International Journal of Engineering and Techniques - Volume 3 Issue 5, Sep - Oct 2017

RESEARCH ARTICLE OPEN ACCESS

Optimal Placement and Sizing of DG using IPSO and GHS Algorithms by considering Technical and Economic Impacts of DG on Distribution System

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Abstract

Increasing demand on conventional distribution system emerges the distributed energy sources to place near the consumer premises to maintain the reliability of supply. DG also includes the benefits of reduced power loss, improved voltage profile and also reduced transmission and distribution costs. Placement of DG sources have some impact on existing distribution system. The impacts may be technical, economical or environmental. In this paper we have introduced technical and economic benefits of DG. Planning of DG size and location is necessary to obtain the satisfactory performance. In this paper improved particle swarm optimization(IPSO) and global harmony search(GHS) algorithms are used to minimize the objective function. In these methods of optimization, DGs are randomly placed at each bus and size is obtained. Then these results are compared with previous results and optimal location and sizes corresponding to optimal location are obtained. Here, objective function is the function of impact indices on distribution system due to placement of DG . Forward-backward sweep method is considered for studying the load flow of radial distribution system over various techniques available.

Keywords — **Distributed Generation(DG), Power Flow, Placement And Sizing, Improved Particle Swarm Optimization (IPSO), Global Harmony Search(GHS), Objective function.**

I. INTRODUCTION

Distributed generators are the smallest generating units placed near the consumer premises by the consumer itself or by the individual electricity providers. Distributed generation capacity is range from 1 kilowatt to 10 Megawatts. DG technologies may be renewable or non-renewable. But renewable sources like wind or solar power technologies are preferred due to its environmental benefits.

There are four types of DGs which are shown below:

Type 1 DG (0<PF_{DG}<1) : It is capable of injecting real and reactive power.

Type 2 DG (0<PF_{DG}<1) : It is capable of injecting real but consumes reactive power (sign=-1).

Type 3 DG (PF_{DG}=1) : It is capable of injecting real power only (sign=0).

Type 4 DG (PF_{DG}=0) : It is capable of injecting reactive power only (sign=∞).

Nowadays electricity demand is increasing rapidly, with this increasing demand on the distribution system, losses also increases hence voltage profile will become poor. To overcome this, distributed sources are provided over conventional generating stations because of the improved technical, economical and environmental benefits. Integration of DGs in distribution system leads to reduced loss and improved voltage profile.

Load flow studies are carried out to study the system behavior before placing DG. In this paper backward-forward load flow method is considered over various load flow techniques are available. Load flow studies are also conducted after placing DG to find the optimal DG size as explained below. This will shows whether the obtained DG location and size are optimal or not. In this, DG units are randomly placed at each bus and load flow studies are carried out to obtain voltage profile and real power losses at each bus. Why we need to find optimal location is because the improper location of DG leads to poor voltage profile and increased power loss. And similarly optimal sizing of DG also necessary for the better improvement in the system performance. Optimization techniques are used as tools for finding the optimal location and size of DG by calculating various performance impacts which effects the existing distribution system due to placement of DG. These optimization algorithms are iterative procedures hence if the objective function becomes constant for certain number of iteration then that solution will be considered ad optimal solution. In this paper, the problem is to minimize or maximize the impact indices of DG on distribution system under the certain constraints.

II. BACKWARD/FORWARD SWEEP ALGORITHM

Listed below summarize major steps of the proposed solution algorithm with appropriate equations.

Backward sweep:

1) Assume rated voltages at end nodes only for 1st iteration and equals the value computed in the forward sweep in the subsequent iteration.

2) Start with end node and compute the node current using equation (1). Apply the KCL to determine the current flowing from node i towards node i+1 using equation (2), start from end nodes.

$$Ii = \left(\frac{Si}{Vi}\right)^{*} \qquad (1)$$

$$I(i, i+1) = I(i+1) + \frac{\sum currents\ in\ branches}{emanating\ from\ node\ i+1} \qquad (2)$$

3) Compute with this current the voltage at i^{th} node using equation (3). Continue this step till the junction node is reached. At junction node the voltage computed is stored.

$$V(i) = V(i+1) + I(i, i+1) * Z(i, i+1) \qquad (3)$$

4) Start with another end node of the system and compute voltage and current as in step 2 and 3.

5) Compute with the most recent voltage at junction node, the current using equation (1).

6) Similarly compute till the reference node.

7) Compare the calculated magnitude of the rated voltage at reference node with specified source voltage.

Stop if the voltage difference is less than specified criteria, otherwise forward sweep begins.

Forward Sweep:

1) Start with reference node at rated voltage.

2) Compute the node voltage in forward direction from reference node to end nodes using equation (4).

$$V(i+1) = V(i) + I(i,i+1) * Z(i,i+1) \quad (4)$$

3) Again start backward sweep with updated bus voltage calculated in forward sweep.

After calculating node voltages and line currents using standard BW/FW sweep algorithm, the line losses are calculated. The complex power, Sij from bus i to bus j and Sji from bus j to bus i, as are calculated using equation (5) and (6).

$$Sij = Vi * Iij^* \quad (5)$$

$$Sji = Vj * Iji^* \quad (6)$$

The total I^2R loss (P_L) in a distribution system having n number of branches is given by:

$$P_{Lt} = \sum_{i=1}^{n} I_i^2 \times R_i \quad (7)$$

Here I_i is the magnitude of the branch current and R_i is the resistance of the i^{th} branch respectively. The branch current can be obtained from the load flow solution. The branch current has two components, active component (I_A) and reactive component (I_r). The loss associated with the active and reactive components of branch currents can be written as:

$$P_{La} = \sum_{i=1}^{n} I_{ai}^2 \times R_i \quad (8)$$

$$P_{Lr} = \sum_{i=1}^{n} I_{ri}^2 \times R_i \quad (9)$$

III. PROBLEM FORMULATION

The problem of optimal sizing and placement of DGs in appropriate buses in the system, making the problem such a way reducing real power losses, operating cost and enhancing the voltage stability, and other impacts which becomes the objective function. The objective function is given in equation (10),

$$Ft = w1 \times PLI + w2 \times VDI + w3 \times CL + w4 \times CD \quad (10)$$

Where, w1+w2+w3+w4 = 1 and PLI, VDI and CL are active impact indices i.e., power loss index, voltage deviation index and cost of energy loss respectively.

These weights are indicated to give the corresponding importance to each impact indices for the penetration of DG with load models and depend on the required analysis (e.g., planning, operation, etc.). The weighted normalized indices used as the components of the objective function are due to the fact that the indices get their weights by translating their impacts in terms of cost.

Impact Indices:

Active Power Loss Index (PLI):

The active power loss index (PLI) decides the performance of the active power loss of the whole system in different cases. It can be expressed by considering , PLDG and *PL* are the active power losses with DG and with-out DG of the system.

$$PLI = \frac{PLDG}{PL} \quad (11)$$

Where, PLDG is the total real power losses of the distribution system after inclusion of DG. PL is the total real system losses without DG in the distribution system. The lower the values, the better the benefits in terms of loss reduction accrued to DG location.

Voltage Deviation Index (VDI):

This voltage profile performance throughout the system given by the voltage deviation index (VDI). It can be given on the basis of the deviation of system voltage from the reference or rated value (V_n). The minimum the voltage deviation index denotes the better the system performance and improvement in voltage profile. This index can be given as:

$$VDI = \sum_{i=1}^{N} \frac{Vi - Vn}{Vn} \qquad (12)$$

Where, n-is the total no. of buses. The Vn and Vi are the reference voltage and the system bus voltage value in pu respectively.

Cost of energy losses (CL):

The annual cost of energy loss is given by,

$$\mathrm{CL} = (\mathrm{TRPL}) * (\mathrm{Kp} + \mathrm{Ke} * \mathrm{Lsf} * 8760)\ \$ \qquad (13)$$

Where, TRPL: Total Real Power Losses; Kp: annual demand cost of power loss ($/kW); Ke: annual cost of energy loss ($/kW h); Lsf: loss factor

Loss factor is expressed in terms of load factor (Lf) as below:

$$\mathrm{LSF} = \mathrm{k} * \mathrm{Lf} + (1 - \mathrm{k}) * \mathrm{Lf2} \qquad (14)$$

The values taken for the coefficients in the loss factor calculation are:

k = 0.2, Lf = 0.47, K_p = 57.6923 $/kW, K_e = 0.00961538 $/kW h.

Generation Cost Of DG(C_{DG}):

Renewable energy generation is characterized by high installation cost, low operation and maintenance cost and no fuel cost. The generation cost without considering environmental factor can be expressed as:

$$C_d = \left(\frac{r(1+r)^n}{(1+r)^n - 1}\right)\left(\frac{C_{az}}{87.6k}\right) + (C_{OM}) + C_f \qquad (15)$$

Where k is the coefficient of average capacity;

$$k = \frac{Annual\ power\ supply}{8760 * rated\ power\ supply} \qquad (16)$$

C_d is the generation cost, 0.01$/(kWh); n is the repayment period of investment, ordinally equal to the lifetime of equipment, a; C_{OM} is the cost of operation and maintenance, 0.01$/(kWh); C_{az} is the cost of installation/investment, $/(kWh); r is the fixed annual rate, %; C_f is the cost of fuel for generating one kWh of electricity, it equals zero for renewable energy. Based on above expression, the cost of DG for generating one kWh of electricity may be expressed as follows:

$$C_h = \sum_{i=1}^{m} \propto_i \left[\left(\frac{r(1+r)^n}{(1+r)^n - 1}\right) \times \left(\frac{C_{az,i}}{87.6k_i}\right) + (C_{OM,i}) + C_f\right] \qquad (17)$$

This is a hybrid system composed of m kinds of distributed generation technologies. Where α_i is the proportion of i^{th} kind of distributed generation in the total power output.

IV. BASIC PARTICLE SWARM OPTIMIZATION ALGORITHM

Particle swarm optimization, abbreviated as PSO, is based on the behavior of a colony or swarm of insects, such as ants, termites, bees, and wasps; a flock of birds; or a school of fish. The particle swarm optimization algorithm mimics the behavior of these social organisms. The word *particle* denotes, for example, a bee in a colony or a bird in a flock. Each individual or particle in a swarm behaves in a distributed way using its own intelligence and the collective or group intelligence of the swarm. As such, if one particle discovers a good path to *food,* the rest of the swarm will also be able to follow the good path instantly even if their location is far away in the swarm. The PSO algorithm was originally proposed by Kennedy and Eberhart in 1995.

In the context of multivariable optimization, the swarm is assumed to be of specified or fixed size with each particle located initially at random locations in the multidimensional design space. Each particle is assumed to have two characteristics: a *position* and a *velocity*. Each particle wanders around in the design space and remembers the best position (in terms of the food source or objective function value) it has discovered. The particles communicate information or good positions to each other and adjust their individual positions and velocities based on the information received on the good positions.

The position and velocity of the ith particle in the N-dimensional search space are represented as $X_i = (x_{i1}, \ldots, xi_n)$ and $V_i = (v_{i1}, \ldots, x_{in})$, respectively. The particles best position achieved during the search process is recorded and denoted by Pbesti = $(x_{i1}^{Pbest}, \ldots, x_{in}^{Pbest})$. The best particle among all the particles in the population is denoted by Gbesti = $(x_{i1}^{Gbest}, \ldots x_{in}^{Gbest})$. The velocity and position update of each particle in the (k+1) next step can be calculated by the following formulae of (18) and (19) as

$$X_i^{k+1} = X_i^k + V_i^{k+1} \qquad (18)$$

Where, the velocity of individual i at iteration k+1 is given by

$$V_i^{k+1} = V_i^k + C_1 rand_1 \times \left(Pbest_i^k - X_i^k\right) + C_2 rand_2 \times (Gbest^k - X_i^k) \qquad (19)$$

X_i^k : position of individual i at iteration k, X_i^{k+1} : position of individual i at iteration k+1, V_i^k : velocity of individual i at iteration k, c1 : cognitive factors, c2 : social factors, $Pbesti^k$: the best position of individual i until iteration k, $Qbest^k$: the best position of the group until iteration k, rand1 , rand2 : random numbers between 0 and 1.

Improvement to the Particle Swarm Optimization Method:

It is found that usually the particle velocities build up too fast and the maximum of the objective function is skipped. Hence an inertia term, w, is added to reduce the velocity. Usually, the value of w is assumed to vary linearly from 0.9 to 0.4 as the iterative process progresses. The velocity of the jth particle, with the inertia term, is assumed as,

$$V_i^{k+1} = wV_i^k + C_1 rand_1 \times \left(Pbest_i^k - X_i^k\right) + C_2 rand_2 \times (Gbest^k - X_i^k) \qquad (20)$$

The inertia weight ‘w’ was originally introduced by Shi and Eberhart in 1999 to dampen the velocities over time (or iterations), enabling the swarm to converge more accurately and efficiently compared to the original PSO algorithm with Eq. (18). Equation (19) denotes an adapting velocity formulation, which improves its fine tuning ability in solution search. Equation (20) shows that a larger value of ‘w’ promotes global exploration and a smaller value promotes a local search. Thus a large value of ‘w’ makes the algorithm constantly explore new areas without much local search and hence fails to find the true optimum. To achieve a balance between global and local exploration to speed up convergence to the true optimum, an inertia weight whose value decreases linearly with the iteration number has been used:

$$w = w_{max} - \frac{w_{max} - w_{min}}{iter_{max}} \times iter \qquad (21)$$

Where w_{max} and w_{min} are the initial and final values of the inertia weight, respectively, and imax is the maximum number of iterations used in PSO. The values of w_{max} = 0.9 and w_{min} = 0.4 are commonly used.

Algorithm for finding Optimal DG Sizing Using IPSO:

The PSO-based approach for solving the optimal placement of DG (OPDG) problem to minimize the objective function takes the following steps :

Step 1 : Load the Input data of all the buses and lines, and bus voltage limits.

Step 2 : Calculate the loss using distribution load flow based on backward sweep-forward sweep method.

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

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

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

Step 6 : Choose the particle associated with the minimum *individual best Pbest* of all particles, and set the value of this *Pbest* as the current overall best i.e., *Gbest*.

Step 7 : Update the velocity and position of particle using equations (20) and (18) respectively.

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

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

V. HARMONY SEARCH ALGORITHM

HS algorithm, invented in an analogy with music improvisation process, is a high-performance metaheuristic algorithm which uses stochastic random search instead of a gradient search. Simple concept, few parameters to adjust, and easy implementation make HS as the main rival of other evolutionary algorithms. Musicians seek to find a pleasing harmony by adjusting the pitches of their instruments. The quality of the improvised harmony is evaluated by an aesthetic standard. In music improvisation, each musician sounds any pitch within the possible range, jointly making one harmony vector. If all the pitches compose a fine harmony, the player memorizes that experience, and the opportunity to compose a fine harmony increases next time. Similarly, the optimization process attempts to discover the global optimum of the problem on the hand. The quality of each solution vector is measured by putting the values of the decision variables into the objective function. If the solution vector has a good quality, that experience is memorized, and the opportunity to make a good solution will increase next time. Fig. 1 indicates the analogy between music improvisation and engineering optimization. In general, when musicians want to improvise one pitch, they utilize one of the three rules: 1) playing a pitch from their memory, 2) playing a pitch near-by one pitch from their memory, and 3) playing a pitch from possible range randomly. In HS, each solution is called harmony and represented via a *d*-dimensional vector including decision variables. At the beginning of the algorithm, a population of harmony vectors are randomly generated in the search space and stored in the harmony memory (HM). Then, a new harmony is improvised. Each decision variable is adjusted by one of the three rules: 1) selecting a value from the HM, 2) selecting a value near-by one value from the HM, and 3) selecting a value from the possible range randomly. Accordingly, the worst harmony of the HM is removed and replaced by the new harmony if the quality of the new harmony is better than that of

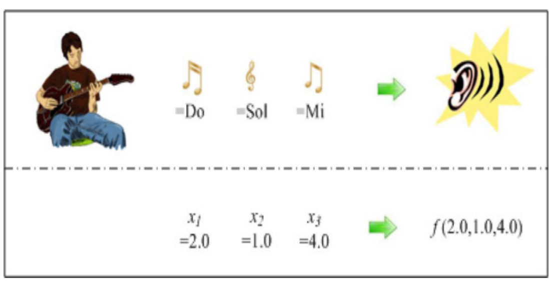

Figure1. Analogy between music improvisation and engineering problem.

the worst harmony. The key parameters which have a profound effect on the performance of HS are HM considering rate (*HMCR*), pitch adjusting rate (*PAR*), and bandwidth of generation (*BW*). These parameters can be potentially useful in adjusting convergence rate of the algorithm to optimal solution. *HMCR* is the possibility with which a value is selected from the HM. It is introduced to escape from local optima when all parts of the global solution do not exist in the HM. The value of *PAR* will determine the possibility of generating a value near-by one value chosen from the HM. This parameter is employed to improve the solutions and escape from local optima, and *BW* is used to provide a balance between local and global search. *PAR* and *BW* are dynamically updated by the following formulas

$$PAR(t) = PAR_{min} + \frac{PAR_{max} - PAR_{min}}{iter_{max}} * iter \qquad (22)$$

$$BW(t) = BW_{max} exp^{\left[\frac{ln\left[\frac{BW_{min}}{BW_{max}}\right]}{iter_{max}} * iter\right]} \qquad (23)$$

where PARmax and PARmin are the maximum and minimum pitch adjusting rates, respectively, *t* denotes the iteration index, $iter_{max}$ is the maximum number of iterations, and BWmax, BWmin are, respectively, the maximum and minimum bandwidths.

The steps of the HS algorithm used in this paper, are as follows:

Step 1: initially, harmony memory size (HMS), *HMCR*, PARmax, PARmin, $iter_{max}$, BWmax, and BWmin are set.

Step 2: the HM is initialized with HMS randomly generated solution vectors in the search space using

$$x_i(j) = l(j) + \alpha \times (u(j) - l(j)) \qquad (24)$$

where $i = 1, 2, \ldots, HMS$ denotes harmony's index, $j = 1, 2, \ldots, d$ is the decision variable's index, α is a random number uniformly from the interval [0, 1], and $l(j)$, $u(j)$ are, respectively, the lower and upper bounds of *j*th decision variable. Hence, the HM is a matrix of $HMS \times N$ dimension.

Step 3: the objective function value for each harmony is calculated.
Step 4: a new harmony vector $X_i^{'}$ is improvised as Fig. 2. where rand is random number from the interval [0, 1] and N is the decision variable.

For i = 1 to N
  If rand ≤ HCMR then
    $X_i^{'} = X_i^j$, where j = 1 to HMS
      If rand ≤ PAR
  $X_i^{'}=X_i^{'}\pm BW*rand$ (BW = band width)
      End if
    Else if
    $X_i^{'} = l(j) + (u(j) - l(j))*rand$
  End if
End for

Figure2. Improvisation of a new harmony in original HS algorithm.

Step 5: the new harmony is checked to see whether it is in the search space. If it is in the search space, its objective function value is computed. If the quality of the new harmony is better than that of the worst harmony, the worst harmony is eliminated, and the new one is added to the HM.
Step 6: Step 3 to step 5 are repeated until a predefined number of iterations $iter_{max}$ is reached.

Global Harmony Search (GHS) Algorithm

To improve the performance of HS algorithm, authors in, inspired by the PSO algorithm, have presented methods by modifying the pitch adjustment rule of HS using the best harmony vector of the HM. Like other optimization algorithms, HS algorithm extremely suffers from premature convergence, particularly when the dimension is high and there are many local optima. The major reason of premature convergence is that the best harmony is not a global best, and optimization algorithm is trapped in local minima. To conquer the problem of premature convergence, optimization algorithm has to be able to provide an effective way to control the diversity of its generations. As a helpful way to circumvent this problem, GHS algorithm proposes that a predefined number of HM harmonies with the best qualities (harmonies with the best objective function values) are selected as the best harmonies. Then, to generate a new harmony, a probabilistic approach is employed to select the interesting best harmony for improvisation process. By taking this way into account, the probability of generating a harmony with better quality increases, because the new harmony is improvised using the information of the best harmonies.

For i = 1 to N
  If rand ≤ HCMR then
    $X_i^{'} = X_i^j$, where j = 1 to HMS
      If rand ≤ PAR
        $X_i^{'} = X_k^{best}$,
      End if
    Else if
    $X_i^{'} = l(j) + (u(j) - l(j))*rand$
  End if
End for

Figure3. Improvisation of a new harmony in GHS algorithm.

The steps of the GHS algorithm are the same as those of HS algorithm, only the step 4 is replaced as Fig. 3. A major drawback of the IHS is that the user needs to specify the values for *BWmin* and *BWmax* which are difficult to guess and problem dependent. Inspired by the concept of swam intelligence as proposed in particle swam optimization (PSO), a new variation of HS is proposed. In a global best PSO system, a swam of individuals fly through the search space. Each particle represents a candidate solution to the optimization problem. The position of each particle is influenced by the best position visited by itself and the position of the best particle in swam. The new approach, called global-best harmony search (GHS), modifies the pitch adjustment step of the HS such that the new harmony can mimic the best harmony in the HM. Thus, replacing the BW parameter altogether and adding a social dimension to the HS. Intuitively, this modification allows the GHS to work efficiently on both continuous and discrete problems. The GHS has exactly the same steps as the IHS with the exception that the pitch adjustments step.

VI. RESULTS AND DISCUSSIONS

The proposed algorithms were tested on IEEE 33-bus(shown in figure1)radial distribution test system and the results obtained from IPSO and GHS methods are compared. The base values used are 100 MVA and 12.66 kV. A DG limits are considered in the range of 0.1 MW to 1.2 MW. In this study, we have considered that the DG is operated at unity power factor. The first bus is considered as the feeder from the generation or transmission system. The remaining buses of the distribution system except the reference buses are considered for the placement of a DG of given size within the constraints considered. Results obtained from the load flow before and after placement of DG for the 33-bus radial distribution system are as shown below in the table1. From the load flow, results obtained are voltage profile and power loss at each buses which are useful for the comparing the status of the system before placing DG and after placing DG. Similarly results obtained after running optimization algorithms are shown below in the table2 for the comparison of both the algorithms of IEEE 33-bus radial distribution system.

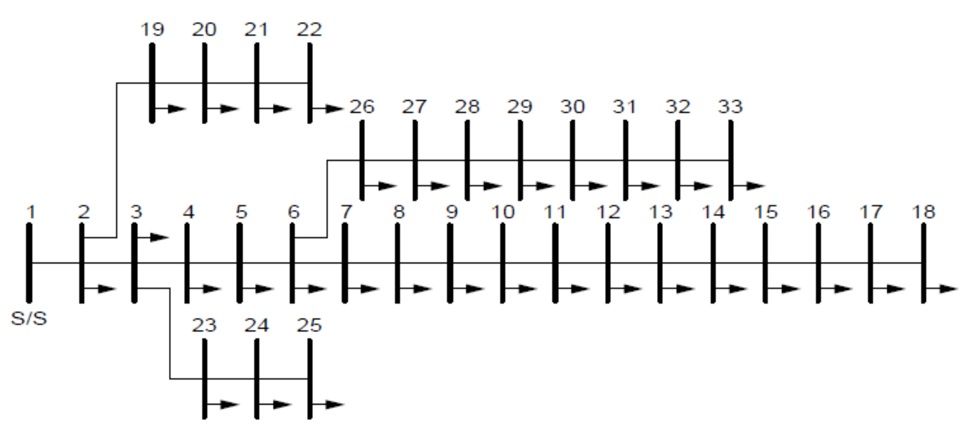

Figure4. IEEE 33-bus radial distribution system

To study the effectiveness of the proposed method (GHS: $HMCR$ = 0.95, PARmax = 0.69, PARmin = 0.1, BWmax = 1, BWmin = 0.001), its performance is compared with PSO with adaptive inertia weight (PSO-w: learning rate $c1$ = $c2$ = 2, and inertia weight linearly decreases from 0.9 to 0.4 during run time). In this problem we have considered three number DGs.

Voltage profile before and after placing DG, cost curves and active power loss at each bus of 33-bus radial distribution system are shown below in the figures5, 6 and 7 respectively. And table2 shows the results obtained from both algorithms, from this we can say that time taken for each iteration is reduced in GHS method . DG size is small in GHS method when compared to size obtained in IPSO hence, installation cost of DG in GHS is less.

Bus no	Without DG		With DG			
			IPSO		GHS	
	Vwodg (pu)	Ploss wodg*10^4 (kw)	Vwdg (pu)	Ploss wdg*10^4 (kw)	Vwdg (pu)	Ploss wdg*10^4 (kw)
1	1.0000	0	1.0000	0	1.0000	0
2	0.9970	1.2292	0.9986	0.3992	0.9986	0.3997
3	0.9829	5.2036	0.9931	1.5580	0.9931	1.5598
4	0.9754	2.0033	0.9901	0.6651	0.9901	0.6612
5	0.9680	1.8830	0.9874	0.6075	0.9875	0.6046
6	0.9495	3.8524	0.9792	1.2380	0.9794	1.2331
7	0.9460	0.1944	0.9768	0.0449	0.9771	0.0373
8	0.9323	1.1859	0.9722	0.2085	0.9739	0.1944
9	0.9260	0.4260	0.9713	0.0718	0.9738	0.0966
10	0.9202	0.3615	0.9709	0.0737	0.9742	0.1087
11	0.9193	0.0564	0.9710	0.0152	0.9734	0.0503
12	0.9178	0.0898	0.9714	0.0302	0.9719	0.0800
13	0.9116	0.2717	0.9728	0.1359	0.9661	0.2419
14	0.9093	0.0743	0.9734	0.0601	0.9640	0.0662
15	0.9079	0.0364	0.9720	0.0318	0.9626	0.0324
16	0.9065	0.0287	0.9707	0.0250	0.9613	0.0255
17	0.9045	0.0256	0.9688	0.0224	0.9594	0.0228
18	0.9038	0.0054	0.9683	0.0047	0.9588	0.0048
19	0.9965	0.0161	0.9981	0.0160	0.9981	0.0160
20	0.9929	0.0832	0.9945	0.0829	0.9945	0.0829
21	0.9922	0.0101	0.9938	0.0100	0.9938	0.0100
22	0.9916	0.0044	0.9932	0.0043	0.9932	0.0043
23	0.9793	0.3181	0.9918	0.0645	0.9917	0.0665
24	0.9726	0.5143	0.9897	0.0936	0.9895	0.0954
25	0.9693	0.1287	0.9909	0.0990	0.9862	0.1244
26	0.9476	0.2599	0.9787	0.1244	0.9788	0.1225
27	0.9450	0.3327	0.9782	0.1685	0.9780	0.1637
28	0.9336	1.1294	0.9744	0.6130	0.9735	0.5863
29	0.9254	0.7828	0.9719	0.4638	0.9706	0.4369
30	0.9218	0.3893	0.9720	0.2823	0.9703	0.2570
31	0.9176	0.1593	0.9680	0.1432	0.9663	0.1437
32	0.9167	0.0213	0.9672	0.0192	0.9655	0.0192
33	0.9164	0.0013	0.9669	0.0012	0.9652	0.0012

Table1. load flow results before and after placing DG of a 33-bus system

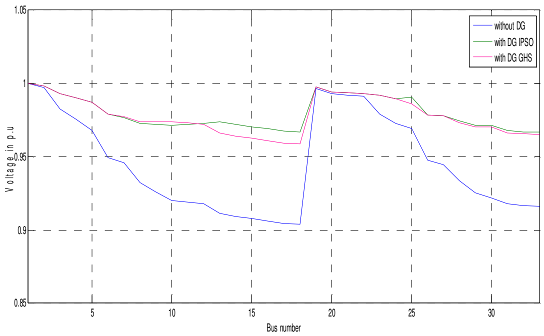

Figure5. voltage profile of 33-bus system at each bus

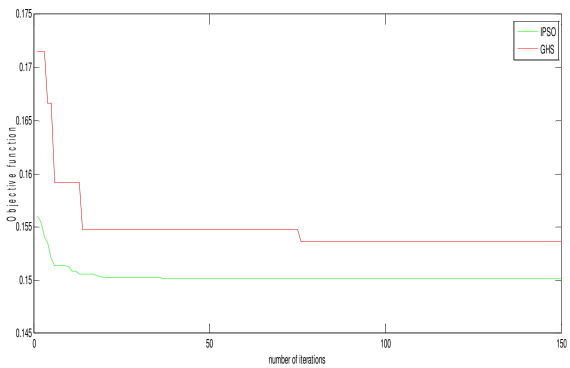

Figure6. convergence characteristics of 33-bus system

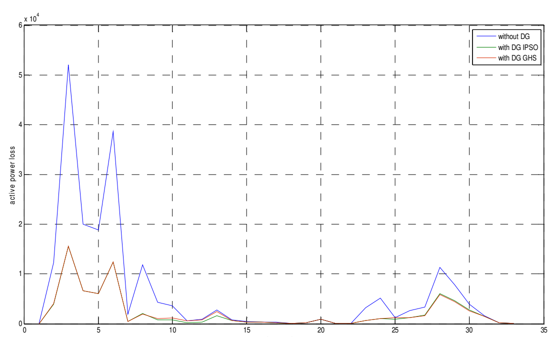

Figure7. active power loss of 33-bus system at each bus

Method	Parameter	Before Placing dg	After placing DG		
				DG Location	DG size (MW)
IPSO	Ploss *10^4	0.1593 0.0743 0.2599	0.1432 0.0651 0.1239	31 14 26	1.0348 0.7943 0.7709
	Vdi	0.0826 0.0911 0.0525	0.0578 0.0742 0.0376		
	Cl	0.1224 0.0571 0.1998	0.1071 0.0486 0.0927		
	Cdg *10^6 (Rs)	-	63.761 48.947 47.501		
	Total Ploss (kw)	210.787 0	73.8005		
	Elapsed time	17.359221 seconds			
GHS	Ploss *10^4	0.1287 0.1593 0.0564	0.1244 0.1437 0.0503	25 31 11	0.7641 0.9461 0.8897
	Vdi	0.0307 0.0826 0.0810	0.0210 0.0532 0.0473		
	Cl	0.0990 0.1224 0.0434	0.0930 0.1075 0.0376		
	Cdg *10^6 (Rs)	-	47.085 58.301 54.824		
	Total Ploss (kw)	210.787 0	75.4940		
	Elapsed time	16.200661 seconds			

Table2. results obtained from IPSO and GHS iterative algorithms

CONCLUSION

In this paper, problem of location and sizing of DG was converted to the optimization problem by considering the various impact indices like active power loss index, voltage deviation index, installation cost of DG and cost of energy losses in distribution system. objective function for this proposed method is a combination of these four impact indices. IPSO and GHS algorithms were applied to solve this optimization problem and obtained optimal location and sizing of DG for IEEE 33-bus radial distribution system. Results obtained shows that voltage profile is improved, real power losses are decreased and also cost of energy losses are reduced after placing DG. Finally installation cost of DG corresponding to optimal DG size is calculated.

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