Optimal Size and Location of Distributed Generations using Differential Evolution (DE)

Israfil Hussain
Electrical Engg. Dept, Royal Group of Institutions
Guwahati, Assam, India
israfilhussain1@yahoo.co.in

Anjan Kumar Roy
Electrical Engg. Dept National Institute of Technology
(NIT), Silchar, Assam, India
anjan_kumarroy@rediffmail.com

***Abstract*— To improve the overall efficiency of power system, the performance of distribution system must be improved. This paper presents a new methodology using Differential Evolution (DE) for the placement of DG units in electrical distribution systems to reduce the power losses and to improve the voltage profile. Unlike the conventional evolutionary algorithms that depend on predefined probability distribution function for mutation process, differential evolution uses the differences of randomly sampled pairs of objective vectors for its mutation process. The Due to the increasing interest on renewable sources in recent times, the studies on integration of distributed generation to the power grid have rapidly increased. The distributed generation (DG) sources are added to the network mainly to reduce the power losses by supplying a net amount of power. In order to minimize the line losses of power systems, it is equally important to define the size and location of local generation. The suggested method is programmed under MATLAB software and is tested on IEEE 33-bus test system and the results are presented. The method is found to be effective and applicable for practical network**

***Keywords-component;* Distributed Generation, Power Loss Reduction, Differential Evolution**

I. INTRODUCTION

As a relatively new population-based optimization technique, differential evolution has been attracting increasing attention for a wide variety of engineering applications including power engineering. Unlike the conventional evolutionary algorithms that depend on predefined probability distribution function for mutation process, differential evolution uses the differences of randomly sampled pairs of objective vectors for its mutation process. Consequently, the object vectors' differences will pass the objective functions topographical information toward the optimization process and therefore provide more efficient global optimization capability.

Minimizing power loss by finding the optimal size, location and operation point of DG-unit was suggested in [8]. The authors of [9] employed the GA for Optimal Power Flow (OPF) to minimize the DG-unit's active and reactive power costs. Two examples of DG-unit optimization cases were considered, with and without reactive power injection. Significant reduction in the search space was attained by eliminating the DG-unit size. However, DG-unit dispatching can cause operational problems in the distribution feeders. An algorithm was offered in [10] to maximize the reduction of load supply costs as well as operational schedules for all feeder load levels exploiting EP. The optimal solution was selected based on maximum cost reduction, which was attained through evaluating the cost of DG-unit supply scenarios based on the base case.

Differential evolution was first proposed over 1994–1996 by Storn and Price atm Berkeley as a new evolutionary algorithm (EA) [1, 2]. Differential evolution (DE) is a stochastic direct search optimization method. It is generally considered as an accurate, reasonably fast, and robust optimization method. The main advantages of DE are its simplicity and therefore easy use in solving optimization problems requiring a minimization process with real-valued and multimodal (multiple local optima) objective functions. DE uses a non-uniform crossover that makes use of child vector parameters to guide through the minimization process. The mutation operation with DE is performed by arithmetical combinations of individuals rather than perturbing the genes in individuals with small probability compared with one of the most popular EAs, genetic algorithms (GAs). Another main characteristic of DE is its ability to search with floating point representation instead of binary representation as used in many basic EAs such as GAs. The characteristics together with other factors of DE make it a fast and robust algorithm as an alternative to EA, and it has found an increasing application in a number of engineering areas including power engineering.

II. FORMULATION OF OPTIMIZATION MODEL FOR LOS MINIMIZATION

A new method is introduced to minimize the losses associated with the absolute value of branch currents by optimally placing DG units. The problem of DG unit placement consists of determining the size, location and number of DG units to be installed in a distribution system such that maximum benefits are achieved while operational constraints at different loading levels are satisfied. The total power loss in a distribution system having 'n' number of branches is given by

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

I_i is the current magnitude and R_i is the resistance. I_i can be obtained from load flow study. The branch current has two components: active component I_a and reactive component I_r. The total losses associated with these two components can be written as

$$P_{TL} = P_{La} + P_{Lr} \quad (2)$$

$$P_{TL} = \sum_{i=1}^{n} I_{ai}^2 R_i + \sum_{i=1}^{n} I_{ri}^2 R_i \quad (3)$$

For a given configuration of a single source radial distribution network, the losses P_{La} associated with the active component of branch current cannot be minimized because all the active power must be supplied by the source at the root bus. This is not true if DG units are to be placed at different locations for loss reduction that is real power can be supplied locally by using DG units of optimum size to minimize P_{La} associated with the active component of branch current. However there is significant change in reactive power loss with DG unit in distribution system.

A. Identification of Optimal DG Location

This algorithm determines the optimal size and location of DG units that should be placed in the system to minimize loss. First optimum sizes of DG units for all nodes are determined for base case and best one is chosen based on the maximum loss saving. This process is repeated if multiple DG locations are required by modifying the base system by inserting a DG unit into the system one-by-one.

A. 1 Methodology

Consider RDN with 'n' branches. Let a DG unit be placed at bus 'm' and 'β' be a set of branches connected between the source and DG unit. If the DG unit is placed at bus 'X' then 'β' consists of branches X_1, X_2 X_3 …………, X_n. The DG unit supplies active component of current I_{DG} and for radial distribution network it changes only the active component of current of branch set 'β'. The current of other branches is not affected by the DG unit. Thus new active current I_{ai}^{new} of the i^{th} branch is given by

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

Where DG_i =1; if branch $i \in \beta$

=0; otherwise

I_{ai} is the active component of current of i^{th} branch in the original system obtained from the load flow solution. The P_{La}^{com} is associated with the active component of branch currents in the compensated system. For a DG unit placed at node 'k', the system losses are

$$P_{La}^{com} = \sum (I_{ai} + DG_i I_{DG})^2 R_i + \sum_{k+1}^{n} I_{ai}^2 R_i + \sum_{i=1}^{n} I_{ri}^2 R_i \quad (5)$$

The power saving, S is the difference between equation 8 and 10 due to the introduction of DG unit at node 'k' is given by

$$S = P_{La} - P_{La}^{com}$$
$$= -2 I_{DG} \sum_{i=1}^{n} DG_i I_{ai} R_i - I_{DG}^2 \sum_{i=1}^{k} DG_i R_i \quad (6)$$

The DG current I_{DG} that provides maximum saving can be obtained from

$$\frac{\delta S}{\partial I_{DG}} = -2 \sum_{i=1}^{n} DG_i I_{ai} R_i - I_{DG} \sum_{i=1}^{k} DG_i R_i = 0 \quad (7)$$

The DG current for maximum saving is

$$I_{DG} = -\frac{\sum_{i=1}^{k} DG_i I_{ai} R_i}{\sum_{i=1}^{k} DG_i R_i}$$

$$I_{DG} = -\frac{\sum_{i \in \beta} I_{ai} R_i}{\sum_{i \in \beta} R_i} \quad (8)$$

The corresponding DG size is

$$P_{DG} = V_k I_{DG} \quad (9)$$

V_k is the magnitude of voltage at bus k.The optimum size of DG at each bus is determined using eqn (9). Then saving for each DG is determined using eqn (6).The DG with highest saving is the candidate location for DG placement. When the candidate bus is identified and DG is placed, the load flow is carried out to calculate the new loss and new voltage.

An advantage of deploying DG-units in distribution networks is to minimize the total system real power loss while satisfying certain operating constraints. The power flow algorithm offered in [8] is applied in this paper.

The mathematical formulation of the mixed integer nonlinear optimization problem for the DG-unit application is as follows:

1. The objective function is minimizing the total system real power loss as follows:

$$Obj.Fun. = \min \sum_{i=1}^{n} I_i^2 R_i \quad (10)$$

2. The inequality constraints are the system's voltage limits i.e., ±5% of the nominal voltage value.

$$|V_{\min}^{spec}| \le |V_i^{sys}| \le |V_{\max}^{spec}| \qquad i = 1, 2, 3 \ldots n \quad (11)$$

3. In addition, the thermal capacity limits of the network's feeder lines are treated as inequality constraints:

$$S_{i,i+1}^{sys} \le S_{i,i+1}^{rated} \ge S_{i+1,i}^{sys} \quad i = 1, 2, \ldots n \quad (12)$$

4. The boundary (discrete) inequality constraints are the DG-unit' size (kVA) as follows:

$$| S_{DG}^{\min} | \leq | S_{DG} | \leq S_{DG}^{\max} \qquad i = 1, 2, 3 \ldots\ldots n \qquad (13)$$

Since the DGs are added to the system one by one, the sizes obtained by single DG placement algorithm are local optima not global optimum solution. The global optimal solution is obtained if multiple DGs are simultaneously placed in the system by using DE algorithm. This method is explained in next section.

III. DE FUNDAMENTALS

As a member of the EA family, DE also relies on the initial population generation, mutation, crossover, and selection through repeated generations until the termination criteria is met. The fundamentals of DE are introduced accordingly in the sequel.

1 Initial Population
2 Mutation and Recombination to Create New Vectors
3 Selection and the Overall DE

1. Initial Population

DE is a parallel direct search method using a population of N parameter vectors for each generation. At generation G, the population P^G is composed of x_i^G , i = 1, 2, . . . , N. The initial population P^{G0} can be chosen randomly under uniform probability distribution if there is nothing known about the problem to be optimized:

$$X_i^G = X_{i(L)} + rand[0,1] * (X_{i(H)} - X_{i(L)}) \text{-----}(14)$$

where $X_{i(L)}$ and $X_{i(H)}$ are the lower and higher boundaries of d-dimensional vector $X_i = \{x_{i,j}\} = \{x_{i,1}, x_{i,2}, x_{i,3}, \ldots x_{i,N}\}^T$. If some a priori knowledge is available about the problem, the preliminary solution can be included to the initial population by adding normally distributed random deviations to the nominal solution.

2. Mutation and Crossover/Recombination to Create New Vectors

The key characteristic of a DE is the way it generates trial parameter vectors throughout the generations. A weighted difference vector between two individuals is added to a third individual to form a new parameter vector. The newly generated vector will be evaluated by the objective function. The value of the corresponding objective function will be compared with a predetermined individual. If the newly generated parameter vector has lower objective function value, it will replace the predetermined parameter vector. The best parameter vector is evaluated for every generation in order to track the progress made throughout the minimization process. The random deviations of DE are generated by the search distance and direction information from the population. Correspondingly, this adaptive approach is associated with the normally fast convergence properties of a DE.

Mutation in DE1

For each parent parameter vector, DE generates a candidate child vector based on the distance of two other parameter vectors. For each dimension j∈ [1, d], this process is shown in (23) as is referred to as scheme DE 1 by Storn and Price [1]:

$$X^{G+1} = X_{r3}^G + F \bullet (X_{r1}^G - X_{r2}^G) \text{----------}(15)$$

where the random integers r1≠ r2≠ r3≠i are used as indices to index the current parent object vector. As a result, the population size N must be greater than 3. F is a real constant positive scaling factor and normally F∈(0, 1+). F controls the scale of the differential variation ($X_{r1}^G - X_{r2}^G$) (Fig. 1) [1, 3].

Selection of this newly generated vector is based on comparison with another DE1 control variable, the crossover constant CR∈ [0, 1], to ensure the search diversity. Some of the newly generated vectors will be used as child vector for the next generation, and others will remain unchanged.

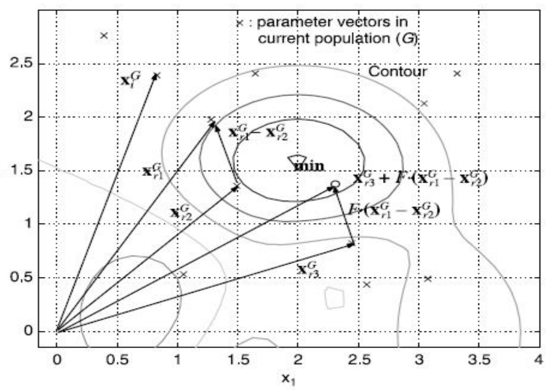


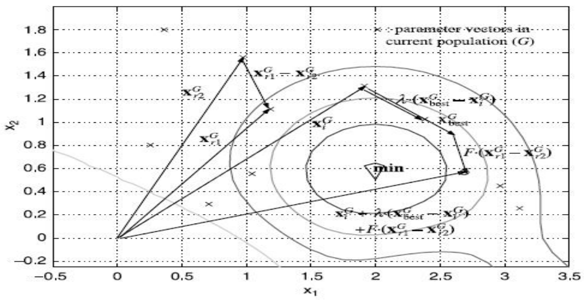
FIGURE 1 Vector representation of the child vector creation procedure with DE1 from vectors of current generation, where the dotted closed lines are the contour toward the minimal solution point.

Mutation in DE2

The DE1 scheme in creating a candidate vector can be revised to include the impact from the best vector X_{best}^G of the current generation. An additional control variable l is used in this so called DE2 scheme as shown in (3):

$$X^{G+1} = X_i^G + \lambda \bullet (X_{best}^G - X_i^G) + F \bullet (X_{r1}^G - X_{r2}^G) \text{----}(16)$$

where the current best vector through λ provides increased greediness of the search process. The contribution of the current best vector is shown in Fig.2. This is useful for noncritical objective functions. The same procedure can be used to ensure the search diversity by comparing with the crossover probability CR as shown in the pseudo-code for



creation procedure in DE (mutation and recombination).

FIGURE 2.Vector representation of the child vector creation procedure with DE2 from vectors of current generation, where the dotted closed lines are the contour toward the minimal solution point.

3. Selection and the Overall DE

The selection process of DE follows the typical EA process. Each new vector X is compared with xi. The new vector x0 replaces xi as a member of the next generation if it produces a better solution than xi. The procedure is given in [1, 3, 4–6].

IV. RESULTS AND DISCUSSION

The total loads of the 33-bus system are 3720 kW and 2300 kVar. Data of this system is given in [7].

Here four 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 I

Case	Bus Location	DG Sizes(MW)	Total Size (MW)
I	6	2.59	2.59
II	6	1.9023	2.55
	14	0.6469	
III	6	1.667	3.29
	14	0.7361	
	31	0.8904	
IV	6	0.7973	3.04
	14	0.6469	
	31	0.8188	
	24	0.7824	

TABLE II

Case	Losses after DG (KW)	Losses before DG (KW)	Saving (KW)	Loss Reduction %
I	110.89	210.84	99.95	47.40
II	91.29		119.55	56.70
III	78		132.84	63
IV	69.551		141.29	67.01

As the number of DGs installed is increasing the saving is also increasing. In case IV maximum saving is achieved but the number of DGs is four. Though case IV is optimal 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 III: Comparison of Voltage improvement

Case No.	Proposed Method Minimum Voltage	Proposed Method % Improvement
Base Case	0.9039	
Case-I	0.94681	4.53
Case-II	0.9543	5.28
Case-III	0.97603	7.38
Case-IV	0.97823	7.60

The voltage profile for all cases is shown in Figure 3, Figure 4, Figure 5 and Figure 6. In all the cases voltage profile is improved and the improvement is significant.

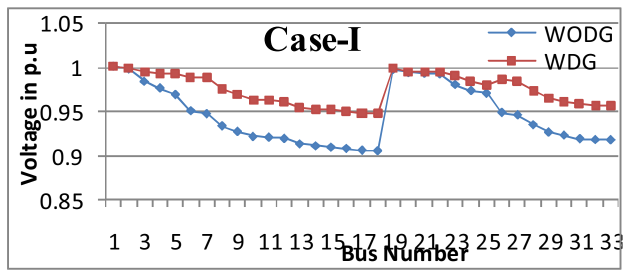


Figure 3

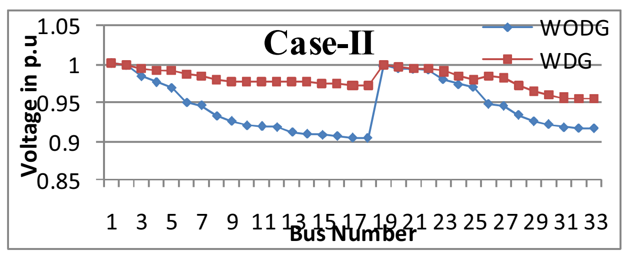


Figure 4

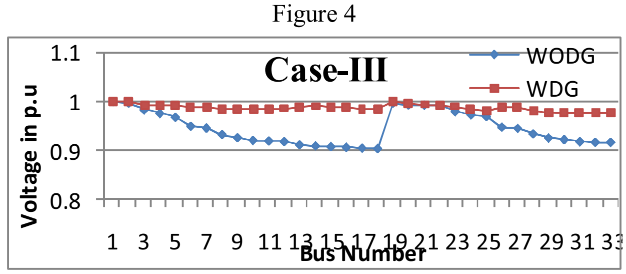


Figure 5

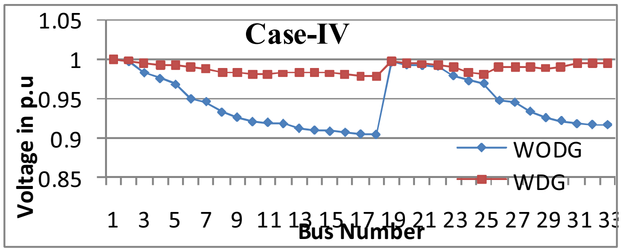


Figure 6

The convergence characteristics of ABC algorithm for all cases are shown in figure 7, figure 8, figure 9 and in figure 10

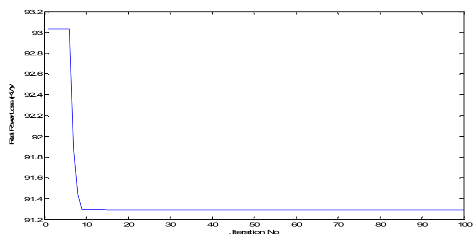


Figure 7

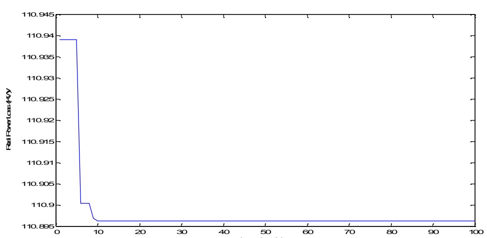


Figure 8

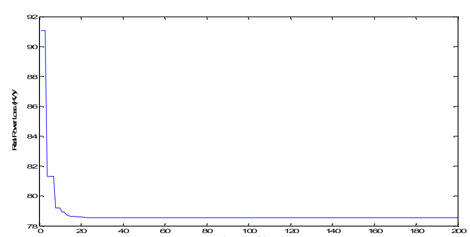


Figure 9

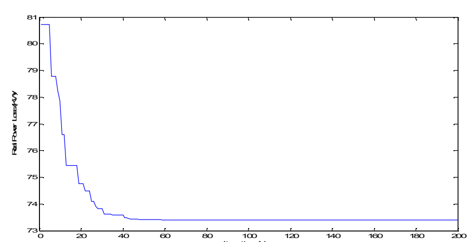


Figure 10

IV. CONCLUSION

This paper presents a method for determination of the optimal DG location in radial distribution network. The method utilizes a simple load flow method for calculation of power flow and losses in the network. The total system losses is used as an objective of the optimal DG problem.Differential evolution is an efficient heuristic algorithm for search and optimization.DE operates on floating point representation of variables to be optimized. Like other evolutionary algorithms, DE is capable of handling non convex, non differentiable complex optimization problems. The main advantages of a DE come from its simple but effective mutation process to ensure the search diversity as well as to enhance the search effectiveness with the information from the objective function directly. This chapter compared DE with other evolutionary algorithms to present DE as an alternative for EA. It should be noted that DE has been used in solving a variety of engineering optimization problems and is attracting more and more interest from scientists and engineers looking for an alternative optimization technique in many areas.

Evidently as Figures 7, 8, 9 and figure 10 demonstrated, that the DE algorithm has excellent solution quality and convergence characteristics. The performance of the proposed algorithm shows its superiority and potential for solving complex power system problems in future publications

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