Applied Energy 119 (2014) 384–393

Contents lists available at ScienceDirect

Applied Energy

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

Extraction of solar cell parameters from a single current–voltage characteristic using teaching learning based optimization algorithm

Sanjaykumar J. Patel [a], Ashish K. Panchal [b], Vipul Kheraj [a,c,*]

[a] Department of Applied Physics, SV National Institute of Technology, Surat 395007, India
[b] Electrical Engineering Department, SV National Institute of Technology, Surat 395007, India
[c] Department of Electrical & Computer Engineering, University of Utah, Salt Lake City, UT 84112, USA

HIGHLIGHTS

- Teaching learning based optimization (TLBO) algorithm is investigated to extract solar cell parameters.
- The TLBO is implemented using LabVIEW.
- All five solar cell parameters are extracted from single illuminated *I–V* characteristic.
- The results are found to be highly reliable and reproducible.

ARTICLE INFO

Article history:
Received 15 June 2013
Received in revised form 17 December 2013
Accepted 7 January 2014

Keywords:
Solar cell
Parameters extraction
TLBO algorithm
I–V characteristics

ABSTRACT

The determination of values of solar cell parameters is of great interest for the evaluation of solar cell performance. This paper proposes a simple, efficient and reliable method to extract all five parameters of a solar cell from a single illuminated current–voltage (*I–V*) characteristic using teaching learning based optimization (TLBO) algorithm. The TLBO is implemented by developing an interactive numerical simulation using LabVIEW as a programming tool. The effectiveness of the algorithm has been validated by applying it to the reported *I–V* characteristics of different types of solar cells such as silicon, plastic and dye-sensitized solar cells as well as silicon solar module. The obtained values of parameters by the TLBO algorithm are found to be in very good agreement with reported values of parameters. The algorithm is also applied to the experimentally measured *I–V* characteristics of a silicon solar cell and a silicon solar module for the extraction of parameters. It is observed that the TLBO algorithm repeatedly converges to give consistent values of solar cell parameters. It is demonstrated that our program based on TLBO algorithm can be successfully applied to a wide variety of solar cells and modules for the extraction of parameters from a single illuminated *I–V* curve with minimal control variables of the algorithm.

1. Introduction

Solar energy is one of the most important renewable energy sources as it is clean, safe and plentiful in nature. The solar cell converts the energy of photons coming from the sunlight directly into electrical energy on the basis of photovoltaic effect. The overall performance and the conversion efficiency of a cell rely upon various physical parameters such as series resistance (R_s), shunt resistance (R_{sh}), ideality factor (n), photocurrent (I_{ph}) and saturation current (I_o). Therefore, the knowledge of these parameters is always desirable not only to evaluate the performance of a cell but also to improve the design, fabrication process and quality control of the cell [1]. These parameters can be determined by considering the solar cell in terms of its equivalent circuit described by various models such as single-diode model [2–5], double-diode model [6], or three-diode model [7]. Although, the double-diode and three diode models are more accurate as they take into account the space charge recombination current as well as leakage current, the single diode model has been extensively used for solar cell parameters extraction problems owing to its simplicity and adequate reliability for a wide variety of solar cells [2–5]. The current (I) – voltage (V) relation of a solar cell for a single diode model is given by,

$$I = I_{ph} - I_o\left[e^{\frac{q(V+IR_s)}{nk_BT}} - 1\right] - \frac{V+IR_s}{R_{sh}} \tag{1}$$

From Eq. (1), it is clearly seen that the direct parameter extraction from experimental *I–V* characteristic data is limited by the non-linear and transcendental nature of the *I–V* relation of a solar cell.

* Corresponding author at: Department of Applied Physics, SV National Institute of Technology, Surat 395007, India. Tel.: +91 9904334220.
E-mail address: vipulkheraj@gmail.com (V. Kheraj).

0306-2619/$ - see front matter © 2014 Elsevier Ltd. All rights reserved.
http://dx.doi.org/10.1016/j.apenergy.2014.01.027

Over the years, several methods have been reported for the extraction of solar cell parameters. Some of these methods employ analytical [8–10,2] or numerical [1,11–14] techniques to determine the parameters from experimental *I–V* characteristic. Analytical techniques require the knowledge of some selected values of *I–V* characteristic such as short-circuit current, open-circuit voltage, current and voltage at the maximum power, and slopes of the *I–V* characteristic at the axis intersections. This approach is generally based on simple formulae and may be affected by the correctness of the selected points on the *I–V* curve. On the other hand, the *I–V* characteristic exhibits highly non-linear behavior and the correctness of the selected points may introduce a significant error in the extracted parameters.

Numerical techniques involve certain mathematical algorithms like curve fitting algorithm to fit all the point on the *I–V* characteristic in order to extract the solar cell parameters. Using such algorithm, we can get an accurate result because all the points on the *I–V* curve are utilized. In addition, the deviation of several data points may not severely affect the accuracy of the parameters as in the case of the analytical method. However, the accuracy of these techniques depends on the types of fitting algorithm, the fitting criterion, objective function and the starting values of the parameters [11]. Moreover, this method cannot guarantee the global convergence because it depends strongly on the initial values of the parameters such as number of iterations and tolerance criteria.

In recent years, techniques based on evolutionary algorithms (EAs) have gained significant attention in the field of the solar cell parameters extraction because of their effectiveness and flexibilities [15,16]. Among the evolutionary algorithms, genetic algorithm (GA) has been extensively used for the solar cell parameters extraction [17–20]. GA also outperforms the quasi-Newton methods, curve fitting methods and other optimization algorithms. However, there are deficiencies related to GA performance [21]. Here, in particular, the degradation of the efficiency is mainly observed when highly hypostasis objective functions are used, i.e. when the parameters being optimized are highly correlated. In addition, the crossover and mutation operators do not always guarantee better fitness of offspring because individuals in the population have similar structure and their average fitness is high towards the end of evolutionary process. Moreover, in the case of multivariable optimization problem, the GA has the tendency to get trapped in local minima instead of global optimum, which can be attributed to the inappropriate selection of crossover and mutation rate probability. On the other hand, optimization of the proper rate of such operators is very tedious and it varies from problem to problem.

Recently, particle swarm optimization (PSO) has been investigated for the extraction of solar cell parameters [22–24]. Although PSO offers several advantages over GA, one must also take into the consideration the limitations associated with the PSO, viz. (1) it cannot guarantee the consistency of extracted parameters and (2) it requires a large number of iterations to converge the solution to the global optimum [24]. Moreover, the inappropriate selection of key parameters such as acceleration constants (c_1 and c_2) and inertia weight may also lead to trap the search process in local optimum instead of global one [25]. In general, all nature-inspired population based algorithms such as evolutionary algorithm and PSO are highly sensitive to the control parameters. Moreover, the selection of these control parameters, for example crossover and mutation operators in GA or inertia weight in PSO are highly problem specific.

In recent year, teaching–learning-based optimization (TLBO) algorithm proposed by Rao et al. [26] has emerged as new promising global optimization algorithms capable of solving wide range of optimization problems. There are some features of the TLBO algorithm that make it a very effective algorithm. For example, the algorithm is very simple and easy to implement. It requires a very few control variables like population size and number of iterations in order to achieve the global optimum solution. Moreover, these control operators are not very problem specific. Apart from these, the convergence to the final solution is almost independent from the initial population. So far, to the best of our knowledge, the TLBO algorithm has not been investigated for the solar cell parameters extraction problem. Hence, here we report a study on the effectiveness of the TLBO algorithm for the extraction of solar cell parameters. We applied the algorithm to extract all the five parameters of the solar cell from a single *I–V* characteristic data measured under illumination, which is feasible only with a very few methods. The algorithm is implemented through an interactive program prepared using LabVIEW (laboratory virtual instrument engineering workbench, version-10) as a programming tool.

In this work, the validity, consistency and the robustness of the TLBO algorithm are verified by applying the algorithm to the *I–V* characteristics of a silicon solar cell [27], a plastic solar cell [2], a dye-sensitized solar cell (DSSC) [3] and a silicon solar module [27]. The *I–V* characteristics were synthesized from the reported values of parameters using Newton–Raphson method. The parameters were extracted from these synthesized *I–V* curves using the TLBO algorithm and compared with the reported values that extracted by other methods for the respective solar cell in the literatures. After validation, the TLBO algorithm is applied to the experimental *I–V* characteristics of a monocrystalline silicon solar cell as well as a polycrystalline silicon solar module, measured at our lab in order to extract the desired parameters.

2. Description of TLBO algorithm

The TLBO algorithm employs the concept of teaching–learning process in a classroom. It is a simple population based optimization algorithm that uses a population of solutions to proceed to the global optimum based on the real numbers. A group of learners in the classroom are considered as population. The algorithm is inspired by passing on knowledge within a classroom environment, where learners (i.e. individuals) first obtain their knowledge from a teacher and then they also interact with each other to propagate the knowledge. The design variables to be optimized are analogous to different subjects offered to learners. The learners are evaluated by means of a problem specific objective function called 'fitness function'. Thus, how good or bad a learner 'X' is can be represented by the value of the fitness function $F(X)$, also called the fitness of the learner. Thus, the fitness of a population is improved by the propagation of knowledge though two phase: (1) Teacher Phase (2) Learner Phase.

2.1. Teacher Phase

This is the first stage of the TLBO algorithm where initially learners learn from the teacher. The teacher is considered as a highly learned person in the population who shares his or her knowledge with other learners in the classroom. The quality of the teacher directly affects on the outcome of the learners. It is obvious that a good teacher trains learners in such way that they can have better fitness in terms of their results. During this phase, algorithm tries to improve the fitness of other individuals (X_i) by moving their positions towards the position of the teacher ($X_{teacher}$) by using the mean value of individuals (X_{mean}). Generally, the mean value of individuals decides the quality of individuals in the population. The teacher modifies the learners in the classroom according to the following Eq. (2).

$$X_{new} = X_i + r \cdot (X_{teacher} - (T_F \cdot X_{mean})) \tag{2}$$