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Parameters identification of photovoltaic models using hybrid adaptive Nelder-Mead simplex algorithm based on eagle strategy

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HIGHLIGHTS

- A novel algorithm EHA-NMS is proposed for parameters identification of PV models.
- The EHA-NMS is based on adaptive Neld-Mead simplex, ABC and new eagle strategy.
- The eagle strategy consists of coarse exploration, coarse and fine exploitation.
- The NMS is improved by an adaptive mechanism on the shrinkage coefficient.
- The EHA-NMS features better convergence and reliability than reported algorithms.

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ABSTRACT

Fast accurate and reliable identification of photovoltaic (PV) model parameters based on measured current-voltage (IV) characteristic curves is significant for the analysis, evaluation and diagnosis of the operating status of in-situ PV arrays to optimize solar energy conversion. Although many techniques have been proposed, it is still challenging to achieve both fast and accurate parameters identification with high reliability. In this paper, based on a new eagle strategy, an improved adaptive Nelder-Mead simplex (NMS) hybridized with the artificial bee colony (ABC) metaheuristic, EHA-NMS, is proposed to improve parameters identification of PV models. The proposed novel eagle strategy consists of three cascaded stages: coarse exploration, coarse exploitation and fine exploitation, through which the strong global exploration of ABC and the powerful local exploitation of NMS merits are combined and the high computation burden of ABC and the high probability of being trapped in local minima of NMS drawbacks are alleviated. The EHA-NMS is compared with some state-of-the-art algorithms on three benchmark problems of model parameters identification of a R.T.C France solar cell and Photowatt-PWP201 PV module which are commonly adopted in the literature. The intensive experiment result and analysis show that the EHA-NMS outperforms other state-of-the-art techniques especially in terms of convergence and reliability. Due to the high computation efficiency, the EHA-NMS can be easily ported to embedded systems to realize online real-time parameters identification of PV models.

1. Introduction

To deal with the issues of climate change, environment pollution and so on, utilization of solar energy through photovoltaic (PV) and/or thermal systems is rapidly increasing in recent years worldwide [1–4]. PV systems usually operate in harsh outdoor environment and their PV arrays are prone to deteriorate and may even undergo various faults due to harsh weather condition and aging [5–8], which greatly affect the solar energy utilization efficiency and even cause safety issues. Therefore, in order to optimize PV systems, it is important to evaluate the actual behavior of PV arrays in operation through accurate modeling based on measured IV curve data [9–11]. Several PV models have been successfully applied to simulate the behavior of PV systems, among which there are two commonly adopted lumped-parameter non-linear circuit models, i.e., single-diode and double-diode equivalent model [12–15]. The accuracy of PV models greatly depends on their model parameters. However, the model parameters usually are not directly available from manufacturers and they will change

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due to aging and faults. Therefore, it is important to identify the model parameters based on experimental current-voltage (I-V) characteristic curves, and various parameter identification techniques have been proposed in recent years [10,15–18].

Parameters identification techniques for PV models proposed in the literature can be generally categorized into three classes: the analytical methods [19–23], the numerical methods [17,18,24–29] and the hybrid methods [20,30,31]. The analytical methods usually formulate some explicit equations and directly calculate the parameters using the rating parameters given by manufacturer or few key points of the experimental I-V curve such as short-circuit current, the open-circuit voltage, maximum power point (MPP) current and voltage. Although they feature simplicity and fast calculation, the parameters are derived only by few key points and therefore the accuracy is susceptible to measurement noise.

In order to overcome the drawback of analytical methods, various deterministic and stochastic numerical methods have been proposed to improve the performance of parameters identification by minimizing the overall error between all data points of the experimental and simulated I-V curve. The deterministic methods include Newton–Raphson method [29], Levenberg–Marquardt algorithm [32], Pattern Search (PS) [33] and so on. Although these methods usually are quite efficient and powerful in local search, they are prone to be trapped in local minima. Hence, their accuracy is not reliable because parameters identification of PV models is a non-linear multi-modal problem containing several local minima. Moreover, the convergence is dependent on the chosen initial points. If the starting point is far from the optima, the convergence speed will be very low and thus the efficiency is not guaranteed. In recent years, many researchers turned to explore various stochastic numerical methods, such as differential evolution [27,28,34], genetic algorithm [35–37], simulated annealing (SA) [38], particle swarm optimization [39], artificial bee colony (ABC) [26], flower pollination algorithm [25], bird mating optimization [40], bacterial foraging algorithm [30], cat swarm optimization [17], generalized oppositional teaching learning [18], and so on. Although these algorithms are good at global search and thus are suitable for multi-modal problems, they usually require high computation resource due to stochastic search mechanisms and large population. Therefore, their convergence speed is limited and they are not suitable for real-time applications.

For the sake of avoiding the drawback and exploiting the advantage of current analytical methods and numerical methods, some hybrid methods were proposed [32,41,42]. Dkhichi et al. proposed a method combing the Levenberg–Marquardt (LM) with simulated annealing (SA), in which the damping factor of LM at each iteration by SA [32]. Jovanovic et al. proposed cuckoo search (CS) hybridized with Nelder-Mead simplex (NMS) [41], in which the Levy flight of CS is replaced by NMS. These methods hybridized two different algorithms in each iteration, and thus the number of function evaluation in one iteration is not reduced or even increases. Therefore the improvement of the convergence is limited, and their overall performance is not significantly improved compared to the best reported result in the literature. Therefore, there still exists the need to develop new hybrid methods.

To further improve the efficiency and reliability of parameters identification of photovoltaic models while achieving the best accuracy, based on a proposed new three-stage eagle strategy and improved Nelder-Mead simplex, a novel hybrid algorithm called EHA-NMS is proposed in this paper. The EHA-NMS hybridizes the improved adaptive Nelder-Mead simplex deterministic direct search method [43] and the artificial bee colony stochastic global search algorithm [44] using the three-stage eagle strategy [45]. In the first stage of the new eagle strategy, the ABC algorithm is run for coarse exploration, which finds some good initial points for the second stage in few iterations. In the second stage, multiple NMS are run for coarse exploitation. In the third stage, a single improved adaptive NMS is run for fine exploitation. The proposed algorithm takes advantage of the fast initial convergence of ABC to overcome the initial point issue of NMS, utilizes multiple NMS to alleviate the local optima issue of NMS, and exploit the powerful local search ability of single adaptive NMS to quickly find the optima. Due to the high computation efficiency, the proposed EHA-NMS algorithm can be easily ported to embedded platforms to develop online IV curve measurement and analysis systems for real-time energy conversion optimization. Based on the identified parameters and measured irradiance and temperature, accurate modeling and model update can be carried out.

The rest of the paper is organized as follows. Section 2 discusses the photovoltaic models and formulates the optimization problem for parameters identification. Section 3 introduces the standard ABC and the adaptive NMS algorithm and presents the proposed hybrid algorithm based on the eagle strategy. In Section 4, intensive experiments and analysis are carried out, and the advantage of the proposed EHA-NMS algorithm is verified by comparison with some state-of-the-art algorithms especially the best reported algorithm Rcr-IJADE [28].

2. Photovoltaic modeling and problem formulation

In the literature, there exist many photovoltaic models that describe the I-V characteristics of the solar cells and/or photovoltaic modules. The most common ones are the single-diode model and double-diode model detailed as follows [10].

2.1. Solar cell model

Because of good simplicity and accuracy, single-diode and double-diode models are the most commonly adopted models, the schematic of which are illustrated in Fig. 1. The models consist of a current source I_{ph} modeling the photovoltaic current, one or two diodes modeling the PN junction of solar cell, a shunt resistor modeling the leakage current, and a series resistor modeling the contact resistance. By applying Kirchhoff's current law (KCL) to the node K in the schematics, the following equations Eqs. (1) and (2) can be obtained.

$$I_{ph} = I_D + I_{sh} + I_L \tag{1}$$

$$I_{ph} = I_{D1} + I_{D2} + I_{sh} + I_L \tag{2}$$

According to the Shockley equation, the current of the diode is described by Eq. (3), where the I_s represents the saturation current, n represents the diode ideal factor, R_s represents series resistance, R_{sh} represents the shunt resistance, the V_t represents the junction thermal voltage, and the term $(V_L + R_sI_L)$ is the voltage on the diode. The Vt is defined by Eq. (4), in which q is the electron charge ($1.60217646 \times 10^{-19}$ C), k is the Boltzmann constant ($1.3806503 \times 10^{-23}$ J/K), and T is the temperature of the junction in Kelvin. According to the Ohm's law, current of the shunt resistance is drawn by Eq. (5).

$$I_D = I_s\left[\exp\left(\frac{V_L + R_sI_L}{nV_t}\right) - 1\right] \tag{3}$$

$$V_t = \frac{kT}{q} \tag{4}$$

$$I_{sh} = \frac{V_L + R_sI_L}{R_{sh}} \tag{5}$$

Therefore, combining the Eqs. (1)–(5), the relationship among the output current, output voltage and model parameters for the single and double diode models of the solar cell are given by Eqs. (6) and (7), respectively. There are five unknown parameters (Iph, Is, n, Rs, Rsh) to be identified for the single-diode model, while