IMPROVED GENETIC ALGORITHM APPLIED TO DISTRIBUTED GENERATION ALLOCATION CONSIDERING DIFFERENT LOAD PROFILES

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Abstract— This paper presents an improved genetic algorithm to solve the distributed generation (DG) allocation problem in radial electrical energy distribution systems. The problem is formulated as a matter of nonlinear mixed integer programming, since it presents integer variables, which indicate the position where the DG will be allocated, and continuous variables, associated with electrical values (voltage, current, active and reactive power losses and power flow). In the proposed formulation, different load levels are considered. The objective is to minimize costs produced by system losses and the implementation and maintenance expenses of the distributed generation. The proposed methodology has been successfully tested for distribution systems with 70 and 135 buses.

Keywords— Distributed Generation, Radial Distribution Systems, Improved Genetic Algorithm.

1 Introduction

Changes in economic and regulatory scenarios, environmental awareness to minimize impacts, the need for more flexible electrical systems and restrictions for construction of new transmission lines carry the energy systems to a decentralized and small-scale model (Dunn, 2000). Current electrical systems that comply with consumer demand are characterized by conventional or centralized generation. This type of system has large power plants, associated with primary energy sources, connected to extensive transmission and distribution lines.

In this context, distributed generation (DG) is involved in the search for efficient and decentralized energy systems, if well planned and implemented. Despite that the DG concept exists for more than a century, recent discussions on the subject produced various definitions for this type of generation, as demonstrated by (Severino et al., 2008). The INEE. (2016) says that DG can be defined as any generating source with production destined, the most part, to local or nearby loads without need for long transmission lines.

In specialized literature, there is a vast amount of content with different approaches on the subject. The work in (Khalesi et al., 2011) presents a multi-objective function for optimal DG allocation in distribution systems, in order to minimize power losses, increase systems reliability indicators and improve the voltage profile. Load levels are considered to obtain more realistic results.

In (Kazemi and Sadeghi, 2009) the proposed work has an algorithm for DG allocation which aims to reduce losses and ensure that the voltage profile remains at acceptable levels. The algorithm is based on power flow and is divided into two steps. First, the buses are classified by the loss reduction criteria. Second, allocates the DG and calculates the new voltage levels after the allocation.

In the work presented by (Grisales et al., 2015) a hybrid algorithm is proposed based on a (Chu and Beasley, 1997), which determines the candidate node for installation. The dispatch of power is performed by the particles swarm algorithm, which allows to vary the function goal according to the system requirements, improving the profile voltages or reduced losses. The use of wind, photovoltaic or small hydroelectric plants is considered, according to the topology and weather conditions of the site where the DG will be located.

This article objective is to propose a mathematical model for DG allocation, which considers the costs of installation and maintenance of a DG and the costs of active system losses. To solve this problem, an improved genetic algorithm (IGA) is used in order to insert the DG, considering it's active and reactive power is fixed to all load levels, since different load levels are used, thus, reducing losses and improving voltage profile.

This work is divided into five sections. Section II presents the mathematical model for DG allocation, Section III exposes the IGA and the characteristics used for the solution of the problem. In section IV the IGA results are presented for two main systems. The main conclusions of this paper are presented in Section V.

2 Mathematical modeling

The allocation of the DGs is formulated as a mathematical optimization problem, where the objective is to minimize installation and maintenance costs as well as the network operating costs (power losses).

Distributed generation allocation is analyzed as a nonlinear mixed integer problem, due to the presence of integer variables, which indicates the

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allocated DG position, and the associated electrical continuous variables of the electric system (voltages, currents, power flows and losses of active and reactive power). The proposed modeling of this article is displayed as follows.

$$Min.\ f_o = \sum_{k=1}^{nb} n_k^{dg}.(c_k + r_k.T.P_k^{dg}) + \sum_{d=0}^{nt} k_e^d T_d P_d^{loss} \tag{1}$$

subject to

$$\sum_{i=1}^{nb} P_i^S - \sum_{i=1}^{nb} P_{i,d}^D - \sum_{ij\epsilon\Omega_L} (P_{ij,d} + I_{ij,d}^2.R_{ij}) + \sum_{i=1}^{nb} P_i^{dg}.n_i^{dg} = 0; \tag{2}$$

$$\sum_{i=1}^{nb} Q_i^S - \sum_{i=1}^{nb} Q_{i,d}^D - \sum_{ij\epsilon\Omega_L} (Q_{ij,d} + I_{ij,d}^2.X_{ij}) + \sum_{i=1}^{nb} Q_i^{dg}.n_i^{dg} = 0; \tag{3}$$

$$0 \le P_i^S \le \overline{P_i^S} \qquad \forall\ i\ \epsilon\ \Omega_b; \tag{4}$$

$$0 \le Q_i^S \le \overline{Q_i^S} \qquad \forall\ i\ \epsilon\ \Omega_b; \tag{5}$$

$$0 \le P_i^{dg} \le \overline{P_i^{dg}} \qquad \forall\ i\ \epsilon\ \Omega_b; \tag{6}$$

$$0 \le Q_i^{dg} \le \overline{Q_i^{dg}} \qquad \forall\ i\ \epsilon\ \Omega_b; \tag{7}$$

$$\underline{V} \le V_{i,d} \le \overline{V} \qquad \forall\ i\ \epsilon\ \Omega_b; \tag{8}$$

$$\underline{I_{ij}} \le I_{ij,d} \le \overline{I_{ij}} \qquad \forall\ ij\ \epsilon\ \Omega_l; \tag{9}$$

$$\sum_{k=1}^{nb} n_k^{dg} \le \overline{n^{dg}} \tag{10}$$

$$n_k^{dg} \epsilon \{1, 0\} \tag{11}$$

such that

nb is the number of buses; c_k is a constant representing the cost of installation; n_k^{dg} is a vector filled with binary values, which indicate the presence or absence of DG; T is the total time used by the system; r_k is a constant that represents the cost of maintenance of a DG; k_e^d is the power cost parameter for each load level; nt is the number of system load profiles; P_k^{dg} is the active power installed by DG; T_d is the period for the load profile; $P_d^{loss} = I_{ij,d}^2.R_{ij}$ are the total active power losses for each period; P_i^S and Q_i^S are the active and reactive power injected by the substation, respectively; $P_{i,d}^D$ and $Q_{i,d}^D$ are the active and reactive power demands for bus i, at the load level d, respectively; $P_{ij,d}$ and $Q_{ij,d}$ are the active and reactive power flow, respectively; $I_{ij,d}^2 R_{ij}$ and $I_{ij,d}^2 X_{ij}$ are the active and reactive losses in the sector ij, respectively, as shown in Fig. 1 of $I_{ij,d}^2 \overrightarrow{Z}_{ij}$ (impedance), R_{ij} and X_{ij} are resistance and reactance of the branch ij; P_{ki}^{dg} and Q_{ki}^{dg} are the active and reactive powers inserted by distributed generation; $\overline{P_i^S}$ and $\overline{Q_i^S}$ are the maximum acceptable values for active and reactive power entered by the substation, respectively, for all buses (Ω_b); $\overline{P_i^{dg}}$ and $\overline{Q_i^{dg}}$ are the maximum acceptable values for active and reactive power entered by DG, respectively, to Ω_b; $V_{i,d}$ bus voltage i for charge level d; $\underline{V}$ and $\overline{V}$ are the minimum and maximum acceptable values for Ω_b, respectively; $\underline{I_{ij}}$ and $\overline{I_{ij}}$ are the minimum and maximum acceptable values for the current in the whole set of lines respectively (Ω_l); $\overline{n^{dg}}$ is a constant representing the maximum number of DGs installed in the system.

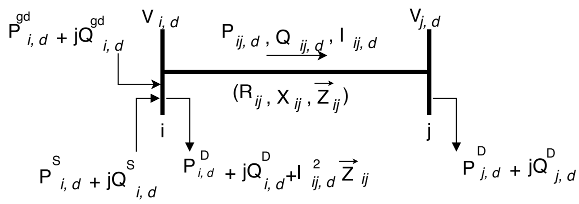

Figure 1: Simplified system representation.

The objective function shown in (1) contains two summations. The first, exposes the DG installation and maintenance costs. Maintenance costs considers different expenses involved in energy acquisition. The second one represents the losses cost for each load level.

To calculate the losses, P_i^{loss}, the power flow Backward-Forward Sweep (Shirmohammadi et al., 1988) algorithm is used.

The load levels represent the system demand for a period of time T_i, this paper considers three load profiles – high, medium and light.

The constrains considered in the problem are those traditionally used in literature (Baran and Wu, 1989), (Pereira et al., 2016): the power flow balance ((2) and (3))–shown in figure 1–, the substation power limits ((4) and (5)), the buses voltage limit (8) and the branch current limit (9).

Injected power restrictions are defined in (6) and (7).

The restriction (10) presents the maximum, $\overline{n^{dg}}$, number of DGs to be inserted into the system.

The (11) constraint refers to the type of data contained in vector n_k^{dg}, where 1 is used to indicate the existence of a DG in a given bus and 0 for the absence of DG.

In any violation of these restrictions, the ob-

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jective function will suffer a penalty, by adding a very high value.

3 Improved Genetic Algorithm

This work uses an improved genetic algorithm (IGA) based on (Chu and Beasley, 1997) ideas, which is a meta-heuristic technique for solving nonlinear problems. The GA mimics genetic evolution and biological selection of individuals behaviors in a computer programming format (Holland, 1975).

Following features are the difference between IGA and the traditional GA (Holland, 1975): 1) there is a fitness and an unfitness function, which are used to identify the objective function value and quantify feasibility of the tested solution, respectively; 2) replaces only one individual in the population for each iteration and 3) each individual goes through a local improvement strategy.

The flowchart shown in figure 2, presents the main steps of the IGA used in this work.

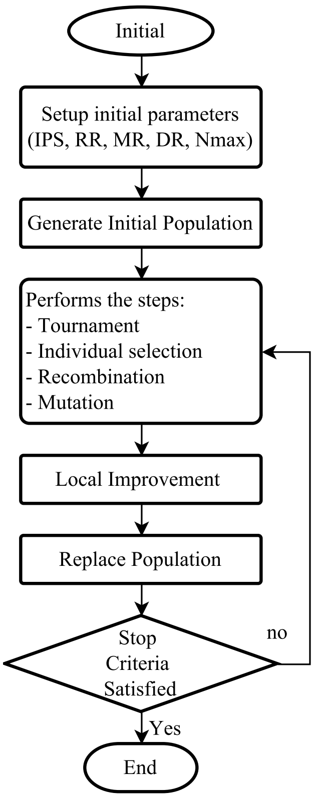

Figure 2: Flowchart IGA.

The flowchart has these steps: Setup the control parameters – size of the initial population (IPS), recombination rate (RR), mutation rate (MR), diversity rate (DR) and maximum number of iterations(N_{max})– creation of the initial population, tournament selection, recombination, mutation, local improvement, replacement and verification of the stop criteria.

Each step is described as follows:

3.1 Codification

An individual is represented by a vector with size equal to the number of buses in the system, as shown in Fig 3. This vector is filled in a binary form, where 1 is the point of allocation.

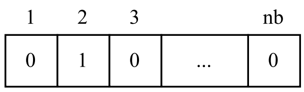

Figure 3: Example encoding for an individual.

3.2 Initial population

Initial population is represented by a matrix $IPS \times nb$ nb, where individuals in the population are randomly generated.

3.3 Selection

The adopted selection process is based on the tournament method. In this method, two groups of potential parents are generated, each group will consist of k individuals, randomly chosen within the current population. In each group the best individual is chosen, which has the best objective function. At the end of this process, two individuals are selected, named as parents, who are employed in the recombination step (Gallego et al., 2009).

3.4 Recombination

Recombination proceeds with a cut at a single point, chosen in random order, as shown in Figure 4. Further, it can be noted that each child inherits characteristics of both parents. At the IGA proposed, only one children will continue to the next step, the chosen is the one with a lower objective function.

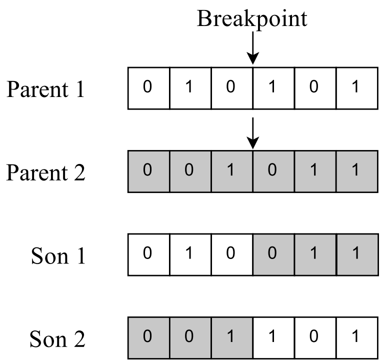

Figure 4: An example of a recombining step.

3.5 Mutation

According to the mutation rate, individual points are selected at random to change their state, as seen in figure 5. This process can generate individuals who break the amount of allocated DGs, so a check must be made to that number, if it is higher than the limit, the amount of DGs over the limit is eliminated. With the individual within bounds, the objective function is calculated. This process is done for all possible combinations of DG allocations within the limits, and the combination that has the best answer to the objective function is selected.

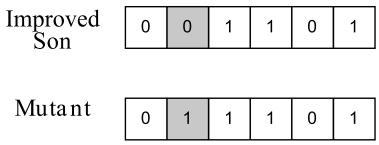

Figure 5: Example of a mutation step.

3.6 Local improvement

A neighborhood search is performed, consisting of a search in the buses near the DG allocation point, in order to improve response of the objective function. If this goal is achieved the individual is modified, otherwise, the DG remains in the original bus.

3.7 Replacement

After the local improvement stage, the generated individual enters the current population if it satisfies the following conditions: it is not within the current population and have a better objective function than the worst individual of the current population. Otherwise, the individual will be discarded.

3.8 Stop criteria

If the best solution does not change in a range of N iterations the algorithm is said convergent and the best individual of the current population is exposed. If N_{max} is reached before the algorithm converges the program stops.

4 Results

The proposed methodology was tested in two radial distribution systems: 70 bus (Baran and Wu, 1989) and 135 bus (Guimaraes and Castro, 2011).

The cost of installation $c_k = 150k\$/MW$ and maintenance cost $r_k = 0.5\$MVAh$ (Pereira et al., 2016).

The parameters used are presented in table 1.

The algorithm was implemented in C ++, using a computer with processor $Core^{(TM)}$ i5 - 3210M, 2.50 GHz.

Table 1: IGA Parameters.

Feature	Used values
Initial Population(IPS)	40 individuals
Mutation Rate(MR)	5%
Diversity Rate(DR)	1%
Maximum Number of Iterations(Nmax)	10000

4.1 System 70 buses

System topology is shown in Figure 6, where its total load is $S = 3.8021$ MW + j2.6946 MVar.

Parameters for this system are: energy cost $k_e^0 = 0.7$ \$/kWh, $k_e^1 = 1.78$ \$/kWh and $k_e^2 = 2.95$ \$/kWh, for each load level. Maximum and minimum values adopted for system voltages are respectively 1.05 to 0.90 per unit (p.u.). The load levels considered are $S_0 = 1.25$ (heavy), $S_1 = 1.0$ (medium) and $S_2 = 0625$ (light). Each charge level has a distinct duration $T_0 = 1000h$,$T_1 = 6760h$ and $T_2 = 1000h$. It is proposed to allocate only one DG 1MW with power factor, inductive, 0.95 and stop criteria of $N = 20$ iterations.

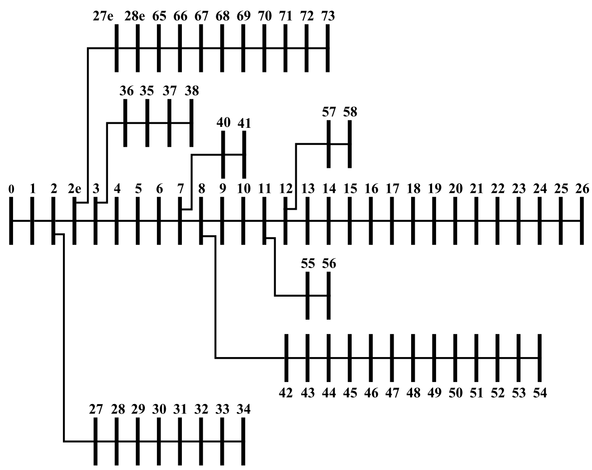

Figure 6: Line diagram of the radial system with 70 buses.

The initial cost without DG allocation, relative to system losses, is \$ 3202084.75. Table 2 refers to losses − active and reactive − and minimum voltage levels for each load level for the system without DG allocation.

Table 2: Initial solution to the system with 70 buses (without DGs).

	Load Level	Power Active (kW)	Power Reactive (kVar)	Voltage Minimum (p.u.)
1	1.250	367.76	166.57	0.8852
2	1.000	224.56	101.98	0.9102
3	0.625	82.24	37.49	0.9456
	Total:	674.55	306.04	-

The solution found by the algorithm is the allocation of a DG in bus 50 with a total cost of \$ 2258780.50, being \$154610.51 the installation and maintenance expenses,active losses cost was \$ 2104170.00. Thus, the total active power losses and costs are reduced by 34.29% and 29.46%, respectively.

Table 3 presents the losses and minimum voltages for each voltage level considering the DG allocation at bus 50. The computational time required to find the answer was 0.056 seconds.

Table 3: 70 buses system, considering DG allocation.

		Power		Voltage
	Load Level	Active (kW)	Reactive (kVar)	Minimum (p.u.)
1	1.250	248.32	115.28	0.9247
2	1.000	146.92	68.47	0.9469
3	0.625	55.08	25.46	0.9788
	Total:	450.32	209.21	-

Comparing data from tables 2 and 3, there is a notorious reduction in total active losses of approximately 33 % and voltage levels achieved a considerable improvement, justifying the high amount of money used to install the DG.

IGA convergence characteristics for the system 70 buses is shown in Figure 7. Note that the algorithm converges to the answer in less than 55 iterations.

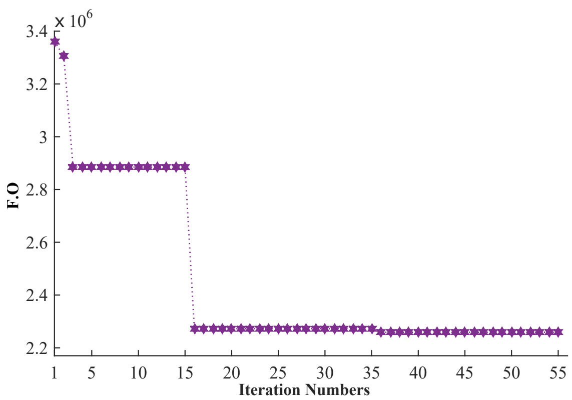

Figure 7: IGA convergence characteristic for the 70 buses system.

To verify the validity of the results, the method was tested with random seeds to the random number generator, and thus converging closely to the same answer. This behavior is shown in figure 8 to the 70 buses system.

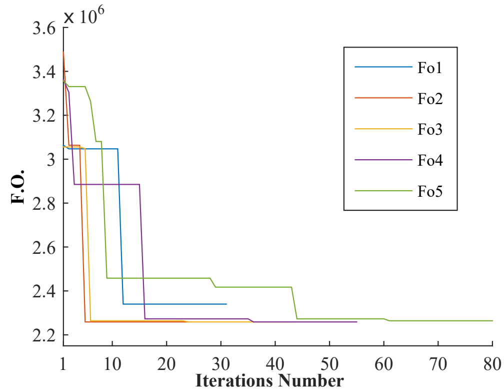

Figure 8: IGA convergence characteristic for the 70 buses system, with different initial populations where each curve (F.O.1, F.O.2, F.O.3, F.O.4, F.O.5, F.O.6) is a different seed to the random number generator.

4.2 System 135 buses

The parameters for this system are: energy cost k_e = 0.06 \$/kWh, to all load level, cost of installation $c_k = 150k\$/MW$ and maintenance cost $r_k = 0.5\$MVAh$. The maximum and minimum values adopted for system voltages are respectively 1.05 to 0.90 per unit (p.u.). Load levels are considered S_0 = 1.8 (high), S_1 = 1.0 (average) and S_2 = 0.5 (light). Each charge level has a distinct duration $T_0 = 1000h$, $T_1 = 6760h$ and $T_2 = 1000h$. It is proposed to allocate two DG with 2MW, power factor 0.95, inductive, with the stopping criteria of N = 100 iterations, considering a period of 20 years. System total load is S = 18,31 MW + j.7.93 MVar.

Cost of losses without DG allocation are \$ 3974710.75 and table 4 refers losses, active and reactive, and voltage levels, minimum, for each load level for the DG without allocation system.

Table 4: System with 135 buses without DG allocation.

		Power		Voltage
	Load Level	Active (kW)	Reactive (kVar)	Minimum (p.u.)
1	1.8	1084.11	2378.73	0.8985
2	1.0	318.23	698.18	0.9388
3	0.5	76.91	168.72	0.9686
	Total:	1479.25	3245.62	-

After using the IGA for DG allocation, the best positions found were in bus 12 and 155 with a total cost of \$ 3713878.25, being \$ 668842.06 the cost of implementation and maintenance, and the cost of active losses as \$ 3045036.25, so the cost of implementation is only 18% of the total cost.

In Table 5, active and reactive losses are presented, along with the minimum voltage levels for each load level, considering DG allocation in buses 12 and 155. The computational time required to find the answer was 0.770 seconds.

Comparing the results of Table 4 with Table 5, there is a reduction in 20.37 % for active losses and 21.27 % in reactive losses. In this system the

Table 5: System with 135 buses considering DGs allocations.

		Power		Voltage
	Load Level	Active (kW)	Reactive (kVar)	Minimum (p.u.)
1	1.8	867.34	1884.44	0.8833
2	1.0	236.05	509.78	0.9379
3	0.5	74.47	161.16	0.9735
	Total:	1177.86	2555.37	-

improvement in the voltage profile is barely noticeable, since the reactive power injection, which is the primary responsible for improvements in the voltage profile, is insignificant to the system.

5 Conclusion

In this paper, a mathematical model for optimal allocation of distributed generators in radial distribution systems was proposed. This mixed integer linear problem is solved using a meta-heuristic technique named as improved genetic algorithm (IGA).

The mathematical model combined with the meta-heuristics techniques presented optimum solutions, to the allocation problem, and also have a good computational performance for medium and large electrical energy distribution systems.

With the obtained results, it was demonstrated that the DG allocation reduces the overall system losses. Also, an improvement of the voltage profile was observed for each load level considered.

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