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A new high performance method for determining the parameters of PV cells and modules based on guaranteed convergence particle swarm optimization

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HIGHLIGHTS

- Guaranteed convergence particle swarm optimization (GCPSO) is proposed to determine the parameters of PV cells and modules.
- The proposed new method is evaluated using experimental data in three different case studies.
- The GCPSO method determine reliable solutions quickly and accurately.
- The proposed GCPSO mitigates premature convergence problem and particle swarm stagnation.
- It provides better performance than many other popular optimization methods.

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ABSTRACT

Determining the mathematical model parameters of photovoltaic (PV) cells and modules represents a great challenge. In the last few years, several analytical, numerical and hybrid methods have been proposed for extracting the PV model parameters from datasheets provided by the manufacturers or from experimental data, although it is difficult to determine highly reliable solutions quickly and accurately. In this paper, we propose a new method for determining the PV parameters of both the single-diode and the double-diode models, based on the guaranteed convergence particle swarm optimization (GCPSO), using experimental data under different operating conditions. The main advantage of this method is its ability to avoid premature convergence in the optimization of complex and multimodal objective functions, such as the function that determines PV parameters. To validate performance, the GCPSO method was compared with several analytical, numerical and hybrid methods found in the literature. This validation considered three different case studies. The first two are important reference case studies in the literature and have been widely used by researchers. The third was performed in an experimental environment, in order to test the proposed method under a real implementation. The proposed methodology can find highly accurate solutions while demanding a reduced computational cost. Comparisons with other published methods demonstrate that the proposed method produces very good results in the extraction of the PV model parameters.

1. Introduction

Energy production constitutes an enormous challenge for this century. Thus, the technologies for the production of electrical energy through renewable resources will have an important role, not only due to the increase in global public awareness concerning the need for environmental protection, but also the need to decrease fossil fuel dependency in the production of electrical energy, mostly due to the high levels of carbon intensity and, in the case of countries where fossil fuel energy is entirely derived from importation (as in the Portuguese case), the risks associated with supply.

With the advent of this new paradigm, there is a need for reliable modelling techniques to rigorously predict the production of electrical energy, in particular photovoltaic (PV) energy production. Such prediction depends mainly on climatic factors (especially temperature and solar radiation), but also on the mathematical model being used for the PV cell or module, as well as on the available information that conditions/determines the corresponding modelling technique.

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Nomenclature

c_1, c_2	positive constants of acceleration
d	search space dimension
gbest	global best position
itermax	maximum number of iterations allowed
I	measured current [A]
I_0, I_{01}, I_{02}	diode reverse saturation currents [μA]
I_d, I_{d1}, I_{d2}	diode currents [A]
I_{mpp}	current at the maximum power point [A]
I_{ph}	photoelectric current [A]
I_{sc}	short-circuit current [A]
$\hat{I}$	estimated current [A]
$\bar{I}$	arithmetic mean of measured current [A]
k	Boltzman constant [J/K]
n, n_1, n_2	diode ideality factors
N	number of the experimental I-V data pairs
N_p	number of particles in the population
N_s	number of cells connected in series
p	particle number of the population N_p
pbest	personal best position
q	electron charge [C]
r_1, r_2	random numbers in [0,1]
R_p	parallel resistance [Ω]
R_s	series resistance [Ω]
R^2	determination coefficient
S_c, f_c	threshold parameters of successes and failures
t	current iteration
T	temperature [K]
V	measured voltage [V]
V_{mpp}	voltage at the maximum power point [V]
V_{oc}	open-circuit voltage [V]
V_t	thermal voltage [V]
x	particle position
AE	absolute error
IAE	individual absolute error
MAE	mean absolute error
MBE	mean bias error
MSE	mean squared error
RMSE	root mean square error
SSE	sum squared error
STD	standard deviation
ξ	weighted RMSE
ρ	scale factor
τ	parameters of the models
ϕ	velocity restriction auxiliary constant
ν	particle velocity
χ	velocity restriction constant
ψ	index of the global best particle
ω	inertia weight

Several mathematical models in the literature simulate the behaviour of the PV cell or module under different operating conditions, including the single-diode model [1,2], the double-diode model [3,4], the multidiode model [5,6] and the multidimension diode model [7,8]. However, the main models found in the technical literature on this matter are the single-diode model (characterized by 5 parameters) and the double-diode model (characterized by 7 parameters). Recently some other models have emerged aiming to better characterize the behaviour of the different PV technologies, such as the multidiode model, with m-diodes connected in parallel, characterized by $3 + 2m$ parameters. Theoretically, more diodes ($m > 2$) can be added to the equivalent PV cell or module electrical circuit to better analyse the effects that take place in the P-N junction [5]. Another example is the multidimension diode model, which allows the increase in the number of parallel-connected diodes, as well as series-connected diodes, creating a network of diodes arranged in such way as to increase accuracy [8]. The present model aims to obtain a higher accuracy in parameter extraction for thin film technologies [7]. The accuracy of each of these models is closely related with the parameters to be extracted.

PV modelling techniques can be grouped according to either the available information or the type of method. On one hand, the available information constrains how the parameter extraction that characterizes the mathematical model is performed. Parameters can be extracted from information in the datasheets provided by the manufacturers [2,4,9–12] or extracted from the experimentally measured current-voltage (I-V) characteristic curve [5,13–18]. On the other hand, there are normally three method categories: analytical methods [19–24], numerical methods [1,25–31] and hybrid methods [32–42].

The analytical methods are usually formulated through elementary functions [3,43,44] applied to specific characteristic points of the I-V and P-V curves or by means of simplifications/approximations that convert equations into the explicit form, e.g., the Lambert W function [45–47]. Although calculations are simple and quick, several approaches require the resolution of a system of nonlinear, multivariable and multimodal equations (with several local optimal solutions), where performance depends upon the initial solution [37,48]. Other aspects that negatively affect performance are the error measurement of the characteristic points of the I-V and P-V curves, as well as the need to perform simplifications/approximations giving rise to lower accuracy [28,49]. In [9] a method is proposed for the extraction of the five parameters of the single-diode model based on five analytical equations without any simplification, using datasheets provided by the manufacturers under the standard test conditions (STC). However, [50] concludes that in the approach proposed by [9] the fifth equation is not linearly independent from the remaining equations. Consequently, the solution proposed by [9] is not unique, allowing infinite solutions.

Several reduction techniques, known as reduced forms (RF) that lower the dimensions of the search space, are presented in [15,51]. With these reduction techniques, the five parameters that characterize the single-diode model are divided into two independent parameters: the ideality factor of the diode (n) and the series resistance (R_s); and three dependent parameters: the photoelectric current (I_{ph}), the reverse saturation current of the diode (I_0), and the parallel resistance (R_p). Therefore, the number of solutions is decreased and the problem of the five parameters for the single-diode model becomes convex. In [18] another method using the same concept is presented: reduced-space search (RSS).

In order to mitigate the disadvantages of the analytical methods, recently several authors used deterministic and stochastic numerical methods to extract the parameters that characterize the mathematical model of the PV cell or module. The Newton-Raphson method (NRM) [13] or the Levenberg-Marquardt algorithm (LM) [17] are examples of such deterministic methods. Despite being very efficient methods, in a local search they can converge prematurely upon local minima; to be applied they need continuity, convexity, and differentiability conditions; and, moreover, their efficiency is dependent upon initial positioning [37,40]. There are a greater variety of stochastic methods, including genetic algorithm (GA) [52], particle swarm optimization (PSO) [53], harmony search (HS), grouping-based global HS (GGHS) and innovative global HS (IGHS) [54], artificial bee swarm optimization (ABSO) [55], bird mating optimizer (BMO) [56], cuckoo search (CS) [57], teaching learning based optimization (TLBO) [58], simplified TLBO (STLBO) [59], generalized oppositional TLBO (GOTLBO) [60], self-adaptive TLBO (SATLBO) [61], artificial bee colony (ABC) [62], improved ABC (IABC) [63], modified ABC (MABC) [64], biogeography-based optimization with mutation strategies (BBO-M) [65], mutative-