A city-level assessment of residential PV hosting capacity for low-voltage distribution systems considering rooftop data and uncertainties

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A B S T R A C T

The increasing trend of small-scale residential photovoltaic (PV) system installation in low-voltage (LV) distribution networks poses challenges for power grids. To quantify these impacts, hosting capacity has become a popular framework for analysis. However, previous studies have mostly focused on small-scale or test feeders and overlooked uncertainties related to rooftop azimuth and tilt. This paper presents a comprehensive evaluation of city-level PV hosting capacity using data from over 300 real LV systems in Varberg, Sweden. A previously developed rooftop azimuth and tilt model is also applied and evaluated. The findings indicate that the distribution systems of the city, with a definition of PV penetration as the percentage of houses with 12 kW installed PV systems, can accommodate up to 90% PV penetration with less than 1% risk of overvoltage, and line loading is not a limiting factor. The roof facet orientation modeling proves to be suitable for city-level applications due to its simplicity and effectiveness. Sensitivity studies reveal that PV system size assumptions significantly influence hosting capacity analysis. The study provides valuable insights for planning strategies to increase PV penetration in residential buildings and offers technical input for regulators and grid operators to facilitate and manage residential PV systems.

1. Introduction

Due to the urgency of mitigating climate change, there has been a growing trend towards decentralized electricity generation at a small scale within electricity distribution systems, allowing more active participation of end-users by installing power generators in their own buildings [1]. Before 2020, residential photovoltaic (PV) system installations were increasing around the world, with a peak of more than 16 GW of new installations in 2019 [2]. This development raises some challenges in power grids, such as potential overvoltage and overloading, particularly in low-voltage (LV) distribution systems [3,4]. Therefore, many studies have aimed to investigate the impacts of integrating PV systems in the distribution grid with varying focuses, such as power quality [5], the impacts of several new large loads [6], probabilistic approaches [7–10], large scale assessments [11,12], and the combination with energy management [13].

One of the key methods to quantify the impacts of PV systems on low-voltage networks is through the so-called hosting capacity. It is a transparent framework for analysis that determines the maximum amount of PV power generation that can be installed in a specific grid while maintaining the operational quality of the system [14,15]. In general, PV hosting capacity analysis requires the declaration of three parameters: the phenomenon (e.g., over-voltage, line loading, losses), the performance indices for the chosen phenomenon (e.g., 99% values of the 15-min RMS values), and the limit (e.g., 1.05 of nominal voltage).

PV hosting capacity analysis, however, has high uncertainties from both aleatory and epistemic uncertainty sources [16]. The tilt and azimuth of PV panels are among the most significant uncertainties in PV system performance [17]. This is because the direct, diffuse, and reflected solar radiation components hit the surface of the panels at different angles, depending on these two angles and on the location, time of day, and time of year [18]. The importance of tilt and azimuth uncertainties was discussed in [19] and the significance of using accurate rooftop data was demonstrated in [10,17].

While many studies have investigated the PV hosting capacity in low-voltage networks, there are some important features that have not been well-studied before. First, the majority of hosting capacity analyses in LV networks were conducted at a small-scale level, and some of these studies were carried out using test feeders rather than real grids. Some exceptions include [11], which investigated the hosting capacity for 50,000 real low-voltage networks in Brazil, and [12] which performed such analysis for 338 low-voltage networks in the Swedish municipality of Herrljunga.
Second, existing studies have rarely employed real rooftop azimuth and tilt data. Refs. [10,17] are among the studies that utilized real rooftop data for small-scale low-voltage networks. Ref. [17] also proposed a method to model a set of azimuths and tilts for multiple houses when such data is unavailable. The method, however, has not been tested, and, importantly, has not been compared to real data in large-scale LV network simulations. Third, although the method has wide applicability, a hosting capacity study is valid only for specific grids and for specific assumptions. Hence, an investigation with a specific location that has never before been studied is valuable as it adds to the accumulated knowledge on hosting capacity in different types of grids and locations.

Considering the aforementioned needs, a comprehensive study on city-level PV hosting capacity considering real rooftop data at a specific location is required. The previously proposed method to model rooftop azimuth and tilt uncertainties in [17] would benefit from validation and comparison to real rooftop data in a city-level hosting capacity assessment. Additionally, the impact of specific assumptions on hosting capacity would be valuable to evaluate.

In this paper, therefore, a comprehensive evaluation of city-level PV hosting capacity is investigated for more than 300 real LV systems in the Swedish city of Varberg. This study utilizes extensive data set of rooftops model for around 37,000 buildings and historical load profiles for around 11,800 end-customers. The hosting capacity analyses were performed using time-series analyses for one year with a resolution of one hour. Voltage profiles and line loading are evaluated as the chosen phenomena. Furthermore, the previously developed rooftop azimuth and tilt model in [17] is utilized to further validate its effectiveness by comparing the power flow simulation results from solar irradiance profiles using the proposed method in [17] to results from solar irradiance profiles based on LiDAR-based rooftop data.

The contributions and merits of this work can be summarized as follows:

- Application of a comprehensive time-series hosting capacity method utilizing actual city-level grid data, supported with real measurement data of power consumption and complemented with a power consumption model to address missing data.
- Inclusion of real distribution building rooftop tilt and azimuth values for the entire city to improve the PV generation model.
- Consideration of roof facet conditions to determine the PV allocation for multiple penetration levels.
- Application and evaluation of a previously developed rooftop azimuth and tilt model in [17], to further validate its effectiveness in large-scale LV network simulations.

This paper is organized as follows. Section 2 describes the overview of this paper. Section 3 presents the data used in this study. In Section 4 the models and methods utilized are described. The results are presented in Section 5 and discussed in Section 6. Conclusions are drawn in Section 7.

2. Overview of the paper

A schematic overview of the data and methodology employed in this paper is illustrated in Fig. 1. The process can be divided into two main steps: the solar irradiance model step and the power flow simulation step. The solar irradiance model step aims to model solar irradiance profiles on the tilted roofs using three distinct methods for determining the rooftop azimuth and tilt. Meanwhile, the power flow simulation process generates the power flow simulation results for each solar irradiance profile.

For the solar irradiance model step, the required inputs include rooftop azimuth and tilt values and horizontal solar irradiance profiles. Three different sets of rooftop azimuth and tilt data and models were utilized for comparison. Initially, the rooftop azimuth and tilt values were derived from LiDAR-based data to calculate the actual hosting capacity within the grid, as described in Section 3.2. Then, the results of this investigation were compared with two alternative methods for representing rooftop azimuth and tilt. The first approach involves the use of a rooftop azimuth and tilt model proposed in [17]. This model enables the inclusion of rooftop azimuth and tilt uncertainties even without explicit azimuth and tilt data, although it requires more validation and comparison with real rooftop data in a city-level hosting capacity assessment. The second method is based on the common assumption that roof facet orientations are uniformly optimal. More detailed information on these models is provided in Section 4.2.1.

Tilted solar irradiance profiles are subsequently utilized as the input for the power flow simulation step, along with PV array sizes, to generate the PV generation profiles. PV array size are varied for sensitivity analysis purposes. The procedure for producing the PV power generation profiles is detailed in Section 4.2.3. These PV power generation profiles, together with grid data detailed in Section 3.1 and building load data (explained in Section 3.3 and Section 4.3), are employed in power flow simulations to generate the simulation results.

3. Data

3.1. Grid data

The distribution grid for this study consists of four three-phase MV (10 kV) and 334 three-phase LV (400 V) networks with 11,602 customer connection points. The grid is located in the Swedish city of Varberg. The geographical dispersion of all 334 LV networks is shown in Fig. 2. The power grid covers both a rural area and small urban areas. The distribution grid is connected to the transmission grid through four HV/MV substations. These substations have on-load tap changers for voltage control and the values are kept constant for the MV side voltages of the substations throughout the year and are not used for voltage control for end-users. The MV/LV transformers, however, do not have on-load tap changers.

General information about the LV systems is given in Table 1. From the table one can observe that even though the LV systems are located in the same municipality, the characteristics of the systems are widely diverse. This can be seen from the large standard deviation and the wide range between the 10th and 90th percentile for all three parameters.

3.2. Rooftop data

This paper examines the potential impacts of residential rooftop PV systems across the city of Varberg, Sweden, utilizing a LiDAR-based rooftop dataset covering the entire city. The dataset includes nearly 90,000 roof facets from approximately 37,000 buildings. The number of roof facets exceeds the number of buildings due to the fact that many buildings have multiple roof facets. Among these buildings, 11,800 are categorized as residential buildings.

The LiDAR-based data used in this study were acquired using a previously developed model described in Lingfors et al. [20] and validated in Lingfors et al. [21]. The general overview of this method are shown in Fig. 3. This method has been previously applied to another Swedish city, Uppsala, and has been utilized in various studies [17,22]. Interested readers are referred to [20] for further explanation of this method.

Table 1

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Average</th>
<th>Standard deviation</th>
<th>10th and 90th percentile</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of customers</td>
<td>36.46</td>
<td>40.47</td>
<td>3–90.6</td>
</tr>
<tr>
<td>Circuit total length (km)</td>
<td>3.02</td>
<td>2.31</td>
<td>0.57–6.29</td>
</tr>
<tr>
<td>Average X/R ratio</td>
<td>0.21</td>
<td>0.16</td>
<td>0.09–0.37</td>
</tr>
</tbody>
</table>
Fig. 1. Schematic overview of the paper.

Fig. 2. Geographical dispersion of low voltage substations in Varberg used in the load flow simulations.

Fig. 3. Overview of method used to produce LiDAR-based rooftop data from [20].
The inputs to the model consist of low-resolution LiDAR data (0.5–1 pts/m²), with solar irradiance on the roof surfaces calculated using the Hay and Davies transposition model [23]. Orientation and shading considerations were taken into account to determine the potential number of PV modules that can be installed on each rooftop, specifically where the annual irradiation exceeds 900 kWh/m², making PV installations economically viable in a Swedish context [24].

The LiDAR-based rooftop data used in this study contain the following information:

- Building coordinates.
- Azimuth of every roof facet.
- Tilt angle of every roof facet.
- Number of PV modules that can be fit with an annual irradiation of at least 900 kWh/m².

3.3. Load data

The electricity load data is based on real measurements spanning the years 2020 through 2021. For most buildings, the data for the year 2021 is complete and used as is. When there are missing data points for 2021, they are filled by referring to the corresponding measurements from 2020, matching the date and hour. If this is not sufficient to cover the entire year, the electricity load models for the buildings, explained in Section 4.3, are utilized to create simulated load and complete the data.

4. Methods

4.1. Hosting capacity analysis assessment

As outlined in Section 1, the hosting capacity assessment involves three main components: selecting the phenomenon, defining the performance indices, and establishing the limits. For this study, the following elements have been chosen:

- Bus voltages. Voltage profiles must conform to the following criteria: the voltage should be below 1.1 per unit (pu) for all values, excluding only the lowest and highest 1% of values. In this context, we refer to voltage profile as the phenomenon, with the indices denoting the 99% of values from the one-hour-resolution simulations, and the limit is set at 1.1 pu.
- Line loading. Line loading must consistently remain below capacity limits at all times and in all locations. Here, the phenomenon is the line loading, with 100% of values as indices, and the limit is 100% line loading capacity.

After selecting the hosting capacity parameters, several configurations are required to conduct the load flow simulations for each case and penetration level as follows:

- Penetration levels. The penetration levels range from 0% to 90%, with an increase of 15%. The penetration level represents the percentage of houses equipped with PV systems. Note that the penetration level here is the penetration level of residential buildings, which accounted for only 26% of all buildings.
- PV system size. Each PV system is assumed to have a rated capacity of 12 kW, based on a survey conducted in 2020 in Sweden, which indicates that 55% of grid-connected PV systems installed on single-family buildings have a rated capacity between 10 and 20 kW, and 45% have a rated capacity between 5 and 10 kW [25]. Lower and higher values of 6 and 18 kW will be used later in a sensitivity analysis.
- PV allocation. The PV allocation is based on rooftop data, assuming a building with a more suitable roof facet will have a PV system installed earlier. The same allocation is used also for both the case with the proposed azimuth and tilt model and the uniformly optimum roofs.

<table>
<thead>
<tr>
<th>Penetration level</th>
<th>Proportion of flat roofs</th>
</tr>
</thead>
<tbody>
<tr>
<td>10%</td>
<td>0%</td>
</tr>
<tr>
<td>20%</td>
<td>0%</td>
</tr>
<tr>
<td>30%</td>
<td>0%</td>
</tr>
<tr>
<td>40%</td>
<td>0%</td>
</tr>
<tr>
<td>50%</td>
<td>16.27%</td>
</tr>
<tr>
<td>60%</td>
<td>17.90%</td>
</tr>
<tr>
<td>70%</td>
<td>15.34%</td>
</tr>
<tr>
<td>80%</td>
<td>13.43%</td>
</tr>
<tr>
<td>90%</td>
<td>11.93%</td>
</tr>
<tr>
<td>100%</td>
<td>10.74%</td>
</tr>
</tbody>
</table>

- Time-series duration and resolution. The duration is set to one year, with a one-hour resolution, for the year 2021. This choice is motivated by the resolution of the available load consumption data.
- Simulation tools. The grid simulations were performed using a Python-based pandapower, an open-source tool specializing in automated symmetric distribution system analysis [26]. This tool is well-suited for the selected electricity distribution systems, which include typical Swedish distribution grids featuring three-phase power distribution all the way to the customer connection points.

4.2. PV system model and uncertainties

4.2.1. Rooftop azimuth and tilt

In this study, the rooftop azimuth and tilt values from LiDAR are initially employed to determine the actual hosting capacity within the grid. Then, the results of this investigation are compared with two other methods for representing rooftop azimuth and tilt. The first approach involves modeling rooftop azimuth and tilt using the method proposed in [17]. The second method compares the results with the commonly used assumption that the roof facet orientations are assumed to be uniform and optimal.

The proposed method in [17] involves three simple steps, outlined below:

1. **Determine the proportion of flat roof buildings.** Begin by determining the number of buildings with flat roofs at each penetration level.
2. **Generate azimuth and tilt distributions.** Utilize the proposed equations to get the distributions of rooftop azimuth and tilt for each penetration level.
3. **Sample non-flat roof buildings.** Sample from the derived distributions to assign rooftop azimuth and tilt values to the remaining non-flat roof buildings.

By using these three steps, the proposed method characterizes the rooftop azimuth and tilt for a diverse range of buildings in the area of interest. This approach ensures a better representation of building types, thus enhancing the accuracy of the overall analysis.

For the first step, the proportion of flat roofs for each penetration level is obtained from a reference study [17]. The specific proportions are listed in Table 2. However, since the penetration levels considered in this study differ slightly from those in the reference, we interpolate the proportions for the penetration levels at 45% and 75%. The proportion for the 45% penetration level is chosen as the average between the proportions at 40% and 50%, and similarly, the proportion for the 75% penetration level is taken as the average between the proportions at 70% and 80%.

Then, for the second step, the azimuth and tilt distributions are obtained from [17] and are modeled as follows.
Random variables describing the roof azimuth and tilt for penetration level \( x \) can be expressed by:

\[
K_{\text{azimuth}} = K_1 S + K_2 (1 - S),
\]

for azimuth, and

\[
K_{\text{tilt}} = K_3 S + K_4 (1 - S),
\]

for tilt, where \( K_1 \) and \( K_4 \) are random variables for non-flat roof azimuth and tilt, respectively, while \( K_2 \) and \( K_4 \) are random variables for flat roof azimuth and tilt, respectively. \( S \) is a random variable that is either one (flat roof) or zero (tilted roof). Therefore, \( S \) has a Bernoulli distribution:

\[
S \sim \text{Bernoulli}(f),
\]

where \( f \) is the proportion of flat roofs at that penetration level.

Since the flat roof corresponds to \( 0^\circ \) for both azimuth and tilt angles, \( K_1 \) and \( K_4 \) are degenerate distributions of zero and Eq. (1) and Eq. (2) can be simplified to:

\[
K_{\text{azimuth}} = K_1 S
\]

and

\[
K_{\text{tilt}} = K_3 S.
\]

For the azimuth, the model was based on the hypothesis that roof facets are uniformly distributed in all directions. Thus, the azimuths at every penetration level \( x \) are represented by the following uniform distribution:

\[
K_1 \sim U(-180x, 180x),
\]

with minimum value of \(-180x\) and maximum value of \(180x\).

For the tilt, a normal distribution is used. The non-flat roof tilt for every penetration level \( x \) will be represented by a normal distribution:

\[
K_3 \sim N(\mu_{tilt}(x), (\sigma_{tilt}(x))^2),
\]

with mean value \( \mu_{tilt}(x) \) and variance \( (\sigma_{tilt}(x))^2 \). \( \mu_{tilt}(x) \) and \( \sigma_{tilt}(x) \) are proposed by Ref. [17] as follow:

\[
\mu_{tilt}(x) = -0.078x + 26.295,
\]

\[
\sigma_{tilt}(x) = 0.028x + 6.429,
\]

where \( x \) is the penetration level.

In the third step, the samples were drawn from distributions generated based on Eq. (8) and 2 using Python and the NumPy library’s random module.

4.2.2. Solar irradiance model

In this study, solar irradiance data for the Swedish city of Varberg was produced from the STRÅNG [27] model for the year 2021 with latitude 57.10°N and longitude 12.25°E. The STRÅNG model produces irradiance data at hourly intervals covering most of Sweden with a resolution of \(2.5 \times 2.5\) km [27]. The dataset provided includes solar irradiance values for the entire year, covering the annual seasonality and corresponding with the power consumption measurement data.

To get the in-plane irradiance, the solar irradiance data from the STRÅNG model was processed using an irradiance model implemented with the pvlib.irradiance.get_total_irradiance function from pvlib python library, developed by Sandia National Laboratories using the Hay and Davies method [28–30]. In the Hay and Davies model, the diffuse radiation on the tilted plane \( I_dT \) is calculated as:

\[
I_dT = I_d \left( A R_0 + (1 - A) \left( \frac{1 + \cos \beta}{2} \right) \right)
\]

where \( I_d \) is the diffuse radiation on the horizontal plane, \( A \) is the anisotropic index, the ratio between the incident beam and the extraterrestrial radiation on the horizontal plane. \( R_0 \) is the geometric factor, and \( \beta \) is the plane’s inclination.

This function requires surface azimuth and tilt which were obtained from the rooftop azimuth and tilt as explained in Section 4.2.1, and extraterrestrial radiation, calculated with the pvlib.irradiance.get_extra_radiation function from pvlib python library, which determines extraterrestrial radiation from day of year.

4.2.3. PV power generation

The PV power generation model employed in this study was implemented using the pvlib.PVSystem class from the pvlib python library developed by Sandia National Laboratories [30]. The model represents an inverter and the PV modules that supply DC power to the inverter based on the specified in-plane irradiance and module parameters. This particular model has been employed in various studies, including those conducted by Louwen et al. [31] and Holmgren et al. [32].

4.3. Missing load

In this study, missing data for hourly electricity use in residential buildings was filled in using a so-called urban building energy model (UBEM), developed in [33,34]. The UBEM makes use of geometrical information of buildings from GIS data and estimates the non-geometrical information, e.g., construction and material, occupancy, and occupants-related energy use as well as heating, ventilation, and air conditioning (HVAC) systems from pre-defined building archetypes. These building archetypes represent the diversity of residential buildings using a few
categories of buildings divided based on their type and construction period. By importing this information to the UBEM, simplified, yet accurate, models of residential buildings are formed and simulated under prevailing weather conditions. The simulation result represents the electricity load in individual buildings. It includes the load for household appliances and lighting as well as space heating and domestic hot water in case the building is electrically heated.

As regards the missing load, as illustrated in Fig. 4, after identifying the buildings with missing load, in an automated procedure, available information on buildings was imported into the UBEM for modeling and simulation of the hourly electricity use data for the year 2021. However, due to the limitation of the UBEM in handling non-residential buildings, the missing data from non-residential buildings were eliminated from the simulations.

5. Results and analysis

This section presents the results from the city-level time-series analysis of PV hosting capacity. It consists of the results from the base case with LiDAR-based rooftop data, rooftop azimuth and tilt model, and sensitivity analysis.

5.1. Base case with LiDAR-based rooftop data

The line loading for all cases in this study remained within permissible limits and therefore, will not be shown in detail. For the voltage, the results for all buses and times were gathered together for each penetration level and were arranged to produce the cumulative distribution function to show the probability of undervoltage and overvoltage. The cumulative distribution function of the voltage in the time-series PV
hosting capacity for the base case, using LiDAR-based rooftop data, is shown in Fig. 5 for six penetration levels.

The first figure displays the probability distribution for all values, while the second one shows the distribution for values between the 1st and 99th percentiles, effectively excluding the minimum and maximum 1% of values. The percentile used for the hosting capacity assessment is often a matter of how much risk the distribution system operator allows or is willing to take [6]. Previous studies used between 1% to 5% from all values or 90% from the PV peak production times only [6,12,13,17]. From the results it can be observed that as penetration levels increase, the probability of overvoltage also increases.

The figure representing all values reveals a long tail at the minimum and maximum values, indicating occurrences of extreme events in both overvoltages and undervoltages. The voltage profiles sometimes exceed the safety limit of 0.90 pu for undervoltages or 1.1 pu for overvoltages, starting from a penetration level of 30% and above.

However, these extreme events are rare, as illustrated in Fig. 5(b) where the most extreme 1% of minimum and maximum values have been removed. By considering this subset of data, it becomes evident that all values remain below 1.10 pu. Additionally, it is noticeable that the maximum voltages experience a significant increase with higher penetration levels. Conversely, the minimum values remain consistent across all penetration levels.

These voltage profiles imply that the distribution networks are capable of accommodating solar PV systems for up to 90% of residential customers, each with a 12 kW installed capacity, without the need for grid reinforcements, assuming a 1% risk threshold taken by stakeholders.

Each line in Fig. 5, however, is the combined value for all 334 low voltage grids. To understand the variations between low voltage networks, Fig. 6 shows the probability distributions of voltage profiles for each of the 334 low voltage networks for the 90% penetration level. It can be seen that the variation is high between the networks.

One low-voltage network seems to have extremely low voltage profiles, potentially being the main cause of undervoltage events across all penetration levels. It is possible that errors exist in either the grid data or load data for this specific network, as it differs significantly from other low-voltage networks.

It becomes evident that the probability of overvoltages varies across different LV networks. Notably, four low voltage networks demonstrate a probability of overvoltages exceeding 5%. On the other hand, it is noteworthy that over 200 substations do not experience overvoltages at all.

5.2. Rooftop azimuth and tilt model

Comparisons of the rooftop models to the actual LiDAR-based rooftop data are given for each penetration in Fig. 7(a) for the azimuth and Fig. 7(b) for the tilt. Note that the model was fitted to building data in [17] and not fitted again in this study to evaluate the generalizability of the proposed model. It can be observed that, in general, the model fits well, even though the azimuth data in this study have considerable peaks around 0° and the tilt data have additional small peaks.

A comparison of probability distributions of voltages from simulations using three rooftop datasets at six penetration levels is presented in Fig. 8. The hosting capacity simulations were performed using LiDAR-based rooftop data, the rooftop model, and a uniformly optimal assumption. At the lowest penetration level of 15%, the voltage distributions from the three different rooftop datasets show similarity. This is attributed to the assumption made both for the LiDAR-based rooftop data and for the rooftop data model, that buildings with more optimal roof facets are prioritized for PV system adoption. Consequently, the roof facets in the lower penetration levels of both scenarios closely resemble those in the uniformly optimal scenario.

As the penetration level increases, more significant distinctions emerge between the results obtained from the uniformly optimal scenarios and the actual LiDAR-based rooftop data. Conversely, the results obtained from the rooftop model consistently demonstrate close similarity to the LiDAR-based rooftop data.

At the highest penetration level of 90%, the difference becomes even more significant. Assuming uniformly optimal roof facets, the voltage at the 99th percentile is 1.11 pu. As a result, when using the same chosen index and limiting voltage values to 99%, the hosting capacity from this dataset is restricted to 75% (or between 75% and 90%; a more exact value would require smaller penetration level increments). Meanwhile, utilizing the rooftop azimuth and tilt model produces identical hosting capacity results to the one using real roof facet orientation data.
These findings highlight the significant disadvantages of assuming optimal roof facets for all buildings, leading to an overestimation of the overvoltage risk at higher penetration levels and, consequently, an underestimation of the PV hosting capacity. Furthermore, the study validates the applicability of the rooftop azimuth and tilt model within the context of this city.

5.3. Sensitivity analysis

The sensitivity analysis aimed to assess the influence of PV system sizes on voltage profiles as the limiting factor. For this purpose, PV systems with sizes of 6 kW and 18 kW were tested at a 90% penetration level using LiDAR-based rooftop data and compared to the base case of 12 kW also using LiDAR-based rooftop data. Fig. 9 shows a comparison of resulting voltages for PV system sizes of 6 kW, 12 kW, and 18 kW at 90% penetration level.

As anticipated, larger PV system sizes lead to notably higher voltages, the main limiting factor. Specifically, the 99th percentiles exceeded the threshold of 1.10. Consequently, in this scenario, increasing the PV system size led to a reduction in hosting capacity, while, conversely, decreasing the size of the PV system significantly mitigated the risk of overvoltage. Here, 99% of voltage readings remained below 1.06. The line loading, however, still remained within permissible limits, even for the 18 kW PV system size.

6. Discussion

The main focus of this study is small-scale PV systems exclusively installed in residential buildings. However, it is essential to acknowledge that PV systems can also be viable options for other types of buildings, including office and commercial buildings. Expanding the scope of this
In this study, a one-hour resolution was used primarily due to the available building power consumption measurement resolutions. However, it is worth noting that this resolution may not be optimal. Previous research, as cited in [35], has shown that using a 15-min resolution instead of 10 s can lead to an overestimation of PV self-consumption. Consequently, the results obtained in this study might overestimate the self-consumption across all scenarios. Despite this limitation, the comparison of results between the LiDAR-based rooftop data, the rooftop model, and the uniformly optimal rooftop scenarios is still expected to remain consistent.

The PV generation model employed in this study considers a variety of rooftop tilt and azimuth configurations that affect the PV power output. However, it utilizes the same solar irradiance data for all PV systems. This assumption implies perfect correlation among all PV systems, which is not necessarily realistic. A study in [36] demonstrates significant spatial decorrelation of solar irradiance between buildings in a city slightly larger than the one examined in this study with a time resolution of 5 min. By assuming a perfect correlation, the impact of distributed PV systems is overestimated, leading to an underestimation of the PV hosting capacity. Nevertheless, when analyzed at an hourly resolution, the impact of spatial decorrelation is less significant [36].

To improve the accuracy of the PV hosting capacity estimation for higher time resolutions, it would be beneficial to account for the spatial decorrelation of solar irradiance between buildings. However, incorporating spatial decorrelation into time-series profiles is challenging. While the study in [36] proposes a method to model the decorrelation for stochastic approaches, it does not directly address time-series data.
Therefore, conducting a study specific specifically on this topic would be highly valuable.

The proposed method to model roof facet orientation appears to work well for this city, and it is especially crucial for higher penetration levels. However, there are still some substantial assumptions in the PV power model that simplify the complexity, which may not hold true in reality. For instance, PV system installation on flat roofs could potentially take advantage of optimal azimuth and tilt angles or increase the tilt to mitigate the impact of soiling. This issue has been raised in [17], but it remains unaddressed in the current paper.

Additionally, this study makes the assumption that the PV system size is uniform across all buildings and varies it during sensitivity analysis. However, it still relies on the underlying assumption that the PV size is determined solely based on individual interests. Another approach, which involves maximizing the PV system size on buildings with better roof facets, can be an alternative. It would increase the total PV output efficiency and total PV electricity production. However, it is also prone to lower self-consumption and higher losses. This approach also requires coordination within the community and may need to involve other technologies such as smart controllers and storage. Therefore, it should be well motivated. Nevertheless, extending this study in that direction could prove to be highly beneficial.

As can be seen, some assumptions and methods utilized in this study may lead to an overestimated hosting capacity, while others may underestimate it. Therefore, there is no exact final conclusion regarding this matter. Instead, it emphasizes the existence and importance of uncertainty modeling in hosting capacity calculations. This highlights the need for further studies focusing on uncertainty modeling.

7. Conclusions

This paper presents a comprehensive assessment of residential PV hosting capacity at the city level using a time-series method, incorporating massive LiDAR-based rooftop data, grid data, and power consumption measurements. The study covers 334 LV networks with over 11,000 customer connection points and is supported by data from 90,000 roof facets across approximately 37,000 buildings.

The findings reveal that the city's distribution system can accommodate a 90% penetration level of PV with less than 1% risk of overvoltage. However, there is significant diversity in results between low-voltage networks, which can be attributed to the varying characteristics among them. This underscores the importance of conducting city-level assessments for hosting capacity, as planning, regulation, and operation of the distribution system are not done at the individual substation level. Additionally, line loading does not present a limiting factor for PV adoption in the studied system.

The method used to model roof facet orientation proves effective for city-level applications, given its simplicity and accuracy compared to LiDAR-based rooftop data. It is recommended for future studies to employ this model. Sensitivity analyses confirm that the hosting capacity analysis is sensitive to the PV system size.

The results from this study offer valuable insights for planning strategies aimed at increasing PV penetration in residential buildings. Moreover, they also serve as technical input for regulators and grid operators to facilitate and manage PV systems in residential buildings.

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.

Data availability

The data that has been used is confidential.

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References


CRediT authorship contribution statement

Umar Hanif Ramadhani: Writing – review & editing. Writing – original draft, Visualization, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. Fatemeh Johari: Writing – review & editing, Visualization, Validation, Data curation. Oskar Lindberg: Writing – review & editing, Resources, Project administration, Methodology, Data curation. Joakim Munkhammar: Writing – review & editing, Validation, Supervision, Conceptualization. Joakim Widén: Writing – review & editing, Validation, Supervision, Methodology, Funding acquisition, Conceptualization.


