Optimal Integration of Distributed Generations with Network Reconfiguration using a Pareto Algorithm

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Received: 05.07.2017 Accepted:13.08.2017

Abstract- This paper suggests multi-objective management operations based on network reconfiguration while allocating and sizing Distributed Generations (DGs) allocation and sizing. The optimization problem is solved considering multiple objectives: active power loss minimization, annual operation cost (installation, maintenance, and active power loss cost) reduction, and system voltage profile improvement. An original Pareto-based evolutionary algorithm is proposed to equally optimize multiple objective functions providing Pareto optimal solutions, where the network manager can select an option. A fuzzy set theory is used to select the best compromise solution among the obtained Pareto set. The algorithm is successfully implemented on MATLAB software and the simulations are investigated for the integration of a single and multiple DGs. The obtained results prove the efficiency of the suggested method for the network manager to find the optimal network configuration, the optimal DG location and sizing considering multiple criteria, and the beneficial effects of applying these multi-objective management operations for more than a single DG in the distribution network.

Keywords Distribution network; distributed generation, distribution network reconfiguration, evolutionary algorithm, Pareto optimality.

1. Introduction

In the last decade, there has been a growing interest in power system management operations so as to improve the distribution network technically and economically. The first study of the power system enhancement was performed by Merlin and Back [1] who gave the idea of distribution network reconfiguration for the mitigation of active power loss. The distribution network reconfiguration can be defined as a process that handles the open /close status of sectionalizing switches and tie-switches in order to find the best network configuration that optimizes different criteria (active power loss, reliability, voltage profile…)while satisfying operational constraints. In the literature, the reconfiguration process has been used by several studies to enhance the power quality of the distribution network, such as power loss mitigation and voltage profile improvement [2], [3], [4].

Besides the beneficial effects of the network reconfiguration in a power system, the integration of Distributed Generations (DGs) can be considered as another alternative for the power quality enhancement of a distribution network. The DG can be defined as ‘‘An electric power generation within distribution networks or on the customer side of the network’’[5].

For the last decade, there has been a growing interest in renewable energy sources due to the increased demand for electricity and the significant depletion of fossil fuel. Therefore, research on the integration of DGs into a distribution network has become very popular [6], [7], [8], [9]. Indeed, the placement of DG in optimal locations and with appropriate sizes may bring about various benefits to the power system such as active power loss and line loading reduction, reactive power requirement mitigation, and voltage profile improvement. To solve this problem, a lot of researchers have put forward various optimization techniques (e.g. conventional, artificial intelligence and hybrid intelligent system techniques) [10].

In the literature, the traditional studies of an optimal DG integration in the distribution network have considered the power loss as a main objective to minimize. Thus, the optimization problem has been tackled as a mono-objective using the analytical approach [11], [12] or the heuristic and metaheuristic methods, like the particle swarm optimization [13] , the vector swarm optimization algorithm [14], and the genetic algorithm [15].

Recently, several studies have introduced other objectives to optimize the problem of sitting and sizing DG, namely voltage stability improvement, operation cost reduction, and greenhouse gas emissions. According to the literature, this multi-objective approach has been tackled in two ways: for the first case, the objective functions have been aggregated with proper weights to constitute a single objective. This approach is has been widely presented in several studies utilizing artificial intelligent techniques as the genetic algorithm based methods (BSOA [16], GA [17]), the computational methods (ICA [18], MNLP [19], ALOA [20]), and the hybrid optimization techniques (GA/Fuzzy [21], HPSO [22]). A key limitation of these methods is that are not able to optimize multi-objectives equally. Another disadvantage is the use of the weighted aggregation leading to a long research effort. In the second case, multi-objectives are solved using the Pareto optimality. This concept is not discriminating because all objective functions are optimized equally providing the Pareto set of optimal solutions. However, the primary approach would generate only one solution while choosing weights of each objective. To avoid this drawback, several recent studies have adopted the multi-objective evolutionary algorithms based on the Pareto optimality concept to find the best locations and sizing of DGs, for instance INSGAII [23], IMOHS [24], MOShBAT [25]. These evolutionary algorithms provide a set of Pareto optimal solutions where the network can select an option.

The operations of an optimal DGs integration and distribution network reconfiguration are usually studied separately. Nevertheless, the combination of these two sub-problems together can bring more benefits to the whole system. In the literature, there have been few studies tackling the network reconfiguration at the same time with an optimal allocation and sizing of DGs. Most of these researchers consider power loss as a single objective to minimize [23-25].Thus, the main contribution of this work consists in introducing a multi-objective aspect to the problem of a simultaneous network reconfiguration and optimal integration of DGs. In this paper, the objective functions of the proposed problem consist in minimizing the active power loss, reducing the annual operation cost and enhancing the voltage profile of the distribution network. An evolutionary algorithm based on the Pareto optimality concept, called the Strength Pareto Evolutionary Algorithm 2 (SPEA2) is chosen to solve the optimization problem. This technique provides the network manager with a set of Pareto optimal solutions. In order to facilitate the decision making, a fuzzy set theory is proposed to extract the best compromise solution among the Pareto set. The theories of spanning trees are introduced to the genetic operators of the SPEA2 technique so as to generate feasible network configurations respecting the topological constraints.

The multi-objective optimization problem is implemented to an IEEE 33 bus distribution network using the suggested method. Multiple and single DG optimal integrations are investigated. The results demonstrate the benefits of combining the network reconfiguration with the optimal placement and sizing of multiple DGs in the distribution network.

The remainder of this paper is organized as follows. In section 2, the problem formulation of the optimization problem is presented. In section 3, the principle concept of the proposed method is present and applied to the problem. In section 4, the simulations, the results, and the comments are detailed. Finally, section 5 concludes with a summary.

2. Problem Formulation

The problem of the simultaneous reconfiguration and optimal integration of DGs consists in finding a radial configuration of the distribution network as well as the best locations and sizes of DGs that optimally minimize the active power loss, the annual operation cost and the nodal voltage deviation. This combinatorial problem is considered as a multi-objective optimization problem, which is formulated as follows:

2.1. Objective function

2.1.1 Minimization of active power loss:

The first objective function is to minimize the sum of active power losses in all branches, which is defined as:

$$f_1 = PL = \sum_{b=1}^{N_b} R_b \cdot I_b^2 \tag{1}$$

where I_b is the module of current in the branch b , R_b is the resistance of the branch b ,and N_b is the set of branches.

2.1.2 Minimization of annual operation cost ($/year)

The second objective function to minimize is the annual operation cost. This objective function is composed of the cost of maintenance, the installation and the active power loss after sitting DGs in the distribution network. In our case of study, a DG is assumed to be a photovoltaic generation (solar DG) with a stable unity factor. This objective function is presented ad follows:

$$f_2 = \left(C_{inst} + C_{main}\right) \cdot P_{DG_{total}} + C_{PL} \tag{2}$$

where C_{inst} and C_{main} are the installation cost and maintenance cost per kWh, respectively. $P_{DG_{total}}$ is the total active power generation of solar DGs and C_{PL} is the cost of the active power loss.

The computation of the active power loss is listed as follows:

$$C_{PL} = EL \cdot (EC \cdot T) \tag{3}$$

where EC is the unitary cost of the active power loss (\$/kWh), T is the duration in hours a year (8760 hours), and EL is the active power loss (kWh) defined as follows:

$$EL = F_{ls} \cdot PL \tag{4}$$

where F_{ls} is the factor of the active power loss depending on the load demand during a period of time. All parameters of the cost of the annual operations are listed in Table 1.

2.1.3 Minimization of voltage deviation

The third objective function to minimize is the voltage deviation between the nodal the voltage and the rated voltage magnitude. Bus voltage magnitude is a pertinent indicator of the system security and power quality.

Table 1. Parameters of operation cost

Installation cost (C_{inst})	3000 \$/KWh
Maintenance cost (C_{main})	30 \$/KWh
Unitary cost of power loss (EC)	0.06 \$/KWh
Factor of the active power loss (F_{ls})	0.27

The objective function can be written as:

$$f_3 = \sum_{i=0}^{n} \left(\frac{V_i - V_{rated}}{V_{\max} - V_{\min}} \right)^2 \tag{5}$$

where V_i is the voltage magnitude at the bus i, V_{rated} is the rated voltage magnitude, and $V_{\max}$ and $V_{\min}$ are the maximum and minimum allowable values of nodal voltage magnitude, respectively.

2.2 Constraints

The combined reconfiguration and the optimal allocation and sizing of solar DGs in the distribution network must respect certain system security and topological constraints.

2.2.1 Equality constraint

The power balance constraint is defined as follows:

$$P_{sub} + P_{DG_{total}} - \sum_{i=1}^{n} P_{load_i} - P_L = 0 \tag{6}$$

2.2.2 Inequality constraints

- Bus voltage limits:

$$V_{\min} \le V_i \le V_{\max} \tag{7}$$

The voltage V_i at each bus i should be kept between its minimum and maximum values.

- Branch current limits:

$$\left| I_b \right| \le I_b^{\max} \tag{8}$$

The module of the current I_b at each branch should not exceed its maximum thermal value $I_b^{\max}$.

- DG capacity constraint:

In general, the penetration rate of DGs varies according to the renewable energy policies of countries. In this work, it is assumed that the total injected capacity of renewable DGs should be between 10% and 60% of the total active power load in the distribution network; i.e.:

$$0.1 \times \sum_{i=1}^{n} P_{load_i} \le \sum_{i=1}^{N_{DG}} P_{DG_i} \le 0.6 \times \sum_{i=1}^{n} P_{load_i} \tag{9}$$

2.2.3. Topological constraint

The distribution network configurations determined during the evolutionary process should be radial. Moreover, there must be no loops in the network and all loads must be supplied. In this study, the theories of spanning trees [27] is used for the distribution network reconfiguration. According to these theories, the condition of reliability can be expressed as follows:

$$\sum_{b=1}^{N_b} \beta_b = n - N_{sub} \tag{10}$$

where β_b is a binary variable that represents the status of a branch (0-open, 1-closed), n is the number of network buses, and N_{sub} is the number of substations.

3. Proposed Evolutionary Computation

3.1. Overview of Strength Pareto Evolutionary Algorithm 2

The SPEA2 is a multi-objective optimization technique based on the concept of Pareto optimality to solve non-linear and complex problems. This method is an improved version of its SPEA predecessor, developed by the scholar Zitzler and published in his report [28], where the author proved the efficiency of the SPEA2 by performing comparisons with other evolutionary methods such as SPEA, NSGAII, and PESA. The obtained results showed that the SPEA2 and the NSGAII have the best performance overall, but in larger dimensional objective space, the SPEA2 is better than the NSGAII.

The SPEA2 is adopted in this paper to solve the problem of a simultaneous network reconfiguration and an optimal integration of DGs. The characteristics of this technique are detailed below:

3.1.1. Pareto optimality concept

The SPEA2 technique is based on the concept of Pareto optimality to solve multi-objective optimization problems. In fact, the "non-dominance" relationship between solutions is used to determine the concept of Pareto optimality. A solution x^* will dominate (is better than) a solution x (denoted by $x^* \prec x$) if the following two conditions are true:

- If $f_i(x^*) \le f_i(x)$ with $i = 1, ..., N_{obj}$
- There is at least one j such that $f_j(x^*) < f_j(x)$

The solution x^* is called non-dominated since there is no x that dominates it. The Pareto optimality is determined from the non-dominance relationship as follows: A solution x^* is

Pareto optimal if it does not exist a solution $x \in \Omega$ better than x^*, where Ω is a feasible set. All non-dominated solutions (vectors) form the Pareto optimal set are defined as follows:

$$P^* = \left\{x^* \in \Omega\right\} \tag{11}$$

The objective values of Pareto in the objective space constitute the Pareto Front. Figure 1 illustrates the evolutionary process towards the Pareto front.

3.1.2. The truncation operator

In the SPEA2, the solutions with the best fitness values will be copied to an external archive that has a constant size.

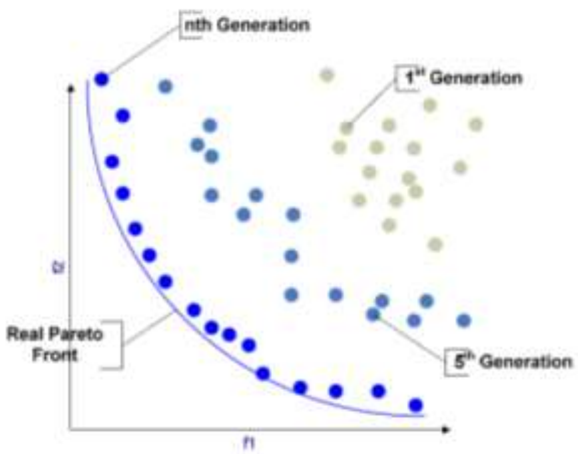

Fig. 1. Evolution of solutions toward Pareto front

Consequently, when the set of non-dominated solutions is larger than the archive, a truncation operator will be used to remove solutions until the non-dominated set fits the archive. The truncation operator is applied iteratively to delete individuals with the closest distance to another individual. If there are several individuals with a minimum distance, the second one with the shortest distance will be removed, and so forth. The truncation operator prevents the non-dominated set from being lost and ensures the well spread of solutions in the Pareto front. This truncation operator is defined as follows:

$$\forall 0 < k < \left|\overline{P_{t+1}}\right| : \sigma_i^k = \sigma_j^k \vee$$

$$\exists 0 < k < \left|\overline{P_{t+1}}\right| : \left[\left(\forall 0 < l < k : \sigma_i^l = \sigma_j^l\right) \wedge \sigma_i^k < \sigma_j^k\right]$$

where $\overline{P_{t+1}}$ is the external archive, σ_i^k is the distance of i to its k^{th} nearest neighbor in $\overline{P_{t+1}}$, and l is the index of the second individual with the smallest distance. Figure 2 illustrates the mechanism of the truncation operator.

3.1.3. Best compromised solution

The SPEA2 technique offers a set of Pareto optimal solutions, from which the network manager can select a final solution, regarding their preference. In this paper, a fuzzy set theory [29] is adopted to extract the best compromise solution among the Pareto set. This decision-making theory is formulated as follows:

$$\mu_i = \begin{cases} 1, & f_i \le f_i^{\min} \\ \dfrac{f_i^{\max} - f_i}{f_i^{\max} - f_i^{\min}}, & f_i^{\min} \le f_i \le f_i^{\max} \\ 0, & f_i \ge f_i^{\max} \end{cases} \tag{12}$$

where μ_i is the membership function of the i^{th} objective function f_i and $f_i^{\max}$ and $f_i^{\min}$ present respectively the maximum and minimum values of the i^{th} objective function respectively.

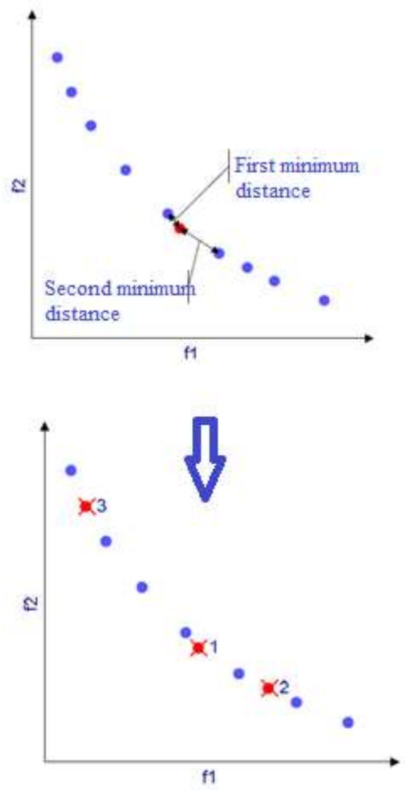

Fig. 2. SPEA2 truncation operator

The fuzzy decision will be applied to extract the best compromised solution in Pareto optimal solutions. That is:

$$\mu_h = \max\left\{\frac{\sum_{i=1}^{N_{obj}} \mu_i}{\sum_{h=1}^{M}\sum_{i=1}^{N_{obj}} \mu_i^h}\right\} \tag{13}$$

where M is the number of non-dominated solutions and N_{obj} is the number of optimization objectives.

3.1.4. SPEA2 algorithm and flowchart

As explained above, the SPEA2 technique was invented to solve multi-objective optimization problems. This technique is mainly based on the genetic algorithm, the evolutionary operations (truncation operator, density estimation, etc), and the Pareto optimality concept. The SPEA2 overall algorithm is explained step by step as follows:

Step 1: Generate an initial population P_0 and create the empty external archive (external set) $\overline{P_0} = \varnothing$; Set $t = 0$.

Step 2: Calculate the fitness values of individuals in P_t and $\overline{P_t}$. Each individual i in the archive and the population is assigned a strength value $Strength(i)$, representing the number of solutions which it dominates:

$$Strength(i) = \left|\left\{ j \mid j \in \left(P_t + \overline{P_t}\right) \wedge i \text{ f } j \right\}\right| \tag{14}$$

where $|.|$ is the cardinality of a set (the number of elements in a set), and $+$ stands for a multi-set union.

On the basis of the $Strength$ values, the raw fitness is determined by the strengths of its dominators in both the archive $\overline{P_t}$ and the population P_t . The raw fitness $Rfitness(i)$ of an individual i is calculated as follows:

$$Rfitness(i) = \sum_{j \in P_t + \overline{P_t},\, j \text{ f } i} Strength(j) \tag{15}$$

The nondominated individuals have the same raw fitness values $Rfitness(i) = 0$. However, a high $Rfitness(i) = 0$ value means that the individual i is dominated by many individuals. Hence, additional density information is incorporated to discriminate between individuals having identical raw fitness values. The density estimation technique used in the SPEA2 is an adaptation of the nearest neighbor method [28]: For each individual i the distances (in objective space) to all other individuals j in the archive and the population are calculated and stored in a list. After sorting the list in an ascending order, the k^{th} element gives the distance sought for. As a common setting, k is expressed as follows:

$$k = \sqrt{N + \overline{N}} \tag{16}$$

where N is a population (P_t) size and $\overline{N}$ is an archive ($\overline{P_t}$) size.

The density $Density(i)$ corresponding to i is defined by:

$$Density(i) = \frac{1}{\sigma_i^k + 2} \tag{17}$$

By adding $Density(i)$ to the raw fitness value $Rfitness(i)$ of an individual i is an individual i yields its fitness $Fitness(i)$:

$$Fitness(i) = Rfitness(i) + Density(i) \tag{18}$$

Step 3: Environmental selection: Copy all nondominated individuals in P_t and $\overline{P_t}$ to $\overline{P_{t+1}}$. If $\overline{P_{t+1}}$ exceeds $\overline{N}$, then reduce the external archive size by means of the truncation operator (explained in section 3.1.2 above).

Step 4: Termination: If $t = t_{\max}$ (maximum number of generations) then stop.

Step 5: Mating selection: Perform the binary tournament selection with a replacement on $\overline{P_{t+1}}$. Increment the generation counter ($t = t + 1$) and go to step 2.

The flowchart of the SPEA2 technique applied to the optimization problem of a combined network configuration and sitting and sizing optimal DGs is depicted in Fig. 3.

3.2. Application of SPEA2 to problem of simultaneous network reconfiguration and integration of DGs

In this paper, the SPEA2 is applied to the proposed problem by introducing specific modifications to its genetic operators. The adaptation of the SPEA2 to the suggested problem is explained below in details:

3.2.1 Genetic encoding

The first step of the evolutionary SPEA2 process consists in generating the initial population. Actually, the individuals should be properly coded for solving the optimization problem of the network reconfiguration, simultaneously with the integration of optimal DGs. This genetic encoding is illustrated as follows:

$$ind_i = \begin{bmatrix} s_1, s_2, ..., s_{n_{open}}, loc_1, loc_2, \\ ..., loc_{N_{DG}}, P_{DG_1}, P_{DG_2}, ..., P_{DG_{N_{DG}}} \end{bmatrix} \tag{19}$$

where ind_i is an individual i of the population; $s_1, s_2, ..., s_{n_{open}}$ are the set of positions of open switches of a possible configuration of the network; $loc_1, loc_2, ..., loc_{N_{DG}}$ are the set of possible locations of solar DGs; and $P_{DG_1}, P_{DG_2}, ..., P_{DG_{N_{DG}}}$ are the capacities of each solar DG.

The individuals generated for the initial population are evaluated according to security and topological constraints.
The individuals of the initial population as well as the new population generated by the genetic operators are evaluated using a load flow calculation. The only ones that satisfy the topological and security constraints are maintained. A load flow method based on "backward forward sweep" is utilized in this work. This load flow technique is known by its simplicity and its adaptation to radial distribution networks [30].

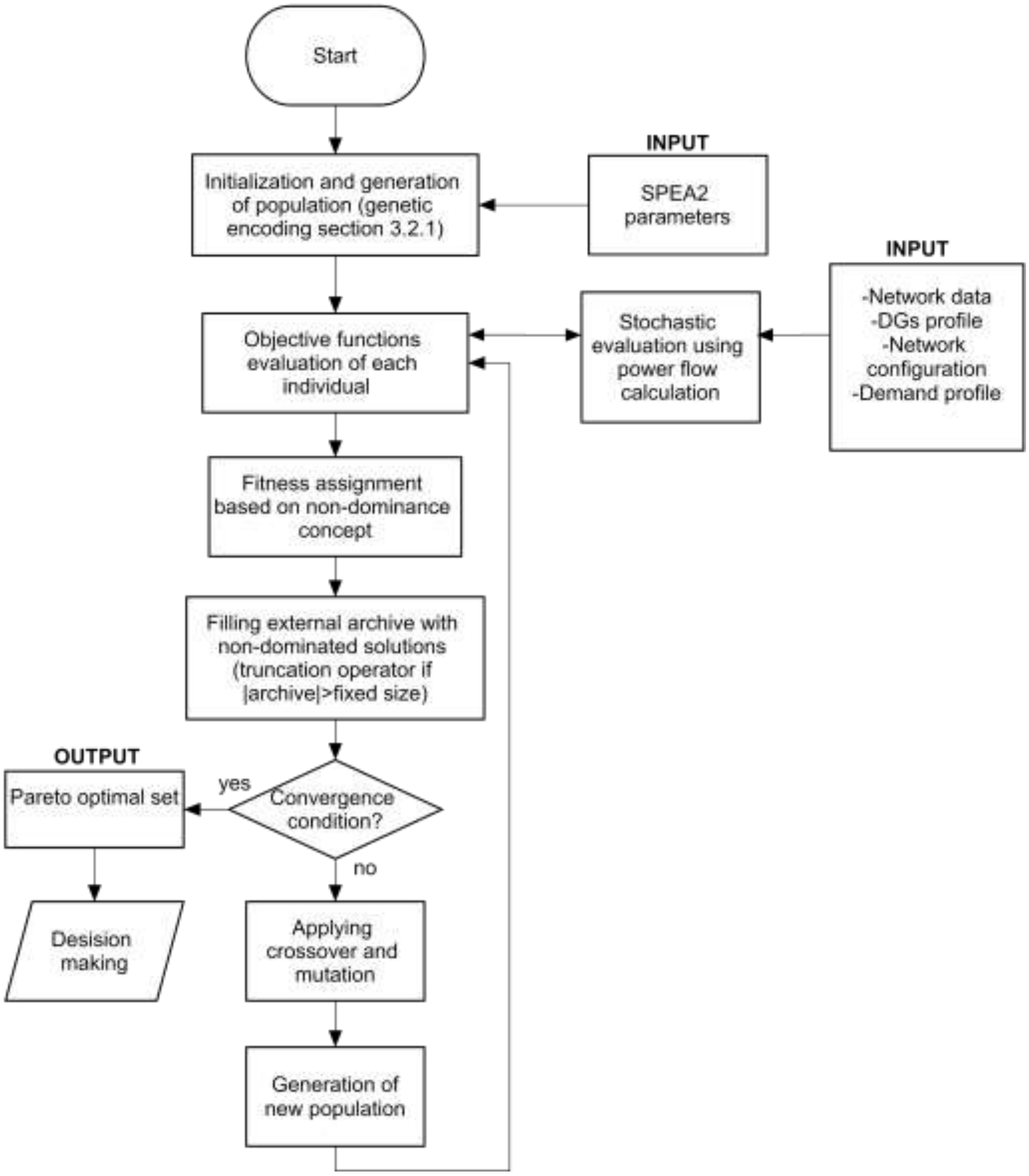

Fig .3. Flowchart of proposed method

3.2.2. Genetic operators

Mutation and crossover operations have an important role in the evolutionary process. These genetic operators ensure the creation of new individuals, and thus the diversity in the research space. A part of decision variables presents a possible network configuration (indices of open switches), so when applying classical genetic operators, non feasible configurations can be obtained from isolated nodes, loops, and non radial structures. For this purpose, the genetic operators are modified by introducing the theories of spanning trees to preserve the radial structure of the obtained network configurations.

Firstly, the property of Kruskal based on the theories of spanning trees is applied in the crossover operator by exchanging one or several branches between two spanning trees (network configurations) in order to obtain new ones with a radial structure. This property is defined as follows [31]:

Let U and Q be two spanning trees of a graph G and let $a \in U$, then, there exists $b \in Q$ such that $U - a - b$ is also a spanning tree in the graph G.

After that, the mutation operator is applied by randomly selecting an open branch to be exchanged by another one in the same spanning tree while preserving its radial structure. This procedure needs the determination of the opened loop to which the selected branch belongs. Therefore, a "depth in first algorithm" [27] based on the idea of backtracking is used to find the closed branches forming this loop. This method ensures the preservation of the radial structure of the mutated configuration.

4. Numeric Simulations and Comments

The optimization problem of simultaneous network reconfiguration and optimal placement and sizing of DGs is solved using the proposed evolutionary computation SPEA2. The program is developed in the MATLAB software. The simulations are carried out on the IEEE 33 bus radial distribution system [23] presented in Fig..4. The IEEE 33 bus is a 12.66 KV radial distribution network, which has 5 open switches with branch number s33-s34-s35-s36-s37. The total active and reactive loads of the test system are respectively 3.715 MW and 2.3 MVAR.

4.1. Benefits of combining network reconfiguration and DG integration

In order to illustrate the benefits of combining the integration of DGs with the network reconfiguration, two scenarios are simulated utilizing the suggested method and taking into acount the same penetration rate of the DG (the penetration rate is between 10% and 60% of the total load of the system):

- Scenario 1: Solving the problem of optimal allocation and sizing 3 DGs for active loss minimization without network reconfiguration.
- Scenario 2: Solving the problem of 3 DGs integration combined with optimal network reconfiguration for active power loss minimization.

The obtained results using the proposed method are compared with the existing studies in the literature investigating the benefits of combining the integration of DGs and network reconfiguration. In these researches, the authors used the following methods: the Fireworks Algorithm (FWA) and the Harmony Search Algorithm (HSA) to solve the optimization problem. As observed in Table 2, the suggested method converges to the best minimum values of the active power loss for the two scenarios that reaches 62.15% for scenario 1 and 71.38 % for scenario 2. Yet, for the other methods, the power loss reductions obtained for the two scenarios are inferior to 60% and 70%, respectively. Consequently, the proposed method can be an efficient tool to solve this combinatorial optimization problem thanks to its high convergence ability and accuracy. Thus, the SPEA2 technique is chosen for solving the multi-objective problem for the next section.

Besides, the obtained system voltage profile is observed for both scenarios. As depicted in Fig. 5., most bus voltage values will be improved more significantly when combining the network reconfiguration with the DG integration (scenario 2) rather than when integrating the DGs without a reconfiguration (scenarios 1). Indeed, the bus with the weakest voltage value is enhanced to 0.9721 p.u for scenario 2, which is above the minimum threshold of 0.95 p.u.

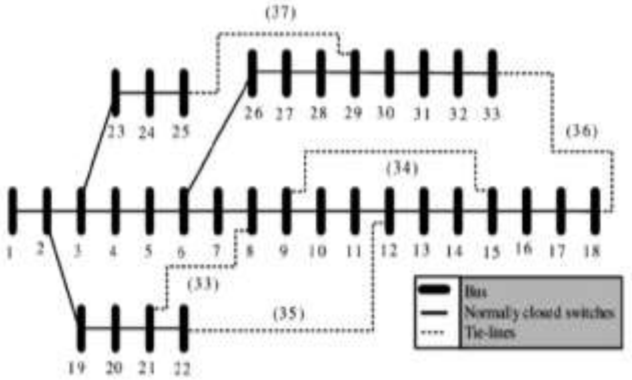

Fig.4. IEEE 33-bus distribution network

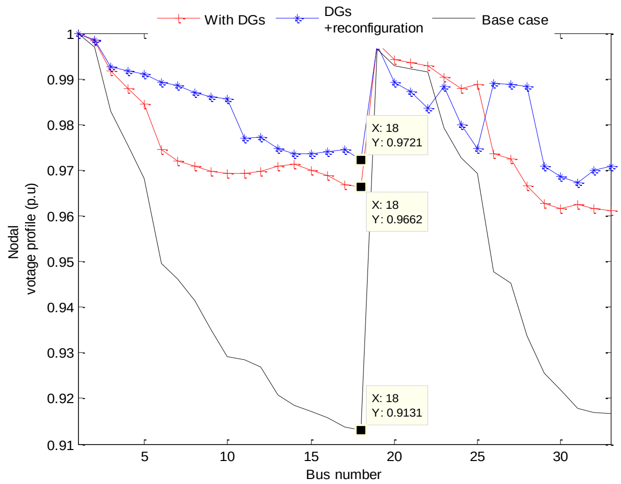

Fig. 5. Bus voltage profile improvement before and after combining network reconfiguration with DG integration

4.2. Bi-objective optimization

The present section and the next one treat the main contribution of this work, which consists of solving the problem of simultaneous network reconfiguration and optimal DG integration considering the equal optimization of multiple objectives without using the weighted summation or converting the objectives to the same measurement unit. In this section, we start by taking into account the bi-objective optimization. In fact, the problem is solved for two pairs of objective functions in order to investigate the relation among them. Furthermore, the comparisons are performed between single and multiple allocations of DGs. The DG type in this work is assumed to be a solar DG composed of photovoltaic modules (type of 100 W). The optimal size (number of modules for installation) and locations (number of bus) are determined simultaneously with the optimal network configuration utilizing the suggested optimization method.

The simulations are done in two cases of bi-objective optimization considering in each case a pair of objective functions to minimize. A set of Pareto optimal solutions is obtained in each case, which is presented by Pareto fronts in Fig.6-8.

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Table 2. Benefits of proposed operations in power loss reduction

Scenarios	Proposed method SPEA2	FWA [3]	HSA [26]
Base case	Network configuration: s33, s34, s35, s36, s37 *PL* (kW): 202.67		
Scenario1 (only DG integration)	Network configuration: s33, s34, s35, s36, s37 DG locations: 31-25-14 DG capacity (MW): 0.7429 (31) 0 .7429 (25) 0.7429 (14) *PL* (kW): 76.711 *PL* reduction%: 62.15	Network configuration: s33, s34, s35, s36, s37 DG locations: 14-18-32 DG capacity (MW): 0.5897(14) 0.1895(18) 1.0146(32) *PL* (kW): 88.68 *PL* reduction%:56.24	Network configuration: s33, s34, s35, s36, s37 DG locations: 18-17-33 DG capacity (MW): 0.1070(18) 0.5724(17) 1.0462(33) *PL* (kW): 96.76 *PL* reduction%:52.26
Scenario 2 (DG + reconfiguration)	Network configuration: s10, s28, s31, s33, s34 DG locations: 7-25-17 DG capacity (MW): 0.7237(7) 0.7419(25) 0.7429(17) *PL* (kW): 57.987 *PL* reduction%: 71.38	Network configuration: s7, s14, s11, s32, s28 DG locations: 32-29-18 DG capacity (MW): 0.5367(32) 0.6158(29) 0.5315(18) *PL* (kW): 67.11 *PL* reduction%:65.53	Network configuration: s7, s14, s10, s28, s32 DG locations: 32-31-33 DG capacity (MW): 0.5258 0.5586 0.5840 *PL* (kW): 73.05 *PL* reduction%: 63.95

The best compromise solution of each case is extracted from the Pareto front using the fuzzy set theory and provided in Table 3 and Table 4. The bi-objective optimization results are presented for a single and three solar DGs allocations as to investigate the difference.

4.2.1. Minimization of active power loss and operation cost

The conflicting relation between the active power loss and operation cost is depicted in Figure.5. As observed, the Pareto front shows that the objective functions of the power loss and the operation cost have a reciprocal distribution of solutions. Basically, a minimum value of the active power loss (61.91 kW) corresponds to a higher value of the operation cost (6,305 M$/year) and a minimum value of the operation cost (3,390 M$/year) gives a higher value of the power loss (80.18 kW). This conflicting relation is also observed between the other pairs of objective functions presented in Fig. 5-7

Table 3 illustrates the best compromise solution obtained for the minimization of the active power loss and the annual operation cost. According to the obtained results, it is observed that the combined network reconfiguration with the optimal integration of three solar DGs provides a better reduction in the active power loss (67.787 kW) than for a single solar DG (91.798 kW). However, this can lead to higher operation cost since the capacity of the integrated solar DG increases with the number of its allocations in the distribution network.

4.2.2. Minimization of active power loss and voltage deviation

The best compromise solution obtained for the minimization of the active power loss and nodal voltage is detailed in Table 4. As it can seen, the simultaneous network reconfiguration and the integration of three DGs ensures a better improvement of the voltage profile, which reaches a total deviation of (0.785 p.u), rather than with a single solar DG (0.986 p.u).

According to the results of the two cases of bi-objective optimization, it can be deduced that the network reconfiguration in parallel with optimal integration of solar DGs guarantees a better power quality enhancement (power loss reduction and voltage profile improvement) with the allocation of multiple DGs allocations rather than with a single DG. On the other hand, the allocations of multiple solar DGs can lead to higher operation cost compared with a single solar DG integration.

In the framework of power system planning, the installation cost is related only to the first year of integration. Thus the reduction in the power loss cost will compensate the insignificant amount of the annual maintenance cost. As a consequence, over the years, there will be economic benefits gained from the installation of multiple solar DGs, and they will be more important for the allocation of multiple solar DGs rather than for a single solar DG integration.

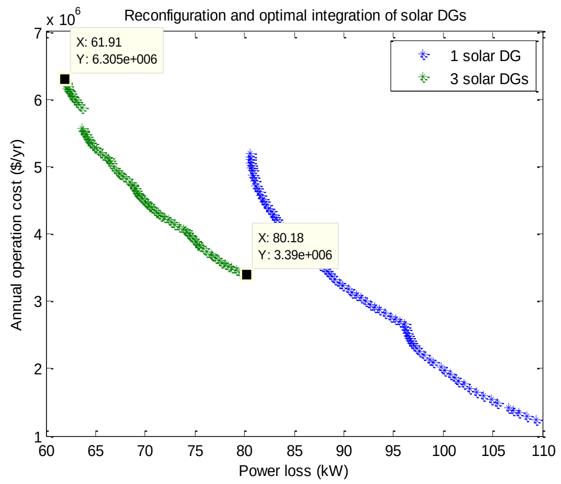


Fig. 6. Pareto fronts of power loss and operations cost

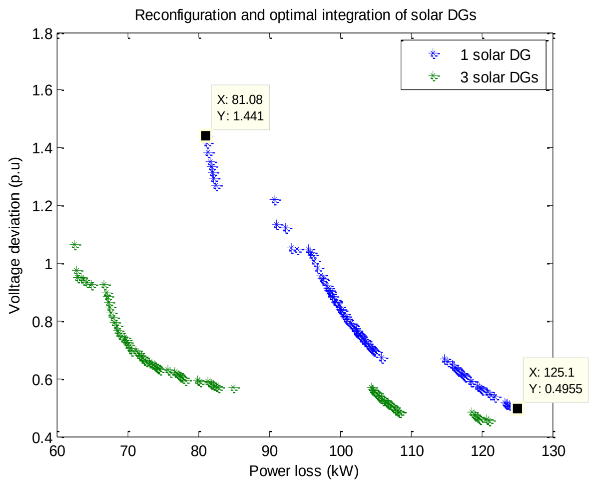


Fig.7. Pareto fronts of power loss and voltage deviation

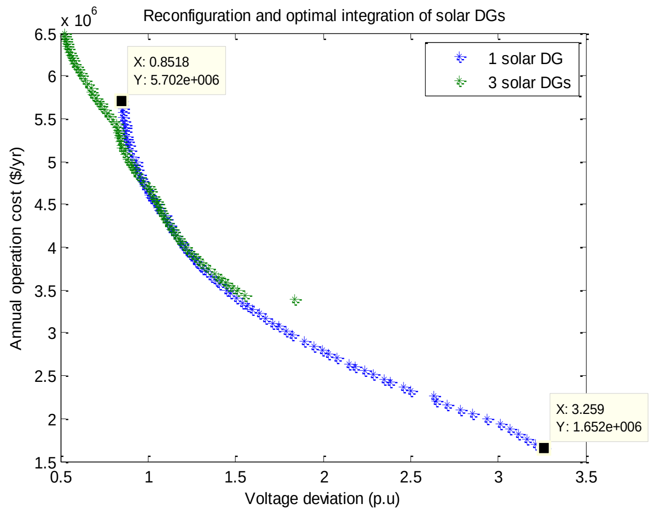


Fig. 8. Pareto fronts of voltage deviation and operations cost

Table 3. Compromise solution of power loss and cost minimization

Number of solar DGs	Power loss (kW)	Annual operations cost (M$/yr)	Optimal network configuration	Optimal solar DG location	Optimal solar DG capacities (MW)
1 DG	91.798	2,409.774	s7, s10, s14, s30, s37	33	0.7914 (7914 modules)
3 DG	67.787	4,569.782	s7, s9, s14, s28, s30	25 14 32	0.4471 0.3915 0.6663

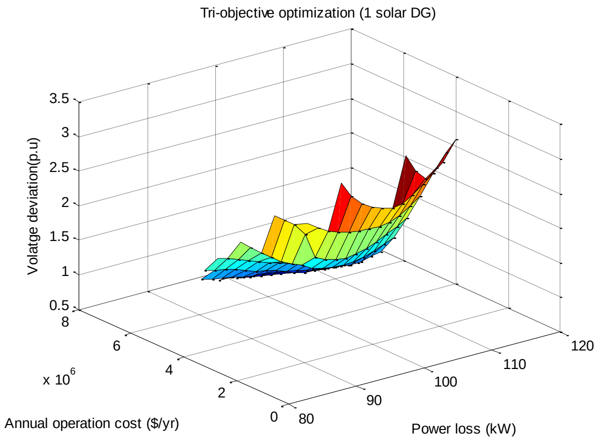
Table 4. Compromise solution of power loss and voltage deviation

Number of solar DGs	Power loss (kW)	Total voltage deviation (p.u)	Optimal network configuration	Optimal solar DG location	Optimal solar DG capacities (MW)
1 DG	86.057	0.986	s10, s14, s15, s26, s33	30	2.2289
3 DG	65.086	0.785	s7, s10, s13, s28, s36	31 29 17	0.7386 0.7004 0.7429

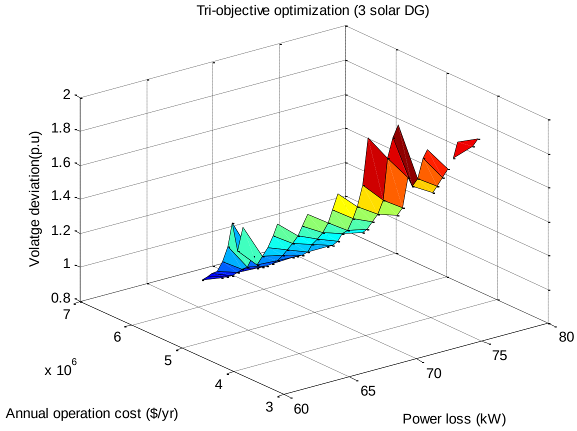
4.3. Tri-objective optimization

In this section, the optimization problem of the simultaneous network reconfiguration and the optimal integration of solar DGs is solved considering three objective functions (tri-objective optimization) of the active power loss, the operation cost and voltage deviation. As mentioned in the previous sections, the proposed evolutionary technique, the SPEA2, ensures a simultaneous and equal optimization of multiple objective functions without utilizing the weighted sum as in the most studies in the literature.

Figure.9 (a) and Figure 9 (b) depict the Pareto surface of the optimal solutions that are obtained from the simulation of both cases (allocation of a single and multiple solar DGs). The best compromise solution calculated by the fuzzy set theory is presented in Table 5., where the optimal network configuration and the best locations and sizing of solar DGs are given with their corresponding values of objective functions. The same observations as in the bi-objective optimization can be seen regarding the preference of integrating solar DGs in multiple locations resulting in a better reduction in the power loss and the voltage deviation in the distribution network. The proposed method provides a set of Pareto optimal solutions. As a result, the network manager has the freedom to choose the best compromise solution by selecting from the database of Pareto optimal solutions the one that responds to his/her optimization preference.



(a)



(b)

Fig.9. Pareto surfaces (a single and multiple solar DGs)

5. Conclusion

In this paper, the management operation of a simultaneous distribution network reconfiguration and an optimal integration of solar DGs has been successfully applied considering multiple optimization criteria. The objective functions include the minimization of the active power loss, the operation cost and the total voltage deviation, with respect to the system topology and security constraints.
An original combination of the evolutionary algorithm SPEA2 and the theories of spanning trees has been used to solve the optimization problem. The proposed method gives a Pareto set providing the network manager with multiple choices of optimal solutions. The simulations have been successfully carried out for the allocation and sizing of a single and multiple solar DGs. The obtained results prove that the network reconfiguration with simultaneous placement and sizing of multiple solar DG is more beneficial in terms of power quality enhancement than with a single solar DG. Furthermore, this study gives the network manager a robust tool to optimize the distribution network technically and economically. Future work will be dedicated to the resolution of the current optimization problem for different renewable DG technologies. The target is to solve this complex problem taking into consideration the time sequence variation in power generated by renewable DGs generation and in load.

Table 5. Compromise solution of the tri-objective optimization

Number of solar DGs	Power loss (kW)	Operations cost (M$/yr)	Total voltage deviation (p.u)	Optimal network configuration	Optimal solar DG location	Optimal solar DG capacities(MW)
1 DG	84.005	4,363.016	1.660	s7, s10, s14, s28, s34	32	1.436
3 DG	64.532	6,002.509	1.002	s7, s11, s14, s28, s32	32 29 17	0.5974 0.7212 0.6595

Acknowledgement

The authors gratefully recognize the technical and financial support of the Ministry of Higher Education and Scientific Research in Tunisia.

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