Generating Sequential PV Deployment Scenarios for High Renewable Distribution Grid Planning

Preprint

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National Renewable Energy Laboratory

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Generating sequential PV deployment scenarios for high renewable distribution grid planning

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***Abstract*—This paper introduces a novel approach for generating solar photovoltaic (PV) plant deployment scenarios for grid integration planning. The approach guarantees consistency among scenarios of the same deployment by ensuring that higher penetration scenarios contain PV units deployed in lower penetration scenarios. It also constrains the size and spatial distribution of the PV plants and considers three placement types. A case study on a real-world distribution system proves that the precepts of scenario consistency, deployment diversity, and placement are met. The study further investigates the impact of the resulting scenarios via a stochastic hosting capacity analysis. Results indicate that the ratio between PV and load sizes, referred to as the nodal PV penetration factor (NPPF), is a key driver of the grid integration impact. By reducing the NPPF from 5 to 2, the maximum hosting capacity increased by at least 112%. The study also reveals that scenarios under random placement can lead to higher hosting capacity values.**

Keywords— Photovoltaics, energy systems integration, PV scenario generation, hosting capacity, grid integration planning.

I. Introduction

As the world embraces the decarbonization of its power system, grid operators must understand how their systems would fare under various future PV deployment scenarios. To this end, detailed interconnection or integration planning studies are critical. Such studies require the development of realistic scenarios of distributed photovoltaics (DPV). While it is vital to investigate system level constraints in the impact analysis phase, it is equally important to consider nodal or local constraints in the scenario generation phase. An example of such a constraint is the amount of DPV that is allowable at a node given local circumstances such as demand and service transformer size. Very few authors have considered the impact of local or nodal grid constraints when generating DPV deployment scenarios at increasing penetration levels.

Ding et al. [1] used a Monte Carlo approach to generate PV deployment scenarios with PV locations selected randomly and then assigning one aggregate PV unit to each location. This type of stochastic analysis only generates DPV systems randomly, without considering local or nodal capacity constraints to accommodate DPV units. Further, Arshad et al. [2] used a Monte Carlo approach to generate several possible customer permutations with a uniform probability distribution function to randomly distribute DPV systems. Arshad et al. assumed that all the PV nodes have the same amount of active power generation, but, again, this does not reflect realistic deployment scenarios. Navarro-Espinosa et al. [3] used a Monte Carlo analysis to account for uncertainties resulting from size, location, and behavioral characteristics of solar PV units integrated in low-voltage distribution systems. Further, Avramidis et al. [4], applied a Monte Carlo simulation framework taking into consideration the stochastic behavior of the various network elements to assess distributed energy resource impact and demand side flexibility. However, probabilistic analysis based on Monte Carlo simulation is challenging for two reasons. Operational profiles are generated by computationally intensive optimization. It also relies on a large pool of statistically representative demand profiles to sample from [5].

Liu et al. [6] also used the stochastic approach and random DPV deployment scenarios for hosting capacity analysis, and Ceylan et al. [7] used a Monte Carlo method for DPV system integration. Al-Alamat et al. [8] used a deterministic approach in an iterative simulation. The approach increases DPV size at each step on all nodes to determine the hosting capacity in a distribution feeder based on knowledge of the grid's topology and parameters. This deterministic approach assumes that all PV sources are producing the same amount of power, which does not represent a realistic deployment scenario. Ismael et. al have provided an extensive review of the research and advances made in hosting capacity analysis. Over the years, several analytical, stochastic, and deterministic methods have emerged to generate PV deployment scenarios for hosting capacity analysis [9].

In the PV scenario generation phase, very few authors have considered, local or nodal circumstances (such as the size of spot loads at the connecting nodes) coupled with other factors, such as being near or far from the feeder head. The existing literature has considered stochastic or deterministic DPV deployment scenarios, with only random cases, and with the assumption that all PV sources are injecting the same amount of power.

In this work, we introduce a novel approach to generate DPV deployment scenarios for the realistic and robust planning of DPV integration into distribution grids. The proposed approach explicitly accounts for different spatial distributions of PV units as well as their size relative to corresponding spot load. Many deployment samples or paths can be generated for integration planning studies.

Our contribution in this area is fourfold:

o In the DPV scenario generation, we introduce a sequential PV deployment approach that enables the control of PV unit clustering along a distribution feeder.

o We introduce a load-relative bound on customer PV capacity which we refer to as the NPPF.

o We explicitly ensure consistency among PV scenarios belonging to the same deployment sample.

o We study the sensitivity of the grid impact from the NPPF and PV unit placement.

The remainder of this paper is organized as follows. Section 2 presents the methodology of the proposed approach. In Section 3, we present a case study in which PV scenarios are generated for an 11.5 kV distribution feeder across three placement types and four NPPF values. We evaluate the integration impact of each scenario. Section 4 concludes the paper.

II. Methodology

A. PV scenario generation

The PV deployment scenario generation method exposed in this paper aims to provide (i) a sequence of PV scenarios that are consistent in the order of penetration levels and (ii) diversified PV deployment pathways to grid integration targets. To this end, the algorithm presented in Fig. 1 uses a multi-penetration level and multi-sample approach. For a given distribution feeder, one can define any valid penetration margin. Many deployment pathways are often necessary in PV grid integration planning. The method presented in this work designs each deployment pathway or sample as a succession of PV unit batch deployment in which higher penetration scenarios must have all PV plants deployed in lower penetration scenarios, as expressed by equation (1):

$$(PV_i)_k^s \subset (PV_i)_p^s \quad \forall\, k < p \tag{1}$$

where $(PV_i)_p^s$ is the series of PV units in the deployment sample, *s*, at penetration level, *p*. Note that a PV deployment scenario is thus referenced by the couple (*p, s*), with *p* its penetration level and s the deployment pathway of the sample to which it belongs.

A key factor that affects how much impact a PV deployment would have on the distribution grid is the location of the PV units. Jain et al. found that voltage and thermal impacts of PV scenarios depend on the placement of the PV units, whether they are clustered close to the substation or at the tail end of the feeder [10]. To account for the importance of location, we develop three substation-referenced distance-based PV unit placement categories: namely, close to substation, far from substation, and random. We use metric distance to measure the closeness of a customer to the substation.

In the close and far placement categories, the distance interval from the closest bus to the substation to the farthest bus from the substation is sliced into *n* equal-length search segments. To generate the PV deployment scenarios, the PV candidate buses are randomly and sequentially drawn from one search segment at a time. The larger the number of search segments, the shorter each segment, and consequently the closer the PV units are bound to be. Hence, at low penetration levels, the spread or clustering of PV units can be controlled by the number of search segments.

For the close placement category, the search segments are explored from the closest segment to the substation to the farthest. For scenarios in the far placement category, the search segments are explored in the reverse order, i.e., from the farthest segment from the substation to the closest. The PV candidate search ends when the target PV penetration is reached. In the random placement category, however, only one search segment is formed, which covers all candidate buses. From this unique search segment, candidates are randomly drawn, and a PV capacity is assigned to each candidate bus.

In this work, we assume that the size, P_i of the PV unit for customer i is bounded by a threshold value, P_i^{max}, proportional to the customer's peak load, $Load_i$. The proportionality factor, referred to in this paper as the PV factor or the NPPF, is given by equation (2):

$$NPPF_i = \frac{\tau_i LF_i}{CF_i} \tag{2}$$

where LF_i is the load factor of customer *i*, CF_i is the capacity factor of the solar PV of customer *i*, and τ_i is the target maximum portion of the annual energy consumption that customer *i* would want solar PV to offset. The relationship between the energy consumption, EC_i, and generation, EG_i, is given by equation (3):

$$EG_i = \tau_i EC_i \tag{3}$$

The total energy, EG_i, generated by a PV unit, *i*, with the capacity factor, CF_i, and size, ${P_i}^{max}$, during the time period, *T*, is given by (4):

$$EG_i = CF_i {P_i}^{max} T \tag{4}$$

Similarly, the total energy, EC_i, consumed by the corresponding load, i, with the load factor, LF_i, and size, $Load_i$, is given by (5):

$$EC_i = LF_i Load_i T \tag{5}$$

Merging (3), (4), and (5) leads to (6):

$$CF_i P_i^{max} = \tau_i LF_i Load_i \tag{6}$$

Thus:

$$NPPF_i = \frac{{P_i}^{max}}{Load_i} = \frac{\tau_i LF_i}{CF_i} \tag{7}$$

Consequently, the PV capacity for customer *i* must satisfy (8):

$$P_i \leq NPPF_i Load_i \tag{8}$$

Another size-binding parameter considered in PV scenario generation is the surface area that is available for installation.

The proposed PV scenario generation approach is presented by the flowchart in Fig. 1.

B. PV scenario grid impact analysis

To evaluate the PV scenarios and assess their impact on the grid, we conduct a capacity integration analysis. In this analysis, every PV scenario is screened for voltage, thermal loading, and reverse power flow limits across a set of system-level bounding conditions.

All passing scenarios must result in voltage values within any utility-specific standard. They must also result in line and transformer loadings less than their rated capacities. The reverse power flow limit is set as a percentage of the total load on the feeder. For utility systems where no back-feed is allowed at the substation for protection reasons, the limit is set to zero; thus, violations can be of any or a combination of the following types: undervoltage, overvoltage, line overload, transformer overload, and reverse power flow.

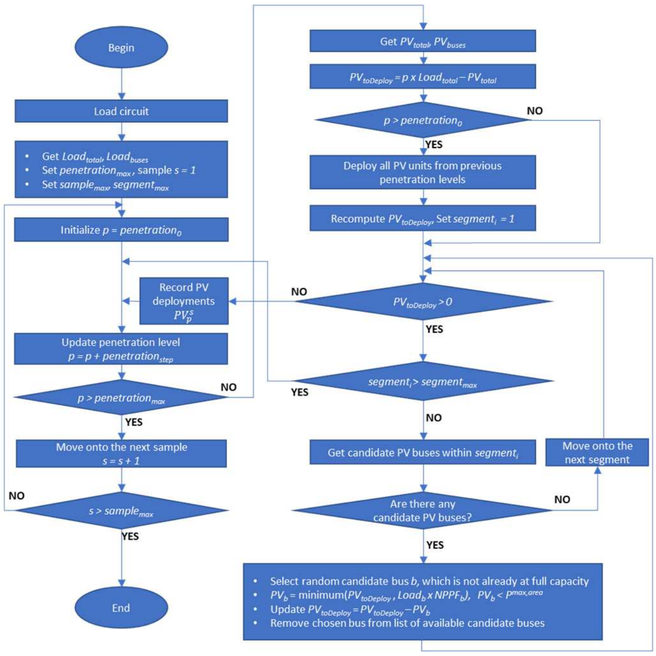

Fig. 1. Proposed PV deployment scenario generation approach

III. Case Study

The objective of this case study is twofold, demonstrating our proposed PV scenario generation methodology and deriving the implications of the placement and size thresholds of PV units for the hosting grid. To this end, we conduct the following two analyses:

- Comparison of PV scenarios at 20% and 40% penetration levels within the same deployment sample or pathway across all three placement types: close, far, and random.
- Sensitivity of grid impact and feeder hosting capacity regarding PV placement and size threshold.

The proposed approach is implemented and evaluated in Python coupled with OpenDSSDirect[1], a Python direct-mode interface to OpenDSS, used as the power flow simulation engine.

A. Test feeder

The proposed PV scenario generation methodology is evaluated and tested on an 11.5 kV, real-world distribution feeder serving 86 customers, with a maximum non-coincident load of 3.2 MW. The network is built around 1273 buses and 1186 lines. No PV unit originally exists on the test feeder. Fig. 2 shows its peak load condition voltage values mapped on the network topology.

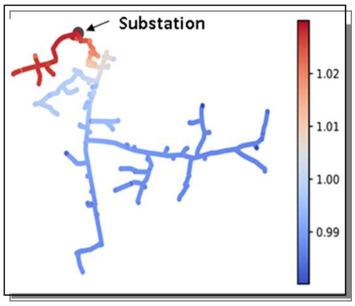

Fig. 2. Test feeder voltage mapped on the topography in peak loading condition—voltage in p.u.

B. Results and discussion

1) Deployment consistency and PV unit spatial distribution:

Consistency among PV scenarios of the same deployment path captures what happens in practice. When connecting a new PV unit, the existing ones are not removed. In addition, consistency allows to fully identify an entire deployment sample as a target pathway to a given penetration.

To demonstrate how the proposed scenario development approach ensures consistency in PV deployment among consecutive penetration levels, we examine two scenarios—20% and 40% penetration levels for the above-presented feeder. Next, we showcase how our proposed approach spatially distributes the PV units on the network under the three placement types: close, far, and random. Fig. 3 presents the deployment consistency between the 20% and 40% penetration scenarios and their spatial distributions under the close, far, and random PV unit placements with NPPF = 3.

As shown in Fig. 3, in the close and far placement scenarios, the PV units represented by squares are clustered near the feeder head and tail, respectively. On the other hand, random placement scenarios are neither restricted to the head nor to tail end of the feeder; rather, PV units are spatially randomly distributed across the feeder. Note that for all placement types, the PV units deployed in the 20% penetration level scenario are also deployed in the 40% penetration scenario. This confirms the sought-after consistency among consecutive penetration levels in the PV deployment scenarios.

2) Integration impact sensitivity to PV unit placement and NPPF:

To evaluate the integration impact of the scenarios that we developed with the proposed approach, we conduct a feeder hosting capacity analysis. As input to the impact study, we generate 30 PV deployments that have 30 penetration levels each. The penetrations range from 5% to 150% at 5% increments. So, each hosting capacity analysis investigates 900 PV deployment scenarios. In this case study, the 900 PV scenarios were generated in 4.83 seconds.

The operating parameters considered are voltage, thermal loading, and reverse power flow. In this case study, as per the

[1] https://dss-extensions.org/OpenDSSDirect.py/

electric utility company's standard, voltage values outside of the [0.9, 1.1] interval are considered violations, as are transformer and line loadings exceeding 100%. We set the reverse power flow threshold at 20% of the feeder's non-coincident peak load. Any reverse power exceeding this threshold, flowing to the substation, is considered a violation.

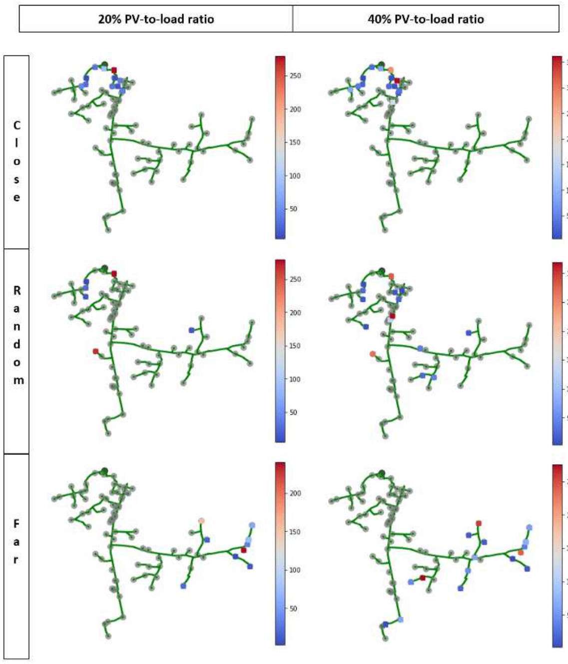

Fig. 3. PV deployment consistency and spatial distribution of PV units. The PV units are represented by colored squares, with the color indicating their capacity in kW on the scale shown by the color bars.

For each of the 900 PV deployment scenarios, the impact on the distribution grid is evaluated across three bounding conditions extracted from the aggregate load and PV profiles. The conditions correspond to maximum load, maximum PV to load, and minimum daytime load. We refer to this analysis as a multi-timepoint hosting capacity analysis (MTHCA). Each MTHCA investigates 2700 power flow simulations for voltage, thermal, and reverse power flow. Fig. 4 shows a color-coded violation map of an MTHCA conducted with PV scenarios generated with NPPF = 3 under the random placement type. Violations encountered are transformer overload, RPF, and overvoltage. The figure also shows the spatial distribution of the PV deployment scenario with the highest capacity that yields no violation, corresponding to 80% penetration and deployment type 10.

As shown in Fig. 4, the ability of the test feeder to host DPV is first limited by the thermal loading of the service transformers. Because there is no transformer overloading in the existing case, this violation is caused by the integration of PV scenarios as early as 5% penetration in deployments 3, 6, 11, and 29. Given that the PV power injection depends on the size of the PV units, constraining individual PV unit's capacity, as in equation (3), is critical. This constraint could significantly reduce the probability of service transformer overloading. This explains why reducing NPPF from 3 to 2 leads to the first transformer overloading occurring at 10%.

To determine the sensitivity of the integration impact with regard to the PV unit placement and size (constrained by the NPPF), we perform the MTHCA for four NPPF values (2, 3, 4, 5) and for all three placement types: close, random, and far. Uniform NPPF values exceeding 1.5 are selected to ensure that the target maximum PV penetration level of 150% is achievable. The combination of NPPF values and placement types, results in 12 MTHCAs that comprise our sensitivity analysis. Fig. 5 shows the minimum and maximum hosting capacity values from each of the 12 MTHCAs. The maximum hosting capacity (Max HC) refers to the maximum penetration level at which we can find at least one PV scenario that does not cause any violation. For example, in Fig. 4, Max HC is 80%. The minimum hosting capacity (Min HC) is the highest penetration level below and at which all PV scenarios cause no violation. In the analysis presented in Fig. 4, the Min HC is 0%.

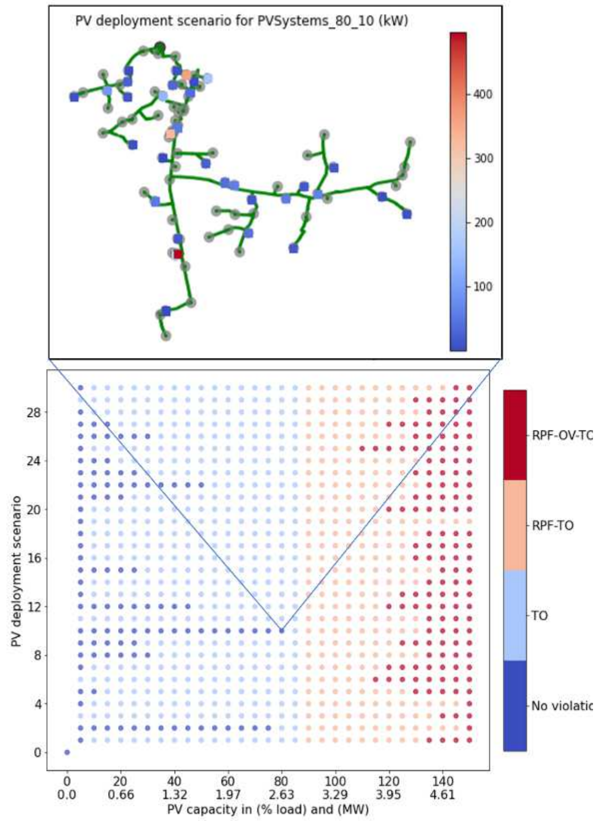

Fig. 4. Sample violation map of system PV hosting capacity analysis along with the spatial distribution of the passing PV scenario with the highest capacity (kW). Here OV stands for overvoltage, RPF is reverse power flow and TO is transformer overload.

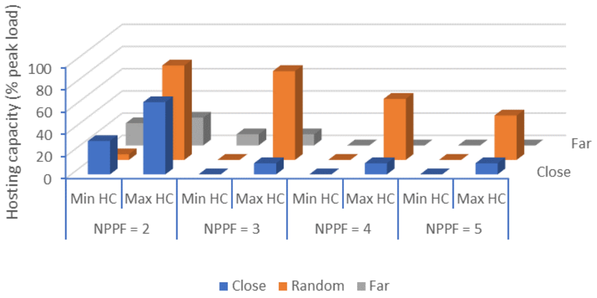

Fig. 5. Sensitivity of system hosting capacity to NPPF and PV unit placement

Based on the sensitivity analysis results shown in Fig. 5, there is a clear indication that the lower the NPPF, the higher the maximum hosting capacity. In fact, local violations, such as overvoltage and transformer overloads, are likely to occur when installed PV capacity is relatively high compared to the corresponding spot load. Therefore, with lower NPPF values, local violations are significantly mitigated. By reducing the NPPF from 5 to 2, the maximum hosting capacity increases from 10% to 65% for close placement, from 40% to 85% for random placement, and from 0% to 25% for far placement.

Results also indicate that random placement yields a higher maximum hosting capacity. In fact, random placement is more likely to capture a more diverse set of scenarios, whereas close and far placement might be restricted by their clustering nature. Consequently, random placement results in a wider hosting capacity range, i.e., the lowest Min HC and the highest Max HC. Even for the random placement where the maximum hosting capacity values are the highest, the maximum hosting capacity increases by 112% when the NPPF decreases from 5 to 2.

IV. Conclusion

In this paper, we propose a novel methodology for generating PV scenarios for grid integration planning studies. The proposed approach explicitly accounts for the spatial distribution of PV units as well as their maximum allowable capacities relative to the corresponding peak spot loads. A case study on a real-world distribution feeder reveals that higher PV grid integration capacities can be achieved with random PV placement and with lower nodal PV to spot load ratios or NPPF. These results suggest that the NPPF limit is an interesting indicator that regulators and utilities should consider in the evaluation of new PV integration plans, as the choice of NPPF can significantly impact the amount of PV the network can host. Among all PV placement types investigated, random placement can be considered as a reference placement because it leads to wider hosting capacity margins. In future work, we will explore an optimization-based PV deployment method that explicitly ensures diversified and homogeneous PV scenario sets with regard to the siting and sizing of PV units for grid integration planning.

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