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Evolutionary algorithms for the design of grid-connected PV-systems

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ABSTRACT

The sale of electric energy generated by photovoltaic (PV) plants has attracted much attention in recent years. The installation of PV plants aims to obtain the maximum benefit of captured solar energy. The current methodologies for planning the design of the different components of a PV plant are not completely efficient. This paper addresses the optimization of the design of PV plants with solar tracking, which consists of the optimization of the variables that make up the PV plant to obtain the minimum electric (Joule) losses possible. These variables are the size and distribution of solar modules in the solar tracker, the distribution of the solar trackers in the field and the choice of inverter. Evolutionary algorithms (EAs) are adaptive methods based on natural evolution that may be used for searching and optimization. Four different EAs have been used for optimizing the design of PV plants: steady-state genetic algorithm, generational genetic algorithm, CHC algorithm and DE algorithm. In order to test the performance of these algorithms we have used different proposed fields to mount PV plants. The results obtained show that EAs, and specifically DE with rand mutation schemes, are promising techniques to optimize design of PV plants. Furthermore, the results are contrasted with nonparametric statistical tests to support our conclusions.

1. Introduction

The viability of a photovoltaic grid-connected plant (PVGCP) (Swanson, 2009) can be affected by several factors (Swider et al., 2008), such as the initial capital cost of the system, the generation unit costs (Kenneth & Jared, 2010), the selling price of the generated energy and the PVGCP capital cost subsidization rate. The generation unit costs is the factor that is easiest to be optimized, since both the initial investment cost and the sales value of the energy generated are external factors independent of the photovoltaic (PV) plant itself. Therefore we address the problem of the optimization of PVGCPs from the point of view of their initial installation, with the goal of maximizing the generated energy.

Conventional methodologies (empirical, analytical, numerical, hybrid, etc.) (Asiedu & Chen, 1997; Bartoli, Cuomo, Fontana, Serio, & Silvestrini, 1984) for designing PV systems have generally been used for places where the weather data, such as irradiation, temperature, humidity, clearness index and wind speed, are required and the information concerning to the place where we want to establish the PV system is available (Hernández, Medina, Davidson, & Jurado, 2007), because these approaches need long-term meteorological data for their operations. In this particular case, these methods present a good solution for projecting PV systems and their accuracy is achieved by using data from daily global irradiation series. However, these techniques could not be applied for projecting PV systems in remote and isolated areas, where the relevant meteorological data, especially regarding solar radiation, are not available. In order to deal with this situation, we need methods that are capable of optimizing the design of PV systems using all their variables.

The design of PV systems can be viewed as a continuous optimization problem, and so it could be solved using evolutionary algorithms (EAs). These techniques (Eiben & Smith, 2003; Fernández, García, Luengo, Bernadó-Mansilla, & Herrera, 2010; García & Herrera, 2009) have been successfully used in different continuous optimization problems (Triguero, García, & Herrera, 2010, 2011), such as the design of large power distribution systems (Ramírez-Rosado & Bernal-Agustín, 2001). EAs have proved to perform well in complex problems with linear or non-linear cost functions.

In recent years, several studies have appeared in the specialized literature in which generated power for PV systems is optimized (Baños et al., 2011). Particle swarm optimization (PSO) (Kennedy & Eberhart, 1995), Genetic algorithms (GAs) (Goldberg, 1989) and differential evolution (DE) (Storn & Price, 1997) are three effective evolutionary optimization techniques for continuous spaces. In fact, PSO has been used to optimize the sizing of a PVGCS with fixed structures (Kornelakis & Marinakis, 2010), and inverters (Vural, Der, & Yildirim, 2011), and results have been compared with GAs in terms of efficiency. Other works, such as (Koutroulis,

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Kolokotsa, Potirakis, & Kalaitzakis, 2006), use GAs to optimize the design of stand-alone photovoltaic/wind systems. Furthermore, the DE algorithm has been used to determine the tilt angle in PV modules (Vural, Der, & Yildirim, 2010). To the best of our knowledge, evolutionary techniques have not yet been applied to optimizing PVGCSs with solar tracking.

In this paper we address the problem of the optimization of PV plants with trackers in terms of unit generation costs, decreasing electrical losses that occur in the PV plant and therefore increasing the generated energy. Four different EAs have been analyzed in terms of their efficiency in several defined problems which consist of 40 fields with different dimensions, steady-state GA (Glover & Kochenberbe, 2003), generational GA (Glover & Kochenberbe, 2003), the CHC algorithm (Eshelman, 1991) and the DE algorithm (Price, Storn, & Lampinen, 2005; Storn & Price, 1997). In these fields, the algorithm should choose and distribute the elements that make up the PV plant in such a way as to generate the minimum possible electric losses. Each of these elements, for instance the size of the PV panels or their distribution on the structure, will be part of the solution of the problem, which will allow us to know the Joule losses in electrical conductors in the installed capacity of this configuration.

The experimental study will include a statistical analysis based on nonparametric statistical tests and will involve a total of 40 fields with different parameter selections for each EA.

The rest of the paper is organized as follows: Section 2 describes the background of PV systems and the EAs used. In Section 3 we present the use of EAs for optimizing the PV plant design. Section 4 discusses the experimental framework, presents the analysis of results and shows the analysis of the convergence of each EA population. Finally, in Section 5 we summarize our conclusions.

2. Background

In this section, we deal with the main aspects of the PV plants with trackers and the EAs used. Section 2.1 presents a background on PV plants with trackers. Sections 2.2 and 2.3 show the main characteristics of GA and CHC algorithms, and finally, Section 2.4 shows the main components of the DE algorithm.

2.1. PV plant with trackers

The main components of a PV plant with trackers are the field where will be installed the PV plant, the tracking structures that will be distributed in this field, the PV modules on the monitoring structures, the inverters which convert direct current into alternating current and the electrical conductors that carry electrical energy from the PV modules to the inverters. Electrical losses in the transport of electrical energy in those electrical conductors can be calculated as follows:

$$P = 2 \cdot R \cdot I^2 \tag{1}$$

where I is the intensity of current passing through a conductor, and R is the electrical resistance, which depends on the section s, length L and resistivity ρ of the conductor, which for copper conductors can take the value $\rho = 0.017241 \frac{\Omega \cdot m^2}{m}$ (Ω ohms and m meters (Elgerd, 1971)), and are related as in the equation:

$$R = \frac{\rho \cdot L}{s} \tag{2}$$

The section of the conductor is determined by the electric intensity it is capable of bearing and the allowable voltage drop for that tranche. In our case the main condition that defines the section of the conductor is the voltage drop, because the current through the conductors is much lower than the intensities that they bear. Therefore the conductor section is defined by the permissible voltage drop as follows:

$$\Delta V = \frac{2 \cdot LP}{\mu \cdot s \cdot V} \tag{3}$$

where P is the electrical power flowing through the conductor, μ the electrical conductivity of the copper conductor that depends on temperature but can take a standard value of $\mu = 58.0 \frac{m}{\Omega \cdot m^2}$ and V the line voltage (Elgerd, 1971).

The conductor's length is determined by the distance from the tracking structure to the inverter. In a rectangular field, inverters will be located at the geometric center of the field. Thus, once we know the distances from each of the tracking structures to the geometric center of the field and the electrical current flowing from each tracker to the inverter, we can calculate the electric (Joule) losses produced. Obviously, the most interesting configurations, are those in which the current through the conductors is as low as possible and the voltage at which current flows is as high as the inverter allows. The intensity and voltage are not only defined by the electrical parameters of the PV modules chosen, but also depend on the several series–parallel associations that exist within the tracking structures. The physical parameters of the PV modules, such as height and width, will define the size of the tracking structures, and therefore, the separation between them to ensure that none cast shadows on surrounding structures. This will limit the number of trackers that are installed in the field.

2.2. Genetic algorithms (GAs)

GAs have proved to perform well in many optimization problems (Maaranen, Miettinen, & Penttinen, 2007). GAs are stochastic search methods that have been successfully applied in many search, timetabling, scheduling and machine learning problems and have been especially used in engineering, biology and medicine (Haida et al., 1991). GAs are inspired by evolutionary operators such as mutation, selection and crossover (Goldberg, 1989).

A GA starts with a population of M candidate solutions, called individuals or chromosomes. It is usual to denote each individual as a D-dimensional vector $X_{i,G} = \left\{x^1_{i,G}, \ldots, x^D_{i,G}\right\}$. The initial population should cover the entire search space as much as possible. In this problem, this is achieved by uniformly randomizing individuals. The subsequent generations in GA are denoted by $G = 0,1,\ldots,G_{max}$. Fig. 1 shows the outline of a GA.

Traditionally, a solution is represented as a binary string of 0 and 1, but other encodings are also possible (Ronald et al., 1997). In our case we will focus on a real codification, where the crossover operator can only be used between genes occupying the same position within the individuals and the mutation operator can only mutate the gene within the maximum and minimum values that the variable can take. In each generation, the fitness of every individual in the population is evaluated, and multiple individuals are stochastically selected from the current population (based on their fitness), and modified to form a new population. The new population is then used in the next iteration of the algorithm.

2.3. CHC algorithm

The main idea that differentiates the CHC evolutionary algorithm (Eshelman, 1991) from the GA is that CHC algorithm involves the combination of a selection strategy with a very high selective pressure, and several components inducing a strong diversity. The four main components of the algorithm are shown as follows:

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```
1: Begin GA
2: Initialize the population
3: Evaluate initial population
4: while convergence criteria is not satisfied do
5:    Begin Create new population
6:    for population size/2 do
7:       Begin reproductive cycle
8:       Perform competitive selection
9:       Apply genetic operators to generate new solutions
10:   end for
11:   Evaluate solutions in the population
12:   Perform competitive selection
13:   Apply genetic operators to generate new solutions
14:   Evaluate solutions in the population
15: end while
```

Fig. 1. GA algorithm basic structure.

- *Elitist selection*. The M members of the current population are merged with the offspring population obtained from it and the best M individuals are selected to compose the new population.
- *Highly disruptive crossover, HUX*. It crosses over exactly half of the non-matching individuals, where the bits to be exchanged are chosen at random without replacement. In this way, it guarantees that the two offspring are always at the maximum Hamming distance from their two parents, thus proposing the introduction of a high diversity in the new population and lessening the risk of premature convergence.
- *Incest prevention mechanism*. During the reproduction step, each member of the parent (current) population is randomly chosen without replacement and paired for mating. However, not all these couples are allowed to cross over. Before mating, the Hamming distance between the potential parents is calculated and if half this distance does not exceed a difference threshold d, they are not mated and no offspring coming from them is included in the offspring population. The aforementioned threshold is usually initialized to $D/4$ (with D being the individual length). If no offspring is obtained in one generation, the difference threshold is decremented by one. The effect of this mechanism is that only the more diverse potential parents are mated, but the diversity required by the difference threshold automatically decreases as the population naturally converges.
- *Restart process*. It is only applied when the population has converged. The difference threshold is considered to measure the stagnation of the search, which happens when it has dropped to zero and several generations have been run without introducing any new individual in the population. Then, the population is reinitialized by considering the best individual as the first chromosome of the new population and generating the remaining $M-1$ by randomly flipping a percentage of their bits.

2.4. Differential evolution

DE follows the general procedure of an EA. As in the previous algorithms, DE usually begins with a uniform random population to cover the entire search space as much as possible.

2.4.1. Mutation operation

After initialization, DE applies the mutation operator to generate a mutant vector $V_{i,G}$, with respect to each individual $X_{i,G}$, in the current population. For each target $X_{i,G}$, at the generation G, its associated mutant vector $V_{i,G} = \left\{V^1_{i,G}, \ldots, V^D_{i,G}\right\}$. The method of creating this mutant vector is that which differentiates one DE scheme from another. Six of the most frequently referenced strategies are listed below:

- "DE/Rand/1":

$$V_{i,G} = X_{r^i_1,G} + F \cdot \left(X_{r^i_2,G} - X_{r^i_3,G}\right) \tag{4}$$

- "DE/Best/1":

$$V_{i,G} = X_{best,G} + F \cdot \left(X_{r^i_1,G} - X_{r^i_2,G}\right) \tag{5}$$

- "DE/RandToBest/1":

$$V_{i,G} = X_{i,G} + F \cdot (X_{best,G} - X_{i,G}) + F \cdot \left(X_{r^i_1,G} - X_{r^i_2,G}\right) \tag{6}$$

- "DE/Best/2":

$$V_{i,G} = X_{best,G} + F \cdot \left(X_{r^i_1,G} - X_{r^i_2,G}\right) + F \cdot \left(X_{r^i_3,G} - X_{r^i_4,G}\right) \tag{7}$$

- "DE/rand/2":

$$V_{i,G} = X_{r^i_1,G} + F \cdot \left(X_{r^i_2,G} - X_{r^i_3,G}\right) + F \cdot \left(X_{r^i_4,G} - X_{r^i_5,G}\right) \tag{8}$$

- "DE/RandToBest/2":

$$V_{i,G} = X_{i,G} + F \cdot (X_{best,G} - X_{i,G}) + F \cdot \left(X_{r^i_1,G} - X_{r^i_2,G}\right) + F \cdot \left(X_{r^i_3,G} - X_{r^i_4,G}\right) \tag{9}$$

The indices $r^i_1, r^i_2, r^i_3, r^i_4, r^i_5$ are mutually exclusive integers randomly generated within the range $[1, NP]$, which are also different from the base index i. These indices are randomly generated once for each mutation. The scaling factor F is a positive control parameter for scaling the difference vectors. $X_{best,G}$ is the best individual of the population in terms of fitness.

2.4.2. Crossover operator

After the mutation phase, a crossover operation is applied to increase the potential diversity of the population. The DE algorithm

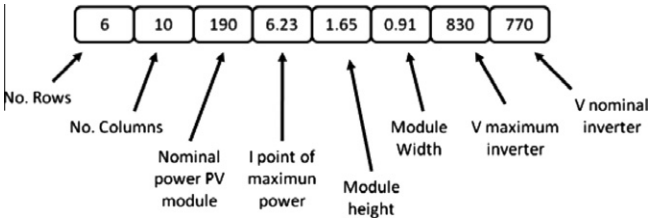

Fig. 2. Example of individual for the PVGCP.

Table 1
Design problem ranges.

Parameter	Minimum	Maximum
No. rows	5	9
No. columns	8	14
Module power (W)	150	290
I maximum power point (A)	4.49	10.23
Module height (m)	1.324	2.000
Module width (m)	0.800	1.061
Maximum inverter voltage (V)	700	880
Nominal inverter voltage (V)	600	800

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can use three kinds of crossover schemes, known as 'Binomial', 'Exponential' and "Arithmetic" crossovers. This operator is applied to each pair of the target vector $X_{i,G}$ and its corresponding mutant vector $V_{i,G}$ to generate a new trial vector that we denote $U_{i,G}$. The mutant vector exchanges its components with the target vector $X_{i,G}$.

We will focus on the binomial crossover scheme, which is performed on each component whenever a randomly picked number between 0 and 1 is less than or equal to the crossover rate (CR), The CR is a user-specified constant within the range [0,1), which controls the fraction of parameter values copied from the mutant vector. This scheme may be outlined as

$$U^j_{i,G} = \begin{cases} V^j_{i,G} & \text{if rand}(0,1) <= CR \text{ or } j = j_{\text{rand}} \\ X^j_{i,G} & \text{Otherwise} \end{cases} \quad (10)$$

where rand $(0,1) \in [0,1]$ is a uniformly distributed random number, j ranges in $\{1,2,\ldots,D\}$, and $j_{rand} \in \{1,2,\ldots,D\}$ is a randomly chosen index, which ensures that $U_{i,G}$ gets at least one component from $V_{i,G}$.

Finally, we describe the arithmetic crossover, which generates the trial vector $U_{i,G}$ like this,

$$U_{i,G} = X_{i,G} + K \cdot (V_{i,G} - X_{i,G}) \quad (11)$$

where K is the combination coefficient which is usually used in the interval [0,1]. This strategy is known as "DE/CurrentToRand/1".

2.4.3. Selection operator

When the trial vector has been generated, we must decide which individual between X_{i_G} and $U_{i,G}$ should survive in the population of the next generation $G+1$. The selection operator is described as follows:

$$X_{i,G+1} = \begin{cases} U_{i,G} & \text{if } f(U_{i,G}) \text{ is better than } f(X_{i,G}) \\ X_{i,G} & \text{Otherwise} \end{cases} \quad (12)$$

where $f(\,)$ is the fitness function to be minimized. If the new trial vector yields a solution equal to or better than the target vector, it replaces the corresponding target vector in the next generation; otherwise the target is retained in the population. Therefore, the population always gets better or retains the same fitness values, but never deteriorates. This one-to-one selection procedure is generally kept fixed in most of the DE algorithms.

3. Evolutionary algorithms for optimizing the design of PVGCPs with trackers

In this section we explain the structure of the problem, as well as each of the solutions that have been adopted for its resolution. The problem that arises is, given a rectangular field with specific dimensions and latitude, the algorithm will try to find the optimal configuration in which the Joule losses in electrical conductors from trackers to inverters are minimal.

Typically, when dealing with genetic algorithms, the set of variables that make up the solution of our problem are denoted as a chromosome, while, in EAs it is defined as an individual. Thus, we can say that a chromosome consists of genes, while for EAs the individual consists of attributes. Henceforth, we shall always refer to them as individuals and attributes (Eiben & Smith, 2003).

3.1. Parameter encoding and individual structure

First of all, it is necessary to define the solution codification. In the proposed EAs, each individual in the population encodes a complete solution, that is, all the variables which form the design of a PV plant are encoded sequentially in each individual. In fact, one individual is composed of nine different variables, as Fig. 2 shows. The maximum and minimum values of these variables are previously specified; thus the algorithm does not go beyond this range in its search, and does not lead to inconsistent solutions. It is important to note that these ranges are adjustable at the start of calculation. Thus, to solve our problem, the values found in the catalogs of the leading manufacturers of photovoltaic modules and inverters have been introduced as limiting values for these ranges. Following the ideas established in Jingqiao and Sanderson (2009), the values of each individual are generated randomly.

3.2. Generating new configurations

After the initialization process, each evolutionary algorithm enters an iterative loop in order to perform different operations with the purpose of defining new individuals $U_{i,G}$. Mutation and crossover operators generate new configurations in each generation with the ideas established in Section 2. After applying these operators, it is necessary to check that the individual $U_{i,G}$ has been generated with correct values for all features of the prototypes, i.e. to check that the values are in the correct range (Table 1).

3.3. Fitness function

In order to evaluate the generated configuration we need to define a fitness value for each individual. In our case, the fitness values will be measured as the Joule losses obtained by this configuration as shown in Eq. 13. The fitness function is guided by the Joule losses because, as stated previously, this is one of the most important factors in the design for PV systems. Indeed, there are other losses in a PV plant, but we have decided to start the optimization problem of a grid connected PV plant considering only the Joule losses which are electrically more tractable and influenced by the series–parallel topology connection of the PV modules. In addition, the algorithm eliminates self-shading losses, because for each solution obtained, it estimates the value of the tracking structure surface and thus it is able to distribute the trackers so that there are no self-shading losses.

$$P(\%) = \frac{\sum_{i=1}^{N} \frac{2 \cdot \rho \cdot L_i \cdot I_i^2}{s_i}}{No.\ Rows \cdot No.\ Columns \cdot Pw \cdot N} \quad (13)$$

where P is the percentage of Joule losses in all the conductors of the PV plant, over the installed power. N is the number of trackers installed in the field, ρ is the copper conductor resistivity, $No.$ Rows

Table 2
Fields chose for our problem.

Field	Dimension X (m)	Dimension Y (m)	Field	Dimension X (m)	Dimension Y (m)
1	130	90	21	485	415
2	150	100	22	500	450
3	185	100	23	500	500
4	200	135	24	530	485
5	200	150	25	530	510
6	210	165	26	570	510
7	250	150	27	600	525
8	280	180	28	605	550
9	280	210	29	620	540
10	300	200	30	600	600
11	300	250	31	650	600
12	300	300	32	680	620
13	325	275	33	700	620
14	335	290	34	730	600
15	350	300	35	750	610
16	400	315	36	750	680
17	420	350	37	800	700
18	450	350	38	825	680
19	400	400	39	860	800
20	470	380	40	900	900

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Table 3
Parameter specification for all the methods employed in the experimentation.

Algorithm	Parameters
Steady-state GA	PopulationSize = 50, Iterations = 400, One-point crossover, Crossover prob. = 1.0, Mutation prob. = 0.1
Generational GA	PopulationSize = 50, Iterations = 400, α value (BLX-α) = 0.5, Crossover prob. = 0.9, Mutation prob. = 0.2
CHC	PopulationSize = 50, Iterations = 400, HUX Crossover, α value (BLX-α) = 0.5, Hamming dist. = D/4
DE	PopulationSize = 50, Iterations = 400, F = 0.5, CR = 0.7, Binary crossover
DE	PopulationSize = 50, Iterations = 400, F = 0.5, CR = 0.9, Binary crossover

and *No*. Columns are the number of rows and columns of PV modules placed on each tracker, and *Pw* is the nominal power of each PV module.

Thus, once the fitness function is defined, the individuals with smallest values of the fitness function are more likely to pass their attributes onto the next generation:

$$X_{i,G+1} = \begin{cases} U_{i,G} & \text{if Joule losses } (U_{i,G}) <= \text{Joule losses } (X_{i,G}) \\ X_{i,G} & \text{Otherwise} \end{cases} \quad (14)$$

4. Experimental framework and results

In this section we show the factors and issues related to the experimental study. We provide the details of the areas chosen for the experimentation and the parameters of the algorithms in Section 4.1. In Section 4.2 we propose the statistical tool to perform a comparison between all evolutionary techniques considered. Section 4.3 shows the results of the different schemes of EAs proposed, and subsequently we compare them and identify the best EA scheme by using the statistical tests. Finally, Section 4.4 shows a graphical representation of the convergence capabilities of EA models.

4.1. Experimental framework

The performance of the algorithms is analyzed using 40 fields proposed. These have been chosen randomly from fields of standard dimensions where PVGCPs have been installed. Table 2 summarizes the properties of the selected areas. For each field, it shows the size (dimensions *X* and *Y*). We have chosen a similar value of 37 degrees latitude, the same for all fields proposed, to compare fields that are in the same geographical area. Table 1 shows the maximum and minimum values that all variables of our individuals can take.

The parameters of the algorithms used are presented in Table 3. These values have been established in order to compare the algorithms fairly. Hence, the number of iterations has been fixed empirically to 400, with the same values for all algorithms. Furthermore, the EAs considered, steady-state GA, generational GA, CHC and DE, have been initialized with the same number of individuals. The parameters of DE are set to $F = 0.5$ and $CR = 0.7$ and 0.9 as used or recommended in Jingqiao and Sanderson (2009). The remaining parameter values are chosen according to the respective authors of the algorithms, assuming that they were optimally chosen. For each field, each algorithm has been executed ten times with different seeds so that the results presented are the mean and standard deviation of the ten simulations.

4.2. Statistical tools for analysis

In this paper, we use the hypothesis testing techniques to provide statistical support for the analysis of the results (García, Fernández, Luengo, & Herrera, 2009; Sheskin, 2006) and identifying the most relevant differences found between the methods. Specifically, we will use nonparametric statistical tests, due to the fact that the initial conditions that guarantee the reliability of the parametric tests may not be satisfied, causing the statistical analysis to lose credibility with parametric tests. These tests are suggested in the studies presented in Luengo, García, and Herrera (2009), García and Herrera (2008) and García et al. (2009, 2010), where their use in the field of Machine Learning is highly recommended.

Throughout the study, we perform a multiple comparison between all the evolutionary techniques considered, using the Friedman Aligned-Ranks test (Hodges & Lehmann, 1962) to detect statistical differences among a group of results. Later, post hoc procedures like Holm's or Finner's will find out which algorithms are distinctive among the $1 * n$ comparisons performed. We have used the KEEL software tool (Alcalá-Fdez et al., 2011) to apply this statistical test.

More information about these tests and other statistical procedures can be found at http://sci2s.ugr.es/sicidm/.

Table 4
GAs and CHC results.

Field	Steady-state GA		Generational GA		CHC		Field	Steady-state GA		Generational GA		CHC	
	Mean	S.D.	Mean	S.D.	Mean	S.D.		Mean	S.D.	Mean	S.D.	Mean	S.D.
1	0.3968	0.0090	0.2998	0.0174	**0.2712**	0.0246	21	1.0397	0.1013	0.8376	0.0830	**0.7350**	0.0382
2	0.4108	0.0278	0.3294	0.0271	**0.3098**	0.0126	22	1.1205	0.1134	0.9590	0.0813	**0.8173**	0.0631
3	0.4645	0.0136	**0.3649**	0.0268	0.3655	0.0211	23	1.0986	0.1230	0.9077	0.0326	**0.8022**	0.0286
4	0.4583	0.0451	0.4180	0.0170	**0.3787**	0.0114	24	1.2183	0.1492	0.8826	0.0582	**0.8689**	0.0522
5	0.5282	0.0388	0.4378	0.0183	**0.4075**	0.0274	25	1.2666	0.1461	0.8950	0.0621	**0.7945**	0.0148
6	0.5233	0.0293	0.4459	0.0158	**0.4051**	0.0206	26	1.1453	0.1598	0.9567	0.0802	**0.8896**	0.0388
7	0.5685	0.0366	0.4676	0.0244	**0.4341**	0.0164	27	1.2932	0.1995	1.0086	0.1265	**0.9507**	0.1114
8	0.5840	0.0643	0.5134	0.0209	**0.4703**	0.0284	28	1.3775	0.1174	**0.9248**	0.0632	0.9295	0.0616
9	0.6202	0.0506	0.5551	0.0418	**0.4752**	0.0234	29	1.4817	0.1301	0.9639	0.1158	**0.9493**	0.0823
10	0.6668	0.0748	0.5130	0.0321	**0.5009**	0.0273	30	1.3389	0.2427	1.1007	0.1571	**0.9608**	0.1064
11	0.6917	0.0193	0.5548	0.0203	**0.5135**	0.0213	31	1.3029	0.0264	1.0009	0.0281	**0.9869**	0.0611
12	0.7458	0.0199	0.5704	0.0557	**0.5312**	0.0226	32	1.5384	0.1241	1.0163	0.0848	**0.9896**	0.0245
13	0.7535	0.1005	0.6586	0.0412	**0.5413**	0.0169	33	1.5049	0.1124	1.2050	0.0776	**1.0642**	0.0404
14	0.7385	0.0359	0.5731	0.0470	**0.5366**	0.0036	34	1.4059	0.2404	1.1079	0.0926	**1.0483**	0.0529
15	0.7823	0.0611	0.6374	0.0415	**0.5968**	0.0333	35	1.5020	0.0832	1.0520	0.0202	**1.0425**	0.0421
16	0.8133	0.1043	0.7111	0.0541	**0.6231**	0.0230	36	1.4785	0.1961	1.2135	0.1280	**1.1283**	0.0484
17	0.9358	0.1197	0.7243	0.0663	**0.6425**	0.0110	37	1.6077	0.1751	1.3593	0.1378	**1.2198**	0.0900
18	0.9707	0.0643	0.7977	0.0480	**0.7230**	0.0688	38	1.6568	0.1902	1.3064	0.1372	**1.2956**	0.1094
19	0.9727	0.1032	0.7591	0.0279	**0.7052**	0.0845	39	2.0137	0.0980	1.5327	0.1273	**1.3108**	0.1165
20	1.0176	0.0771	0.7791	0.0414	**0.7214**	0.0504	40	2.1479	0.2771	1.4053	0.0909	**1.3750**	0.0830
							Average	1.0545	0.4411	0.8286	0.3130	**0.7576**	0.2941

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Table 5
Differential evolution results with CR = 0.7.

Field	DE/Rand/1		DE/Best/1		DE/RandToBest/1		DE/Best/2		DE/Rand/2		DE/RandToBest/2	
	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.
1	0.2441	0.0051	0.2477	0.0068	0.2475	0.0018	**0.2409**	0.0083	0.2484	0.0022	0.2467	0.0000
2	**0.2836**	0.0059	0.2874	0.0010	0.2872	0.0010	0.2865	0.0001	0.2865	0.0001	0.2865	0.0001
3	0.3359	0.0056	**0.3323**	0.0053	0.3389	0.0046	0.3383	0.0014	0.3329	0.0054	0.3383	0.0014
4	0.3603	0.0043	0.3709	0.0043	0.3626	0.0003	0.3626	0.0003	**0.3575**	0.004	0.3624	0.0001
5	**0.3644**	0.0047	0.3695	0.0017	0.3682	0.0001	0.3682	0.0001	**0.3644**	0.0047	0.3682	0.0001
6	**0.3746**	0.0039	0.3816	0.007	0.3805	0.0025	0.3863	0.0036	0.3794	0.0003	0.3793	0.0001
7	0.4146	0.0016	**0.4112**	0.0085	0.4174	0.0019	0.4143	0.0055	0.4118	0.0041	0.4145	0.0009
8	0.4376	0.0055	0.4552	0.0039	0.4471	0.0007	0.4448	0.0059	**0.4369**	0.0003	0.4412	0.0052
9	0.4469	0.0047	0.4561	0.0007	0.4556	0.0008	0.4511	0.0031	**0.4444**	0.0035	0.4542	0.0029
10	0.4678	0.0001	0.4657	0.0087	0.4682	0.0008	0.4661	0.0056	**0.4631**	0.0096	0.4678	0.0001
11	0.4823	0.0081	**0.4812**	0.0106	0.4887	0.0021	0.4863	0.0001	0.4823	0.0081	0.4863	0.0001
12	0.4995	0.0130	0.5553	0.0698	0.5074	0.0063	0.5049	0.0099	**0.4915**	0.0096	0.4980	0.0145
13	0.5115	0.0017	0.5565	0.0554	0.5129	0.0084	0.5058	0.0074	**0.5045**	0.0053	0.5106	0.0001
14	0.5213	0.0116	0.5253	0.0086	0.5313	0.0004	0.5268	0.0099	**0.5211**	0.005	0.5309	0.0001
15	0.5386	0.0086	0.5695	0.0252	0.5485	0.0020	0.5285	0.0098	**0.5244**	0.0116	0.5360	0.0142
16	0.5892	0.0032	0.5935	0.0049	0.5923	0.0035	0.5881	0.0000	**0.5793**	0.0064	0.5852	0.0126
17	0.6212	0.0001	0.6238	0.0006	0.6245	0.0001	0.6141	0.0096	**0.6068**	0.0104	0.6113	0.0109
18	0.6475	0.0042	0.6510	0.0004	0.6507	0.0004	0.6500	0.0060	**0.6369**	0.0160	0.6499	0.0001
19	0.6276	0.0112	0.6281	0.0124	0.6368	0.0032	**0.6269**	0.0120	0.6304	0.0034	0.6331	0.0001
20	0.6696	0.0109	0.6941	0.0134	0.6740	0.0124	0.6737	0.0059	**0.6538**	0.0114	0.6793	0.0023
21	0.7033	0.0031	0.7082	0.0021	0.7060	0.0015	**0.6894**	0.0122	0.6989	0.0109	0.6896	0.0124
22	0.7304	0.0148	0.7269	0.0160	0.7398	0.0016	0.7391	0.0021	**0.7123**	0.0132	0.7394	0.0001
23	0.7599	0,0154	0.7691	0,0006	0.7692	0.0008	0.7614	0.0071	**0.7327**	0.0168	0.7629	0.0083
24	0.7801	0.0000	0.7816	0.0018	0.7835	0.0018	0.7830	0.0015	**0.7551**	0.0124	0.7801	0.0001
25	0,7963	0,0010	0.7999	0.0016	0.7964	0.0010	**0.7819**	0.0168	0.7956	0.0001	0.7956	0.0001
26	0.8259	0.0005	0.8277	0.0011	0.8292	0.0020	0.8125	0.0181	**0.7904**	0.0001	0.8261	0.0005
27	0.8576	0.0022	0.8588	0.0002	0.8598	0.0013	0.8187	0.0020	0.8457	0.0155	**0.8148**	0.0001
28	0.8694	0.0122	**0.8612**	0.0178	0.8690	0.0148	0.8760	0.0005	0.8663	0.0168	0.8758	0.0005
29	**0.8526**	0.0162	0.8807	0.0003	0.8815	0.0016	0.8804	0.0004	0.8801	0.0001	0.8809	0.0001
30	0.8995	0.0027	0.9036	0.0030	0.9005	0.0035	0.8755	0.0202	**0.8512**	0.0228	0.8987	0.0017
31	0.9299	0.0192	0.9418	0.0009	0.9410	0.0013	0.9390	0.0007	**0.9105**	0.0232	0.9396	0.0001
32	0.9543	0.0217	0.9769	0.0017	0.9738	0.0026	0.9635	0.0198	**0.9378**	0.0173	0.9675	0.0184
33	0.9681	0.0209	0.9956	0.0067	0.9752	0.0203	0.9746	0.0180	**0.9676**	0.0138	0.9800	0.0184
34	0.9859	0.0179	**0.9850**	0.0243	1.0056	0.0006	0.9949	0.0080	0.9986	0.0008	1.0030	0.0030
35	1.0117	0.0179	1.0057	0.0227	1.0251	0.0010	1.0137	0.0205	**1.0020**	0.0269	1.0239	0.0001
36	**1.0451**	0.0244	1.0670	0.0015	1.0657	0.0013	**1.0451**	0.0245	1.0649	0.0002	1.0662	0.0005
37	**1.1031**	0.0201	1.1186	0.0001	1.1154	0.0028	1.1175	0.0022	1.1032	0.0199	1.1131	0.0001
38	1.1122	0.0207	1.1389	0.0302	1.1259	0.0021	1.1244	0.0025	**1.1120**	0.0206	1.1226	0.0002
39	1.2103	0.0224	1.2270	0.0002	1.2224	0.0013	1.2235	0.0009	**1.1879**	0.0274	1.2219	0.0010
40	1.2994	0.0244	1.2943	0.0308	1.3069	0.0247	1.2933	0.0290	**1.2709**	0.0212	1.3190	0.0030
Average	0.7033	0.2700	0.7131	0.2709	0.7108	0.2730	0.7043	0.2708	**0.6960**	0.2669	0.7075	0.2737

4.3. Results of EA schemes

In this section we analyze the results obtained by 3 schemes of EAs and 12 different schemes of DE, in terms of Joule losses. Tables 4–6 collect the average and standard deviation (SD) in accuracy obtained over the 40 areas considered. The best result for each area is highlighted in bold. These tables are composed of three columns for each EA model. The first one identifies the field number, the second the average of the ten executions performed with different seeds and the third the standard deviation. Finally, the last row indicates the average of the forty fields and standard deviations for each EA scheme studied.

Table 7 presents the statistical analysis conducted by nonparametric multiple comparison procedures for Joule losses. More specifically, we have used the Friedman aligned (FA) procedure (Hodges & Lehmann, 1962) to compute the set of rankings that represent the effectiveness associated with each algorithm (second column). The table is ordered from the best to the worst ranking. In addition, the third column shows the adjusted p-value with the Holm's test (Holm APV) (Holm, 1979). Finally, the fourth column presents the adjusted p-value with the Finner's test (Finner APV). Note that DE/Rand/2 with CR = 0.7 is established as the control algorithm because it has obtained the best FA ranking. We will establish a level of significance $\alpha = 0.1$ to determine whether the null hypothesis has been rejected. Those APV highlighted in bold point out methods outperformed by the control one, at a $\alpha = 0.1$ level of significance.

Some observations can be made from these tables:

- As we can observe, when the size of the different fields increases, the Joule losses also increment with all the algorithms due to the increasing lengths of electrical conductors.
- All the DE schemes have given better average results than CHC and GAs algorithms. Note that the same size of population and number of iterations have been used for GAs, CHC and DE.
- Tables 5 and 6 show that the most competitive algorithms for DE, in terms of Joule losses, are the DE/Rand/2 with CR = 0.7 and DE/Rand/2 with CR = 0.9. Consequently, in our problem, *Rand* mutation schemes outperform on average the rest of DE schemes.
- In DE schemes, the number of difference vectors to be perturbed by the mutation operator does seem to be an important factor that influence over the final result obtained
- The p-value of the FA test, shown in Table 7, is lower than 0.005, meaning that significant differences have been detected between the methods of the experiment.
- The statistical test confirms that DE/Rand/2 with CR = 0.7 significantly outperforms the other EAs schemes that are not based on DE ($\alpha = 0.1$). However, it is important to point out, that the

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Table 6
Differential evolution results with CR = 0.9.

Field	DE/Rand/1		DE/Best/1		DE/RandToBest/1		DE/Best/2		DE/Rand/2		DE/RandToBest/2	
	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.
1	0.2470	0.0008	0.2875	0.0501	0.2502	0.0018	0.2459	0.0063	**0.2425**	0.0071	0.2484	0.0022
2	**0.2807**	0.0072	0.2867	0.0003	0.2883	0.0012	0.3381	0.0610	**0.2807**	0.0072	0.2866	0.0002
3	0.3383	0.0014	0.3861	0.0591	0.3827	0.0543	0.3394	0.0001	**0.3350**	0.0051	0.3394	0.0001
4	0.3624	0.0000	0.4054	0.0354	0.3761	0.0151	**0.3594**	0.0042	0.3603	0.0043	0.3626	0.0003
5	0.3651	0.0039	0.3717	0.0041	0.3881	0.0109	0.3695	0.0017	**0.3568**	0.0071	0.3682	0.0001
6	0.3793	0.0000	0.4057	0.0468	0.3894	0.0016	0.4023	0.0462	**0.3784**	0.0089	0.3810	0.0036
7	0.4156	0.0023	0.4405	0.0451	0.4174	0.0019	**0.4121**	0.0113	0.4127	0.0009	0.4165	0.0023
8	0.4410	0.0057	0.5037	0.0687	0.4516	0.0046	0.4479	0.0001	**0.4369**	0.0002	0.4418	0.0072
9	0.4530	0.0029	0.4591	0.0053	0.4505	0.0074	0.4565	0.0001	**0.4457**	0.0035	0.4565	0.0001
10	0.4697	0.0001	**0.4660**	0.0106	0.4810	0.0140	0.4690	0.0010	0.4686	0.0010	0.4686	0.0009
11	0.4863	0.0001	0.5378	0.0499	0.4940	0.0085	0.4883	0.0017	**0.4741**	0.0048	0.4823	0.0081
12	0.4958	0.0071	0.5185	0.0058	0.5395	0.0388	0.4943	0.0011	**0.4861**	0.0072	0.5073	0.0052
13	0.5123	0.0021	0.5298	0.0036	0.5196	0.0020	0.5132	0.0021	**0.5066**	0.0081	0.5071	0.0062
14	**0.5163**	0.0088	0.5359	0.0045	0.5817	0.0524	0.5312	0.0007	0.5260	0.0061	0.5220	0.0123
15	0.5372	0.0128	0.5462	0.0103	0.5917	0.0831	0.5474	0.0076	**0.5449**	0.0033	0.5476	0.0001
16	0.5910	0.0037	0.5960	0.0024	0.5896	0.0073	0.5765	0.0096	**0.5730**	0.0129	0.5901	0.0044
17	0.6210	0.0020	0.6752	0.0994	0.7082	0.1027	0.6220	0.0011	**0.6183**	0.0022	0.6234	0.0013
18	0.6483	0.0034	0.7038	0.0654	0.6504	0.0001	0.6501	0.0005	**0.6372**	0.0126	0.6489	0.0024
19	0.6244	0.0119	0.6480	0.0133	0.6662	0.0335	0.7307	0.1361	**0.6093**	0.0145	0.6326	0.0054
20	0.6769	0.0004	0.7909	0.1369	0.6827	0.0060	0.6681	0.0161	**0.6499**	0.0087	0.6716	0.0049
21	**0.6782**	0.0011	0.7156	0.0064	0.7071	0.0022	0.7046	0.0003	0.6937	0.0134	0.7060	0.0015
22	0.7301	0.0145	**0.7258**	0.0146	0.7492	0.0174	0.7376	0.0005	0.7336	0.0134	0.7344	0.0175
23	0.7563	0.0145	0.7810	0.0064	0.7777	0.0079	0.7670	0.0039	**0.7420**	0.0198	0.7561	0.0065
24	0.7760	0.0054	0.9067	0.1717	0.7749	0.0109	0.7799	0.0002	0.7779	0.0019	**0.7682**	0.0159
25	0.7964	0.0010	1.0235	0.1750	0.7985	0.0017	0.7983	0.0020	0.7956	0.0001	**0.7904**	0.0124
26	0.8261	0.0005	0.9797	0.1697	0.8404	0.0331	0.8198	0.0148	**0.8107**	0.0191	0.8201	0.0149
27	0.8566	0.0027	0.9363	0.0885	0.8603	0.0014	0.8603	0.0014	0.8536	0.0028	**0.8457**	0.0155
28	0.8588	0.0212	0.9777	0.1248	0.8772	0.0016	0.8587	0.0212	**0.8511**	0.0199	0.8756	0.0004
29	0.8756	0.0058	0.8876	0.0070	0.8809	0.0001	0.8807	0.0004	0.8727	0.0061	**0.8675**	0.0148
30	0.8981	0.0017	0.9047	0.0007	1.0634	0.2002	0.8840	0.0222	**0.8518**	0.0169	0.9014	0.0039
31	**0.9012**	0.0192	0.9307	0.0327	0.9621	0.0277	0.9396	0.0001	0.9199	0.0231	0.9173	0.0191
32	0.9694	0.0144	0.9744	0.0032	1.1573	0.2194	0.9721	0.0004	**0.9504**	0.0165	0.9762	0.0017
33	0.9960	0.0064	0.9901	0.0007	0.9904	0.0009	0.9894	0.0003	**0.9684**	0.0211	0.9891	0.0001
34	1.0022	0.0027	1.0045	0.0012	1.0173	0.0223	**0.9832**	0.0229	0.9928	0.0061	1.0010	0.0033
35	1.0241	0.0003	1.0282	0.0036	1.0263	0.0019	1.0241	0.0003	**1.0239**	0.0001	1.0241	0.0003
36	1.0649	0.0002	1.1297	0.0606	1.0670	0.0007	1.0655	0.0005	1.0541	0.0216	**1.0460**	0.0251
37	1.1131	0.0000	1.2254	0.2189	1.1749	0.0729	1.0943	0.0254	**1.0815**	0.0259	1.1131	0.0001
38	1.1225	0.0002	1.5421	0.2074	1.1254	0.0019	1.1249	0.0023	**1.0914**	0.0253	1.1021	0.0248
39	1.2214	0.0000	1.2263	0.0010	1.3395	0.2302	1.2214	0.0000	**1.1999**	0.0264	1.2248	0.0028
40	**1.2702**	0.0252	1.3979	0.0816	1.3546	0.0414	1.2807	0.0277	1.2784	0.0297	1.2946	0.0296
Average	0.7050	0.2713	0.7596	0.3061	0.7361	0.2884	0.7112	0.2677	**0.6972**	0.2675	0.7065	0.2705

Table 7
Average FA rankings of all the employed methods.

Algorithm	FA ranking	Holm APV	Finner APV
DE/Rand/2 0.7	169.4875	–	–
DE/Rand/2 0.9	176.9125	1.0000	0.8481
DE/Rand/1 0.7	204.6875	1.0000	0.3856
DE/Best/2 0.7	210.9750	1.0000	0.3290
DE/Rand/1 0.9	212.3250	1.0000	0.3290
DE/RandToBest/2 0.9	225.4125	0.8283	0.2063
DE/RandToBest/2 0.7	226.9750	0.8283	0.2063
DE/Best/2 0.9	248.6500	0.2879	**0.0709**
DE/RandToBest/1 0.7	254.9125	0.2203	**0.0543**
DE/Best/1 0.7	261.7625	0.1556	**0.0399**
DE/RandToBest/1 0.9	351.7500	**0**	**0**
DE/Best/1 0.9	402.1250	**0**	**0**
CHC	462.5750	**0**	**0**
Generational GA	528.8500	**0**	**0**
Steady-state GA	570.1000	**0**	**0**
P-value by the FA test = 0.00161			

Holm's procedure states that the differences of the best DE scheme over two DE schemes are significant ($\alpha = 0.1$). Finner procedure goes further, pointing out also the difference with other three more DE schemes.

4.4. Convergence analysis

One of the most important issues in the development of any EA is the analysis of the convergence of its population. If the EA does not evolve in time, it will not be able to obtain suitable solutions.

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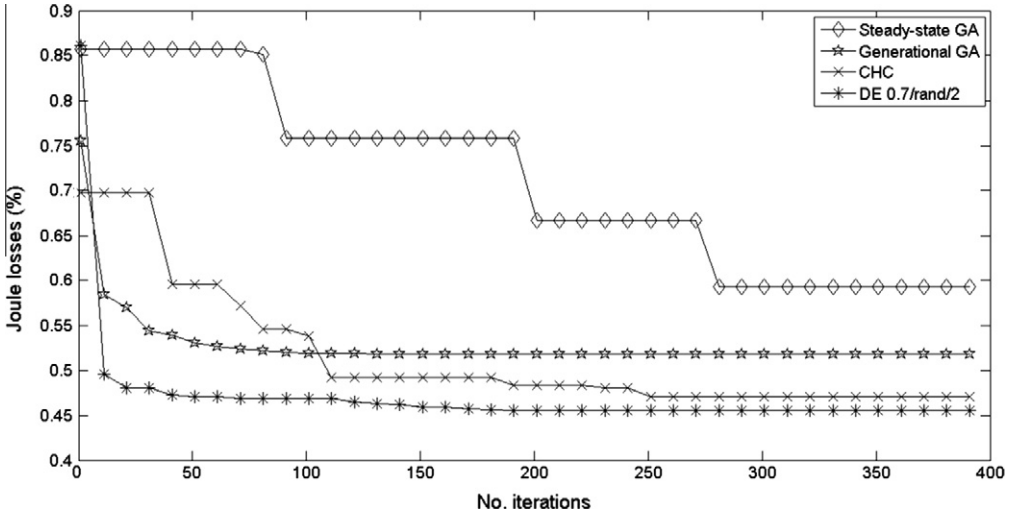

Fig. 3. EAs map of convergence.

We show a graphical representation of the convergence capabilities of EA models in Fig. 3. Specifically, DE/Rand/2 with CR = 0.7, CHC, generational GA and steady-state GA.

To perform this analysis we have selected the 400 × 400 standard field. The graphics show a line representing the fitness value of the best individual of each population. The *X*-axis represents the number of iterations carried out, and the *Y*-axis represents the fitness value (Joule losses) currently achieved.

As we can see in the graph, DE and CHC algorithm quickly find promising solutions and they do not need so many ratings to find a promising solution, although DE finds better solutions.

Observing the map of convergence in Fig. 3, we can highlight the DE algorithm as a promising optimizer because it is able to reach highly accurate results very fast, which implies that the DE scheme needs a small number of iterations.

5. Conclusions

This contribution presents a use of EAs for solving the problem of the design of PVGCPs with trackers. The optimization problem consists of choosing the variables that make up the PV plant to minimize Joule losses in electrical conductors that carry electrical current generated by PV modules to the distribution transformer.

Four different EAs have been used: steady-state genetic algorithm, generational genetic algorithm, CHC algorithm and DE algorithm. Forty standard fields have been randomly generated and the response of each algorithm has been analyzed by statistical tests and graphs of convergence.

Finally, after the comparison of the several EAs used we can conclude that for our particular problem, DE algorithm provides the best results thanks to its balance between exploration and exploitation. Rand mutation schemes outperform the rest of DE schemes studied.

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