APPLICATION OF FUZZY AND PSO FOR DG PLACEMENT FOR MINIMUM LOSS IN RADIAL DISTRIBUTION SYSTEM

M. Padma Lalitha[1], V. C. Veera Reddy[2], V. Usha[2] and N. Sivarami Reddy[3]
[1]Department of Electrical and Electronics Engineering, Annamacharya Institute of Technology and Sciences, Rajampet, A.P., India
[2]Department of Electrical and Electronics Engineering, S. V. U. C. E, S. V. University, Tirupathi, A.P., India
[3]Department of Mechanical Engineering, Annamacharya Institute of Technology and Sciences, Rajampet, A.P., India
E-Mail: padmalalitha_mareddy@yahoo.co.in

ABSTRACT

This paper presents a new methodology using fuzzy and Particle Swarm Optimization (PSO) for the placement of Distributed Generators (DG) in the radial distribution systems to reduce the real power losses and to improve the voltage profile. A two-stage methodology is used for the optimal DG placement. In the first stage, fuzzy approach is used to find the optimal DG locations and in the second stage, PSO is used to find the size of the DGs corresponding to maximum loss reduction. The proposed method is tested on standard IEEE 33 bus test system and the results are presented and compared with an existing method.

Keywords: DG placement, fuzzy approach, PSO, loss reduction, radial distribution system.

INTRODUCTION

Distributed or dispersed generation (DG) or embedded generation (EG) is small-scale power generation that is usually connected to or embedded in the distribution system. The term DG also implies the use of any modular technology that is sited throughout a utility's service area (interconnected to the distribution or sub-transmission system) to lower the cost of service [1]. The benefits of DG are numerous [2, 3] and the reasons for implementing DGs are an energy efficiency or rational use of energy, deregulation or competition policy, diversification of energy sources, availability of modular generating plant, ease of finding sites for smaller generators, shorter construction times and lower capital costs of smaller plants and proximity of the generation plant to heavy loads, which reduces transmission costs. Also it is accepted by many countries that the reduction in gaseous emissions (mainly CO_2) offered by DGs is major legal driver for DG implementation [4].

The distribution planning problem is to identify a combination of expansion projects that satisfy load growth constraints without violating any system constraints such as equipment overloading [5]. Distribution network planning is to identify the least cost network investment that satisfies load growth requirements without violating any system and operational constraints. Due to their high efficiency, small size, low investment cost, modularity and ability to exploit renewable energy sources, are increasingly becoming an attractive alternative to network reinforcement and expansion. Numerous studies used different approaches to evaluate the benefits from DGs to a network in the form of loss reduction, loading level reduction [6-8].

Naresh Acharya *et al.*, suggested a heuristic method in [9] to select appropriate location and to calculate DG size for minimum real power losses. Though the method is effective in selecting location, it requires more computational efforts. The optimal value of DG for minimum system losses is calculated at each bus. Placing the calculated DG size for the buses one by one, corresponding system losses are calculated and compared to decide the appropriate location. More over the heuristic search requires exhaustive search for all possible locations which may not be applicable to more than one DG. This method is used to calculate DG size based on approximate loss formula may lead to an inappropriate solution.

In the literature, genetic algorithm and PSO have been applied to DG placement [10-13]. In all these works both sizing and location of DGs are determined by GA. In this paper, the optimal locations of distributed generators are identified based on the sensitivity analysis applied to fuzzy and a PSO based technique which takes the number and location of DGs as input has been developed to determine the optimal size (s) of DG to minimize real power losses in distribution systems. The advantages of relieving PSO from determination of locations of DGs are improved convergence characteristics and less computation time. Voltage and thermal constraints are considered. The effectiveness of the proposed algorithm was validated using 33-Bus Distribution System [14]. To test the effectiveness of proposed method, results are compared with the results of an analytical method reported in [15]. It is observed that the proposed method yield more savings as compared to analytical method.

2. TOTAL REAL POWER LOSS IN A DISTRIBUTION SYSTEM

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

$$P_{Lt} = \sum_{i=1}^{n} I_i^2 Ri \qquad (1)$$

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:

$$P_{La} = \sum_{i=1}^{n} I_{ai}^2 Ri \qquad (2)$$

$$P_{Lr} = \sum_{i=1}^{n} I_{ri}^2 Ri \qquad (3)$$

Note that for a given configuration of a single-source radial network, the loss P_{La} associated with the active component of branch currents cannot be minimized because all active power must be supplied by the source at the root bus. However by placing DGs, the active components of branch currents are compensated and losses due to active component of branch current are reduced. This paper presents a method that minimizes the loss due to the active component of the branch current by optimally placing the DGs and thereby reduces the total loss in the distribution system. A two stage methodology is applied here. In the first stage optimum location of the DGs are determined by using fuzzy approach and in the second stage PSO method is used to determine sizes of the DGs for maximum real loss reduction.

3. IDENTIFICATION OF OPTIMAL DG LOCATIONS USING FUZZY APPROACH

This paper presents a fuzzy approach to determine suitable locations for DG placement [16]. Two objectives are considered while designing a fuzzy logic for identifying the optimal DG locations. The two objectives are: (i) to minimize the real power loss and (ii) to maintain the voltage within the permissible limits. Voltages and power loss indices of distribution system nodes are modeled by fuzzy membership functions. A fuzzy inference system (FIS) containing a set of rules is then used to determine the DG placement suitability of each node in the distribution system. DG can be placed on the nodes with the highest suitability.

For the DG placement problem, approximate reasoning is employed in the following manner: when losses and voltage levels of a distribution system are studied, an experienced planning engineer can choose locations for DG installations, which are probably highly suitable. For example, it is intuitive that a section in a distribution system with high losses and low voltage is highly ideal for placement of DG. Whereas a low loss section with good voltage is not ideal for DG placement. A set of fuzzy rules has been used to determine suitable DG locations in a distribution system.

In the first step, load flow solution for the original system is required to obtain the real and reactive power losses. Again, load flow solutions are required to obtain the power loss reduction by compensating the total active load at every node of the distribution system. The loss reductions are then, linearly normalized into a [0, 1] range with the largest loss reduction having a value of 1 and the smallest one having a value of 0. Power Loss Index [15] value for i^{th} node can be obtained using equation 4.

$$PLI(i) = \frac{(Lossreduction(i) - Lossreduction(\min))}{(Lossreduction(\max) - Lossreduction(\min))} \qquad (4)$$

These power loss reduction indices along with the p.u. nodal voltages are the inputs to the Fuzzy Inference System (FIS), which determines the nodes that are more suitable for DG installation.

3.1. Implementation of fuzzy method

In this paper, two input and one output variables are selected. Input variable-1 is power loss index (PLI) and Input variable-2 is the per unit nodal voltage (V). Output variable is DG suitability index (DSI). Power Loss Index range varies from 0 to 1, P.U. nodal voltage range varies from 0.9 to 1.1 and DG suitability index range varies from 0 to 1.

Five membership functions are selected for PLI. They are L, LM, M, HM and H. All the five membership functions are triangular as shown in Figure-1. Five membership functions are selected for Voltage. They are L, LN, N, HN and H. These membership functions are trapezoidal and triangular as shown in Figure-2. Five membership functions are selected for DSI. They are L, LM, M, HM and H. These five membership functions are also triangular as shown in Figure-3.

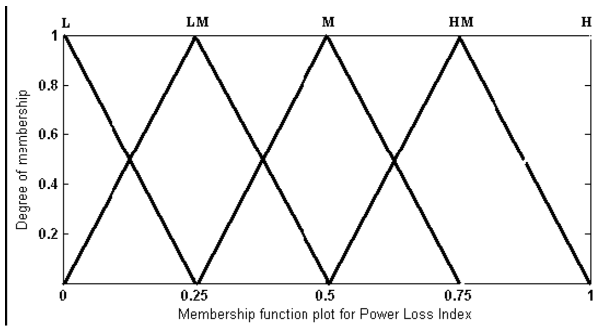

Figure-1. Membership function plot for PLI.

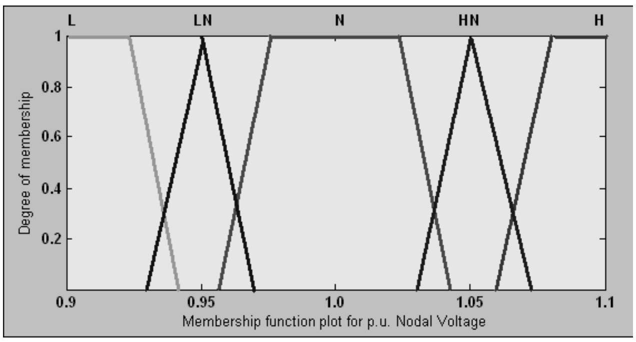

Figure-2. Membership function plot for voltage.

ARPN Journal of Engineering and Applied Sciences

www.arpnjournals.com

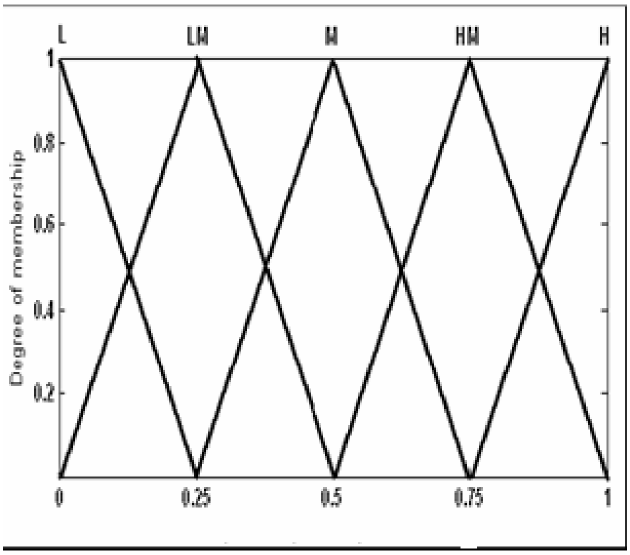

Figure-3. Membership function plot for DSI.

For the DG allocation problem, rules are defined to determine the suitability of a node for capacitor installation. Such rules are expressed in the following form:

IF premise (antecedent), THEN conclusion (consequent). For determining the suitability of DG placement at a particular node, a set of multiple-antecedent fuzzy rules has been established. The inputs to the rules are the voltage and power loss indices and the output is the suitability of capacitor placement. The rules are summarized in the fuzzy decision matrix in Table-1. In the present work 25 rules are constructed.

Table-1. Fuzzy decision matrix.

AND		Voltage				
		LL	**LN**	**NN**	**HN**	**HH**
DSI	**L**	LM	LM	L	L	L
	LM	M	LM	LM	L	L
	M	HM	M	LM	L	L
	HM	HM	HM	M	LM	L
	H	H	HM	M	LM	L

4. PARTICLE SWARM OPTIMIZATION

4.1. Introduction

Particle swarm optimization (PSO) is a population-based optimization method first proposed by Kennedy and Eberhart in 1995, inspired by social behavior of bird flocking or fish schooling [17]. The PSO as an optimization tool provides a population-based search procedure in which individuals called particles change their position (state) with time. In a PSO system, particles fly around in a multidimensional search space. During flight, each particle adjusts its position according to its own experience (This value is called Pbest), and according to the experience of a neighboring particle (This value is called Gbest), made use of the best position encountered by itself and its neighbor (Figure-4).

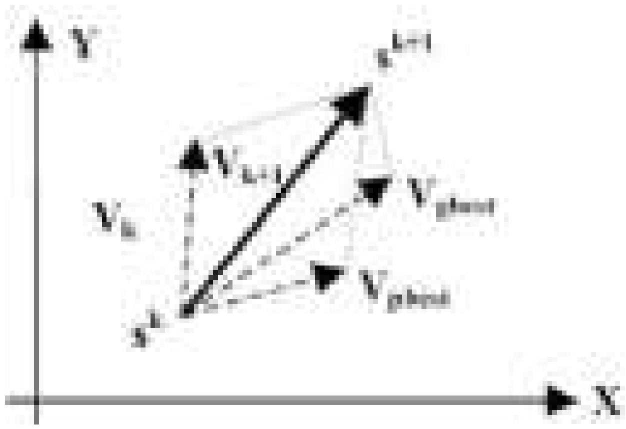

Figure-4. Concept of a searching point by PSO.

This modification can be represented by the concept of velocity. Velocity of each agent can be modified by the following equation:

$$v_{id}^{k+1} = \omega v_{id}^{k} + c_1 rand \times \left(pbest_{id} - s_{id}^{k}\right) + c_2 rand \times \left(gbest_{d} - s_{id}^{k}\right) \tag{5}$$

Using the above equation, a certain velocity, which gradually gets close to pbest and gbest can be calculated. The current position (searching point in the solution space) can be modified by the following equation:

$$S_{id}^{k+1} = S_{id}^{k} + v_{id}^{k+1} \tag{6}$$

where s^k is current searching point, s^{k+1} is modified searching point, $v^k$is current velocity, $v^{k+1}$is modified velocity of agent *i*, v_{pbest} is velocity based on pbest,, v_{gbest} is velocity based on gbest, n is number of particles in a group, *m* is number of members in a particle, $pbest_i$ is pbest of agent *i*, $gbest_i$ is gbest of the group, ω_i is weight function for velocity of agent *i*, C_i is weight coefficients for each term.
The following weight function is used:

$$\omega_i = \omega_{\max} - \frac{\omega_{\max} - \omega_{\min}}{k_{\max}} . k \tag{7}$$

Where, ω_{min} and ω_{max} are the minimum and maximum weights respectively. *K* and $k_{\max}$ are the current and maximum iteration. Appropriate value ranges for C_1 and C_2 are 1 to 2, but 2 is the most appropriate in many cases. Appropriate values for ω_{min} and ω_{max} are 0.4 and 0.9 [18], respectively.

ARPN Journal of Engineering and Applied Sciences

4.2. Problem formulation

$$Min\left\{P_{Lt} = \sum_{i=1}^{n} \left|I_i\right|^2 R_i\right\} \tag{8}$$

Subject to voltage constraints:

$$\left|V_{i\,\min}\right| \le \left|V_i\right| \le \left|V_{i\,\max}\right| \tag{9}$$

Current constriants:

$$\left|I_{ij}\right| \le \left|I_{ij\,\max}\right| \tag{10}$$

Where I_i is the current flowing through the i^{th} branch which is dependent on the locations and sizes of the DGs. Locations determined by fuzzy method are given as input.so the objective function is now only dependent on the sizes of the DGs at these locations.

R_i is the resistance of the i^{th} branch.

V_{imax} and V_{imin} are the upper and lower limits on i^{th} bus voltage.

I_{ijmax} is the maximum loading on branch ij.

The important operational constraints on the system are addressed by equations 8 and 9.

4.3. Algorithm to find the DG sizes at desired locations using PSO algorithm

The PSO-based approach for finding sizes of DGs at selected locations to minimize the real power loss is as follows:

Step 1: Randomly generates an initial population (array) of particles with random positions and velocities on dimensions in the solution space. Set the iteration counter *k* = 0.

Step 2: For each particle if the bus voltage and line loading are within the limits, calculate the total real power loss. Otherwise, that particle is infeasible.

Step 3: 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 4: 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 Gbest.*

Step 5: Maximum fitness and average fitness values are calculated. Error is calculated using the equation 7.

Error = (maximum fitness - average fitness) … (11S)

If this error is less than a specified tolerance then go to step 9.

Step 6: Update the velocity and position of particle using equations (5) and (6), respectively.

Step 7: New fitness values are calculated for the new positions of all the particles. If the new fitness value for any particle is better than previous pbest value then pbest value for that particle is set to present fitness value. Similarly gbest value is identified from the latest pbest values.

Step 8: The iteration count is incremented and if iteration count is not reached maximum then go to step 2.

Step 9: gbest particle gives the optimal DG sizes in *n* candidate locations and the results are printed.

5. RESULTS AND DISCUSSIONS

First load flow is conducted for IEEE 33 bus test system [7]. The power loss due to active component of current is 136.9836 kW and power loss due to reactive component of the current is 66.9252 kW. Optimal DG locations are identified based on the DSI values. For this 33 bus system, four optimal locations are identified. The candidate locations with their DSI values are given in Table-2.

Table-2. Buses with DSI values.

Bus No.	DSI
32	.92
30	.7982
31	.75
18	.75

With these locations, sizes of DGs are determined by using PSO algorithm described in section 4. The sizes of DGs are dependent on the number of DG locations. Generally it is not possible to install many DGs in a given radial system. Here 4 cases are considered. In case I only one DG installation is assumed. In case II two DGs, in case III three DGS and in the last case four DGs are assumed to be installed. DG sizes in the four optimal locations, total real power losses before and after DG installation for four cases are given in Table-3.

Table-3. Results of IEEE 33 bus system.

Case	Bus locations	DG sizes (Mw)	Total size (MW)	Losses before DG installation (kW)	Loss after DG installation (kW)	Saving (kW)	saving/ DG size
I	32	1.2931	1.2931	203.9088	127.0919	76.817	59.405
II	32	0.3836	1.5342	203.9088	117.3946	86.5142	56.39
	30	1.1506					
III	32	0.2701	1.5342	203.9088	117.3558	86.553	56.41
	30	1.1138					
	31	0.1503					
IV	32	0.27006	1.86176	203.9088	90.4794	113.4294	60.93
	30	0.8432					
	31	0.1503					
	18	0.5982					

The last column in Table-3 represents the saving in Kw for 1 MW DG installation. The case with greater ratio is desirable. The first case is economically best than other cases but the saving is not maximum. In case 2 and 3 total size of DGs and savings are almost same but the number of DGs are two in case 2 and three in case 3. So case 3 can be discarded because of high installation cost. In case 4 maximum saving is achieved but the numbers of DGs are four. Though the ratio of DG size to saving is minimum of all cases which represent optimum solution but the numbers of DGs involved are four so it is not economical by considering the cost of installation of 4 DGs. But in view of reliability, quality and future expansion of the system it is the best solution.

Table-4 shows the minimum voltage and % improvement in minimum voltage compared to base case for all the four cases. In all the cases voltage profile is improved and the improvement is very significant in case 4. The voltage profile for all cases is shown in Figure-5.

Table-4. Voltage improvement with DG placement.

Case No.	Bus No.	Min. voltage	% change
Base case	18	0.9118	
Case 1	18	0.9314	2.149
Case 2	18	0.9349	2.533
Case 3	18	0.9349	2.533
Case 4	14	0.9681	6.175

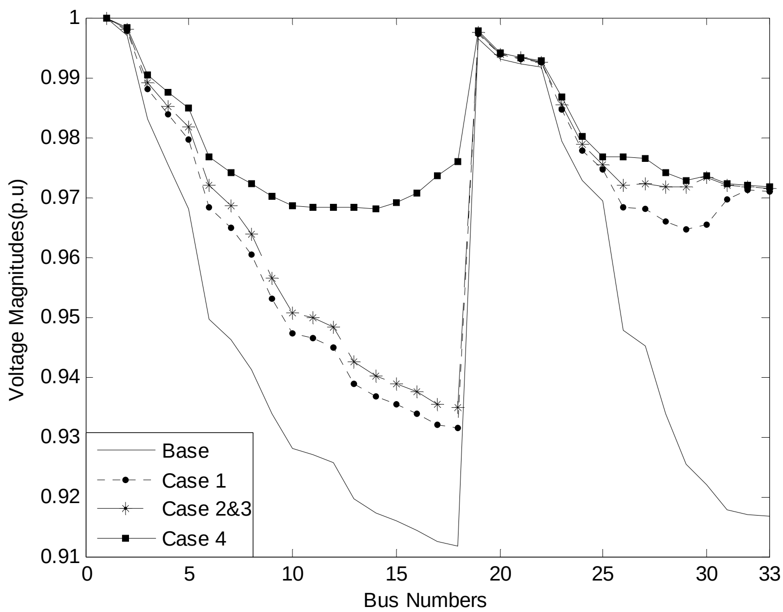

Figure-5. Voltage profile with and without DG placement.

Table-5 shows % improvements in power loss due to active component of branch current, reactive component of branch current and total active power loss of the system in the four cases considered. The loss due to active component of branch current is reduced by more than 50% in least and nearly 80% at best. Though the aim is reducing the P_{La} loss, the P_{Lr} loss is also reducing due to improvement in voltage profile. From Table-VI it is observed that the active power loss is reduced by 37% in case 1 and 55% in case 4.

Table-5. Loss reduction by DG placement.

Case No.	P_{La} (kW)	**% Saving**	P_{Lr} (kW)	**% Saving**	P_{Lt} (kW)	**% Saving**
Base case	136.9836	----	66.9252	----	203.9088	----
Case 1	62.7085	54.22	64.3834	3.7979	127.0919	37.45
Case 2	53.6323	60.847	63.7623	4.726	117.3946	42.43
Case 3	53.5957	60.874	63.7601	4.729	117.3558	42.45
Case 4	27.8837	79.64	62.5957	6.469	90.4794	55.63

Table-6. Loss reduction by DG placement

Case No.	P_{La} (kW)	**% Saving**	P_{Lr} (kW)	**% Saving**	P_{Lt} (kW)	**% Saving**
Base case	136.9836	----	66.9252	----	203.9088	----
Case 1	62.7085	54.22	64.3834	3.7979	127.0919	37.45
Case 2	53.6323	60.847	63.7623	4.726	117.3946	42.43
Case 3	53.5957	60.874	63.7601	4.729	117.3558	42.45
Case 4	27.8837	79.64	62.5957	6.469	90.4794	55.63

The convergence characteristics of the solution of PSO for all the four cases are shown in Figure-6.

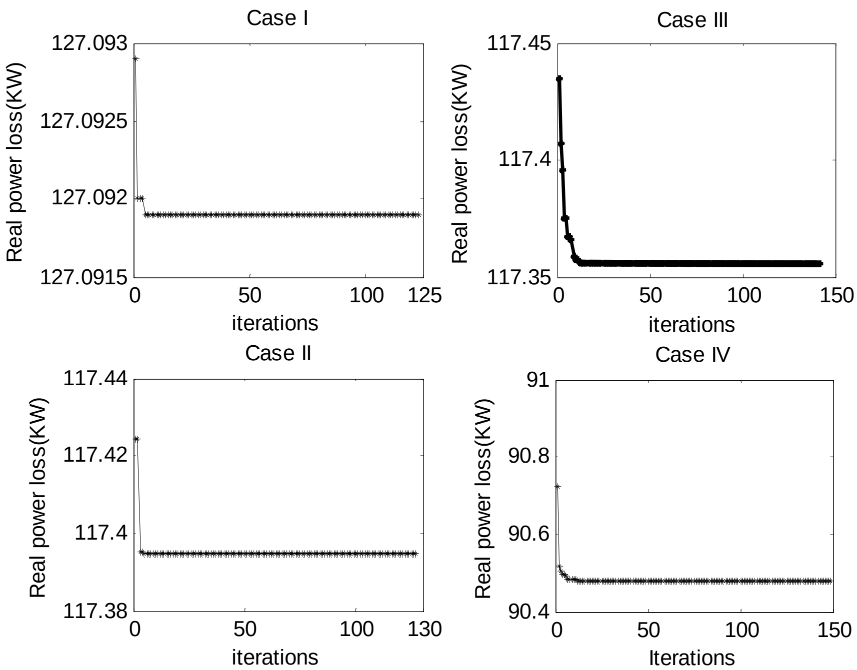

Figure-6. Convergence characteristic of the 33 bus test system.

Table-6 shows the minimum, average and maximum values of total real power loss from 100 trials of PSO algorithm. The average CPU time is also shown.

Table-6. Performance of PSO algorithm for IEEE 33 Bus System.

Total real power loss (kW)	**Case I**	**Case II**	**Case III**	**Case IV**
Min	127.0919	117.3946	117.3558	90.4794
Average	127.0919	117.3946	117.3558	90.4794
Max	127.0919	117.3946	117.3558	90.4794
Average time (Min.)	0.667	0.7715	0.9823	1.063

5.1. Comparison performance

A comparison of results by proposed method with an existing analytical method [15] is shown in Table-7.

Table-7. Comparison of results of 33-bus system by PSO method and other existing method.

Case	**Bus locations**	**Sizes** (Mw)		**Total size** (Mw)		**Saving** (Kw)	
		PM	**AM**	**PM**	**AM**	**PM**	**AM**
1	32	1.2931	1.1883	1.2931	1.1883	76.817	76.3619
2	32	0.3836	0.3244	1.5342	1.416	86.5142	86.0246
	30	1.1506	1.0916				
3	32	0.2701	0.2106	1.5342	1.416	86.553	86.0628
	30	1.1138	1.0551				
	31	0.1503	0.1502				
4	32	0.27006	0.2106	1.8423	1.86176	113.6166	113.4294
	30	0.8432	0.8031				
	31	0.1503	0.1502				
	18	0.5982	0.5803				

Savings by PSO algorithm are a little higher than the existing analytical method. The reason for this is in analytical method approximate loss formula is used. Table-8 shows comparison of voltage profile improvement by the two methods. The minimum voltage and % improvement in minimum voltage compared to base case for all the four cases, for the two methods discussed, are shown in this Table. For all the four cases the improvement is better for the PSO method.

Table-8. Comparison of voltage improvement.

Case No.	**Min voltage**		**% improvement**	
	PM	**AM**	**PM**	**AM**
Base case	0.9118		---	
Case 1	0.9314	0.9299	2.149	1.985
Case 2	0.9349	0.9333	2.533	2.358
Case 3	0.9349	0.9333	2.533	2.358
Case 4	0.9681	0.9659	6.175	5.933

From the above Tables it is clear that beyond producing the results that matches with those of existing method, proposed method has the added advantage of easy implementation of real time constraints on the system like time varying loads, different types of DG units etc., to effectively apply it to real time operation of a system.

6. CONCLUSIONS

In this paper, a two-stage methodology of finding the optimal locations and sizes of DGs for maximum loss reduction of radial distribution systems is presented. Fuzzy approach is proposed to find the optimal DG locations and a PSO algorithm is proposed to find the optimal DG sizes. Voltage and line loading constraints are included in the algorithm.

This methodology is tested on IEEE 33 bus system. By installing DGs at all the potential locations, the total power loss of the system has been reduced drastically and the voltage profile of the system is also improved. Inclusion of the real time constrains such as time varying loads and different types of DG units and discrete DG unit sizes into the proposed algorithm is the future scope of this work.

REFERENCES

[1] G. Celli and F. Pilo. 2001. Optimal distributed generation allocation in MV distribution networks. Power Industry Computer Applications. Pica 2001. Innovative Computing For Power - Electric Energy Meets The Market. 22nd IEEE Power Engineering Society International Conference. pp. 81-86.

[2] P.A. Daly, J. Morrison. 2001. Understanding the potential benefits of distributed generation on power delivery systems. Rural Electri Power Conference, 29 April- 1 May. pp. A211- A213.

[3] P. Chiradeja, R. Ramakumar. 2004. An approach to quantify the technical benefits of distributed generation. IEEE Trans Energy Conversion. 19(4): 764-773.

[4] Kyoto Protocol to the United Nations Framework Convention on climate change. http://unfccc.int/resource/docs/convkp/kpeng.html

[5] R.E. Brown, J. Pan, X. Feng and K. Koutlev. 1997. Siting distributed generation to defer T and D expansion. Proc. IEE. Gen, Trans and Dist. 12: 1151-1159.

[6] E. Diaz-Dorado, J. Cidras, E. Miguez. 2002. Application of evolutionary algorithms for the planning of urban distribution networks of medium voltage. IEEE Trans. Power Systems. 17(3): 879-884.

[7] M. Mardaneh, G. B. Gharehpetian. 2004. Siting and sizing of DG units using GA and OPF based technique. TENCON. IEEE Region 10 Conference. 3: 331-334, 21-24.

[8] Silvestri A. Berizzi, S. Buonanno. 1999. Distributed generation planning using genetic algorithms. Electric Power Engineering, Power Tech Budapest 99, Inter. Conference. p. 257.

[9] Naresh Acharya, Pukar Mahat, N. Mithulanathan. 2006. An analytical approach for DG allocation in primary distribution network. Electric Power and Energy Systems. 28: 669-678.

[10] G. Celli, E. Ghaini, S. Mocci and F. Pilo. 2005. A multi objective evolutionary algorithm for the sizing and sitting of distributed generation. IEEE Transactions on power systems. 20(2): 750-757.

[11] G. Carpinelli, G. Celli, S. Mocci and F. Pilo. 2005. Optimization of embedded sizing and sitting by using a double trade-off method. IEE proceeding on generation, transmission and distribution. 152(4): 503-513.

[12] C.L.T. Borges and D.M. Falcao. 2006. Optimal distributed generation allocation for reliability, losses and voltage improvement. International journal of power and energy systems. 28(6): 413-420.

[13] Wichit Krueasuk and Weerakorn Ongsakul. Optimal Placement of Distributed Generation Using Particle Swarm Optimization. M. Tech Thesis. AIT, Thailand.

[14] M. E. Baran and F. F. Wu. 1989. Network reconfiguration in distribution systems for loss reduction and load balancing. IEEE Transactions on Power Delivery. 4(2): 1401-1407.

[15] M. Padma Lalitha, V.C. Veera Reddy, N. Usha. 2009. Optimal DG placement for maximum loss reduction in radial distribution system. International journal of emerging technologies and applications in engineering, technology and sciences.

[16] M. Padma Lalitha, V.C. Veera Reddy, N. Usha. 2009. DG placement using Fuzzy for maximum loss reduction in radial distribution system. International journal of computers applications in engineering, technology and sciences. (Accepted).

[17] Kennedy J and Eberhart R. 1995. Particle Swarm Optimizer. IEEE International Conference on Neural Networks (Perth, Australia), IEEE Service Center Piscataway. NJ, IV, pp. 1942-1948.

[18] Eberhart, R.C. and Shi Y 2000. Comparing inertial weights and Constriction factor in particle Swarm optimization. Proceeding of the 2000 International Congress on Evaluationing Computation, San Diego, California, IEEE Service Center, Piscataway. NJ. pp. 84-88.