International Journal on
"Technical and Physical Problems of Engineering"
(IJTPE)
Published by International Organization on TPE (IOTPE)

ISSN 2077-3528
IJTPE Journal
www.iotpe.com
ijtpe@iotpe.com

March 2010	Issue 2	Volume 2	Number 1	Pages 50-54

OPTIMAL DG ALLOCATION IN DISTRIBUTION NETWORK USING STRENGTH PARETO MULTI-OBJECTIVE OPTIMIZATION APPROACH

A. Moeini A. Darabi H. Yassami M.H. Sadeghi

Faculty of Electrical & Robotic Engineering, Shahrood University of Technology, Shahrood, Iran
ali_moeini135@yahoo.com, darabi_ahmad@hotmail.com, hossein_yassami@yahoo.com, mhsadeghi64@gmail.com

Abstract- Nowadays, DGs are widely used in the power systems to improve the overall conditions of the network. Less environmental impact, high electric efficiency, low variable maintenance cost, quick start up, low installation cost and many other benefits, encourage the system manager to utilize this type of generation in the network. One of the most important issues about DG is allocation size and place of DG in the network to achieve optimal using of it. Strength Pareto as a multi-objective algorithm optimizes DG size and place while DG cost and system total power loss are optimization objectives. This program gives several results which all of them are optimal and designer could select one of them according to his interest. This result is known as Pareto front. Pareto front is compared with result of GA and its capability is shown.

Keywords: Distributed Generation (DG), Genetic Algorithm, Multi-Objective Optimization, SPEA.

I. INTRODUCTION

Distributed Generation (DG) system, which has widespread usage, is defined as an electric power source of limited size (usually few KW to few MW) and is connected directly to the distribution level at substation or distribution feeder; or at customer level. There are many DG technologies including photovoltaic, wind turbine, fuel cells, small and micro-sized turbine packages, internal combustion engine generators, and reciprocating engine generators [1].

Studies have shown that adding DGs to the electric power system reduces the active power loss, improves the loadability on different buses and decreases the stability index and the system security. The system performance improvement on the system depends largely on where the DG is located [2]. One of the major problems about Distributed Generation in distribution system is how system owner can allocate DG's to get the optimized using of them. Many researchers have worked on this problem with various objective functions. In [3] and [4] have been tried to study the impact of DG placement on reliability and efficiency as a objective function in optimization. In [5] a single objective fitness function is used to minimize with some constraints. In [6] DG is optimized with a view to volt and VAR control in network by GA. Also in [7] GA correlated by simulated annealing, is nominated to optimize the DG allocation. Aforementioned papers treats with DG allocation as a single-objective problem.

In the present paper, a new method based on artificial intelligence is used to optimize the size and place of presented DGs. Power loss and DG cost are two important factors that this paper considerers them as objective function where DG size and place are optimization variables. The Strength Pareto Evolutionary Algorithm (SPEA) is optimization approach. The program produces a set of solutions known as Pareto Optimal Front (POF) which all of them are optimal and designer could select one of them according to his interest.

II. PROBLEM FORMULATION

A common load flow procedure like Newton Raphson (NR) and Gauss-Seidel have less accuracy and takes many time to reach convergence in distribution network, because the ratio of X/R is small in respect of the transmission network. So to analysis of DG effect on the network and calculating the active power loss of the grid, backward-forward load flow method for distribution system [8] is considered. Backward-forward load flow is based on KVL and KCL laws. This method determines the current of any line and the voltage of any bus in four following stages:

1. *Node injection currents*

Whereas the loads data are available, we can calculate the injected current of each node by (1):

$$I_i^k = \frac{S_i^*}{(V_i^{k-1})^*} \qquad (1)$$

S_i : Given apparent load of the ith node

I_i : The current of ith node in iteration k

V_i^{k-1} : The voltage of ith node in iteration $k-1$

In the first iteration all nodes voltages are assumed to be one Pu.

2. *Backward sweep*

In this step the current of all branches are calculated from the end-customer nodes towards root node by (2):

$$J_L{}^k = I_i{}^k + \sum branches \quad derived \quad from \quad node \quad k \tag{2}$$

where

L : Branch index

$J_L{}^k$: Current of Lth branch in iteration k

3. *Forward sweep*

Update the voltage magnitude of all nodes by calculated current in step 2 by (3):

$$V_i{}^k = V_j{}^k - Z_L \times J_L{}^k \tag{3}$$

where $V_i{}^k$ and $V_j{}^k$ are the voltages of two nodes that are connected via a branch with impedance equal to Z_L.

4. *Convergence indexes*

Calculate the apparent power of any load with new earned voltage and active and reactive power mismatch using these equations:

$$S_i{}^k = V_i{}^k (I_i{}^k)^* \tag{4}$$

$$\Delta P_i{}^k = \text{Re al}[S_i{}^k - S_i] \tag{5}$$

$$\Delta Q_i{}^k = \text{Image}[S_i{}^k - S_i] \tag{6}$$

$\Delta P_i{}^k$: Active power mismatch in iteration k

$\Delta Q_i{}^k$: Reactive power mismatch in iteration k

Repeat step 1, 2, and 3 until results satisfies the convergence indexes. Load flow program will stop when $\Delta P_i{}^k$ and $\Delta Q_i{}^k$ enter into initially defined boundary.

In this paper, DG is assumed like a source in any possible node where injecting active power to the network. Reactive powers of all DGs are assumed initially zero. With DG embedding in the network, equation (1) should be revised to equation (7).

$$I_i{}^k = \frac{(S_i - P_{DG_i})^*}{(V_i{}^{k-1})^*} \tag{7}$$

P_{DG_i} : assigned DG to ith node

The objective function is minimized subject to the some specified constraints, related with electrical requirements for the distribution networks and DG operation:

a) Voltage magnitutes of all nodes should be within the defined standard limits allowed by regulation.

$$V_{min} \le V_j \le V_{max} \tag{8}$$

b) The power generated by DG units must be less or equal to its maximum load of the network.

$$\sum P_{DG_i} \le \sum P_{Load_i} \tag{9}$$

P_{Load_i} : the amount of the load at ith node

III. MULTI-OBJECTIVE OPTIMIZATION

One way of handling a multi-objective or vector objective problems is to combine the goals of the optimization problem and constructing a scalar function and then using a common scalar optimization approach to solve the problem. The major dilemma of this methodology is unavailability of any straightforward method for combining the objectives or goals of the problem while they vary constantly.

Game theory concept is applicable for a multi-objective optimization problem in its own original status needless to any modification or combining the objectives but of course it requires an evolutionary method to reach globally optimum results [9]-[12]. Some advanced evolutionary method are as [11]:

- Niched Pareto Genetic Algorithm (NPGA)
- Hajela's and Lin's Genetic Algorithm (HLGA)
- Vector Evaluated Genetic Algorithm (VEGA)
- Non-dominated Sorting Genetic Algorithm (NSGA)
- Strength Pareto Evolutionary Algorithms (SPEA)

One of the most successful approaches is the SPEA [11] which is based on Pareto Optimality concept. Generally, a multi-objective optimization problem can be represented as:

Minimize:

$$g = f(x) = (f_1(x), \ldots f_i(x), \ldots f_k(x) \tag{10}$$

Subjected to:

$$x = (x_1, x_2, \ldots x_n) \in X \quad \& \quad y = (y_1, y_2, \ldots, y_k) \in Y$$

A. Definition

The vector a in the search space dominates vector b if:

$$\begin{aligned} &\forall_i \in \{1,2,\ldots,k\}: f_i(a) \ge f_i(b) \\ &\exists_j \in \{1,2,\ldots,k\}: f_j(a) > f_j(b) \end{aligned} \tag{11}$$

If at least one vector dominates b, then b is considered dominated vector otherwise it is called non-dominated. Each non-dominated solution is regarded optimal in the sense of Pareto or called Pareto Optimal. Obviously, any Pareto Optimal solution is comparatively the most optimal one in terms of at least one of the objective functions. The set of all non-dominated solutions is called Pareto Optimal Set (POS) and the set of the corresponding values of the objective functions is called Pareto Optimal Front (POF) or simply Pareto Front.

B. Strength Pareto Evolutionary Algorithm (SPEA)

The SPEA which takes benefits from many features of some other approaches is used in this paper. Figure 1 shows a flowchart of the approach which includes the following major steps [9].

SPEA Algorithm:

1. Generate an initial population P and create the empty external non-dominated set P'.
2. Paste non-dominated members of P into P'.
3. Remove all solutions within P' which are covered by any other members of P'.
4. If the number of externally stored non-dominated solutions exceeds a given maximum N', prune P' by means of clustering.
5. Calculate the fitness of all individuals in P and P'.
6. Use tournament selection with replacement and select individuals from P and P' until the mating pool is filled.
7. Apply crossover and mutation operators as usual.
8. If the maximum number of generations is reached, then stop, else go to step 2.

Fitness evaluation is also performed in two steps. First, the individuals in the external non-dominated set *P'* are ranked. Then, the individuals in the population *P* are evaluated. For more details, the readers are referred to [11].

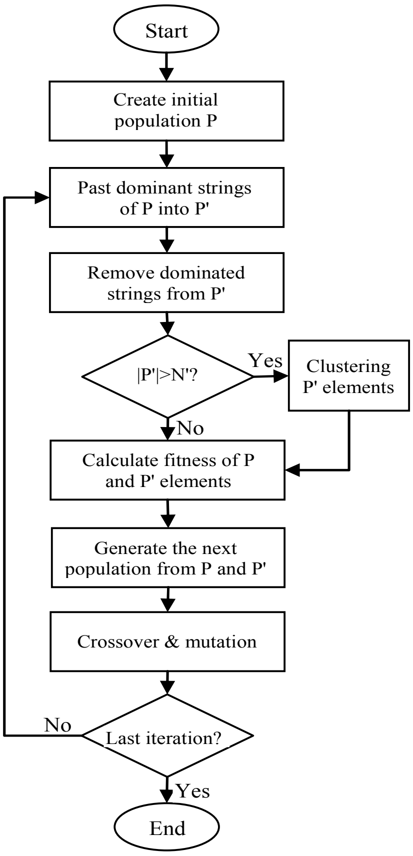

Figure 1. Strength Pareto flowchart

IV. SIMULATION RESULTS

In order to establish the effectiveness of proposed algorithm to solve the problem of sizing and sitting of DG units, a developed program in Matlab environment is used. Simulation is carried out on a 28-node distribution system shown in figure 2. This system's information is given in appendix. A real-code chromosome represents each solution of DG allocation. As regards to real-code SPEA a roulette wheel scheme is used for selection mechanism in cooperation with single-point simple mutation. Both crossover and mutation operators are used by pre-specified probabilities. At last because of tuning the SPEA, a population size of 72 and 100 generations is set. The simulation experience shows that these initial values for the case study distribution system, guarantee the convergence of algorithm to a satisfactory solution.

Four application types of Distributed Generations is selected similar to [14] regards to their size ranges, costs and types. It is assumed that installation and other lateral costs will come back within several years. So, marginal cost is supposed as shown in Table 1.

Figure 3 shows the results of SPEA optimization compare with sum weighted single objective GA optimization with same set for similar options. As it seen, the Pareto front which is result of SPEA has a soft slope. This shows that there is a rational relationship between DG cost and power loss. Another important point is that GA's result doesn't dominate any of Pareto front. This confirms that SPEA have a better convergence to optimal result. As it said a designer could select one of Pareto front according to his favorite.

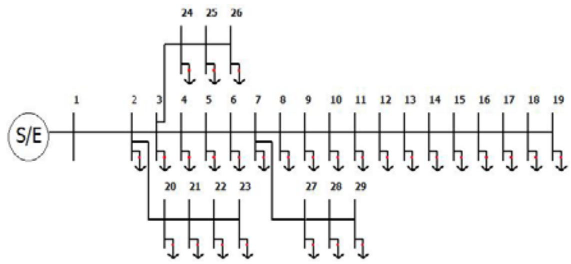

Figure 2. 28 bus system test case

Table 1. Selected DGs with their characteristic

Characteristics	Size range (KW)	Marginal cost ($)
Solar cell	30	100
Fuel cell	45	150
Wind turbine	60	300
Internal combustion engine	90	6000

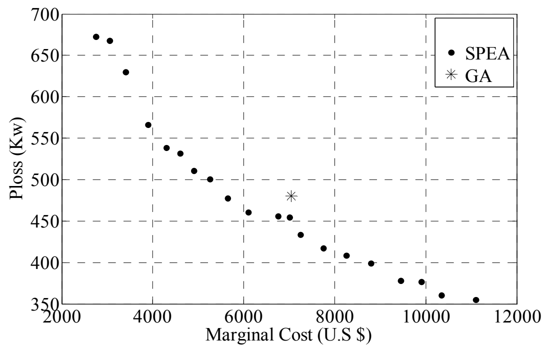

Figure 3. Optimization results

For more comparison, magnitude of bus voltages with and without DG are shown in Figure 4. This figure illustrates that, adding DG to distribution system improves the profile of voltages in all buses.

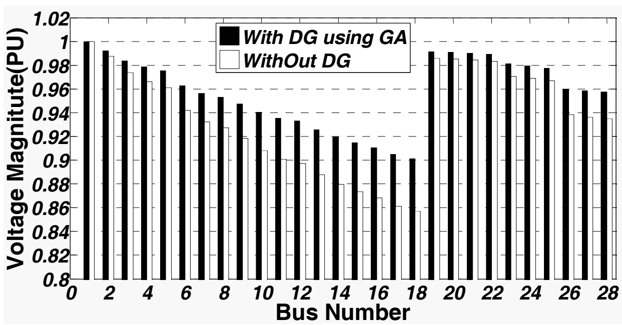

Figure 4. Voltage profile

Table 2 includes the result of DG planing via GA. Porposed algorithm that has been setted by proper objective functions, has attempted to assign the Distributed Generations to all nodes of the test system to achieve the best allocation.

Table 2. DG allocation via genetic algorithm

Node	Size (KW)
1	45
2	30
3	90
4	90
5	30
6	90
7	60
8	45
9	30
10	45
11	90
12	90
13	30
14	0
15	30
16	45
17	60
18	60
19	45
20	30
21	0
22	45
23	90
24	0
25	0
26	45
27	90
28	60

V. CONCLUSIONS

In this paper a multi-objective optimization approach; SPEA was introduced. This algorithm was applied to optimum sizing and placement of distributed generations in a distribution system. To improve the accuracy and decrease the running time, a forward-backward load flow was used proper to distribution systems structure. The optimization problem had two objectives which were DG cost and systems total power loss. Simulation results gave many designs that all of them were optimum and could be selected as our favorite design. Also a comparison with GA proved our method's capability.

APPENDICES

Table 3. 28 node load data

Node	Active Load (KW)	Reactive Load (KVAR)
1	21	9
2	15	6
3	30	12
4	60	30
5	45	21
6	30	18
7	105	60
8	96	54
9	120	75
10	30	12
11	51	36
12	90	51
13	105	60
14	15	3
15	75	45
16	30	12
17	120	87
18	600	474
19	45	30
20	51	24
21	45	18
22	120	60
23	30	12
24	90	75
25	180	90
26	60	15
27	150	90
28	450	300

Table 4. 28 node line data

From Bus	To Bus	Resistance (Ω)	Reactance (Ω)
1	2	1.265	0.526
2	3	1.546	0.658
3	4	0.949	0.395
4	5	0.637	0.263
5	6	2.53	1.053
6	7	1.897	0.79
7	8	1.012	0.421
8	9	1.897	0.79
9	10	2.53	1.053
10	11	1.911	0.54
11	12	0.955	0.27
12	13	2.866	0.81
13	14	2.866	0.594
14	15	2.102	0.54
15	16	1.911	0.81
16	17	2.866	0.54
17	18	1.911	0.54
2	19	2.389	0.675
19	20	0.955	0.27
20	21	1.911	0.54
21	22	3.439	0.972
3	23	3.734	0.702
23	24	2.102	0.594
24	25	3.822	1.08
6	26	1.911	0.54
26	27	0.955	0.27
27	28	0.955	0.27

REFERENCES

[1] A.D.T Le, M.A. Kashem, M. Negnevitsky and G. Ledwich, "Maximising Voltage Support in Distribution Systems by Distributed Generation", TENCON IEEE, pp. 1-6, Nov. 2005.

[2] X. Chen and W. Gao, "Effects of Distributed Generation on Power Loss, Loadability and Stability", IEEE Southeastcon, pp. 468-473, April 2008.

[3] L. Wang and C. Singh, "Reliability-Constrained Optimum Placement of Reclosers and Distributed Generators in Distribution Networks Using an Ant Colony System Algorithm", IEEE Transactions on Systems, Man and Cybernetics - Part C: Applications and Reviews, Vol. 38, No. 6, November 2008.

[4] D. Zhu, R.P. Broadwater, K.S. Tam, R. Seguin and H. Asgeirsson, "Impact of DG Placement on Reliability and Efficiency With Time-Varying Loads", IEEE Transactions on Power Systems, Vol. 21, No. 1, February 2006.

[5] C. Tautiva and A. Cadena, “Optimal Placement of Distributed Generation on Distribution Networks”, Transmission and Distribution Conference and Exposition, Latin America, IEEE/Pes, 2008.
[6] T. Niknam, A.M. Ranjbar and A.R. Shirani, “Impact of Distributed Generation on Volt/Var Control in Distribution Networks”, IEEE Power Tech Conference, Bologna, Italy, 2003.
[7] M. Gandomkar, M. Vakilian and M. Ehsan, “A Combination of Genetic Algorithm and Simulated Annealing for Optimal DG Allocation in Distribution Networks“, CCECE/CCGEI, Saskatoon, IEEE 2005.
[8] D. Shirmoharmnadi, H.W. Hong, A. Semlyen and G.X. Luo, “A Compensation-Based Power Flow Method for Weakly Meshed Distribution and Transmission Networks”, IEEE Transactions on Power Systems, Vol. 3, No. 2, May 1988.
[9] H. Singh, “Introduction to Game Theory and its Application in Electric Power Markets“, IEEE Computer Application in Power, Vol. 12, pp. 18-22, Oct. 1999.
[10] K. Bo and S. Gi-Yoonkim, “Solution of Multi-Objective Optimization Problems: Co-Evolutionary Algorithm based on Evolutionary Game Theory“, School of Electrical Engineering, Artificial Life and Robotics, pp. 174-185, 2004.
[11] E. Zitzler and L. Thiele, “Multi-Objective Evolutionary Algorithms: A Comparative Case Study and the Strength Pareto Approach“, IEEE Transactions on Evolutionary Computation, Vol. 3, No. 4, pp. 257-271, November 1999.
[12] T.L. Turocy and B.V. Stengel, “Game Theory“, CDAM Research Report LSE-CDAM, 8 October 2001.
[13] W. EI-Khattam, K. Bhattacharya, V. Hegazy and M.M.A. Salama, “Optimal Investment Planning for Distributed Generation in a Competitive Electricity Market“, IEEE Transactions on Power Systems, Vol. 19, No. 3, pp. 1674-1684, August 2004.
[14] “White Paper on Distributed Generation, National Rural Electric Cooperative Association”, August 2007.

BIOGRAPHIES

Ali Moeini was born in Neishaboor, Iran, on June 26, 1984. He graduated from the Ferdowsi University of Mashhad, Mashhad, Iran, in 2007. His areas of interest are evolutionary algorithms, power market, distributed generation and power system studies.

Ahmad Darabi received the B.Sc. degree in electrical engineering from Tehran University, Tehran, Iran in 1989 and the M.Sc. degree in the same field from Ferdowsi University of Mashhad, Mashhad, Iran, in 1992. He obtained the Ph.D. degree with the electrical machine group, Queen’s University, Belfast, UK, in 2002. He is now an associate professor and has been with Faculty of Electrical and Robotic Engineering, Shahrood University of Technology, Shahrood, Iran from 1993. His research activities are mostly on design, modeling and manufacturing of miniature electrical machines and generating sets.

Hossein Yassami was born in Zanjan, Iran on September 21, 1984. He received the B.Sc. degree in electrical engineering from Zanjan University, Zanjan, Iran, in 2007, and the M.Sc. degree in electrical engineering from Shahrood University of Technology, Shahrood, Iran in 2009. His areas of interest are evolutionary algorithms and power system studies

Mohammad Hossein Sadeghi was born in Isfahan in 1985. He received the B.Sc. degree in power electrical engineering from Shahid Bahonar University of Kerman, Kerman, Iran. Currently, he is a M.Sc. student in the same field with the Faculty of Electrical and Robotic Engineering, Shahrood University of Technology, Shahrood, Iran. His research activities are on design and modeling of special hysteresis motors and distributed generation. He is now a member of special machines research group of Shahrood University of Technology.