Energy 93 (2015) 1515–1522

Contents lists available at ScienceDirect

Energy

journal homepage: www.elsevier.com/locate/energy

An improved free search differential evolution algorithm: A case study on parameters identification of one diode equivalent circuit of a solar cell module

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ARTICLE INFO

Article history:
Received 5 March 2015
Received in revised form
9 July 2015
Accepted 11 August 2015
Available online 19 November 2015

Keywords:
Differential evolution algorithm
Mathematical modeling
Parameter identification
Solar cells

ABSTRACT

The present paper deals with the parameter identification of one diode model equivalent circuit of solar cell modules from real data acquired in different temperature conditions. We termed this procedure as an optimization problem and solved it through the FSDE (Free Search Differential Evolution) algorithm as well as a novel IFSDE (Improved FSDE) approach. The IFSDE is compared with other well-known metaheuristics, namely genetic algorithms, harmony search and particle swarm optimization, showing overall better results for the proposed IFSDE approach. In particular, the IFSDE is better in escaping local optima and obtained better results. Identified results are compared with acquired data, what shows the validity of the proposed algorithm.

1. Introduction

Due to greenhouse effect, the evidence of global warming and the increasing interest to obtain energy from renewable sources; solar energy has become increasingly applied and researched. There is a quite rapidly growth with a rate of 25–40% of photovoltaic electricity annual production [1], what naturally makes the interest of solar energy become more and more popular.

Among the problems faced in solar energy engineering, the problem of solar cell parameter identification consists of determining the optimal values correspondent to the working conditions from measured data, which are used to define for example a current–voltage curve. In recent years, a number of works have addressed this issue. In Ref. [2], the authors used the DE (Differential Evolution) algorithm to model photovoltaic modules considering the effects of irradiance and temperature. [3], proposed the use of DE to extract the parameters of solar modules of different types from various manufacturers operating at different environmental conditions with synthetic data. In a series of works from the same authors, the parameters of a 57 mm diameter silicon solar cell manufactured by R.T.C. France are obtained by (i) HS (Harmony Search) algorithm and its variants [4] (ii) an artificial bee swarm optimization algorithm [5] and (iii) bird mating optimizer [6]. A novel adaptive DE algorithm is proposed in Ref. [7] that is applied to the extraction of solar cell parameters with experimental current and voltage data. In Ref. [8], the authors obtained the values of the parameters of photovoltaic module using reference data analytically, transforming the estimation procedure into a constrained nonlinear optimization problem based on the generalized reduced gradient algorithm. Ref. [9] showed the modeling procedure of solar photovoltaic modules using a modified bacterial foraging algorithm, with better results when compared to GAs (Genetic Algorithms) and artificial immune systems. In Ref. [10], the authors

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http://dx.doi.org/10.1016/j.energy.2015.08.019
0360-5442/

investigated the estimation of the parameters of fuel and solar cells through the application of simplified teaching-learning based optimization algorithms, which employs a chaotic map in the mutation operator. The authors in [11] proposed a methodology for self-growing radial basis functions neural networks trained by a GA to model the current/voltage relationship of a photovoltaic panel. The authors in [12] provide a comparison among three metaheuristic optimization algorithms, namely GA, PSO (Particle Swarm Optimization) and DE, in the task of parameter extraction based on the two diode model for solar cells, showing overall better results for the DE algorithm.

On the other hand, the original DE (Differential Evolution), originally proposed by Ref. [13], has shown lately good results when solving engineering optimization problems [14]. Other examples of identification problems solved with the DE algorithm found in the literature are, for example, parameter identification of photovoltaic generators [3,7] and nonlinear system identification through nonlinear autoregressive with exogenous inputs models [15]. A recent thorough review of the state-of-the-art of the algorithm, its improvements and applications is available in Ref. [16]. The DE algorithm is a population based metaheuristic which is inspired in the evolution process, making analogy between the crossover and mutation operators in nature with the generation of new individuals during the search procedure. The DE algorithm is simple, effective and is one of the most powerful population based metaheuristics for solving real-parameter optimization problems [16] – though binary versions of the algorithm are also available and also show good results with respect to other techniques [17]. Recent research has focused at adaptive control of the project parameters [18–20], what is particularly interesting for the designer which has less parameters to tailor in each specific application. Project parameters are usually problem dependent and generally a range of parameters is given (which are refined by the user in a tedious trial and error procedure).

The FS (Free Search) is a global population based derivative-free algorithm [21]. It is based on the idea of representing the behavior of animals by the abstractions of sense and mobility. Even though as reported in Refs. [22,23] that the key concepts for implementing this approach are not available in the literature, the idea of FS has inspired its use especially together with DE. In Ref. [23] the authors proposed a FS with adaptive DE Exploitation and Quantum-Inspired Exploration in Ref. [22], the authors proposed the hybridization of FS and DE with OBL (Opposition-Based Learning) [24], showing promising results when compared to the standard DE for a number of test functions. OBL is based on the idea of performing jumps in the search space, at say each iteration, using the worst position found so far by an algorithm. It has been applied to a variety of other optimization algorithms such as e.g. DE for continuous function optimization [25], PSO [26–29], gravitational search algorithm [30] and artificial bee colony for controller tuning [31]. A recent overview of its utilization was written by Ref. [32].

In the lines of the previous works previously mentioned, the main goal of the present paper is to solve the problem of parameter identification with the application of the FSDE (Free Search Differential Evolution) algorithm. The motivation is that, even with fewer project parameters, FSDE has reported better results when compared to other algorithms. We confirm this hypothesis also in the present case of parameter estimation. Secondly, we aim at achieving a better model by fine tuning the optimization algorithm. Being so, we improve the original FSDE algorithm by using a simple strategy that makes the algorithm to provide better results and to converge faster. The novel approach is compared in many simulation runs with different initial conditions with other metaheuristics available in the literature, namely GA [33], HS [34], and PSO [35], showing favorable results for the IFSDE approach. The main results are that FSDE provides better results for the problem of PV parameter extraction when compared to standard algorithms found in the literature and that the improved FSDE version outperforms its original FSDE version, by the application of a simple mechanism based on the influence of the best individual in the population. This encourages the use of the herein proposed version to other parameter extraction problems and even extend its application to other fields of knowledge where continuous parameter optimization is sought.

The remaining of this paper is organized as follows. The optimization problem as case study used for test of the efficacy of the approaches is given in Section 2. In Section 3, the FSDE algorithm is stated, together with its improved version IFSDE. The results when comparing the FSDE approaches with other well known metaheuristics are stated in Section 4. The conclusion and future research directions are given in the Section 5, which ends the document.

2. Current-voltage characteristic of PV system

In the present section, basic notions are given in order to clarify the procedure for obtaining solar cells parameters and its problem formulation. Specifically, Subsection 2.1 gives an overview of PV modeling, while Subsection 2.2 formulates the problem of solar cell parameter identification as an optimization procedure.

2.1. PV modeling

Under illumination, an ideal solar cell is modelled as a light generated current source in parallel with a rectifying diode [36]. Consequently, three unknown parameters, namely, photogenerated current (I_{ph}), diode saturation current (I_{sd}) and diode ideality factor (n), make the parameters of the equivalent circuit model. For considering the PV cell metal contacts and the semiconductor material bulk resistance, an improved model, called R_s-model, was developed [37–39] by taking into account a series resistance (R_s) to the model. Though R_s-model is more accurate, it shows serious deficiencies under high temperature variations since it does not account for the open circuit voltage coefficient [37]. In addition, R_s-model is suitable for crystalline PV cell and leads to significant inaccuracy when it is applied to the thin-film technology [40]. Another modification was suggested by adding a shunt resistance (R_{sh}) to the diode to consider the partial short circuit current path near the cell's edges resulted from the semiconductor impurities and non-idealities [41–43]. This type of the model is known as the single diode model (or R_{sh}-model). Owing to the ability of providing a good compromise between simplicity and accuracy, single diode model has received considerable attention and has been used widely.

The terminal current, I_t, of the single diode PV model can be expressed as follows:

$$I_t = I_{ph} - I_d - I_{sh} \tag{1}$$

where I_d is the diode current and I_{sh} denotes the shunt resistor current.

By using Shockley equation for the diode current and substituting the current of the shunt resistor, Eq. (1) is rewritten as represented in the following equation:

$$I_t = I_{ph} - I_{sd}\left[\exp\left(\frac{q(V_t + R_s I_t)}{nkT}\right) - 1\right] - \frac{V_t + R_s I_t}{R_{sh}} \tag{2}$$