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RESEARCH ARTICLE

A Scalable Geospatial Data-Driven Localization Approach for Modeling of Low Voltage Distribution Networks and Low Carbon Technology Impact Assessment

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ABSTRACT The electrification of heat and transport through the uptake of low carbon technologies (LCTs) is expected to pose significant planning and management challenges for distribution network operators (DNOs) in the coming decades. Therefore, to support investment decision making there is a requirement to understand the impact LCTs will have on low voltage (LV) distribution network infrastructure across diverse geographical areas. However, LV networks are not only radically different in terms of topology and physical asset characteristics, but also in terms of the demand they serve which is sensitive to the diversity of local conditions such as climate, consumer demographic and building stock. As such, there is an increasing requirement to capture elements of this diversity in the development of LV network and LCT modeling approaches to better quantify place-based LCT impact and to inform the quantification of local area flexibility. In turn, using Python and OpenDSS, this work presents a novel scalable approach to localized LV network and LCT impact modeling by coupling two methodologies; a LV network model development methodology and a LCT impact assessment methodology which accounts for both the electrification of heat and transport with consideration for the diversity of residential heat demand. The methodology is demonstrated on LV networks in Scotland through quantification of LCT network impact against key network assessment metrics. The findings demonstrate the value in spatial and temporal high-resolution modeling at scale, emphasizing a need to consider the combined impact of electrified heat and transport in future network investment planning.

INDEX TERMS Distribution networks, GIS, heat pumps, electric vehicles, flexibility management.

I. INTRODUCTION

A. MOTIVATION

A key component of achieving major carbon emissions reduction targets will be the electrification of existing widely used carbon-intensive technologies in the domestic heating and transport sectors [1]. With up to 913,000 electric vehicles (EVs) and up to 564,000 heat pumps (HPs) anticipated in the north of Scotland by 2045, the displacement of internal combustion engine vehicles with EVs and conventional gas boilers with HPs is expected to be at the forefront of this electrification [2]. The nature of these technologies dictates that they will be connected to low voltage (LV) distribution networks. However, as existing LV networks were not designed to accommodate their variable demand requirements, distribution network operators (DNOs) are tasked with the challenge of economically ensuring appropriate investment in infrastructure and the development of new management

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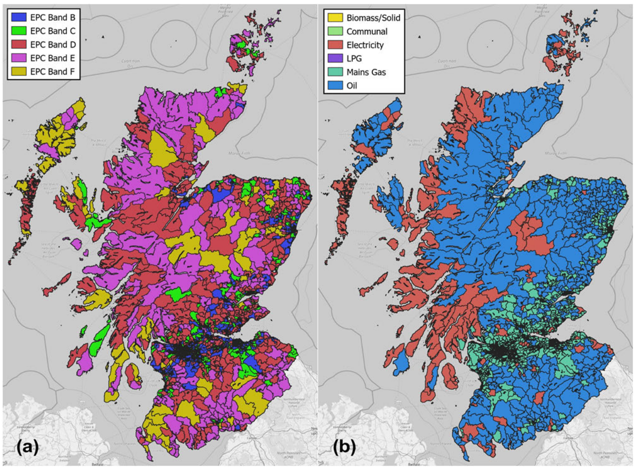


FIGURE 1. Diversity in building stock across Scotland (excluding Shetland) based on available EPC data from the homes energy efficiency database mapped to geospatial data zone boundaries. (a) EPC band. (b) heat source.

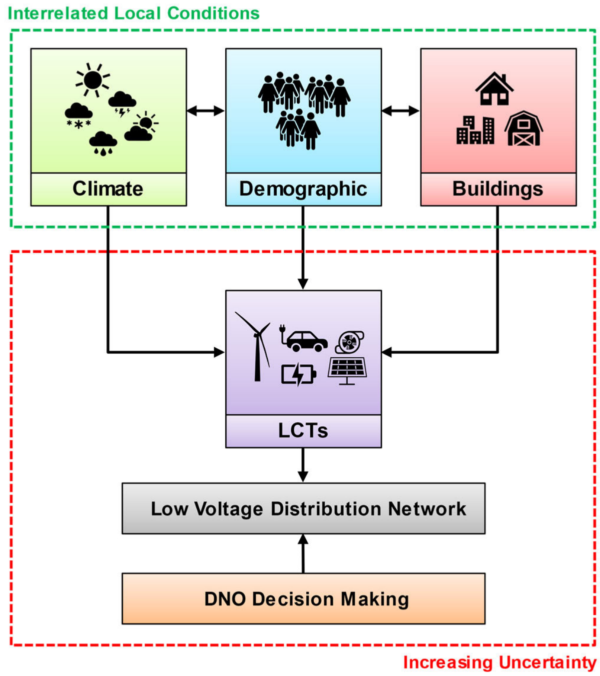


FIGURE 2. High level overview of how interrelated local conditions are contributing to an increasing uncertainty in DNO decision making.

solutions to support their uptake without compromising network resiliency [3]. To ensure cost efficient investment, there is a growing requirement to reduce the uncertainty surrounding the impact these technologies will have on existing infrastructure in different geographic areas [2]. Such insights will support DNO decision making by informing the network planning and management requirements of key infrastructure. Also, supporting wider decarbonization efforts within the context of local area energy planning by informing stakeholders such as local authorities on the impacts of their decarbonization strategies.

A significant challenge with achieving the decarbonization of heat and transport at the volumes and scales required is that across any given DNO license area, sections of LV network are not only diverse in network topology and the underlying physical characteristics but also in terms of the demand they serve which is sensitive to the diversity of local conditions such as local climate, consumer demographic and building stock which can be key influencing factors for LCT uptake and utilization [4], [5], [6]. To emphasize the scale of diversity in building stock across Scotland, Fig. 1 is presented where available household energy performance certificate (EPC) data from the homes energy efficiency database (HEED) [7] is mapped to geospatial data zone boundaries[1] highlighting the variations in household energy performance and heat source.

At present, the direct impact local conditions have on domestic heat and transport demand is not yet fully understood [4] and therefore the uncertainty of LCT impact on LV distribution networks is exacerbated across different geographical areas. Fig. 2 highlights that this uncertainty is further exacerbated when there are a combination of LCTs of different types connected within the network which are influenced by a complex interdependency of these local conditions. This motivates the authors to further investigate the scalability of high-resolution LV network modeling in tandem with localized combinational LCT impact modeling within the context of electrified heat and transport.

B. RELATED LITERATURE

1) DISTRIBUTION NETWORKS

Historically, due to the relatively predictable nature of residential LV network demand there was a limited technical requirement for modeling of LV networks; subsequently, consumer demand was typically modeled as lumped loads with a greater emphasis placed on the high voltage (HV) and transmission networks [8]. However, the need to accurately model these networks has evolved and is now of significant interest to DNOs as they look to support and manage the uptake of LCTs on their networks [9]. In recognition of that need, literature such as [10], [11], [12], and [13] considered the use of fractal geometry in a bid to capture the complexity and disparate nature of LV networks. This approach along with others e.g., [14], allows for modeling of 'generic' LV networks that are useful for broad assessments where less consideration is placed on specific networks and their locale. However, in order to conduct more comprehensive place-based assessments of physical infrastructure, literature such as [15] has identified that geographic information system (GIS) data which includes technical and spatial information of infrastructure has significant network modeling potential. The GIS driven LV distribution network models developed in [15] and [16], have been extensively validated

[1] Data zones are groups of Census output areas which have populations of between 500 and 1,000 household residents.

and used in numerous works including [15], [17], [18], [19] demonstrating the value of GIS data-driven modeling for LV network development. However, since the publication of [15] and [16] GIS data quality and modeling capability has progressed in line with the need for detailed localized place-based modeling [20], [21].

2) IMPACT OF LCT UPTAKE

Due to the stochastic demand requirements of LCTs, numerous studies including [11], [22] have been concerned with the impact their uptake will have on existing LV network infrastructure. Other impact assessment works such as [17], [23], and [24] have also focused on understanding the network impact associated with individual technologies and were used as means of demonstrating modeling capability. However, these works did not consider the simultaneous impact from different types of LCTs. In [25], the combinational impact of multiple LCTs on household demand profiles is explored. However, network impact is neglected. Additionally, in [26], although the impact of electrified heat and transport is explored, only a single network is considered. While there is a wealth of research on the effects individual LCTs have on distribution networks, and some area-specific combinational works, there is limited research on the combinational effects of EVs and HPs on network infrastructure across different locations with diverse characteristics. Primarily as detailed modeling of these technologies and the LV networks typically involves a trade-off between modeling effort and scalability. Works such as [15], have looked to overcome this where Navarro-Espinosa et al. use a Monte Carlo assessment technique to stochastically assign HP and EV demand profiles, which were produced from heating demand data and EV trial data respectively, to network models of 128 UK distribution feeders in order to evaluate the voltage and thermal impacts of these technologies for a set of penetration scenarios. However, existing works tend not to consider the geographical and demographic context of the households involved. The principle of incorporating locally-specific dimensions into LV and LCT network modeling has been considered in works such as [6], where consumer demographic information is used in a probabilistic assessment of EV penetration on a GIS modeled distribution network demonstrating the potential of diversified EV charging and in [27] which considers PV and HP modeling via a probabilistic building physics modeling approach. However, there remains scope to progress place-based LCT impact modeling by accounting for local conditions and highly representative LV network modeling.

3) CONTRIBUTION

From the related literature described in Section I-B it is evident that although works have explored this research space, gaps remain within the collective knowledge and therefore this paper aims to address them as follows:

Firstly, this work recognizes that the diversity of LV distribution networks, consumer demographic and building stock across a geographic area presents a complex set of interdependence that requires consideration when developing LV network models and modeling LCT demand. Therefore, a scalable data-driven modeling methodology is described in this work (Section II) that includes the mapping and integration of external local-specific spatial datasets with network GIS data and builds on the existing works (described in Section I-B.1) used to develop 'generic-GIS' electrical network models by including a local spatial reference that is used to support high-resolution place-based analysis and granular localized LCT demand modeling.

Secondly, a localized LV network assessment methodology is presented (Section III) which incorporates modeling of both EVs and HPs. Where works described in Section I-B.2 infer heat demand from metadata for HP modeling, this work couples two established methods to convert geospatially linked gas demand to equivalent electrical heat demand (Section III-A.1) to account for the diversity of domestic heat demand across different consumer demographics and building stock. The developed methodology takes a statistical approach to LCT impact assessment where the primary objective is to demonstrate model scalability and provide justification against the literature that such modeling is valuable and necessary.

These two methodologies are coupled together to form a novel scalable approach to localized LV network LCT impact assessment which is summarized by Fig. 3. The value of which is outlined in terms of its ability to inform DNO decision making.

The remainder of the paper is organized as follows. Section II describes the localized LV network development methodology by detailing the data, mapping and heuristic used to develop detailed representative LV network models. Section III describes the localized LV network assessment methodology by detailing the EV and HP modeling techniques and summarizing the assessment metrics used to quantify impact. Section IV provides a breakdown of the results and relevant discussion, and Section V concludes the work and provides a recommendation for future research.

II. LOCALIZED LV NETWORK DEVELOPMENT

This section of the paper describes the methodology used to develop localized LV network models which is summarized by Fig. 4. This includes a description of the data used to drive model development and the associated transformation process. A description of the approach used to model domestic consumer demand across different geographical areas is also provided along with a summary of a small sample of developed networks.

A. DESCRIPTION OF GIS DATA

In support of this research, GIS data for Scottish hydro electric power distribution (SHPED) was made available to the authors in the form of shapefiles, which is a geospatial vector data format developed by the environmental systems research institute (ESRI) [28]. This includes spatial and technical

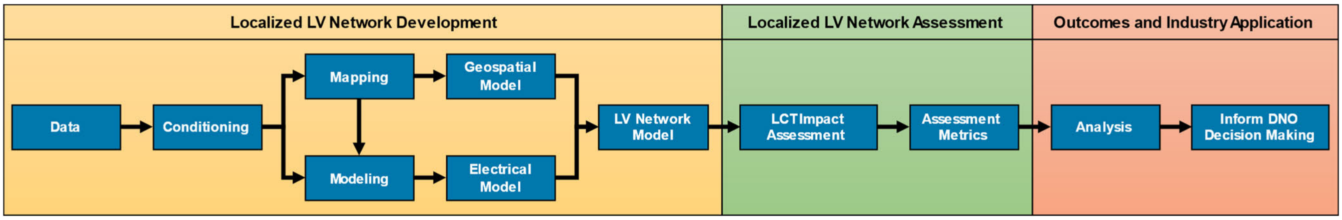


FIGURE 3. High-level overview of the methodology coupling for localized LV network LCT impact assessment.

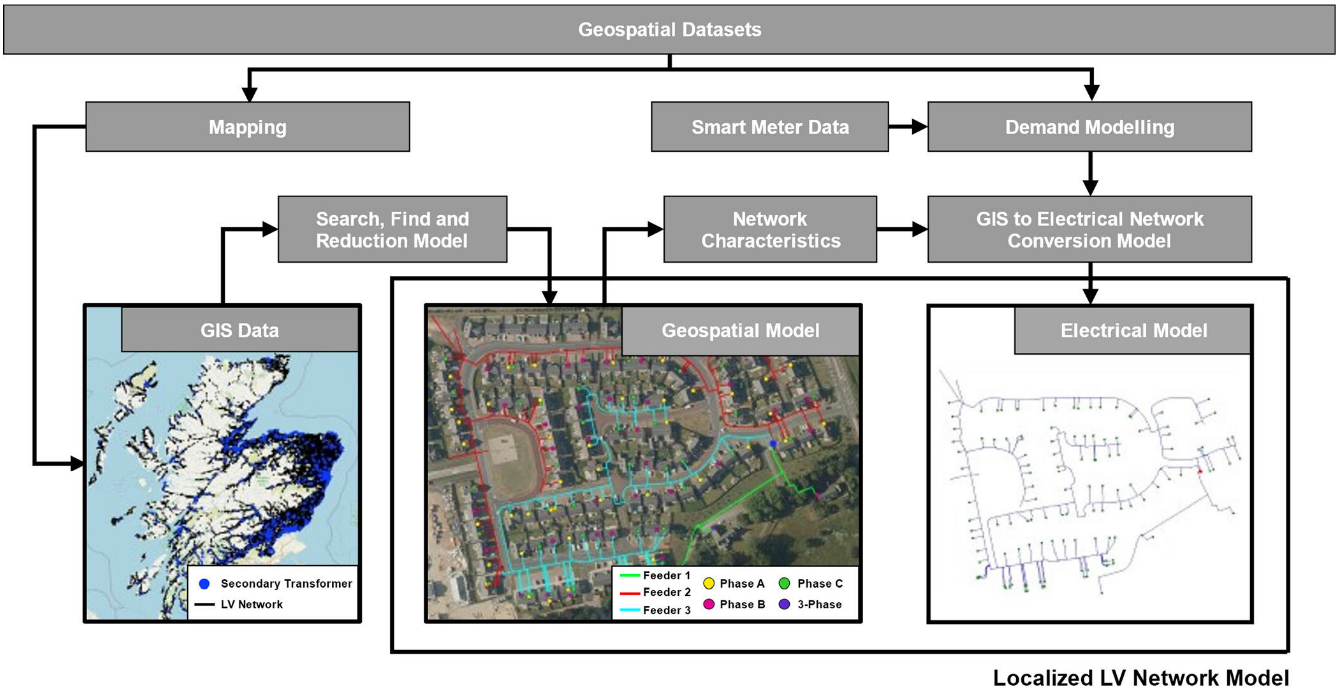


FIGURE 4. High-level overview of the localized LV network development methodology.

information for all infrastructure across their entire license area which supplies the north of Scotland, specifically in relation to this work:

- **Substations:** both primary and secondary transformers.
- **Cables and Overhead Lines:** HV and LV underground cables and overhead lines.
- **Service Locations:** points where a service is provided i.e., consumer load points.
- **Switching Devices:** switchgear e.g., fuses and link boxes.

The modeling developed in this work is tailored to this GIS data which is suitable for modeling of LV networks in both rural and urban population centers. However, the hierarchical methodology could be applied to any GIS network dataset.

B. DESCRIPTION AND MAPPING OF EXTERNAL DATASETS

As previously mentioned, GIS network data can be integrated with external geospatial datasets. This advances the network models beyond 'generic-GIS' electrical models and allows for enhanced classification of networks and localized place-based modeling. The following describes the external datasets considered in this work and their integration with the GIS network data.[2]

1) ANNUAL POSTCODE LEVEL GAS DEMAND

For on-gas networks, the department for business, energy & industrial strategy (BEIS) records information relating to the annual postcode level gas consumption [29]. This includes the mean annual consumption (kWh) for each postcode in 2018 (updated December 2020). This information is first mapped to the shapefile containing geospatial digital postcode boundaries for Scotland and then information availability is mapped to the GIS service points i.e., each service point would have a status that indicates if gas consumption demand data is available for the associated postcode. For visual inspection, GIS modeling software QGIS [30], can be used to overlay the gas detailed postcode boundaries with the GIS network. This

[2]The mapping was carried out in Python and the GeoPandas package [33] was used to manage the geospatial data stored within each shapefile.

again allows for targeted modeling, as areas of interest can be inspected, and GIS data quality assessed before undertaking further detailed network modeling. The mapping of this data directly links to the HP modeling approach used in this work.

2) SCOTTISH INDEX OF MULTIPLE DEPRIVATION

The Scottish index of multiple deprivation (SIMD) is the Scottish Government's standard approach to identifying areas of multiple deprivation which is based on seven domains: income, employment, education, health, access to services, crime and housing [31]. It is essentially an area-based measure of relative deprivation across 6,976 small areas known as data zones that are ranked from most deprived (ranked 1) to least deprived (ranked 6,976) [31]. The 2020 SIMD geospatial data is obtained from [32] and an SIMD decile of 1-10 used to categorize the 6,976 data zones is mapped to the GIS service points. This provides a means of conducting detailed socio-technical modeling [21] that has the ability to inform government policy and potentially the network operator. For example, due to the current cost of LCTs, areas of lower social deprivation are likely to see an initial uptake that requires network investment and reinforcement [2]. However, areas of higher social deprivation using carbon intensive technologies cannot be ignored or 'left behind' in the energy transition as they too will need to decarbonize in order to achieve net zero in the timescales required. Therefore, the transition to low carbon alternatives will have to be affordable or policy through political and regulatory decisions will be necessary to support those in these areas to realize the legally binding net zero targets. What exactly those decisions will look like and how policy makers and local government will address this unique challenge is an on-going difficulty. Nevertheless, these decisions will ultimately have an impact on electricity infrastructure though the extent of which still remains unclear. As a result, there is a growing need for targeted socio-technical and infrastructure linked modeling which this mapping can support.

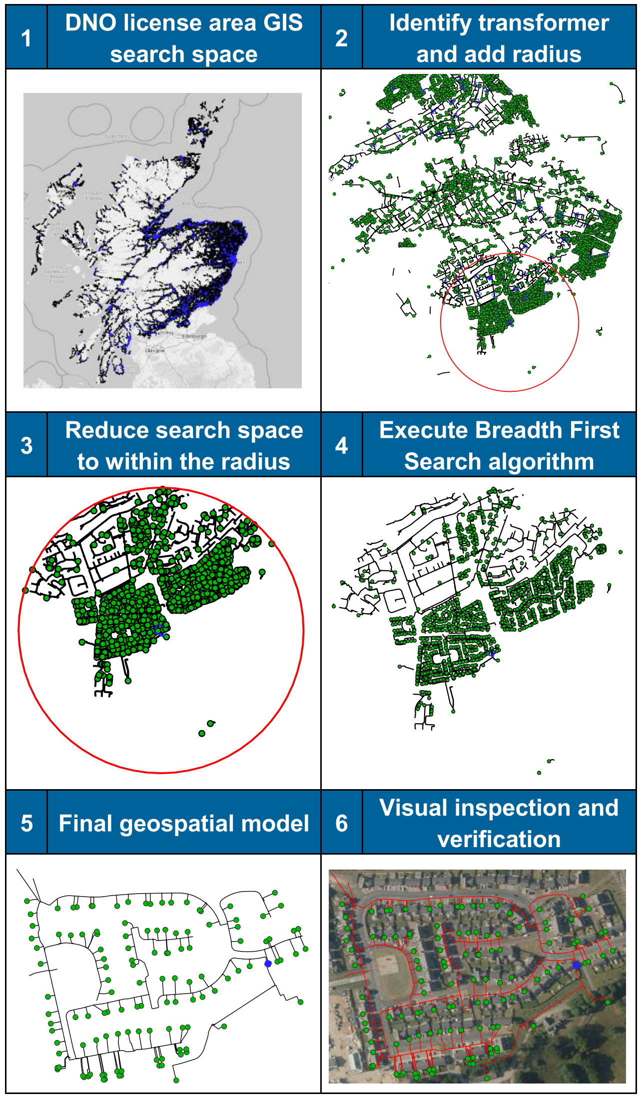


FIGURE 5. **Example of the Search, Find and Reduction model.**

C. GIS TO NETWORK MODEL TRANSFORMATION METHODOLOGY

The GIS to electrical network transformation methodology is split into two models; the *Search, Find and Reduction Model*, and the *GIS to Network Conversion Model*, where the approach used to develop these models is described in detail within this section. These models have been developed in Python with use of the GeoPandas package [33]. The electrical network models are developed in OpenDSS [34] which allows for unbalanced quasi-static time-series analysis via the Python COM interface.

1) SEARCH, FIND AND REDUCTION MODEL

In order to model each secondary transformer and associated LV network independently, the *Search, Find and Reduction* model has been developed for this work. Fig. 5 demonstrates the model functionality for a single secondary transformer. From the initial extremely large search space which covers the entire north of Scotland, a single transformer of interest is identified (DNOs will have their own specific reasons for selecting a particular transformer and associated network to analyze, this could be due to the characteristics of the transformer, the characteristics of the load supplied by it, or any other number of reasons including concerns raised with the volume of EV/HP uptake for a specific area as identified through forecasting. The transformers and networks selected for this work have been used to demonstrate the methodology and areas with comparatively different heat demand have been selected for the analysis) and a suitably 'large' radius applied. From this, the GIS data search space is then reduced to within this radius. The radius is modeled to be sufficiently 'large' that the associated LV network of any given transformer would not extend beyond the radius boundary.

For cabling, the GIS stores spatial information in the form of one or more sequences of coordinates that create a

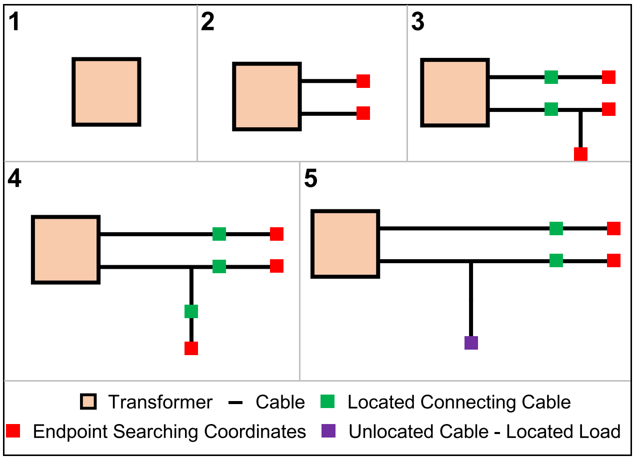


FIGURE 6. Demonstration of the Breadth First Search algorithm for cable and load connectivity.

multi-point line i.e., a series of coordinates form a segment, and a series of segments form a multi-point line, and a series of multi-point lines would then in principle form a feeder. However, this format does not support the connectivity of lines necessary for conventional power flow modeling (as multi-point lines are not connected), therefore, to facilitate this, common points (individual sets of coordinates) must be identified where one or more multi-point lines start or end. From this, a breadth first search (BFS) algorithm is executed within the now significantly reduced search space and the common points or 'nodes' are used to drive the algorithm (note that multi-point lines containing start or end points within a multi-point line are also identified). BFS is a graph-based search algorithm that begins at a given node known as the root node (in this case the transformer's coordinates) and then explores all neighboring nodes [35]. For each of the neighboring nodes, it then explores the available solution space, and this continues until all connected nodes are located [35]. BFS algorithms are often computationally expensive therefore by reducing the search space, modeling time is significantly improved. The algorithm is executed to locate all LV cabling connected to the transformer and then when all cabling is located, the algorithm is executed based on the network endpoints to locate the associated loads. An example of this process is demonstrated in Fig. 6.

In [36], a number of GIS data quality related issues were raised when using BFS algorithms for line connectivity, particularly in relation to multi-point line start and end coordinates not matching i.e., there is a 'small' gap between the lines which influences the algorithm's ability to identify connecting lines. However, it is noted that since [36], the quality of GIS data has significantly improved, and although still existing to some degree the issues raised are far less prominent for cabling in the observed dataset. In an attempt to account for this in the current modeling a search tolerance has been used to identify start and end points in close proximity when no identically matching coordinates are found before searching for network service points. It is noted that this is also an issue when there are link boxes in between lines, therefore all link boxes have been assumed open and essentially operate as a breaking point between feeders supplied from different transformers.

To validate the generated models an expected number of feeders and consumers for each feeder is compared with the final generated network. Should these match, the model would then be visually inspected by a network planner, overlaying the geospatial model on different visualization maps. The judgement of model feasibility and representativeness therefore lies with this actor. Should the connection points not match for any particular reason, e.g., lack of data or an error with the connectivity, the same actor would be required to investigate the reasoning. In a future scenario with increased visibility through improvements in monitoring and digitalization additional functionality can be built in that would help to minimize the need for this verification stage and to manage model uncertainty e.g., use of strategically placed monitoring and smart meter data at the LV level to support validation.

2) GIS TO ELECTRICAL NETWORK CONVERSION MODEL

Having generated the independent shapefiles for the transformer, cabling and loads, these are then converted from GIS data format to OpenDSS power flow modeling format using the conversion model presented in Fig. 7. The individual multi-point lines are first identified, and it can be seen that multi-point lines do not always start at the end of another but often at a pair of coordinates within the multi-point line. This poses a challenge for conventional electrical modeling bus definition. Therefore, the associated joints based on intersecting vertices (essentially where pairs of coordinates match) are identified and the multi-point lines are segmented at these points maintaining raw cable information and adjusting cable length. Another dataset challenge is the orientation of the coordinate sequences stored in the multi-point lines. Therefore, these are re-orientated as necessary to improve model workability. An optional step is then to further segment the lines to individual pairs of coordinates for granular representation. Finally, the shapefiles are converted to OpenDSS network format by translating all raw GIS network information into the electrical technical parameters necessary for LV network modeling in OpenDSS e.g., cable length and type, transformer rating and phasing. No detailed information for line impedance values and current ratings is provided in the GIS dataset therefore these are taken from [37], [38], and [39] and aligned with cable type as applicable. Fundamentally, the availability and quality of the technical information recorded in the GIS database is what drives the accuracy and representativeness of the developed LV networks. This is varied across the license area and as expected, is particularly lacking in areas where the DNO would have historically had limited visibility e.g., sparsely located remote rural networks with low consumer populations and an aged infrastructure.

To develop detailed and highly representative LV network models, areas with higher data availability were focused on.

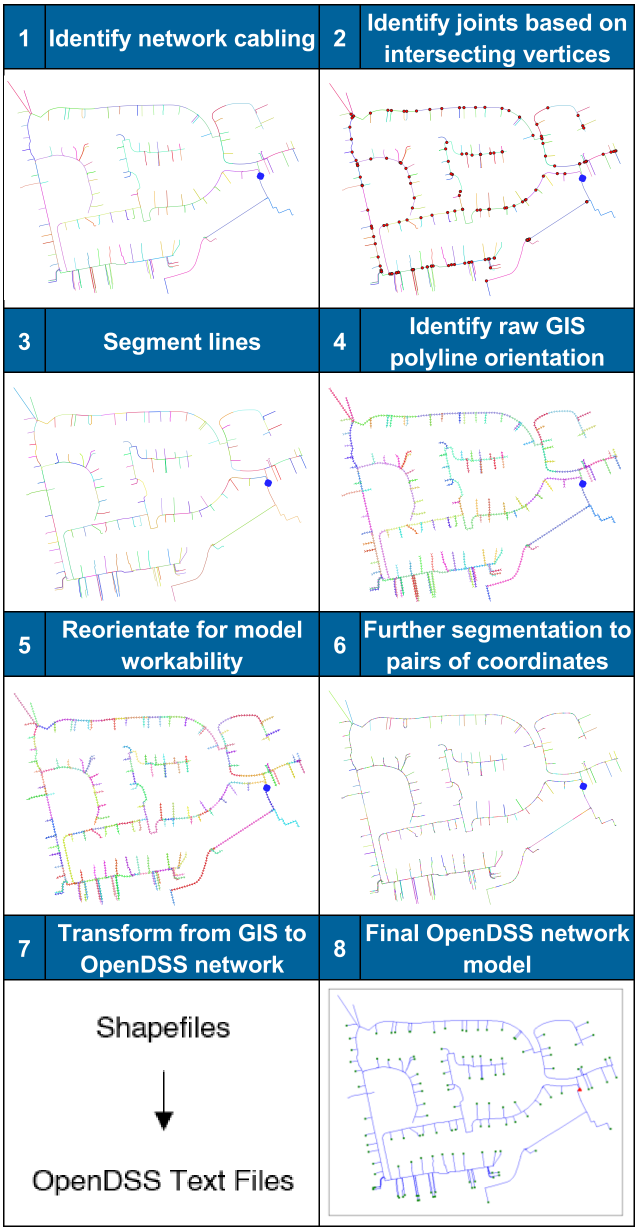


FIGURE 7. Process involved in the GIS to Electrical Network Conversion model.

However, a point of consideration with this approach is the possibility that higher data availability may indicate that these areas of network have recently been developed e.g., new housing estates that have been sized with consideration for the uptake of LCTs and an energy efficient building stock.

D. DEMAND MODELING

As smart meter data is unavailable for the areas concerned in this work, the domestic demand baseload is modeled from smart meter data recorded during the low carbon London (LCL) project from 2011–2014 [40]. Following a similar approach as adopted in [19], more than 1800 daily profiles for each day in a winter period between 01/12/2013 – 27/02/2014 are considered to represent a worst-case demand scenario.

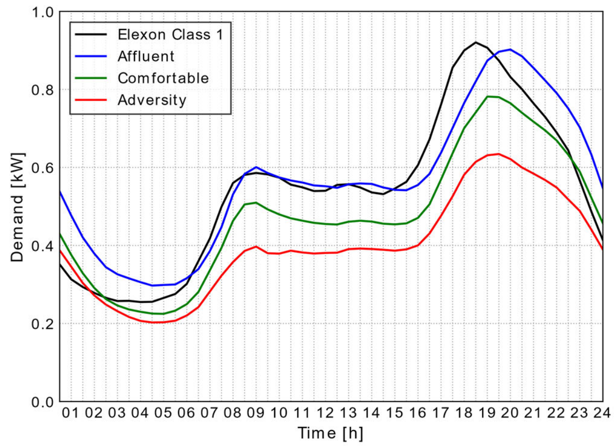


FIGURE 8. Base winter weekday demand profile for each Acorn category compared with generic Elexon winter weekday profile.

TABLE 1. Summary of sample network characteristics [29].

Network	No. Feeders	No. of Loads	Phase Distribution A	Phase Distribution B	Phase Distribution C	Total Cable Length (m)	Average Annual Postcode Gas Demand (kWh)
1	5	316	135	91	90	8,305	18,937
2	6	406	141	136	129	9,688	9,368
3	4	125	46	43	36	3,114	13,353
4	5	176	60	63	53	5,652	20,749
5	2	41	13	13	15	945	13,658
6	2	89	43	24	22	2,498	16,036

In deployment of the smart meters, consumers were classified into three categories based on CACI Acorn Group [41]; 'Affluent', 'Comfortable' and 'Adversity'. From the smart meter daily profiles, an average daily winter load profile for each Acorn category is obtained. Fig. 8 compares these with the generic class 1 Elexon profile [42]. The figure shows the variation in demand between the Acorn categories, indicating that 'Affluent' consumers have the greatest consumption and 'Adversity' the lowest. To account for heterogeneity in consumer demographics across a geographic area the baseload profiles shown are aligned to a simple distribution of the SIMD for each consumer. This considers consumers baseload demand 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. This alignment ensures the marginal variation in conventional domestic demand is captured across different areas of LV network.

E. FINAL DEVELOPED NETWORKS

Fig. 9 presents an area in the north of Scotland highlighting the location of several developed LV distribution network models. These networks have been sampled to demonstrate the scalability of the modeling methodology across a geographic area. A breakdown of the key individual network characteristics is presented in Table 1 with the topology of

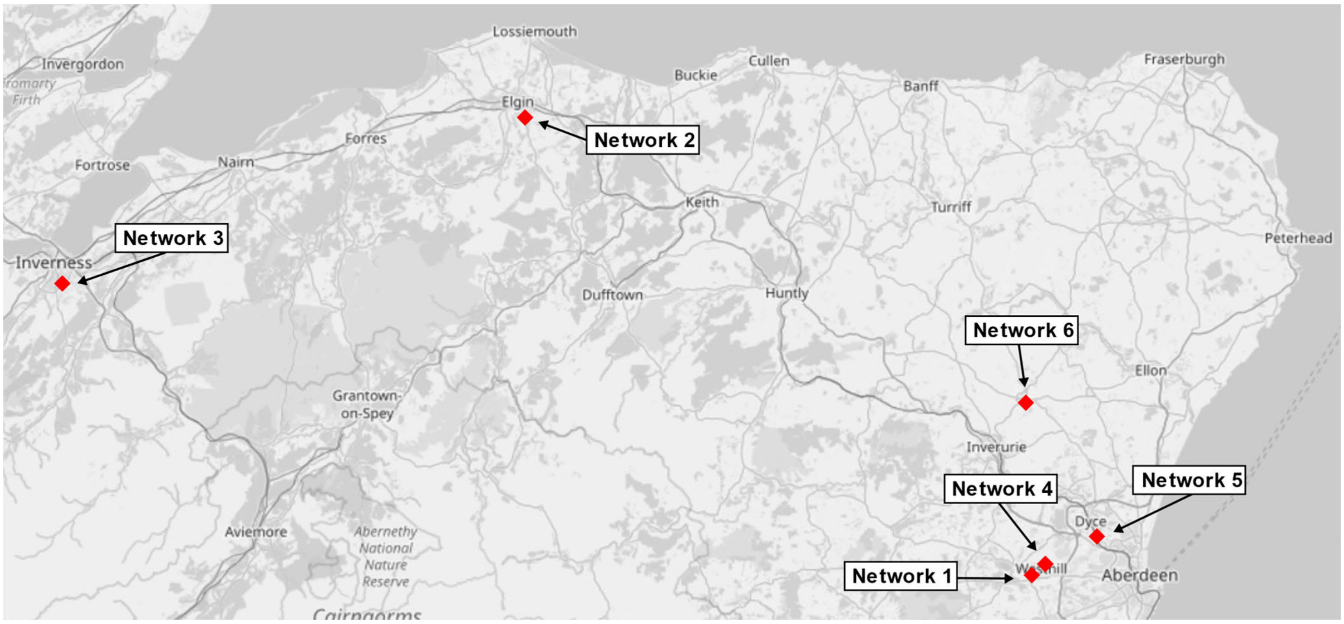


FIGURE 9. **Location of sample networks across northern Scotland demonstrating methodology scalability.**

each provided in the appendix. The allocation of loads to phases is provided in the raw GIS data, characterized by the DNO as 'Surveyed', 'Derived' or 'Assumed'. Networks with higher concentration of surveyed loads have been focused on. However, derivation and assumption of individual load phase allocation is unavoidably present in certain instances.

The networks are classified based on the Urban Rural 2016 6-fold classification [43] and fall into the categories of either Large Urban Areas, Other Urban Areas and Accessible Small Towns. They are connected to the gas network and annual postcode level gas demand consumption data is available. In Fig. 11, an example of network 2 and the associated postcode boundaries (the individual colors represent each postcode associated with the network) is shown. As previously described, each postcode has an associated annual mean gas demand which is used to develop representative localized HP demand profiles. Individual postcode and the associated gas demand information are available from public domain sources in the UK [29]. An average postcode mean annual gas demand for the related postcodes is provided for each network in Table 1 to give some insight into the varying gas demand requirements.

III. LOCALIZED LV NETWORK ASSESSMENT

In this section, a detailed combinational LCT impact assessment methodology is developed and coupled to the methodology described in Section II. The corresponding sections describe this coupling and detail the assessment approach and LCT modeling techniques used. The metrics used to quantify the results are also described.

A. LCT IMPACT ASSESSMENT METHODOLOGY

A detailed summary of the developed methodology and coupling is presented in Fig. 10, where the mathematical notation presented is described as follows: t represents the daily time interval taken based on the number of half hourly intervals in a day, n represents the number of load sample iterations and p represents the percentage penetration of HPs and EVs distributed in the network (note these can vary independently). The impact assessment is performed on the electrical model and the geospatial model is used to support the modeling of localized HPs.

1) HEAT PUMP MODELING

A household's electrical heat load is directly proportional to its heat demand. In turn, household heat demand is a complex interdependent function of several components combining building physical parameters as well as occupant behavioral routines [5]. This complexity is further compounded by the specific parameters of a household's HP e.g., rating, heat source and efficiency [5], as this governs the relationship between heat output and electrical demand. However, due to the interdependency of multiple components the full extent of combined localized influences is currently still largely unknown [4]. This in part, is due to a lack of high-resolution datasets that can be used to validate and support the development of data-driven and physics-based modeling. Therefore, sufficiently granular technical information is limited, particularly in the public domain and as a result, reliance is often placed on Census type data which has its own limitations. Nevertheless, the core issue of incorporating localization into the methodology by translating local building and behavioral parameters into a direct or electrical heat demand that can be validated remains.

For this study, in the absence of sufficiently granular technical information surrounding household physical and behavioral parameters, two established approaches for modeling heat electrical demand, the *Heat Demand Magnitude*

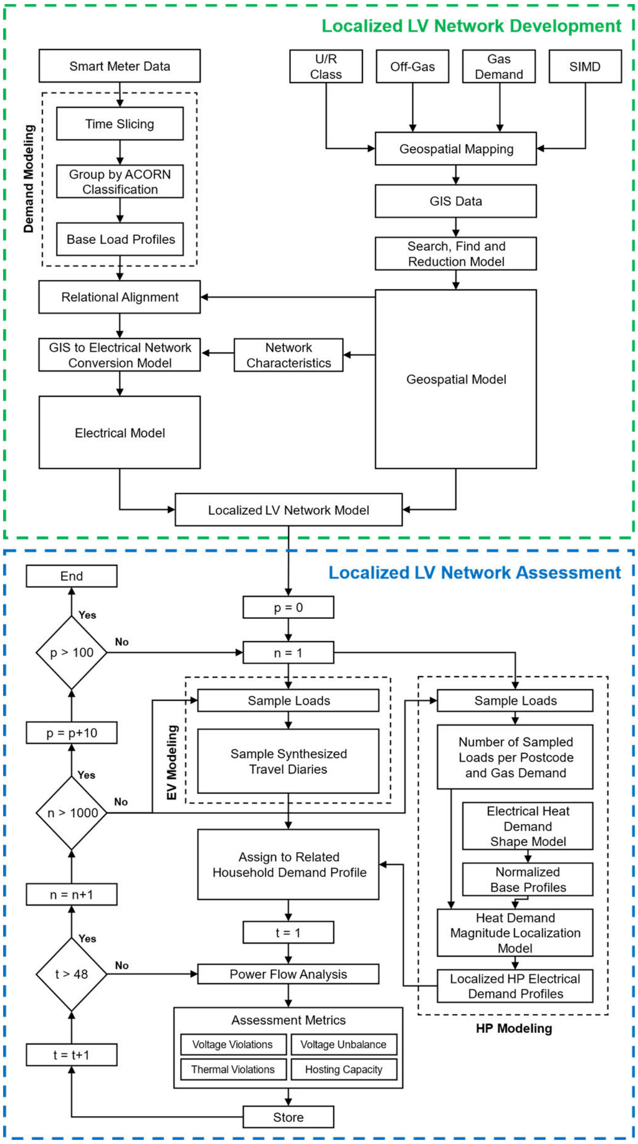


FIGURE 10. Localized LV network development and assessment methodology coupling.

Localization Model and the *Electrical Heat Demand Shape Model* developed in [5], are combined in order to construct locally sensitive half-hourly electrical heat demand profiles. A summary of the combined modeling approach is outlined by Fig. 11 and a brief description of each model component is provided as follows.

Heat Demand Magnitude Localization Model: is used to transform individual postcode level gas demand data (previously mapped and described) into a daily demand magnitude that is proportionally scaled to local physical and behavioral components that influence heat demand. This postcode level gas demand serves as a proxy for local building, climate and behavioral parameters. Firstly, a gas conversion efficiency (η) is used to transform the raw annual gas demand $\left(D_G^{annual}\right)$ into an equivalent annual direct heat demand $\left(D_H^{annual}\right)$ as shown in (1). For this work, a fixed gas boiler efficiency of 80% has been used. This has been obtained by taking an average of over 2000 different mains gas boiler models with efficiencies ranging from 55% to 90.3%. The recorded efficiencies are based on the seasonal efficiency of domestic boilers in the UK (SEDBUK) rating scheme and are stored in a database that is used to support UK building energy performance assessments [44]. D_H^{annual} is then converted into a daily heat demand $\left(D_H^{daily}\right)$ through (2) and (3) by assuming that heat demand varies sinusoidally throughout the year in accordance with temperature variation, D_H^{annual} provides the area under the sinusoid which defines the amplitude and offset parameters and subsequently the daily demand variation throughout the year and x corresponds to day of year.

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

$$\begin{aligned} D_H^{annual} &= \int f(x)\, dx \\ &= \int_0^{365} D_{amp} \cdot sin\left(\frac{2\pi}{365}x + \phi\right) + D_{off}\, dx \end{aligned} \tag{2}$$

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

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

The default amplitude $\left(D_{amp}\right)$ and offset $\left(D_{off}\right)$ parameters have been applied. These fit parameters were tested versus monitored gas meter data collected at 30-minute intervals for several thousands of customers as part of the energy demand research project (EDRP) [45] and monitored HP heat and electrical demand data obtained from the renewable heat premium payment (RHPP) dataset which features 2-minute resolution data collected from 418 air and ground source HPs in the UK from October 2013 to March 2015 [46]. The daily heat demand is transformed into a daily electrical demand $\left(D_E^{daily}\right)$ via a coefficient of performance (COP) through (4). From the RHPP dataset HP COP typically ranges from 2 to 4 [46] which is comparable to the air and ground source HP COPs presented in [47]. However, as with gas boiler efficiency this parameter is sensitive to temperature and is variable depending on specific installation as well as manufactures model. A fixed COP of 3 is used for this study.

Electrical Heat Demand Shape Model: developed in [5] is used to transform the daily electrical demand into a set of half-hourly demand figures sensitive to local temperature conditions. The modeling approach incorporates monitored HP data from the RHPP dataset and is validated against operational demand data collected during the LCL HP trials [48]. Fundamentally, the work in [5] identified common recurring electrical heat demand profiles that repeat within the RHPP dataset, despite the disparate geographical and demographic conditions. These have been normalized for an ambient temperature of 0°C which is used to simulate the worst-case winter cold conditions. The normalized profiles are then used as the basis for HP daily load shape forming and are sampled accordingly.

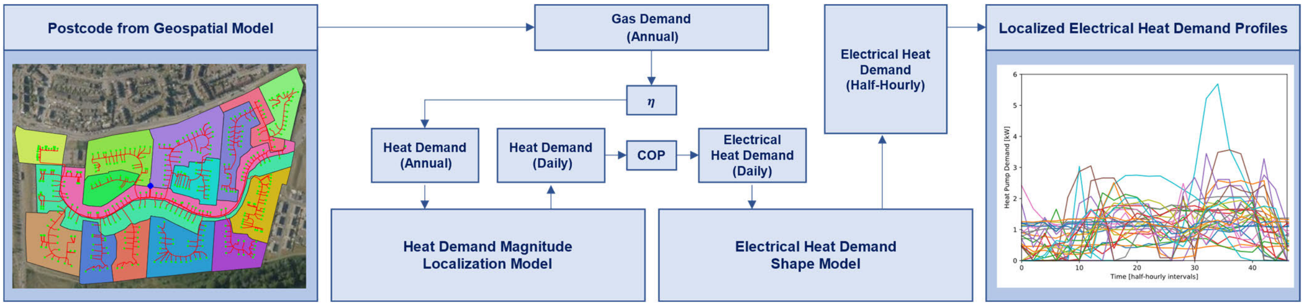


FIGURE 11. Methodology used to convert annual gas demand to localized electrical heat demand profiles.

2) ELECTRIC VEHICLE MODELING

In addition to traditional power rating and capacity challenges, a difficult aspect of EV modeling is the uncertainty surrounding consumer behavior. External factors are expected to influence consumer routines and as a consequence EV charging patterns. In this work, residential EV charging schedules are adopted in an attempt to capture elements of this 'socially-driven' charging behavior by employing the use of synthesized 'travel diaries' previously developed in [49] and [50] and used in other works including [19]. The developed charging schedules are based on UK national travel survey (NTS) car travel data for between 2002 and 2016 [51].

As in [50], EV modeling considers 'routine charging schedules' to be the primary charging scenario. These charging schedules consider the principle of least inconvenience to the consumer, in that charging has become routine and aligned around social rhythms. Consumers plug their vehicles in on arrival at their residence regardless of the vehicle's state of charge and also seek the maximum state of charge gain allowed within the parking duration and by the charging constraints. These charging patterns are essentially uncontrolled in that there is no incentivization for scheduling or optimization that facilitates demand side management. This is taken into consideration within the analysis and discussion. In addition, this work assumes all households have the necessary EV charging infrastructure at each residence and assumes that a maximum of one EV can be charged at each residence at any given interval. The authors note that due to the additional demand requirement, multiple residential EV charging could further exacerbate the presented findings. A set of 10,000 winter weekday charging schedules have been derived with a fixed 7.4 kW rating (high power 'fast' home charging, typically a single phase 32 A, 230 V connection) across a range of 'typical' vehicle battery sizes: 24, 30, 40, 60 and 75 kWh. Note that an inverter efficiency of 88% [52] has been used for the heuristic which is further described in [49] and [50].

B. ASSESSMENT METRICS

Three different assessment metrics are used to quantify the impact of LCT uptake on the concerned LV distribution networks: network violations, voltage unbalance and hosting capacity. These metrics demonstrate the methodology outlined in this paper and are summarized as follows:

1) NETWORK VIOLATIONS

Thermal overload and over/under voltage are network issues that can occur as a result of LCT uptake [53]. Over/undervoltage relates to when the upper and lower statutory voltage limits (+10%, −6% in GB) [54], are breached. An overvoltage situation can occur when the current injected by LCTs such as solar PV or vehicle-to-grid exceeds the current absorbed by the local demand, causing the voltage to rise beyond the upper statutory limit. An undervoltage situation can occur due to an increase in demand from LCTs such as HPs and from EV charging that would see additional current flow to the network, consequently causing the voltage to drop beyond the lower statutory limit [53]. Thermal overload relates to when the current exceeds the rated current capacity of the assets, typically applicable for cables and transformers [53]. Excess current can cause overheating and subsequent damage to the assets which can increase network losses, impact longevity and reduce reliability. As a result, voltage and thermal violations are considered to be key metrics for quantifying the impact of LCT uptake and are subsequently used in this work.

2) PHASE UNBALANCE

In the development of LV distribution networks, network planners typically try to balance the network with symmetrical distribution of load across the three-phases. This ensures maximum utilization of available cable capacity, minimization of losses and reduced asset degradation. However, this can be an extremely challenging undertaking and some form of asymmetrical load distribution across individual phases exists in most LV networks. As a consequence, LV networks in practice are generally considered to be unbalanced networks where the phase unbalance (or imbalance) primarily stems from asymmetrical load distribution and temporal variations in load magnitude [55]. This unbalance results in an unequal distribution of power across the conventional three-phases and can result in an increase in network losses and an underutilization of network capacity. A number of works have raised concern with the potential detrimental impact LCTs will have on phase unbalance e.g., in [56] the impact of solar PV was considered. This is of particular concern for already heavily unbalanced networks which are common in practice (particularly in a remote rural setting). ENA Recommendation P29 [57] provides insight into the planning limits for voltage unbalance in the UK, indicating that unbalance should be estimated using the voltage unbalanced factor (VUF) at any given measurement point, expressed by (7) which is calculated from (5) and (6) as described in [58]. Where V_{ab}, V_{bc}, and V_{ca} are the three-phase unbalanced line voltages, V_p and V_n are the two symmetrical components of the line voltages, $a = 1\angle 120°$ and $a^2 = 1\angle 240°$.

$$V_p = \frac{V_{ab} + (a \times V_{bc}) + \left(a^2 \times V_{ca}\right)}{3} \tag{5}$$

$$V_n = \frac{V_{ab} + \left(a^2 \times V_{bc}\right) + (a \times V_{ca})}{3} \tag{6}$$

$$VUF = \frac{|V_n|}{|V_p|} \times 100\% \tag{7}$$

As DNOs are expected to conform to this standard, and of the expressed concerns with voltage unbalance on network losses and hosting capacity, this work considers the VUF as a key assessment metric in quantifying LCT impact.

3) HOSTING CAPACITY

The hosting capacity relates to how much LCT penetration a given LV network can accommodate without breaching network operating standards or component physical limits [53]. Providing the DNO with insight into how much LCT uptake will reduce conventional network headroom and at what penetration management solutions may be necessary. From this, credible uptake forecasts can give an indication as to when these solutions may be necessary. This then allows for a cost-benefit analysis and technical appraisal of the potential management solutions necessary to mitigate risk and maintain network resiliency. Currently, DNOs are taking a ‘flexibility first’ approach at the direction of the GB network regulator (Ofgem) [59], [60]. Therefore, the hosting capacity is considered to be a highly informative assessment metric in relation to the constrained flexibility potential. In this work the hosting capacity is measured in terms of headroom based on the apparent power that instigates a network voltage or thermal violation on each individual feeder [19]. This can be expressed as:

$$H_{f,t} = min(S_f^{Tlim}, S_f^{Vlim}) - S_{f,t} \tag{8}$$

where $H_{f,t}$ is the headroom for each feeder f at time t, $S_{f,t}$ is the apparent power on each feeder, S_f^{Tlim} is the thermal limit of each feeder head cable obtained from:

$$S_f^{Tlim} = 3 \times I_f^{lim} \times V_{max} \tag{9}$$

I_f^{lim} is the maximum current rating of the feeder head cable and V_{max} is the maximum allowable voltage which is +10% of the nominal in this instance. S_f^{Vlim} is obtained by using a similar linear regression method as adopted in [19]. Fig. 12 provides an example of this for network 1 feeder 5 where

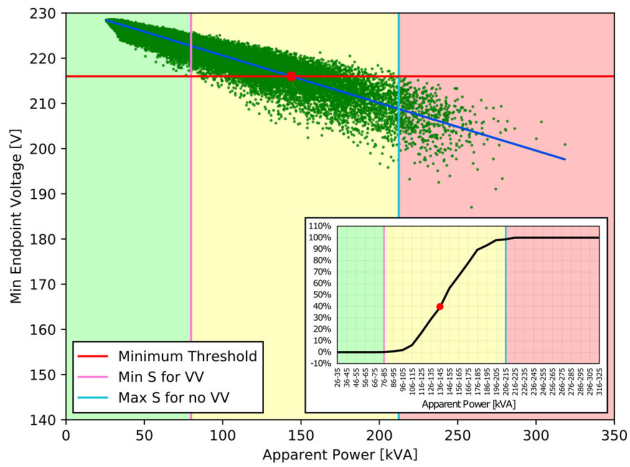


FIGURE 12. Minimum endpoint voltage vs apparent power (S) to determine voltage violation (VV) headroom operating regions.

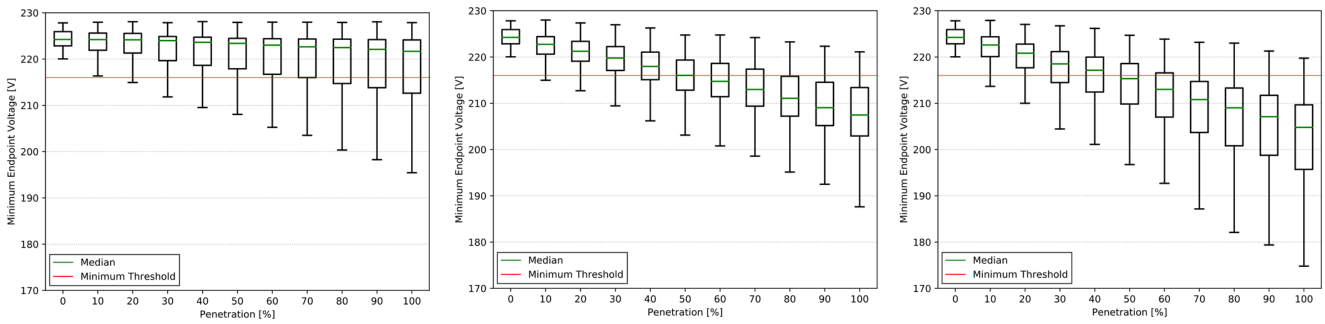
S_f^{Vlim} is based on the minimum $S_{f,t}$ that results in a voltage violation. The region to the left of this value (highlighted in green) is used for the network headroom assessment in this work and would be considered the standard operating region for network operators. The yellow region is where headroom is likely to be more dynamic and dependent on LCT usage patterns and install location. The distribution also shown in Fig. 12 indicates that the voltage violation likelihood increases with $S_{f,t}$ in this region. With this, there is an opportunity to develop active solutions that have the capability to unlock and efficiently utilize the capacity available in this operating region which would be the subject of future research.

IV. RESULTS AND DISCUSSIONS

The coupled methodology described in the previous sections is formalized through the assessment of two different LV networks (network 1 and 2 in Fig. 9) to demonstrate the potential for scalable localized LV network modeling and the necessity for combinational LCT impact assessments. Such quantification provides modeling justification and supports place-based network investment decision making and emphasizes the potential for area specific flexible network management. The assessment of each network considers three scenarios for each metric; scenarios 1 and 2 consider the uptake of EVs and HPs in isolation and scenario 3 considers a combination of both HPs and EVs. Scenarios 1 and 2 allow for distinction of individual technology impact which supports analysis of scenario 3. The results and discussion section are categorized against the key assessment metrics defined previously in Section III-B. Note that the two networks have radically different heating requirements with network 1 having an average postcode gas demand of 18,937 kWh compared with network 2 which has 9,368 kWh.

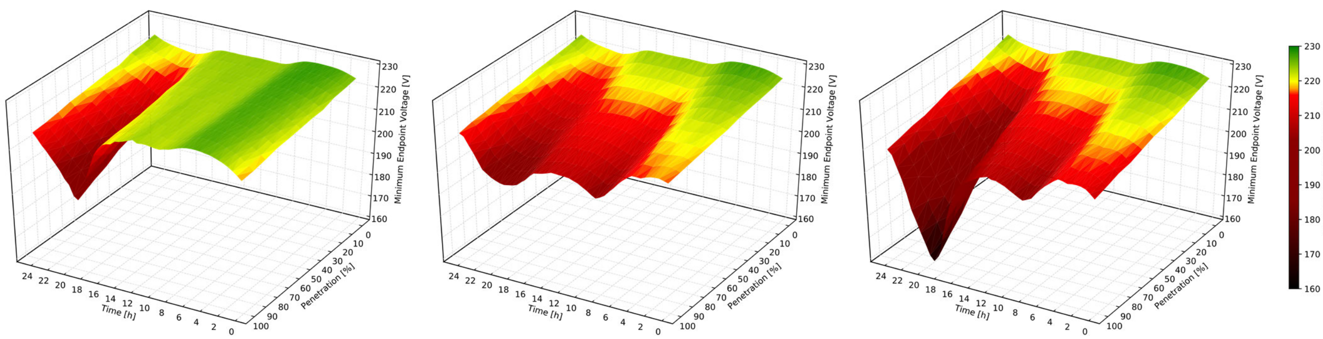
A. NETWORK VIOLATIONS

Figs 13-15 and Figs. 16-18 summarize the results for the statistical impact assessment of voltage violations for



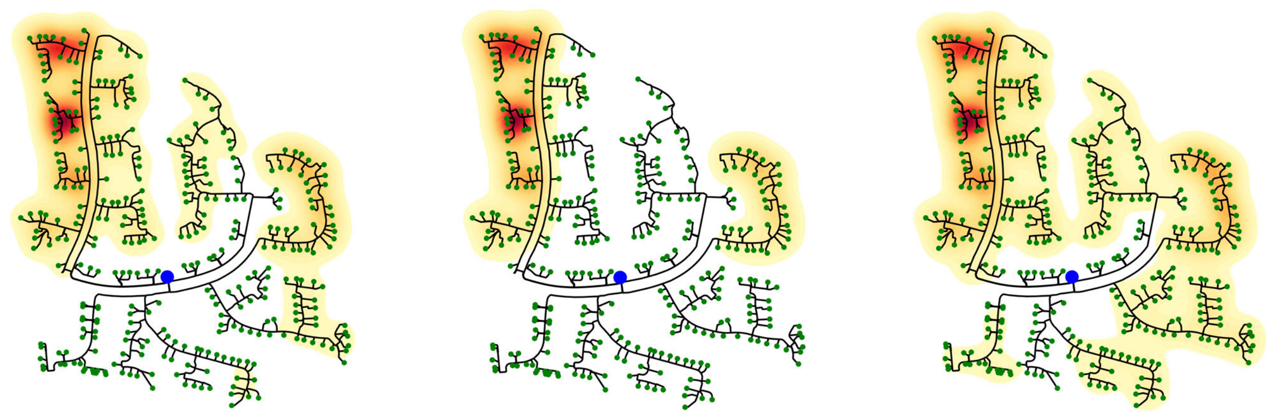
(a) (b) (c)

FIGURE 13. Minimum endpoint voltage vs LCT penetration for network 1. (a) EV scenario (b) HP scenario and (c) Combined scenario.



(a) (b) (c)

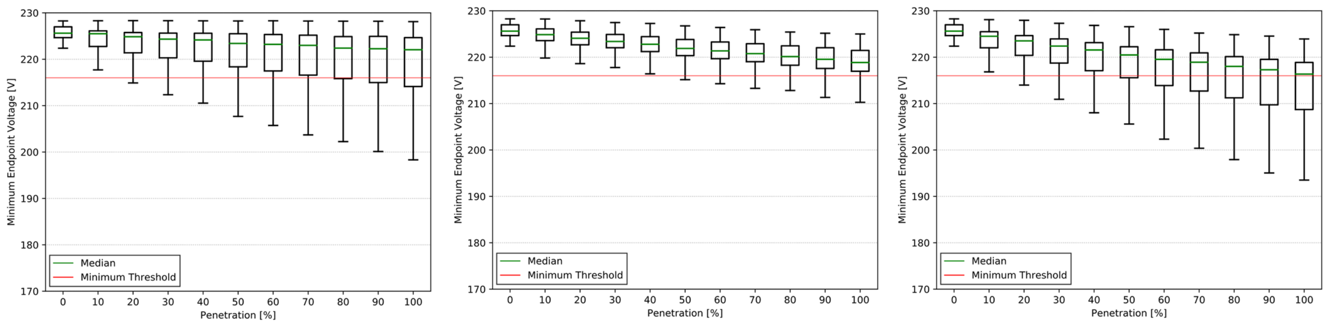
FIGURE 14. Average minimum endpoint voltage vs time vs penetration for network 1. (a) EV scenario (b) HP scenario and (c) Combined scenario.



(a) (b) (c)

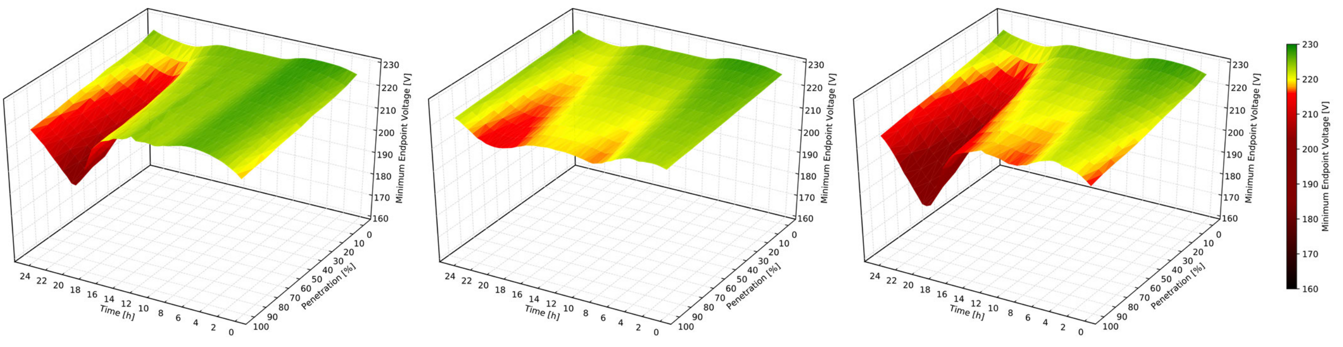
FIGURE 15. Concentration of network buses with voltage violations for network 1. (a) EV scenario (b) HP scenario and (c) Combined scenario.

networks 1 and 2 respectively. Fig. 13(a) – (c) and Fig. 16(a) – (c) consider the range of minimum network endpoint voltages against a range of technology penetrations. For the EV scenario in both instances a broad range of minimum endpoint voltage is identified for each penetration quantity across the sample. Such variation is reflective of EV location and the variation in charging patterns. It can be seen that the lower statutory limit of 216 V is breached in certain cases with as little as 20% penetration. The impact from EVs is similar on both networks though network 1 is marginally worse. In terms of voltage violations from HP penetration, network 1 is significantly worse than network 2. This is to be somewhat expected due to the influence of heat demand localization in the modeling. Where analysis suggests that



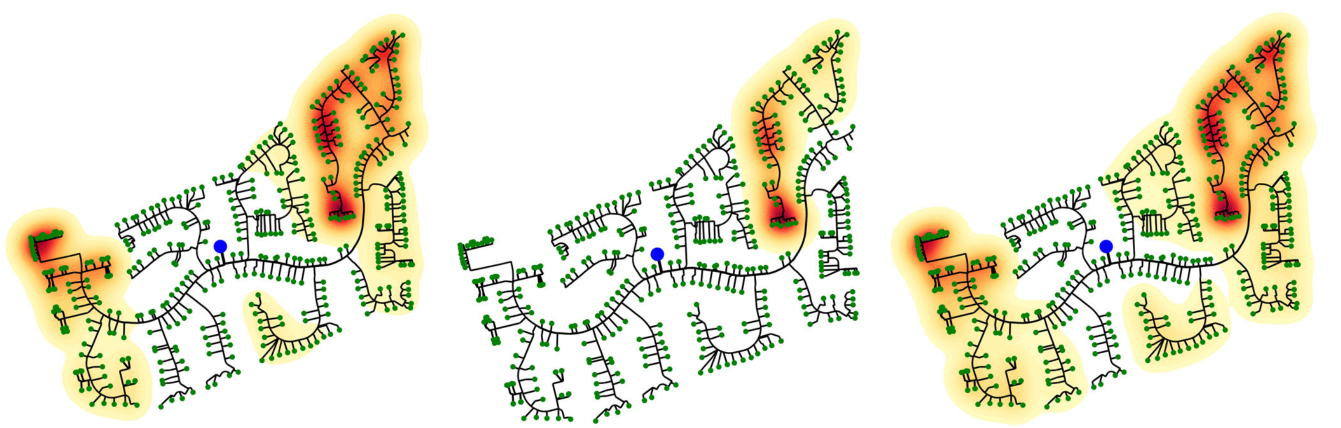
(a) (b) (c)

FIGURE 16. Minimum endpoint voltage vs LCT penetration for network 2. (a) EV scenario (b) HP scenario and (c) Combined scenario.



(a) (b) (c)

FIGURE 17. Average minimum endpoint voltage vs time vs penetration for network 2. (a) EV scenario (b) HP scenario and (c) Combined scenario.



(a) (b) (c)

FIGURE 18. Concentration of network buses with voltage violations for network 2. (a) EV scenario (b) HP scenario and (c) Combined scenario.

the associated housing stock for network 2 has been built within the last decade therefore is likely to have increased building efficiency compared with an aged building stock for network 1. Other factors such as average uilding floor area size and consumer affluence may be influencing the recorded gas demand. In the case of the combined scenario, the number of violations are significantly increased. This emphasizes the scale of the combined impact of both EVs and HPs on both networks.

In Fig. 14(a) – (c) and Fig. 17(a) – (c), the average minimum endpoint voltage across all samples for each penetration and associated time interval is presented for network 1 and 2 respectively. The three-dimensional aspect allows for time series analysis of individual technology impact. For the EV scenario on both networks, voltage violations primarily occur around the traditional evening peak as penetrations increase. This is a direct consequence of the modeled routine charging schedules, in that consumers would typically plug-in on their return home from work. The combined effect of all consumers having similar evening charging patterns results in a significant increase in demand and a large drop in the minimum endpoint voltage. For the HP scenario, voltage violations occur around the same time in the evening at higher penetrations though with less of a drop. However, unlike with the EVs an early-morning dip in the minimum endpoint voltage is noticeable and can be attributed to morning space heating demand requirements. This is particularly prominent on network 1 at higher penetrations and less evident for network 2. The combined scenario for both networks, results in a much larger drop at the evening peak with increased early-morning violations at higher penetrations, specifically for network 1. This combined impact is highly significant, particularly when considering demand side management applications. In isolation the EV scenario indicates peak shaving through scheduled EV charging could be deployed to reduce the evening peak demand with minimal impact during other periods of the day. However, the combined scenario identifies that with the mixture of EVs and HPs in the network, unconstrained peak shaving or scheduled charging may coincide heat demand requirements. This is exacerbated for network 1 which has greater early morning violations at increased penetrations than in network 2, indicating that network 2 may have more scope for flexible management than network 1. Ultimately, this emphasizes the need to consider a combination of different LCTs in parallel when conducting impact assessments and in the development of flexible demand side management techniques that are sensitive to the mixture of key LV connected LCTs and the inherent heterogeneity of local conditions.

The voltage violation density heatmaps shown in Fig. 15(a) – (c) and Fig. 18(a) – (c), provide further insight into the extent the combined LCT impact has across the two independent networks. The figures show spatially the concentration of network buses where a voltage violation has occurred at any time interval across the sample. The darker end of the color scale indicates a higher density of violations i.e., voltage violations occur more frequently at these buses than others. As expected, there are a higher number of violations in the combined scenarios and in the EV scenarios compared with the HP scenarios. The concentration of voltage violations increases with distance in relation to the secondary transformer and is therefore prominent on the longest feeders. However, the number of consumers connected to each feeder, the electrical distance between consumers, phase allocation and cable impedance are several other potential contributing factors influencing where these violations occur in the network. Fundamentally, the heatmaps presented indicate that a combined uptake of both EVs and HPs is likely to result in an increase in the number of voltage violations across different areas of network. The authors acknowledge that transient voltage excursions are allowed according to the distribution network code within allowable limits and that sufficiently granular data may reveal additional perturbations which must be borne in mind when assessing outcomes.

Analysis of cable thermal violations suggests that voltage is likely to be the more problematic of the two for network operators. For the EV scenario on network 1, the percentage of cables in breach of their rating steadily increased from about 1% of cables at around 40% penetration to around 4% at 100% penetration during the evening peak. The HP scenario was less prominent only reaching 2% of all cables at 100% though the early morning demand requirements introduce a minor spike to 1% of cables at 100% penetration. The combined scenario reached a total of 10% of cables for 100% penetration. Analysis of network 2 showed similar behavior around the evening peak for the EV and combined scenarios although had no thermal violations in the HP scenario. Ultimately these are relatively low values in comparison to the scale of voltage violations and anecdotally, under current practice it would not be uncommon for DNOs to overload cabling and accept the losses and asset degradation consequences. However, this is likely to be challenging in future network operation which requires loss minimization and improved capacity management for flexible operation.

B. PHASE UNBALANCE

The phase unbalance results are presented in Fig. 19(a) – (c) and Fig. 20(a) – (c) for network 1 and 2 respectively, where the VUF measurement is taken at the LV side of the secondary transformer and at each feeder endpoint. Phase unbalance is often overlooked at these voltages within the literature as many studies opt to model loads as 3-phase balanced connections due to lack of phasing visibility. However, the results presented indicate that increased consideration regarding HP and EV impact on phase unbalance may be necessary going forward. For both networks in the EV scenario, as penetrations increase, as does the spread of the VUF, particularly, during the evening peak period (this is more prominent on network 1). For the HP scenario on network 1 the VUF increases as a result of increasing penetrations around the early morning and the evening peak though the impact is less prominent than the EV scenario. The combined scenario sees a significant increase in the voltage unbalance factor across the day where the spread increases resulting in an increase in the number of cases exceeding the recommended 2% threshold. For network 2 the uptake of HPs has far less of an impact on the VUF and the spread is more contained across the day. Note that it can be seen from Table 1 that network 2 has a more evenly distributed phase allocation than network 1. This emphasizes that phase unbalance is likely to be exacerbated in areas where high degrees of unbalance already exist and by the uptake of multiple LCTs which are diverse in size and use patterns. Also indicating that the heterogeneity in network topology and localization will have an influence on the scale of this impact.

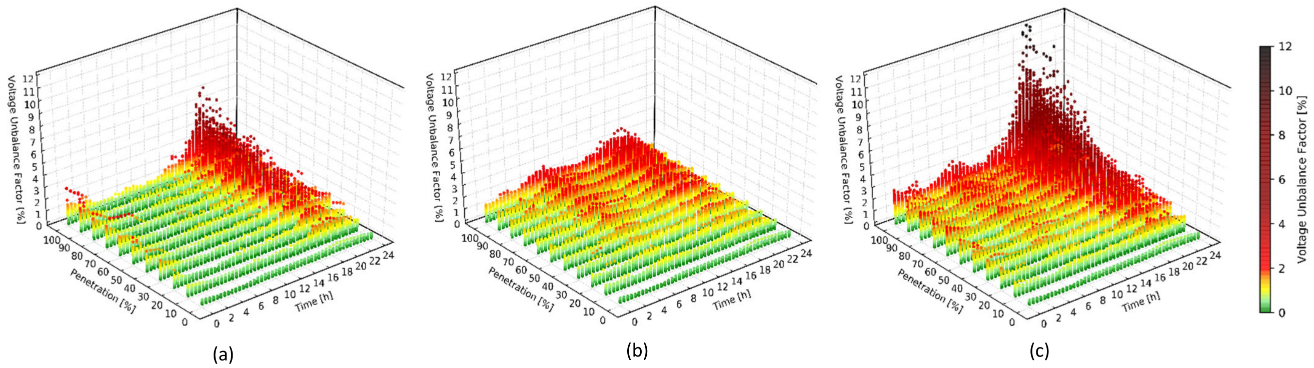


FIGURE 19. Voltage unbalance factor vs time penetration for network 1. (a) EV scenario (b) HP and (c) Combined scenario.

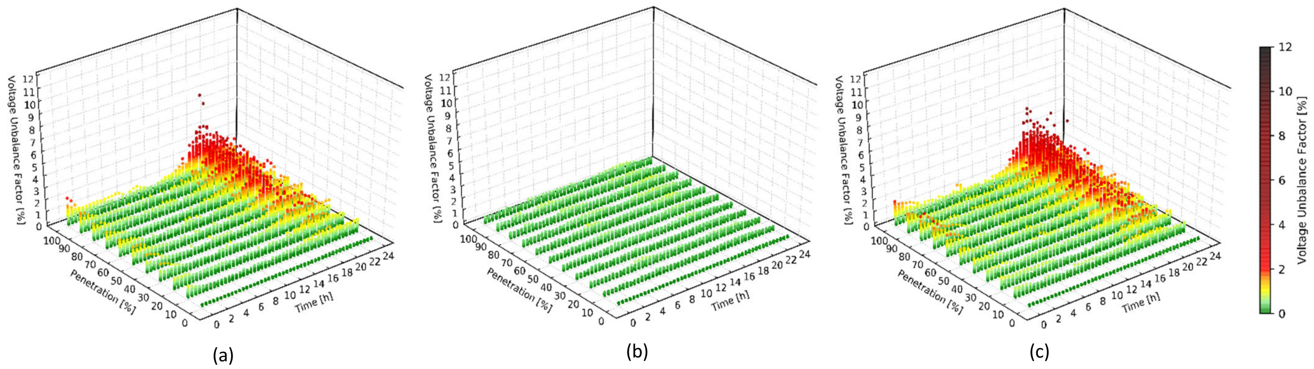


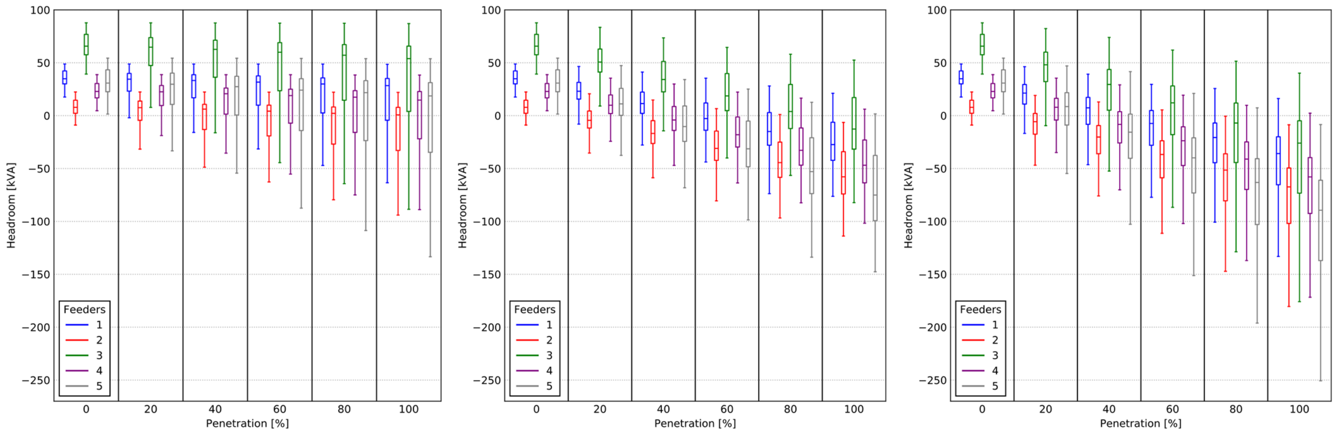
FIGURE 20. Voltage unbalance factor vs time penetration for network 2. (a) EV scenario (b) HP and (c) Combined scenario.

C. HOSTING CAPACITY

Fig. 21(a) – (c) and Fig. 22(a) – (c) present the results for the hosting capacity assessment where network headroom is compared with LCT penetration for the feeders in networks 1 and 2 for each of the scenarios. The headroom is negative when $S_{f,t}$ has exceeded either S_f^{Tlim} to result in a thermal violation of the feeder head cable or S_f^{Vlim} to move beyond the green region as previously discussed and demonstrated in Fig. 12. The results emphasize that network headroom decreases as the penetrations increase across each scenario. The rate of this reduction varies between feeders due to a number of factors including the number of loads connected to each feeder, phase allocation, cable type/rating and feeder length. In the EV scenario the distribution for each feeder remains skewed unlike in the HP scenario as penetrations increase due to the modeled routine dependent EV charging profiles. In the combined scenario network headroom is significantly reduced in comparison with the individual EV and HP scenarios. The findings also emphasize that to adopt flexible management solutions at an aggregated level, the headroom imbalance between feeders would have to be taken into consideration. LCT management by an aggregator or third party would require full visibility in this eventuality to ensure network limits are respected when managing assets across multiple feeders. The approach used in this work seeks to demonstrate the impact of increasing penetrations and uptake of LCTs with different usage patterns on network headroom. However, to maximize network headroom for flexible applications a more refined approach that accounts for all network cabling and individual phases should be adopted.

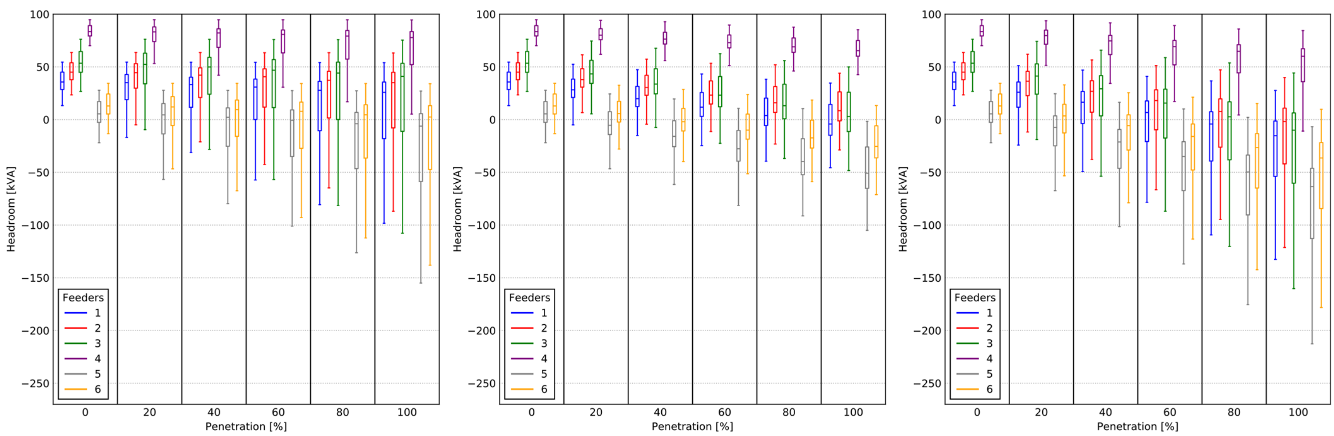
D. SUMMARY

To summarize, the results demonstrate the developed modeling capability through a series of scenarios on two different LV networks. The findings emphasize that the uptake of both EVs and HPs in parallel is expected to cause significant challenges for network operators, particularly as LCT penetrations increase. This is quantified as part of the studies considered. Similar trends exist across the different scenarios in that as LCT penetration levels increase as does the frequency of voltage and thermal violations with voltage violations being the more dominant. The time at which these violations occur is a critical issue that without regulation is subject to individual technology usage patterns. An increase in violations around the traditional evening peak is observed along with an increase in the early morning for the HP scenarios and an increase of the VUF is also observed in



(a) (b) (c)

FIGURE 21. **Network headroom vs penetration for each feeder in network 1. (a) EV scenario (b) HP scenario and (c) Combined scenario.**



(a) (b) (c)

FIGURE 22. **Network headroom vs penetration for each feeder in network 2. (a) EV scenario (b) HP scenario and (c) Combined scenario.**

certain instances around similar times. The overall network headroom decreases as penetrations increase. However, this reduction varies non-uniformly across individual feeders. By adopting a localized approach to HP modeling the results shown in this work provide the basis for understanding how variations in local heat demand may influence overall HP impacts further demonstrating the value of scalable localized modeling.

V. CONCLUSION AND FUTURE WORK

This work has developed and demonstrated a novel scalable approach to LV network and LCT impact assessment that can be used to support place-based infrastructure investment decision making. The developed localized LV network modeling methodology can be used to support a wide range of LV network studies from spatial and temporal social-technical modeling of demand to the development of locally sensitive demand side management techniques through enhanced flexibility quantification. This methodology is guided by high-resolution network information supporting the scalability necessary for network modeling in different geographic regions comprised of diverse local characteristics. This work has evidenced that the method has the capability to reduce the uncertainty surrounding EVs, HPs and demand diversity. This can facilitate the development of techniques that better capture and characterize the impact of local conditions on LCT demand profiles and the subsequent impact on the LV network beyond existing published work in this area. As the developed methodology utilizes GIS data and geospatial datasets of varying spatial and temporal resolutions it has limitations that are not uncommon with data-driven modeling approaches, these include data availability, quality and quantity. However, this work has shown that in general these challenges can be managed to support enhanced modeling.

The resulting case study network models are analyzed through a localized LV network assessment methodology that accounts for the impact of both EVs and HPs with consideration for the diversity in domestic heat demand. The impact

FIGURE 23. Network 1.

FIGURE 24. Network 2.

FIGURE 25. Network 3.

FIGURE 26. Network 4.

assessment study is used as a means of demonstrating the suitability of the scalable LV network development methodology and the value of place-based LV networks, but also to probe gaps in the literature that relate to electrified heat and transport impact assessments and the approaches taken to model diversity in heat demand at granular resolutions. Multiple assessment metrics are used to demonstrate the modeling approach and to quantify the impact on key network infrastructure.

The findings emphasize that the impact from both EVs and HPs is significantly exacerbated when they are adopted in parallel rather than in isolation. The work also identified potential challenges with unconstrained flexible demand side management approaches, e.g., the potential for flexible EV peak shaving techniques to coincide with space heating demand. This indicates that a mix of LCTs should be considered in the development of such techniques and that existing capacity constraints in addition to local conditions will influence the suitability of flexible network management applications, emphasizing that different areas of network may require bespoke solutions.

Future work would look to include detailed localized forecasting of EV and HP uptake to further expand upon the high-resolution modeling described, this would provide enhanced insight into the challenges which social diversity presents for local network infrastructure investment planning. Additionally, as it is considered that decarbonization of off-gas networks typically found in a rural setting are of priority in that many gas connected urban networks may follow alternative decarbonization pathways. There is an opportunity to further develop the modeling and understanding from this work to specifically target off-gas networks in a rural environment at the next stage of research investigation.

Future work would also look to overcome the limitations with using monitored smart meter trial data recorded in different locations with different demand requirements and characteristics from the target area. Although as described in Section II-D a method has been used in this work to align the monitored data as best as possible to the target area by considering the demographic of the consumers. This is ultimately still an approximation and different methods could

FIGURE 27. Network 5.

FIGURE 28. Network 6.

be applied in absence of monitored data. Additionally, use of Voronoi polygons could be investigated to explore further computational reductions and efficiency improvements in the localized network generation methodology. Functionality to carry out sensitivity analysis that accounts for the uncertainty of different network characteristics e.g., cable type and phasing could also be introduced to the methodology.

APPENDIX
SAMPLED NETWORKS

Figs. 23–28.

ACKNOWLEDGMENT

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