Particle Swarm Optimization for Photovoltaic Model Identification

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***Abstract*—This paper proposes a comprehensive modeling and parameters extraction method of solar photovoltaic module based on the Particle Swarm Optimization algorithm. The characteristic curves of photovoltaic panel are obtained by using only the information provided by the manufacturer data-sheet, avoiding the need to carry out experimental data. The performance and the accuracy of the proposed method are evaluated by applying the one-diode model and the results are compared with those obtained by the well-known Lambert W function. The proposed method shows a higher performance.**

***Index Terms*—Particle Swarm Optimization, Photovoltaic module, Modeling, Simulation.**

I. Introduction

Photovoltaic panels are composed by photovoltaic cells connected in series or parallel. The type of connection depends on the voltage and current values in order to produce the desired levels. The choice of these values is of fundamental importance for the efficiency of the converters that determine the energy produced by the photovoltaic panels. The aim of this paper is to obtain the characteristic curves of photovoltaic panel using only the information provided by the manufacturer data-sheet, avoiding the need to carry out experimental data.

There are several approaches that can be found in the literature to extract the parameters which characterize the photovoltaic panels. These approaches depend on the information available. This information can be obtained from characteristics curves (I-V) measured experimentally or, by the current and voltage levels at the characteristic points which can be found in the manufacturers data-sheets (short circuit current, I_{sc}, maximum power point (I_{mpp} and V_{mpp}), the open circuit voltage, V_{oc}, and the temperature coefficients of open-circuit voltage and short-circuit current (α_v and α_i, respectively).

Several estimation techniques have been reported for extracting the parameters through characteristics curves (I-V) measured experimentally. These techniques can be divided into analytical and numerical methods [1]. Analytical methods necessitate certain modeling conditions to make it applicable such as continuity, convexity and differentiability, involving heavy computations and tedious algebraic manipulation [2]. As an alternative, numerical methods such as flower pollination algorithm [3], time varying acceleration coefficients particle swarm optimisation [4], artificial bee swarm optimization [5] simulated annealing [6], Levenberg Marquardt algorithm combined with simulated annealing [7], are excellent choices to deal with nonlinear, non-differentiable and stochastic problems without involving excessive mathematical computations. However, the main issue of this approach is that it relies on measured data rather than information available in manufacturers data-sheets. Moreover, it requires measuring the cell temperature of the photovoltaic module, which is not an easy task [8].

On the other hand, estimation techniques to extract the parameters which caracterize the photovoltaic panels from information provided by manufacturers data-sheets, traditionally, consists on the resolution of a system of nonlinear equations, which requires numerical methods to determine the parameters that characterize the model under the standard test condition (STC), and for that employing three to five fundamental working points of the characteristic curve [9], [10]. Several authors proposed different equations/approaches to be used to extract the parameters. A recurrent approach in the literature [11] that allows the determination of the several parameters that characterize the mathematical model of a photovoltaic panel lies in the Lambert W function. By using this function, the mathematical model can be expressed as an explicit formula.

Recently, in order to avoid a considerable computational effort necessary to solve the system of equations to extract parameters that characterize the photovoltaic panel, employ artificial intelligence techniques, for example: Neural Networks [12]–[14] and Fuzzy Logic [15]. Although Neural Networks and Fuzzy Logic are powerful tools, for highly dynamic systems in adaptive computation with parallel processing and competent information to deal with the nonlinear characteristics of the photovoltaic panels, they need large computational time and/or training. Another methodology involving Artificial Intelligence techniques suited to deal with this photovoltaic panel nonlinear characteristic is the Swarm Intelligence [16]–[18].

In this paper, a particle swarm optimization (PSO) algorithm is applied to extract the optimal parameters that characterize the photovoltaic panel. To validate the proposed method, the one-diode model was used that guarantees the compromise between simplicity and precision. The results are compared with those obtained by the well-known Lambert W function.

This paper is organized in five sections. In the second one is presented a bibliographical revision of the main models that characterize a photovoltaic panel; in section 3, a description as well as a general conception of the Particle Swarm Optimization algorithm is done; in section 4, the one-diode mathematical model parameters obtained by using the new technique and the proposed algorithm are presented. Finally, the last section concludes the paper.

II. Mathematical models

Several models are proposed in the literature with the aim of simulating the photovoltaic cells operating behavior under different conditions. The main models that represent the photovoltaic cells are: the one-diode model, the two-diodes model, the multi-diodes model and the Bishop model. The one–diode model, Fig.(1), is characterized by five parameters: the photoelectric current I_{ph} proportional to the irradiance, the reverse saturation current of the diode I_{sat}, its ideality factor of the diode m, the resistor R_s, and the resistor R_p [19], [20]. Approximated models can be derived from the Eq.(1), considering the R_p resistor infinite (four parameters model) or the diode ideality factor as ideal allied to the previous condition (three parameters model).

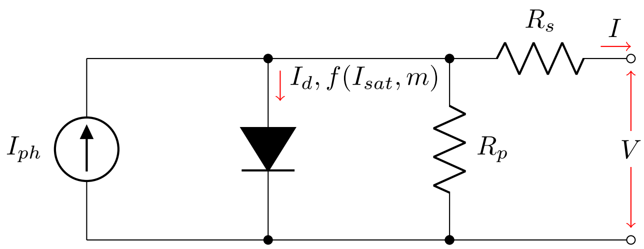

Figure 1. One–diode mathematical model of a photovoltaic cell.

$$I = I_{ph} - I_{sat}\left[\exp\left(\frac{e\,(V + I \times R_s)}{mk_bT}\right) - 1\right] - \frac{V + I \times R_s}{R_p} \tag{1}$$

Another model found in the literature is two-diodes model [21]–[23]. This model is characterized by seven parameters, the parameters previously described for the one-diode model, the ideality factor of the second diode and also its reverse saturation current, Fig.(2). From Fig.(2) and applying Kirchhoff law, the Eq.(2) can be obtained. The number of parameters can be reduced to five if the identity factors are specified as $m_1 = 1$ and $m_2 = 2$. Alternative models are found in the literature, with greater or lesser complexity, allowing to determine a different number of parameters.

$$I = I_{ph} - I_{sat_1}\left[\exp\left(\frac{e(V+I\times R_s)}{m_1 k_b T}\right) - 1\right] - I_{sat_2}\left[\exp\left(\frac{e(V+I\times R_s)}{m_2 k_b T}\right) - 1\right] - \frac{V+I\times R_s}{R_p} \tag{2}$$

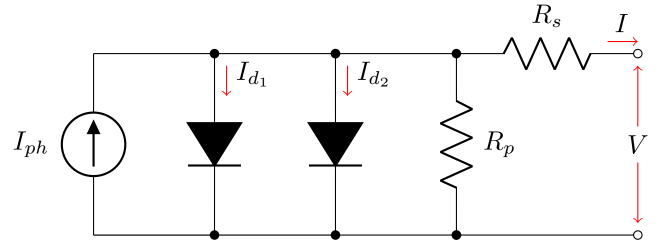

Figure 2. Two–diode mathematical model of a photovoltaic cell.

Another model considered in the literature is the multi-diodes model [24], constituted by n diodes. Theoretically, more diodes can be added to the circuit in Fig.(3) to better account the distributed and localized effects in solar cells, such as Auger recombination; however, their contributions are negligible when compared with the results from the previous models [24]. The model is characterized by $3+2n_d$ parameters and Eq.(3), where n_d is the number of diodes in the circuit.

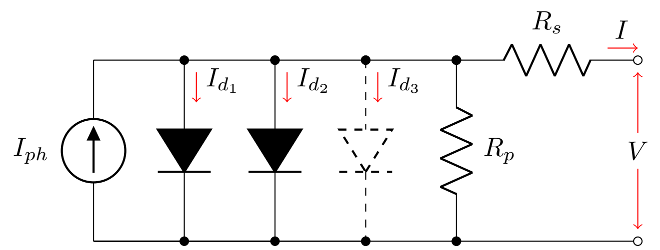

Figure 3. Multi–diode mathematical model of a photovoltaic cell.

$$I = I_{ph} - \sum_{i=1}^{n_d} I_{sat_i}\left[\exp\left(\frac{e\,(V + I \times R_s)}{m_i k_b T}\right) - 1\right] - \frac{V + I \times R_s}{R_p} \tag{3}$$

Finally, we present the Bishop model, Fig.(4), used when a photovoltaic panel is submitted to non–uniform conditions of radiations (shade for example). In this case, some cells can move the working point from the first to the second quadrant. In order to model this characteristic, it is necessary to introduce in the mathematical model the term proposed in [25], which is given by Eq.(4) and Eq.(5). This characteristic is considered to be a nonlinear multiplication factor that affects the current in the resistor R_p. Although the approach by Bishop is frequently used in the literature, it has been criticized for not being physically correct, once this physical phenomenon should affects the whole PN junction and not only the current in the resistor R_p [26].

$$I = I_{ph} - I_{sat}\left[\exp\left(\frac{e\,(V + I \times R_s)}{mk_bT}\right) - 1\right] - I_{shunt} \tag{4}$$

in which

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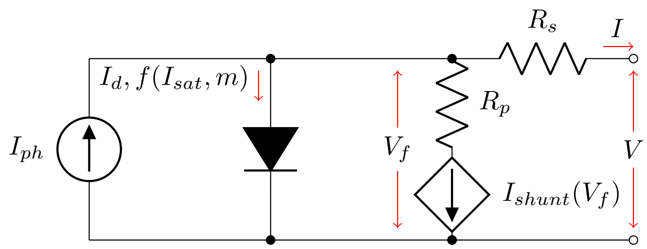

Figure 4. Bishop mathematical model of a photovoltaic cell.

$$I_{shunt} = \frac{V_j}{R_p}\left(1 + \alpha\left(1 - \frac{V + IR_s}{V_{br}}\right)^{-m}\right) \qquad (5)$$

III. Particle Swarm Optimization

The particle swarm optimization algorithm is inspired by cooperation and social behavior principles. This algorithm has particle populations, where each one represents a possible solution. For each particle there is a velocity related to it, which is adjusted with an update equation that consider the historic of individual and collective experiences [27], [28]. The main idea is to change the position of each particle with certain velocities in order to find the best solution. In each iteration the particle and the population performances are evaluated with a fitness function and each particle velocity is incremented or decremented in the direction of their best solution (x_{pbest}), as well as in the direction of the best performance of the global best solution (x_{gbest}), Fig.(5).

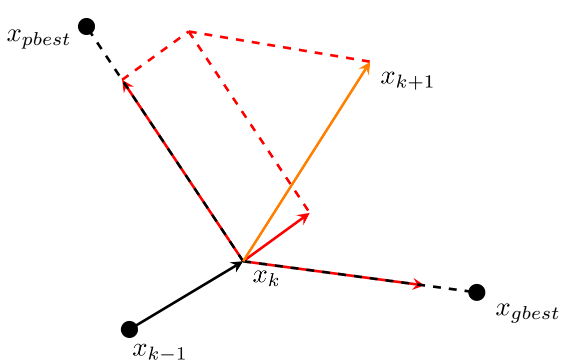

Figure 5. Graphical representation of the particle evolution.

The most important aspect for the algorithm performance is its topology, the way that the particles communicate between each other. There are many topologies in the literature where the more common are: (i) Star topology –every particle communicates with each other; (ii) Ring topology –each particle only communicates with a certain k number of adjacent neighbors; (iii) Cluster topology –certain particles perform the communication between the clusters and inside each cluster the particles communicate with each other; (iv) Von Neumann topology –the particles are connected in a way where the particles in one extremity communicate with particles in the opposite extremity [27], [28].

The velocity for each particle can be defined by Eq.(6),

$$v_k = \psi v_{k-1} + \zeta_1 \left(x_{pbest} - x_k\right) + \zeta_2 \left(x_{gbest} - x_k\right) \qquad (6)$$

and

$$x_{k+1} = x_k + v_k \qquad (7)$$

where the positive constants ζ_1 and ζ_2 are defined by;

$$\begin{aligned} \zeta_1 &= r_1 C_1 \\ \zeta_2 &= r_2 C_2 \end{aligned} \qquad (8)$$

The positive constants C_1 and C_2 are the acceleration and the inertial weight, they should respect the Eq.(9) so that the particle velocities and the particle positions do not diverge.

$$\begin{aligned} & C_1 + C_2 \leq 4 \\ & \psi > 0.5 \left(C_1 + C_2\right) - 1 \end{aligned} \qquad (9)$$

The pseudo code of the PSO algorithm is shown in Alg.(1).

Algorithm 1 Particle Swarm Optimization Algorithm

Define the dimension of the problem $\rightarrow d$;
Define the number of particles $\rightarrow n$;
Positioning the particles in the search region;
Define the maximum number of iterations $\rightarrow iter_{max}$;
while $iter < iter_{max}$ **do**
    for $k = 1 : n$ **do**
        $Evalute f_{x_k}$;
        if $f_{x_k} < f_{x_{pbest}}$ **then**
            $f_{x_{pbest}} = f_{x_k}$;
            $x_{pbest} = x_k$
        end if
        if $f_{x_k} < f_{x_{gbest}}$ **then**
            $f_{x_{gbest}} = f_{x_k}$;
            $x_{gbest} = x_k$
        end if
    end for
    for $i = 1 : n$ **do**
        $v_k = \psi v_{k-1} + \zeta_1 \left(x_{pbest} - x_k\right) + \zeta_2 \left(x_{gbest} - x_k\right)$
        $x_{k+1} = x_k + v_k$
    end for
end while

IV. Experimental Results

To validate the proposed method, the one-diode model was used that guarantees the compromise between simplicity and precision and is used by several authors. It was employed the photovoltaic panel Kyocera KC85T, whose parameters have been summarized in Tab.(I). However, the fact that Eq.(1) does not admit an explicit solution means a significant limitation. This limitation can be overcome through the Lambert W function used by several authors [11], [29], [30]. Another solution that can be found in the literature to overcome this constraint is the use of numerical methods, as for example, the Newton–Raphson, whose algorithm is described in Alg(2).

Algorithm 2 Newton–Raphson Algorithm

calculate:
$F_{(i)} = \left(I_{ph} - I_{sat}\left[\exp\left(\frac{e\left(V_{(i)}+I_{(i)}R_s\right)}{mk_bT}\right)-1\right] - \frac{V_{(i)}+I_{(i)}R_s}{R_p} \right) - I_{(i)}$;
while $\left|F_{(i)}\right| < tol$ **do**
  calculate:
  $F_{(i)} = \left(I_{ph} - I_{sat}\left[\exp\left(\frac{e\left(V_{(i)}+I_{(i)}R_s\right)}{mk_bT}\right)-1\right] - \frac{V_{(i)}+I_{(i)}R_s}{R_p} \right) - I_{(i)}$;
  calculate:
  $\frac{\partial F_{(i)}}{\partial I} = \left(\frac{-I_{sat}R_s\left[\exp\left(\frac{e\left(V_{(i)}+I_{(i)}R_s\right)}{mk_bT}\right)\right]}{\frac{mk_bT}{e}} \right) - \frac{R_s}{R_p} - 1$
  calculate:
  $I_{(i)} = I_{(i)} - \frac{F_{(i)}}{\frac{\partial F_{(i)}}{\partial I}}$
end while

In order to efficiently solve the problem of identification of the five parameters that characterize the model in Fig.(1), which corresponds to Eq.(1), from information provided by manufacturers on data-sheets, the optimization algorithm proposed considers three variables, the resistors R_s, R_p and the ideality factor m as independent variables and two dependent variables, the photoelectric current I_{ph} and the reverse saturation current of the diode I_{sat}. By using this reduced space search it is possible to increase the accuracy of the algorithm. The multi–objective function consists of the determination of the working point that corresponds to the maximum power, but it is necessary to guarantee that this point occurs in the corresponding value of the pair voltage–current, indicated on the manufacturer data-sheet, otherwise the working point that corresponds to the maximum power can be reached by a different voltage–current pair. The multi–objective function is given by the expressions in Eqs.(10) and (11), that follows. The algorithm for determining the R_s, R_p resistors and the ideality factor m is implemented accordingly to Alg.(3).

$$f\left(R_s, R_p, m\right) = \min\left(F\right) \tag{10}$$

$$F = \begin{array}{l} \left|P_{mpp\to STC} - P_{mpp\to(m,R_s,R_p)}\right| + \\ \left|V_{mpp\to STC} - V_{mpp\to(m,R_s,R_p)}\right| + \\ \left|I_{mpp\to STC} - I_{mpp\to(m,R_s,R_p)}\right| \end{array} \tag{11}$$

The Lambert W function method was also implemented in order to establish a comparison between its results to those obtained with the proposed method. In Tab.(II) are shown the values of the parameters obtained by the two different methods, as well as the value of the objective function given by the Eqs.(10) and (11), employing four hundred points to discretize the characteristic curve of the pair voltage-current for $V \in 0 \le V \le V_{oc}$.

Table I
PARAMETERS OF THE PHOTOVOLTAIC PANEL KC85T.

N_s	36	V_{mpp}	17.4 V
I_{mpp}	5.02 A	α_v	-8.21e-2 (V/ °C)
V_{oc}	21.7 V	α_i	2.2e-3 (A/ °C)
I_{sc}	5.34 A	P_{mpp}	87 W

Algorithm 3 Algorithm for determining the R_s, R_p resistors and the ideality factor m.

Define the dimension of the problem $\to d$;
Define the number of particles $\to n$;
Positioning the particles in the search region;
Define the maximum number of iterations $\to iter_{max}$;
while $iter < iter_{max}$ **do**
  for $k = 1 : n$ **do**
    Calculate the dependent parameters of the m factor;
    Compute Newton–Raphson algorithm by Alg.(2);
    Find the maximum value of $V(j)I(j)$;
    Evaluate f_{x_k};
    if $f_{x_k} < f_{x_{pbest}}$ **then**
      $f_{x_{pbest}} = f_{x_k}$;
      $x_{pbest} = x_k$
    end if
    if $f_{x_k} < f_{x_{gbest}}$ **then**
      $f_{x_{gbest}} = f_{x_k}$;
      $x_{gbest} = x_k$
    end if
  end for
  for $i = 1 : n$ **do**
    $v_k = \psi v_{k-1} + \zeta_1\left(x_{pbest} - x_k\right) + \zeta_2\left(x_{gbest} - x_k\right)$
    $x_{k+1} = x_k + v_k$
  end for
end while

Table II
CALCULATED PARAMETERS BY THE DIFFERENT ALGORITHMS.

Parameters	Lambert W function algorithm	PSO algorithm
R_s	0.2764 Ω	0.2966Ω
R_p	499.87 Ω	6243.8Ω
m	1.0712	1.489
I_{ph}	5.34 A	5.34 A
I_{sat}	1.6421e-09 A	1.8108e-9 A
F	0.1024	0.0184

Analyzing Tab.(II) one can verify that the proposed optimization algorithm shows a high performance, as it can be verified by the objective function. We shall also verify a significant difference in the values of the parameters that characterize the model of Fig.(1) obtained by the two different methods. Figs.(6) and (7) illustrate the characteristic curve

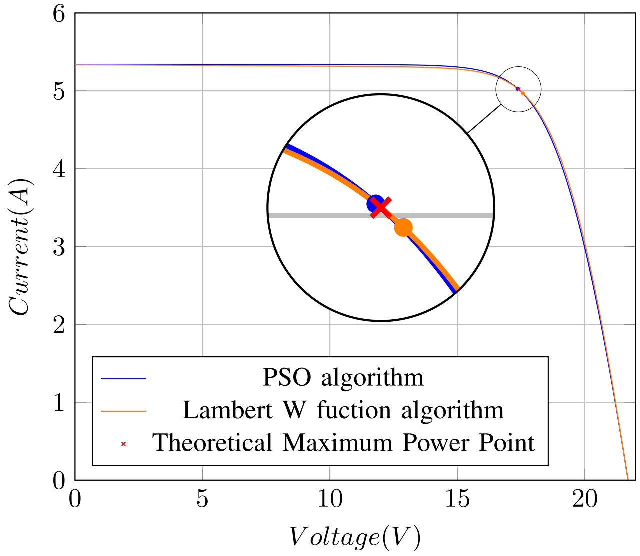

Figure 6. Voltage–current characteristics curves obtained by the different algorithms.

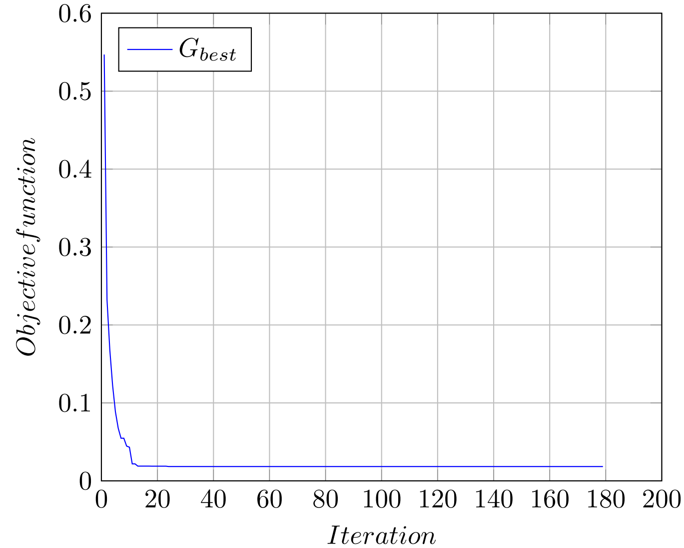

Figure 8. Convergence process of proposed algorithm during the identification process of the parameters.

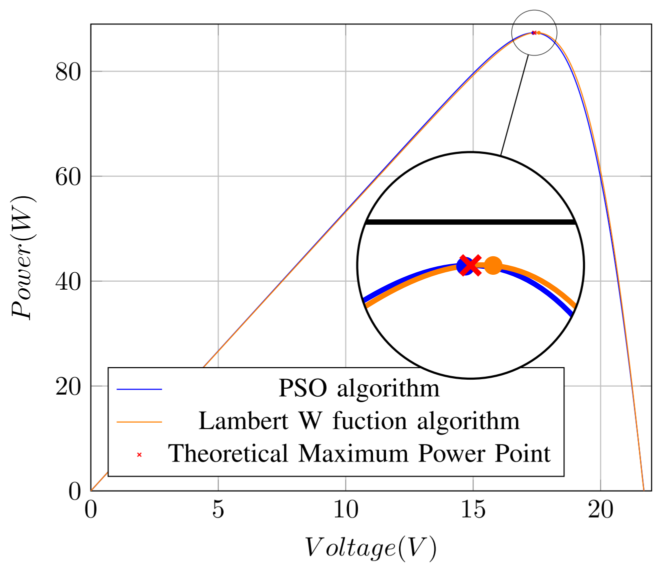

Figure 7. Voltage–power characteristics curves obtained by the different algorithms.

of the pair voltage–current and voltage–power, respectively, calculated by the two different algorithms. One can verify a significant improvement of the proposed optimization algorithm, both in the current values as in the voltage values, with respect to the point of maximum power. The maximum power point calculated by the Lambert W function algorithm does not present a better result. As matter of fact, the working point that corresponds to the maximum power, when compared to the proposed algorithm, shows a higher error, as it can be seen in Fig.(7).

The Fig.(8) illustrate the global best solution (G_{best}) of the objective function during the iterations. As can be seen, the convergence rate of the proposed algorithm is fast. The proposed algorithm converged in 179 iteration, corresponding to 25.32 seconds. The computing tasks are implemented on a laptop with an Intel Core i5-2450 @2.50 GHz CPU, 6 GB RAM and Windows 10 64 bit operating system.

V. Conclusion

The identified model is essential to simulate the behavior of the photovoltaic panels at any operating condition. The proposed method holds great flexibility, simplicity and precision, being used for any existing model and performing both under the reference conditions as well as out off these conditions. By the experiments held, it has been verified that the proposed model is better than the so called classic methods in the determination of the parameters that characterize the photovoltaic panel.

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