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Optimal sizing and sitting of distributed generation using Particle Swarm Optimization Guided Genetic Algorithm

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ABSTRACT

This paper attempts to minimize losses and at the same time maintain acceptable voltage profiles in a radial distribution system. Distributed generation (DG) is a hot topic due to the ever increasing demands for electrical energy. Thus this paper optimally size and place DGs in appropriate buses in the system, making the problem such a way reducing real power losses, operating cost and enhancing the voltage stability, which becomes the objective function. Voltage profile improvement is considered as a constraint in finding the optimal placement of DG. Since the problem involves optimization of variables, a new hybrid optimization method integrating two powerful well established techniques is proposed. The prime idea of the proposed technique is to utilize the key features of both techniques to collectively and effectively search for better optimization results. The proposed algorithm is applied and demonstrated on the IEEE 33- and 69-bus distribution systems. The results obtained depict the effectiveness of the proposed hybrid GA-PSO algorithm in comparison with those of GA and PSO methods when applied independently.

Keywords: Distributed generation, Genetic algorithm, particle swarm optimization, hybrid technique

INTRODUCTION

This topic of placing and optimal sizing of renewable energy systems also known as DG in the existing power system network seems to be significant in the present situation, there is a quantum of literature exists for the past two decades. Perhaps the complexity involved in this problem paves way for new optimization techniques, there are plenty of literatures depicts the usage of traditional techniques to solve the problem [1]. This paper will review a few literatures recently addresses this problem. In such a way, a method is proposed for locating and sizing DG units to improve the voltage stability margin, using the mixed-integer nonlinear programming, so as to taking into account the probabilistic nature of load and DG, thereby prioritizing buses which are sensitive to voltage profile and thus improve the voltage stability margin.

In [2], a new solution method based on a Bacterial Foraging Optimization algorithm is proposed to reduce the total power loss and to improve the voltage profile of the radial distribution systems, in the presence of Distributed Generation unit. Similarly in [3], a new metaheuristic, population-based optimization approach that employs an artificial bee colony (ABC) algorithm to determine the optimal DG-unit's size, power factor, and location in order to minimize the total system real power loss. Following this, an improved non-dominated sorting genetic algorithm-II (INSGA-II) has been proposed for optimal planning of multiple distributed generation (DG)[4]. First, multiobjective functions that take minimum line loss, minimum voltage deviation, and maximal voltage stability margin into consideration have been formed. Then, using the proposed INSGA-II algorithm to solve the multiobjective planning problem has been described in detail.

Subsequently in [5], Particle Swarm Optimization (PSO) algorithm is used to solve the multi-objective problem. The PSO method is found more advantageous than the previous work in terms of voltage profile improvement, maximization of system loadability, reduction in power system losses and maximization of bus and line voltage stability.

In a recent advancement, a hybrid configuration of ant colony optimization (ACO) with artificial bee colony (ABC) algorithm called hybrid ACO–ABC algorithm is presented [6], for optimal location and sizing of distributed energy resources The proposed algorithm is a combined strategy based on the discrete (location optimization) and continuous (size optimization) structures to achieve advantages of the global and local search ability of ABC and ACO algorithms, respectively.

Consequently, an ordinal optimization (OO) method for specifying the locations and capacities of distributed generation (DG) such that a trade-off between loss minimization and DG capacity maximization is presented in [7]. Similarly, in [8], a new optimization algorithm based on integrating the use of genetic algorithms and tabu search methods to optimal allocation of dispersed generation resources in distribution networks. The proposed algorithm finds how much distribution losses can be reduced if dispersed generations are optimally allocated at the demand side of power system.

In [9], a Mixed Integer Non-Linear Programming (MINLP) formulation for loss minimization is proposed. Here the problem has two phases, namely Siting Planning Model (SPM) and Capacity Planning Model (CPM) thereby reducing the search space and computational time. In [10], a simple and efficient approach for the placement of multiple Distributed Generators (DG) in a radial distribution system. The approach determines the optimal locations and size of DGs with the objective of improving the voltage profile and loss reduction. Loss sensitivity factors (LSF) are used to select the candidate locations for the multiple DG placements and Simulated Annealing (SA) is used to estimate the optimal size of DGs at the optimal locations determined.

A hybrid method based on improved particle swarm optimization (IPSO) algorithm and Monte Carlo simulation is proposed in [11]. The proposed algorithm is applied to the practical 33-bus distribution system and results are compared with other versions of PSO and artificial bee colony (ABC) algorithm. Similarly, in [12], a harmony search algorithm with differential operator is proposed to install multiple DG units optimally in distribution system with an objective of minimizing active power loss and improving voltage profile [13,14].

Based on the above review of literature in solving the optimal sizing and placement of DG, this paper is proposing a new hybrid algorithm that integrates the GA and the PSO in more effective way to solve the placement and sizing problem.

Problem formulation

The problem of optimally 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, which becomes the objective function.

The objective function is given in eqn (1)

$$F_t = w_1 f_1 + w_2 f_2 + w_3 f_3 \tag{1}$$

The line losses are described in eqn (2)

$$f_1 = \frac{\sum_{i=1}^{L} \left(p_{lineloss}(i)\right)_{afterDG}}{\sum_{i=1}^{L} \left(p_{lineloss}(i)\right)_{beforeDG}} \tag{2}$$

Voltage profile of the system is given in eqn (3)

$$f_2 = \frac{\sum_{i=1}^{N} \left| V_i - V_{i,ref} \right|_{afterDG}}{\sum_{i=1}^{N} \left| V_i - V_{i,ref} \right|_{beforeDG}} \tag{3}$$

The VSI is described in eqn (4)

$$f_3 = \frac{1}{VSI(k)_{afterDG}} \tag{4}$$

Such that,

$$VSI(k) = |V_i|^4 - 4\left(P_k \cdot X_{ik} - Q_k \cdot R_{ik}\right)^2 - 4\left(P_k \cdot R_{ik} + Q_k \cdot X_{ik}\right) \cdot |V_i|^2$$

Apart from these technical formulations, the constraints that decide the optimality of the solution is formulated below:

The weighting factors are subject to eqn (5)

$$|w_1| + |w_2| + |w_3| = 1 \tag{5}$$

Followed by the load flow equations as constraints:

$$P_{swing} + \sum_{i=1}^{N_{DG}} P_{DG}(i) = \sum_{i=1}^{L} P_{lineloss}(i) + \sum_{q=1}^{N} Pd(q) \tag{6}$$

$$Q_{swing} + \sum_{i=1}^{N_{DG}} Q_{DG}(i) = \sum_{i=1}^{L} Q_{lineloss}(i) + \sum_{q=1}^{N} Qd(q) \tag{7}$$

The voltage profile constraints:

$$V_{\min} \le |V_i| \le V_{\max} \tag{8}$$

The load flow equations considering Distributed generations:

$$\sum_{i=1}^{N_{DG}} P_{DG}(i) \le \frac{3}{4} \times \left[\sum_{i=1}^{L} P_{lineloss}(i) + \sum_{q=1}^{N} Pd(q)\right] \tag{9}$$

$$\sum_{i=1}^{N_{DG}} Q_{DG}(i) \le \frac{3}{4} \times \left[\sum_{i=1}^{L} Q_{lineloss}(i) + \sum_{q=1}^{N} Qd(q)\right] \tag{10}$$

The real power limits of the Distributed generation

$$P_{DG}^{\min} \le P_{DG}(i) \le P_{DG}^{\max} \tag{11}$$

The reactive power limits of the Distributed generation

$$Q_{DG}^{\min} \le Q_{DG}(i) \le Q_{DG}^{\max} \tag{12}$$

The line flow of the various lines in the considred test system:

$$S_{Li} \leq S_{Li(rated)} \tag{13}$$

The main purpose of the above problem formulation is optimally size and place DGs in appropriate buses in the system, making the problem such a way reducing real power losses, operating cost and enhancing the voltage stability.

PROPOSED SOLUTION METHODOLOGY

This section will describe how two powerful optimization algorithms inspired by natural selection are integrated together to effectively solve complex optimization problems. Two powerful algorithms widely applied in several literature to solve complex engineering optimization problems: one is GA and the other is PSO. Since both the algorithms are sufficiently discussed in detail in several published literatures, this paper will give an overview of these methods and will describe the proposed hybrid GA-PSO method subsequently.

A. Genetic Algorithm: An Overview

GA is a randomized search method inspired based on biological evolutionary rue of survival of the fittest [15]. GA starts its search from the set of population strings that are assumed as potential solutions, randomized within the search range. Inspired by natural evolution, the algorithm will evolve new potential solutions called as off-springs from previous parents. Perhaps GA is limited for exploration features, causing slow or poor convergence and poor robustness. Thus problems like premature convergence and trapping local optima are prone when dealing complex optimization problems.

B. Particle swarm optimization: An Overview

PSO is one of the latest evolutionary techniques developed by Eberhart and Kennedy [16,17]. PSO is inspired based on social interaction of bird flocking or fish schooling. The particles also called as potential solutions, move throughout the multidimensional solution space and the positions of each particles were adjusted according to its own best position, and best among all its group. PSO does fall under the survival of the fittest algorithm as the entire group will be used from beginning to end. Slow or poor convergence and poor robustness are again a demerit for PSO.

C. Proposed architecture of the hybrid GA-PSO:

The main idea behind this proposal is, after the fitness evaluations are made for each parent in the present population, selection will be done using roulette wheel and two parents are selected based on their fitness ranking and crossover will be performed. In this crossover, two parents will share their chromosomes to produce two off-springs, which will be the new parent in the next generation.

Unlike this regular crossover, which will lead to possible dramatic change in search direction due to crossover exchange, among this two parents the best individual will be used as gbest and the other one will be retained as pbest. Thus only one parent will be disturbed and produced by this operation derived from PSO. This will help the hybrid algorithm to search the space exhaustively [18]. Additionally this PSO operation will not be done for the entire crossover phase, instead a random of 50% in the beginning stage and gradually reduced to 5% of the total population in the entire run of the algorithm.

$$x_i^{k+1} = x_i^k + v_i^{k+1} \tag{14}$$

$$v_i^{k+1} = v_i^k + c_1 rand(x_i^k - pb) + c_2 rand(x_i^k - gb) \tag{15}$$

As an example, let us assume two parents are selected for crossover as shown in Fig 1. The fitness value for parent A, B and offspring is 13458, 8889, 8850 respectively. Now instead of this, we use a velocity equation to update the position of parent B using the idea derived from PSO and the equation is given for reference.

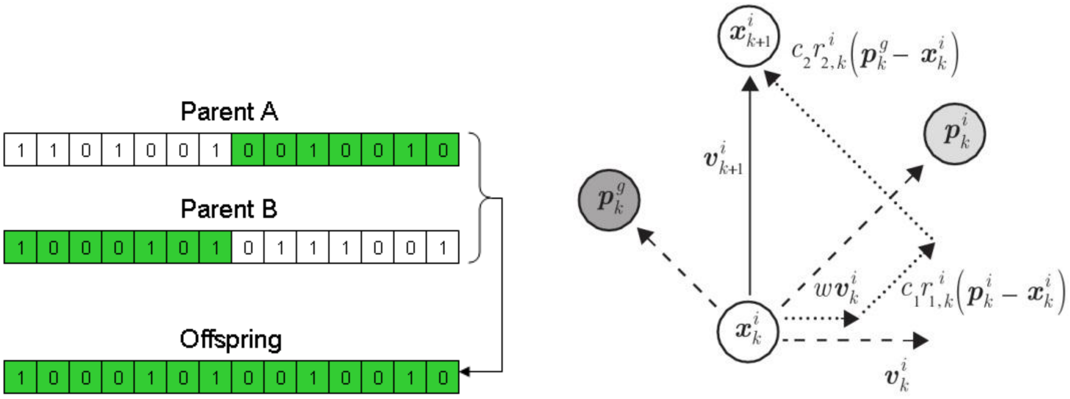

Figure 1(a). Crossover operation in GA **(b).** Velocity and position update in PSO

Here the gbest is 13458, pbest is 8889. With regular parameter setting the new position for parent B will be estimated as 7452 using the velocity and position update equation in (1 & 2). Thus the possibility of arriving at better results will be large when going for this hybridization approach. Thus the proposed shift of production of new population in GA will be guided by PSO with a 50% probability is established. A detailed flowchart of the proposed hybrid GA-PSO algorithm is shown in figure 2.

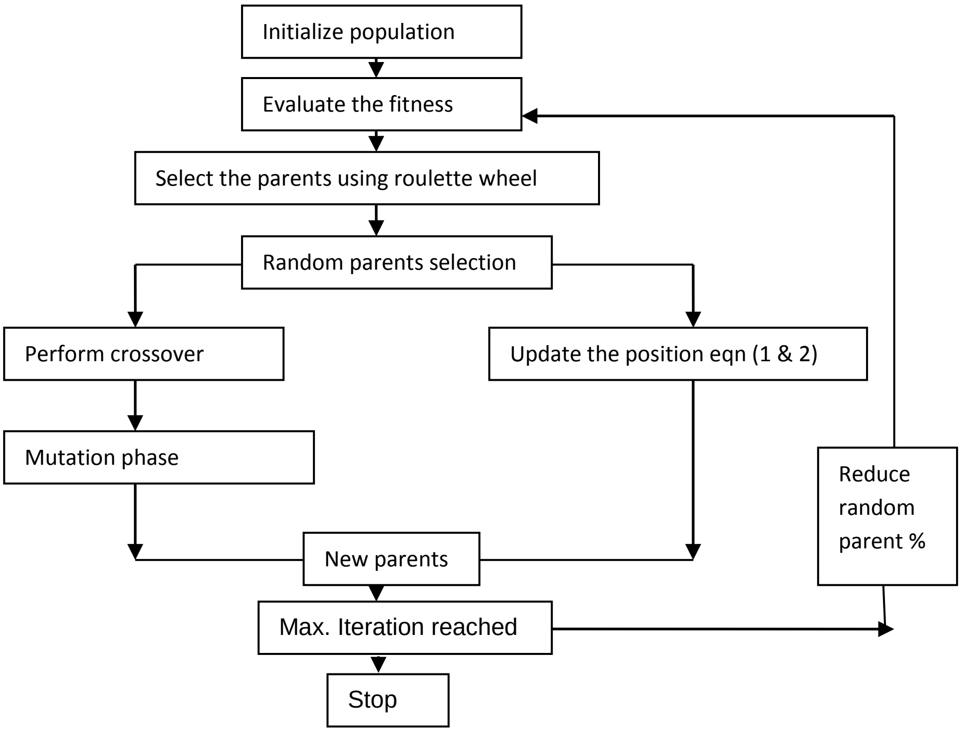

Figure 2. Flowchart of the proposed hybrid GA-PSO

The percentage of random parents selected will be reduced during the course of run from 50% to 5% using the following equation (3):

$$rndprnt = ((0.5 - 0.05) / \max iter) \times iter \qquad (16)$$

In the next section the proposed algorithm will simulated for 2 benchmark problems to optimally place and size the DG in distributed network.

NUMERICAL SIMULATIONS:

To illustrate the effectiveness of the proposed hybrid approach, two well established test systems, an IEEE-33 bus and IEEE-69 bus systems are used in this section. The parameters of the PSO and GA are initialized for the hybrid algorithm and will be used throughout this simulation. Simulation results are obtained using the MATLAB simulator and the optimal location and sizing of DG unit are well demonstrated.

IEEE-33 Bus system results

The first demonstration using the proposed hybrid GA-PSO technique is conducted in a IEEE-33 bus system. The system parameters and other network data can be found in [13,14]. The system has 33 buses, 32 transmission lines with the total real power load of 3.72MW and the total reactive power load of 2.3 MVAr respectively. Loss sensitivity factor is the key aspect for the optimal placement of the DG. Obviously the bus which has high sensitivity is proficient of inducing voltage instability. The losses are estimated from the general load flow equations and the losses are listed in order. Thus the first three buses with higher transmission losses are considered for placing the DGs.

The final objective function values of the IEEE 33 bus system is summarized in Table 1. From the table it can be seen the objective function values of the proposed hybrid GA-PSO is better than those two methods when allowed to solve independently. The voltage profile of this system is shown in figure 3 for all the three techniques, where the proposed hybrid technique has proved its superiority over the other two methods. Similarly in figure 4, the voltage profiles are plotted for the proposed hybrid GA-PSO for both the DGs placed and before that.

Table 1: Performance analysis of the 33-bus system after DG installation.

Method	Objective function value				
	f1	f2	f3	Bus no.	DG size (MW)
Hybrid GA-PSO	0.1027	0.0121	1.0509	32 16 11	1.189 0.859 0.921
GA	0.1063	0.0407	1.0537	11 29 30	1.5 0.4228 1.0714
PSO	0.1053	0.0335	1.0804	13 32 8	0.9816 0.8297 1.1768

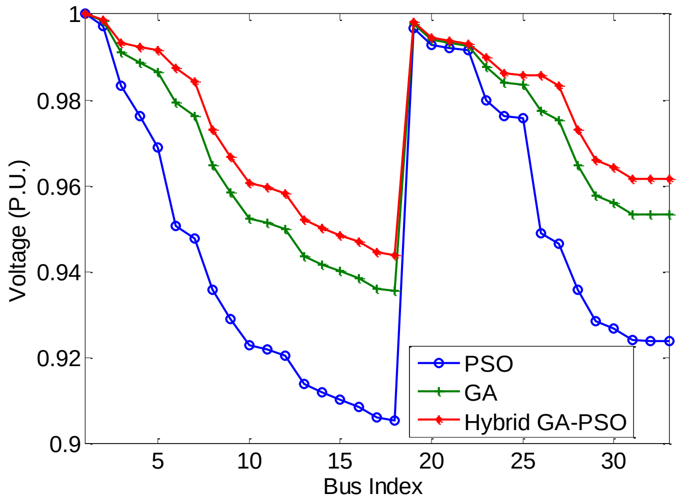

Figure 3: Voltage profile for the IEEE 33 bus system

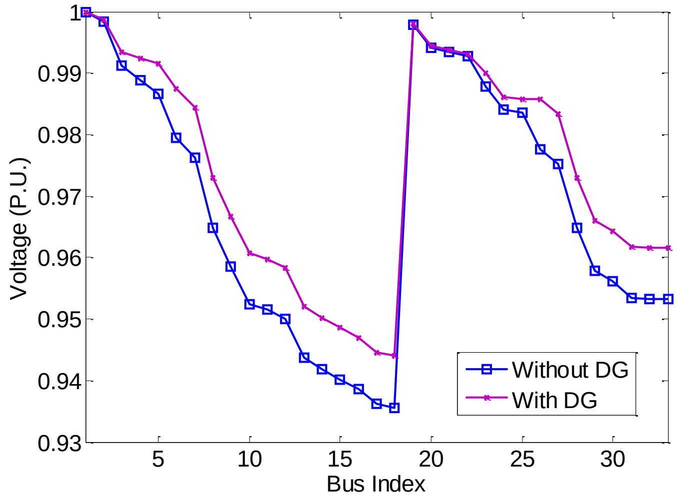

Figure 4: Voltage profile for the IEEE 33 bus system using the proposed method

IEEE-69 bus system results

The second demonstration using the proposed hybrid GA-PSO technique is conducted in a IEEE-69 bus system. The system parameters and other network data can be found in [13,14]. The system has 69 buses, 68 transmission lines with the total real power load of 3.80 MW and the total reactive power load of 2.69 MVAr respectively. Loss sensitivity factor is the key aspect for the optimal placement of the DG. Obviously the bus which has high sensitivity is proficient of inducing voltage instability. The losses are estimated from the general load flow equations and the losses are listed in order.

Thus the first three buses with higher transmission losses are considered for placing the DGs.

Table 2: Performance analysis of the 69-bus system after DG installation.

Method	Objective function value				
	f1	f2	f3	Bus no.	DG size (MW)
Hybrid GA-PSO	0.0807	0.0029	1.0231	63 61 21	0.8837 1.1918 0.9097
GA	0.089	0.0012	1.0303	21 62 64	0.9297 1.0752 0.9848
PSO	0.0832	0.0049	1.0335	61 63 17	1.1998 0.7956 0.9925

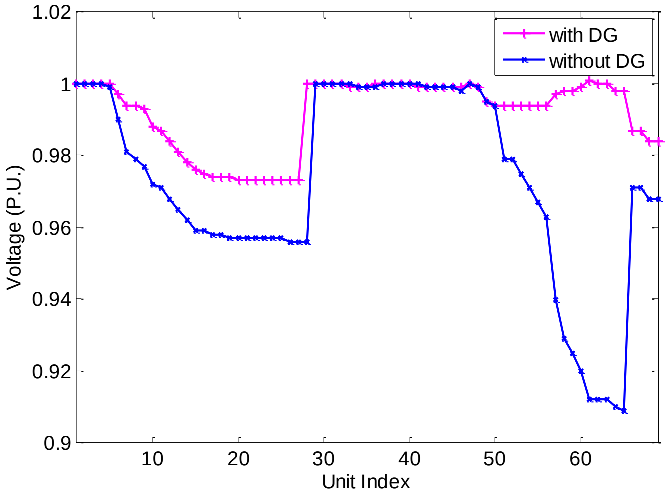

Figure 5: Voltage profile for the IEEE 69 bus system

The final objective function values of the IEEE 69 bus system is summarized in Table 2. From the table it can be seen the objective function values of the proposed hybrid GA-PSO is better than those two methods when allowed to solve independently. The voltage profile of this system is shown in figure 5, where the the voltage profiles are plotted for the proposed hybrid GA-PSO for both the DGs placed and before that.

CONCLUSION

This paper determines to minimize losses and at the same time maintain acceptable voltage profiles in a radial distribution system. Distributed generation (DG) is a hot topic due to the ever increasing demands for electrical energy. Thus this paper optimally size and place DGs in appropriate buses in the system, making the problem such a way reducing real power losses, operating cost and enhancing the voltage stability, which becomes the objective function. Voltage profile improvement is considered as a constraint in finding the optimal placement of DG. Since the problem involves optimization of variables, a new hybrid optimization method integrating two powerful well established techniques is proposed. The prime idea of the proposed technique is to utilize the key features of both techniques to collectively and effectively search for better optimization results. The proposed algorithm is applied and demonstrated on the IEEE 33- and 69-bus distribution systems. The main advantage of the proposed technique is that it is easy to implement and capable of finding feasible, optimal or near optimal solutions with less computational effort.

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