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DISTRIBUTED GENERATION ALLOCATION TO IMPROVE STEADY STATE VOLTAGE STABILITY OF DISTRIBUTION NETWORKS USING CLONAL SELECTION ALGORITHM

M. Sedighizadeh[1] , A. Rezazadeh[2] , D. Dehghani [2], M. Mohammadi[2]
1-Faculty of Engineering and Technology, Imam Khomeini International University, Qazvin, 34194, Iran, Email: m_sedighi@sbu.ac.ir
2-Faculty of Electrical and Computer Engineering, Shahid Beheshti University, Tehran, Iran

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Abstract

In this paper, our purpose would be optimal distributed generation allocation for stability enhancement, in radial distribution systems. Voltage stability is related with stable load and acceptable voltage in all system buses. The instability is divided into steady state and transient voltage instability Based on the time spectrum of the incident of the phenomena. The analysis is accomplished using a steady state voltage stability index which can be evaluated at each node of the distribution system. Several optimal capacities and locations are used to check this result. The location of DG has the main effect voltage stability on the system. effect of location and capacity on incrementing steady state voltage stability in radial distribution systems are examined through clonal selection algorithm and finally the results are compared to (PSO) on the terms of speed, accuracy and convergence.

Keywords: Distributed Generation, Voltage Stability, Allocation, Clonal Selection Algorithm, Particle Swarm Optimization.

1. Introduction

The necessity for flexible electric systems, changing regulatory and economic scenarios, energy savings and environmental impact are providing impetus to the development of Distributed Generation (DG) (wind turbines, photovoltaic, fuel-cells, biomass, micro turbines plants, etc.), which is predicted to play an increasing role in the electric power system of the future. Because of this penetration of DG sources in ranges from sub-kW to multi-kW the use of this source in distribution networks is increasing throughout the world.

Distributed Generation can be explained as an electrical power source connected directly to the distribution network or on the consumer side of the meter. It may be implied in simple term as small-scale electricity market.

A general explanation was suggested in [1], which are now widely accepted as follows: ‘‘Distributed Generation is an electric power source connected directly to the distribution network or on the customer site of the meter’’. Explanations of DGs do not define them as the technologies that can be used vary widely. However, a categorization of different technology groups of DGs such as non-renewable DG and renewable DG seems possible. From distribution system planning point of view, DG is a feasible alternative for new capacity, particularly in the competitive electricity market environment, and has immense benefits such as short lead time and low investment risk since it is built in modules, small-capacity modules that can track load deviation more closely, small physical size that can be installed at load centers and does not need government approval or search for utility area and land availability, and existence of a large range of DG technologies [2]. For these reasons, the first signs of a possible technological change are beginning to arise on the international scene, which in the future can involve the presence of a consistently generation produced with small and medium size plants directly connected to the distribution network (LV and MV) and characterized by good efficiencies and low emissions. This will create new problems, and almost certainly, the need of new tools and managing these systems.

The planning of the electric system at the presence of DG requires defining of several factors including the best technology to be used, the number and the capacity of the units, the best location, the type of network connection, etc. The effect of DG on operating characteristics of the system such as electric losses, voltage profile, stability, and reliability needs to be appropriately evaluated. The problem of DG allocation and sizing is of great importance. Installing DG units at no optimal places may result in an increase in system losses, implying an increase in costs, and therefore, having an opposite effect to what is desired. As a result, using an optimization method capable of indicating the best solution for a given distribution network can be very useful for system planning engineers. Selecting the best places for installing DG units and their preferable sizes in large distribution systems is a complex combinatorial optimization problem.

Voltage stability is related with stable load and acceptable voltage in all system buses. The instability is divided into steady state and transient voltage instability according to the time spectrum of the incident of the phenomena.

When there is a disturbance in a power system which has a state of voltage instability, an uncontrollable progressive reduction will arise. Voltage stability analysis often requires examination of system state losses and a lot of other related scenarios. Due to this, the established rationale based on steady state analysis is more feasible and it can create an overall forecasting about voltage reaction problems as well. Voltage stability phenomenon is completely known in distribution systems. In radial distribution system resistance to reluctance ratio is high which causes a lot of power loss, hence radial distribution systems are kinds of power systems which are flawed by voltage instability.

The presence of DGs in distribution networks can affect many of the utilizing factors which reduce losses, THD networks and voltage stability by making changes in the path through which power passes. Among these the size and location of DGs are important factors.

In this paper the effect of location and capacity on increasing steady state voltage stability in radial distribution systems are examined through Clonal Selection Algorithm (CSA) and finally the results are compared to Particle Swarm Optimization Algorithm (PSO) on the terms of speed, accuracy and convergence. The analysis is performed using a steady state voltage stability index presented by M. Charkravorty and et.al in [4]. This index can be estimated at each node of radial distribution system. The suggested algorithm is applied on the Khoda Bande Loo distribution test feeder in Tehran.

2. Clonal Selection Algorithm

Clonal Selection principle is a form of natural selection [3] and it describe the essential features which contain adequate diversity, discrimination of self and non-self and long-lasting immunologic memory.

The main idea of clonal selection theory lies in that the antibodies can selectively react to the antigens, which are the native production and spread on the cell surface in the form of peptides. When exposed to antigens, the immune cells that recognize and eliminate the antigens will be selected and arouse an effective response against them. The reaction leads to cell proliferating clonally and the colony has the same antibodies. Consequently, the process of clonal selection actually consists of three main steps: Clone: descend a group of identical cells from a single common ancestor through asexual propagation. Mutation: gain higher affinity mainly through hypermutation [4]. Selection: select some excellent individuals from the sub-population generated by clonal proliferation. Assuming the objective function and restraining conditions of optimization are the antigens invading the body and candidate solutions are the antibodies recognizing antigens, then the process of optimization can be considered as the reaction between antigens and antibodies, and the affinity between the antigens and the antibodies are the matching degree between objective function and solutions.

In this section, we present and analyze our proposed clonal selection algorithm. Fig.1 shows the flow of the proposed algorithm. Generally, the proposed model can be described as follows:

Step1. Initialize the population of antibodies that is, creating an initial pool of m antibodies randomly (candidate solutions $(Ab_1, Ab_2, \cdots, Ab_r)$.

Step 2. Compute the affinity of all antibodies ($A(Ab_1), A(Ab_2), \cdots, A(Ab_r)$, where A(.) is the function to compute the affinity.

Step 3. Select the n (n < m) best (fittest) individuals based on their affinities from the m original antibodies. These antibodies will be referred to as the elites.

Step 4. Place each of the n selected elites in n separate and distinct pools in a descending order of the affinity $(Ab_1, Ab_2, \cdots, Ab$. They will be referred to as the elite pools.

Step 5. Clone the elites in each elite pool with a rate proportional to its fitness, i.e., the fitter the antibody, the more clones it will have. The amount of clone generated for these antibodies is given by:

$$p_i = \text{round}(\frac{(n-i)}{n} \times ($$

Where i is the ordinal number of the elite pools, Q is a multiplying factor which determines the scope of the clone and round (.) is the operator that rounds its argument towards the closest integer. After this step, we can obtain $\sum$ antibodies just as ($Ab_{1,1}, Ab_{1,2}, \cdots, Ab_{1,p_1}; \cdots; Ab_n$ $Ab_{n,2}, \cdots, Ab_{n,}$)

Step 6. Subject the clones in each pool through either hypermutation or receiver editing processes. Some of the clones in each elite pool undergo the hypermutation process and the remainders of the clones pass the receiver editing process. The mutation number (P_h and P for hypermutation and receptor editing, respectively) are defined as follows:

$$P_{hm} = \lambda \cdot$$
$$P_{re} = (1 - \lambda) \cdot$$

Where λ is a user-defined parameter which determines the complementary intensity between the hypermutation and receiver editing. In our perior work [5], we had demonstrated that an equivalent level of P_h: P, that is, λ = 0.5 will lead the CSA algorithm to a better performance. After this step, we obtain $\sum$ mutated antibodies just as

$$(Ab'_{1,1}, Ab'_{1,2}, \cdots, Ab'_{1,p_1}; \cdots; Ab'_{n,1}, Ab'_{n,2}, \cdots, Ab'_{n,p_n})$$

step 7. All of the mutated antibodies enter into a reselect process where the mutated ones Ab are judged to compare with their parent antibody Ab according to the following updating rule:

$$Ab''_{i,j} = \begin{cases} Ab_{i,j} & \text{if } A(Ab_{i,j}) > (Ab'_{i,j}) \\ Ab'_{i,j} & \text{if } A(Ab_{i,j}) \le (Ab'_{i,j}) \end{cases}$$

Then we can obtain $\sum$ updated antibodies just as:

$$(Ab''_{1,1}, Ab''_{1,2}, \cdots, Ab''_{1,p_1}; \cdots; Ab''_{n,1}, Ab''_{n,2}, \cdots, Ab''_{n,p}.$$

Step 8. Determine the fittest individual

$B_i(A(B_i) = \max\{(Ab''_{i,1}, Ab''_{i,2}, \cdots, Ab''_{i,p_i})\}, i = 1,2,\cdots, r$ in each elite pool from amongst its updated clones.

Step 9. The n antibodies $(B_1, B_2 \cdots, B$ are subjected to the apoptosis process in a descending order. The best m antibodies can survive and enter into the elite pools, the rest n-m antibodies are eliminated.

Step10. Replace the worst c (η = c/m) elite pools with new random antibodies earned once every k generations. It is interesting to point out that this step was expected to preserve the diversity and preserve the search from being trapped in local optima in CSA.

Step 11. Determine if the maximum number of generation G_m to evolve is reached. If it has, terminate and return the best antibody; if it has not, return to step 4.

Hypermutation and receptor editing play complementary roles in the act of affinity maturation. Hypermutations allow the immune system to explore the local area by making small alterations and receiver editing offers the ability to escape from local minima.

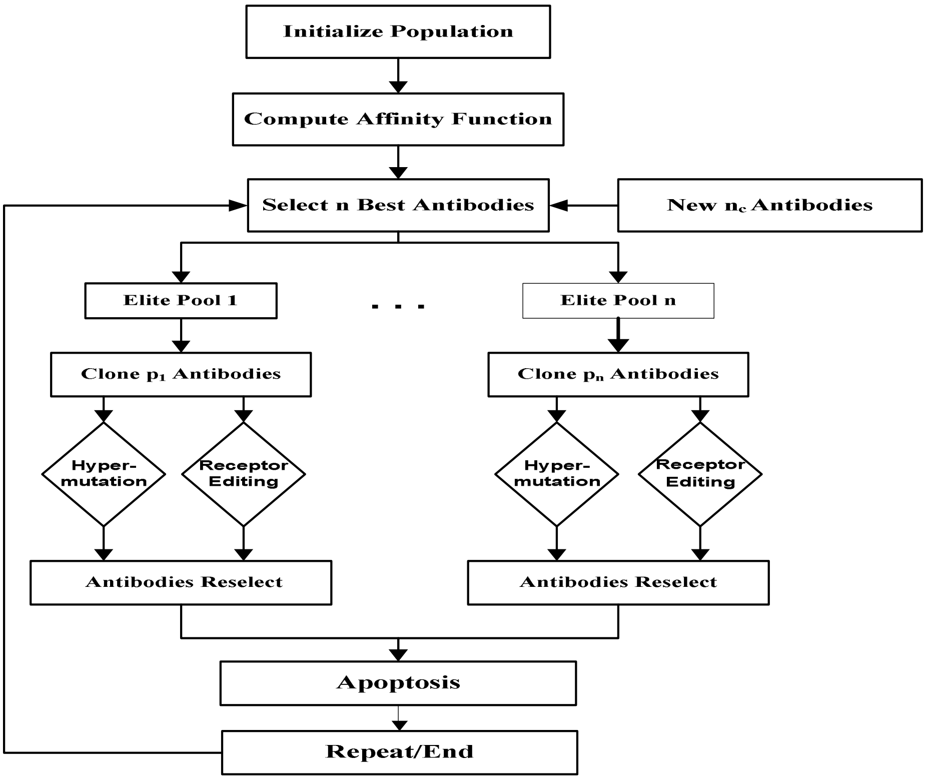

Fig. 1. Flowchart of the clonal selection algorithm.

3. Voltage Stability Index

A new steady state voltage stability index is proposed by M. Charkravorty and et.al in [6] for identifying the node, which is most sensitive to voltage collapse. One method load flow for radial distribution systems was presented by D. Das and et.al in [7] to formulate this index. According to Equation (1) the steady state voltage stability index for each bus.

$$SI(m2) = |V(m1)|^4 - 4.0\{P(m2)x(jj) - Q(m2)r(jj)\}^2 - 4.0\{P(m2)r(jj) - Q(m2)x(jj)\}|V(m1)|^2$$

Where

$SI(m2)$ Voltage stability index of node n ($m2 = 2,3,\dots,N$).

NB The total number of nodes.

jj Branch number.
$r(jj), x(jj)$ Resistance and reactance of branch .
$v(m1)$ Voltage of node n.
$v(m2)$ Voltage of node n.
$P(m2)$ Total real power load fed through node n.
$Q(m2)$ Total reactive power load fed through node n.

Steady state voltage stability index is extracted for the two node equivalent system shown in Fig. 2.

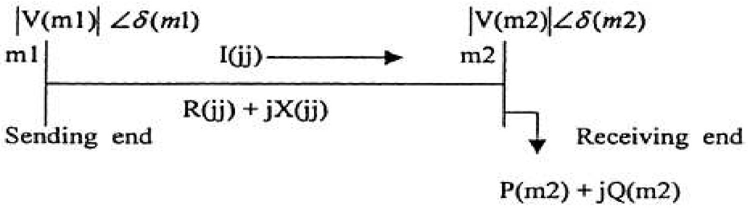

Fig. 2. Electrical equivalent of two node system.

Actually,

$P(m2)$ Sum of the real power loads of all the nodes beyond node n plus the real power load of node n itself plus the sum of the real power losses of all the branches beyond node n.

$Q(m2)$ Sum of the reactive power loads of all the nodes beyond node n plus the reactive power load of node n itself plus the sum of the reactive power losses of all the branches beyond node n.

For all of the network buses, the following Fitness function is defined:

$$\text{Fitness Function} = \sum SI(m \quad mi = 2,3,4,\ldots, N$$

Case Study

A system was selected from one part of Tehran distribution network. The SLD (single line diagram) of the network is illustrated in Fig. 3. It is a MV feeder with 13 buses. Table 1 and Table 2 provide the data of lines and buses.

Initially, a load flow was run for the case study without installation of DG. Their results are illustrated in Table 3.

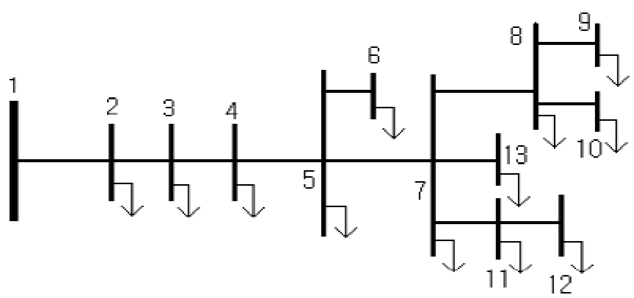

Fig. 3. Single line diagram of feeder.

Table 1. Lines data

Line Characteristics			
From	To	R^{ohm}	X^{ohm}
1	2	0.176	0.138
2	3	0.176	0.138
3	4	0.045	0.035
4	5	0.089	0.069
5	6	0.045	0.035
5	7	0.116	0.091
7	8	0.073	0.073
8	9	0.074	0.058
8	10	0.093	0.093
7	11	0.063	0.05
11	12	0.068	0.053
7	13	0.062	0.053

TABLE 2. Buses data

Bus Characteristics		
Bus Number	P^{kw}	Q^{kvar}
1	0	0
2	890	468
3	628	470
4	1112	764
5	636	378
6	474	344
7	1342	1078
8	920	292
9	766	498
10	662	480
11	690	186
12	1292	554
13	1124	480

TABLE 3. Results of power flow without installation

Bus Characteristics	
Bus Number	Stability Index
2	0.9729
3	0.9486
4	0.9429
5	0.9332
6	0.9329
7	0.9221
8	0.9199
9	0.9191
0	0.9181
11	0.9174
12	0.9198
13	0.9189

4. Results and Disscussion

Reference [8] gave us a method synthesizing optimal power flow and clonal selection algorithm (CSA) to find the best combination of sites within a distribution network for connecting DGs. Reference [9] performed same method by Particle Swarm Optimization (PSO). The results are evaluated for integration of three DG into the distribution system. These results are earned while assuming that all the generators operate at a power factor of 0.9.

The analysis for this system has been done by appraising of value of steady state voltage stability index. A load flow solution for the system using Newton-Raphson load flow method is performed first. Then the results of the load flow are used to estimate the powers P(m2) and Q(m2) at each node. Finally the SI index has been appraised.

The results of optimal capacity and location of DG for case study by CSA and PSO are illustrated in Table 4. The impact of installing three DGs in the case study network with optimal capacity and location is presented in Table 5.

Comparing the results in Table 3with those of Table 5, we can conclude that with installing three DGs, the voltage instability is improved and the results that assembled by PSO method is more optimum than CSA method. Fig 3 shows voltage instability of the case study network without and with three optimal DGs.

In this study we compare CSA and PSO methods on the terms of speed, accuracy and convergence.

These methods are implemented with MATLAB software.

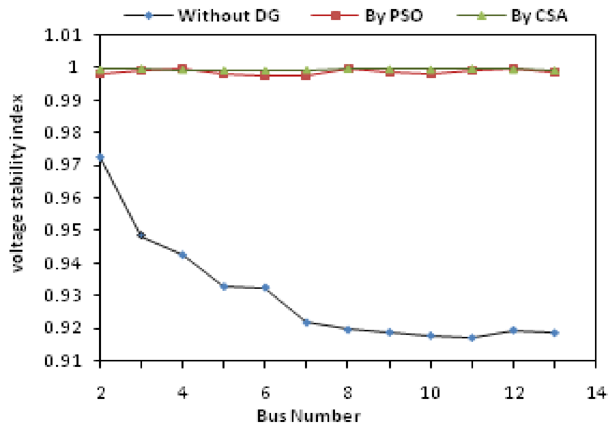

Figure 3. Voltage stability index of the case study network without and with three optimal DGs.

Table 4. Optimum capacity and location

Solution	Bus NO.	DG Capacity	Cost Function
By Clonal Selection Algorithm	3	3.4838	0.083442
	8	4.3727	
	11	3.8685	
By Particle Swarm Optimization	4	4.0573	0.0834177
	8	4.6701	
	12	2.8894	

Table 5. Results of power flow and harmonic power flow with installation

Bus Characteristics		
Bus Number	Stability Index By CSA	Stability Index By PSO
2	0.9997	0.9986
3	1.0000	0.9994
4	0.9996	1.0000
5	0.9994	0.9983
6	0.9993	0.9980
7	0.9996	0.9978
8	1.0000	1.0000
9	0.9998	0.9991
10	0.9997	0.9981
11	1.0000	0.9996
12	0.9997	1.0000
13	0.9994	0.9990

5. Conclusions

In this paper, the results of applying PSO algorithm and CSA algorithm to the optimal allocation of DGs in distribution networks were presented. The effectiveness of the proposed algorithm in solving DG allocation problem was demonstrated through a numerical example. Distribution test feeders of Tehran city were solved by means of the proposed algorithms. The results of both algorithms displayed that the better solution quality and accuracy of the PSO in comparison with the CSA but in the number of iterations CSA was better than PSO.

6. References

[1] Distributed generation: a definition; Thomas Ackermann , Göran Andersson, Lennart Söder; Electric Power Systems Research 57 (2001) 195–204; December 2000.

[2] M. Gandomkar, M. Vakilian, M. Ehsan, “A combination of genetic algorithm and simulated annealing for optimal DG allocation in distribution networks,” CCECE/CCGEI, Saskatoon, May 2005 IEEE, PP.645-648.

[3] M. Mathur, S.B Karale, S. Priyee, V.K jayaraman and B.D. kulkarni, “Ant colony approach to continuous function optimization, “ industrial & engineering Chemistry Research, vol.39, pp.3814-3822, 2000

[4] C. Berek and M. ziegner, “The maturation of the immune response”,Immune Today, vol. 14,pp.400-402,Agust 1993.

[5] S. Gao, H. Dai, G. Yang, and Z. Tang, “A novel clonal selection algorithm and its application to traveling salesman problems,”IEICE Trans. Fundamentals, vol.E90-A, no.10, pp.2318-2325, oct.2007.

[6] M. Charkravorty and D. Das, “Voltage stability analysis of radial distribution networks,” International Journal of Electrical Power & Energy Systems, Vol. 23, No. 2, pp. 129-135, 2001.

[7] D. Das, D. P. Kothari, and A. Kalam, “Simple and efficient method for load flow solution of radial distribution networks,” Electrical Power & Energy Systems, Vol. 17, No. 5, pp. 335-346, 1995.

[8] Shangce GAO, WeiWANG, Hongwei DAI, Fangjia LI and Zheng TANG, “Improved Clonal Selection Algorithm Combined with Ant Colony” IEICE TRANS. INF. & SYST., Vol..E91–D, No.6 JUNE 2008.

[9] Y. Alinejad-Beromi, and M. Sedighizadeh, and M. Sadighi, “A particle swarm optimization for sitting and sizing of Distributed Generation in distribution network to improve voltage profile and reduce THD and losses,” 43rd International Universities Power Engineering Conference, 2008. UPEC 2008.