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Violation-mitigation-based method for PV hosting capacity quantification in low voltage grids

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ABSTRACT

Hosting capacity knowledge is of great importance for distribution utilities to assess the amount of PV capacity possible to accommodate without troubling the operation of the grid. In this paper, a novel method to quantify the hosting capacity of low voltage grids is presented. The method starts considering a state of fully exploited building rooftop solar potential. A downward process is proposed—from the starting state with expected violations on the grid operation to a state with no violations. In this process, the installed PV capacity is progressively reduced. The reductions are made sequentially and selectively aiming to mitigate specific violations: nodes overvoltage, lines overcurrent and transformer overloading. Evaluated on real data of fourteen low voltage grids from Austria, the method proposed exhibits benefits in terms of higher hosting capacities and lower computational costs compared to stochastic methods. Furthermore, it also quantifies hosting capacity expansions achievable by overcoming the effect of the violations. The usage of a potential different from solar rooftops is also presented, demonstrating that a user-defined potential allows to quantify the hosting capacity in a more general setting with the method proposed.

1. Introduction

Installations of distributed generation (DG), most notably solar photovoltaic (PV), in low voltage grids are occurring around the globe and the trend is expected to rise due to environmental incentives [1]. To assess the impact of DG at low, medium, and high penetration levels on the operation of low voltage grids, several studies were carried out [2–5]. These studies show that major concerns in the operation of low voltage grids due to DG penetration relate to voltage/frequency variations, thermal overloading, power quality and protection problems [3]. Consequently, one major concern from distribution system operators (DSOs) ought to be: how much DG can be installed in the low voltage grids before facing the aforementioned operational problems? This concern was addressed recently by introducing the concept of hosting capacity [6–9]. Even though hosting capacity can relate to any DG technology, we refer to PV hosting capacity as PV is the most common technology deployed in low voltage grids worldwide [1].

Hosting capacity refers to the maximum amount of installed PV capacity that can be accommodated in a low voltage grid without causing operational problems. Relevant considerations in order to quantify the hosting capacity are: (i) the characteristic of the low voltage grid and its elements (e.g., loads, transformers, lines, topology); (ii) the operational problems to be considered relevant to a study-case, most commonly based on grid violations due to nodes overvoltage and thermal overloading of lines and transformers [6]; (iii) the assessment period: either a worst-case snapshot assessment to get conservative hosting capacity values; or time-series assessment that better represents the interaction of the elements of the grid and thus provide more accurate values for the hosting capacity [10].

Systematic methods for hosting capacity quantification in low voltage grids are available in the literature. These can be broadly classified as: rules-of-thumb, analytics, stochastics, and optimization-based methods [6,7,11–13]. Rules-of-thumb methods have been the first methods to roughly quantify the hosting capacity by most DSOs. Although they are easy to implement, the hosting quantities reached are usually quite conservative as high safety margins are considered [7]. Analytics or deterministic methods intent to provide the theoretical maximum value of the hosting capacity by considering all the possible scenarios caused by PV installations and load consumption. In practice, this is so far infeasible for large networks as it entails tens of millions of power flow simulations to evaluate the hosting capacity [6,7]. Rather than the maximum hosting capacity, stochastic methods provide a set of hosting capacity values based on the simulations of different configurations to represent uncertain variables (mostly driven by the location and size of future PV installations). Those variables are randomly established and

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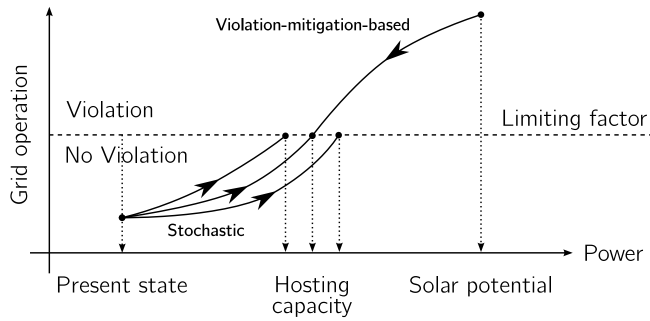


Fig. 1. Stochastic upward process and the heuristic downward process as proposed for hosting capacity quantification.

increased in an upward process until violations in the grids emerge. Thereafter, hosting capacity is usually featured using probabilistic distribution functions. Accuracy on the results depends upon the number of configurations considered to represent the various uncertainties [14–19]. Optimization based methods aim to maximize the PV installed capacity while meeting the grid constraints using optimal-power-flow techniques. The difficulties in application of these methods are the feasibility to find a globally optimal solution given the complexity and inherent non-convexity [11,12,20].

Overall, rules-of-thumb methods are likely to be displaced by more sophisticated methods, if the latter provide simplified methodologies requiring information readily available to DSOs. Analytical and optimization-based methods have the potential to provide the global maximum for the hosting capacity, however, the computational cost and the feasibility on the results are still to be demonstrated. Stochastic methods have been applied to real grid data [6,7], and some commercial tools have been developed [13]. Thus, stochastic methods represent a well-established state-of-the-art, and, therefore, will also be used as a reference case in this paper to contrast the performance of the method proposed.

Despite their inherent benefits, stochastic methods ignore the state of the grid in the process of assessing the hosting capacity, meaning that increases made in the PV installed capacity at different nodes of the grid are subject of randomness rather than of operational grid conditions. In fact, randomness appears as a solution to deal with the decision-making of how and where to increase PV capacities in any upward process. On the other hand, the actual extent of the hosting capacity based on the solar potential is usually not considered. Only Grabner et al. [19] presented a study of the hosting capacity taking into account the solar potential of the grid based on building roofs. It employs a stochastic method including rooftop potential data to improve the modeling of PV generation. The aforementioned aspects can be disadvantageous acknowledging that nodes in a grid can have great differences in the ability to accommodate PV units, either due to operational conditions or due to solar potential virtue at a node level. Moreover, stochastic methods usually rely on reduced period of assessment (one timestep [16], 2 hours [17], 1 day [18]), although studies [6,10] show that the accuracy of the results might be degraded by short time-series simulation periods. Yet, long simulation periods considerably increase the computational costs of stochastic methods, as multiple configurations are already needed to represent stochastic variables.

In this paper, we present a novel method to quantify the hosting capacity in low voltage grids. We propose a heuristic downward process that takes into account the operational state of the grid. The concept of the downward process is depicted in Fig. 1. Our proposed method considers a fully exploited solar potential in all nodes of a grid as the starting condition. Then, the installed capacity of PV units are sequentially and selectively reduced aiming to mitigate existing violations in the grid operation. The violations considered are nodes overvoltage, lines overcurrent and transformer overloading. The metrics to define the violations are according to local practices based on EN50160 standard [21]. New violations that consider harmonics, stability or protection issues are being suggested [22], and advanced metrics for voltage violations are being proposed [23]. Even though additional violations and metrics can be incorporated in the structure of the method proposed, as it will be shown later, standard violations and metrics are used as the common framework to evaluate the performance of the method proposed and compare it against well-established stochastic methods. To this aim, the hosting capacity of fourteen low voltage grids from Austria are quantified using both methods.

The main features of the method proposed can be summarized as follows:

- it quantifies hosting capacity values closer to the global maximum while requiring lesser computational time compared to stochastic methods;
- it quantifies expansions of the hosting capacity by overcoming the effect of the grid violations;
- it has the advantage to adapt the potential used in the hosting capacity quantification according to the user interest, e.g., building-rooftop based, equally distributed, unequally distributed.

Evaluations of the different means to enhance the hosting capacity, such as PV control features (e.g., voltage regulation, curtailment), online-tap changer on transformers, flexible devices (e.g., electric vehicles, batteries), are not the intention of the present paper. Such analysis, however, can be performed using the method proposed as it will be pointed out later in the paper.

The rest of the paper is structured as follows: Section 2 provides an overview of stochastic methods and introduces relevant scientific work used as references to contrast the performance of the method proposed, which is presented in detail in Section 3. Section 4 presents the characteristics of the real low voltage grids used in the study, as well as the simulation framework. The results and discussion are presented in Section 5. Finally, the conclusions are drawn in Section 6.

2. Stochastic methods

Fig. 2 depicts the general concept of stochastic methods for hosting capacity quantification in low voltage grids as proposed in literature [15–19]. The grid data comprises all known variables available from the DSO for a specific low voltage grid, i.e., data such as: grid topology, transformer(s) data, line data, load nodes, type of loads connected at each node, annual consumption of loads. The amount and quality of the grid data available to the DSO depends on the degree of digitization of the infrastructure, however, the current trend for DSOs is to collect more and accurate data.

While the behavior of some variables are assumed to be known with relatively high accuracy, uncertain variables are modeled via random processes. Uncertain variables mainly represent the stochastics of PV installations regarding locations, installed capacity or size, and time-dependant production. Conventional loads such as households, business, public facilities, are sometimes also represented by uncertain variables within the quantification process [16,18], despite the fact that many DSOs have already enough data to faithfully represent load behavior. In general, uncertain variables are set and a time-series power flow simulation is performed. Then, based on desired conditions, the algorithm decides whether a new set of uncertain variables is created or whether to stop the execution of the algorithm and settle on the hosting capacity derived. The two approaches by Breker et al. [16] and Torquato et al. [17] shall be used as references to contrast the performance of the method proposed. Both methods are opensource and have been applied to real grid data. The two methods are discussed in a more detailed manner hereafter, the corresponding flowcharts are shown in Fig. 3.

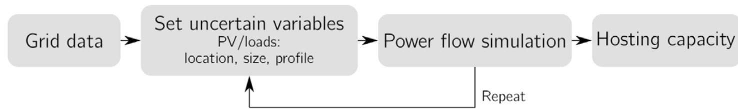


Fig. 2. Concept of stochastic methods for hosting capacity quantification.

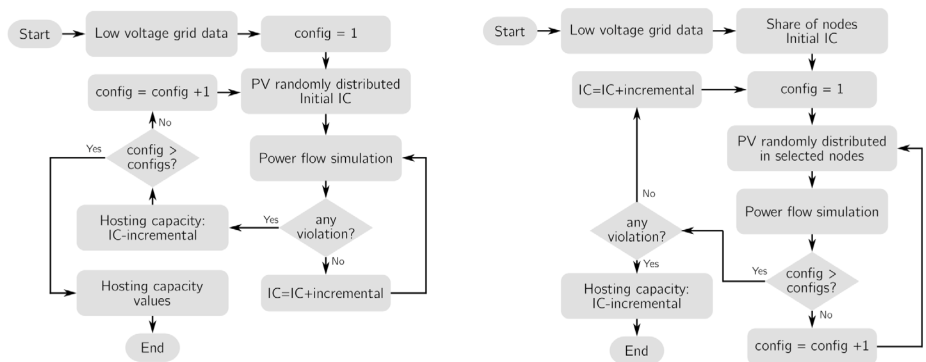


Fig. 3. Flowchart of stochastic methods as proposed by Breker et al. [16] (left) and Torquato et al. [17] (right). IC refers to the total PV installed capacity in the grid, $config$ and $configs$ are the counter and the total number of configurations, respectively.

In Breker et al. [16], once the grid and loads are modeled, PV units are placed in all nodes of the grid (excluding unfeasible nodes: bypass nodes, nodes for lines re-distributions, or similar). The peak power of each PV unit is set randomly such that the total initial installed capacity equals a starting value, e.g., 1 kWp (kilowatt-peak). Having established this initial configuration ($config = 1$), a power flow simulation is performed. If according to established constrains no violation in the grid operation is observed, the total installed capacity is increased by a number or a factor keeping the initial proportion of PV units in the present configuration. Otherwise, if a violation results from the current configuration, the last viable hosting capacity is stored, and a new configuration of PV units is created. The process is repeated until the total number of configurations ($configs$) is reached.

In Torquato et al. [17], having the grid and loads modeled, PV units are placed randomly in a user defined share of nodes, e.g., 20%. The size of each PV unit is set to be proportional to the annual energy consumption of the loads connected at the same connection point, such that the total initial installed capacity equals a starting value, e.g., 1 kWp. Using this initial configuration, a grid simulation is performed and relevant results related to the state of the grid are stored. The process of (i) randomly placing PV units in a defined number of nodes, (ii) keeping the proportion of PV units to the loads' annual energy consumption, and (iii) having the same total installed capacity, is repeated until the number of configurations are completed. After completion, if no violation is found, then the total installed capacity is increased by a number or a factor. Otherwise, the hosting capacity is determined for the proportion of nodes considered exhibiting PV generation.

The total number of configurations ($configs$) refers to a user-defined parameter. Breker et al. [16] stated that 100 configurations is adequate to get a sufficient accuracy for their method, while Torquato et al. [17] used 50 configurations for their method.

3. Proposed violation-mitigation-based method

In general, the hosting capacity quantification problem can be described as optimization problem, the solution being the single PV capacities installed to reach the maximum hosting capacity in the grid.

$$(P_1^*, \dots, P_N^*) = \arg \max_{(P_1,\dots,P_N)} \sum_{n\in\mathcal{N}} P_n,$$

such that

$$P_n \geq 0, \forall n \in \mathcal{N},$$

$$\text{and no violations occur.} \tag{1}$$

$\mathcal{N} = \{1, \dots, N\}$ being the set of nodes in the grid and P_n referring to the installed PV capacity at node n.

In the following, the grid violations considered are specified by constraints. We assume that the grid can be represented as directed simple graph $(\mathcal{N}, \mathcal{L})$ consisting of nodes and lines, where lines are given as pairs of nodes, if a connection exists, i.e.,

$$\mathcal{L} = \left\{(n, m) : n, m \in \mathcal{N}, n \neq m\right\}. \tag{2}$$

At $t \in \mathcal{T} = \{1, \dots, T\}$ of the time steps considered in a time-series simulation, the voltage at a single node n is described by $u_{n,t}$. Then, constraints to reflect violations due to overvoltage can be defined as:

$$u_{n,t} \leq u_1^{\max}, \forall n \in \mathcal{N}, \forall t \in \mathcal{T}, \tag{3}$$

$$\sum_{t\in\mathcal{T}} H(u_{n,t} - u_2^{\max}) \leq t^{\max}, \forall n \in \mathcal{N}. \tag{4}$$

Here, $u_1^{\max}$ defines the upper voltage limit not to be exceeded. The second voltage limit $u_2^{\max}$ is only allowed to be exceeded in 5% of the simulation period [21], i.e, $t^{\max} = 0.05T$. Here, H refers to the Heavyside function, i.e.,

$$H(x) = \begin{cases} 1 & x > 0 \\ 0 & x \leq 0 \end{cases}. \tag{5}$$

At time step t, the current at the line $l = (m, n) \in \mathcal{L}$ is given by $i_{(m,n),t}$, the constraint to reflect the maximum allowed current $i_{(n,m)}^{\max}$ at that line then reads

$$i_{(n,m),t} \leq i_{(n,m)}^{\max}, \forall (n, m) \in \mathcal{L}, \forall t \in \mathcal{T}. \tag{6}$$

The reverse power S at the transformer is limited by $S^{\max}$, described by the constraint

$$S_t \leq S^{\max}, \forall t \in \mathcal{T}. \tag{7}$$

We propose a heuristic to solve the problem defined in Eq. (1) starting from the initial value given by the solar potential, i.e.,

$$P_n^{(0)} = P_n^{\max}, \forall n \in \mathcal{N}. \tag{8}$$

Checking for violation of the constraints defined in (3), (4), (6), (7), the algorithm calculates the new hosting capacity (downwardly) $P^{(i+1)} = (P_1^{(i+1)}, \dots, P_N^{(i+1)})$ from the current values reached after i iterations $P^{(i)} = (P_1^{(i)}, \dots, P_N^{(i)})$ by using the following mitigation processes (with a reduction-step of P_{step}):

- If voltage constraints (3) or (4) are violated, all PV units connected to the violated nodes are identified and in sum reduced by P_{step} to

$$P_n^{(i+1)} = P_n^{(i)}\left(1 - \frac{P_{\text{step}}}{\sum_{n\in\mathcal{V}_u} P_n^{(i)}}\right), \forall n \in \mathcal{V}_u, \tag{9}$$

$$\mathcal{V}_u = \left\{ n \in \mathcal{N} : P_n^{(i)} > 0 \wedge \left(u_{n,t} \geq u_1^{\max} \vee H(u_{n,t} - u_2^{\max}) > t^{\max} \right) \right\}. \tag{10}$$

this relies on the premise that if there is overvoltage violation in a node, it is because: (i) the violated node has a PV connected; or (ii) there is at least one PV connected to a nearby node in which there is overvoltage violation too; or (iii) both cases.
- If current constraints are violated (6), all lines with overcurrent violation are identified. For each line, the downstream PVs are identified. A downstream PV is defined as any PV unit located downstream the line with respect to the distribution transformer (the downstream boundary is the transformer itself to account for meshed topologies). Only downstream PVs might contribute to the current flowing through the line causing overcurrent, as in the non-PV condition, lines are assumed to supply existing loads without violations. Then, the installed capacity of all identified downstream PVs (accounting all lines with violation) are reduced in total by P_{step} to

$$P_n^{(i+1)} = P_n^{(i)}\left(1 - \frac{P_{\text{step}}}{\sum_{n\in\mathcal{V}_i} P_n^{(i)}}\right), \forall n \in \mathcal{V}_i, \tag{11}$$

$$\mathcal{V}_i = \left\{ n \in \mathcal{N} : P_n^{(i)} > 0 \wedge n \in \mathcal{D} \right\}, \tag{12}$$

where $\mathcal{D}$ is the collection of all downstream PVs.
- In case of transformer overloading, i.e., violation of constraint (7), all PV units are reduced according to the excess power P_{ex} at the transformer, i.e.,

$$P_n^{(i+1)} = P_n^{(i)}\left(1 - \frac{P_{\text{ex}}}{\sum_{n\in\mathcal{V}_p} P_n^{(i)}}\right), \forall n \in \mathcal{V}_p, \tag{13}$$

$$\mathcal{V}_p = \left\{ n \in \mathcal{N} : P_n^{(i)} > 0 \right\}, \tag{14}$$

$$P_{\text{ex}} = \max_{t\in\mathcal{T}} H(S_t - S^{\max}). \tag{15}$$

From Eqs. (9), (11) and (13), we observe that selected PV units contribute to the reduction (P_{step}) an amount proportional to its size. This is supported by the logic that larger PV installations are more likely to contribute more to the violation considered, not only at the immediate point of connections, but also on their surroundings.

The algorithm stops, as soon as a feasible point is found, i.e. that fulfills all constraints (3), (4), (6), (7). It should be noted that to reach a solution, the non-PV condition of the grid must be free of violation (i.e., existing assets should supply existing loads without violations) which is a sensible assumption.

Although the grid violations considered are based on nodes overvoltage, lines overcurrent and transformer overloading additional violations can be incorporated within the structure of the method proposed by defining their constrains and mitigation processes. Moreover, new constrains considering advances metrics, e.g., for voltage violations [23], can also be considered.

The order in which the mitigation of violations are executed might influence the resulting hosting capacity, mainly because the mitigation of a particular violation can have collateral effects on other violations. All possible orders of mitigation are given in Table 1. In Section 5, the effect of the order of mitigation on the hosting capacity quantification is evaluated, and, based on the results, the most preferable order is selected.

The flowchart diagram of the method proposed considering one specific order of mitigation is shown in Fig. 4. First, the grid and loads are modeled. Then, solar potential is determined for all nodes of the grid. From this starting condition, violations can be expected to emerge in the initial power flow simulation. The mitigation of violations are executed sequentially, i.e., only if a type of violation is mitigated completely, the next type of violation is handled by the algorithm. The selection and reduction of the installed capacity of PV units are done following the mitigation process as defined in Eqs. (9)–(15). After each PV reduction, a power flow simulation is performed to determine the new state of violations. For a worst-case assessment ($\mathcal{T}$ consists only in one timestep), loads are set to zero and PVs are set to their installed capacity (peak capacity) in a snapshot power flow simulation. When finally no violation is found, the last installed capacity of PV units is considered to be the hosting capacity at individual nodes. The aggregation of the latter results in the hosting capacity of the grid.

It is still possible to accelerate the mitigation processes of overvoltage and overcurrent violations. In these processes, selected PV units can be grouped by the feeder they belong to, knowing that the effect of a PV unit from a feeder has no effect in the violations of other feeders (considering the transformer as a slack bus with fix value). Then, the reduction-step (P_{step}) is set for each group. This grouping proceeding is optional and only meant to speed up the reductions process in the proposed method. Thus, it has no effect on the resulting hosting capacity.

It is worth to mention that in the present paper, we do not intent to include features than might enhance the hosting capacity, e.g., voltage regulators, PV curtailments, flexible demands, energy storages. It is understood, however, that those features can be integrated within the the power flow simulation (Fig. 4) to evaluate their impact on the hosting capacity quantification.

Table 1
Possible orders of violation mitigation.

ID	Sequence				
order1	Trans. over.	→	Overcurrent	→	Overvoltage
order2	Trans. over.	→	Overvoltage	→	Overcurrent
order3	Overcurrent	→	Trans. over.	→	Overvoltage
order4	Overcurrent	→	Overvoltage	→	Trans. over.
order5	Overvoltage	→	Trans. over.	→	Overcurrent
order6	Overvoltage	→	Overcurrent	→	Trans. over.

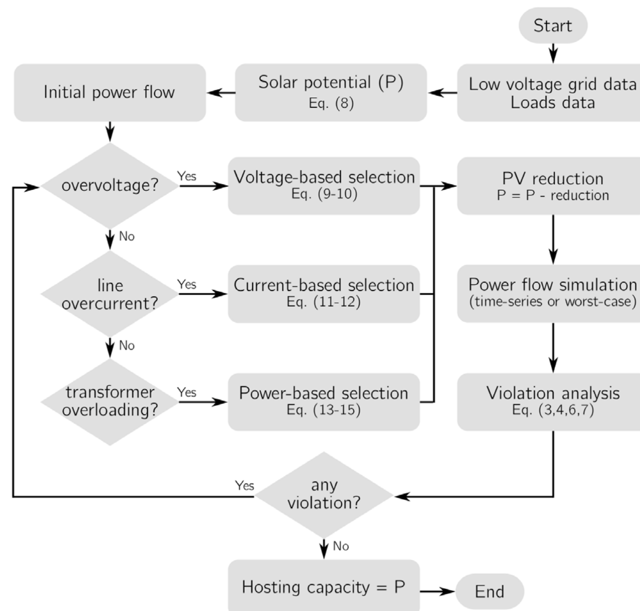


Fig. 4. Proposed violation-mitigation-based method flowchart considering a specific order.

Table 2
Main characteristics of the low voltage grids under study.

Grid	Rated power (kVA)	Load nodes	Length (km)	Annual energy (MWh)	Power factor
1	400	24	5.8	160	0.96
2	400	146	11.9	1014	0.97
3	1260	221	12.7	3064	0.98
4	400	112	16.3	818	0.89
5	1000	24	4.5	1793	0.95
6	250	37	3.8	474	0.96
7	800	110	7.1	947	0.96
8	630	160	10.7	1227	0.96
9	630	160	15.4	1417	0.96
10	1260	20	2.6	780	0.96
11	630	137	12.6	1216	0.95
12	630	36	6.5	877	0.96
13	1030	140	10.8	1933	0.96
14	160	22	5.2	143	0.96

4. Simulation framework

Fourteen grids were selected among over a thousand existing low voltage grids managed by the local DSO Vorarlberger Energienetze GmbH [24]. The DSO handpicked the grids representing different typical configurations and provided all the data used to model the grids including information of the distribution transformer (numbers, rated power), loads (location, load type, annual energy consumption), lines (connectivity, cable type, length), and buildings (rooftop solar potential). An overview of the main characteristic of the selected grids is presented in Table 2. The geographical representation of the fourteen grids are shown in Fig. A.11, in the Appendix.

In order to perform a time-series simulation, the load profiles for residential consumers are represented by real smart meter data collected from a field test of a local energy provider illwerke vkw AG [25]. The metering data were pre-processed to clean and fix inconsistencies before usage, then a smart meter database was set with 351 households measured for a period of a year with a time resolution of 15 minutes. The smart meter data is assigned to residential consumers using the annual energy consumption as the matching criteria. For other consumers, e.g. business, public facilities, standard load profiles from the Austrian clearing and settlement agency [26] are used. The standard profiles are scaled according to the annual energy consumption of the particular consumer. The power factor of the loads was tuned based on active and reactive power measurements at six substations, for the rest an average power factor of 0.96 was used.

Using the geographic information system (ARCGIS) available to the DSO, the solar power potential is estimated for the rooftops of all buildings connected to the low voltage grid. Typical PV power profiles from the region of the grid with a 15-minutes resolution are used and scaled to match the installed capacity of a particular PV installation.

The power flow simulation is implemented using the backward forward sweep flow method as proposed by Ghatak and Mukherjee [27, 28]. The simulation was conducted considering the low voltage side of the transformer as the slack node with a reference voltage of 1 p.u. The voltage limits $u_2^{\max}$ and $u_1^{\max}$ are considered 1.06 p.u. and 1.09 p.u., respectively. The latter is in compliance with the DSO practice to account for voltage drops at the medium voltage side of the transformer. We conducted time-series simulations with a time resolution of 15 minutes for a period of a week, in the summer season when solar production is high. Although a week period is fair enough to demonstrate the performance of the method proposed, longer periods are equally applicable as our method proposed relies on reduced computational cost as it is demonstrated later in the following section. For the simulations, we used a notebook with a dual core (Intel Core i7-6500, 2.6 GHz) and 8 GB of RAM.

To achieve a fair comparison of the method proposed against the stochastic methods selected, the following adaptions are made to the descriptions found in literature. We consider conventional loads to be known variables, which are modeled with the grid data provided by the DSO. In all three methods, all nodes in the grid are considered to be feasible for PV installations (excluding bypass nodes, nodes for lines re-distributions, or similar). The incremental factor in both stochastic methods is set to 10% [16], and the reduction-step (P_{step}) in the method proposed is set to 1 kWp. Moreover, we use the same simulation period of a week and the same violations in the quantification of the hosting capacity using the three methods.

5. Results and discussion

This section is divided into four subsections. First, we investigate the impact of the violation-mitigation order on the resulting hosting capacity, and, based on that derive the most preferable order. Second, we compare the method proposed to the two selected stochastic methods from literature with respect to performance and computational costs. Then, in Section 5.3, we investigate the method proposed in detail and discuss additional features thereof. Finally, we evaluate the effect of using a user-defined potential instead of the rooftop solar potential to provide an approach to apply the method proposed in an even more general setting.

5.1. Effect of the order of mitigations

As described in Section 3, there are six possible orders (see Table 1) to mitigate violations before reaching the hosting capacity using the method proposed. Fig. 5(a) shows the relative variation (with respect to the average) of hosting capacities for the 14 grids considering the six orders. From this figure, the following observations can be made: (i) for most grids, 11 out of 14, the variation due to reordering is minimal, within the range of ±3.3%; and (ii) high negative deviations, which correspond to lower hosting capacity values, are mainly found for $order1$ and $order2$, whereas the orders showing higher positive deviations, i.e., higher hosting capacities, are $order4$, $order5$, and $order6$. It is worthwhile to note that $order1$ and $order2$ consider the mitigation of the transformer overloading at the start. This suggest that PV power reductions in order to mitigate transformer overloading violations have lower collateral effects on other violations than the overvoltage and overcurrent mitigation processes.

Fig. 5(b) shows the hosting capacities relative to the highest value (of a respective grid) achieved among the six orders. The relative values are grouped by the order and represented with boxplots. Clearly, $order4$, $order5$ and $order6$ perform better than the rest and among these, $order6$ provides a hosting capacity that is more likely to be the maximum among all the orders. Therefore, $order6$ is the preferable order to quantify the hosting capacity using the method proposed and will be used hereafter.

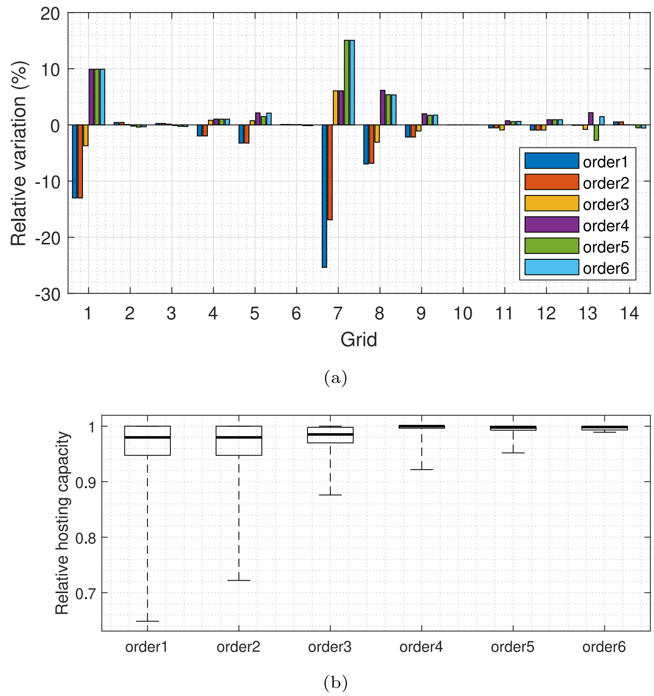


Fig. 5. Effect of the violation mitigation order on the hosting capacity quantification based on the proposed method for the 14 grids: (a) relative variation in hosting capacity with respect to the average of all six orders; (b) relative hosting capacities grouped by the order. A relative value is calculated with respect to the highest value achieved among the six orders of a respective grid.

5.2. Comparison to stochastic methods

In order to contrast our method, we have implemented the stochastic methods proposed by Breker et al. [16] and Torquato et al. [17] to quantify the hosting capacity, as described in Section 2. Fig. 6(a) shows the quantified hosting capacity using the three methods for the 14 grids. A worst-case scenario was additionally evaluated using the method proposed only to show that the corresponding hosting capacities are conservative compared to a time-series assessment (also using the method proposed), also noted in literature [29]. As a worst-case assessment is a common practice among planning engineers, the method proposed can adopt such criteria too.

For all grids investigated, the hosting capacity obtained using the method proposed is either equal or even higher than the ones computed based on the stochastic methods. This means that the method proposed is able to identify hosting capacities closer to the global maximum, providing DSOs higher margins to manage the accommodation of new PV installations in their grids.

The computation time required for the three methods is depicted in Fig. 6(b) and reflects the number of simulations needed before reaching the hosting capacity. For the stochastic methods, the computational time is highly dependent on the number of configurations to consider as well as in the incremental step to move from one configuration to the other. For them, the upward process was done using an incremental factor of 10%, meaning that PV installed capacity is increased to 110% of the present value at each iteration. This led to have wider incremental step, thus shorter computational time. This is particularly relevant for long simulation periods, in which using an incremental step of 1 kWp can make stochastic methods impractical due to the computational burden. Although the method proposed used a reduction step of only 1 kWp, it achieved remarkable shorter computational times than the stochastic methods.

In summary, the benefits of using the proposed method are shown in Fig. 6(c), showing at least an equal, but mostly significantly higher

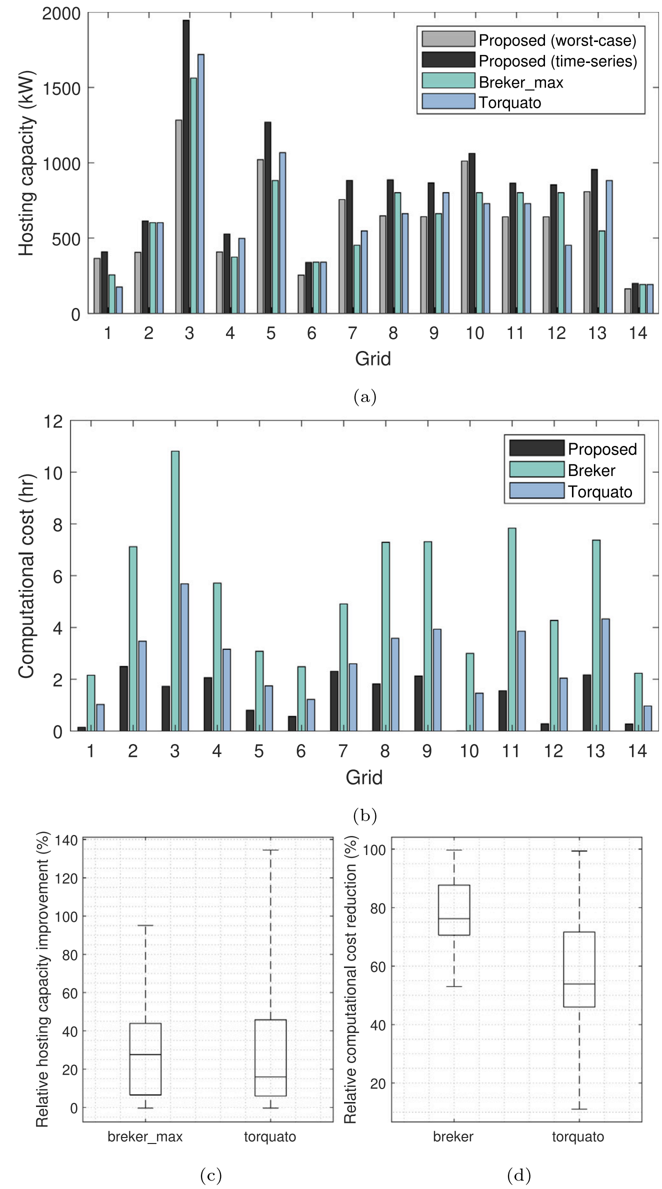
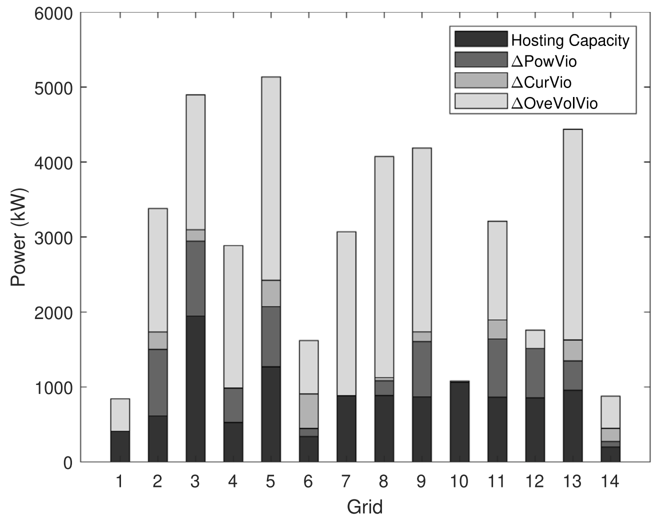


Fig. 6. Comparison to the stochastic methods as proposed by Breker et al. [16] and Torquato et al. [17]: (a) quantification of the hosting capacity; (b)computational time required by each method for each grid for a week period of assessment; (c) comparison in hosting capacity relative to the method proposed; (d) comparison in computational costs relative to the method proposed.

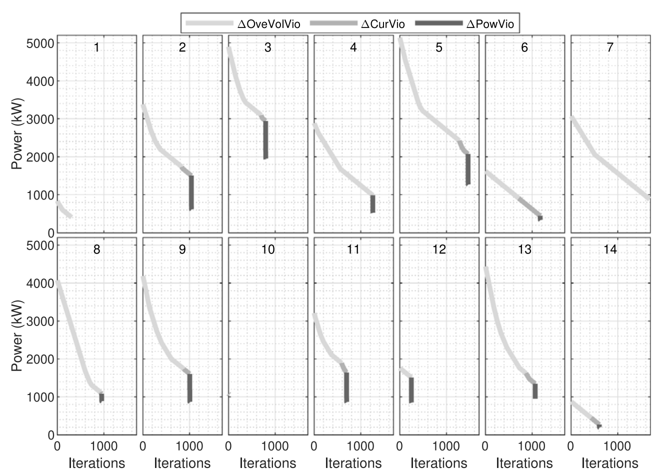
hosting capacity than the stochastic methods. Additionally, the computational costs are significantly reduced, as can be seen in Fig. 6(d). This makes the method well-suited to implement on a larger set of grids. Nonetheless, the computational cost can be further reduced with almost no effect on the outcomes as it is shown in the following subsection.

5.3. Violation mitigation process

The rooftop solar potential for the 14 grids is depicted in Fig. 7(a) as the aggregation of stacked bars. The differences of solar potential between the grids are mainly caused by the amount of building roofs currently available for PV installations in each of the grids. The PV power reductions made in order to mitigate violations in the selected order ($order6$): overvoltage ($\Delta OveVolVio$), overcurrent ($\Delta CurVio$) and overloading at the transformer ($\Delta PowVio$), are also depicted in the same figure. First, it is observed that not all mitigations are required



(a)



(b)

Fig. 7. Application of the method proposed applied to the 14 test grids: (a) from the solar potential (aggregation of staked bars) to the hosting capacity, where power reductions were made to mitigate violations due to overvoltage ($\Delta OveVolVio$), overcurrent ($\Delta CurVio$) and transformer overloading ($\Delta PowVio$); (b) reduction process accounting for the number of iterations required to mitigate the respective violations until hosting capacity is reached.

to reach the hosting capacity. An example of this is $grid1$, after overvoltage violations are mitigated, the grid does not exhibit other types of violation. Second, the power reduction in transition from the solar potential to the hosting capacity shows a wide range of values. For instance, in $grid10$, having a relatively small solar potential, the PV power reduction due to mitigation is minimal. Third, the last violation mitigated which represents the limiting factor of the hosting capacity varies between grids. Overvoltage represents the limiting factor for $grid1$ and $grid7$, overcurrent is the limiting factor for $grid10$, while for all the other grids, the transformer overloading limits the hosting capacity.

The amount of the total power reduced influences the number of iterations required to reach the hosting capacity. Fig. 7(b) shows the PV power reduction process accounting for the number of iterations required to mitigate each violation. For all grids, most of the iterations needed are spent on the mitigation of overvoltage violations, owing to the related mitigation is the first mitigation to perform with a reduction-step of only 1 kWp. On the other hand, iterations in the transformer overloading mitigation process are few. That is because there,

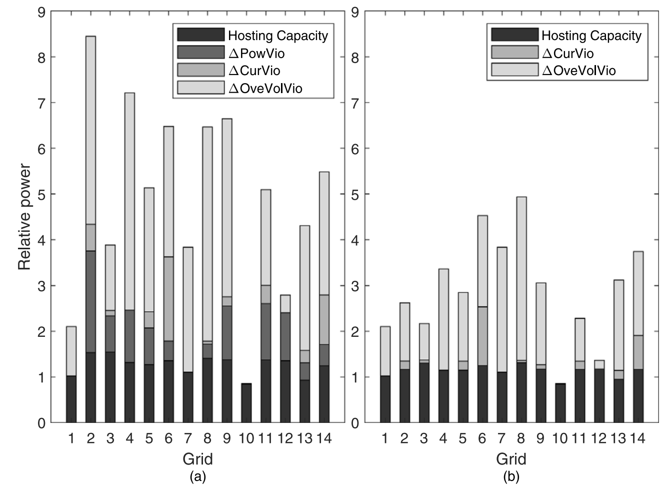


Fig. 8. (a) Hosting capacity and solar PV power reductions normalized with respect to the transformer rated power. (b) Hypothetical situation where transformer upgrades are assumed for grids with transformer overloading as a limiting factor.

the reduction step is ruled by the excess of overloading rather than by 1 kWp as for the overvoltage and overcurrent mitigation processes. It is worth noting that the number of iterations, thus the computational time, can be reduced significantly by slightly increasing the reduction-step (P_{step}). For instance, by increasing the reduction-step from 1 kWp to 2 kWp the total iterations in the overvoltage mitigation process can be reduced to half, while knowingly increasing the uncertainty only by approx. 1 kWp in the resulting hosting capacity.

The hosting capacities and the power reductions, presented in Fig. 7(a), are normalized with respect to the transformer size (rated power) of each grid, and the result is depicted in Fig. 8a. The following observations are drawn for the latter figure:

- The rooftop solar potential varies from 0.86 to 8.45 times the transformer size for the grids. While the hosting capacities are in the range of 0.84 and 1.54, where the lower value is the result of a poor rooftop solar potential.
- The higher the solar potential relative to the transformer size, the larger the power reduction needed to be made in the overvoltage mitigation process. Having a front-line position, overvoltage mitigation is responsible to reduce PV installed capacity to more sensible values (in average, below 2.3) before handing over to other types of mitigations if necessary.
- $\Delta PowVio$ and $\Delta CurVio$ quantities also represent expansions in the hosting capacity after overcoming the effect of their respective violations: transformer overloading and overcurrent in the lines.

Transformer overloading being the limiting factor means that by only increasing the transformer size, the hosting capacity will increase correspondingly. The extent in which the hosting capacity can be increased by only increasing the transformer size is determined by $\Delta PowVio$. So, for instance looking at $grid2$ (Fig. 8a), the hosting capacity could reach 3.75 times the present transformer size only by upgrading the transformer of the grid. Fig. 8b presents a hypothetical situation in which the transformer size of each grid is increased by its respective $\Delta PowVio$ in order to increase the hosting capacity. This is done for the grids with transformer overloading as the limiting factor (all grids, except $grid1$, $grid7$ and $grid10$). In this hypothetical scenario, it would make no difference in promoting the hosting capacity to further increase the size of the transformer, as other problems such as overcurrent or overvoltage would emerge regardless.

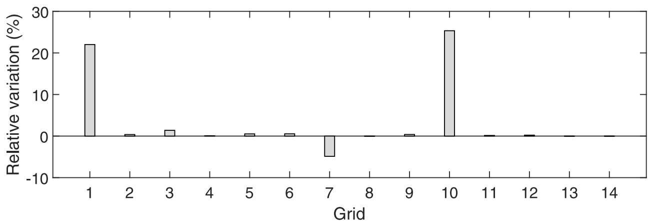


Fig. 9. Relative variation in hosting capacity using the user-defined potential with respect to the rooftop solar potential.

5.4. Hosting capacity quantification based on user-defined potential

Considering the rooftop solar potential to quantify the hosting capacity can be one approach. Other approach might want to include grounded-based PV installations too. Moreover, hosting capacity quantification based solely on the grid strength (rather than on external factors such as building infrastructure availability) can be of interest for DSOs; in which case a high and equally distributed initial potential in all nodes might be more appropriate. With this aim, the method proposed can be generalized with the use of a user-defined potential, as shall be shown hereafter.

From the previous subsection, the highest relation between the hosting capacity and the transformer rated power for the grids evaluated was found to be approx. 1.54. As being undoubtedly high enough, we consider an user-defined potential per grid of four times the transformer rated power, and distribute the potential equally on all nodes of the grid. The resulting hosting capacities using the user-defined potential are compared with the hosting capacities using rooftop solar potential (showed in the previous subsection), and the relative variations of the results are depicted in Fig. 9. From this figure, it is observed that for eleven grids the variation can be neglectable, as it is below 1.4%. These grids have been identified in Section 5.3 to be those for which the limiting factor for the hosting capacity is overloading in the transformer.

Fig. 10 shows example grids for which the limiting factor is the transformer overloading ($grid13$) as well as overvoltage or overcurrent ($grid1$ and $grid7$). The figure shows the potential and resulting hosting capacity at each node considering rooftop solar and the user-defined (equally distributed) potential as the starting point of calculations. Nodes are sorted from low to high rooftop solar potential to facilitate visibility. On one hand, for $grid13$, despite the fact that rooftop solar potential is much larger than the user-defined potential for several nodes, the resulting hosting capacity is nearly equal (see Fig. 9). This can be explained considering that the last reductions made in these grids happen in the transformer overloading mitigation process, thus the aggregation of PV installed capacities of all nodes is limited by the transformer size, regardless of their distribution within the grid. Nonetheless, it is also observed that the distribution (shape) of the hosting capacity per node tend to be similar either using rooftop or the equally distributed potential, meaning that the power reductions are targeted to those PV installations that harm the operation of the grid.

On the other hand, $grid1$ and $grid7$ have considerable variation in the hosting capacity using the equally distributed potential. $grid1$

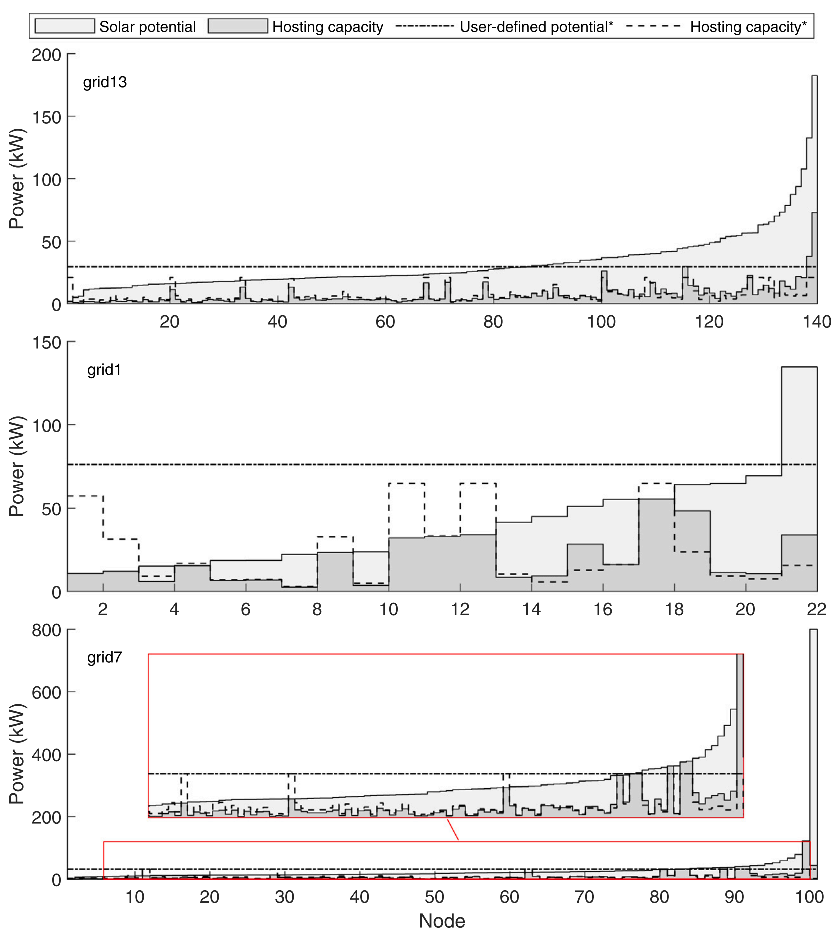


Fig. 10. Per node display of hosting capacity on example grids using both, rooftop solar and user-defined (with asterisk) potential. Nodes are sorted from low to high rooftop solar potential to facilitate visibility. $grid13$ has transformer overloading as the limiting factor. $grid1$ and $grid7$ have overvoltage or overcurrent as the limiting factor for the hosting capacity.

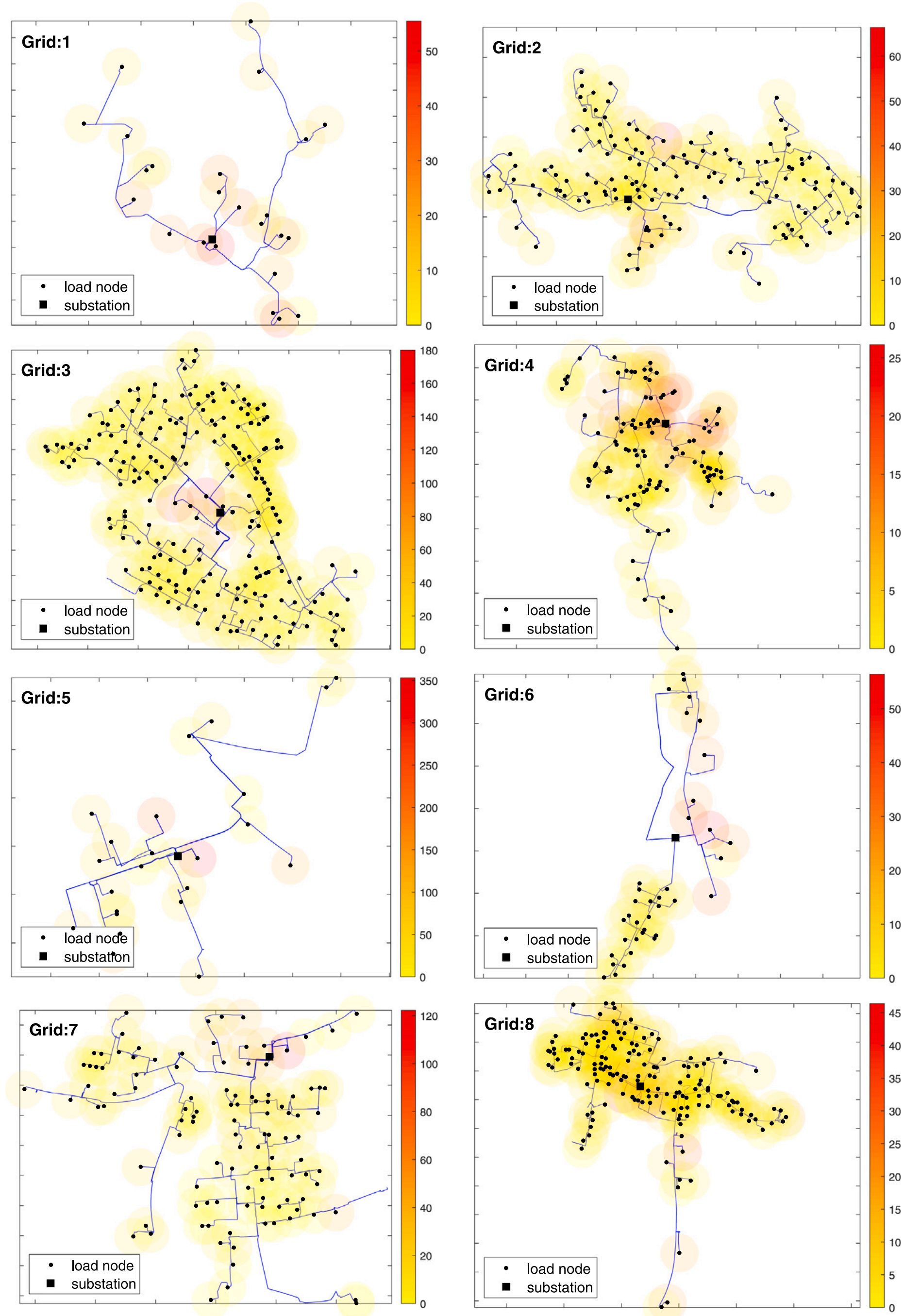


Fig. A.11. Geographical representation of the Austrian low voltage grids used for evaluation. The heatmap represents the hosting capacity, in kWp, at each node quantified using the method proposed.

shows higher hosting capacity, and $grid7$ shows lower hosting capacity, as seen in Fig. 9. For $grid1$, it is observed (Fig. 10) that using the equally distributed potential results in considerable higher hosting capacities in some nodes in comparison with rooftop solar potential usage (even to the extent to exceed the rooftop solar potential capability; e.g., nodes 1, 10, and 12). For $grid7$, one can observe similar features as described previously for $grid1$, however those features are countered by high hosting capacities resulting from the rooftop solar potential. E.g., it is observed that in node 99 (right side of zoomed box) the resulting hosting capacity is much larger than the equally distributed potential.

In summary, the proposed method can be applied in a more general setting with the use of a user-defined potential. If compared with the results based on rooftop solar potential the equally distributed potential provides nearly equal results for the cases with transformer overloading as the limiting factor. Otherwise, the results are subject to variations. These variations can be seen on two ways: (i) using user-defined potential can lead to higher hosting capacity, especially if they exhibit higher values per node than the rooftop solar potential; and (ii) user-defined potential can undermine the rooftop potential at certain nodes, leading to lower hosting capacity quantities.

6. Conclusions

We presented a novel method to quantify the hosting capacity of low voltage grids. Our method proposes a downward process that takes into account the operational state of the grid in the quantification process.

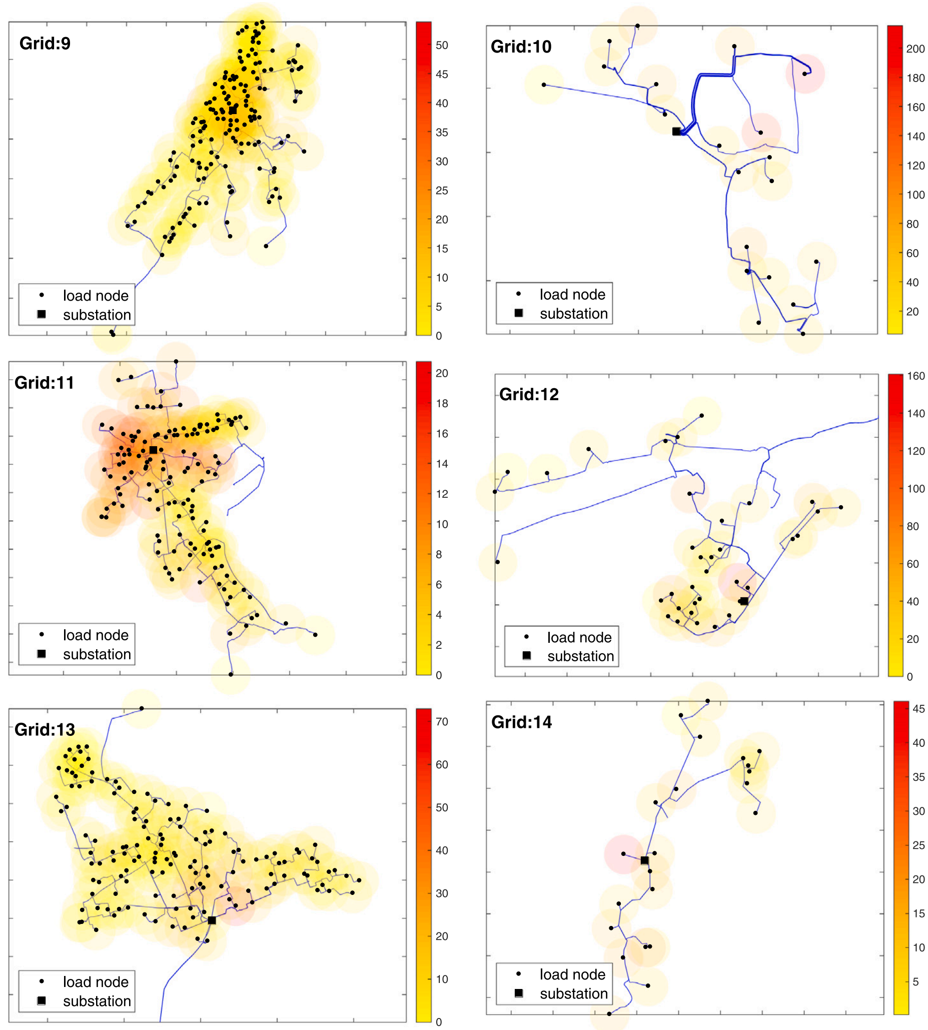


Fig. A.11. (*continued*).

Evaluated on fourteen Austrian distribution grids, the results achieved were compared to stochastic methods in literature. The results showed that while requiring lesser computational time, the method proposed is able to provide equal or higher hosting capacity than stochastic methods. Higher hosting capacities mean higher margins for DSOs to manage upcoming PV installations without the need of grid reinforcements. As reducing the computational burden of such a method is important to facilitate large-scale implementations, it appears promising for real world applications of DSOs.

Furthermore, the proposed method already quantifies possible expansions in hosting capacity as additional outcomes of its application. In case of transformer overloading being the limiting factor, the expansion achievable by a transformer upgrade is quantified. Further expansion is quantified and can be achieved by overcoming overcurrent violations.

Finally, we demonstrated that even without the use of a rooftop solar potential, a quantification of the hosting capacity is still possible based on a user-defined potential, which provides a more general applicability of the method proposed.

CRediT authorship contribution statement

Ruben Lliuyacc-Blas: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Data curation, Writing – original draft, Visualization. **Peter Kepplinger:** Investigation, Resources, Writing – reviewing and editing, Visualization, Supervision, Funding acquisition.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix. Low voltage grids

See Fig. A.11.

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