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Extraction of electrical parameters for one diode photovoltaic model using quasi-oppositional Rao-1 optimization algorithm

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Abstract

Usually the model parameters of photovoltaic (PV) cells are unavailable in their datasheet provided by the manufacturers. Hence, the problem of extracting appropriate PV parameters is of high importance, and has been highly attracted by researchers. This paper presents a new method to estimate the parameters of the one diode model (ODM), namely quasi-oppositional Rao-1 optimization algorithm (QORao-1). The present method uses only addition and multiplication operations with a quasi-oppositional-based learning process, in order to improve the exploration capability of the original Rao-1 algorithm. Hence, an attractive amelioration in the Root-Mean-Square-Error (RMSE) values is acquired. Comparative performance analysis demonstrates that the QORao-1 algorithm has better performance in terms of robustness and accuracy while estimating the PV parameters than many well-known algorithms.

Keywords: Modelling; Optimization; Parameters identification; Photovoltaic; Rao-1 algorithm

1. Introduction

Recently, the development and the exploitation of environmentally friendly energy sources is becoming a crucial topic to avoid the catastrophic consequences such as ozone layer erosion, air pollution, acid rain and greenhouse gas emissions resulting from the continuing use of fossil fuels. Solar energy is the major energy source among different renewable energy resources due to its sustainability and abundance across the world. In particular, photovoltaic (PV) systems have achieved prevalent applications due to their superiority in terms of zero emission, abundant reserves, noise free, cost decreased from years to years, etc. Rigorous modelling and detailed information are required for all PV systems and diverse industrial application. Unfortunately, the necessary information to model the basic component (i.e., solar cells) of a complete PV system are inaccessible and do not provided by all manufacturers data sheets. Therefore, how to identified these unknown parameters to optimize, manage and simulate a complex PV system has attracted several researchers in recent years and many confident solutions have been proposed to deal with it [1]. According to the mostly research works published in the field of PV parameter estimation methods, these methods are classified into three main categories: numerical (or iterative) [2, 3], analytical (or non-iterative) [4] and the artificial intelligence (or optimization) [5] methods. The last category is widely used in recent years to overcome some of the existing failures observed while using the other methods such as convexity, differentiability, and the sensibility to the initial values. In this problem, an appropriate optimization algorithm must be applied to minimize an objective function, frequently based on the mean of squared errors between the estimated values and the experimental data [5-16].

Huge number of algorithms have already been utilized to identify the PV parameters, such as the Rao-1 algorithm and its variants [6-8], enhanced Levy flight bat algorithm (ELBA) [9], enhanced Harris Hawks optimization (EHHO) [10], the SGDE algorithm [11], Slime Mould Algorithm (SMA) [12], a variant of butterfly optimization algorithm (EABOA) [13], an improved marine predators algorithm (IMPA) [14], Random learning gradient based optimization (RLGBO) [15], and the Runge-Kutta optimizer (RUN) [16]. The first mentioned method has been widely utilised and investigated in the last few years due to its simplicity, gradient-free mechanism, better local optimum avoidance, and flexibility compared to the other algorithms. Moreover, considerable recent works have proposed more advanced techniques since the No-free lunch (NFL) theorem [17] states that no algorithm can present best performances in all optimization problems. The main idea of this paper is to applied a novel version of Rao-1 algorithm [18] to estimate the parameters of solar cells. This novel version is called 'quasi oppositional based Rao-1 (QORao-1) algorithm' and its key idea is to diversify the search space in all iteration and enhance the exploration capability of the original algorithm which results to achieving a better solution. The proposed method has been tested on the R.T.C. France PV cell which is considered as the widely used cell in the literatures and compared with ten recent algorithms. Obtained results show that the proposed QORao-1 surpasses the basic Rao-1 and all reported algorithms. Indeed, the QORao-1 algorithm can achieve lower RMSE values, in this case study.

The rest of this paper is organized as follows, Section 2 presents ODM and the applied objective function for parameters extraction. The quasi-oppositional Rao-1 optimization algorithm is introduced in Section 3. In Section 4, comparative and simulation results are provided. Finally, Section 5 concludes the paper.

2. Photovoltaic model and objective function

2.1 One diode model

The ODM electrical presentation shown in Fig. 1 is an extremely used model for demonstrating and explaining the PV cells' features due to its simplicity and accurate results. The output current is calculated using the Kirchhoff's law as follows:

$$I_{pv} = I_{ph} - I_0 \left[exp\left(\frac{q(V_{pv}+I_{pv}R_s)}{nkT}\right) - 1\right] - \frac{V_{pv}+I_{pv}R_s}{R_{sh}} \quad (1)$$

where n is the diode ideality factor, k is the Boltzmann's constant, T is the cell temperature, q is the electron's charge, Iph is the photocurrent, I_0 is the reverse saturation current, Rs and Rsh are the series and shunt resistances, respectively.

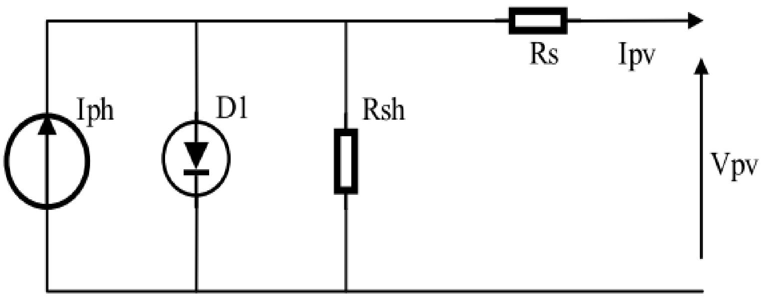


Fig 1. One diode circuit presentation of a PV cell model.

2.1 Objective function

The accuracy of a heuristic optimization algorithm for solving engineering problem is evaluated using an objective function. For a correct extraction of the different PV parameters, the RMSE (Eq. 2) which often utilised in most of research is selected as an objective function in this paper

$$RMSE = \sqrt{\frac{1}{M}\sum_{j=1}^{M}(I_{meas} - I_{esti})^2} \quad (2)$$

where, I_{meas} is the measured current, I_{esti} is the estimated current and M is the number of points.

3. Quasi-oppositional Rao-1 optimization algorithm

In the basic Rao1 algorithm if $Y_{j,k,i}^{old}$ is the value of the j^{th} variable for the k^{th} candidate during the i^{th} iteration within a population P then this value is updated as follow:

$$Y_{j,k,i}^{new} = Y_{j,k,i}^{old} + r_{j,i}(Y_{j,best,i} - Y_{j,worst,i}) \quad (3)$$

where, $r_{j,i}$ is a random number in $[0, 1]$, $Y_{j,best,i}$ and $Y_{j,worst,i}$ are the best and the worst candidate values of the j^{th} variable, respectively; and $Y_{j,k,i}^{new}$ is the updated value of $Y_{j,k,i}^{old}$.

The quasi-opposite value of $Y_{j,k,i}$is:

$$Y_{j,k,i}^{q} = rand(a, b) \tag{3}$$

where $a = (Y_j^L + Y_j^U)/2$ and $b = Y_j^L + Y_j^U - Y_{j,k,i}$; a is the centre of the search space; Y_j^L and Y_j^U are the upper and lower limits of the j^{th} variable; and b is the opposite value of $Y_{j,k,i}$. In addition, the overall difference between the measured current and simulated current is calculated by the RMSE.

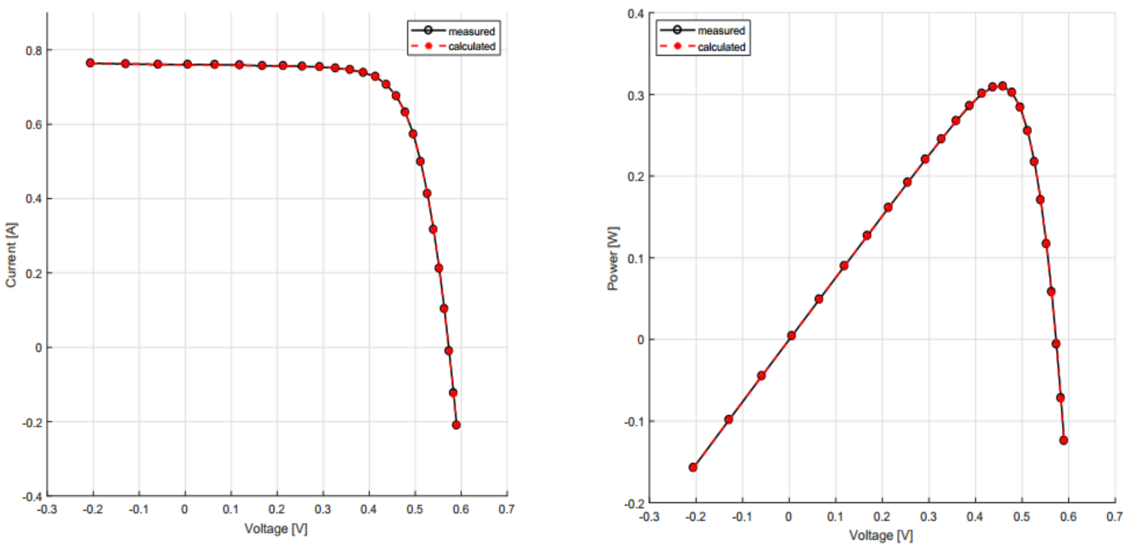
4. Simulation results

The QORao-1 is applied with the RTC France silicon PV cell with $57mm$ diameter at a temperature of $33°C$ and $1000W/m^2$ incident irradiance. The extracted parameters and their corresponding RMSE of the used algorithm and ten recent algorithms are given in Tab. 1. It can be observed from this result that the QORao-1 has the minimum RMSE value (7.730062968 × 10^{-4}), the same as the LCROA method, and outperforms all other presented algorithms.

Table 1. The best solution obtained from different algorithms for the ODM.

Item	**I_{ph} [A]**	**I_0 [μA]**	**n**	**R_S [Ω]**	**R_{sh} [Ω]**	**RMSE [10^{-4}]**
Rao-1	0.760787	0.31073	1.51692	0.036546	52.8963	7.730063234
QORao-1	0.760788	0.31067	1.51690	0.036547	52.8853	7.730062968
LCROA [7]	0.760787	0.31068	1.51690	0.036547	52.8898	7.730062968
MRao-1 [8]	0.760776	0.32302	1.48114	0.036377	53.7185	9.860219
ELBA [9]	0.760776	0.32302	1.48118	0.036377	53.7185	9.860219
EHHO [10]	0.760775	0.323	1.48124	0.036375	53.7428	9.8602
SGDE [11]	0.76078	0.32302	1.48118	0.036377	53.7185	9.860218779
SMA [12]	0.76076	0.32314	1.48114	0.03637	53.7149	9.84820
EABOA [13]	0.76077	0.32293	1.48115	0.03638	53.76600	9.8602
IMPA [14]	0.76078	0.32302	1.48118	0.03638	53.71852	986021878
RLGBO [15]	0.76078	0.32302	1.48118	0.03638	53.71870	9.86022
RUN [16]	0.76076	0.32000	1.48025	0.03642	53.67071	9.86242

In addition, Fig. 2 presents the I-V (a) and P-V (b) curves simulated from the ODM designed with the extracted parameters by the best QORao-1 solution. Clearly, it can be observed that the estimated parameters give out a precise I-V and P-V characteristic that accurately replicate the experimental data.



(a) (b)

Fig. 2. I -V and P -V curves of the ODM. (a) I -V curve, and (b) corresponding P-V curve.

5. Conclusion

This study presents a new application of the QORao-1 algorithm for the first time to identify the unknown parameters of one diode model. The main idea of this paper is to accurately design the ODM from the proper identification of their parameters. The proposed method contains a quasi-oppositional learning process to ensure the diversity in the exploration phase. The RTC France silicon PV cell is utilized to test the functionality, with the RMSE between the measured and the estimated data as an objective function to be minimized and the results are compared with ten recent competitor algorithms. The final results illustrate that QORao-1 can exactly replicate the experimental data and surpasses all other techniques in terms of lower RMSE value.

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