Clonal Selection Algorithm for DG Sources Allocation for Minimum Loss in Distribution System

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Abstract: Distributed Generation (DG) is a promising solution to many power system problems such as voltage regulation, power loss, etc. This paper presents a new methodology using Fuzzy and Artificial Immune System(AIS) for the placement of Distributed Generators(DG) in the radial distribution systems to reduce the real power losses and to improve the voltage profile. A two-stage methodology is used for the optimal DG placement. In the first stage, an analytical method is used to find the optimal DG locations and in the second stage, Clonal Selection algorithm of AIS is used to find the size of the DGs corresponding to maximum loss reduction. This algorithm is a new population based optimization method inspired by cloning principle of human body immune system. The advantage of this algorithm is that the population size is dynamic and it is determine by the fitness values of the population. The proposed method is tested on standard IEEE 33 bus test system and the results are presented and compared with different approaches available in the literature. The proposed method has outperformed the other methods in terms of the quality of solution and computational efficiency.

Keywords: *DG placement, Meta heuristic methods, Artificial Immune Systems, Clonal Selection algorithm, loss reduction, radial distribution system.*

1. Introduction

Distributed or dispersed generation (DG) or embedded generation (EG) is small-scale power generation that is usually connected to or embedded in the distribution system. The term DG also implies the use of any modular technology that is sited throughout a utility's service area (interconnected to the distribution or sub-transmission system) to lower the cost of service [1]. The benefits of DG are numerous [2, 3] and the reasons for implementing DGs are an energy efficiency or rational use of energy, deregulation or competition policy, diversification of energy sources, availability of modular generating plant, ease of finding sites for smaller generators, shorter construction times and lower capital costs of smaller plants and proximity of the generation plant to heavy loads, which reduces transmission costs. Also it is accepted by many countries that the reduction in gaseous emissions (mainly CO_2) offered by DGs is major legal driver for DG implementation [4].

The distribution planning problem is to identify a combination of expansion projects that satisfy load growth constraints without violating any system constraints such as equipment overloading [5]. Distribution network planning is to identify the least cost network investment that satisfies load growth requirements without violating any system and operational constraints. Due to their high efficiency, small size, low investment cost, modularity and ability to exploit renewable energy sources, are increasingly becoming an attractive alternative to network reinforcement and expansion. Numerous studies used different approaches to evaluate the benefits from DGs to a network in the form of loss reduction, loading level reduction [6-8].

Naresh Acharya *et al* suggested a heuristic method in [9] to select appropriate location and to calculate DG size for minimum real power losses. Though the method is effective in selecting location, it requires more computational efforts. The optimal value of DG for minimum system losses is calculated at each bus. Placing the calculated DG size for the buses one by one, corresponding system losses are calculated and compared to decide the appropriate location. More over the heuristic search requires exhaustive search for all possible locations which may not be applicable to more than one DG. This method is used to calculate DG size based on approximate loss formula may lead to an inappropriate solution.

In the literature, genetic algorithm and PSO have been applied to DG placement [10-13].In all these works either sizing or location of DGs are determined by these methods. This paper presents a new methodology using Clonal selection algorithm[14-17] for the placement of DG in the radial distribution systems. The Clonal algorithm is a new population based meta heuristic approach inspired by Clonal principle of immune system of human body. The advantage of this algorithm is that it does not require external parameters such as selection, cross over rate and mutation rate as in case of genetic algorithm and differential evolution and it is hard to determine these parameters in prior. The other advantage is that the global search ability in the algorithm is implemented by introducing hyper mutation which differs from mutation in GA in two ways. One is the mutation rate is very high that every solution is mutated here and the second one is the mutation is not a single bit mutation. The advantage of Clonal algorithm is its dynamic population size.

In this paper, the optimal locations of distributed generators are identified based on single DG placement method[18] and Clonal optimization technique which takes the number and location of DGs as input has been developed to determine the optimal size(s) of DG to minimize real power losses in distribution systems. The advantages of relieving Clonal method from determination of locations of DGs are improved convergence characteristics and less computation time. Voltage and thermal constraints are considered. The effectiveness of the proposed algorithm was validated using 33-Bus Distribution System [19].To test the effectiveness of proposed method; results are compared with different approaches available in the literature. The proposed method has outperformed the other methods in terms of the quality of solution and computational efficiency.

2. Theoretical Background

The total I^2R loss (P_L) in a distribution system having n number of branches is given by:

$$P_{Lt} = \sum_{i=1}^{n} I_i^2 Ri \qquad (1)$$

Here I_i is the magnitude of the branch current and R_i is the resistance of the i^{th} branch respectively. The branch current can be obtained from the load flow solution. The branch current has two components, active component (I_a) and reactive component (I_r). The loss associated with the active and reactive components of branch currents can be written as:

$$P_{La} = \sum_{i=1}^{n} I_{ai}^2 Ri \qquad (2)$$

$$P_{Lr} = \sum_{i=1}^{n} I_{ri}^2 Ri \qquad (3)$$

Note that for a given configuration of a single-source radial network, the loss P_{La} associated with the active component of branch currents cannot be minimized because all active power must be supplied by the source at the root bus. However by placing DGs, the active component of branch currents are compensated and losses due to active component of branch current is reduced. This paper presents a method that minimizes the loss due to the active component of the branch current by optimally placing the DGs and thereby reduces the total loss in the distribution system. A two stage methodology is applied here. In the first stage optimum location of the DGs are determined by using single DG placement method and in the second stage Clonal selection algorithm is used to determine sizes of the DGs for maximum real loss reduction.

3. Identification Of Optimal DG Locations By Single DG Placement Algorithm

This algorithm determines the optimal size and location of DG units that should be placed in the system to minimize loss. First optimum sizes of DG units for all nodes are determined for base case and best one is chosen based on the maximum loss saving. This process is repeated if multiple DG locations are required by modifying the base system by inserting a DG unit into the system one-by-one.

3.1. Methodology

Assume a single-source radial distribution system with n branches and DG is to be placed at bus $\boldsymbol{m}$ and α be set of branches connected between source and bus $\boldsymbol{m}$. The DG produces active current I_{DG}, and for radial network it changes only active component of branch current of set α. The currents of other branches are unaffected. Thus new active current I_{ai}^{new} of i^{th} branch is given by

$$I_{ai}^{new} = I_{ai} + D_i I_{DG} \qquad (4)$$

where D_i = 1; if branch $i \in \alpha$
= 0; otherwise

The loss P_{La}^{com} associated with active component of branch currents in new system is given by

$$P_{La}^{com} = \sum_{i=1}^{n} (I_{ai} + D_i I_{DG})^2 R_i \qquad (5)$$

The saving S is difference between equation 3 and 5 and is given by

$$\begin{aligned} S &= P_{La} - P_{La}^{com} \\ &= -\sum_{i=1}^{n} (2 D_i I_{ai} I_{DG} + D_{DG} I_c^2) R_i \end{aligned} \qquad (6)$$

The DG current I_{DG} that provides maximum saving is obtained from

$$\frac{\partial S}{\partial I_{DG}} = -2\sum_{i=1}^{n} (D_i I_{ai} + D_i I_{DG}) R_i = 0 \qquad (7)$$

The DG current for maximum saving is

$$I_{DG} = -\frac{\sum_{i=1}^{n} D_i I_{ai} R_i}{\sum_{i=1}^{n} D_i R_i} = -\frac{\sum_{i \in \alpha} I_{ai} R_i}{\sum_{i \in \alpha} R_i} \qquad (8)$$

The corresponding DG size is

$$P_{DG} = V_m I_{DG} \qquad (9)$$

V_m is voltage magnitude of bus-m. The optimum size of DG at each bus is determined using eqn (9). Then saving for each DG is determined using eqn (6).The DG with highest saving is candidate location for single DG placement. When the candidate bus is identified and DG is placed, the process is repeated to identify subsequent buses for DG placement.

3.2. Algorithm for Single DG Placement

Step 1: Conduct load flow analysis for the original system .

Step 2: Calculate I_{DG} and DG size using equations 8 & 9 for buses i=2…n.

Step 3: Determine saving using equation 6, for buses i=2…n.

Step 4: Identify the maximum saving and the corresponding DG size.

Step5: The corresponding bus is candidate bus where DG can be placed. Modify the active load at this bus and conduct the load flow again.

Step 6: Check whether the saving obtain is more than 1kW. If yes, go to step 2. Otherwise, go to next step.
Step 7: print all the candidate locations to place DG sources and the sizes.

Since the DGs are added to the system one by one, the sizes obtained by single DG placement algorithm are local optima not global optimum solution. The global optimal solution is obtained if multiple DGs are simultaneously placed in the system by using ABC algorithm as explained in next section.

4. Identification Of Optimal DG Sizes By Clonal Algorithm

4.1. Introduction to Artificial Immune System

The 'artificial immune system' is an approach which used the natural immune system as a metaphor for solving computational problems, *not* modeling the immune system [14]. The main application domains of AIS are anomaly detection, pattern recognition, computer security, fault tolerance, dynamic environments, robotics, data mining, optimization, and scheduling. The 'immune system' (IS) can be considered to be a remarkably efficient and powerful information processing system which operates in a highly parallel and distributed manner. It contains a number of features which potentially can be adapted in computer systems; recognition, feature extraction, diversity, learning, memory, distributed detection, self-regulation, threshold mechanism, co-stimulation, dynamic protection, and probabilistic detection. It is unnecessary to replicate *all* of these aspects of the IS in a computer model, rather they should be used as general guidelines in designing a system.

There are a number of different algorithms that can be applied to many domains, from data analysis to autonomous navigation [14]. These immune algorithms were inspired by works on theoretical immunology and several processes that occur within the IS. The AISs lead to the development of different techniques, each one mapping a different mechanism of the system. For examples, the *Artificial Immune Networks* as proposed by Farmer et al. [15], the *Clonal Selection Algorithm* proposed by de Castro and Von Zuben [16], and the *Negative Selection Algorithm* introduced by Forrest et al. [17]. Immune network models are suitable to deal with dynamic environments and optimization problems, algorithms based upon the clonal selection principle are adequate to solve optimization and scheduling problems, and the negative selection strategies are successfully applied to anomaly detection.

4.2. Application of Clonal Selection Algorithm to determine DG unit sizes

The clonal selection algorithm (CSA) is inspired by the immunological processes of *clonal selection* and *affinity maturation*. When an antigen is detected, those antibodies that best recognize this antigen will proliferate by cloning. This process is called *clonal selection principle* [6]. The clonal selection principle is used to explain how the IS 'fights' against an antigen. When a bacterium invades our organism, it starts multiplying and damaging our cells. One form the IS found to cope with this replicating antigen was by replicating the immune cells successful in recognizing and fighting against this disease-causing element. Those cells reproduce themselves asexually in a way proportional to their degree of recognition: the better the antigenic recognition, the higher the number of clones (offspring) generated. During the process of cell division (reproduction), individual cells suffer a mutation that allows them to become more adapted to the antigen recognized: the higher the affinity of the parent cell, the lower the mutation they suffer. The algorithm is given below.

Step 1. ***Initialization***: initialize a population of antibodies (feasible sizes of DG unit at predetermined locations). Each antibody represents a solution in the search space.
Step 2. ***Selection:*** All the antibodies are selected in optimization version
Step 3. ***Affinity Evaluation***: determine the affinity of selected antibodies (affinity = 1/Power Loss)
Step 4. ***Cloning or proliferation***: The selected antibodies will be cloned (reproduced) independently and proportionally to their affinities, generating a repertoire of clones: the higher the affinity, the higher the number of clones generated for each of the selected antibodies;
Step 5. ***Hyper-mutation*** : The repertoire of clones is submitted to an affinity maturation process inversely proportional to the affinity, generating a population of matured clones: the higher the affinity, the smaller the mutation rate;
Step 6. ***Affinity evaluation:*** determine the affinity of matured clones
Step 7. ***Reselection :*** From this set of mature clones re-select the higher affinity clones
Step 8. Finally, replace the *d* lowest affinity antibodies from the population of the antibodies by new individuals generated randomly to maintain the diversity in population.

The main operators in CSA are *cloning, mutation and* re*selection*. All solutions are selected for cloning and a number of clones are generated for each solution. Almost all clones will be mutated to produce new feasible solutions for the next generation since '1- selection probability' would give a high mutation rate for each clone. But only new solutions with high affinity will be selected to replace the low affinity solutions in the current population. The process will be repeated until the stopping criteria are met.

In our implementation, it was assumed that the *n* highest affinity antibodies were sorted in ascending order after Step 3, so that the amount of clones generated for all these *n* selected antibodies was given by (5):

$$N_c = \sum_{i=1}^{n} round\left(\frac{\beta.N}{i}\right), \tag{5}$$

where Nc is the total amount of clones generated, β is a multiplying factor, N is the total amount of antibodies and *round*( ) is the operator that rounds its argument towards the closest integer. Each term of this sum corresponds to the clone size of each selected antibody, e.g., for $N = 100$ and $\beta = 1$, the highest affinity antibody ($i = 1$) will produce 100 clones, while the second highest affinity antibody produces 50 clones, and so on.

5. RESULTS AND DISCUSSION

First load flow is conducted for IEEE 33 bus test system[7]. The power loss due to active component of current is 136.9836 kW and power loss due to reactive component of the current is 66.9252 kW. A program is written in "MATLAB" to implement single DG placement algorithm . For the first iteration the maximum saving is occurring at bus 6. The candidate location for DG is bus 6 with a loss saving of 92.1751 kW. The optimum size of DG at bus 6 is 2.4886 MW. By assuming 2.4886 MW DG is connected at bus 6 of base system and is considered as base case. Now the candidate location is bus 15with 0.4406 MW size and the loss saving is 11.4385 KW. This process is repeated till the loss saving is insignificant. The results are shown in Table I.

The candidate locations for DG placement are taken from single DG placement algorithm i.e. 6,15,25,32. With these locations, sizes of DGs are determined by using Clonal Algorithm described in section 4. The sizes of DGs are dependent on the number of DG locations.

TABLE I.
SINGLE DG PLACEMENT RESULTS

iteration No.	Bus No.	DG Size (MW)	Saving (KW)
1	6	2.4886	92.1751
2	15	0.4406	11.4385
3	25	0.6473	7.6936
4	32	0.4345	8.1415

Generally it is not possible to install many DGs in a given radial system. Here 4 cases are considered. In case I only one DG installation is assumed. In case II two DGs, in case III three DGS and in the last case four DGs are assumed to be installed. DG sizes in the four optimal locations, total real power losses before and after DG installation for four cases are given in Table II.

TABLE II.
RESULTS OF IEEE 33 BUS SYSTEM

Case	bus locations	DG sizes (MW)	Total Size (MW)	losses before DG installation (kW)	loss after DG installation (kW)	Saving (kW)	saving/ DG size
I	6	2.5775	2.5775		105.0231	98.8857	39.9
	6	1.9707					
II	15	0.5757	2.5464		89.9619	113.9469	44.75
	6	1.7569					
	15	0.5757					
III	25	0.7826	3.1152		79.2526	124.6562	40.015
	6	1.0765					
	15	0.5757					
	25	0.7824					
IV	32	0.6538	3.0884	203.9088	66.5892	137.3196	44.86

The last column in Table II represents the saving in kW for 1 MW DG installation. The case with greater ratio is desirable. As the number of DGs installed is increasing the saving is also increasing. In case4 maximum saving is achieved but the number of DGs is four. Though the ratio of saving to DG size is maximum of all cases which represent optimum solution but the number of DGs involved is four so it is not economical by considering the cost of installation of 4 DGs. But in view of reliability, quality and future expansion of the system it is the best solution.

Table III shows the minimum voltage and % improvement in minimum voltage compared to base case for all the four cases. In all the cases voltage profile is improved and the improvement is significant. The voltage profile for all cases is shown in Figure 1.

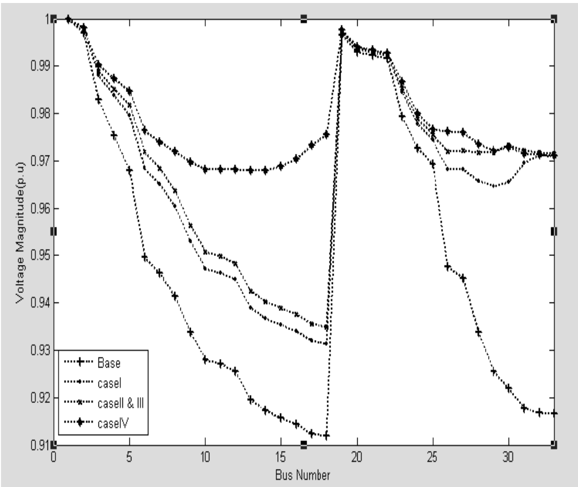

Figure 1. Voltage profile with and without DG placement for all Cases

TABLE III.
VOLTAGE IMPROVEMENT WITH DG PLACEMENT

case No.	Bus No.	Min Voltage	% change
Base case	18	0.9118	
case1	18	0.9314	2.149
case2	18	0.9349	2.533
case3	18	0.9349	2.533
case4	14	0.9679	6.153

Table IV shows % improvements in power loss due to active component of branch current, reactive component of branch current and total active power loss of the system in the four cases considered. The loss due to active component of branch current is reduced by more than 68% in least and nearly 96% at best. Though the aim is reducing the P_{La} loss, the P_{Lr} loss is also reducing due to improvement in voltage profile. From Table 5 it is observed that the total real power loss is reduced by 48.5% in case 1 and 67% in case 4.

TABLE IV.
LOSS REDUCTION BY DG PLACEMENT

case No.	P_{La} **(kW)**	**% Saving**	P_{Lr} **(kW)**	**% Saving**	P_{Lt} **(kW)**	**% Saving**
Base case	136.9836	----	66.9252	----	203.9088	----
case1	43.2029	68.46	61.9297	7.46	105.1326	48.44
case2	28.5651	79.15	61.4845	8.13	90.0496	55.84
case3	18.1166	86.77	61.2138	8.53	79.3303	61.1
case4	5.6123	95.9	61.0493	8.78	66.6616	67.31

The convergence characteristics of the solution obtained by Clonal selection algorithm for all the four cases are shown in figure 2.

Table V shows the minimum, average and maximum values of total real power loss from 100 trials of Clonal selection algorithm. The average number of iterations and average CPU time are also shown.

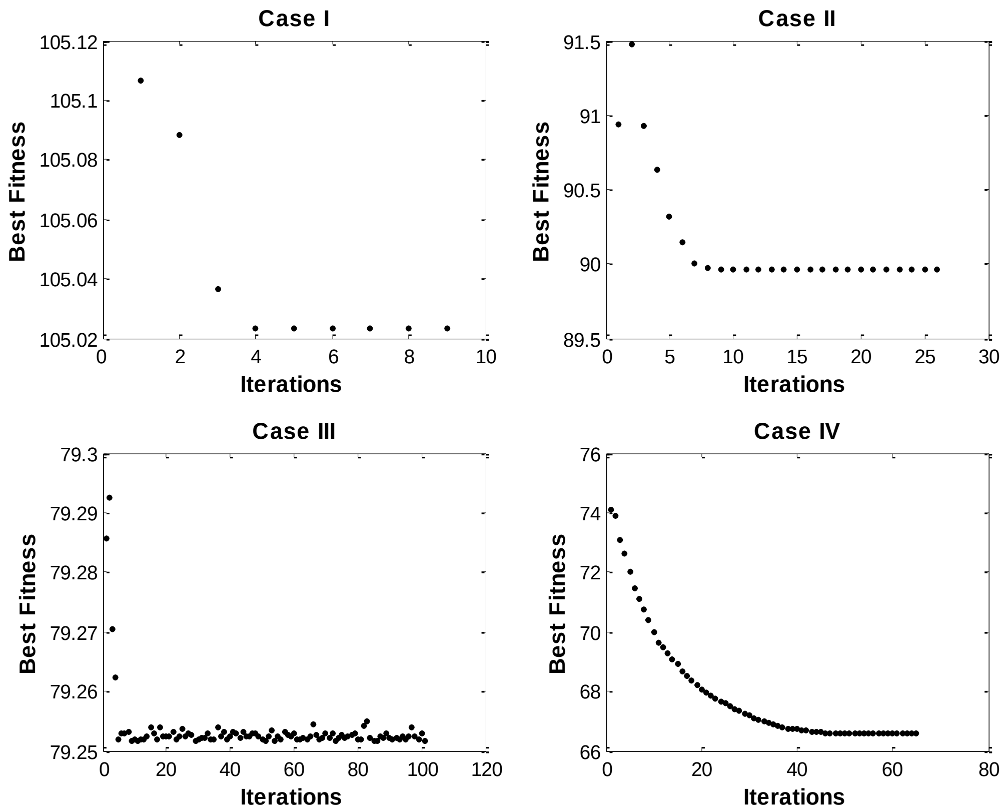

FIGURE II. Convergence characteristic of Clonal selection algorithm for 33 bus test system.

TABLE V.
PERFORMANCE OF CLONAL SELECTION ALGORITHM FOR IEEE 33 BUS SYSTEM

Total real power loss (kW)	Case I	Case II	Case III	Case IV
Min	104.813	89.752	79.012	66.029
Average	105.023	89.9619	79.2515	66.5892
Max	105.424	90.12	79.856	66. 759
No. of Antibodies	50	50	50	50
Avg. No. of iterations	8.257	24.384	62.896	67.903
Average Time (Sec.)	1.563	9	21.25	28.937

5.1. Comparison Performance

To demonstrate the validity of the proposed method the results of proposed method are compared with an existing PSO method [20]. The comparison is shown in Table VI.

TABLE IV.
COMPARISON OF RESULTS OF IEEE 33-BUS SYSTEM BY PROPOSED METHOD AND OTHER EXISTING METHOD

Case	Bus locations	sizes(Mw)		Total Size(Mw)		saving(Kw)	
		Clonalg	PSO	Clonalg	PSO	Clonalg	PSO
1	6	2.5775	2.5775	2.5775	2.5775	98.8857	98.8857
2	6	1.9707	1.9707	2.5464	2.5464	113.9469	113.9469
	15	0.5757	0.5757				
3	6	1.7569	1.7569	3.1152	3.1152	124.6562	124.6562
	15	0.5757	0.5757				
	25	0.7826	0.7826				
4	6	1.0765	1.0765	3.0884	3.0884	137.3196	137.3196
	15	0.5757	0.5757				
	25	0.7824	0.7824				
	32	0.6538	0.6538				

From the above table it is clear that the proposed method is producing the results that matches with those of existing method. To demonstrate the supremacy of the proposed method the convergence characteristics are compared with that of PSO algorithm as shown in Table VII. Both the number of iterations and computation time are less for Clonal selection algorithm. The only disadvantage of the proposed method is, it is producing slightly different results for each run.

6. CONCLUSIONS

In this paper, a two-stage methodology of finding the optimal locations and sizes of DGs for maximum loss reduction of radial distribution systems is presented. An analytical method is proposed to find the optimal DG locations and a Clonal Selection algorithm is proposed to find the optimal DG sizes. Voltage and line loading constraints are included in the algorithm.

The validity of the proposed method is proved from the comparison of the results of the proposed method with other existing methods. The results proved that the proposed algorithm is simple in nature than GA and PSO so it takes less computation time. This algorithm has the advantage of dynamically changing population size for each iteration depending on fitness value. By installing DGs at all the potential locations, the total power loss of the system has been reduced drastically and the voltage profile of the system is also improved. Inclusion of the real time constrains such as time varying loads and different types of DG units and discrete DG unit sizes into the proposed algorithm is the future scope of this work.

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