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Photovoltaic Parameters Estimation Using Hybrid Flower Pollination with Clonal Selection Algorithm

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ABSTRACT Extracting the parameters of photovoltaic (PV) cell is a vital process to accurately simulate the behavior of the cell. Various techniques are used to extract these parameters such as iterative, and metaheuristic methods. Although metaheuristic methods require more test points on the PV module, through this paper the optimization function is chosen to accurately adjust the I-V curve of the PV module based on less number of test points yet still achieve higher accuracy. A modified hybrid flower pollination method with clonal selection algorithm is suggested to extract the PV parameters and is compared with various metaheuristic methods to estimate the PV parameters of the single diode model, the two-diode model. In addition, modeling the PV at various irradiance and temperature levels was performed. Results show an excellent curve fitting for I-V characteristics and more accurate results in estimating the unknown parameters of PV cell.

Keywords: PV Model, Single Diode Model, Two Diode Model, Flower Pollination, Modified Flower Pollination

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1. INTRODUCTION

The fast decline of conventional energy sources increases the need to use renewable energy sources. By 2016 renewable energies share by more than 24 % of total electricity consumption worldwide [1]. Energy generation based on photovoltaics is one of the most competitive renewable energy sources.

PV market is increasing rapidly and it is governed by the reduction in panel cost and increasing capacity factor. In 2016, PV contributed by at least 303 GW DC which is 4.8 GW more than the one from concentrated solar thermal power [1]. In Egypt, energies about 154 MW from photovoltaic cells and 3035 MW from solar panels were produced [2]. Various technologies are used to manufacture PV cells as crystalline silicon (monocrystalline, polycrystalline), thin film (amorphous silicon, Cadmium Telluride, copper indium gallium selenide), nanotechnology (tandem, super tandem, intermediate band) [3].

Modeling of PV cell is a fertile research area that aims to model the behavior of the cell using the electrical circuit to accurately predict the performance and efficiency. It helps to correctly track the maximum power point and simulate the whole system performance along with the power conditioning and storage units [4]. The model should be accurate, robust, take low computational time, gives correct I-V data close to experimental data at various working conditions [5].

Section (II) introduce the various model used to simulate PV characteristics, section (III) starts from Villalva et al. method to extract PV parameters while the current paper presents modification to eliminate the assumptions of Villalva method and produce an objective error function for extracting the required PV parameters based on five test points namely: maximum power, open circuit voltage, shorts circuit current, half open circuit voltage, average of maximum power voltage and open circuit voltage. The hybrid flower pollination with clonal selection algorithm (FPA-CSA) is suggested to minimize the objective error function. A lot of metaheuristic techniques was used in recent years to extract the PV parameters these techniques which varied in result accuracy, number of technique's parameters, technique complexity. Through this paper, a wide range of metaheuristic techniques was used to extract the PV parameters, and results showed that FPA-CSA provided the least error when compared with famous metaheuristic techniques. FPA-CSA has more changeable parameters than the other techniques which increase the complexity of the algorithm. Section (IV) deals with extracting PV parameters at various environmental conditions mainly changing in irradiance and temperature using FPA-CSA technique.

2. THE PV MODEL

Various approaches are used to accurately simulate the behavior of PV cell, although circuit model of PV cell is the most popular approach which uses a relatively simple circuit model to simulate the electrical characteristics of PV cell [6, 33].

2.1. The Ideal Model of PV

As the PV cell is mainly a semi-conductor material, it can be modeled as the *P-N* junction that emits current when exposed to sunlight [6, 7].

The diode current is given as:

$$I_D = I_S * [\exp\left(\frac{q*V_D}{aKT}\right) - 1] \quad (1)$$

Where I_D is the diode current, I_s is the diode reverse saturation current, q is the absolute value of electron charge, V_D is the diode voltage, a is the diode ideality factor, K is the Boltzmann's constant and T is the cell temperature in Kelvin.

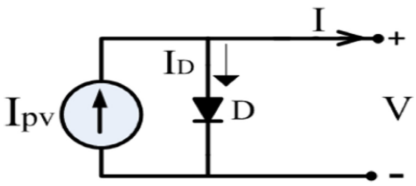

Fig.1. Ideal single diode model

The output current is given in Equation 2 where I_{pv} is the light current.

$$I = I_{PV} - I_S * [\exp\left(\frac{q*V_D}{aKT}\right) - 1] \quad (2)$$

Although the ideal model is simple, it can't provide a realistic model for PV behavior as it doesn't consider the effect of contact resistance between silicon and electrodes, electrode resistance and the leakage current.

2.2. Single Diode Model (with Rs and Rp).

The single diode circuit [8] is shown in Figure 2.

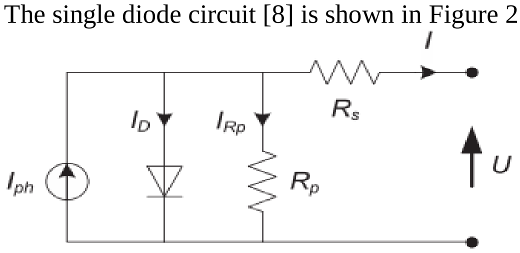

Fig.2. Single diode model

The output current is given in Equation 3 considering the effect of contact resistance by adding the series resistance (R_s) and the leakage current through adding shunt resistance (R_p).

$$I = I_{PV} - I_S\left[\exp\left(\frac{q*(V_D+I*R_S)}{aKT}\right) - 1\right] - \frac{V_D+I*R_S}{R_P} \quad (3)$$

2.3. Two-Diode Model

The two-diode model shown in Figure 3 compensates the effect of recombination current loss in the depletion region by adding a second diode to the PV cell model. The output current is given in Equation 4 where I_{S1} represents the first diode current and I_{S2} represents the recombination current. The advantage of this model is that unlike the single diode models, it provides appropriate accuracy in low irradiation values [6, 9-11].

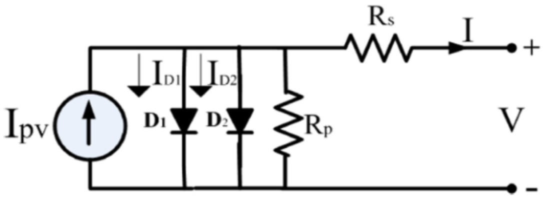

Fig.3. Two diode model

$$I = I_{PV} - I_{S1} * \left[\exp\left(\frac{q*(V_D+I*R_S)}{a_1KT}\right) - 1\right] - \frac{V_D+I*R_S}{R_P} - I_{S2} * \left[\exp\left(\frac{q*(V_D+I*R_S)}{a_2KT}\right) - 1\right] \quad (4)$$

According to Equation 4 the two-diode model takes into account the effect of the contact resistance and leakage resistance through adding the series resistance and the shunt resistance and the diode current through adding diode current I_{S1} and recombination current through adding second diode current I_{S2}.

2.4. Other PV Models

There is also three diode model, an explicit model that doesn't use equivalent circuit. It is used in a situation like resonance with cables, interaction with switching frequency harmonics, underdamped current. To model the reverse bias process and dynamic characteristics, a dynamic model is suggested [3, 12, 13].

3. ESTIMATING UNKNOWN PARAMETERS OF THE PV CELL

In general, the manufacturer datasheet provides special test points as the open circuit, short circuit and maximum power point voltage and current wherein single diode model there are five unknowns namely: photon current, saturation current, ideality factor, series resistance, and shunt resistance.

For the two-diode model, there are seven unknowns namely: photon current, series resistance, shunt resistance, first diode ideality factor, second diode ideality factor, first diode saturation current and second diode saturation current.

Finding the unknowns of the PV cell is essential to correctly simulate the cell behavior. Various methods are used to estimate these parameters as analytical methods, artificial intelligence and hybrid methods.

3.1. Villalva, Gazoli and Filho Model

Villalva et al. proposed a model to determine the five parameters of single diode model, based on adjusting I-V curve to three common points: open circuit, short circuit, and maximum power point.

Three assumptions are used to find saturation current, ideality factor and light current as follow:

1. $1 \leq a \leq 1.5$
2. $I_{PV} \sim I_{SC}$.
3. $Io = \frac{I_{Sc}+K_I*(T-To)}{\exp\left[\frac{(V_{OC}+K_V*[T-To])}{a*vt}\right]-1}$

where V_T is the thermal voltage and equals to ($N_s.k.t/q$) and N_s is the cells connected in series.

Two parameters are still unknown, namely series and shunt resistance. Those are adjusted based on a unique pair of (R_s, R_p) that match the maximum power point, in other words, the maximum power calculated by the model.

($P_{max,m}$) equal to datasheet maximum power ($P_{max,e}$), is given by the following equation [7, 14]:

$$P_{max,e}=V_{mp}[I_{pv} - Io(\exp(\frac{q}{kT}\frac{V_{mp}+R_sI_{mp}}{aN_s}) - 1) - \frac{V_{mp}+R_sI_{mp}}{R_P}] \quad (5)$$

3.2. Metaheuristics Methods

Metaheuristics methods can be used as an optimization technique for Equation 5, without assuming any parameter of the PV model [32].

Through this study, a range of metaheuristics methods are reviewed and used to optimize Equation 5, such as: Particle Swarm (PS)[15,16], Genetic Algorithm (GA)[17], Pattern Search (Pt.S)[18], Simulated Annealing (SA)[19], Cuckoo Search [20, 21, 22] (CS) and Hybrid Cuckoo Search with Nelder-Mead Simplex(CS-NMS)[23], Whale Optimization Algorithm (WOA)[24-25], Grey Wolf Algorithm (GWA)[26], Ant Lion Algorithm (ALA) [27], Flower Pollination Algorithm (FPA) [28], Hybrid Flower Pollination with Clonal Selection Algorithm (FPA-CSA) [29].

FPA-CSA is considered to minimize the objective function to extract PV parameters, where flower pollination algorithm is enhanced by combining it with the clonal operator in current study.

Flower pollination is the process of transferring pollen between flowers through pollinator, and this process can be cross-pollination or self-pollination. In cross-pollination, pollens from different plants can be transferred while in self-pollination only pollens from same plant type are transferred. This process can also be biotic which needs a pollinator or abiotic which needs no pollinator. Another important property is the plant constancy property where plant attract the pollinators to it and by-pass other plants. The pollination process can be either local (abiotic and self-pollination) or global (biotic and cross-pollination), so a switch probability P is presented to switch between the two types of pollination.

The clonal selection algorithm is based on generating antibodies for various viruses each of them is activated by a certain virus and the selected antibodies are cloned and mutated.

The principle of hybridization is presented in [29], where local pollination step size is scaled, then the best solutions are selected at each population. The best 14 solutions were selected and cloned proportionally to its fitness as the pseudo code of the algorithm in this study as it is shown in Table 1.

The reason why FPA-CSA provide more accurate results lays on having the property of global pollination from FPA algorithm which clonal selection enhance by choosing the best solution and cloning them.

Table 1. Pseudo-Code of FPA-CSA

1- Minimize or maximize the objective function **f(x)**, x=(x1, x2,….xd)
2- Create a random initial population **pop** of the size n.
3- Identify **g*** which is the best solution in **pop.**
4- Identify **P ε [0,1]** which is a switch probability between global and local pollination.
5- **While** (gen < Max Generation Num)
6- **If rand > p**, // perform global pollination
7- For each Xi in the Pop
8- Draw a (d-dimension) step vector L which obeys a levy distribution.
9- Global pollination via $X_i^{t+1} = X_i^t + \gamma_1 L(g^* - X_i^t)$
10- **End for**
11-**Else**
12- Select best m solutions from the **Pop** to form **ClonesPop** population.
13- Clone solution in **ClonesPop** proportional to affinity.
14- **For** each solution in **ClonesPop**
15- Draw ε from a uniform distribution in [0,1].'
16- Randomly choose j and k from **Pop.**
17- Perform local pollination via $\mathbf{X_i^{t+1} = X_i^t + \gamma_2 \varepsilon (X_j^t - X_k^t)}$.
18- **End for**
19- **End if.**
20- Select best solutions from **Pop** and **ClonesPop** to from **NewPop** population.
21- Replace **Pop** by **NewPop.**
22- Find the current best solution **g***.
23- If **g*** doesn't chane, for the successive 100 iteration, with a value more than 10^{-6}, keep **g*** .
24- Replace **Pop** by a new randomly generated one.
25- gen=gen+1.
26- **End while.**
27- **Print g***

The previous algorithms are tested using MATLAB software, and with a computer equipped with an Intel Core i5 processor. A list of parameters used for each algorithm is shown in the Table 2 (2,000 iterations for each), under same bounds.

Table 2. Parameters of metaheuristic methods

Algorithm	*Parameters*
Particle Swarm	35 Particles
Cuckoo Search	35 Nests, discovery rate = 0.25.
ALA	35 Search Agent
WOA	35 Search Agents
FPA	Population size 35, Probability switch: 0.8 γ = 0.01, for Levy flight λ = 1.5
GWA	35 Search Agents
FPA-CSA	Population size: 35, Probability switch: 0.8, cloning array = [9, 8, 7, 6, 5, 4, 3, 2, 1, 1, 1, 1, 1, 1], γ 1 = 1, γ2 = 3, for Levy flight λ = 1. 5

For PS, GA, PS and SA, default built-in MATLAB codes were used in the test.

Each method is used to estimate the five unknown parameters of single diode model based on single optimization function by minimizing the absolute error of ($P_{max,m}$-$P_{max,e}$) proposed by Villalva et al in Equation 5. For both Astro power AP 110 model and Kyocera KC-40T shown in Appendix I & II. SA, then FPA-CSA provide superior error as shown in Table 3, which makes the maximum power point matches exactly with one reported in the datasheet point I-V curve for SA method was plotted in Figure 4 to clearly identify the models fitting with the rest of remarkable points mainly open circuit and short circuit.

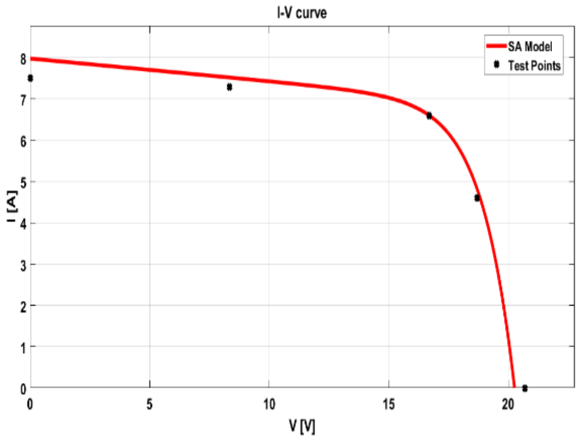

Fig. 4. I-V curve using SA algorithm based on Villalva et al. for single diode model for AP-110 Module

Although SA presents extremely small error in calculating the maximum power point but it doesn't fit curve in other points as in open circuit and short circuit points as the objective function only accounts on maximum power point and no assumption is made for other unknowns.

On the other hand, the objective function can be based on the summation of error as shown in [30], so the objective function can be modified to consider five test points namely: open circuit, short circuit, maximum power point, half open circuit voltage and average of maximum power voltage and open circuit voltage as follows:

$$\text{Error}=\text{Abs}\,(P_{max,m}-P_{max,e})+\text{Abs}\,(V_{oc,m}-V_{oc,e})+\text{Abs}\,(I_{sc})+\text{Abs}\,(V_{x,m}-V_{x,e})+\text{Abs}\,(V_{xx,m}-V_{xx,e}) \quad (6)$$

where V_x is half of the voltage at maximum power point and V_{xx} is average of maximum power voltage and open circuit voltage test point based on M. Siddiqui et al. [30].

To determine the efficiency each metaheuristic method is tested to find the least error when applied to suggested error optimization function, a summary of results is found in the Table 4.

FPA-CSA then CS provide better results than the other methods, I-V curve is plotted to examine fitting the data in Figure 5.

Where I_O= 1.5246e-06 A, I_{PV}= 7.5135 A, a= 1.4576, R_P=49.9999Ω, R_S= 0.08999Ω.

Table 4. Results of metaheuristic methods for AP 110 Model based on five test points for single diode model.

Algorithm	*Error*
Genetic Algorithm	0.4041
Particle Swarm	0.542
Pattern Search	1.159
Simulated Annealing	1.095
Cuckoo Search	0.3768
Cuckoo Search- Nelder-Mead	0.5733
Ant Lion	0.6420
Whale Algorithm	0.4284
Flower Pollination	0.3816
Grey Wolf Optimizer	0.5118
Flower Pollination- Clonal Selection	**0.373**

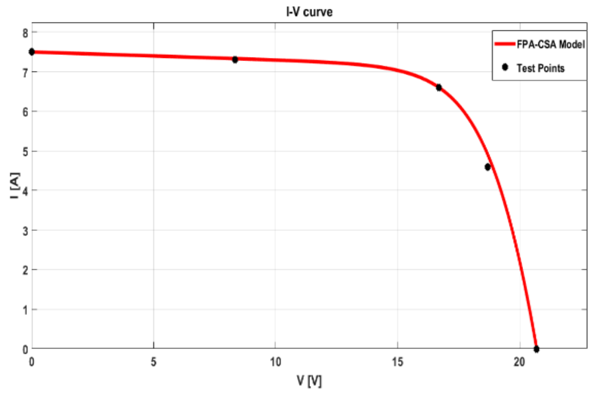

Fig. 5. I-V Curve for AP-110 module using FPA-CSA using single diode model based on five test points

The model present very good fitting for I-V characteristics with a slight error.

Again, the metaheuristic methods were tested to extract the parameters of two diode model for AP-110 module based on the previous five test points as shown in the Table 5.

Table 5. Two-diode model optimization results for metaheuristic methods

Algorithm	*Error*
Genetic Algorithm	0.5166
Particle Swarm	0.4076
Pattern Search	0.7476
Simulated Annealing	0.7529
Cuckoo Search	0.3964
Cuckoo Search- Nelder-Mead	0.6035
Ant Lion	0.56634
Whale Algorithm	1.2788
Flower Pollination	0.4073
Grey Wolf Optimizer	0.83851
Flower Pollination- Clonal Selection	**0.3739**

Table 3. Results of meta-heuristic methods and estimated five parameters

	GA	*PS*	*Pt. S*	*SA*	*CS*	*CS-NMS*	*ALA*	*WAO*	*FPA*	*GWA*	*FPA-CSA*
Error	5.4e-6	4.3e-7	8.4e-08	5.6e-14	2.5e-6	1.9e-7	1.9e-9	1.2e-8	5.9e-6	2.01e-5	1.4e-9
Io	1.95e-6	1.50e-6	1.00e-6	3.20e-6	4.98e-6	1.24e-6	4.99e-6	1.06e-6	1e-6	1.85e-6	2.8e-6
Ipv	7.80	7.65	7.12	7.84	7.91	7.99	8	7.86	7.42	8	7.50
A	1.41	1.42	1.50	1.45	1.49	1.43	1.50	1.46	1.43	1.48	1.49
Rp	38.25	36.03	48.19	40.45	49.53	16.25	49.99	18.35	38.73	16.75	42.21
Rs	0.020	0.038	0.010	0.010	0.030	0.011	0.048	0.072	0.057	0.016	0.012

Once again FPA-CSA then CS present more accurate results in the two-diode model to accurately detect the seven model parameters based on minimizing the error in Equation 6.

The seven parameters extracted using FPA-CSA are as shown in Table 6.

Table 6. Seven parameters extracted using FPA-CSA for AP 110 model

Parameter	*Value*
I_{01}	1.743159e-08 A
I_{PV}	1.743159e-08 A
a_1	1.4579
R_P	50 Ω
R_S	0.090 Ω
I_{O2}	1.5072e-06 A
a_2	1.4576

I-V curve of the seven-parameter model using FPA-CSA is shown in Figure 6.

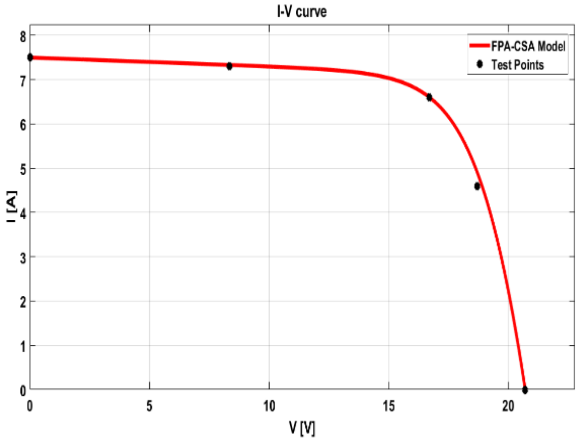

Fig.6. I-V curve of the seven-parameter model using FPA-CSA two diode model based on five test points

For convenience, the best two metaheuristic methods namely: FPA-CSA and CS were tested to extract two diode parameters for KC-40T model where errors were computed as 0.0358 and 0.0426, respectively. It was shown again that FPA-CSA shows superiority over other methods.

Two diode model parameters for KC-40T are shown in Table 7.

Table 7. Seven parameters extracted using FPA-CSA for AP 110 model

Parameter	*Value*
I_{01}	2.4299e-08 A
I_{PV}	2.6486A
a_1	1.69999
R_P	2.13128e3 Ω
R_S	0.45439 Ω
I_{O2}	1.146e-08 A
a_2	1.219

4. MODELING OF PV CELL AT DIFFERENT IRRADIANCE LEVEL AND TEMPERATURES

The previous work models the PV cell at reference conditions namely 1000 W/m^2 irradiance at 25 °C.

It is necessary to model the PV cell at various environmental conditions, mainly the irradiance level and temperature, as the unknown parameters of the PV depend on both irradiance and temperature [31, 34].

The MPF-CSA is tested to estimate the parameters of two diode model for the KC-40T model at low irradiance, namely 400 W/m^2 and at 50 °C, based on test points in [30]. Results are shown in Figure 7 which show excellent fitting for the I-V characteristics at various operating conditions.

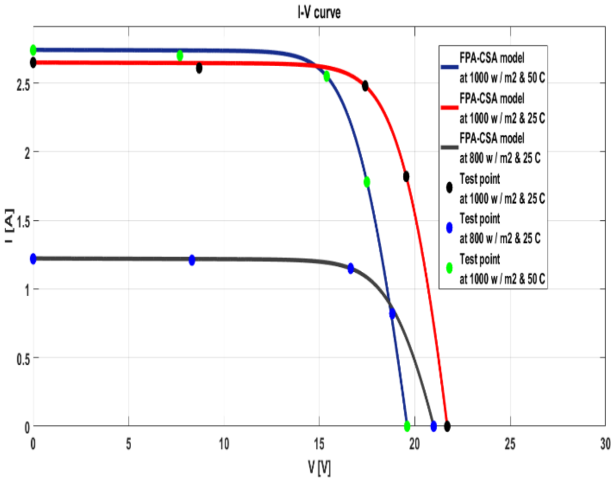

Fig. 7. Two diode model at 1000 W/m^2 + 25°C, 400 W/m^2 + 25°C and 1000 W/m^2 + 50°C for KC-40T model

4. CONCLUSION

Flower pollination algorithm hybridized along with colonel selection algorithm (FPA-CSA) was tested to extract the parameters of PV module along with various metaheuristic methods. Firstly, objective function depends only on settling the I-V curve on MPPT, SA then FPA-CSA where the most effective methods with the least errors 5.68e-14, 1.40e-9 respectively. Although these results are rather tricky as settling the curve at only MPPT doesn't ensure fitting the entire curve.

A proposed modification on the objective function was introduced in order to fit the curve at common point as open circuit voltage, short circuit current, half open circuit voltage, average of maximum power voltage and open circuit voltage along with MPPT. Results in Tables 3, 4 shows the FPA-CSA ranks as number one among other metaheuristic methods followed by FPA and CS methods as shown in Figure 8.

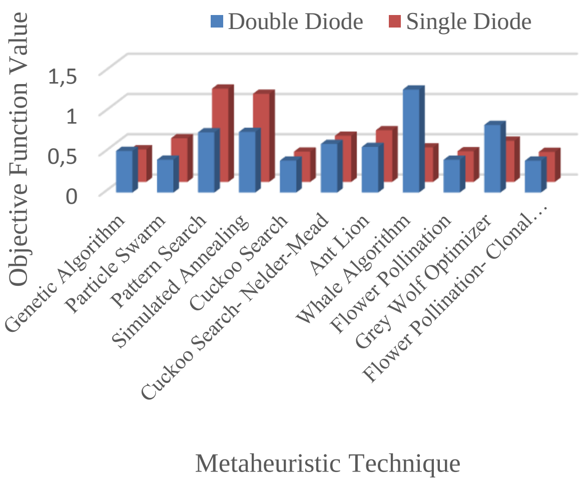

Fig. 8. Comparison between metaheuristic methods objective function result for both single diode model and double diode model

The obtained I-V curve based on the suggested objective function using FPA-CSA produce the most accurate curve fitting to the practical test points with the least error.

Either five parameters model or seven parameters model proved to provide high accuracy and less error in modeling even when compared with a variety of artificial intelligence techniques such as particle swarm, genetic algorithm, simulated annealing, etc.

Objective function better includes minimization of error in the five remarkable points (OC, SC, MP, V_x, and V_{xx}) for more accurate results which require only two test points as first three points are typical datasheet information.

Further addition of experimental points can improve the accuracy of the model although it increases the complexity of the objective function.

Although FPA-CSA has more parameters which make it more complex compared to original FPA it provides more accuracy, the problem of excessive parameters can be handled as a separate optimization problem to select the appropriate parameters for the required problem.

The proposed algorithm works efficiently with various environmental conditions and presents accurate modeling for the PV cell especially with two diode model. It presents more accurate results at low irradiance level.

Further improvement can be made by having a secondary optimization problem which include estimation of sensitivity parameters of the transitional equations to exclude the need for various test points at different environmental conditions [34].

The modeled PV circuit can be used to simulate the PV behavior at actual environment along with normal and faulty conditions thus predicting cell behavior and providing appropriate precautions.

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APPENDICES

Appendix I: Data of KC 40 T Model at 1000 W/m^2 and 25 °C

Parameter	Value
I_{SC}	2.65
V_{OC}	21.7
I_{MP}	2.48
V_{MP}	17.4
N_S	36
Current Temp. Coefficient	0.00106
Voltage Temp. Coefficient	-0.0821

Appendix II: Data of AP 110 Model at 1000 W/m^2 and 25 °C

Parameter	Value
I_{SC}	7.5
V_{OC}	20.7
I_{MP}	6.6
V_{MP}	16.7
N_S	36
Current Temp. Coefficient	0.0034
Voltage Temp. Coefficient	-0.08

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