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MULTI-OBJECTIVE DISTRIBUTION FEEDER RECONFIGURATION BY CONSIDERING ENERGY NOT SUPPLIED WITH DISTRIBUTED GENERATION

Sankaramoorthy Muthubalaji, Veluchamy Malathi

Original scientific paper
Nowadays, the operational performance of the Distribution system can be improved by exchanging the functional links between the elements of the system, called reconfiguration. This paper aims at achieving such optimization through the reconfiguration of distribution systems taking into account various criteria. The newness of the method is in the fact that optimization is evaluated on active power distribution systems i.e by incorporating the distributed generators directly to the main distribution system. This paper presents a proficient method for solving the multi-objective reconfiguration of radial distribution systems with regard to distributed generators. The conformist distribution feeder reconfiguration (DFR) problem cannot meet the reliability requirements. The recommended approach considers reliability (Energy Not Supplied), voltage deviation and power loss problem simultaneously. By taking the reliability objective into account, the DFR problem becomes more complicated than before and it needs to be solved with a precise algorithm. Therefore this study utilizes Non Dominated Sorted Genetic Algorithm-II (NSGA-II) for DFR and Gravitational Search Algorithm (GSA) for DG placement is to find the optimal location and sizing of DGs which minimizes real power loss, Energy Not Supplied (ENS) and improves voltage profile of the network.

Keywords: *distributed generation; Distribution Feeder Reconfiguration (DFR); Energy not Supplied (ENS); GSA; NSGA-II*

Rekonfiguracija multi-objektivnog distribucijskog napojnog voda s obzirom na neisporučenu energiju distribuirane proizvodnje

Izvorni znanstveni članak
Danas se učinkovitost distribucijskog sustava može poboljšati zamjenom funkcionalnih poveznica između elemenata sustava, to jest rekonfiguracijom. Cilj je rada postići takvu optimizaciju rekonfiguracijom distribucijskog sustava uzimajući u obzir različite kriterije. Novina ove metode je u činjenici da se optimizacija procjenjuje na aktivnim sustavima raspodjele energije tj. ugrađivanjem distribuiranih generatora direktno u glavni distribucijski sustav. U radu se predstavlja napredna metoda za rješavanje multi-objektivne rekonfiguracije sustava radijalne distribucije u odnosu na distribuirane generatore. Konformistički promatran problem rekonfiguracije distribucijskog napojnog voda (DFR) ne može zadovoljiti zahtjevima za pouzdanošću. Preporučeni pristup uzima simultano u obzir problem pouzdanosti (neisporučena energija), devijacije u naponu i gubitka energije. Uzimajući u obzir pouzdanost, DFR problem postaje složeniji nego ranije i treba se riješiti preciznim algoritmom. Stoga se u ovom radu koristi Non Dominated Sorted Genetic Algorithm-II (NSGA-II) za DFR i Gravitational Search Algorithm (GSA) za optimalnu lokaciju i veličinu DG-ija jer se tako minimalizira stvarni gubitak energije, neisporučene energije (ENS) i poboljšava profil napona mreže.

Ključne riječi: *distribuirana proizvodnja; neisporučena energija (ENS); GSA; NSGA-II; rekonfiguracija distribucijskog napojnog voda (DFR)*

1 Introduction

In general, distribution system consists of a group of interconnected radial circuits. The efficient operation of distribution systems can only be achieved by modifying the open/closed status of sectionalizing-switches (normal closed) and tie switches (normal open) of the distribution systems. Reconfiguration is done especially for three purposes: 1. for loss reduction, 2. for load balancing, and 3. for service restoration [1].

Various methods have been proposed for solving the Distribution System Reconfiguration (DSR) problems. In [2], by optimal distribution system configuration, the lowest current is determined by the optimal power flow method. Other techniques like Quadratic programming [3] and network partitioning techniques [4], a heuristic nonlinear constructive method [5] are used in earlier stages. These methods find admirable solutions for the medium size systems and are not suitable for large systems [6]. In recent years, new heuristic optimization algorithms like Genetic Algorithm (GA) [7 ÷ 11], Non-dominated Sorting Genetic Algorithms (NSGA) [12], matroid theory [13], other meta-heuristics techniques like plant growth [14], Particle Swarm Optimization (PSO) [15], tabu search [16] and ant colony search [17, 18] have been proposed for DSR problem. They are aimed to deal with large system with fast execution time [19]. Recently DSR problem with distributed generation (DG) and capacitor allocation [20, 21] received much attention. Distributed Generation is a small-scale power generation that is directly connected to the distribution system or to the customer side of the meter. The benefits of DG are given in [22, 23]. The power system performance can be enhanced to a greater extent only when the DGs are installed at proper location with proper capacity. Similar to DSR problem, several techniques and optimization algorithm, real coded genetic algorithm (RCGA) [24], Evolutionary Algorithm (EA) [25] have been proposed to optimize the location and sizing of distributed generation. Bacterial for aging algorithm (BFOA) [26] has been discussed for the reconfiguration problem. In [27] Harmony search algorithm was discussed for the DG placement. In [29,30] NSGA is used to solve the three multi objective optimization problems and the result suggests that NSGA can be successfully used to find multiple Pareto optimal solutions the knowledge of which could be very useful to the designers and decision makers.

This paper proposes a method to reconfigure the distributed system with DG. A multi objective optimization algorithm, Gravitational Search Algorithm (GSA) is used to find the optimal location and sizing of DG, which minimizes real power loss, Energy Not Supplied (ENS) and improves voltage profile of the network. Non-Dominated Sorting Genetic Algorithm-II (NSGA-II) is used to find the switches to be opened in distributed system in order to minimize the real power loss and to improve voltage profile. GSA is a heuristic stochastic swarm-based search algorithm in the field of numerical optimization, based on the gravitational law and laws of motion. Like many other nature inspired algorithms, it needs refinements to maximize its performance in solving various types of problems. In addition to the problem encoding that sometimes can be a challenge, fine tuning its parameters plays a significant role balancing the search time versus solution quality. This algorithm is relatively recent and not heavily explored [30]. NSGA is a popular non-domination based genetic algorithm for multi-objective optimization. NSGA –II is based on the concept of Pareto dominance Incorporates elitism. It solves the optimization problems with reduced computational complexity and requires no knowledge of gradient information about the response surface. NSGA II is very resistant to finish with local optima and this special feature of NSGA II makes it more suitable for a wide variety of optimization problems in all fields of engineering. Due to these unique features, NSGA II becomes predominantly suitable for the problem proposed here. The proposed approaches have been tested on IEEE 33-bus radial distribution system and the results are presented. In this work, simulation is done using MATLAB. Even though there are several methods for the multi objective reconfiguration, the usage of Distributed Generation (DG) by considering reliability indices, particularly Energy Not supplied is rarely presented in the literature survey.

2 DG Placement

2.1 Problem formulation

Problem formulation is nothing but the formulation objective function with some constrained and decision variables. The objective function for DG placement is to find the optimal location and sizing of DGs which minimizes real power loss, Energy Not Supplied (ENS) and improves voltage profile of the network. It is mathematically formulated as

$$\min f1 = \sum_{l=1}^{nl} P_L^l \quad (1)$$

$$\min f2 = \sum_{i=1}^{nb} ENS_i \quad (2)$$

$$\min f3 = \sum_{i=1}^{nb-g} V_{D_i} \quad (3)$$

where,

P_L^l - Real power loss in 1st branch

nl - No of branches in a network

g - No of generator nodes in a network

ENS_i - ENS of node i which is given by,

$$ENS_i = P_i \sum_{i,j\in V, i\neq j} \left(U_{j,i} + U'_{j,i}\right) \quad (4)$$

where,

$V = \{1,2,\dots..nb\}$,

nb - No of nodes in a network

P_i - Real power at bus I

$U_{j,i}$ and $U'_{j,i}$ - Service unavailability associated with their construction time of all the branches connecting the node.

V_{D_i} - Voltage deviation of load bus i, which is given by,

$$V_{D_i} = (1 - V_i)^2 \quad (5)$$

where,

V_i - Voltage at bus ip.u.

2.2 Real power and bus voltage constraints

Real power limit of distribution feeders for the network should not be exceeded.

$$P_{\mathrm{pq}} \le P_{\mathrm{pq}}^{\max} \quad (6)$$

where,

P_{pq}- Actual real power flow of the feeder between buses p and q

$P_{\mathrm{pq}}^{\max}$ - Maximum thermal limit for the feeder between buses p and q.

Voltage magnitude at each bus must lie within their permissible ranges and it is given by,

$$V_{\mathrm{b}}^{\min} \le V_{\mathrm{b}} \le V_{\mathrm{b}}^{\max} \quad (7)$$

where,

V_{b} - Voltage at bus b

$V_{\mathrm{b}}^{\max}$ - Maximum voltage at bus b

$P_{\mathrm{b}}^{\min}$ - Minimum voltage at bus b.

2.3 DG rating constraints

The ratings of *DG* units must be constrained between its maximum and the minimum levels as given as follows,

$$P_{DG,i}^{\min} \le P_{DG,i} \le P_{DG,i}^{\max} \quad (8)$$

where,

$P_{DG,i}$ - *DG* capacity at bus *i*

$P_{DG,i}^{\max}$ - Maximum *DG* capacity that can be placed at bus *i*

$P_{DG,i}^{\min}$ - Minimum *DG* capacity that can be placed at bus *i*.

2.4 Constraint for placing Number of *DG*

$$0 \le DG_{no} \le 3\,. \quad (9)$$

DG_{no} - Number of *DG*s

3 Optimization algorithm

3.1 Gravitational search algorithm

GSA is an optimization algorithm, which works based on law of gravity and law of motion. In GSA, a set of agents is called as objects and their masses are introduced by using law of gravity and law of motion in order to find the local optima in solution. The steps involved in the searching process are given as follows [19, 20]:

1) Consider a system with *N* agents and the mass of the i^{th} agent is given by,

$$X_i = \{x_i^1, \dots.., x_i^d, \dots..x_i^n\}\, i = 1,2,\dots., N \quad (10)$$

where, x_i^d is the position of i^{th} masses in the d^{th} dimension and n is the total number of agents.

2) For all the agents fitness value is calculated. Among the fitness values, the best and the worst fitness are found out using

$$best(t) = \min fit_i(t) \tag{11}$$
$$worst(t) = \max fit_i(t) \tag{12}$$

where
$fit_i(t)$ is the fitness value of the i^{th} agent at time t.

3) The gravitational constant $G(t)$ at time t is calculated using the following function by having the initial value G_0,

$$G(t) = G_0 e^{-\propto \frac{t}{T}} \tag{13}$$

4) Updation of mass of each agent is done by

$$m_i(t) = \frac{fit_i(t) - worst(t)}{best(t) - worst(t)} \tag{14}$$
$$M_i(t) = \frac{m_i(t)}{\sum_{k=1}^{N} m_k(t)} \tag{15}$$

5) Based on the law of gravity, the force acting on the i^{th} mass is calculated as

$$F_i^d(t) = \sum_{j=kbest, j\neq 1}^{N} rand_j G(t) \frac{M_j(t).M_i(t)}{\|X_i(t), X_j(t)\|_2 + \varepsilon} (x_j^d(t) - x_i^d(t)) \tag{16}$$

where
$kbest$ is the set of first k agents with best fitness value and biggest mass
$rand_j$ - Random number between 0 and 1
$M_i(t)$ and $M_j(t)$ are the gravitational masses of the i^{th} agent and the j^{th} agent
$\|X_i(t), X_j(t)\|_2$ is the Euclidian distance between the i^{th} agent and the j^{th} agent
ε is the small constant.

6) Then the acceleration of an agent is calculated as

$$a_i^d(t) = \frac{F_i^d(t)}{M_i(t)} \tag{17}$$

7) Finally the velocity and the position of each agent will be updated as

$$V_i^d(t+1) = rand_i \times V_i^d(t) + a_i^d(t) \tag{18}$$
$$x_i^d(t+1) = x_i^d(t) + V_i^d(t+1) \tag{19}$$

8) Execution stops when the stopping criterion is reached.

Table 1 GSA Parameter

Parameter	Value
Population size	30
G_0	100
α	20
No of iterations (T)	100

The parameters for GSA used in this paper are given in Tab. 1.

In our problem the population was chosen as 30, since in IEEE 33 bus system there are 30 (Bus 2 – Bus 32) possibilities to place the DG. Other parameters were chosen as constant value [31], in such a way to obtain the optimal value.

4 Reconfiguration of distribution system

4.1 Problem formulation

Reconfiguration of feeders in distribution system should be done such as to minimize the real power loss and to improve the voltage profile of the network. It can be mathematically written as

$$\min f1 = \sum_{l=1}^{nl} P_L^l \tag{20}$$

$$\min f2 = \sum_{i=1}^{nb-g} V_{D_i} \tag{21}$$

where
P_L^l - Real power loss in a line l
nl - No of branches in a network
nb - No of nodes in a network
g - No of generator nodes in a network
V_{D_i} - Voltage deviation of load bus i.

It is given as,

$$V_{D_i} = (1 - V_i)^2 \tag{22}$$

where,
V_i - Voltage at bus i in p.u

4.2 Real power and bus voltage constraints

Real power limit of distribution feeders for the network should not be exceeded.

$$P_{\text{pq}} \leq P_{\text{pq}}^{\max} \tag{23}$$

where,
P_{pq} - Actual real power flow of the feeder between buses p and q
$P_{\text{pq}}^{\max}$ - Maximum thermal limit for the feeder between buses p and q.

Voltage magnitude at each bus must lie within their permissible ranges and it is given by,

$$V_{\text{b}}^{\min} \leq V_{\text{b}} \leq V_{\text{b}}^{\max} \tag{24}$$

where,
V_{b} - Voltage at bus b
$V_{\text{b}}^{\max}$ - Maximum voltage at bus b
$P_{\text{b}}^{\min}$ - Minimum voltage at bus b.

4.3 Radiality constraints

Under this constraint the radial structure of network should not be affected and all the nodes should be energized.

5 Optimization algorithm for reconfiguration

5.1 Non-Dominated Sorting Genetic Algorithm (NSGA)

NSGA is a multi-objective optimization technique also known as Pareto optimization. It is an area of multiple criteria decision making, that is simultaneously optimizing the multiple objective. A solution is called non dominated Pareto optimal, if none of the objective functions can be improved in value without degrading some of the other objective values [32].

In NSGA-II, first the off spring population Q_t (of size N) using the parent population P_t (of size N) is created.The usual genetic operators such as single- point crossover and bit-wise mutation operators are used in this process. Next, to form an intermediate population R_t of size $2N$ the two population was combined. Thereafter, the fitness of each offspring in the $2N$ population was evaluated using the multiple objective functions. At this stage, non-dominated sorting procedure over the $2N$ population was carried out to rank and divide the individuals into different non-dominated fronts. Thereafter, the new parent population P_t+1 by choosing individuals of the non-dominated fronts was created, one at a time. The individuals of best ranked fronts first followed by the next-best and so on, till obtaining N individuals. Since the intermediate population R_t has a size of $2N$, those fronts which could not be accommodated were discarded. In case there is space only for a part of a front in the new population, crowded-distance operator was used to determine the individuals among those in the front that are from the least crowded regions. Such individuals were chosen so as to fill up the required number in the new population P_t+1.

Table 2 NSGA-II Parameters

Parameter	Value
No of population	20
No of generation	200
Cross over probability	0,9
Mutation probability (1/N - no of decision variables)	0,2
Crossover index	20
Mutation index	20

The complete NSGA-II procedure is given below:

BEGIN

While generation count is not reached

Begin Loop

- Combine parent P_t and offspring population
- Q_t to obtain population R_t of size $2N$.
- Perform Non-dominated Sort on R_t and assign ranks to each Pareto front with fitness F_i.
- Starting from Pareto front with fitness F_1, add each Pareto-front F_i to the new parent population P_t+1 until a complete front Fi cannot be included.
- From the current Pareto-front F_i, add individual members to new parent population P_t+1 until it reaches the size N.
- Apply selection, crossover and mutation to new parent population P_t+1 and obtain the new offspring population Q_t+1.
- Increment generation count.
- End Loop

END

The parameters for NSGA-II used in this paper are given in Tab. 2.

6 Results and Discussions

The enactments of suggested methods are tested on IEEE- 33 bus radial distribution system using MATLAB. The single line diagram of test system is shown in Figure 1. The test system comprises 33 buses, 32 sectionalizing switches and 5 tie line switches. In this network, sectionalizing switches which are normally closed are numbered from 1 to 32 and tie-switches which are normally opened are numbered from 33 to 37. Simulation is carried by taking three cases into account such as Case1: base case, Case 2: Test system without reconfiguration with multiple DG, Case 3: Reconfigured network with multiple DG.

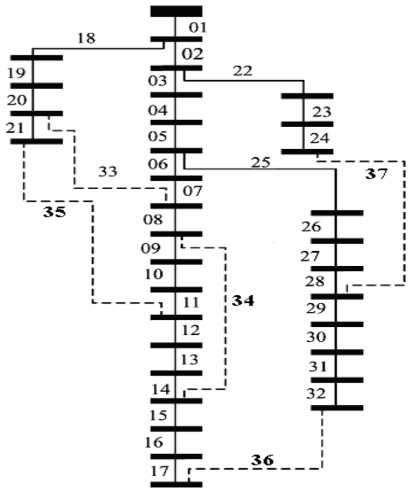

Figure 1 Single line diagram of IEEE 33 bus radial distribution System

6.1 Case1: Base Case

In this approach, forward and Backward Sweep Algorithm is used for load flow analysis since it is steadfast and gives accurate results for distribution system [28]. The load flow is performed on test system without connecting tie line Switches and without any DG., it resulted that real power loss, voltage deviation as 210,0594 and 0,1328 respectively. The Energy Not Supplied (ENS) was also obtained as 11,8406 kWh/yr.

6.2 Case 2: Test system without reconfiguration with multiple DG

Gravitational Search Algorithm (GSA) used for the optimization of multiple DG location, DG ratings and the achieved results are shown in Tab. 3. The fitness curve obtained for multiple DG using GSA is shown in Fig. 2 when the two DGs are located at 32, 18 the real power loss is minimized to 166,4732 kW. By adding one more DG, the power loss is again minimized to156,3369 kW the voltage deviation also improved from 0,1328 to 0,0749. When we are placing the multiple DGs at the optimized location as shown in Tab. 4. The ENS also gets reduced from $11,8406\times10^4$ kWh/yr to 3,3210×104 kWh/yr.

Table3 Effects of single and multiple DGs

S. No	Case	DG location	DG size (kW)	Real power loss (kW)	Voltage Deviation	ENS × 10^4 kWh/yr
1	Base case	-	-	210,0594	0,1328	11,8406
2	With 1 DG	[23]	[149,97]	192,1160	0,1035	3,3842
3	With 2 DG	[32 18]	[149,99 109,21]	166,4732	0,0857	3,3536
4	With 3 DG	[17 32 12]	[124,34 139,99 132,40]	156,3369	0,0749	3,3210

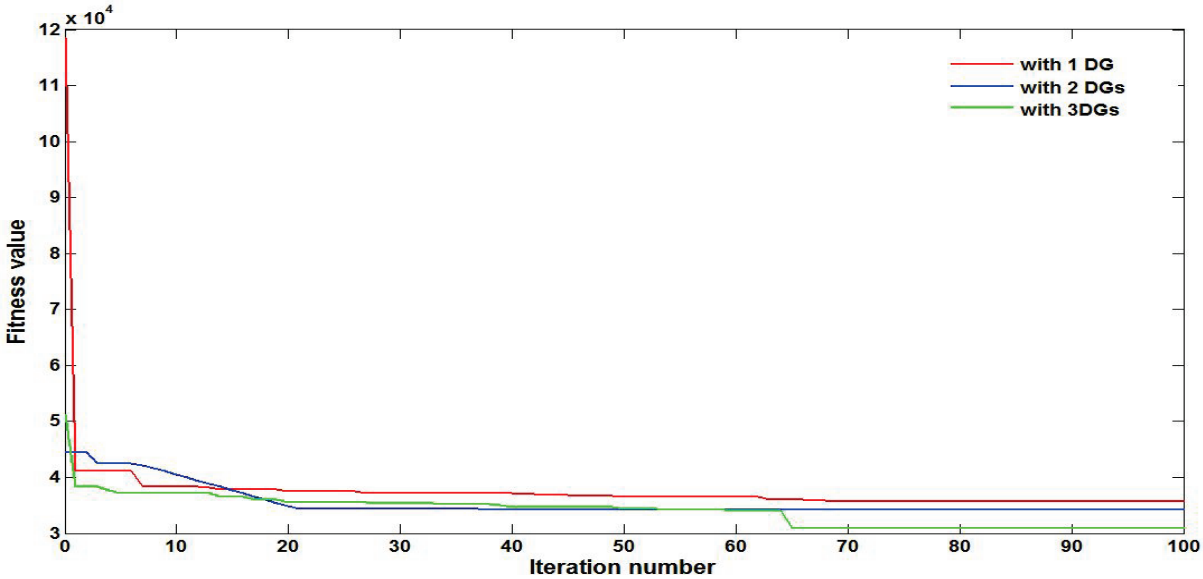

Figure 2 Fitness curves obtained with single and multiple DGs using GSA

Table 4 Reconfiguration results with single and multiple DGs using NSGA-II

S. No	Case	Switches Opened	Real power loss (kW)	Voltage deviation	ENS × 10^4 kWh/yr
1	With 1 DG	[7 13 10 17 28]	97,1218	0,0395	3,3842
2	With 2 DG	[33 12 10 15 22]	70,6359	0,0273	3,3536
3	With 3 DG	[7 14 11 15 28]	58,9464	0,0211	3,3210

6.3 Case 3: Reconfigured network with multiple DG

In this case, reconfiguration is done using NSGA for the test system after installing DGs at their proper location. The effects of this reconfiguration on system with DGs are obtained and it is shown that both real power loss and voltage deviation get minimized more than those of other 2 cases, as shown in Tab. 4. The graph showing the voltage profile for all the three cases is shown in Fig. 3. From this figure it can be revealed that by having the NSGA based reconfigured network with DG, the voltage profile has been improved more. The Tab. 5 gives the comparison of results obtained for all three cases. The ENS was not affected by the reconfiguration since we have taken this as independent to the line configuration.

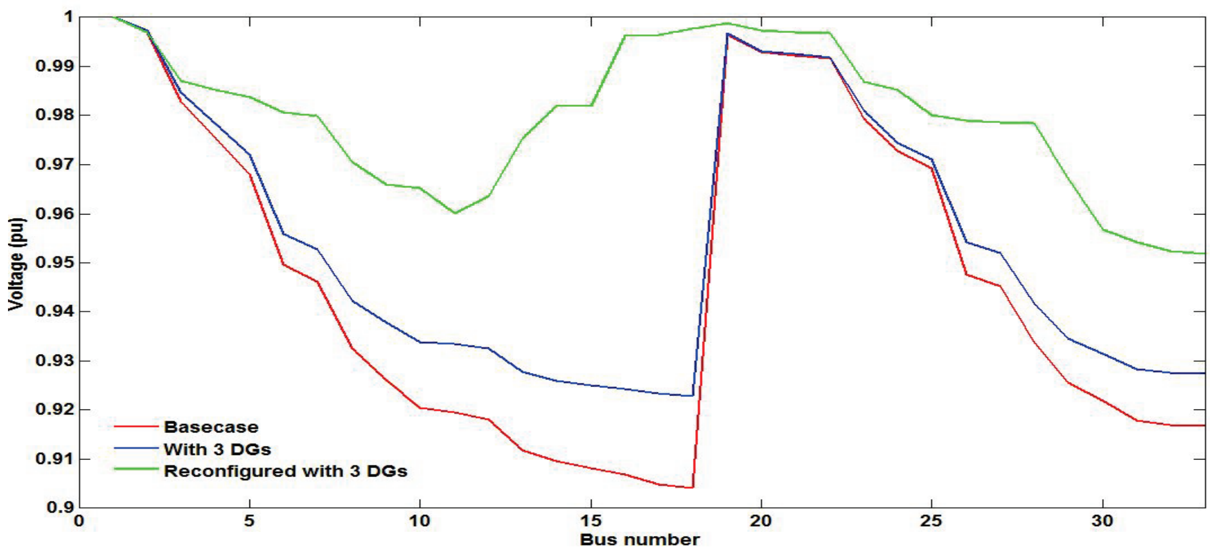

Figure 3 Voltage profile of the IEEE-33 bus radial distribution system

Table 5 Comparison result with and without reconfiguration by incorporating DGs

S. No	No. of DGs	Without reconfiguration			With reconfiguration		
		Real power loss (kW)	Voltage deviation	ENS $\times 10^4$ kWh/yr	Real power loss (kW)	Voltage deviation	ENS $\times 10^4$ kWh/yr
1	1	192,1160	0,1035	3,3842	97,1218	0,0395	3,3842
2	2	166,4732	0,0857	3,3536	70,6359	0,0273	3,3536
3	3	156,3369	0,0749	3,3210	58,9464	0,0211	3,3210

7 Conclusion

Reconfiguration exemplifies one of the most important dealings which can improve the performance of a distribution system. An optimal reconfiguration of a power distribution system is not a new problem but is still a difficult one and nowadays has new challenges. Besides active power losses, the DG placement problem and reconfiguration problem is formulated as a non-linear optimization problem with the objective of loss minimization and voltage profile improvement by considering the Energy Not Supplied (ENS). The location and sizing of multiple DGs were optimized using Gravitation Search Algorithm (GSA). For reconfiguration, the optimal switches to be opened in distributed system were found using Non-Dominated Sorting Genetic Algorithm (NSGA). The criteria for optimization have been evaluated on active power distribution systems. The simulation studies on test systems have emphasized that the feeder reconfiguration problem can be more efficiently solved with NSGA than in the case of distributed generators connected directly to the main distribution system. This paper deals with an original genetic algorithm (based on NSGA-II) to solve the problem in a non-prohibitive execution time.

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Authors' addresses

Sankaramoorthy Muthubalaji, Associate Professor
Lathamathavan Engineering College
Alagarkovil, Madurai, Tamilnadu,
India, 625 301
E-mail: muthusa15@gmail.com

Veluchamy Malathi, Professor
Anna University, Regional Office Madurai,
Madurai, Tamilnadu,
India, 625 007
E-mail: vmeee@autmdu.ac.in