J. Basic. Appl. Sci. Res., 2(6)6277-6284, 2012

ISSN 2090-4304
Journal of Basic and Applied Scientific Research
www.textroad.com

Optimal Distributed Generation Planning in Radial Distribution Systems Using Body Immune Algorithm

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ABSTRACT

This paper presents a new methodology based on the Body Immune Algorithm for optimal placement and estimation of distributed generator (DG) capacity in the radial distribution systems in order to reduce the real power losses and improve the voltage profile and un-supplied energy. The proposed method considers the options of the DGs installation and takes more number of significant parameters into account compare to the previous studies that consider only a few parameters in their optimization algorithms. Some of the so-called cost parameters considered in the proposed approach are: loss reduction, voltage profile improvement, environmental effects, fuel price and costs of load prediction for each bus. Using an optimal Body Immune Algorithm in the proposed optimization method, a destination function that includes all of the above-mentioned cost parameters has been optimized. Furthermore, this method is capable of changing the weights of each cost parameter in the destination function of the Body Immune Algorithm as well as the matrix of coefficients in the DIGSILENT environment. The proposed method has been applied and simulated on a sample IEEE 9-bus network. The obtained results show that any change in the weight of each parameter in the destination function of the Body Immune Algorithm and in the matrix of coefficients leads to a meaningful change in the prediction of the location and capacity of the prospective DG.
Keywords: Body Immune Algorithm, Distributed Generation, DG placement, Radial distribution systems

1. INTRODUCTION

Distributed Generation (DG) is a small generator spotted throughout a power system network, providing the electricity locally to load customers of the network [1]. Also for improvement of power system situation such as correction of voltage profile, increment of stability, decrement of loses power, etc, it is necessary that the installation of DGs in power system become systematical [2]. The DG can be an alternative for industrial, commercial and residential applications. DG makes use of the latest modern technology which is efficient, reliable, and simple enough so that it can compete with traditional large generators in some areas [3].

Generally, DG effects in distribution network depend on several factors such as the DG place, technology issues, capacity and the way it operates in the network. DG can significantly increase reliability, reduce losses and save energy while is cost effective, though it suffers from some disadvantages because of the isolated power quality functioning, and voltage control problems. Generally, planners assess DG functioning in two respects: costs and benefits. Cost is one of the most important factors that should be considered regarding DG application [4-5]. When installation and operation of distributed generation supplies are implemented based on optimization procedures, it can provide significant technical and economical advantages for the distribution companies [6].

In the most of the literatures only some parts of the effective parameters in DG placement problem have been considered. The optimal DG placement defined in [7] takes reliability, loss reduction, and load prediction into account while it fails to take into account the other parameters such as productivity, cost effectiveness, and type of DG. The optimal DG placement defined in [8] takes productivity, cost effectiveness, loss reduction, and reliability and DG type into account and fails to consider other parameters. In [9] only focuses on three parameters: DG cost, loss reduction and reliability. Also in [10] defines its optimal DG placement method taking DG capacity, cost effectiveness and loss reduction into account. In addition, in [11] defines its optimal placement method taking stability, loss reduction and productivity into account. In [12] optimal DG placement method takes loss reduction and load prediction into account. These fail to consider all aspects and parameters involving optimal DG placement. The present study is an attempt to define optimal DG placement by taking all pertinent parameters (loss reduction, voltage profile improvement, effects on environment, fuel price and load prediction cost) into consideration in optimization.

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1.1 THE RESEARCH OBJECTIVE

The main objective of this paper is to show that each of the effective parameters appeared in the multi-objective destination function (DF) of the proposed method, which optimizes the DG installation location, and strength of variables, has direct impact on the optimized DG placement. This work shows that the DG placement optimization can be carried out with the purpose of voltage profile improvement and loss reduction which possibly cause the capacity of the DG to be floating.

2. THE PROPOSED METHOD

In the present study, for the above-mentioned purpose, a destination function (DF) should be defined that includes all of the proposed parameters. In this study to compute the capacitance and location of DG in the distribution system, the immune algorithm has been used. The destination function (DF) of the immune algorithm is a cost function that includes most of the known parameters such as cost of decreasing losses, cost of voltage profile enhancement, cost incurred due to effects on environment and cost of the fuel used by DG sources and cost of load prediction for each bus and for the buses in which the load amount is not predictable and has following equation:

$$DF_{cost(x)} = F_1 C_{loss} + F_2 C_{vpi} + F_3 C_a + F_4 C_f + F_5 C_l \ (\frac{\$}{Kwh}) \tag{1}$$

Where:

$DF_{cost(x)}$: Destination function
C_{loss}: Cost of losses in the network
C_{vpi}: Cost of voltage profile enhancement
C_a: Cost incurred due to effects on environment
C_f: Cost of the fuel used by DG sources
C_l : Cost of load prediction for each bus
F_1: Coefficient of transferring losses to cost
F_2: Coefficient of transferring voltage profile enhancement to cost
F_3: Coefficient of transferring effects on environment to cost
F_4: Coefficient of transferring fuel used by DG sources to cost
F_5: Coefficient of transferring load prediction for each bus to cost

To define the destination function in (1), we have to convert all parameters to per unit to make them additive, this was accomplished by applying "*F*" coefficients (F_1-F_5). To calculate the cost of loss, first load flow is carried out in DIGSILENT software and then the results are used to calculate the losses and ultimately they are multiplied by the loss price. To calculate the cost of voltage profile improvement for each bus, the voltage difference for each bus is calculated before and after DG installment and the difference figure is multiplied by the cost of voltage profile improvement. To calculate pollution reduction cost using DG sources, the present study takes into account the variability of these coefficients for each bus depending on the type of the DG technology, and the cost incurred due to pollution which is calculated [13].

It is noteworthy that each of the coefficients of the environmental pollutions effects, fuel price and load prediction have been defined in DIGSILENT environment in the form of a matrix where these parameters are variable of each bus. Such values are shown in Tables 1-12. This paper has two major goals: 1) Improvement of voltage profile, 2) Loss reduction. There are also some limitations based on which the destination function should be defined [14]:

1) $V_{bus}^{\min} \le V_{bus} \le V_{bus}^{\max}$
2) $(Loss \ \ with \ \ DG) < (Loss \ \ without \ \ DG)$

According to the first limitation authorized voltage of a certain bus depends on the minimum and maximum voltages of the bus. Also, second limitation states that the loss reduces when DG exists in the prospective location.

3. SIMULATION NETWORK

In the proposed work, in order to observe and compare the results with those of the specified destination function, an IEEE 9-bus distribution network has been selected as a sample. It should be noted that the specified destination function could be generalized to be used for all distribution networks with any number of buses.

Moreover, the optimization algorithm of the destination function is a Body Immune Algorithm. The single line diagram of the network is illustrated in Fig. 1.

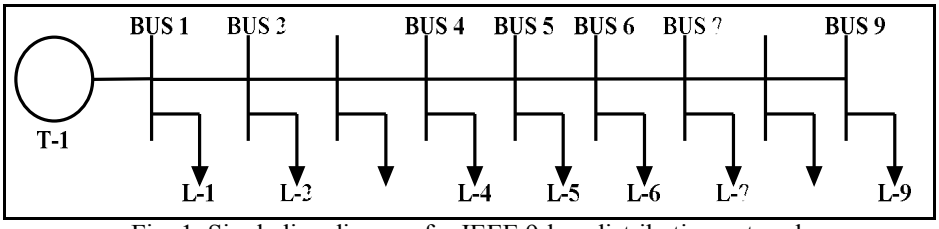

Fig. 1: Single line diagram for IEEE 9-bus distribution network

According to Fig. 1, 9-bus network contains one feeding source in bus 1. Tables 1 and Table 2 show the data on the lines and buses [15].

TABLE 1.DATA ON THE LINES

Sen.bus	Res.bus	R(ohm)	X(ohm)
0	1	0.4127	0.1233
1	2	0.6053	0.2514
2	3	1.2051	0.7463
3	4	0.6084	0.6984
4	5	1.7276	1.9831
5	6	0.7886	0.9053
6	7	1.1644	2.0552
7	8	2.7166	4.7953
8	9	3.0264	5.3434

TABLE 2. DATA ON THE BUSES

No.bus	P(kw)	Q(kvar)
1	1840	460
2	980	340
3	1790	446
4	1598	1840
5	1610	600
6	780	110
7	1150	60
8	980	130
9	1640	200

4. THE BODY IMMUNE ALGORITHM IMPLEMENTATION

Immune algorithm is one of the optimization algorithms in the problem solving that inspired from Clonal selection theory in the body immune system [16]. This algorithm is used for optimization with multi function. Steps of immune algorithm implementation are summarized as follows:

1. Coding: is mapping from problem area to search area (creating cells with enough length called anti body).
2. Production of initial population: in this stage, anti bodies labeled randomly to create population of zero generation
3. and by load distribution it's appropriation will be judge.
4. Affinity: similarity of anti bodies to each other is a parameter called dependency and is given by (2):

$$AFF_{mn}^{a-a} = \frac{1}{1+E(2)} \quad (2)$$

where m and n are two distinct anti bodies and AFF is diversity between two anti bodies that is given by (3):

$$E_j(N) = \sum_{ij=1}^{N} P_{ij}\, Log P_{ij} \quad (3)$$

where P_{ij} is the probability of un-similarity between i^{th} anti body and j^{th} gen with next un-similar cell.

5. Selecting anti bodies with high dependency: after calculating dependency level of anti bodies those have high level of dependency will be selected to continue.
6. Doing genetic action: on the anti bodies with low dependency, genetic actors (e.g. mutation and crossover) imply to increase their level of dependency.
7. Clonal stage: in this step anti bodies with high dependency are chosen as the next population in the second generation.
8. Controlling stop or continuation condition: in the steps 3 to 7, the number of generations and the best anti bodies that are the answer of the problem are updated until convergence achievement.

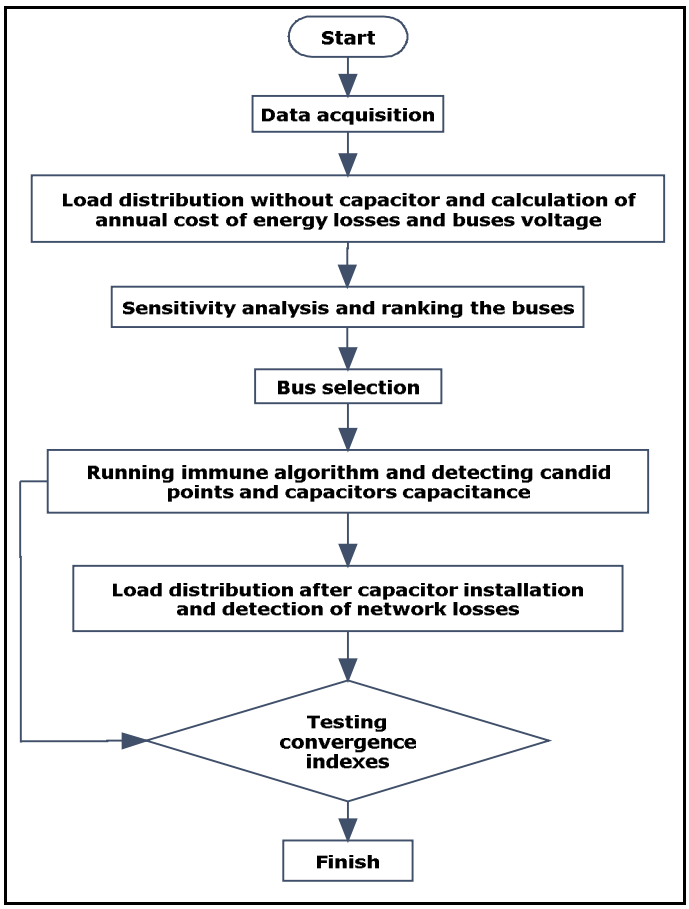

Fig. 2: Body Immune Algorithm computational procedure

Used anti body in the immune algorithm to solving capacitor placement in this study has n member. Each member showing one bus in the network. Value of this buses in the ith position showing capacitance of installable capacitors in the ith bus. One general sample of anti bodies shown in the Fig. 3.

1 2 3 4 ..... n

Fig. 3: Used anti body in the immune algorithm

Initial generation form this anti bodies, numbered randomly for starting the program.

5. Simulation Procedure

This study aims to optimize the placement of DG and assess DG capacity using weight coefficients for various parameters independently taking cost into account. The coefficients of the first case shown in Table 3 include loss-reduction parameters like voltage profiles, environmental factors, fuel price and load prediction in the destination function of the Body Immune Algorithm shown by (k_1-k_5) in the destination function. However, other coefficients shown in Table 4 are related to the weight of parameters for the effects of environmental factors, fuel price and load prediction which are defined in an input matrix for the simulation software. In this case, since parameters related to loss reduction and voltage profile are calculated automatically, the coefficients of these parameters are not considered in the input matrix for the software. Thus, generally, parameters for any network have two conditions of weight coefficients with any number of buses. This has been achieved using Body Immune Algorithm optimization in DIGSILENT environment. The parameter changes are illustrated because they are variable in each bus. Optimization is carried out with Body Immune Algorithm using a cost function. For this purpose, changes in the coefficients of the parameters are specified due to their variability in each bus. Optimization of the destination function has been carried out using a Body Immune Algorithm.

To assess the effect of loss reduction, voltage profile coefficient, environmental coefficient, fuel price and load prediction cost on the program, the program output was examined under two conditions (1), (2). For this purpose, different coefficients were applied to destination function parameters. Table 3 presents coefficients applied to parameters under the first condition, where parameters may vary depending on the place of the bus.

Table 3: Coefficients applied to the parameters under the first (1) condition

Coefficient	Parameter	Coefficients applied to each parameter in destination function
F_1	Loss reduction	35%
F_2	Voltage profile	20%
F_3	Effects on environment	15%
F_4	DG fuel cost	20%
F_5	Load prediction cost	10%

In addition, Table 4 presents an example of the weight of each parameter such as environmental pollution, fuel price and load prediction under the first condition. Table 5 presents program outputs regarding to the optimal capacity and placement of the prospective DG.

Table 4: An example of the weights of each parameter

Bus No	Coefficients applied in each bus to effect on environment	Coefficient applied in each bus to fuel price	Coefficients applied in each bus to load prediction cost
1	10%	5%	15%
2	15%	10%	10%
3	10%	15%	15%
4	10%	25%	5%
5	5%	15%	15%
6	15%	5%	10%
7	10%	10%	20%
8	25%	15%	10%

6. SIMULATION RESULT

The proposed method has been developed in DIGSILEN and MATLAB environments. The optimization algorithm in the present study is a Body Immune Algorithm. Table 5 presents the candidate position for DG installation in a 9-bus network as well as the capacity of optimal DG in terms of (KW) using LII and VPII indexes.

Table 5: The algorithm outputs

DG name	Location	Capacity (KW)
DG	BUS 6	437
Loss before DG	Loss after DG	LII
0.131458	0.125732	0.956442
VPI without DG	VPI with DG	VPII
0.084524	0.095284	1.127301

Also, in the above outlet, line loss reduction index is defined by:

$$LII = \frac{LL_{WDG}}{LL_{WODG}} \tag{2}$$

Where LL_{WDG} and LL_{WODG} are the losses incurred with and without DG presence, respectively. This indicator can have the following implications under the following three conditions:

- LII<1: DG reduces loss
- LII=1: DG is not effective
- LII>1: DG increases loss

Furthermore in Table 5, VPII indicates voltage profile improvement and shows the effect of DG placement on the voltage profile which is defined as follows [17-18]:

$$VPII = \frac{VP_{WDG}}{VP_{WODG}} \tag{3}$$

Where VP_{WDG} and VP_{WODG} are the voltage profiles with and without DG presence, respectively, and can be interpreted as follows under the following conditions:

- VPII<1: DG has a negative effect on network voltage
- VPII=1: DG is not effective
- VPII>1: DG has a positive effect on network voltage

To observe the effect of each parameter including environmental pollution, fuel price and load prediction cost, we changed the coefficients applied to each parameter in each bus in the form of a matrix. Table 6 presents the weight of another example of parameters such as environmental pollution, fuel price and load prediction, under condition of Table 3. In addition, Table 7 presents program outputs regarding to optimal capacity and placement of DG.

Table 6: An example of the weights of each parameter

Bus No	Coefficients applied in each bus to effect on environment	Coefficients applied in each bus to fuel price	Coefficients applied in each bus to load prediction cost
1	20%	15%	10%
2	15%	20%	15%
3	10%	15%	25%
4	20%	10%	5%
5	5%	10%	10%
6	10%	15%	10%
7	5%	10%	5%
8	15%	5%	20%

Table 7: The algorithm outputs

DG name	Location	Capacity (KW)
DG	BUS 7	545
Loss before DG	Loss after DG	LII
0.129962	0.112316	0.864221
VPI without DG	VPI with DG	VPII
0.083472	0.094612	1.133457

To test the program results under a different condition, we change all coefficients applied to the parameters of the destination function. Table 8 presents coefficients applied to parameters under different condition of Table 3. In addition, Table 9 presents the weight of parameters such as environmental pollution, fuel price and load prediction, under the same condition of Table 8. Also, Table 10 presents program output with regard to the optimal capacity and placement of DG.

Table 8: Coefficients applied to the parameters under the second (2) condition

Coefficient	Parameter	Coefficient applied to each parameter in destination function
F_1	Loss reduction	20%
F_2	Voltage profile	30%
F_3	Effects on environment	25%
F_4	DG fuel cost	15%
F_5	Load prediction cost	10%

Table 9: An example of the weights of each parameter

Bus No	Coefficients applied in each bus to effect on environment	Coefficients applied in each bus to fuel price	Coefficients applied in each bus to load prediction cost
1	15%	20%	10%
2	10%	10%	15%
3	15%	20%	10%
4	10%	5%	20%
5	5%	10%	10%
6	25%	15%	15%
7	10%	15%	15%
8	10%	5%	5%

Table 10: The program outputs

DG name	Location	Capacity (KW)
DG	BUS 5	617
Loss Before DG	Loss after DG	LII
0.132673	0.122168	0.920820
VPI without DG	VPI with DG	VPII
0.090432	0.098213	1.086042

To observe the effect of each parameter including environmental pollution, fuel price and load prediction cost, we changed again the coefficients applied to each parameter in each bus. Table 11 presents the weight of another example of parameters such as environmental pollution, fuel price and load prediction under the same conditions of Table 8. Finally, Table 12 presents program outputs with regard to the optimal capacity and placement of DG.

Table 11: An example of the weights of each parameter

Bus No	Coefficients applied in each bus to effect on environment	Coefficients applied in each bus to fuel price	Coefficients applied in each bus to load prediction cost
1	15%	10%	10%
2	5%	20%	25%
3	10%	10%	15%
4	15%	15%	5%
5	10%	10%	10%
6	15%	15%	5%
7	10%	5%	20%
8	20%	15%	10%

Table 12: The program outputs

DG name	Location	Capacity (KW)
DG	BUS 8	593
Loss before DG	Loss after DG	LII
0.125623	0.117835	0.938084
VPI without DG	VPI with DG	VPII
0.0926923	0.098451	1.062127

7. CONCLUSION

The values of Distributed Generation are very dependent on its size and location as it was installed in distribution feeders. Hence, in this paper the optimal DG placement and estimation of distributed generator (DG) capacity in power distribution networks using a immune algorithm based multi-objective optimization for sitting and sizing of distributed generation resources in distribution systems has been performed in order to minimize the cost of power losses and energy which is not supplied. In this paper, we studied the effects of the significant parameters to optimally enhance the cost parameters (such as loss reduction, voltage profile improvement, environmental effects, fuel price and costs of predicting load of each bus). The cost parameters are variables, which are dependent on the status and position of each power network bus.

It has been shown that any changes made in the weight of parameters such as loss reduction, voltage profile coefficient, coefficient of environmental pollution, fuel price and load prediction cost in the destination function of Body Immune Algorithm directly affect the optimal DG capacity and placement. In the end, the DG placement will be carried out with the purpose of improving voltage profile and loss reduction which cause the distributed generation capacity to be floating.

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