ANALYSIS OF IMPORTANCE SAMPLING AND CONTINGENCY IN ELECTRIC POWER SYSTEM SECURITY

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ABSTRACT

Power system security has become one of the most important issues in power system operation due to intensive use of transmission network and it is strongly tied with contingency analysis. However with the introduction of more variable generation sources such as wind power and due to fast changing loads power system security analysis will also have to incorporate sudden changes in injected powers that are not due to generation outages. The probability of failure induced by changes in grid state is evaluated by the Monte Carlo simulation method. A comparison to crude Monte Carlo (CMC) and Importance sampling (IS) method is performed for standard IEEE-33 bus system. Importance sampling method indicates a major increase in simulation efficiency by reducing number of samples.

Keywords: Contingency, Crude Monte Carlo Method, Importance Sampling, Particle Swarm Optimization, Power System Security.

I INTRODUCTION

Power system stability has been recognized as an important problem for secure system operation since the 1920s [1]. In order to maintain the reliability of an electric power system at an appropriate level and at low cost, it is essential that voltage stability be accurately assessed. There are a number of methods for assessing voltage stability. There is a large conflict of interest between the market perspective, where a large capacity to transfer power through the electric power grid is required, and the security perspective, where secure operation is the main objective. To satisfy both objectives to the largest possible extent, an adequate balance between security and capacity is preferable. This, in turn, calls for an efficient method for evaluating the security of a certain operating state. With the introduction of large amounts of wind power, which is a more variable energy source than conventional hydro-, nuclear-, and heat-power plant generation, more concern has to be put to the stochastic changes in injected power, when evaluating the operation security.

As a stable operating point of the power system drifts, it may eventually change its properties and become unstable; clearly this is a situation the system operator would like to avoid. To use an electric power system in an efficient and reliable way, several issues will have to be considered. One of these issues is voltage stability. It will be of great importance to keep the operating point within the stable domain, or else instability will occur, leading to undesirable events such as system blackout. The main attention has been put to outages in the grid or in the production units. In evaluating the probability of failure induced by changes in grid state, there are two popular methods: the contingency enumeration method and the Monte Carlo simulation method.

The contingency enumeration method enumerates all contingencies that are considered plausible and analyses the severity of each contingency. One example of such a method is the N-1-criterion [9], which states that the system should remain stable after losing any single component. Hence, according to the N-1-criterion, the contingencies that are considered plausible are all the contingencies where one component in the system fails, and all contingencies with more than one failure are considered to have such a small probability of occurring that they can be neglected in a security analysis of the power system. As the size of the system increases, so does the risk of failure of multiple components in the system within a short time-frame. Therefore, methods for identifying high risk N-K contingency situations were suggested in [3].

A contingency not leading to immediate loss of stability may still reduce stability margins so that a plausible change in injected power following a contingency leads to instability before preventive measures have time to take effect. Whether one uses the contingency enumeration method or the Monte Carlo method to generate the state of the grid and the generating units, some concern will, thus, also have to be taken to the change in operating conditions induced by change of loads or change in production in more variable production units like wind- or wave-power plants.

One technique that has been applied successfully in stochastic analysis of dynamic systems of high dimension is the *double and clump* (D&C) [8] method. D&C provides a means to increase the number of samples which are expected to contribute to the estimation of low probability regions. In analogy to the importance sampling technique, these contributing samples are considered as important samples. The increase of the important samples is carried out by the doubling procedure. To keep the sample size constant, from the viewpoint of computational efficiency, the number of less important samples is reduced through the clumping procedure. Unfortunately this method requires heuristic knowledge of which sample values that is important and should be doubled and which that are not so important and can be clumped. Therefore, it is not that suitable in power system security evaluation.

II PROBLEM FORMULATION

In power system operation, there are number of stable operation criteria that have to be fulfilled at all times. These criteria are [7],

2.1 Voltage Stability

There must for each set of injected power p exist a vector such that the power flow equations, f(x, p) =0 are fulfilled. Furthermore, the operating point (x, p) must always be a stable operating point, so that after any small change in operating conditions, the system returns to stable operation.

2.2 Thermal Stability

Due to limitations in the power system equipment, some of the equipment such as power-lines will be disconnected if the current flowing through the equipment becomes too large. Therefore, the electric power transfers in the system cannot be allowed to exceed some set maximal value.

2.3 Voltage Limits

The voltages at certain nodes might have to be kept within a predefined interval.

2.4 Optimal placement of DG in distribution network problem is to minimize the real power losses and improve the voltage profile, which is calculated as follows:

$$F1(X) = PL = \sum_{i=1}^{Nbr} RiIi^2 \qquad (1)$$

Where, R_i and I_i are resistance and actual current of the ith branch, respectively. N_{br} is the number of the branches.

III MONTE CARLO METHOD

Monte Carlo methods provide approximate solutions to a variety of mathematical problems by performing statistical sampling experiments. They can be loosely defined as statistical simulation methods, where statistical simulation is defined in quite general terms to be any method that utilizes sequences of random numbers to perform the simulation. Thus Monte Carlo methods are a collection of different methods that all basically perform the same process. This process involves performing many simulations using random numbers and probability to get an approximation of the answer to the problem. Thus the analysis of the approximation error is a major factor to take into account when evaluating answers from these methods. The attempt to minimize this error is the reason there are so many different Monte Carlo methods. The various methods can have different levels of accuracy for their answers, although often this can depend on certain circumstances of the question and so some method's level of accuracy varies depending on the problem. Different types of Monte Carlo methods are

- Crude Monte Carlo
- Acceptance-rejection Monte Carlo
- Stratified sampling
- Importance sampling

This is illustrated well in the [12]. In this paper CMC and IS method is implemented with the numerical example of IEEE-33 bus system, and compare their answers in terms of number of sample and the accuracy of their approximations. Probability distribution function (pdf) for 33 bus system is shown in figure 1.

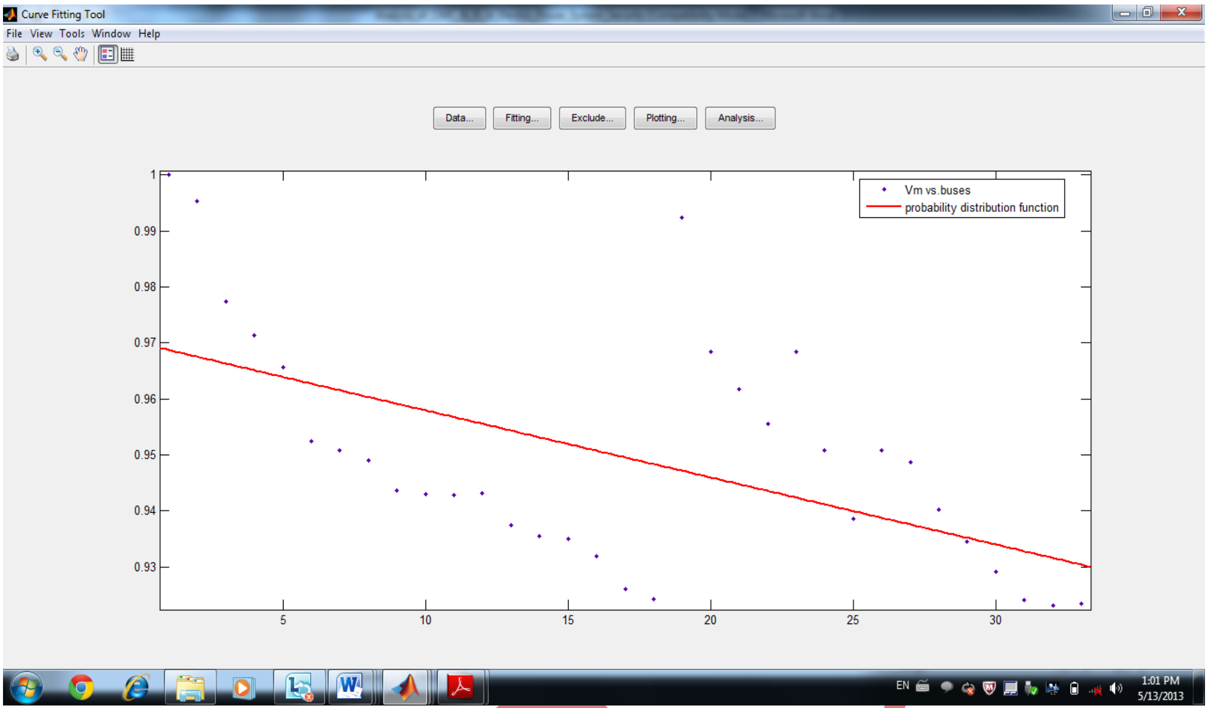

Fig 1: Graph shows the probability distribution function for 33 bus system in importance sampling method.

IV PRACTICAL SWARM OPTIMIZATION

The particle swarm optimizer (PSO) algorithm is first presented by Dr. Kennedy and Dr. Eberhart, and it is a random evolution method based on intelligent search of the group birds [11]. It has quick convergence speed and optimal searching ability for solving large-scale optimization problems. The method uses a number of different "particles" that move around in the feasible domain, each particle has a mass and a speed. Velocity and position of each particle is given in below equations:

$$V_{ik+1} = WV_{ik} + C_1 \times rand_1 \times P_{besti} - S_{ik} + C_2 \times rand_2 \times G_{besti} - S_{ik} \quad (2)$$

$$S_{ik+1} = S_{ik} + V_{ik+1} \times \Delta t \quad (3)$$

Where

V_{ik} = Velocity of agent i at k^{th} iteration

V_{ik+1} = Velocity of agent i at $(k + 1)^{th}$ iteration

W = the inertia weight

$C_1 = C_2$ = Weighting factor (0 to 4)

S_{ik} = Current position of agent at k^{th} Iteration

S_{ik+1} = Current position of agent at $(k + 1)^{th}$ Iteration

$iter_{max}$ = Maximum iteration number

$rand_1$, $rand_2$ = the random numbers selected between 0 and 1.

$P_{besti} = P_{best}$ of agent i

$G_{besti} = G_{best}$ of the group

Δt is change in time step from two successive iterations.

The PSO-based approach for solving optimal placement of distributed generation (OPDG) problem to minimize the loss takes the following steps; flow chart is shown in figure 2

Step 1: Input line and bus data, and bus voltage limits.

Step 2: Calculate the loss using Newton's Raphson method.

Step 3: Randomly generates an initial population (array) of particles with random positions and velocities on dimensions in the solution space. Set the iteration counter k=0.

Step 4: For each particle if the bus voltage is within the limits, calculate the total loss. Otherwise, that particle is infeasible.

Step 5: For each particle, compare its objective value with the individual best. If the objective value is lower than P_{best}, set this value as the current P_{best}, and record the corresponding particle position.

Step 6: Choose the particle associated with the minimum individual best P_{best} of all particles, and set the value of this P_{best} as the current overall best G_{best}.

Step 7: Update the velocity and position of particle.

Step 8: If the iteration number reaches the maximum limit, go to Step 9. Otherwise, set iteration index k=k+1, and go back to Step 4.

Step 9: Print out the optimal solution to the target problem. The best position includes the optimal locations and size of, DG, and the corresponding fitness value representing the minimum total real power loss.

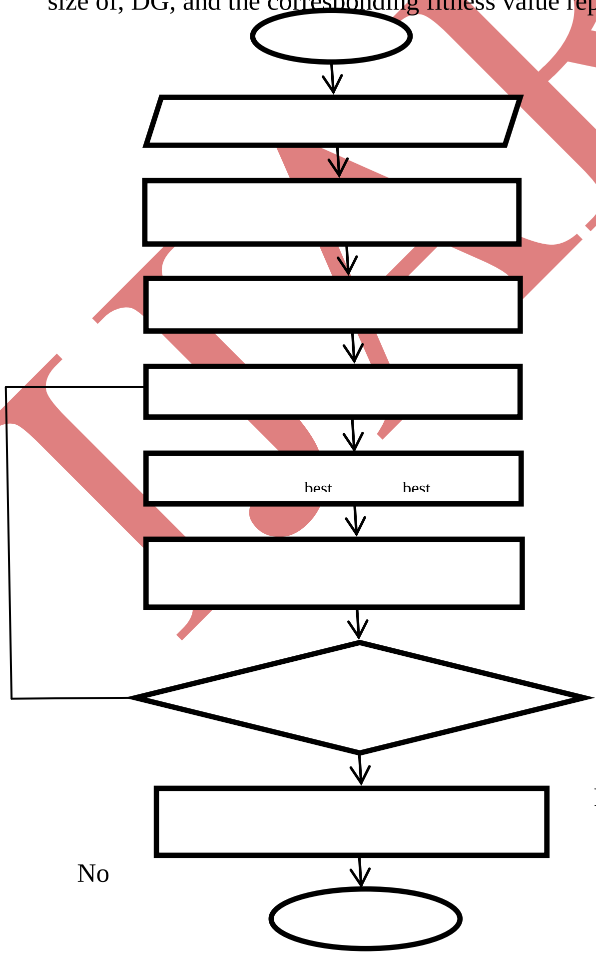

Figure 2: Flow chart of PSO

V CONTINGENCY SELECTION

Contingency analysis process involves the prediction of the effect of individual contingency cases, the process becomes very tedious and time consuming when the power system network is large. In order to alleviate the above problem contingency screening or contingency selection process is used. The process of identifying the contingencies that actually leads to the violation of the operational limits is known as contingency selection. The contingencies are selected by calculating a kind of severity indices known as Performance Indices (PI). These indices are calculated using the conventional power flow algorithms for individual contingencies in an off line mode. Based on the values obtained the contingencies are ranked in a manner where the highest value of PI is ranked first. The analysis is then done starting from the contingency that is ranked one and is continued till no severe contingencies are found.

There are two kind of performance index which are of great use, these are active power performance index (PI_p) and reactive power performance index (PI_V). PI_p reflects the violation of line active power flow and is given below:

$$PIp = \sum_{i=1}^{L} (Pi/Pimax)^{2n} \qquad (4)$$

Where

P_i = Active Power flow in line i

P_{imax} = Maximum active power flow in line i

n is the specified exponent

L is the total number of transmission lines in the system.

If n is a large number, the PI will be a small number if all flows are within limit, and it will be large if one or more lines are overloaded. Here the value of n has been kept unity. The value of maximum power flow in each line is calculated using the formula:

$$P_{imax} = (V_i * V_j)/X \qquad (5)$$

Where,

V_i= Voltage at bus i obtained from NR solution

V_j= Voltage at bus j obtained from NR solution

X = Reactance of the line connecting bus “I” and bus “j”

Another performance index parameter which is used is reactive power performance index corresponding to bus voltage magnitude violations. It mathematically given in equation 6:

$$PI_V = \sum_{i=1}^{Npq} \left[\frac{2(Vi - Vinom)}{Vimax - Vimin}\right]^2 \qquad (6)$$

Where

V_i= Voltage of bus i

V_{imax} and V_{imin} are maximum and minimum voltage limits V_{inom} is average of V_{imax} and V_{imin}

N_{pq} is total number of load buses in the system flow chart for contingency selection technique is shown in Fig. 3

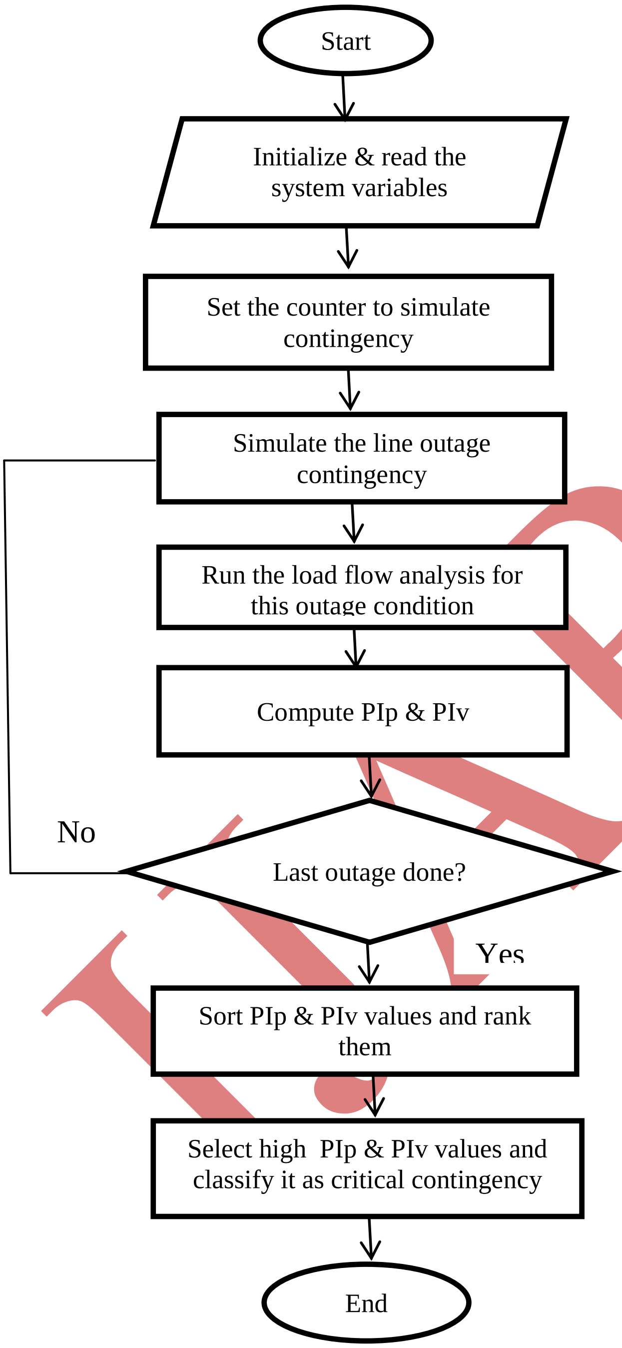

Figure3: Flow chart of contingency selection

VI NUMERICAL EXAMPLE

In this section, a numerical example will be presented. The aim of the numerical example is to show the efficiency of the importance sampling technique proposed in this paper. The calculations will be performed on the IEEE 33-bus system depicted in fig-4.

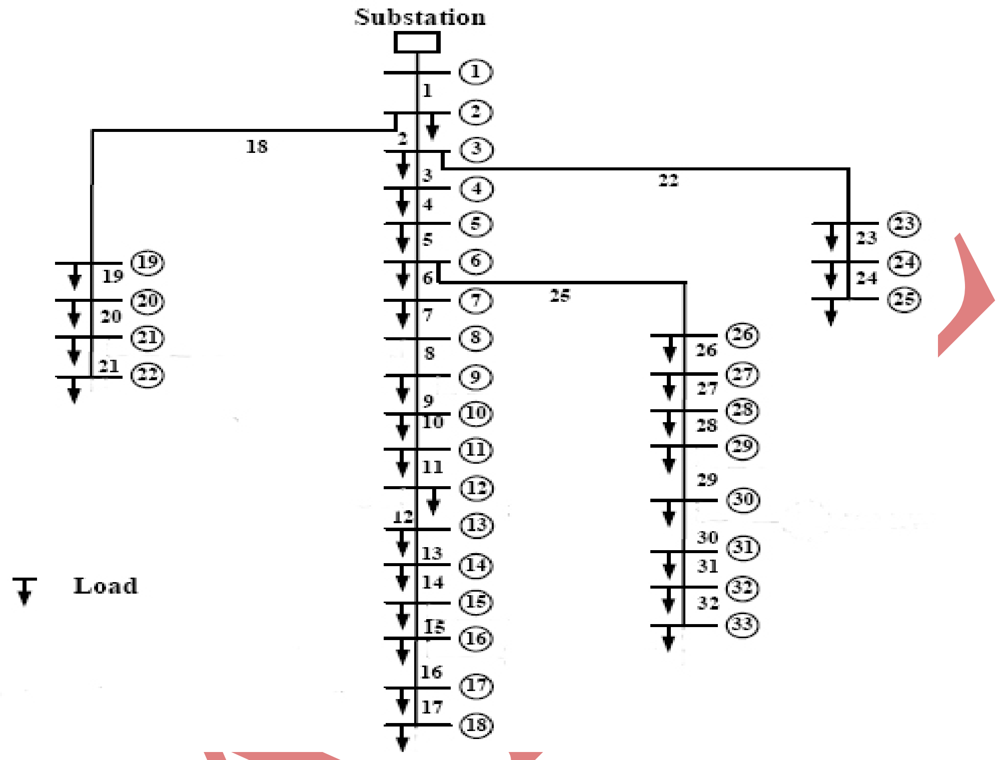

Figure 4: IEEE 33-bus system.

VII SIMULATION RESULT

The test system for the case study is radial distribution system with IEEE 33 buses as shown in Figure 4 [13].The total loads for this test system are 3.72 MW and 2.3 MVR. The original total real power loss and reactive power loss in the system are 208KW and 148 KVAR respectively. The substation voltage is 12.66 KV and the base of power is 10.0MVA.The current carrying capacity of branch No.1-9 is 400 A, and the other remaining branches including the tie lines are 200A. The minimum and maximum voltages are set at 0.95 and 1.05 p.u. respectively. The load data are given in Table A1 and branch data is in Table A2. PSO parameters are, population size is 10, maximum iteration is 50, inertia weight is 0.9, weighting factor C_1=C_2=1.2.

The improvement in the voltage profile after optimally placing the DGs is shown in Figure 5. Without DG, the bus no. 18 has the lowest voltage of 0.923p.u. and the bus voltage has improved to 0.975p.u. after installing DG. For the 33 bus system, as shown in table 1, the PSO can obtain the loss reduction. That is DG can reduce the total real power loss by 52.64%.

The samples obtained in crude Monte Carlo and importance sampling method for IEEE 33 bus system is shown in figure 6 and 7 which indicates number of samples to be selected for individual bus. Table 2 indicates the number of samples obtained in both the method. Lesser the sample lesser the variance thus computational time is reduced and increases the efficiency. Voltage profile of 33bus system before and after implementing crude Monte Carlo (CMC) method and importance sampling method is shown in figure 8 and 9 respectively. This shows less voltage fluctuation in the range 0.95-1.05 p.u.

Contingency analysis is performed for IEEE 33 bus system in which the load buses at 5,11,16,21,25,29 are changed to generator bus and all the line resistance and reactance's are changed to 100Ω. The performance index for both active and reactive power is found, highest value of performance index is ranked first which indicates severity. As per the results 24th bus is the most affected and 16th bus is less affected.

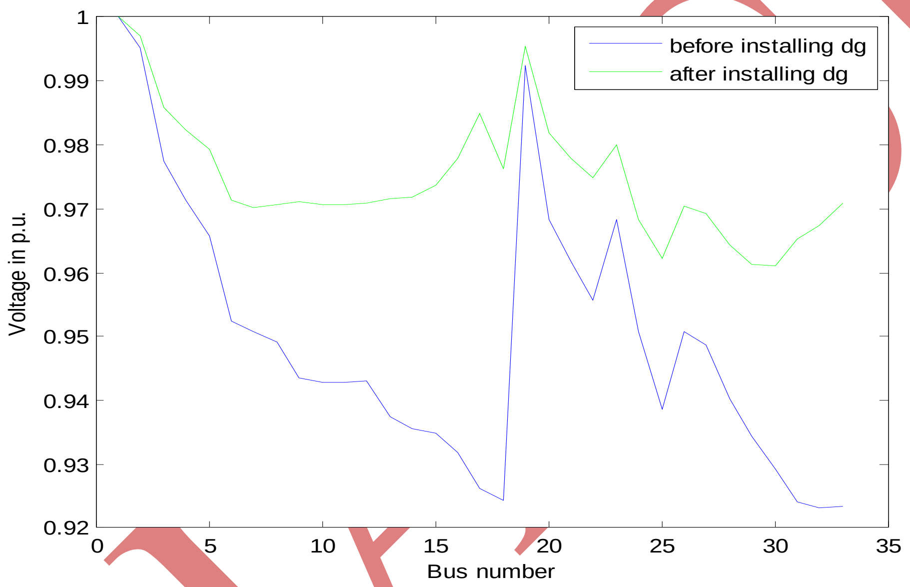

Figure 5: Voltage profile of 33 bus system before and after implementing DG

TABLE: 1

Simulation results of 33 bus system before and after placing DG

Loss in the initial bus system	208kW
Loss in the system after placing a DG	98.5kW
Loss reduction	109.5kW
Loss reduction [%]	52.64%

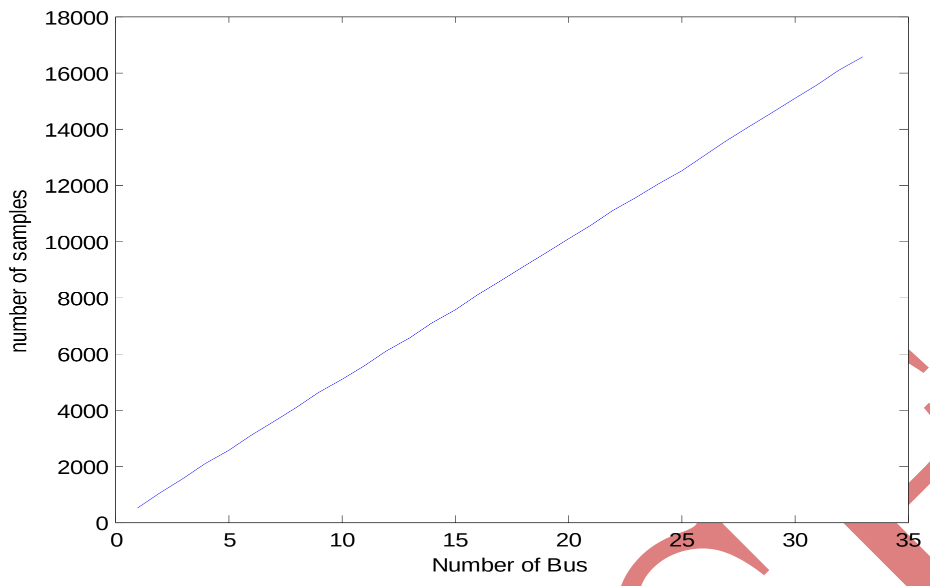

Figure 6: Samples obtained for 33 bus system after implementing crude Monte Carlo (CMC) method

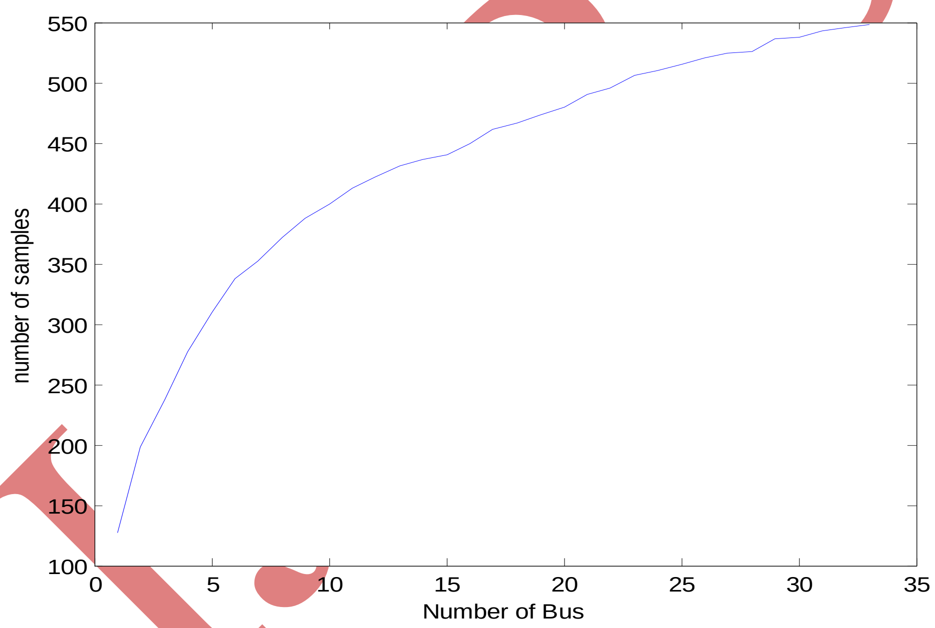

Figure 7: Samples obtained for 33 bus system after implementing Importance sampling (IS) method

TABLE: 2

Simulation result of 33 bus system after implementing the CMC and IS method

METHOD	Crude-Monte-Carlo	Importance sampling
Number-of-samples obtained for IEEE-33-Bus system	16482	548

Figure 8: Voltage profile of 33bus system before and after implementing crude Monte Carlo (CMC) method.

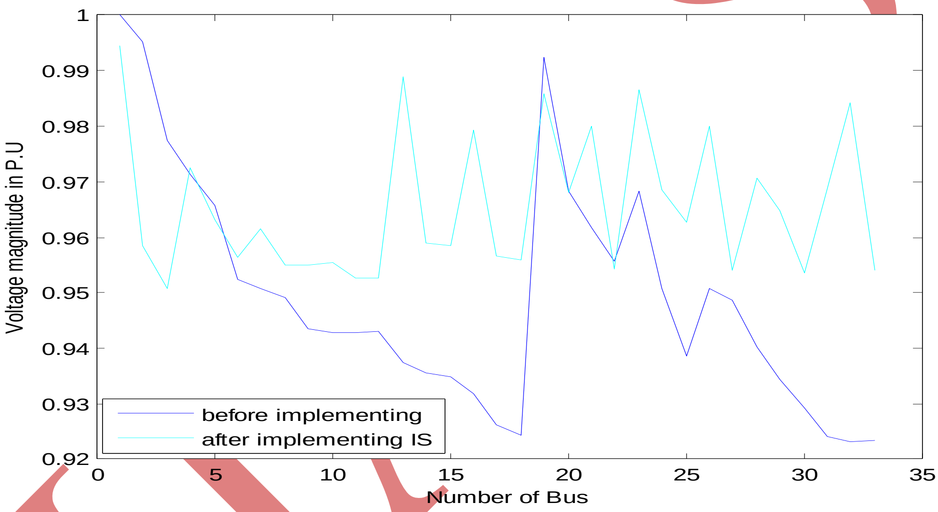

Figure 9: Voltage profile of 33bus system before and after implementing Importance sampling (IS) method.

VIII CONCLUSIONS

Voltage profile is improved by locating a DG using PSO which shows the loss reduction. Probability of failure induced by changes in grid state is evaluated by Monte-Carlo simulation method. Analysis of Crude-Monte-Carlo method and Importance sampling method is implemented to IEEE-33 bus system and results shows that lesser the number of samples lesser the variance which improves the voltage stability.

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APPENDIX

Appendix

TableA1. Load data for 33-bus distribution system

Bus No.	P_L (kW)	Q_L (kVAr)	Bus No.	P_L (kW)	Q_L (kVAr)
2	100	60	18	90	40
3	90	40	19	90	40
4	120	80	20	90	40
5	60	30	21	90	40
6	60	20	22	90	40
7	200	100	23	90	50
8	200	100	24	420	200
9	60	20	25	420	200
10	60	20	26	60	25
11	45	30	27	60	25
12	60	35	28	60	20
13	60	35	29	120	70
14	120	80	30	200	100
15	60	10	31	150	70
16	60	20	32	210	100
17	60	20	33	60	40

TableA2. System data for 33-bus distribution system

Branch Number	Sending end bus	Receiving end bus	R (Ω)	X (Ω)
1	1	2	0.0922	0.0470
2	2	3	0.4930	0.2512
3	3	4	0.3661	0.1864
4	4	5	0.3811	0.1941
5	5	6	0.8190	0.7070
6	6	7	0.1872	0.6188
7	7	8	0.7115	0.2351
8	8	9	1.0299	0.7400
9	9	10	1.0440	0.7400

Branch Number	Sending end bus	Receiving end bus	R (Ω)	X (Ω)
10	10	11	0.1967	0.0651
11	11	12	0.3744	0.1298
12	12	13	1.4680	1.1549
13	13	14	0.5416	0.7129
14	14	15	0.5909	0.5260
15	15	16	0.7462	0.5449
16	16	17	1.2889	1.7210
17	17	18	0.7320	0.5739
18	2	19	0.1640	0.1565
19	19	20	1.5042	1.3555
20	20	21	0.4095	0.4784
21	21	22	0.7089	0.9373
22	3	23	0.4512	0.3084
23	23	24	0.8980	0.7091
24	24	25	0.8959	0.7071
25	6	26	0.2031	0.1034
26	26	27	0.2842	0.1447
27	27	28	1.0589	0.9338
28	28	29	0.8043	0.7006
29	29	30	0.5074	0.2585
30	30	31	0.9745	0.9629
31	31	32	0.3105	0.3619
32	32	33	0.3411	0.5302
34	8	21	2.0000	2.0000
36	9	15	2.0000	2.0000
35	12	22	2.0000	2.0000
37	18	33	0.5000	0.5000
33	25	29	0.5000	0.5000