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Electric Power Grids Distribution Generation System For Optimal Location and Sizing—An Case Study Investigation by Various Optimization Algorithms

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Abstract: In this paper a variable's involved in assessing the quality of a distributed generation system are reviewed, aiming to minimize the electric power losses (unused power consumption) and optimize the voltage profile. To provide this assessment, several experiments have been made to the IEEE 34-bus test case and various actual test cases with the respect of multiple DG units. The possibility and effectiveness of the proposed algorithm for optimal placement and sizing of DG in distribution systems have been verified. Finally, four algorithms were trailed: simulated annealing (SA), hybrid genetic algorithm (HGA), genetic algorithm (GA) and variable neighbourhood search. The HGA algorithm was found to produce the best solution at a cost of longer processing time.

Keywords: optimization; simulated annealing; genetic algorithm; power losses; power consumption

1. Introduction

In the past decade increased distributed generation (DG) has led to profound changes in electricity distribution networks. Several factors have driven DG (defined as production of electricity close to consumption centers) including new technological advances in the production of electricity on a small scale, a preference for the use of renewable resources, difficulties in network expansion and a growing interest in incorporating demand and active agents in the electricity markets [8]. DG can contribute to reducing losses, improving voltage profile, improving reliability and postponing investments [7]. However, as noted in [5], harnessing the benefits of DG depends largely on its location, sizing and network features. That is why in the past decade's alternative methodologies for proper location and sizing have been explored.

In [6] a literature review of techniques used for the location and optimal sizing of DG in distribution networks is presented. The authors classify the techniques according to analytical methods, metaheuristics and mathematical programming. It should be noted that for the problem under study metaheuristics techniques have significant advantages over classical mathematical programming because of the nonlinear and non-convex relationships in the location and sizing of DG. On the other hand, the main weakness of metaheuristics is that they do not guarantee obtaining a global optimum. However, metaheuristics may provide a solution or set of high quality solutions. Another advantage that lies with metaheuristics techniques is that they allow the use of more detailed models of network operation than the analytical model. To apply mathematical programming techniques to the problem of optimal location and sizing of DG, it is necessary to use linearization or approximations to the equations in the balance of power.

Metaheuristic optimization techniques have been widely used in the location and design of the DG. These techniques include genetic algorithms, tabu search and colonies of particles. In [1] a model of multi-objective optimization was presented to determine the location and optimal sizing of DG using the technique of simulated annealing. The elements were modelled power losses, the number of generators, the voltage profile and power injected by the DG. The method sought a

solution that would improve the voltage profile and reduce losses to the minimum DG units in the system. In [13] the authors presented a population-based metaheuristic based on the parasitic reproductive behaviour of some species of cuckoos (cuckoo search algorithm) for the location and optimal sizing of DG. The advantage of this algorithm was that it required a few parameters to calibrate. The aim of the study was the reduction of active power losses.

Hybrid methods combine two or more search techniques in order to exploit their potential and compensate for their deficiencies. The most common methods combine population hybrid techniques with methods that enhance some kind of local search or alternatively, heuristic methods with classical mathematical programming. In [3] a combination of simulated annealing and genetic algorithms for optimal location of DG comes with network distribution. The objective was to minimize losses. The authors showed that the combination of GA with simulated annealing was more effective than using only GA. In [11] a method to maximize the benefit to network operators and owners of distributed generation in a deregulated electricity market hybrid algorithm was presented. As well as simultaneously optimizing the benefits to the distribution company and to the owner of the DG their method also considered the uncertainty of demand and energy prices.

In [13] a hybrid algorithm was presented that improved stress profiles and reduced emissions using a particles' gravitational colony search to determine the proper location and sizing of the DG that minimized loss. The aim of this article is to contribute to the discussion on the effectiveness of heuristic and metaheuristic methods for optimal dimensioning and location of DG. To this end, four different techniques were implemented and compared, namely i) simulated annealing, ii) variable search environment, iii) genetic algorithm and iv) a hybrid method that combines variable search environment with a genetic algorithm. To test the efficiency of these methods, they were applied to various tests in a distribution system (34 bars) that is widely used in the technical literature.

2. Background Mathematical Formulation

The objective function of the proposed problem is to improve the voltage profile and reduce system losses. To this end the indexes defined in [2] described below are taken. The rate of voltage profile, denoted as IPT, is defined by equation (1). This index takes into account the voltage and the bars of the system as a load factor. This makes it more important to maintain proper tension in bars under higher demand.

$$IPT = \sum_{\{i=1\}}^N V_i L_i \quad (1)$$

Variables: V_i : Tension in the bar i (p.u); L_i : Load in bar i (p.u); and N : Total number of bars. The rate of improvement of voltage profile, denoted as IMPT is given by the equation (2).

$$IMPT = \frac{IPT_{\{wDG\}} - IPT_{\{woDG\}}}{IPT_{\{woDG\}}} \times 100 \quad (2)$$

Variables: $IPT_{\{wDG\}}$ is the index of the system voltage profile with DG (p.u.) and $IPT_{\{woDG\}}$ is the profile index stress the system without DG (p.u.). Note that the IMPT denotes the percentage improvement in IPT with DG. The second objective is to reduce active losses and compare losses with the system with and without DG, given by the equation in (3).

$$IPT_{\{wDG\}} = \sum_{\{K=1\}}^N I_{\{K,wDG\}}^2 R_{KD_k} + LL_{\{wDG\}} \quad (3)$$

A similar expression can reflect *woDG* conditions. The equation variables are described as follows:

$IPT_{\{wDG\}}$: Index line losses with DG.

R_k : Resistance in line K (p.u / km)

D_k : Length in line K (km).

$I_{\{K,wDG\}}^2$: Current line k with DG (p.u).

$LL_{\{wDG\}}$: Index line losses with DG.

$LL_{\{woDG\}}$: Index line losses without DG.

$I_{\{K,woDG\}}^2$: Online K stream without DG (p.u).

While the percentage reduction in losses in the line is income tax is given by equation (4):

$$IRPL = \frac{IPL_{\{wDG\}} - IPL_{\{woDG\}}}{IPL_{\{woDG\}}} \times 100 \quad (4)$$

The objective function is to minimize the reduction rates of losses and to improve the voltage profile. In this case you should be using weighting factors W_1 and W_2 dimensions for each rate in order to assess their importance in the optimization process. The optimization problem to solve is described by expressions form (5) to (17).

$$f(x) = w_{1IRPL} + w_{2IMPT} \quad (5)$$

Where the subject of the previous equation is:

$$0 \leq w_1 \leq 1; m = 1,2 \quad (6)$$

$$\sum_{\{m=1\}}^2 w_m = 1 \quad (7)$$

$$u_i P_{Gi} - P_{Di} - V_i \sum_{k=1}^{nb} [V_k (g_{ik} \cos \theta_{ik} + b_{ik} \sin(\theta_{ik}))] = 0 \quad (8)$$

$$u_i Q_{Gi} - Q_{Di} - V_i \sum_{k=1}^{nb} [V_k (g_{ik} \sin \theta_{ik} + b_{ik} \cos(\theta_{ik}))] = 0 \quad (9)$$

$$P_{ik} = V_i^2 g_{ik} - V_i V_k g_{ik} \cos(\theta_{ik}) - V_i V_k b_{ik} \sin(\theta_{ik}) \quad (10)$$

$$Q_{ik} = V_i^2 b_{ik} - V_i V_k b_{ik} \cos(\theta_{ik}) - V_i V_k g_{ik} \sin(\theta_{ik}) \quad (11)$$

$$S_{ik}^2 = P_{ik}^2 + Q_{ik}^2 \quad (12)$$

$$P_{Gi}^{\min} \leq V_i \leq P_{Gj}^{\max} \quad (13)$$

$$V_i^{\min} \leq V_i \leq V_i^{\max} \quad (14)$$

$$S_{ik} \leq S_{ik}^{\max} \quad (15)$$

$$N_{DG} \leq N_{DG}^{\max} \quad (16)$$

$$u_i \in \{0,1\} \quad (17)$$

Where $P_{\{Gi\}}$ and $Q_{\{Gi\}}$ are the active and reactive power respectively, delivered by a unit of DG if it is located in the bar i . Note that not all bars have DG. DG for each unit must be assigned to a binary variable (called u_i). For simplicity, it is not considered that the DG inject or take reactive power from the network, so $Q_{\{gi\}} = 0$. $P_{\{Di\}}$ and $Q_{\{Di\}}$ correspond to power demands active and reactive bar i , respectively. Also nb is the number of bars, $\theta_{\{ik\}}$ is the angular opening between the bars and k ; $g_{\{ik\}}$, and $b_{\{ik\}}$ are the real and imaginary, respectively, of the nodal admittance matrix parts. Constraints (8) and (9) represent the balance equations and reactive power, respectively. Restrictions (10), (11) and (12) represent the equations of active power flow, reactive and apparent power, respectively. The restrictions (13), (14) and (15), consider the power limits injected by the DG, limits voltage network and load flow limits, respectively. The constraint (16) indicates the maximum number of units DG needs to consider and restriction (17) indicates the binary nature of the variables u_i (1 if with DG and 0 if without DG). The model described by equations (5) - (17) corresponds to a problem in mixed integer nonlinear programming which is highly dimensional and non-convex having multiple local optima, which justified its solution using the search methods illustrated in this article.

3. Methodology on Hybrid Optimization Algorithm

To address the problem of optimal location and the sizing of DG described in the previous section four techniques were used as combinatorial optimization: Simulated Annealing, Variable Descending Search Environment, Genetic Algorithm and Hybrid Genetic Algorithm. A brief description of each technical solution as adopted in this study is presented.

3.1. Simulated Annealing

Simulated Annealing (SA) emulates the annealing process in steel and ceramics, which involves heating and then slowly cooling the material to vary its physical properties. This procedure was introduced in [9]. In each iteration of the SA some neighbours of the current status are evaluated and probabilistic decision made between making the transition to a new state or remaining in the current state. If the neighbour solution enhances the value of the objective function is accepted with probability 1, otherwise the probability of accepting by the Metropolis criterion given by equation (18) where the parameter c corresponds to the temperature.

$$Prob(\text{accept } \hat{x}) = \begin{cases} 1 & , f(\hat{x}) < f(x) \\ \exp\left(-\frac{f(\hat{x}) - f(x)}{c}\right) & , f(\hat{x}) \geq f(x) \end{cases} \quad (18)$$

SA assesses unattractive solutions in the early stages, then as the temperature parameter is reduced, the search becomes more selective, lessening the declines in the objective function.

3.2. Variable Search Environment Descending

Environment Variable Search (EVS) is a metaheuristic based on a local search in a changing neighbourhood (also known as environment structure). Variations in EVS are given the names *down*, *reduced*, *basic* or *general* EVS. This paper considered an extension of EVS known as Variable Search Environment Descending (VSED) in which the current solution obtained from the change in a local search is implemented; as long as this one has found a better solution. VSED is illustrated below [4] as the following:

- Initialization: Select the set of environments, structures $N_k, k = 1, \dots, k_{\max}$ to be used in the descent. Find an initial solution x ;
- Iterations: Repeat until no improvement is obtained (until there is no more optimization that we can get).

In the following sequence:

- (1) Make $k \rightarrow 1$.
- (2) Repeat until $k = k_{\max}$ the following:
 - (a) Exploration of the environment: Find the best solution x' of the k^{th} neighborhood of $x(x' \in N_k(x))$
 - (b) Move or not: If the obtained solution x' is better than x , do $x \rightarrow x', k \rightarrow 1$; otherwise do $\rightarrow k + 1$.

In the study presented in this article, environments or neighbourhoods were defined as the size (increase or decrease the capacity of the DG) and location (DG move to a neighbouring node).

3.3. Genetic Algorithm

Genetic Algorithms (GA) solve optimization problems by simulating natural selection or "survival of the fittest" [10]. The general routine of a GA is to generate an initial population of random or pseudo-random solutions. Each individual in the population is defined by a string of bits. In this case, the objective function is to evaluate the power flow as a consequence of the

location and sizing of the DG. For a given tournament a number of individuals are selected. The number of tournaments is equal to the size of the population. Recombination is made at one randomly selected point. The mutation is created by changing a bit (zero to one) randomly with a given probability of occurrence. Individuals generated in the process of recombination and mutation replaces existing individuals if they are better than their predecessors. Two stopping criteria are considered; the maximum number of iterations or the maximum number of iterations without improvement of the objective functions.

3.4. Hybrid Genetic Algorithm

Hybrid methods (HGA) seek to combine the advantages of two or more metaheuristics for high quality solutions. The most common hybrid methods combine population methods (e.g. Genetic Algorithms) with local search methods (Simulated Annealing, Variable Search Environment) or exact methods (linear programming, nonlinear)[16]. In this paper a method population (GA) combined with a local search method (VSED) was implemented. The flowchart of the implemented algorithm is illustrated in Fig.1 below. The HGA structure retains essentially the GA structure described in the previous section; however, after mutation and before replacing the individuals of the next generation it performs a local search in order to find better quality individuals in the current generation. As already described in the GA, only individuals exhibiting improvement in the objective function are included in the new generation.

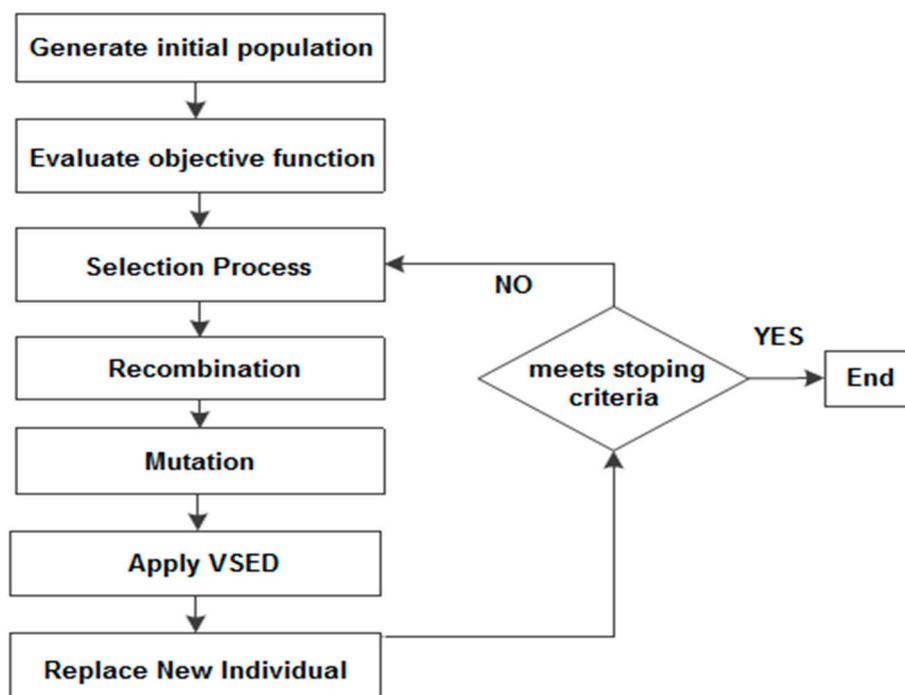


Figure 1: Diagram of HGA Algorithm.

4. Numerical Simulation Test and Investigation Results

In Fig. 2 a distribution system of 34 bars is illustrated. The maximum network demand is 15,8 MW with a power factor of 0.95 lag. It may include up to 4 DG units, each one represented with a maximum power of 2.0 MW. Candidate solutions with DG units are penalized in the objective function (to minimize the loss in power) in order to make them less attractive. Note that according to the formulation (equation (17)) the algorithm may select other number DG units up to the maximum.

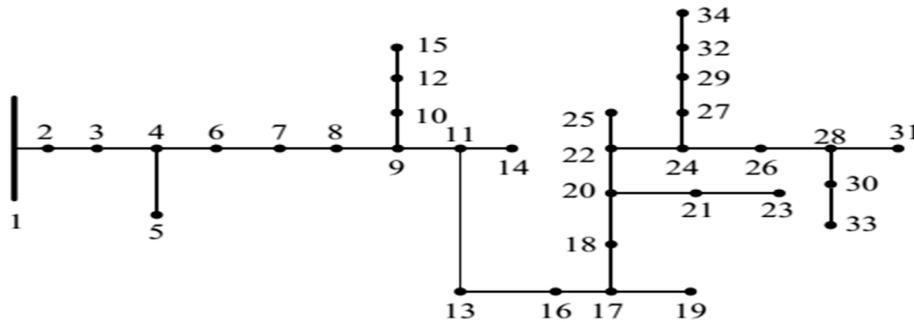


Figure 2: Distribution System of 34 bars.

The distribution of demand in each of the network nodes is shown in Fig. 3. It can be seen that a significant part of the demand is in the first bars.

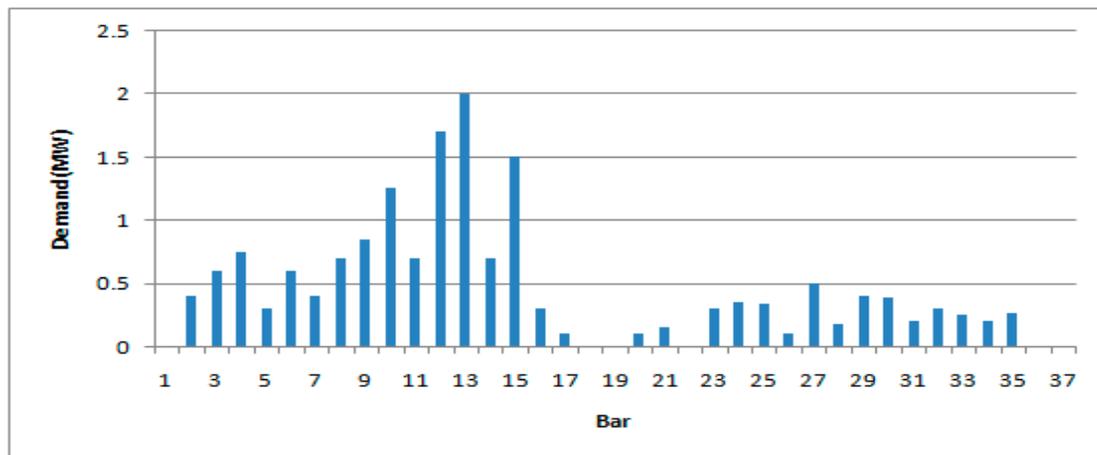


Figure 3: Distribution of demand in the system of 34 bars.

4.1. Coding Solutions

Table 1: Codification of DG size.

Code	Size(MW)	Code	Size(MW)
1000	0.25	1100	1.25
1001	0.50	1101	1.50
1010	0.75	1110	1.75
1011	1.00	1111	2.00

A chain of 4 binary bits was used to represent each used generator. The first bit represented the state of the generator (generator 1, the generator does not exist 0); the remaining 3 bits represented the power level of the generator. Thus, 1000 denoted minimum capacity (0.25 MW), while the chain 1111 represented a generator with maximum capacity (2.0 MW). Table 1 illustrates the equivalence. Table 2 illustrates the code of a particular candidate solution comprising $4 \times nb$ bits, where nb was the number of bars in the system. Bars 1, 2, 4 and $nb-1$ have no generator; while bars 3 and nb have generating capacities of 1.0 and 2.0 MW, respectively.

Table 2: Solution candidates encoding.

Bus1	Bus2	Bus3	Bus4	Bus nb-1	Bus nb
0100	0011	1011	0111	0011	1111

4.2. Weighted Factors Calibration

Before starting the optimization process weighting factors must be assigned to the two objectives under study (IRPL and IMPT) in order to assess the relative fitness of particular solutions. This requires a diagnosis without DG base case. This diagnosis was made by a load flow calculation with and without DG. The load flow analysis was performed by software Matpower [15] with DG modelled as bars where active power could be injected. In Fig. 4 and Fig. 5, the voltage profile and line losses, respectively, with and without DG are illustrated.

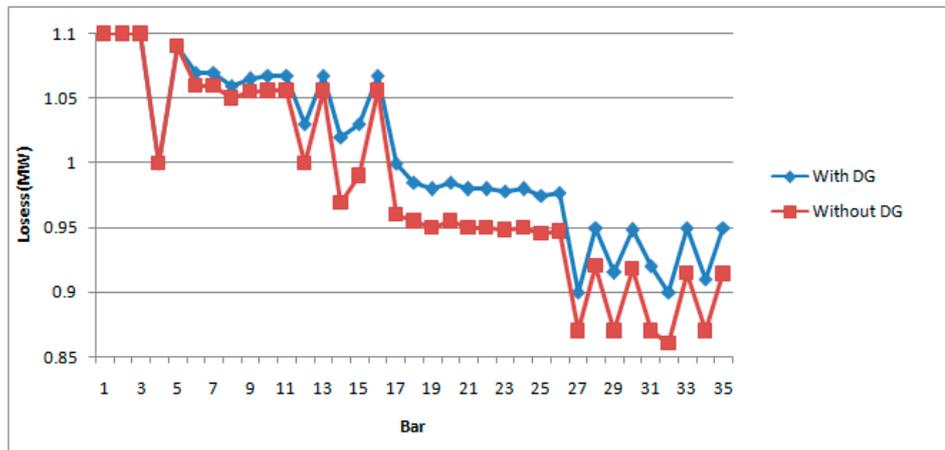


Figure 4: Voltage profile system of 34 bars with and without DG.

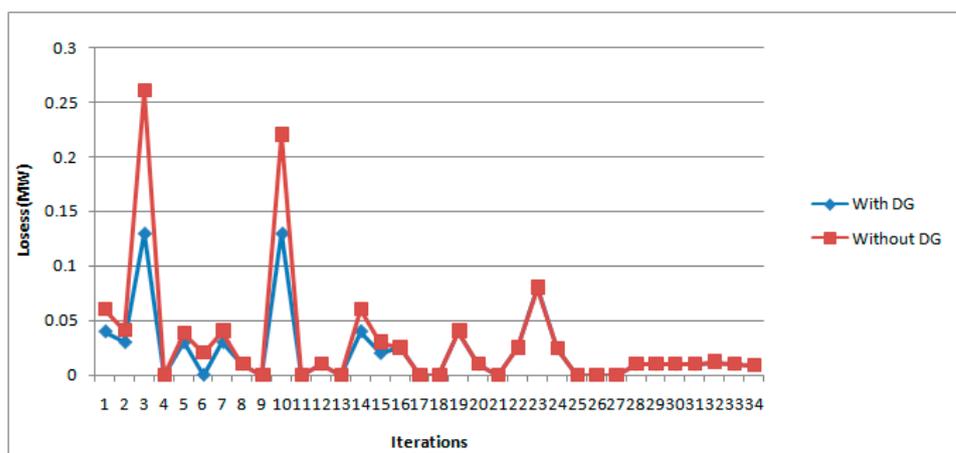


Figure 5: Line losses of 34 bar system with and without DG.

Table 3: Values of IRPL and IMPT for candidates with randomly generated solutions.

Simulation	IRPL	IMPT	IRPL/IMPT
1	41,884	1,513	27,682
2	50,127	2,806	17,864
3	43,297	2,124	20,385
4	57,487	2,478	23,199
5	34,329	1,878	18,280
6	30,287	1,079	26,070
7	44,238	2,567	17,233
8	30,234	1,969	15,355

A case with 4 units of DG is illustrated; each with 1 MW located in the bars 5, 10, 15 and 20. In Fig. 4 it may be noted that even adjusting the tension in the substation at 1.1 p.u., when DG were not tensions, the last bars were below 0.9 p.u. featuring voltage regulation (percentage difference between the maximum and minimum system voltages) exceeding 20%. However, when DG was introduced to the system stresses increased, especially in remote substation busbars, causing the voltage regulation in these rods to fall to 17.5%. On the other hand, total losses without DG amounted to 959.5 kW systems and with DG were 555.8 kW. When calculating indices IMPT and IRPL by the expressions (2) and (4) respectively values obtained were $IMPT = 1.5135$ and $IRPL = 41.8848$. These indices were calculated for different solution candidates (location and DG sizing) randomly generated resulting in the data given in Table 3. It can be seen that IRPL was much higher than IMPT in all simulations. This was because the percentage of loss reduction was more significant than the improvement in voltage profile. On average, IRPL was about 20 times greater than IMPT as seen in the fourth column of Table 3. If the indexes were optimized without using weighting factors that would favour solutions that reduced losses in order to improve tensions. Weighting factors $w_1 = 0.05$ and $w_2 = 0.95$ were assigned in order to give similar importance to IMPT and IRPL objectives in the optimization process. However, the manager of the planning system can select other values to give more importance to a particular target.

4.3. Results using Simulated Annealing

To start the SA, a base solution that meets the criterion of maximum number of generators is generated. From there neighbouring solutions are explored according to the criteria stated in equation (18). This means that early in the process the probability of accepting poorer quality solutions is high, but as the process evolves that probability is restricted. Thus, the principle of seeking diversity is privileged and at the end of the simulation it intensifies the search for better solutions. After performing several trial runs with different SA algorithm parameters, initial and final temperature was calibrated at 3.0 and 0.5, respectively, and at each iteration the temperature was reduced by 0.01. In Table 4 and Fig 6 the best solution found (after 190 iterations) and the convergence of the algorithm illustrated by the SA. In this case the time for calculation was 1.2 minutes. A computer Intel Core i3 2.4 GHz with 4 GB of RAM was used in all simulations.

Table 4: Best result using SA.

Bar	Size (MW)	$w_1 IRPL$	$w_2 IMPT$	FO
8	1,5			
17	1,75			
22	2	2,9578	4,3747	7,3325
29	1,5			

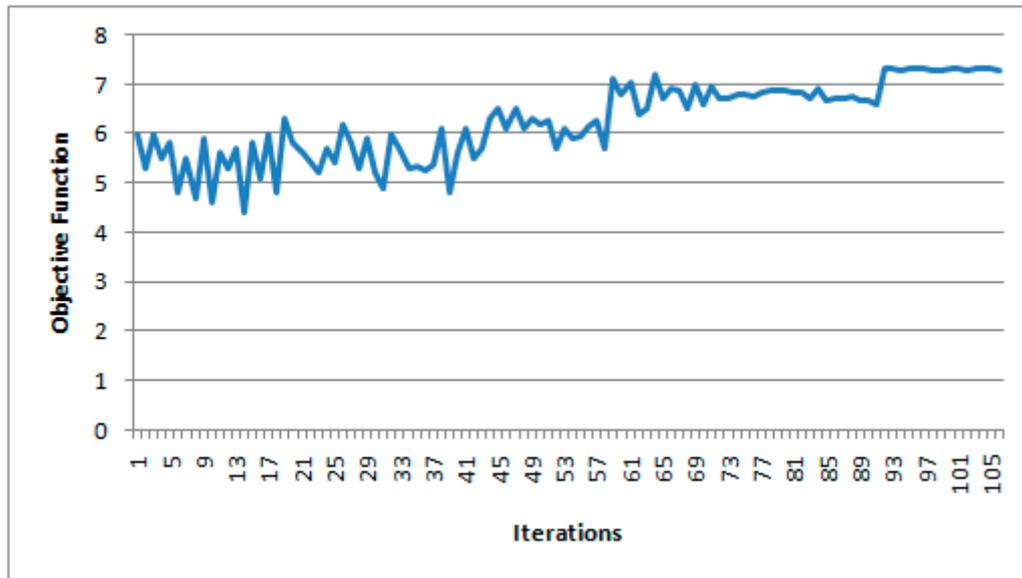


Figure 6: Convergence process in SA.

4.4. Results using Variable Search Environment Descending

The size and location of the DG defined the VSED environment. A base solution of individuals was explored to better the environment by following the instructions as described in the methodology section. The search continues until it either passes a certain number of iterations or until no improvement is achieved over previous iterations. In Table 5 the best found VSED is illustrated. Here 22 iterations were performed by evaluating the structure of 8 individuals with a computation time of 2.1 minutes.

Table 5: Best result using VSED.

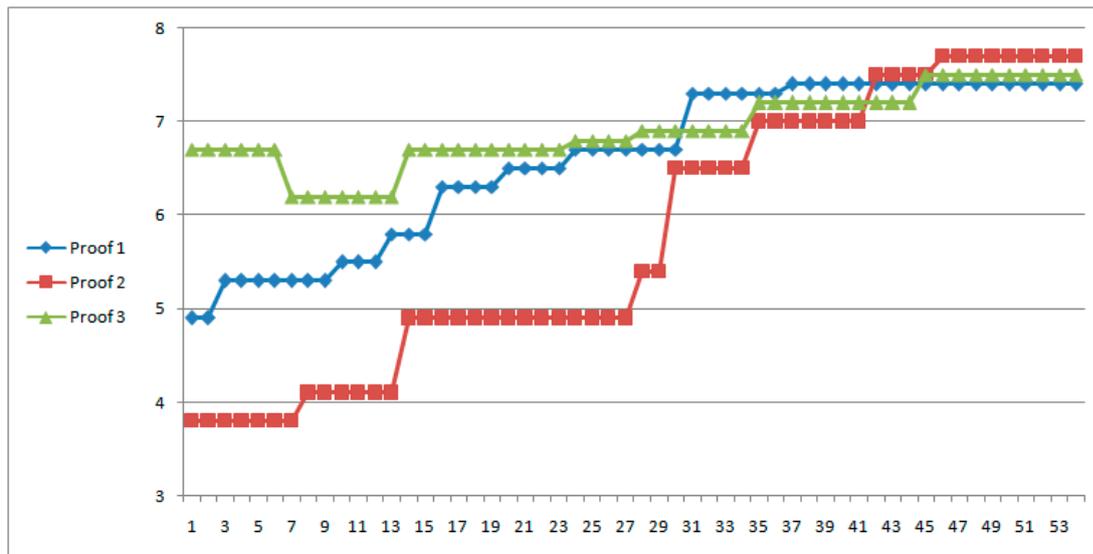
Bar	Size (MW)	w_1 IRPL	w_2 IMPT	FO
5	2,0			
10	2,0			
21	1,5	3,9274	3,8313	7,7857
31	1,5			

4.5. Results using the Genetic Algorithm

The implemented GA solution used a coding chromosome structure as illustrated in Table 2. An initial population of possible solutions was generated pseudo-randomly which led to new solutions of better quality achieved by implementing a sequence of selection, recombination and mutation as described in the methodology section. The GA parameters of initial population size, mutation rates and recombination were calibrated through repeated runs. It was noted that with small initial populations, poor quality responses were obtained. By increasing the number of individuals in the initial population the quality of solutions improved, but the computing time increased. The best solution was found with a population of 100 individuals and mutation and recombination rates of 10% each. The computation time to find the best solution was 2.9 minutes after 90 iterations. The best result is shown in Table 6 while Fig. 7 shows the process of convergence for different tests. It can be seen that even though the initial populations were of different quality, the tests converged to solutions of similar quality.

Table 6: Best result using GA.

Bar	Size (MW)	w_1 IRPL	w_2 IMPT	FO
10	2,5			
15	1,5			
26	1,5	3,8887	3,7836	7,6723
29	1,25			

**Figure 7:** Process of convergence for 3 different GA tests.

4.6. Results using the Hybrid Genetic Algorithm

Table 7: Best result using HGA.

Bar	Size (MW)	w_1 IRPL	w_2 IMPT	FO
12	1,7			
13	2,0			
22	1,0	4,0573	3,9201	7,9774
30	1,25			

As mentioned above the HGA implemented combined the GA described in the previous section with VSED. That is, after applying the traditional operators of GA and prior to the population replacement in each iteration, the fitness of individuals was increased using VSED. The same parameters were calibrated as for with traditional GA. Table 7 presents the best solution found. It was observed for all tests that the computational time was considerably greater than that required by the other algorithms implemented; however, the quality of the response was better. The best answer was found after only 6 iterations in a computation time of 12.6 minutes.

5. Comparative Performance Index of Algorithms

The best result was obtained using HGA; however, this is the method that took longer to find a high quality solution. The fastest converging test algorithm was the simulated annealing, but

solutions obtained with the other methodologies were of better quality. The VSED required less iteration to converge compared to the SA, but its computing time per iteration was greater and to be evaluated in terms of iteration, two structures of the neighbourhood were needed. HGA generated the highest quality solutions when using large initial populations of 100 individuals. Fig. 8 compares the computation time for the methods used, where the HGA stands out as relatively slow. The best solution found (see Table 7) showed an 80.2% reduction in losses compared to the base case without DG.

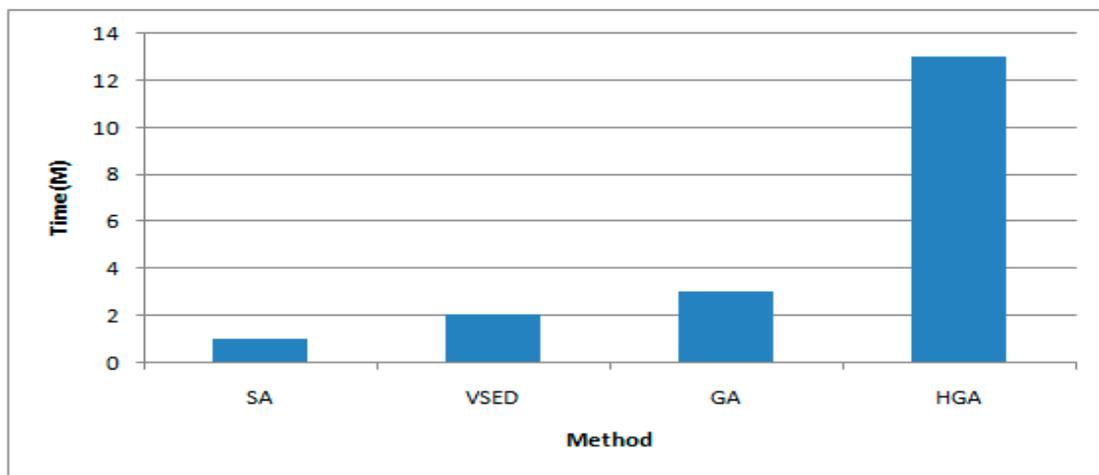


Figure 8: Search time comparison.

6. Conclusion

In this study, four algorithms were compared to obtain the optimum location and sizing of DG in distribution systems: SA, VSED, GA and HGA. The implemented methodologies based on these optimization algorithms were all successful in finding high quality solutions. In the trialled application tests the best results were obtained using HGA, which combines genetic algorithm and VSED. It was observed that the optimum percentage of DG penetration of the test system varied between 6 and 7 MW installed at the start bar and the end bar for substantial improvement using DG units of 1-2 MW. In addition, the optimum location and sizing for DG allowed a substantial improvement of the voltage profile of the network and reduced losses of 80.2 per cent in the test system. Regarding computation times, the fastest method was SA; however VSED and the HGA showed better results.

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Conflicts of Interest: Declare conflicts of interest or state "The authors declare no conflict of interest."

References

1. Aly, A.I., Hegazy, Y.G. and Alsharkwy, M.A., A simulated annealing algorithm for multi-objective distributed generation planning, *IEEE Power and Energy Society General Meeting*. 2010.
2. Chiradeja, P.; Ramakumar, R., An approach to quantify the technical benefits of distributed

- generation, *IEEE Trans.* 19 (4), pp 764-773, 2004.
3. Gandomkar, M. Vakilian, M. and Ehsan M., A combination of genetic algorithm and simulated annealing for optimal DG allocation in distribution networks, *Canadian Conference on Electrical and Computer Engineering*, pp 645-648, 2005.
 4. Nemanja Nedić, Srđan Vukmirović, Lendak Imre, Darko Čapko, A Genetic Algorithm Approach for Utility management System Workflow Scheduling, *Information Technology and Control*, Vol 39, No 4, 2010.
 5. Hung, D.Q. and Mithualananthan, N., Multiple distributed generation placement in primary distribution networks for loss reduction, *IEEE Transactions on Power Systems*, 60(4), 1700-1707, 2013.
 6. Georgilakis, P.S. and Hatziargyriou N.D., Optimal distributed generation placement in power distribution networks: models, methods and future research, *IEEE Transactions on Power Systems*, 28(3), pp 3420-3428, 2014.
 7. Hung, D.Q., Mithualananthan, N., and Bansal R.C., Analytical expressions for DG allocation in primary distribution networks, *IEEE Transactions on Power Systems*, 25(3), pp 814-820, 2010.
 8. Jonghe De C., Hobbs, B.F. and Belmans, R. Optimal generation mix with short-term demand response and wind penetration, *IEEE Transactions on Power Systems*, 27(2), 830-839, 2011.
 9. Kirkpatrick, S. Gellat, C.D. and M.P. Vecchi. Optimization by simulated annealing, *Journal of Statistical Physics*, 34(5), pp 975-986, 1983.
 10. Rashedi R., and Hegazy T., Capital renewal optimisation for large-scale infrastructure networks: genetic algorithms versus advanced mathematical tools, *Structure and Infrastructure Engineering: Maintenance, Management*, 11(3), pp 253-262, 2015.
 11. Soroudi, A., Ehsan, M., Caire, R., and Hadjsaid, N., Hybrid immune-genetic algorithm method for benefit maximization of distribution network operators and distributed generation owners in a deregulated environment, *IEEE Power and Energy*, 5(9), pp 961-972, 2011.
 12. Tan, W.S., Hassan, M.Y., Rahman, H.A., and Abdullah, M.P., Multi-distributed generation planning using hybrid particle swarm optimization-gravitational search algorithm, *IET Generation Transmission & Distribution*, 7(9), pp 929-942, 2014.
 13. Tan, W.S., Hassan, M.Y., Majid, M.S., Rahman, H.A., Allocation and sizing of DG using Cuckoo search Algorithm, *IEEE International Conference on Power and Energy*. 2012.
 14. Y. C. Lee. C. Lan., et al. A Pan-Tilt orienting mechanism with parallel axes of flexural actuation, *Trans. Mechatron.* pp: 1100-1112, 2013.
 15. Zimmerman, R.D., Murillo-Sanchez, C.E., and Thomas R.J., Matpower: a steady-state operations planning and analysis tools for power systems research and education, *IEEE Transactions on Power Systems*, 26(1), pp 12-19, 2011.
 16. Hui Cao, Lixin Jia, Gangquan Si, Yanbin Zhang, " A Variable Selection Method for Pulverizing Capability Prediction of Tumbling Mill Based on Improved Hybrid Genetic Algorithm" *Information Technology and Control*, Vol 40, No 3, 2011