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Parameters Estimation of Photovoltaic Modules Using Differential Evolution Metaheuristic Method

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Abstract. This paper presents the analysis of the differential evolution (DE) metaheuristic method, which is used to estimate some parameters employed in the equivalent electrical circuit that represents the photovoltaic (PV) cell model. The DE algorithm is an evolutionary algorithm that can be designed to search global optimal points with fast convergence time and present accurate results, requiring few control variables to be set. The accuracy of reproducing the characteristics of the PV module depends on the knowledge of some PV cell model parameters, such as series and shunt resistances, diode ideality factor, and diode reverse saturation current. Once the referred parameters are not usually given in the manufacturers' datasheet, their determination can be achieved by the DE algorithm, employing data and the current-voltage (I-V) characteristic curve provided by the PV module manufacturers. The technique is designed to minimize the error between the reference I-V curve and the I-V curve reproduced by the DE algorithm. Through simulation results, the feasibility of the DE algorithm to estimate the desired parameters of a PV cell is validated, and the algorithm's performance to reach the best solution with fast convergence and a small iteration number is evaluated.

Keywords. Differential evolution, Metaheuristic method, Parameter estimation, Photovoltaic modules.

1. Introduction

In recent years, several types of research about renewable energy sources have been widely developed to overcome the problems of significant power demand, possible exhaustion of energy resources, and environmental pollution [1], [2].
In this context, in recent years, photovoltaic solar energy has been highlighted for electrical power generation since there is no pollutant generation during energy conversion, easy maintenance, and long-term economic prospects [3]–[5].

Photovoltaic modules convert solar energy into electricity. In particular, a photovoltaic module comprises several individual solar cells composed of semiconductor material that convert sunlight into electricity [6], [7]. Furthermore, the material of solar cells is directly related to their efficiency, and it is well known that the electrical voltage and current of cells may vary with climate conditions, such as solar irradiance and temperature.

In addition, maximum power point tracking (MPPT) techniques are often employed in PV systems to ensure maximum power extraction and improve the overall PV system performance [8]–[10].
However, computer simulator programs play an essential role in the design and dynamic analysis to guarantee the development of a reliable and efficient PV generation system and allow the implementation of system controls and MPPT techniques [11].

The mentioned simulator programs mainly depend on the accuracy of the PV module model. The models represent the electrical characteristics of the PV cells. Literature has presented them using equivalent circuits based on electrical parameters, which affect the whole system's performance [12]–[14]. Generally, parameters such as series and shunt resistances, diode reverse saturation current, and typical PV module datasheets do not usually provide a diode ideality factor. Thus, solar cell characterization becomes a challenge. Furthermore, analytical approaches deal with non-linear equations requiring numerical extraction techniques and iterative methods with extensive computation [15].

For optimization purposes, some methods, such as adaptive extremum-seeking control and evolutionary algorithms (EA), have been employed in PV systems [16]–[19]. Specifically, genetic algorithms (GA) have been proposed to obtain the solution and extract the PV modules' parameters [17]–[19]. Although GA algorithms solve optimization problems, the shortcomings imply hasty convergence and low speed [20].

Differential Evolution (DE) is a metaheuristic algorithm classified as an evolutionary algorithm introduced by [21]. This algorithm appears to be a better alternative to GA in many other cases [22]–[24]. The DE method employs a very effective approach relying on a few control variables to be set and guarantees rapid convergence time, accuracy, and consistency of the solutions [20]. The DE method presents a mutation strategy, a genetic operator, based on the distribution of a substantial number of difference vectors, reducing the probability of reaching local minimum points, being a technique robust and efficient to leading with non-linear and non-continuous functions [21], [25].

In this work, a DE metaheuristic algorithm is investigated and employed to estimate the parameters of the PV module (Sunmodule Plus SW 245 SolarWorld [26]). The DE algorithm uses the characteristic I-V curve obtained from the PV module datasheet as input. Furthermore, the algorithm performs a fitness function, resulting in the I-V curve with the estimated parameters. In this approach, algebraic manipulations are not required, and the DE algorithm works as a function approximator, in which the main target is to minimize the absolute errors between the estimated and reference I-V curves. Simulation results are shown to validate the DE algorithm, and their effectiveness is evaluated in terms of accuracy, convergence speed, and number of iterations.

2. Mathematical Modeling of the PV Cell

The photovoltaic cell can be modeled by the equivalent circuit based on a single diode model, as shown in Fig. 1. This modeling is well performed and has been used in most PV systems applications [9], [13], [27], [28].

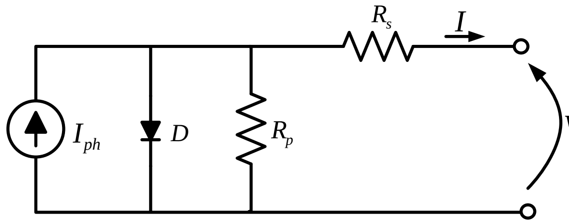

Fig. 1. Photovoltaic cell equivalent circuit.

The output current of the photovoltaic cell is determined as:

$$I = I_{ph} - I_r\left[e^{q\left(\frac{V+IR_s}{\eta KT}\right)} - 1\right] - \frac{V+IR_s}{R_p} \tag{1}$$

where V and I are the respective voltage and current of the cell; I_{ph} is the photocurrent, I_r is the reverse saturation current; R_s and R_p are respective the series and parallel associated resistances; q electron charge ($1.6\text{x}10^{-19}$), k is the Boltzmann constant ($1.38\text{x}10^{-23}$), T is the temperature in K (Kelvin), and η is the ideality factor of p-n junction.

On the other hand, Fig. 1 represents the model of an individual PV cell. However, commercial PV modules consist of several interconnected cells. In this case, (1) is rewritten as given in (2), where N_s is the number of the series connected cells.

$$I = I_{ph} - I_r\left[e^{q\left(\frac{VN_s+IR_s}{\eta kT}\right)} - 1\right] - \frac{VN_s+IR_s}{R_p} \tag{2}$$

In this paper, (2) is the function used to perform the characteristic I-V curve, which is considered comparison data in the objective function of the problem statement. Hence, the solution provides the electrical parameters of the PV module.

3. Problem Statement

The main objective is to estimate the parameters expressed by a vector stated as:

$$\rho = [R_s \quad R_p \quad I_r \quad \eta] \tag{3}$$

The estimation problem is formulated as an optimization problem with minimization, and a fitness function is determined to evaluate the vectors and test the estimated parameters. The fitness function is expressed in (4) and represents the mean square error (J), where N is the number of iterations of the metaheuristic algorithm; I_t is the current from the datasheet considered the theoretical input data; and I_e is the current obtained from estimated parameters.

$$J = \sum_{i=1}^{N}(I_t - I_e)^2. \tag{4}$$

A small value of J implies a small deviation between the estimated and the real PV module parameters. Ideally, J should be null.

4. Differential Evolution Metaheuristic Method

The DE algorithm works on a population of individuals submitted to genetic operators: mutation, crossover, and selection. After that, each individual is evaluated as a possible solution, and the updating process is repeated until a satisfactory solution is attained; otherwise, a termination criterion can be settled [29].

A. Initialization

An initial population of NP vectors is randomly generated. The index G demonstrates the generation to which the vector belongs:

$$x_{i,G}, \ i = 1, 2, \ldots NP \tag{5}$$

where $x_{i,G}$ are called target vectors, and the number of elements in each vector is equivalent to the number of the parameters to be estimated.

B. Mutation

In the mutation process, new vectors are created by adding the weighted difference between two target vectors to another vector.

The equation described in (6) is used to obtain the mutant vector $v_{i,G+1}$, where three different vectors $x_{r_1,G}, x_{r_2,G}, x_{r_3,G}$ are randomly selected in the range of [1, NP]. The vector $x_{r_1,G}$ is called a base vector, and the indexes i, r_1, r_2, r_3 are integers and distinct. F is the mutation factor usually chosen in the range of [0,2] and is used to weight the differential operation $(x_{r_2,G} - x_{r_3,G})$.

$$v_{i,G+1} = x_{r_1,G} + F(x_{r_2,G} - x_{r_3,G}) \quad (6)$$

Fig. 2 illustrates the mutation scheme on a graphic representation.

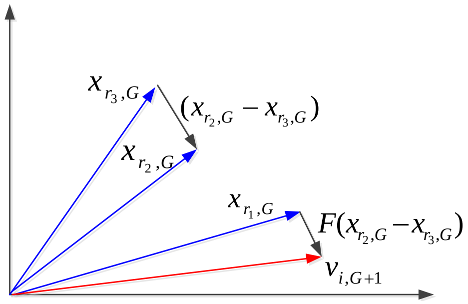

Fig. 2. Graphic representation of the mutation process of the differential evolution method.

C. Crossover

Crossover is an operation adopted in the DE in order to rely on diversity among mutant individuals. Therefore, the elements of the mutant vectors $v_{i,G+1}$ are combined with the elements of the target vectors $x_{i,G}$. This combination yields the trial vector $u_{i,G+1}$, as in (7), where C_r is known as the crossover rate, which is a control variable set in the range of [0,1]. The trial vector can be obtained according to Fig. 3.

$$u_{i,G+1} = \begin{cases} v_{i,G+1}, & rand_i \le C_r \\ x_{i,G}, & rand_i > C_r \end{cases} \quad (7)$$

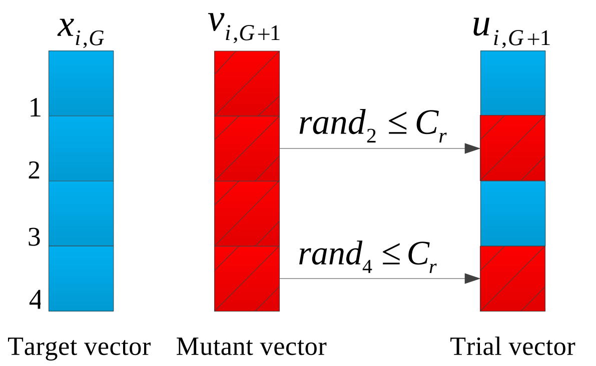

Fig. 3. Illustration of the crossover process in the Differential Evolution method, considering each vector with four parameters.

D. Evaluation and Selection

If the trial vector $u_{i,G+1}$ gets better in the fitness function when compared with the target vector $x_{i,G}$, the best solution for the problem statement is the trial vector. Then, the trial vector swaps the target vector in the next generation. This operation is called selection, and it is described as:

$$x_{i,G+1} = \begin{cases} u_{i,G+1}, & J(u_{i,G+1}) < J(x_{i,G}) \\ x_{i,G}, & otherwise \end{cases} \quad (8)$$

where *J* is the fitness function.

E. Pseudocode

The evolutionary algorithms can be described as a continuous process of cycles of evolution until the convergence criteria are satisfied. In this case, the pseudocode considered to the DE algorithm is divided into the following steps:

1) Settling values of *NP*, C_r, *F*, and *G*;
2) Randomly initialize the population;
3) Evaluate the fitness function of each individual;
4) Repeat the process until the convergence criteria are achieved, where:
   For each individual:
   - ✓ Select the target vector and the base vector;
   - ✓ Randomly select two individuals from the population;
   - ✓ Calculate the weighted difference vector;
   - ✓ Add the base vector to the mutant vector to obtain the trial vector;
   - ✓ Evaluate the trial vector and select the vector with the better fitness;

   End for each individual.
5) End of the algorithm.

5. Simulation Results

In this paper, the PV module parameters are estimated considering its operation at standard test conditions (STC), *i.e.*, solar irradiation of 1000 W/m² and temperature of 25ºC.

The analyzed photovoltaic module is manufactured by SolarWorld®, whose model specification is SW 245 Mono. The PV module characteristic I-V curve, obtained from the datasheet information, was considered an input parameter of the DE algorithm, which was implemented using the software MATLAB®.

Fig. 4 shows the algorithm's input curve, while the PV module parameters can be found in Table I.

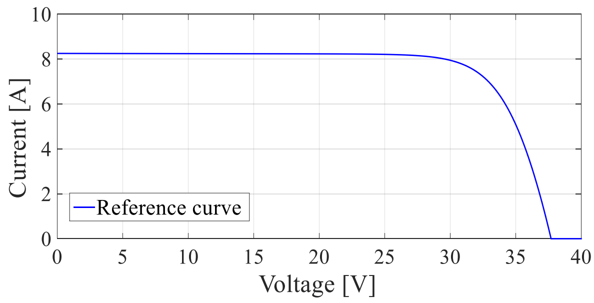

Fig. 4. PV module characteristic I-V curve used as parameter input of the DE algorithm.

Table I. - Parameters of the photovoltaic (PV) Module at STC

PV PANEL PARAMETERS	VALUES
Maximum PV power	245 W
MPP Voltage	30.8 V
MPP Current	7.96 A
Open circuit voltage	37.7 V
Short circuit current	8.25 A

The control variables of the DE algorithm are presented in Table II. There are no rules to choose these variable values. However, in most cases, the mutation factor is usually determined $F > 0.4$ [21]. In addition, a high value can be set for the crossover rate to intensify the population diversity and improve the convergence. Moreover, C_r is desirable to have a high value once the estimated parameters are highly related [30]. The NP and G selections depend on the characteristics and complexity of the problem, and they can be empirically set. However, the higher the NP, the longer is the convergence time.

Table II. - Control variables defined in the DE algorithm.

DE CONTROL VARIABLES	VALUES
Population size (NP)	20
Mutation Factor (F)	0.8
Crossover rate (C_r)	0.9
Maximum number of Generation (G)	100

In the DE algorithm, a value of less than 0.01 was also selected as convergence criteria for the fitness function. Thus, the algorithm continues running if the error between the reference and estimated I-V curves is greater than 1%.

The estimated parameters through the algorithm are specified in Table III. Fig. 5 compares the PV module characteristic curve (IxV) obtained from the estimated parameters and the datasheet (reference). In addition, the PV module characteristic power-voltage curve (P-V) is also obtained, as shown in Fig. 6.

According to Fig. 5, it can be observed that the DE algorithm converged to a feasible solution, which can approximate the I-V simulated curve to the reference curve.

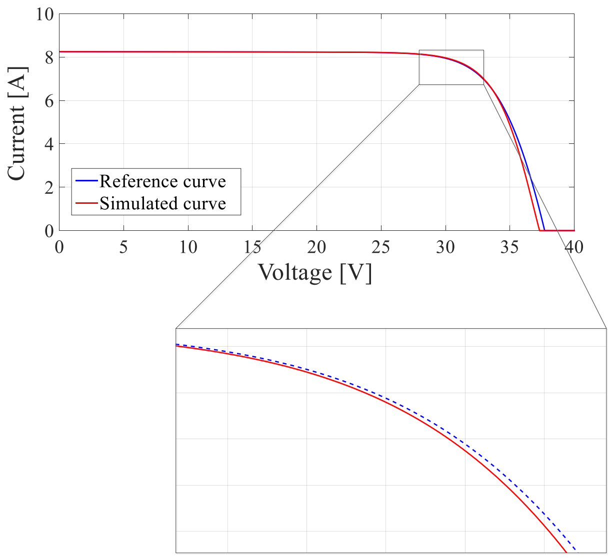

Fig. 5. Simulated I-V curve with estimated parameters by the DE algorithm and reference I-V curve.

Table III. - Estimated parameters from the DE algorithm.

ESTIMATED PV MODULE PARAMETERS	VALUES
Series resistance (R_s)	2.45223 mΩ
Parallel resistance (R_p)	17.4014456 Ω
Reverse saturation current (I_r)	1.19734×10^{-8} A
Ideality factor (η)	1.1104331

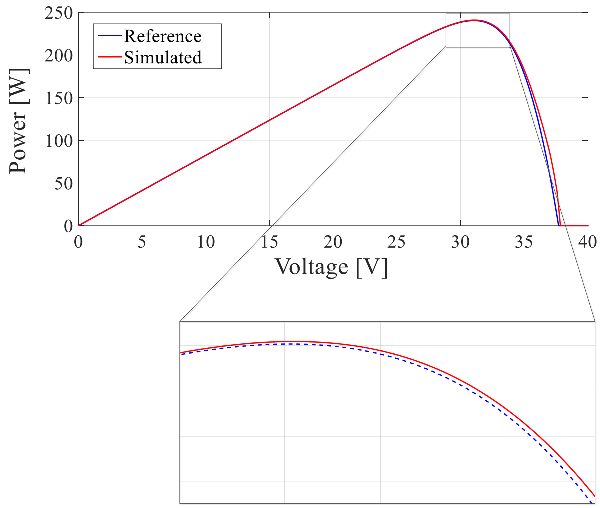

Fig. 6. Simulated P-V curve with estimated parameters by the DE algorithm and reference P-V curve.

The algorithm performance can be evaluated in terms of accuracy, converge time, and iteration number. The accuracy is observed according to the error, *i.e.*, the algorithm's final fitness function value. This error represents the difference between the referenced and simulated curves, as can be noted in Fig. 5. On the other hand, the convergence time depends on the time that the algorithm takes to achieve the best problem solution, and the iteration number is defined by means the number of consecutive repetitions of the algorithm until the best solution is reached. Table IV summarizes the main performance aspects obtained from the simulation results.

Table IV. – Performance of the DE algorithm.

PARAMETERS	VALUES
Mean squared error (J)	0.00158757292
Converge time (t_c)	0.058511 s
Number of iterations (N)	2

The mean squared error J value was 0.00158757292, which means a slight difference between the simulated I-V curve with estimated parameters from the DE algorithm and the reference I-V curve. Thus, the algorithm detected the solution in a convergence time of 0.058511 seconds with only two iterations.

The convergence time and number of interactions, which vary according to the initial number of the population NP, were considered satisfactory for this case.

6. Conclusion

This paper presented the study and application of the evolutionary algorithm based on the DE metaheuristic method for parameter estimations from the model of the photovoltaic module, which was modeled by an equivalent circuit. The manufacturer does not usually give parameters, such as the series and parallel resistance, the diode reverse saturation current, and the ideality factor of the p-n junction. Therefore, estimating these parameters is necessary to represent the solar cell and the PV module.

In order to identify these parameters, the DE algorithm was used as an input reference for the data and the reference current-voltage curve (I-V) provided by the PV module datasheet.

Based on the computational results, it can be noted that the simulated PV module characteristic curve (I-V) using the estimated parameters is very similar to the reference I-V curve (datasheet). Thus, it can be concluded that the DE algorithm can estimate the PV module parameters, which was able to reproduce accurately both PV module I-V and P-V curves.

The algorithm based on the DE method performed well and proved to be a feasible solution for estimating the PV array parameters once algebraic manipulations are not required. Moreover, the DE method could converge to a great solution in a satisfactory convergence time and with a small iteration number.

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