the work, supported by P.D. and G.S. in developing workflows for network modelling. S.F. wrote the initial draft manuscript, excluding sections describing network modelling, which were written by P.D. C.C. and J.N. read and provided suggestions on the draft manuscript. S.F. and C.C. carried out manuscript revision. S.F. curated and managed the geographical data in the UKLCTD and scenario development. S.F. led data analysis, supported by C.C. P.D. led the network modelling, produced the maps and conducted additional data analysis.

Competing interests

The authors declare no competing interests.

Additional information

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