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Multiple learning backtracking search algorithm for estimating parameters of photovoltaic models

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HIGHLIGHTS

- MLBSA is proposed to identify the parameters of PV models.
- Multiple learning strategy aims to balance exploration and exploitation abilities.
- Elite method based on chaotic local search is used to refine population quality.
- Comprehensive experimental results indicate the competitive performance of MLBSA.

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ABSTRACT

Obtaining appropriate parameters of photovoltaic models based on measured current-voltage data is crucial for the evaluation, control, and optimization of photovoltaic systems. Although many techniques have been developed to solve this problem, it is still challenging to identify the model parameters accurately and reliably. To improve parameters identification of different photovoltaic models, a multiple learning backtracking search algorithm (MLBSA) is proposed in this paper. In MLBSA, some individuals learn from the current population information and historical population information simultaneously, which aims to maintain population diversity and enhance the exploration ability. While other individuals learn from the best individual of current population to improve the convergence speed and thus enhance the exploitation ability. In addition, an elite strategy based on chaotic local search is developed to further refine the quality of current population. The proposed MLBSA is employed to solve the parameters identification problems of different photovoltaic models, i.e., single diode, double diode, and photovoltaic module. Comprehensive experimental results and analyses demonstrate that MLBSA outperforms other state-of-the-art algorithms in terms of accuracy, reliability, and computational efficiency.

1. Introduction

To solve the issues of climate change, environmental pollution, and depletion of classical fossil fuels, increasing attention has been focused on the using of renewable energy in recent years [1,2]. Among renewable energy sources, solar energy is regarded as one of the most promising renewable sources due to its wide availability and cleanliness [3–5]. It is converted into electricity and supply power through photovoltaic (PV) systems [6]. However, PV systems usually operate in harsh outdoor environment and their PV arrays are easy to be deteriorated, this greatly affects the utilization efficiency of solar energy [7]. Therefore, to control and optimize PV systems, it is very important to evaluate the actual behavior of PV arrays in operation using accurate model based on measured current-voltage data [8]. Two steps are needed to model the PV models: (1) the mathematical model formulation, and (2) the model parameters identification [9,10]. Several mathematical models have been developed and proved to be successful in describing the performance and nonlinear behavior of PV systems [11]. Among them, the single diode model and double diode model are widely used in practice [12]. Furthermore, the accuracy of PV models primarily depends on their model parameters that usually are unavailable and varying due to aging, faults, and volatile operating conditions. Hence, accurately and reliably identify model parameters is indispensable to the evaluation, optimization, and control of PV

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systems, and this motivates the development of various parameter identification methods over recent years [4,13,14].

The problem of estimating the PV models parameters is often defined as an optimization problem, and thus an objective function is necessary. Given that the measured current-voltage data involves a certain degree of noise, leading to the search space determined by the objective function is nonlinear and multimodal with multiple local optimal [15,16]. Some researchers have concentrated on using deterministic techniques, such as the least squares [17], the iterative curve fitting [18], and the tabular method [19], to solve the parameters identification problem. Since deterministic techniques generally are gradient-based methods, although these methods are powerful in local search, they are easy to be trapped in local optimal. In addition, the implementation of deterministic techniques requires numerous model restrictions such as convexity and differentiability, and many deterministic methods are highly sensitive to their initial solutions, which results in a lower efficiency when the initial point is far from the global optimal [15,20].

The heuristic methods inspired by various natural phenomena are a promising alternative to deterministic algorithms. They impose no restrictions on the problem formulation, thus can be easily used for various problems. Numerous heuristic methods and their variants have been proposed and used to estimate the PV models parameters in the past decade. Ishaque et al. [21] proposed a penalty based differential evolution (P-DE) to estimate the parameters of solar PV modules at varied environmental conditions. Muhsen et al. [3] developed a DE with integrated mutation (DEIM) for identifying the unknown parameters of double diode PV module model. Jiang et al. [22] developed an improved adaptive DE (IADE) based parameter identification approach by modifying the scaling factor and crossover rate. Askarzadeh and Rezazadeh [23] employed artificial bee swarm optimization (ABSO) to identify the solar cell parameters. Rajasekar et al. [24] used the bacterial foraging algorithm (BFA) to model the solar PV characteristics accurately. Niu et al. [15] put forward a simplified teaching–learning-based optimization (STLBO) to obtain the parameters of proton exchange membrane fuel and solar cells. Patel et al. [25] used TLBO to extract all the solar cell parameters from a single illuminated current-voltage data of different kinds of solar cells. Yuan et al. [26] developed a mutative-scale parallel chaos optimization algorithm (MPCOA) for solving the designed parameter estimation problem. Oliva et al. [27] applied artificial bee colony (ABC) to determine the parameters of solar cells accurately, and then they proposed an improved chaotic whale optimization algorithm (CWOA) for the same problems [9]. Askarzadeh and Coelho [28] simplified the bird mating optimizer (BMO) to extract the parameters of module model at different operation conditions. Ma et al. [29] compared and analyzed the performance of six bio-inspired optimization algorithms on the parameters estimation of single diode model. Chen et al. [30] studied the parameters estimation problem of solar cell models by using the proposed generalized oppositional TLBO (GOTLBO). Allam et al. [31] proposed month flame optimizer (MFO) for the parameters estimation of three diode model. Awadallah [32] designed five variants of BFA to estimate the parameters of PV module from nameplate data. Nunes et al. [1] proposed a guaranteed convergence particle swarm optimization (GCPSO) to determine the parameters of PV cells and modules. Jordehi [33] put forward a time varying acceleration coefficients PSO to estimate parameters of different PV models. Lin et al. [34] presented a modified simplified swarm optimization (MSSO) algorithm to extract the parameters of solar cell models. Chen et al. [35] developed a hybrid teaching-learning-based artificial bee colony (TLABC) for the solar PV parameters estimation problems. The results obtained by these heuristic algorithms are better than those found by deterministic methods considering robustness and accuracy. However, since the identification of PV models parameters is a multimodal problem containing many local optima, it is very difficult to achieve the global optimal solution for a considerable amount of heuristic algorithms. Furthermore, many heuristic algorithms have several parameters need to be experimentally tuned, this affects their efficacy, accuracy, reliability, and scalability. Hence, looking for a competitive algorithm that can accurately and reliably identify the parameters of different PV models with satisfied computation time is still a challenging task.

Backtracking search algorithm (BSA) is a new population-based heuristic method proposed by Civicioglu for solving real-valued numerical optimization problems [36]. The algorithm has a simple structure and only one control parameter need to be set, and its performance is insensitive to the initial value of control parameter [37,38]. BSA has a memory pool that randomly maintains individuals of the previous generation population, which is used to generate the search-direction matrix by combining with the current population. Due to its flexibility and efficiency, BSA and its variants have been widely applied to a wide range of real-world optimization problems, such as economic dispatch problems [39,40], optimal power flow [41,42], parameter identification [43,44], feature selection [45], artificial neural network [46,47], community detection [48], flow shop scheduling [49,50], and nonlinear optimal control problem [51]. However, as a young algorithm, BSA has some disadvantages and its performance need to be further improved. The first is that only the historical population information is utilized to guide the search and the information in current population is not used sufficiently, which cannot maintain the population diversity efficiently and thus the exploration ability of BSA is weak. The second is that there is no guidance as approach to the current best individual during the evolution process, which leads to slow convergence speed and poor exploitation ability of BSA. In addition, to the best of our knowledge, no attempts to use BSA in handling the parameter identification problems of PV models have been reported in the literature.

The aim of this paper is to develop a multiple learning backtracking search algorithm (MLBSA) that has the capability to accurately and reliably extract the parameters of PV models with satisfied computation burden. In MLBSA, according to a random probability, some individuals update their positions by learning from the historical population information and current population information simultaneously, which can enhance the population diversity. While other individuals renew their positions guided by the best individual of current population to improve the convergence speed. In this way, the appropriate balance between the exploration and exploitation abilities can be achieved. Besides, to further refine the quality of current population, an elite mechanism based on chaotic local search is introduced. In order to evaluate the performance of MLBSA, it is compared with other state-of-the-art algorithms on parameters identification problems of different PV models, i.e., single diode, double diode, and PV module. Extensive experimental results and analyses indicate that MLBSA exhibits superior performance regarding accuracy and reliability with competitive computation efficiency.

The main contributions of this paper are as follows:

- A new method MLBSA is proposed to efficiently determine the parameters of PV models. In MLBSA, individuals randomly select different update equations for learning to balance the exploration and exploitation abilities.
- An elite mechanism based on chaotic local search is also developed to refine the quality of current population in each generation.
- The effectiveness of MLBSA is comprehensively tested through parameters identification problems of different PV models.

The remainder of this paper is organized as follows. Section 2 presents the problem formulation of PV models. Section 3 introduces the basic BSA algorithm. Section 4 presents the proposed MLBSA in detail. Section 5 displays the experimental results and analysis on different PV models. Finally, Section 6 concludes this paper.