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Multi-objective evolutionary algorithms for the design of grid-connected solar tracking systems

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ABSTRACT

The decentralization of electrical power production is conducive to a more effective and harmonious use of energy resources. For this reason, photovoltaic grid-connected plants (PVGCPs) as well as other renewable energy sources have come into the spotlight in recent years since they improve the supply of electrical power to the grid. The optimization of PVGCP design has been previously addressed in terms of electrical losses with successful results. However, PVGCP performance can be further enhanced if other characteristics, such as power capacity, are taken into consideration. This paper focuses on the optimization of the design of photovoltaic plants with solar tracking. The research described had the following two objectives: (i) the maximization of power capacity; (ii) the minimization of electrical losses. This problem was solved with multi-objective evolutionary algorithms, which have proved to be powerful optimization techniques that are useful for a wide range of objectives. This paper focuses on the NSGA-II and SPEA2, two well-known multi-objective algorithms, and describes how they were used to optimize PVGCPs. The resulting sets of solutions provide the flexibility and adaptability needed to build a PVGCP. These algorithms were thus found to be an effective tool for enhancing PVGCP performance.

Introduction

The progressive depletion of fossil fuel reserves as well as the constant rise in CO_2 emissions and an ever increasing energy demand has led to the growing use and exploitation of renewable energy sources. One of these sources is solar energy obtained from photovoltaic (PV) systems. They are currently being subsidized by many national governments throughout the world. Not surprisingly, the decentralization of electricity production has also become an important goal [1]. This is due to the fact that when electricity is locally generated near urban areas, this reduces electricity losses [2]. Photovoltaic grid-connected systems (PVGCSs) are often used to supply the local grid with the total energy produced by PV modules.

Before the installation of a PVGCS, various parameters must be considered, such as the irradiance, temperature, and wind at the proposed location. This is necessary in order to evaluate the viability and profitability of the PVGCS. Nevertheless, even after these steps are completed, the design of the distribution and sizing of a PV plant with solar trackers is far from a simple task [3]. There are a large number of variables that must be taken into account. These variables determine the efficiency and effectiveness of the PV plant. Depending on the potential location of the PV plant, it may be better to opt for a lower number of large solar trackers or on the contrary, a higher number of small ones. Whatever the solution, it will affect the distance between trackers, the length of the electrical conductors, and the choice of inverters. Thus, the design of PV systems can be viewed as a continuous optimization problem, which can be solved by evolutionary algorithms (EAs) [4–6].

EAs have been instrumental in the optimization of PVGCPs [7,8]. However, these single-objective techniques can only optimize one of the targets of the system. In [7], genetic algorithms [9] and differential evolution [10,11] were applied to find the optimal distribution and sizing of photovoltaic modules, solar trackers, and inverters. The authors aimed to minimize electrical losses. In most cases, the use of a given field is not optimal because the evolutionary algorithm only focuses on reducing power losses, regardless of the power capacity being installed at the site.

A wide range of optimization problems have more than one target, which means that they can only be addressed with multi-objective evolutionary algorithms (MOEAs) [12,13]. Such

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algorithms have been effectively used to design both stand-alone PV systems and PVGCSs. In [14], the MOEA known as NSGA-II [15] was used to find the optimal design of hybrid PV-wind energy systems by formulating it as a multi-objective optimization problem. In [16], the MOEA used was based on particle swarm optimization [17] to optimize the environmental benefit and total net profit of the systems useful life. In [18], by means of evolutionary multi-objective programming, objectives were formulated to maximize the expected technical and economic performance indicators for system design.

This paper proposes the use of MOEAs, which are able to maintain a balance between two or more goals and can perform well as powerful optimization techniques with several objectives. More specifically, our research focuses on two well-known multi-objective algorithms, called the NSGA-II and the SPEA2, and analyzes their capacity to optimize PVGCPs. The resulting solutions provide the flexibility and adaptability needed to build a PVGCP. These algorithms thus showed themselves to be an effective tool for enhancing the performance of PVGCPs.

To analyze the effectiveness of these techniques in the design of PVGCPs, several fields were studied as well as the response of each of the MOEAs applied to their optimization. The results are represented by curves or fronts on Cartesian axes showing the numerical values of the two objectives (installed power capacity and electrical losses). These sets of designs provided more flexible solutions that were in consonance with our needs and invaluable in choosing the optimal solution for our field.

The rest of the paper is organized as follows: 'Background' describes the background of PV systems and the MOEAs used; 'MOEAS for optimizing the design of PVGCPs with trackers' explains and justifies the use of MOEAs for optimizing PV plant design; 'Experimental framework and results' presents the experimental framework used in this research, discusses the results obtained, and provides an analysis of the convergence of each EA population. Finally, in 'Conclusions', we summarize the conclusions that can be derived from this study.

Background

'PV plants with trackers' gives an overview of the main features of PV plants with solar trackers and the MOEAs used. 'Strength pareto evolutionary algorithm' and Non-dominated sorting genetic algorithm' describe the main characteristics of SPEA2 and NSGA-II algorithms, respectively.

PV plants with trackers

The main components of a PV plant with solar trackers are the following: (i) the field where the PV plant will be installed; (ii) the trackers that will be distributed in this field; (iii) the PV modules on the monitoring structures; (iv) the inverters that convert direct current into alternating current; and (v) the electrical conductors that convey electrical energy from the PV modules to the inverters. The electrical losses in the transmission of electrical energy through the electrical conductors can be calculated with the expression in (1):

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

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. In the case of copper conductors, this resistivity can take the value $\rho = 0.017241 \frac{\Omega \cdot \mathrm{m}^2}{\mathrm{m}}$ (Ω ohms and m meters [19]). The variables are related as shown in (2):

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

The section of the conductor is determined by the intensity of the electrical current that it is able to carry and the allowable voltage drop for that section. In our case, the main condition defining the section of the conductor was the voltage drop. This is because the current through the conductors was much lower than the intensities that they were able to carry. Therefore, the conduction section was defined by the permissible voltage drop as shown in (3).

$$\Delta V = \frac{2 \cdot L\, P}{\mu \cdot s \cdot V} \tag{3}$$

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 $\mu = 58.0 \frac{m}{\Omega \cdot \mathrm{m}^2}$ and V the line voltage [19].

The conductor length is determined by the distance from the tracking structure to the inverter. In a rectangular field, inverters are generally 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, it is possible to calculate the electrical (Joule) losses produced. Obviously, the most interesting configurations are those in which the current flow through the conductors is as low as possible and the voltage at which the 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. They also depend on the various series–parallel associations within the tracking structures. Physical parameters of the PV modules, such as height and width, define the size of the tracking structures, defining the separation between them. It ensures that none casts shadows on surrounding structures. This evidently limits the number of trackers that can be installed in the field.

Moreover, the maximum installed power is calculated by adding the nominal power of each of the trackers installed on the ground. For this reason, there will be solutions in which the result of the first objective is very good, even though the number of solar trackers installed on the field is very low compared to the trackers that would fit on it.

Multi-objective algorithms

There are many types of multi-objective optimization algorithms [20]. This research used the SPEA2, and NSGA-II, two of the most widely used MOEAs in renewable energy optimization [21], to optimize the efficiency of a PVGCP. Fig. 1 shows the basic structure of an MOEA. The following subsections briefly describe these two approaches.

Objectives

Each chromosome is associated with a two-dimensional objective vector. Its elements express the degree to which the following two objectives are fulfilled:

```
Generate initial population P_0 - size N
Evaluate P_0
t = 0
while (stopping criterion T is not satisfied)
    Recombination P_t
    Evaluate P_t
    Select P_{t+1}
    t = t + 1
end while
```

Fig. 1. MOEA basic structure.