

# Optimal DG Allocation in Distribution Network

A. Safari, R. Jahani, H. A. Shayanfar, J. Olamaei

**Abstract**—This paper shows the results obtained in the analysis of the impact of distributed generation (DG) on distribution losses and presents a new algorithm to the optimal allocation of distributed generation resources in distribution networks. The optimization is based on a Hybrid Genetic Algorithm and Particle Swarm Optimization (HGAPSO) aiming to optimal DG allocation in distribution network. Through this algorithm a significant improvement in the optimization goal is achieved. With a numerical example the superiority of the proposed algorithm is demonstrated in comparison with the simple genetic algorithm.

**Keywords**--Distributed Generation, Distribution Networks, Genetic Algorithm, Particle Swarm Optimization.

## I. INTRODUCTION

NOWADAYS the Distributed Generation (DG) is taking more relevance and it is anticipated that in the future it will have an important role in electric power systems. DG includes the application of small generators, scattered throughout a power system, to provide the electricity service required by the customers. DG can be powered by both conventional and renewable energy sources [1]. Several DG options are fast becoming economically viable [2-10]. Technologies of the DG allocation can be obtained by a complete enumeration of all feasible combinations of sites and sizes of DGs in the network. The artificial intelligence techniques are the most widely employed tool for solving most of the optimization problems. These methods (e.g. genetic algorithm simulated annealing and tabu search) seem to be promising and are still evolving. The publications are on the DG allocation by application of genetic algorithm (GA) [11,12]. Tabu Search (TS) algorithm is used for the DG allocation in distribution systems [13]. Analytical approaches minimizing line losses were also utilized for the DG allocation as provided in [14]. In [15], the authors have integrated DG in distribution systems using power systems studies coupled with linear programming method. Analyzing these studies, the consideration of uncertainty in the DG allocation in distribution systems is neglected. Papers [16]-[17] utilized evolutionary programming for identifying the placement of DG in distribution systems.

A new hybrid algorithm for evaluation of the DG site and size in MV networks is proposed. The GA and PSO are employed for the DG allocation. The results showed that the

proposed combined GA and PSO method is better than the simple GA in terms of the solution quality and number of iteration.

## II. DISTRIBUTED GENERATION

Distributed generation is expected to become more important in the future generation system. In general, DG can be defined as electric power generation within the distribution networks or on the customer side of the network. A wide variety of DG technologies and types exists: renewable energy source such as wind turbines, photovoltaic, micro-turbines, fuel cells, and storage energy devices such as batteries. The importance of the DG is now being increasingly accepted and realized by power engineers. From the distribution system planning point of view, DG is a feasible alternative for new capacity, especially in the competitive electricity market environment and has immense benefit such as [18-19]:

- Short lead-time and low investment risk since it is built in modules.
- Small-capacity modules that can track load variation more closely.
- Small physical size that can be installed at load centers and does not need government approval or search for utility territory and land availability.
- Existence of a vast range of the DG technologies for these reasons, the first signs of a possible technological change are beginning to arise on the international scene, which could involve in the future the presence of a consistently generation produced with small and medium size plants directly connected to the distribution network (LV and MV) and characterized by good efficiencies and low emissions. This will create new problems and probably the need of new tools and managing these systems.

## III. PROBLEM FORMULATION

The problem is to determine allocation and size of the DGs which minimizes the distribution power losses for a fixed number of DGs and specific total capacity of the DGs. Therefore, the following assumptions are employed in this formulation [13, 20]:

- The maximum number of installable DGs is given ( $D$ ).
- The total installation capacity of the DGs is given ( $Q$ ).
- The possible locations for the DG installation are given for each feeder.
- The upper and lower limits of node voltages are given.
- The current capacities of the conductors are given.

The objective function in this optimization problem is:

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$$OF = \sum_{i=1}^n P_i \quad (1)$$

Where,  $P_i$  is the nodal injected power at bus  $i$ , and  $n$  is the total number of buses. If the total injected power of distributed generation was constant as  $C$  MW, this equality constraint should be expressed in form of a penalty function as shown [20]:

$$OF = \sum_{i=1}^n P_i + \alpha \left( \sum_{k=1}^L P_k - C \right) \quad (2)$$

#### Constraints:

Maximum number of DGs:

$$\begin{aligned} V_i &\leq V_n \pm \Delta V \\ I_i &\leq I_i^{\max} \\ (k &= 1, 2, \dots, L, l = 1, 2, \dots, M, g = 1, 2, \dots, N) \end{aligned} \quad (3)$$

Total capacity of DGs:

$$\sum_{l=1}^M \sum_{g=1}^N G_g n_{gl} \leq Q \quad (4)$$

One DG per installation position:

$$\sum_{g=1}^N n_{gl} \leq 1 \quad (5)$$

Upper and lower voltage limits:

$$V_i \leq V_n \pm \Delta V \quad (6)$$

Current capacity limits:

$$\begin{aligned} I_i &\leq I_i^{\max} \\ (k &= 1, 2, \dots, L, l = 1, 2, \dots, M, g = 1, 2, \dots, N) \end{aligned} \quad (7)$$

Where,

$P_i$  : Nodal injection of power at bus  $i$ ,

$P_k$  : Load power of bus  $k$ ,

$V_i$  : Magnitude of voltage of bus  $i$ ,

$V_n$  : Nominal magnitude of voltage in the network,

$G_g$  : Capacity of  $g^{\text{th}}$  DG,

$n_{gl}$  : 0-1 variable for determining whether one DG with  $g^{\text{th}}$  capacity is allocated at  $l^{\text{th}}$  location (1: allocated, 0: not allocated),

$L$  : Total number of load buses,

$M$  : Total number of DG location candidates,

$N$  : Total number of capacity types of DGs,

$Q$  : Total installation capacity of DGs,

$D$  : Maximum number of installable DGs,

$\alpha$  : Penalty weight of equality constraint,

$C$  : Total injected dispersed generation for network,

$\Delta V$  : Maximum permissible voltage deviation,

$I_i$  : Current of section  $i$ ,

$I_i^{\max}$  : Maximum current capacity of section  $i$ .

#### IV. IMPLEMENTATION OF HGPSOA

The genetic algorithm can handle any kind of objective functions and constraints without much mathematical requirements about the optimization problems. GA has been touted as a class of general-purpose search strategies for optimization problems. In GA, variables of a problem are represented as genes in a chromosome, and the chromosomes are evaluated according to their fitness values. GA starts with a set of randomly selected chromosomes as the initial population that encodes a set of possible solutions. Through natural selection and genetic operators, mutation and crossover, chromosomes with better fitness are found. The genetic operators alter the composition of genes to create new chromosomes called offspring. The selection operator is an artificial version of natural selection, a Darwinian survival of the fittest among population, to create populations from generation to generation, and chromosomes with better fitness have higher probabilities of being selected in the next generation.

The PSO starts with a population of random solutions "particles" in a D-dimension space. The  $i^{\text{th}}$  particle is represented by  $X_i = (x_{i1}, x_{i2}, \dots, x_{iD})$ . Each particle keeps track of its coordinates in hyperspace, which are associated with the fittest solution it has achieved so far. The value of the fitness for particle  $i$  (pbest) is also stored as  $P_i = (p_{i1}, p_{i2}, \dots, p_{iD})$ . The global version of the PSO keeps track of the overall best value (gbest), and its location, obtained thus far by any particle in the population. The PSO consists of, at each step, changing the velocity of each particle toward its pbest and gbest according to Eq. (1). The velocity of particle  $i$  is represented as  $V_i = (v_{i1}, v_{i2}, \dots, v_{iD})$ . Acceleration is weighted by a random term, with separate random numbers being generated for acceleration toward pbest and gbest. The position of the  $i^{\text{th}}$  particle is then updated according to Eq. (2) [13]:

$$\begin{aligned} v_{id} &= w \times v_{id} + c_1 \times \text{rand}() \times (P_{id} - x_{id}) \\ &\quad + c_2 \times \text{rand}() \times (P_{gd} - x_{id}) \end{aligned} \quad (8)$$

$$x_{id} = x_{id} + cv_{id} \quad (9)$$

Where,  $P_{id}$  and  $P_{gd}$  are pbest and gbest. The positive constants  $c_1$  and  $c_2$  are the cognitive and social components that are the acceleration constants responsible for varying the particle velocity towards pbest and gbest, respectively. Variables  $r_1$  and  $r_2$  are two random functions based on uniform probability distribution functions in the range [0, 1]. The use of variable  $w$  is responsible for dynamically adjusting the velocity of the particles, so it is responsible for balancing

between local and global searches, hence requiring less iteration for the algorithm to converge [12]. The following weighting function  $w$  is used in Eq. (1):

$$w = w_{\max} - \frac{w_{\max} - w_{\min}}{\text{iter\_max}} \text{iteration} \quad (10)$$

Where,  $\text{iter\_max}$  is the maximum number of iterations and  $\text{iteration}$  is the current number of iteration. The Eq. (3) presents how the inertia weight is updated, considering  $w_{\max}$  and  $w_{\min}$  are the initial and final weights, respectively [12]. The considered optimization problem can be solved by either particle swarm intelligence or genetic algorithm. A combination of GA and PSO is utilized to overcome the drawbacks of using each of them solely, named GAPSO optimization algorithm. Genetic algorithm has the capability of global optimum finding but low convergence speed near global optimum, on the contrary, PSO has high convergence speed but the probability of trapping on local optimum. In the proposed algorithm, individuals are coded to a chromosome that contains variables of the problem.

GA and PSO are applied to conduct searching optimum for the parameter set of the power system stability. The major steps of the proposed algorithm are:

*Step 1:* Define the varying range of the parameters and objective function over the parameters.

*Step 2:* Set generation  $\text{gen}=0$ .

*Step 3:* Initialize population of GA and particles of PSO.

*Step 4:* Evaluate population of GA and particles of PSO.

*Step 5:* Perform selection operator of GA.

*Step 6:* Perform crossover and mutation operators of GA.

*Step 7:* Modify each particle's searching point by Eqs. (8) and (9).

*Step 8:* Evaluate new population of GA and new particles of PSO.

*Step 9:* If the termination criterion has satisfied, then stop; otherwise  $\text{gen}=\text{gen}+1$  and go to step 5.

For the initialization of GA, the initial population  $P$  is generated randomly except that preferably one parameter set of the PSS are set by the expert. For GA, chromosomes encoded as the parameter set are encoded into binary string and the mapping from a binary string to a real number ( $r$ ) is calculated as follows:

$$r = \min_r + \text{binrep} \times \frac{(\max_r - \min_r)}{2^l - 1} \quad (11)$$

Where,  $\min_r$  is the minimum value of the input variable,  $\max_r$  the maximum value of the input variable, and  $\text{bin}$  represents the decimal value of length  $l$ . The traditional roulette selection with elitism is performed as the selection operator, and it ensures that the best chromosome is selected into the new generation, for GA. The two point crossover will act on parents to generate offspring. Mutation is keeping diversity in the population for the PSO. The initial particles  $p \in [\min_r, \max_r]$  are randomly generated, and new particles are created by Eqs. (9) and (10). The inertia weight,  $k$  is given by:

$$k = (k_1 - k_2) \times \frac{(\text{MAXGEN} - \text{gen})}{\text{MAXGEN}} - k_2 \quad (12)$$

Where,  $k_1$  and  $k_2$  are the initial and final values of weight, respectively;  $\text{gen}$  is the current generation number and  $\text{MAXGEN}$  is the maximum number of generation. The solution of the problem is represented by a binary coding. As in the example, 4 types of DGs are used for each MV candidate bus, 3 bits are considered for coding: one for presenting the DG on bus and 2 bits for type of the DG. The fitness for GA and PSO is computed by maximizing the inverse of overshoot, defined as:

$$\text{Fitness} = \frac{1}{OF} \quad (13)$$

Finally, the optimization process is repeated until the termination criterion has been satisfied. In this study, the size of the initial population for GA and PSO is 50.

## V. CASE STUDY

In order to test the proposed algorithm, the 34-node IEEE distribution test feeder has been considered [20]. A number of tests on the performance of the proposed algorithm have been carried out on the example to determine the most suitable HGAPSO parameters setting. Table 1 show the control parameters which have been chosen after running a number of simulations. Figure 1 shows the convergence process of the GA and HGAPSO when employed to solve the optimization problem of this test network.

TABLE I  
HGAPSO SETTING PARAMETERS

Population size	50
crossover probability	50
mutation probability	0.02
MAXGEN	100
$C_1, C_2$	1
$l$	10
$k_1$	0.9

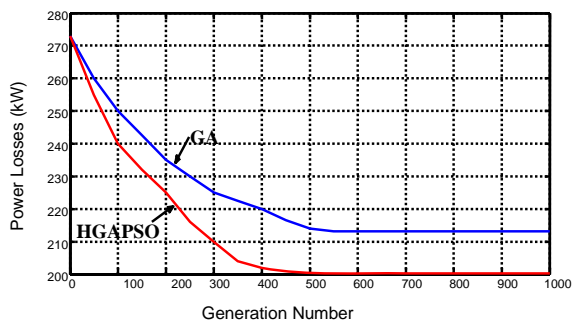


Fig. 1. Power losses reduction with generation number

In order to facilitate comparison with genetic algorithm, optimal allocation of DGs in this case study, the simple GA was used. Simulation result is given in Table II. It can be seen that the proposed method achieves good performance and decreases the power losses in comparison with the simple GA.

TABLE II  
COMPARISON GA AND HGAPSO

Algorithms	Total Capacity of Installed DG (kW)	Power Losses (kW) with DG
Simple GA	200	212.52
HGAPSO	200	200.24

VI. CONCLUSIONS

In this paper the results of application of hybrid genetic-particle swarm optimization algorithm to the optimal allocation of DGs in distribution network is presented. The allocation problem is converted into an optimization problem which is solved by a HGAPSO technique. The effectiveness of the proposed algorithm to solve the DG allocation problem is demonstrated through a numerical example. The IEEE 34-node distribution test feeders have been solved with the proposed algorithm and the simple genetic algorithm. The results demonstrated the better characteristics of the HGAPSO algorithm in comparison with the GA especially in terms of solution quality and number of iterations.

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