Effective Modeling of Photovoltaic Modules Using Sailfish Optimizer

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Abstract – *The current study proposes a novel meta-heuristic technique called sailfish optimizer (SFO) to design reliable photovoltaic (PV) modeling models. Unlike others, the proposed technique employs two populations (prey and predator) instead of one to effectively reach the desired solution. This unique propriety can substantially augment the probability of locating the global optimum as well as accelerating the search process. Moreover, to show the efficacy of the algorithm, the results are compared with some literature techniques such as Salp-Swarm-Optimizer (SSA), Whale Optimization (WOA), Artificial-Bee-Colony (ABC), and Particle-Swarm Optimization (PSO) methods. Eventually, the proposed SFO algorithm demonstrated a remarkable amelioration in terms of accuracy with Root-Mean-Square-Error of 13E-3 A.*

Keywords: *Parameters extraction, Photovoltaic cells, Double-diode model, Meta-heuristic algorithms, Sailfish Optimizer*.

Received: 12/05/2022 – Revised 05/06/2022 – Accepted: 22/06/2022

I. Introduction

In the last decades, fossil energy has been consumed tremendously due to human being activities. This consumption has led to problems of energy shortage as well as an increase in environmental concerns. Experts at the Paris conference (2015) have declared that the earth's temperature has reached a critical point [1], and to overcome this issue, the world governments have decided to develop clear and practical policies that respect the ecological balance and promote sustainable development [2].

Today, solar PV energy is viewed as one of the strategic sources that are able to fulfill present and future energy needs and mitigate environmental risks simultaneously [3, 4]. PV generators convert directly solar irradiance into useful power. Voltage is produced across the PV cell terminals when sunlight reaches the N-layer (negative) of the PV cell. However, PV cells generate unregulated voltage. In order to design a robust control system for PV generators with constant output voltage, good performance analysis using accurate modeling and simulation is required. In this context, various mathematical models have been developed in the literature to simulate the real PV cell's behavior including single-diode (SD) [5], double-diode (DD) [6], and three-diode models [7]. Among all, the DD model is the noteworthy one due to its great balance between accuracy and simplicity in predicting PV cell output characteristics. Before modeling the PV cells using DD model, there are a number of unknown parameters that need to be determined first. Researchers have used certain analytical correlations to address this problem for instance: K. Et-torabi method [8], Villalva algotithm [9], Celik approach and others [10]. However, the above-mentioned methods are time-consuming, and they have been developed based on many simplifications, which reflect negatively on the quality of the results. For these reasons, researchers have developed another way to treat the system as an optimization problem. Guided by this idea, meta-heuristics optimization algorithms are intensively employed to eliminate the drawbacks conducted by analytic approaches and extract the best parameters [11].

Meta-heuristic algorithms are random search and population-based methods. They were inspired from biological or physical phenomena. They have demonstrated their effectiveness in many engineering applications including parameters identification. A survey in the literature revealed many techniques have been applied in PV cell parameters tasks. The most recent studies, which proposed the salp swarm theory to determine the parameters of the dual diode model. Similarly, FOR ANOTHER RESEARCH GROUP who presented the butterfly flame optimization algorithm to extract the parameters of multicrystalline solar cells with special emphasis on the three-diode model [12,13]. As an extreme case, one study tested the performance of the bacterial foraging algorithm in shedding parameters of SD-DD models using only the three points highlighted in the manufacturer's nameplate [14-16].
From the previous review, we can see that a variety of meta-heuristic methods with different levels of accuracy have been applied. However, this domain remains hot and still evolving over time. In other word, there still chances to be conducted to find new improvements. For these reasons, the present paper intends to apply a new met-heuristic optimization algorithm for determining the parameters of PV cells with high accuracy. To examine the precision, robustness, and efficacy of the suggested algorithm, the results are compared with some state-of-art methods namely SSA [17], WOA [18, 19], ABC [20], and PSO [21, 22].
Identifying the unknown parameters of Photovoltaic (PV) models is extremely important to accurately assess the behavior of the device. Many methods are used in this context, however, majority of them struggle to find the true parameters due to the nonlinear and complex nature of the mathematical model. This study presents a novel approach based on metaheuristics optimization methods to solve this still complex engineering problem. The core goal of the work is design a high quality PV modeling models that are able to produce estimations close the real ones.

II. PV cells Modeling

PV cells behavior is represented in double diode model by a photoelectric current source I_{ph} connected in parallel with a P–N junction diode. A second diode is added to portray the recombination loss in the depletion region [6]. Moreover, tow resistances *Rs* and *Rp* are incorporated to represent the cell ohmic losses (*Rs*) due to wiring contacts, and *Rp* leakage current resistance in the P–N junction [23]:

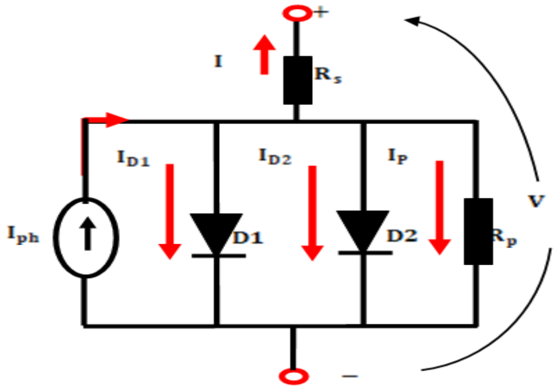

Figure 1. Double diode model

The overall output current is given in Eq. (1) with the meaning of each element in Table 1:

$$I = Iph - Is1\left[\exp\left(\frac{V + Rs \times I}{n1 \times Vt}\right) - 1\right] - Is2\left[\exp\left(\frac{V + Rs \times I}{n2 \times Vt}\right) - 1\right] - \frac{V + Rs \times I}{Rp} \quad (1)$$

It is worth mentioning that Eq. (1) includes seven unknown parameters i.e., I_{ph}, I_{s1}, I_{s2}, n_1 , n_2, R_s and R_p, which need to be determined. This step is described below.

Table.1. Parameters of DD model [23]

Symbol	Name	Unit
V	Cells output voltage	V
V_t	Thermal Voltage	V
I	Cells output current	A
I_{ph}	Photo-current	A
Is_1, Is_2	Diode reverse saturation current	A
Ns	Number of Cells in series	-
τ	Cell Temperature	K
Q	Electron charge (q=1.60217646E-19)	C
K	Boltzmann constant (K=1.3806503E-23)	J/K
n_1,n_2	Diode Ideality factor	-
Rs	Series resistance	Ω
Rp	Parallel resistance	Ω

III. Objective function

The mathematical model is said to be accurate if the experimental and estimated I-V data match with each other, meaning that the difference between them is neglegable. Based on the above, the root-mean-square-error between the experimental and estimated I-V points given in Eq. (1) is generaly considered as the objective function (OF).

In Eq. (2), all the parameters are known except *Iph*, I_{s1} I_{s2} ,n_1, n_2,*Rs,and Rp*, since I_{est} is as a function of the stated parameters. These parameters are limites by bounderies as depicted in Table 2. The ultimate goal now is to adjust the values of the parameters randomly based on the algorithm until good accordance is achieved.

$$OF\ (V, I, r) = RMSE\ =\ \sqrt{\frac{\sum_{1}^{N}(I_{exp}-I_{est})^2}{N}} \qquad (2)$$

N is the samples number. I_{exp} and I_{est} are the experimental and estimated current of the cell panel respectively.

Table.2. Parameters variation range

Parameter	LB	UB
I_{ph} (A)	3.6	4.0
I_{s1} (A)	1E-9	1E-6
I_{s2} (A)	1E-7	1E-4
n_1, n_2(-)	1	2.5
R_s (Ω)	0	1
R_p (KΩ)	0.1	10

IV. Sailfish Optimizer Algorithm (SFO)

SFO is a population-based search method. It was proposed in 2019 by Shadravan [24]. The method mimics the foraging behavior of a sailfish school. Unlike other faunas, sailfish uses less effort and saves more energy while hunting its prey.

Figure 2. Sailfish hunting mechnism

The foraging behavior of the sailfish optimizer is conducted by the following steps:

IV.1. Elitism

In random search algorithms, the best solution can be missed while adjusting the search agent position. Here, the elitism step is employed to copy the fittest particle (best solution) into the future generation. In each iteration, the best sailfish position is taken as elite. As a consequence of a continuous attack the sardines shall be injured by slashing motion. The position of injured sardine in each iteration is saved and selected as the best target to collaborate in hunting with the sailfish.

IV.2. Attack-alternation strategy

Sailfish work to herd and injury the prey. This behavior allows sailfish to adjust their positions according to the location of the other hunters. It was observed that the search agents provide the exploration phase by searching a large section of the search space to discover the promising solutions that are not refined before. The sailfish attacks in all orientations and within a shrinking-circle. This mechnism is simulated using Eq. (3) [24]:

$$X^i_{new\_SF} = X^i_{elite\_SF} - \lambda_i \times \left[rand(0,1) \times \left(\frac{X^i_{elite\_SF} + X^i_{injured\_S}}{2} \right) - X^i_{old\_SF} \right]$$

(3)

$$\lambda = 2 \times rand(0.1) \times PD - PD \qquad (4)$$

Where $X^i_{new\_s}$ and $X^i_{injued\_s}$ are the position of the elite sailfish and injured sardine respectively. *Rand (0, 1)* is a random number in (0-1), λ_i is a random coefficient that mimics the sailfish divergence from each-other and convergence of it from the prey.

$$PD = 1 - \left(\frac{N_{SF}}{N_{SF} + N_S} \right)$$

PD signifies the prey density, a correlation is given in Eq .(5) to calculate *PD* by combining both the number of sailfish N_{sf} and sardines N_s. Practically, the sardines number N_{sf} is larger than sailfish N_{sf}, therefore, N_{sf} is taken as a fraction or percentage *PP* of N_s .

$$N_{sf} = PP \cdot N_s \qquad (6)$$

In this paper *PP=0.3*, but make sure that N_{sf} is always an integer.

IV.3. Hunting and catching prey

During hunting procedure, sailfish's bills hits and injury a large number of sardines in the school. The power of sailfish's will be decreased over the time. Also, due to frequent attacks, the power of the prey will reduce as well. Power of this reduction could give information to the prey about the sailfish location to escape from it. Clearly, some sardines will be hit by sailfish's bill and quickly be captured. Whereas, other sardines will be forced to adjust their positions according to the current best sailfish $X^{i}_{elite\_SF}$. The new position of the ith sardine $X^{i}_{old\_s}$ is given as:

$$X^{i}_{new\_s} = rand\ (0.1)\ (X^{i}_{elite\_SF} - X^{i}_{old\_s} + AP) \qquad (7)$$

Where $X^{i}_{old\_s}$ and $X^{i}_{new\_s}$ are the previous and updated sardines positions successively. *AP* is the sailfish's attack power at each iteration.

$$AP = A\ [1 - (2\ It\ .\ \varepsilon)] \qquad (8)$$

A and ε are coefficients (A=4, ε =0 .001) and *It* is the

itération number. Notice that *AP* is linearly decreasing number from *A* to 0 to simulate the reducing sailfish attack due to sardine's maneuverability [24].

AP parameter can help in selecting the sardines α and that have to adjust their positions and finding the remaining sardines variable β:

$$\alpha = NS\ .\ AP \qquad (9)$$
$$\beta = di\ .\ AP \qquad (10)$$

Where *NS* is the sardines number in each cycle and di is the variables number at i[th] iteration. According to *AP*, if sailfish intensity is low (AP < 0.5) just α sardines will update their positions and β is the variables number. Else ($AP \geq 0.5$) the position of all sardines will be updated. A pseudo-code is given to implement the method [24].

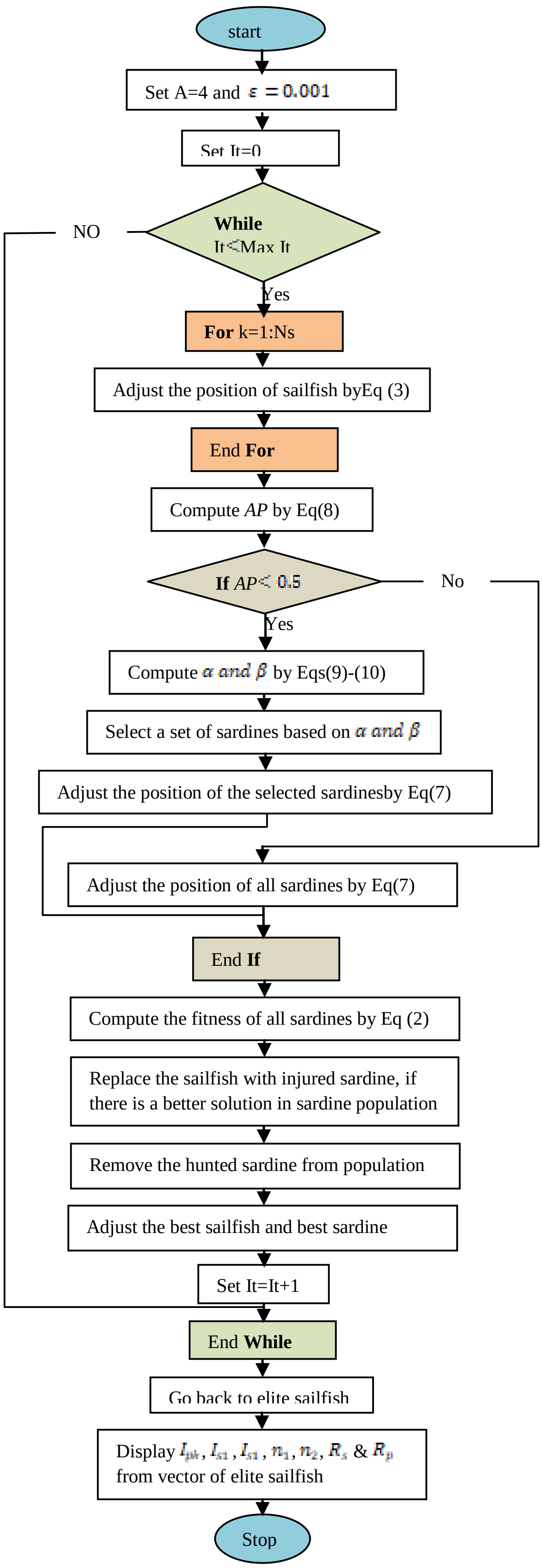

Figure 3. Flowchart of the Sailfish Optimizer

V. Experiment and results analysis

V.1. Experimental steps

To identify the cell parameters, a number of experiments were performed at the laboratory first. An industrial VA200 solar analyzer was utilized to extract the experimental I-V curves automatically. The remaining equipment connected to the system is shown in Figure 4.

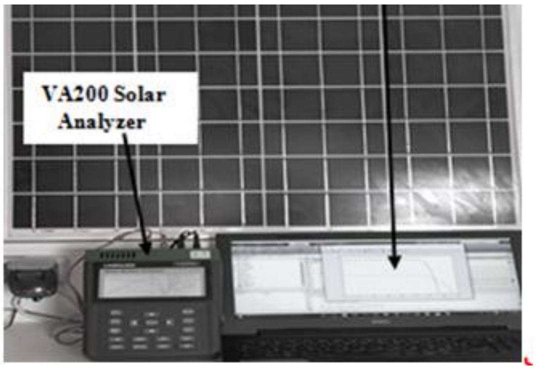

Figure 4. Experiments platform

Moreover, for a meaningful investigation, the results of the suggested algorithm were compared with some state-of-the-art methods namely SSA [17], WOA [18, 19], ABC [20], and PSO [21, 22]. Named algorithms were used in many research papers for extracting the PV cell parameters. The controlling coefficients of them are fixed as original papers recommend. Additionally, for a fair comparison, agents number was set equal to 30 particles in each algorithm. The results were executed for 100 independent runs and the best parameters are taken as a desired solution.

V.2. Case study 1 (I-V characteristics)

It is worthy to remember that there are 7 unknown parameters that have to be optimized. The extracted best parameters are displayed in Table 3. They have been fed-back to the model to estimate I-V curve at G = 735 W/m^2 and T = 48 °C.

Figure 5 represents the plotted I-V curves for all algorithms.

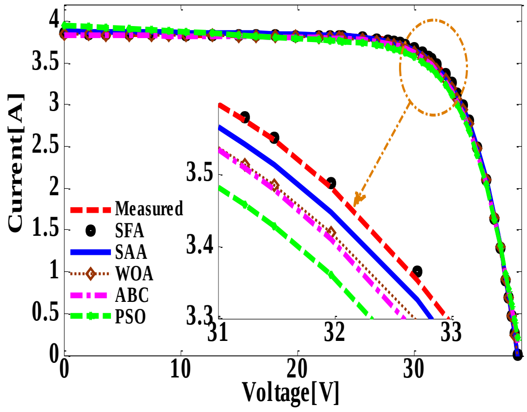

Figure 5. I-V curves at G=735W/m2 & T=48°C

It can be observed that around the short circuit and open voltage points all the methods are showing good accordance. However, around the maximum power point (MMP) some differences are detected. A closer view shows that the suggested method attain the highest accuracy, meaning that the global optimum (GO) is well explored by SFO. In contrast, the results of other approaches are less accordance and they failed to track the GO. The results in Table III validate these observations. SFO placed in first position with RMSE of 13.2 E-3 followed by WOA which has ranked in second position with RMSE of 19.9E-3 A, SSA has positioned third with RMSE of 24.3E-3 A. ABC & PSO methods exhibit the lowest precision with RMSE of 101.6E-3A and 103.9E-3A respectively.

Table 3. Results of the simulation

	SFO	SSA	WOA	ABC	PSO
Iph(A)	3.869	3.872	3.865	3.853	3.948
Is1 (A)	2.253E-7	7.711E-7	5.818E-7	9.064E-7	4.933E-7
Is2 (A)	1.582E-6	2.349E-5	7.934E-6	4.725E-5	9.301E-5
n1 (-)	1.173	1.266	1.242	1.295	1.852
n2 (-)	1.807	2.291	2.348	1.995	1.838
Rs (Ω)	0.373	0.289	0.307	0.255	0.020
Rp(Ω)	636.086	780.591	662.059	645.269	538.223
OF(A)	13.2 E-3	24.3 E-3	19.9 E-3	101.6 E-3	103.9 E-3
Iteration	43	78	146	254	186
Rank	1	3	2	4	5

V.3. Case study 1 (I-V characteristics)

Figure 6 represents the objective function evolution over the course of iterations for all tested algorithms. It is apparent that the suggested method has shown rapid convergence compared to others.

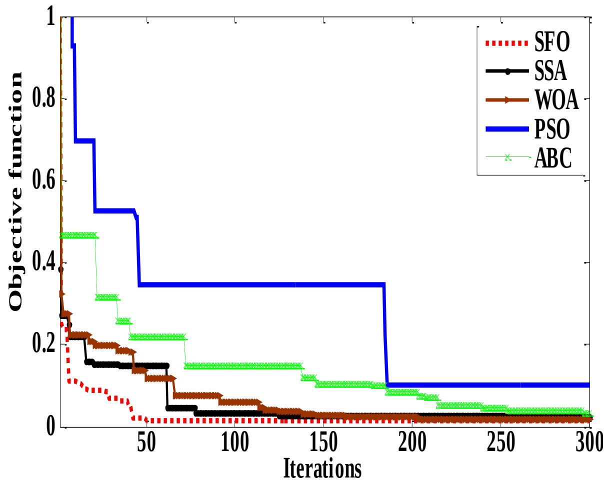

Figure 6. Convergence speed

The desired solution has been reached only in 43^{th} iteration. Furthermore, SSA and WOA have approximately the same inclination curve; however, SSA has hit the target on 78^{th} iteration as second place, and WOA in 146^{th} iteration in third place. ABC-PSO methods showed some delay while settling down. But, unfortunately they have converged to the local minimium without escaping from it. Based on iterations number, ABC (iteration of 254^{th}), and PSO (iteration of 186^{th}) algorithms were ranked in last positions. These results signify that the suggested algorithm has high potential in explored the search area in very short-time. The explanation for the rapidity of the method is that the SFA employs two populations (population of prey and predator) instead of one to search for the solution. The school of sardines also assists the predators in searching process. In other words, the randomly motion of sardines itself can separate the weakest particles in the school and then get easily captured by sailfish. This unique hunting strategy can dramatically accelerate the convergence speed of the method. However, this behavior is not observed in the other methods.

VI. Conclusion

Accurate PV cells parameters identification has a significant impact on predicting the power of the PV installation. Thus, the demand for more accuracy is always required. In this study, a novel swarm intelligence optimization algorithm called sailfish optimizer is applied for the first time to model the outputs of PV cells. The idea was to determine the optimal unknown parameters by minimizing the error between the experimental characteristic curves with the estimated ones. The main difference between this applied algorithm and others is its efficacy in finding the optimal parameters with high accuracy and noticeable rapidity. A comparison was undertaken with several state-of-the-art meta-heuristic algorithms to show the effectiveness of the proposed algorithm. The main outcomes of the study can be pointed out as follows:

- The performance of the Sailfish optimizer is tested in this study to solve modeling problems of PV generators.
- An accurate PV model for SW 175 polycrystalline PV panel has been established.
- Among many techniques, the Sailfish optimizer produced the highest accuracy with RMSE of 13.2 E-3.
- The study revealed that the proposed method has a great potential to avoid local optimum and has converged rapidly to the desired solution with minimum iterations (i.e., 43 iterations).

Finally, from this work, it can be stated that the Sailfish optimizer is a powerful technique. Its results were motivating and even excited us to perform other studies to test the efficacy of this method in addressing other engineering problems for instance modeling fuel cell generators.

Declaration

- The authors declare that they have no known financial or non-financial competing interests in any material discussed in this paper.
- The authors declare that this article has not been published before and is not in the process of being published in any other journal.
- The authors confirmed that the paper was free of plagiarism.

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