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Review

Optimal network reconfiguration and renewable DG integration considering time sequence variation in load and DGs

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ABSTRACT

Several studies of distribution network enhancement focused only on the optimization of either the integration of distributed generations (DG) or network reconfiguration. However, very few researches have been done for distribution network reconfiguration simultaneously with the DG location and sizing. This paper presents a multi-objective management operations based on network reconfiguration in parallel with renewable DGs allocation and sizing for minimizing active power loss, annual operation costs (installation, maintenance, and active power loss costs) and pollutant gas emissions. The time sequence variation in wind speed, solar irradiation and load are taken into consideration. An efficient evolutionary technique based on the Pareto optimality is adopted to solve the problem. A fuzzy set theory is used to select the best compromise solution among obtained Pareto set. The obtained results prove the efficiency and the accuracy of the suggested method for the network manager to find the optimal network configuration simultaneously with DG location and sizing considering multiple criteria.

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1. Introduction

In the last decade, there has been a growing interest in renewable energy sources due to the increased demand of the electricity and the significant depletion of fossil fuel. Therefore, research on the integration of distributed generations (DG) [1] into the distribution network has become very popular. 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, many researchers have proposed various optimization techniques (e.g. conventional, artificial intelligence and hybrid intelligent system techniques) [2].

In the literature, the traditional studies of optimal DG integration in the distribution network consider the power loss as the main objective to minimize, thus, the optimization problem is tackled as a mono-objective using analytical approach [2,3,4] or heuristic and meta-heuristic methods, e.g., ant lion optimization algorithm [5], mixed integer non-linear programming [6], genetic algorithm [7].

Recently, several studies have introduced other objectives to optimize in the problem of sitting and sizing of DGs such as voltage stability improvement, operation costs reduction, greenhouse gas emissions, etc. According to the literature, this multi-objective approach is tackled in two ways: for the first case, the objective functions are aggregated with proper weights to constitute a single objective. This approach is presented widely in several studies using artificial intelligent techniques such as genetic algorithm based methods (BSOA [8], GA [9]), computational methods (ICA [10], MNLP [11], ALOA [5]) and hybrid optimization techniques (GA/Fuzzy [12], HPSO [13]). A key limitation of these methods is that are not able to optimize multiple objectives equally, also the use of weighted aggregation leads to a long research effort. In the second case, the 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 used to generate only one solution with choosing weights of each objective. In order to avoid this disadvantage, several recent researches have adopted the multi-objective evolutionary algorithms based on the Pareto optimality concept to find the best locations and sizing of DGs, e.g., NSGAII [14], INSGAII [15], IMOHS [16], MOShBAT [17], etc. These evolutionary algorithms provide a set of Pareto optimal solutions where the network can select an option.

Besides the beneficial effects of the integration of DGs in a power system, the network reconfiguration can be considered as another alternative for the loss reduction in the distribution network. 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 while satisfying operational constraints. The first study of network reconfiguration was done in 1975 by Merlin and Back for active power loss reduction [18]. Over the years, several studies have been dedicated to solving the network reconfiguration by introducing other criteria to optimize such as the system reliability indices, voltage profile, etc.

The literature on distribution network reconfiguration shows a variety of optimization methods to solve this multi-objective problem such as weighted aggregation based techniques (genetic algorithms [19,20], modified honey bee mating optimization [21], binary group search [22], etc.) and Pareto optimality based techniques (shuffled frog leaping algorithm [23], NSGAII [24], artificial immune systems [25]).

The distribution network reconfiguration and the optimal integration of DGs are usually studied separately. However, the integration of these two sub-problems together can bring more benefits to the whole system. There are very few studies in the literature studying the network reconfiguration simultaneously with optimal allocation and sizing of DGs. The most of these researchers consider the power loss as a single objective to minimize. One of the first examples of these studies are presented in Refs. [26–28] where authors have investigated the significant reduction of power loss when combining reconfiguration and integration of DGs.

Recently, there are rare studies that have introduced other objectives to optimize to this complex problem. In Ref. [29], authors solved the problem considering the objective of minimizing the active power loss, increasing the feeder loading balance balancing and enhancing the voltage profile of the system using fuzzy-ACO (ant colony optimization) based on the Pareto optimality concept. However, they considered only a single DG based on PV array and DSTATCOM for determining their optimal location and size. In a recent paper [30], authors solved the problem using a multi-objective method based on bang-big crunch algorithm. They determined the sizes of DGs without considering their optimal placements. In Ref. [31], authors used an improved particle swarm optimization technique (IPSO) to solve the multi-objective problem of combined reconfiguration and optimal DGs integration. However, the utilized method considers the weighted sum of objective functions and thus, the objectives are not optimized equally as when using the Pareto optimality concept.

In previous papers that are reviewed above, the DGs models are assumed to be deterministic; however, they are intermittent in nature, especially in the case of DG based on renewable energy.

In this paper, we aim to solve the problem of simultaneous network reconfiguration and optimal allocation and sizing of DGs based on solar and wind energy, considering the research gaps of the previous studies mentioned above. An evolutionary technique called SPEA2 (Strength Pareto Evolutionary Algorithm 2) is proposed to solve the multi-objective optimization problem. This technique is based on obtaining a set of Pareto optimal solutions. An original combination of SPEA2 and spanning trees theories in order to generate feasible network configurations respecting the topological constraints. The objectives of the proposed problem consist of minimizing the active power loss, reducing the annual operation costs and also the gas emissions produced by the power plant feeding the substation of the distribution network. Then, a fuzzy set theory is used to extract the best-compromised solution from the obtained Pareto set. In addition, the stochastic nature of DGs based renewable energy is taken into account by solving the problem, according to hourly variation of solar irradiation, wind speed and load.

The remainder of this paper is organized as follows. In section II, the mathematical formulation for reconfiguration and DG sizing and allocating is presented. In section III, the model of DGs based renewable energy is described. In section IV, the principle concept of the proposed method is presented and applied to the problem. In section V, simulations, results, and comments are detailed. Finally, section VI concludes with a summary.

2. Problem formulation

The problem of simultaneous reconfiguration and optimal integration of DGs aims to find the optimal radial topology of the distribution network as well as the best location and sizes of DGs in order to minimize active power loss, annual operation cost and pollutant gas emissions. This nonlinear combinatorial problem is considered as a multi-objective optimization problem MOO with the following mathematical formulation [36]:

$$x = [x_1, x_2, ..., x_{nv}] \tag{1}$$

$$\min\left(f_1(x), f_2(x), ..., f_{N_{obj}}(x)\right) \tag{2}$$

$$\text{s.t.}\ \ h_i(x) = 0,\ \ i = 1, ..., p \tag{3}$$

$$g_i(x) \leq 0,\ \ i = 1, ..., q \tag{4}$$

where x is the decision vector and nv is the number of decision variables of the optimization problem. In our case of study, there are 3 sets of variables types that are the possible network configuration, the DG locations and sizes. $f_1(x), f_2(x), ..., f_{N_{obj}}(x)$ present the different objective functions to minimize and N_{obj} is the number of objective functions of the problem.

$h_i(x)$ and $g_i(x)$ are the equality and inequality constraints that should be satisfied. p and q are the number of equality and inequality constraints, respectively. In the next section, the objective functions and the constraints of the optimization problem are presented in details.

2.1. Objective functions

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 [21]:

$$f_1 = P_L = \sum_{b=1}^{N_b} R_b \cdot I_b^2 \tag{5}$$

where P_L is the total active power losses of the network, I_b is the module of current in the branch b, R_b is the resistance of branch b, and N_b is the set of branches.

2.1.2. Minimization of annual operation costs

Operation costs reduction is considered as an important issue in distribution network economics. It includes the total cost of DG installations, maintenance and active power loss. This objective function is as:

$$f_2 = f_{\cos\,t} = \left(C_{ins} + C_{main_{PV}}\right) \cdot P_{PV} + \left(C_{ins} + C_{main_{wind}}\right) \cdot P_{wind} + C_L \tag{6}$$

where $C_{ins_{PV}}$ and $C_{ins_{Wind}}$ are the installation costs of solar and wind turbine DGs per kW, respectively. C_{mainPV} and $C_{main_{wind}}$ are the maintenance costs of photovoltaic and wind DGs, respectively. P_{PV} and P_{wind} are the optimal installation sizes of photovoltaic and wind DGs. C_L is the annual cost of active power loss, which is calculated at peak load period as follows [4]:

$$C_L = EL \cdot (EC \times 8760) \tag{7}$$

where EC is unitary cost of active power loss in $/kWh and EL is the active power loss value in kW, which is defined as:

$$EL = F_{ls} \cdot P_{L_{pic}} \tag{8}$$

where $P_{L_{pic}}$ is the total active power loss at peak load and F_{ls} is the active loss factor for a given period (1 year in this study). All parameters of the annual operation costs are listed in Table 1:

2.1.3. Minimization of pollutant gas emissions

In the last decade, most governments in the world have been paid a considerable attention to air pollution caused by greenhouse gas emissions. Therefore, in this study, the minimization of gas emissions due to the integration of renewable DGs is taken into consideration. The gas emissions values are calculated according to the variation of power produced by the thermal plant feeding the distribution network substation after integration of DGs.

The emissions objective function to minimize is defined as follows [14]:

$$f_3 = f_{emission} = \sum_{i=1}^{N_p} K_i \cdot P_{sub} \tag{9}$$

Table 1
Parameters of operation cost.

Installation cost of photovoltaic DGs per kW ($C_{ins_{PV}}$)	3000 $
Installation cost of wind DGs per kW ($C_{ins_{wind}}$)	1000 $
Annual maintenance cost of photovoltaic DGs per kW ($C_{main_{PV}}$)	30 $
Annual maintenance cost of wind DGs per kW ($C_{main_{wind}}$)	35 $
Unitary cost of active power loss EC	0.06 $/kWh
The active power loss factor F_{ls}	0.48

Table 2
Pollutant gas emission intensities [14].

Gas	SO_2	NO_x	CO_2	CO
Emission intensity (g/kWh)	6.48	2.88	623	0.1083

where N_p is the number of types of pollutant gas; K_i is the emission intensity of the i^{th} pollutant gas from the thermal plant that feeds the substation; P_{sub} is the active power generated by the substation, which is expressed as:

$$P_{sub} = \sum_{i=1}^{N_{cus}} P_{load_i} + P_L - \sum_{j=1}^{N_{DG}} P_{DG_j} \tag{10}$$

where P_{load_i} is the load at node i, N_{cus} is the number of customer nodes, P_{DG_i} is the active power generated from the DG j , and N_{DG} is the number of DGs installed in power system. The emission intensities of the different pollutant gases are illustrated in Table 2.

2.2. Constraints

The combined reconfiguration and optimal allocation and sizing of renewable 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:

$$P_{sub} + \sum_{j=1}^{N_{DG}} P_{DG_j} - \sum_{i=1}^{N_{cus}} P_{load_i} - P_L = 0 \tag{11}$$

2.2.2. Inequality constraints

- Bus voltage limits:

$$V_{\min} \le V_i \le V_{\max} \tag{12}$$

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

- Branch current limits:

$$|I_b| \le I_b^{\max} \tag{13}$$

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

- DG capacity constraint:

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

$$0.1 \times \sum_{i=1}^{n} P_{load_i} \le \sum_{i=1}^{N_{DG}} P_{DG_i} \le 0.6 \times \sum_{i=1}^{n} P_{load_i} \tag{14}$$

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 the spanning trees (graph theories) [32] is used for the distribution network reconfiguration. According to these theories, the radial structure of a *graph*, which is in our case a distribution network configuration, can be verified as follows:

$$\sum_{b=1}^{N_b} \beta_b = n - N_{sub} \tag{15}$$

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. Renewable DG generation output

The models of renewable DG output generations, used in this study, are defined according to the metrological variables (solar irradiance, temperature and wind speed). Once, the network manager is provided with the forecast data of the metrological variables for the period of study, it will be possible to determine the variation in the power output of renewable DGs for each time sequence of the period, which will be used in the research of an optimal solution of the problem.

In fact, the variation in the DG power output and load causes the variation in the load flow of the power system. The time sequence variation in the load flow intervenes in the search process of the best network configuration and DG locations and sizes that provide the optimal reduction in power losses, pollutant gas emissions and operations cost. The power output of each renewable DG used in this study (i.e. wind turbine and solar generator based on photovoltaic modules) is calculated utilizing its corresponding power generation function, which is defined in detail in the next subsections.

3.1. Solar DG power output

The active generation output of solar DG is calculated by the summation of the total energy produced by the photovoltaic (PV) modules. The adopted computational method of PV module has been used by several studies in the literature [33], [34]. This power generation function takes into consideration the solar irradiance, the ambient temperature, and the characteristics of the PV module. The active generation output of a PV module is expressed as a function of the solar irradiance as follows:

$$P_{DG_{PV}}(ir) = N_{PV} \cdot FF \cdot V_y \cdot I_y \tag{16}$$

where ir is the solar irradiance (W/m^2), FF is the fill factor, V_y and I_y are the voltage and the current outputs of the PV module, respectively. These parameters are presented in details in the equations below:

3.1.1. The module fill factor

The fill factor FF measures the quality of a solar module. It is defined as the ratio of the maximum, obtained power output from the module, to the product of open circuit voltage and short-circuit current [33,34,43]:

$$FF = \frac{V_{MPPT} \cdot I_{MPPT}}{V_{oc} \cdot I_{sc}} \tag{17}$$

where V_{MPPT} and I_{MPPT} are respectively the voltage and current maximum power point, respectively. I_{sc} and V_{oc} are the short-circuit current (A) and the open-circuit voltage (V), respectively.

3.1.2. The module voltage output

The voltage output of a solar module is calculated as follows [33,34]:

$$V_y = V_{oc} - T_{emp_V} \cdot Tc_y \tag{18}$$

where T_{emp_V} is the voltage temperature coefficient (V/°C) and Tc_y is the temperature of the PV module (°C) expressed as [33,34]:

$$Tc_y = T_{amb} + ir \cdot \left(\frac{N_{ot} - 20}{0.8}\right) \tag{19}$$

where T_{amb} and N_{ot} are the ambient temperature and the nominal operating temperature (°C) of the PV module, respectively.

3.1.3. The module current output

The current output of the module is defined in function of the solar irradiance ir, the short-circuit current I_{sc} (A), the ambient temperature T_{amb} (°C), and the current temperature coefficient T_{emp} (A/°C). That is [33,34]:

$$I_y = ir \cdot (I_{sc} + T_{emp_I} \cdot (Tc_y - 25)) \tag{20}$$

3.2. Wind turbine DG power output

The output power of wind turbine DG (WT) depends on the wind speed as well as the parameters of the power performance curve (Fig. 1). The WT DGs are classified according to their speed regulation capacity and their power output into two categories, i.e. fixed speed WT DG and variable speed WT DG. Commonly, the variable speed WT DG type is the most preferred by utilities for integration in distribution networks [35]. Indeed, this type of WT DG ensures a more efficient power caption from the wind speed than fixed speed WT DG, also it provides voltage and frequency control in the network. The power generation function of a typical wind turbine is expressed as follows [34]:

$$P_{DG_{wind}} = \begin{cases} 0 & V_{wind} < V_{cin} or V_{wind} > V_{cout} \\ P_{rated} \cdot \dfrac{V_{wind} - V_{cin}}{V_N - V_{cin}}, & V_{cin} \le V_{wind} \le V_N \\ P_{rated} & V_N \le V_{wind} \le V_{cout} \end{cases} \tag{21}$$

where V_{cin}, V_{cout} and V_N are the cut-in speed, the cut-out speed and nominal speed of wind turbine, respectively. V_{wind} is the wind speed and P_{rated} is the rated output power of turbine that is be defined as:

$$P_{rated} = 0.5 \cdot \rho \cdot A \cdot V_{wind}^3 \cdot C_p \tag{22}$$

where A is the swept area of rotor [34,36] ρ is the density of air, V_{wind} is wind speed, and C_p is the power co-efficient.

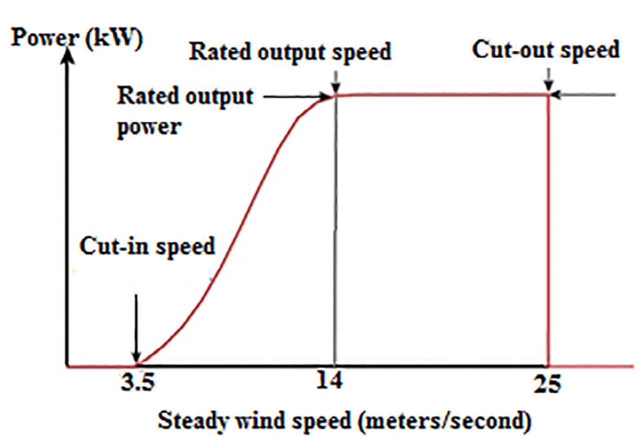

Fig. 1. Wind turbine power output with steady wind speed.

4. Proposed optimization method and its application to network reconfiguration problem in parallel with DG integration

In this work, several criteria are considered in solving the problem of network reconfiguration in parallel with DG integration. In this framework, the evolutionary approach is chosen thanks to its developed potential in solving multi-objective optimization problems [37].

In general, evolutionary algorithms have the same structure of genetic algorithms but with certain modified operators such as the selection and the reproduction. Furthermore, despite the classical approaches, the evolutionary algorithms are based on the Pareto optimality that has the feature of optimizing multiple objectives equally without discrimination. Thus, a set of optimal solutions can be obtained in a single run instead of several runs as in classical methods. At the end of the evolutionary process, a set of optimal solutions are obtained presenting the Pareto front where the optimizer can select an option.

4.1. Overview of Strength Pareto Evolutionary Algorithm 2

An evolutionary algorithm called the Strength Pareto Evolutionary Algorithm 2 (SPEA2) is adopted, in this paper, to solve the problem of simultaneous network reconfiguration and optimal integration of DGs.

The proposed SPEA2 is a multi-objective evolutionary algorithm developed by the scholar Zitzler in 2001 and published in his report [38], which is an improved version of SPEA [39] (developed by the same author in 1999).

As an evolutionary algorithm, SPEA2 has the structure of genetic algorithms with modifications in certain operations such as selection and reproduction. In general, a genetic algorithm is based on the biology evolution. It uses a population of individuals, also known as chromosomes: Each one represents a possible solution to the optimization problem. All individuals are assigned fitness values, based on their performance, and only the fittest individuals are combined through a crossover and mutation operations to produce offspring. The selection, crossover and mutation operations are repeated across generations in order to create individuals that are fitter than their predecessors. The termination condition corresponds to a specified number of generations or until all the population converges to a single individual (solution).

All evolutionary algorithms, including SPEA2, differ from the genetic algorithm in the fitness assignment by using the dominance concept (explained in the next section) to rank solutions. This concept leads, at the end of the evolutionary process, to a set of Pareto optimal solutions instead of one. Furthermore, the dominance concept ensures an equally optimization of objective functions without discrimination, which lead to more accurate solutions.

The only similarity of SPEA2 and its previous version, SPEA [39], is that both use an external archive to conserve the fittest solutions. However, SPEA is criticized for its lack of efficiency in its fitness assignment procedure and external archive exploitation. Indeed, in SPEA fitness assignment, individuals are dominated by the same

Pareto member receive the same level of fitness, which is not realistic, and also the Pareto optimal solutions dominate a large number of solutions are assigned worse fitness instead of better one [40]. In addition, the clustering procedure used by the SPEA technique tends to lose optimal solutions that are in the extremes of the archive and sometimes leads to the non convergence of solutions [41].

In response to the SPEA criticisms, a new version, called SPEA2, is developed with new features including a more complicated selection of operations (i.e. fitness assignment and environmental selection): Firstly, unlike the SPEA clustering mechanism, SPEA2 uses a new archive truncation operator (defined in section 4.2.3 and Appendix A.2), which guarantees the preservation of boundary solutions from loss. For of an overloaded archive, this operator uses a density estimation technique, in order to conserve only the optimal solutions in less crowded regions, which leads to better results in terms of convergence and spread.

Secondly, SPEA2 differs from other evolutionary algorithms, such as SPEA, NSGAII and PESA, in the way it performs the fitness assignment (explained in details in section 4.2.2). Indeed, the SPEA2 method is the only evolutionary algorithm that uses the nearest neighbor density technique estimation (see Appendix A.1) in its fitness calculation mechanism, which provides a better guidance of the research process. Furthermore, this feature allows the SPEA2 method to provide more accurate and well spread solutions than the other evolutionary algorithms [38]. Finally, unlike SPEA, SPEA2 uses a fixed size of the archive, which is conserved constant by the truncation operator and only the fittest individuals of the archive participate in recombination process. Thus, a high quality offspring can be obtained.

SPEA2 is also a well-tested algorithm that has been verified to outperform other state of the art counterparts. In fact, according to certain studies of performance analysis in the literature [38,42] this technique has been demonstrated to outperform SPEA, PESA, and NSGAII in multiple test problems. Kinkle [42] and Mori [43] compared NSGAII and SPEA2 in solving practical problems (a multi-objective environmental/economic dispatch problem and distribution network expansion planning) and demonstrated that the solutions obtained using SPEA2 were better than NSGA II in terms of convergence and diversity.

Owing to these features, SPEA2 is chosen to be applied to the multi-objective planning framework presented in this paper. The application of the suggested SPEA2 to our case study is explained in details in the next sub-section.

4.2. Optimization problem resolution using SPEA2

The aim of the problem of simultaneous network reconfiguration and optimal DG integration is to find the best radial configuration of the distribution network and the optimal locations and sizes of DGs that satisfy a single objective or multiple ones fixed by the network manager.

In this work, multiple objectives are considered for minimization, e. i., the active power loss, the operation costs and the pollutant gas emissions.

In this section, the different steps of this multi-objective optimization problem resolution are explained using the proposed SPEA2 technique.

4.2.1. Generation of initial population

The SPEA2 technique starts by a random generation of an initial population P_0 of individuals (chromosomes) and an external archive A_t where the best individuals will be copied in the selection step of the algorithm. An individual presents a possible decision vector of the optimization problem. According to our case of study, an individual is composed of a possible radial network configuration as well potential DG locations and sizes.

The radial structure of distribution networks topology is defined as the indices of its opened switches that can be changed to give other possible radial network configurations. These latter are generated randomly when creating the initial population, so unfeasible ones can be obtained, such as network structures including closed loops or islanded nodes. Thus, referring to graph theories, the Depth First Search (DFS) algorithm [32] is put forward to evaluate the feasibility of the generated network configurations.

The DFS is defined as a recursive algorithm that involves exhaustive searches of all nodes and their incident closed branches from terminal nodes to the source node by using the idea of backtracking. The radial structure and the feasibility of the obtained configurations are proved when each node in the graph (the network) has a unique path between it and the source node.

Added to that, each generated individual is evaluated according to the problem security constraints. Hence, a power flow calculation is done for each combination of network configuration and DG locations and sizes to verify whether the solution causes any violation of the system security constraints (bus voltage and branch current limits presented in section 2.2). The verification is performed utilizing the load flow calculation based on the Backward Forward Sweep (BFS) method [44]. This load flow technique is widely used in many studies of distribution network optimization thanks to its simplicity and promptness.

The genetic encoding of individuals in this study is presented as follows:

$$ind_i = \left[s_1, s_2, ..., s_{n_{open}}; loc_1, loc_2, ..., loc_{N_{DG}}; P_{DG_1}, P_{DG_2}, ..., P_{DG_{N_{DG}}}\right]^T \tag{23}$$

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

Only feasible individuals satisfying the topological and security constraints of the optimization problem will be maintained in the initial population.

4.2.2. Fitness assignment

In this step, the objective-function values of each individual of the population are calculated in order to evaluate them according to their fitness values. In the proposed SPEA2, the performance calculation is based on the relationship of "*dominance*" that determines the Pareto optimality concept. The definitions of the dominance relationship are as follows [15]:

A solution x_1^* dominates (is better than) a solution x_2^* (denoted by $x_1^* \prec x_2^*$) if and only if:

$$\textbf{1)}\ \forall i,j \in \left\{1,2,...,N_{obj}\right\}, \exists f_i(x_1^*) \le f_j(x_2^*) \wedge f_i(x_1^*) < f_j(x_2^*) \quad \text{for } j \ne i \tag{24}$$

2) For $\Omega = \{x_i^*, i = 1, ..., n_{solutions}\}$, solution x^* is said to be a non-dominated solution (Pareto solution) of the set of Ω if $x_i^* \in \Omega$, and there is no solution $x_j^* \in \Omega$ for which x_j^* dominates $x^*, j \ne i$.

In our case of study, a solution x^* is an individual (a possible combination of network configuration and DG locations and sizes). The set functions f present the different objective functions of the problem, namely the active power loss, the operation costs and the pollutant gas emissions.

3) Assume that set P^* contains all non-dominated solutions of $x^* \in \Omega$, then $PF = \{[f_1(x^*), f_2(x^*), \ldots, f_{Nobj}(x^*)]^T, x^* \in P^*\}$ is the Pareto front of set Ω.

SPEA2 is based on a complicated fitness assignment (see appendix A.1) that simultaneously takes into account the non-domination rank of each individual in the population and its density information. Therefore, individuals that dominate a large number of other ones in the population and that are not in crowded regions of the Pareto front are considered as the fittest.

The purpose of using such a fitness assignment is to push the search of optimal solutions towards less crowded regions and to help obtain a well-spread Pareto front.

Fig. 2 shows the Pareto front structure of our case of study when considering two objective functions to minimize. In this example, active power loss and operation costs are considered as the objective functions of the problem. Each non-dominated solution presents the set of objective functions corresponding to an optimal composition of network reconfiguration and DG locations and sizes (decision vector). The purpose of this is to obtain a shape of the Pareto front, as the one depicted in Fig. 2, where the optimal solutions are uniformly distributed along it. This Pareto front shape is a proof of the efficiency and accuracy of an optimization algorithm.

4.2.3. Environmental selection

In the environmental selection of the proposed SPEA2, the fittest individuals are copied to an external archive with a specified size to keep them from loss during the crossover and mutation operations. The archive is updated from one generation to another by adding new non-dominated individuals until the size of the archive overflows. In this case, a truncation operator (see Appendix A.2) intervenes by conserving the best non-dominated solutions in less crowded regions for the next generation and removing the others. This operator is iteratively applied until the archive reaches its fixed size. This truncation strategy preserves the fittest and the most spread solutions that will constitute the mating pool of the recombination step.

4.2.4. Genetic recombination

In the suggested SPEA2, individuals are selected from the archive for reproduction. The selection approach is based on a tournament selection where the best non-dominated individuals in less crowded regions are preferred for recombination. Commonly, SPEA2 will use uniform crossover and mutation operators when the decision variables are of an integer or float type. However, in our case of study, a network configuration is encoded as indices of the

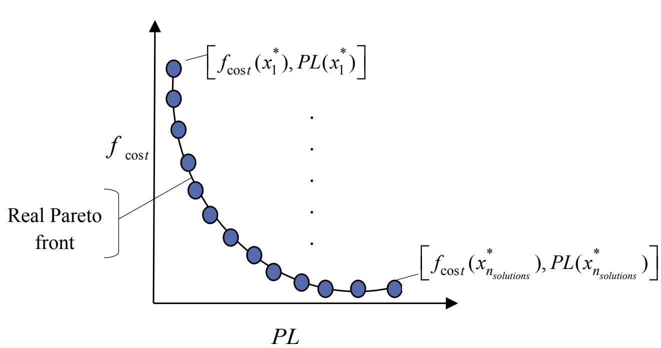

Fig. 2. Pareto front shape of power-loss and operation-cost minimization.

network's open switches; thereby, non feasible configurations can be obtained like isolated nodes, loops, and non radial structures. To prevent this drawback, spanning-tree theories are applied to the crossover and mutation operators so as to preserve the radial structure of the obtained network configurations.

Firstly, in the crossover step the property of Kruskal based on the spanning-tree theories is utilized by exchanging one or several branches between two network configurations that present the parents to obtain new ones (offspring) with radial structures. This property is defined as follows [45]:

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

The mutation operator is applied using the same property by randomly selecting an open branch to be exchanged by another one in the same spanning tree while preserving its radial structure. After the reproduction step, the new obtained individuals are evaluated according to the problem's constraints, and only feasible ones will constitute the population of the next generation. The algorithm is iteratively repeated until a specified number of generations is reached or the fitness values of individuals remain constant through generations.

The reproduction is a very pertinent step in the evolutionary process. In fact, the creation of new individuals ensures the diversity of solutions and their convergence towards the Pareto front.

4.3. Best compromise solution

The resolution of the problem of combined network configuration and DG placement and sizing provides, at the end of the evolutionary process of the proposed SPEA2, a set of Pareto optimal solutions corresponding to the best values of objective functions. The network manager can select, from this Pareto set, a final solution regard to his preference. Otherwise, a decision-making based on fuzzy set theory [46] can be used to extract the best compromise solution among the Pareto set. The membership function of this theory is formulated as follows:

$$\mu_i^j = \begin{cases} 1, & f_i \le f_i^{\min} \\ \dfrac{f_i^{\max} - f_i^j}{f_i^{\max} - f_i^{\min}}, & f_i^{\min} \le f_i \le f_i^{\max} \\ 0, & f_i \ge f_i^{\max} \end{cases} \tag{25}$$

where μ_i^j is the membership function of the j^{th} solution for the i^{th} objective function f_i^j, and $f_i^{\max}$ and $f_i^{\min}$ present the maximum and minimum values of the i^{th} objective function among all non-dominated solutions, respectively.

The fuzzy decision will be applied to extract the best compromise solution x^{j*} in Pareto optimal solutions, such that:

$$\mu^{j*} = \max_{j=1,\ldots,M} \left\{ \frac{\sum_{i=1}^{N_{obj}} \mu_i^j}{\sum_{j=h}^{M} \sum_{i=1}^{N_{obj}} \mu_i^h} \right\} \tag{26}$$

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

4.4. Flowchart of the proposed method

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

5. Tests and results

The application of the proposed method to the optimization problem of simultaneous network reconfiguration and integration of DGs is implemented in MATLAB's environmental programming. The simulations are carried out on the 33 IEEE bus power system [47], 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. The corresponding line impedances, and the active and reactive power can

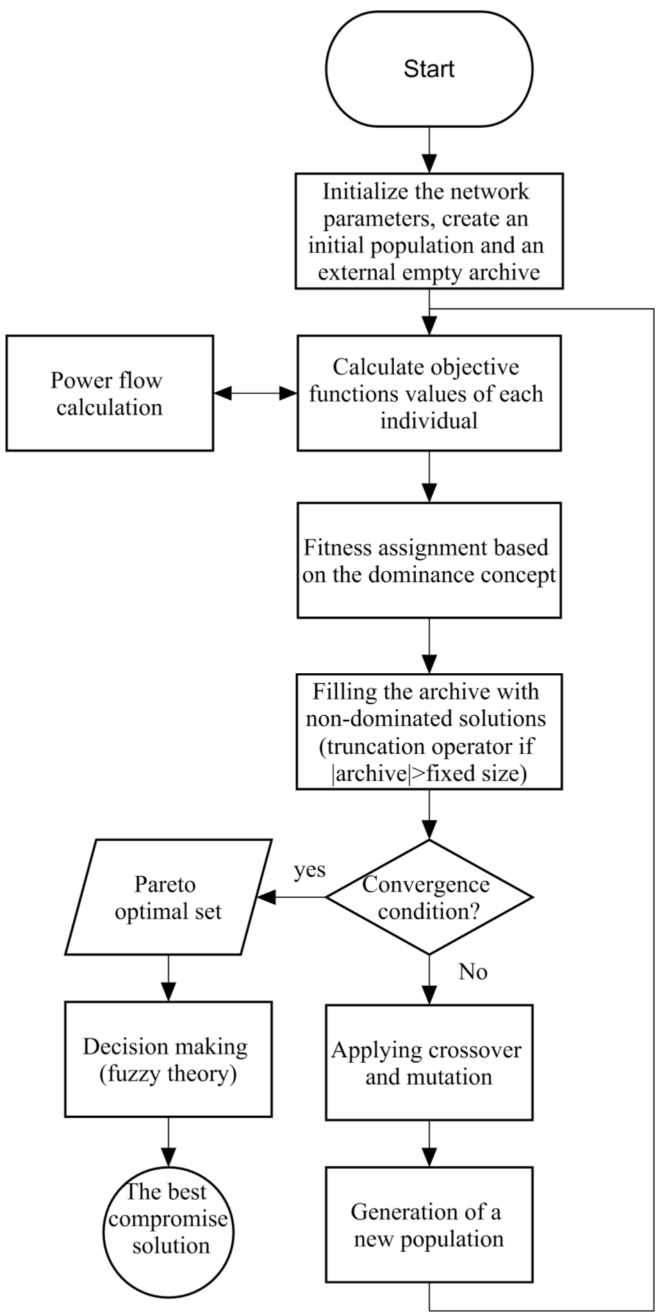

Fig. 3. Flowchart of proposed method.

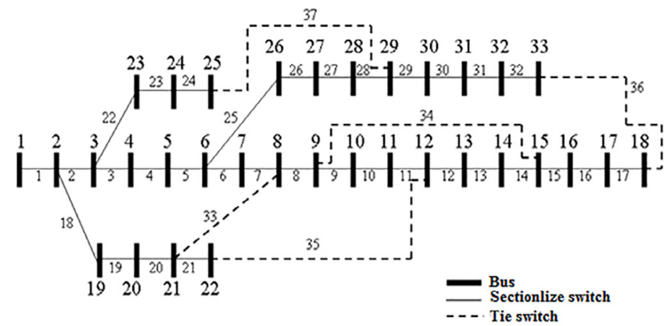

Fig. 4. IEEE 33 buses test system.

be found in Ref. [15].

5.1. 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 account the same penetration rate of the DG:

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

The obtained results of the two simulation scenarios are presented in Table 3. It is clear, the scenario 1 where the DG is optimally integrated without the network reconfiguration, provides a 47.88% reduction of active power loss. However, the active power loss is reduced by 60.23% of the scenario 2. These results justify the benefits of combining the network reconfiguration and the DG integration in minimizing the active power loss of the distribution network.

Besides, the obtained bus voltage profile for the two scenarios is investigated. It is observed from Fig. 5, that the bus voltage values are improved more significantly when combining the network reconfiguration with the DG integration (scenario 2) than when integrating a DG only (scenarios 1). Indeed, the minimum voltage for scenario 2 is enhanced to 0.9616 p. u, which is above the minimum threshold of 0.95 p. u.

5.2. Mono-objective optimization

There are few studies in the literature treating the problem of simultaneous reconfiguration and optimal integration of DG in the distribution network, and most of them have considered a single objective to minimize (active power loss) [48], [27]. In this section, the proposed method is compared with other techniques that were utilized in the literature to solve this problem. The comparisons are based on similar assumptions and initial conditions, which are:

Table 4 illustrates the obtained results using the proposed method (SPEA2) as well as those in the literature (harmony search algorithm (HSA) and fireworks algorithm (FWA)). As seen, the suggested method provides an optimal solution, giving the best reduction of active power loss (71.11%) comparing with the other methods. Consequently, the SPEA2 could be considered as an efficient tool for solving the proposed problem due to its high convergence ability and accuracy.

Table 3
Benefits of the proposed operations in power loss reduction.

Scenarios	Configuration	Optimal DG location	Optimal DG size (MW)	Active power loss (kW)	% Power loss reduction
Base case	s33, s34, s35, s36, s37	–	–	202.67	–
Scenarios1 (only DG integration)	s33, s34, s35, s36, s37	6	2.229	105.63	47.88%
Scenarios 2 (DG + reconfiguration)	s9, s14, s27, s33, s34	29	1.930	80.59	60.23%

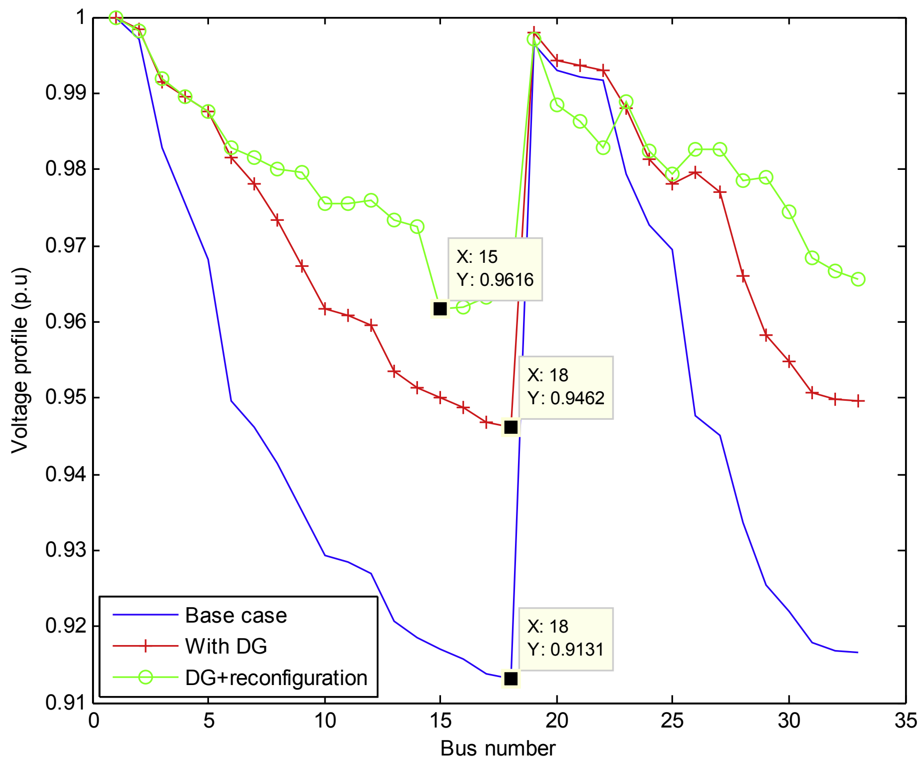

Fig. 5. Bus voltage profile improvement before and after combining the network reconfiguration with DG integration.

Table 4
Comparison with other studies in mono-objective optimization.

Method	Active power loss (kW)	%Power loss reduction	Optimal network configuration	Optimal Locations of DGs	Optimal sizes (MW) of DGs
Base case	202.67	–	s33, s34, s35, s36, s37	–	–
HSA [48]	63.95	68.44%	s7, s14, s10, s32, s28	32	0.5258
				31	0.5586
				33	0.5840
FWA [27]	67.11	66.88%	s7, s14, s11, s32, s28	32	0.5367
				29	0.6158
				18	0.5315
The proposed method	58.55	71.11%	s11, s27, s30, s33, s34	18	0.6910
				29	0.7334
				8	0.7429

5.3. *Bi-objective optimization*

The purpose of the bi-objective optimization is to investigate the relation among the different objective functions considered in this work. Thus, the problem of simultaneous network reconfiguration and optimal DG integration is solved considering the minimization of a pair of objective functions in each case. Simulations are performed for each case using the proposed method and considering the following assumptions:

- 3 DGs are considered for integration in IEEE 33 bus test system.
- The penetration rate is between 10% and 60% of the total load of the system.
- Two objectives to minimize in each case.

Distribution relations of the Pareto optimal solutions among different objective functions are depicted in Fig. 6. As seen in Fig. 6 (a), the Pareto front of optimal solutions is a linear distribution for active power loss objective and gas emissions objective. The relation between annual operation costs objective and gas emissions objective is shown in Fig. 6 (b). The Pareto front in Fig. 6 (b) presents a reciprocal distribution for two objectives. Indeed, a minimum value of operation costs (3390 M$/yr) corresponds to a high value of

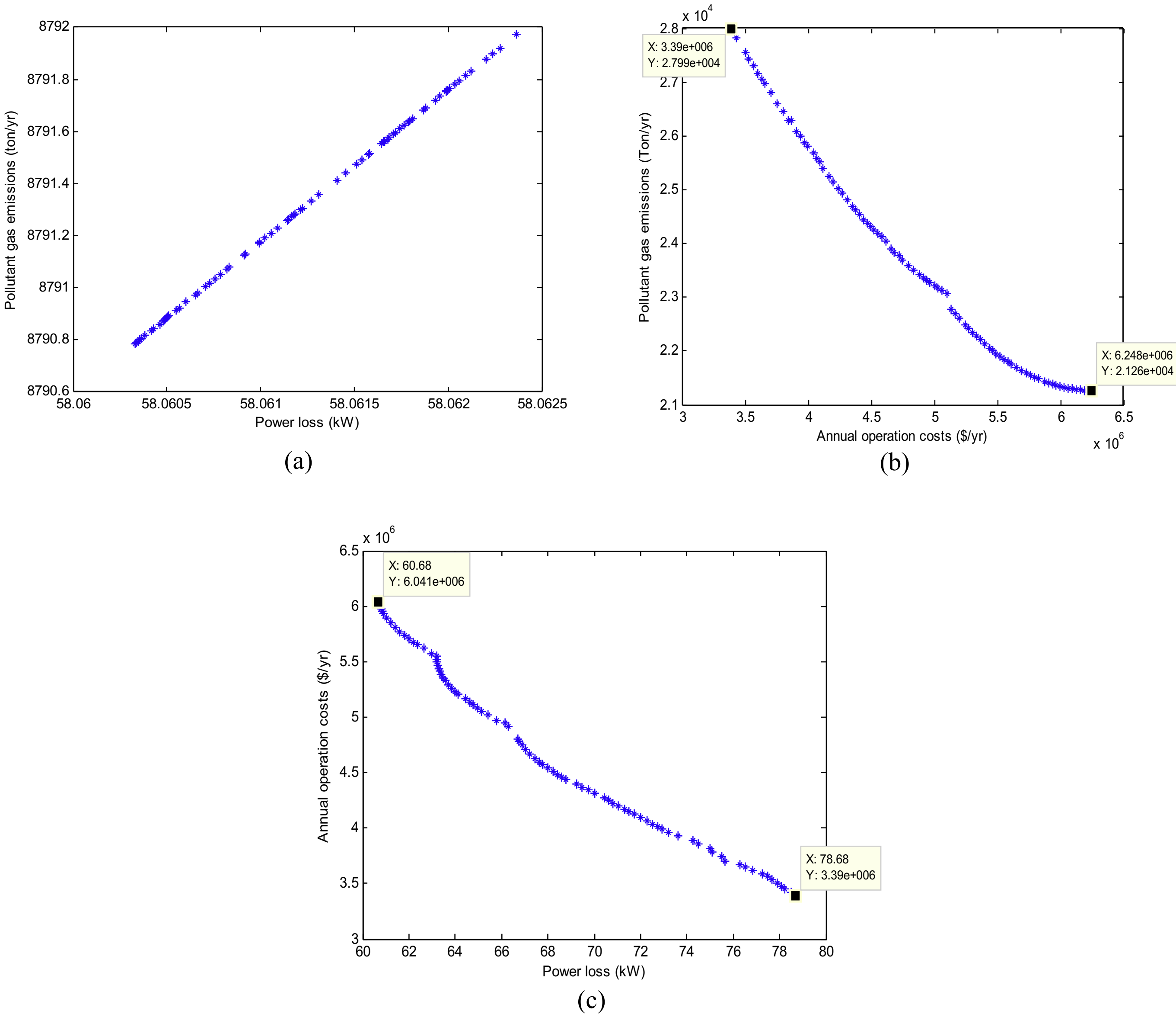

Fig. 6. Relation between different objective functions.

gas emissions (27990 ton/year) and vice versa. Fig. 6 (c) shows also a contrasting relation between the active power loss objective and annual operation costs. According to the Pareto front, the minimum value of active power loss (60.68 kW) corresponds to a higher value of operation cost (6041 M$).

The best compromise solutions of the bi-objective optimization problems are presented in Tables 5–7. The compromise solution of each case is extracted from the Pareto set using the fuzzy set theory

Table 5
The best compromise solution of active power loss and costs minimization.

Active power loss (kW)	Annual operation costs (M$/year)	Optimal network configuration	Optimal DGs locations	Optimal DG sizes (MW)
67.787	4569.788	s7, s9, s14, s28, s30	25	0.4471
			14	0.3915
			32	0.6664

Table 6
The best compromise solution of active power loss and emissions minimization.

Active power loss (kW)	Pollutant gas emissions (MTon/year)	Optimal network configuration	Optimal DGs locations	Optimal DG sizes (MW)
60.225	8985	s7, s10, s14, s28, s31	24	0.7416
			30	0.6689
			18	0.7429

Table 7
The best compromise solution of emissions and costs minimization.

Pollutant gas emissions (MTon/year)	Annual operation costs (M$/year)	Optimal network configuration	Optimal DGs locations	Optimal DG sizes (MW)
22,479	5245.109	s7, s8, s10, s27, s32	29	0.6384
			15	0.6775
			31	0.4125

(defined in section 4) in order to facilitate the decision making of the network manager.

5.4. Experiment on tri-objective optimization considering time sequence variance in renewable DGs and load

In this section, we propose to solve the network reconfiguration simultaneously with optimal sitting and sizing of renewable DGs taking into account the time sequence variance in load and DGs. Indeed, in the literature, the optimization problem of parallel network reconfiguration and optimal integration of renewable DGs has been solved considering a constant power generation model. However, these types of DGs (PV and WT DG) are intermittent in the real world and depend on environmental and geographical location. Furthermore, taking into account the time variation of load and DG generation allows the network manager to be provided by an accurate and more realistic solution of optimal network configuration and DG sizes and locations.

The hourly data of renewable DG power outputs are calculated using their corresponding power generation functions (defined in section 3) and the load forecasts of an average day in a summer season, which is assumed as a reference period of the optimization study. The curves of the hourly variance in the PV DG, WT DG and load of an average summer day as example of study are illustrated in Fig. 7 (a), (b) and (c).

This optimization problem is solved using the proposed SPEA2 and considering tri-objective functions to minimize, i.e. active power loss, annual operation costs and pollutant gas emissions. Two types of renewable DGs will be installed, that are WT DG and PV DG. The rated unit power of each wind turbine and PV module is set

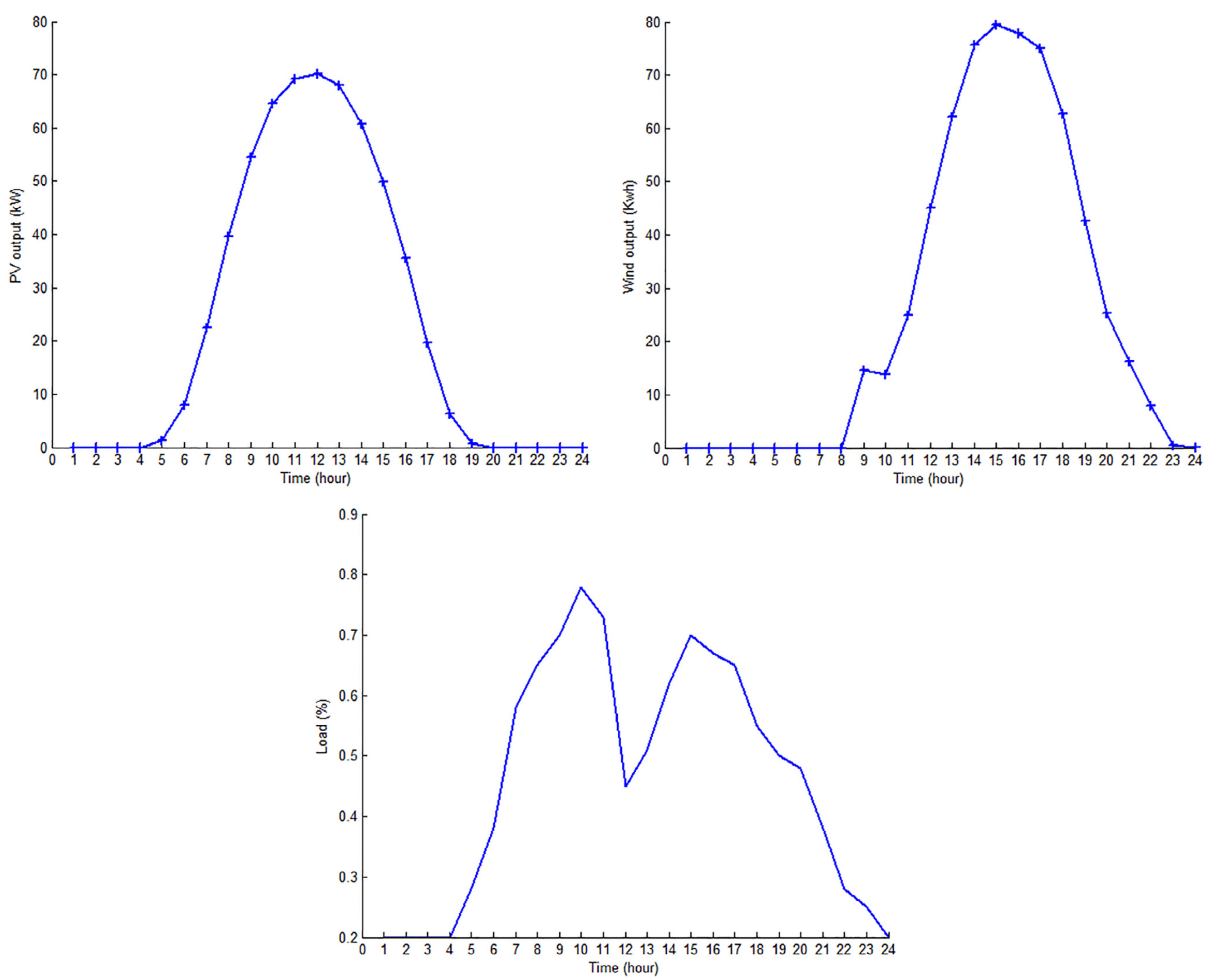

Fig. 7. Hourly average variation curves of PV, WT DGs and load (on an average summer's day example).

Table 8
Optimal solutions of 24 h.

Hour	Optimal configuration	PV DG		WT DG		Active power loss (kW)	Operation costs (M$/yr)	Pollutant gas emissions (MTon/yr)
		Optimal Location	Optimal Size (MW)	Optimal location	Optimal size (MW)			
1	Base case: s33, s34, s35, s36, s37	–	–	–	–	202.67	28.761	21,705
2	s33, s34, s35, s36, s37	–	–	–	–	202.67	28.761	21,705
3	s33, s34, s35, s36, s37	–	–	–	–	202.67	28.761	21,705
4	s33, s34, s35, s36, s37	–	–	–	–	202.67	28.761	21,705
5	S7, s9, s29, s34, s36,	32	0.170182	–	–	11.9019	516.791	6019
6	s7, s9, s14, s28, s36	31	0.1579	–	–	19.863	481.562	7982
7	s7, s9, s14, s28, s36	31	0.23030	–	–	42.932	703.000	11,725
8	s7, s21, s31, s37, s17	25	0.712583	–	–	62.663	2169.294	12,503
9	s7, s10, s27, s32, s34	16	0.420650	25	0.746481	51.902	231,014.003	10,905
10	s7, s10, s13, s28, s36	30	0.551347	17	0.379990	65.965	118,700.054	13,372
11	s7, s8, s9, s32, s37	15	0.568230	32	0.613227	52.217	190,502.054	10,881
12	s10, s14, s28, s33, s36	31	0.368027	8	0.21203	24.455	66,403.999	7985
13	s7, s10, s14, s28, s31	33	0.391721	29	0.506069	26.572	157,014.438	7985
14	s7, s11, s14, s28, s32	32	0.434409	16	0.303035	57.667	94,632.185	13,011
15	s7, s8, s32, s 34,s37	30	0.512284	16	0.302455	57.196	94,560.507	12,589
16	S9, s14, s17, s26, s33	30	0.421373	27	0.321599	58.829	100,444.017	123,669
17	s7, s8, s14, s17, s27	29	0.456865	12	0.302279	46.324	94,392.312	10,717
18	s7, s10, s13, s26, s36	31	0.570452	8	0.210289	35.815	66,401.772,	9255
19	s7, s9, s14, s27, s31	33	0.224800	25	0.520183	28.446	160,819.999	8482
20	s7, s9, s15, s28, s34	–	–	31	0.599558	23.637	184,773.599	7,664
21	s7, s9, s14, s16, s28	–	–	31	0.499919	19.323	153,977.945	7113
22	s7, s9, s14, s16, s27	–	–	31	0.399941	11.716	123,181.825	5464
23	s7, s8, s28, s31, s34	–	–	15	0.273965	6.418	81,299.817	3979
24	s9, s14, s25, s32, s33	–	–	30	0.199920	3.789	61,590.618	3132

to 100 kW and 100 W, respectively. For simplicity, each DG is PQ type with stable unitary power factor.

Taking into account the time sequence variance in renewable DGs (solar irradiation, wind speed and temperature), and the load on an average summer day as an example, the proposed multi-objective problem is optimized at each time sequence. The optimal solutions of each time period are presented in Table 8, from which a best compromise solution (network configuration and DG locations and sizes) is chosen, from the obtained hourly solutions, in order to be applied to the distribution network. This compromise solution is considered as the best solution that simultaneously provides the optimal values of objective functions without discrimination. In this case, the fuzzy set theory is put forward to help the network manager to extract this best compromise solution, to be applied to the power system, referring to the hour that provides the best values of objective functions.

As seen in Table 8, there are no optimal solutions of PV DG location and sizing at 1~4th, and 20–24th time periods; this is due to the weak or the absence of solar irradiance at these time sequences. For WT DG location and sizing, there are no optimal solutions at 1~8th time period because the wind speed intensity is less than the value of the interlocking of the wind turbine. In return, the period of the common functioning of PV DG and WT DG is during 9–19th time period, where the optimal location and sizing of both renewable DGs are obtained.

During the period of the common functioning, the obtained optimal solutions provided a significant reduction of active power loss and pollutant gas emissions that reached about 88% and 63% at hour 12, respectively. The variations of these objective functions before and after the simultaneous network reconfiguration and

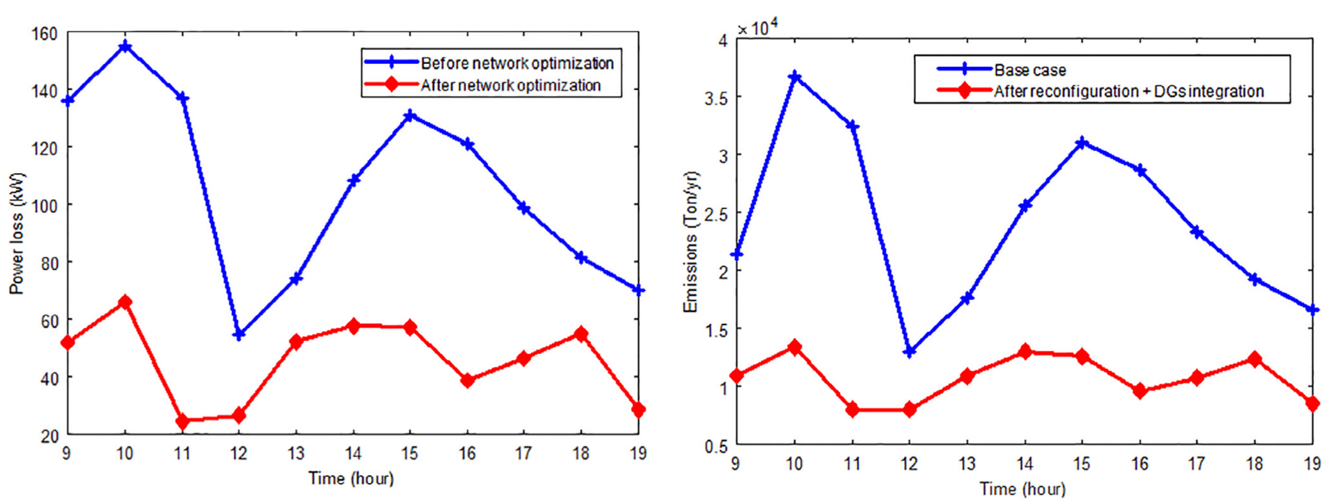

Fig. 8. Time sequence variance in power loss and emissions before and after network optimization.

Table 9
The best compromise solution.

Optimal configuration	PV DG		WT PV		Power loss (kW)	Operation costs (M$/an)	Pollutant gas emissions (MTon/yr)
	Optimal location	Optimal size (MW)	Optimal location	Optimal size (MW)			
s10, s14, s28, s33, s36	31	0.368027 (36802 modules)	8	0.506069 (5 WT)	24.455	66403,999	7985

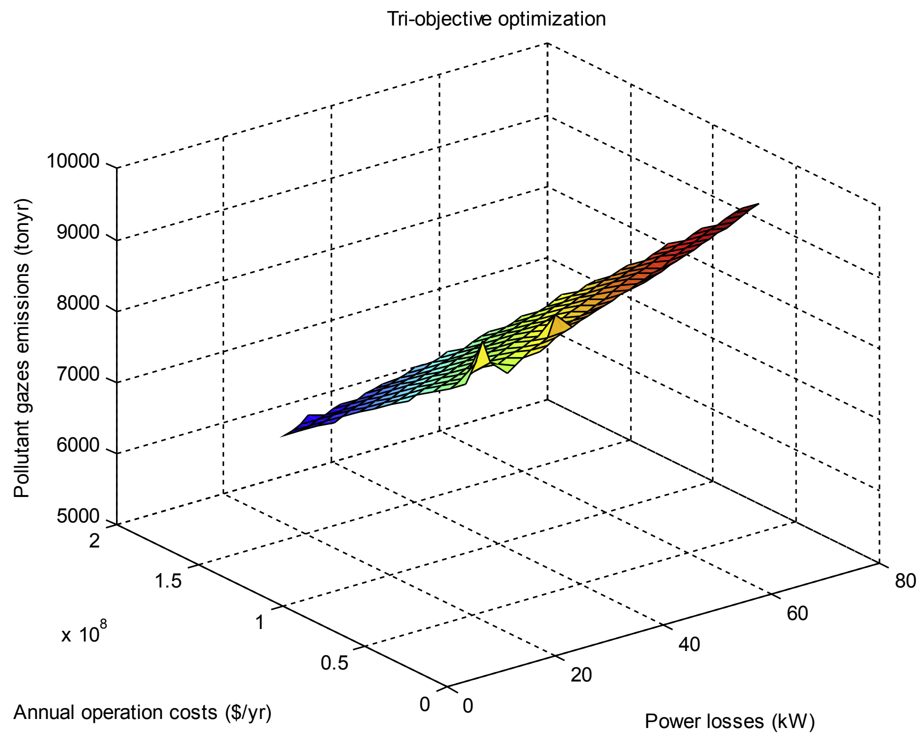

Fig. 9. Pareto surface of optimal solutions.

optimal integration of the renewable DGs are depicted in Fig. 8.

The best obtained compromise solution is referred to hour 12. It provides the optimal network configuration, as well as the best locations and sizing of the renewable DGs ensuring the most significant benefits for the whole power system (Table 9). It ensures a reduction of 88% of power loss and 63% of pollutant gas emissions, as well as a best minimum value of annual operation costs compared with those of other periods. Consequently, this solution is chosen to be applied to the power system for the period of planning (summer season).

The Pareto surface depicted in Fig. 9 presents the database of Pareto optimal solutions corresponding to hour 12. Consequently, the network manager have the choice between considering the best compromise solution or selecting from the Pareto set the one responding to his preference.

6. Conclusion

In this paper, a multi-objective optimization model of simultaneous distribution network reconfiguration and optimal renewable DG allocation and sizing is established. The objective functions include minimization of active power loss, operation cost and pollutant gas emissions considering topological and security constraints. The Pareto optimality-based SPEA2 algorithm is used to solve the optimization problem. The SPEA2 technique provides as results a set of Pareto optimal solutions where the network manager can select an option. The proposed method is tested for mono-objective optimization with and without considering the combination of reconfiguration and integration of DGs. According to the obtained results, the suggested method converges to the best minimum value of objective function compared to the other methods in the literature. Besides, the benefits of combining the distribution network reconfiguration with DG integration are investigated. Then, the main contribution of this work is successfully achieved by solving the optimization problem considering the time sequence variance in renewable DGs and load. Multi-period optimal solutions are obtained and the best compromise solution is extracted using a fuzzy set theory. This solution provides a reduction of 88% of active power loss and 63% of pollutant gas emissions with the best value of operation costs (66404 M$/year).

Acknowledgement

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Appendix A. SPEA2's fitness and environmental selection

A.1. SPEA2's fitness assignment

Each individual i in the archive A_t and the population P_t is assigned a strength value $S(i)$ representing the number of solutions (individuals), which it dominates:

$$S(i) = |\{j | j \in (P_t + A_t) \wedge i \succ j\}| \tag{A.1.1}$$

where $|.|$ denotes the cardinality of a set (the number of elements in a set). On the basis of the S values, the raw fitness is determined by the strengths of its dominators in both archive and population. The raw fitness $R(i)$ of an individual i is calculated:

$$R(i) = \sum_{j \in P_t + A_t, j \succ i} S(i) \tag{A.1.2}$$

Since the non-dominated individuals would have the same raw fitness values $R(i) = 0$, while a high $R(i)$ value means that individual i is dominated by many individuals. Therefore additional density information is incorporated to discriminate between individuals having identical raw fitness values. The density estimation technique used in SPEA2 is an adaptation of the nearest neighbor method for each individual i the distances (in objective space) to all other individuals j in archive and population are calculated and stored in a list. After sorting the list in ascending order, the k^{th} element gives the distance sought. As a common setting, k equal to the square root of the entire population $k = \sqrt{n_{pop} + n_{archive}}$. Where n_{pop} is a population (P_t) size and $n_{archive}$ is an archive (A_t) size.

The distance between the individuals $i$and k is denoted as σ_i^k. Density $D(i)$ corresponding to i is defined by:

$$D(i) = \frac{1}{\sigma_i^k + 2} \tag{A.1.3}$$

By adding $D(i)$ to the raw fitness value $R(i)$ of an individual i yields its fitness$Fitness(i)$:

$$Fitness(i) = R(i) + D(i) \tag{A.1.4}$$

A.2. SPEA2's environmental selection

In the environmental selection step, all non-dominated individuals are copied from P_t and A_t to A_{t+1} (the archive of the next generation). If size of A_{t+1} exceeds $n_{archive}$ then reduce A_{t+1} by means of truncation operator defined as follows:

$$\begin{aligned} &\forall 0 < k < |A_{t+1}| : \sigma_i^k = \sigma_j^k \vee \\ &\exists 0 < k < |A_{t+1}| : \left[\left(\forall 0 < l < k : \sigma_i^l = \sigma_j^l \right) \wedge \sigma_i^k < \sigma_j^k \right] \end{aligned} \tag{A.2.1}$$

where σ_i^k is the distance of i to its k^{th} nearest neighbor in A_{t+1}, l is index of the second individual with the smallest distance.

Otherwise if size of A_{t+1} is less than $n_{archive}$ then fill $A_{t+1}$with dominated individuals in A_t , and P_t, by sorting the multi-set $P_t + A_t$ according to the fitness values and copy the first individuals with $Fitness(i) \geq 1$from the resulting ordered list to A_{t+1}.

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