Improved Quality Parameter Estimation of Photovoltaic System Models based on SAO Algorithm

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ABSTRACT

Solar energy provides one of the most favorable options regarding the transition to clean energy sources. The parameters of a photovoltaic (PV) system play determine its performance under various scenarios. The PV model parameter estimation is an example of nonlinear planning. This study proposes a novel use of the established Smell Agent Optimizer (SAO) algorithm to anticipate the undefined parameters of the PV model's single-diode and two-diode equivalent circuits. This study aims to create a precise PV model that can accurately characterize its performance under changing operational conditions. The desired objective function is defined as the square of the mean squared error between the model's current-voltage curve and the measured curve.

Keywords-photovoltaic systems; parameter identification; SAO algorithm

I. INTRODUCTION

Renewable energy sources, such as solar and wind energy, have recently gained popularity in various applications, both stand-alone and grid-connected, due to their sustainability, cheap operating costs, and zero pollution generation. [1-2]. Solar energy is considered the most widespread renewable energy globally. PV panels are characterized by a shortened installation period, uncomplicated design, noisiness, and long operation life [3-4]. A single PV cell produces only a mean voltage of 0.5─0.65 V [5]. To generate a larger effective voltage, multiple PV cells must be connected in series to form a single module [6]. Adding several modules in series and parallel may elevate voltage and current, respectively. This arrangement of modules results in an array [7]. There are three key points in PV datasheets relating to the I/V relationship of the PV system in ordinary atmospheric conditions. This includes produced voltage at no load (V_{nl}), current at short circuit (I_{sc}), and voltage (V_{mp}) and current (I_{mp}) with maximum generated power (P_{max}). Nevertheless, these points are not enough to describe such PV systems for further study. In reality, these conditions alter continuously. To ensure a satisfactory performance analysis of PV systems under various operating conditions, PV cells, modules, and arrays must always have a correct I/V relationship. PV cells' I/V characteristics can be predicted using two familiar models, namely the one-diode and two-diode models (ODM and TDM). To define ODM efficiently, five uncertain parameters must be determined, including diode ideality factor, photo-generated current, saturation current, series resistance, and shunt resistance, TDM requires knowledge of seven parameters. Moreover, there is the triple diode model that can be employed to model PV models. This model involves nine unknown parameters. Still, both ODM and TDM have been given special attention in the current study. Modeling and simulating the behavior of PV system components, including solar cells, is critical in the conceptualization or analysis phase of PV systems. In general, the simulation of PV systems includes two stages of mathematical modeling and formulation and then the estimation of model parameters. After choosing the desired model, one must use the characteristics of the solar cells or panels provided by the manufacturers in their catalogue to obtain the necessary parameters. The main feature used to estimate the parameters of the solar cell model is the current-voltage (I-V) curve, which can be obtained physically in the laboratory under specific conditions. Due to the vast number of cells in a PV system, particularly in high-capacity power plants, a modeling error in one cell may result in a considerable error in the entire system model. Therefore, one of the main challenges in modeling solar cells is the accurate and appropriate estimation of their equivalent circuit parameters [8-10]. The current methods used to estimate these parameters are divided into two categories: analytical and numerical methods. In analytical methods, generally, the information included in the product catalogue, such as open circuit voltage, short circuit current, maximum power point voltage, and maximum power point current, is used to obtain the I-V characteristic [11-13]. These approaches are easier to build, but their accuracy is highly dependent on the initialization chosen in the algorithm, and in some circumstances, they do not converge to an acceptable solution. To address the limitations of analytical methods, researchers employ numerical (deterministic and metaheuristic) methods that incorporate all of the measured points on the I-V curve, resulting in a trustworthy and valid answer. Classic optimization methods such as iterative curve fitting [14], Newton-Raphson method [15], and Lambert W-function [16] are deterministic methods. Using the deterministic approach in optimization problems brings limitations such as differentiability and convexity of the objective function [17]. Another drawback of these methods is their high sensitivity to initial values and getting trapped in locally optimal solutions. Therefore, the current paper is concentrated in the performance comparison of optimization algorithms such as the SAO and PSO.

II. EQUIVALENT CIRCUIT OF SOLAR CELLS WITH ODM AND TDM MODELS

The total current that moves in the cell is expressed in (1) and the diode current that can be exposed is presented in (2). The diode voltage is shown in (3) and the cell voltage is a function of temperature as in (4). Finally, the total current outputted from the cell is shown in (5) [18].

$$I = I_{PV} - I_D - I_P \tag{1}$$

$$I_D = I_{sD}\left[e^{\left(\frac{V_D}{\alpha V_t}\right)} - 1\right] \tag{2}$$

$$V_D = V + R_S I \tag{3}$$

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

$$I = I_{PV} - I_{sD}\left[e^{\left(\frac{V+R_S I}{\alpha V_t}\right)} - 1\right] - \frac{V+R_S I}{R_P} \tag{5}$$

III. SYSTEM DISCREPTION AND PROBLEM-FORUMULATION

The design in Figure 1 shows the overall process and explains where the algorithm will be implemented for parameter estimation [19].

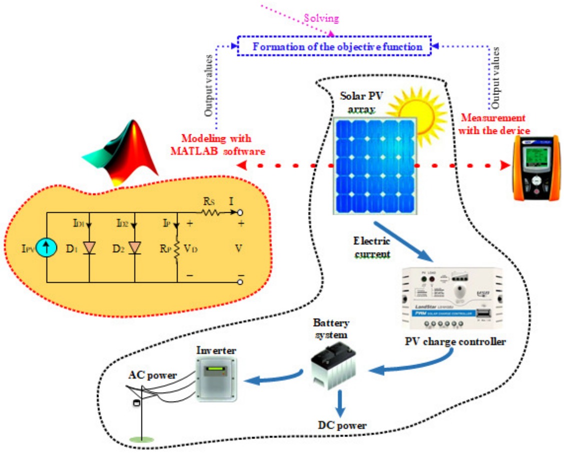

Fig. 1. Overview of the proposed structure of PV parameter estimation.

The objective function consists of the difference between the modeled $I_{mdl}(x)$ and the measured (I_{msrd}) values based on Root Mean Square Error (RMSE). The Vector variables for ODM and TDM are, respectively:

$x = [I_{PV}, I_{sD}, \alpha, R_S, R_P]$

$x = [I_{PV}, I_{sD1}, I_{sD2}, \alpha_1, \alpha_2, R_S, R_P]$

$$\mathrm{F(x)} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(\mathrm{I_{mdl}(x)} - I_{\mathrm{msrd}})^2}$$

IV. SMELL AGENT OPTIMIZER ALGORITHM

The Smell Agent Optimizer (SAO) algorithm is an innovative and nature-inspired optimization technique that draws inspiration from the olfactory system of the behavior of insects such as ants and their ability to communicate. In order to optimize the problems, SAO was designed and developed as a metaheuristic algorithm. SAO is adjusted to solve complex optimization problems and does not impose a significant computational burden by mimicking the behavior of agents that navigate their environment using smell as their guiding sense. SAO is a stochastic search technique that uses a population or swarm of individual elements where animals detect and follow the scent of food or other attractive sources. Each animal shows an independent achievement solution to a problem and adjusts its own flying experience in the boundary space to find the optimal solution. The agents converge towards favorable areas of the solution space by iteratively modifying and improving their positions based on the strength and direction of the encountered odors. These agents generate and release "smell" in the form of candidate solutions, which diffuse through the search space and attract other agents. By iteratively updating and improving their positions based on the intensity and direction of the encountered smells, the agents converge toward promising regions of the solution space. SAO's ability to exploit the principles of smell-guided navigation makes it a powerful and efficient optimization algorithm applicable to a wide range of real-world problems. A comparison with three more algorithms will prove its efficiency. The considered algorithms (PSO, TLBO, BBO) were depicted from [21-24].

The main SAO parameters are:

- Initial Step Size (α_0): Determines the initial step size for the optimization process.
- Decay Rate (γ): Controls the rate at which the step size decays over iterations.
- Minimum Step Size (α_{min}): Sets the minimum step size allowed during the optimization.
- Maximum Iterations (N_{max}): Specifies the maximum number of iterations the optimizer will perform.
- Tolerance (ϵ): Defines the tolerance for convergence, determining when the optimizer should stop.
- Learning Rate (η): Influences how much the optimizer adjusts the parameters in each step.
- Momentum (μ): Helps in accelerating gradient vectors in the right directions, leading to faster converging.

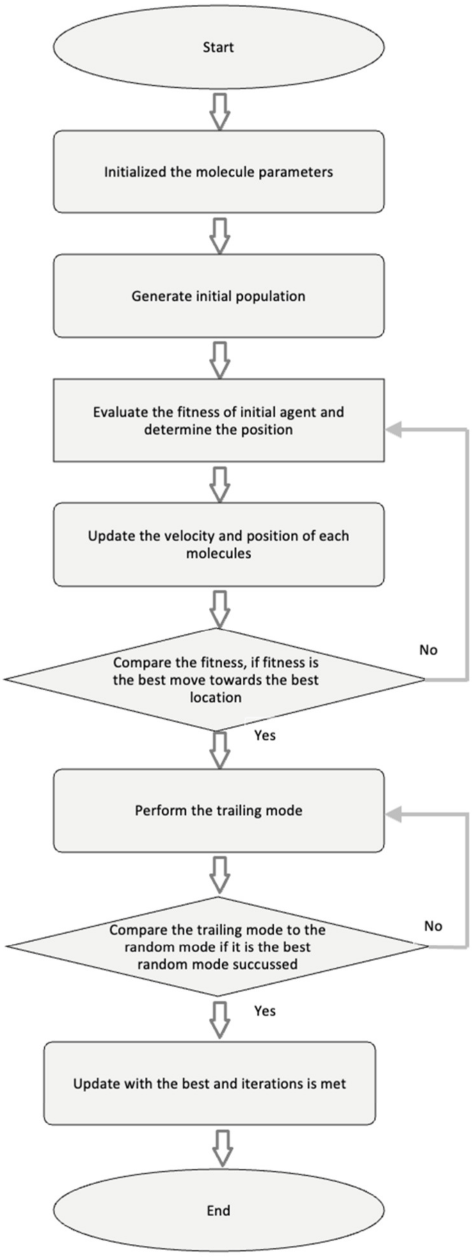

Fig. 2. Overview of the algorithm flowchart.

- Regularization (λ): Applies a penalty to the model to prevent overfitting by controlling the complexity of the model.
- Population Size: Number of solutions in each iteration.
- Mutation Rate: Probability of mutation in the genetic algorithm.
- E^{worst} and E^{best} represent the number of elements produced with the worst and the best fit value and k_{max} represents the maximum number of generations considered in the optimization process.

V. SIMULATION RESULTS

To estimate the parameters of the solar cell model, the measured current-voltage characteristic of the solar cell is needed. The cell considered in this article is a commercial R.T.C. France silicon solar cell with a diameter of 57 mm. The characteristics of this cell include 26 pairs of current and voltage numbers at a temperature of 33 °C and radiation of 1000 W/m^2. The upper and lower limit values of the parameters for the ODM and TDM models are:

ODM: $l = [0, 0, 1, 0, 0]$

$u = [1, 0, 2, 0.5, 100]$

TDM: $l = [0, 0, 0, 1, 1, 0, 0]$

$u = [1, 10^{-6}, 10^{-6}, 2, 2, 0.5, 100]$

In this paper, the adjustment parameters of the SAO algorithm were limited to E^{worst}, E^{best}, k_{max} and based on the best solutions obtained, $E^{best} = 20$, $E^{worst} = 0$, and $k_{max} = 100$ were obtained. It is worth mentioning that, in general, the RMSE values in the TDM model are higher in most cases compared to the ODM model. The reason for this is the addition of two parameters and another nonlinear function to the problem. Especially since these two parameters are effective in the nonlinear part of the model (or the diode) and make the estimation problem more difficult. Another advantage of the SAO algorithm is that the minimum and median value of RMSE in the TDM model is lower compared to the ODM model, while the performance of other algorithms has dropped in the TDM model, except for the minimum in the DE algorithm. The convergence curve of all algorithms used to estimate the TDM model parameters is shown in Figure 4.

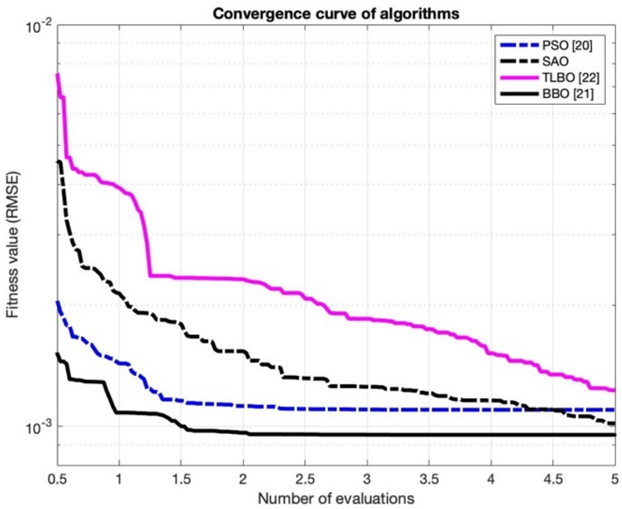

Fig. 3. Convergence curves for the ODM model.

In order to create the mathematical model of the SAO, the following presumptions were made, in relation to the flowchart shown in Figure 2. Although each agent has a unique smell capacity, the agents all react to odorant molecules in the same way. The smell molecules are not attracted to one another. Every molecule has its own unique concentration smell, even if there are more than one smells. The smell molecules continuously evaporate from the smell source in the agent's direction. The evaporation of the smell molecule was negligible in comparison with the velocity of the smell agent. SAO algorithm has a good convergence performance as can be seen in Figures 3 and 4.

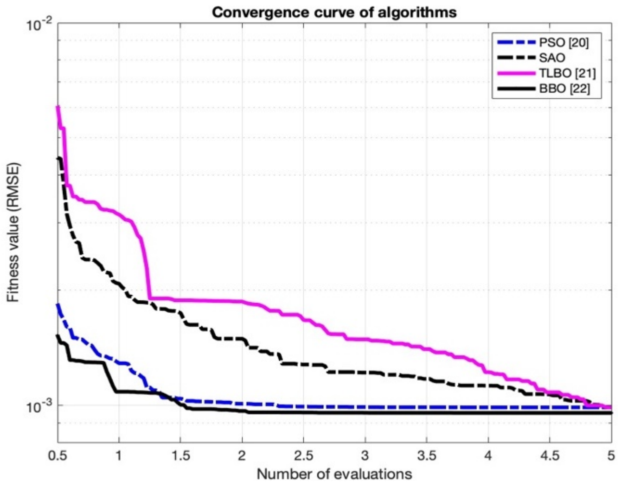

Fig. 4. Convergence curves for the TDM model.

In the following, the performance of the SAO algorithm in estimating PV module parameters is evaluated under the influence of temperature and radiation changes. Table I shows the specifications of the PV module according to the catalogue information. Figures 5 and 6 show the performance of the SAO algorithm in modeling the optimal PV output with the points measured by the device, respectively, for the I-V and P-V characteristics for different radiations at a temperature of 25°C. By matching the output of the optimized model with the measured points, the values of the PV module were estimated with better accuracy under various conditions. Table II shows the parameter values estimated by the SAO algorithm. The parameters of the model in the best solution of the SAO are presented in Table III.

TABLE I. SPECIFICATIONS OF THE PV MODULE UNDER STUDY

Type (Kyocera)	V_{mp}	I_{mp}	P_{max}	V_{oc}	I_{sc}
KD240GX-LFB2	29.8	8.06	240.188	36.9	8.59

TABLE II. VALUES OF ESTIMATED PV MODULE PARAMETERS

Type (Kyocera)	I_{PV}	I_{sD}	R_s	R_P	n	P_{max} (Calculated)
KD240GX-LFB2	8.6134	3.22×10^{-11}	0.3485	129.9159	0.0047	240.179

TABLE III. ESTIMATED PARAMETERS FOR THE ODM AND TDM MODEL FOR ONE CELL

Algorithm	I_{PV} (A)	I_{SD1} /I_{SD2} (µA)	Alpha 1 and alpha 2	R_S (Ω)	R_P (Ω)
SAO (ODM)	0.76077	0.32301	1.48117	0.03636	54.65936
SAO (TDM)	0.76078	0.33846 0.27869	0.27869 1.46879	0.03468	54.65926

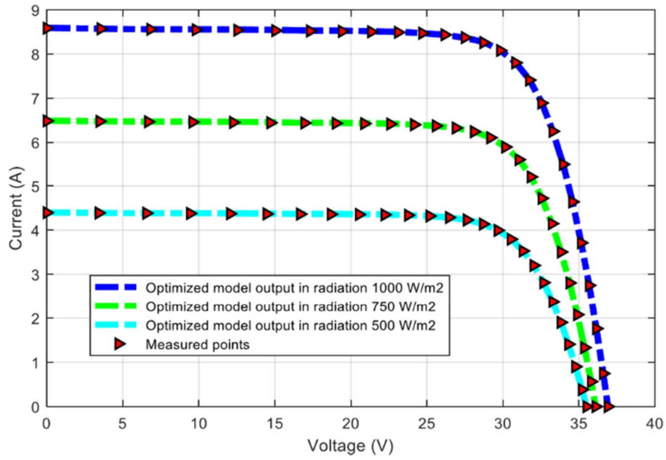

Fig. 5. I-V characteristic under different radiations at 25°C.

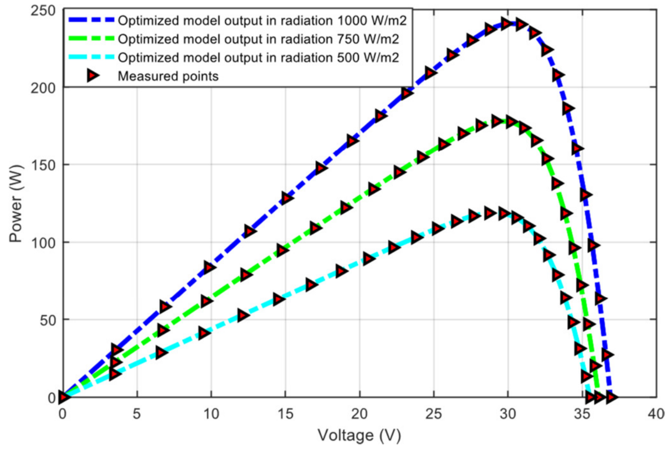

Fig. 6. P-V characteristic under different radiations at 25°C.

VI. CONCLUSION

The Smell Agent optimization algorithm is used to help define PV system settings under changing conditions. This is the goal of this study, and the efficiency of the proposed approach is demonstrated in the results by comparing it to more than four optimization methods. The test was conducted under varied radiation and temperature settings, as it is well known that PV temperature varies greatly depending to the location of the overall PV generator. The results show a perfect estimation for the PV parameters, which can assist protect the Panels from any future difficulties that may arise. It can be seen that the error of estimation is approximately equivalent to 0.00001 for the paralle resistance and 0.00002 for the serial resistance.

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