2018

Probabilistic Risk Assessment of Power Quality Variations and Events under Temporal and Spatial Characteristic of Increased PV Integration in Low-Voltage Distribution Networks

Shivananda Pukhrem

Malabika Basu

Michael Conlon

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Shivananda Pukhrem, *Student Member, IEEE*, Malabika Basu, *Member, IEEE*, and Michael F. Conlon, *Member, IEEE*

***Abstract*—The aim of this paper is to perform a probabilistic risk assessment of power quality variations and events that may arise due to high photovoltaic distributed generation (PVDG) integration in a low-voltage distribution network (LVDN). Due to the spatial and temporal behavior of PV generation and load demand, such an assessment is vital before integrating PVDG at the existing load buses. Two power quality (PQ) variations such as voltage magnitude variation and phase unbalance together with one PQ abnormal event are considered as the PQ impact metrics. These PQ impact metrics are assessed in terms of two PQ indices, namely site and system indices. A Monte Carlo based simulation is applied for the probabilistic risk assessment. From the results, site overvoltage shows a likely impact to observe as the PVDG integration increases. The probability of 20% of customers violating 1.1 p.u. at 100% penetration level is 0.5. Integration of PVDG reduces the voltage unbalance as compared with no or low PVDG penetration. There is a higher probability of observing deep sag at the site as PVDG integration increases. This probabilistic approach can be used as a tool to assess the likely impacts due to PVDG integration against the worst-case scenarios.**

***Index Terms*—Distributed generation, photovoltaic, power distribution planning, overvoltage, voltage unbalance, voltage sag, Monte Carlo methods, temporal, spatial.**

I. Introduction

CURRENTLY, most PVDGs are integrated either in passive or reactive approach. Both passive and reactive integration approaches suffer potential deterioration of the LVDN and subsequently create the requirement of oversizing the LVDN [1]. Again, the reactive integration approach may have resolved some of the critical issues at the operational stage, but difficulties persist in coping with the curtailment of energy from PVDG and the associated network losses. To overcome such potential deterioration of the network, an active planning approach can be envisaged for the given specific network. Such an active planning approaches include an exhaustive assessment of the risk associated with increased integration of PVDG in the LVDN.

Increasing integration of non-firm single phase PVDG in LVDN may degrade the power quality of supply, possibly beyond general limits [2]. Notably, the increased integration of PVDG impact the level of transients due to large current variations, on observed voltage fluctuation due to intermittent sources [3], on phase unbalance due to dispersed integration of single phase PVDG and on voltage sags due to increased short circuit currents [4]. According to [2], there are two types of power quality (PQ) impact metrics which are distinguished by the method of measurement. They are i) PQ variations which are recorded at predefined instants and ii) incidents triggering cascaded PQ events in the network. These two PQ impact metrics can be further categorised into two PQ indices [4], namely site and system indices. For each index and for each PQ impact metric, the risk associated with integrating large numbers of dispersed PV generations can be assessed [5].

The need for probabilistic studies on determining the impact of PV generation in LV networks was highlighted in [2] and [6]. A report from EPRI [7] recommends a stochastic approach in determining the PV hosting capacity in a distribution network. The stochasticity was mainly on the position and size of the PV generation while the steady state impact was performed deterministically i.e., considering worst case scenarios such as maximum recorded PV generation with minimum recorded load profiles. As specified by the authors in [2], the long-term measurement data is valuable in determining the steady state impact in a power distribution feeder. Further, EN 50160 [8] presents the voltage characteristic in a probabilistic manner such as the 95% level over a given time, the voltage magnitude should be within a given limit. Above all, a specific customer with a PV installed may not coincide with the worst-case scenarios. Consideration of worst case scenarios may strictly restrict in estimating the PV hosting capacity. For this reason, a combination in stochasticity of the PV location, size, and generation profiles together with the demand load profiles will represent a probabilistic scenario based study. A similar study was reported in [9] where the authors performed probabilistic impact assessment from the low carbon technologies in an LV distribution system.

Manuscript received August 10, 2017; revised December 4, 2017; accepted January 14, 2018. Date of publication January 24, 2018; date of current version April 17, 2018. Paper no. TPWRS-01246-2017. *(Corresponding author: Malabika Basu.)*

The authors are with the School of Electrical and Electronic Engineering, Dublin institute of Technology, Dublin 8, D08 NF82 Ireland (e-mail: shivananda.pukhrem@mydit.ie; mbasu@ieee.org; michael.conlon@dit.ie).

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Digital Object Identifier 10.1109/TPWRS.2018.2797599

Therein, the authors leverage Monte-Carlo simulation. In the same vein, Klonari et al. in [10] utilizes smart meter data to performed probabilistic estimation of PV hosting capacity. But [9] considered only voltage variation due to varying PV generation as a PQ impact study. A probabilistic power flow analysis was studied in [11] where the probability distribution of power flow responses are estimated using a non-parametric fixed bandwidth kernel density estimation. The choice of bandwidth highly influences the kernel density estimation [12] and therefore, the choice of constant bandwidth may not represent an appropriate probability distribution for power system responses. A new probabilistic technical impact assessment was studied in [13]. But, [13] again lacks the stochasticity in the peak PV generation value and profile together with PVDG location. A Monte-Carlo based PV hosting capacity was reported in [14] but considers the hourly stochastic analysis of PV and load profile by taking the time periods of the day when PV generation is likely to be high. Further, [14] lacks the temporal and spatial characteristic of both PV generation and load demand profiles.

Consideration of the high amount of PVDG integration in an existing LVDN requires statistical information on its impact on the operation of a power system. The distribution network is highly dispersed and diverse and often characterised as a heterogeneous system [1]. In this work, the temporal and spatial characteristics of both load demand and PV generation profiles are leveraged to perform a stochastic random process study through a Monte-Carlo simulation. This aims to quantify the likely impacts of the operation of the power system by considering two PQ impact metrics. The succeeding aim is to further assess the impact observed from the Monte-Carlo simulation against the worst-case scenarios. Here the worst-case scenarios are i) maximum demand with no generation and, ii) no demand with maximum generation. The remaining part of the paper is sectionalized as follows, Section II briefly describes the specification of the distribution network and the assumption made in this work. Section III summarizes the impact metrics considered. Section IV presents the PQ impact studies. Probabilistic analysis and conclusion are presented in Sections V and VI, respectively.

II. Network Description and Assumptions

A. Network Description

The original IEEE European LVDN [15] is considered as a test bed for this study and is shown in Fig. 1. It has a Dy (delta-star) sub-station transformer of 800 kVA rating and consists of 905 three phase nodes. This distribution network represents a typical 4 wires 3 phase low-voltage distribution network as seen in most part of the European countries.

The original test bed had 55 single-phase domestic customers. Out of the 55 customers, phases A, B, and C accommodate 38.2%, 34.5% and 27.3% of the loads respectively.

B. Assumptions

For this study, a high-atitude demographic region is chosen. From the Whitworth Meteorological Observatory [16], a 5-minute resolution of 30 sunny days representing the month

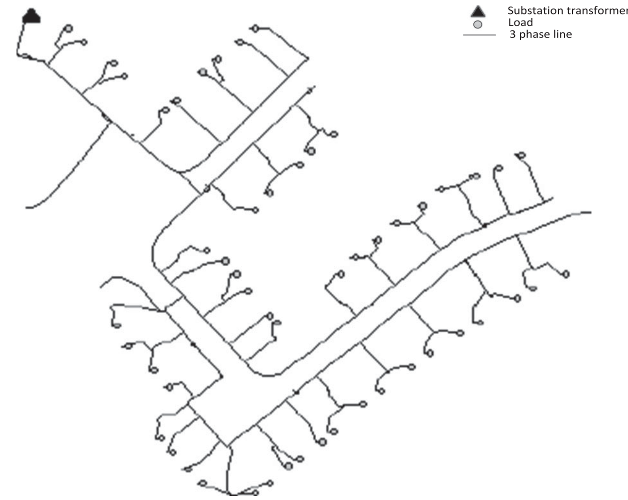

Fig. 1. One-line diagram of the European low voltage test feeder.

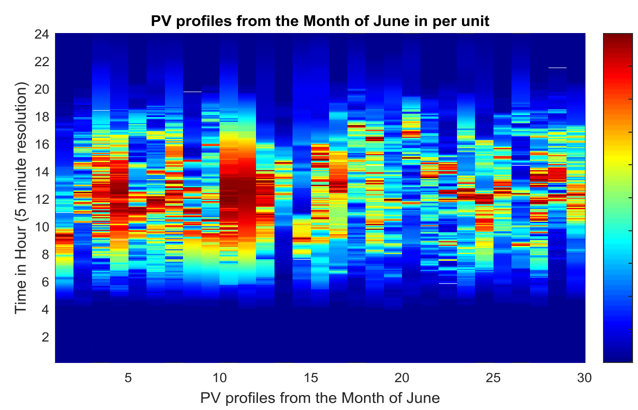

Fig. 2. Checkerboard plot of the PV profiles for the month of June 2015 in per unit.

of June from the year 2015 is considered for the PV generation profiles and is shown in Fig. 2. As an example, it can be seen from Fig. 2, the per unit solar generation at 12 noon on 15th of June is in between 0.1 and 0.2, whereas, the per unit solar generation at 12 noon on 11th of June is in between 0.9 and 1. Similarly, a pool consisting of 200 load profiles with 5-minute resolution, which reflects the temporal behavior of load consumption pattern from Low Carbon Technology (LCT) project [17] is considered as the domestic load profiles and is shown in Fig. 3. From Fig. 3, typically it can be seen that the per unit load consumption is in between 0–0.3 for the duration between midnight until 3 am. Again, starting from 6 pm until midnight, most of the houses consume more electricity showing a generic load consumption pattern.

Each of the 55 customers are assumed to have a 0.95 lagging power factor whereas the PVDG is assumed to export power at unity power factor. The peak PV generation levels are randomly varied between 1 and 5 kW in steps of 1 kW. Similarly, the peak load demands are randomly varied between 1 and 10 kW in steps of 1 kW. The IEEE EU LVDN is characterised by the spatial and temporal behavior of the load demand. Together with the temporal behavior of PV generation, various

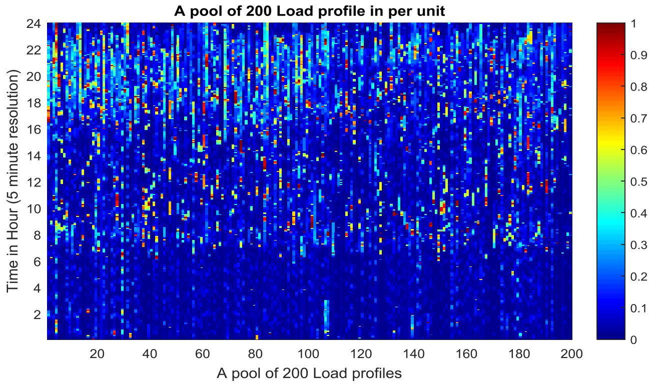

Fig. 3. Checkerboard plot of the load demand for the 200 days representing a temporal behavior in per unit.

stochastic scenarios can be analyzed. Furthermore, the consideration of randomness in defining the peak PV generation, peak load demand and location of PV generation provides stochasticity in performing a probabilistic risk assessment. Here, the PV generations are allowed to connect only to the existing load buses i.e., 55 load buses in total. A quasi-time series power flow OpenDSS [18] for every 5 minutes is chosen as the preferred simulation tool. The implementation of the probabilistic study is performed in a co-simulation platform between MATLAB and OpenDSS.

III. Impact Metrics

A. PQ Impact Metrics

As discussed earlier, there are two types of PQ impact metrics considered, namely PQ variations and PQ events respectively. The PQ variations are small variations in voltage and current waveforms which primarily occur in the normal operating condition of the power system [2], [4]. For instance, PQ variations include long and short voltage fluctuations, unbalances and harmonics. Accumulated PQ variations could lead to premature aging of the LVDN assets such as transformer insulation, tap position etc. [19], whereas very high levels of variation may lead to equipment failure [20]. The PQ events are characterised by large and sudden deviations from the normal voltage waveform. Voltage sags and transients are known PQ events [19]. Further PQ events can be classified into normal which are expected events and abnormal events [2]. Normal events are due to power system switching occurrence during transformer and capacitor energisation. Abnormal events are more concerned with the integration of distributed generation such as PVDG. For instance, short circuits and earth faults are considered as abnormal events. About 70% of the faults in a distribution network are unsymmetrical single to line ground (SLG) faults [21] and is considered one of high risked abnormal events. Such abnormal events lead to severe voltage sags [19]. Under such abnormal events, large reactive power flows are required during voltage recovery after the faults. But this requirement of large reactive power may lead to high inrush current from the capacitance which may lead blowing up the fuses or other sensitive power electronic components [19]. Voltage sag is a multi-dimensional phenomenon that includes measuring voltage sag and detecting them [22]. In this work, overvoltage and voltage unbalance due to the stochastic integration of increased PVDG are considered as PQ variations whereas voltage sag due to random SLG faults is taken as a PQ events.

B. PQ Impact Indices

Two PQ indices, namely site and system indices are considered here. The single site index refers to any particular PQ impact metrics at the point of connection of PVDG to the utility grid. The system index refers to a segment or the entire distribution system. Normally, the system index represents a value of a weighted distribution [4]. In this work, a segment of the distribution network observed by the monitoring device located at the secondary terminal of Dy sub-station transformer is assumed to provide the PQ system indices.

IV. PQ Impact Studies

A. Probabilistic Study

For each PQ impact metrics namely variations and events, a probabilistic study considering both temporal and spatial is performed. Fig. 4 represents the Monte Carlo simulation to assess PQ variation metrics. Herein, both PVDG and load demand are characterized by each respective pool of profiles. The location of each load bus is obtained in to order connect new PVDG randomly in the existing load buses. A penetration level, n, is defined at the beginning of the Monte Carlo simulation. So, when the number of PVDG installed customer i.e., N_pv is 11, then penetration level n is equal to 20%. The penetration level is incremented by 20% up to 100% for every 100 different stochastic scenarios (see the appendix). Each stochastic process designated by '*MC*' is characterised by re-defining the existing loads and connecting new PVDGs randomly in the existing load buses for each penetration level. In total, there are 500 different stochastic processes. The existing loads are re-defined in two manners, peak load values and load demand profiles. The peak load demand values for each 55 customers are randomly varied from 1 to 10 kW and has a rectangular distribution [20]. Similarly, the corresponding load demand profile is randomly selected from the pool of 200 load profiles and also has a rectangular distribution. The rectangular distribution is defined by its probability density function (pdf) '$f(x)$' and has a uniform value between the lower bound '*a*' and the upper bound '*b*'. The pdf is given by

$$f\left(x\right) = \frac{1}{b-a}\,;a \leq x \leq b. \tag{1}$$

The connection of new PVDG is allowed only to the buses where the loads are already existed in the LVDN. For each penetration level '*n*', the customer that wishes to install PVDG is determined by '*N_pv*' permutation of total load buses i.e., '*L*' through an ordered sampling without replacement [23]. This

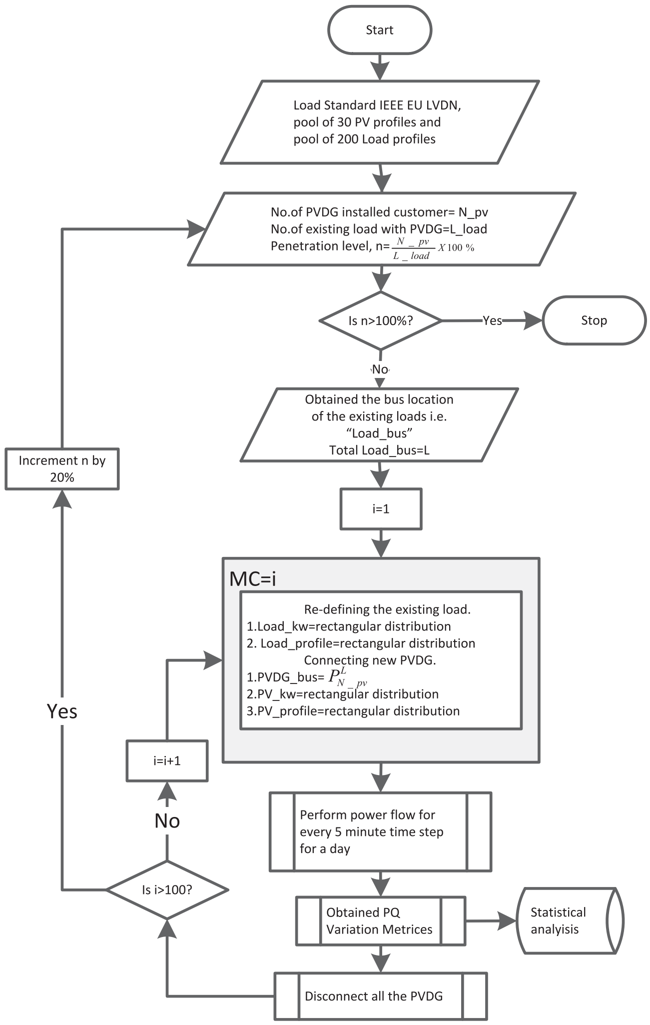

Fig. 4. Monte Carlo simulation to assess PQ variation metrics.

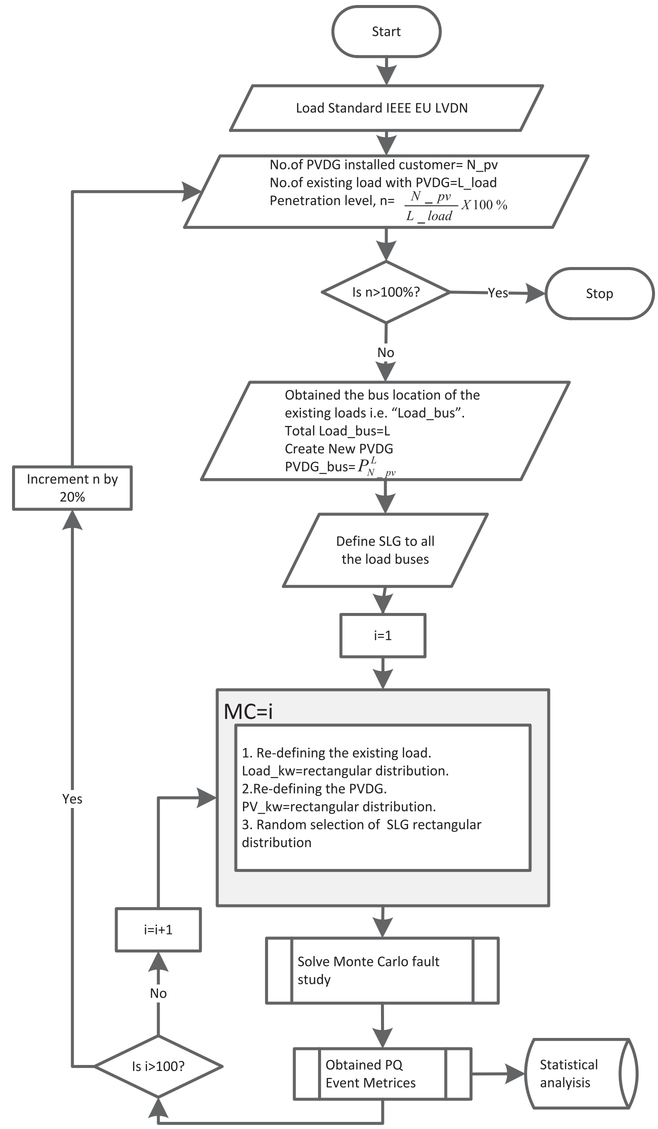

Fig. 5. Monte Carlo simulation to assess PQ event metrics.

type of sampling is designated by '$P^L_{N\_pv}$', and is given by

$$P^L_{N\_pv} = L * (L-1) * \dots * (L - N_{pv} + 1). \qquad (2)$$

The peak PVDG generation ('PV_kW') values randomly vary from 1 to 5 kW and have a rectangular distribution given by (1). Similarly, the corresponding PVDG generation profile is randomly selected from the pool of 30 PV profiles and has a rectangular distribution. A phasor mode power flow is solved in OpenDSS for every 5 minutes through the MATLAB COM interface. Finally, the PQ variation metrics are obtained from the power flow for further statistical analyses. Before proceeding to the next Monte-Carlo simulation, i.e., when $MC = \mathrm{i}+1$, all the installed PVDGs are disconnected and repeats the same process of re-defining and connecting new PVDG in the LVDN. The EN 50160 [8] is adopted to measure the voltage magnitude variation i.e., the voltage magnitude should be within $\pm 10\%$ of the nominal voltage for 95% of a defined period (typically one week) and voltage unbalance i.e., the unbalance should be less than 2% for 95% of a defined period (typically one week).

Fig. 5 represents the Monte Carlo simulation to assess PQ event metrics. A penetration level, *n*, is defined at the beginning of the Monte-Carlo simulation. The penetration level is incremented by 20% up to 100% for every 100 different stochastic scenarios. The location of each load bus is obtained to connect new PVDG randomly in the existing load buses. As discussed earlier, for each penetration level, '*n*', the new PVDG connection to the existing load bus is performed by '*N_pv*' permutation of '*L*' through an ordered sampling without replacement. A list of SLG faults is defined for all the load buses which will later select one randomly at a time for each Monte-Carlo fault study. Voltage drop and recovery are associated with applying and clearing the fault but observing the voltage sag depends on the method of monitoring the sag [19]. From the network description, there are 55 loads in the LVDN. Therefore, there will be 55 SLG faults in which phases A, B and C represent 38.2%, 34.5% and 27.3% of the total SLG faults respectively.

Herein, both PVDG and load demand are characterized by their peak value in order to assess the voltage sag at the system and site (where loads are connected) due to SLG faults.

Each stochastic process, MC, is characterised by re-defining the peak values of the existing loads and PVDGs for each penetration level followed by performing a random SLG fault. In total, there are 500 different stochastic processes. The peak values of each load randomly vary between 1 to 10 kW and have a rectangular distribution. Similarly, for each penetration level, the peak value of each PVDG is also randomly varied between 1 to 5 kW and has also rectangular distribution. The random selection of each SLG fault from the 55 SLG faults is again represented by a rectangular distribution. A Monte-Carlo fault study is performed in OpenDSS [24] and finally, the PQ event metrics are obtained for further statistical analyses. The fault study mode in OpenDSS selects a random fault object from the list of faults and disables the current fault object before the next Monte-Carlo fault study proceeds. Only the peak magnitude of the voltage sags for a recorded duration (i.e., sampled either for one cycle or for half cycle) due to the SLG fault will be monitored in this fault study analysis. The remaining voltage will adopt to quantify the voltage sag during SLG fault events [19]. So, the term '*deep sag*' and '*shallow sag*' will be used here. A deep sag is a sag with a low magnitude of remaining voltage whereas the shallow sag is a sag with a large magnitude of remaining voltage. Voltage sag duration, phase angle jumps during the unsymmetrical faults and point-on-wave, waveform distortion, or the transients at the start and end of the events are not considered for this study. It is further considered that, due to the assumption of monitoring the voltage sag as a peak magnitude, an overshoot immediately after the sag will be observed.

B. Worst Case Study

Consideration of worst case study will enable in comparing the results obtained from the probabilistic study in further assessing the PQ impact metrics due to increased PVDG integration. For the PQ variation metrics, two worst case scenarios can be considered, namely, '*Worst case 1*' i.e., 100% penetration level of PVDG together with maximum recorded PV generation with minimum recorded load profiles or zero load demand, and '*Worst case 2*' i.e., 0% penetration level of PVDG together with maximum recorded load demand profiles. For the *Worst case 1*, all the 55 customers have PVDG installed in their premises with peak generation of 5 kW at unity power factor (upf) and follow the maximum recorded PV generation profile from the pool of 30 sunny days. Furthermore, there is no consideration of load demand in this case. In the *Worst case 2* all the 55 customers have peak load demand of 10 kW with no PVDG installed and follows the maximum recorded load demand profile from the pool of 200 load profiles. The maximum recorded PV generation and load demand profiles from their respective pools are shown in Fig. 6.

Similarly, for PQ events two worst case scenarios can be considered, namely, '*Worst case 3*' i.e., 100% penetration level of PVDG with peak generation of 5 kW at upf. In this case, there is no consideration of load demand. And '*Worst case 4*' i.e., 0% penetration level of PVDG together with peak load demand of 10 kW for all the 55 customers.

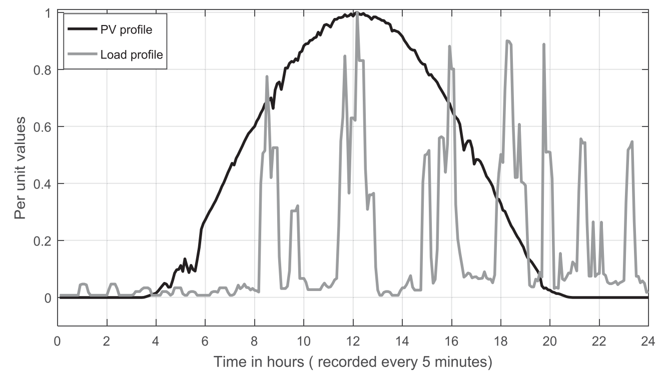

Fig. 6. Maximum recorded PV generation and load demand profiles.

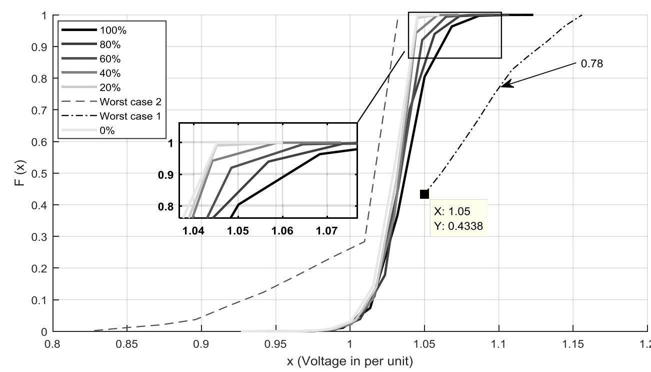

Fig. 7. CDF of site indices for overvoltage metric.

V. Probabilistic Analysis

A. PQ Variations Metrics and Indices

From the Monte Carlo simulation, cumulative distribution functions (CDFs) can be computed for each case study and for each PQ variation metrics and indices. For overvoltage metrics, voltage in per unit represents the random variable x and F(x) represents the CDF of x. In total, there are 8 CDFs for each penetration level. The corresponding CDF enables to measure the probability of occurring overvoltage at the site for each case study. From Fig. 7, the probability of occurring overvoltage i.e., 1.1 p.u at the site is 0.78 approximately for '*Worst case 1*'. Further, it can be seen that the CDFs of all the penetration levels stay within the two worst case scenarios. Again, from Fig. 7 the CDFs of case studies, namely 60%, 80% and 100% penetration levels together with '*Worst case 1*' show that there is a probability of occurrence of overvoltage by a certain percentage of the customers. This is explained in Fig. 8.

Referring to Fig. 8, the percentage of customers violating 1.1 p.u represent the random variable xs and F(xs) represents the complementary CDF (CCDF) evaluated at xs in four case studies, namely 60%, 80% and 100% penetration levels together with '*Worst case 1*'. The CCDF allows to represent how frequent a random variable exceeds a particular limit. From Fig. 8, the probability of 20% of customers violating 1.1 is 0.5 in the case of 100% penetration level, 0.35 in the case of 80% penetration level and 1 in the case of '*Worst case 1*'. Again, the probability of maximum percentage, i.e., 85% (approximately)

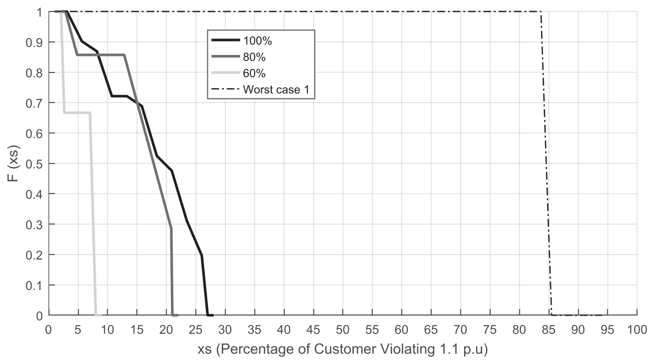

Fig. 8. CCDF of % of customer violating overvoltage.

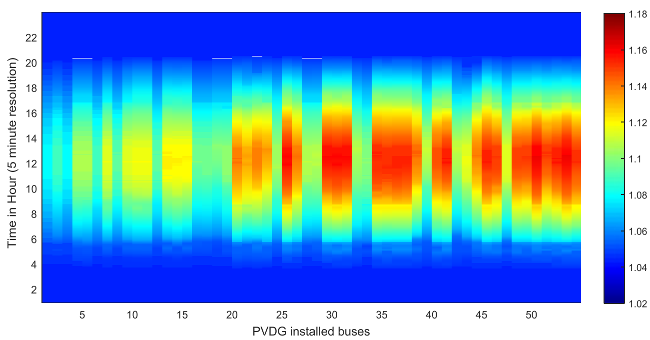

Fig. 9. Voltage checkerboard plot of all 55 customers in p.u for *'worst case 1'* study.

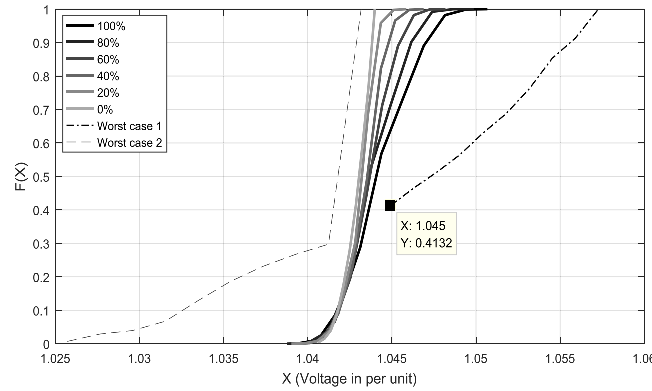

Fig. 10. CDF of system indices for overvoltage metric.

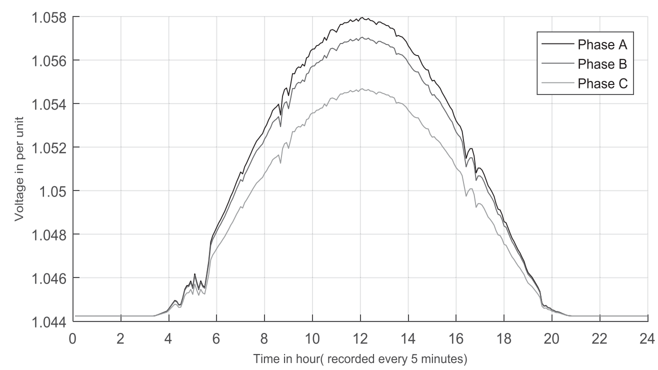

Fig. 11. Three phase voltages at substation transformer.

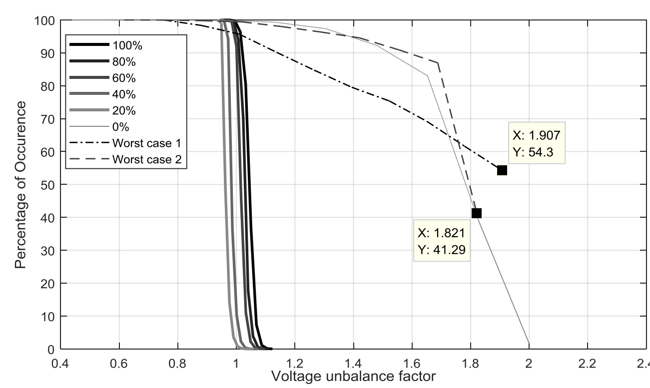

Fig. 12. Percentage of site voltage unbalance factor.

of the customers violating 1.1 p.u is 0.8 in the case of '*Worst case 1*'. Whereas, the probability of maximum percentage, i.e., 25% (approximately) of the customers violating 1.1 p.u is 0.2 in the case of 100% penetration level. But less than 5% of customers are likely to experience overvoltage in all the four cases. Thus, these CCDF trails show that as the penetration level increases, there is a higher probability of percentage of customers observing overvoltage.

It can be seen in Fig. 7 that, the probability of occurrence of minimum voltage, i.e., 1.05 p.u is about 0.43 for '*Worst case 1*'. This can be further seen in Fig. 9 that most of the customers have a minimum voltage in between 1.04 p.u to1.06 p.u. Fig. 9 represents the checkboard plot for the voltages observed in all 55 nodes. This particular plot is made for *'Worst case 1'*. It can be observed here that under *'Worst case 1'*, voltage profile starts to increase down the feeder. From midday till afternoon maximum voltage rise can be observed from node 25 onwards.

Similarly, in the case of overvoltage system indices, voltage in per unit represents the random variable X and $\mathrm{F}(X)$ represents the CDF of X. In total, there are 8 CDFs for each penetration level. The corresponding CDF enables to measure the probability of occurrence of overvoltage at the site for each case study. From Fig. 10, the probability of occurrence of overvoltage (i.e., 1.1 p.u) at the system is 0 for all the 8 cases. But the probability of occurrence of minimum voltage of 1.045 p.u is 0.4 in the case of '*Worst case 1*'. This can be further seen in Fig. 11 that the minimum voltage for all the three phase voltages at substation transformer is about 1.04 p.u in the case of '*Worst case 1*'.

For each index, the unbalance factor is computed and quantified against the standard i.e., the voltage unbalance factor should be less than 2% for 95% of a defined period. The unbalance site indices are computed at the three-phase node where the customers connect their single-phase service cable. Therefore, there are 55 three phase nodes to consider for site voltage unbalance. To quantify the percentage of occurrence of voltage unbalance that exceeds a defined threshold limit, a cumulative plot of voltage unbalance factor versus percentage of occurrence (i.e., duration) are shown in Figs. 12 and 13. These graphs are essentially a CCDF. Fig. 12 shows the site voltage unbalance factor for 8 different cases. It can be seen here that the percentage of occurring the voltage unbalance factor of almost 1.8 is 60% in the three cases, namely, 0% penetration level, '*Worst*

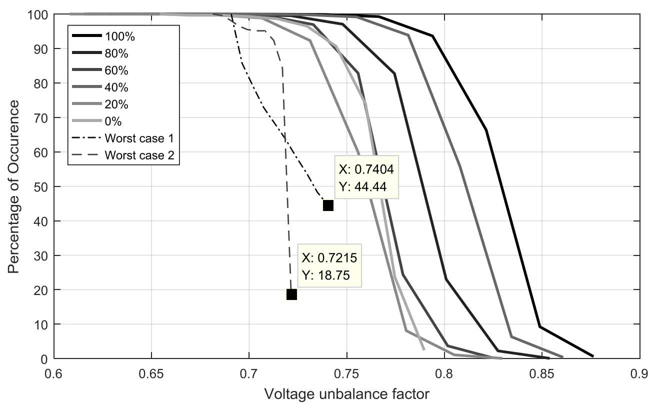

Fig. 13. Percentage of site voltage unbalance factor.

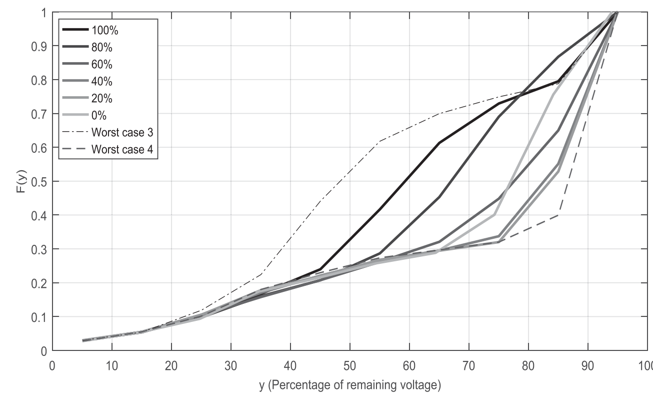

Fig. 14. CDF of site indices for voltage sag.

case 1' and '*Worst case 2*'. This increase in voltage unbalance at 0% penetration is a normal due to unbalance loading in the LVDN. However, '*Worst case 1*' and '*Worst case 2*' are the extreme conditions and stays within the limit. The percentage of occurring maximum voltage unbalance factor of 1.907 is 54.3% in the case of '*Worst case 1*'. And, the percentage of occurring maximum voltage unbalance factor of 1.821 is 41.29% in the case of '*Worst case 2*'. The unbalance factor primarily depends on the loading in each phase. It can be recalled that out of the 55 customers, phases A, B and C accommodate 38.2%, 34.5% and 27.3% of the loads respectively, showing a certain level of balance loading and is shown in Fig. 12 as 0% penetration.

A further observation from Fig. 12 shows that the integration of PVDG reduces the voltage unbalance factor. This is primarily due to the phase cancellation between the phases. But as the PVDG penetration increases from 20% to 100%, the voltage unbalance factor starts to increase by a small factor. The percentage of occurring maximum voltage unbalance factor of about 1 to 1.2 is 100% of all the 8 cases. This means that most of the time the voltage unbalance factor at each three phase nodes will be within 1–1.2 meaning it will stay within the limit. Overall, it can be concluded here that, PVDG integration alleviates voltage unbalance in the LVDN.

The system index voltage unbalance factor is shown in Fig. 13. The unbalance factor is within the limit for all the 8 cases. Similarly, here, as the penetration of PVDG increases from 0% to 100%, the voltage unbalance increases by a small factor. The percentage of occurring minimum voltage unbalance factor of 0.74 is 44.44% in the case of '*Worst case 1*'. And, the percentage of occurring minimum voltage unbalance factor of 0.72 is 18.75% in the case of '*Worst case 2*'. Further, the percentage of occurring maximum voltage unbalance factor of about 0.7 to 0.75 is 100% of all the 8 cases. This means that most of the time the voltage unbalance factor at the transformer will be within 0.7 to 0.75. Overall, the voltage unbalance at the transformer will be within the limit in all the 8 cases.

B. PQ Events Metrics and Indices

From the Monte Carlo simulation, cumulative distribution functions (CDFs) can be computed for each case study and for each PQ event metrics and indices. As discussed earlier, the observed voltage sags will be represented as a percentage of the remaining voltage due to Monte-Carlo fault study. For voltage sags site index, the remaining voltage represents the random variable y and F (y) represents the CDF of y. The corresponding CDF enables to measure the probability of observing certain percentage of the remaining voltage for a particular case study. Higher percentage of remaining voltage means it is a shallow sag i.e., the low fault current. Whereas, lower percentage of remaining voltage means it is a deep sag i.e., high fault current. From Fig. 14, until 40% of remaining voltage, all the case studies have the same CDF except the '*Worst case 3'*. Starting from 45% of remaining voltage, the F(y) gradually increases as the penetration of PVDG increases with '*Worst case 3*' showing the highest probability of occurring the remaining voltage ranging between 30% to 80%. That means '*Worst case 3*' has the highest probability of seeing lower percentage of remaining voltage i.e., deep sag (high fault current). When F(y) $= 0.4$, '*Worst case 4*' shows high percentage of remaining voltage around 85% which mean a shallow sag. Again, the '*Worst case 4*' shows the highest probability of occurrence of high percentage of remaining voltage i.e., shallow sag. From this analysis, it can be concluded that the presence of PVDG together with load demand contributes to the fault current at the load buses leading to voltage drop. As the penetration of PVDG increases, higher probability of occurrence of lower percentage of remaining voltage or deep sag is observed. But depending on the type of generator model, voltage sags might be different. Here during Monte Carlo fault study, the PV generator is switched into a dynamic mode by converting it into the Thevenin's equivalent and finally to Norton's equivalent [25].

Similarly, for voltage sags system index, the remaining voltage represents the random variable z and F (z) represents the CDF of z. The corresponding CDF enables to measure the probability of observing certain percentage of the remaining voltage for a particular case study. From Fig. 15, the CDFs of 40%, 60%, 80% and 100% penetration levels together with '*Worst case 3*' follow the same trail or relatively similar slope. This trail signifies that all the CDFs correspond to shallow sag which means low fault current at the point where these voltage sags are measured i.e., at the secondary side of Dy transformer. This is true because the integration of DG along the feeder will reduce

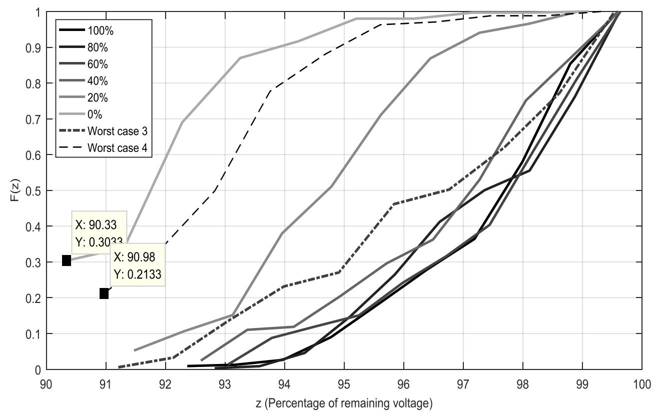

Fig. 15. CDF of system indices for voltage sag.

TABLE I
CONFIDENCE INTERVALS OF TWO SAMPLES SIZE NAMELY 100 AND 1000 FOR 5 CASES WITH 95% CONFIDENCE LEVEL

Penetration in %	Sample size =100		Sample size =1000		Absolute Error	
	Average Time = 180 seconds		Average Time = 1800 seconds			
	Confidence interval		Confidence interval			
	low	high	low	high	low	high
0	1.0316	1.0358	1.0329	1.0343	0.0013	0.0016
20	1.0332	1.0373	1.0345	1.0359	0.0014	0.0014
40	1.0353	1.0397	1.0366	1.0381	0.0013	0.0017
60	1.0377	1.0427	1.0392	1.0409	0.0015	0.0019
80	1.0396	1.0453	1.0417	1.0435	0.0021	0.0018
100	1.0426	1.0491	1.0447	1.0468	0.0021	0.0024

or lower the fault current contribution at the beginning of the feeder i.e., substation Dy transformer for fault beyond the DG location [2]. This means that if the fault occurs beyond the DG location down the feeder, the fault current seen at the upstream feeder will be lower. Due to the random integration of PVDG and random occurrence of SLG fault, the fault current seen at the upstream feeder or secondary side of a substation transformer is low. With the increased random integration of PVDG, the fault current seen at the upstream feeder can be even lower and this is one of the cases observed in Fig. 15.

For the case studies, 0% of penetration level, 20% of penetration level and '*Worst case 4*' are concerned, the $\mathrm{F}(z)$ increases as the percentage of remaining voltage increase. This is because the fault current seen by the upstream feeder is normal since there is less or no PVDG contribution towards the fault current. With 20% of penetration level, the $\mathrm{F}(z)$ is lower as compared with 0% of penetration and '*Worst case 4*'.

VI. CONCLUSION

This study proposes the consideration of two PQ impact metrics and indices as a means to measure the likely impacts of increased PVDG integration under spatial and temporal behavior of both PV generation and load demand. For each PQ impact metrics, 8 different cases were considered, namely, PVDG penetration levels at 0%, 20%, 40%, 60%, 80%, and 100%, a maximum generation with zero demand and maximum demand with zero generation. A Monte Carlo simulation is chosen as a tool for such stochastic process. From the results, site overvoltage shows a likely impact that will persist as the PVDG integration increases. The probability of the maximum percentage of customer violating 1.1 is higher in the case of '*Worst case 1*' (i.e., maximum generation with zero demand) than in the case of 100% penetration level. At the 100% penetration level, the maximum percentage of customer violating 1.1 p.u is 25% and the probability of occurrence is 0.2. Further about 20% of customers will violate 1.1 p.u at the 100% penetration level and the probability of occurrence is 0.5. However, less than 5% of the customers will observe overvoltage in four case studies, namely 60%, 80% and 100% penetration levels together with '*Worst case 1*', whereas, the system overvoltage stays within the limit.

In terms of site voltage unbalance, integration of PVDG reduces the voltage unbalance as compared with no PVDG integration or low penetration level. This is mainly due to the phase cancellation. This increase in voltage unbalance at 0% penetration is a normal due to unbalance loading in the LVDN. Overall, the site and system voltage unbalance stay within the limit for all the 8 different cases. In the case of site voltage sag, as the penetration of PVDG increases, higher probability of occurrence of lower percentage of remaining voltage or deep sag is observed. However, the system voltage sags are quite different from that of the site. The probability of occurrence of lower remaining voltage or deep sag reduces as the penetration of PVDG increases. This is because PVDG integration reduces the fault current seen at the upstream feeder.

In conclusion, the increased integration of PVDG poses some threat to the performance of the power system. From the probabilistic study, overvoltage poses the highest threat, whereas voltage unbalance stays within the limit. Further, increased integration of PVDG will contribute towards fault current leading to deep sag at the site. This probabilistic approach can be used as a tool to identify the likely impacts due to PVDG integration at the existing load buses. This will enable in quantifying the likely impacts against the worst-case scenarios.

APPENDIX

The proposed Monte Carlo simulation considerd 100 samples or simulations to estimate the parameter of interest. The choice of this samples was determined to compromise between computational time and the accuracy of the estimation. One specific site PQ variation impact metric i.e., overvoltage was chosen to determine the accuracy of the estimation. 1000 samples size have chosen to perform Monte Carlo simulation to determine the site overvoltage for 5 cases i.e., 0%, 20%, 40%, 60, 80% and 100%. A confidence level of 95% is chosen which contains a true parameter i.e., mean. This true parameter signifies that the mean of the true population of samples size '*n*' is 1. Table I shows the confidence intervals of two samples size namely 100 and 1000 for 5 cases with 95% confidence level.

The absolute error from Table I shows that sampling size of 100 is a good estimation for 95% confidence level for the corresponding confidence intervals at a tenth of the computation time as compared with sampling size of 1000.

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Shivananda Pukhrem (S'18) received the B.E (Hons.) degree in electrical and electronics engineering from Visvesvaraya Technological University, Belgaum, India, in 2011, and the M.Sc. degree in renewable energy system from Wroclaw University of Technology, Wroclaw, Poland, in 2013. He is currently working toward the Ph.D. degree in electrical engineering at the School of Electrical and Electronic Engineering, Dublin Institute of Technology, Dublin, Ireland.

From 2014 to 2016, he was involved in EU FP7 project entitled "PV CROPS." His Ph.D. research endeavor includes an active planning and operation for improving the high share of nonfirm DG integration in public distribution network. He is a Student Member of the CIGRE.

Malabika Basu (S'99–M'03) received the B.E. and M.E. degrees in electrical engineering from Bengal Engineering College, Shibpur, Kolkata, India, in 1995 and 1997, respectively, and the Ph.D. degree in electrical engineering from Indian Institute of Technology, Kanpur, Kanpur, India, in 2003.

From 2001 to 2003, she was a Lecturer with Jadavpur University, Kolkata, India. From 2003 to 2006, she was a Arnold F. Graves Postdoctoral Fellow with Dublin Institute of Technology, Dublin, Ireland, where she has been a Lecturer from 2006, and a Senior Lecturer since 2016. She has authored or coauthored more than 90 technical publications in various international journals and conference proceedings. Her research interests include grid integration of renewable energy sources, power quality conditioners and power quality control and analysis, photovoltaics and wind energy conversion, and smart grid and microgrids.

Michael F. Conlon (M'88) received the Dip.E.E., B.Sc. degree from Dublin Institute of Technology, Dublin, Ireland, in 1982, and the M.Eng.Sc. degree and the Ph.D. degree from the University College, Galway, Ireland, in 1984 and 1987, respectively, all in electrical engineering.

He was with Monash University, Melbourne, VIC, Australia, and VENCorp, Melbourne. He is currently the Head of the School of Electrical and Electronic Engineering with the Dublin Institute of Technology, Dublin, where he is also the Director of the Electrical Power Research Centre. His current research interests include power systems analysis and control applications, power systems economics, integration of wind energy in power networks, analysis of distribution networks, and quality of supply and reliability assessment.