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Smart Grid Reconfiguration Using Genetic Algorithm and NSGA-II

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Abstract:- *Distribution grid reconfiguration is one of the methods of accommodating more DG into the electric grid. Increased penetration of distributed generators (DGs) is one of the characteristics of smart grids. Distribution Grid Reconfiguration defined as altering the topological structure of distribution feeders by changing the open/closed states of sectionalizes and tie switches so that the objective function is minimized and constrained are met. The purpose of an optimal DN reconfiguration problem is to identify an optimal radial operating structure that minimizes one or many objective like minimal power loss, voltage deviation etc. Grid reconfiguration Considered as nondeterministic optimization problem. Proposed method is Genetic Algorithm (GA) it iteratively solves a problem by improving the candidate solution based on certain criteria. It is based on the principle of evolution. When multiple objectives can be optimized, GA fails to find solution. In order to overcome this disadvantage, the concept of Pareto optimality is introduced. Non-dominated sorting genetic algorithm -II (NSGA-II) is one such optimization method based on the principle of GA. It makes use of non-dominated ranking and crowding distance which inherently preserve elitism and presents parameter lessnichingoperator.*

Keywords:- *Grid reconfiguration, optimization, Genetic Algorithm, NSGA-II, Smart Grid.*

I. INTRODUCTION

The distribution network (DN) reconfiguration is a process that consists in changing the status of the network switches in order to resupply the non-energized areas after a fault occurrence, or optimize given criteria. For instance, the energy losses depend on the topology and the load of the network. By changing the network topology (configuration), the active power losses can be reduced, the voltage profile can be improved. Determining the optimal DN reconfiguration consists in finding the optimal radial topology for a given objective (e.g. loss minimization) according to the load values. Genetic Algorithm (GA) is a meta-heuristic optimization method, that is, it iteratively solves a problem by improving the candidate solution based on certain criteria. It is based on the principle of evolution. GA, being a stochastic optimization method has probabilistic elements incorporated into the algorithm which helps it in escaping from the local optimum and find the global optimum. The major steps involved in a typical GA are initializing the population, crossover, mutation, selection and termination based on the termination criterion. By using crossover operation, two parents are combined to form offspring. Mutation operation adds randomness to the population and hence will prevent the search from being caught in local optima. When multiple objectives are to be optimized, GA uses weighting functions to combine the various objectives and then handles the resulting function as a single objective function. This approach has a disadvantage that the final result of the optimization is biased depending on the weights used. In order to overcome this disadvantage, the concept of pareto optimality is introduced. There are several algorithms that work on this concept. Non-dominated sorting genetic algorithm –II (NSGA-II) is one such optimization method based on the principle of GA. It makes use of

'non-dominated ranking' and 'crowding distance' which inherently preserve elitism and presents parameter less niching operator[3].

II. PROBLEM IDENTIFICATION

Problem under consider is grid reconfiguration problem. Grid configuration problem is formed as optimization problem. To optimize few objectives of power system like minimal power loss, voltage deviation and current deviation using appropriate grid topology considering a test network.

III. TEST NETWORK

Fig.1 shows the 16 node MV test distribution network without DGs. The characteristics of the network is as shown below:

1. The network is balanced three phase network.
2. The network has three feeder nodes (nodes 1 to 3) ; 13 load nodes (nodes 4 to 16) and also there is an option of connecting 3 DGs in the network; one on each of the following nodes (nodes 7, 12 and 16)
3. The loads are modeled as PQ lodes.
4. All the sectionalizes and the tie lines are equipped with switches that can be closed and opened remotely.

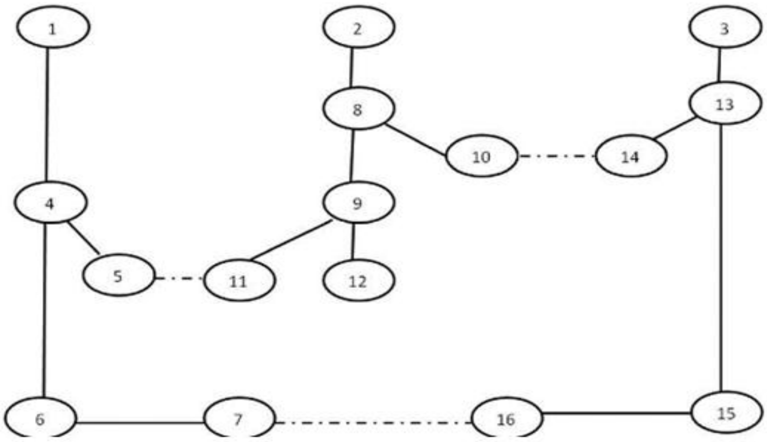

Fig.1: 16 - Node MV Test Distribution Network

B. Objectives

Apply appropriate grid topology by which optimize some objectives. a. Minimize real power loss.
b. Minimize sum of voltage deviation.
c. Minimize sum of current drawn from the feeders
d. Minimize real power loss & Minimize sum of voltage deviation.
e. Minimize real power loss, Minimize sum of voltage deviation & Minimize sum of current drawn from the feeders.
Consider a 16 node distribution test network.

C. Mathematical Formulation Of Objectives

Formulation of the three objectives is as follows: Minimize real power loss:

Minimize $\sum_{i=1}^{n} I_i^2 R_i$
Where n is the total number of branches

I_i is the branch current
R_i is the resistance of branch iMinimize sum of voltage deviations:
Minimize Minimize $\sum_{i=1}^{n} I_i^2 R_i$

$$\sum_{j=1}^{N} |V_{rated} - V_j$$

Where N is the total number of nodes is the rated voltage at node j
is the V_{rated} voltage at node j

D. CONSTRAINTS:

1. Radiality constraint: the network should remain radial after reconfiguration, that is, no more than one feeder should feed any given load.
2. Load serving constraint: all the loads in the network should be fed, that is, no load should go without
1. power supply.
2. Voltage constraint: the voltage deviation in any of the node should not be more than the specified limit.

IV. METHEDOLOGY USED

This paper uses, simple genetic algorithm for single objective optimization. Multi-objective optimization is handled with the help of simple genetic algorithm and NSGA-II and the results are compared. NSGA-II is a variant of simple genetic algorithm. The selection, cross over and mutation operators are similar to that of simple GA but the way multiple objectives are handled is different. In GA the various objectives are combined using a weighting factors and are treated as one single objective. In NSGA-II, the solutions are sorted based on the non-dominance rank and the crowding distance. A short description of the steps involved is as follows. An in-depth explanation of the various steps involved can be found in [3].

1. For every solution calculate the 'non-domination rank', that is, the number of solutions that dominate the solution.
2. The above procedure is repeated until all the solutions are categorized into various non-dominated front based on their non-domination rank. All the solutions that have their non-domination rank as zero will find their place in the first non-dominated front. A solution that has a high value for the non-domination rank means that there are many solutions better than it.
3. For solutions with the same non-domination rank, NSGA-II calculates 'crowding distance' which is a measure of the distance between adjacent solutions. The larger the value of the crowding distance, the farther is the solution from its adjacent solutions.
4. The 'crowded-comparison operator' is used for selection. The operator works on the principle that between two solutions varying in their non-domination ranks, the solution with lower rank is preferred and between two solutions within the same non-dominated front, NSGA-II chooses that solutions that has larger value for
5. 'crowding distance' since it guarantees better spread and variety in the population.
6. For creating a new population of size N, a combined population of previous generation (of size N) and current generation (of size N) is formed. This combined population (2N solutions) is then sorted based on the nondomination. Elitism is ensured since all the members of the previous and the current population are considered. The solutions belonging to the first non-dominated front are selected first followed by the solutions in the subsequent non-dominated front until the offspring population reaches the value N.
7. The cross over, mutation and binary tournament selection (based on crowded-comparison operator) are performed on the new population to create the offspring population of size N. The parameters for the optimization using GA are as follows: Binary representation, that is, 0 Open (off) switch & 1 Closed (on) switch; Roulette wheel selection; Single point crossover; Bit inversion mutation. The termination criterion is predefined number of generations. Elitism is included in order to preserve the best found individual. The radiality and load serving constraints are enforced by manipulating the cross over and the mutation operators, that is, the operators will be applied repeatedly in a given set of individual(s) until these constraints are satisfied. The node voltage constraint is enforced using penalty function. Backward-forward power flow method is used for the power flow analysis.

Simulation Result:
Possible Radial Network Configuration:
Chromosome 1:

1	1	1	1	1	1	1	1	1	1	1	1	1	0	0	0

Chromosome 2:

1	1	1	1	1	1	1	0	1	1	0	1	0	1	1	1

Chromosome 3:

1	1	1	1	1	1	1	1	1	1	0	1	1	0	1	0

Chromosome 4:

1	1	1	1	1	1	1	1	1	1	0	1	0	0	1	1

Chromosome 5:

1	1	1	1	1	1	1	1	1	1	0	1	0	0	1	1

Chromosome 6:

1	1	1	1	1	1	1	0	1	1	1	1	1	1	0	0

Chromosome 7:

1	1	1	1	1	1	1	1	1	1	1	1	0	0	0	1

Chromosome 8:

1	1	1	1	1	1	1	0	1	1	1	1	1	1	0	0

Chromosome 9:

1	1	1	1	1	1	1	1	1	1	0	1	1	0	1	0

Chromosome 10:

1	1	1	1	1	1	1	1	1	1	0	1	1	0	1	0

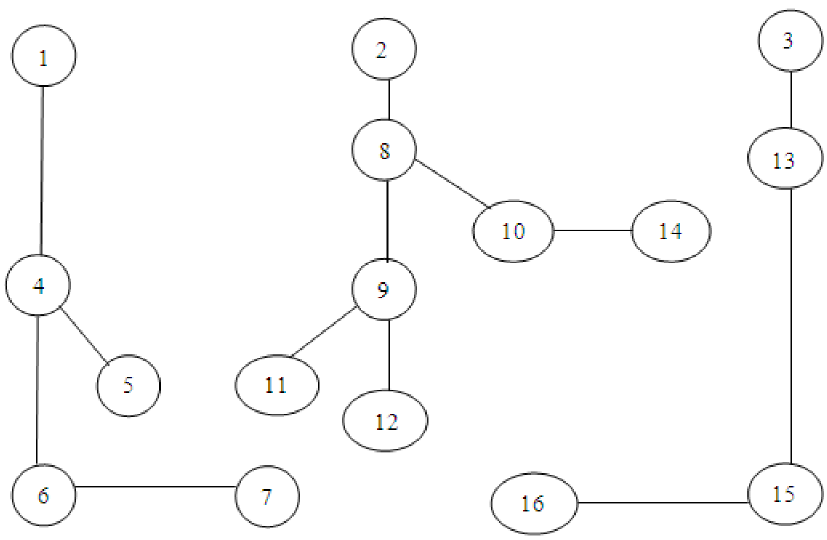

FIG. 2: Random radial network configuration network for chromosome-3:

Simulation Result for Optimum Power Loss without DG and with DG

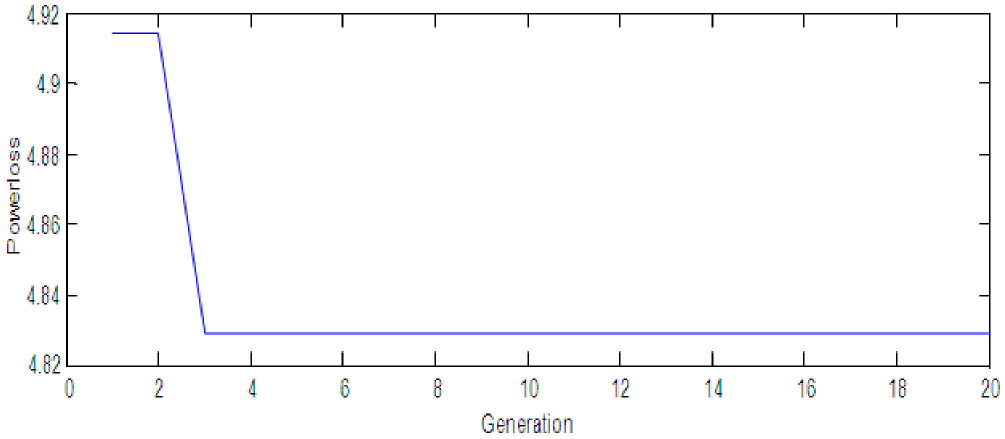

FIG. 3: Optimum power loss without DG

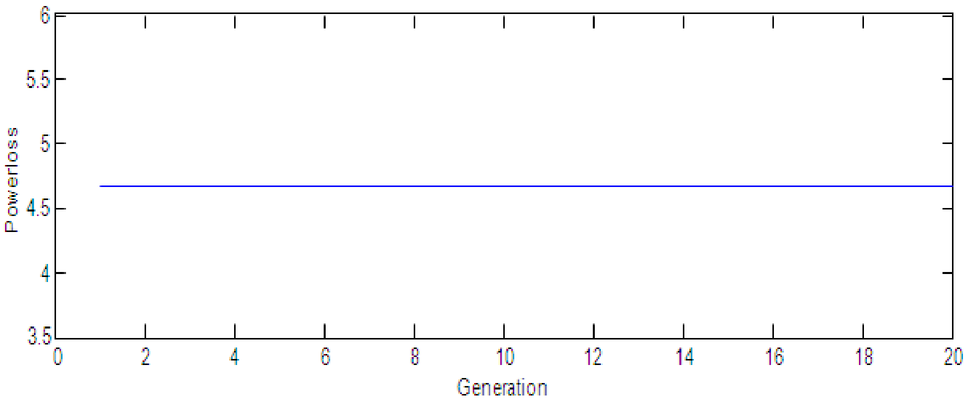

FIG. 4: Optimum power loss with DG

Simulation Result for Voltage Deviation Without DG and With DG

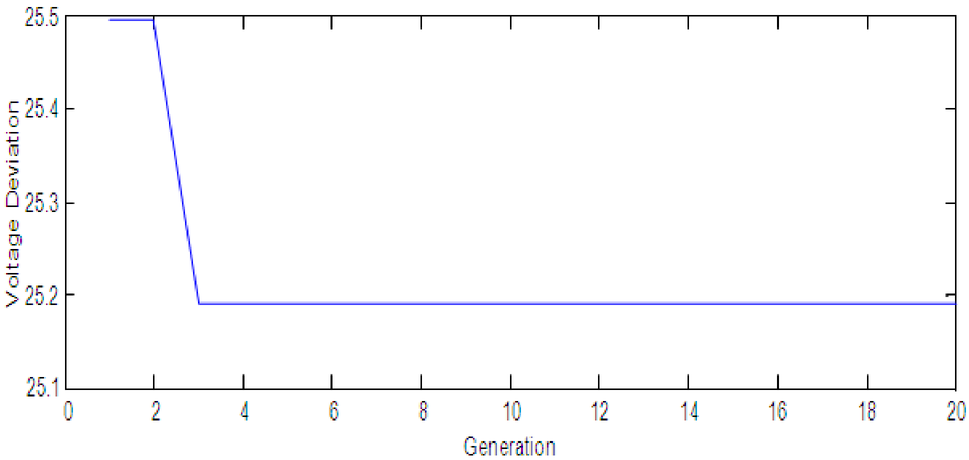

FIG. 5: Voltage Deviation without DG

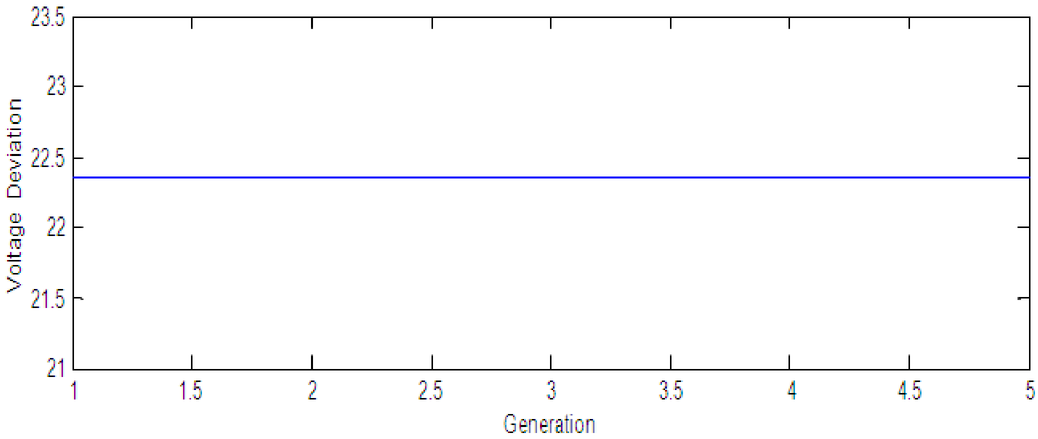

FIG. 6: Voltage Deviation with DG

Simulation Result for Feeder Current:

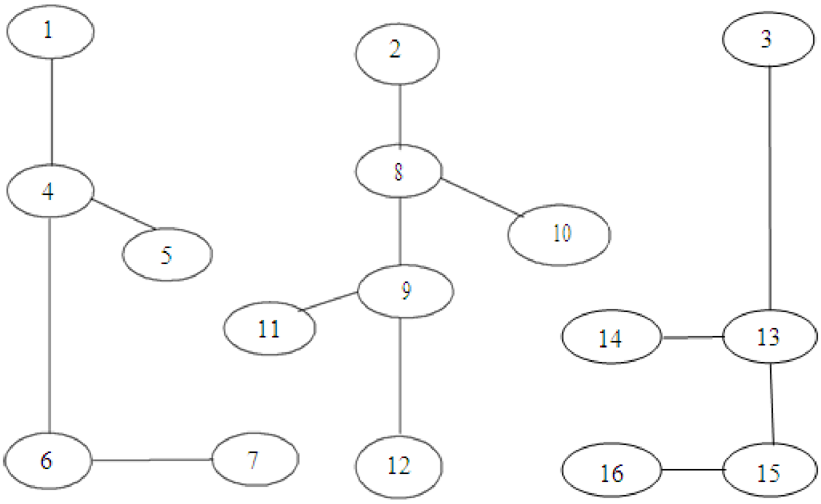

FIG. 7: Radial Grid Configuration for Feeder Current

V. CONCLUSIONS

In this project I have conclude date using GA optimize objectives like feeder current, power losses with DG and Without DG and also optimize the voltage deviation with DG and without DG. Result show that using DG we can minimize the losses and voltage deviation.

VI. FUTURE WORK

In future I will optimize multiobjective function like voltage deviation and feeder current, feeder current and power losses and power losses and voltage deviation. Also optimize voltage deviation, feeder current and power losses simultaneously using NSGA-II.
Compare Result of NSGA-II with GA.

REFERENCES

[1]. Fang, X., Misra, S, Xue, G., & Yang, D. (2012). Smart grid—The new and improved power grid: Asurvey. Communications Surveys & Tutorials, IEEE, 14(4), 944-980.
[2]. Hong, Y. Y.,& Ho, S. Y. (2005). Determination of network configuration considering multiobjective in distribution systems using genetic algorithms. Power Systems, IEEE Transactions on, 20(2), 1062-1069.
[3]. Coelho, A., Rodrigues, A. B., & Da Silva, M. G. (2004, November). Distribution network reconfiguration with reliability constraints. In Power System Technology, 2004. Power Con 2004.2004nInternational Conference on (Vol. 2, pp. 1600-1606).IEEE.

[4]. Deb, K., Pratap, A., Agarwal, S., & Meyarivan, T. A. M. T. (2002). A fast and elitist multiobjective genetic algorithm: NSGA-II. Evolutionary Computation, IEEE Transactions on, 6(2), 182-197.
[5]. Mendoza, J., López, R., Morales, D., López, E., Dessante, P., & Moraga, R. (2006). Minimal loss reconfiguration using genetic algorithms with restricted population and addressed operators: real application. Power Systems, IEEE Transactions on, 21(2), 948-954.
[6]. Lin, W. M., & Chin, H. C.(1998). A new approach for distribution feeder reconfiguration for loss reduction and service restoration. Power Delivery, IEEE Transactions on, 13(3), 870-875.
[7]. Zhu, J. Z. (2002). Optimal reconfiguration of electrical distribution network using the refined genetic algorithm. Electric Power Systems Research, 62(1), 37-42.
[8]. Balamurugan, K., & Srinivasan, D. (2011, December). Review of power flow studies on distribution network with distributed generation. In Power Electronics and Drive Systems (PEDS), 2011 IEEE Ninth International Conference on (pp. 411-417).IEEE.
[9]. Sedghi, M. (2014). Analysis and Comparison of Load Flow Methods for Distribution Networks Considering Distributed Generation. International Journal of Smart Electrical Engineering, 1(1).
[10]. Chiang, M.(2008). Nonconvex optimization of communication systems. Advances in Mechanics and Mathematics, 3, 137-196.
[11]. Ramaswamy, P. C., & Deconinck, G. (2012, October). Smart grid reconfiguration using simple genetic algorithm and NSGA-II. In Innovative Smart Grid Technologies (ISGT Europe), 2012 3rd IEEE PES International Conference and Exhibition on (pp. 1-8).IEEE.