GENETIC ALGORITHMS PERFORMANCES ASSESSMENT FOR OPTIMAL LOCATION AND SIZING OF DISTRIBUTED GENERATION

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Lucrarea abordează problema amplasării optime a surselor de generare distribuită în reţelele electrice de distribuţie cu ajutorul algoritmilor genetici. Se studiază influenţa valorilor parametrilor interni ai algoritmilor genetici asupra performanţelor acestora. Rezultatele relevă o puternică legătură dintre aceste valori şi rezultatele obţinute, subliniînd necesitatea acordării parametrilor înaintea utilizării algoritmilor genetici.

The paper addresses the problem of optimal allocation of distributed generation sources in an electrical distribution network. The proposed solution method is based on genetic algorithms and the study is centered on the influence of genetic algorithms' parameters upon their performances. The results show that different parameter set-ups lead to different solutions and that a process of parameter tuning is necessary before using the genetic algorithms.

Keywords: distributed generation, genetic algorithms, selection methods, roulette wheel selection, crossover fraction.

1. Introduction

Distributed power generation (DG) refers to small generating units installed near load centers, avoiding the need to expand the network in order for it to cover new load areas or to support the increased energy transfers that would be necessary for satisfying the demand.

The challenge of identifying the optimal locations and sizes of DG has generated research interests all over the world and many efforts have been made in this direction.

Studies have indicated that inappropriate locations and sizes of DG may lead to higher system losses than the ones in the existing network [1].

Numerous papers have been written on this subject, referring to either "optimal capacity allocation" [2], "DG placement" [3] or even "capacity evaluation" [4].

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The literature suggests a wide variety of objectives and constraints, but two main approaches emerge: finding optimal locations for defined DG capacity and finding optimal capacity at defined locations.

Of all benefits and objectives of DG implementation, the idea of implementing DG for loss reduction needs special attention. This is why many studies have been performed on this matter, the following presentation being by no means exhaustive.

A very detailed study on the influence of DG location and size upon system losses is given in [5]. It is shown that, as the size of DG in increased at a particular bus, the losses are reduced, eventually reaching a minimum. If, however, the size is further increased, the losses start to increase as well and may become larger than the ones in the initial network. A conclusion that rises from this study is that DG size should only reach a capacity that can be consumed within the distribution substation boundary. This can be explained by the fact that the distribution system was initially designed for predicted power flows, and the new ones cannot be supported by the small-sized conductors. The need to prepare a methodology which is able to optimally designate DG allocation and sizing within a distribution network arises from the above-stated considerations.

Adaptations of genetic algorithms have been studied in papers like [6-9], with the objective of minimizing system losses and maintaining acceptable voltage levels.

An analytical approach is used in [6] to decide the appropriate DG location, based on losses and sensitivity analysis. Afterwards, a genetic algorithm (GA) is used to compute the optimal DG size to be installed at that location. The objective is to minimize the active power losses and the methodology is tested on the IEEE 69-bus network. Studies are performed for one and two distinct connection points for DG units, showing that smaller capacities lead to less power losses.

The approach presented in [7] also aims at minimizing the active power losses, but uses GAs to simultaneously search for both location and size of DG. The algorithm is run for different loading conditions (peak, medium and low), for a 10-bus, 33-bus and 75-bus system, concluding that losses vary with system loads.

A recent study [10] proposes a new approach, based on particle swarm optimization (PSO), considering an objective function consisting of voltage profile improvement index and line loss reduction index. Thus, the solution given by the PSO algorithm increases the maximum loadability of the system. The network used for testing was a 30-bus IEEE system.

This paper continues the work in [11, 12, 13] by perfecting GAs to optimize the allocation and sizing of DG. The objective is to minimize the active power

losses, while certifying acceptable loading conditions and voltage profiles through the network.

2. Problem formulation

Consider a distribution network, given by its impedance (depending on the characteristics of the conductor material and lengths), topology and the connected loads.

The objective of this study is to reduce active power losses by connecting a DG unit of optimal size, in an optimal location, keeping the voltage and branches loading within acceptable limits. This can be formulated as an optimization problem with the objective function depending on two integer variables: location and size of DG unit. This objective function can be written as:

$$
\begin{aligned}
O &= \sum_{i,j \in k} (P_i - P_j) = \\
&= \sum_{i=1}^{n} \sum_{j=1}^{n} \left(\frac{R_{ij} \cos(\delta_i - \delta_j)}{V_i V_j}(P_i P_j + Q_i Q_j) + \frac{R_{ij} \sin(\delta_i - \delta_j)}{V_i V_j}(Q_i P_j - P_i Q_j) \right)
\end{aligned}
\tag{1}
$$

where n is the number of buses, R_{ij} is the resistance of line between buses "i" and "j", P_i, Q_i are net real and reactive power injections in bus "i" and V_i, δ_i are the voltage magnitude and angle at bus "i".

The minimization must take place without violating the operational constraints:
• Power flow balance equations. The balance of active and reactive powers must be satisfied in each node:

$$
P_i = P_{DG,i} - P_{Di} = U_i \sum_{k=1}^{n} [U_k[G_{ik}\cos(\theta_i - \theta_k) + B_{ik}\sin(\theta_i - \theta_k)]]
$$

$$
Q_i = -Q_{Di} = U_i \sum_{k=1}^{n} [U_k[G_{ik}\sin(\theta_i - \theta_k) + B_{ik}\cos(\theta_i - \theta_k)]]
\tag{2}
$$

where the $P_{DG,i}$ and Q_{Di} represent the active and reactive power at bus "i".
• Power flow limits. The apparent power that is transmitted through a branch l must not exceed a limit value, $S_{i\max}$, which represents the thermal limit of the line or transformer in steady-state operation:

$$
S_i \leq S_{i\max}.
\tag{3}
$$

• Bus voltages. For several reasons (stability, power quality, etc.), the bus voltages must be maintained around the nominal value:

$$
U_{i\min} \leq U_{inom} \leq U_{i\max}.
\tag{4}
$$

In practice, the accepted deviations can reach up to 10% of the nominal

values.

• DG size

$$P_{DG} \leq P_{DG\,max} \,. \tag{5}$$

The optimization problem described by the objective function and constraints detailed in this section represents the mathematical model for the optimal location and sizing of a DG unit in a distribution network, minimizing power losses and investment costs.

3. Genetic algorithms

It has been shown in [12] that the location and size of DG have great importance upon the operating conditions of a distribution power network and that genetic algorithms are a suitable method for solving this allocation problem. This study addresses the problems emerging when using GAs, with emphasis on the dependence between the internal parameters of GAs and their performances.

Genetic Algorithms are a way of solving problems by emulating the mechanism of evolution as found in natural processes. They use the same principles of selection, recombination and mutation to evolve a set of solutions toward a "best" one.

Because of the intrinsic parallelism of GAs, they can explore the search space in multiple directions at the same time. This is why they are suited for nonlinear problems of high complexity and dimensionality, for which the objective function (transposed into a fitness measure) have a complex look (discontinuous, noisy, time-dependent, with many local optima). GAs avoid getting trapped into local optima because they use populations of candidate solutions and therefore there are always multiple comparison values, unlike, for example, hill-climbing or gradient-based methods [14].

Before using any of the GA models, the problem must be represented in a suitable format that allows the application of genetic operators. GA-s work by optimizing a single entity, the fitness function. Hence, the objective function and the constraints of the problem at hand must be transformed into some measure of fitness.

Encodings. The first feature that should be defined is the type of representation to be used, so that an individual represents one and only one of the candidate solutions. A candidate solution (or chromosome) designed in this paper for the problem of finding the optimal location and size of one DG unit is a two-component vector (Fig. 1). The first component represents the location, the node in which the DG should be connected, and can take values from 1 to the number of buses in the network. The second component represents the DG size and can take values from 0 to 2000 kW. A population of possible solutions will be evolved

from one generation to another, in order to obtain an optimum setup, i.e. a very well fitted individual.

Position(node number)	Size (max. 2 MW)

Fig 1. Chromosome encoding for one DG unit to be allocated

Fitness Function. This function is responsible for measuring the quality of chromosomes and it is closely related to the objective function. The objective function for this paper is computed using equation (1). The constraints of this particular problem do not explicitly contain the variables (the genes in this case) and therefore the effect of the constraints must be included in the value of the fitness function. The constraints are checked separately and the violations are handled using a penalty function approach. The overall fitness function designed during this study is:

$$f(x) = O + \xi \cdot \sum_{i=1}^{nr} bal_i + \zeta \cdot \sum_{k=1}^{n} thermal_k + \vartheta \cdot \sum_{k=1}^{n} voltage_k \qquad (6)$$

where the first two terms are the ones in the objective function and the following are penalty functions. The element bal_i is a factor equal to 0 if the power balance constraint at bus i is not violated and 1 otherwise. The sum of these violations represents the total number of buses in the network that do not follow constraint (2) and it is multiplied by a penalty factor meant to increase the fitness function up to an unacceptable figure, therefore making the solution unfeasible. The second and third sums in the fitness function represent the total number of violations of constraints (3) and (4) respectively and they are also multiplied by penalty factors. The last three sums in this fitness function are a measure of unfeasibility for each candidate solution x. The penalty factors used in this study were set to 10000.

The constraint expressed in equation (5) is satisfied each run, as the limits for each individual are set within the main GA routine: the first component (location) varies between 0 and the number of buses and the second component (size) varies accordingly to eq. (5).

Selection Methods. The selection methods specify how the genetic algorithm chooses parents for the next generation. In this study, two selection methods were tested. The first method was Roulette Wheel Selection, which chooses parents by simulating a roulette wheel with different sized slots, proportional to the individuals' fitness. The second method tested was Tournament Selection. Each parent is chosen as the best individual from a random selection of k individuals, where k is a preset number – tournament sizes of 2, 4 and 6 were tested here.

Crossover Mechanism. The crossover mechanism is responsible for the way in which the genetic material is mixed between individuals. The one-point crossover exchanges the genetic information found after a random position in the two selected parents.

The crossover is applied in each successive generation with a certain probability, known as the crossover fraction or rate. A large crossover rate decreases the population diversity, but in this problem a higher exchange of genetic material is needed.

Mutation Mechanisms. This mechanism is very important from the genetic diversity point of view, and it prevents landing a local, sub-optimal solution. The mutation rate is highly connected with the crossover fraction. The mutation mechanism used in this study implies generating a random gene number and flipping the bit found at that position.

Stopping Criteria. Other important decision variables are the stopping criteria. Some of the most widely used stopping criteria are:

- the *maximum number of generations* that the GA will compute: after computing this preset number of generations, the GA stops and the best result until then is considered to be optimal;

- *time limit*: specifying the maximum number of seconds the algorithm will run, this criterion stops the GA after a predefined computational time;

- *fitness limit*: the algorithm stops when encounters a fitness value smaller than a preset target value;

- *stall generations*: the GA terminates when no improvements in the best fitness values take place for a predefined number of generations. This can be regarded as a stagnation in the evolution process.

- *stall time*: acts the same as the stall generations criterion, but the predefined parameter is the computational time.

For example, if the computational time for each generation is high (due to a large number of individuals or the nature of the problem – like in the case of DG placement, where power flows are computed for each individual in each generation) and the stall time limit is set to a low value, the algorithm will not get the chance to explore the whole space, as the GA will terminate even before few generations will be computed. If the maximum number of generations is set to a small number and the population size is also small, then the algorithm will not be able to compute all the generations needed in order to find the optimal solution, as it will stop after completing the specified number of generations. The same argument is also applicable for the time limit criterion. The most accurate way to stop the GA is after finding a fitness value lower than the targeted one, but there are some problems for which the solution is not known a priori, so a fitness target is impossible to be set. On the other hand, the algorithm may never land a solution with the fitness lower than the targeted one, making the criterion unfeasible. The

GA stops when any of the stopping criteria is met, on a first come first served basis.

4. Case study

In order to assess the performances of the proposed GA setups in solving the DG allocation and sizing problem, the IEEE 69-bus distribution test system has been considered. The system has 68 sections with a total load of 3800 kW and 2690 kVAr (Fig. 2). The network data can be found in [15]. The total active power losses are equal to 225kW and total reactive power losses are equal to 102.2 kVAr.
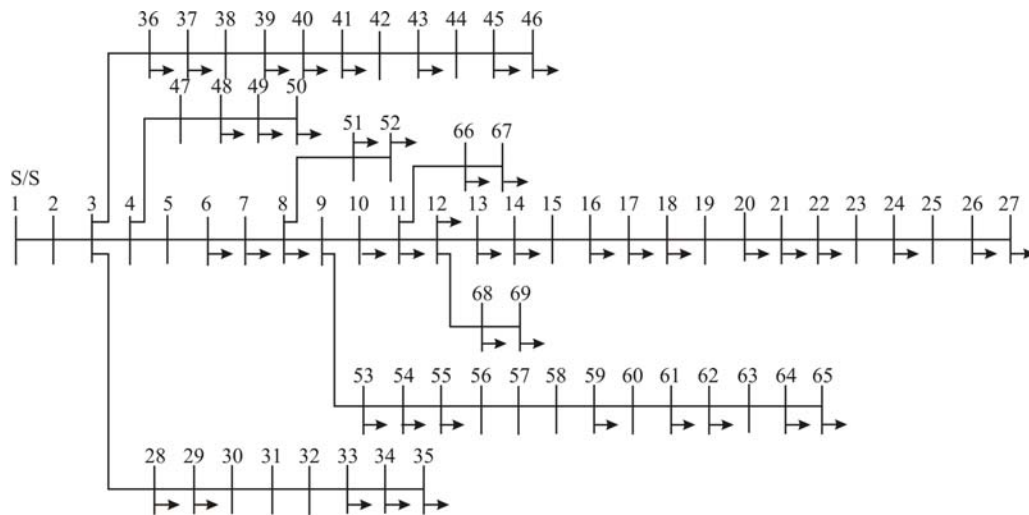

Fig. 2. 69-bus radial distribution network

As it was shown above, the process of solving the DG allocation problem with genetic algorithms implies a number of parameters that have to be specified. The population size is a discrete parameter that sets the number of individuals that the GA evolves in each generation. It comes naturally that a small number of individuals in a population may result in a premature convergence, may not provide enough covering of the search space and so the algorithm would become unreliable. On the other hand, using a very large number of individuals means that a very large number of possible solutions have to be assessed, and so the computational time increases drastically. The crossover rate and mutation rate are continuous variables, defined over the interval [0, 1]. If the mutation rate becomes too high, then the search becomes a random one; if the crossover rate becomes too high, the search can get trapped within local minima. A balance between these two values has to be found, in order to improve the algorithm's performances. The

selection method is a discrete parameter, referring to different methods, like tournament or roulette wheel, mentioned above. This variable is also accompanied by the parameters concerning the selection method. As an example, the tournament selection also implies the tournament size. The crossover mechanism can be viewed in a similar way.

Accordingly to the above remarks, a GA could be fully specified by a set of bounded parameters, which influence its performances [16].

Finding the optimal values for each of the parameters in the above-described set becomes a *problem within a problem*. The parameters are dependent on one another. If an algorithm gives good results with a set-up, for example roulette wheel selection, crossover rate of 0.85, single-point crossover method and a population size of 40, changing just one of the parameters (for example a value of 20 for population size) can make the algorithm perform poorly.

It must be specified that the number of tuning methods are virtually infinite and the following study is an empirical approach, with the sole intention of showing the importance of choosing the proper values for these parameters, highlighting their influence upon the performances of GAs. For simplicity reasons, only the case of one DG unit is addressed.

Selection mechanism

Because GAs are based on random numbers, one cannot be sure that a single run would be sufficient to obtain the optimal solution. Therefore, to overcome this problem, the algorithm was run 10 times for tournament selection with tournament sizes of 2, 4 and 6, and 10 times for roulette wheel selection. Fig. 3 shows the empirical cumulative distribution function after each set of 10 runs. All simulations were performed with a population size of 50 individuals and a crossover rate of 0.7.

We can conclude that the roulette wheel selection leads to smaller amounts of power losses.

Population size

In order to set the best value for the population size, the algorithm was run 10 times for each population size between 20 and 80, with an increment of 10. The empirical cumulative distribution functions (CDF) for all cases are plotted in Fig. 4.*a*. As it can be seen, the minimum losses values are obtained for 80 individuals in each generation. However, looking at the computational time, Fig. 4.*b*, it increases with the population size, as more fitness functions have to be computed each generation. A balance has to be found between these two aspects. Fig. 4.*b* shows that a population size of 80 would lead to unacceptable computational time. As Fig. 4.*a* shows similar results for population sizes of 50, 60 and 70, taking into consideration the corresponding computational time, a value of 50 for this parameter can be considered as suitable.
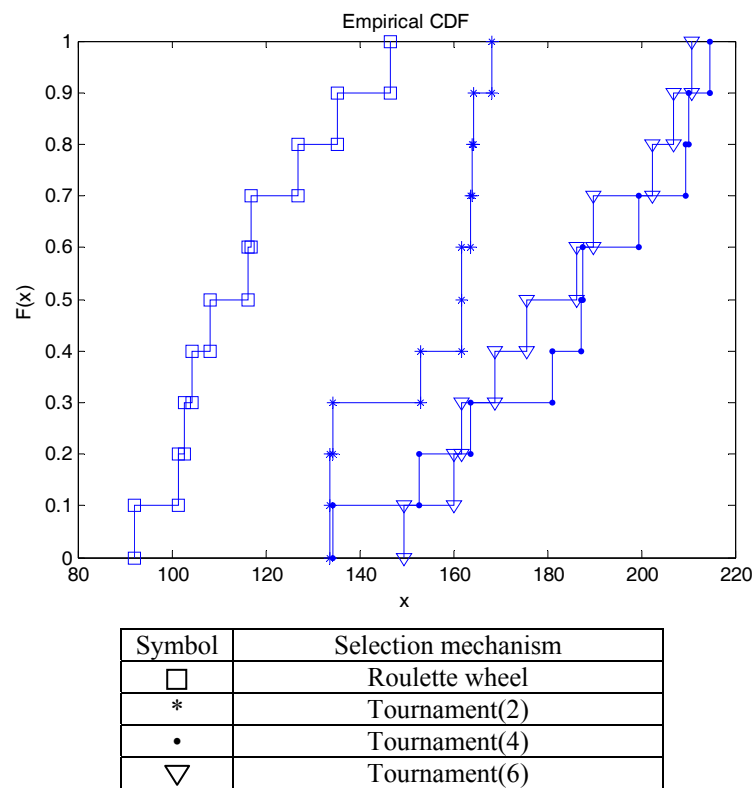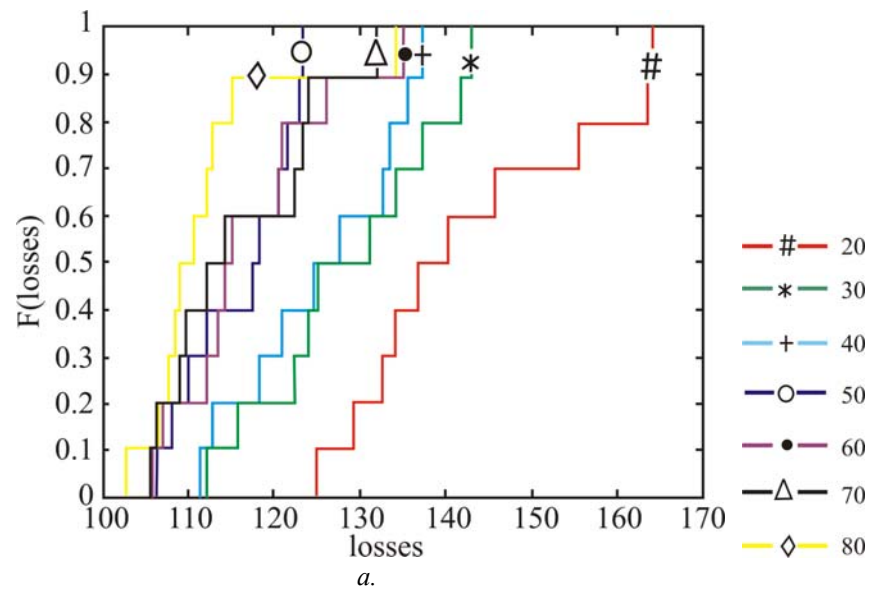
Symbol	Selection mechanism
□	Roulette wheel
*	Tournament(2)
•	Tournament(4)
▽	Tournament(6)

Fig. 3. Empirical CDF after 10 runs for roulette wheel and tournament selection of size 2, 4 and 6

—#—	20
—*—	30
—+—	40
—O—	50
—•—	60
—△—	70
—◇—	80

a.

b.

Fig.4. CDF for losses (*a*) and computational time (*b*) for different population sizes

Crossover fraction

Having set the population size set to 50, we can analyze the crossover rate and its importance upon the performance of the algorithm. This parameter specifies the percentage of individuals that enter the mating pool in order to exchange genetic material. They will produce crossover children. The algorithm was run 20 times for each crossover fraction between 0 and 1, with an increment of 0.1. Fig. 5 plots the minimum fitness value obtained during the 20 runs for each crossover rate against the respective crossover rate value.
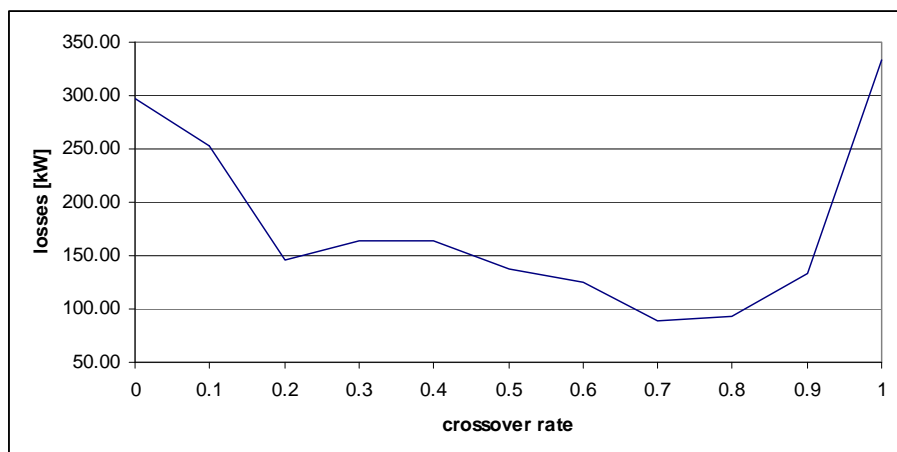

Fig. 5. Crossover fraction importance upon the performance of the GA

The plot shows that the crossover rate for the DG allocation problem for the 69-bus network should be around 0.7. A higher crossover fraction implies better genetic information exchange between parents, guiding the search, but a lower one increases diversity within the generations and provides the algorithm a better chance of finding the optimal solution by better covering the search space. A fraction of 1 means that all children, other than elite individuals, are crossover children, while a crossover fraction of 0 means that all children are obtained from mutation. The tests show that neither of these extremes is an efficient strategy for optimizing a function. The results of a run for a crossover rate of 1 are presented in Fig. 6, showing both the evolution of the mean and best fitness values at each generation and the average distance between individuals. The average distance shows how the search space is explored by the individuals. A small distance means less exploring. If the crossover rate is set to 1, then all the individuals in the next generations are obtained by crossover, except the elite ones, meaning that no mutation takes place whatsoever.

The algorithm gets trapped in the same best solution, as no diversity mechanisms occur. The search is over-guided and the initial solution guides the algorithm throughout the run without allowing it to explore the search space.

The only genetic material is the one of the individuals from the first generation, randomly generated. The algorithm recombines this material and no new genes are created, because no mutation takes place. The average distance between the individuals becomes zero, as they are all identical. The algorithm runs until the stall generations parameter value is reached.

Fig. 7 shows the plot for a run with a crossover rate of 0, meaning that the individuals in each generation are exclusively created by mutation.

In this case, the random changes that the algorithm applies only slightly improve the fitness value of the best individual from the first generation. The upper plot shows some improvement in the mean fitness value in some of the generations, but no crossover takes place and so the method more likely becomes a random search. The best fitness plot from Fig. 7 demonstrates that the algorithm does not converge.

The above interpretation concerning GA parameters shows the strong link between the parameters and the performances of GAs. The operations described above can, however, take place in any other random order, each case resulting in different outputs. The tuning of parameters in GAs is still an open topic, especially because dynamic methods have to be applied due to the strong interconnections between these parameters.
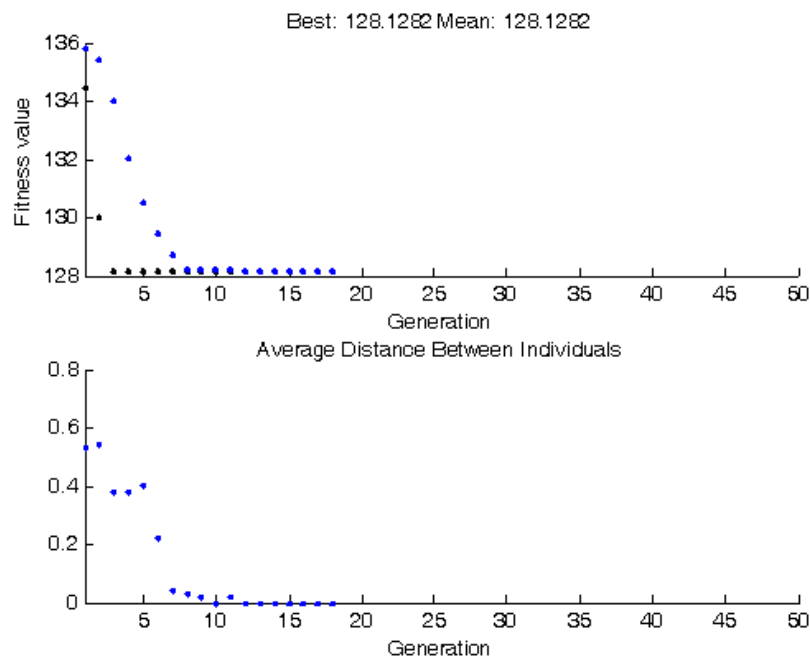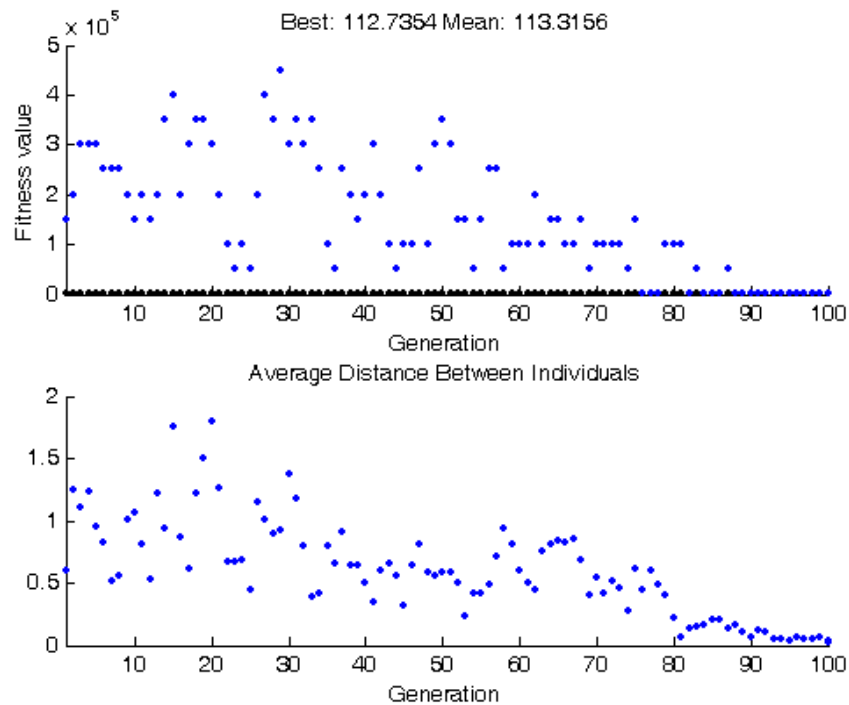
Fig. 6. GA results for a crossover rate of 1

Fig. 7. GA results for a crossover rate of 0

5. Conclusions

The studies highlight the importance of properly choosing the parameters' values when using genetic algorithms for the problem of optimal DG location and sizing. The objective function is related to the active power losses within the network, and the fitness function incorporates the operational constraints by using penalty functions.

Two selection mechanisms are tested: roulette wheel and tournament of different sizes, and the results show that each set-up leads to different values. The cumulative distribution function is used to emphasize the most suited mechanism, which, in this case, resulted to be the roulette wheel.

The population size was another parameter that has been varied, and the results show, taking into consideration both power losses and computational time, that a balance has to be found between them, thus resulting in an optimal population size of 50 individuals for this problem.

The crossover fraction is responsible for the genetic material exchanging intensity and it represents another important parameter of GAs. The algorithm was run for different crossover fractions and the most suited value resulted around 0.7. Two extreme cases were also tested, for a crossover rate of 0 and 1. For the crossover rate set to 0, all offspring are created via mutation, and thus the search becomes random rather than directed. For a crossover rate of 1, the genetic material is exchanged intensively and after a few generations all individuals start to be alike, thus leading to a stagnation of evolution.

The performance of GAs depends on their parameters, which are interrelated, and a tuning procedure must take place before taking the results as granted. A robust tuning method should look for all parameters in the same time, in order to obtain an optimal set-up.

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