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Optimization of distributed generation location and capacity for improving voltage profile and reducing loss using genetic algorithm (SPEA) with proposing a new index

Hasan Jalili^{1*}, Abdolreza Karamizadeh¹, Mohammad Javad Foroughi¹, Mehdi Pazhoohesh² and Mahdi Jalili¹

¹Neyshabur Branch, Islamic Azad University, Neyshabur, Iran.

²University of Southampton, United Kingdom.

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With new changes in power systems, opportunity for new technologies has been made. Among such new technologies is Distributed Generator (DG). DGs have lots of advantages such as: reducing electricity cost, managing congestion in transmission lines, reducing loss, improving voltage profile etc. So it is forecasted that DGs will have increasing contribution in supplying the electricity demanded by customers in future. Artificial intelligence techniques are among the most common tools that are being used in DG allocation optimization problems. Genetic algorithm (GA) is one of these techniques which is an effective tool for solving optimization problem. In this paper a method is proposed for DG capacity and placement optimization in distribution systems using GA. The goal is to reduce active power loss and improve voltage profile.

Key word: Distributed generation, genetic algorithm, voltage profile, active power loss.

INTRODUCTION

With new changes in power systems, opportunity for new technologies has been made. Among such new technologies is Distributed Generator (DG) (Khoa and Binh, 2006). DGs have lots of advantages such as: reducing electricity cost, managing congestion in transmission lines, reducing loss, improving voltage profile etc (Kamalinia and Afsharnia, 2007). So it is forecasted that DGs will have increasing contribution in supplying the electricity demanded by customers in future (Calderaro and Piccolo, 2005). In addition, installation of DG can decrease the costs related to transmission of electricity to remote places. Also because of using new and renewable energy in DG, it can help protect the environment. Determination of the optimal location and

capacity of DG units in distribution systems with various objective functions have been continuously studied in recent years. Some of these objectives are minimization of feeder active power loss reduction (Nara et al., 2001; Rahman and Rahim, 2004), minimization of production cost of the network (Celli and Pilo, 2001; El-Khattam and Bhattacharya, 2004; El-Khattam and Hegazy, 2005; Gandomkar et al., 2005), harmonic reduction (Xin-mei et al., 2004) and voltage profile improvement (Alinejad-Beromi et al., 2007). In this paper, using 'genetic algorithm', a method for optimization of location and capacity of DG to reduce active power losses and improve voltage profile is presented. Subsequently, DG resources are briefly discussed. Thereafter an introduction to genetic algorithm is presented. Then, problem formulations are done. As follows, it describes how to solve the optimization problem. A practical example is studied in thereafter. The results and simulation is also presented. Finally, conclusions are

*Corresponding author. E-mail: hasan.jalili65@gmail.com. Tel: +989151584735.

Table 1. Characteristics of the GA used in this paper.

50	Number of chromosomes
1000	Max number of population
0.85	Probability of crossover
0.01	Probability of mutation

presented.

DISTRIBUTED GENERATION PLANT

Some of the advantages of DG units are (Aliabadi and Behbahani, 2008):

- i) Power loss reduction.
- ii) High reliability.
- iii) Voltage profile improvement.
- iv) Improved power quality.
- v) Produce less pollution than conventional power plants (Priyantha and Wijayatunga, 2004).
- vi) Require less time to install compared with traditional plant (Jahromi and Farjah, 2007).
- vii) Easy to find place for installation of these units because of their small size (Gandomkar and Vakilian, 2005).

Optimization procedure

Genetic algorithm

Genetic algorithm is an efficient tool for solving optimization problems. It has the great ability to find optimum solution among all solutions (Gandomkar and Vakilian, 2005). This algorithm consists of 4 stages:

- i) Produces an initial population randomly,
- ii) Calculate fitness function for each chromosome and select the best ones (selection).
- iii) Produces new chromosomes from ones selected in stage 2 (crossover).
- iv) Execute mutation on the chromosomes created in previous stages with the probability of 1 to 3% for assuring randomness of the algorithm and thus increasing the reliability of it. Characteristics of the GA used in this paper are presented in Table 1.

Multi-objective optimization

One trivial way of handling a multi-objective or vector objective problems is to combine the desired goals of the optimization problem and construct a scalar function and

then use a common scalar optimization approach to solve the problem. The major problem of this methodology is the unavailability of any straightforward methods for combining the objectives or goals of the problem while they vary constantly. Some advanced evolutionary method are as (Rafiei et al., 2009):

- i) Niche Pareto genetic algorithm (NPGA).
- ii) Hajela's and Lin's genetic algorithm (HLGA).
- iii) Vector evaluated genetic algorithm (VEGA).
- iv) Non-dominated sorting genetic algorithm (NSGA).
- v) Strength Pareto evolutionary algorithms (SPEA).

One of the most successful approaches is the SPEA (16) which is based on Pareto optimality concept. Generally, a multi-objective optimization problem can be represented as:

Minimize

$$g = f(x) = (f_1(x), \dots, f_i(x), \dots, f_k(x)) \quad (1)$$

Subject to

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

Definition

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

$$\forall i \in \{1, 2, \dots, k\}: f_i(a) \geq f_i(b) \quad (2)$$

$$\exists j \in \{1, 2, \dots, k\}: f_j(a) > f_j(b)$$

If at least one vector dominates b , then b is called dominated otherwise it is called non-dominated. Each non-dominated solution is regarded optimal in the sense of Pareto or called Pareto optimal. Obviously, between any pair of points on Pareto set, one is the best in terms of one of the objectives. 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.

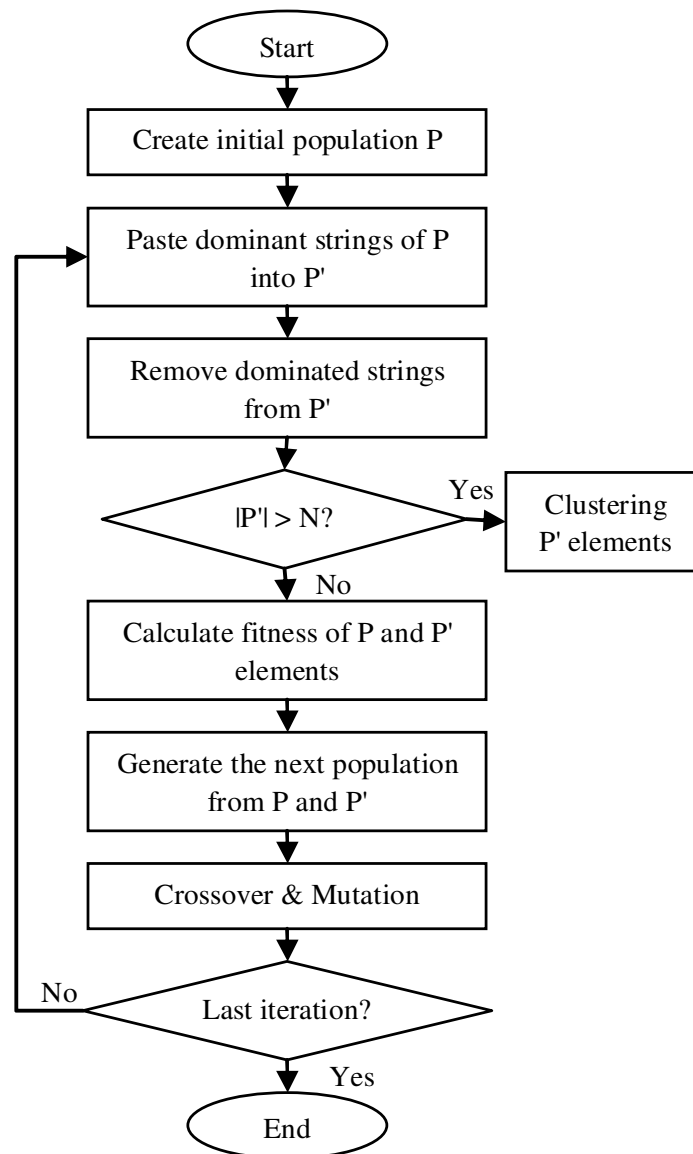


Figure 1. Strength Pareto flowchart.

Strength Pareto evolutionary algorithm (SPEA)

The SPEA takes benefits from several features of some other similar approaches with high diversity and fast convergence. Figure 1 shows a flowchart of the approach which includes the following major steps (Rafiei et al., 2009):

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 binary 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,

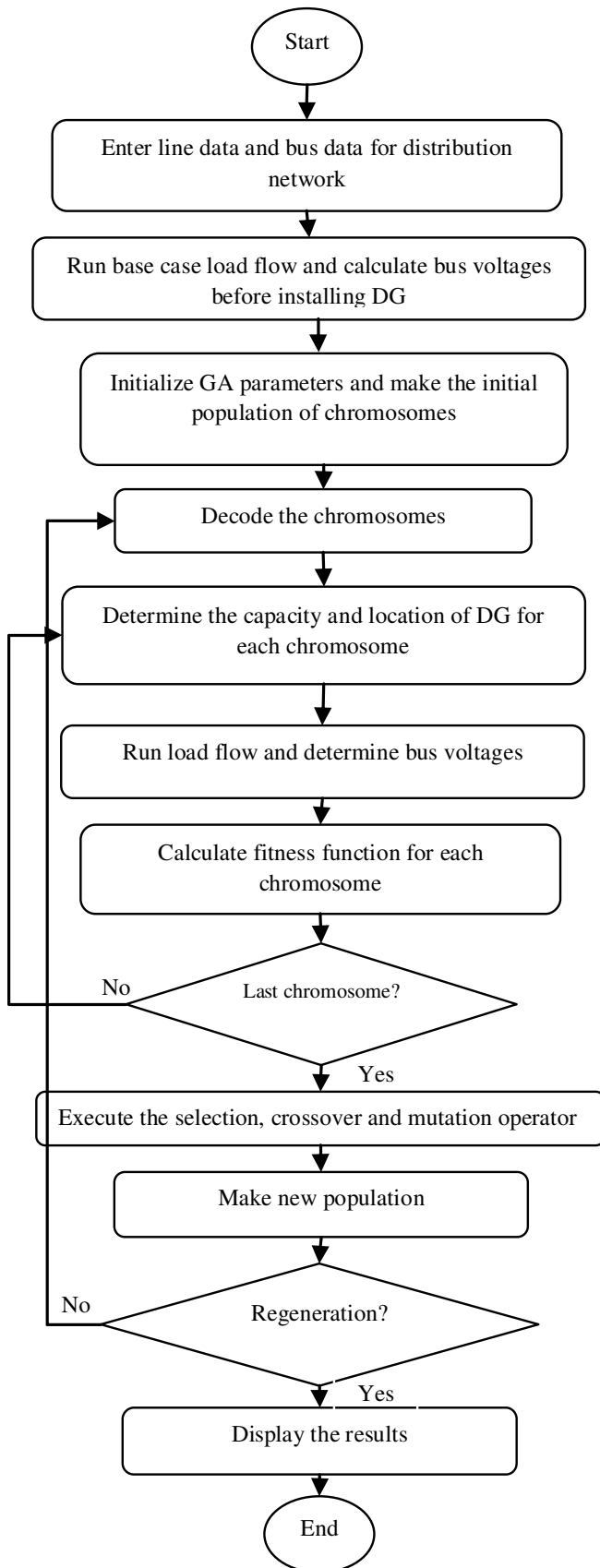


Figure 2. The proposed algorithm flowchart.

the individuals in the external non-dominated set P' are ranked. Then, the individuals in the population P are evaluated. More details can be found in Rafiei et al. (2009).

Problem formulation

$$\text{Minimum } \Delta V = \sum_{i=1}^n k_i \Delta V_i$$

$$\text{Subject to } \Delta V_i = |V_{ref} - V_i|$$

$$k_i = \left(\frac{P_{L_i}}{\sum_{j=1}^n P_{L_j}} \right)$$

$$0.95^{pu} \leq V_i \leq 1.05^{pu}$$

$$V_{ref} = 1^{pu}$$

(3)

The main purpose of the proposed algorithm is to find optimum location and capacity for installation of DG units. In the first step, the objective is to study the effect of index k_i in Equation 1 on the voltage profile of distribution network. Where n is the total number of buses in the network. ΔV_i is the voltage deviation of bus i from nominal voltage and ΔV is the weighted sum of all voltage deviations. The weights k_i are so that the more heavily loaded buses are more important in the objective function. It should be considered that for buses without any load, k_i is defined to be equal to that of the most lightly loaded bus. In the next study, voltage profile and loss is simultaneously optimized.

Problem-solving algorithm

Flowchart of the algorithm

The flowchart of the proposed algorithm is presented in Figure 2. The presented algorithm, first, receives network data such as line data and bus data. Then using a distribution network load flow bus voltages before installing DG unit is computed. In the next step, GA parameters such as mutation and crossover are set as that are mentioned in Table 1. Also, initial population of chromosomes is produced. This initial population is consists of two part, so a number of genes (bits) are related to location and others to capacity. Furthermore, these chromosomes is converted from binary to decimal or, say, decoded. After decoding, capacity and location of DG for each chromosome is determined. Thus next step is to perform load flow and obtain voltage profile for each

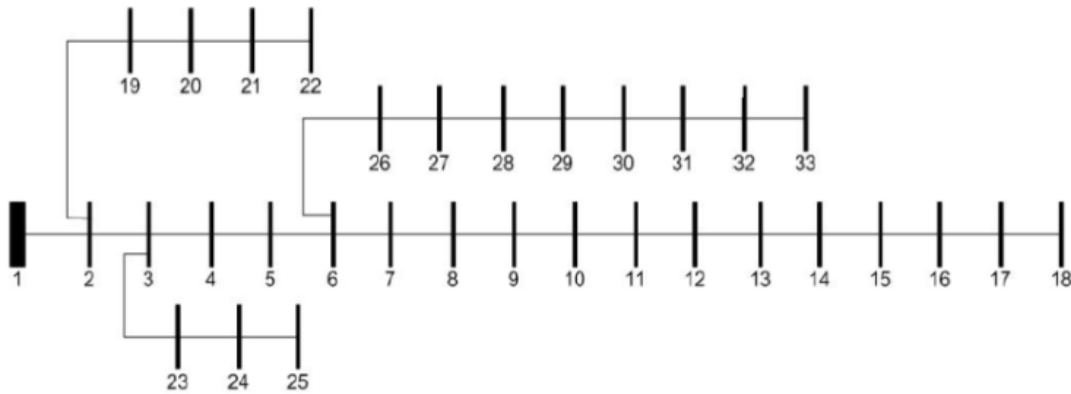


Figure 3. One line diagram of 33 bus network.

Table 2. Optimal location and capacity of DG unit with the proposed index.

Reactive power (pu)	Active power (pu)	Bus number
0.5	1.8258	12

Table 3. Optimal location and capacity of DG unit without the proposed index.

Reactive power (pu)	Active power (pu)	Bus number
0.5	1.671	12

chromosome. Those chromosomes that result in better voltage profile are selected as parents for next generation. Next step is to perform mutation and crossover on these selected parents and produce the next generation population. This process is repeated until some stop condition is reached.

A method for load flow calculation in distribution network

Many real-time programs in the distribution system automation domain such as reactive power planning, switching, state estimation etc need an efficient and robust load flow program. Such a method must be able to model special feature of distribution system such as:

- i) Radial or loop structure,
- ii) Multi-phase or unbalanced operation,
- iii) Spray and unbalanced loads,
- iv) Wide range of resistances and reactance's.

Because of these special features we cannot use conventional load flow methods which are used in transmission system such as Gauss-side or Newton-Raphson in distribution system. Particularly, simplification assumption in standard fast-decoupled Newton-Raphson method is mostly invalid in distribution network. Thus a different method is needed to consider all of the especial characteristics of distribution networks. Detailed description of this

method and its advantages over conventional methods is mentioned in Jen-Hao (2003).

Practical case study

A 33 bus network is used as the case study for proposed algorithm. Its one-line diagram is illustrated in Figure 3 (Borges and Falcao, 2003). The DG active and reactive power limit will be as follows:

$$\begin{aligned}
 1.4^{pu} &\leq P_{DG} \leq 2^{pu} \\
 0^{pu} &\leq Q_{DG} \leq 0.5^{pu}
 \end{aligned}
 \tag{4}$$

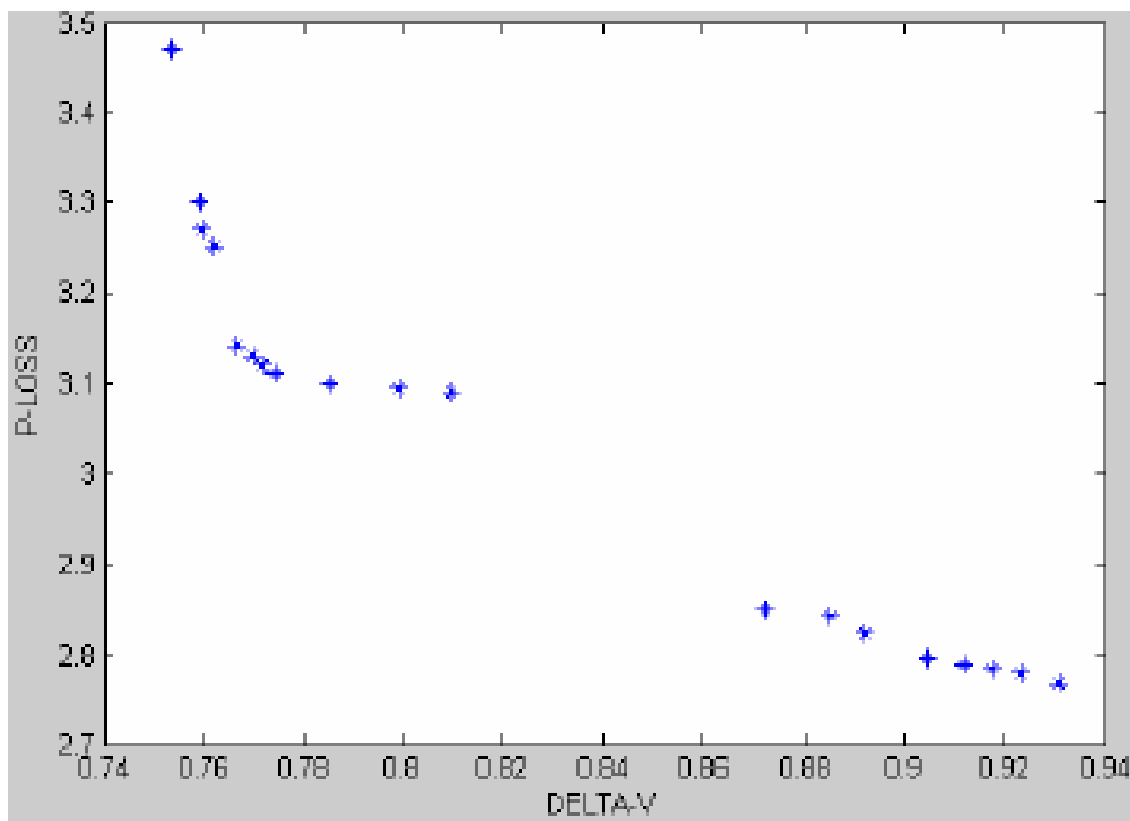
In the proposed algorithm, DG location and capacity is optimized simultaneously.

RESULTS OF SIMULATIONS

The optimal location and capacity of DG unit is presented in Tables 2 and 3 and the results of installing this unit is presented in Table 4. It can be seen that using the new index, voltage profile is better improved. The results of optimization of voltage profile and loss using GA with the new index is illustrated in Figure 4 and Table 4. This figure illustrates the points which the installation of DG in

Table 4. Result of DG installation for voltage profile improvement.

Bus number	Bus voltage without DG	Bus voltage with the proposed index	Bus voltage without the proposed index
6	0.9497	0.9818	0.9784
7	0.9462	0.9827	0.9788
8	0.9413	0.9875	0.9825
9	0.9351	0.9963	0.9898
10	0.9292	1.0058	0.9976
11	0.9284	1.0076	0.9991
12	0.9269	1.0062	1.0021
13	0.9208	1.0006	1.0154
14	0.9185	0.9985	1.0134
15	0.9171	0.9972	1.0121
16	0.9157	0.9959	1.0109
17	0.9137	0.9941	1.0090
18	0.9131	0.9935	1.0085

**Figure 4.** Optimal points obtained from simulations.

that points have no advantages with respect to each other; because each of these points has one advantage and one disadvantage with respect to others. In the other words, each of these points is an optimal point and can be selected as optimal point considering network requirements. These points are called Pareto domain.

The characteristics of some of these points are presented in Table 5.

Conclusion

In this paper, GA is used for optimization of capacity and

Table 5. Location and capacity of DG for simultaneous improvement in voltage profile and loss.

Optimal active power capacity of DG (pu)	Optimal reactive power capacity of DG (pu)	(Optimal location of DG (bus number))
1.82	0.5	12
2	0.5	9
1.75	0.5	9
1.94	0.5	9
1.97	0.5	9
1.7	0.5	29
1.63	0.5	29
1.85	0.5	29
1.95	0.5	29

location of distributed generation in distribution system, although a new index is proposed for improvement in voltage profile. The proposed method is successfully applied to a 33 bus distribution network. The simulation results show that the proposed index can improve the installation of DG in distribution network.

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