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Optimal Embedded Generation Allocation in Distribution System Employing Real Coded Genetic Algorithm Method

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***Abstract*—**This paper proposes a new methodology for the optimal allocation and sizing of Embedded Generation (EG) employing Real Coded Genetic Algorithm (RCGA) to minimize the total power losses and to improve voltage profiles in the radial distribution networks. RCGA is a method that uses continuous floating numbers as representation which is different from conventional binary numbers. The RCGA is used as solution tool, which can determine the optimal location and size of EG in radial system simultaneously. This method is developed in MATLAB. The effect of EG units' installation and their sizing to the distribution networks are demonstrated using 24 bus system.

***Keywords*—**Embedded generation (EG), load flow study, optimal allocation, real coded genetic algorithm (RCGA).

I. Introduction

IN the past, information concerning embedded generation (EG) or distributed generation (DG) penetration levels in transmission grid studies and voltage stability effects could not be evaluated. Analytical approaches and modeling techniques for transmission system planning was not available to guide bulk transmission engineers in the evaluation of optimal incorporation of EG technologies. This is largely due to the fact that distributive technologies have not been considered as having impact on the bulk transmission system. This modeling concern became even more apparent in the new millennium. One of the key alternatives proposed was the utilization of EG to meet the requirements of the electrical system. This question could not be properly answered at the time and the popularity for engaging in this research is very low.

As a result of restructuring of electricity markets and the targets laid down for renewable energy, increasing amounts of EG that being connected to distribution networks are become significant. For example, in December 2004, it was estimated 200 MW of EG installed in South Australia. The implementation of EG basically depends on different country policy and also depend on implementing small or large EG installations [1].

To accommodate this new type of generation, the existing distribution network should be utilized and developed in an optimal manner. The problems related to the location and the size of EG that to be installed and integrated with existing network need to be handled wisely. In addition, the cost of the number of units of EG is also need to be taken into the consideration. Thus, the engineers should play a vital role to consult the authorities and policy makers in term of technical aspects when to implement this technology.

Several approaches have been proposed in literature to determine the optimal allocation of EG in the distribution networks. To date, artificial intelligence (AI), evolutionary computation and optimization techniques are among the popular techniques that are normally used to solve these matters. The optimal allocation of DG using ant colony search algorithm (ACSA) is proposed in [2]. The property of ACSA or ant colony optimization (ACO) is adapted to solve the optimal location and size of EG. The problem of this method is the rates of ant colony regulating parameters need to be determined using experimental approach. However, the result obtained from this method is said better than GA as the authors' comparison.

The using of evolutionary programming (EP) to determine optimal allocation and sizing for EG is proposed in [3]. The authors use the sensitivity indices as the tools to predict the placement of EG at a particular bus. The disadvantage of this method is the optimal location and size of EG unit need to be done twice using EP. Firstly, the location of EG is obtained using sensitivity indices, and then the size of EG unit will be determined. However, the effect of reactive power output is considered in this method. The incorporation of particle swarm optimization (PSO) for optimal distribution generation sizing and allocation is proposed in [4]. The related works on GA for optimal allocation of EG has been proposed in [5]. Nevertheless, the implementation of GA to EG unit optimal allocation is not explained clearly. DG allocation using analytical method is proposed in [6, 7]. The authors use losses sensitivity factor to determine the optimal location and size of DG.

The uncertainty modeling for the management of DG using PSO is proposed in [8]. The main intention of this research is

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to address a multistage stochastic model for the operation of DG. This paper basically discusses and emphasizes on economic aspect for DG installations. The combination of DG with shunt capacitors placements is discussed in [9]. The optimal allocation for the cost of DG is also proposed using PSO. A comparison of evolutionary methods for optimal operation of DG is proposed in [10]. The comparison has been made for the cost of active and reactive powers generated by DG using the following techniques: GA, differential evolution, ACO, PSO and tabu search.

This paper presents a technique for determination of optimal allocation of EG using real coded genetic algorithm (RCGA). The concept is simple and different from conventional GA. The representation of variables is coded in real floating number, not in binary number. In addition, the location and size of EG unit can be determined simultaneously by using this technique. This paper is organized as follows. The concept of continuous RCGA is discussed in Section II. The application of RCGA to optimal allocation of EG is discussed in Section III. In Section IV, the case study including discussion is presented. Finally, conclusion is stated in Section V.

II. Real Coded Genetic Algorithm

Genetic Algorithm (GA) is a stochastic technique that searching for the solution of optimization problem by using model of natural phenomena, viz. genetic inheritance and Darwinian strive for survival. The idea of GA is to do what a nature does and GA is designed as a subset of evolutionary computation algorithms. GA allows a population composed of many individuals to evolve under specified selection rules to a state that maximizes the “fitness” (i.e. minimizes the cost) function. The method is developed by Holland [11] and popularized by Goldberg [12]. GA approach can be divided into two: binary and continuous real number. For this paper, real coded GA (RCGA) is used since it has an advantage in the accurate representation of the continuous parameter.

A. Representation

If the chromosome has N_{par} parameters (an N-dimensional optimization problem) given by $p_1, p_2, \ldots, p_{Npar}$, then the single chromosome is written as an array with 1 x N_{par} elements as follows:

$$chromosome = [p_1, p_2 ....., p_{Npar}] \tag{1}$$

B. Initialization

RCGA does not work with a single string but with a population of strings, which evolves iteratively by generating new individuals taking the place of their parents. Normally, the initial population is generated at random.

C. Evaluation Function

The performance of each string is evaluated according to its fitness. Fitness is used to provide a measure of how individuals have performed in the problem domain. The choice of objective and fitness function is proposed in the next section.

D. Genetic Operators

With an initial population of individuals and evaluated through its fitness, the operators of RCGA begin to generate a new and improved population from the old one. A simple RCGA consists of three basic operations: selection, crossover and mutation.

Selection determines which individuals are chosen for crossover and a process in which individual chromosomes are copied according to their fitness. Parents are selected according to their fitness performance and this can be done through several methods. For this paper, *roulette wheel* selection method is used. The novelty of this method and others can be seen deeply in [12].

Crossover is a process after the parents chromosomes are selected from *roulette wheel* method. It is a process that each individual will exchange information to create new structure of chromosome called offspring. In this paper, the single-point arithmetic crossover method is used. The concept is modified from [13] to prevent loss of information if extrapolation method is used. It begins by randomly selecting a parameter in the first pair of parents to be crossover at point:

$$\alpha = round\{random * N_{par}\} \tag{2}$$

Let

$$parent_1 = [p_{m1}, ...p_{m\alpha}, ..., p_{mNpar}] \tag{3}$$

$$parent_2 = [p_{d1}, ...p_{d\alpha}, ..., p_{dNpar}] \tag{4}$$

where m and d subscripts discriminate between the *mom* and *dad* parent. Then the selected parameters are combined to form new parameters that will appear in the offspring, as follow:

$$p_{new1} = p_{m\alpha} - \beta[p_{m\alpha} - p_{d\alpha}] \tag{5}$$

$$p_{new2} = p_{d\alpha} + \beta[p_{m\alpha} - p_{d\alpha}] \tag{6}$$

where β is also a random value between 0 and 1. The new offspring that created from this crossover can be described as follow:

$$offspring_1 = [p_{m1}, ...p_{new1}, ..., p_{mNpar}] \tag{7}$$

$$offspring_2 = [p_{d1}, ...p_{new2}, ..., p_{dNpar}] \tag{8}$$

Although selection and crossover are applied to chromosome in each generation to obtain a new set for better solutions, occasionally they may become overzealous and lose some useful information. To protect these irrecoverable loss or premature convergence occur, mutation is applied. Mutation is random alteration of parameters with small probability called probability of mutation (0-50%). Multiplying the mutation rate by the total number of parameters gives the number of parameters that should mutated. Next, random numbers are chosen to select of the row and columns of the parameters to be mutated. A mutated parameter is replaced by a new random parameter.

III. RCGA for Optimal Allocation of EG

In this section, RCGA is proposed to find the optimal size and location of EG units in the distribution system to minimize the total loss in the system. By minimizing the loss, the voltage profile at each bus is also will expected to be improved. This method requires load flow to be run several times. After finding the best location and the size simultaneously for EG, the algorithm is finished. The objective function is the results of total loss of the system, P_{Loss} to be minimized, H as follows:

$$H = \min\left(\sum_{j=1}^{nline} P_{Loss}\right) \tag{9}$$

where *nline* is number of transmission lines in the system. Before incorporated RCGA to optimal allocation of EG, some factors need to be considered: (1) coding the variables into a finite string or chromosome and (2) mapping the objective function into a fitness form. The variables of the optimal allocation of EG problem are coded in the following manner. Firstly, each variable X is coded as the continuous floating numbers that range from 0 to 1. Then, the variables are concatenated to construct a multivariable string. The total multivariable or the length of chromosome is equal to *(num_EG* x *2)* as shown in Fig. 1. Each EG representatives need to multiple with 2 because the first variable represents the location and the second one represents the size of EG.

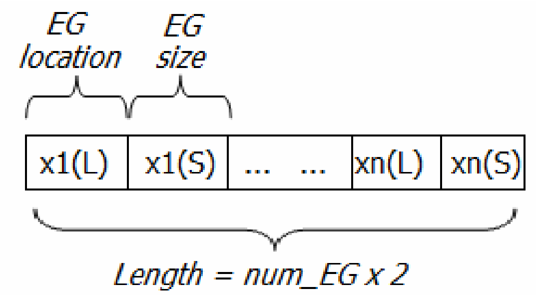

Fig. 1 Chromosome

After evaluating each chromosome, the objective function in equation (9) is transformed and normalized to a fitness scheme to be maximized as follows:

$$f = \frac{1}{1+H} \tag{10}$$

The process of incorporation of GA to optimal allocation of EG is shown in Fig. 2.

IV. Case Study and Discussion

The method proposed has been tested on 24-bus radial distribution systems. The algorithm has been programmed in MATLAB. The load flow program of Newton-Raphson that has been developed in [14] is used. This test system consists of one substation and 23 distribution buses. Fig. 3 shows this test system with a total real and reactive power demand is 1074 kW and 511 kVar respectively. The data for this system is tabulated in Appendix. To obtain the optimal location and size of EG, the GA properties are set as follows:

- Selection: *roulette wheel*
- Crossover probability, $\rho_c = 0.9$,
- Mutation probability, $\rho_m = 0.5$,
- Population = 40,
- Number of EG unit = 1 or 2
- EG size = 0.01 MW < P^{EG} < 2.5 MW
- Maximum iteration = 50

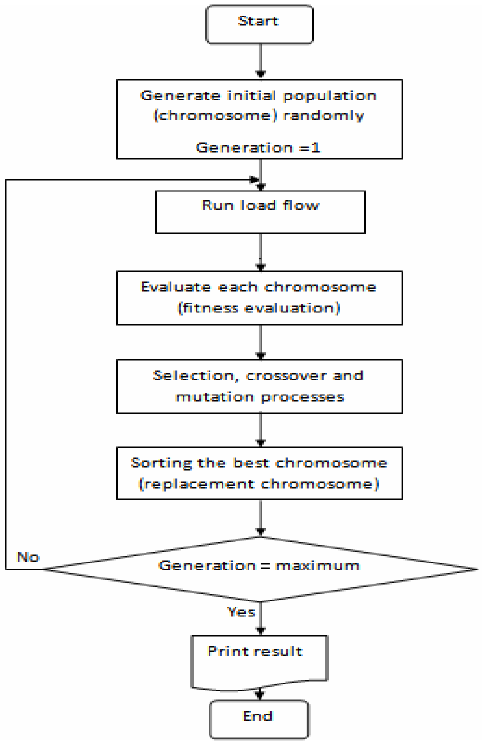

Fig. 2 Flow of optimal allocation of EG using RCGA

To study the impact of EG installation on the system performance, the following three cases are considered:

Case 1: Calculate the distribution network losses and minimum voltage magnitude before the EG installation.

Case 2: Repeat case 1 with the 1 EG included once its optimal location and sizing are determined.

Case 3: Repeat case 1 with the 2 EGs included once its optimal location and sizing are determined.

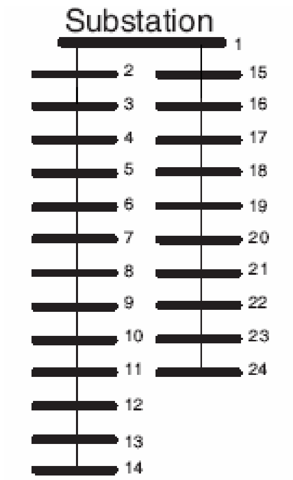

Fig. 3 24-bus radial distribution system

The reason of using until two units of EG is due to the cost of installation issue. Since this test system is small in size, it is adequate to install up to two units of EG. Fig. 4 shows the objective function, *H* versus iteration for case 2. The minimum value of loss is 0.0099 MW. From this simulation, the EG unit that needed to be installed is at bus 10 with the size of 0.3386 MW. The installation of EG unit at bus 10 has improved about 60% for the power losses in the system. Fig. 5 shows the simulation result of two units of EG installed in this system. EG units that needed to be installed are at bus 10 with the size of 0.3296 MW and at bus 19 with the size of 0.3282 MW. The installation of EG unit at these buses has improved about 73.6% for the power losses in the system. The comparison from case 1, case 2 and case 3 are reported in Table I.

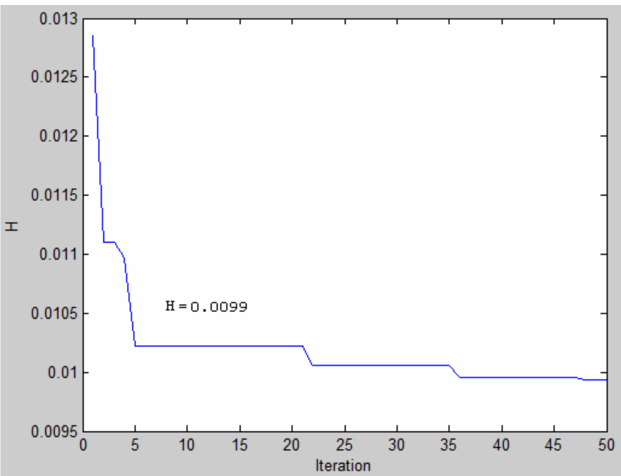

Fig. 4 Objective function, *H* vs. Iteration for case 2

To study the EG sizing impact on the losses of the distribution system, for case 2, the real power output of EG installed at bus 10 is varied between its rating limits and the distribution network power losses are calculated for each given power output. Fig. 6 shows that once the EG power output exceeded the optimal value, power losses will tend to increase beyond the minimal value. This situation is same with case 3.

Table II shows the comparison of voltage profile at each bus in the system before and after installation of EG for these 3 cases. From this table, it can be seen that the voltage profile is improved from the base case. However, the improvement of the voltage profile between case 2 and case 3 is not very significant for this test system.

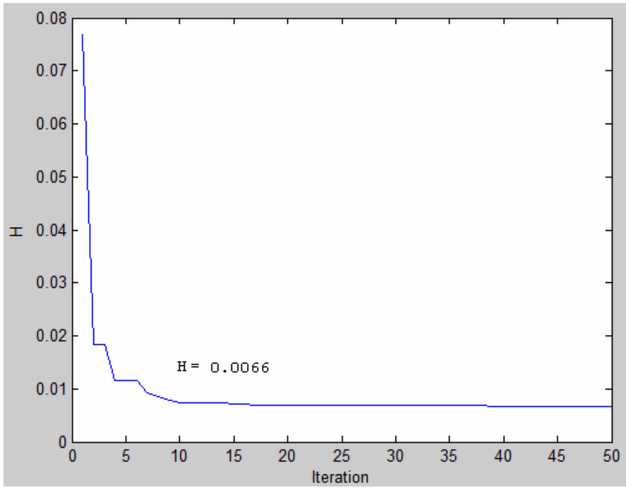

Fig. 5 Objective function, *H* vs. Iteration for case 3

TABLE I
RESULTS FOR CASE 1, 2 AND 3

	Case 1	Case 2	Case 3
Real Power Losses (MW)	0.025	0.0099	0.0066
Minimum Bus Voltage (p.u)	0.93766 @ bus 14	0.97975 @ bus 24	0.97907 @ bus 14

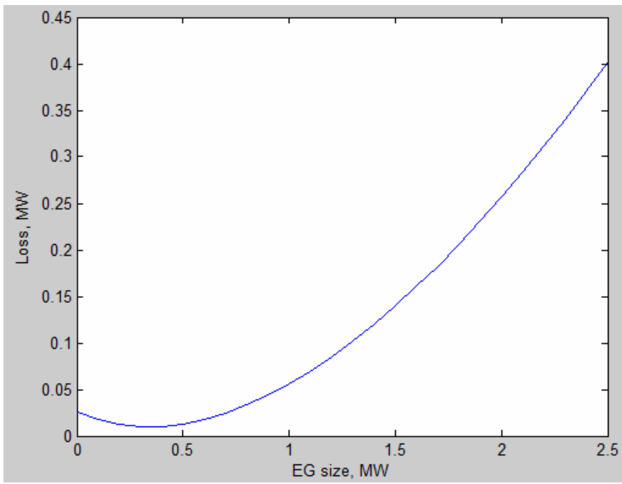

Fig. 6 Loss vs. EG size variation in MW installed at bus 10

The most important issue that needed to take into account for consideration before this technology can be implemented is the cost of EG. For this situation, the effect of voltage profile improvement is not so significant between one and two EG installations. However, the losses minimization is very significant if two EGs are installed in this system. Thus, the results are very dependably to policy makers and assisted by technical person whether the cost of installation is the main issue or the total losses minimization is the main priority at a particular distribution system.

TABLE II
VOLTAGE PROFILE BEFORE AND AFTER EG INSTALLATION

Bus	Voltage before EG		Voltage with 1 EG		Voltage with 2 EG	
	|V|	Angle(°)	|V|	Angle(°)	|V|	Angle(°)
1	1	0	1	0	1	0
2	0.98743	-0.23999	0.9937	0.07932	0.99356	0.07097
3	0.9771	-0.42443	0.9892	0.19713	0.9889	0.18097
4	0.96839	-0.58252	0.9858	0.31986	0.98539	0.29652
5	0.96105	-0.71805	0.9834	0.44728	0.98285	0.41729
6	0.95482	-0.83452	0.9818	0.57994	0.98112	0.5437
7	0.94945	-0.9361	0.9809	0.72067	0.98009	0.67841
8	0.94641	-0.86057	0.9819	0.80514	0.98097	0.76262
9	0.94307	-0.9241	0.9822	0.94122	0.9812	0.8938
10	0.94059	-0.97158	0.9829	1.07094	0.98188	1.0192
11	0.93907	-1.0008	0.9815	1.04415	0.98042	0.99236
12	0.93811	-1.01923	0.9806	1.02728	0.97951	0.97544
13	0.93777	-1.02594	0.9802	1.02113	0.97917	0.96928
14	0.93766	-1.02803	0.9801	1.01921	0.97907	0.96736
15	0.99768	-0.04062	0.9977	-0.04062	0.99857	0.00686
16	0.99539	-0.08103	0.9954	-0.08103	0.99734	0.02364
17	0.99169	-0.14642	0.9917	-0.14642	0.99582	0.07551
18	0.98844	-0.20434	0.9884	-0.20434	0.99518	0.15922
19	0.98578	-0.25229	0.9857	-0.25229	0.99527	0.26078
20	0.9837	-0.29026	0.9837	-0.29026	0.99321	0.22353
21	0.98228	-0.31686	0.9823	-0.31686	0.99181	0.19744
22	0.98111	-0.33891	0.9811	-0.33891	0.99065	0.17581
23	0.98023	-0.35534	0.9802	-0.35534	0.98978	0.15969
24	0.97975	-0.36443	0.9798	-0.36443	0.98931	0.15078

V. CONCLUSION

This paper has presented an approach to solve the optimal EG allocation and sizing problem using RCGA. The real continuous floating numbers are used as representation of the parameters in each chromosome. The single-point arithmetic crossover method as one of GA operators makes this approach success to find the best combination of location and sizing of EG problems simultaneously. The effectiveness of RCGA was demonstrated and tested. The results show that incorporating the EG in the distribution system can reduce the total line power losses and improve the voltage profiles. The proposed method was tested on 24-bus distribution system.

APPENDIX

TABLE III
CONVERGED BUS DATA FOR 24-BUS SYSTEM

Bus	Voltage		Load		Generation	
No.	Mag.	Angle(°)	MW	MVar	MW	MVar
1	1	0	0	0	1.07257	0.51313
2	0.98743	-0.2399	0.067	0.017	0	0
3	0.9771	-0.4244	0.035	0.017	0	0
4	0.96839	-0.5825	0.035	0.017	0	0
5	0.96105	-0.7180	0.035	0.017	0	0
6	0.95482	-0.8345	0.035	0.017	0	0
7	0.94945	-0.9361	0.035	0.017	0	0
8	0.94641	-0.8605	0.035	0.017	0	0
9	0.94307	-0.9241	0.035	0.017	0	0
10	0.94059	-0.9715	0.035	0.017	0	0
11	0.93907	-1.0008	0.035	0.017	0	0
12	0.93811	-1.0192	0.035	0.017	0	0
13	0.93777	-1.0259	0.035	0.017	0	0
14	0.93766	-1.0280	0.035	0.017	0	0
15	0.99768	-0.0406	0.103	0.051	0	0
16	0.99539	-0.0810	0.103	0.051	0	0
17	0.99169	-0.1464	0.103	0.051	0	0
18	0.98844	-0.2043	0.062	0.031	0	0
19	0.98578	-0.2522	0.062	0.031	0	0
20	0.9837	-0.2902	0.062	0.031	0	0
21	0.98228	-0.3168	0.023	0.011	0	0
22	0.98111	-0.3389	0.023	0.011	0	0
23	0.98023	-0.3553	0.023	0.011	0	0
24	0.97975	-0.3644	0.023	0.011	0	0
	Total		1.074	0.511	1.07257	0.51313

TABLE IV
LINE DATA OF 24-BUS SYSTEM

From bus	To bus	R (p.u)	X (p.u)
1	2	1.7154	1.6248
2	3	1.5957	1.5114
3	4	1.4627	1.3855
4	5	1.3563	1.2847
5	6	1.2766	1.2091
6	7	1.2367	1.1713
7	8	1.1303	0.0706
8	9	1.0239	0.9689
9	10	0.9109	0.8628
10	11	0.6981	0.6612
11	12	0.5851	0.5542
12	13	0.3191	0.3023
13	14	0.1995	0.1889
1	15	0.266	0.2519
15	16	0.3191	0.3023
16	17	0.6516	0.6172
17	18	0.7846	0.7431
18	19	0.8271	0.7834
19	20	0.9069	0.859
20	21	1.0399	0.9849
21	22	1.1462	1.0857
22	23	1.2792	1.2116
23	24	1.4122	1.3376

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