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# Optimal Allocation of Distributed Solar Photovoltaic Generation in Electrical Distribution System under Uncertainties

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**Abstract** – In this paper, a new approach is proposed to select the optimal sitting and sizing of distributed solar photovoltaic generation (SPVG) in a radial electrical distribution systems (EDS) considering load/generation uncertainties. Here, distributed generations (DGs) allocation problem is modeled as optimization problem with network loss based objective function under various equality and inequality constrains in an uncertain environment. A boundary power flow is utilized to address the uncertainties in load/generation forecasts. This approach facilitates the consideration of random uncertainties in forecast having no statistical history. Uncertain solar irradiance is modeled by beta distribution function (BDF). The resulted optimization problem is solved by a new Dynamic Harmony Search Algorithm (DHSA). Dynamic band width (DBW) based DHSA is proposed to enhance the search space and dynamically adjust the exploitation near the optimal solution. Proposed approach is demonstrated for two standard IEEE radial distribution systems under different scenarios.

**Keywords**: Electrical distribution systems, Dynamic harmony search algorithm, Renewable distributed generation, Boundary power loss

## 1. Introduction

The ever-increasing demand of electric power, exhaustions of conventional power resources, environmental problems and limitation on transmission network have created increased interest in development of distributed generation (DG) technology. DGs are the small power generation units directly placed in electrical distribution level networks. Optimal selection of size and sitting of DGs can reduce the transmission power losses, on peak operating costs, and improve the voltage profile and reliability of the distribution system [1]. Now a days, solar and wind based DGs are frequently used in radial distribution networks.

In the literature, studies of allocation of DGs are carried out to achieve the different objectives. Kayal and Chanda [2] presented an approach for optimally allocating the solar and wind based DGs in the EDS in order to minimize the energy loss, and, to improve the security and voltage profile of the system. An optimization method is employed in [3] for allocation of DGs to achieve the aim of minimization of active power loss and improve the voltage profile of the system. In some of the literature, optimal allocation of DG is studied in order to minimize the grid dependency; to maximize the profit with constraint of voltage limit, line loading capability, power quality and system security [4-6]. In [5], Shaaban et.al. have proposed a method to allocate renewable DGs in order to maximize the worth of local distribution utility and customers connected to EDS. Keane and O'Malley [6] optimize the size and locations of DGs using constrained linear programming with objective of maximization of DG generation in the distribution system.

There are number of analytical and meta-heuristic methods used in the research literature. In [7-8], analytical methods are used to solve the problem of optimal sitting and sizing of DGs. A current injection based expression is used by Acharya et.al. [7], to allocate the DGs in distribution network with objective of minimization of power losses. Whereas in [8-9] power based expression have been used in the analytical approach for DG allocation. In order to find the optimal location and size of DGs in EDS, power loss and voltage profile based multi-objective function is solved using improved harmony search algorithm (IHSA) [10]. Hybrid meta-heuristic approaches like genetic based tabu search algorithm [11] and a combination of genetic algorithm and particle swam optimization (PSO) [12] are employed to identify the optimal locations and capacities of DGs. El-Zonkoly [13] have proposed a multi objective index based technique to find the size and sitting of multiple DGs in an EDS. PSO algorithm is used to solve the problem in order to reduce the power loss and MVA flows, improve the voltage profile and loadability of the system. Optimal DG allocation problem have been solved by oppositional teaching learning based optimization (QTLBO) approach in [14]. It was achieved by using opposition-based learning (OBL) and quasi OBL concepts along with teaching learning based optimization (TLBO) in order to speed up the

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convergence. In [15], multi objective problem of DG planning in power distribution network is solved using single objective function (OF). Probabilistic load flow based GA is used to solve the OF under uncertainties of load growth, DG power generation etc. System uncertainties associated with time varying loads are considered using probabilistic model in planning of a distribution system [16]. In this planning, optimal allocation of DGs are evaluated by TRIBE PSO and ordinal optimization. These approaches are based on the statistical data. A fuzzy based model has been developed in [17] to allocate the DG in radial power distribution system under uncertainties. GA is used to solve the power loss based OF.

From the literature review it is observed that efficient selection of DGs capacity/size and location in the network is very essential and depends on various operating and system parameters. Many of the methods discussed in literature have successfully been applied to evaluate the size and sitting of DGs in order to achieve the optimized performance of distribution systems. But, most of the studies are done using crisp data for load/generation forecast. However, uncertainties exist in power systems and must be addressed in any analysis or optimization. These uncertainties are even more important in planning studies, as we are dependent on future forecast. Some attempts are available to handle these uncertainties in a probabilistic way. This needs the historical data to be available. The accounts for random uncertainties remain a challenge. It is very difficult to predict an accurate load and DG generation in EDS planning. Moreover it is comparatively easy to give the range of load/generation values [18]. Hence, a boundary power flow based approach is utilized in this paper for determining the size and location of DGs while considering the uncertainties in load/generation forecasts. These boundary values of load/ generation have been successfully used in the analysis of different power system problems like boundary power flow (BPF) [19], transmission network expansion planning [20] etc. In this paper, BPF based approach is proposed to solve the problem of DG allocation in EDS. A solar photovoltaic-based DG is assumed for the placement in this analysis. The uncertainties in load as well as solar photovoltaic generation are considered. Solar photovoltaic output is modeled through probabilistic distribution.

Many meta-heuristic approaches have been applied for optimal DG placement and sizing in literature. These techniques sometimes suffer from slow convergence and local optimality. In this paper, harmony search algorithm (HSA) is used with modification in bandwidth. HSA was first developed by Greem et al. [21] and is based on improvisation process of musicians to find a melody music. HSA is modified with dynamic bandwidth (DBW) to enhance the search space and self-adjust the DBW near the convergence level [22]. The rest of the paper is organized as follows.

Probabilistic distributed SPVG model is discussed in section 2. Problem formulation is presented in section 3. Detailed explanation of dynamic HSA based DG allocation strategies can be found in section 4. Section 5 consists of description of tests systems and renewable resources. Simulation results and discussions are given in section 6. Conclusions of the work are portrayed in section 7.

## 2. Probabilistic distributed SPVG model

SPVG power generation is highly influenced by random phenomenon of solar irradiance and ambient temperature. Solar irradiance and ambient temperature are intermittent in nature and depends on meteorological and geographical conditions. Hence, detailed analysis of DG power generations at installed location is very important at the planning stage for effective and uninterrupted utilization of DGs. Stochastic characteristics of solar irradiance can be represented by beta probability distribution function (BPDF) [23]. Over a selected period of time *'h'*, beta distribution of irradiance (kW/m$^2$) is given as

$$f_b(s) = \left\{ \begin{array}{ll} \frac{\Gamma(\alpha+\beta)}{\Gamma(\alpha)\Gamma(\beta)} s^{(\alpha-1)}(1-\alpha)^{(\beta-1)} & 0 \le s \le 1, \alpha, \beta \ge 0 \\ 0 & Otherwise \end{array} \right\} \quad (1)$$

$$\beta = (1-v)\left(\frac{v(1-v)}{\sigma^2} - 1\right) \quad (2)$$

$$\alpha = \frac{v\beta}{1-v} \quad (3)$$

Where, beta function is expressed by $\Gamma(\bullet)$ and $f_b(s)$ is the beta distribution function (BDF) of the random variable '$s$'. '$s$' is the solar irradiance in kW/m$^2$. $\alpha$ and $\beta$ are the parameter of BDF. Values of these parameters depends on the mean ($v$) and slandered deviation ($\sigma$) of '$s$'.

Main factors influencing the output power of the SPVG are irradiance, ambient temperature of the site and parameters of solar panels. Maximum power generated by SPVG can be calculated at specified irradiance '$s$' as

$$PG_{SPVG}(s) = N \times FF \times V_h \times I_h \quad (4)$$

Where, $N$ is the number of modules used in PV array. $V_h$ and $I_h$ are output voltage and output current respectively. They are functions of module temperature. $FF$ is the fill factor of the module. For a specific time segment '$h$' these parameters are evaluated by following relations-

$$FF = \frac{V_{MPP} \times I_{MPP}}{V_{OC} \times I_{OC}} \quad (5)$$

$$V_h = V_{OC} - K_v \times T_{Ch} \quad (6)$$

$$I_h = S_h\left[I_{SC} + K_i\left(T_C - 25\right)\right] \quad (7)$$

**Table 1.** Parameters of a PV Module [23]

| Parameters | Values |
|---|---|
| $T_A$ | 30.76 $^0$C |
| $N_{OT}$ | 43 $^0$C |
| $I_{MPP}$ | 7.76 A |
| $V_{MPP}$ | 28.36 V |
| $I_{SC}$ | 8.38A |
| $V_{OC}$ | 36.96 V |
| $K_i$ | 0.00545 A/$^0$C |
| $K_v$ | 0.1278 V/$^0$C |

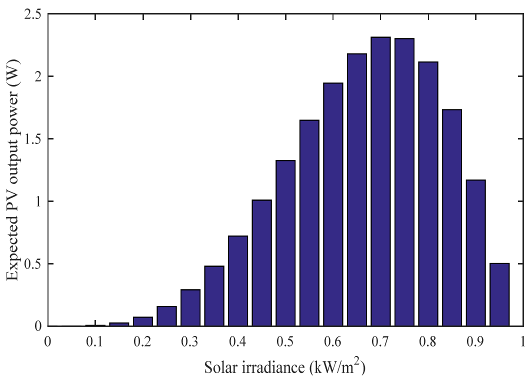



**Fig. 1.** Expected PV output at 12:00-13:00 hours in a day of summer season

$$T_{Ch} = T_A + S_h\left(\frac{N_{OT} - 20}{0.8}\right) \tag{8}$$

$V_{OC}$ and $I_{SC}$ are the open circuit voltage in volts and short circuit current in amperes. Voltage and current at maximum power points (MPP) are denoted by $V_{MPP}$ and $I_{MPP}$ respectively. $T_{Ch}$, $T_A$ and $N_{OT}$ are the cell, ambient and nominal operating temperature in $^0$C, respectively. Whereas, $K_v$ and $K_i$ are the voltage and current temperature constants. From above modeling of SPVG, it can be observed that if a module parameters and operating parameters are known or evaluated, then the power output of SPVG can be calculated using Eq. 4. An example is given to understand the evaluation of SPVG power. A parameter of a solar photovoltaic (PV) module is given in Fig 1. Let the values of mean and standard deviation of solar irradiance at a specified time interval 12:00-13:00 hour of a day in summer season is 0.663 kW/m$^2$ and 0.162 kW/m$^2$, respectively. The expected value of output powers of module are depicted in Fig. 1. Total power of the module in given interval is obtained by integrating the area covered in the Fig. 1. It is found that expected output power during 12:00-13:00 hour is 97.179 W.

## 3. Problem Formulation

Generally in the power distribution system planning, size and location of distributed generation (DG) is determined using deterministic data of load and generation. In most of the planning models peak load demand and maximum capacity of the DGs at different nodes are considered. However, DG generation and load data are the forecasted data. Therefore, these data are very uncertain and intermittent in nature because of load variability, climatic and geographical conditions. Power system operation depends on the load and generation scenarios. It is very difficult to obtain the exact value of load/generation specification for the planning and analysis. However, it is easy to specify the load/generation data in reasonable range instead of exact one. In this work, specified range of uncertainties in loads and DG generations are considered for allocation of DGs in the power distribution system. A boundary value approach is employed to handle these non-statistical uncertainties, effectively.

### 3.1 Objective function

Objective of DGs allocation planning is to find the appropriate location and size of the DGs to be integrated, so that the total active power loss and grid power demand ($P_{grid}$) during that planning horizon is optimum subject to the power system constraints. Output variables like voltage magnitude at each node, branch current and power flows are uncertain with uncertain input variables (Load demand and DG generation). Therefore, total system loss is also uncertain. For specified range of input data, range of output variable can be found with boundary power flow method. Hence, the range of total active power loss can be determined by boundary analysis approach for given range of input data. The objective of the planning is to find the optimal location and size of SPV based DGs in an uncertain environment. It can be formulated as an optimization problem with power loss based objective function represented as in Eq. (9)

$$Minimum\, F = \sum P_{LOSS} \tag{9}$$

$P_{Loss}$ is calculated as summation of losses for three typical seasons, occurring periodically over a year. Out of the 12 months of a year, 3 months are considered as winter season, 6 months as summer season and 3 month as autumn season. In each season a typical day is considered and 24 hours load and SPVG data for that day is taken for calculation of total real power losses in the system as per Table 7 and 8.

In order to find the total loss in presence of specified range of uncertainties, upper and lower boundary power flows are determined as in [19] and [20]. Similarly, boundary active power losses can be calculated using BPF. Therefore, average power loss in uncertain environment is given as

$$Average\, P_{loss} = \frac{P^{upper}_{loss\_boundary} + P^{lower}_{loss\_boundary}}{2} \tag{10}$$

Where, $P_{loss\_boundary}^{upper}$ and $P_{loss\_boundary}^{lower}$ are upper and lower boundary value of output variable $P_{loss}$.

### 3.2 Constraints

The following constraints need to be satisfied,

- *Power flow constraints:* Total power injected at a bus should be equal to difference of total generation (power supplied by utility and power generated by DGs) and demand (total load and losses) at that bus.

$$PG_{SS} + \sum PG_{DG} - \sum P_{load} - P_{loss} = 0 \quad (11)$$

$$QG_{SS} - \sum Q_{load} - Q_{loss} = 0 \quad (12)$$

$PG_{ss}$ and $QG_{ss}$ are active and reactive power supplied by utility substation. $P_{loss}$ and $Q_{loss}$ are the active and reactive power loss. $P_{load}$ and $Q_{load}$ are the active and reactive power demand. $PG_{DG}$ is the power generated by DGs.

- *Bus voltage constraint*: The voltage at each bus should be within permissible limit.

$$V_{i\,min} < V_i < V_{i\,max} \quad (13)$$

$V_{i\,min}$ and $V_{i\,max}$ are the minimum and maximum voltage magnitude limits on $i^{th}$ bus respectively. Whereas, $V_i$ stands for actual voltage at $i^{th}$ bus.

- *DG penetration Constraint*: The power generated by each DG should be less than or equal to maximum DG capacity.

$$P_{DG\,i} \le P_{DG\,max\,i} \quad (14)$$

$$\%\ \text{penetrations of DG}\ \left(P_{DG\,total}\right) \le \Omega \quad (15)$$

Where,

$$\Omega = \frac{\sum PG_{DG}}{\sum P_{load}} \times 100 \quad (16)$$

Constraint (14) represents the max capacity of DG that can be installed at $i^{th}$ node. Net grid power demand in distribution system is reduced and voltage profiles of the buses are improved with penetrations of DGs (renewable DGs, SPVDGs). The effect of high penetration is accounted by an index (Ω) given in Eq. (15, 16).

## 4. DG Allocation Strategy Using Dynamic Harmony Search (DHS)

In this section, strategy to solve the DG allocation problem under uncertain environment is discussed. Proposed strategy is described in three subroutines: i) Boundary power flow with DGs to evaluate the power loss and bus voltages, ii) selection of harmony memory iii) DHS operators (Band width) to update the solution in different improvisations.

### 4.1 Boundary power flow with DSPVG model

In order to take care of uncertainties in load/generation specifications, boundary power BPF approach has been employed for power system operations and planning [20], [24]. BPF is carried out by taking a specified range of uncertainty in load demand and generation at each node. BPF process starts with deterministic power flow (DPF) solutions. Details of these two power flow approaches can be found in [18] and [19]. Characteristics of distributed solar power generations are highly influenced by weather conditions and geographical locations. Stochastic nature of DSPVG can be characterized by probability distribution function (PDF) over the specified time period. DSPVG model is discussed in previous sections. After placing the DSPVG at bus *i*, active power demand at node *i* can be modified as

$$P_{Di}^{DG} = P_{Di}^{base} - P_{DGi} \quad (17)$$

$P_{Di}^{DG}$ is the net demand at node *i* after placement of DSPVG with size of $P_{DGi}$ at the same node. $P_{Di}^{base}$ is the base load connected at $i^{th}$ node.

The major steps to incorporate the stochastic model of DSPVG in BPF are given as follows:

1. Read the data.
2. Select the size and locations of DSPVGs and calculate the equivalent power demands
3. Run the DPF with crisp data. Evaluate the Jacobian *'J'* and total power loss for the distribution system.
4. Start the boundary power flow with DPF solutions.
5. Evaluate the extreme value of active power loss $P_{loss\,max/min}$ as

$$P_{loss\,max/min} = P_{loss0}^{m} + H(Y_{sp} - Y_{cal}) \quad (18)$$

Where, $H$ is the sensitivity vector with elements of $H_j$. $H_j$ is the sensitivity of $P_{loss}$ with change in load/generation at $j^{th}$ bus. H can be calculated as

$$H = G \times K$$
$$G = \left[\frac{P_{loss}}{d\theta},\ \frac{P_{loss}}{dV}\right]_{at\ latest\ values\ of\ \theta\ and\ V} \quad (19)$$

Here, $K$ is the inverse of Jacobian evaluated at latest state variables ($V$, $\theta$). $P_{loss0}^{m}$ is the active power loss at $m^{th}$ iteration and $Y_{cal}$ is the function value evaluated at latest state variables. $Y_{sp}$ is the vector of input variables and can be represented by an interval $\left[Y_{sp}^{\min}, Y_{sp}^{\max}\right]$. Selection of $Y_{sp}$ depends on the sign of associated $P_{loss}$ sensitivity $H_j$ and desired minimum or maximum value of $P_{loss}$. If $P_{loss\ min}$ is desired, then $Y_{sp\ j} = Y_{sp}^{min}$ if $H_j$ is positive and $Y_{sp\ j} = Y_{sp\ j}^{\max}$ if $H_j$ is negative. Similarly, if maximum eigenvalue is interested, then $Y_{sp\ j} = Y_{sp\ j}^{\max}$ , if $H_j$ is positive and $Y_{sp\ j} = Y_{sp}^{min}$ if $H_j$ is negative.

6. Update the input specification with selected load/ generation, $Y_{sp}$.
7. Check for the convergence of BPF, if not go to step 4.
8. Save the extreme value (minimum or maximum) of $P_{loss}$.

**Note :** Boundary value of $P_{loss}$ cannot be obtained directly from boundary values of state variables $\theta$ and $V$.

### 4.2 Selection of harmony memory

Harmony search algorithm (HSA) is a recently developed and is popular meta-heuristic optimization algorithm. This algorithm is based on musician's improvisation process to achieve a melody harmony. There are five algorithm parameters: Harmony memory size (HMS), Harmony memory considering rate (HMCR), pitch adjusting rate (PAR); number of improvisations (NI), or stopping criterion and the band width (BW). New harmony vector is generated after considering all vectors existing in current harmony memory (HM) which makes algorithm more flexible. Details of the algorithm and function of these parameters are given in [25]. In this paper, a harmony vector consisting of the solution candidates is represented by the information of total number, locations and size of the DGs. Harmony values of a harmony vector (HM') can be given as

$$HM' = [No.of\ \ DGs \mid DG_{loc1} DG_{loc2} \ldots\ldots \\ \ldots DG_{loc\ n} \mid DG_{size\,1} DG_{size\,2} \ldots DG_{size\,n}] \tag{20}$$

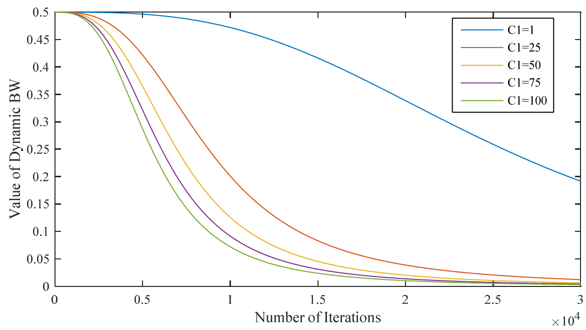
### 4.3 DHS with dynamic band width operator

Various research and modifications in HSA have been carried out to enhance the performance of the algorithm. In [22] dynamic band width approach is proposed to improve the performance and time complexity of HSA. Ideology behind this concept is to use wider BW to make use of whole search space and dynamically adjust the BW towards the optimal solution. HSA integrated with this self-adaptive nature is named as dynamic HSA (DHSA). In this approach, BW depends upon number of iterations (NI) required to solve the optimization problem. In order to have better understanding, a brief description of dynamic BW is presented here.

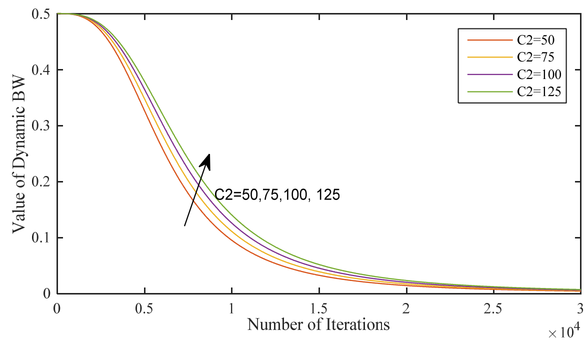
The objective of dynamic BW (DBW) in HSA is to improve the exploration and exploitation characteristics of the algorithm. DBW depends on permissible limits of decision variables. It is a decreasing function of current iteration and total number of iterations specified for the problem. The selection of total number of iterations (termination condition) depends on the desired precision level of solution. In this improvisation methodology, iteration count is non-uniform throughout the simulation. Moderate number of iterations are required in starting whereas large number of iterations are desired near the point of convergence. This characteristics is similar to low pass filter and can be represented by an expression given in Eq. (21).

$$BW(i) = \frac{\kappa}{1 + \mu\left(i/_{Iter}\right)^{L}} \tag{21}$$

Where, $\kappa$ and $\mu$ are the constant parameters. These parameters can evaluated using specified limits of BW. According to Kalivarapu, et.al. [22], minimum value of BW ($BW_{min}$) should be very small. Effective value of maximum BW ($BW_{max}$) is generally assumed to be 10 % of the domain for a range of decision variables. *'i'* and *'Iter'* are the current iteration and total number of iterations. The exponent L∈ ℜ, must be greater than 1. $\kappa$ is approximately equal to $BW_{max}$. Value of $\mu$ is evaluated with the empirical formula expressed in Eq. (22).




(a)




(b)

**Fig. 2.** Values of DBW with respect to iterations (a) constant C1, (b) Constant C2

$$\mu = C_1 \times ln\left(\frac{BW_{max}}{C_2 \times BW_{min}}\right) \tag{22}$$

$C_1$ & $C_2$ are the constants and their numerical values are experimentally evaluated. Some experimental graphs for selection of $C_1$ and $C_2$ are given in Fig. 2. In order to achieve the continuous and effective decrement in BW with growing iterations, values of $C_1$ and $C_2$ are selected to be 50 and 100 respectively.

Dynamic BW given in Eq. (21) is more effective for the problems having low decision variables (5 to 8 variables). For highly complex engineering optimization problems this algorithm is further modified to a discontinuous adaptive dynamic BW (DADBW) base HSA. DADBW is very effective for the optimization problems with large number of decision variables [25]. Expression for the DADBW is given as follow

$$BW(i) = \begin{cases} BW(i) = \dfrac{\kappa}{1+\mu\left(i / Iter\right)^L} & ;i < pivot \\ BW_{min} & ;i \geq pivot \end{cases} \tag{23}$$

Pivot is an optimum iteration number (generally Iter/2) where discontinuity of DBW occurs. In this paper this value is selected to be 45% of the total number of iterations (Iter). Dynamic values of DBW against the iteration *'i'* are depicted in Fig. 3. Flow chart for the simulation steps of DGs allocation using DHSA is presented in Fig. 4.

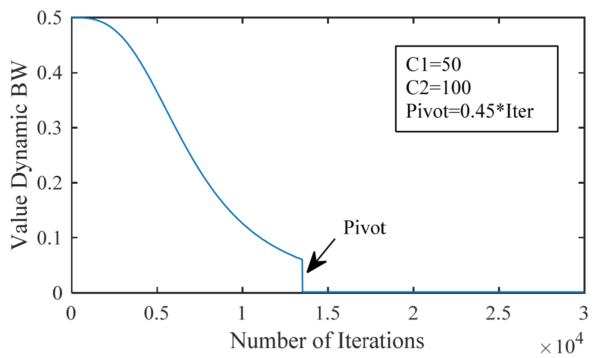



**Fig. 3.** Variation of DBW with number of iterations corresponding to Eq. (23)

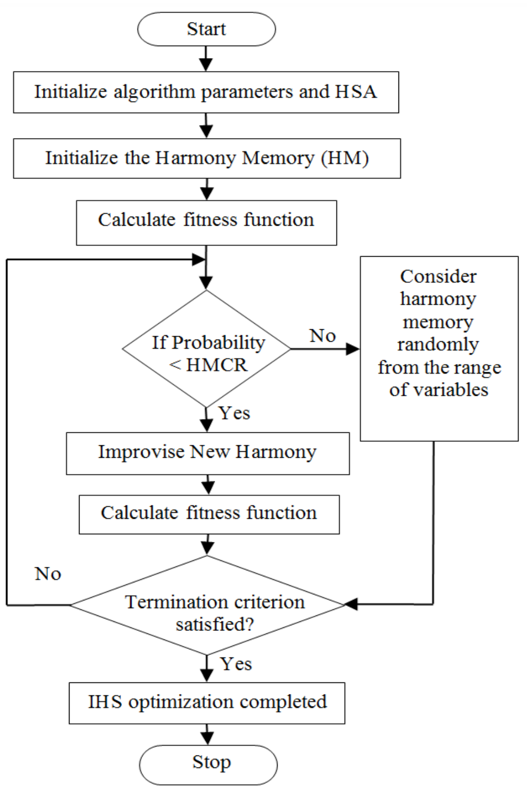



**Fig. 4.** Flow chart of DHSA optimization algorithm for DG allocation

## 5. Test Systems and Renewable Energy Sources

Proposed approach is applied to two standard radial distribution systems: a) IEEE 10 bus system and b) IEEE 33 bus system. Both the systems are portrayed in Fig. 5 and 6, respectively. Test system data can be found in [26] and [15]. Total peak demand of first and second test system is 13.6048 MVA and 4.0854 MVA respectively. In this study, maximum and minimum range of node voltage is set as

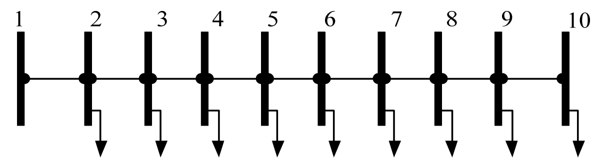



**Fig. 5.** Schematic single line diagram of IEEE 10 bus radial distribution system

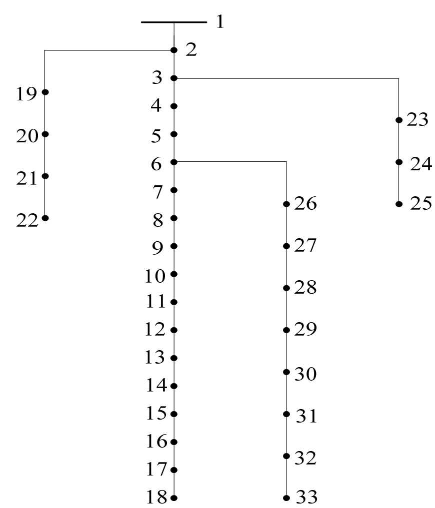



**Fig. 6.** Schematic single line diagram of IEEE 33 bus radial distribution system

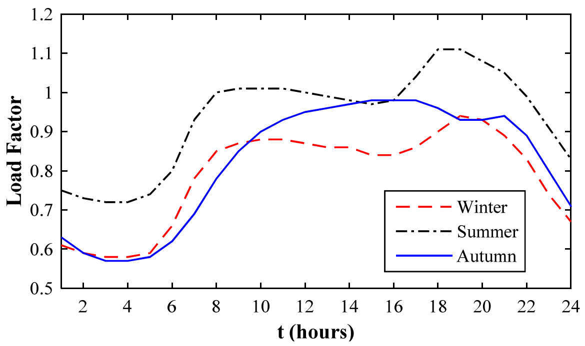



**Fig. 7.** Loading scenario in different seasons

1.1 and 0.9 pu respectively. Maximum number of locations for distributed renewable energy sources (DRES) in IEEE 10 bus and 33 bus test systems are selected to be 3 and 5 respectively. Distributed SPVG are selected as DRES. Three seasons, summer (March-August), autumn (September-November) and winter (December-February) of a complete year is chosen. Hourly load scenarios of all three season are given in Fig. 7. Hourly solar irradiance data for these seasons taken from [2] is given in appendix. Beta PDF are generated for each hour (for example Fig. 1). Uncertainty range in load and SPVG output powers are assumed to be ±10% and ±5% of their specified/ forecasted values, respectively. These uncertainties are used for demonstration of results, however one can use this approach with different level of uncertainty for each load/generation for the planning of DGs in EDS, effectively.

## 6. Simulation Results and Discussions

In order to demonstrate the potential of proposed approach, computer simulations are performed in MATLAB environment. Deterministic power flow solutions are obtained with N-R load flow method. Uncertainties in load/generation are accounted by boundary power flow approach as explained in previous sections. Optimal locations and size of the solar photovoltaic based DGs are obtained by boundary value approach embedded DSHSA for the following three cases.

I. 0% uncertainty in load/generation
II. ±10 % uncertainty in load at each bus and 0% uncertainty in SPVG
III. ±10 % uncertainty in load at each bus and ±5% uncertainty in each SPVG

*Case I* is simply a case of normal DG placement problem without uncertainties. In these cases, base loads and rated/forecasted power of DGs in 12:00-13:00 hours of each season are used for the DG planning. Active power loss based objective function is solved by proposed DHSA. At the outset, algorithm parameters are selected after

**Table 2.** Optimal allocation of DGs in 10 bus system

| DGs | Case I | | Case II | | Case III | |
|---|---|---|---|---|---|---|
| | Location | Size (MW) | Location | Size (MW) | Location | Size (MW) |
| DG1 | 5 | 4.5797 | 6 | 3.6155 | 6 | 3.6109 |
| DG2 | 8 | 3.0701 | 8 | 2.0706 | 8 | 2.3207 |
| DG3 | 10 | 2.3191 | 10 | 2.2831 | 10 | 2.3669 |

**Table 3.** Comparison of solutions for various cases of 10-bus system (for 12:00-13:00 hour, summer)

| Network Parameters | Without SPVGs | With SPVGs | | |
|---|---|---|---|---|
| | | Case I | Case II | Case III |
| Total peak Load (MW) | 13.6048 | 13.6048 | 13.6048 | 13.6048 |
| Power loss (kW) | 981.2136 | 76.9090 | 89.6807 | 86.6892 |
| Min. node Voltage (pu) | 0.8374 | 0.9769 | 0.9761 | 0.9785 |
| Total DG Penetration (MW) | 0 | 9.9689 | 7.9693 | 8.2986 |
| % Penetration | 0 | 73.27 | 58.57 | 60.99 |

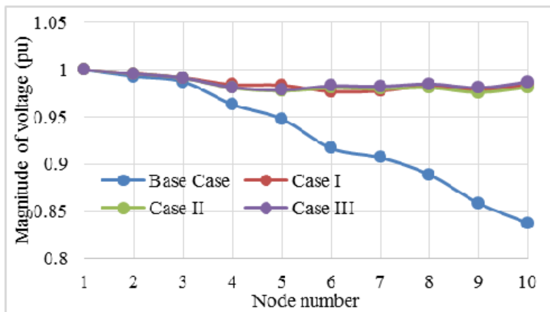



**Fig. 8.** Voltage profile of 10 bus radial distribution system

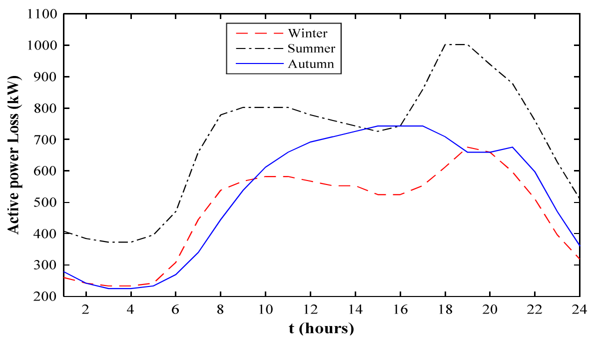



**Fig. 9.** Hourly active power loss in 10 bus system in different season without SPVGs

multiple trials. In this work, values of HMS, HMCR and NI are chosen to be 15, 0.95 and 1000, respectively, after complete parametric analysis. Range of PAR is evaluated as [0.02 0.99]. Minimum and maximum values of BW are selected as 0.5 and 0.001. Pivot value is calculated as 45 % of total iterations. However, in meta-heuristic optimization, no conclusion can be made with results of single run. Thus, more than 30 trials are carried out to evaluate the results. Optimal size and locations of DGs in 10 node network are obtained with different cases and given in Table 2 and 3. Voltage profiles of the system are portrayed in Fig. 8. With these results, it can be found that the size of DGs and hence losses are changed with level of uncertainties. Also, in some cases optimal locations of DGs may vary from the locations obtained in analysis without uncertainties. Therefore, for appropriate selection of locations and size, uncertainties in data must be accounted. Hourly active power loss of 10 node distribution system without SPVGs is shown in Fig. 9. After determination of the optimal location and size of SPVGs, hourly power losses in different seasons are depicted in Fig. 10.

To show the potential of the proposed dynamic search algorithm, the results have also been taken with normal improved harmony search algorithm (IHS) [27] for 33 bus system for Case I (Table 4). Table 4 shows that by the proposed method, more reduction in losses has achieved, with improvement in voltage profile as compared to normal IHS. Table 5 shows the optimal allocation of SPVGs in 33 node system by proposed method; for case I, II and III. The comparative analysis for all cases is given in the Table 6. SPVGs penetration is decreased with increase in uncertainty (case I to case III). Variations in size of SPVGs are also observed. Voltage profiles of the system with and without SPVGs at peak hours in summer season are depicted in Fig. 8. Impact of SPVGs integration on performance of radial EDS is studied with and without uncertainties for different season in Fig. 11 and 12. Hourly variations in network power loss are shown in Fig. 12.

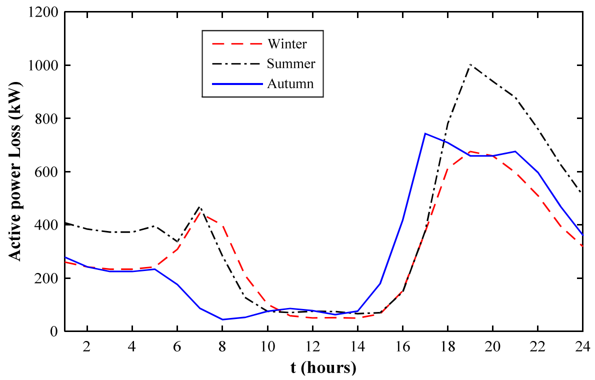



**Fig. 10.** Hourly active power loss in different season when SPVGs are optimally allocated in 10 bus system

**Table 4.** Comparative results with various techniques for 33 bus system

| | | Without DG | By IHS | Proposed Method (Case I) |
|---|---|---|---|---|
| Power Loss (kW) | | 202.6783 | 65.7991 | 65.6753 |
| Min. Voltage | | 0.9131 | 0.9713 | 0.9755 |
| DG1 | Location | - | 3 | 7 |
| | Size (MW) | | 0.0810 | 0.9819 |
| DG2 | Location | - | 7 | 14 |
| | Size (MW) | | 0.9030 | 0.6319 |
| DG3 | Location | - | 14 | 21 |
| | Size (MW) | | 0.5840 | 0.2989 |
| DG4 | Location | - | 24 | 24 |
| | Size (MW) | | 0.9620 | 1.0477 |
| DG5 | Location | - | 31 | 31 |
| | Size (MW) | | 0.7050 | 0.7649 |

**Table 5.** Optimal allocation of DGs in 33 bus system

| DGs | Case I | | Case II | | Case III | |
|---|---|---|---|---|---|---|
| | Location | Size (MW) | Location | Size (MW) | Location | Size (MW) |
| DG1 | 7 | 0.9819 | 7 | 0.9912 | 7 | 0.9758 |
| DG2 | 14 | 0.6319 | 14 | 0.6319 | 14 | 0.6281 |
| DG3 | 21 | 0.2989 | 24 | 0.6034 | 21 | 0.2966 |
| DG4 | 24 | 1.0477 | 25 | 0.4537 | 24 | 1.0407 |
| DG5 | 31 | 0.7649 | 31 | 0.7653 | 31 | 0.7603 |

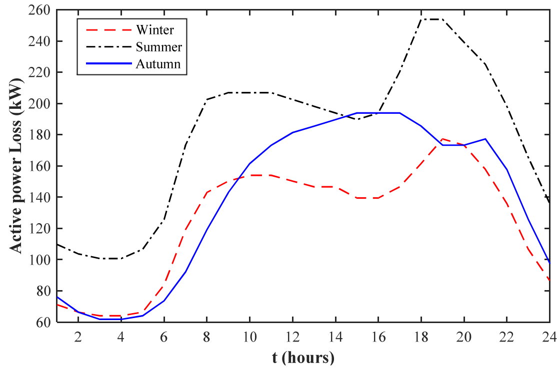



**Fig. 11.** Hourly active power loss in 33 bus system in different season without SPVGs

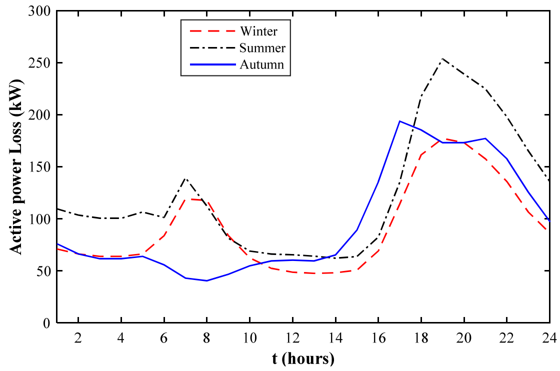



**Fig. 12.** Hourly active power loss in different season when SPVGs are optimally allocated in 33 bus system

**Table 6.** Comparison among the solutions in different cases of 33 bus system (for 12:00-13:00 hour, summer)

| Network Parameters | Without SPVGs (Base case) | With SPVG | | |
|---|---|---|---|---|
| | | Case I | Case II | Case III |
| Total peak Load (MW) | 4.0865 | 4.0865 | 4.0865 | 4.0865 |
| Power loss (kW) | 202.6783 | 65.6753 | 65.7075 | 65.5488 |
| Minimum node voltage (pu) | 0.9130 | 0.9755 | 0.9755 | 0.9752 |
| Total DG penetration (MW) | 0 | 3.7253 | 3.4456 | 3.7015 |
| % Penetration | 0 | 91.16 | 84.31 | 90.57 |

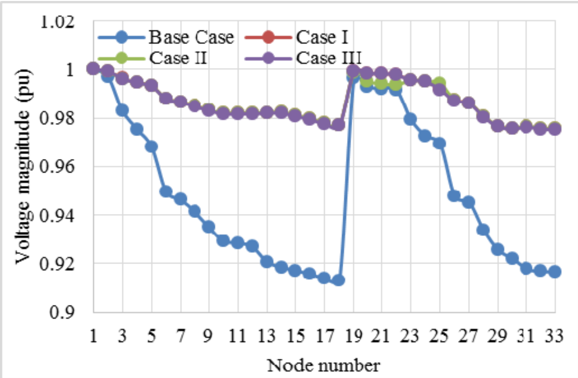



**Fig. 13.** Voltage profile of 33 bus radial distribution system for Case I, II and III

Results shows that the power flow pattern changes with the level of uncertainties; it leads to change in the system losses and finally optimal location of DGs. Therefore, consideration of uncertainties, which cannot be avoided in real power system operation is very important during the system planning. Voltage profile of the system is also improved with optimal integration of SPVGs. Impact of uncertainties on voltage profile of the system is shown in the Fig. 13.

## 7. Conclusions

In this paper, very simple and efficient strategy for DGs allocation planning under uncertainties of loads and DGs output powers is presented. First the boundary value approach is introduced to accommodate the load/generation uncertainties in the optimization problem. Then the boundary power losses are calculated to formulate the objective function. A new DWB based HSA is proposed to solve the objective function in order to obtain the optimal siting and sizing of SPVGs in distributed power system. BPDF is used to estimate the output power of SPVGs. The proposed methodology can handle the non-statistical uncertainties associated with load/generation forecast, model and system parameters. Moreover, the system planner/designer is never sure about the crisp data. Hence, proposed methodology, allows a power system planner/designer to use range of data; rather than the crisp data. This method can be easily implemented for optimal allocation of renewable energy mixed DGs in a complex power distribution networks.

## Acknowledgment

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## Appendix

**Table 7.** Mean ($\varphi_s$) and standard deviation ($\sigma_s$) of solar irradiance (kW/m$^2$)

| Hours | Summer | | Autumn | | Winter | |
|---|---|---|---|---|---|---|
| | $\varphi_s$ | $\sigma_s$ | $\varphi_s$ | $\sigma_s$ | $\varphi_s$ | $\sigma_s$ |
| 1 | 0 | 0 | 0 | 0 | 0 | 0 |
| 2 | 0 | 0 | 0 | 0 | 0 | 0 |
| 3 | 0 | 0 | 0 | 0 | 0 | 0 |
| 4 | 0 | 0 | 0 | 0 | 0 | 0 |
| 5 | 0 | 0 | 0 | 0 | 0 | 0 |
| 6 | 0.07 | 0.021 | 0.07 | 0.029 | 0 | 0 |
| 7 | 0.081 | 0.036 | 0.217 | 0.043 | 0.001 | 0.006 |
| 8 | 0.237 | 0.056 | 0.398 | 0.08 | 0.067 | 0.042 |
| 9 | 0.4 | 0.087 | 0.546 | 0.112 | 0.205 | 0.082 |
| 10 | 0.523 | 0.127 | 0.644 | 0.133 | 0.337 | 0.12 |
| 11 | 0.632 | 0.156 | 0.682 | 0.149 | 0.443 | 0.142 |
| 12 | 0.663 | 0.162 | 0.664 | 0.145 | 0.516 | 0.161 |
| 13 | 0.657 | 0.164 | 0.592 | 0.128 | 0.539 | 0.158 |
| 14 | 0.612 | 0.147 | 0.473 | 0.099 | 0.479 | 0.151 |
| 15 | 0.497 | 0.143 | 0.312 | 0.063 | 0.378 | 0.124 |
| 16 | 0.349 | 0.116 | 0.14 | 0.03 | 0.241 | 0.085 |
| 17 | 0.203 | 0.081 | 0.005 | 0.011 | 0.087 | 0.061 |
| 18 | 0.068 | 0.063 | 0.002 | 0.008 | 0.002 | 0.008 |
| 19 | 0.003 | 0.012 | 0 | 0 | 0 | 0 |
| 20 | 0 | 0 | 0 | 0 | 0 | 0 |
| 21 | 0 | 0 | 0 | 0 | 0 | 0 |
| 22 | 0 | 0 | 0 | 0 | 0 | 0 |
| 23 | 0 | 0 | 0 | 0 | 0 | 0 |
| 24 | 0 | 0 | 0 | 0 | 0 | 0 |

**Table 8.** Loading scenario in different seasons.

| Hours | Winter | Summer | Autumn |
|---|---|---|---|
| 1 | 0.61 | 0.75 | 0.63 |
| 2 | 0.59 | 0.73 | 0.59 |
| 3 | 0.58 | 0.72 | 0.57 |
| 4 | 0.58 | 0.72 | 0.57 |
| 5 | 0.59 | 0.74 | 0.58 |
| 6 | 0.66 | 0.80 | 0.62 |
| 7 | 0.78 | 0.93 | 0.69 |
| 8 | 0.85 | 1.00 | 0.78 |
| 9 | 0.87 | 1.01 | 0.85 |
| 10 | 0.88 | 1.01 | 0.90 |
| 11 | 0.88 | 1.01 | 0.93 |
| 12 | 0.87 | 1.00 | 0.95 |
| 13 | 0.86 | 0.99 | 0.96 |
| 14 | 0.86 | 0.98 | 0.97 |
| 15 | 0.84 | 0.97 | 0.98 |
| 16 | 0.84 | 0.98 | 0.98 |
| 17 | 0.86 | 1.04 | 0.98 |
| 18 | 0.90 | 1.11 | 0.96 |
| 19 | 0.94 | 1.11 | 0.93 |
| 20 | 0.93 | 1.08 | 0.93 |
| 21 | 0.89 | 1.05 | 0.94 |
| 22 | 0.83 | 0.99 | 0.89 |
| 23 | 0.74 | 0.91 | 0.80 |
| 24 | 0.67 | 0.83 | 0.71 |

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