Smart Grid Reconfiguration Using Simple Genetic Algorithm and NSGA-II

Parvathy Chittur Ramaswamy, *Student Member, IEEE*, and Geert Deconinck, *Senior Member, IEEE*

***Abstract*--Increased penetration of distributed generators (DGs) is one of the characteristics of smart grids. Distribution grid reconfiguration is one of the methods of accommodating more DG into the electric grid, which is illustrated with the help of a 16 node test network in this paper. The reconfiguration of the distribution grid involves changing the grid topology thereby optimizing a few objectives. In addition to the inclusion of DGs, grid reconfiguration also helps in achieving minimal power loss, minimal voltage deviation etc. In this paper the grid reconfiguration problem is formulated as an optimization problem. Simple genetic algorithm (GA) and its variant NSGA-II are used for solving the optimization problem. For a simple test system like the 16 node system discussed in this paper, simple GA is efficient enough to find the global optimum for a single objective optimization. The paper also illustrates the advantage of NSGA-II compared to simple GA when multiple objectives are considered.**

***Index Terms*— Distribution grid, Genetic algorithm, Grid reconfiguration, NSGA-II, Optimization, Smart grid**

I. Introduction

Distribution grid reconfiguration is defined as altering the topological structure of distribution feeders by changing the open/closed states of sectionalizers and tie switches so that the objective function is minimized and the constraints are met [1]. In a smart distribution grid this is possible remotely. From the above definition of distribution grid reconfiguration it can be understood that it involves optimization. The following paragraphs give a brief introduction to the optimization techniques used in this paper.

Genetic Algorithm (GA) is a metaheuristic 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 [2].

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. Nondominated 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]

Section II of the paper discusses the existing works in the field of optimization techniques used for grid reconfiguration and a review of the literature on grid reconfiguration. Section III includes the problem statement. Results are discussed in section IV. Section V deals with the conclusions that are derived from the results.

II. Literature review

Grid reconfiguration presents challenging issues due to the non-convex optimization needed because of non-convex objectives, integer constraints and large number of inequalities to explicitly describe the power flow in the system [4]. The distribution grid reconfiguration belongs to the category of nondeterministic combinatorial optimization problems (NP-hard) [5], [6]. It is conventionally considered a mixed-integer non linear programming problem. To solve such a problem, classical methods, e.g. mixed-integer programming, quadratic programming etc can be applied. However, in some cases, the mentioned methods fail to provide global optima and only reach local optima. Moreover, some classical methods cannot handle the integer problems. The two foregoing shortcomings can be overcome if an evolutionary method is utilized. It is independent of the objective function type and constraints-renders [1]. Metaheuristics methods like GA, Particle Swarm Optimization, Simulated Annealing or their variations are commonly used in solving such problems [1], [5], [7], [8], [9].

The distribution network topology coding is fundamental for the GA convergence [5] and hence is one of the challenges that need to be addressed when using GA for grid reconfiguration. Binary encoding, real number encoding and Prufer number encoding are the commonly used coding methods for the grid reconfiguration problem. The disadvantage with the binary encoding is that after the application of the genetic operators, it cannot be guaranteed that the resulting individual will be a feasible solution and hence additional mesh check needs to be incorporated into the algorithm in order to ensure the feasibility of the solution.

P. Chittur Ramaswamy (pramaswa@esat.kuleuven.be) and G. Deconinck (geert.deconinck@esat.kuleuven.be) are with K.U.Leuven, Leuven, Belgium.

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According to [9] this additional mesh check can be avoided with the use of Prufer number encoding. It encodes the vertex (node or bus) rather than the edge encoding (branch or switch) done when using binary encoding. Reference [5] tries to enhance the search space by developing efficient genetic operators. Graph and Matroid theories are used in order to provide better GA operators. The operators are so formulated that all resulting individuals after GA operators are feasible configurations. This avoids tedious mesh checks for topology constraint validation. This means that the formulation of the operators is complicated and is a challenge faced if GA is used for the grid reconfiguration application. Reference [10] proposes two sequential encoding strategies: subtractive and additive. The subtractive strategy begins with the meshed network obtained by closing all the switches and sequentially opens one switch at a time until a radial topology is achieved. The additive encoding strategy does the inverse. That paper proposes that these techniques will reduce the solution search space only to radial and connected networks without demanding any specific genetic operator. Reference [8] proposes to reduce the search space by using a codification strategy wherein the population is created by branches that form fundamental loops and also uses "accentuated crossover" and "directed mutation" (specialized genetic operators) that reduce the search space, analyzing only feasible radial topologies. Reference [11] gives an overview of the relevance of grid reconfiguration in smart grids and the use of GA as an optimization tool in achieving the control objectives.

Reference [5], [12], [13] performs distribution grid reconfiguration with an objective of reducing losses. Reference [14] aims at configuring a distribution grid for minimum loss considering N-1 security of DGs. Distribution network reconfiguration with reliability constraints are discussed in [7]. Grid reconfiguration in order to achieve multiple objectives like minimizing the cost of active power generated by the distribution companies, the cost of active power generated by the DG units etc are dealt in [1]. Multiple objectives for grid reconfiguration during faults are discussed in [9]. Distribution network reconfiguration with an aim of phase load balancing is described in [15]. Reference [16] includes network reconfiguration and loss allocation for distribution systems with DG. Network reconfiguration for minimum power loss in balanced and unbalanced distribution systems with high penetration of DG is presented in [17].

III. Problem Statement

The problem under consideration is grid reconfiguration for a test distribution grid in order to fulfill various single and multi objectives and multiple constraints.

A. Test Network

Fig.1 shows the 16 node MV test distribution network without DGs. Fig.2 shows the 16 node MV test distribution network with DGs connected to node 7, 12 and 16. Appendix provides the system data and parameters for the 16 bus distribution network. The characteristics of the network are as follows:

1. The network is a 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 loads
4. The DGs are assumed to supply constant power for the chosen time interval T (and hence are modeled as negative load)
5. All the sectionalizers and the tie lines are equipped with switches that can be closed and opened remotely

B. Objectives

1) *Without DG*
   a. Minimize real power loss
   b. Minimize sum of voltage deviations
2) *With DG*
   a. Minimize real power loss
   b. Minimize sum of voltage deviations
   c. Minimize sum of currents drawn from the feeders
   d. Minimize real power loss & Minimize sum of voltage deviations
   e. Minimize real power loss & sum of voltage deviations & sum of currents drawn from the feeders

C. Mathematical Formulation of objectives

From section III.B it can be noticed that the paper handles three main objectives or a combination of them. The mathematical 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 i

Minimize sum of voltage deviations:
Minimize $\sum_{j=1}^{N} |V_{rated} - V_j|$
Where N is the total number of nodes
V_{rated} is the rated voltage at node j
V_j is the voltage at node j

Minimize sum of currents drawn from the feeders:
Minimize $\sum_{k=1}^{F} I_k$
Where F is the total number of feeders
I_k is the current through each feeder

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 power supply
3. Voltage constraint: the voltage deviation in any of the node should not be more than the specified limit
4. All the three feeders should serve at least their corresponding adjacent nodes, that is, the feeder nodes 1, 2

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& 3 should serve at least node 4, 8 and 13 respectively.

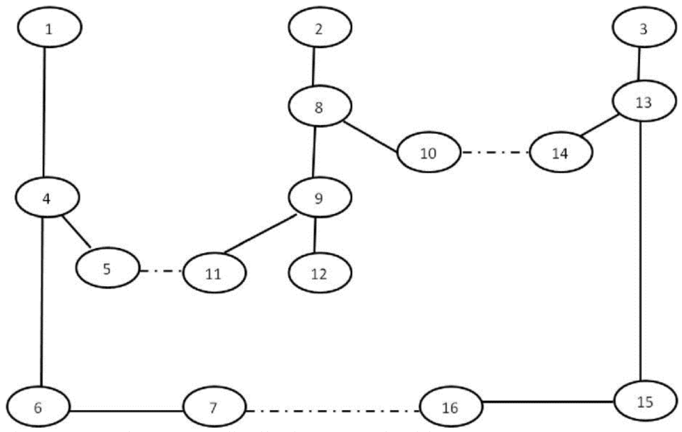

Fig. 1. 16 node MV test distribution network without DG

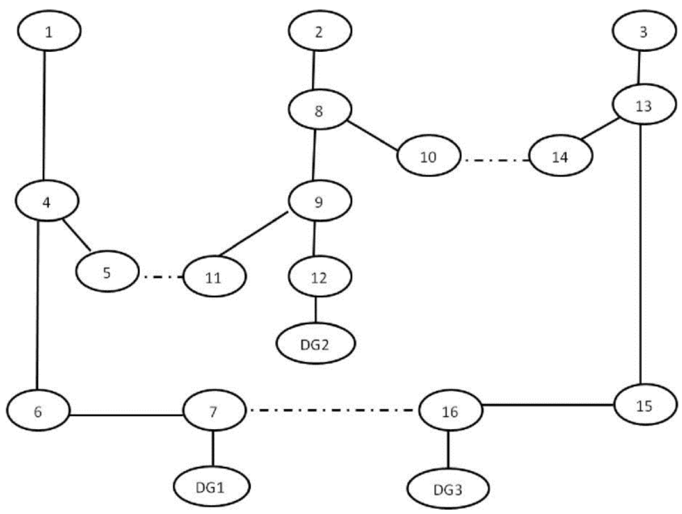

Fig. 2. 16 node MV test distribution network with DG

E. Methodology used

From section II, III.B and III.D it is clear that grid reconfiguration is indeed a non-convex optimization problem, and can be better handled by evolutionary methods because of the reasons stated in section II. 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 'crowding distance' since it guarantees better spread and variety in the population.
5. 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 non-domination. 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. 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.

IV. Results and Discussion

For the chosen test network, the paper chooses a time interval T. During this time interval it is assumed that DG1 and DG3 are delivering 2.5 MW each and DG2 is delivering 5MW. The paper tries to optimize the network for the single objective functions (III.B.1.a, III.B.1.b and III.B.2.a to III.B.2.c) like minimizing the real power loss, minimizing the sum of voltage deviations and minimizing sum of currents drawn from the feeders using GA. For each of the multi objective optimization (III.B.2.d and III.B.2.e) the results obtained with GA and NSGA-II are presented and compared.

All the numerical values presented for power, sum of voltage deviations and sum of feeder currents are per phase values.

A. Without DG

Fig. 3 and Fig. 4 are the results of optimizing the test network with an objective of minimizing the real power loss.

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Fig. 3 shows the plot of number of generations vs. the minimum active power loss for best found individual until that generation. Fig. 4 shows the reconfigured grid which provides the minimum power loss.

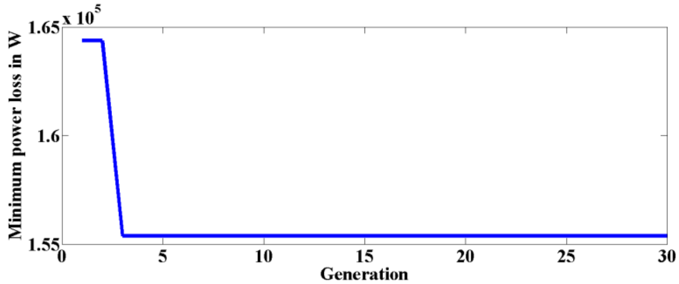

Fig. 3. Plot of number of generations vs. the minimum active power loss without DG

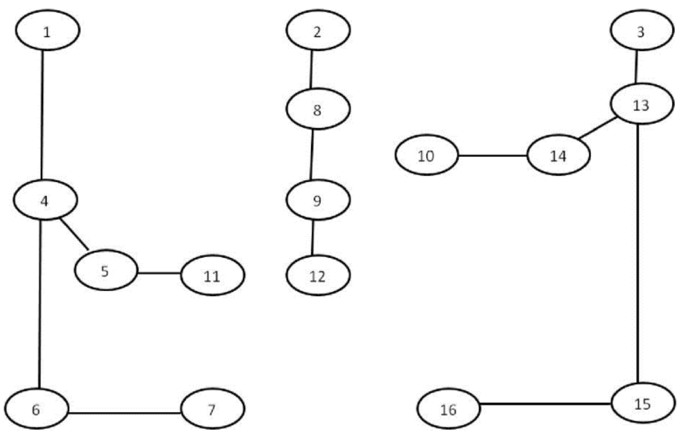

Fig. 4. Configuration for minimum power loss without DG

Fig. 5 and Fig. 6 are the results of optimizing the test network with an objective of minimizing the sum of voltage deviations. Fig. 5 shows the plot of number of generations vs. the sum of voltage deviations for best found individual until that generation. Fig. 6 shows the reconfigured grid which will provide the minimum sum of voltage deviations.

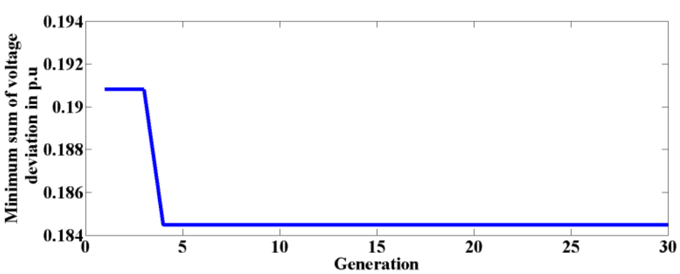

Fig. 5. Plot of number of generations vs. the minimum sum of voltage deviations without DG

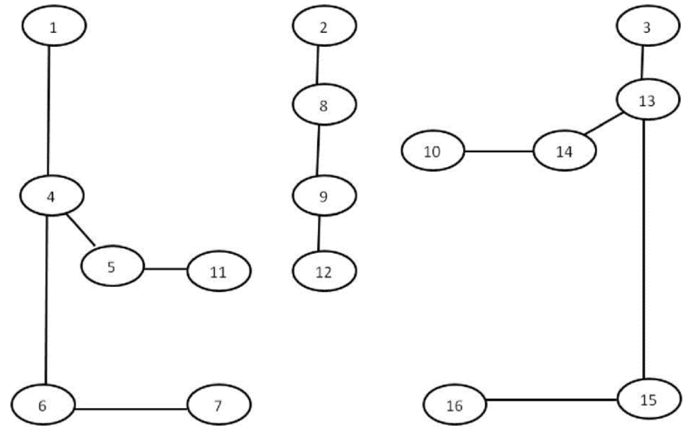

Fig. 6. Configuration for minimum sum of voltage deviations without DG

B. With DG

For all the simulation in this subsection, the test grid is modeled in such a way that optimization algorithm always has the option of connecting or disconnecting the three DGs from the network. It is up to the optimization algorithm to decide whether the final configuration should have the DGs included or not.

Fig. 7 and Fig. 8 are the results of optimizing the test network with an objective of minimizing the real power loss. Here, Fig. 7 shows the plot of number of generations vs. the active power loss for best found individual until that generation. Fig. 8 shows the reconfigured grid which will provide the minimum power loss.

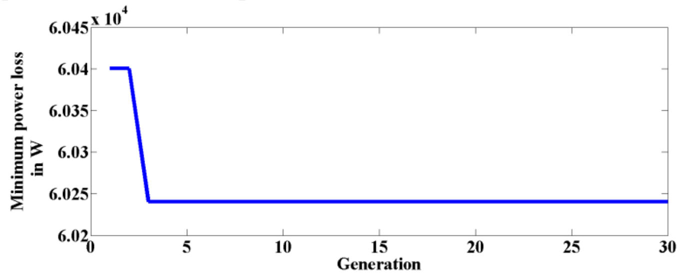

Fig. 7. Plot of number of generations vs. the minimum active power loss with DG

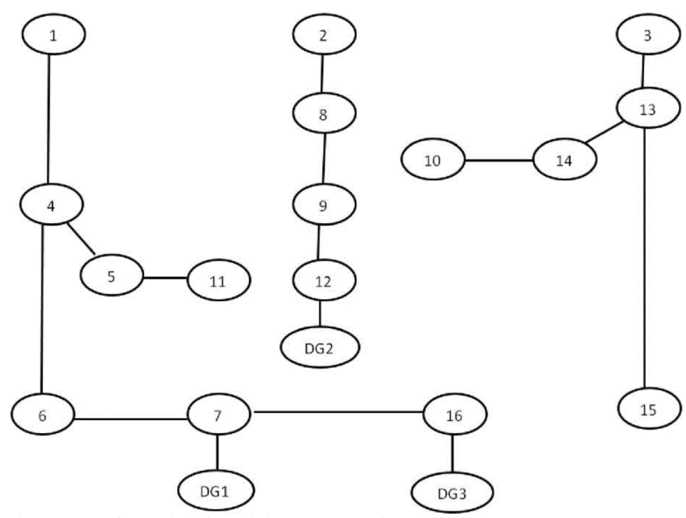

Fig. 8. Configuration for minimum power loss with DG

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Fig. 9 and Fig. 10 are the results of optimizing the test network with an objective of minimizing the sum of voltage deviations. Fig. 9 shows the plot of number of generations vs. the sum of voltage deviations for best found individual until that generation. Fig. 10 shows the reconfigured grid which will provide the minimum sum of voltage deviations.

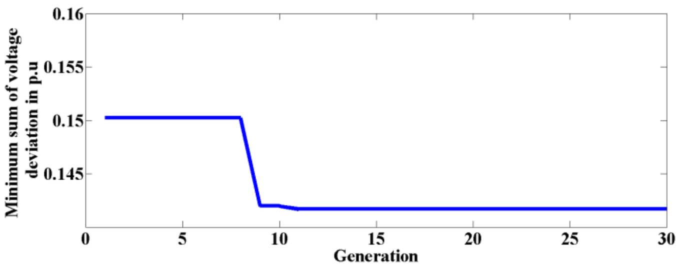

Fig. 9. Plot of number of generations vs. the minimum sum of voltage deviations with DG

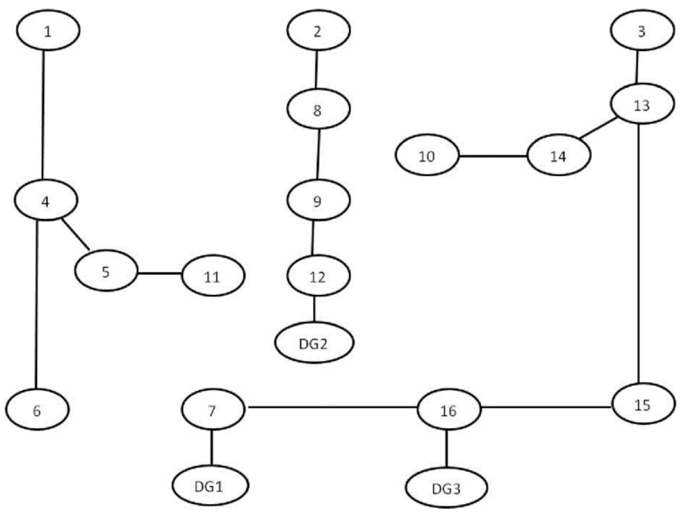

Fig. 10. Configuration for minimum sum of voltage deviations with DG

Fig. 11 and Fig.12 are the results of optimizing the test network with an objective of minimizing the sum of currents drawn from the three feeders. Fig.11 shows the plot of number of generations vs. the sum of currents drawn from the three feeders for best found individual until that generation. Fig. 12 shows the reconfigured grid which provides the minimum sum of feeder currents drawn.

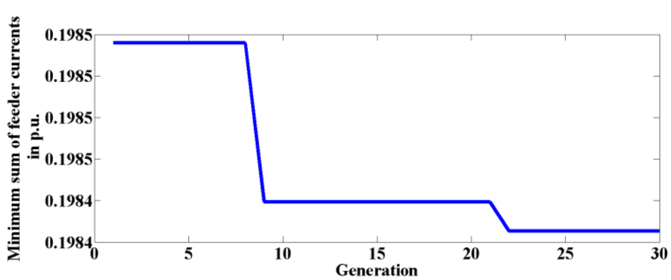

Fig. 11. Plot of number of generations vs. the minimum sum of feeder currents with DG

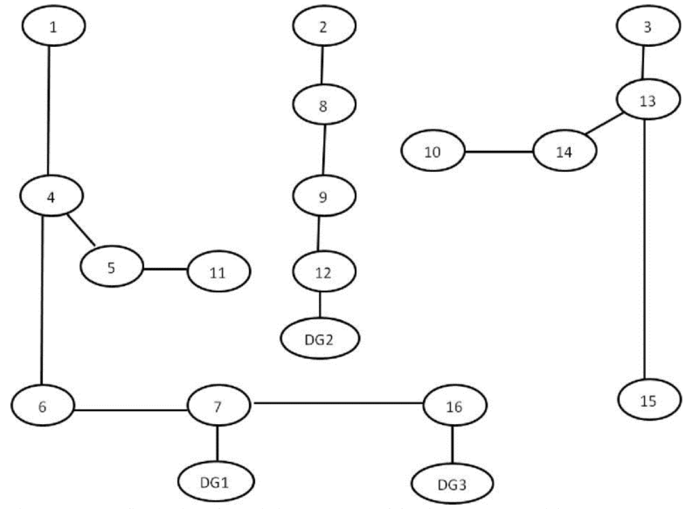

Fig. 12. Configuration for minimum sum of feeder currents with DG

From Fig. 8 and Fig. 12 it can be observed that the configuration that results in the minimum power loss is the same as the configuration that provides minimum sum of feeder currents drawn.

Also, it can be observed from the above results that the configuration with the inclusion of DG performs better with respect to the objectives than the configuration without DG. This shows the advantage of having distributed generation in an electrical network. Table I provides the numerical values for the various single objective optimization discussed so far in this paper.

TABLE I
RESULTS FOR SINGLE OBJECTIVE OPTIMIZATION

Objective function	DG Status	Numerical value per phase
Minimize power loss	Without DG	155.37 kW
Minimize sum of voltage deviations	Without DG	$1.8446 * 10^{-1}$ p.u
Minimize power loss	With DG	60.24 kW
Minimize sum of voltage deviations	With DG	$1.4168 * 10^{-1}$ p.u
Minimize sum of currents drawn from the three feeders	With DG	$1.984253 * 10^{-1}$ p.u

It can be observed from Fig. 4 and Fig. 6 that the configuration that results in the minimum power loss without DG is the same as the configuration that results in the minimum sum of voltage deviations without DG. But it can be observed from Fig. 8 and Fig. 10 that the configuration that results in the minimum power loss with DGs is not the same as the configuration that results in the minimum sum of voltage deviations when DGs are present. This result shows that a configuration that leads to minimum power loss need not necessarily always be a configuration that provides minimum sum of voltage deviations. This result encouraged the authors to look at the multi objective optimization, the result of which will be discussed further in this paper.

Fig. 13 and Fig. 14 show the results of using GA for optimizing the multi objective optimization of minimizing the power loss and the sum of voltage deviations. The DGs are present in the network. The two objectives are combined to form a single objective using weights. The first run (Run1) of

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the code gives a result different from the second run (Run2) of the same code. Fig. 13.a and Fig. 13.b show the plot for Run1 and Run2 of the GA code respectively. Fig 14.a and Fig 14.b depicts the configuration of the distribution grid corresponding to Run1 and Run2 respectively. This shows a disadvantage with the using of weights, that is, depending on the weight chosen for each objective the result can be manipulated/ biased.

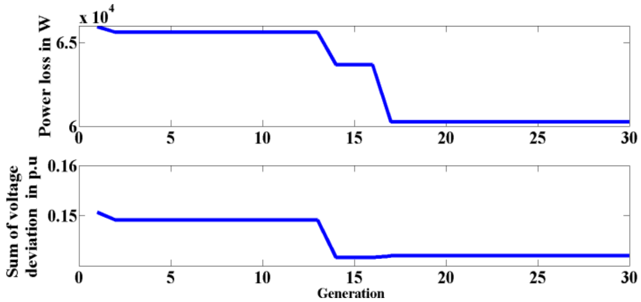

Fig. 13.a. Plot of number of generations vs. the power loss with DG (upper graph) for Run1 of GA
Plot of number of generations vs. sum of voltage deviations with DG (lower graph) for Run1 of GA

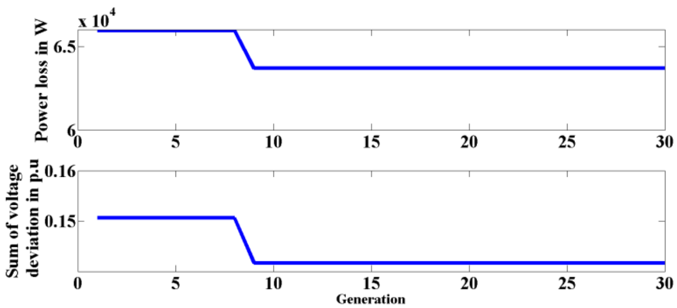

Fig. 13.b. Plot of number of generations vs. the power loss with DG (upper graph) for Run2 of GA
Plot of number of generations vs. sum of voltage deviations with DG (lower graph) for Run2 of GA

In order to overcome the above mentioned disadvantage with the use of weights, this paper uses NSGA-II for the optimization of the multiple objectives. Within a single run of the NSGA-II program the non-dominated solutions in the pareto optimal front has been obtained. In this paper we call them Non-dominated solution I and Non-dominated solution II. The configuration corresponding to the Non-dominated solution I and Non-dominated solution II are the same as those shown in Fig. 14.a and Fig. 14.b. This result clearly shows the advantage of using the concept of pareto optimality over the weighting function method.

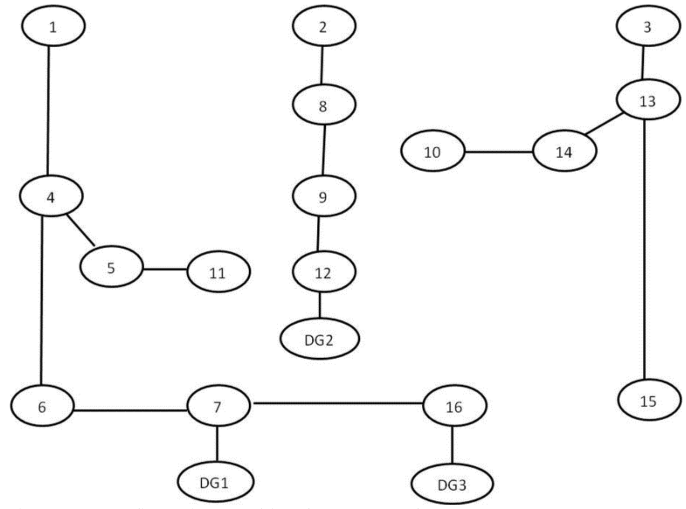

Fig. 14.a. Configuration resulting from Run1 of GA

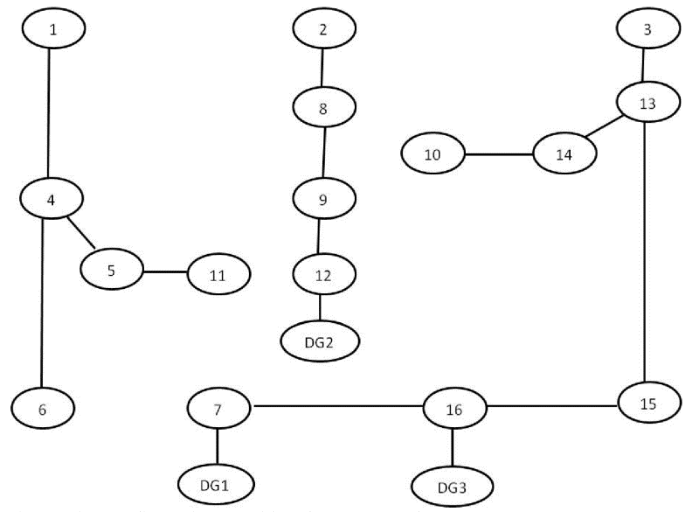

Fig. 14.b. Configuration resulting from Run2 of GA

The final simulation is done for optimizing three objectives namely minimizing real power loss, minimizing sum of voltage deviations and minimizing the sum of feeder currents drawn with DG. For this optimization NSGA-II was used. The pareto optimal front consists of two solutions. These solutions are the same as the Non-dominated solution I and Non-dominated solution II obtained for the two objective function discussed earlier. The reason for having only two elements in the pareto optimal front even with three objectives, is because two of the objectives are mutually aiding objectives. The objective of minimizing the power loss resulted in the same configuration as that for the objective of minimizing the sum of feeder currents when they were treated as single objectives and solved using GA. This result shows that the concept of pareto optimality is efficient and useful only when the objectives are fully or at least partially conflicting.

It can be observed that Fig. 14.a is the same as Fig. 8 and Fig. 14.b is the same as Fig. 10. This shows that the optimum values for minimum power loss objective and the value for the sum of voltage deviations for this configuration and the optimum values for minimum sum of voltage deviations objective and the value for the power loss for this configuration are non-dominating with respect to each other.

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Numerically, (60.24kW, 1.41967*10^{-1} p.u) and (63.676 kW, 1.4168*10^{-1} p.u.) are mutually non-dominating. Table II provides the numerical values for the various multi-objective optimization discussed so far in this paper.

TABLE II
RESULTS FOR MULTI OBJECTIVE OPTIMIZATION

Objective function / Optimization method used / DG status	Numerical value per phase
Minimize power loss and Minimize sum of voltage deviations/GA /with DG	**Power loss in kW**
	Run1: 60.24; Run2: 63.676
	Minimum sum of voltage deviations in p.u
	Run1: 1.41967*10^{-1} ; Run2: 1.4168*10^{-1}
Minimize power loss and Minimize sum of voltage deviations /NSGA-II/with DG	**Power loss in kW**
	Non-dominated solution I: 60.24 Non-dominated solution II: 63.676
	Minimum sum of voltage deviations in p.u
	Non-dominated solution I: 1.41967*10^{-1} Non-dominated solution II: 1.4168*10^{-1}
Minimize power loss and Minimize sum of voltage deviations and Minimize sum of currents drawn from the three feeders/NSGA–II/with DG	**Power loss in kW**
	Non-dominated solution I: 60.24 Non-dominated solution II: 63.676
	Minimum sum of voltage deviations in p.u
	Non-dominated solution I: 1.41967*10^{-1} Non-dominated solution II: 1.4168*10^{-1}
	Minimum sum of feeder currents in p.u
	Non-dominated solution I: 1.1984*10^{-1} Non-dominated solution II: 1.1986*10^{-1}

V. CONCLUSION

The results show that simple GA is able to find the global optima efficiently for the simple network (16 node MV test distribution network) considered in this paper without the requirement for complicated representation and complicated GA operators. Also, for the chosen test network without DG, the configuration that provides minimum sum of voltage deviations in the test network is the same as the configuration that provides minimum power loss. This means that the two objectives are not totally conflicting objective functions.

For optimizing the single objectives of minimizing power loss, minimizing sum of voltage deviations, minimizing the sum of currents drawn from the feeders in the test distribution network with DGs, simple GA is efficient. Also, for the chosen test network, the configuration that provides minimum sum of feeder currents is the same as the configuration that provides minimum power loss. But the configuration that provides minimum sum of voltage deviations is not the same as the configuration that provides minimum power loss. This result shows that the objective of minimum power loss and the objective of minimum sum of voltage deviations are partially conflicting objectives and hence can be considered as objectives for a multiobjective optimization problem. Also, the network configurations that include DGs perform better with respect to the various objectives than the network configurations without DGs.

For multiobjective optimization problems, simple GA fails to find the entire possible non-dominated optimal front. This is because of the bias introduced due to the weighting functions used. This disadvantage of simple GA can be overcome with the use of the NSGA-II which deals with pareto optimal solutions. The results also show that the concept of pareto optimality will be efficient and useful only when the objectives are fully or at least partially conflicting.

VI. APPENDIX

The system data and parameters for the 16 bus test distribution network.

Initial Bus	End Bus	Line		End bus load		End bus Capacitor (MVAR)
		R (p.u.)	X (p.u.)	P (MW)	Q (MVAR)	
1	4	0.075	0.1	2.0	1.6	-
4	5	0.08	0.11	3.0	1.5	1.1
4	6	0.09	0.18	2.0	0.8	1.2
6	7	0.04	0.04	1.5	1.2	-
2	8	0.11	0.11	4.0	2.7	-
8	9	0.08	0.11	5.0	3.0	1.2
8	10	0.11	0.11	1.0	0.9	-
9	11	0.11	0.11	0.6	0.1	0.6
9	12	0.08	0.11	4.5	2.0	3.7
3	13	0.11	0.11	1.0	0.9	-
13	14	0.09	0.12	1.0	0.7	1.8
13	15	0.08	0.11	1.0	0.9	-
15	16	0.04	0.04	2.1	1.0	1.8
5	11	0.04	0.04	-	-	-
10	14	0.04	0.04	-	-	-
7	16	0.09	0.12	-	-	-

The base chosen for the analysis is 100MVA, 23kV.

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VIII. Biographies

Parvathy Chittur Ramaswamy (Student Member '09) received the M.S. degree from Portland State University, Portland, Oregon, USA in 2009. Currently she is a PhD student at the Katholieke Universiteit Leuven, Belgium. Her PhD involves research on grid reconfiguration as key intra-grid control application in smart grids. Stochastic multiobjective optimization is used to implement the above mentioned control application. The research concentrates on the distribution grid control especially in the context of smart grids.

Geert Deconinck (Student Member' 88, M' 96, S' 2000) is professor at the Katholieke Universiteit Leuven (Belgium). He is a staff member of the research group ELECTA (Electrical Energy and Computing Architectures) at the Department of Electrical Engineering (ESAT). He performs research on the design of dependable system architectures for industrial automation and control, the assessment of their dependability attributes and the impact on infrastructure interdependencies. Specific interests include middleware for adaptive fault tolerance, overlay networks for resource discovery, robust embedded system design, dependability modeling and functional safety and dependable grid computing, all in a context of power and communication infrastructures. He is member of the IEEE SMC TC on Infrastructure Systems and Services and chairman of the TI society BIRA on industrial automation. He received his M.Sc. in Electrical Engineering and his Ph.D. in Engineering from the K.U.Leuven, Belgium in 1991 and 1996 respectively. He is a Certified Reliability Engineer (ASQ), a senior member of the IEEE and of the IEEE Reliability, Computer and Power Engineering Societies.

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