Scaling Hosting Capacity Analysis for Large Electrical Distribution Systems

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Abstract - **The rapid growth of renewable generation, driven by increasing concerns about climate change, sustainable energy sources, and energy independence, has presented significant challenges for distribution system operators (DSOs). Integrating intermittent sources while ensuring grid stability and reliability demands a robust evaluation of hosting capacity (HC) in power distribution networks. However, prevailing HC analysis methodologies predominantly rely on conservative assumptions or worst-case scenarios, often leading to impractical and unreliable outcomes. Commercial tools, though offer readily available solutions for hosting capacity analysis, suffer from limitations as they typically assess HC of individual nodes independently or focus on only a few distributed scenarios.**

More elaborate methods have been proposed, attempting to cope with the complexity and stochastic nature of the HC problem. However, not much consideration has been given to their scalability to large distribution systems.

In response to the complexity and stochastic nature of the HC problem, this paper introduces an efficient methodology based on stochastic power system simulations and statistical analysis. The proposed approach undergoes comprehensive assessments to substantiate its efficacy, with a key focus on validating its accuracy for reliable HC estimates. Utilizing the bootstrap method, a resampling technique, multiple samples are generated to mimic possible Distributed Energy Resources (DERs) deployments, enabling estimation of confidence intervals for HC metrics.

By applying statistical analysis to power system simulation results, insights into the expected variability and uncertainty of the problem are gained. These insights guide the selection of the minimum number of DER deployment scenarios necessary to ensure an efficient and well-informed HC assessment process.

The proposed methodology effectively addresses the challenges of HC analysis, offering scalability to large distribution networks. Its efficiency and enhanced accuracy make it a valuable tool for DSOs in facilitating the integration of renewable generation in a dependable and practical manner.

Keywords - hosting capacity, renewable generation integration, distribution systems, bootstrap application.

I. Introduction

Hosting Capacity (HC) can be defined as the amount of additional DERs (typically measured in active power) that can be connected to the distribution network without major changes in the grid asset, and without causing the degradation of selected performance indexes below predetermined thresholds. Performance indexes and thresholds are subject to variation based on regional practices, codes, and standards.

The power system can be analysed in terms of its existing development status or planned expansion levels. Within these two perspectives, hosting capacity assessments encompass different aspects and considerations, reflecting the specific stage and anticipated changes in the power system's evolution. In both cases, it is crucial to acknowledge that the deployment of Distributed Energy Resources (DERs) may follow a stochastic process, beyond the control of the Distribution System Operators (DSOs). This process aligns with individual customer needs and economic capabilities. In fact, hosting capacity can exhibit significant sensitivity to the way the DER deployment will unfold. Considering worst-case scenarios as reference values, can lead to excessively conservative assessments [1], [2], [3], and [4]. This becomes even more apparent when combining hundreds of feeders, as it is highly unlikely that worst-case scenarios would occur in all of them.

Some research papers proposed a combination of three different methods to calculate hosting capacity, namely the forward, backward, and “all together” methods [5], [6], and [7]. Thus, describing the hosting capacity with the set of the three calculated values. These three methods encompass three distinct processes for DER deployment: the forward method progresses from transformer terminals to the end of the feeder, the backward method starts from the end and moves towards the transformer terminals, and the "all together" method involves a uniform and progressive deployment along the feeder. This approach is computationally efficient, as it involves only three deployment scenarios, but the range of hosting capacity results may be significantly wide, making difficult for the stakeholder to take strategic decisions. Moreover, there is no guarantee that the three methods (forward, backward and “all together”) are representative of all the possible DER deployments.

To address this issue, a stochastic approach utilizing Monte Carlo simulation is proposed in both [8] and [9]. In these papers, the notion of congestion risk is introduced. This risk is represented by a quasi-sigmoidal function, with the x-axis denoting the values of newly installed Distributed Energy Resource (DER) power, and the y-axis representing the congestion risk, defined as the probability of encountering at least one violation in the system, irrespective of the position and distribution of the DERs in the grid, or equivalently to the cumulative density function (CDF) of the hosting capacity. The relevant probability distribution function can be easily derived from these congestion risk curves.

The above approach as the advantage of fully describing the hosting capacity by its CDF and PDF. However, the amount of Monte Carlo iterations (required for obtaining a statistically significant sample of scenarios) is a relevant limitation of the method, especially for the analysis of large distribution networks, with hundreds of feeders and thousands of nodes.

The methodology presented in the present paper is based on similar stochastic approach, but it leverages the use of statistical technique, such as bootstrap, to identify an optimal trade-off between accuracy and computation effort, as described in the successive part of this paper.

When scaling the analysis of HC to large distribution grids, it is crucial to account for the stochastic nature of distributed energy resources (DERs) deployment, while also adopting a computationally efficient method and being able to estimate the accuracy of the results. The value of this paper is to provide such a method.

The upcoming sections will provide a comprehensive explanation of the methodology its application on a simplified system, and a demonstration of its application.

II. METHODOLOGY

A. General Considerations

When addressing the challenge of large-scale renewable deployment, it is important to recognize that relying solely on conservative hosting capacity values may offer certain assurances, but it would not realistically reflect the actual hosting capacity of the feeder. This limitation arises from the fact that the minimum hosting capacity is typically determined when concentrating a significant portion of renewables in remote locations, which represents only one or few of the countless possible configurations for renewable deployments. Therefore, a stochastic approach is proposed, to address these limitations.

On the other hand, the number of potential renewable deployment combinations can be astronomically high. For instance, in the case of Photovoltaic (PV) connections, considering all possible combinations of varying numbers of PVs at different locations, the total number of combinations would be 2^n, where n represents the number of nodes in the feeder. More concretely, even for a modest 20-node feeder, we would have over one million combinations. For a feeder with 40 nodes, the number of combinations would exceed 10^{11}. Additionally, the injected power can vary across different nodes. Consequently, the actual number of possible scenarios becomes uncountable.

Conversely, in the assessment of hosting capacity there is often a specific point of estimate of interest, such as the average value[1]. In this case, statistical tools, such as bootstrap analysis can be used to create a relevant confidence interval around this estimate.

It is pertinent to note that a trade-off exists between result accuracy and computational effort. Increasing the number of analysed scenarios enhances the statistical model's ability to provide more precise estimates, as the standard error of the estimate is dependent on the sample size (for the mean, the standard error is proportional to $1/\sqrt{\mathrm{n}}$).

As discussed, the proposed approach can be conveniently divided in two activities: the first activity is the calculation of the hosting capacity for a number of potential DER deployment scenarios. This activity is conducted with the aid of power system simulation tools. While the second activity is to apply statistical methods to determine the desired point estimate of the hosting capacity and the relevant confidence interval (i.e. 95% CI).

In the next subsections, these two activities are discussed.

B. Calculation of the Hosting Capacity

One common method to determine the hosting capacity at a single node involves gradually increasing the generation power at that node until certain predefined constraints are breached. These constraints typically pertain to factors such as minimum and maximum operating voltage, equipment loading (such as lines and transformers), excessive elevation of short circuit current, reverse power at the transformer point, or maximum harmonic distortion limits.

The analysis can be performed on a per-constraint basis, evaluating each constraint individually, and selecting the most restrictive constraint as the reference value for the hosting capacity. A Monte Carlo approach can be employed, where potential deployments of DERs along the feeders are randomly selected. Alternatively, the analysis can be conducted independently for all nodes along the feeder (one node at time), representing a very specific subset of all the potential renewable energy generation deployment scenarios[2].

The Monte Carlo approach presents the advantage of not being dependent on the number of nodes in the feeders. This is particularly beneficial for feeders with a limited number of nodes, as the accuracy of the results may deteriorate if a small number of scenarios is analysed.

Most commercial tools (i.e. [13], [14], [15], [16], [17], and [18]) offer readily available modules for individual hosting capacity analysis at each node of the feeder, and some tools may also have predefined distribution patterns for multiple generation points. Usually, the implementation of Monte Carlo analysis can be achieved with the assistance of automation scripts, such as those written in the Python programming language.

Regardless of the method employed, the analysing of hosting capacity typically proceeds with the two following steps:

1. For each constraint, determine the critical operating conditions using load flow time series analysis over a selected period (e.g., 24 hours, a month, or a year) with intervals of 60, 30, or 15 minutes. This process will identify the most critical, yet realistic, combination of load and generation to be used in the static (single point in time) load flow analysis;
2. Calculate the hosting capacity for a sufficient number of potential DER deployment scenarios. This process is detailed in Section III.C.

It shall be noted that not all constraint violations carry the same level of criticality. For instance, consider a scenario where the hosting capacity is constrained by a single overload at a short service line in the feeder. Such an issue could be swiftly resolved with a negligible investment. However, including this event in the analysis might

[1] The same apply for other statistics, for example a specific measure of quantile could be used too.

2 See Appendix I for more considerations on this topic.

obscure more realistic values of the hosting capacity. Therefore, in most cases it is reasonable to neglect constraint violations occurring in minor grid elements, such as service lines. A proper discernment of constraint violations and their handling is crucial to obtain realistic results.

C. *Application of Statistical Methods*

After obtaining the values of hosting capacity for a subset of cases of size *n*, in this paper we use bootstrap to generate a probability distribution for the average hosting capacity and to determine its confidence interval (i.e. 95% confidence interval).

We recall that the bootstrap involves generating a large number of resamples (e.g., 10,000) with replacement from the same subset of simulation scenarios. A point estimate is then calculated for each iteration, and the collection of these point estimates forms a probability distribution function.

More formally, considering the point estimate the bootstrap method is based on the following theory:

The population mean μ is defined as:

$$\mu = \int x dF(x) \tag{1}$$

Where $F(x)$ is the cumulative distribution function of the random variable X (i.e. hosting capacity).

The sample mean is the same functional of the empirical distribution function:

$$\hat{F}(x) = \frac{1}{n}\sum_{i=1}^{n} I(X_i < x) \tag{2}$$

Where $X_i, \ldots, X_n$ denote the data (i.e. hosting capacity of each simulation scenario). Therefore the bootstrap estimator of the population mean μ, is the sample mean, $\overline{X}$:

$$\overline{X} = \int x d\hat{F}(x) = \frac{1}{n}\sum_{i=1}^{n} X_i \tag{3}$$

The algorithm for the bootstrap, to determine mean, standard error and the (1-α) confidence interval of the hosting capacity is the following:

1. Calculate the mean of the original sample of hosting capacity results:

$$\hat{\theta}_n = \frac{1}{n}\sum_{i=1}^{n} X_i \tag{4}$$

2. Draw a bootstrap sample (with replacement) $X_i^*, \ldots, X_n^* \sim \hat{F}(x)$, and compute:

$$\hat{\theta}_n^* = \frac{1}{n}\sum_{i=1}^{n} X_i^* \tag{5}$$

3. Repeat the previous step B times, yielding estimators $\hat{\theta}_{n,1}^*, \ldots, \hat{\theta}_{n,B}^*$

4. Let be:

$$\overline{\theta} = \frac{1}{B}\sum_{j=1}^{B} \hat{\theta}_{n,j}^* \tag{6}$$

5. Calculate the bootstrap standard error as

$$\hat{s} = \sqrt{\frac{1}{B}\sum_{j=1}^{B} (\hat{\theta}_{n,j}^* - \hat{\theta}_n)^2} \tag{7}$$

6. Let be:

$$\hat{F}(t) = \frac{1}{B}\sum_{i=1}^{B} I(\sqrt{n}(\hat{\theta}_{n,j}^* - \hat{\theta}_n) \le t) \tag{8}$$

7. Let the confidence interval be:

$$C_n = \left[\hat{\theta}_n - \frac{t_{1-\propto/2}}{\sqrt{n}}, \hat{\theta}_n - \frac{t_{\propto/2}}{\sqrt{n}}\right], \tag{9}$$

where $t_{1-\propto/2} = \hat{F}^{-1}(1-\propto/2)$, and $t_{\propto/2} = \hat{F}^{-1}(\propto/2)$,

Since we lack access to the entire population, we resort to resampling with replacement from a subset of simulated cases, which is a typical practice in bootstrap applications. This approach introduces two types of errors. The first stems from the finite nature of the sample size, denoted as n. The second arises from the finite value of B, the number of resampling iterations. However, we have the flexibility to make B arbitrarily large (i.e. B = 10,000). As a result, we can disregard the error associated with the finite value of B.

In general, achieving a relatively narrow confidence interval is desired to make the results more relevant. Increasing the sample size undoubtedly leads to narrower confidence intervals, but it comes at the cost of increased computational effort. This consideration becomes particularly crucial when scaling the analysis of hosting capacity to large distribution networks, where balancing computational resources and obtaining accurate results is of utmost importance.

In the next section, a simplified case study is conducted to determine the width of the confidence interval as a function of the sample size (number of simulated scenarios). This analysis aims to make a critical decision on the minimum number of simulation cases that need to be analysed.

III. Case Study

A. *The Grid*

The case study focuses on the deployment of Photovoltaics (PV) generation in a Low Voltage (LV) feeder.

The grid being investigated is a radial low voltage distribution system consisting of two branches. It is supplied by a 100 kVA 33/0.415 kV transformer. There are a total of nine nodes within the grid where renewable energy generators, specifically PV systems, can be connected (LV transformer terminal excluded). The grid configuration is illustrated in Fig. 1. The feeder has a relatively small size, for the forthcoming explanations.

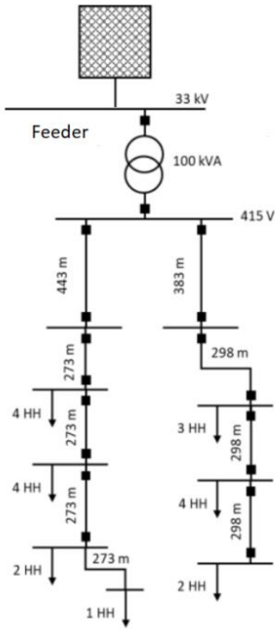

Fig. 1. Simple LV Distribution System. There are 9 nodes where PV systems can be connected, excluding the LV transformer terminals. HH indicates the number of households at the node.

The model, including transformer data, lengths of the lines, cable cross sections, number of households at the nodes, and load patterns is adopted from [10].

We define a PV deployment scenario as a random number of PVs connected at random nodes of the feeder. For simplicity, we assume that all PVs have an equal rated power.

Since the number of nodes is relatively small, we have the ability to simulate all potential PV deployment scenarios. In this case, there are a total of 2^9 possible scenarios, resulting in a total of 512 unique combinations, representing the finite population.

These 512 scenarios are simulated in DIgSILENT PowerFactory.

B. Hosting Capacity Analysis (Full Population)

For each PV deployment scenario, the hosting capacity has been calculated by uniformly increasing the power of the connected PVs, until any of the selected constraints (thermal, loading, short circuit) are violated. The same procedure is repeated for all the 512 scenarios.

The average hosting capacity h of the feeder is then calculated with the following equation:

$$h = \frac{1}{512}\sum_{i=1}^{512} H_i = 61.688\ kW \tag{10}$$

The histogram of h is shown in Fig. 2.

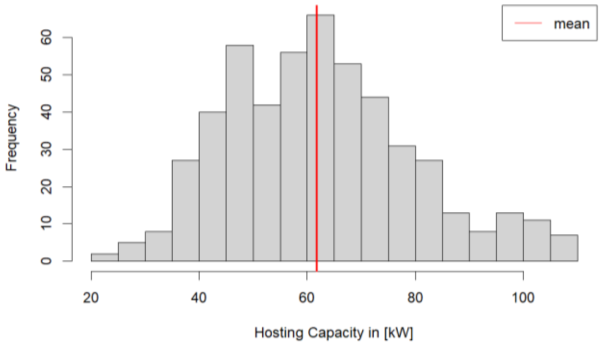

Fig. 2. Histogram of the Hosting Capacity (512 Scenarios). The red line indicates the mean of hosting capacity, representing our population mean.

From the set of hosting capacity values, the cumulative density function (CDF) can be also determined (see Fig. 3).

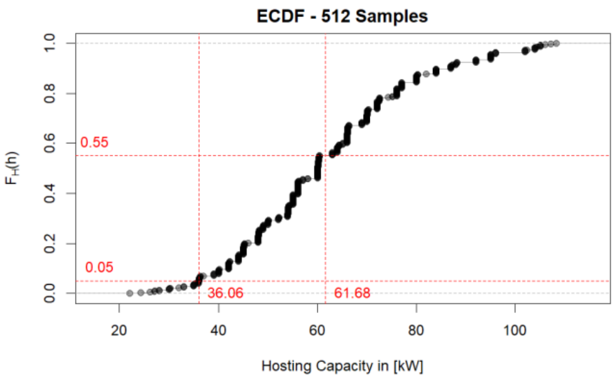

Fig. 3. ECDF (512 Scenarios). The probability of achieving a hosting capacity equal to or higher than the mean value (61.68 kW) is 0.45 (1 - 0.55 = 0.45). However, for a more conservative approach with a 95% probability, a hosting capacity of 36.06 kW would be considered

The Cumulative Distribution Function (CDF) provides the probability $F_H(h)$ of hosting capacity values being equal to or below its argument. Using this information, it becomes straightforward to calculate the more relevant probability of hosting capacity being equal to or above a specific value. ($1-F_H(h)$).

Depending on the project objectives we can either refer to the mean value, or to a specific quantile of the bootstrap estimate (i.e. 0.05 quantile). The proposed methodology is applicable in both cases. In this paper, we use the mean value, which could be a reasonable choice for large distribution networks.

In real-world scenarios, feeders typically consist of a larger number of nodes, much higher than 9, making it impractical to analyse every single possible PV deployment scenario. Consequently, the true distribution of hosting capacity and its mean are not accessible and they shall be estimated through the statistical analysis of a subset of the potential PV deployment scenarios.

The upcoming subsection will focus on analysing various subsets sizes (number of analysed scenarios). This analysis aims to explore the impact of considering different subsets of PV deployment scenarios on the overall results.

C. Statistic Analysis for a Subset of Scenarios

To assess the accuracy of the proposed method, here we conducted 100 independent bootstraps (each with 1000 resampling iterations). Each of the 100 independent bootstraps represents a different potential sample (of the same size) from the whole population. This process is repeated for different sample sizes, allowing the visualization of the estimated standard error for several bootstraps.

In an actual situation, the bootstrapping process is applied to only one subset of simulation scenarios, derived by the power system analysis.

The diagram of Fig. 4 displays the calculated standard errors for various numbers of PV deployment scenarios. The red lines illustrate the standard errors computed through the bootstrap methods, whereas the black circles (connected by the solid line) depict the standard error, calculated using the population standard deviation σ (usually unknown), which is derived from the hosting capacity values of all 512 PV deployment scenarios (finite population):

$$SE(h) = \frac{\sigma}{\sqrt{n}} \cdot \sqrt{\frac{512 - n}{512 - 1}} \tag{11}$$

Where n is the sample size (i.e. number of simulation cases).

It shall be noted that the above $SE(h)$ includes a finite population correction factor $\sqrt{(512 - n)/(512 - 1)}$, to account that the population is finite (512 cases).

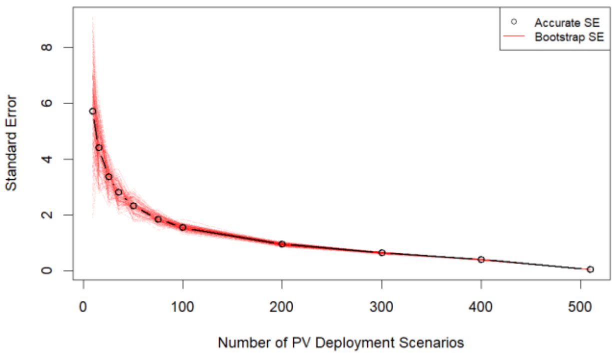

Fig. 4. Standard Error vs Number of Scenarios. The black circles connected by a solid line repreasent the accurate standard error (SE), while the red lines represent the standard error estimated through the bootstraps. The plot shows the results of 100 indipendent bootstraps, each one with 1000 resampling. Each of the 100 independent bootstraps refers to a new sample from the population but of the same size.

For the bootstrap, a more elaborated method than the basic bootstrap algorithm presented in section II.C has been used to make it suitable for finite population. In particular, the method proposed in [12], based on pseudo-population, has been arbitrarily selected. Several others bootstrap methods are available for finite population [11].

From the results of Fig. 4, two quite obvious but important facts can be inferred:

1. The true standard error monotonically decreases. As expected, increasing the number of PV deployment scenarios reduces the SE(h) - see eq. (4) -, eventually approaching zero for the whole population ($n = 512$);
2. The standard error calculated with the bootstrap is closer to the actual standard error (black circles in Fig. 4) when the number of analysed PV deployment scenarios (n) increases. It can be seen that for small sets of scenarios, the bootstrap estimation of the standard error has quite high and hardly acceptable variance around the true value.

The next step would be to determine the minimum number of scenarios that allow for acceptable confidence intervals.

The diagram of Fig. 5 presents the half-width of the 95% CI, which is the margin of error associated with the confidence interval, the distance between the point estimate and an endpoint. The y-axis is normalized to the population mean, so that it provides a per units measure of this error. More concretely, a y-axis value of 0.1 correspond to a maximum of $\pm$10% error from the estimated mean (with probability 95%).

The black solid line represents the values calculated using the standard deviation of the population and applying the finite population correction factor. The red lines represent the values for 100 independent bootstrapping (each one with 1000 resamples).

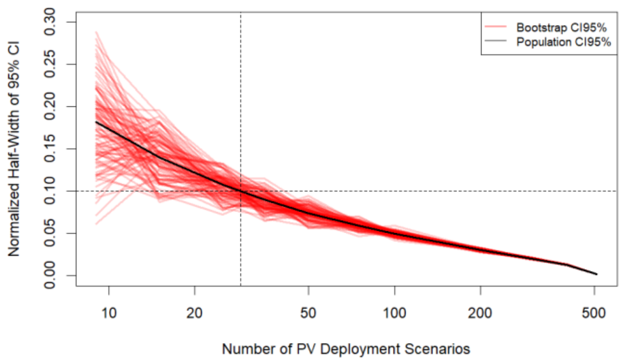

Fig. 5. Normalized Half-Width of the Confidence Interval (95%) for the mean hosting capacity. The dashed lines provide a reference for a 95% CI Half-Width of 10%, corresponding to $n = 30$ scenarios.

The selection of the number of scenarios depends on the specific project requirements, and it is a trade-off between computational costs and desired accuracy. For example, if we would like to find a hosting capacity which is within $\pm$10% of the true mean (in average), with a probability of 95%, at least a number of 30 PV deployment scenarios shall be selected for this small case study.

The above $\pm$10% error shall be considered as average, as it is dependent on the selected scenarios, as clear by observing the red lines of Fig. 5.

In Fig. 6, three histograms are presented for the average hosting capacity relevant to three different sample sizes, namely 30, 100 and 200. The population mean (red line) is usually unknown, but the random confidence interval would embrace this value with a 95% probability.

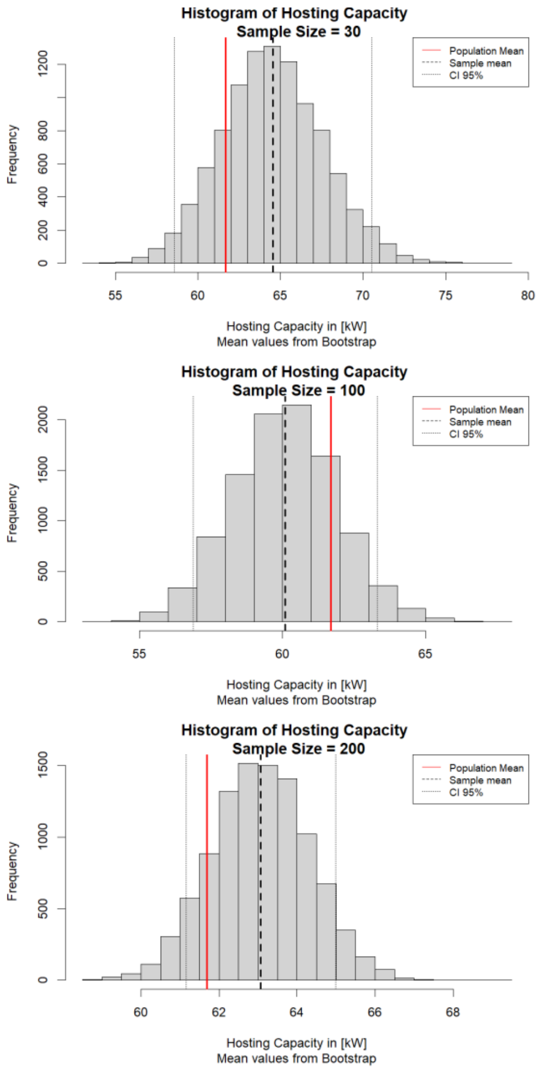

Fig. 6. Histogram of the average hosting capacity for three different sample sized (30, 100, and 200). As expected, the confidence interval becomes narrower when increasing the sample size.

In the following section, we present additional considerations regarding the selection of simulation scenarios. Although these considerations are not directly pertinent to the current research, we believe they can serve as a source of motivation for further exploration in this field.

IV. Conclusions

In conclusion, this research paper has emphasized the critical importance of striking an optimal balance between computational effort and result accuracy when assessing hosting capacity in large distribution networks. Leveraging stochastic power system simulations and probability theory, including probability and cumulative density functions, point estimates, and confidence intervals, appeared as a promising method for such assessments.

The proposed approach was successfully demonstrated through a simple case study, where statistical outcomes were compared against the true value of expected hosting capacity. The limited size of the case study allowed for the determination of the true value, which is typically unknown, due to the finite number of potential DER deployment[3].

Currently, the same method has been applied by Tractebel Engineering GmbH in a real-world application for a large distribution system, with 44 feeders and hundreds of nodes per feeder. Ongoing research on this topic continues to explore and refine the methodology.

Appendix I

In this Appendix I, further consideration on the selection of the potential DER deployment scenarios is discussed.

In particular, drawing from project experience, we have observed that for feeders with a substantial number of nodes, employing the specific subset of hosting capacity values relevant to the independent hosting capacity of each node of the feeder (single-nodes scenarios) often yields conservative results for the estimation of the expected hosting capacity.

Further research is ongoing to determine the general validity of the conservative nature of this approach.

Generally speaking, the use of a conservative approach could be highly desirable, especially in cases where there is a significant need to reduce the number of simulation scenarios.

In other words, by opting for a conservative approach, we intentionally sacrifice a certain degree of accuracy in our estimations. However, this trade-off comes with the distinct advantage of substantially reducing the number of simulated scenarios required for the analysis.

The conservative nature of approach would ensure that our estimations remain on the safe side, providing eventually a buffer for potential uncertainties or variations in real-world conditions. This cautious stance can be particularly valuable in situations where a comprehensive analysis with a vast number of scenarios may be computationally too intensive.

In essence, the adoption of single-node scenarios could strike a balance between accuracy and efficiency, allowing the achievement of reliable results while streamlining the simulation process significantly.

An intriguing observation is that the hosting capacity values for DERs dispersed across multiple nodes in most situations fall within the range of the maximum and minimum hosting capacity evaluated at the same individual nodes. This behaviour further reinforces the conservative nature of the approach, as it captures the potential variability in hosting capacity across the whole feeder.

In Fig. 7, the ECDFs of 100 random equally sized sets of scenarios – red solid lines – are compared with the ECDF relevant to the single-nodes scenarios – black solid line. The blue scatter points represent the ECDF of the whole population.

[3] With the assumption that DERs have the same size.

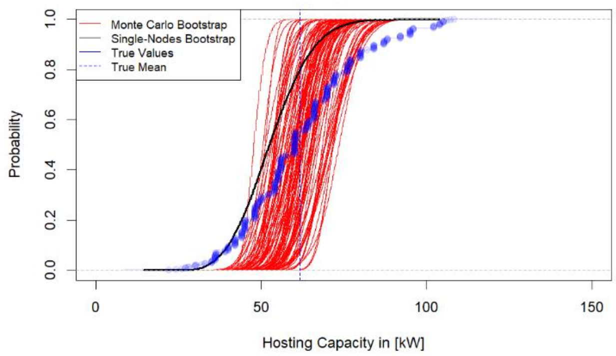

Fig. 7. Estimated Cumulative Distribution Function (ECDF) of 100 random equally sized sets of scenarios (red solid lines) compared to the single-nodes scenarios (black solid line). When referring to the true mean, the single-nodes scenarios provide a quite conservative result.

Observing the results of Fig. 7, when reference is made to the true mean – blue vertical dashed line the CDF of single-nodes scenarios is indeed among the most conservative (CDF shifted on the left).

V. Acknowledgments

The constructive feedback, inspiring conversations, and ongoing interest shown by Tractebel Engineering GmbH have been invaluable in shaping the direction and outcome of this project. Their dedication to fostering a conducive environment for research has been deeply appreciated.

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