Hybrid Ant Colony Robust Genetic Algorithm for Optimal Placement of Renewable Distributed Generation and Storage units in Distribution Networks

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Abstract: This paper presents a multi-objective algorithm to support sizing and placement of Renewable Distributed Generation with storage units (RDG&S) in radial distribution networks. Two objectives are considered in the model, the first one is focused in the minimization of the RDG&S units capital costs and the second one in the minimization of system losses.

This approach uses a hybrid Ant Colony Genetic Algorithm (ACGA) divided in two steps. At the first step of the approach an Ant Colony (AC) acts to face with the uncertainty of the problem and to deal with instabilities of the initial data. This way a good Pareto front, which is used to feed the initial population of da Genetic Algorithm (GA). At the second step, an Elitist Robust Genetic Algorithm with a secondary population is used, to characterize the non-dominated Pareto Optimal Frontier. In this algorithm the concept of robustness is operationalized in the computation of the fitness value assigned to solutions. The results presented in this approach demonstrates the real capabilities of the proposed algorithm to generate a well-spread and more robust effective non-dominated Pareto Optimal Frontier.

Key-Words: Renewable Distributed Generation, Storage units, Ant Colony optimization, Genetic Algorithms, Distribution Networks.

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1 Introduction

Energy resources in our modern world are running out very fast, so it is urgent that we find new ways of generating electricity, which is self-sustaining, easy to manage and has high efficiency [1]. In this context DG technologies appear as the natural substitute of electric generation focused on centralized plants mitigating many problems, such as the high level of dependence on imported fossil fuels, the environmental impact of high concentrations of greenhouse gases and other pollutants, electric network transmission losses and the necessity for continuous upgrading of transmission and distribution facilities [1, 2]. Using DG, smaller amounts of energy are produced by, modular energy conversion units, which are often located close to electricity consumers avoiding transmission power losses. The development of new-generation technologies and power electronics are the key issues that have attracted many investors. Despite these advantages many issues are however, still pending concerning the integration of DGs within the existing power system networks; that require special attention [3, 4]. Specifically the way how their integration have changed the system from passive to active networks and the change with serious impact on both the reliability and operation of the network as a whole [2]. In addition to this situation is the non-optimal placement of DG, which can result in an increase in the system power losses with consequence in the voltage profile [5]. However when DG is strategically sized and placed in the network it can reduce transmission and distribution losses, fossil fuel emissions, reduce capital costs and improve distribution energy quality and security [5, 6].

The DG placement problem has therefore attracted the interest of many research in the last decade [7], since it can provide useful input for the derivation of incentives and regulatory measures for some market players, DSOs, regulators, and policy makers. This requires that the models used for planning the future architecture of electricity systems recognise that high levels of DG penetration in the distribution network can no longer be considered as a passive appendage to the transmission network. The entire system has to be redesigned and operated in an integrated manner. In addition, this operation of increased complexity must be carried out by a system under multiple management agents and market players.

Many mathematical approaches, such as nonlinear programming, quadratic programming and linear programming, have been used solve placement and sizing of DG problems [2, 5]. Unfortunately, this kind of problem is a highly nonlinear and a multimodal optimization problem. Therefore, conventional optimization methods that makes use of derivatives and gradients, in general, are not able to locate or identify the “Optimal solution”.

The best way to deal with the problem of locating and sizing DG units in a distribution network are usually stated as multi-objective planning problems. In fact, most of the real world problems have multiple, conflicting and incommensurate evaluation aspects so

if we want to assess good solutions that relate investment costs vs. power losses it is usual to benefit one objective and worse another. Multi-objective models have the capability to better reflect reality, incorporating objectives of distinct nature that are weighed by decision-makers (DM) and planning engineers to select good compromise solutions having in mind their practical implementation. These models enable to work with the conflicting nature of the objectives and the trade-offs in a way to identify satisfactory compromise solutions providing non-dominated solutions eliminating most of the difficulties associated to classical methods [8, 9].
To meet the increasing demands in the design of real world multi-objective problems, many evolutionary algorithms, PSO, Genetic Algorithms, Tabu-search, Ant colony and many others have been used. As can be see some algorithms are used successfully to mimic the corresponding natural, or physical, or social phenomena such as the ant colony optimization [10-11]. Ant colony optimization (ACO) is a metaheuristic inspired by the shortest path searching behaviour of ant colonies in their working day trails. Since the first usage of this algorithm researchers have designed ACO algorithms to deal with multi-objective problems in a way to have a set of solutions that satisfy both convergence and diversity criteria [11-12].

The mathematical model proposed in this paper involves discrete and continuous variables as well as nonlinear constraints, related to power flow equations. Therefore, due to the presence of multiple objective functions, non-linear relations, and its combinatorial nature the model is hard to solve using classic mathematical programming algorithms [3, 4]. Therefore, a hybrid Ant Colony algorithm associated to a Genetic Algorithm has been used to solve the problem of optimal placement and sizing of RDG&S units in radial distributed networks where two objective functions are considered: minimizing installation costs and minimizing system losses. The AC uses two colonies to guarantee more diversity. Associated to the GA an elitist strategy has been implemented aimed at increasing the performance, both accelerating the convergence speed towards the non-dominated frontier and ensuring that the solutions attained are indeed non-dominated ones and are well-spread over the frontier. In order to influence the iterative process and obtain more robust solutions, a robustness concept is embedded in the fitness with a non-dominance test [9]. At each non-dominance front, the more robust solutions are more likely to bring their contribution to future ant colony generations. This was the way found to deal with the uncertainty that surrounds real problems. The greatest motivation and contribution of this work, shows that this way of implementing a hybrid ACGA increases both, performance and convergence speed towards non-dominated and well-spread solutions, when compared with other approaches.
In this section the motivation around the problem and it's interest for the future networks has been provided. The problem formulation is presented in section 2. In section 3, the developed ACGA is presented and computed solutions obtained are analysed. Section 4 reports results of a case study. Finally, some conclusions are drawn in section 5.

2 Problem Formulation

The following formulation illustrates the effect of RDG&S units, on the load demand of radial distribution network. Here DG technologies are automatically associated to storage unites (usually Lithium batteries) to overcome some operational problems like variability of the renewable resource. In radial networks, bus voltage decreases as the distance from the distribution transformer increases, and may become lower than the minimum voltage allowed by the utility. Utilities usually solve this problem by upgrading facilities, increasing the tap ratio of the distribution transformer, and/or by switching on the shunt capacitors and reinforcing distributions lines. By providing a portion of energy on site, RDG&S units reduce branch current, which in turns leads to the reduction of power losses and increasing voltage throughout the feeder.

The proposed approach deals with the location and sizing of RDG&S units in order to obtain the benefits associated with lower power loss and lower investment costs of installation of RDG&S units [9].
Hence, it can be formulated as the following optimization problem:

$$\min \sum_l \sum_n \sum_m \left[\sum_i C_i \cdot y_{i_{nm}}^{\,l}\right]$$

$$\min \sum_l \sum_n \sum_m r_{nm}^l \frac{P_{nm}^{l^2} + Q_{nm}^{l^2}}{V_{nm}^{l^2}}$$

s.t.

$$\sum_i y_{i_{nm}}^{\,l} \le 1, \forall m, n, l$$

$$V_{nm_{MIN}}^l \le V_{nm}^l \le V_{nm_{MAX}}^l, \forall\ m, n, l$$

$$y_{i_{nm}}^{\,l} \le av_{nmi}^l \quad \forall\ m, n, l, i$$

The MO problem is a constrained non-linear optimization problem with mixed variables (due to the presence of modular sizes of DG units).

Technology Installation Costs

For installation cost minimization is given by:

$$\min \sum_l \sum_n \sum_m \left[\sum_i C_i \cdot y_{i_{nm}}^{\,l}\right] \qquad (1)$$

where C_i represents the installation cost of the RDG&S unit i with a certain nominal power (kW), installed on bus l (from the derived feeder n of the main feeder m). $\boldsymbol{x}^l_{i\,nm}$ are the binary decision variables, that defines if a RDG&S unit (i), is installed.

Active Power System Losses

This objective minimizes the real power losses arising from line branches.

$$\min \sum_l \sum_n \sum_m r^l_{nm} \frac{P^{l^2}_{nm} + Q^{l^2}_{nm}}{V^{l^2}_{nm}} \qquad (2)$$

where, r^l_{nm} is the ohm value of bus l (from the derived feeder n of the main feeder m), and P^l_{nm} and Q^l_{nm} are the corresponding active and reactive power flow.

Constraints

In addition to the constraints of physical nature related to the load flow equations some other constraints were considered:

- at most only one kind of defined (RDG&S unit) can be placed in each bus (avoiding multiple installations).

$$\sum_i y^l_{i\,nm} \leq 1, \forall m, n, l$$

- related with quality of service, regarding the upper and lower limit imposed by legislation, $[V^l_{nm_{MIN}}, [V^l_{nm_{MAX}}]$, of voltage in each bus .

$$V^l_{nm_{MIN}} \leq V^l_{nm} \leq V^l_{nm_{MAX}}, \forall\, m, n, l$$

- what kind of (RDG&S unit) can be placed in each bus (pre-defined by local characteristics, son, wind,…).

$$y^l_{i\,nm} \leq av^l_{nmi} \quad \forall\, m, n, l, i$$

where av^l_{nmi} is a binary coefficient, if it assumes the value 0 it means that a specific RDG&S unit cannot be install in bus l. If the value is 1 it means that the technology i can be installed at bus l.

3 Proposed Algorithm

This section presents a new hybrid algorithm for solving the problem of placement and sizing RDG&S units in distribution networks. The algorithm optimizes two objective functions; minimizing costs of installation of RDG&S units and the network losses. The flowchart of the proposed algorithm is illustrated in Fig 1.

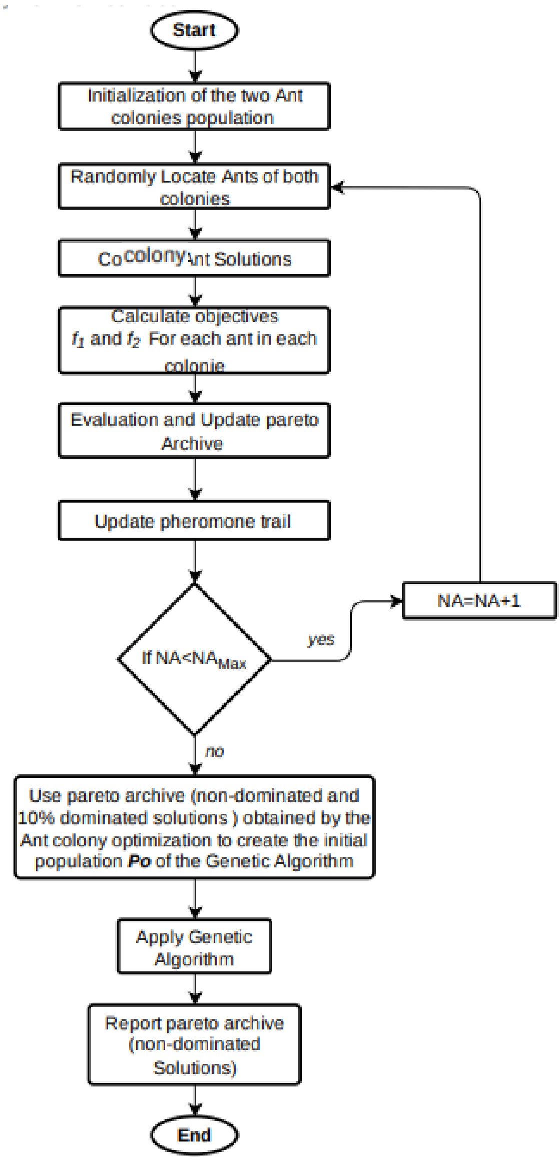

Fig. 1: The Flowchart of the proposed hybrid algorithm

The proposed algorithm integrates the merits of both Ant Colony Optimizations (ACO) [11] and GA [9] and by enhancing ACO through GA, a strong and robust algorithm was created. The main steps of the proposed algorithm are:

1: Colonies. In a multi-objective optimization problem, because of incommensurability and confliction among objectives functions need to be optimized simultaneously. This step starts with the definition of the number of colonies F with its own pheromone structure, where F *represents* the number of objectives to optimize, in this case F=[f_1, f_2].

2: Initialization. This step begins with the initialization of pheromones trails, where a given value β_0^α is attributed, known as the pheromone information in the current iteration, α=(1, 2) assumes the objectives to optimize. At this stage the Pareto set are initialized as empty. To know the ant pheromone concentration of each path a multi-pheromone ant colony optimization was implemented to this problem, which requires a representation of *n* variables for each ant, where each variable *i* has a set of n_i options (bus) with their values l_{ij}, where i=1, 2, …, n) and j=1, 2, …, n_i) generating a fully connected graph with the detailed information about their associated pheromone concentrations. The process starts by generating *x* ants' position from the population (solutions), these are generated randomly, meaning that each ant *y*, $y \in \{1,2, \ldots, x\}$ has a position with a selected value for each variable according to the associated pheromone with this value. This process is repeated for each objective. Consequently the path of each ant represents the bus and its respective value.

3: Evaluation. The Ant Colony optimization is parameterized by the number of ant colonies and the number of associated pheromone structures. For a matter of consistency of results, all the colonies have the same number of ants. Each colony tries to optimize an objective considering the pheromone information associated to it´s own colony, where each colony is determined knowing only the relevant part of a solution. This methodology guaranties that all colonies search in different regions of the non-dominated front, creating more diversity of solutions.

4: Trail Update. At the moment that pheromone trails are updated, a decision has to be made on which of the constructed solutions laying pheromone to choose. The quantity of pheromone left behind represents the past experience of the colony with respect to a chosen passage. Then, at each sequence every ant constructs a solution, and pheromone trails are updated.

After all ants have constructed their solutions, pheromone trails are updated as can be followed by two steps:

- Step 1, to prevent premature convergence, pheromone trails are reduced by a constant factor to simulate evaporation;
- Step 2, in a way to reinforce good solutions, some pheromone are laid on components of the best solution. Changing pheromone concentration associated with each possible route (variable value).

5: Solution Construction. When the pheromone is updated after one iteration, the next iteration will begin with the modification of the ants' paths (this means with the variable values) in a manner, that respects pheromone concentration and some heuristic preference. For each ant and for each dimension new candidates construct a new group that replaces the older one. In other words in each colony an ant changes the value for each variable according to the transition probability expressed in the following equation.

$$P_{ij}^{\alpha}(t) = \begin{cases} \dfrac{\left[\beta_{ij}^{\alpha}(t)\right]^{\alpha}}{\sum_{j \epsilon n_i}\left[\beta_{ij}^{\alpha}(t)\right]^{\alpha}} & \forall j \in n_i \\ 0 & \text{otherwise.} \end{cases}$$

Where, $p^{\alpha}_{ij}(t)$ is the Probability that option l_{ij} is chosen by ant *y* for variable *i* at iteration *t*.

6: Archived Solutions. The set of non-dominated and a few dominated solutions are stored in an archive. During the optimization search, the set of solutions is updated. At each iteration, the current solutions obtained are compared to those stored in a Pareto "ideal" archive; all dominated solutions within a predefined radius τ of domination (a set of about 10% of the generated solutions) and the non-dominated ones are added to the set.

7: Genetic Algorithm. An elitist robust GA algorithm is implemented to use the archived solutions obtained from the Ant colony optimization. This elitist strategy ensures, the solutions are indeed non-dominated and are well spread over the frontier. This strategy uses a secondary population where each individual (solution) are only feasible non-dominated solutions.

In order to force the GA process towards more robust solutions, the degree of robustness in the variable space was embedded in the fitness.

The details of the GA are shown below.

Genetic Algorithm used

ate the initial population satisfying the problem constraints with NP_0 solutions,
ed from step 6 of the Ant colony algorithm)
ate P_0 with real fitness (Compute the fitness of each individual in P_0)
mine P_S (initial secondary population obtained from P_0)
$P_S > NP_0$ then
    $P_S = P_0$ (Copy all solutions from P_0 to P_S)

    ShP_0 (Apply sharing mechanism to P_0 to select NP_S solutions)
ate Population: $P_{(iter)} = P_S$
er=1 to $iter_{Max}$) (maximum number of iterations is attained)
n
ild $P_{(iter+1)}$ (the next generation of NP_0 solutions)
ly elitism: $P_{(iter+1)} = E$ (introduce *E* solutions from P_S in $P_{(iter+1)}$)
epeat
Selection: ST_2 (Select 2 individuals ST_4 from $P_{(iter)}$ by tournament)
enetic operators to 2 individuals selected above ST_2)
$P_{(iter+1)} = GO_2$
ntil ($NP_{(iter+1)} \leq NP_0$)
ss (Compute the fitness of each individual in $P_{(iter+1)}$)
termine NPs_{cand} (solutions that are candidate to belong to PS)
late $P_{S(iter+1)}$
$P_S \geq NPs_{cand}$ then
$P_{S(iter+1)} = NPs_{cand}$ (Copy all NPs_{cand} solutions to P_S)
se
$ShNPs_{cand}$ (Apply sharing mechanism to all NPs_{cand} solutions)
ate Population: $P_{(iter+2)} = P_{(iter+1)}$
or

This procedure aims at finding a good compromise among the different non-dominated solutions for sizing and sitting of RDG&S units, The goal is to provide the DM with dedicated information about the a set of non-dominated solutions and the underlying trade-offs, which could be used to support the choice of a satisfactory compromise plan of investment.

4 Case Study

The methodology described in section 3 to characterize the optimal Pareto front, and provide decision support in the multi-objective model presented in section 4, has been applied to a distribution network with 86 nodes and 16 lateral feeders.

Five types of RDG&S units are considered for possible installation, as in table 1.

Table 1. RDG&S units considered for instalation

G&S unit type	DG Technology and storage unit	talled capacity (kW)
1	oltaics + 100kWh Li-ion Bat.	250
2	neration (Biomass)	500
3	Turbine + 20kWh Li-ion Bat.	100
4	oltaics + 50kWh Li-ion Bat.	150
5	Turbine + 100kWh Li-ion Bat.	250

The characteristics of this approach enables the DM to preform experiments adjusting different sets of parameter, throughout the process.

The initial parameters used are:

- Initial population size *NA* (number of Ants) of each Ant Colony and *NP* (solutions of the pareto front result from da AC optimization that will be the initial populations for the GA);
- Set value parameters α, $\beta_0{}^{\alpha}$, *x*, *y*, *i* , *j* and $P_{ij}^{\alpha}(t)$;
- Set the secondary population size *NPS* of the GA;
- Set the number of elite individuals *E* introduced in the main population of the GA;
- Set the number of generations, Mutation probability *mp* and Crossover probability *cp*.

In Fig. 2, we can see the initial population and the Pareto front of final population obtained by this hybrid algorithm. As can be seen the initial population is very disperse because it is generated randomly. The Pareto front obtained is the result of the adjustments made to the algorithm parameters.

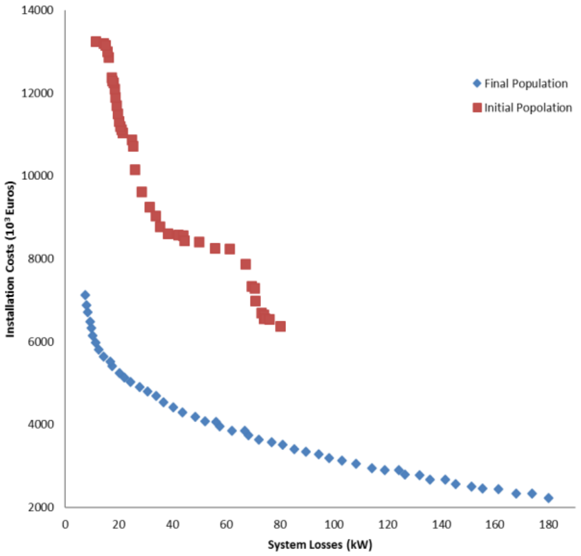

Fig. 2: Initial populations and Final population

Fig. 3, shows the Pareto front of the population evolution at the first stage of the algorithm. Here it's possible to verify that the population resulted from the two colonies (*Final Populations AC_1* and *Final Populations AC_1*) of the AC algorithm present nominated and non-dominated solutions in the well-defined Pareto fronts. When at the second stage, the GA is applied to these solutions AC_1 and AC_1)), the final very well defined Pareto front with more robust non-dominated solutions.

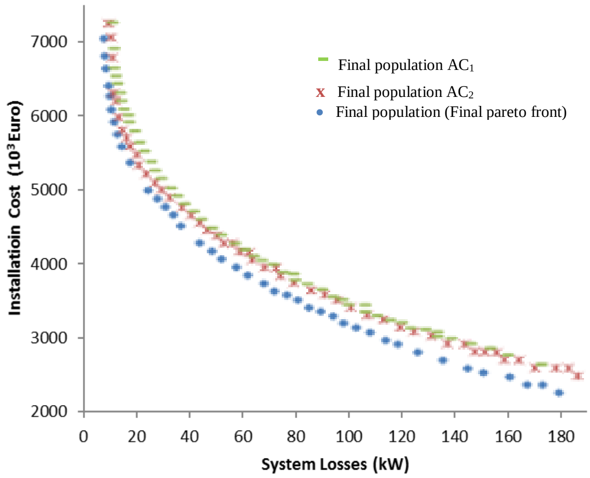

Fig. 3: Evolution of the solutions after the ACO and final front of the GA.

In Table 3 are presented the values of the losses experienced by the network before the installation of RDG&S units, for a chosen load scenario.

Table 3. Initial losses of the considered network

Active losses (kW)	*Reactive losses (kVAr)*
903,21	*1211,30*

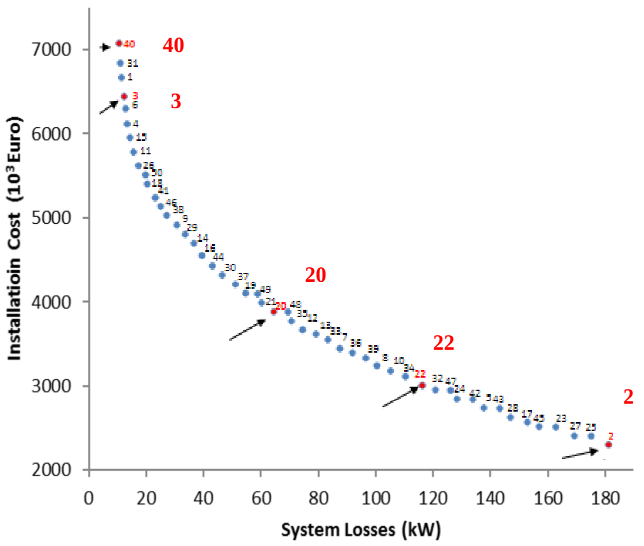

Fig. 4: Final population with 40 solutions

Fig. 4 displays the Pareto front, in the objective function space (objective function system losses and installation costs). Since the algorithm has embedded the robustness concept, the DM has the guarantee that all solution in the pareto front are very robust solutions. So this set of solutions on the non-dominated frontier is used by the DM as the input to select a final compromise solution with the smallest uncertainty.

For example, if the DM considers the solutions identified with the red color in Fig. 4 as good compromise plans according to the two conflicting objectives, the results are illustrated in Fig. 5 and 6.

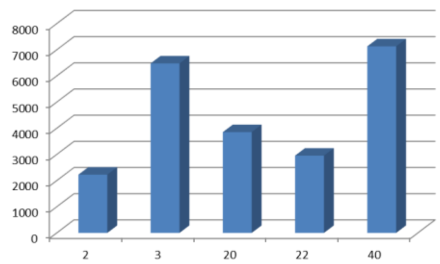

Fig. 5: Instalation costs (10^3 €) from solutions 2, 3, 20, 22 and 40 marked by the DM.

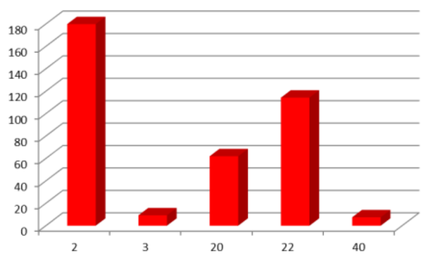

Fig. 6: Sytem active power losses (kW) from solutions 2, 3, 20, 22 and 40 marked by the DM.

As can be seen in table 5 there is a real reduction of the active power losses in the network comparing with the initial situation (before any equipment is installed).

Table 5. Reduction of losses in persentage compared with the initial condition (without RDG&S units instaled)

Solution	2	12	33	38	9
ctive losses eduction (%)	0,1	8,9	3,1	7,3	,2

If solution 20 is the chosen one, table 6, shows the buses where the DG units would be installed.

Table 6. Installed DG in network buses (solution 20).

Bus	.4	17	30	23	48	51	54	55	57	58	61	71	73	76	82	83
Type of* RDG&S unit *installed	1	1	1	1	1	1	2	1	1	1	1	1	2	1	1	

5 Conclusion

In this paper, the problem of location and sizing of RDG&S units in distributed networks has been modeled as a multi-objective problem. Two objective functions of technical and economical nature are considered in the model: minimization of total power losses and minimization of RDG&S unit installation costs.

The algorithm developed is based on a Hybrid ACGA, characterizing the optimal Pareto frontier that represents a set of distributed solutions, which can be chosen by the DM for practical implementation.

Firstly, aaccording to a set of predefined parameters a defined number of solutions are generated randomly, creating two AC. Secondly, an AC algorithm is applied aimed to deal with the uncertainty and instabilities of the problem, as a final result we have strong solutions, which are used to feed the initial population of da GA. The GA uses an Elitist Robust Algorithm with a secondary population, to characterize the non-dominated Pareto Optimal Frontier. In this algorithm the concept of robustness is operationalized in the computation of the fitness value assigned to solutions.

The use of the Ant colony optimization shows its importance designing effective combinatorial optimization solutions, and when its combined with the GA shows that his algorithm is aimed to obtain the input information (obtained from the output of the robust Algorithm) necessary to develop a decision support system. As can be seen in the case study this decision support system may be integrated in radial distribution networks, generating very good results. To summarize we can say that using this kind of approach we can obtain better performance and more robust solutions using less computing resources. This was a reality using radial distribution networks, our intention is to test and adjust this algorithm for more complex networks using multiple voltage stages and integrating smart grids.

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