ELECTRIC VEHICLE HOSTING CAPACITY IN LOW-VOLTAGE NETWORKS CONSIDERING THE PROBABILITY OF CONCURRENT CHARGING

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Abstract

With the rapid development of electric vehicles (EVs) and the growing number of charging stations installed in distribution networks, distribution system operators (DSOs) are facing greater uncertainty and may experience more frequent violations of network operating limits. This work proposes an approach for estimating the maximum EV charging station penetration a low-voltage (LV) distribution network can accommodate without introducing line or transformer overloading, or voltage issues. This is referred to as the EV hosting capacity (HC) of the network. Unlike photovoltaic (PV) installations that behave almost uniformly in the same region, EV charging station usage depends heavily on customer habits. This makes EV HC estimation significantly more challenging. The HC is estimated using a Monte Carlo approach which allows to address the uncertainties in future EV charging station deployment. Compared to prior work, our contribution lies in introducing a random variable indicating EV stations charging concurrency. This variable quantifies the percentage of customers simultaneously charging their EV during the peak hour, and is estimated by analysing the EV owners charging behaviour through consumption profiles. Tests on a real-world distribution network show that our approach avoids overly pessimistic HC estimates and precipitate investment decisions.

1 Introduction

The ongoing electrification of the transport sector is accelerating the deployment of electric vehicles (EVs) across Europe. Driven by decarbonisation targets and technological progress, EV adoption is expected to increase significantly in the coming years, with substantial impacts on distribution network planning and operations [1]. While this transition supports climate objectives, it also introduces new technical challenges for distribution system operators (DSOs), particularly at the low-voltage (LV) level [2].

LV networks were originally designed for relatively predictable and diversified residential loads. The increasing penetration of EV charging stations introduces high-power and potentially coincident demand, which may lead to transformer and feeder overloading as well as voltage limit violations if not properly managed [3]. Quantifying the maximum EV penetration that can be accommodated without breaching operational constraints has therefore become a central planning issue, commonly addressed through the concept of hosting capacity (HC) [4].

While HC methodologies are well established for distributed generation—particularly photovoltaic (PV) systems—EV charging presents additional challenges due to its strong dependence on user behaviour. Charging time, duration, and power levels vary significantly across users, leading to uncertainty in the simultaneity of charging events. This simultaneity strongly influences peak loading and voltage profiles in LV feeders [5].

To address this uncertainty, several studies have proposed stochastic and Monte Carlo–based frameworks to evaluate EV HC more realistically [6]. Other works have introduced robust or probabilistic optimisation approaches to account for variability in charging demand and its interaction with network constraints [7]. In addition, coordinated or smart charging strategies have been shown to significantly increase effective HC by mitigating peak loading conditions [8].

Despite these advances, many approaches still rely on simplified assumptions regarding charging coincidence or insufficiently exploit behavioural data. This highlights the need for probabilistic frameworks that explicitly incorporate realistic charging concurrency modelling to provide accurate and operationally relevant HC estimates for LV distribution networks.

This paper proposes a Monte Carlo–based methodology to estimate the EV HC in a LV distribution network while explicitly modelling charging concurrency uncertainty. For that purpose, a random variable indicating whether a charging station is active or not is introduced. The percentage of EV charging station owners simultaneously charging their vehicle is derived from a statistical analysis of EV charging behaviour through measured consumption profiles. By incorporating this parameter into the simulation framework, the proposed approach provides a more accurate representation of aggregated charging demand. Our algorithm is tested on a real-world LV distribution network operated by RESA, the electricity and gas DSO in Liège, Belgium.

This paper is organised as follows. Sec. 2 details the methodology for determining the effective EV charging capacity, the reconstruction of charging profiles, and the Monte Carlo approach. Sec. 3 presents the EV charging profile reconstruction along with the HC results obtained for the RESA distribution network. Finally, Sec. 4 concludes the paper.

2 Methodology

This section outlines the methodology developed to evaluate the HC for EVs within an LV distribution network. First, we determine the maximum admissible power an EV charging station can draw, defined as the minimum between the charging station's rated power and the grid connection limit. We then introduce a random binary variable to represent a station's operating status during the peak hour. When multiplied by the maximum power, this variable reflects the station's actual contribution to the peak EV demand. This demand is derived from an analysis of consumption time-series, which estimates the simultaneity factor (i.e., the percentage of EV owners charging concurrently during the peak hour). Finally, we detail our Monte Carlo method and the random variables integrated into the model.

2.1. Determination of the effective EV charging capacity

While the power consumed by an EV charging station is primarily determined by its nominal rating, it is ultimately constrained by the physical capacity of the grid connection. In Belgium, charging stations for private individuals are generally categorized into five discrete nominal ratings: $\overline{P}_{\text{EV}} = 2.3, 3.7, 7.4, 11$ or 22 kW. However, customers with high-capacity charging stations may not have sufficient contractual power P_{contract} to operate their charging station at full capacity. In this situation, smart charging stations can adapt the power delivered to the EV so that the total power consumed by the customer does not exceed the contractual power. The maximum active power of an EV charging station is therefore given for each customer j by

$$P_j^{\text{EV,max}}\,[\text{kW}] = \min\{\overline{P}_j^{\text{EV}}, (P_j^{\text{contract}} - P_j^{\text{c, max}})\}, \tag{1}$$

where $P_{\text{c, max}}$ is the active power representing domestic consumption (excluding the charging station consumption) at the peak hour of the network. Moreover, following our assumptions, the reactive power consumed by the EV charging station is neglected:

$$Q_j^{\text{EV,max}}\,[\text{kVAR}] \approx 0. \tag{2}$$

To compute the network HC in a worst-case consumption scenario, we should take into account charging station effective charging capacity for each grid customer owning a charging station. However, considering a worst-case scenario where the power consumed by each customer charging stations j is $P_j^{\text{EV,max}}$ is tantamount to assuming that all EV owners charge their vehicles simultaneously. While it is reasonable to assume that PV installations within a given region operate at their maximum capacity simultaneously, such an assumption is not realistic for EV charging stations. Indeed, not only do consumers have different charging habits, but more importantly, EVs do not usually need to be charged every day. Furthermore, assuming every EV owner charges simultaneously creates a scenario with an unrealistically high network load, which inevitably leads to an underestimation of the HC. To overcome this, we introduce a binary random variable Z into the problem, multiplying the maximum charging power and modelling whether the station is active, reflecting realistic simultaneous charging :

$$P_j^{\text{EV,real}} = Z\, P_j^{\text{EV,max}}. \tag{3}$$

This random binary variable is defined as:

$$Z = \begin{cases} 1 & \text{if the EV is charging,} \\ 0 & \text{otherwise.} \end{cases} \tag{4}$$

This variable takes the value 1 for $\alpha \times 100\%$ of randomly selected charging stations and the value 0 otherwise. Here α represents the concurrency factor (i.e. the proportion of EV owners charging concurrently during the peak hour). The introduction of the variable α allows to reflect the uncertainty surrounding which network customers are charging their EVs simultaneously at the peak hour of the network. This factor is empirically determined by reconstructing and analysing EV charging profiles from real-world data.

2.2. Reconstruction of the EV charging profiles

We conducted a detailed analysis of the behaviour of charging station owners by investigating their smart meter data (in kWh) recorded every 15 minutes. The aim was to detect EV charging periods in their consumption profile, which enables us to count the number of customers simultaneously charging their EVs during the network peak hour.

Let's take a closer look at how this is done. First, the energy consumed during each quarter of an hour is obtained by subtracting two successive index measurements:

$$\Delta E\,[\text{kWh}] = E(t + \Delta t) - E(t) \;\text{ with }\; \Delta t = 15\text{min}. \tag{5}$$

The average power consumed during this quarter of an hour is

$$\bar{P}\,[\text{kW}] = 4\,\Delta E. \tag{6}$$

As shown in Fig. 1, an EV is assumed to be charging when $\Delta E \geq 1$ kWh (corresponding to an average power $\bar{P} \geq 4$ kW) for at least 4 consecutive periods (i.e. 1 hour), to avoid detecting energy-intensive appliances such as ovens which are generally used for shorter periods of time. Each profile includes a baseline consumption, which accounts for the household's domestic load excluding the charging station. By assuming a typical baseline of approximately 0.3 kW, this detection rule effectively identifies charging events from terminals with a capacity of 3.7 kW or greater.

To accurately isolate the consumption of the charging station alone, the baseline must be estimated and subtracted from the total profile. This baseline is calculated as the average total consumption measured immediately before and after the detected charging period (see Fig. 1):

$$E_{\text{baseline}} = \text{avg}\left(E_{\text{before charge}} + E_{\text{after charge}}\right). \tag{7}$$

The consumption of the charging station is then calculated as the median value of the total consumption during the charging period, from which the calculated value of the baseline is subtracted (see Fig. 1):

$$E_{\text{EV charge}} = \text{median}\left(E_{\text{during charge}}\right) - E_{\text{baseline}}. \tag{8}$$

Here we have assumed that the charging station consumption is constant throughout the entire charging process. However, this is not always the case in practice, nevertheless the profiles show that the consumption fluctuations during charging are usually less prominent compared to the EV consumption. The assumption of constant charging consumption is then not far from reality, and will not have a major impact on the conclusions about HC.

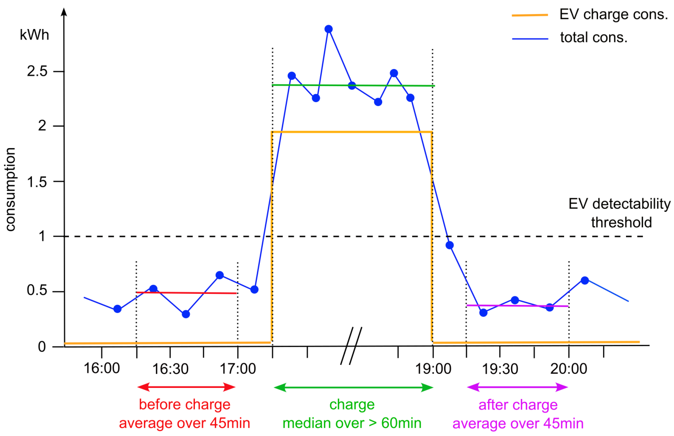

Figure 1: Schematic representation of our method for reconstructing EV charging periods (orange curve) based on the quarter-hourly consumption profile of a customer (blue curve).

2.3. HC computation: Monte Carlo approach

Due to the unpredictability of the customer behaviour regarding EV charging stations installation in the future, we used a Monte Carlo approach to simulate a large number of different scenarios for different possible penetration rates of the EV charging stations. Penetration is defined as the total installed capacity of charging stations (active or not) in the network divided by the substation nominal power. In this context, the stochastic HC is given by the penetration rate of EV charging stations below which none of the simulated scenarios causes a violation in the network.

First, it is necessary to define the random variables of the problem. The characteristics of these variables are presented in Table 1. There are two random variables, denoted X and Y, representing the location and capacity of the EV charging stations under study, respectively. Additionally, the random variable Z models the charging station's operating status. All of these variables are discrete. The location variable X takes its values from the set of customers that do not yet have an EV charging station, denoted $C \backslash C_{\text{EV}}$, where C denotes the set of all customers and C_{EV} the set of those already equipped with a charging station. This location is drawn according to a uniform distribution, which means that each location, i.e. customer, has the same probability of being selected. Note that the distribution could be improved by including some knowledge about customer's households and whether they have a garage.

Four EV charging stations' capacities Y are considered: 2.3, 3.7, 7.4 and 11 kW. Note that we do not consider 22 kW charging stations in the Monte Carlo simulations. Indeed, the maximum admissible power that private individuals can draw from the grid is almost always below this value, and a power reinforcement request is quite expensive. The probability distribution here depends on the type of customer: a customer with a single-phase connection to the network has a uniform probability of having a 2.3, 3.7 or 7.4 kW charging station, while a customer with a three-phase connection will have one of the four possible capacities installed with a uniform probability. Finally, the operating status of an EV charging station is defined as a binary variable $Z \in \{0, 1\}$, where $P(Z = 1) = \alpha$. This concurrency factor α represents the proportion of EVs charging simultaneously across the network. The actual power consumed by station j is then determined by $Z \times P_j^{\text{EV,max}}$.

The flowchart in Fig. 2 details how our Monte Carlo algorithm works. For a given LV network model, the algorithm starts from an initial consumption scenario corresponding to a historical worst-case situation, i.e. the most restrictive condition currently observed on the network.

The stochastic HC estimation relies on an iterative process over the number N of installed charging stations in the network. Let $S^{\max}$ be the maximum number of scenarios simulated for a fixed number of charging stations, and $L^{\max}$ the maximum number of possible locations for these stations. The process begins with $N = 1$ (a single installation added to the network), then follows the steps below, repeated as many times as there are scenarios to generate for the current value of N:

1. **Generating a scenario:** A random sample of location, capacity and operating status is drawn for each of the N charging stations to be added. This scenario is represented by a vector (l_i, c_i, s_i), where l_i denotes the location, c_i the capacity and s_i the operating status of the i-th charging station.

2. **Penetration rate:** Calculation of the penetration rate associated with the scenario.

3. **Adding the scenario to the network:** Add the N charging stations to the network with the location, capacity and operating status that were drawn in step 1.

4. **Running power flow:** Run a power flow on the network subject to the scenario added in the previous step.

5. **Compile limiting factors:** Compute the minimum voltage and the maximum load observed in the lines and at the transformer.

Once all $S^{\max}$ scenarios for a given N are completed, N is incremented. The procedure terminates when $N = L^{\max}$, at which point the final HC is estimated.

3 Results

In this section, we present our results regarding the HC of EV charging stations in a real-world LV distribution network.

Table 1: Description of the random variables for the EV charging station HC problem.

Random variable	Description	Type	Possible values	Distribution
X	Location	Discrete	$C \backslash C_{\text{EV}}$	Uniform
Y	Charging capacity	Discrete	$\mathcal{Y} = \{2.3, 3.7, 7.4, 11\}$ kW	$\begin{cases} [\frac{1}{3}, \frac{1}{3}, \frac{1}{3}, 0] & \text{if single-phase customer} \\ [\frac{1}{4}, \frac{1}{4}, \frac{1}{4}, \frac{1}{4}] & \text{if three-phase customer} \end{cases}$
Z	EV state of charge	Discrete	$\mathcal{Z} = \{0, 1\}$	$[(1-\alpha), \alpha]$

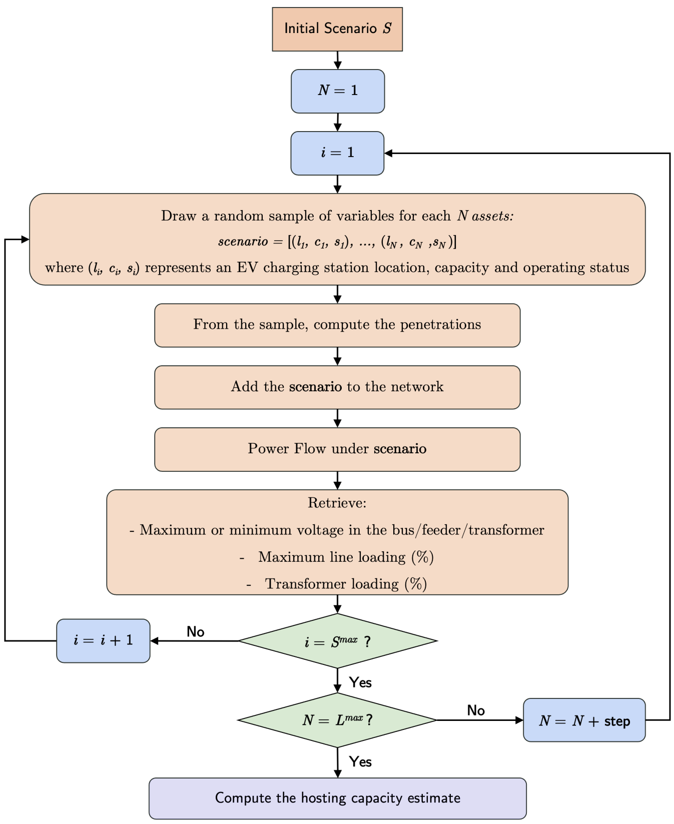

Figure 2: Flowchart showing the steps of the Monte Carlo algorithm used to estimate stochastic HC.

3.1. *Detection of the EV charging periods*

We applied the method described in Sec. 2.2 to identify the EV charging periods among the consumption profiles of customers with EV charging stations. For this purpose, we used smart meter data providing the index measurements every 15 minutes over a period of 3 months during winter. Fig. 3 illustrates the EV charging profile reconstruction for a customer on the RESA network. This figure shows that the EV charging profile is accurately reconstructed. The reconstructed profile clearly shows daily evening charging sessions at full power. Additionally, closer inspection of the peak magnitudes suggests the station likely has an 11 kW capacity.

Finally, thanks to this analysis, we can find the value of the parameter α. First, the individual consumption profiles of all EV owners in the study area are aggregated across the three-month duration to pinpoint the 15-min timestep of maximum collective demand. We then count the number of charging periods detected among all these customers at that precise moment. For the part of the rural distribution network considered in this study, we find that 26% of customers with charging stations charge their EVs simultaneously during the network's peak hour. We will therefore consider $\alpha = 0.26$ in the following calculations.

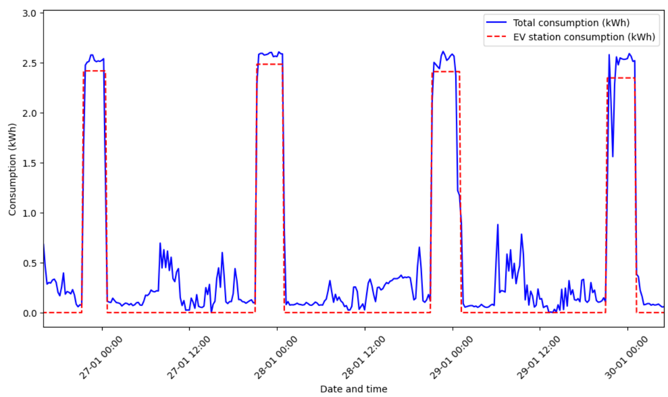

Figure 3: Example of reconstruction of an EV charging profile (red curve) from the smart meter consumption data (blue curve) for a customer of the distribution network of RESA.

3.2. *HC computation*

We tested our Monte Carlo method described in Sec. 2.3 taking into account the probability of concurrent charging of the EVs on a real-world LV distribution network of RESA, assuming perfect balance. At each time step, a worst-case scenario with peak domestic load and zero PV production is considered. Existing charging stations remain fixed, while new stations are added randomly with increasing penetration. Power flow analysis is performed for each scenario.

Fig. 4 shows minimum voltage level versus EV penetration rate for a transformer network of RESA, for each simulated scenario. Line/transformer loading violations are also displayed through circle colouring. The voltage minimum limit is 0.92 p.u., and line/transformer loading is limited to 100% of their maximum capacity. HC is defined as the first penetration value where at least one scenario violates these constraints (green area-yellow area boundary). In this case, the HC of the network is 63%, which means that the total charging station installed capacity (active or not) should not exceed 63% of the substation nominal power. Moreover, here under-voltages will be the first contingencies appearing in the network.

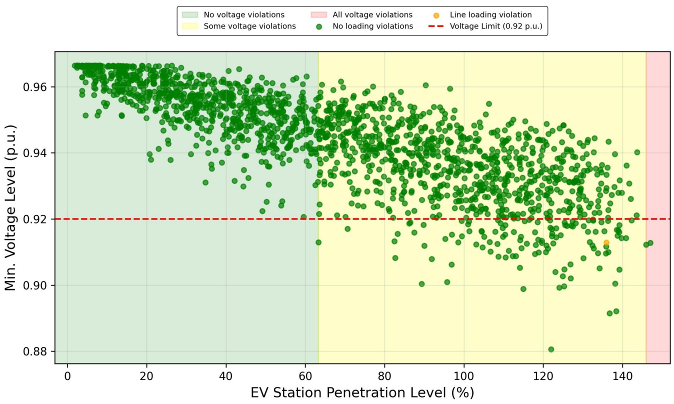

Figure 4: Minimum voltage level (in p.u.) calculated per EV charging station scenario for a transformer network of RESA, considering the worst-case consumption scenario as the initial scenario. The HC value is given by the boundary between the green area and the yellow area.

Fig. 5 shows the resulting EV HC, which corresponds to the total accepted EV penetration rate for each transformer network of a subpart of the distribution network of RESA. A "none" penetration rate means that the initial state of the network (without adding more charging stations) already contains violation of some voltage or line/transformer loading constraints. Considering actual charging station concurrency, some transformer networks can accommodate more than 100% penetration, well above estimates based on simultaneous charging. Indeed, the later assumption dramatically underestimates the HC. For instance, for the transformer network studied at Fig. 4, considering simultaneous operation of all installed EV charging stations reduces the HC from 63% to 16%.

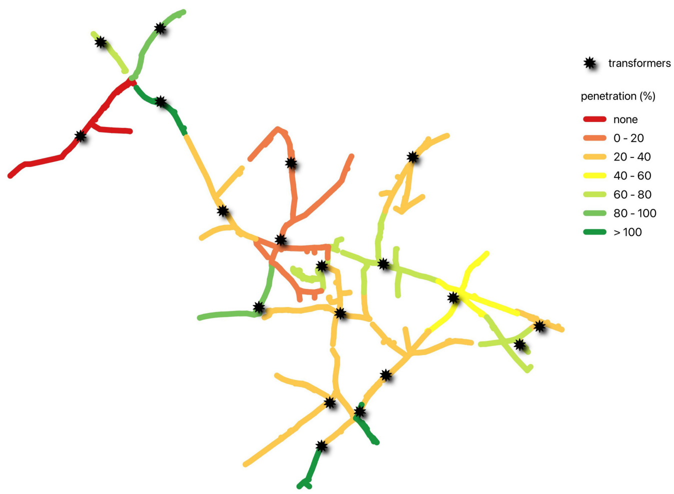

Figure 5: Total EV charging station penetration rates (in %) accepted per transformer network of a subpart of the distribution network of RESA, considering the worst-case consumption scenario as the initial scenario.

4 Conclusion

In this paper, we estimated the EV charging station HC in the LV distribution network of RESA, the electricity and gas operator in Liège, Belgium. For that purpose, we used a Monte Carlo approach to simulate a large number of scenarios to address the uncertainties in future EV charging station deployment. To avoid overly pessimistic estimations of network HC, which may lead to premature investment decisions, we introduced a binary variable into the problem that multiplies the maximum charging power to model whether the station is active, thereby reflecting a realistic simultaneous charging scenario. The percentage of customers simultaneously charging their EV at the peak hour of the network was estimated by analysing the charging station owners consumption profiles. This analysis provided an accurate estimation of the EV charging profiles for charging station owners. Considering actual charging station concurrency, our HC results show that some transformer networks of the studied distribution network can accommodate more than 100% penetration, well above estimates based on simultaneous charging. The proposed approach therefore provides DSOs with a practical and robust tool for EV integration planning under uncertainty.

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