Hybrid Genetic Algorithm for the Optimal Location of Distributed Generation in Distribution Systems

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***Abstract*— This paper presents a novel approach based on a genetic algorithm combined with an artificial neural network and a reduced variable neighborhood search to find the optimal location of distributed generation in electric distribution systems. The objective function consists in minimizing active power losses. The main contribution of the paper consists in the combination of metaheuristic techniques along with artificial intelligence to solve a multi-modal non-convex problem. The use of an artificial neural network avoids the calculation of power flows, while the neighborhood search, applied at the end of each iteration, allows the algorithm to explore a wider search space and eventually, escape from local optimal solutions.**

The proposed approach was tested on a 13 bus distribution system showing the robustness and applicability of the model.

***Index Terms*—Distributed generation, genetic algorithms, artificial neural networks, neighborhood search.**

I. NOMENCLATURE

The following nomenclature is used throughout the paper.

A. Indexes

r : Branch index.
i, k : Bus indexes.
j : Distributed generation index.

B. Parameters

P_{Di} : Active demand in bus i.
Q_{Di} : Reactive demand in bus i.
$V_i^{\min}$: Minimum and maximum voltage magnitude at bus i.
$V_i^{\max}$: Maximum voltage magnitude at bus i.
$P_{Gj}^{\min}$: Minimum active power limit of DG unit j.
$P_{Gj}^{\max}$: Maximum active power limit of DG unit j.
$Q_{Gj}^{\min}$: Minimum reactive power limit of DG unit j.
$Q_{Gj}^{\max}$: Maximum reactive power limit of DG unit j.
$S_{ik}^{\max}$: Maximum apparent power flow in line connecting nodes i, k.
nr : Total number of branches.
nb : Total number of buses.
g_{ik} : Real part of the i,k element of the admittance bus matrix
b_{ik} : Imaginary part of the i,k element of the admittance bus matrix.
$S_{ik}^{\max}$: Maximum apparent power flow in line i,k.
$ngd^{\max}$: Maximum number of DG units to be allocated in a single bus.

C. Variables

μ_i : Binary variable that indicates whether there is (1) or there is not (0) DG in bus i.
P_{Gj} : Active power supplied by DG unit j.
Q_{Gj} : Reactive power supplied by DG unit j.
V_i : Voltage magnitude at node i.
θ : Voltage angle.
S_{ik} : Apparent power flow in line connecting nodes i, k.
ngd_i: Number of DG units to be allocated in bus i.

II. INTRODUCTION

DISTRIBUTION system planners must guarantee the supply of economical and reliable electricity to customers. With recent advances in small-scale generation technologies, the use of distributed generation (DG) can provide an economical and environmentally friendly solution to meet the load growth in distribution systems.

In recent years, the presence of DG in distribution systems has become increasingly common. The reasons for this trend include the unbundling of electricity markets, along with

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stronger constraints for the building of new transmission and distribution lines based on environmental issues.

Several studies have shown that if DG is properly sized and placed, it can be used as an effective way to reduce active and reactive power losses, improve voltage profile, increase reliability, reduce pollutant emissions and delay further investments in expanding the network [1]-[2]. In this context, different methodologies have been proposed in the specialized literature for the optimal location of DG units. Such methodologies include the use of analytical approaches [3]-[4], mathematical programming [5]-[6], Genetic Algorithms [7]-[8], Tabu Search [9] and particle swarm optimization [10]. Also, some authors have proposed hybrid methods; most of them combine Genetic Algorithms with other techniques such as Immune Algorithms [11], Particle Swarm Optimization [12] and Optimal Power Flow [13].

The mathematical model for the optimal location of DG presented in this paper consists of a mixed integer nonlinear programming problem. Integer (binary) variables represent whether there is or there is not DG in a given bus; furthermore, real variables such as voltage angle and magnitude are taken into account. On the other hand, power losses are quadratic by nature and the power balance and power flow expressions are nonlinear (for an AC power flow model of the network). In consequence, the resulting model is non-convex and multi-modal (with multiple sub-optimal solutions). Such type of problems are better handled by metaheuristic techniques.

In this paper the authors propose a hybrid approach applied to the optimal location of DG for reducing power losses in distribution systems. Such approach consists on the combination of Genetic Algorithms, Artificial Neural Networks and Variable Neighborhood Search.

III. Mathematical Formulation

The mathematical formulation of the problem being addressed is presented in (1)-(10).

$$Min \sum_{r=1}^{nr} I_r^2 R_r \tag{1}$$

Subject to:

$$\mu_i P_{Gi} - P_{Di} - P_i(V,\theta) = 0 \tag{2}$$

$$\mu_i Q_{Gi} - Q_{Di} - Q_i(V,\theta) = 0 \tag{3}$$

$$P_i(V,\theta) = V_i \sum_{k=1}^{nb} \left[V_k \left\{ g_{ik} \cos(\theta_{ik}) + b_{ik}\, sen(\theta_{ik}) \right\} \right] \tag{4}$$

$$Q_i(V,\theta) = V_i \sum_{k=1}^{nb} \left[V_k \left\{ g_{ik}\, sen(\theta_{ik}) - b_{ik} \cos(\theta_{ik}) \right\} \right] \tag{5}$$

$$ngd_i \le ngd^{max} \tag{6}$$

$$P_{Gj}^{\min} \le P_{Gj} \le P_{Gj}^{\max} \tag{7}$$

$$Q_{Gj}^{\min} \le Q_{Gj} \le Q_{Gj}^{\max} \tag{8}$$

$$V_i^{\min} \le V_i \le V_i^{\max} \tag{9}$$

$$S_{ik}^2 = P_{ik}^2 + Q_{ik}^2 \tag{10}$$

$$P_{ik} = V_i^2 g_{ik} - V_i V_k g_{ik} \cos(\theta_{ik}) - V_i V_k b_{ik}\, sen(\theta_{ik}) \tag{11}$$

$$Q_{ik} = -V_i^2 b_{ik} + V_i V_k b_{ik} \cos(\theta_{ik}) - V_i V_k g_{ik}\, sen(\theta_{ik}) \tag{12}$$

$$|S_{ik}| \le S_{ik}^{\max} \tag{13}$$

Equation (1) represents the objective function which consists on the minimization of active power losses. Equations (2) and (3) account for the active and reactive power balance equations, respectively. Equations (4) and (5) represent the active and reactive power injections as function of voltage magnitudes and angles. Equation (6) limits the number of DG units that can be allocated in a node. Equations (7) and (8) represent the active and reactive generation limits of the DG units, respectively. Equation (9) represents the voltage limits of every node in the network. Equation (10) accounts for the nature of apparent power flow (composed by both, active and reactive power flows). Equations (11) and (12) correspond to the mathematical expressions of active and reactive power flows, respectively. Finally, equation (13) accounts for the apparent power flow limits in all lines.

IV. Hybrid Genetic Algorithm Approach

A Genetic Algorithm (GA) is a metaheuristic technique designed to mimic the process of natural evolution. In a GA a population of candidate solutions (also called individuals) is evolved toward better solutions. The algorithm starts from a population of randomly generated individuals; in each iteration (also called generation), such individuals must pass through a series of GA operators in order to find better solutions. The stopping criteria can be a maximum number of iterations without improvement of the fitness function and/or a total maximum of iterations.

In this paper a GA is used as the main frame of the optimization problem. An Artificial Neural Network (ANN) is used as a subroutine of the GA, and has been trained to compute the fitness of the candidate solutions, avoiding the use of power flow solvers. Finally, a neighborhood search is carried out at the end of every iteration to search for better solutions. A flowchart of the proposed approach is shown in Figure 1.

The codification of a candidate solution consists on a string of binary numbers. Such string is variable depending on the number of DG units to be considered for optimal allocation. In this case a 13 bus test system is under analysis. Then, the location of every DG unit can be coded with four binary numbers, each binary number representing the node where the DG unit is allocated. Note that 4 binary numbers would code from 0 to 15; consequently, non existing bus numbers 0, 14 and 15 must be avoided or penalized in the objective function. Table 1 shows an example of the binary codification. Observe that the length of the string is 20 (5 DG units, which location is coded with 4 binary numbers each). The string provided in

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Table 1 indicates that the DG units must be allocated in buses 1, 13, 9, 4 and 2.

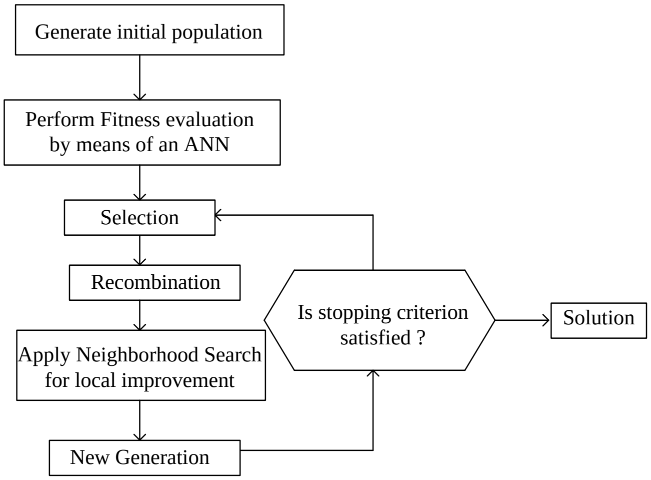

Fig. 1. Flowchart of the proposed approach

TABLE I
STRUCTURE OF THE BINARY CODIFICATION

	DG 1	DG 2	DG 3	DG 4	DG 5
Bus	1	13	9	4	2
Binary	0 0 0 1	1 1 0 1	1 0 0 1	0 1 0 0	0 0 1 0

To start the iterative process an initial population is randomly generated. Then, the ANN computes the fitness of each individual (in this case the fitness function represents the active power losses). The more fit individuals are selected through tournament and generate new individuals through the recombination step (a single point recombination was implemented).

The proposed ANN allows to improve the time response of the hybrid GA and avoids the use of power flow solvers. Such ANN consists in a hidden layer and an output layer as shown in Figure 2.

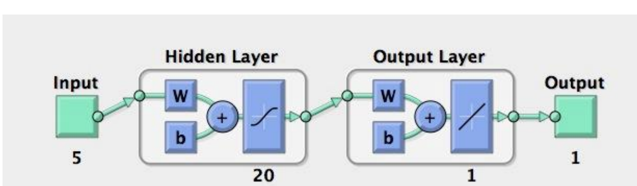

Fig. 2. Structure of the ANN

The training of the ANN was made using the well known Levenberg/Marquard Backpropagation Algorithm. The results of the training are presented in Table 2 where MSN stand for The Mean Square Error and R is the linear regression coefficient. The MSE of the ANN is shown in Figure 3.

TABLE II
RESULTS OF THE ANN TRAINING

	Samples	MSE	R
Training	1345	4.1544 e -6	9.9953 e -1
Validation	288	5.0942 e -6	9.9947 e -1
Testing	288	5.5287 e -6	9.9942 e -1

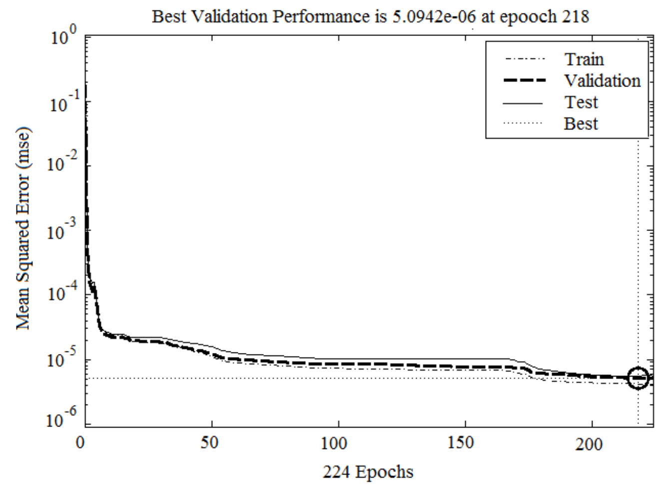

Fig. 3. MSE of the ANN

The neighborhood search is the last procedure of each generation. Such search is performed in order to obtain better solution candidates; it modifies each of the elements changing one bit at a time and them selects the best option in the neighborhood.

V. TESTS AND RESULTS

To validate the proposed approach the 13 bus distribution system shown in Figure 4 was considered. Tables 3 and 4 provide the data of lines and buses [14]. All DG units considered in the analysis are supposed to have a maximum capacity of 1 MW.

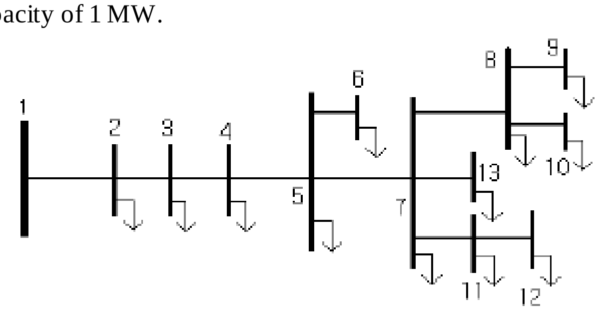

Fig. 4. 13 bus distribution test system

The active power losses of the system under study without DG are 797.05 kW. Several tests were carried out with the proposed hybrid GA obtaining an overall power loss reduction of 29.35% (power losses with DG = 563.1 kW) with three DG units located in bus 13 and one located in bus 4. An initial population of 20 individuals and a maximum of 40 generations were used. The tests were run using a computer with a 2.26GHz Intel Core 2 Duo processor and 3Gb of RAM memory. The average time to run the tests was around one minute. However, without the ANN the average time would increment up to 7 minutes. This shows that once the ANN is trained, it can significantly reduce the computation time of the algorithm.

TABLE III
LINE DATA OF THE 13 BUS DISTRIBUTION SYSTEM

Line	R[Ohm]	X[Ohm]
1-2	0.000176	0.00138
2-3	0.000176	0.00138
3-4	0.00045	0.00035
4-5	0.00089	0.00069
5-6	0.000116	0.00035
5-7	0.00073	0.00091
7-8	0.00074	0.00073
8-9	0.00093	0.00058
8-10	0.00063	0.00093
7-11	0.00063	0.0005
11-12	0.00068	0.00053
7-13	0.00062	0.00053

TABLE IV
BUS DATA OF THE 13 BUS DISTRIBUTION SYSTEM

Bus	Active demand (kW)	Reactive demand (KVAR)
1	0	0
2	890	468
3	628	470
4	1112	764
5	636	378
6	474	344
7	1342	1078
8	920	292
9	766	498
10	662	480
11	690	186
12	1292	554
13	1124	480

VI. CONCLUSIONS

A hybrid Genetic Algorithm for the optimal location of distributed generation was presented in this paper. Results on a 13 bus distribution system showed the robustness and applicability of the proposed approach. The main contribution of this paper consists on the combination of metaheuristic techniques in the solution of a non-convex multi-modal optimization problem.

The use of an ANN proved to be a suitable tool to reduce the time response of the hybrid algorithm. Further work will include the impact of demand response and different types of distributed generation technologies.

VII. ACKNOWLEDGMENT

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VIII. REFERENCES

[1] A. Barin, L. F. Pozzatti, L. N. Canha, R. Q. Machado, A. R. Abaide, and G. Arend, “Multi-objective analysis of impacts of distributed generation placement on the operational characteristics of networks for distribution system planning,” *International Journal of Electrical Power & Energy Systems*, vol. 32, no. 10, pp. 1157–1164, Dec. 2010.

[2] M. Junjie, W. Yulong, and L. Yang, “Size and Location of Distributed Generation in Distribution System Based on Immune Algorithm,” *Systems Engineering Procedia*, vol. 4, no. 2011, pp. 124–132, Jan. 2012.

[3] N. Acharya, P. Mahat, and N. Mithulananthan, “An analytical approach for DG allocation in primary distribution network,” *International Journal of Electrical Power & Energy Systems*, vol. 28, no. 10, pp. 669–678, Dec. 2006.

[4] T. Gözel, M.H. Hocaoglu, "An analytical method for the sizing and siting of distributed generators in radial systems", *Electric Power Systems Research*. 79 (2009) 912–918.

[5] C. Dent, L. Ochoa, and G. Harrison, “Network distributed generation capacity analysis using OPF with voltage step constraints,” *Power Systems, IEEE*, vol. 25, no. 1, pp. 296–304, 2010.

[6] N. Khalesi, N. Rezaei, M.-R. Haghifam, "DG allocation with application of dynamic programming for loss reduction and reliability improvement", *International Journal of Electrical Power & Energy Systems*. 33 (2011) 288–295

[7] R.K. Singh, S.K. Goswami, "Optimum allocation of distributed generations based on nodal pricing for profit, loss reduction, and voltage improvement including voltage rise issue", *International Journal of Electrical Power & Energy Systems*. 32 (2010) 637–644

[8] J.M. López-Lezama, J. Contreras, A. Padilha-Feltrin, "Location and contract pricing of distributed generation using a genetic algorithm", *International Journal of Electrical Power & Energy Systems*, 36 (2012) 117–126.

[9] I. J. Ramírez-rosado and J. A. Domínguez-navarro, “New multiobjective tabu search algorithm for fuzzy optimal planning of power distribution systems,” *Power Systems, IEEE* vol. 21, no. 1, pp. 224–233, 2006.

[10] M. H. Moradi and M. Abedini, “A combination of genetic algorithm and particle swarm optimization for optimal DG location and sizing in distribution systems,” *International*

Journal of Electrical Power & Energy Systems, vol. 34, no. 1, pp. 66–74, Jan. 2012.

[11] A. Soroudi, M. Ehsan, R. Caire, and N. Hadjsaid, "Hybrid immune-genetic algorithm method for benefit maximisation of distribution network operators and distributed generation owners in a deregulated environment," *IET Generation, Transmission & Distribution*, vol. 5, no. 11, p. 961, 2011.

[12] M.H. Moradi, M. Abedini, "A combination of genetic algorithm and particle swarm optimization for optimal DG location and sizing in distribution systems", *International Journal of Electrical Power & Energy Systems*. 34 (2012) 66–74.

[13] G.P. Harrison, A. Piccolo, P. Siano, a. R. Wallace, "Hybrid GA and OPF evaluation of network capacity for distributed generation connections", *Electric Power Systems Research*. 78 (2008) 392–398.

[14] Y. Alinejad-Beromi, M. Sedighizadeh and M. Sadighi, "A particle swarm optimization for sitting and sizing of distributed generaion in distribution network to improve voltage profile and reduce THD and losses" 43th International Utilites Power Engineering Conference (UPEC), 2008, pp 1-5.

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