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Optimal allocation of distributed generator in a radial distribution system using genetic algorithm and particle swarm optimization

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Many areas in power systems require solving one or more nonlinear optimization problems. Optimal allocation of distributed generators (DGs) is one of them. This paper proposes two optimization methods to determine the optimal allocation of distributed generators in radial distribution systems (RDS), for the purpose of maximizing power loss reduction and improving voltage profile. The proposed methodology uses Genetic Algorithm (GA) and Particle Swarm Optimization (PSO) to optimize the objective function and is used to compare it with the analytical method of optimization. The Genetic Algorithm and Particle Swarm Optimization methods are tested on a standard radial distribution test systems, which is, IEEE 33 bus RDS using MATLAB R2008b. The results indicate that the optimal location of the DG is at bus number 6, with a power loss reduction of 83.3 kW.

Keywords: *Radial Distribution system/network (RDS/RDN), Distributed Generator (DG), Genetic Algorithm (GA), Particle Swarm Optimization (PSO).*

1.0 INTRODUCTION

The rising concern about environmental pollution has made Distributed Generators (DG) to be a convenient substitute of the fast depleting centralized systems. Their successfully integration into the network using new-generation technologies and power electronics have attracted many investors. Despite these advantages many issues are however, still pending concerning the integration of DGs within the existing power system networks; that require special attention [1–2].

Specifically the integration has changed the system from passive network to active networks and the change has serious impact on both the reliability and operation of the network as a whole [3]. In addition to that, the non-optimal placement of DG can result in an increase in the system power losses and the consequence is that the voltage profile can fall below the allowable limit [4]. Hence optimal placement of DG is highly required in order to minimize overall power system losses and therefore improve voltage profiles as utilities are seriously facing technical and non-technical issues, which may likely compound the situation.

Chiradeja and Ramkumar [5] have presented a general approach and set of indices to assess and quantify the technical benefits of DG in terms of voltage profile improvement, line loss reduction and environmental impact reduction. Khan and Choudry [6] have developed an algorithm based on analytical approach to improve the voltage profile and to reduce the power loss under distributed load conditions with low power factor for single DG as well as multiple DG systems.

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Hung et al. [7] has used an improved analytical method for identification of the best location and optimal power factor for placing multiple DGs to achieve loss reduction in large scale primary distribution networks. Kamel and Karmanshahi [8] have proposed an algorithm for optimal sizing and siting of DGs at any bus in the distribution system to minimize losses and found that the total losses in the distribution network would reduce by nearly 75%, if DGs were located at the optimal locations with optimal sizes.

Genetic Algorithm and Particle Swarm Optimization (PSO) algorithm are evolutionary algorithms used in optimization problems. They also find applications in power system as described in [9].

In this paper application of GA and PSO to determine optimal allocation of DG proved to be an efficient technique. The effectiveness of this approach is demonstrated on an IEEE standard radial distribution system (RDS) (33-bus). The active power loss with DG is taken as the objective function to be minimized. The methods proposed are simple and requires less computational time for determining optimal placement and sizing of DG when compared to the analytical and other evolutionary optimization methods.

2.0 FORMULATION OF OBJECTIVE FUNCTION

In any optimization process, it is important to define the objective function to be optimized.

2.1 Total Real Power loss in a distribution system

The total I^2R loss (P_{Lt}) (in watts (W)) in a distribution system having *nb* number of branches is given by:

$$P_{Lt} = \sum_{i=1}^{nb} I_i^2 R_i \quad ....(1)$$

Here I_i is the magnitude of the i^{th} branch current (in amperes (A)) and R_i is the resistance of the i^{th} branch (in ohms (Ω)) 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 reacting components of branch currents can be written as:

$$P_{La} = \sum_{i=1}^{nb} I_{ai}^2 R_i \quad ....(2)$$

$$P_{Lr} = \sum_{i=1}^{nb} I_{ri}^2 R_i \quad ....(3)$$

Where I_{ai} = Real $\{I_i\}$ and Iri = Img $\{I_i\}$

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 component of branch currents are compensated and losses due to active component of branch current is reduced. This topic 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.

2.2 Methodology

Assume that a single-source radial distribution system with *nb* branches and a DG is to be placed at bus *m* and α be a set of branches connected between the source and bus m. the DG produces active current IDG, and for a radial network it changes only the active component of current of branch set α. The current of other branches ($\notin = \alpha$) are unaffected by the DG. Thus the new active current I_{ai}^{new} (in amperes (A)) of the i^{th} branch is given by

$$I_{ai}^{new} = I_{ai} + D_i I_{DG} \quad ....(4)$$

Where Di = 1; if branch i ∊ α
= 0; otherwise

The loss P_{La}^{com} (in watts (W)) associated with the active component of branch currents in the compensated currents in the compensated system (when the DG is connected) can be written as

$$P_{La}^{com} = \sum_{i=1}^{nb} (I_{ai} + D_i I_{DG})^2 R_i \quad \text{....(5)}$$

This equation represents the objective function. (Active power loss with DG).

The loss saving *S* (in watts (W))is the difference between equation (3) and (5) is given by

$$S = P_{La} - P_{La}^{com}$$

$$= -\sum_{i=1}^{nb} (2D_i I_{ai} I_{DG} + D_i^2 I_{DG}^2)\, R_i \quad \text{....(6)}$$

The DG current IDG that provides the maximum loss saving can be obtained from

$$\frac{\partial S}{\partial I_{DG}} = \sum_{i=1}^{nb} (D_i I_{ai} + D_i I_{DG})\, R_i = 0 \quad \text{....(7)}$$

Thus the DG current for the maximum loss saving is

$$I_{DG} = -\frac{\sum_{i=1}^{nb} D_i I_{ai} R_i}{\sum_{i=1}^{nb} D_i R_i} = -\frac{\sum_{i \in \alpha} I_{ai} R_i}{\sum_{i \in \alpha} R_i} \quad \text{....(8)}$$

The corresponding DG size is

$$P_{DG} = V_m I_{DG} \quad \text{....(9)}$$

V_m is the voltage magnitude of the bus m. The optimum size of the DG for each bus is determined using eqn. (9). The DG location with highest loss saving is identified as candidate location for single DG placement.

3.0 GENETIC ALGORITHM (GA)

Genetic Algorithms are the main paradigm of evolutionary computing. GAs are inspired by Darwin's theory about evolution – the *"survival of the fittest"*. In nature, competition among individuals for scanty resources results in the fittest individuals dominating over the weaker ones.

(i) GAs are the ways of solving problems by mimicking processes nature uses: i.e., *Selection, Cross-over, Mutation and Accepting*, to evolve a solution to a problem.

(ii) GAs are *adaptive heuristic search* based on the evolutionary ideas of natural selection and genetics.

(iii) GAs are intelligent exploitation of *random search* used in optimization problems.

(iv) GAs, though randomized, exploit *historical information* to direct the search into the region of better performance within the search space.

Figure 1 shows the general scheme of process of GA.

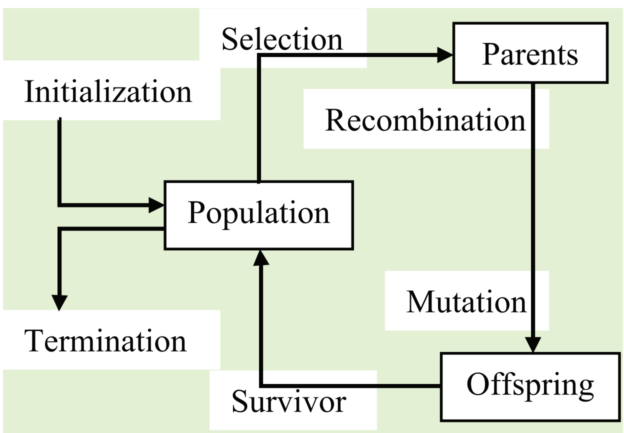

FIG. 1 GENERAL SCHEME OF PROCESS OF GA

The following algorithm describes the steps for determination of optimal location and size of a Distribution Generator (DG) in a Radial Distribution test network using Genetic Programming.

Step 1: Read the line data and bus data of the given test system. Read maximum iterations

Step 2: Identify the substation bus. Conduct distribution load flow analysis [10] on the test system and store the branch currents and bus voltages.

Step 3: Calculate the real power loss using eq. (2).

Step 4: Initialize a population of random number of particles (chromosomes). Each chromosome corresponds to a bus number. Initialize iteration count to zero.

Step 5: Calculate the active power losses with DG (fitness values) of these chromosomes using eq. (5).

Step 6: Select the parents for mating using Roulette-wheel selection.

Step 7: Generate offsprings from the selected parents using Heuristic (or Arithmetic) crossover operator.

Step 8: Mutate the offsprings using Uniform mutation operator and a use defined mutation rate. Check whether the chromosomes are within bounds. If not, set these chromosomes to the upper bound or lower bound solutions of the search space.

Step 9: Incorporate the mutated offsprings into the new generation of population.

Step 10: Increment the iteration count. If iteration count reaches maximum iteration then go to next step. Otherwise, go back to step 5.

Step 11: Using Roulette-wheel selection rules, the chromosome with least power loss (fitness value) is the candidate location for DG placement. Calculate the size of the DG at this location using the eq. (9).

4.0 PARTICLE SWARM OPTIMIZATION (PSO)

Particle Swarm Optimization (PSO) is another evolutionary computation technique developed by Eberhart and Kennedy in 1995, which was inspired by social behavior of bird flocking and fish schooling. PSO has its roots in artificial life and social psychology, as well as in engineering and computer science. It utilizes a “population” of particles that fly through the problem hyperspace with given velocities. At each iteration, the velocities of the individual particles are stochastically adjusted according to the historical best position for the particle itself and the neighborhood best position. Both the particle best and the neighborhood best are derived according to a user defined fitness function. The movement of each particle naturally evolves to an optimal or near-optimal solution. The word “swarm” comes from the irregular movements of the particles in the problem space, now more similar to a swarm of mosquitoes rather than a flock of birds or school of fish.

While GA can rapidly locate good solutions, even for difficult search spaces, it has some disadvantages associated with it:

Unless the fitness function is defined properly, GA may have a tendency to converge towards local optima rather the global optimum of the problem.

Operating on dynamic data sets is difficult;

For specific optimization problems, and given the same amount of computation time, simpler optimization algorithms may find better solutions than GAs.

PSO has some advantages over other similar optimization techniques such as GA, namely the following.

PSO is easier to implement and there are fewer parameters to adjust.

In PSO, every particle remembers its own previous best value as well as the neighborhood best; therefore, it has a more effective memory capability than the GA.

PSO is more efficient in maintaining the diversity of the swarm (more similar to the ideal social interaction in a community), since all the particles use the information related to the most successful particle in order to improve themselves, whereas in GA, the worse solutions are discarded and only the good ones are saved; therefore, in GA the population revolves around a subset of the best individuals.

In the real number space, each individual possible solution can be modeled as a particle that moves through the problem hyperspace. The position of each particle is determined by the vector $x_i \in \mathbb{R}^n$ and its movement by the velocity of the particle $x_i \in \mathbb{R}^n$ as shown in (10).

$$\vec{v_i}(t) = \varphi_{ic}\vec{v_i}(t-1) + \varphi_1 . r_1 . (\vec{p_b} - \vec{x_i}(t-1)) + \varphi_2 . r_2 . (\vec{p_g} - \vec{x_i}(t-1)) \quad \text{....(10)}$$

$$\vec{x_i}(t) = \vec{x_i}(t-1) + \vec{v_i}(t) \quad \text{....(11)}$$

Where φ_1, φ_2 and φ_{ic} are positive numbers and r1 and r2 are two random numbers with uniform distribution in the range of [01].

The velocity update equation in (10) has three major components.

(i) The first component is sometimes referred to as *"inertia", "momentum"*, or *"habit"*. It models the tendency of the particle to continue travelling in the same direction it has been travelling. This component can be scaled by a constant as in the modified versions of PSO.

(ii) The second component is a linear attraction towards the best position ever found by the given particle: p_b (whose corresponding fitness value is called the particle's best: p_{best}), scaled by a random weight $\varphi_1 . r_1$. This component is referred to as *"memory"*, *"self-knowledge"*, *"nostalgia"*, or "remembrance".

(iii) The third component of the velocity update equation is a linear attraction towards the best position found by any particle: p_g (whose corresponding fitness value is called global best: g_{best}), scaled by another random weight $\varphi_2 . r_2$. This component is referred to as *"co-operation"*, *"social knowledge", "group knowledge",* or *"shared information"*.

In general, the maximum value for sum of the constants should be 4.0, meaning $\varphi_1 + \varphi_2 = 4$. A good starting point has been proposed in numerous references to be $\varphi_1 = \varphi_2 = 2$.

The general expression for the inertia weight can be given as

$$\varphi_{ic} = (\max\_iter - iter)/\max\_iter \quad \text{....(12)}$$

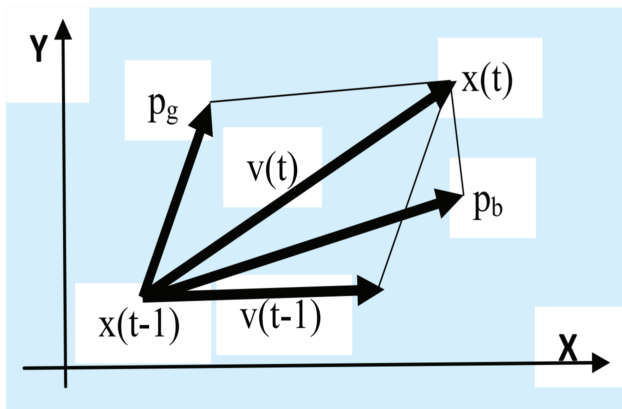

FIG. 2 CONCEPT OF SEARCH BY PSO

Since the search space in an integer search space, the Integer PSO is used in order find the optimal location of the DG to minimize the active power loss of the network (fitness function). Figure 2 shows the concept of search by PSO.

The following algorithm describes the steps for determination of optimal location and size of a Distribution Generator (DG) in a Radial Distribution test network using Particle Swarm Optimization (PSO).

Step 1: Read the line and bus data of the radial distribution test system. Read maximum iterations.

Step 2: Identify the substation bus. Conduct distribution load flow analysis [10] on the test system and store the branch currents and bus voltages.

Step 3: Calculate the real power loss using eq. (2).

Step 4: Generate an initial population of particles. Each particle corresponds to bus location. Set iteration count to zero. Read the constants of memory component and social component.

Step 5: Calculate the active power losses with DG (fitness values) of these particles using eq. (5).

Step 6: For each particle, compare objective values of present position with its local best (P_{best}) and in case the value is less than that P_{best} then set this value as current $P_{best.}$

Step 7: Compare the minimum of the objective values of P_{best} with that of g_{best}, in case it is less than that of g_{best} then set that as new g_{best} value and record particle position.

STEP 8: Update velocity and position of the particle using equation (10) and (11). Calculate inertia weight using (12).

Step 9: Increase iteration count by 1 and repeat steps 5 to 8 until iteration count reaches maximum iteration or if convergence criteria (standard deviation of particles is close to zero) is satisfied.

Step 10: The particle with the minimum power loss is the best particle and the bus location corresponding to that particle is the candidate location for optimal allocation of DG.

Step 11: Determine the DG size at the candidate location using eq. (9).

5.0 SIMULATION RESULTS

The Analytical method [4], Genetic Algorithm and Particle Swarm Optimization methods for optimal allocation of Distribution Generator (DG) are carried out for the IEEE 33-bus RDN system using MATLAB R2008b software.

The following table show the comparison between the Analytical method, Genetic Algorithm and Particle Swarm Optimization methods. The base MVA is taken as 30 MVA and base kV is taken as 11 kV for all three systems for distribution load flow. The operating power factor is taken as 0.8.

The active power loss without DG placement is **135.9** kW

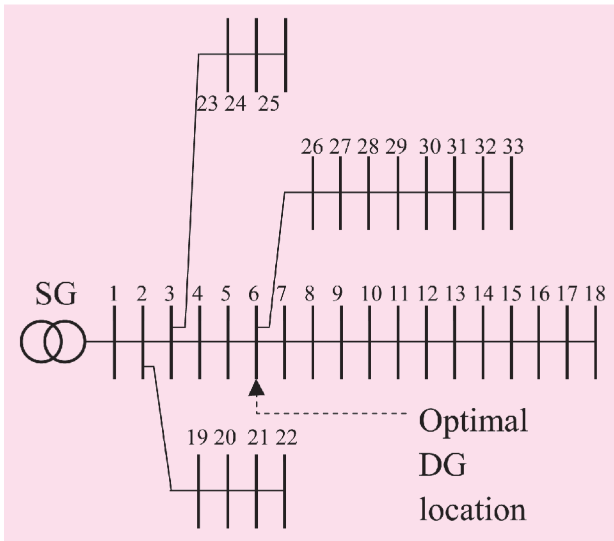

FIG. 3 SINGLE LINE DIAGRAM OF IEEE 33- BUS RDS, WITH BUS 6 AS THE OPTIMAL DG LOCATION (SG-SUBSTATION GENERATOR)

(i) The optimal location of DG placement for minimum power loss is bus number 6.

(ii) The minimum power loss after placing DG at the optimal location is **52.7 kW.**

(iii) Hence, the maximum power loss savings is **83.3 kW.**

(iv) The optimal size of the DG is **2.5 MW.**

(v) The percentage reduction in power loss is **61.26%.**

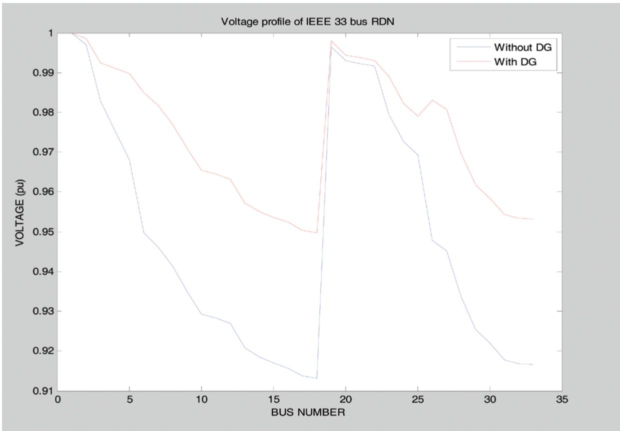

FIG. 4 VOLTAGE PROFILE OF IEEE 33 BUS RDN (WITH AND WITHOUT DG)

The single line diagram, line and bus data for IEEE 33-bus Radial Distribution Network can be found in the reference [10].

The following Table 1 depicts some of the power loss savings of connecting a DG at various nodes, and also the power loss savings at the optimal location.

TABLE 1

COMPARISON OF POWER LOSS SAVINGS AT DIFFERENT LOCATIONS OF DG PLACEMENT

DG location	**Power loss savings (kW)**
6	**83.3** (max)
18	51.3
22	33.8
33	65.0

Here, power loss savings is the difference between power loss with DG and power loss without DG.

The following Table 2 shows the comparison of processing time required by each optimization method to obtain the optimal solution.

TABLE 2

COMPARISON OF OPTIMIZATION PROCESSES

Optimization Method	**Processing time (sec)**
Analytical Method	2.4
GA	0.21
PSO	0.18

6.0 CONCLUSION

Distribution Generators (DG) interconnection to distribution system provides many techno economic benefits which depends on its allocation in the distribution system. So siting and sizing of DG is a key issue in planning of Distributed Generation.

Solving an optimization problem is one of the common scenarios that occur in most engineering applications. As the complexities of the problem increase, more complicated optimization techniques have to be used. However, these analytical methods are not easy to implement for most of the real-world problems. The issues are of particular importance when solving optimization problems in a power system. As a highly non-linear, non-stationary system with noise and uncertainties, a power network can have a large number of states and parameters. Hence we resort to evolutionary computational techniques.

This paper presents two methods, the Genetic Algorithm (GA) and Particle Swarm Optimization (PSO), for optimal allocation of DG considering active power loss reduction as the objective function. The following conclusions can be drawn based on the simulation results.

(a) It is apparent that there is considerable reduction in power loss and more importantly there is considerable improvement in the voltage profile of the distribution network, which is a practical problem of many rural distribution system and also critical from the operation point of customer equipments connected to it which face problem of voltage drop very often.

(b) The GA and PSO algorithms are faster compared to the analytical method of single DG placement. The PSO algorithm, in particular, is faster and simpler compared to GA. This is because PSO particles are more efficient in maintaining diversity of the swarm than the chromosomes of GA, and also there are much fewer parameters to adjust in PSO when compared to GA.

7.0 SCOPE FOR FUTURE WORK

In reality, Radial Distribution systems may contain distribution transformers (which have not been included in this paper). They may easily be incorporated into the calculations for bus voltage and branch current calculations using the method proposed in this paper.

Also, the active and reactive power demands are specified as constant values. In actual power system operations, different categories and types of loads might be present. The nature of these types of loads is such that active and reactive power are dependent on the voltage and frequency of the system. Common static loads for active and reactive power are expressed in a polynomial or an exponential form. Such loads can be incorporated into the load data and tested.

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