Extraction of Solar Module Parameters using a Novel Optimization Technique

Hossam E. Ahmed
Department of Electrical Engineering, College of Engineering, Northern Border University, Saudi Arabia | Electrical Engineering Department, Benha Faculty of Engineering, Benha University, Egypt
hossam.ahmed@nbu.edu.sa

Yehya I. Mesalam
Department of Industrial Engineering, College of Engineering, Northern Border University, Saudi Arabia | Industrial Engineering Department, Faculty of Engineering, Zagazig University, Egypt
yehya.mesalam@nbu.edu.sa (corresponding author)

Shaaban M. Shaaban
Department of Electrical Engineering, College of Engineering, Northern Border University, Saudi Arabia | Department of Engineering Basic Science, Faculty of Engineering, Menoufia University, Egypt
shaban.awdallah@nbu.edu.sa

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ABSTRACT

The parameters of a Photovoltaic (PV) model are pivotal in gauging its efficiency under varying sunlight irradiances, temperatures, and different load scenarios. Determining these PV model parameters poses a complex non-linear optimization challenge. This study is based on a new metaheuristic optimization algorithm called the Pelican Optimization Algorithm (POA) to discern the unknown parameters of the PV model. The suggested POA algorithm underwent testing using a monocrystalline panel, encompassing its single-diode configuration. The objective function is designed to minimize the root of the mean squared errors between the predicted and actual current values, adhering to specific parameter constraints. Various statistical error metrics were utilized to emphasize the performance of the proposed algorithm. A comparative analysis with other well-established algorithms was conducted, indicating that POA stands out as highly competitive since it showcases superior efficiency in parameter identification compared to its counterparts.

Keywords-PV cells; parameter extraction; modeling; POA; optimization

I. INTRODUCTION

Parameter estimation of solar PV (photovoltaic) models is crucial for accurately predicting the performance, efficiency, and behavior of solar panels under various environmental and operating conditions. By determining the precise values of these parameters, researchers and engineers can optimize the design, operation, and integration of solar panels into larger systems, ensuring they produce maximum power output and operate efficiently. Furthermore, accurate parameter estimation aids in system diagnostics and health monitoring, allowing for timely maintenance, longer lifespan, and consistent energy production, which is essential for the viability and cost-effectiveness of solar energy solutions.

PV datasheets typically highlight three primary points concerning the I/V relationship under standard test conditions (STC) – ambient temperature (T) of 25°C, solar irradiance (G) of 1 kW/m^2, and 1.5 air mass [1]. These are the no-load terminal voltage (V), short-circuit current (I_{sc}), and both voltage (V_{mp}) and current at peak power (P_{max}). However, these specified data points alone are insufficient for extended PV system studies, as environmental conditions constantly fluctuate. A precise I/V representation across all operating conditions is crucial for an in-depth performance analysis of PV systems. The I/V characteristics of PV cells are typically represented using two prevalent models: the One-Diode Model (ODM) and the Two-Diode Model (TDM) [2-4]. Notably, while the TDM demands more computational resources than the ODM, the performance efficiency difference between them is marginal. The ODM requires the accurate determination of five parameters, whereas the TDM needs seven. There is also a triple diode model, which requests the identification of nine parameters. However, this research primarily focuses on ODM.

The characterization of solar cell behavior typically relies on the ODM usage. For effective enhancement of PV system efficiency through simulation studies, it is imperative to accurately estimate and identify model parameters [5, 6]. Many researchers focus on refining PV model parameters using diverse design methodologies. These optimization techniques can be primarily categorized as deterministic or heuristic when examined from an algorithmic point of view. Both approaches address parameter extraction by transforming it into an optimization task, drawing on specific reference points from the given I-V characteristic curve. Deterministic techniques, such as the least squares (based on the Newton method [3] and Lambert W-functions [7, 8], place certain constraints on the objective functions, namely continuity, convexity, and differentiability. Moreover, they are prone to influences from initial conditions and gradient details. This makes them susceptible to becoming ensnared in local optima, especially when navigating multifaceted multimodal challenges. These constraints lead deterministic strategies to face obstacles when tasked with solving nonlinear, multimodal parameter extraction issues. On the other hand, heuristic strategies are more versatile, not being bound by strict conditions related to the optimization problem's structure. This allows them to bypass the pitfalls of sensitivity to initial conditions and gradient details. As a result, there has recently been a surge in interest regarding these methods. Some of the successfully employed heuristic techniques for PV model parameter extraction encompass Genetic Algorithms (GAs) [9], Particle Swarm Optimization (PSO) [10], Differential Evolution (DE) [11], Artificial Bee Colony (ABC) optimization [12], Harmony Search (HS) [13], teaching–learning-based optimization [14], Chaotic Whale Optimization Algorithm (CWOA) [15], Lévy flight trajectory-based Whale Optimization Algorithm (LWOA) [16], hybrid PSO-WOA [17], IJAYA [5], and Hybrid Firefly and Pattern Search Algorithm (HFAPS) [18].

In this study, we have integrated the Pelican Optimization Algorithm (POA) for parameter extraction of PV cells [19]. The POA is founded on simulating the natural hunting behaviors of pelicans. In this algorithm, the search agents are depicted as pelicans in search of food sources.

This article presents several notable contributions, which are:

- A novel approach to identifying parameters in solar PV models using the POA is proposed.
- The POA is applied to estimate unknown parameters for ODM.
- The experiments are conducted using monocrystalline PV panels.
- The proposed POA and five additional algorithms (CWOA, LWOA, PSO-WOA, IJAYA, and HFAPS) were simulated and their outcomes were compared. The comparison was primarily based on statistical error and cost function values.

II. MODELING OF A SOLAR PV SYSTEM

The estimation of PV module performance and the design of power systems hinge upon the current-voltage (*I-V*) electrical characteristics exhibited by the modules across varying solar radiation degrees and diverse temperatures [19]. For simulating PV cells and modules, equations mirroring the intrinsic attributes of the cells have been suggested. The literature has put forth numerous electrical models to simulate PV cells under different conditions. These models vary in complexity based on the number of parameters to be identified, such as the *Rs* (series resistance) and *Rsh* (shunt resistance). At their core, these models enhance the fundamental model, which is composed of a diode symbolizing the PN junction and a current source indicative of the received solar energy [20]. To achieve a more accurate representation of PV cell behavior in specific operating conditions, several additional elements can be incorporated. The most utilized models are ODM and TDM.

A. Solar PV System Modeling. The One-Diode Model

The ODM, also known as the single diode model or simply the diode model, is a widely used mathematical representation of the electrical behavior of a solar cell or of a PV cell. This model is applicable to various types of solar cells, including monocrystalline and polycrystalline cells.

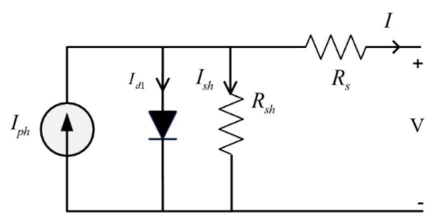

Fig. 1. The one-diode model.

Equation (1) models how the output current (*I*) of the PV cell varies with voltage (*V*), considering factors like photocurrent (I_{ph}), diode current (I_{d1}), reverse saturation current (I_{sd1}), diode ideality factor (α_1), temperature (*T*), the constant of Boltzmann (K), the electron charge (*q*), and series and shunt resistance (R_s,R_{sh}).

$$I = I_{ph} - I_{d1} - I_{sh} \tag{1}$$

with:

$$I_{d1} = I_{sd1}\left(e^{\left(\frac{q(V+R_s I)}{\alpha_1 KT}\right)} - 1\right)$$

B. Objective Functions for Extracting PV Parameters

The objective functions in the parameter extraction process serve as mathematical criteria that guide the optimization process. The procedure of obtaining optimal parameter values involves comparing the estimated current values to the actual experimental ones. To achieve this, it is essential to utilize an objective function that aims to minimize the Root Mean Square Error (RMSE) across various measured data points [21, 22]:

$$RMSE = \sqrt{\frac{1}{N}\left(\sum_{i=1}^{N}\left(I_m - I_e\right)\right)^2} \tag{2}$$

where *N* is the number of samples, which must be big enough to attain the global optimum, while the measured and estimated current are denoted by I_m and I_e.

The objective function is employed with the primary goal of reducing the RMS) across a diverse range of measured data points. In the case of the ODM, the objective function is formulated as depicted in (3):

$$f_{ODM} = \sqrt{\frac{1}{N}\left(\sum_{i=1}^{N}\left(I_m - I_{ph} + I_{sd1}\left[e^{\left(\frac{q(V+R_s I)}{\alpha_1 KT}\right)}-1\right]+\frac{V+R_s I}{R_{sh}}\right)\right)^2} \tag{3}$$

III. PELICAN OPTIMIZATION ALGORITHM FOR PV PARAMETER ESTIMATION

In this section, the conceptual foundation and mathematical framework of the proposed swarm-inspired POA are introduced.

A. Hunting Strategies and Characteristics of Pelicans

Pelicans are social birds with elongated beaks and pouches for catching prey. They often live in sizable groups and predominantly feed on fish [23, 24]. These birds hunt collaboratively, diving from heights to corner fish in shallow waters. Upon capturing, they expel excess water from their pouch before consuming it [25]. Their strategic hunting techniques showcase their natural intelligence. This behavior serves as the foundation of the proposed algorithm.

B. Mathematical Modeling

The suggested POA operates as a population-centric algorithm, with pelicans representing its constituents. Within such algorithms, every constituent signifies a potential solution. Each constituent recommends variable values for the optimization challenge based on their location within the search domain. At the outset, these constituents are randomly set based on the problem's lower and upper constraints, as described by (4).

$$x_{i,j} = l_j + rand.\left(u_j - l_j\right) \tag{4}$$

where i = =1, 2, …..N, j = 1, 2,…..m.

Let $x_{i,j}$ denote the value of the j^{th} variable determined by the i^{th} potential solution. Here, N signifies the total number of population members, m represents the count of problem variables, and *rand* is a random number between [0, 1], whereas l_j and u_j are the lower and upper boundaries of the j^{th} problem variable, respectively. In POA, the members of the pelican population are depicted using a matrix termed as the population matrix, as shown in (5). In this matrix, each row corresponds to a potential solution, and the columns highlight the suggested values for the variables in question.

$$X = \begin{bmatrix} X_1 \\ \vdots \\ X_i \\ \vdots \\ X_N \end{bmatrix}_{N\times m} = \begin{bmatrix} x_{1,1} & \cdots & x_{1,j} & \cdots & x_{1,m} \\ \vdots & \ddots & \vdots & \iddots & \vdots \\ x_{i,1} & \cdots & x_{i,j} & \cdots & x_{i,m} \\ \vdots & \iddots & \vdots & \iddots & \vdots \\ x_{N,1} & \cdots & x_{N,j} & \cdots & x_{N,m} \end{bmatrix}_{N\times m} \tag{5}$$

Let X represent the pelican population matrix, with X_i signifying the i^{th} pelican. In POA, every member of the population corresponds to a pelican, representing a potential solution for the given challenge. As a result, the problem's objective function can be gauged for each potential solution. The outcomes of this function are expressed using a vector, referred to as the objective function vector, depicted in (6):

$$F = \begin{bmatrix} F_1 \\ \vdots \\ F_i \\ \vdots \\ F_N \end{bmatrix}_{N\times 1} = \begin{bmatrix} F(X_1) \\ \vdots \\ F(X_i) \\ \vdots \\ F(X_N) \end{bmatrix}_{N\times 1} \tag{6}$$

where F represents the vector of the objective function and F_i signifies the computed value of the objective function corresponding to the i^{th} pelican.

The suggested POA emulates the tactics and actions of pelicans during their predatory pursuits to refine potential solutions. The pelicans' hunting approach is replicated through two phases.

- Approaching prey (exploratory phase).
- Gliding over the water's surface (refinement phase).

1) Phase 1: Approaching Prey

During the initial stage, pelicans determine the position of their prey and navigate towards this pinpointed zone. Emulating this behavior enhances the scanning and exploration capacity of the POA across various regions of the search domain. A key aspect in the POA is the random generation of the prey's location within the search area. This amplifies the exploratory efficiency of the POA in thoroughly probing the solution space. The pelican's method in moving to the prey's location is represented mathematically in (7):

$$x_{i,j}^{P_1} = \begin{cases} x_{i,j} + rand\left(p_j - I.x_{i,j}\right), F_p < F_i; \\ x_{i,j} + rand\left(x_{i,j} - p_j\right), \text{else} \end{cases} \tag{7}$$

where $x_{i,j}^{P_1}$ represents the updated state of the i^{th} pelican in the j^{th} dimension according to phase 1, I is a random variable taking values of either 1 or 2, p_j denotes the prey's location in the j^{th} dimension, and F_p represents its corresponding objective function value. The parameter I, is chosen anew for each iteration and member. When this parameter assumes a value of 2, it induces a greater shift for a member, potentially directing that member to uncharted regions of the search domain. Hence, the parameter I significantly influences the explorative capacity of the POA in thoroughly investigating the search domain.

In POA, a pelican's new location is adopted if there is an improvement in the objective function value at that spot. This kind of update, termed as "efficient updating," prevents the algorithm from venturing into sub-optimal regions. This methodology is captured in (8):

$$X_i = \begin{cases} X_i^{P_1}, & F_i^{P_1} < F_i \\ X_i, & \text{else} \end{cases} \quad (8)$$

where $X_i^{P_1}$ represents the newly computed position for the i^{th} pelican, derived during the first phase. Within this context, $x_{i,j}^{P_1}$ signifies the j^{th} dimension of this new position, while $F_i^{P_1}$ represents its corresponding objective function value.

2) Phase 2: Gliding over the Water's Surface

During this phase, once the pelicans arrive at the water surface, they spread their wings across it, pushing fish upwards before scooping them up with their throat pouch. This tactic ensures that more fish in the targeted region are captured. Replicating this activity enables the proposed POA to hone in on superior points within the hunt zone. This step enhances the localized search capability and the refinement efficiency of the POA. Mathematically speaking, the algorithm scrutinizes points around the pelican's position to converge to an optimized solution. This hunting behavior is represented in (9):

$$x_{i,j}^{P_2} = x_{i,j} + R.\left(1 - \frac{t}{T}\right).(2.rand - 1).x_{i,j} \quad (9)$$

where $x_{i,j}^{P_2}$ denotes the updated position of the i^{th} pelican in the j^{th} dimension. The constant R is set at 0.2. The term $R(1-t/T)$ defines the neighborhood radius around $x_{i,j}$, t stands for the current iteration, and T represents the total number of iterations. This term acts as a measure for localized searching around each member, aiding convergence to a superior solution. In the initial stages, its value is high, implying broader search vicinity for each member. However, as iterations progress, this value shrinks, narrowing the search vicinity. Consequently, the algorithm refines its search, allowing to gravitate towards solutions that are closer, if not exactly, to the global optimum. During this phase, effective updating is utilized to determine whether to accept or decline the new position of the pelican, as represented in (10):

$$X_i = \begin{cases} X_i^{P_2}, & F_i^{P_2} < F_i \\ X_i, & \text{else} \end{cases} \quad (10)$$

where $X_i^{P_2}$ represents the newly computed position of the i^{th} pelican, derived during the second phase. Within this context, $x_{i,j}^{P_2}$ signifies the j^{th} dimension of this new position, while $F_i^{P_2}$ represents its corresponding objective function value.

Once all members of the population have undergone updates from the two phases, the top solution is refreshed considering the current population state and objective function values. The algorithm then proceeds to the next cycle, and the steps outlined based on (7)–(10), are reiterated until the process concludes. At the end, the most favorable solution identified across all iterations is offered as a near-optimal answer to the specified issue. Figure 2 depicts the steps of the POA in flowchart form.

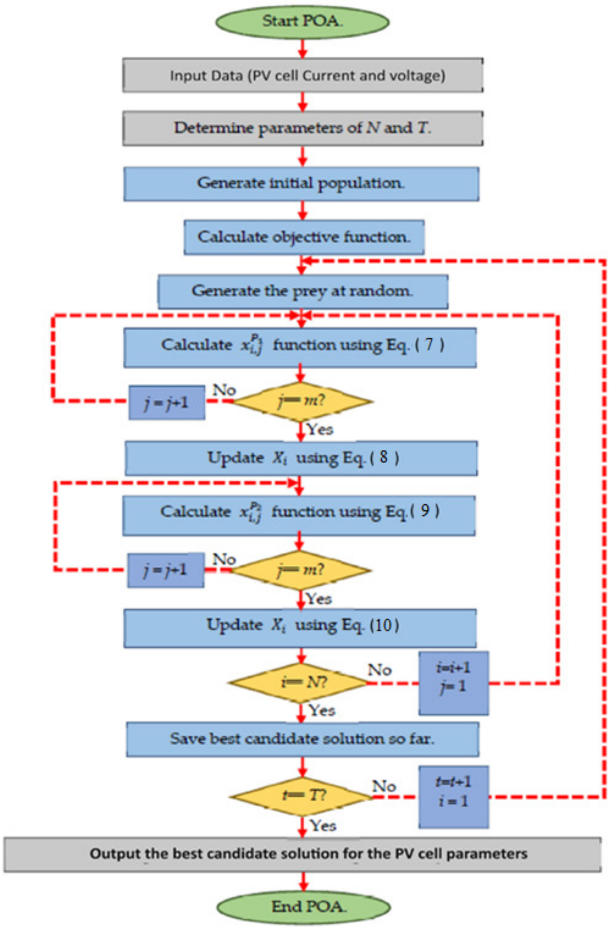

Fig. 2. POA flowchart

IV. EXPERIMENTAL RESULTS AND DISCUSSIONS

Utilizing MATLAB Simulink 2021, we conducted simulations with the RTC France Company mono-crystalline module under specific conditions of solar irradiance G = 1000 W/m^2 and temperature T = 33 °C. We contrasted the results from our parameter identification approach with those from other optimization algorithms to assess the precision of POA.

A. Comparative Analysis of ODM Parameter Extraction

The ODM estimated parameters from all considered algorithms are shown in Table I. Figure 3 graphically represents the various outcomes. It is evident that the results achieved from POA, have the smallest error for the majority of the values.

TABLE I. EXTRACTED ODM PARAMETERS

Approach	I_{ph} (A)	I_0 (μA)	R_p (Ω)	R_s (Ω)	α
POA	**0.7607**	**0.3107**	**52.89**	**0.036**	**1.477**
CWOA	0.7600	0.2831	62.61	0.0371	0.0371
LWOA	0.7602	0.4607	0.035	75.46	1.5177
PSO-WOA	0.7597	0.314	0.0366	58.80	1.4783
IJAYA	0.7608	0.3228	0.0364	53.75	1.4811
HFAPS	0.7607	0.3226	0.0363	1.481	53.67

TABLE II. STATISTICAL RESULTS

	HFAPS	**IJAYA**	**PSO-WOA**	**LWOA**	**CWOA**	**POA**
IAT	0.0217	0.02151	0.02267	0.0222	0.0208	0.01845
RMSE	0.000992	0.00098	0.00101	0.0010	0.00096	0.0008441
SSE	2.56E-05	2.50E-05	2.69E-05	2.93E-05	2.41E-05	1.85E-05
MAE	0.0008346	0.00082	0.00087	0.00085	0.0008	0.0007096

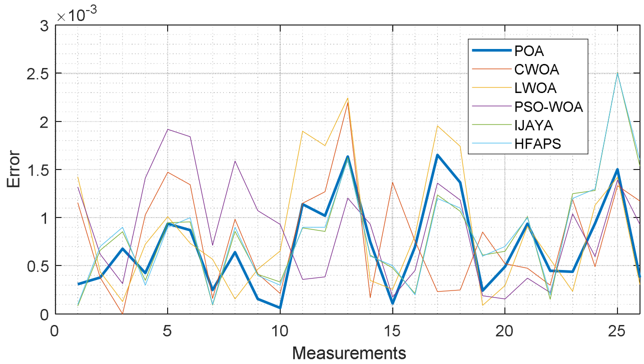

Fig. 3. Calculated errors obtained by POA, CWOA, LWOA, PSO-WOA, IJAYA, and HFAPS algorithms for the ODM case.

To assess the accuracy of the derived parameters, we compare the current-voltage and power-voltage characteristics obtained from the estimated parameters via the POA method with the experimental and estimated data. Figure 4 provides a visual representation of this comparison, focusing on the ODM scenario.

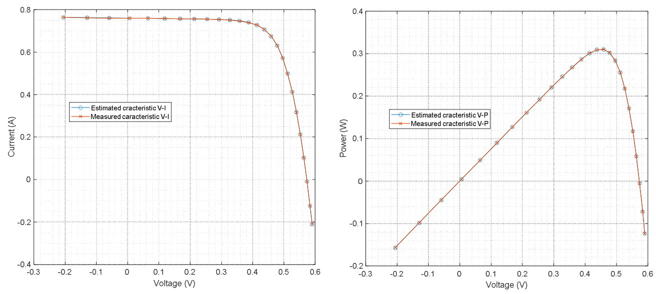

Fig. 4. Experimental and measured I-V characteristics achieved through the proposed POA for the ODM case.

The characteristics results presented in Figure 5 demonstrate a strong agreement between the reconstructed ODM and the measured data. Figure 5 depicts the convergence curves for various PV cell models. Overall, all the models display a satisfactory with POA results showing the most rapid convergence rate. In Figure 5, the illustrated average fitness functions are essentially a representation of the fitness associated with the extraction parameters for PV cells. The standout advantage of the results delivered by POA, especially when juxtaposed against other optimization algorithms, lies in its distinct capability to minimize error and ensure rapid convergence. This is evident particularly with ODM and TDM. The efficient and precise performance of POA makes it an invaluable tool for applications that require high accuracy and quick adaptability.

(a)
(b)
(c)

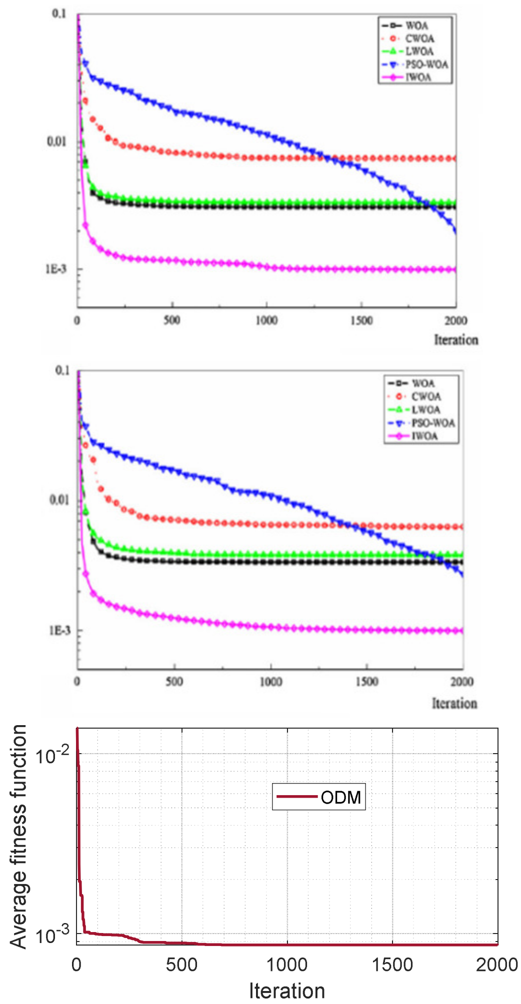

Fig. 5. Average fitness functions. Values obtained for (a) ODM, (b) TDB by various optimization algorithms [16]. (c) Fitness function for ODM using POA.

V. CONCLUSION

The Pelican Optimization Algorithm (POA) was designed to boost the accuracy of parameter extraction in solar cells. Its efficacy was assessed with regard to monocrystalline PV cell types within a single diode model. To ascertain its relative performance, the POA results were compared with the ones of other methods documented in prior studies. Both statistical evaluations and graphical representations indicated the notable precision and stability of POA, positioning it ahead of the other known methods.

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