Combined PV-EV-HP Hosting Capacity Analysis of a Belgian Low-Voltage Distribution Network

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***Abstract*—This paper presents an analysis of the combined hosting capacity (HC) of photovoltaic panels (PVs), electric vehicles (EVs), and heat pumps (HPs). The HC problem is defined using a generic formalism previously introduced in the literature. It is applied to a reconstruction of a low-voltage Belgian electrical distribution network, which was reconstructed using the topological path identification (TPI) methodology. Exogenous data needed for the HC analysis is provided by an observation tool developed by the Belgian distribution system operator (DSO), RESA. To ensure a realistic representation of the impact of the combined technologies, time-series with a granularity of 15 minutes are used. Results show that under-voltage is encountered rapidly for both EV and HP penetrations higher than 50%. Over-voltage is not faced before 75% of PV penetration. By contrast, even with high penetration rates for all three technologies, the lines of the case study network are not overloaded.**

***Index Terms*—Distributed Generation, Hosting Capacity, Distribution Network, Topological Path Identification**

I. Notations

N	Network
T	Time

Sets

$\mathcal{P}$	Set of network issues
$\mathcal{N}$	Set of nodes
$\mathcal{E}$	Set of edges
$\mathcal{C}$	Set of customer nodes
$\mathcal{H}$	Set of types of technologies { PV, EV, HP}
$\mathcal{I}_h$	Set of installation options of technology $h \in \mathcal{H}$
$\mathcal{T}$	Set of time steps, $\mathcal{T} = \{1, ..., T\}$.
$\mathcal{S}$	Set of all scenarios
$\mathcal{S}^c$	Set of considered scenarios
$\mathcal{S}^c_{\mathbf{a}}$	Set of considered scenarios with penetration $\mathbf{a}$
$\mathcal{A}^c$	Set of considered penetrations
$\mathcal{A}^f$	Set of feasible hosting capacities

Variables

$V_{\max}$	Maximal Voltage limit
$V_{\min}$	Minimal Voltage limit
$V_{t,n}$	Voltage at node n at time-step t
$I_{t,e}$	Current at edge e at time-step t
I^l_e	Nominal current of edge e
$L_{t,e}$	Edge e loading at time-step t
$L_{\max}$	Overloading threshold
$P_{t,c}$	Power consumption of customer c at time-step t
$P_{t,c,h}$	Power consumption or production at time-step t of technology h installed at customer c
$i_{\mathbf{s},c,h}$	The installation of the technology h at customer c in scenario $\mathbf{s}$

II. Introduction

The urge for carbon neutrality driven by the European Union (EU) has led to a significant increase in purchase rates in recent years of electric vehicles (EVs), photovoltaic panels (PVs), and heat pumps (HPs). Such increases in low-voltage distribution networks can stress some networks to their safety operation limits. Determining the combined hosting capacity (HC) of PV-EV-HP systems is a crucial metric for distribution system operators (DSOs) to assess the ability of a power network to accommodate these technologies without adverse effects and plan investments accordingly.

While the topic of HC has been well-researched for several decades, studies involving combined technologies seem to be less mature. There are three categories of methods to evaluate PV-EV-HP HC:

(i) Individually, by evaluating each technology independently;
(ii) Simultaneously, by evaluating combined pairs of technologies;
(iii) Simultaneously, by evaluating all three technologies combined.

The first category (i) is the straightforward increment of the traditional PV HC. For instance, authors in [1] individually compute the HC of the PVs, EVs, and HPs technologies. The second category (ii) accounts for the cumulative influence of a pair of technologies on the network. In [2], the combined effects of the PVs-EVs, EVs-HPs, and PVs-HPs pairs are studied. The third category (iii), which aims to assess the combined impact of all three technologies, is addressed in more recent studies. Authors in [2] consider several penetrations per technology while in [3] equal penetration levels (e.g., 25% for all technologies) are considered. To simultaneously account for multiple technologies, most HC studies focus on the second category (ii) as the third one (iii) is difficult to formalise and complex to implement. To address this problem of formalism, the authors of [4] have proposed a generic formalism for the HC problem with multiple technologies. This formalism enables a comprehensive analysis of all aspects of HC, facilitating clear communication in the field. It also allows for consistent comparison of results and tracking of advancements over time. This paper exploits this formalism on a real-life combined HC problem with multiple technologies (PV-EV-HP).

Additionally, the study carries out an HC analysis using several independent penetration rates for each technology. To ensure the accuracy of this analysis, empirical data provided from available information from RESA, a Belgian DSO, is used. Using empirical data provides practical insights into network behaviour under actual operating conditions. Authors in [2], [5] use a real network but, as time-series related to the used network are not available, they use publicly available standard load profiles (SLP) for customer loads. In [3], authors use both a real network and the customer loads associated with it. In this study, a real low-voltage distribution network as well as the smart meters data for the loads are used.

To summarise, the contributions of this paper are:

- Adopting the generic formalism [4] for the combined HC problem with three technologies simultaneously (PV-EV-HP) ;
- Using a reconstruction of a real low-voltage distribution network along with its smart meter data;
- Analysing the impact of combined PV-EV-HP on several penetration rates.

The rest of the paper is structured as follows: Section III introduces the HC problem. Section IV presents the case study. Section V develops the implementation to compute the combined HC and Section VI discusses the obtained results. Finally, Section VII concludes the paper with a summary and future prospects.

III. Problem Statement

This paper follows the formalism defined in [4], interested readers are encouraged to consult the original paper.

Let N be an unbalanced three-phase network. The network, N, is composed of nodes and edges. The sets of all nodes and edges are denoted by $\mathcal{N}$ and $\mathcal{E}$, respectively. The network contains a set of customers $\mathcal{C}$, that is a subset of the nodes: $\mathcal{C} \subset \mathcal{N}$.

The study is conducted over a period of time T and the set of all time-steps is $\mathcal{T} = \{1, ..., T\}$, a time-step of $\mathcal{T}$ is referred to as t. For each time-step t, the consumption of a customer $c \in \mathcal{C}$ is denoted as $P_{t,c}$. In addition to their load, customers can install new technologies from a set of new technologies $\mathcal{H}$. The technologies can have different sizes, and the set of the possible sizes for a technology $h \in \mathcal{H}$ is $\mathcal{I}_h$. The production or consumption of a technology $h \in \mathcal{H}$ of a customer $c \in \mathcal{C}$ at time-step $t \in \mathcal{T}$ is denoted $P_{t,c,h}$.

Given that customers can install different technologies with different options at different time-steps, different possible scenarios are possible. Each scenario represents a combination of installed technologies across the network. The set of all scenarios is referred to as $\mathcal{S}$. A scenario $\mathbf{s}$ from this set, $\mathbf{s} \in \mathcal{S}$, is formally defined as the tuple of installed sizes of each technology at each time-step for each customer:

$$\mathbf{s} = (i_{c,h,t} | \forall c \in \mathcal{C}, h \in \mathcal{H}, t \in \mathcal{T}) \tag{1}$$

where $i_{c,h,t} \in \mathcal{I}_h$ is the size of the technology h installed at customer c at time-step t. Note that bold characters are used for tuples.

Given that the set of all possible scenarios is intractable, a subset of it, defined as $\mathcal{S}^c$, is considered for the analysis. The construction of this subset is further explained in Section IV.

Let $\mathcal{A}^c \in \mathbb{R}^{|\mathcal{H}|}$ be the set of all considered penetrations. A penetration $\mathbf{a} \in \mathcal{A}^c$ is a tuple that gauges the amount of new installations in the network for each technology in a given scenario. The function $\mathbf{g}(\mathbf{s}) : \mathcal{S}^c \rightarrow \mathcal{A}^c$ computes the penetration tuple for a given scenario $\mathbf{s}$:

$$\mathbf{g}(\mathbf{s}) = (g_h(\mathbf{s}) \mid \forall h \in \mathcal{H}) \tag{2}$$

where the penetration of a technology is chosen as the ratio of the number of customers with that technology installed to the total number of customers, and computed using the function $g_h(\mathbf{s})$ defined as:

$$g_h(\mathbf{s}) = \frac{|\{c \in \mathcal{C} \mid i_{\mathbf{s},c,h} \neq \emptyset\}|}{|\mathcal{C}|} \tag{3}$$

where $i_{\mathbf{s},c,h}$ designates the installation of the technology h at customer c in the scenario $\mathbf{s}$.

To detect if any issue occurred in scenario $\mathbf{s}$ the function f is defined as follows:

$$f(\mathbf{s}) = \begin{cases} 1, & \text{if } \exists t \in \mathcal{T} : f_t(\mathbf{s}) = 1; \\ 0, & \text{otherwise,} \end{cases} \tag{4}$$

where f_t is the function that detects any issue that occurred in the scenario $\mathbf{s}$ at time-step t. This function f_t that detects the considered issues $\mathcal{P}$ is defined as:

$$f_t(\mathbf{s}) = \begin{cases} 1, & \text{if } \bigvee_{p \in \mathcal{P}} f_t^p(\mathbf{s}); \\ 0, & \text{otherwise,} \end{cases} \tag{5}$$

where $f_t^p(\mathbf{s})$ is the function that evaluates if the issue $p \in \mathcal{P}$ occurs at time-step t of scenario $\mathbf{s}$. Two voltage level (VL) issues are considered: over- (OV) and under-voltage (UV); alongside the overloading (OL) of the lines. Therefore, the set of considered issues is $\mathcal{P} = \{\text{VL}, \text{OL}\}$.

The voltage level issues are detected by the function $f_t^{VL}(s)$ defined as follows:

$$f_t^{VL}(\mathbf{s}) = \begin{cases} 1, & \text{if } \exists n \in \mathcal{N} : V_{\text{min}} > V_{t,n} > V_{\text{max}}; \\ 0, & \text{otherwise,} \end{cases} \tag{6}$$

where $V_{t,n}$ is the voltage of node n at time t and, V_{min} and V_{max} are, respectively, the minimal and maximal allowed voltages. The function $f_t^{OL}(\mathbf{s})$ detects lines overload, and is defined as:

$$f_t^{OL}(\mathbf{s}) = \begin{cases} 1, & \text{if } \exists e \in \mathcal{E} : L_{t,e} = \frac{I_{t,e}}{I_e^l}, L_{t,e} > L_{\text{max}}; \\ 0, & \text{otherwise,} \end{cases} \tag{7}$$

where $L_{t,e}$ is the edge loading at time-step t, $I_{t,e}$ is the current at edge e at time t, I_e^l is the nominal rated current of edge e and L_{max} is the threshold for line overloading.

The voltages $V_{t,n}$ at each node and the currents $I_{t,e}$ at each edge are obtained by computing a power flow (PF) on the network with both the customers' loads ($P_{t,c}$) and the installations' production or consumption ($P_{t,c,h}$):

$$\{V_{t,n}, \forall n \in \mathcal{N}\}, \{I_{t,e}, \forall e \in \mathcal{E}\} = \mathrm{PF}_{\mathrm{N}}(P_{t,c}, P_{t,c,h}), \forall t \in \mathcal{T}. \tag{8}$$

The HC is the set of penetrations the network can sustain while not encountering any issues. In this study, the HC is chosen as the feasible penetrations $\mathcal{A}^f$, defined in [4], which are penetrations that are associated with scenarios with no issues:

$$\mathcal{A}^f = \{\mathbf{g}(\mathbf{s}) | \forall \mathbf{s} \in \mathcal{S} : f(\mathbf{s}) = 0\}. \tag{9}$$

IV. Case study

This section introduces the case study network along with exogenous data and outlines the scope of the study.

A. Network

The network considered in this paper is a reconstruction of a real Belgian distribution network.
The network is reconstructed using the topological path identification (TPI) methodology proposed in [6]. The network is obtained by using transformation functions to transform raw data from the DSO into well-defined information. An optimisation algorithm identifies the optimal paths to connect customers to their respective feeders.

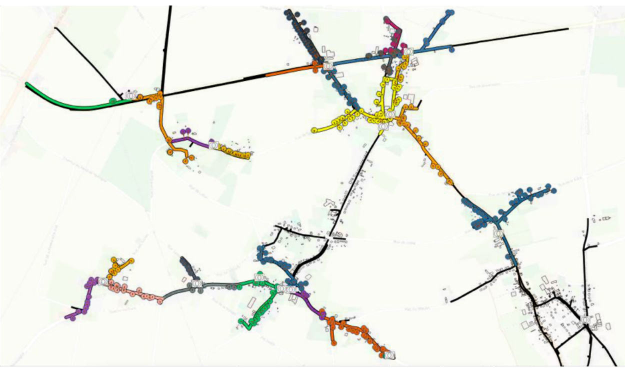

Fig. 1: Representation of the reconstructed Belgian network. Each colour represents a feeder and the substations are presented using the common two-circle symbol.

Figure 1 shows the full reconstructed network. This is a three-phase unbalanced network, where customers are connected to either only one phase or all three of them.

Given its size and the radial operation of the network, the proposed HC computation will focus only on one substation, but the work can be extended to the whole network. The selected substation is shown in Fig. 2.

The substation has two feeders, distinguished by purple (left feeder) and blue (right feeder) lines. Different feeders are only interconnected at the MV/LV substation itself, or through switches that can be opened or closed to control power flow. Table I details the number of elements per category of the considered subnetwork. In the remainder, this subnetwork is referred to as the network.

Fig. 2: Considered network which consist of a subpart of the reconstructed Belgian network that have one single substation connected to two-feeders.

TABLE I: Description of the considered single MV/LV transformer network.

Category	Number of elements.
customers	23
lines	42
feeders	2
MV/LV substations	1

Among the 23 customers present in the network, 15 of them have smart meters (SM). Both single-phase customers and customers without an SM are randomly connect to a phase. As the time series for customers without SM are missing, an SM time series from a customer with a similar annual consumption is attributed to these customers.

B. Technologies

The considered technologies are: PVs, EVs and HPs leading to technology set: $\mathcal{H} = \{\mathrm{PV}, \mathrm{EV}, \mathrm{HP}\}$. The penetration tuple defined in Eq. (2) is:

$$\mathbf{g}(\mathbf{s}) = \big(g_{PV}(\mathbf{s}), g_{EV}(\mathbf{s}), g_{HP}(\mathbf{s})\big). \tag{10}$$

For each technology, the set of options is limited to their size. A single PV installation of size of 20 PVs with a 290-watt peak is available. Two types of EV chargers, 3kW and 7kW, and two heat-pump sizes, 7.5kW and 15kW, are available. The different available sizes per technologies are summarised in Tab. II.

TABLE II: Technology size per technology type.

Technology type	Technology size
PV	$\mathcal{I}_{\mathrm{PV}} = \{0,\ 20 \times 290W_{peak}\}$
EV	$\mathcal{I}_{\mathrm{EV}} = \{0,\ 3kW,\ 7kW\}$
HP	$\mathcal{I}_{\mathrm{HP}} = \{0,\ 7.5kW,\ 15kW\}$

In this study, the size of a given technology for a customer cannot change during the time period and new installations are added at the first time-step ($t = 0$), thus $i_{c,h,0} = i_{c,h,t}, \forall c \in \mathcal{C}, h \in \mathcal{H}, t \in \mathcal{T}$.

C. Considered scenarios

The considered scenario set $\mathcal{S}^c$ is constructed by first reducing the considered penetration set $\mathcal{A}^c = \{\mathcal{A}^c_h \mid \forall h \in \mathcal{H}\}$: for each technology $h \in \mathcal{H}$, the considered penetrations are $\mathcal{A}^c_h = \{25\%, 50\%, 75\%, 100\%\}$. Since these penetration levels are independent for each technology, the total number of possible combinations is the

TABLE III: Probabilities of installing any type of technology per household size with the corresponding assumption on the number of people per household.

People per Household	**Household size ($\mathbf{m^2}$)**	**Probability** (%)
1	[0,50)	20
2	[50, 75)	40
3	[75, 100)	50
4	[100, 125)	60
5 or +	[125, Inf)	80

product of the number of choices for each technology. Therefore, the total number of possible combination in $\mathcal{A}^c$ is $|\mathcal{A}^c| = 4 \times 4 \times 4 = 64$.

Given a tuple $\mathbf{a} \in \mathcal{A}^c$, the size of the subset $\mathcal{S}^c_{\mathbf{a}}$ is m, with $m \in \mathbb{R}^+$. The value m represents the number of scenarios analysed for each penetration tuple $\mathbf{a}$. In this study, m is chosen as 100 as it is a good trade-off between the number of scenarios tested and the total computation burden.

As the number of considered scenarios is restricted, each customer $c \in \mathcal{C}$ is assigned a probability for any technology $h \in \mathcal{H}$. This probability represents the likelihood of the customer c of installing the technology h. When building a scenario $\mathbf{s} \in \mathcal{S}^c_{\mathbf{a}}$, the probabilities are used to decide which customer will install a particular technology. The probabilities are chosen proportional to the household size as considering the household size enables the accounting for the socio-economic aspect of buying a new technology and reflects the link between the household size and the installation of new technologies. Larger households are generally associated with higher income levels, and studies suggest these customers are more likely to adopt these technologies [7].

Five groups of household size are considered: a person living alone, referred to as isolated; two-people household, three-people household, four-people household, and five-or-more-people household. The distribution of customers in $\mathcal{C}$ in these categories is shown in Fig. 3. Table III gives the number of people per household size and the associated probabilities of installation. In this work, in the absence of specific supporting data, for a given customer, the probabilities of installing each technology are assumed equal.

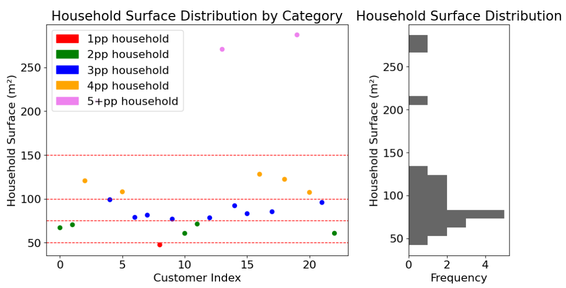

Fig. 3: Customers to household size distribution.

D. Exogenous data

Exogenous data gathers all the necessary input data, except the network itself, needed to compute the HC. The main exogenous data is the customers' load profiles and the new technologies' profiles. Both customer load profiles and technology profiles were provided by RESA. Customer load profiles are directly taken from SM data while technology profiles are derived from raw data and predictions done using the Sirius tool [8].

Simulating an entire year for each penetration with a 15-minute granularity for all considered scenarios would be computationally challenging. To reduce this burden while still using time-series to allow one to compute a relevant hosting capacity, one strategy consists of reducing the window of time steps considered in a day, as in [9]. Another approach is to cluster the year into representative days and reduce the evaluated time steps to only these days. As only considering parts of the day does not reduce the workload sufficiently when considering PV-EV-HP, the representative days approach is used in this paper to reduce the computational workload.

The representative days are the same as the Sirius study [8]. These are either days when the load is completely different from other days and thus do not represent many days in the year but rather an impactful day; or days when the load profile behaviour is highly common in the year. In total, twelve days are designated as representative days. The numbers of days that are similar during the year to the considered representative days are presented in Tab. IV.

TABLE IV: Number of days in a year of 366 days that are similar to the considered representative days.

Day	**# similar days**	**Day**	**# similar days**
1	33	**7**	20
2	42	**8**	42
3	13	**9**	23
4	24	**10**	3
5	51	**11**	10
6	55	**12**	50

E. Uncertainties

The process of computing the HC depends on future installations, which leads to uncertainties. Two categories of uncertainties for HC were introduced by [10]: epistemic uncertainties which are due to lack of knowledge and aleatory uncertainties which come from elements that are inherently stochastic [4]. In this study, uncertainties from both categories are considered. Table V gathers the uncertainties by technology type and if they are considered or not. In addition to these and as previously mentioned, the installation type, which is an epistemic uncertainty, is considered.

TABLE V: Summary of the considered uncertainties by technology type.

Installation type	Uncertainties		
	Epistemic		Aleatory
	Localisation	Size	Production/ consumption
PV	✓	✗	✓
EV	✓	✓	✗
HP	✓	✗	✗

V. Implementation

The iterative implementation of HC analysis for the combined PV-EV-HP technologies of the Belgian network is showcased in the flowchart in Figure 4.

The voltage thresholds used for the detection of issues are from the European EN50160 standard: $V_{min} = 0.95$ and $V_{max} = 1.05$ in Eq. (6). As the time step granularity is 15 min, the duration limit of EN50160 is not considered as it evaluates mean voltage over 10-minute periods. For the lines, an overload (OL) in Eq. 7 of at most $L_{\max} = 150\%$ of the nominal rate of the lines is allowed.

VI. Results

The HC as defined in Eq. (9) is given as follows:

$$\begin{aligned}\mathrm{HC} = \{&(25-50\%, 25\%, 25-100\%),\\ &(25\%, 50\%, 25-100\%),\\ &(25\%, 100\%, 100\%),\\ &(50\%, 75\%, 25-75\%),\\ &(25\%, 75-100\%, 25-50\%),\\ &(50\%, 100\%, 25-50\%),\\ &(50\%, 50\%, 25-100\%)\}.\end{aligned}$$

Recall that the penetration tuple is defined in Eq. (10) as (a_{PV}, a_{EV}, a_{HP}).

To analyse the HC and the different penetrations, a graphical approach is used as in [11] as it enables to show the combined penetrations. For readability, all voltage points for all customers and time-steps given a penetration are plot on Fig. 5 on a hypothesis space of continuous probability density functions (PDFs). The same is done for line loadings in Fig. 6. As anticipated based on the findings of other studies, the lines are not overloaded for all the PV penetrations. There is also no overloading for all EV and HP penetrations, which was not anticipated. It is worth to mention that the transformer load does not even reach 40% of its rated capacity.

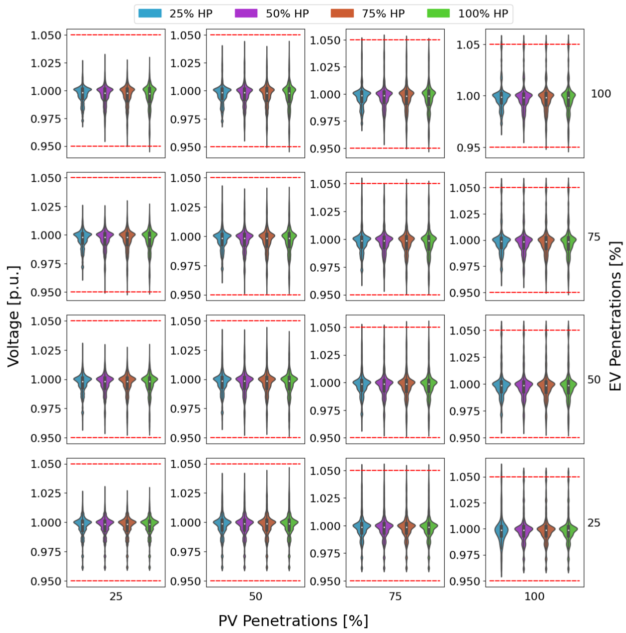

Fig. 5: HC analysis for bus voltages using violin plots.

The voltage level constraints are, as usual, more limiting. OV is not encountered before 75% of PV penetration. Under-voltage is encountered rapidly for both EV and HP penetrations higher than 50%.

DSOs may decide to accept some scenarios with issues to increase the HC since, from the results, it appears that most tuples are just outside the limits for a small number of scenarios. For example, the tuple $(25\%; 75\%, 75\%)$ presents a small amount of scenarios with a slight UV. Indeed, considering the median or the 3rd percentile, shown in the boxplot, would lead to a bigger hosting capacity set with higher penetrations allowed.

The granularity of 25% for the penetration rate in this case study was arbitrarily chosen to provide a broad overview of the network's hosting capacity. However, this can be further refined with smaller increments to examine specific areas of interest more closely. Additional simulations with finer granularity around key regions can offer deeper insights and allow for more precise assessments where needed.

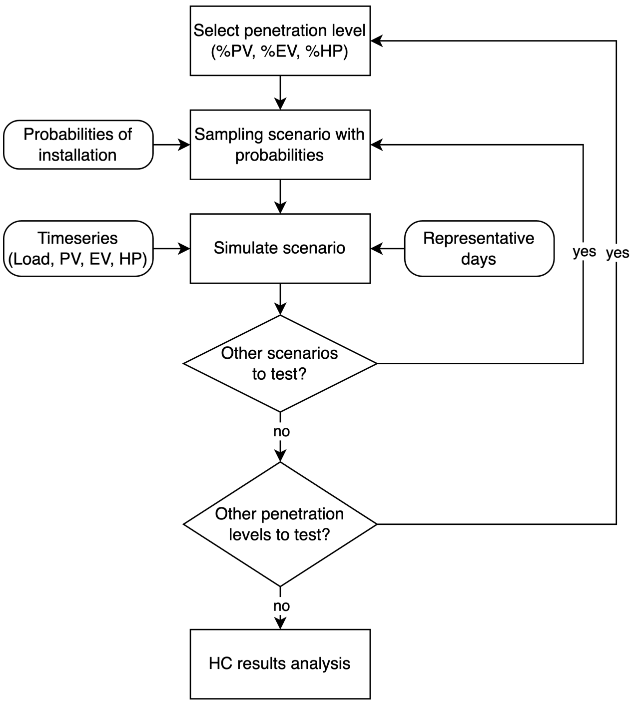

Fig. 4: Flowchart describing the implementation of the presented HC analysis.

VII. Conclusion

This paper proposes a combined PV-EV-HP HC analysis, following the formalisation [4] of the HC, on a Belgian network. The analysis conducted with the real data available to the DSO and the usage of probabilities of installation for each technology allowed for a more realistic evaluation of the HC. The results obtained show that the network allows the installation of up to 50% of penetrations for every technology, while 75% penetration rates are still acceptable if the DSO accepts a number of scenarios with some issues in the network.

To extend this work, considering quasi-static time-series (less the 10 min) would allow one to perform a dynamic hosting capacity analysis, taking into account the duration

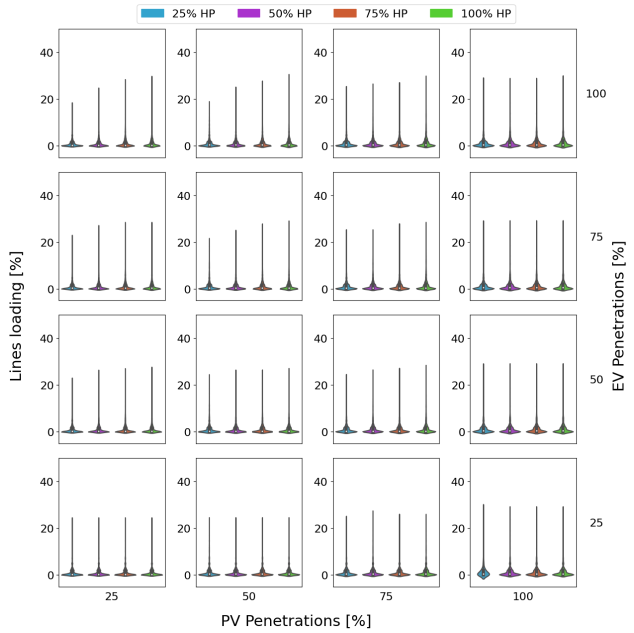

Fig. 6: HC analysis for line loadings using violin plot.

of the issues. Furthermore, another set of representative days as well as a thoroughly studied motivation behind their selection would lead to a baseline that could validate the obtained results for the considered days. This means carefully considering different factors, such as typical weather conditions, energy consumption patterns, and any seasonal variations, to ensure that these days reflect a range of real-world situations.

Pairing the present work with network management techniques that are used to enhance the hosting capacity should be considered as an extension. Indeed, this extension could use techniques such as dynamic operating envelopes (DOEs) that manages the operation of distributed energy resources (DERs) [12] or active network management (ANM), which manages the overall network infrastructure [13]. Enhancing the hosting capacity with these techniques would increase the resilience, reliability, and overall efficiency of the distribution networks, with a better energy management in the face of increasing renewable penetration.

Finally, collecting socio-economic data would significantly enhance the ability to model and implement more realistic probabilities when attributing installations to different customer segments. By incorporating factors such as income levels, property types, energy consumption patterns, and regional demographics, it becomes possible to better understand which groups are more likely to adopt distributed energy resources. This data-driven approach allows for the creation of more accurate, granular models that reflect the diversity of customer behaviour and financial capabilities.

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