Calculating the Maximum Penetration of Electric Vehicles in Distribution Networks with Renewable Energy and V2G

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***Abstract*—The uptake of electric vehicles and distributed energy generation is adding significant new demand to distribution networks, however it is unknown whether this can be accommodated by existing infrastructure. This paper first presents an Optimisation approach for determining the maximum penetration of electric vehicles that can be accommodated within a distribution network in conjunction with renewable energy and battery storage. An alternative approach, utilising Network Impact Tokens is then introduced, simplifying the original Optimisation approach while providing accurate results. The electric vehicle hosting capacity of the network is then analysed with increasing penetration of solar generation, battery storage and the use of V2G, showing that distributed generation can increase the the electric vehicle capacity by up to 38%.**

I. Introduction

The rapid uptake of electric vehicles and distributed renewable energy generation technologies, such as rooftop solar photovoltaic (PV) panels, are causing unprecedented power demand and major issues in low-voltage distribution networks. It is therefore important for distribution system operators (DSOs) to assess their existing network infrastructure to determine its readiness for accommodating EV charging, and if required, analyse suitable approaches to increase the EV hosting capacity.

A number of studies have calculated the hosting capacity as the number of EVs which can charge simultaneously. Four different optimal power flow models were compared in [1] to calculate the maximum number of EVs that could charge simultaneously at each hour of the day. The authors of [2] constructed an optimisation problem considering reactive power compensation provided by EV chargers to maximise the number of charge points that could simultaneously operate at peak load. Shaaban et al. [3] analysed optimal sizing and location of distributed generation (DG) installations within the network to maximise the penetration of EVs subject to network constraints, based on EV charging at peak load. A multi-feeder study was conducted in [4], evaluating the maximum number of residential EV charge points that could be simultaneously operated across the feeders before a voltage violation occurs.

Evaluating the hosting capacity with simultaneous charging at peak load analyses the worst case scenario, however smart charging can enable significantly more EVs to be accommodated, resulting in an underestimation of a network's capacity. Kamruzzaman and Benidris [5], presented a coordinated charging strategy to increase the EV penetration by adjusting the charge power based on EV type and journey distance. Three charging strategies were presented in [6] with loss-optimal charging resulting in the highest EV penetration as the charging achieved a flatter load profile.

Interaction between high and medium voltage networks was considered in [7], with the hosting capacity of EVs and PV maximised by optimally utilising available resources and the flexibility of EVs. Zaidi et al. proposed a cumulative distribution function approach for determining the maximum penetration of EVs considering voltage unbalance and voltage drop [8]. Parallel computing was utilised in [9] to significantly reduce the computational time for determining the EV hosting capacity using a binary search and power flow confirmation method. Other studies, including [10] also calculated the the hosting capacity by iteratively increasing the number of vehicles in the study until network constraints were violated. This iterative approach of evaluating a number of EVs in the network against any constraints before adjusting the number accordingly and repeating the study can be significantly slower than calculating the maximum penetration through a single optimisation problem, as power flows or optimisations must be computed at each iteration before the maximum penetration is found. In addition, the load profiles selected during each iteration can have a big impact on whether a given penetration can be accommodated.

The EV hosting capacity can also be found through the calculation of the capacity of the network to accommodate extra load in addition to the base load. The authors of [11] maximised the Distribution System Loading Margin (DSLM) based on a Monte Carlo simulation of the daily demand profile subject to network constraints, with the expected maximum EV penetration then calculated for uncontrolled and smart EV charging strategies. The smart charging approach took the uncontrolled EV charging profile as an input, solving an optimisation problem to maximise the penetration of charging EVs. The additional load that the network could accommodate over peak load conditions was calculated in [12] by raising the load at each node individually by a set amount and performing

The authors acknowledge the Engineering and Physical Sciences Research Council (EPSRC) for Doctoral Training Grant EP/R513039/1

a power flow study to determine whether any grid limits are violated. The concept of Hourly Extra Available Power (HEAP) was presented in [5], calculated by increasing the hourly power at nodes until the voltage limits were violated. The smart charging strategy then incorporated the HEAP to determine the charge rate for each EV and the number of EVs that can charge. Zhao et al. proposed the EV Chargeable Region model as a scheduling strategy to maximise the EV hosting capacity for each node, utilising shunt capacitors and voltage regulators [13].

However, there is little research into determining the maximum EV penetration when DG and V2G are also considered, and network load capacity approaches have not yet been applied to studies involving these additional energy resources.

This paper presents an optimisation problem to calculate the maximum penetration (hosting capacity) of EVs that a residential distribution network can accommodate in conjunction with solar PV, energy storage, smart EV charging and V2G. The maximum EV penetration is defined here as the number of EVs, expressed as a percentage of the number of houses in the network, that are able to recharge fully within the 24h period, subject to network power limits and constraints on the EVs movements and charging. Maximising the number of EVs that depart fully charged ensures optimal usage of the network and energy resources - no alternative control strategy for EV charging, discharging and renewable resources can result in a greater number of EVs departing fully charged. A Monte Carlo simulation is performed to evaluate the capacity of the network under a variety of baseload, EV demand and driving patterns, and renewable energy generation profiles to capture real-world variations. An alternative load capacity based method, referred to as the Network Impact Token approach is then proposed to simplify and speed up the hosting capacity calculation. The results of the study show the importance of energy resources in facilitating EV charging and also enables DSOs to model the impact of new demand profiles and cost-effectiveness of potential network hardware upgrades on the maximum EV penetration.

II. Optimisation Approach

In this section, the optimisation problem for calculating the maximum EV penetration is presented.

A. *Network Model and Load Profiles*

A 24 hour period is studied, from 8am to 8am the next day, using the IEEE 2015 Low Voltage European Test Feeder, which supplies 55 houses across 3 phases [14].

A set of 1000 summer baseload profiles have been generated based on real load profiles provided by Electricity North West [15]. Similarly, 1000 solar generation profiles have been generated with each house assigned a solar array capacity of either 3, 5 or 7 kWp to generate its PV generation profile. The base solar irradiance data is for June to analyse the greatest impact of solar generation on the EV hosting capacity [16]. A set of EV profiles have been generated based on estimated travel patterns, with the majority of EVs departing in the morning to travel to work and returning early evening, with other EVs remaining at home but potentially making another journey later in the day. The energy requirements of EVs have been randomly selected based on the premise that increasing EV ranges will mean that multiple journeys are made before EVs are plugged in to recharge. Every house is allocated an EV to enable any set of EVs to fully charge, independent of their location in the network and chosen load profiles.

The 24-hour period is divided into 144 timesteps of ten minute duration, with all loads assumed to be constant over the ten-minute period. The total number of timesteps is defined as T, while t refers to any one of the individual steps with duration ΔT. The number of houses in the network is denoted K, and the set of all houses, $\mathcal{K}$.

B. *Network Initialisation*

A series of power flow studies are first performed on the network to determine parameters used in the optimisation problem. For these studies, every house is allocated the same generic baseload profile, and no DG, battery storage or EVs are considered in the network at this point. The benefit of using the generic load profile is that the power flow results generate a set of parameters specific to the networks' topology and hardware (e.g. line impedances, phase connections etc) and only have to be run once for a given network topology, but can be used to estimate the effect of any loads on the network.

Firstly, a power flow study is run for the entire network across all timesteps. A single timestep is then chosen (such as $t = 100$), and for each house in turn the generic baseload value is increased by 1 kW and the power flow re-run. Lastly, the previous step is repeated but by decreasing the load by 1 kW at each house instead. The results of this process allow the voltage and current sensitivity matrices to be calculated, which are defined as the change in voltage at each node and change in current in each line as a result of a change in load at a different node. The four calculations of positive (increased load) and negative (decreased load) voltage sensitivity matrices, $\mathbf{W}^+$ and $\mathbf{W}^-$, and current sensitivity matrices $\mathbf{L}^+$ and $\mathbf{L}^-$ are based on the approach given in [17].

C. *Optimisation Problem*

As the maximum EV hosting capacity of a network depends on a number of factors, such as the baseload, DG energy production, EV energy requirements and movement patterns, a Monte Carlo simulation is used to calculate the distribution of the maximum EV penetration as these vary. At each repeat of the Monte Carlo, each household is allocated a random baseload and EV profile, and a random group of houses are allocated solar DG profiles in accordance with the desired DG penetration of the study, and the following optimisation problem is solved. In total, 1000 repeats are completed to see the distribution in EV hosting capacity caused by variations in these factors.

1) Optimisation Objective: The optimisation maximises the number of EVs that reach full charge by departure:

$$\Lambda_{\max}^{EV} = \max_{\chi_{\text{energy}}} \Lambda^{EV} \tag{1}$$

where $\Lambda_{\max}^{EV}$ is the maximum EV penetration of the network, χ_{energy} is the controllable set of energy resources, consisting of the charge and discharge rate of each EV, the amount of discharging of the stationary battery, the amount of solar energy used for loads and battery charging and Ψ_k, and Λ^{EV} is the percentage of EVs that fully charge, calculated by:

$$\Lambda^{EV} = \frac{1}{K} \sum_{k \in \mathcal{K}} \Psi_k \times 100 \tag{2}$$

where Ψ_k is a binary indicator variable denoting if the EV at house k achieves full charge.

2) Baseload: Because the power flows were computed using the generic load profile, the difference between the real baseload and generic profile must be calculated and included in the optimisation as an additional load.

$$BL_{\Delta_k}^t = BL_{\text{real}_k}^t - BL_{\text{generic}}^t \tag{3}$$

3) Distributed Generation and Battery Storage: The penetration of distributed generation Λ_{DG}, is defined as the percentage of houses that have installed solar PV panels and battery storage. A random set of houses in the network are allocated DG based on Λ_{DG}. The use of these energy resources is constrained in the optimisation problem subject to:

Solar power produced $P_{\text{DG},k}$ can either be consumed by the network $P_{\text{DG}_{\text{cons}},k}^t$, stored in the house's battery $P_{\text{DG}_{\text{bat}},k}^t$, or must be curtailed $P_{\text{DG}_{\text{curtail}},k}^t$:

$$P_{\text{DG},k}^t = P_{\text{DG}_{\text{cons}},k}^t + P_{\text{DG}_{\text{bat}},k}^t + P_{\text{DG}_{\text{curtail}},k}^t \tag{4}$$

The amount of energy stored in the battery at house k at time t is given by $B_{\text{store}_k}^t$. The initial energy stored in the battery at $t = 0$ is 0 kWh, and cannot fall below 0 kWh, nor exceed the battery's capacity B_{cap_k} of 7 kWh.

$$B_{\text{store}_k}^t = B_{\text{store}_k}^0 + \sum_{n=1}^{t} \left(P_{\text{DG}_{\text{bat}},k}^n - P_{\text{bat}_{\text{dis}},k}^n \right) \cdot \Delta T \tag{5}$$

where $P_{\text{bat}_{\text{dis}},k}^n$ is the battery discharge rate at timestep n. The battery charge rate must be less than or equal to the power produced by the PV panels, and the maximum discharge rate is set to 7 kW.

$$0 \leq P_{\text{DG}_{\text{bat}},k}^t \leq P_{\text{DG}}^t \tag{6}$$

$$0 \leq P_{\text{bat}_{\text{dis}},k}^t \leq 7 \tag{7}$$

4) Electric Vehicles: The EV charge rate $P_{EV_{\text{ch}},k}^t$ is constrained as:

$$-3 \cdot \Psi_{\text{V2G}} \leq P_{EV_{\text{ch}},k}^t \leq 7 \cdot EV_{\text{present}} \tag{8}$$

where Ψ_{V2G} is a binary variable indicating whether V2G is enabled. The maximum discharge rate of the EV battery for V2G is set as -3 kW, the maximum EV charge rate is set at 7 kW and $EV_{\text{present},k}$ is a binary value indicating if the EV is at home and able to charge. The state of charge (SoC) of the EV at house k is given by:

$$SoC_k^t = SoC_{\text{in},k} - SoC_{J,k}^t + \times \sum_{n=1}^{t} P_{EV_{\text{ch}},k}^t \cdot \frac{\Delta T \cdot \eta}{B_{\text{cap},k}} \tag{9}$$

where $SoC_{\text{in},k}$ is the initial SoC of EV k, $SoC_{J,k}^t$ is the SoC consumed by the EV on any journeys between $t = 1$ and the current timestep t, η is the charging efficiency (90%) and $B_{\text{cap},k}$ is the battery capacity of the EV.

If EV k can be scheduled to fully charge by its departure time T_{dep}, $SoC_{\text{deficit},k}$ equals 0. Two binary indicator variables are used to indicate whether full charge is achieved - if so, $\Psi_k = 1$ and $\Psi_k^- = 0$.

$$SoC_{\text{deficit},k} = 1 - SoC_k^{T_{\text{dep}}} \tag{10}$$

$$\Psi_k^- \geq SoC_{\text{deficit},k} \geq -1 \cdot \Psi_k \tag{11}$$

$$\Psi_k + \Psi_k^- = 1 \tag{12}$$

To prevent some EVs from fully discharging to further increase the number of fully charged EVs, a final constraint ensures that if an EV engages in V2G, it cannot leave with a lower SoC than when it arrived.

$$\sum_{t=1}^{T} P_{EV_{\text{ch}},k}^t \geq 0 \tag{13}$$

5) Constraints on the Distribution Network: The operation of the distribution network is subject to constraints on transformer power, maximum line currents and bus voltages. Absolute values are taken of the power flow results for compatibility with Matlab's optimisation solvers.

The voltage at each house node k resulting from additional baseload, EV charging and DG is given by:

$$\begin{aligned} V_{k,3\phi} = |V_k^{3\phi}| + \mathbf{W^+}_{k,j} \times \left(P_{EV_{\text{ch}},j}^t + BL_{\Delta_j}^t \right) \\ + \mathbf{W^-}_{k,j} \times \left(P_{\text{bat}_{\text{dis}},j}^t + P_{\text{DG}_{\text{cons}},j}^t \right) \quad \forall j \in \mathcal{K} \end{aligned} \tag{14}$$

Similarly, the line currents at line segment l are given by:

$$\begin{aligned} I_{l,3\phi} = |I_l^{3\phi}| + \mathbf{L^+}_{l,j} \times \left(P_{EV_{\text{ch}},j}^t + BL_{\Delta_j}^t \right) \\ + \mathbf{L^-}_{l,j} \times \left(P_{\text{bat}_{\text{dis}},j}^t + P_{\text{DG}_{\text{cons}},j}^t \right) \quad \forall j \in \mathcal{K} \end{aligned} \tag{15}$$

The load on the transformer is given by:

$$S_{\text{trans}} = \sum_{\phi=1}^{3} |V_{\text{trans}_{3\phi}}| \cdot I_{1,3\phi} \tag{16}$$

where $V_k^{3\phi}$ is the voltage at house k and $I_l^{3\phi}$ is the current at line l calculated from the initial power flow study, $V_{\text{trans}_{3\phi}}$ is the transformer voltage and $I_{1,3\phi}$ is the current in the first line of the feeder at each phase.

The optimisation constraints are formulated as:

$$\underline{V} \leq |V_{k,\phi}| \leq \bar{V} \quad \forall k, \phi \tag{17}$$

$$|I_{l,\phi}| \leq I_{\max_{l,\phi}} \quad \forall l, \phi \tag{18}$$

$$S_{\text{trans}} \leq S_{\text{trans}_{\max}} \tag{19}$$

where $\underline{V}$ and $\bar{V}$ are the lower and upper voltage bounds of the network, -6% and +10%, respectively, $I_{\max_{l,\phi}}$ is the maximum current rating of line l, and the maximum power rating of the transformer is $S_{\text{trans}_{\max}}$.

III. Network Impact Token Approach

While the Optimisation approach provides an accurate method for calculating the maximum EV penetration in a distribution network, it is extremely slow to solve and performing sufficient repeats of a Monte Carlo simulation to calculate a reliable value for the maximum EV penetration can take several days. Therefore, a faster approach is required to enable DSOs to use this approach to quickly analyse the impact of different loads and network hardware on the EV capacity.

Therefore, this novel Network Impact Token approach is proposed which utilises the calculation of the capacity of the network to accommodate additional load to speed up the EV capacity calculation. Loads at each house have different impacts on the amount of spare capacity remaining within the network, based on its location in the network and phase connection, termed here the house's Network Impact Value (NIV). Combined with the extra network capacity, the problem can be reformulated in terms of these values, rather than the network power constraints, while still ensuring the network operates within its limits.

A. Calculating the Load Capacity of the Network

As with the Optimisation approach in Section II, an initialisation stage calculates the voltage and current sensitivity matrices and the amount of load capacity in the network. A new optimisation problem is solved to calculate the amount of additional load each house can use without violating the network constraints during each timestep:

$$\max_{LC} \sum_{t=1}^{T} \sum_{k \in \mathcal{K}} LC_k^t \tag{20}$$

where $LC_{k,t}$ is the amount of additional load capacity available to house k at time t. Constraining this problem by the network's voltage, current and power limits (17)-(19) moves the complexity of ensuring that these limits are not violated from the main problem of calculating the maximum EV penetration to this initialisation phase, dramatically increasing the speed with which the EV capacity can be calculated.

This optimisation problem calculates a value of the load capacity for each house k at each timestep t, subsequently referred to as the number of Network Impact Tokens (NITs) available, denoted as $NIT_{\text{avail}_k}^t$. The total NIT capacity across the entire network is then given by:

$$NIT_{\text{capacity}}^t = \sum_{k \in \mathcal{K}} NIT_{\text{avail}_k}^t \tag{21}$$

As with the voltage and current sensitivity matrices, the same approach is used to find the change in NIT_{capacity}^t resulting from an increase and decrease in load at each house. The two resulting values for each house are that house's NIVs, NIV_k^+ and NIV_k^-, respectively. Solar power generation, battery discharge and V2G can further increase the total number of NITs available. Every load or power injection in the network is equated to a number of NITs, given by (22) and (23), respectively.

$$NIT_{\text{load},k} = P_{\text{load},k} \cdot NIV_k^+ \tag{22}$$

$$NIT_{\text{gen},k} = P_{\text{gen},k} \cdot NIV_k^- \tag{23}$$

where $NIT_{\text{load},k}$ is the number of NITs required to accommodate a load of $P_{\text{load},k}$ kW and $NIT_{\text{gen},k}$ is the number of NITs generated for the network as a result of generation of $P_{\text{gen},k}$ kW. To calculate the maximum EV penetration, the same optimisation problem is solved as presented in Section II, but without the grid constraints in Section II-C5. To ensure that the charging of EVs and use of other energy resources does not violate any network limits, this new constraint is added to the optimisation problem instead:

$$NIT_{\text{capacity}}^t + \sum_{k \in \mathcal{K}} NIT_{\text{gen},k}^t \geq \sum_{k \in \mathcal{K}} NIT_{\text{load},k}^t \tag{24}$$

IV. Results and Discussion

With a DG penetration of 50% and the use of V2G, Figure 1 shows the distribution of the maximum EV penetration values calculated from each of the 1000 repeats of the Monte Carlo simulation for the Optimisation and Network Impact Token approaches.

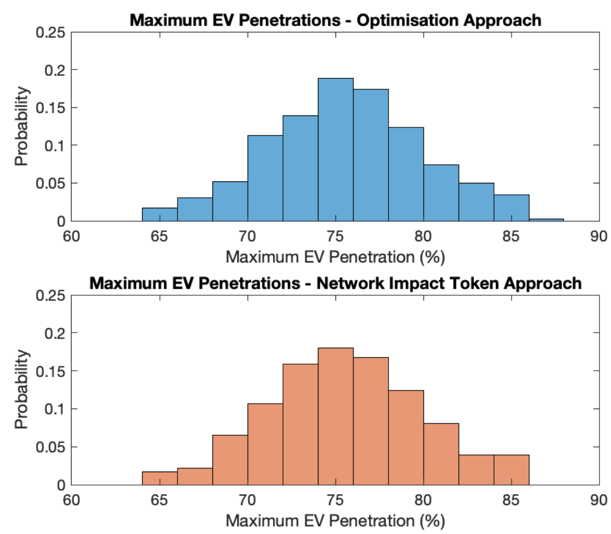

Fig. 1. Comparison of distribution of maximum EV penetration calculated from both optimisation and Network Impact Token approaches

It can be seen that the results generated from the NIT approach match those calculated through the Optimisation approach with a high level of accuracy, confirming its validity and reliability in calculating the maximum EV penetration. Key statistics for the two sets of results confirms this - the mean EV penetration is 75.2% and 75.1% for the Optimisation and NIT approaches, respectively, and the 20$^{\text{th}}$ percentiles are both 71%. The 20$^{\text{th}}$ percentile has been chosen as the overall EV penetration value for subsequent results, providing a conservative estimate for the maximum network capacity.

A major advantage of the NIT approach is the significant decrease in computational time to run the Monte Carlo simulation. Table I gives the average time in seconds to solve a single repeat of the Monte Carlo simulation, showing that the NIT approach can be calculated between 50-90 times faster than the Optimisation approach, enabling sufficient repeats to be performed to capture the variations in load, EV behaviour and solar generation.

TABLE I
Average computation time for single repeat of Monte Carlo simulation

	No V2G		With V2G	
DG Pen	Optimisation	NIT	Optimisation	NIT
0%	319.5 s	7.4 s	1440.5 s	15.6 s
25%	1349.0 s	22.9 s	2300.1 s	23.4 s
50%	2401.8 s	33.1 s	3296.2 s	41.5 s
100%	3687.6 s	47.8 s	4484.5 s	53.4 s

One of the key contributions of this study is to analyse how the penetration of distributed generation and battery storage, along with the use of V2G, affects the maximum EV penetration. Figure 2 shows the maximum penetration of EVs in the network as the penetration of Solar DG increases, both with and without the use of V2G. As would be expected, as the penetration of solar PV and battery storage increases, the EV penetration also increases due to the additional power available in the network. Compared with 0% DG, the maximum EV penetration can be increased by 38% if every house is equipped with DG. However, the inclusion of V2G has little impact on the maximum EV penetration, with at most 1 additional EV accommodated with V2G.

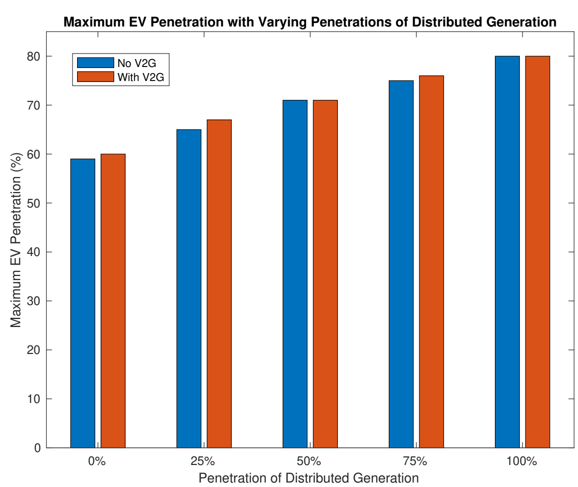

Fig. 2. Maximum EV penetration under different penetrations of solar PV installation and V2G usage within the network

V. Conclusion

A novel approach for calculating the maximum penetration of EVs in a low-voltage distribution network has been presented. The proposed approach offers great flexibility allowing DSOs to evaluate EV capacity in any scenario, and assess the impact of renewable energy generation, battery storage and V2G technologies on the maximum EV capacity. It is shown that full DG penetration can increase the EV hosting capacity by 38%. The Network Impact Token method retains a high level of accuracy but offers significant computational speed increases, enabling it to be used in a Monte Carlo simulation and provide useful results to DSOs.

Acknowledgment

This work has made use of the Hamilton HPC Service of Durham University

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