Symbiotic organisms search based multi-objective optimal placement of distributed generators considering uncertainty of source and load

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Abstract

Integration of Distributed Generation (DG) in the Distribution network will reduce the network expansion costs and increase the network reliability in terms of reduction in voltage magnitude deviations. This paper presents Symbiotic Organisms Search (SOS) based technique for finding out the best size and position of DG in Radial Distribution networks to improve the voltage profile and voltage security state of the Distribution network. The primary objectives of the paper are minimization of bus voltage variation and maximization of voltage stability index (VSI) of the network as a multi objective optimization problem in presence of uncertainty of sources and loads. In this paper the uncertainty of solar power, wind power and load are modelled using 2m Point Estimate Method along with SOS algorithm. To show the effect of DG placement on voltage security state of Distribution system, the system is classified into three states based on the values of VSI. Simulation results as obtained from two standard (IEEE) radial distribution networks prove the efficiency and accuracy of the proposed SOS method. The results of SOS based method are compared with some other techniques as found in recent literature, which shows that SOS algorithm outperforms other standard optimization techniques.

Keywords: distributed generation; radial distribution network; Symbiotic Organisms Search; voltage security; voltage stability indicators.

1. INTRODUCTION

Due to increase in environmental concern and restructuring of electricity market, the uses of Distributed Generation (DG) in the Distribution network have been increased. Integration of DG in the distribution system influence the
power flow, voltage profile, voltage stability, reliability and loadability of the system [1]. Proper allotments of DG in the Distribution network can improve the operating state of the distribution system [2]. As the $R/X$ ratio of the Distribution system is high; the power losses in the Distribution system are higher than the transmission system. Again being the last assembly between generation site and consumer, distribution system suffers from power quality problem. To remove all of these problems it is required to install renewable DGs of ideal size at optimal location in the distribution systems [3]. Because arbitrary placement of DG may increase the power loss, the power flow may be in the opposite direction and it may increase heat generation in feeders [4].

In literature different technical and economic objectives are used for DG installation in the distribution networks [5]. Paper [6] uses a probabilistic Voltage Stability Index which combines the cumulants with maximum entropy technique for study of radial distribution network considering uncertainty. In [7] a new and fast method for tracing the P-V curve to analyse voltage stability is used. Reference [8] proposes an analytical method of DG assignment and sizing for reducing the loss of the system. In Reference [9] backtracking search optimization algorithm is utilised to form the objective function which reduces the system real power loss and improves voltage profile. In reference [10] many conventional and metaheuristic techniques are discussed, followed by a review and discussion of different analytical techniques for allocation of DG. Reference [11] presents a multi-objective function for minimizing annual total cost and the risk of distribution network considering correlations among generation and load uncertainties. Grey wolf optimization technique is used in reference [12] to minimize reactive power loss and improve voltage profile. Modified traditional firefly method is used in reference [13] for optimal allocation and size of the DG with an aim to reduce active power loss or to reduce the daily energy loss. Reference [14] uses Shuffled bat algorithm to minimize power losses, cost and voltage deviation. Ant lion optimization technique minimizes line loss and improves voltage profile and Voltage Stability Index (VSI) for optimal DG placement in Distribution system [15]. In reference [16] placement of large-scale utility-owned wind DG is performed using cumulative probabilistic distribution function and congestion improvement ratio. Article [17] suggests a teaching learning-based method for DG placement where the objective function is loss reduction, voltage profile improvement, improvement in annual saving and maximization of VSI. Monte Carlo dependent multi-objective optimal placement of renewable DG using Open computing language is done in reference [18] using line loss and cost of DG as the objective function. Reference [19] uses investment cost, highest income, lowest environmental cost and minimum loss as objective function for DG assignment under uncertainty by Dempster-Shafer evidence theory and affine arithmetic method. A new stochastic method based on optimal power flow and sensitivity analysis is proposed in reference [20] for allocation of DG in the Distribution system with an aim of loss reduction of the system. Genetic Algorithm is used in reference [21] to find optimal size of DG and optimal reconfiguration of the network with an aim to minimize line losses, minimize total harmonic distortion and to improve voltage profile of the network. Reference [22] proposes a novel multi-objective opposition based chaotic differential evolution algorithm for ideal placement of DG considering power loss, yearly economic loss and voltage deviation as objective function. In reference [23] uncertainties in the output power of renewable energy sources are considered by proposing a new formulation which is accomplished by Particle Swarm Optimization (PSO) algorithm based optimal location and sizing wind, solar and fuel cell in the distribution system. Multi-objective Taguchi approach is presented in reference [24] for best allotment of DG in small and large distribution system where the objective functions are minimization of real power loss, minimization of reactive power loss, minimization of node voltage deviation, maximisation of voltage stability margin (VSM) and maximisation of VSI.
A novel chaotic stochastic fractal search method is used in reference [25] for determining the optimal siting, sizing and number of DG units in the distribution system where the objective function is minimisation of power loss. For different loading condition the optimal sizing and siting of DG will be different. Reference [26] examines how the optimal solution changes due to different load composition and for this a local PSO variant algorithm is proposed as the solution algorithm. Reference [27] uses a hybrid technique to optimize the position and size of DG units for reducing losses in the distribution system. The hybrid technique is a combination of Grasshopper Optimization Algorithm and Cuckoo Search algorithm. A novel approach for DG placement is shown in reference [28] where firstly weak buses are determined using Voltage Stability Margin Index while optimum size of DG unit is computed by MATLAB curve-fitting approximation. In reference [29] a recent optimization method named improved raven roosting optimization algorithm is used for optimal placement of DG in radial distribution system where the technical issues are considered by a weighted multi-objective index. In reference [30] the Pareto-front of non-dominated solutions is obtained from the contradictory relationship between reduction in MVA rating of DGs and reduction of power losses of the system by using multi-objective differential evolution algorithm. In reference [31] minimization of system total real power loss is considered as the main objective whereas optimal location and size of different DG types are determined using a hybrid technique composed of weight–improved particle swarm optimization (WIPSO) and gravitational search algorithm (GSA) called hybrid WIPSO-GSA algorithm.

The discussed heuristics optimization methods in literature provides an approximate solution when classical methods fail but the convergence speed of these algorithms are slow and many of them fail to find the optimal solution. On the other hand analytical techniques also alone are not suitable for optimal placement of DGs [32]. In the earlier paper of the same authors DG placement problem was solved by Spider Monkey Optimization (SMO) technique with only voltage deviation minimization as the objective function. But the correct solution may not be found in case of SMO technique because of arbitrary parameters [33].

So, in the present paper the authors have improved their previous work by using Symbiotic Organisms Search (SOS) and considering a multi objective optimization problem consisting of minimization of voltage deviation and maximization of VSI simultaneously. SOS is better than some other population based algorithms as it offers Mutualism strategy to modify candidate solutions which was not used in PSO and Differential Evolution. A unique characteristic feature of SOS is the use of another mutation operator, Parasitism. The main advantage of SOS is that specific parameters are not required to run the algorithm [34].

The reference papers have shown the effect of DG allocation on loss reduction, voltage profile improvement or increase in the value of indicator but in this proposed work the effect of DG allocation on the voltage security state of the Distribution system is also shown. To increase the efficiency of the SOS, weighted sum technique [35] is also incorporated to solve the multi-objective problem which can generate different Pareto Optimal solutions. Due to restructuring of power system and unpredictable nature of renewable energy sources it is very important to model the uncertainty of power systems. In this paper 2m Point Estimation Method (2mPEM) which is a non-iterative, efficient, simple, and easy technique with no convergence problem, is utilized to model the generator and load uncertainties [36].

SOS technique is used in this paper for DG placement. Using this algorithm the candidate buses for DG allocation along with DG sizes are calculated. Also the outcomes of SOS are crosschecked by Quasi-Oppositional Swine Influenza Model Based Optimization with Quarantine (QOSIMBO-Q) and Swine Influenza Model Based Optimization with Quarantine (SIMBO-Q) [37] to prove its superiority. During contingency, the state of the
Distribution systems under test are categorized into three operating states namely secure, intermediate and emergency by using the values of VSI [38]. This methodology has been tested on two standard IEEE distribution networks. Results show that voltage profile improvement by SOS technique is utmost and it also improves the voltage security states of distribution system as the proposed scheme can increase the indicator value.

2. PROBLEM FORMULATION

2.1. Objective functions

2.1.1 Improvement of voltage profile

Voltage security of a system depends mostly on the bus voltage magnitudes [39]. The system will be more secure for less deviation of the bus voltages from rated magnitude. So, in this paper minimization of voltage variation is considered as the first objective function for improvement of voltage profile at each bus.

The objective function for improvement of voltage profile or reduction in voltage variation for N node network can be written as

\[ f_1 = \text{Min} \sum_{i=1}^{N} (|V_i| - |V_{\text{rated}}|)^2 \]  

(1)

Where, \( V_i \) is the magnitude of voltage at node \( i \) and the magnitude of the rated voltage is \( V_{\text{rated}} \) (which is 1 p.u in this paper).

2.1.2 Improvement of VSI

When contingency occurs in the Distribution system, the value of the system indicator also changes. For this reason, here improvement of stability indicator is considered as the second objective function. Several indices were developed by the researchers to analyse the operating condition of power system. VSI proposed by Chakravorty and Das [38] may be presented as:

\[ VSI = V_k^4 - 4[P_iX - Q_iR]^2 - 4[P_iR + Q_iX]V_k^2 \]  

(2)

Where, \( R \) = line resistance, \( X \) = line reactance, \( V_k \) = voltage of sending end node, \( P_i \) = total real power load available at receiving end node, \( Q_i \) = total reactive power load available at receiving end node.

For stable operation of the radial distribution system, the range of VSI should be between 0 and 1.

The bus for which the value of VSI is lowest is considered as weakest bus of the system. So, equation (2) should be maximized or \( f_2 \) should be minimized which is mathematically represented as follows:

\[ f_2 = \text{Min} \left( \frac{1}{VSI(l)} \right) \]  

(3)

Where, \( l = 1, 2, 3, \ldots, N \)
Value of VSI determines the voltage stability condition of the bus of the distribution system. The DGs should be installed to that bus where the value of VSI is lowest as voltage of such bus is more likely to collapse. As, higher value of VSI means there is a less chance of voltage collapse, in the proposed work VSI improvement is considered as the second objective function which is equivalent to maximizing equation (2) or minimizing $f_2$. The third objective function is a multi-objective problem consisting of minimization of voltage deviation and maximization of VSI. As in the multi-objective problem both the objective functions should be written in minimization form or maximization form, maximization of VSI part is converted into minimization of the inverse of VSI.

2.1.3 Improvement of Voltage Profile and VSI

The third objective function is a multi-objective problem where voltage profile and VSI should be improved simultaneously and is expressed by the following equation:

$$f_3 = \text{Min}(f_1 \times w + f_2 \times (1 - w))$$

(4)

Where $f_1$ and $f_2$ are the functions of improvement of voltage profile and improvement of VSI respectively; $w$ is considered as the weighting factor which varies uniformly between 0 and 1 with a step of 0.05.

2.2. Constraints

2.2.1 Equality Constraint

The equality constraint here is the power balance equation which should be satisfied at each bus:

$$P_{gl} = P_{dl} + V_l \sum_{k=1}^{N} V_k Y_{lk} \cos(\delta_l - \delta_k - \theta_{lk})$$

(5)

$$Q_{gl} = Q_{dl} + V_l \sum_{k=1}^{N} V_k Y_{lk} \sin(\delta_l - \delta_k - \theta_{lk})$$

(6)

Where, $P_{gl}$ and $Q_{gl}$ are generated active and reactive power at bus l, $P_{dl}$ and $Q_{dl}$ are demand of active and reactive power at bus l, $V_k \angle \delta_k$ and $V_l \angle \delta_l$ are the voltage of kth and lth bus respectively, $Y_{lk}$ is the magnitude of the lkth element of admittance matrix and N is the total number of buses.

2.2.2 Inequality Constraints

In this optimization problem there are three inequality constraints which are discussed in the following subsections.

- **Limits of bus voltage magnitude**

  The magnitude of voltage has to lie between the upper and lower values at every node of the network. Voltage magnitude constraint can be written as:
\[ V_i^{\min} \leq V_i \leq V_i^{\max} \]  \hspace{1cm} (7)

Where, \( V_i^{\min} \) and \( V_i^{\max} \) are the minimum and maximum bus voltage magnitudes, considered as 0.95 p.u. and 1.05 p.u. respectively.

**DG active power constraints**

DG capacity at any given location is dependent on sources of energy available at that site. So, it is important to keep DG active power capacity within the upper and lower limits [40].

The range of DG active power can be expressed as:

\[ P_{gl}^{\min} \leq P_{gl} \leq P_{gl}^{\max} \]  \hspace{1cm} (8)

Here,

\[ \sum P_{gl} \leq \sum P_{LOAD} \]  \hspace{1cm} (9)

Where, \( P_{gl}^{\min} \) and \( P_{gl}^{\max} \) are the minimum and maximum value of total real power production of DG, \( P_{LOAD} \) is the total real power load linked in the network and \( N \) denotes the number of nodes. In this study the power injected by the three DGs is considered as less than or equal to total real power load of the system.

**Line Capacity Constraint**

The amount of complex power flowing through a line should be less than its rated value which is expressed by the following equation:

\[ S_i \leq S_{(\text{rated})} \]  \hspace{1cm} (10)

Where, \( S_i \) is the actual complex power at bus \( i \) and \( S_{(\text{rated})} \) is the rated complex power at bus \( i \).

3. **MODELING OF UNCERTAINTIES**

Output power of solar energy based DG is not constant as it depends on solar intensity which is also variable. Output power obtained from the wind power based DG is dependent on wind speed and this also varies from time to time. The amount of load demand also changes. Normally, deterministic forecasts give information about historical performance of the technique but they are unable to estimate the uncertainty associated to a given prediction. So, uncertainty is expressed in the form of probabilistic forecasts. The use of probabilistic forecasts can give higher economic benefits [41]. So, in this paper the variable parameters such as solar intensity, wind speed and load demand are expressed by probability density function.

A significant advantage of probabilistic approach over deterministic approach is that the potential scenarios of the stratigraphic configuration and stratum properties can be sampled according to the characterized
uncertainty and this type of sampled scenarios are more systematic and complete than limited scenarios given by deterministic approach [42].

3.1. Uncertainty of Wind Power

As wind speed is stochastic in nature, the power output from wind turbine is uncertain. In this paper the probability density function of wind is described by Weibull distribution and expressed as follows [11]:

\[
f(v) = \left( \frac{k}{c} \right) \left( \frac{c}{v} \right)^{k-1} \exp \left[ - \left( \frac{c}{v} \right)^k \right]
\]

Where, the constants of Weibull distribution are \(c\) and \(k\).

Normally the wind speed is monitored at a height of 10 m and it is to be converted to wind speed at required height by following equation [11]:

\[
V_H = V_{10} \left( \frac{H}{10} \right)^{\frac{1}{7}}
\]

Where, \(V_H\) is the wind speed at height \(H\) and \(V_{10}\) is the wind speed at 10 m. From the parameters of wind turbine generator and \(V_H\) the value of \(P_{\text{wtg}}\) can be calculated by the following equation [11]:

\[
P_{\text{wtg}} = \begin{cases} 
0 & 0 \leq V_H \leq V_{ci} \text{ or } V_{co} \leq V_H \\
\frac{V_H - V_{ci}}{V_r - V_{ci}} P_r & V_{ci} \leq V_H \leq V_r \\
\frac{V_r - V_{ci}}{V_{co} - V_r} P_r & V_r \leq V_H \leq V_{co}
\end{cases}
\]

Where \(P_{\text{wtg}}\) is the rated active power of wind turbine generator, \(V_{ci}, V_r, V_{co}\) are cut in speed, rated speed and cut out speed of wind turbine generator respectively.

3.2. Uncertainty of Solar Power

Though many factors can affect the output power of solar photo voltaic cell, but for simplicity, the solar intensity, \(S\), in particular, is considered here. The stochastic light intensity, which is known as Beta distribution, can be written as follows [11]:

\[
f(S) = \frac{\Gamma(\alpha + \beta)}{\Gamma(\alpha)\Gamma(\beta)} \left( \frac{S}{S_r} \right)^{\alpha-1} \left( 1 - \frac{S}{S_r} \right)^{\beta-1}
\]

Where \(\alpha\) and \(\beta\) are known as the shape parameters of Beta distribution, rated light intensity is \(S_r\) and \(\Gamma(.)\) is the Gamma function.

The active power obtained from the solar photo voltaic cell can be calculated from the following equation [11]:
\[ P_{pg} = \begin{cases} \frac{P_{pg,r}}{S_r} S \leq S_r \\ P_{pg,r} S > S_r \end{cases} \]  

(15)

Where, \( P_{pg,r} \) is the rated active power of solar photo voltaic cell.

### 3.3. Uncertainty of Load

The load demand of the consumers is different at different days. So, it is also a stochastic variable. To describe the uncertainty of load, Normal distribution is used in this paper. The probability density function for load demand can be written as follows [11]:

\[
f(P_l) = \frac{1}{\sigma_p \sqrt{2\pi}} \exp\left[-\frac{(P_l - \mu_p)^2}{2\sigma_p^2}\right] \]

(16)

\[ Q_l = P_l \tan(\varphi_l) \]  

(17)

Where \( P_l \) and \( Q_l \) denotes random active and reactive power of load respectively; \( \mu_p \) is the mean of active power, \( \varphi_l \) is the power factor of load.

### 3.4. Two-point estimate method

In the present work Hong’s 2m PEM method is used for uncertainty modelling of renewable energy sources and loads [43]. When 2m PEM method is used for stochastic problem, it finds two deterministic points on each side of the mean value for every random variable. In the next step the required problem is solved twice for every random variable by generating two deterministic points where the values of other random variables are taken as equal to their mean value. Here the uncertain variables are solar or wind output and amount of load. In the first step of 2m PEM method the initial values are assigned as follows:

\[ E(A^{(1)}) = 0; E(A^2)^{(1)} = 0 \]

(18)

In the second step, two standard locations and probability are expressed by using equations (19), (20), (21) and (22)

\[
\xi_{m,1} = \frac{\lambda_{m,3}}{2} + \sqrt{n + \left(\frac{\lambda_{m,3}}{2}\right)^2} \quad m = 1, \ldots, n
\]

(19)

\[
\xi_{m,2} = \frac{\lambda_{m,3}}{2} - \sqrt{n + \left(\frac{\lambda_{m,3}}{2}\right)^2} \quad m = 1, \ldots, n
\]

(20)
\[ P_{m,1} = \frac{-\xi_{m,2}}{2n\sqrt{n + (\frac{\lambda_{m,1}}{2})^2}} \quad m = 1, \ldots, n \] (21)

\[ P_{m,2} = \frac{-\xi_{m,1}}{2n\sqrt{n + (\frac{\lambda_{m,3}}{2})^2}} \quad m = 1, \ldots, n \] (22)

Following these equations the two estimated location for the \( m \)th uncertain variable can be written as:

\[ x_{m,1} = \mu_{x,m} + \xi_{m,1} \sigma_{x,m} \] (23)

\[ x_{m,2} = \mu_{x,m} + \xi_{m,2} \sigma_{x,m} \] (24)

Where \( \mu_{x,m} \) and \( \sigma_{x,m} \) represent the mean of random variable \( m \) and variance of random variable \( m \) respectively.

Thereafter the objective function is evaluated for same input parameters and same values for the \( m \)th uncertain variable.

The output variable \( Y \) can be calculated with respect to input variable \( X \) as

\[ Y = f(X) \] (25)

\[ X = \{\mu_{m,1}, \mu_{m,2}, \ldots, x_{m,i}, \ldots, x_{m,n}\} \forall i \in \{1, 2\} \] (26)

For all the random variables calculate the following parameters:

\[ E(Y)^{m+1} \approx E(Y)^{m} + \sum_{i=1}^{2} P_{m,i} h(X) \] (27)

\[ E(Y^2)^{m+1} \approx E(Y^2)^{m} + \sum_{i=1}^{3} P_{m,i} h^2(X) \] (28)

The mean or expected value and standard deviation of \( Y \) can be expressed as:

\[ \psi_Y = E(Y) \] (29)

\[ \sigma_Y = \sqrt{E(Y^2) - \psi_Y^2} \] (30)

4. SOS ALGORITHM
SOS is a meta-heuristic algorithm developed by Cheng and Prayogo in 2014. In this algorithm symbiotic strategies of the organisms among themselves are used to simulate and to survive in the ecosystem. There are three types of symbiotic relationship in nature which are mutualism, commensalism and parasitism. Using these relationships SOS algorithm can be formulated as follows:

4.1. Mutualism Phase

Both the organisms take benefit from each other in the Mutualism phase of SOS. The example of Mutualism is the relationship between bees and flowers. The bees collect nectar from flower to make honey and takes benefit from the flower. At the time of collecting nectar, bees also take pollen grains from the flower and give it to another flower which helps in pollination. This phase can be expressed by the following equations [44]:

\[
X_{knew} = X_k + \text{rand}(0,1)*(X_{best} - \text{Mutual\_Vector})*BF_1
\]

(31)

\[
X_{lnew} = X_l + \text{rand}(0,1)*(X_{best} - \text{Mutual\_Vector})*BF_2
\]

(32)

\[
\text{Mutual\_Vector} = \frac{X_k + X_l}{2}
\]

(33)

Where, \(X_k\) is \(k^{th}\) member organism of the ecosystem and \(X_l\) is a random parameter to interact with \(X_k\).

In equation (31) and (32), vector ‘\(\text{rand}(0,1)\)’ are random numbers. \(BF_1\) and \(BF_2\) are benefit vectors which are either 1 or 2. The mutual relation between organisms \(X_k\) and \(X_l\) is represented by \(\text{Mutual\_Vector}\).

4.2. Commensalism Phase

In nature, relationship is found between two spices where one of them collects food from the other without harming or providing benefit to the other. This is called Commensalism. Such relationship is found between remora fish and shark where remora fish eats the leftover of the shark by always remaining attached with it and cause no benefit or harm to the shark. In this phase \(X_l\) is chosen randomly which will interact with \(X_k\) to create a new organism, \(f_l^{\text{max}}\) by the following equation:

\[
X_{lnew} = X_k + \text{rand}(-1,1)*(X_{best} - X_l)
\]

(34)

Where, \((X_{best} - X_l)\) presents the advantage provided to \(X_k\) by \(X_l\) to raise its benefit in the ecosystem to the highest degree up to \(X_{best}\).

4.3. Parasitism Phase

In the ecosystem if the relationship between two organisms is such that when one gets harmed while the other gets benefitted, then that relationship is called Parasitism. Benefitted organism is named parasite where the harmed
organism is known as host. Example of Parasitism is deer tick which is attached to the host to suck its blood. But, as a carrier of Lyme disease, it cause joint damage and kidney problems with lack of blood to the host, i.e. deer.

Here the host in SOS is $X_i$ which is selected randomly. An artificial organism named as Parasite Vector is created in the search space. When the value of Parasite Vector is better than $X_i$, the position of $X_i$ will be taken by it. On the other hand if the fitness of $X_i$ is higher, the Parasite Vector will not survive in the ecosystem.

5. SOS BASED OPTIMAL PLACEMENT AND SIZING OF DG
For optimal location and sizing of DG based on SOS in the Distribution system the following steps are followed:

Step-1: Initialize ecosystem with eco size, number of iterations, termination criteria and maximum number of fitness function evaluation (max_fit_eval).

Step-2: Number of DG and power output of each DG are initialized by giving the maximum and minimum output of each DG.

Step-3: Create an initial ecosystem by giving random location and size of DG.

Step-4: Run the load flow and check the constraints. If the constraints are satisfied go to next step otherwise again create the ecosystem.

Step-5: The outer loop will continue upto the maximum value of iteration whereas the inner loop will do work until the last member of ecosystem is reached.

Step-6: Mutualism phase- choose organism, $X_i$ such that $X_i \neq X_k$.

Step-7: Determine Mutual_Vector and Benefit Factor (BF).

Step-8: Modify $X_k$ and $X_i$ based on equations (31) and (32).

Step-9: Calculate the fitness value of the modified organism. If the modified organism has higher fitness value, they will replace the old one.

Step-10: Commensalism phase- select organism, $X_j$ randomly such that $X_j \neq X_k$.

Step-11: Modify $X_k$ with the help of $X_j$ based on equation (34).

Step-12: Calculate the fitness value of the new organism. If the fitness value of the new organism is better, it will be retained in the ecosystem.

Step-13: Parasitism phase- select organism, $X_j$ randomly such that $X_j \neq X_k$.

Step-14: Parasite_Vector is created from organism $X_i$.

Step-15: Calculate the fitness value of Parasite_Vector and if the fitness value is higher than $X_j$, the position of $X_j$ will be replaced by Parasite_Vector.

Step-16: Repeat the steps for ecosize.

Step-17: If termination criteria are achieved, stop the process and find the optimal solution for single objective optimization problem, otherwise repeat steps from step 6 to step 16. For multi-objective problem when the current iteration exceeds or is equal to the maximum number of iterations, the result will be stored in an array (Pareto-optimal set) and the iteration will stop, otherwise repeat the steps from step 6 to step 16.
Step-18: For bi-objective problem the value $w$ of will be varied from 0 to 1 in steps of 0.05 and the steps from 3 to step 17 will be repeated until the value of $w$ reaches to 1.

Step-19: In the proposed technique for bi-objective optimization problem different Pareto-optimal solutions are obtained using various weights and then the best compromise result is selected from the optimal Pareto set. The two objective functions have different range and dimensions. So, a fuzzy satisfying method is utilized to normalize the objective functions.

In this paper, for solving multi-objective optimization problem, the best result from the Pareto-optimal front is selected by the fuzzy membership technique which maps the value of objective function into the interval [0, 1]. For the $i$-th objective function, the fuzzy membership function $K_{fi}$ can be written as:

\[
K_{fi} = \begin{cases} 
0, & K_i \leq 0 \\
K_i, & 0 < K_i < 1 \\
1, & K_i \geq 1 
\end{cases}
\]  

(35)

Where,

\[
K_i = \frac{f_i^{\max} - f_i}{f_i^{\max} - f_i^{\min}}
\]  

(36)

Where, $f_i^{\min}$ and $f_i^{\max}$ are the minimum value and maximum value of the $i$-th objective function respectively. The normalized membership function for each solution $j$ can be written as:

\[
FDM^j = \frac{\sum_{i=1}^{n} K_{fi}^j}{\sum_{j=1}^{M} \sum_{i=1}^{n} K_{fi}^j}
\]

(37)

Where, $M$ and $n$ are the values of non-dominated solutions and number of objective functions respectively. The best compromise solution is found for maximum value of $FDM^j$. SOS based optimal DG placement technique is described in Figure 1.

6. SIMULATION RESULTS AND DISCUSSION

SOS algorithm for finding out the best location and rating of DG is simulated in MATLAB and tested on two different distribution networks, first one is IEEE 33 bus radial distribution system (Test system-I) and second one is IEEE 69 bus radial distribution system (Test system-II). In both the networks three DGs are installed using optimization algorithm and the DGs are considered as Type-1 DG, that is, they can inject real power only. The maximum sizes of all the DGs are considered as 1.5 MW. The effect of DG installation on voltage profile, VSI and on the voltage security state of distribution system are also analysed in the present study under all single line contingencies. In this analysis those buses are eliminated from the system which are not getting power due to a particular contingency, for an example, tripping the line between bus 3 and bus 23, bus number 24 and 25 will not
get power for Test system-I. So, bus 24 and 25 are excluded from the reconfigured network for analysis. Similar technique is applicable for every line tripping and in all test systems.

In this paper three different cases are considered for optimal location and sizing of three DGs. Case-1 considers voltage profile improvement, Case-2 is modelled for VSI improvement and Case-3 is a multi-objective problem which considers voltage profile improvement and VSI improvement simultaneously. Initially all the three cases are modelled without considering the uncertainty of solar or wind as well as that of load. In the next part, the effect of uncertain parameters on the objective functions of the distribution systems is studied. SOS method based renewable DG integration in test systems by considering uncertainty requires historical hourly wind speed data and historical hourly solar irradiance data which are utilized to generate Weibull Probability Density Function (PDF) and Beta PDF respectively for every time section. Here it is also considered that the buses of the test system are geographically so close that the solar data, wind data and their corresponding distributions are also same for all the buses. In this study the cut in, rated and cut out speed of the wind DG are considered as 3 m/s, 11.5 m/s and 20 m/s respectively. The scale parameter c and shape parameter K used for Weibull distribution are taken as 8.78 and 1.75 respectively. For Beta distribution the value of shape parameters α and β are taken as 6.38 and 3.43 respectively. The rated output power of all the three DGs are 1.5 MW and they operate at unity power factor. Load demand is modelled in this paper using normal distribution where 5% standard deviation from mean value is considered.

6.1. Test System I: IEEE 33 bus Radial Distribution System

Test System-I has reactive power demand of 2300 kVAR, active power demand of 3715 kW, 33 buses and 32 lines. The base kV and base MVA are 11kV and 100MVA respectively. The data table was utilised from reference [45]. The one-line diagram of IEEE 33 bus radial distribution system is shown in Figure 2. In reference [37] performance of Test system-I is evaluated without installing DG in the system which gives the value of voltage deviation as 0.1338 p.u and VSI \(^{-1}\) as 1.4988.

6.1.1 Objective functions evaluation without considering uncertainty

For performance analysis of Test system-I, three different cases are studied on the basis of three objective functions. In the first case the locations and sizes of DG have been found on the basis of maximization of bus voltage profile as objective function. Case -2 considers improvement of VSI as objective function. A multi-objective function is evaluated in case-3 which finds a compromise solution between maximization of bus voltage profile and improvement of VSI.

Case 1: Improvement of voltage profile

SOS algorithm in case 1 identifies that bus number 7, 13 and 31 are the most excellent locations for DG placement with rating of 1.5 MW, 0.9535 MW and 1.2631 MW respectively as shown in Table 1. The bus numbers and DG sizes by QOSIMBO-Q and SIMBO-Q are also shown in Table 1.

In this case the objective functions for voltage profile improvement are 0.000656 p.u, 0.00066 p.u and 0.00075 p.u by SOS, QOSIMBO-Q and SIMBO-Q algorithm respectively as compared in Figure 3. From Figure 3 it is observed that, optimal DG placement using SOS algorithm delivers the best results compared to QOSIMBO-Q and SIMBO-Q, as the objective function value offered by SOS is smallest. Though voltage profile improvement is considered as the objective function for Case-1, optimal allotment of DG also have some effect on the other
objective function i.e. $VSI^{-1}$ and its value for SOS, QOSIMBO-Q and SIMBO-Q are 1.0685, 1.0685 and 1.0711 respectively. In this case study the voltage deviation decreases from 0.1338 p.u to 0.000656 p.u whereas $VSI^{-1}$ decreases from 1.4988 to 1.0685 by SOS method.

Figure 4 represents the convergence graph of voltage deviation obtained by SOS algorithm in case of DG placement in Test System-I. This graph shows that the SOS algorithm converges for very less number of iterations.

Moreover the effects of installing DG by SOS algorithm on the bus voltage profile of Test System-I, is shown in Figure 5 where it is clear that with proper allotment of DG the minimum voltage magnitude of the system is improved to 0.9836 p.u (at bus 25) which was earlier 0.8820 p.u (at bus 18) under base configuration. Voltage magnitudes of all the buses are also improved due to DG placement by SOS technique.

**Case 2: Improvement of VSI**

When SOS is applied for VSI improvement it is found that bus number 12, 31 and 25 as the appropriate locations for DG placement with rating of 1.5 MW, 1.5 MW and 0.7095 MW respectively. By QOSIMBO-Q and SIMBO-Q also the optimal location and size of DGs are calculated and shown in Table 2.

The value of objective function in this case is 1.02918, 1.02920 and 1.03370 by SOS, QOSIMBO-Q and SIMBO-Q algorithm respectively which are depicted in Figure 6. It is clear from Figure 6 that SOS algorithm provides the lowest value of objective function compared to QOSIMBO-Q and SIMBO-Q algorithms. The value of Voltage deviation due to DG installation by SOS, QOSIMBO-Q and SIMBO-Q algorithm for case-2 are 0.00066 p.u, 0.00066 p.u and 0.00310 p.u respectively. SOS based DG placement decreases voltage deviation from 0.1338 p.u to 0.00066 p.u and decreases $VSI^{-1}$ from 1.4988 to 1.02918.

The convergence graph of $VSI^{-1}$obtained by SOS algorithm in case of DG placement in Test System-I is shown in Figure 7. From the convergence graph it can be said that SOS algorithm converges with very less number of iterations for this case.

**Case 3: Improvement of Voltage Profile and VSI**

Simulation result of bi-objective case which improves voltage profile and VSI simultaneously, selects bus number 31, 25 and 12 as the optimum location of DG placement where the DG sizes are 1.5 MW, 0.7089 MW and 1.5 MW respectively as shown in Table 3. This bi-objective problem is solved by SOS algorithm for Test system-I which will satisfy all the constraints mentioned in subsection 2.2. In Table 3 the results of SOS has been compared with the results of QOSIMBO-Q and SIMBO-Q.

The best compromise solution obtained by SOS algorithm for voltage profile improvement and VSI improvement are 0.000651 p.u and 1.0291 respectively. These values are compared with the results of QOSIMBO-Q and SIMBO-Q in Figure 8 where it is seen that the compromise solution obtained by SOS algorithm is better compared to QOSIMBO-Q and SIMBO-Q algorithm.

Figure 9 presents the pareto-optimal front acquired by SOS algorithm for improving voltage profile and VSI simultaneously in case of three DGs operating with unity power factor. From this graph it is seen that the best compromise solution is obtained by SOS algorithm when the value of Voltage deviation is 0.000651 p.u and the value of $VSI^{-1}$ is 1.0291.

6.1.2 Objective functions evaluation considering uncertainty
As wind and solar power are stochastic in nature and load demands may also vary, it is better to use probabilistic analysis. In this part 2m PEM method coordinated SOS technique again models all the cases which are described in the previous subsections. In this test system three numbers of DG are to be installed, which are of renewable (Wind or Solar) type. So, their outputs are of uncertain nature. Due to this reason output power of the three DGs are 3 uncertain variables. At the same time the test system has 32 load buses which have loads of uncertain nature and due to this there are 32 uncertain parameters in case of load. So, as a whole there are 35 (32+3) uncertain parameters and 70(2× 35) deterministic points to find the optimal solution as 2m PEM method calculates two deterministic points on each side of the mean value for every random variable.

**Case 1: Improvement of voltage profile**

By applying 2m PEM method and SOS in Test system-I for case 1 it is found that the mean of voltage deviation is 0.0051 and the Standard Deviation of voltage deviation is 0.0050. In this case the optimal buses for DG allocation are found as bus number 33, 12, 9.

**Case 2: Improvement of VSI**

By applying the combination of 2m PEM method and SOS for case 2 the Mean and Standard Deviation of VSI -1 are 1.1124 and 0.0441 respectively where the candidate buses for DG allotment are 11, 6, 33.

**Case 3: Improvement of Voltage Profile and VSI**

In case 3 a compromise solution is reached between voltage profile improvement and VSI improvement by modelling the uncertainties in SOS program. The mean and standard deviation of voltage profile improvement are 0.0051 and 0.0050 respectively whereas the mean and standard deviation of VSI improvement are 1.0942 and 0.0349. In this case the candidate buses for DG allocation are bus number 9, 33 and 12. Simulation results of case 1, case 2 and case 3 are shown in Table 4.

6.1.3 Effect of DG Placement on System’s Voltage Security State

As optimal allocation of DG in the distribution system improves the VSI of the system, it also improves the voltage security state of the distribution system. At every single line contingency, VSI values of the system are calculated for Test System-I. Natural Breaks methodology [46] has been used to classify the VSI values into three classes by choosing the suitable group split as there is least divergence in side every data set and highest dissimilarity among groups. These three categories will identify three classes of the operating states of the distribution system, namely, Secure (>0.7185 and <1.00), Intermediate (0.6950-0.7185) and Emergency (<0.6950) state. For some line contingencies after DG allocation the values of VSI of the system may be so improved that the operating states of the system will go to next category. For some contingencies, system’s VSI value and operating states (before and after DG allocation) are depicted in Figure 10 which shows that, proper DG allocation by SOS technique improves the VSI value as well as the operating states of the power network. Due to this, the operating states which were earlier in Intermediate states are now shifted to secure states and similarly, which were in Emergency states are now moved to Secure state.

6.2. Test System II: IEEE 69 bus Radial Distribution System

Test System-II has reactive power load of 2694.1 kVAR, active power load of 3791.89 kW, 69 buses and 68 lines. The base kV and base MVA are 11 kV and 100 MVA respectively. The data of the system are available in
reference [47]. The one-line diagram of IEEE 69 bus radial distribution system is shown in Figure 11. The objective function value of voltage deviation is 0.0993 and that of VSI \(^{-1}\) is 1.4635 [37].

### 6.2.1 Objective functions evaluation without considering uncertainty

The performance of Test system-II is evaluated under three different cases. Case-1 is modelled with SOS for improvement of voltage profile; case-2 is simulated for improvement of VSI whereas case-3 is a multi-objective problem that considers voltage profile improvement and VSI improvement simultaneously.

#### Case 1: Improvement of voltage profile

For three DGs installation in case of voltage profile improvement objective function, the optimal size and location are obtained using SOS algorithm. Bus number 14, 63 and 57 are found as the best possible nodes of the network to place DGs and the ratings are 0.8827 MW, 1.5000 MW and 1.1293 MW respectively as shown in Table 5. The locations and sizes of DGs obtained by QOSIMBO-Q and SIMBO-Q are also shown in Table 5.

A comparison between different techniques for voltage deviation minimization is presented in Figure 12, which reveals that SOS based technique gives greatest outcome compared to the other algorithms such as QOSIMBO-Q and SIMBO-Q in case of delivering lowest value of voltage deviation. Here the value of VSI \(^{-1}\) obtained by SOS, QOSIMBO-Q and SIMBO-Q is 1.0235.

The convergence graph of voltage deviation for Test System-II is shown in Figure 13 from which it is seen that SOS algorithm converges very fast to give the optimal solution.

The voltage magnitudes of all the buses of Test System-II, before DG installation and after DG installation by SOS technique are compared in Figure 14 which shows that there is a definite increase in bus voltage magnitude after DG placement by SOS. Due to SOS based DG installation the minimum value of bus voltage magnitude of the network which was earlier 0.8776 p.u (at bus number 65 under base configuration) has improved to 0.9942 p.u (at bus 50).

#### Case 2: Improvement of VSI

In this case SOS algorithm is used to find the optimal locations and size of 3 DGs where the main aim is improvement of VSI. From the result of case-2 the optimal locations of DG placement are found as bus number 53, 14 and 61 with ratings of 1.3271 MW, 0.8929 MW and 1.5000 MW respectively. A comparison between SOS, QOSIMBO-Q and SIMBO-Q regarding DG size and location is presented in Table 6.

The value of VSI \(^{-1}\) obtained by SOS is 1.00210 whereas the value obtained by QOSIMBO-Q and SIMBO-Q is 1.02350 as shown in Figure 15. Among SOS, QOSIMBO-Q and SIMBO-Q it is found that the proposed SOS technique gives best result compared to the other established algorithms. When DGs are placed based on SOS, QOSIMBO-Q and SIMBO-Q algorithm for minimization of VSI \(^{-1}\), the value of voltage deviation offered by SOS is 0.00038 p.u whereas QOSIMBO-Q and SIMBO-Q finds the value as 0.00049 p.u.

Figure 16 shows the convergence graph of VSI \(^{-1}\) using SOS algorithm in Test System-II which shows high convergence rate of the SOS algorithm in case of DG placement using improvement of VSI as objective function.

#### Case 3: Improvement of Voltage Profile and VSI

In Table 7, the candidate buses for DG allocation along with DG sizes obtained by SOS, QOSIMBO-Q and SIMBO-Q algorithm for bi-objective problem are shown.

The best compromise solution obtained by SOS has value of 0.00024 p.u in case of voltage profile improvement and 1.02348 in case of VSI improvement which are compared with the results of QOSIMBO-Q and
SIMBO-Q algorithm in Figure 17. From Figure 17 it is clear that compromise result obtained by SOS is best compared to the other techniques.

The Pareto–optimal front obtained by SOS for case-3 of Test System-II is shown in Figure 18 which depicts that SOS technique gives optimal solution in case-3 when the value of voltage deviation is 0.00024 p.u whereas the value of VSI \(^{-1}\) is 1.02348.

6.2.2 Objective functions evaluation considering uncertainty
In Test System-II there are 68 load buses which have loads of uncertain nature and three numbers of DG will be installed in the system by optimization having uncertain output power. So, total 71(68+3) uncertain variables are present in Test System–II.

Case 1: Improvement of voltage profile
By adding 2m PEM method based uncertainty modelling with SOS program the mean and standard deviation of voltage deviation are calculated as 0.0017 and 0.0016 respectively. In this case the candidate buses for DG allocation are 13, 57 and 63.

Case 2: Improvement of VSI
Considering the uncertainty of solar, wind and load demand, SOS method finds the appropriate buses for DG allocation are bus number 53, 15 and 61. The mean and standard deviation of VSI \(^{-1}\) are 1.0123 and 1.0052 respectively.

Case 3: Improvement of Voltage Profile and VSI
The best compromise solution obtained by SOS considering uncertainty in bi-objective problem finds mean and standard deviation for voltage deviation as 0.0016 and 0.0015 respectively whereas for VSI \(^{-1}\) the corresponding values are 1.0045 and 1.0048 respectively. In this case bus number 63, 13 and 57 are selected as appropriate buses for DG allocation. Table 8 shows the results of case 1, case 2 and case 3.

6.2.3 Effect of DG placement on system’s voltage security state
If line contingency occurs in presence of DGs, the system will be in more secure position compared to the situation when the system runs without DG. To show the effect of DG placement on Test System II, VSI values of the system are calculated at every single line contingency and depending on these values the system is classified into three states namely Secure (>0.7387 and <1.00), Intermediate (0.6930-0.7387) and Emergency (<0.6930) by Natural Breaks methodology [33]. In Figure 19, VSI values and states before and after DG allocation for some contingencies depicts that the system’s operating states are shifted to Secure position from Intermediate situation and to Intermediate state from Emergency condition when DGs are placed in the system.

7. CONCLUSION
In this paper, SOS algorithm is used for optimal DG placement in the distribution network. Voltage security state improvement of a power network is directly dependent on bus voltage magnitude variation. Voltage level and hence voltage security enhancement of distribution network is achieved in this study by minimization of voltage deviation and minimization of inverse of VSI based multi objective optimization problem. Result obtained from SOS based method has been compared with other methodologies. Simulation findings reveal that, the SOS algorithm delivers superior outcome which is not possible by QOSIMBO-Q and SIMBO-Q. Lowest values of
objective functions are achieved by SOS method which is better than previous standard techniques. The operating states of test systems are classified into three categories and it is found that SOS based DG placement not only minimises the bus voltage magnitude deviation and increase Stability Indicator value of the system but also enhances the voltage security level of the distribution networks under contingent conditions. Thus the proposed methodology may be used as a tool for the modern day’s demand side management.

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**Figure Captions**

**Figure 1.** Algorithm of DG placement by SOS

**Figure 2.** One-line diagram of IEEE 33 bus radial distribution system

**Figure 3.** Comparison of voltage deviation by SOS, QOSIMBO-Q and SIMBO-Q in Test System-I

**Figure 4.** Convergence curve of voltage deviation by SOS algorithm in Test System-I

**Figure 5.** Voltage profile change of Test System-I with installation of DG by SOS

**Figure 6.** Comparison of inverse of VSI by SOS, QOSIMBO-Q and SIMBO-Q in Test System-I

**Figure 7.** Convergence characteristics of VSI-1 of Test System-I by SOS

**Figure 8.** Comparison of voltage deviation and inverse of VSI by SOS, QOSIMBO-Q and SIMBO-Q in Test System-I

**Figure 9.** Pareto-optimal front by SOS for Voltage profile and VSI improvement in Test System-I

**Figure 10.** Change of voltage security state due to optimal placement of DG by SOS in Test System-I

**Figure 11.** One-line diagram of IEEE 69 bus radial distribution system

**Figure 12.** Comparison of voltage deviation by SOS, QOSIMBO-Q and SIMBO-Q in Test System-II

**Figure 13.** Convergence curve of voltage deviation by SOS algorithm in Test System-II

**Figure 14.** Voltage profile change of Test System-II with installation of DG by SOS
Figure 15. Comparison of inverse of VSI by SOS, QOSIMBO-Q and SIMBO-Q in Test System-II
Figure 16. Convergence characteristics of \(\text{VSI}^{-1}\) of Test System-II by SOS
Figure 17. Comparison of voltage deviation and inverse of VSI by SOS, QOSIMBO-Q and SIMBO-Q in Test System-II
Figure 18. Pareto-optimal front by SOS for Voltage profile and VSI improvement in Test System-II
Figure 19. Change of voltage security state due to optimal placement of DG by SOS in Test System-II

Captions of Tables

Table 1. Simulation results of voltage profile improvement for Test System I
Table 2. Simulation results of VSI improvement for Test System-I
Table 3. Simulation results of bi-objective case for Test System-I
Table 4. SOS based simulation results of Test System-I considering uncertainty
Table 5. Simulation results of voltage profile improvement for Test System-II
Table 6. Simulation results of VSI improvement for Test System-II
Table 7. Simulation results of bi-objective case for Test System-II
Table 8. SOS based simulation results of Test System-II considering uncertainty
Figures

Figure-1

Start

Ecosystem Initialization

Iteration=Iteration + 1; i = 1

Identify the best organism (X_max)

Mutualism Phase: choose organism, X_i such that X_i ≠ X_k. Modify X_k and X_i based on equations (31) and (32). Calculate the fitness value for the modified organisms.

No

Reject the modified

Are the modified organisms fitter than the previous?

Yes

Accept the modified

Commensalism phase: select organism, X_i randomly such that X_i ≠ X_k. Modify X_k with the help of X_i based on equation (34). Calculate the fitness value of the new organism.

No

Reject X_new

Yes

Accept X_new

Parasitism phase: select organism, X_i randomly such that X_i ≠ X_k. Parasite_Vector is created from organism X_i. Calculate the fitness value of Parasite_Vector.

Is Parasite_Vector fitter than organism X_k?

No

Keep X_i and delete Parasite_Vector

Yes

Replace X_i with Parasite_Vector

Is i = ecosize?

No

j = j + 1

Is termination criteria achieved?

No

Yes

To find optimal solution follow upto step-17 for single objective problem and upto step-19 for bi-objective problem.

Stop
Figure-2

Figure-3
Figure-4

![Graph showing Voltage deviation (p.u.) vs Iteration Number]

Figure-5

![Graph showing Bus voltage (p.u.) vs Bus Number with comparison between Without DG and With SOS based DG placement]
Figure-12

![Voltage deviation in p.u.](image)

- Voltage deviation in p.u.
- Iteration Number
- Voltage deviation (p.u.)

Figure-13

![Voltage deviation vs. Iteration Number](image)

- Voltage deviation (p.u.)
- Iteration Number
- Voltage deviation $\times 10^{-4}$
Figure 14

![Graph showing bus voltage (p.u.) varying with bus number. The graph compares values with and without DG placement.]

Figure 15

![Bar chart comparing voltage stability index for different methods.]

Voltage stability index $^{-1}$
Figure-16

![Figure-16](image)

Figure-17

![Figure-17](image)
Table 1.

| Method          | Bus No.   | DG size (MW)          |
|-----------------|-----------|-----------------------|
| SOS             | 7,13,31   | 1.5000, 0.9535, 1.2631|
| QOSIMBO-Q [26]  | 7,13,31   | 1.4903, 0.9580, 1.2714|
| SIMBO-Q [26]    | 7,31,13   | 1.0608, 1.4418, 1.0558|

Table 2.

| Method          | Bus No.   | DG size (MW)          |
|-----------------|-----------|-----------------------|
| SOS             | 12,31,25  | 1.5000, 1.5000, 0.7095|
| QOSIMBO-Q [26]  | 12,25,31  | 1.5000, 0.7199, 1.5000|
| SIMBO-Q [26]    | 16,25,33  | 1.4866, 0.6873, 1.4995|

Table 3.

| Method          | Bus No.   | DG size (MW)          |
|-----------------|-----------|-----------------------|
| SOS             | 31,25,12  | 1.5000, 0.7089, 1.5000|
| QOSIMBO-Q [26]  | 12,25,31  | 1.5000, 0.7199, 1.5000|
| SIMBO-Q [26]    | 25,33,12  | 0.7160, 1.5000, 1.5000|

Table 4.

| Case | Mean of voltage deviation | Standard Deviation of voltage deviation | Mean of VSI-1 | Standard Deviation of VSI-1 | Candidate buses for DG allocation |
|------|---------------------------|----------------------------------------|--------------|----------------------------|----------------------------------|
| 1    | 0.0051                    | 0.0050                                 | -            | -                          | 33, 12, 9                       |
| 2    | -                         | -                                      | 1.1124       | 0.0441                     | 11, 6, 33                      |
| 3    | 0.0051                    | 0.0050                                 | 1.0942       | 0.0349                     | 9, 33, 12                      |

Table 5.

| Method          | Bus No.   | DG size (MW)          |
|-----------------|-----------|-----------------------|
| SOS             | 14,63,57  | 0.8827, 1.5000, 1.1293|
| QOSIMBO-Q [26]  | 14,57,63  | 0.8777, 1.1559, 1.4914|
| SIMBO-Q [26]    | 63,14,57  | 1.5000, 0.9011, 1.1320|
Table 6.

| Method     | Bus No.     | DG size (MW) |
|------------|-------------|--------------|
| SOS        | 53,14,61    | 1.327,0.892,1.500 |
| QOSIMBO Q [26] | 58,12,61    | 0.846,1.500,1.4534 |
| SIMBO Q [26] | 12,58,61    | 1.500, 0.800,1.500 |

Table 7.

| Method     | Bus No.     | DG size (MW) |
|------------|-------------|--------------|
| SOS        | 58,15,3     | 0.674,1.500,0.5992 |
| QOSIMBO Q [26] | 62,57,13    | 1.470,1.127,1.1113 |
| SIMBO Q [26] | 13,57,62    | 1.123,1.127,1.500 |

Table 8.

| Case | Mean of voltage deviation | Standard Deviation of voltage deviation | Mean of VSI -1 | Standard Deviation of VSI -1 | Candidate buses for DG allocation |
|------|---------------------------|----------------------------------------|----------------|-------------------------------|----------------------------------|
| 1    | 0.0017                    | 0.0016                                 | -              | -                             | 13,57,63                         |
| 2    | -                         | -                                      | 1.0123         | 1.0052                        | 53,15,61                         |
| 3    | 0.0016                    | 0.0015                                 | 1.0045         | 1.0048                        | 63,13,57                         |

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