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Parameters identification of solar cell models using generalized oppositional teaching learning based optimization

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ABSTRACT

This paper presents a new optimization method called GOTLBO (generalized oppositional teaching learning based optimization) to identify parameters of solar cell models. GOTLBO employs generalized opposition-based learning to basic teaching learning based optimization through the initialization step and generation jumping so that the convergence speed is enhanced. The performance of GOTLBO is comprehensively evaluated in thirteen benchmark functions and two parameter identification problems of solar cell models, i.e., single diode model and double diode model. Simulation results indicate the excellent performance of GOTLBO compared with four well-known evolutionary algorithms and other parameter extraction techniques proposed in the literature.

1. Introduction

The increase in the cost of fossil fuels and their probable depletion, air pollution, global warming phenomenon, and severe environmental laws have resulted in renewable energy sources gaining the attention of many nations to produce electricity [1]. The PV (photovoltaic) system such as solar cell has been obtained increasing interest recently, because of several promising features like renewability, less pollution, ease of installation, and noise-free [2]. For PV systems, it is very important to select a model to closely emulate the characteristics of PV cells [3]. Several models have been introduced and proved to be successful in representing the behavior of the solar cell systems by considering many physical variables. Among them, two equivalent solar cell models are widely used in practice: single and double diode models [4]. The single diode model has five unknown parameters, so it is much more common to use. The double diode model contains seven unknown parameters and offers higher accuracy. Both single and double diode models require the knowledge of all unknown parameters, which is usually not provided by manufactures. Precise parameters of mathematical model play a key role in the simulation, evaluation, and optimization of solar cell systems. As a result, it is necessary to take into consideration the parameters identification with a feasible optimization method [5].

Two main approaches have been used in the literature to solve the parameter identification problems of solar cell models: deterministic and heuristic. Deterministic methods, such as least squares [6], Lambert W-functions [7], and the iterative curve fitting [8], impose several model restrictions such as convexity and differentiability in order to be correctly applied. Therefore, they are very sensitive to the initial solution, and most often lead to local optima.

With the development of soft computing technologies, many heuristic methods, which are of conceptual and computational simplicity, being excellent real-world problem solvers and robust to dynamic environments, capable of solving problems with no known solutions and with no need for analytic expression of the problems, have been applied to the parameter estimation problems of solar cell [9]. GA (Genetic algorithms) [10–12], PSO (particle swarm optimization) [13,14], DE (differential evolution) [15–18], SA (simulated annealing) [19], PS (pattern search) [20], HS (harmony search) [21], TLBO (teaching learning based optimization) [22], ABSO (artificial bee swarm optimization) [2], BBO (biogeography-based optimization) [9], SFLA (shuffled frog leaping algorithm) [23], CS (cuckoo search) [24], and FPA (flower pollination algorithm) [25] have been proposed to improve the parameter accuracy for cell models.

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Nomenclature

a	diode ideality factor
a_1	Diffusion diode ideality factor
a_2	recombination diode ideality factor
I_d	diode currents (A)
I_{d1}	first diode currents (A)
I_{d2}	second diode currents (A)
I_L	cell output current (A)
I_{ph}	photo generated current (A)
I_{sd}	reverse saturation current of diode (A)
I_{sd1}	diffusion currents (A)
I_{sd2}	saturation currents (A)
I_{sh}	shunt resistor current (A)
k	Boltzmann constant (1.3806503×10^{23} J/K)
q	electron charge ($1.60217646 \times 10^{-19}$C)
R_S	series resistance (Ω)
R_{sh}	shunt resistance (Ω)
T	temperature of the junction (K)
V_L	cell output voltage (V)
V_t	junction thermal voltage (V)
ABSO	artificial bee swarm optimization
ANFES	average number of function evaluations
CLPSO	comprehensive learning particle swarm optimizer
CPSO	chaos particle swarm algorithm
DE	differential evolution
EA	evolutionary algorithm
FES	function evaluations
GA	genetic algorithm
GOBL	generalized opposition-based Learning
GOTLBO	generalized oppositional teaching learning based optimization
HS	harmony search
IGHS	innovative global harmony search
jDE	differential evolution with self-adaptive control parameter
NFES	number of function evaluations
OBL	opposition-based learning
OTLBO	opposition-based teaching learning based optimization
PS	pattern search
PSO	particle swarm optimization
R_{cr}-IJADE	repaired adaptive differential evolution
RMSE	root mean square error
SA	simulated annealing
SR	successful rate
STLBO	simplified teaching-learning based optimization
TLBO	teaching learning based optimization
VTR	value to reach

TLBO [26] is a recently proposed population-based algorithm, which simulates the teaching and learning process in the classroom. In this algorithm, students gather knowledge from the lecture delivered by teacher and also through the mutual interaction with other students. TLBO has emerged as one of the simplest and most efficient techniques. It requires few parameters and performs well on many optimization problems. The effectiveness of TLBO and its modified versions have been reported in continuous optimization problems [27,28], combinatorial problems [29], as well as real-world engineering problems [30–31].

In this paper, we develop a new optimization method called GOTLBO (oppositional teaching learning based optimization) for the parameters extraction of both single and double diode models. In GOTLBO, GOBL (generalized opposition-based learning) is integrated with original TLBO through the initialization step and generation jumping so that the convergence speed can be enhanced. The performance of GOTLBO is firstly evaluated on 13 well-known benchmark functions, and compared with those of four EAs (evolutional algorithms), including jDE, CLPSO, TLBO, and OTLBO. GOTLBO performs better than these EAs on the majority of the test functions. Then, GOTLBO is employed to identify the parameters for two solar cell models, i.e., single diode model and double diode model. The simulation results demonstrate that the performance of GOTLBO is very competitive compared with other parameter identification techniques proposed in the literature.

The rest of the paper is organized as follows. Section Problem statement states the problem formulations of solar cell models. Section TLBO briefly introduces basic TLBO. Our proposed approach is presented in Section Proposed approach: GOTLBO. In Section Evaluation GOTLBO on benchmark functions, GOTLBO is evaluated on 13 benchmark functions. Followed by Section Application to parameter identification of solar cell models, GOTLBO is used to solve parameter extraction problems of solar cell models. Finally, the last section concludes this paper.

2. Problem statement

2.1. Single diode model

In the single diode model, as shown in Fig. 1, the output current of solar cell can be formulated as follows [12,17]:

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

where I_L is the cell output current, I_{ph} is the photo generated current, I_d is the diode currents, and I_{sh} is the shunt resistor current. According the Shockley equation, the diode currents I_d can be calculated as:

$$I_d = I_{sd}\left(exp\left(\frac{V_L + I_L R_S}{aV_t}\right) - 1\right) \tag{2}$$

where I_{sd} is reverse saturation current of diode, V_L is the cell output voltage, a is the diode ideality factor, R_S is the series resistance, and V_t is the junction thermal voltage as:

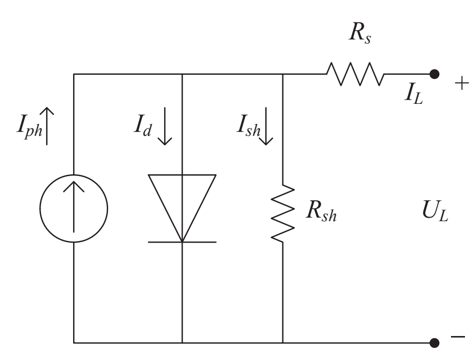

Fig. 1. Equivalent circuit of a single diode model.