Hosting capacity assessment of heat pumps and optimised electric vehicle charging on low voltage networks

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Abstract

The decarbonisation of heat and transport using heat pumps (HPs) and electric vehicles (EVs) will require significant investment in low voltage (LV) networks both in terms of network reinforcement and in the provision of flexibility to avoid network upgrades where appropriate. In this paper, a heuristic methodology is presented to estimate headroom available for domestic EV charging optimisation in LV networks at different penetrations of HPs and a novel zonal approach is applied to EV optimisation. It was found that optimised charging of EVs can allow for a significantly higher penetration of EVs for a given HP penetration within the network, without the need for reinforcement. Significant improvements in terms of network hosting capacity were realised: for example, an increase from 34% EV and 50% HP penetration for dumb charging to 72% EV and 57% HP penetration for optimised charging was available for one particular case study. The level of improvement in hosting capacity was found to be strongly dependent on particular network topology and pre-existing demand; this reinforces the need for further study in unlocking the potential synergies of EV and HP uptake.

Keywords: Heat pump, electric vehicle, EV, low voltage, hosting capacity,

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April 26, 2021

optimisation

Nomenclature

Sets

$\mathcal{N}$	Networks, indexed by n
$\mathcal{C}$	Cases, indexed by c
$\mathcal{Z}$	Zones, indexed by z
$\mathcal{D}$	Loads, indexed by d
$\mathcal{T}$	Time horizon, indexed by t
$\mathcal{E}$	Electric vehicles (EVs), indexed by e
$\mathcal{W}$	Charging windows, indexed by w

Parameters

V^{base}	Base voltage
I_z^{lim}	Feeder head cable current rating at zone z supply point
P^{hp}	Heat pump power demand
E^{hp}	Energy for heat pump
E^{dhw}	Energy for domestic hot water
c_t^{G}	Cost of importing power in £/kwh in time period t
p_e^{max}	Charge capacity of EV e
P_z^{Vlim}	Voltage power flow limit in zone z
$P_{z,t}^{\text{Tlim}}$	Thermal power flow limit in zone z in time period t
$\text{SoC}_{e,w}^{\text{S}}/\text{SoC}_{e,w}^{\text{F}}$	Initial/final state of charge of an EV
η	EV charging/discharging efficiency
γ_e	Constant power charging limit of EV e

Variables

p_t^G	Power required to charge all EVs in time period t
$p_{e,t}^C, p_{e,t}^D$	Charging/discharging of an EV e in time period t
$SoC_{e,t,w}$	State of charge of EV e in time period t and time window w
$P_{z,t}$	Power flow at zonal feeder head cable in zone z in time period t
$H_{z,t}$	Headroom in zone z in time period t
$F_{z,t}$	Footroom in zone z in time period t
$H_{z,t}^{(2)}$	2^{nd} percentile headroom in zone z in time period t
$F_{z,t}^{(2)}$	2^{nd} percentile footroom in zone z in time period t
$V_{z,t}^{\min}$	Minimum voltage in zone z in time period t
n^{EV}	Number of EVs

Acronyms

LV	Low voltage
EV	Electric vehicle
ASHP	Air-source hear pump
V2G	Vehicle to grid
DNO	Distribution network operator
HP	Heat pump
OPF	Optimal power flow
SM	Smart meter demand data
NTS	National Travel Survey

1. Introduction

The hosting capacity of residential low voltage (LV) distribution networks for passenger electric vehicles (EVs) and heat pumps (HPs) is a key factor in achieving decarbonisation goals such as the United Kingdom (UK) Government's target to reach net zero carbon emissions by 2050 [1]. In Great Britain (GB), the electricity system operator's (ESO's) latest long term electricity system forecast, known as future energy scenarios (FES), predicts the number of homes with air source HPs (ASHPs) in 2050 varies from 1.8 million to 18 million, representing between 5.7 to 57% of GB households [2]. There are high levels of uncertainty as to the mix of technologies that will replace natural gas boilers which supplied around 80% of heat demand in 2019 [3]. While hydrogen is being considered as a replacement for natural gas within the existing gas grid infrastructure, the uptake in ASHPs is likely to increase significantly with the phase out of gas boilers.

In terms of EVs, FES 2020 [2] provides a prediction of 30 million EVs between the years 2032 and 2040 which represents the equivalent of the entire GB car fleet based on an expected ban on the sale of new petrol and diesel cars. The motivation for this paper is that the predicted levels of EVs and HPs could require substantial upgrades to the UK electricity networks, estimated as costing up to £36 billion between 2010 and 2050 in [4] and up to £48 billion by 2050 in [5]. The potential reduction in these upgrade costs has been estimated as £20-25 billion using smart EV charging, HP control and voltage regulation in [4] and by 30-40% using smart planning and active network management techniques in [5].

There is a need for research into the hosting capacity of LV networks to reduce the uncertainty around the requirement for network reinforcement, particularly considering the combined effects of HPs and EVs [6] and the extent to which EV optimisation can reduce the impacts of HPs [7]. This paper makes an important contribution to assessing the adequacy of LV networks to meet the net zero challenge, by determining the hosting capacity of a set of existing LV networks for HPs and developing a methodology for optimising domestic EV charging and vehicle to grid (V2G) to maximise EV and HP penetration.

The methodology developed in this paper includes a novel heuristic for three-phase LV network congestion management which estimates network headroom based on both thermal and voltage limits. This heuristic provides a more scalable approach than centralised three-phase optimal power flow (OPF) which is the established approach to LV network congestion management in the literature [8, 9, 10]. Novel aspects of the proposed methodology are that the network headroom calculation is separated from EV charging optimisation which is decentralised across LV network 'zones'. These zones, defined as the combination of feeder and phase to which customers are connected, allow congestion management to be separated into multiple sub-problems which lend themselves to parallelisation thus offering improved solution speed over centralised approaches such as three-phase OPF.

1.1. *EV integration and V2G: literature and trials*

The increasing electrification of transport has lead to research into the potential for EV flexibility to reduce the need for costly network reinforcement, particularly at LV feeder level. Optimisation strategies to reduce cost and emissions have been proposed in [11] where it was found that 70% EV penetration could be accommodated with no voltage violations if the fleet were evenly balanced among phases. The addition of V2G to EV optimisation was studied in [12] where it was shown to provide cost and emissions reductions.

In [13] the EV hosting capacity of three LV networks from the north west of England was studied with distributed phase shifting control, and in one network the maximum EV hosting capacity was increased from 23% to 46% with the balancing of EVs across phases. While these results are valuable in providing indications of EV hosting capacity of LV networks for uncoordinated 'dumb' charging, they do not include results for optimised charging. Furthermore, as is the case in much of the literature, the work considers the effects of EVs alone; they do not consider the combined effect of HPs and EVs or any complementarity between EV optimisation (including V2G) and reducing peak power demands from HPs.

In the My Electric Avenue EV charging trial (2013-2015) [14], it was found through the monitoring of charging events of 215 Nissan Leaf EVs (24 kWh) that for dumb charging the After Diversity Maximum Demand (ADMD) could be increased from the currently used ADMD of 1 kW, up to 2 kW and that 32% of LV feeders across GB will require reinforcement if 40-70% of customers have 3.5 kW chargers. Given that most new domestic EV chargers are likely to be 7 kW[1], there is clearly a need for smart charging to reduce peak demands and network reinforcement costs. In Electric Nation [16], a more recent EV charging trial of 673 EVs with a mixture of 7 kW and 3.6 kW chargers and larger batteries, optimised charging using a time of use (TOU) tariff was successful in shifting the evening demand peak. However, a spike in demand was observed at 10pm due to synchronised response from multiple EVs to the beginning of the lower overnight electricity price. This highlights the need for smart charging to prevent synchronised actions from EV optimisation algorithms causing undesirable network stress events.

A 2019 public study on V2G found that V2G charging could generate significant revenues if located in a distribution network congestion management zone [17]. However, an important factor often overlooked is consideration of the combined effect of HPs and EVs on LV network congestion and the headroom available for EV charging and the provision of V2G. Battery degradation caused by V2G remains a subject of debate: while in [17] and [18] the cost to the consumer of degradation due to V2G cycling is estimated to be between 3.2 - 8.95 p/kWh, in [19] it is suggested that smart control algorithms could reduce battery degradation.

[1]In the UK, there is generally no difference in price between ‘slow’ (3.5 kW) and ‘fast’ (7 kW) home chargers. For example, the WallPod EV charger retails at £320 in the UK for either 3.6 or 7.2 kW configuration [15] – thus it is likely that 7 kW chargers will soon become the norm.

1.2. HP and EV integration: literature and trials

The literature covering the integration of HPs in LV networks can be broadly divided into works that model HPs as inflexible, and only controlled to provide the buildings heating requirements, and those that consider them as flexible and controllable in response to price or network capacity signals [20] while maintaining a required dwelling comfort temperature.

HPs as inflexible demand. One of the most comprehensive works on assessing the impacts of low carbon technologies (LCTs), including inflexible HPs, EVs and PV, on LV networks is reported in [21] and [22] where a Monte-Carlo approach was used to produce probabilities of thermal and voltage violations on models of 25 real LV networks in the North West of England [23]. The work in [21] and [22] is valuable in providing probabilistic estimates of the hosting capacity of real LV networks for LCTs when considered individually and this paper builds on these works by considering the combined effects of LCTs and the optimisation of EVs on a subset of five real LV networks models from [23].

Some analysis on the potential impacts of inflexible HPs and EVs on distribution networks has been carried out by UK distribution network operators (DNOs): in a report by UK Power Networks (UKPN) it was found that higher penetrations of HPs and EVs could increase network reinforcement requirements, particularly at LV feeder level [24]. In the aforementioned work, a limited HP data set (19 customers) was used to assess impacts, which does not allow for full assessment of diversity of demand from a large number of HPs. In a report by UKPN on the opportunities for optimisation of EVs and HPs [7], consideration is given to smart EV charging using TOU tariffs and the management of transformer power flows. This paper extends the work in [24] and [7] by including: a larger HP data set; voltage and thermal limits over the entire LV network; and vehicle-to-grid (V2G) from domestic EVs to mitigate the impacts of peak HP demand on LV networks.

Further studies on inflexible HP demand include [25] where HP demand profile analysis is carried out using 2-minutely metered HP data from 700 HPs.

The ADMD of the HPs was calculated to be 1.7 kW per site which occurs in the morning at around 8am and the GB peak demand is estimated to increase by 14% for 20% HP penetration. While the work in [25] provides useful insights into the aggregated effect of HPs on peak demand, the effect of HPs on LV networks is not studied. In [26], the Monte Carlo method was applied to assessing the impact of flexible EVs and inflexible HPs on a single LV feeder based on synthesised HP demand profiles and simplified EV modelling assumptions. A TOU tariff was applied to EV charging which did not remove voltage violations but shifted the period where voltage violations occurred. To resolve this issue, voltage management techniques are recommended in [26] in conjunction with the TOU tariff. This paper implements this recommendation by representing voltage and thermal limits with an active power 'headroom' which is used as an input to EV optimisation along with a TOU tariff.

In [6], an assessment of LV network capacity for coincident inflexible EV and inflexible HP demand is carried out and it is concluded that urban LV networks have a higher hosting capacity for such loads compared to suburban or rural networks where voltage and transformer load violations can occur even at low EV and HP penetrations. An impact assessment of inflexible HPs and PV using a Monte Carlo approach to modelling LV networks is carried out in [27] where again it was shown that rural feeders are more vulnerable to thermal overloads or under-voltage. In [28], dynamic load modelling of HPs (modelled as inflexible aside from the control of switching sequences) on a test distribution network is carried out and it was found that 37.5% HP penetration could be accommodated if the HPs were equally balanced and controlled to be switched on simultaneously on each of the three phases. This paper extends the above analysis of LV network hosting capacity of HPs and EVs by including the use of EV optimisation and V2G to increase hosting capacities without the requirement for reinforcement.

HPs as flexible demand. A comprehensive summary of the literature on HPs in the context of smart grids can be found in [29] where the fields of application are categorised as grid, renewable energy and price focused. Several papers include modelling of flexible HP operation: in response to price signals [30]; for peak shifting [31]; and for a combination of local voltage control and day-ahead scheduling to avoid peak demand periods [32]. Further examples of flexible HP operation in terms of demand response include: local optimisation of flexibility from HPs and residential battery storage in response to network capacity limits and price signals [33], and aggregated HP demand response to manage transmission level voltage [34].

Although HPs have the potential to provide flexibility, improvements to building insulation or heat storage are required for significant time shifting of thermal demand [26]. With the levels of insulation in existing UK housing stock, it has been shown that HP operating times could only be shifted within a 60-120 minute window without affecting the home-dwellers comfort, which would have limited effect on flattening the morning and evening HP demand pickups [20]. If combined with small-scale battery storage, there is significant potential for peak shaving of HP demand, for example, in [35] it was found that 100% HP penetration could be achieved without increasing the aggregated peak demand of 100 households if 3 kWh of battery storage was installed per household. In the future, with reduced costs of batteries and/or heat storage and improvements in building thermal efficiency, HPs could be a valuable source of flexibility. However, in [7] it is concluded that, based on modelling data from their HP trials, 'HPs are less suitable for smart optimisation', whereas, 'active control of EVs could have benefits for distribution networks'. Thus, in this paper HPs are considered as inflexible and instead the more accessible flexibility from domestic EV charging is optimised, including the use of V2G to reduce the peak demand from HPs.

1.3. Low voltage congestion management

In academic literature, a common solution to managing flexible assets to solve congestion in electricity distribution networks is the use of OPF. There are numerous examples of OPF being applied to distribution networks including [36] and [37], and more recently three-phase OPF has been developed [8, 9], including open source software that has the capability to model LV network constraints as part of multi-period market optimisation [10]. These methods can provide the optimal solution in terms of maximising the use of flexibility at LV, however they can be limited by their tractability in terms of the required computational power and time required to solve non-linear AC OPF formulations. This is especially the case when three-phase OPF, combined with a multi-period optimisation is applied to LV networks with thousands of nodes.

Cloud computing and advances in OPF approaches, such as linearisation and convex relaxations, could improve the tractability of three-phase multi-period OPF [38]. However, it's application conventionally relies on a centralised market where the network constraints are known to the market operator. In practice, the DNO may not be the market operator and it may be beneficial to separate the network modelling and market optimisation activities. The optimisation of flexibility could be carried out by a separate entity, in this paper the entity is assumed to be an 'aggregator'. As highlighted in the Electric Nation trial [16], it is important to provide at least a proxy of network constraints to the aggregator to prevent subsequent actions from causing network stress events. Such an approach is presented in [39], where three-phase OPF is applied to calculating a power 'margin', defined as the maximum power that can be drawn by HPs and EVs at their specific network location within voltage and thermal limits. In [39], the congestion management problem is separated into a two stage optimisation: firstly the power margin calculation is carried out by the DNO; and secondly the EV and HP flexibility optimisation is carried out by the aggregator. In this paper, a similar approach is used in separating the network modelling and EV flexibility optimisation activities, but the first optimisation stage in [39] is replaced with a heuristic zonal headroom calculation to represent 3-phase network constraints. This allows the aggregator optimisation to be parallelised by zone (a set of customers on a section of electrical network) which can significantly improve the tractability compared to a 3-phase OPF method.

1.4. Flexibility market principles

Existing flexibility market trading principles are reviewed in [40] where capacity based limitation services are recommended rather than baseline services which involve a flexibility provider making an adjustment from their baseline position. The method in this paper applies a capacity based headroom limitation to the aggregator which is based on maximising hosting capacity for HPs and EVs while respecting 3-phase LV thermal and voltage constraints. While this paper does not consider market mechanics in detail, a market structure could be developed where an aggregator is rewarded for respecting headroom constraints and in particular for delivering V2G when required. The Universal Smart Energy Framework (USEF) [41], provides a detailed flexibility market framework, which includes the application of congestion zones and congestion points. These mechanisms are predominantly being developed to manage constraints at higher voltages and there is less research in considering active constraint management at LV. This paper compliments the USEF framework by determining congestion zones on LV networks and providing a probabilistic headroom estimate in each zone for use in EV optimisation.

1.5. Contributions

This paper makes significant contributions in terms of assessing the adequacy of LV networks in the transition to net zero and in developing a methodology to optimise EV flexibility to maximise LV hosting capacity for HPs and EVs. Specifically this paper provides:

- a novel tractable 'zonal' approach to congestion management using offline network power flow results to produce probabilistic headroom estimates.
- an alternative to optimal power flow where network EV optimisation can be carried out respecting network constraints, but without a full network model.
- an analysis of HP hosting capacity on a set of representative low voltage

networks using HP demand data from a rich dataset of 700 HPs at 10-minutely timesteps over an 88 day winter period.

- an estimate of combined optimised EV and HP hosting capacity on a set of representative LV networks using EV flexibility to reduce peak demands from HP loads.

This paper estimates the levels of electrification of heat and transport, in terms of penetrations HPs and EVs, that can be achieved on a set of representative LV networks and then assesses the extent to which EV V2G can contribute to increasing LV network hosting capacity for HPs by injecting at times of peak HP demand. The remainder of the paper is as follows: Section 2 outlines the methodology used to assess HP capacity and optimise EVs; Section 3 outlines the HP penetration case studies and representative networks; Section 4 presents the results and discussion; and Section 5 contains conclusions and recommendations for future work.

2. Methodology

To assess the hosting capacity of LV networks for both HPs and EVs, firstly the thermal and voltage effects of HP demand were modelled using the OpenDSS load flow software [42] on a representative set of LV networks for a winter season. Energy demand for heating in winter can be up to five times that of the electricity demand of homes in the UK [43] and the biggest challenge associated with the electrification of heat is the peak demand increase during cold weather [44]. Therefore, a winter season has been selected to assess the hosting capacity of LV network for HPs and EVs during the 'worst case' period of maximum HP demand. In this work, HP demand is not considered to be flexible and historic HP demand data is used to determine limits for HPs-beyond which, thermal and voltage limits are exceeded.

The hosting capacity for EVs is then calculated by optimising EV charging around the headroom remaining once the maximum allowable HP capacity is connected. Reducing the HP penetration can potentially allow a larger penetration of EVs, therefore hosting capacity of EVs is also estimated for different HP penetrations.

The headroom calculation and EV optimisation are carried out by 'zone'– customer groups or sections of electrical network behind a 'pinch point' or network bottleneck. After initial load flow studies, it was found that the feeder head cable is often a pinch point in terms of thermal rating, and on the same feeder, phases should be treated separately due to differing customer numbers on each phase causing unbalanced phases [45]. Therefore, a zone is defined as a unique combination of feeder and phase, e.g., phase 1 feeder 3 is labelled zone 13.

The methodology can be split up into the following steps, each of which is carried out per zone in a set of representative LV networks:

1. HP headroom assessment: determine the maximum penetration of HPs allowable to respect LV network thermal and voltage limits along with the remaining headroom available for EV optimisation at different HP penetrations.

2. EV optimisation: EV charging is optimised using any remaining headroom for different HP penetrations.

3. Validate results: validation of EV charging schedule to check that voltages/currents are within network limits.

The subsequent sections provide more detail on each of the above steps including the associated inputs and expected outputs.

2.1. HP headroom assessment

The methodology for the HP headroom assessment, detailed in Algorithm 1, was to firstly assess the impacts of HP penetrations between 0 and 100% on five selected test networks using the OpenDSS load flow software. Measured smart meter (SM), solar PV and HP demand data is assigned to customers to create realistic demand and generation profiles for an 88 day winter period.

For the purposes of tractability in terms of network modelling time, while at the same time preserving HP data granularity, 10 minute timesteps have been chosen for both the network modelling and subsequent EV optimisation.

Algorithm 1 HP headroom Assessment

```
for each network, n, in 𝒩 do
    for each case, c, in 𝒞 do
        Assign SM, HP and PV profiles to customers based on % penetrations of HP and PV in each case.
        Run load flow for 88 winter days from 1st December 2013 to 26th February 2014.
    for each zone, z, in 𝒵 do
        Calculate P_z^Vlim from simple linear regression of P_{z,t} and V_{z,t}^min for the results of all cases.
        for each c in 𝒞 do
            Calculate headroom H_{z,t} for each timestep t using (1a)
            Calculate footroom F_{z,t} for each timestep t using (1b)
            Determine the 2^nd Percentile (P2) headroom and footroom profiles, H_{z,t}^(2) and F_{z,t}^(2).
        Set HP limit based on case with maximum HP penetration with positive total P2 headroom (∑_{t∈𝒯} H_{z,t}^(2))
        Return P2 headroom and footroom profiles for HP limit case, H_{z,t}^(2) and F_{z,t}^(2), for use in EV optimisation
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In Algorithm 1, $\mathcal{N}$ is a set of representative LV networks, $\mathcal{C}$ is a set of cases of HP penetrations (0-100%), $\mathcal{Z}$ is a set of LV network zones (unique combination of feeder and phase), $V_{z,t}^{\min}$ is the minimum voltage within zone z for each timestep t. $P_{z,t}$ is the apparent power flow into zone z and P_z^{Vlim} is the zonal apparent power flow limit to maintain the zonal minimum voltage above 225 V (0.94 p.u. based on a nominal voltage of 240 V)[2]. The zonal power

[2] The 225 V limit is conservative to allow a margin of error above the UK statutory minimum voltage of 216 V [46].

flow limit is estimated using linear regression of P_z, t and $V_{z,t}^{\min}$ for all cases. In zones where instances of $V_{z,t}^{\min} < 0.94$ p.u occur, P_z^{Vlim} is set as the minimum $P_{z,t}$ at which $V_{z,t}^{\min} = 0.94$ p.u. For example, using the apparent power flow vs minimum voltage plot in Figure 1, P_z^{Vlim} is set at 16.6 kVA.

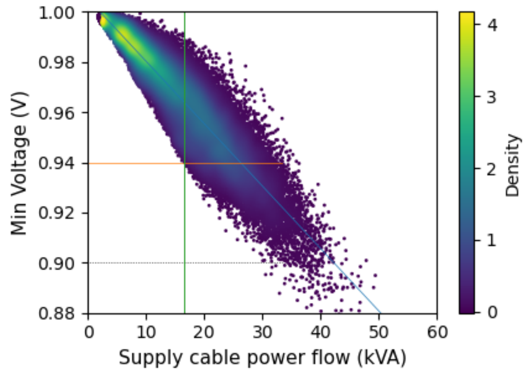

Figure 1: Apparent power flow vs minimum voltage for an example zone

Zonal headroom calculation. The headroom ($H_{z,t}$) and footroom ($F_{z,t}$) are calculated for every zone and timestep based on the power flow at the supply point for the zone $P_{z,t}$, and the lesser of the thermal or voltage power flow limits, $P_{z,t}^{\mathrm{Tlim}}$ and P_z^{Vlim}, respectively:

$$H_{z,t} = \min(P_{z.t}^{\mathrm{Tlim}}, P_z^{\mathrm{Vlim}}) - P_{z,t} \tag{1a}$$

$$F_{z,t} = \min(P_{z,t}^{\mathrm{Tlim}}, P_z^{\mathrm{Vlim}}) + P_{z,t} \tag{1b}$$

where $P_{z,t}^{\mathrm{Tlim}}$ is based on the thermal rating of the feeder head of each zone. In this work, footroom is the possible increase (or decrease) in injection (by V2G or PV) within export limits which is estimated from the power flow plus the rating[3]. For example, if the power flow is 10 kVA (import) and the power flow limit is 10 kVA, the headroom is 0 kVA and the footroom is 20 kVA; if the power

[3]For export constrained cases (e.g., high PV penetrations in summer months), a more accurate estimate of footroom could be obtained based on the maximum voltage constraint,

flow is -5 kVA (export) with a 10 kVA power flow limit, then the headroom is 15 kVA and the footroom is 5 kVA. Commonly at LV, cable ratings are provided in Amps, therefore these are converted into kVA ratings as follows:

$$P^{\mathrm{Tlim}}_{z,t} = \frac{I^{\mathrm{lim}}_z \times V_{z,t} \times V^{\mathrm{base}}}{\sqrt{3}} \times 0.9 \tag{2}$$

where $V_{z,t}$ is the voltage at the zone supply node (in p.u), V^{base} is the base voltage (416 V phase to phase is converted to phase to line voltage) and I^{lim}_z is the zone feeder head cable current rating. The 0.9 factor is a safety margin chosen to ensure sufficient headroom.

2.1.1. Zonal headroom outputs

Using the zonal headroom per timestep, $H_{z,t}$, the 2^{nd} percentile (P2) zonal headroom profile, $H^{(2)}_{z,t}$, is determined to provide a worst case assessment of network hosting capacity for each case of HP penetration. The P2 headroom profile ($H^{(2)}_{z,t}$) is passed to the EV optimisation to prevent actions by the EV aggregator (or entity carrying out the EV optimisation) from causing network thermal or voltage violations. Likewise, the P2 zonal footroom profile is also passed to the aggregator to set bounds on V2G injection to limit the potential for high voltage or thermal violations.

To assess the effectiveness of EV V2G in reducing thermal and voltage violations from HPs, cases are considered where at peak times HP penetrations cause negative headroom (i.e. cause thermal or voltage violations), as long as there is a net positive headroom over the entire day.

2.1.2. Zonal headroom inputs

Heat pump data. The HP profiles have been taken from the UK government Renewable Heat Premium Payment Scheme (RHPPS) [47] which contains 2-minutely data for 700 HPs between October 2013 and March 2015. The data

i.e., the export power flow limit corresponding to the UK statutory maximum voltage of 1.1 p.u for a nominal voltage of 230 V [46]. In this work, the network is import constrained and an approximation of footroom is adequate to limit V2G injections.

has been filtered to include ASHPs and ground source HPs (GSHPs) and to only include full datasets (HPs with data for >90% of timesteps) for 88 days of winter modelled from 1st December 2013 to 26th February 2014[4] which reduces the number of HPs to 106. Of the 106 HPs, 78 of them were ASHPs and 28 were GSHPs. Demand for space heating and water heating is combined and converted from Wh/2min into kW using (3). The HP data has been resampled from 2-minutely to 10-minutely timesteps by sampling the demand every 10 minutes.

$$P^{\mathrm{hp}} = \frac{E^{\mathrm{hp}} + E^{\mathrm{dhw}}}{1000} \times \frac{2}{60} \tag{3}$$

where P^{hp} - HP power demand (kW), E^{hp} - Energy for the HP unit (Wh/2min) and E^{dhw} - Energy for domestic hot water (Wh/2min).

In Figure 2, the HP profiles show the expected morning and early evening pick-ups at around 06:30 and 16:00. In this paper, EV charging will be optimised using the available headroom which will be limited during the morning and evening peak HP demand. An important question addressed in this paper is to what extent V2G can be used to reduce these peaks depending on the travel diaries of EV customers (detailed in section 4.3.3).

[4]The period of 1st of December to 26th February was chosen as it includes the days with the highest 10-minutely mean HP demand for the 106 HPs in the filtered HP data. HP data from winter 2014 was available but not used as the number of HPs will full datasets (HPs with data for >90% of timesteps) in winter 2014 was reduced to 67 and furthermore, the 10-minutely median and 95th percentile HP demand for the winter 2014 dataset was lower than for 2013.

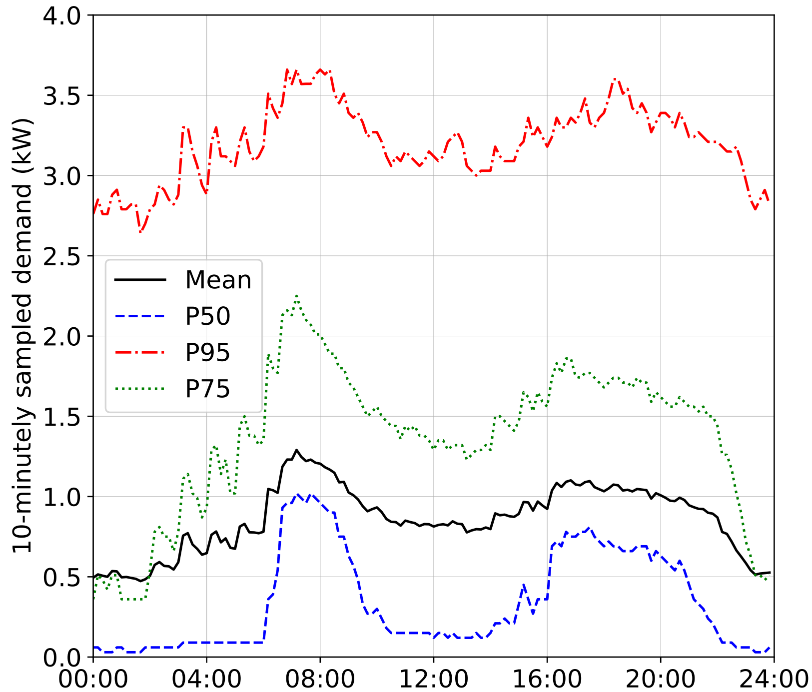

Figure 2: Mean, Median (P50), 75^{th} Percentile (P75) and 95^{th} Percentile (P95) demand for 106 HPs from 12th December 2013 to 26th February 2014; data: [47].

The mean winter demand estimated from the 10-minutely sampled data is 20.7 kWh/day which is significantly higher than the mean daily demand of 13.96 kWh/day for January 2014 reported in another UK HP trial [48] for ASHPs only. Within the 106 HPs used in this work there is a large variation in demand (both in power and energy). Figure 3 shows that the mean daily demand is over 45 kWh/day for four of the HPs which is more than double the average. Two of these HPs were domestic ASHPs with installed capacity of 16 kW, one was an ASHP with 12 kW capacity, and one was a GSHP with 12 kW installed capacity.

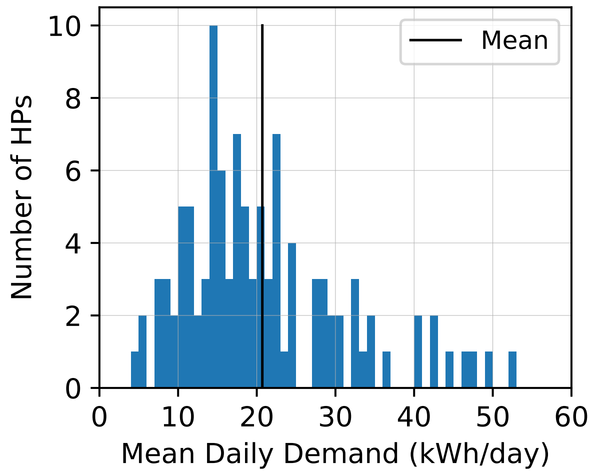

Figure 3: Histogram of mean daily HP demand; data: [47].

Smart meter data. A subset of SM data was taken from the Low Carbon London (LCL) Smart Meter data set [49] which contains half hourly data for 5,567 households between 2011 and 2014. The LCL SM data is classed by CACI Acorn Group [50] and 300 of each of the 'Adversity', 'Comfortable' and 'Affluent' profiles have been sampled which have full data-sets for the 88 days modelled in this work (1st Dec 2013 to 26th Feb 2014).

A minority of customers had a high overnight demand which is most likely overnight storage heating. Figure 4 shows that there is a large jump in demand at midnight for these customers, which suggests the action of a timer which is consistent with storage heater overnight operation with an Economy tariff [51]. These customers have been removed from the SM sample set to prevent heat demand being added twice when HP demand is added to the SM demand.

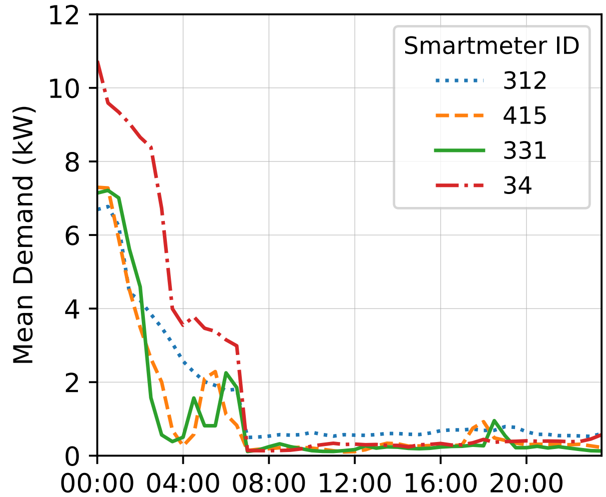

Figure 4: Mean SM demand of four customers with high overnight demand for winter period (1st Dec 2013 - 26th Feb 2014); data: [49].

With the high overnight demand customer profiles removed, in Figure 5, the mean of the remaining 300 customer profiles of each Acorn class for the winter period modelled are comparable to the 1997 Elexon winter weekday class 1 domestic electricity demand profiles from [52]. The Elexon class 2 profiles (also from [52]) are for customers with the Economy 7 tariffs (usually with storage heating) which display the same increase in demand after midnight as seen in the high overnight demand customers.

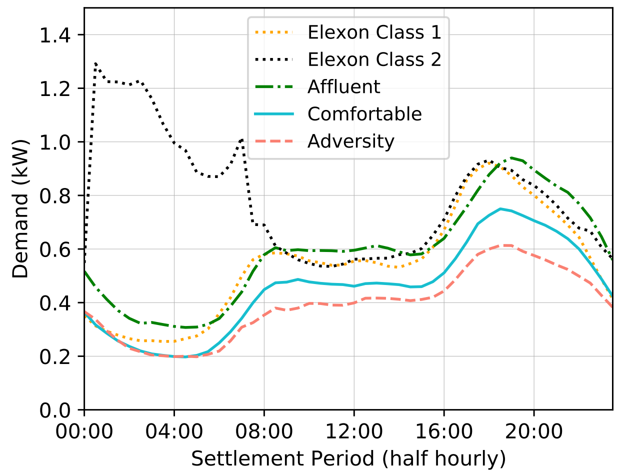

Figure 5: Mean SM demand of 300 customers of each Acorn Group for winter period (1st Dec 2013 - 26th Feb 2014) along with the Elexon winter weekday class 1 and 2 load profiles; data: [49, 52].

PV Data. Although the focus of this paper is on LV network hosting capacity for winter HP and EV demand, domestic PV generation is included as it is likely to increase in uptake in line with HPs and EVs and may positively impact on HP/EV hosting capacity [53].

The distribution of PV capacities has been calculated from domestic PV installations with feed in tariffs in the UK [54] as of December 2019. The resulting histogram of PV capacity for 1000 customers sampled using this distribution is shown in Figure 6.

PV output profiles are created from London Datastore metered PV data [55]. For the 88 days modelled, 4 of the 6 PV sites had a sufficiently complete set of data over this period, the daily PV output profiles for these 4 sites are shown in Figure 7. The PV data was resampled from hourly to 10-minutely resolution using linear interpolation and normalised by dividing the output by the stated capacity from [55]. The capacities of Alverston Close, Bancroft Close, Maple Drive East, YMCA are 3, 3.5, 4, 0.45 kW respectively.

These normalised profiles were then assigned randomly to PV customers and capacities were assigned according to distribution in Figure 6.

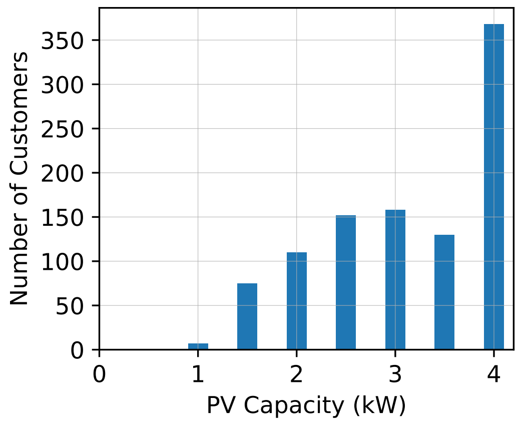

Figure 6: Histogram of PV capacities from domestic PV installations with feed in tariff; data:[54].

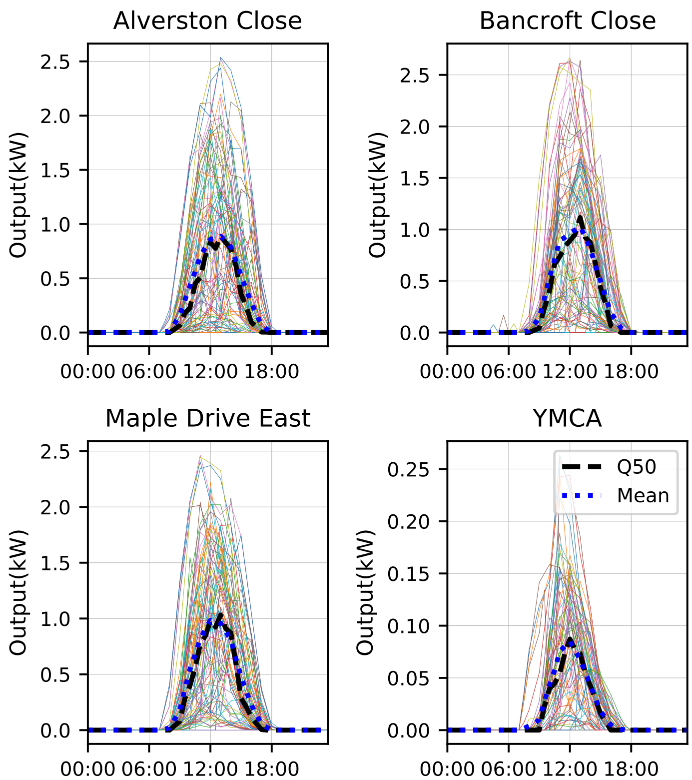

Figure 7: Daily PV profiles for four PV sites with median and mean output for 88 days from 1st Dec 2013 to 26th Feb 2014; data: [55].

2.2. EV capacity assessment

The methodology for EV capacity assessment, summarised in Algorithm 2, involves firstly estimating EV numbers based on available headroom, then optimising the charging of the EVs using charging schedules derived from real travel diary data [56]. The optimisation is repeated 10 times[5] for random samples of EV schedules and the number of EVs is reduced until the EVs can all charge within the available headroom. The resulting optimised charging profiles for

[5]The repetition of 10 times was chosen to ensure EV charging demand is satisfied for a wide range of EV schedules.

each customer are then validated on the LV networks using load flow to ensure voltage and thermal limits are not exceeded.

Algorithm 2 EV capacity assessment

for each n in $\mathcal{N}$ **do**
  for each z in Z **do**
    Estimate number of EVs, n^{EV}, per zone based on total daily P2 headroom divided by 95^{th} Percentile (P95) EV charge requirement.
    while Optimisation Result = Fail **do**
      for $i \in \mathbb{R}, 0 < i \leq 10$ **do**
        Optimise EV charging for random sample of n^{EV} charging schedules.
        if All EV's cannot be charged within P2 headroom **then**
          Optimisation Result = Fail
          $n^{\mathrm{EV}} = n^{\mathrm{EV}} - 1$
  Validate EV charge profiles (for entire network) using OpenDSS load flow to verify voltages and currents are within limits (including HP, SM and PV input data).

2.2.1. EV charging schedules

EV charging schedules are derived using a heuristic methodology described in [57, 58] from National Travel Survey (NTS) car-based travel diaries – making up a dataset of over 3,000,000 trips recorded in Britain between 2002 and 2016 [56]. Travel diaries for each participant are recorded over the course of a week, but the timing of that week is randomly distributed throughout the year. In synthesising the car-based travel diaries for this work (Table 1), all travel diaries were synchronised such that they start on Monday and finish on Sunday. While there are considerable seasonal effects in driving habits (such as weather conditions affecting vehicle energy consumption and the effect of holidays disrupting ordinary commuting patterns), these are not made explicit in the data, nor is the time of year at which each travel diary was recorded. It is clear from analysis of GB energy vectors that intra-seasonal variation in transport fuel demand is minimal, compared to significant variation in gas demand for heating [59]. Charging schedules were synthesised according to the assumption that –

Table 1: Daily routine charging schedule for a subset of 5 EVs

EV ID	Window	Plug-in	Plug-out [1]	$\mathrm{SoC}^{\mathrm{S}}$ (kWh)	$\mathrm{SoC}^{\mathrm{F}}$ (kWh)
5694	1	2140	1150	59.3	60.0
8669	1	1540	1150	4.8	30.0
9602	1	1540	1700	58.5	60.0
9602	2	1710	0730	59.3	60.0
9602	3	1020	1150	51.9	56.5
1931	1	1740	0620	39.5	75.0
1417	1	1830	1150	23.9	30.0

[1] Plug-out times before midday are the following morning (optimisation is carried out for 24 hours from midday to midday the following day).

as charging at home is seen to carry negligible inconvenience – drivers will plug in whenever they arrive home and will seek the maximum gain in SoC allowed by the parking duration, battery capacity and charging power. The energy requirement for each charge event is a function of the EV's travel diary and other charge events that they have undertaken.

For this study, a bank of 10,000 charging schedules (derived from 10,000 car-based NTS travel diaries) is randomly sampled from; these have a range of common battery sizes (24, 30, 40, 60 and 75 kWh) and 7.4 kW chargers. For more information on how the heuristic works, the reader is directed to [57, 58]. A subset of 5 travel diaries is shown in Table 1 for a single day from midday-midday where $\mathrm{SoC}^{\mathrm{S}}$ is the initial SoC at plug-in time and $\mathrm{SoC}^{\mathrm{F}}$ is the final SoC at plug-out time. EV 9602 has 3 charging 'windows' over which the EV is plugged in within the 24h optimisation period.

95^{th} percentile EV charging requirement. The charge requirement for the 95^{th} percentile of daily EV demands is used to make a first estimate of zonal EV

hosting capacity based on daily headroom.

The 10,000 EV charge diaries were randomly sampled 1000 times in sets of 10 EVs with the average daily demand calculated for the 10 EVs each time. The resulting histogram of average daily EV charge, Figure 8, shows an average of 8.9 kWh/day for a set of 10 EVs with a 95^{th} percentile of 14.2 kWh/day. For comparison, the previously mentioned Electric Nation trial recorded an average daily charge of 25-35 miles' worth of range [16]. At a typical EV fuel economy of 15-20 kWh/100 km [60], this equates to an average energy usage of 6-11 kWh per day. The P95 figure is used to ensure that the EV optimisation is successful for 95% of possible EV samples sets if sufficient headroom is available for the duration that EVs are plugged in.

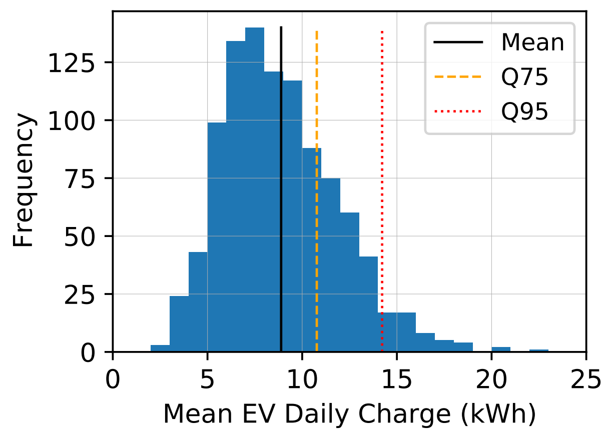

Figure 8: Histogram of Mean Daily EV charge for sets of 10 EVs.

2.2.2. EV optimisation

The objective function of the EV optimisation is to minimise the cost of charging the EV fleet within the headroom available:

$$\min \sum_{t \in T} \left(c_t^G p_t^G \right) \tag{4}$$

where c_t^G is the grid cost of charging in £/kWh at timestep t and p_t^G is the total energy requirement of all EVs in kWh at timestep t. Subject to the following constraints:

Total EV energy requirement.

$$p_t^G = \sum_{e \in \mathcal{E}} \left(p_{e,t}^C - p_{e,t}^D \right) \tag{5}$$

where $p_{e,t}^C$ and $p_{e,t}^D$ are the charge and discharge for an EV e during time t.

Zonal headroom and footroom constraints.

$$-F_{z,t}^{(2)} \leq p_t^G \leq H_{z,t}^{(2)} \tag{6}$$

where $H_{z,t}^{(2)}$ and $F_{z,t}^{(2)}$ are the P2 headroom and footroom in zone z for time t calculated in the HP capacity assessment.

EV SoC constraint.

$$SoC_{e,t,w} = \eta p_{e,t}^C - \frac{1}{\eta} p_{e,t}^D + SoC_{e,t-1,w} \tag{7}$$

where $SoC_{e,t,w}$ is the SoC of the EV e at timestep t in charging window w, respectively. The SoC is the product of the state of the charge in the previous timestep $SoC_{e,t-1,w}$ and any charge/discharge, $p_{e,t}^C$ / $p_{e,t}^D$, during that timestep. η is the charging/discharging efficiency which is assumed to be 0.88 as in [58] and the same for both charging and discharging as in [18].

EV final and initial SoC constraints.

$$SoC_{e,t_s,w} = \mathrm{SoC}_{e,w}^S \tag{8a}$$

$$SoC_{e,t_f,w} = \mathrm{SoC}_{e,w}^F \tag{8b}$$

where $SoC_{e,t_f,w}$ is the SoC of EV e at the final timestep, $t = t_f$, for charging window w which must equal the required final SoC, $SoC_{e,w}^F$, specified in the EV travel diaries. Likewise, $SoC_{e,t_s,w}$ is the SoC of EV e at the first timestep, $t = t_s$, for charging window w which must equal the required initial SoC, $SoC_{e,w}^S$, specified in the EV travel diaries.

Maximum charge power constraint.

$$p_{e,t}^{C} \leq \begin{cases} p_e^{\max}, & SoC_{e,t,w} \leq \gamma_e \\ \left(\dfrac{1 - SoC_{e,t,w}}{1-\gamma_e}\right) p_e^{\max}, & SoC_{e,t,w} > \gamma_e \end{cases} \tag{9}$$

where $p_e^{\max}$ is the charger capacity for EV e and γ_e is 0.8 to represent the constant-current constant-voltage charging power profile typical of EV charging [61].

Maximum discharge power constraint.

$$p_{e,t}^{D} <= p_e^{\max} \tag{10}$$

The optimisation formulation can be written as a Linear Programming (LP) problem that is solved using the cplex [62] solver within OATS [63] optimisation software.

Grid charging price. The grid charging price (c_t^G) includes distribution network related components of the electricity price including the distribution use of system (DUoS) price for LV network domestic customers for 2019/2020 from [64]. The DUoS price has been modified to include a morning 'red time band' (the most expensive time period for the DUoS charge), from 06:00 to 08:30 to account for the morning peak HP demand. An example grid price profile is shown in Figure 9, which also includes a constant battery degradation cost of 3.2 p/kWh from [17] and a V2G price which is set at 17.5 p/kWh based on the utilisation cost of flexibility (secure service) in Western Power Distribution 'Flexible Power' trial [65]. The V2G price is only applied during periods of negative headroom calculated in the HP headroom assessment, $H_{z,t}^{(2)}$, which in the example shown in Figure 9 occurs from 17:00-18:00 and 07:00-08:00. The main purpose of V2G in this work is to reduce thermal and voltage issues caused by peak power demand from HPs, which is indicated by the negative headroom.

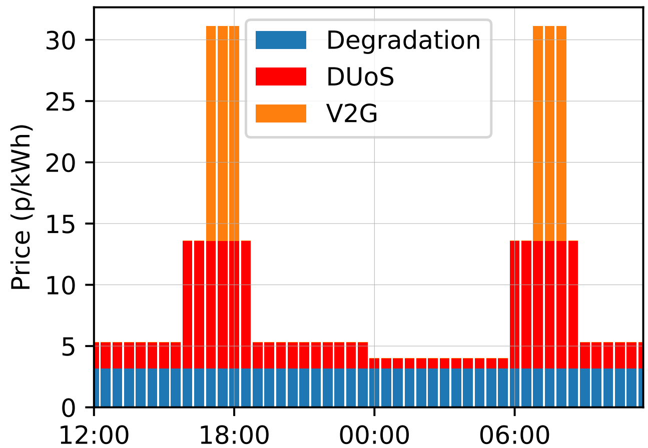

Figure 9: Example grid price profile; data: [64, 17, 65]

The purpose of including a constant battery degradation price is to prevent the EV optimisation (formulated in (4)-(10))[6] from carrying out V2G at any other time than the highest DUoS price and/or periods of V2G request. Without the battery degradation cost, the EV optimisation carries out V2G during periods of the mid-range DUoS price (2.1p/kWh) as it can cost effectively make up this lost charge by charging during periods of the lowest DUoS price (0.8 p/kWh) despite round trip efficiency losses of 22.6%. Given that the cost of battery degradation from providing V2G has been estimated as 3.2 - 8.95 p/kWh [18], V2G should not be carried out for such a small price margin and the inclusion of the battery degradation cost prevents this from happening.

[6]The objective of the EV optimisation is to minimise the cost of charging a fleet of EVs and it is not aimed at estimating real-world costs to consumers for charging individual EVs or providing V2G. The same price is assumed to be paid for export or import to the grid: in practice this would be unlikely to be the case, however, the symmetric price is adequate for minimising EV charging during times of peak HP demand and encouraging V2G dispatch when negative headroom occurs.

3. Case Studies

Case studies are carried out on representative LV networks to assess HP hosting capacity and EV optimisation using the remaining headroom. On each network the following cases are run:

1. 0% HP penetration. 0% PV penetration.
2. 25% HP penetration. 0% PV penetration.
3. 50% HP penetration. 25% PV penetration.
4. 75% HP penetration. 25% PV penetration.
5. 100% HP penetration. 50% PV penetration.

The LV networks utilised in this work are taken from the Low Voltage Network Solutions (LVNS) project [23] which published the largest set of publicly available validated LV network models available in the UK. The LVNS models are of areas in the North West of England and are representative of a range of operational network topologies observed by network operators.

There are 25 LVNS network models with a total of 7539 customers (also referred to as loads) and 128 feeders. The histogram of customer numbers per zone (unique feeder and phase combination), Figure 10, shows that 75% of zones have fewer than 26 customers, the median number of customers per zone is 13.5, and 5% of zones have more than 54 customers.

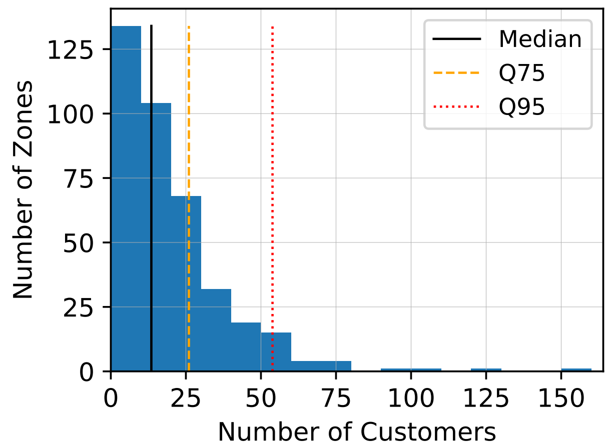

Figure 10: Histogram of number of customers per zone of 128 LVNS feeders; data: [23].

In this work, a subset of five networks has been selected to represent the range of customer numbers per zone in the 25 LVNS networks as customer number is a significant factor in LCT hosting capacity [21]. The subset of five networks (with a total of 34 feeders) are summarised in Table 2 including key network parameters which influence network loading and LCT hosting capacity.

Table 2: Summary of subset of representative LVNS networks selected for modelling

Network	Total loads	Total zones	Median loads/zone	Max loads/zone	Transformer rating (kVA)
Network 1	200	12	14.5	28	750
Network 5	335	24	9.5	55	500
Network 10	64	18	3	8	1000
Network 17	883	21	41	78	1000
Network 18	328	27	11	23	750

These networks can be generalised and related to other LV networks by comparing key network parameters, particularly the number of customers (loads), customers per zone, and the transformer rating. The chosen networks provide a wide range of customer numbers and customers per zone and are aimed at covering the extremes of network LCT hosting capacity for the models available. Further detail on the reasoning behind selecting the subset of five networks is outlined in the following.

Network 1 (Figure 11) has a median customer number per zone close to the median of all LVNS feeders (13.5 customers per zone). However, there is a significant difference in customer numbers between zones and two zones have >26 customers putting them in the highest 25% of customer numbers for all LVNS zones.

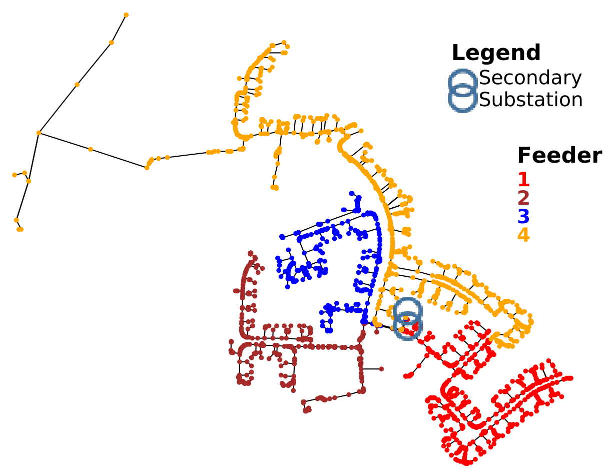

Figure 11: LVNS Network 1

Network 5 (Figure 12) displays extreme variation between zones: 18 of 24 zones have less customers than the LVNS median but three zones have more than 40 customers putting them in highest 10% of zones in the LVNS networks in terms of customer number.

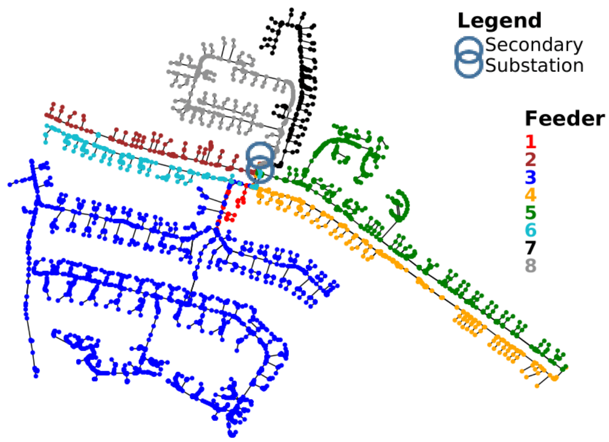

Figure 12: LVNS Network 5

Network 10 (Figure 13) has a small number of customers (64) and is not expected to have any issues with hosting 100% LCTs. In [21], 50% of feeders did not display any issues for up to 100% LCTs and the zones in network 10 all have customer numbers in the lowest 25% of LVNS zones.

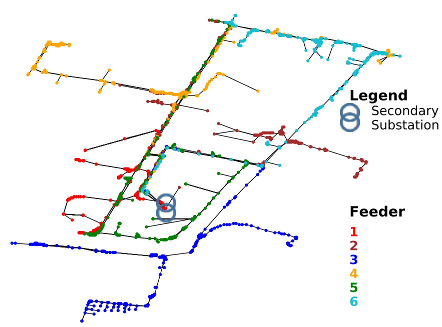

Figure 13: LVNS Network 10

Network 17 (Figure 14) has the most customers of all the LVNS networks (883) and 16 zones have above 26 customers (the 75^{th} percentile of customer number in all LVNS zones) and 5 zones have customer numbers in the highest 5% of all the LVNS feeders. This network is expected to have the lowest hosting capacity for HPs and EVs of all those modelled.

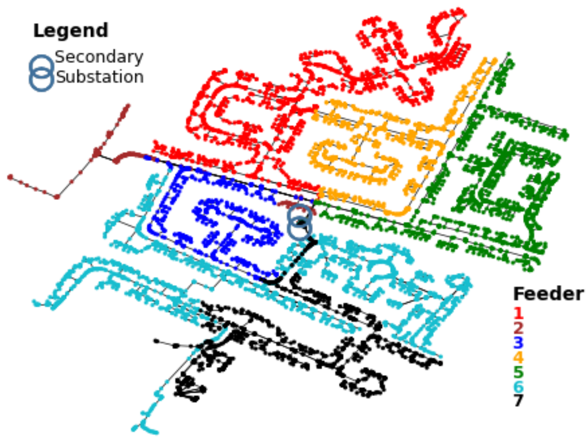

Figure 14: LVNS Network 17

Network 18 (Figure 15) is an example of a network with an average total number of customers (328 compared to the mean of 302 for all LVNS networks) spread fairly evenly across 9 feeders. The median number of loads per zone is lower than the median of all LVNS networks and all zones in network 18 have customer numbers in the lowest 25% of all LVNS networks.

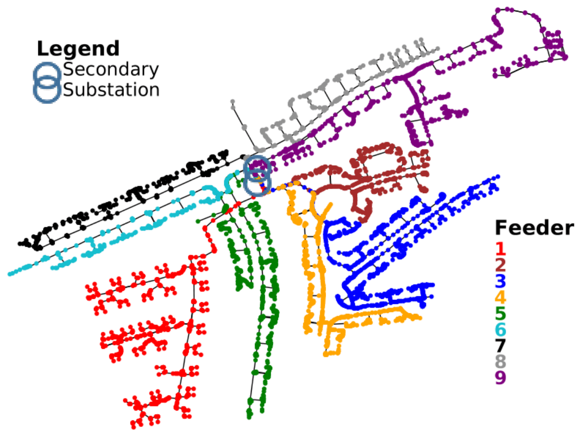

Figure 15: LVNS Network 18

The LVNS OpenDSS networks supplied by [23] are produced from GIS data and often have a large number of redundant branches and nodes that do not enhance electrical representation of the network. In this paper, condensed network models are used from [66] which have been validated as producing results for voltage with a relative error of no more than 3×10^{-11} . Each network is modelled from a 11/0.416 kV secondary transformer with thermal ratings shown in Table 2. The voltage source is set at 1 p.u. and the three phase and single phase short circuit currents (ISC3 and ISC1) are set at the LVNS network default values of 3000 A and 2500 A respectively. SM and HP loads are modelled as having a 0.95 power factor (lagging)[7] and PV generators have a unity power factor. EV charging is modelled as having a 0.98 power factor (lagging) which was found to be the typical EV charging power factor in a trial of 221 residential EVs [68].

[7]HPs could have a power factor lower than 0.95 due to the effect of a booster heating switch [67], however, as HP power factor and reactive power data was unavailable, HPs are assumed to have a power factor of 0.95.

4. Results and Discussion

The hosting capacity for HPs and EVs on five LV networks have been estimated based on the HP headroom assessment and EV optimisation methodologies for 88 days of winter 2013. Results are presented for the following cases: HPs in the absence of EVs, HPs and EVs with dumb charging, and finally HPs and EVs with optimised charging.

4.1. Heat pump hosting capacity

In this work, hosting capacity is determined by the maximum penetration (from the cases modelled), that can be accommodated before voltage and thermal violations occur. Results of low voltage and current violations, along with HP hosting capacity are firstly presented in the absence of EVs. This provides an insight into the requirement for network upgrades to achieve high penetrations of HPs, the headroom available for EVs and the opportunity for V2G to reduce the requirement for network upgrades.

Low voltage violations:. Low voltage violations with customer number for 100% HP penetration are presented for all networks (except network 10)[8] in Figure 16. For zones with customer numbers below 21, there were very few instances of low voltage problems for any penetration of HPs. For 50%, 75% and 100% HP penetrations, the maximum % of timesteps with low voltage observed in any zone with fewer than 21 customers was 0.02%, 0.48% and 1.28% respectively. For reference, a zone with 21 customers is equivalent to a balanced feeder with 63 customers, however as most of the 128 LVNS feeders are not balanced, it is useful to consider hosting capacity by zone rather than feeder.

[8]Network 10 is omitted as no low voltage issues occurred at any HP penetration due to network 10 having fewer than 8 customers in any zone.

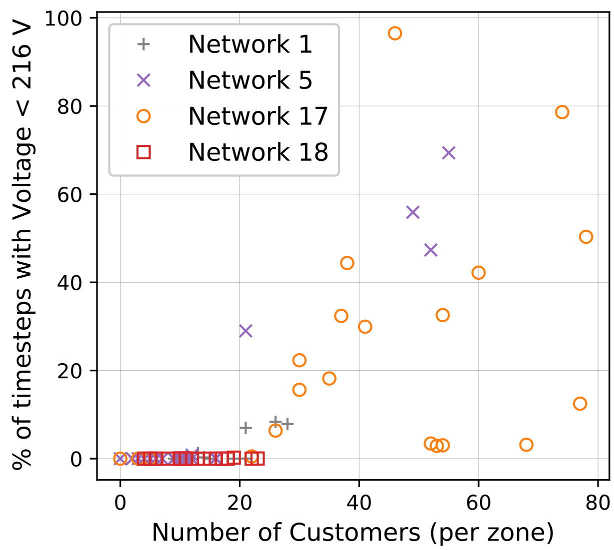

Figure 16: Low voltage (<216 V) frequency (as % of 12,673 timesteps) for winter 2013 per zone for all networks (network 10 has been omitted as no violations occurred) against customer number for 100% HP penetration.

Beyond 21 customers, low voltage problems become more prevalent for 25% HP penetrations and upwards, generally increasing in frequency with increasing customer number and HP penetration (see Figure 17). For 0% HPs, with SM demand only, there were four zones which encountered voltage problems, three in network 17 and one in network 5. These zones had 0.02%, 0.02%, 0.12% and 22.4% of timesteps with low voltage violations corresponding to customer numbers of 35, 55, 74 and 46 respectively.

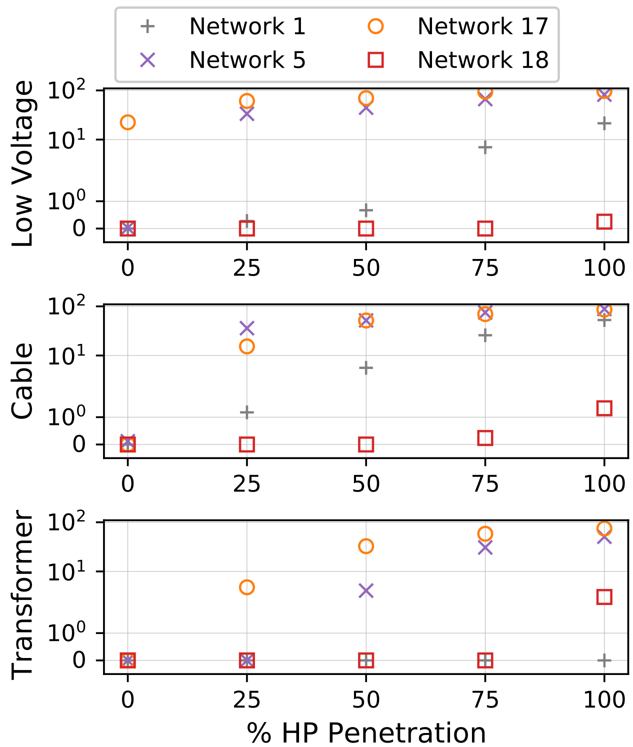

Figure 17: Low voltage, cable and transformer thermal violations (as % of 12,673 timesteps) with HP penetration for each network (network 10 has been omitted as no violations occurred for any HP penetration). In each plot, the y-axis is a symmetric log scale which is linear between 0 and 1 (to allow values of zero and close to zero to be plotted).

The relationship between customer number and low voltage violation percentage is not linear, and in the case of 0% HPs, the zone with the most violations (22.4% of timesteps) does not have the largest number of customers. Customer number alone can only provide a crude prediction of the likelihood of low voltage violations, namely a low likelihood below 21 customers and higher likelihood above 21 customers.

Thermal violations. Figure 18 shows that, as with voltage problems, instances of cable overcurrent were seen in zones with 21 customers and above. Furthermore, it was found that the cable thermal overloads were more probable than the transformer rating being exceeded for all networks. Figure 17 shows that for 25%

HP penetration and below, the transformer limit is exceeded only for network 17. At 50% HP penetration and above, the transformer limits become more of a bottleneck for networks 5, 17 and to a lesser extent network 18.

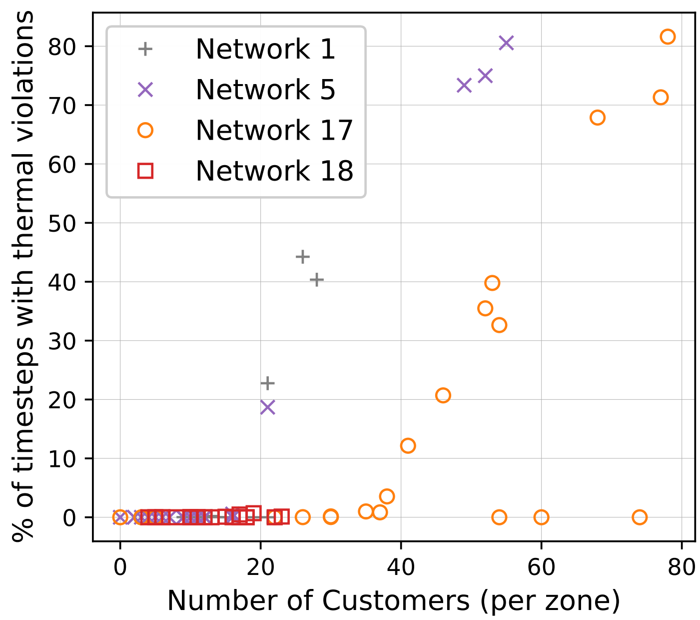

Figure 18: Cable thermal violations (as % of 12,673 timesteps) for winter 2013 per zone for all networks (network 10 has been omitted as no violations occurred for any HP penetration) against customer number for 100% HP penetration .

Overcurrent issues were observed most frequently for lines with ratings below 400 A. In [24], a 400 A current limit has been assumed for all lines, due to an assumed 400 A LV feeder fuse rating and in [21] thermal loading was only considered for the head of the feeder. In this work, ratings are assigned to all cables using cable data from [69] and linecodes from the LVNS OpenDSS model data. Intuitively, the most commonly overloaded lines are the feeder head cables, and on this basis the feeder head were classed as 'pinch points' which were used to calculate headroom (along with the voltage power flow limits) for use in the EV optimisation.

HP Hosting Capacity. In terms of overall network hosting capacity for HPs, in the five LV networks modelled, 24.2% HP penetration can be achieved before any thermal or voltage violations occur (see Table 3). If voltage or thermal violations were acceptable for up to 0.5% of timesteps then this figure would be increased to 27.1%. It is important to note that these figures are based on modelling of HP penetrations in increments of 25% (as per the cases modelled). The HP capacity estimates in this work are conservative and to gain a more accurate estimate, smaller increments of HP penetrations could be modelled. For example, in the case of network 17, transformer thermal violations occurred in 4.8% of timesteps at 25% HPs, which reduced the HP hosting capacity to 0%, however the maximum penetration of HPs in network 17 would be between 0 and 25%.

As previously highlighted, the capacity in an individual zone is affected by the number of customers, and networks with predominantly fewer than 21 loads per zone, in this example networks 10 and 18, can host 100% and 68.9% HPs respectively. However, networks 1,5 and particularly 17, have zones with larger numbers of customers per zone, and especially in the case of network 17, this severely restricts the possible penetration of HPs.

Table 3: Hosting capacity for HPs with zero tolerance of voltage and thermal violations and tolerance of up to 0.5% of timesteps (in brackets). Based on modelling of 25% increments of HP penetration.

Network	HPs	%	Total Customers
Network 1	107 (133)	53.5 (66.5)	200
Network 5	42 (59)	12.5 (17.6)	335
Network 10	64 (64)	100 (100)	64
Network 17	0 (0)	0 (0)	883
Network 18	226 (235)	68.9 (71.6)	328
Total	439 (491)	24.2 (27.1)	1810

Network Upgrade Requirement. For the 34 feeders studied, 75% of the network zones have 21 customers or less (see Figure 19) and of the 128 LVNS feeders, 66% of zones fewer than 21 customers. In practice, upgrades will be required at feeder level, rather than on an individual phase, and 55% of LVNS feeders have a maximum of 21 customers in any zone, which indicates that the majority of LVNS feeders would not require upgrade for up to 100% HP capacity.

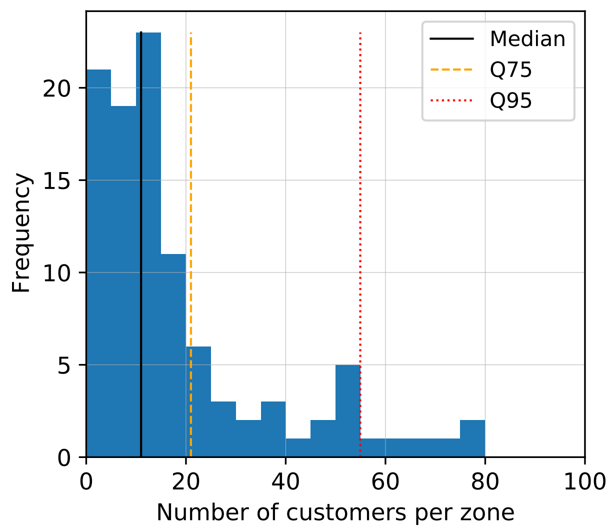

Figure 19: Customers by zone for the five networks with 34 feeders and 102 zones (each feeder has 3 zones)

4.2. Heat pump and dumb EV charging hosting capacity

To provide a baseline for comparing the performance of the headroom and optimised EV charging methodology, results are included for dumb EV charging for each network at different penetrations of HP and EV. As in the HP case, hosting capacity is determined from the maximum penetrations (from those modelled) of EV and HP without thermal or voltage violations.

Dumb EV charge profiles. The dumb EV charging profiles have been calculated from the same travel dairies used in the EV optimisation, using (9) and assuming EVs charge at full power ($p^c_{e,t}$) from the moment they are plugged in until they are fully charged. Using this method, 10,000 daily EV charging profiles were produced, from which a unique profile was used for every EV and every day simulated to capture diversity of charging behaviour. The median and mean of the 10,000 profiles (see Figure 20) show that the peak charge demand occurs around 6:40pm and there is a significant overlap of the period of the highest mean EV charge and evening HP demand (see Figure 2), between 4pm and 9pm. The larger morning HP demand peak does not coincide with significant EV demand, however thermal and voltage violations will be likely to occur during the evening peak.

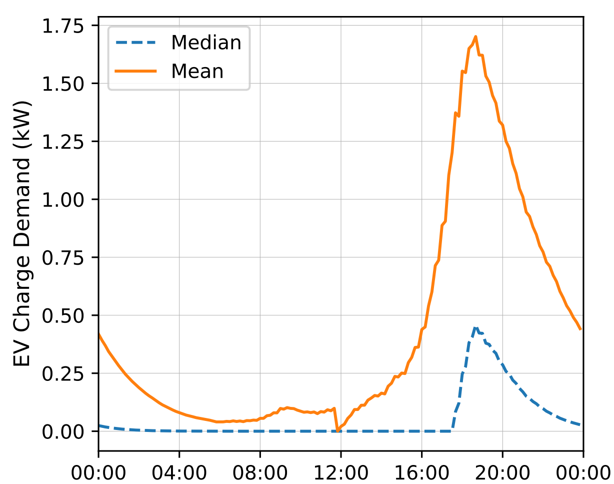

Figure 20: Median and mean daily EV dumb charging profiles from 10,000 daily travel diaries

Voltage and Thermal violations. Using the dumb charging profiles, voltage and thermal impacts were assessed for HP penetrations of 0-50% in 25% increments and EV penetrations from 0-40% in 10% increments for December 2013 which corresponds to 4321 10-minute timesteps.

With the addition of EVs, thermal violations become more frequent and cable thermal violations occur on all networks (except network 10) beyond 30% EVs for 25% HPs (see Figure 21). Network 17 is unable to accommodate even 20% EVs without the transformer being overloaded with 0% HPs and similarly transformer violations occur with 20% EVs at 0% HPs on network 5.

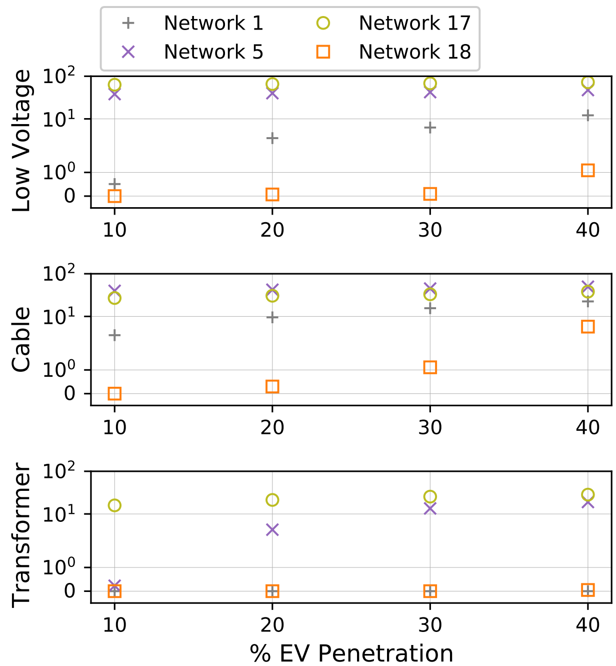

Figure 21: Low voltage, thermal cable and transformer violations (as % of 4,321 timesteps) with EV penetration at 25% HP penetration for each network (network 10 has been omitted as no violations occurred for these HP and EV penetrations). In each plot, the y-axis is a symmetric log scale which is linear between 0 and 1 (to allow values of zero and close to zero to be plotted).

Low voltage violations become slightly more frequent below 21 customers per zone for 25% HPs with 40% EVs (see Figure 22) compared to 100% HPs and no EVs (see Figure 16). This is the case in all networks except network 10, which has no voltage issues at any HP or EV penetration due to having fewer than 8 customers in any zone.

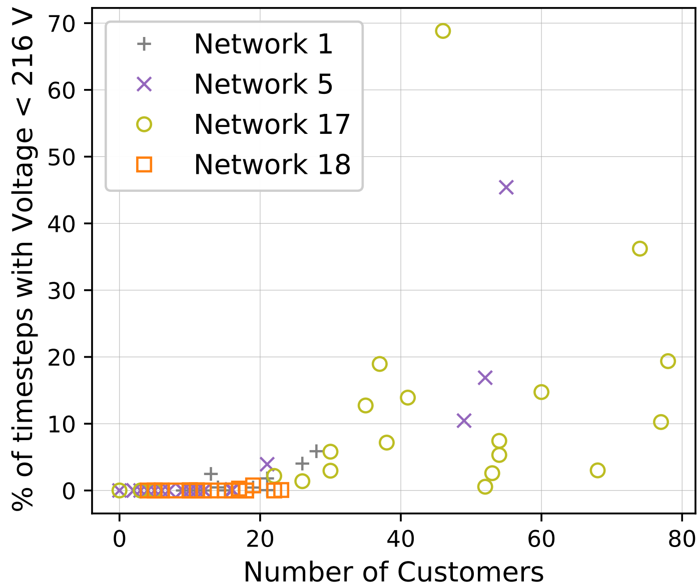

Figure 22: 25% HP and 40% EV penetration (dumb charging) - Low voltage (<216 V) (as % of 4321 timesteps) for December 2013 per zone for all networks (network 10 has been omitted as no violations occurred for these HP and EV penetrations) against customer number.

Overcurrent becomes more prevalent than low voltage below 21 customers per zone with the addition of EVs and in the case of 25% HPs and 40% EVs (see Figure 23), overcurrent increases close to linearly with increasing customer number, particularly steeply for network 1 from 13 customers.

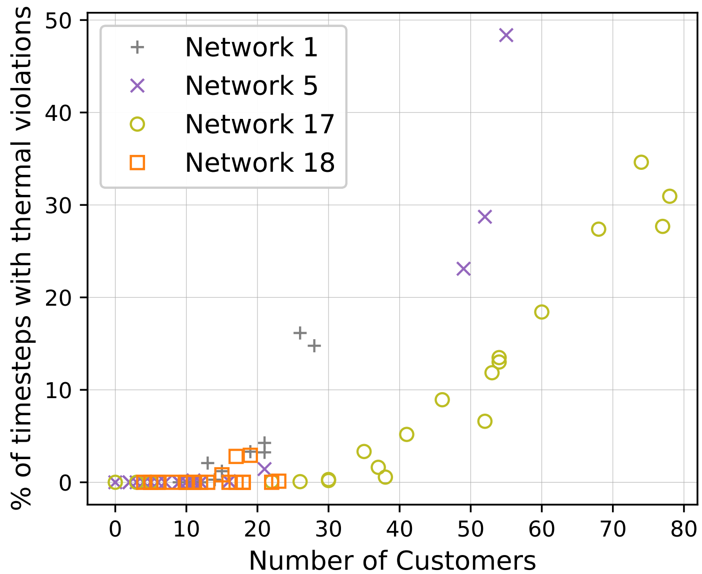

Figure 23: 25% HP and 40% EV penetration (dumb charging) - Cable thermal violations (as % of 4321 timesteps) for December 2013 per zone for all networks against customer number.

HP and dumb EV hosting capacity. The estimated hosting capacity for HPs and EVs with dumb charging is shown in Table 4. HP penetrations above 50% were only modelled for network 10 as in the other networks the EV hosting capacity was below 33.5% at 50% HP penetration and there was little extra benefit to modelling up to 100% HP penetration.

Table 4: Hosting capacity for EVs with dumb charging at different HP penetrations with zero tolerance of voltage, 0.5% tolerance of cable current and 0.5% tolerance of transformer thermal violations[1] (as a % of timesteps). Based on modelling of 25% increments of HP penetration and 10% increments of EV penetration over 4321 10-minute timesteps of December 2013.

Network	0% HP	25% HP	50% HP	75% HP	100% HP	Total
1	62 (31%)	43 (21.5%)	31 (15.5%)	n/a	n/a	200
5	43 (12.8%)	25 (7.5%)	0 (0%)	n/a	n/a	335
10	64 (100%)	64 (100%)	64 (100%)	64 (100%)	64 (100%)	64
17	56 (6.3%)	0 (0%)	0 (0%)	n/a	n/a	883
18	157 (47.9%)	152 (46.3%)	110 (33.5%)	n/a	n/a	328
Total	382 (21.1%)	284 (15.7%)	205 (11.3%)			1810

[1] It is assumed thermal violations are acceptable in <0.5% of timesteps without causing damage to cables and transformers, however, voltage violations are not tolerated due to the minimum voltage of 216 V being a statutory requirement [70].

The limiting factor in EV penetration in most cases is either cable current or transformer overloads. The EV hosting capacity within network 18 is limited by cable overloads beyond 30% EV penetration at 25% HPs (see Figure 21) due to the large evening peak caused by dumb charging. Network 18 was able to host a high percentage of HPs without EVs (68.9%), however it can only host 47.9% EVs without HPs. Network 17 has transformer overloads with even 20% EV penetration and 0% HP penetration. Note: 20% penetration in network 17 equates to 176 customers which is more than double the total number of customers in network 10, hence why network 17 would need upgrading for even low HP and EV penetrations (and EV optimisation would not be able to change this significantly).

4.3. HP and Optimised EV capacity

The stages in estimating the HP and optimised EV hosting capacity, as outlined in Algorithms 1 and 2 were to calculate zonal power flow limits; estimate headroom from the zonal power flow limits; assign HP and EV capacities based on the headroom; carry out EV optimisation, and finally validate the results. As these steps were carried out for multiple zones across five networks, the results of each step are presented for a single zone to illustrate the results of the methodology.

4.3.1. Zonal power flow limit

The zonal power flow limit, P_z^{Vlim}, for each network is calculated from the minimum power flow that resulted in a minimum voltage of 0.94 p.u[9]. An example of the estimation of P_z^{Vlim} for network 1, zone 11 is shown below in Figure 24, where P_{11}^{Vlim}=26.6 kVA. The points on Figure 24 correspond to the 12,673 timesteps of each HP penetration case combined (from 0 to 100% HP penetration in increments of 25%).

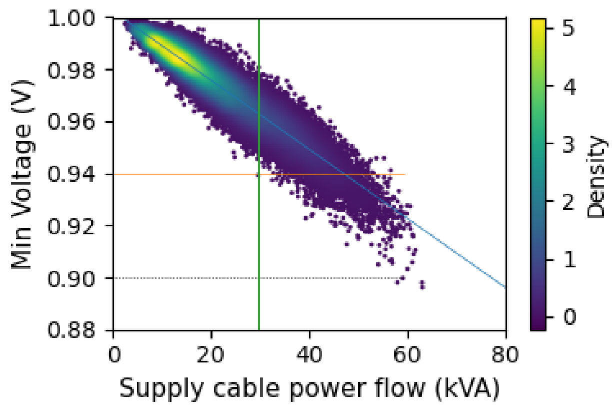

Figure 24: Network 1, Zone 11: Power flow vs Minimum Voltage

Table 5 shows the voltage power flow limit P_z^{Vlim} for each zone in network 1. The feeder head thermal limit, $P_{z,t}^{\mathrm{Tlim}}$, is set by the feeder head line rating of 185 A converted to kVA using (2). $P_{z,t}^{\mathrm{Tlim}}$ varies by a small amount by timestep

[9]The 0.94 p.u limit is conservative and corresponds to a phase to neutral voltage of 225 V for the base voltage of 240 V used in this work. This is to allow a margin of error to prevent additional EV load from causing voltages to drop below 216 V (the UK statutory minimum voltage [46]) which corresponds to 0.94 p.u for a nominal voltage of 230 V.

depending on the supply point voltage, which for network 1, ranges from 0.974 p.u to 1 p.u in the cases modelled. In general, the voltage power flow limit is significantly lower than the thermal limit.

Table 5: Network 1: zonal voltage power flow limit, P_z^{Vlim}, kVA

	Phase		
Feeder	1	2	3
1	26.6	23.9	31.5
2	23.2	20.8	25.9
3	17.1	25.4	18.1
4	21.1	21.6	17.1

4.3.2. Headroom calculation

From (1a) and (1b), the headroom and footroom was calculated for each network, case, zone and timestep. The example of a P2 headroom profile for network 1, zone 11 (Figure 25) shows that there are times where the headroom is negative, which indicates the possibility of voltage or current violations. It should be noted that these P2 headroom profiles are conservative as they are based on a 225 V low voltage threshold, however this safety margin is required to prevent voltages below the statutory limit of 216 V once EV demand is added.

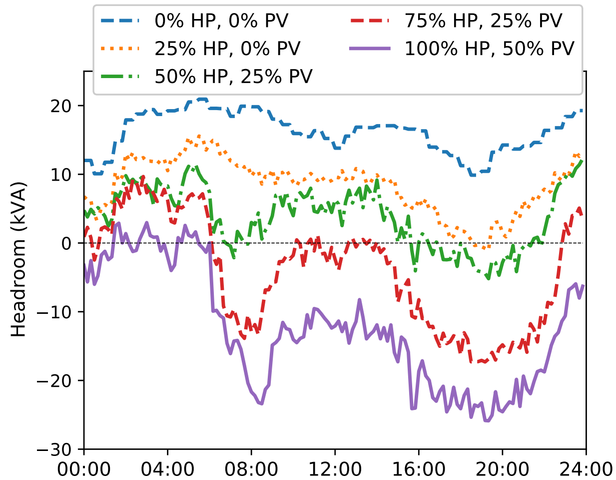

Figure 25: Network 1, Zone 11: P2 headroom for each case

4.3.3. HP and EV capacity assignation

Using the P2 headroom for all zones, achievable HP and EV hosting capacities are estimated per zone. The HP hosting capacity is defined as the highest HP capacity with a net positive P2 headroom profile above a threshold of 120 kVAh over a 24 hour period[10]. For example in zone 11 (Figure 25), 50% HP penetration has a net positive P2 headroom of 91 kVAh which is below the defined 120 kVAh threshold. For 25% HP penetration, the sum of P2 headroom is 200 kVAh which is acceptable as it is above the 120 kVAh threshold. The EV hosting capacity is calculated from the total P2 headroom for the accepted HP capacity case. In the zone 11 example, the total daily P2 headroom for the 25% HP accepted case is converted to 196 kWh assuming a power factor of 0.98. By dividing this sum of daily P2 headroom by the maximum daily EV charge calculated in section (14.2 kWh/day), an initial estimate of 13 EVs is obtained.

[10]This threshold can be tuned to ensure that in the case of headroom profiles with periods of negative headroom, enough headroom is available for a sufficient number of EVs (approximately 8 in this case) to both charge and provide enough V2G to prevent thermal and voltage violations caused by peak HP demand.

By replicating this approach for all zones, a total HP hosting capacity of 30 HPs has been estimated for network 1 with an initial estimate of 124 EVs. The number of EVs must now be refined based on the ability to optimise the charging of this numbers of EVs using the zonal P2 headroom profiles and realistic EV travel diaries.

4.3.4. EV Optimisation

Using the zonal P2 headroom for assigned HP capacities, and an initial estimate of EV numbers, the EV optimisation is carried out for randomly sampled EV travel diaries. As described in Algorithm 2, the number of EVs is reduced until 10 consecutive successful optimisation results is achieved for a given number of EVs. This gives a more realistic estimate of the number of EVs that can be charged based on real travel diaries rather than solely based on total headroom available. On this basis for network 1 the total number of EVs is revised to 88 (44% of customers).

An example of a successful optimisation result for network 1, zone 14 is shown in Figure 26 for 9 EVs with a negative P2 headroom period between 16:00 and 21:00. There is no hard constraint on the optimisation to provide V2G at times of negative headroom, however, the price signal of an added 17.5 p/kWh for V2G results in injection where the EV schedule and headroom allows. For the EV optimisation result of a random sample of 9 EV travel diaries shown in Figure 26, there is some V2G provided between 16:00 and 21:00, however not the full amount requested. This is because there is insufficient headroom to provide any further V2G while still respecting the hard constraint of achieving the required final SoC for each EV.

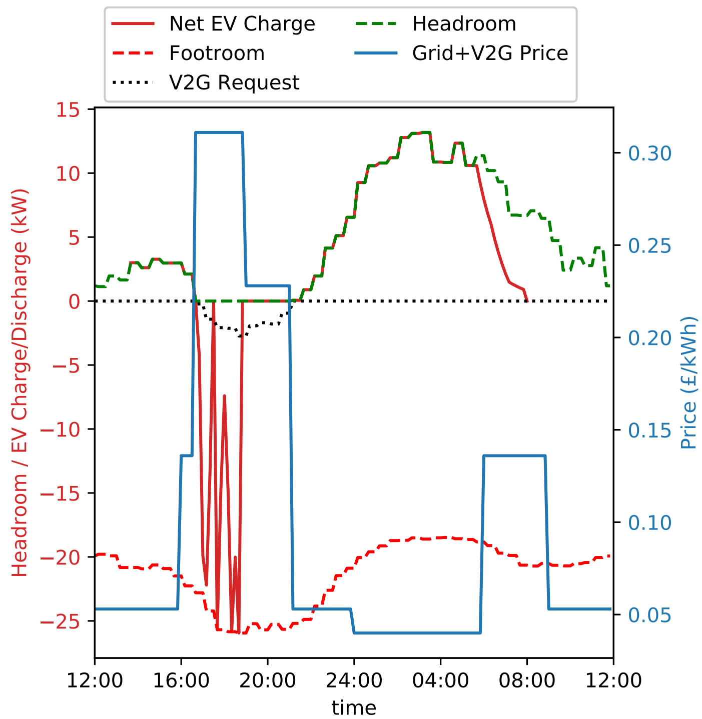

Figure 26: Network 1, Zone 14: Results of EV Optimisation Schedule

If there was more headroom available, fewer EVs to free up headroom, or a relaxation of the requirement to fully charge EVs, then the EVs could provide more V2G. This is illustrated in Figure 27 where the number of EVs has been reduced to 6 and the final state of charge requirement has been relaxed to achieving 97% of the SoC specified in the travel diary.

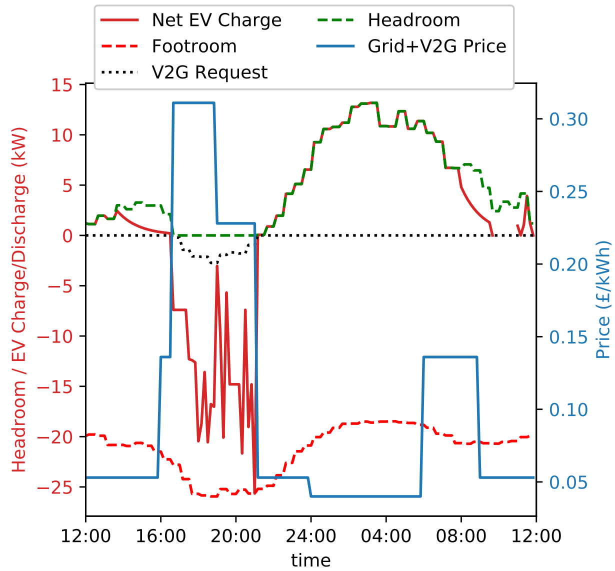

Figure 27: Network 1, Zone 14: Results of EV Optimisation Schedule for 6 EVs

Although in some cases V2G is not fully provided, for most cases the majority of requested V2G was provided and in network 1, for 33 HPs and 82 EVs, an average of 79.1% of V2G requested was provided per zone.

4.3.5. HP and optimised EV hosting capacity validation

From the HP headroom assessment and EV optimisation, the total HP and EV hosting capacity has been estimated for each of the networks. The optimised EV dispatch along with the assigned HP capacity has been validated for each network by carrying out OpenDSS load flow modelling for a subset of worst case sample days. The sample days have been selected as those with the lowest total headroom per zone from the 88 days of winter 2013 modelled during the HP headroom analysis. For example, for network 1 which has 12 zones, the validation would be carried out for the 12 days with the lowest total headroom in the 12 zones.

For a given zone, the EV optimisation is carried out using the same headroom profile each day, but with a different sample of EV travel diaries to capture a range of possible EV charging behaviour (and availability to provide V2G).

The validated HP and optimised EV hosting capacities, shown in Table 6, are significantly higher than for dumb EV charging in three of the five networks assuming current violations in up to 0.5% of timesteps are tolerable. The number of transformer thermal violations is zero for all networks except network 5 which has violations in 0.5% of timesteps.

Table 6: Summary of HP and optimised EV hosting capacity

Network	HPs	EVs	Current Violations [1]	Voltage Violations [1]	V2G Delivered (%)
1	30 (15%)	88 (44.0%)	0	0	79.1
5	88 (26.3%)	110 (32.8%)	0.3	0	81.9
10	64 (100%)	64 (100%)	0.1	0	n/a
17	8 (0.9%)	41 (4.6%)	0.3	0	75.8
18	190 (57.1%)	235 (71.6%)	0.3	0	78
Total	380 (21.0%)	538 (29.7%)			

[1] Violations are in % of timesteps modelled

In total, for the five networks studied, it was possible to host 21% HP and 29.7% EV penetrations without the requirement for additional network upgrades. The total EV hosting capacity is close to double the 15.7% EV penetration that was possible with dumb charging with 25% HPs. In the case of network 17, which has 883 of the 1810 customers in the five networks studied, there was simply not enough headroom to host a significant penetration of HPs or EVs (beyond 4.6%). In networks with such high customer numbers per zone and a large number of total customers, network upgrades will be required to host significant penetrations of HPs and EVs and EV optimisation can only provide very limited gains.

The biggest gains from this method came in network 18, which was limited to 33.5% EV penetration at 50% HP capacity for dumb charging. Using the headroom optimisation method it was possible to increase EV and HP penetrations to 71.6% and 57.1% respectively. The method was also successful in facilitating EV hosting capacities 1.4 times and 2.6 times higher in networks 1 and 5 respectively than the dumb charging case with 0% HPs. These EV capacities were realised with HP penetrations of 15% and 26.3% in networks 1 and 5 respectively. The levels of V2G delivered were above 75% of requested output for networks 1,5 and 18 which, in the case of several zones, allowed higher HP penetrations by injecting power at times with negative headroom where HP demand could otherwise have caused current or voltage violations.

Sensitivity study: modified headroom. A sensitivity case is presented to demonstrate the potential for tuning the headroom calculation and the effect this has on violations and HP and EV numbers. Table 7 shows the HP and EV hosting capacity results when the 5^{th} percentile (P5) headroom is used rather than the P2 headroom.

Table 7: Summary of HP and optimised EV hosting capacity: P5 headroom

Network	HPs	EVs	Current Violations [1]	Voltage Violations [1]	Transformer Violations [1]
1	38 (19.0%)	95 (47.5%)	0%	0%	0%
5	99 (29.6%)	117 (34.9%)	0.6%	0%	1.6%
10	64 (100.0%)	64 (100.0%)	0.1%	0%	0%
17	8 (0.9%)	83 (9.4%)	1.2%	0.2%	0%
18	200 (61%)	242 (73.8%)	0.1%	0%	0.1%
Total	409 (22.6%)	601 (33.2%)			

[1] Violations are in % of timesteps modelled

Using this modified method it was possible to slightly increase the total HP penetration to 22.6% (an increase of 1.6%) but at the expense of voltage violations of up to 0.2%, transformer violations of up to 1.6% and cable current violations up to 1.2% (in terms of % of timesteps modelled in each case). The headroom available for EV optimisation was higher than the base case and the number of EVs increased by 63 (3.4%) across all networks. These results demonstrate some flexibility in the method for prioritising between maximising HP and EV capacity and minimising voltage and thermal violations. The voltage, thermal and transformer violations could be reduced by further tuning of the headroom calculation.

EV optimisation and transformer power flow. The optimisation of EVs has the potential to have a significant impact on the power flows to and from LV secondary substations. In Figure 28 the maximum transformer power flow per 10 minute timestep is shown for network 18 based on the results of all three cases considered: HP only, HP and dumb EV, and HP and optimised EV. Although the penetrations of HP and EV for the cases in Figure 28 are different, it is still useful to compare the timings of peak power flows for each case.

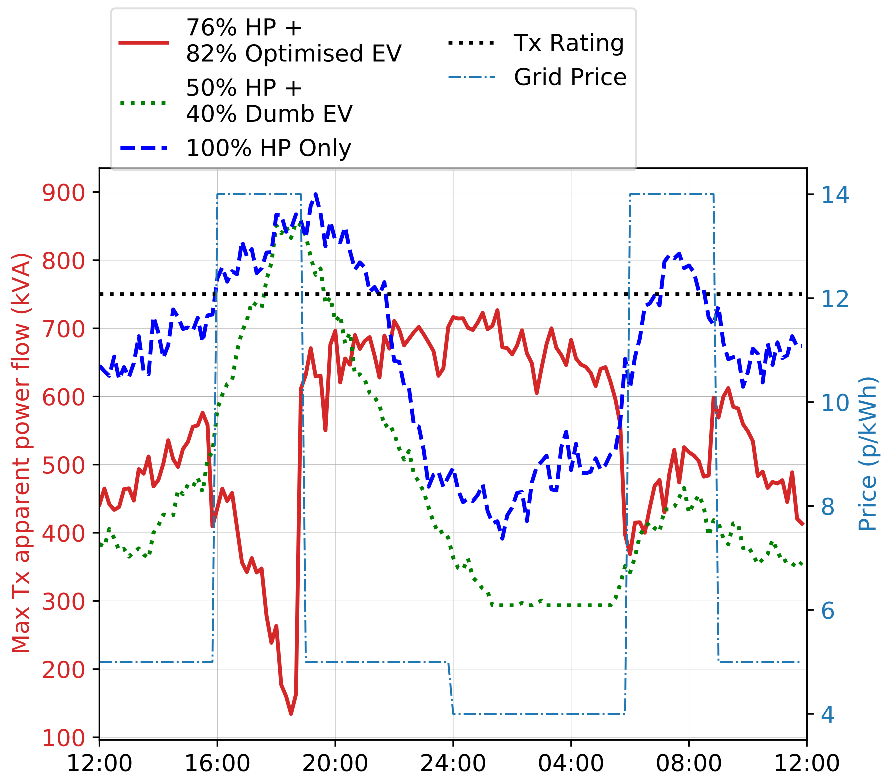

Figure 28: Network 18 maximum transformer flow for optimised EV charging, Dumb EV charging and HP only cases

The EV optimisation is very effective at reducing the peak power flows at the times of the highest DUoS price: for the optimised EV case there is a rapid increase in EV demand after 19:00 and after 09:00 when the DUoS price drops and EV charging increases. The DUoS price signal used in this work could be improved by extending the high price DUoS charge until after the HP peak subsides at 22:00. The example in Figure 28 highlights the importance in choosing the right price signals and limits for EV optimisation. In this example, the headroom limit successfully prevented the post 19:00 and 09:00 spikes in EV charging from causing transformer limits from being exceeded. Using price signals alone, EV optimised dispatch could cause network stress events including violation of voltage, line current and thermal limits, especially when multiple EVs across multiple zones and networks are responding the same price signals [16].

4.3.6. Computation times

The major advantages of the proposed headroom optimisation method when compared to 3-phase multi-period OPF are that network modelling and EV optimisation activities are separated, and that computational times are vastly reduced. For example, the average time taken to optimise a day's EV dispatch at 10-minutely resolution (144 timesteps) for a zone in network 18 with an average of 10 EVs is 2.7 s using a 3.3 GHz i5 processor with 8 GB RAM. By optimising zones in parallel (using multiple processors), a day's EV scheduling for 242 EVs in network 18 across 662 nodes in 27 zones, was carried out in under 20s using a quad core processor. For comparison, using the same 3.3 GHz processor, it took 2 hours to optimise a day's dispatch of 80 EVs at 30-minutely resolution (48 timesteps) by carrying out 3-phase multi-period OPF on the IEEE 13 node test network using the PICOS solver [71] in the OPEN platform [10]. The 3-phase power flow model in OPEN is linear, giving an approximate solution, and the 2 hour computational time is with voltage constraints relaxed. With increasing network size, multi-period OPF can become intractable: for example, for an LV network with 163 nodes and 15 EVs, using the same 3.3 GHz processor as in the previous examples, it was found that for many EV and demand configurations, the optimisation of a day's EV dispatch does not converge (after iterating for several hours) at 10-minutely resolution for single-phase multi-period OPF using the Ipopt[72] non-linear solver within the OATS platform [63].

When considering multiple LV networks which could number into the thousands on a regional level [73], the method proposed in this paper could offer significant improvement in tractability compared to 3-phase multi-period OPF. The offline headroom calculation requires more computational effort depending on the number of timesteps analysed, therefore generalised headroom profiles could be developed based on parameters such as customer number, feeder head line rating or electrical distance rather than calculating a headroom profile afresh for every zone in every network.

4.4. Wider context of this work

Net zero emissions trajectories for the UK [2, 74] all rely on the parallel electrification of heat and transport and the decarbonisation of electricity supply. As variable renewables replace traditional thermal power stations, there is increasing value placed in electricity system flexibility to i) utilise renewable electricity [75] – thereby providing an 'anchor load' incentive for further investment in low carbon generation and ii) minimise the cost of the technological transition [4]. Unlocking the synergies of EVs and HPs will bring further benefits for the environment (such as a reduction in urban air pollution) [76], the economy (the promotion of novel technologies with the potential of high value added manufacturing jobs) [77] and society (the reduction of energy costs) [78].

The method provided in this paper to maximise the use of domestic EV charging flexibility has been shown to increase LV network capacity for domestic HPs and EVs. Smart control methods, such as the EV optimisation strategy proposed in this work, can significantly reduce the required expenditure on network upgrades for the decarbonisation of heat and transport [4]. By considering a range of realistic LV networks, the results of the case studies in this paper provide an indication of networks with the most to gain from EV flexibility in terms of increased HP and EV hosting capacity, and those that have little to gain, which helps to inform DNOs in directing further investment in network reinforcement and flexibility.

The results of this work can be considered to be conservative in the assessment of LV network hosting capacity compared to other works in the literature. Firstly, the subset of RHPPS HP demand profiles used in this work have a higher ADMD than those used in other works [48, 24], and secondly, this work models 7 kW home EV chargers rather than 3-3.6 kW chargers which have been assumed in other works [21, 13].

In the RHPPS HP dataset there is a high proportion of social housing and for this reason in [25] it is concluded that it should not be considered representative of current GB HP installations. In other works such as [78], improved building insulation levels have been assumed, resulting in reduced mean and peak HP demand profiles compared to those used in this work. The results in this work can therefore be considered indicative of the levels of HPs with relatively high demand that can be hosted on a range of LV networks.

There is potential for significant increases in HP hosting capacities of LV networks with improvements in home energy efficiency. Consider that in [20] it is estimated that insulating a typical detached dwelling to passive house standards could reduce HP energy consumption by 76%. However, it is expensive and challenging to retrofit homes with the required energy efficiency improvements and homeowners are unlikely to do so without government policy incentives [79]. Balancing the cost of improved building insulation and reduced electricity supply costs (including network capacity) due to reduced HP demand, should therefore be prioritised by policymakers to minimise the cost of achieving net zero ambitions.

5. Conclusions and future work

This paper makes a contribution to the literature on the decarbonisation of heat and transport by providing a novel method to maximise domestic HP and EV penetration on LV networks using EV optimisation and V2G. New findings are provided on the hosting capacity a set of realistic three-phase LV networks for HPs and optimised EVs. The number of customers per zone, defined as a unique combination of feeder and phase, was identified as an important parameter in assessing the capacity for HPs. Beyond 21 customers per zone, thermal and voltage violations are much more prevalent and HP and EV hosting capacity will be limited without network reinforcement.

The networks studied provided two extremes in terms of customer numbers: EV optimisation was either unnecessary for the smallest network (64 customers) or unable to enable significant HP and EV penetrations in the largest network

(883 customers). In the networks with customer numbers between 200 and 335 which were analysed, it was found that EV hosting capacity could be more than doubled using EV optimisation compared to dumb charging with comparable HP capacities, without the need for additional reinforcement. In these cases, it was found that EV optimisation could enable between 15% - 57% HPs and 33% - 72% EVs without the need for additional reinforcement. These networks have a median customer number of between 9.5 and 14.5 per zone and have sufficient headroom for EV optimisation to provide significant benefit in terms of smoothing peak demand and maximising EV and HP hosting capacity.

The methodology applied in this paper is conservative in that a 'worst case' headroom is used and applied to all days, in future work this could be enhanced by the use of a day-ahead forecasted headroom linked to temperature for example. The optimisation of EVs during the summer could also be studied using the same methodology and alternative travel diaries could be included to reflect changing travel habits such as increased home working. Finally, an important development of the headroom methodology would be in producing generalised headroom profiles linked to key network parameters to save re-calculating the headroom for every zone.

Acknowledgements

This work has been funded through the Engineering and Physical Sciences Research Council (EPSRC) Aggregators as diGital Intermediaries in Local Electricity markets (AGILE) project (EP/S003088/1). The authors would like to thank Matthew Deakin for his technical input on low voltage network modelling.

EPSRC Data Statement: All data produced by this research is contained within the paper and supplementary materials.

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