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Integration of renewable energy sources in smart grids by means of evolutionary optimization algorithms

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ABSTRACT

Nowadays, modern power networks have to face a number of challenges such as growing electricity demand, aging utility infrastructure and not to forget the environmental impact of the greenhouse gases produced by conventional electric generation. In order to increase renewable energy penetration but without disregarding security and reliability matters during the process, distribution power networks need to evolve to a flexible power network, better known as smart grid, in which distributed intelligence, communication technologies and automated control systems work as the driving factors. Taking into consideration this new frame, intelligent optimization techniques emerge as the only suitable way to optimally design this smart grid. In this paper, a generalized optimization formulation is introduced to determine the optimal location of distributed generators to offer reactive power capability. In order to find a suitable solution to such Reactive Power Management problem, genetic algorithms are applied in those cases where different multiobjective functions are to be considered. A more detailed description of the genetic algorithm evolution process is shown in a microgrid example.

1. Introduction

In the last decade, technological evolution and changes in the regulatory and economic environment of the power systems have led to an increasing interest in the use of distributed generation units (DG), considered as small generators units connected to distribution grids (Jenkins, 2000). However, the fact is that power system operators and planners still have to face to the great challenge of integrating this kind of renewable energy sources into power system grids. One of the critical issues arisen out of this context is the Reactive Power Management (RPM) which entails the requested operation and planning actions to be implemented in order to improve both, the voltage profile and the voltage stability (Miller, 1982). Moreover, Reactive Power Management involves the definition of the Reactive Power Planning of VAR sources and the reactive power dispatch of the already installed reactive sources. Lately, and in an attempt to fill the existing gap, Flexible AC Transmission Systems (FACTS) devices have stood out as a feasible option to improve voltage stability by influencing power flows and by improving voltage profiles (Lahatani, Aouzellag, & Mendil, 2010). To reach the optimum application of these devices, it is crucial to find out the optimal location, in which their influence would be more useful as well as to determinate their optimum sizing.

Recently there has been a general upsurge of interest in the concept of smart grids and thus, they are being considered as flexible network, intelligent network or even active power network with a great potential to promote and to increase the renewable energy sources integration. At the same time, they are able to improve system reliability and security. This change requires getting a new perspective on network operating, in which the intelligence must be spread over DG units and FACTS devices, such as Static Var Compensators (SVC) and therefore the distribution power network becomes flexible. Active power networks allow the implementation of an efficient Reactive Power Planning in which the optimum VAR sources location is chosen during the planning stage and, acting this way, an efficient reactive power dispatch could be also achieved by scheduling an optimum regulation of the voltage set point at the generators connection point and at the VAR settings during the reactive power dispatch (Xiong, Cheng, & Li, 2008).

Traditionally, Reactive Power Planning has been formulated as an optimization problem in which the determination of the instantaneous optimal steady state of an electric power system is solved by an Optimal Power Flow problem (OPF) (Raoufi & Kalantar, 2009). In those situations, the optimization algorithm is defined as a single objective function expressed as a mathematical function based on some criteria. In many cases, the main objective is to minimize the fuel cost function and/or the possible system losses.

At this point, the use of heuristic optimization algorithms stands out as the only suitable way to design and to optimally locate reactive power injection units in smart grids considering, at

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the same time, different objectives function such as: improving the voltage stability, maximizing the renewable energy penetration and controlling the network in a coordinated way as it is proposed in this paper.

The objective of the paper is to develop a new Reactive Power Management Strategy for the coordinated handling of reactive power from DG units and FACTS units by applying evolutionary optimization methodologies such as genetic algorithms. The proposed methodology will aid power system operators to determine which is the optimal placement for locating DG units and SVCs devices and which is the amount of reactive power that should be injected in the network to improve the voltage stability maximizing, at the same time, the DG penetration level. The optimization formulation proposed in the paper focuses on Static Var Compensator (SVC). However, it should be emphasized that the developed method could also be applied to any other controllable FACTS devices such as STATCOM as well as to include any other objective function in the multiobjective algorithm.

The content of the paper is organized as follows: Section 2 shows a brief summary of reactive power capabilities from DG units. In Section 3 the Reactive Power Planning formulation is described. A description of the single objective genetic algorithm is shown in Section 4. The GA evolution process is described one stage at a time in Section 5 and the proposed methodology is applied to a 34-bus distribution network in which several DG units with reactive power capabilities are optimally located in Section 6. Concluding remarks are presented in Section 7.

2. Reactive power injection from DG sources

One of the technical barriers for the integration of Renewable Energy Sources (RES) in distribution networks is the exceeding voltage limit violations. Active networks or smart grids require a dynamic reactive power support to the network in order to offer voltage control and reactive power regulation. This could be possible by monitoring the network and by sending signals to the controlled DG generators and FACTS devices such as SVCs.

Fuel cells, photovoltaic systems and small wind turbines are examples of controlled DG units that are connected to the network through static power converters. Models of DG generation sources has been thoroughly investigated by several researchers (Eminoglu, 2009; Hajizadeh & Golkar, 2010 & Suroso & Noguchi, 2010) and all of them have come to the conclusion that the reactive power regulation capability could be easily obtained by controlling the power electronic converter.

It could be considered that active power output from the controlled DG unit, P, will depend, in each situation, on the available weather resource and the DG technical characteristics (Vilar Moreno, Amaris Duarte, & Usaola Garcia, 2002). On the contrary, reactive power output, Q_{GSC}, will be restricted by the active power injected to the grid and by the rating of the coupling power converter S_{GSC} and thus could be expressed as:

$$Q_{GSC} = \pm\sqrt{S_{GSC}^2 - P^2} \tag{1}$$

For the uncontrolled DG such as: diesel generators and Combined Heat and Power (CHP) units, which do not offer the reactive power regulation capabilities, it would be necessary to add an external dynamic reactive power support, such as a Static Var Compensator (SVC) at the Point of Common coupling (PCC) or DG terminals.

A Static Var Compensation (SVC) is a device capable of exchanging capacitive as well as inductive current to maintain or to control specific parameters of the electrical power system. In this paper, the considered SVC corresponds to a TCR (Thyristor Controlled Reactor) as shown in Fig. 1.

In this situation, injected steady-state current is expressed thus:

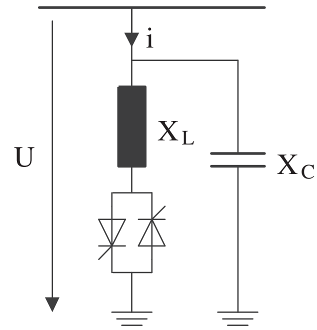

Fig. 1. Static Var Compensator diagram.

$$I = \begin{cases} \frac{U}{X_L}(cos\alpha_{svc} - cos\omega t), & \alpha_{svc} \leqslant \omega t < \alpha_{svc} + \sigma \\ 0, & \alpha_{svc} + \sigma \leqslant \omega t < \alpha_{svc} + \pi \end{cases} \tag{2}$$

where: U voltage at SVC connection point, it is the voltage that it is being controlled; X_L total inductance; X_c capacitor; α_{svc} is the firing delay angle; σ is defined as the SVC conduction angle according to:

$$\sigma = 2(\pi - \alpha_{svc}) \tag{3}$$

Following Fourier (Miller, 1982), the variable susceptance B_{svc} could be expressed as:

$$B_{svc}(\alpha_{svc}) = \frac{2\pi - \alpha_{svc} + \sin 2\alpha_{svc}}{\pi X_L} \tag{4}$$

and the reactive power injected by the SVC, which corresponds to the reactive power injected by the uncontrolled DG at the connection point is:

$$Q_{svc}(\alpha_{svc}) = \frac{U^2}{X_c} - U^2 B_{svc}(\alpha_{svc}) \tag{5}$$

3. Reactive Power Planning formulation

Reactive Power Planning (RPP) is a large-scale, mixed, non-linear, constrained, optimization problem that could be defined as:

$$\min_{x \in R^n} \quad f(x,u)$$
$$\text{subject to} \quad \begin{cases} g(x,u) = 0 \\ h(x,u) \leqslant 0 \end{cases} \tag{6}$$

where:

u are the control variables; $x \epsilon \Re^n$ stands for all the system steady state variables; $f(x,u)$ objective function to minimize; $g(x,u)$ involves the equality constraints; $h(x,u)$ corresponds to the inequality constraints.

3.1. Objective function

By the process of formulating a Reactive Power Planning problem, the choice of objective functions represents the most relevant decision to be made. In fact, many different single objective functions have been already proposed by various authors; Hugang (2008); Hedayati, Nabaviniaki, and Akbarimajd (2008) and Lee and Bai (1995).

Among the numerous available choices in this paper, the following objective function will be considered:

3.1.1. Single objective function

The main factor that tends to cause voltage instability is the inability of a power system to maintain an adequate Reactive Power Management in the network and a proper voltage level

(Ajjarapu, 2006). In most of the cases, the load works as driving force of voltage instability and that is why the algorithm tries to maximize the loadability factor taking into account the minimum voltage allowable limit (normally $U_{min} = 5\%U_N$) according to the utilities grid voltage regulations.

In this situation the load change scenarios, P_D and Q_D could be modified as:

$$P_D = P_{D0}(1+\lambda) \quad (7)$$

$$Q_D = Q_{D0}(1+\lambda) \quad (8)$$

where:

P_{D0}, Q_{D0} original load, base case; λ loadability parameter.

Voltage stability is usually studied by a P–V diagram (Ajjarapu, 2006) as shown in Fig. 2. Loads in all buses are increased proportional to their initial load levels and the generators outputs are increased proportional to their initial generations too. The turning point where the load parameter becomes tangent to the network characteristic would be defined as the Point of Collapse (PoC), at this point $\lambda = \lambda_{critical}$. In the same way, if a load increase beyond this critical value takes place, an unstable equilibrium will arise and consequently the system would be unable to operate any longer. For all the reason above mentioned, in this case, the objective function tries to maximize the loadability parameter considering the minimum allowed voltage value according to the utility regulations (U_{min}, λ_{limit}).

3.1.2. Multiobjective function

Traditionally, optimization problems related to multiple objectives had been solved by means of the linear programming, where one of the objectives was optimized and the others were included in the restrictions. This procedure generates some disadvantages such as:

- Objectives representation by means of restrictions in linear programming could lead to unfeasible problems.
- If the optimization is to be applied in a large system, it will be difficult to find out the restriction that produces the unfeasibility.
- There is not a clear criterion for choosing the suitable objective function and, in many cases, the fulfilment of one single objective could come into conflict with the others.

Multiobjectives algorithms stand out as a procedure to solve these above mentioned problems where the optimal solution of the problem is to be replaced by a set of efficient solutions.

In this section, a multiobjective function is defined as a loadability function of the system and the DG penetration level. Multiobjective approach is defined as:

$$\min F(y) = \alpha f(y) + \beta g(y) \quad (9)$$

where:

$\{f,g\}$ set of the variables to be satisfied; $f(y)$ maximize voltage stability; $g(y)$ minimize DG penetration level; α and β weight parameters.

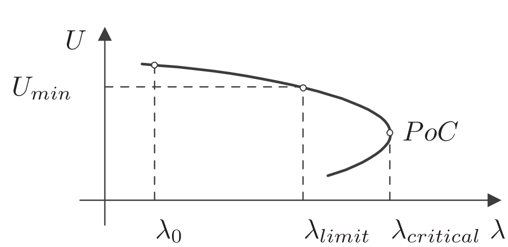

Fig. 2. Voltage loadability.

Parameters α and β could be selected in order to determinate the rate of the mono-objective functions. In this paper, it is assumed that the weight of the individuals objective are equal, so that α and β are selected as $\frac{1}{2}$.

3.2. Constraints

3.2.1. Equality constraints

Basic equality constraints correspond to the power flow equations in every buses.

The power mismatch equations in rectangular coordinates at a bus are given by:

$$\Delta P_i = P_{gi} - P_{di} - P_i \quad (10)$$

$$\Delta Q_i = Q_{gi} - Q_{di} - Q_i \quad (11)$$

where P_{gi} and Q_{gi} are real and reactive powers of generator at bus i, respectively; P_{di} and Q_{di} the real and reactive load powers, respectively; P_i and Q_i the power injections at the node are given by:

$$P_i = U_i \sum_{j=1}^{N} U_j (G_{ij} cos\theta_{ij} + B_{ij} sen\theta_{ij}) \quad (12)$$

$$Q_i = U_i \sum_{j=1}^{N} U_j (G_{ij} sen\theta_{ij} - B_{ij} cos\theta_{ij}) \quad (13)$$

3.2.2. Inequality constraints

Inequality constraints constitute the physical limits of the components or operational constraints in the system.

- Voltage limits at buses
  Voltage level at buses are not allowed to fall outside the maximum and minimum values according to grid voltage regulations.
  $$U_{i,min} \leqslant U_i \leqslant U_{i,max} \quad (14)$$
- Limits of the loadability factor
  Lambda is the loading factor by which the load is increased at all buses and $\lambda \geqslant 0$.
- Limits of the DG power injection
  Active power output is restricted by lower and upper limits.
  $$P_{gi,min} \leqslant P_{gi} \leqslant P_{gi,max} \quad (15)$$

where $P_{gi,min}$, $P_{gi,max}$ are the minimum and maximum operating power respectively. In the case of reactive power, it has to be noted that there are two groups of DG units: the controlled DG and the uncontrolled DG. For the controlled DG, reactive power output is restricted by lower and upper limits, considering in each situation the active power injected to the grid and the rating of the coupling power converter of the controlled DG generators as it is shown in (1).
For the uncontrolled DG, the reactive power (5) is restricted by the maximum and minimum reactive power limits of the SVCs.

- Physical constraints in the DG connection point The potential connection point from the DG to the grid is limited to the geographical area in which the available renewable resource is higher.
  $$Bus_{LocDG_i,min} \leqslant Bus_{LocDG_i} \leqslant Bus_{LocDG_i,max} \quad (16)$$

4. Genetic algorithms

The application of Evolutionary Algorithm like genetic algorithms (GA) in multiobjective optimization problems has received considerable attention in the last years due to the difficulty of extending conventional optimization techniques to multiobjective

Table 1
Chromosome structure.

Stability	DG + SVC		
	$DG_1 + SVC_1$	...	$DG_N + SVC_N$
λ	*Loc* *Q*	...	*Loc* *Q*

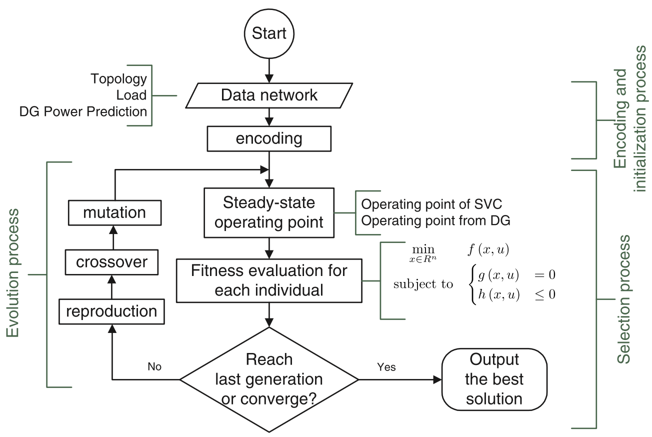

Fig. 3. Optimization process.

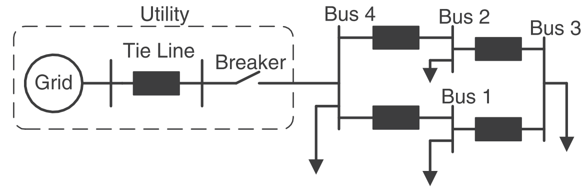

Fig. 4. Four bus microgrid.

Table 2
Initial population of the 4 bus system.

	λ (p.u.)	Bus_{DG}	Q_{DG} (Mvar)
Chromosome 1	0.13205	2	149.537
Chromosome 2	0.69965	2	187.455
Chromosome 3	0.4859	2	233.818
Chromosome 4	0.18272	3	209.539
Chromosome 5	0.10121	3	221.811

Table 3
Evaluation process of 4 bus system.

	FF(*y*)	F(*y*)	Order	Range
Chromosome 1	0	1	3	0.557
Chromosome 2	0	1	4	0.35
Chromosome 3	0	1	5	0.407
Chromosome 4	0.18272	0.8173	1	1
Chromosome 5	0.10121	0.8988	2	0.707

optimization problems (Singh & Singh, 2009). Genetic algorithms (GA) belong to the evolutionary optimization algorithms and they were firstly introduced by Holland in 1975 (Holland, 1975). Starting with an initial population, the algorithm evolves to a new generation of individuals by means of executing reproduction, mutation and crossover operations among the individuals of this population. The main advantages offered by GA over conventional optimization algorithms are:

- GA's do not need initial information about the system to begin the searching process since they work only with the coding (chromosomes) which will be optimized according to the objective functions and the proper constraints.
- The algorithms would be able to explore simultaneously various regions in the search space by using multiple points of the population and iterative characteristics. This represents one of the most important distinctions from the traditional optimization algorithms where only one direction in the search space could be followed.
- Best individuals are selected among parents and offspring generation making the process more likely to converge to a global minimum.

4.1. Encoding

The genetic information of each individual is encoded in its chromosome (Table 1) which is a string of real numbers that corresponds to:

- Bus location.
- Reactive power injected.
- Loadability factor.

If there are n DG units the chromosome length will have:

- $2n$ genes: bus location and reactive power injected by DG unit,
- 1 gene: optimal loadability factor.

Active power injected by each micro-generator is not included in the chromosome since it is assumed that active power from

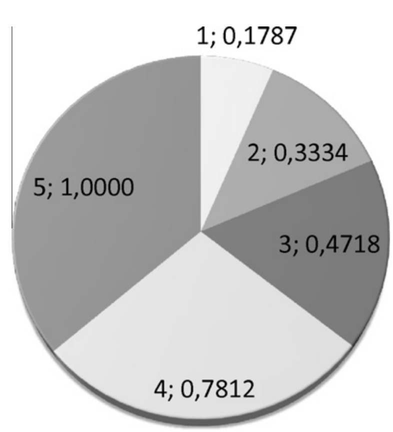

Fig. 5. Cumulative frequency diagram.

Table 4
Cumulative frequency of 4 bus system.

	Range	Frequency	Cumulative freq.
Chromosome 1	0.557	0.1787	0.1787
Chromosome 2	0.5	0.1547	0.3333
Chromosome 3	0.407	0.1384	0.4718
Chromosome 4	1	0.3094	0.7812
Chromosome 5	0.707	0.2188	1

Table 5
Selection process of the 4 bus system.

	Cumulative freq.	*r*	Father
Chromosome 1	0.1787	0.8631	5
Chromosome 2	0.3333	0.3807	3
Chromosome 3	0.4718	0.749	4
Chromosome 4	0.7812	0.1567	1
Chromosome 5	1	0.0581	1

Table 6
Parents of the selection process of the 4 bus system.

	λ (p.u.)	Bus_{SVC}	Q_{SVC}(Mvar)	
Chromosome 5	0.10121	3	221.811	Crossover process
Chromosome 4	0.18272	3	209.539	
Chromosome 1	0.13205	2	149.537	
Chromosome 3	0.48590	2	233.818	
Chromosome 1	0.13205	2	149.537	Mutation process

Table 7
First couple of parents.

	λ (p.u.)	Bus_{SVC}	Q_{SVC}(Mvar)
First couple of parents			
Chromosome 5	0.10121	3	221.811
Chromosome 4	0.18272	3	209.539

Table 8
Second couple of parents.

	λ (p.u.)	Bus_{SVC}	Q_{SVC} (Mvar)
Second couple of parents			
Chromosome 1	0.13205	2	149.537
Chromosome 3	0.48590	2	233.818

DG is merely a piece of information previously known according to the weather and power production forecasts.

4.2. Evaluation

The Fitness Function (FF) assigns a goodness value at each individual of the population and it is employed to drive the evolution process. Each chromosome is assigned a fitness value which determines not only the individual adaptation capacity to the environment but also its estimated survival probability in the following generation. In this study the FF is assigned to be the Loadability parameter λ.

4.3. Selection

The individuals that score the largest fitness values are selected as possible parents because of the fact that they have higher likelihood of survival. So that, the larger the chromosomes fitness, the higher the survival probability in the next generation. Therefore, a roulette wheel selection is used to distinguish which are the best individuals (parents) to be reproduced.

Table 9
Evolution of the crossover process.

	Parents			Children			
	λ (p.u.)	Bus_{SVC}	Q_{SVC} (Mvar)	λ (p.u.)	Bus_{SVC}	Q_{SVC} (Mvar)	
Chromosome 5	0.10121	3	221.811	0.10121	3	209.539	Child 1
Chromosome 4	0.18272	3	209.539				
Chromosome 1	0.13205	2	149.537	0.13205	2	233.818	Child 2
Chromosome 3	0.48590	2	233.818				

Table 10
Mutation process of the 4 bus system.

Parent			*m*	Child		
λ (p.u.)	Bus_{SVC}	Q_{SVC} (Mvar)		λ (p.u.)	Bus_{SVC}	Q_{SVC} (Mvar)
0.13205	2	149.537	0.05	0.89842	3	151.358

Table 11
New population of the 4 bus system.

	Genetic operator	λ (p.u.)	Bus_{SVC}	Q_{SVC} (Mvar)
Population1	Elitism children	0.18271625	3	209.539142
		0.10121454	3	221.810899
	Crossover children	0.10121454	3	209.539142
		0.13205468	2	233.817557
	Mutation child	0.89842469	3	151.358383

4.4. Crossover

The method employs a one-point crossover operation. Thus, after arbitrarily selecting the two chromosome parents the method can arbitrarily choose one crossover point for creating new offspring chromosomes.

4.5. Mutation

The ultimate aim pursued by the mutation operator is to introduce variety in the population. So that, this operator selects arbitrarily individuals from the population and alters some of its characteristics. In this case the mutation operation is achieved with a small probability after crossover and it creates new individuals whose information was not included in previous generations yet.

The complete optimization process is shown in Fig. 3.

5. Example

Considering the system in Fig. 4, it illustrates a four bus micro grid with one load on each node. Total active and reactive load of the system is 500 MW and 309.86 Mvar respectively. This micro grid has a tie line to the local utility, slack bus, at bus number 4 too. The objective to be pursued is to connect a SVC unit, with a maximum rate of 250 Mvar, in the optimum node in order to

Table 12
Evolution of the population of the 4 bus system.

		λ (p.u.)	Bus_{SVC}	Q_{SVC} (Mvar)	F
P_0		0.1321	2	149.54	1
		0.6997	2	187.46	1
		0.4859	2	233.82	1
		0.1827	3	209.54	0.8173
		0.1012	3	221.81	0.8988
P_1	Elitism	0.1827	3	209.54	0.8173
		0.1012	3	221.81	0.8988
	Crossover	0.1012	3	209.54	0.8988
		0.1321	2	233.82	1
	Mutation	0.8984	3	151.36	1
P_2	Elitism	0.1827	3	209.54	0.8173
		0.1012	3	221.81	0.8988
	Crossover	0.1827	3	209.54	0.8173
		0.1012	3	151.36	0.8988
	Mutation	0.1329	3	213.05	0.8671
P_3	Elitism	0.1827	3	209.54	0.8173
		0.1827	3	209.54	0.8173
	Crossover	0.1329	3	213.05	0.8671
		0.1827	3	209.54	0.8173
	Mutation	0.8291	3	135.23	1
P_4	Elitism	0.1827	3	209.54	0.8173
		0.1827	3	209.54	0.8173
	Crossover	0.1827	3	209.54	0.8173
		0.1827	3	209.54	0.8173
	Mutation	0.7937	3	155.33	1
		...	...	...	...
		...	...	...	...
P_{10}	Elitism	0.204	3	282.95	0.7958
		0.204	3	282.95	0.7958
	Crossover	0.1827	3	282.95	0.8173
		0.204	3	209.54	0.8173
	Mutation	0.5526	2	180.46	1
	Best individual	**0.204**	**3**	**282.95**	**0.7958**

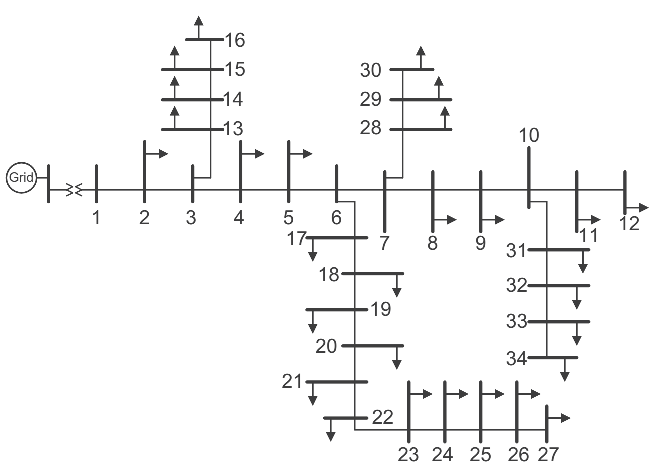

Fig. 6. 34 -Bus distribution network.

maximize the loadability of the system (17) without exceeding an admissible margin of 5% around nominal voltage supply (230 kV) as it is stated in the utility regulations.

5.1. Initial population

The first step in the implementation of the GA is to generate the initial population. There are several methods to obtain this population. In this case, and taking into account the limits of the different variables of the system, the randomize option has been selected as the most suitable one. For the example given, population is composed by five individuals with three genes each one, that correspond to the loading parameter, the DG bus allocation and the reactive power injection respectively.

Table 13
Solution of the GA.

Case	$\lambda_{lim.}$ (p.u.)	Bus_{SVC}	Q_{SVC} (Mvar)
1 Without GD	0	–	–
2 One GD and one SVC	0.06	27	2.77
3 Two GD and two SVC	0.3	11	2.95
		25	2.79
4 Three GD and three SVC	0.74	10	2.15
		23	2.45
		26	2.71

Table 2 shows the initial population. It could be observed that individual #1 corresponds to the chromosome 1 that will locate the DG unit in bus number 2, with a reactive power injection of 149.537 Mvar and with a loadability factor of 13.2%. The loadability parameter represents the systems overload, having in mind the initial loading condition.

5.2. Evaluation

The evaluation process assigns a fitness value to each individual of the population in terms of the Fitness Function FF(y) = λ, (see columns two and three of Table 3) according to the objective function (17). After finishing the evaluation process, a scaling process is applied to the individuals of the population by using the range

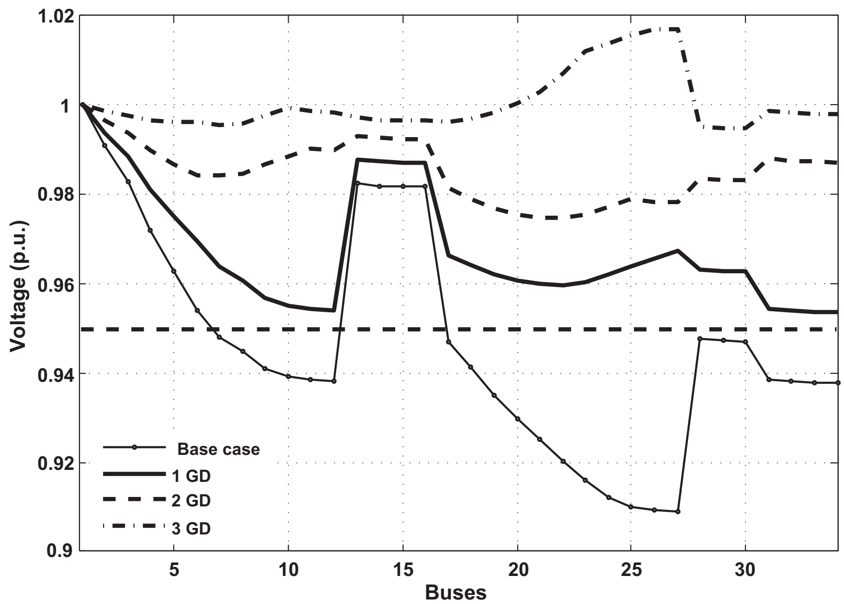

Fig. 7. Voltage profile of the 34-bus network.

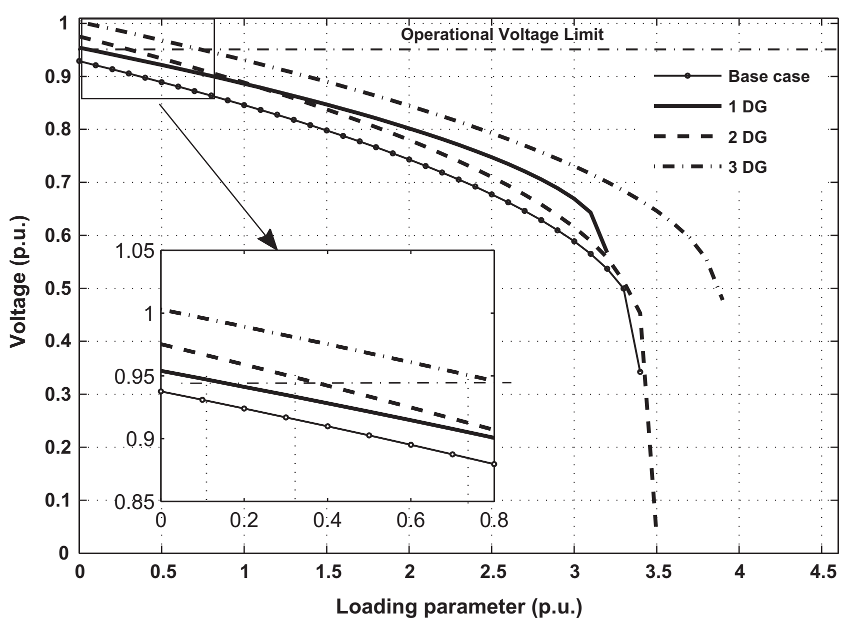

Fig. 8. P–V curves of the 34 bus system.

operation (18). The best individual of the population, which has bigger fitness value (FF), will be assigned the top range value of one.

$$\min F(y) = (1 - FF(y)) \quad (17)$$

$$range = \frac{1}{\sqrt{i}} \quad (18)$$

5.3. Selection

Selection operator is applied to the population in order to obtain the group of parents. In this paper, the roulette method is used. The first step in the selection process is to determinate the frequency of each individual in terms of their ranges. After that, the cumulative frequency of each individual is calculated (Table 4) taking into account that it represents the probability of each individual and could be shown in a circle diagram (Fig. 5).

Once the cumulative frequency of each chromosome has been calculated, a random number r (between 0 and 1) is associated to

Table 14
Maximum loadability and penetration level.

λ_{lim}, (p.u.)	% Penetration
0.62235	70.09

Table 15
Solution of the GA.

Loc,1	P1 (MW)	Q1 (Mvar)	Loc,2	P2 (MW)	Q2 (Mvar)	Loc,3	P3 (MW)	Q3 (Mvar)	Loc,4	P4 (MW)	Q4 (Mvar)
10	1.49	1.8	25	1.5	1.72	21	1.44	1.94	22	1.42	2

Table A.1
Loads data of 34 bus system.

Bus	P_d (MW)	Q_d (Mvar)
1	0	0
2	0.23	0.1425
3	0	0
4	0.23	0.1425
5	0.23	0.1425
6	0	0
7	0	0
8	0.23	0.1425
9	0.23	0.1425
10	0	0
11	0.23	0.1425
12	0.137	0.084
13	0.072	0.045
14	0.072	0.045
15	0.072	0.045
16	0.0135	0.075
17	0.23	0.1425
18	0.23	0.1425
19	0.23	0.1425
20	0.23	0.1425
21	0.23	0.1425
22	0.23	0.1425
23	0.23	0.1425
24	0.23	0.1425
25	0.23	0.1425
26	0.23	0.1425
27	0.137	0.085
28	0.075	0.048
29	0.075	0.048
30	0.075	0.048
31	0.057	0.0345
32	0.057	0.0345
33	0.057	0.0345
34	0.057	0.0345

Table A
Lines data of 34 bus system.

From bus	To bus	R (p.u.)	X (p.u.)
1	2	0.0813	0.0333
2	3	0.0743	0.0306
3	4	0.1142	0.0319
4	5	0.1038	0.0288
5	6	0.1038	0.0288
6	7	0.2181	0.0375
7	8	0.1458	0.025
8	9	0.2181	0.0375
9	10	0.1458	0.025
10	11	0.091	0.0156
11	12	0.0729	0.0125
3	13	0.1092	0.0188
13	14	0.1458	0.025
14	15	0.0729	0.0125
15	16	0.0361	0.0063
6	17	0.1243	0.0347
17	18	0.1139	0.0319
18	19	0.1444	0.0328
19	20	0.1313	0.0299
20	21	0.1313	0.0299
21	22	0.1819	0.0313
22	23	0.1819	0.0313
23	24	0.2181	0.0375
24	25	0.1458	0.025
25	26	0.091	0.0153
26	27	0.0729	0.0125
7	28	0.1092	0.0188
28	29	0.1092	0.0188
29	30	0.1092	0.0188
10	31	0.1092	0.0188
31	32	0.1458	0.025
32	33	0.1092	0.0188
33	34	0.0729	0.0125

each individual of the population. In the given example, parents groups are formed by five individuals, so that, five random numbers are chosen (column *r* of Table 5). The selection of each parent depends not only on the random number, *r*, but also on the cumulative frequency. For each chromosome, its selected parent is the one whose cumulative frequency is immediately above to its random number *r*. In Table 5, it could be seen that for chromosome 1, which has a random number $r = 0.8631$, the parent selected is the one whose cumulative frequency is superior to *r*, which corresponds to chromosome number 5.

Once the fathers are selected, a random reorganization of the parents is made in order to increase the randomness of the whole process (Table 6). As far as this study is concerned, parents involved in the crossover process are the first four, and the rest are reserved for the mutation process.

5.4. Crossover operation

This operator obtains a new individual from a couple of parents. The first step in the crossover process is to select a couple of parents and a random point to perform the crossover operations. In the example, the selected couple of parents are the two first individuals, chromosomes 5 and 4, and the selected crossover point is located between genes 1 and 2; so that, a new offspring individual could be created copying gene 1 from the individual 5 and genes 2 and 3 from the individual 4 (Table 7). For the second couple of parents, the random point to perform the crossover operations is located between genes 2 and 3, and thus the new offspring is created by copying genes 1 and 2 from the individual 1 and gene 3 from individual 3 (Table 8). The final solution is shown in Table 9.

5.5. Mutation

Mutation process incorporates new information in the evolution process. To simplify the case study, in the example high mutation rate has been chosen ($p_m = 0.5$). At the beginning of the mutation process a random number *m* between 0 and 1 is assigned to individuals that participate in the mutation process. In the studied case will be chromosome #1. After that, mutation rate is compared with the random number of each individual; if the random number is lower, all genes of the individual will mutate.

Table 10 shows the mutation process of the example. Parent population is made of five individuals; four of them are used in the crossover process, and thus, only one parent is used in the mutation process which corresponds to individual number 1. The random number m, associated to individual #1, is 0.05, lower than the mutation rate ($p_m = 0.5$), so that, all genes of the individual will mutate and a new offspring will be born.

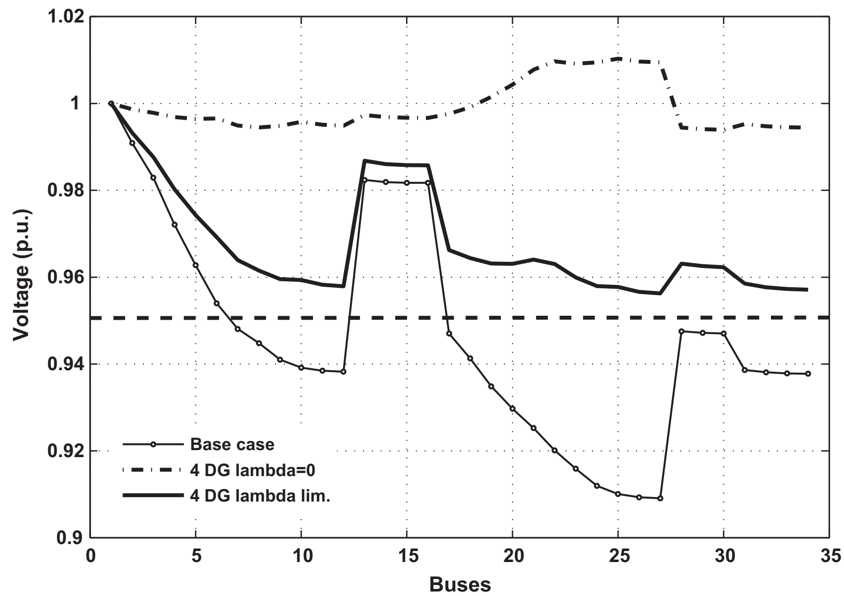

Fig. 9. Voltage profile of the 34 bus system for the multiobjective study.

5.6. New population

After the application of the evaluation, selection, crossover and mutation process, a new population is created. This new population (Table 11) is formed by two individuals obtained by the crossover operation, one for the mutation process, and the other two individuals are the result of applying a new operator called elitism. In that case, elitism operator selects the two individuals of the population which have obtained the top fitness value across the evolution process. In the studied example, the two individuals selected by the elitism process are chromosomes #4 and #5 which are included in the new population.

5.7. Final solution

As it could be observed in the flowchart of Fig. 3, this evolution process is applied till one solution has been found or one of the stop parameters have been reached. The most common considered stop criteria is to reach the limit of the maximum allowable generations or to reach the convergence tolerance between two consecutive populations. Table 12 shows the evolution process of the example.

It could be remarked that the optimal final solution consists in adding one DG unit at bus number 3 with a reactive power capability of 282.95 Mvar and thus, increasing the loadability of the system in a 20%.

6. Application case

In this case, the proposed methodology is applied to a distribution network (Fig. 6) composed by 34 buses (details are included in the appendix). The aim of the optimization methodology is to optimally locate several DG sources that offer reactive power capability spread over the network.

The chromosome length depends on the number of DG units, n, to be located and it will have $(1 + 2 * n)$ genes.

6.1. Maximizing the voltage stability

In order to maximize the power system loadability, the objective function is defined by (17), and the constraints of the problem are the ones defined in Section 3.2.

Table 13 shows the solution proposed by the GA. It could be pointed out that the voltage stability improves as the number of DG units connected to the grid increases too. In the case of adding three DG units, the voltage stability increases up to 74%. Moreover, it could be observed, that the optimal bus location for the connection of the DG units is quite close in the network, in spite of the fact that it depends on the number on units connected to the system.

Fig. 7 shows the voltage profile for the different simulations. It could be highlighted that the incorporation of several DG units with reactive power capability improves the voltage profile of the power systems by smoothing it.

Finally, Fig. 8 shows the voltage stability P–V curves of the different cases. It could be remarked that as the penetration level of DG increases the loadability and the distance to the point of collapse of the system increases too. So, as a conclusion, it could be stated that the incorporation of the DG units in power systems improves voltage stability.

6.2. A multiobjective approach: to increase voltage stability by maximizing the DG penetration level

In this study, the main objective of the proposed methodology applied to the 34 buses network is to determine the optimal allocation of four DG units and, at the same time, to calculate their active and reactive power injection in order to maximize the voltage loadability of the system as well as to increase the DG penetration level. In this case, a multiobjective function that incorporates both single objectives is used as follows:

$$\min F(y) = \frac{1}{2}(1 - f(y)) + \frac{1}{2}\left(\frac{1}{g(y)}\right) \tag{19}$$

where:

$f(y) = \lambda$, optimize loading parameter.

$g(y) = \frac{\sum_{i=1}^{n} P_{GD_i}}{P_{load}}$, represents penetration level.

Tables 14 and 15 show the results of the GA. It could be observed that the maximum power system loadability corresponds to an overload of 62.2% with a maximum penetration level of 70.09%. This condition is reached when one DG unit is connected at bus number 10 with an active and reactive power injection of

1.49 MW and 1.8 Mvar respectively (Table 15); the second DG unit is connected at bus # 25 with an active and reactive power injection of 1.5 MW and 1.72 Mvar; the third DG unit is connected at bus number 21 and injects 1.44 MW and 1.94 Mvar of active and reactive power respectively, and the last DG unit is connected at bus # 22 and injects 1.42 MW of active power and 2 Mvar of reactive power.

Fig. 9 represents the voltage profile of the power systems in the original situation (base case, without DG), and in the case of incorporating four DG units at their optimal allocation without increasing the load (dash-dot line) as well as in the case of the maximum loadability (solid line, overload of 62.2%).

7. Conclusions

The proposed strategy finds out the optimal location of DG units and the optimal reactive power injection in order to improve both, the voltage stability of the system and the DG penetration level. In the optimization algorithm two groups are considered for the distributed generators: on the one hand the controlled DG, which are those coupled to the network through a power converter and, on the other hand, the uncontrolled DG which corresponds to generators that are connected to the grid by synchronous or induction generators. A step-to-step description of the evolutionary process has been detailed in a four bus power system in order to gain understanding of how GA works. Finally, the optimization process has been applied to a 34-bus distribution active power network where the DG units with reactive power capability are optimally located by applying single objective function and multiobjective function.

Genetic algorithm has been proved to be a good method to solve large scale, combinatorial optimization problem, such as reactive power planning in order to increase the DG penetration level at distribution networks increasing, at the same time, the voltage stability. This formulation could very useful for the utility planners and operators, and whatever other situations where reactive power reserve would be needed. The proposed methodology opens up several new possibilities in this field to operate and to design power networks with distributed generation.

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Appendix A

Loads and lines data of the 34 bus system Tables A.1 and A.

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