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Probabilistic load flow for distribution systems with uncertain PV generation

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HIGHLIGHTS

- Latin Hypercube Sampling with Cholesky Decomposition (LHS-CD) is used to maintain voltage profile in distribution network.
- LHS-CD is efficient for complex computations.
- LHS technique is verified for Australian distribution network.
- LHS-CD provides accurate results with reasonably low computation time compare to Monte Carlo technique.

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ABSTRACT

Large integration of solar Photo Voltaic (PV) in distribution network has resulted in over-voltage problems. Several control techniques are developed to address over-voltage problem using Deterministic Load Flow (DLF). However, intermittent characteristics of PV generation require Probabilistic Load Flow (PLF) to introduce variability in analysis that is ignored in DLF. The traditional PLF techniques are not suitable for distribution systems and suffer from several drawbacks such as computational burden (Monte Carlo, Conventional convolution), sensitive accuracy with the complexity of system (point estimation method), requirement of necessary linearization (multi-linear simulation) and convergence problem (Gram–Charlier expansion, Cornish Fisher expansion). In this research, Latin Hypercube Sampling with Cholesky Decomposition (LHS-CD) is used to quantify the over-voltage issues with and without the voltage control algorithm in the distribution network with active generation. LHS technique is verified with a test network and real system from an Australian distribution network service provider. Accuracy and computational burden of simulated results are also compared with Monte Carlo simulations.

1. Introduction

Distribution system is basically designed as a passive network for energy delivery to end users in traditional electricity network. Increasing contribution in electricity generation from PV systems introduce several technical challenges in distribution network. Over-voltage problem is the most alarming among them [1]. Several techniques have already been proposed by researchers to address the over-voltage problem using deterministic load flow studies [2–4]. However, intermittent nature of PV generation introduces substantial amount of uncertainty demanding improved probabilistic power flow studies for improved holistic analysis.

Probabilistic method characterizes the variability in system input (such as generation and load) by suitable probability distribution and thus incorporates the variability or uncertainty into the analysis. The application of probabilistic analysis to the power system load flow was first introduced by Borkowska in 1974 [5]. Monte Carlo (MC) is the traditional approach used for simulating Probabilistic Load Flow (PLF) and performs deterministic load flow repeatedly for significant number of times to represent the entire distribution of system inputs [6,7]. Huge computational burden makes MC simulation unattractive. Alternatively, few of the analytical PLF techniques such as Cumulant method [8–11], point estimation method (PEM) [12,13], multi-linear simulation method (MLSM) [14,15] and Cornish–Fisher expansion [16,17] have been proposed. The Cumulants Combined with Gram–Charlier expansion (CCGC) uses Cumulants and Gram–Charlier series to express the PDF and cumulative distribution function (CDF) to represent

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each input random variable to consider their variability. The power flow calculations are performed using consecutive summation of weighted derivatives of PDF/CDF up to a chosen order of expansion to ensure the convergence. For a non-Gaussian PDF, CCGC faces serious convergence problem. Moreover, the increase in expansion order cannot assure the convergence or any improvement in results [10]. Whereas, PEM calculates the statistical moments of the power flow by running $2m$ number of calculations for m number of input random variables. All the $2m$ calculations are weighted following certain procedures. Though this method comes with reasonable computation time, its accuracy is sensitive to the complexity of the system [13]. MLSM requires linearization of power flow equations around several operating points which is not suitable for systems with non-linear controls [15]. Cornish–Fisher (CF) expansion, although gives better results in the similar situation without any computation burden, its accuracy degrades significantly for non-linear systems.

Recently, uncertainty analysis incorporating PV generation using multi-linear MC [7], CCGC [11], CF [16] and PEM [18] have been proposed. These research works propose PLF analysis incorporating PVs, but do not explore the prevalent over-voltage problems in the current distribution systems. The probabilistic models for PV forecasting [19] and double axis PV tracking [20] are proposed which can be used to represent the PDF of the power produced by PV. Authors in [18] assume PDF to be close to normal whereas [11] assumes it to be Beta. Furthermore, authors in [20] report interesting analysis when the first fourth moments (mean, variance, skewness and kurtosis) of a PDF is investigated in greater details using experimental data for different type of PV installations. The change in the sign of skewness (positive to negative) and kurtosis (low to high) for PDFs in winter and summer further raises a concern on a choice of single PDF for PVs. Similarly, authors in [21] propose PDF models using household power consumption, electric vehicles home-charging and PV generation. It is found that the yearly distribution of the aggregate scenario of multiple uncorrelated households with EV charging and PV generation is not exactly normally distributed. Nevertheless, the seasonal variations of PV generation can be modeled and associated skewness can be reduced via demand-side management and storage. In another work, an interesting approach to measure the probability of over-voltage occurrence in distribution network by estimating the auto consumption potential level and correlation level between prosumers is presented [22], however, no control algorithm is incorporated to address it.

Usually most of the control algorithms developed to address the over-voltage problem in distribution network are non-linear in nature. Any linearization approximation may result in erroneous outcomes. Authors' have developed a coordinated control algorithm to utilize the reactive capability of PV inverter and droop based energy storage in their previous work [3]. The use of such control algorithm makes the system highly non-linear. Moreover, linearization of power flow equations can be performed using the DC load flow in transmission system. A high X/R ratio of transmission line gives the flexibility to neglect the resistance and hence the linearization is adequate. However, such linearization procedures are not applicable to distribution networks. This paper proposes a PLF technique with Latin Hypercube Sampling (LHS) to quantify the over-voltage issues with or without the voltage control algorithm in a residential distribution network even with high penetration of unscheduled PV generation. Rank correlation between the input random variables are also considered in this research using Cholesky Decomposition (CD). The significance of the developed PLF technique can be characterized by its accuracy with largely improved computation time.

This paper is organized as follows: Section 2 gives a brief description of the LHS technique and ranks correlation with Cholesky decomposition. Section 3 introduces the test distribution system under study. It includes PV generation and load demand distribution with associated variation. This section also contains all the simulation results. Section 4 contains the validation of results with real network data.

2. rank-correlated Latin Hypercube Sampling with Cholesky Decomposition

LHS is used in power system analysis that involves the interaction of multiple random variables and as a result, intensive computation is required to obtain the outputs [23,24]. LHS is based on the basic concepts of stratified sampling and permutation. Major steps of LHS for this research are described as follows:

Step 1 – ***Intervals and sampling:*** Considering an output variable, say Y, obtained from k number of input variables, X_k, follows:

$$Y = f(X_1, X_2, \dots, X_k) \tag{1}$$

All the input random variables constitute a distribution vector D which represents their corresponding distribution such as,

$$D = [D_1, D_2, \dots, D_k] \tag{2}$$

Fig. 1 shows the sampling procedure from cumulative distribution of a random variable X_1 (random PV generation values at a given time). The distribution is divided into equal probability intervals along the Y-axis which results in variable distance of realization interval in the X-axis. These intervals are non-overlapping in nature and their number is equal to the sample size. One sample value is taken from each of the intervals as the mid-point along the Y-axis. The sample value may not be the mid-point of corresponding realization interval along the X-axis. The corresponding value from each realization interval is mapped from the mid-point of probability interval (shown in dotted lines from mid-point of probability interval in Fig. 1). In the similar way, sample point (x_s) is taken for all the intervals ($1, 2, \dots, N2$; $N2$ is the LHS sample size). Thus, the sampling vector (S_{X1}) is constructed for the input random variable X_1.

$$S_{X_1} = [X_{s1}, X_{s2}, \dots, X_{si}, \dots, X_{sj}, \dots, X_{sN2}] \tag{3}$$

One significant feature of LHS is its sampling over the entire spectrum of the distribution without discarding any tail-end values. As the tail-end values are less likely to occur, its realization interval distance is much longer compared to that of central values to maintain the equal probability interval. As a result, fewer samples are taken from tail-end value and more samples are taken from highly probably segments. The sampled values thus actually represent the distribution.

Step 2 – ***Construction of Sampling Matrix:*** Repeat Step 1 for all the k input random variables in vector X to form the sampling matrix (S_X) with dimension $N2 \times k$.

$$S_X = [S_{X1}, S_{X2}, \dots, S_{Xk}] \tag{4}$$

where S_{Xk} is the sampling vector for kth input random variable and defined similar to (4).

Step 3 – ***Pairing of sampling values with Ordering Matrix (L):*** In this step LHS pairs the individual sample values obtained from different input variables. Usually the input random variables are correlated for a distribution network. Let us consider, PV generation and load demand at 12 noon are the input random variables for the system. Individual sample points taken by LHS method contain significant correlation between them.