PV Module Parameters Extraction with Maximum Power Point Estimation Based on Flower Pollination Algorithm

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***Abstract*- Modeling of photovoltaic (PV) module remains as an important issue for many applications like monitoring or fault detection. Hence, many models have been proposed in literature, the most popular ones are the single and double diode models. Each model have unknown parameters to be identified. In this paper, a parameters extraction for both single and double diode models by using flower pollination algorithm is proposed. This algorithm is based on flower pollination for optimal reproduction of the plants species and can be considered as an optimization technique. Experimental validation was carried out by comparing the obtained results with real measurements data. In order to give usefulness, the extracted PV module parameters values are incorporated to estimate the maximum power point (MPP) and compared it with the MPP obtained from real data of grid connected photovoltaic system (GCPVS).**

Keywords: *PV modules; Flower pollination algorithm; Parameters extraction; Maximum power point; Grid connected photovoltaic system; meta-heuristic optimization.*

I. INTRODUCTION

In the last years, the renewable energy becomes a more useful resource of the electricity to reduce greenhouse effect; among the most important renewable sources is solar energy. Many systems are provided to exploit this source such as grid connected system, stand-alone system and hybrid system. These systems are based on a PV panels in which the fundamental part is the PV module.

A PV system is not very competitive when demand of electricity increases. In addition, to make the PV system profitable, one must ensure a correct sizing that requires a rigorous study. In order to make the best choice, the best performance and the lowest cost, the prime study is based on the data given by manufacturers; however, the information provided by the manufacturers of PV modules gives an approximate sizing of the PV system. The main objective of this paper is to identify the PV module parameters used for the estimation of the MPP to ensure a better sizing of the PV system.

For PV cell modeling, several models were given in literature; the most common are single and double diode models [1,2]. These models have unknown parameters to be identified in the purpose to improve their accuracy. Therefore, several optimization algorithms have been proposed for PV module parameters extraction. Recently, many algorithms based on stochastic techniques, such as heuristic and meta-heuristic algorithms, are used for extraction of the parameters, among them: Genetic Algorithm (GA) [3], Particle Swarm Optimization (PSO) [4], Harmony Search (HS) [5], Pattern Search (PS) [6], Simulated Annealing (SA) [7], Artificial Bee Colony (ABC) [8], Artificial Bee Swarm Optimization (ABSO) [9] , Modified Artificial Bee Colony (MABC) [10], Bird Mating Optimizer (BMO) [11], Cuckoo Search (CS) [12], Artificial Fish Swarm Algorithm (AFSA) [13], Biogeography Based Optimization Algorithm with Mutation (BBO-M) [14], Artificial Immune System (AIS) [15], Differential Evolution Algorithm (DEA) [16], these algorithms seek to solve the parameters extraction problem of PV module with artificial intelligence approaches.

In this paper, an optimization of the cost function by the Flower Pollination Algorithm (FPA) developed by Xin-She Yang is exploited [17, 18]. This algorithm is an inspiration from the pollination process of flowers. The FPA has some advantages like the convergence of the algorithm is independent of the space of search and also this technique is not related to the initial conditions.

The FPA is applied to solve the problem of the PV module parameters extraction. The extracted parameters have been compared with several experimental I-V curves from two different PV modules manufacturers. Furthermore, the extracted parameters for the single diode model are used in a behavioral model to estimate the MPP that is also compared with experimental data of GCPVS.

This paper is devised into 5 sections, in the first section, the electrical modeling approach of PV module is presented where a focus is carried out on the most popular models such as single and double diode models with brief description and in the last

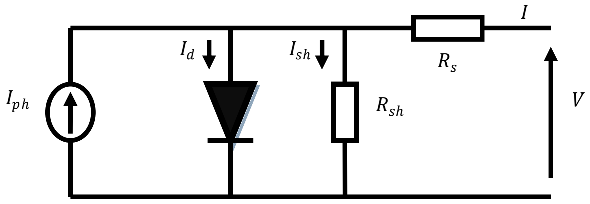


Fig. 1. Equivalent electrical circuit of Single diode model for solar cell.

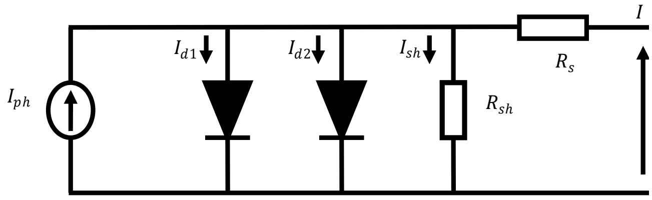


Fig. 2. Equivalent electrical circuit of Double diode model for solar cell.

of this section, the optimization problem is defined, the second section is reserved for the basic steps of the FPA that is explained with appropriate description, the estimation of the current, voltage and power in MPP is presented in the third section, however, the fourth section is affected for simulation and experimental results and in the last section conclusions are addressed.

II. PROBLEM FORMULATION

Based on the electrical approach, several equivalent electrical circuit models have been proposed in literature to describe the behavior of the PV cell. The well-common used models are both single and double diode models. A more detailed description of these models is given in the following sections.

1. Single diode model

As is shown in the Fig. 1, the single diode equivalent circuit model is composed of a current source that represents proportionally the current intensity generated by incident radiation, in parallel with a diode and two serial and parallel resistors R_s and R_{sh} respectively to take into account the dissipative phenomena in the cell [19].

According to the electrical model given previously, the PV cell presents a nonlinear I-V characteristic that represent the variation of the current provided by the cell as function of the voltage as is described in the equations (1-3). I is the current provided by solar cell, I_{ph} , I_d and I_{sh} are the photo-generated current, the diode current and the shunt current respectively. K is the Boltzmann constant, q is the electric charge, T_c is the cell temperature. n is the ideality factor of the diode; I_0 is the saturation current due to diffusion and recombination.

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

$$I_d = I_0 \left[\exp\left(\frac{q(V + R_s I)}{nKT_c}\right) - 1\right] \tag{2}$$

$$I_{sh} = \frac{V + R_s I}{R_{sh}} \tag{3}$$

The substitution of equations (2) and (3) into equation (1) gives the solar cell output current equation (4)

$$I = I_{ph} - I_0 \left[\exp\left(\frac{q(V + R_s I)}{nKT_c}\right) - 1\right] - \frac{V + R_s I}{R_{sh}} \tag{4}$$

I_{ph}, I_0, R_s, R_{sh} and n are unknowns parameters to be identified.

The single diode model is better for simulation superpose, however, this model ignores the recombination effect of the diode, for this, it is not the most accurate model, while for study of solar cell characteristics at critical points, double diode model is more preferable.

2. Double diode model

The double diodes model is derived from the same equivalent circuit of the single diode model with the main difference that the recombination current is divided into I_{01} and I_{02} which represent the recombination in both surface and bulk material. This can be added to the solar cell sub-circuit by simply adding a second diode Such as what is described in the Fig. 2 with n=2 in the schematic of the single diode model [19].

$$\begin{aligned} I = I_{ph} - I_{01}\left[\exp\left(\frac{q(V + R_s I)}{n_1 KT_c}\right) - 1\right] \\ -I_{02}\left[\exp\left(\frac{q(V + R_s I)}{n_2 KT_c}\right) - 1\right] - \frac{V + R_s I}{R_{sh}} \end{aligned} \tag{5}$$

I_{01} and I_{02} are the currents of saturation, n_1 and n_2 are the ideality factors of diodes 1 and 2 respectively. The unknown seven parameters are I_{ph} ,I_{01} , I_{02} , n_1, n_2, R_s and R_{sh} .

3. Objective function

To find the parameters of solar cell models, we must define the cost function to be optimized; the used root mean square error (RMSE) as an objective function is writing in equation (6), the error between the measured value of current I_m and the calculated value using the equation (7) or (8) will be minimized

$$RMSE = \sqrt{\frac{1}{K}\sum_{i=1}^{K} f(I_m, V_m, X)^2} \tag{6}$$

K is the number of measured I-V data; each solution is represented by the vector X, for the single diode model X= $[I_{ph}, I_0, n , R_s, R_{sh}]$ and for the double diode model X= $[I_{ph}, I_{01}, I_{02}, n_1 , n_2, R_s, R_{sh}]$ as defined in equations (7), (8)

III. FLOWER POLLINATION ALGORITHM (FPA)

Flower Pollination Algorithm or flower algorithm is a new meta-heuristic algorithm developed by Xin-She Yang [17, 18]. It's an inspiration from the pollination processes of the flower in the nature. Basely, the main process of this algorithm is the

$$f(I_m, V_m, X) = I_{ph} - I_0\left[\exp\left(\frac{q(V_m + R_s I_m)}{nKT_c}\right) - 1\right] - \frac{V_m + R_s I_m}{R_{sh}} - I_m \tag{7}$$

$$f(I_m, V_m, X) = I_{ph} - I_{01}\left[\exp\left(\frac{q(V_m + R_s I_m)}{n_1 KT_c}\right) - 1\right] - I_{02}\left[\exp\left(\frac{q(V_m + R_s I_m)}{n_2 KT_c}\right) - 1\right] - \frac{V_m + R_s I_m}{R_{sh}} - I_m \tag{8}$$

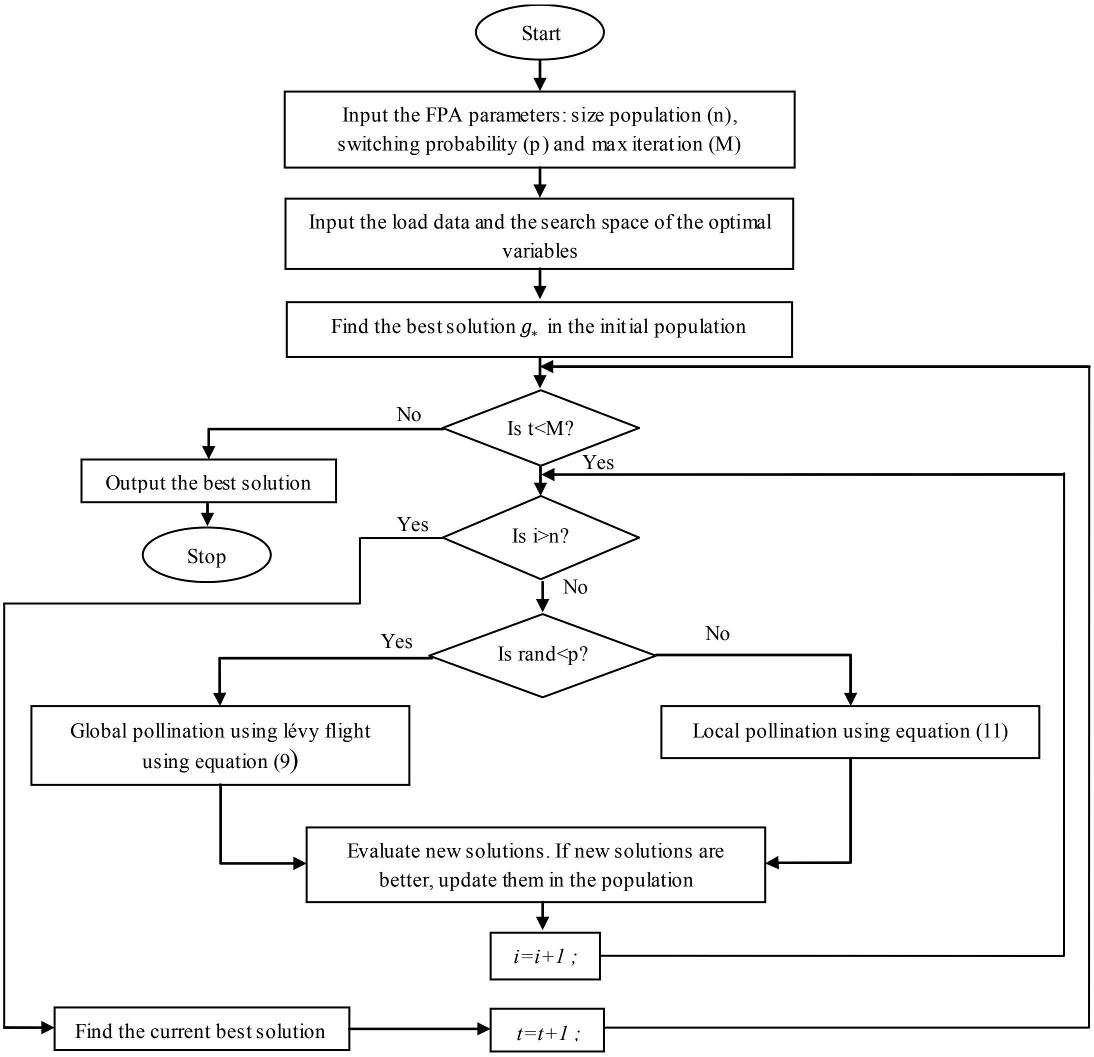


Fig. 3. The flowchart of FPA algorithm.

reproduction by pollination. This process is based on the transfer of pollen from flower to another.

This transfer can be divided into two ways. First way is the transfer by the biotic pollination done by animals that visit the flowers called pollinators. The second transfer way is the abiotic pollination like by wind, gravity or water. Moreover, the pollination can be realized by cross-pollination or self-pollination.

In the process of cross pollination the pollen is delivered to flower from different plant. Whereas, the self-pollination is the pollen moves to the female part of the same flower, or to another flower on the same individual plant (the plant can fertilize itself). Furthermore, in the transfer of pollen at long distance is called global pollination whereas the transfer of the pollen in same plant with different flower is called local pollination. This process is like an optimizing process of plants species. Four rules fundamentals using for the development of FPA as below:

1. The biotic and the cross-pollination can be considered as a global pollination process such as movement obeys Lévy flight behavior (Rule 1).
2. Abiotic and self-pollination can be supposed as local pollination (Rule 2).
3. Flower constancy can be considered as an equivalent to a reproduction probability that is proportionate to the similarity of two flowers involved (Rule3).

4. The pollination can be exchanged between local and global, this exchange controlled by switch probability p and this probability belongs to the range [0 1].

Both the rule one of global pollination and the rule third of flower constancy are formed in equation (9):

$$x_i^{t+1} = x_i^t + L(x_i^t - g_*) \tag{9}$$

x_i^t is the pollen i, in other words is the solution vector x_i at iteration t and g_* is the optimal solution. L is the Levy flights-based step length, this compatible with the force of pollination. The distance of fly of the insect can be long with variable steps; this is drawn from a Lévy distribution

$$L \sim \frac{\lambda\,\Gamma(\lambda)\sin\left(\frac{\pi\lambda}{2}\right)}{\pi}\frac{1}{s^{1+\lambda}} \quad (s \gg s_0 > 0) \tag{10}$$

In the equation (10), the term $\Gamma(\lambda)$ is the standard gamma function, and this distribution is valid for large steps $s > 0$.

The rule two of local pollination is given by equation (11):

$$x_i^{t+1} = x_i^t + \epsilon\left(x_j^t - x_k^t\right) \tag{11}$$

Where x_i^t is the pollen of flower and x_k^t is the pollen of another flower in the same plant species, this case if the flower constancy is in bounded space. Mathematically, if x_i^t and x_k^t comes from the same species or selected from the same population, this become a local random walk if we draw ϵ from a uniform distribution in [0, 1]. The Fig. 3 illustrates the different steps of optimization processes using FPA algorithm.

In this paper, the FPA is applied to get the lowest mean square error between the real and the estimated I-V curves. These estimated curves are obtained from equation (4) in case of a single diode model with five unknown parameters and from equation (5) in case of a double diode model with seven unknown parameters. The parameters will be identified in a well-defined search space for both cost functions as presented in the table 1.

And also, the table 2 as below shows the values of the adjustable parameters for runs the optimization process by the FPA.

TABLE 1. THE SPACE OF SEARCH (LOWER AND UPPER BOUNDS)

Parameter	Lower bound	Upper bound
$\boldsymbol{I}(\boldsymbol{A})$	0	20
$\boldsymbol{R_s}(\Omega)$	0	0.5
$\boldsymbol{R_{sh}}(\Omega)$	0	400
$\boldsymbol{I_{01}}(\mu\boldsymbol{A})$	0	10^{-2}
$\boldsymbol{I_{02}}(\mu\boldsymbol{A})$	0	10^{-2}
$\boldsymbol{n1}$	0	120
$\boldsymbol{n2}$	0	120

TABLE 2

CHARACTERISTICS PARAMETERS OF THE FPA

FPA parameter	Value
Population size (n)	25
Switch probability (p)	0.7
Max iteration (M)	10000

IV. MAXIMUM POWER POINT

In this section, the values at the maximum power point such as the current I_{mpp}, the voltage V_{mpp} and the power P_{mpp} are calculated as presented by equations (12), (13) and (14) based on the values of parameters previously estimated from the single diode model [20].

$$V_{Pmax0} = \frac{V_{pmax}}{1 + C_T(T_j + T_{j0})} + V_T\frac{T_{j0}}{T_j}ln\left(\frac{G_0}{G_{eff}}\right) - I_{Pmax}R_s\left(\frac{G_0}{G_{eff}} - 1\right) \tag{12}$$

$$I_{Pmax0} = I_{Pmax}\frac{G_0}{G_{eff}} \tag{13}$$

$$P_{Pmax} = I_{Pmax} \times V_{Pmax} \tag{14}$$

$G_0 = 1000\ w/m^2$ and $T_{j0} = 25\ °c$ are The irradiation and the temperature in the nominal condition respectively, R_s is the series resistor, $C_T = 0.0044\ k^{-1}$ is the temperature coefficient of power and T_j is the value of cell temperature obtained by equation (15)

$$T_j\left(G_{eff}, T_{amb}\right) = T_{amb} + (NOCT - T_{ambN})\frac{G_0}{G_{eff}} \tag{15}$$

In this equation we note that the relation between the cell temperature and nominal operating cell temperature is defined by NOCT, its value is given by the data sheet $NOCT = 48\ °c$, $G_N = 800\ w/m^2$ and $T_{ambN} = 20°c$ are used for the evaluation of the NOCT, V_T represents the thermal voltage and given by :

$$V_T = \frac{nkT}{q} \tag{16}$$

And more, the manufacture of the PV module gives the values of the voltage and the current at the MPP in nominal working so V_{Pmax0} called the nominal voltage and I_{Pmax0} called the nominal current.

V. SIMULATION AND EXPERIMENTAL RESULTS

Based on the FPA technique and using the I-V measurement data of the two selected Mono-crystalline silicon (mono-Si) PV modules (ISOFOTON106 & Condor 155P), the optimal parameters of both electrical models are extracted. Each I-V curve has 101 samples in a period of 30 seconds. The peak measuring device tracer (PVPM 2540C) is the instrument used for data acquisition. This data allows real I-V curve tracing.

The table 3 represents the electrical parameters given by the PV modules manufacturers.

1. Single diode model

To compare the proposed algorithm with two other algorithms, Firefly algorithm (FA) [21] and simulation annealing algorithm (SA) [22], a convergence efficiency test is required where the optimization process is run twenty times for similar initial conditions. The experimental I-V curve of ISOFOTON module is obtained at a temperature of 46.08°C and an irradiation of 723.37 W/m². The table 4 summarizes the results of comparison.

As can be seen from the table 4, it is very clear that the FPA gives better results for the same range of search. This is expressed by an RMSE of 0.022 and a MEAN of 0.0223 and a STD equal to 1,051E-06.

In addition, the most powerful factor of FPA algorithm is the speed of convergence to the optimal solution, the time of convergence to best solution by FPA is 22 second in 4185 iterations. Whereas, the two other algorithm take more time and more iteration, for the FA algorithm 30 second in 6632 iterations and for the SA algorithm 28 second in 6421 iterations. Moreover, taking into account the RMSE of the three algorithms, the FPA is more accurate according to the two other algorithms as is highlighted in the table 4.

TABLE 3. ELECTRICAL PARAMETERS AT STANDARD TEST CONDITIONS (STC) FOR USED PV MODULES USED

	ISOFOTON 106	CONDOR 155P
$V_{oc}(V)$	17,4	22,45
$I_{sc}(A)$	6,54	9,02
$V_{mp}(V)$	21,6	18,85
$I_{mp}(A)$	6,10	8,4
$P_{mp}(W)$	106	155
$\beta V_{oc}(\%/°C)$	-0,36	-0,32
$\alpha I_{sc}(\%/°C)$	0,06	0,03

TABLE 4. COMPARATIVE STUDY OF THREE METHODS FPA (POLLINATION PROCESS OF FLOWERS), FA (FIREFLY ALGORITHM) AND SA (SIMULATION ANNEALING ALGORITHM) FOR SINGLE DIODE MODEL

Parameter	FPA	FA	SA
$R_s(\Omega)$	0,238	0,0924	0,064
$R_{sh}(\Omega)$	400	318,331	348,805
$I_{ph}(A)$	4,710	4,761	4,841
$I_0(A)$	5,171E-06	0,0001	0,0002
n	50,643	67,175	71,172
$RMSE$	0,022	0,0457	0,064
$MEAN$	0,0223	0,0502	0,087
STD	1,051E-06	0,002	0,037

TABLE 5

COMPARATIVE STUDY BETWEEN EXPERIMENTAL CURVE AND CALCULATED CURVE USING FPA (POLLINATION PROCESS OF FLOWERS), FA (FIREFLY ALGORITHM) AND SA (SIMULATION ANNEALING ALGORITHM) FOR THE DOUBLE DIODE MODEL.

Parameter	FPA	FA	SA
$R_s(\Omega)$	0,166	0,016	0,022
$R_{sh}(\Omega)$	395,010	376,758	259,958
$I_{ph}(A)$	4,674	4,715	4,775
$I_{01}(A)$	1,072E-06	7,571E-05	0,0001
$I_{02}(A)$	1,743E-06	8,085E-05	0,0017
n_1	77,007	68,672	73,155
n_2	51,249	111,123	106,507
$RMSE$	0.0186	0.04321	0,062
$MEAN$	0,0224	0,0472	0,099
STD	0,0038	0,0056	0,037

In the table 4, the optimal value of R_{sh} extracted using the FPA is 400 ohm. This value is the same value of the upper bound of search space. So the algorithm provides a research of the optimal parameters in all space research with minimum iteration in short time. This is due to the switching between the global and local equation. Furthermore, it's increases the likelihood that the algorithms converge to the global optimum.

The figures 4 and 5 show a comparison between the experimental curves and the calculated ones for the two PV modules at different meteorological conditions (temperature and irradiation).

Figures 4 and 5 show clearly the effectiveness of the FPA in the modeling of the PV modules at different test conditions.

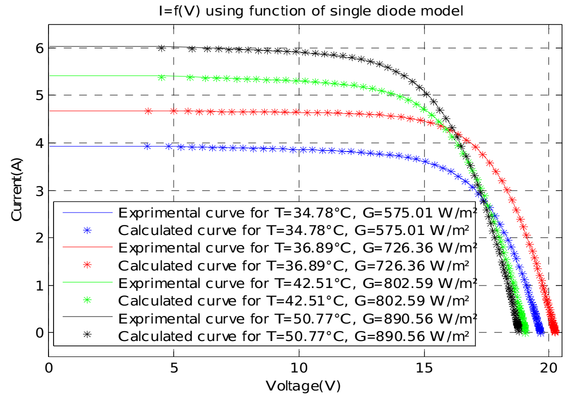
1. Double diode model

To ensure the effectiveness of the algorithm convergence, the FPA is tested in a more complex problem to extract the seven parameters of the double diode model following the same steps as for the single diode model.

From table 5, it's clear that, for the same initial conditions, the FPA gives better results compared to the two other algorithms.

After calculating of the time of the convergence using FPA algorithm, the FPA take 27 second in 7356 iterations. Whereas, the two other algorithms take more time so more iteration, for the FA algorithm 40 second in 9745 iterations and for the SA algorithm 36 second in 9342 iterations.

The Figures 6 and 7 shows also a comparison between the experimental curves and the calculated ones for the two PV modules at different meteorological conditions (temperature and irradiation).



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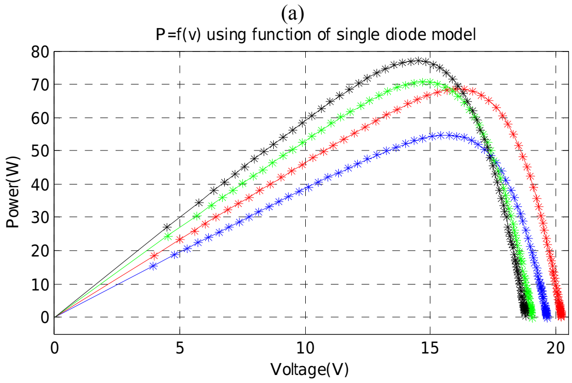
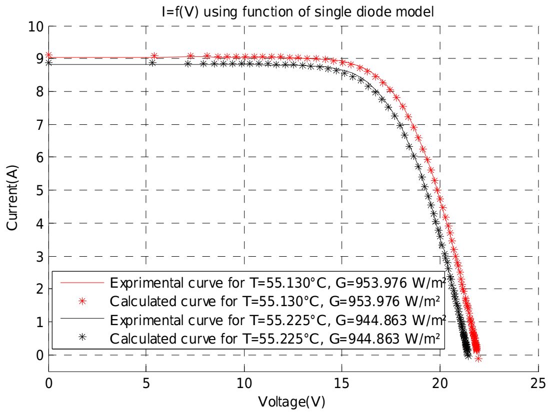


(b)

Fig. 4. Comparison between experimental and calculated I-V curves and P-V curves using single diode model for many meteorological conditions for ISOFOTON 106 module (a) I-V (b) P-V



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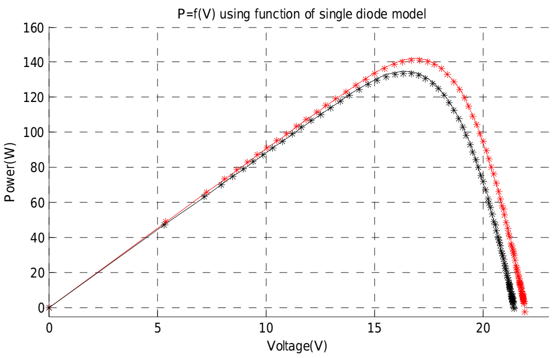

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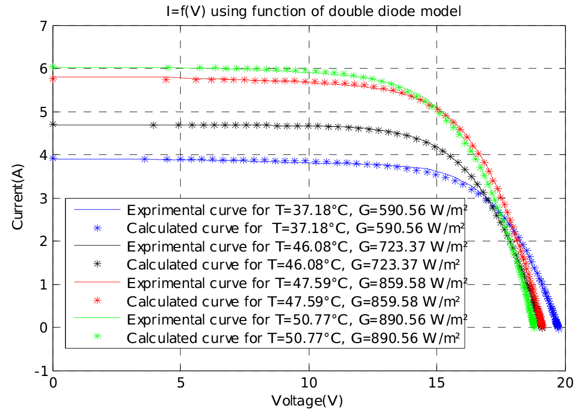
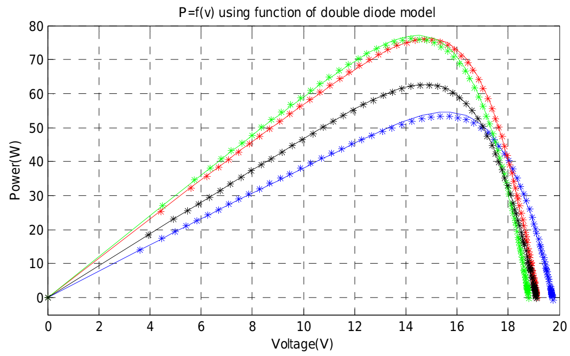
Fig. 5. Comparison between experimental and calculated I-V curves and P-V curves using single diode model for many meteorological conditions for CONDOR 155P module (a) I-V (b) P-V

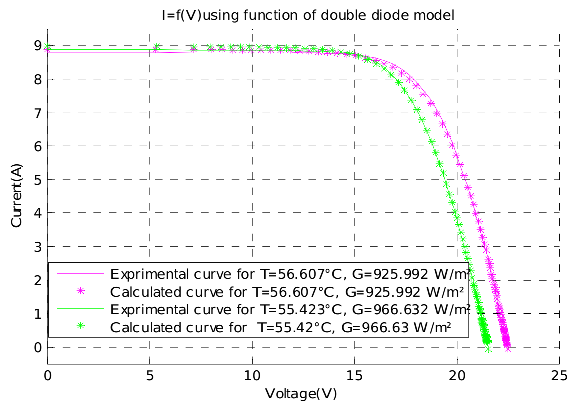


(a)



(b)

Fig. 6. Comparison between experimental and calculated I-V curves and P-V curves using double diode model for many meteorological conditions for ISOFOTON 106 module (a) I-V (b) P-V



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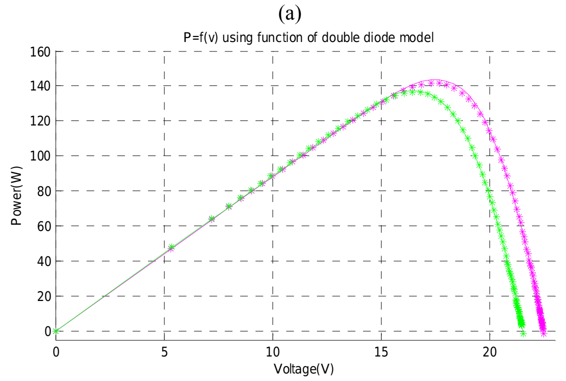
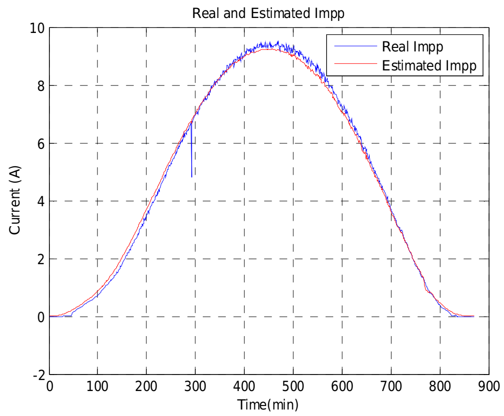
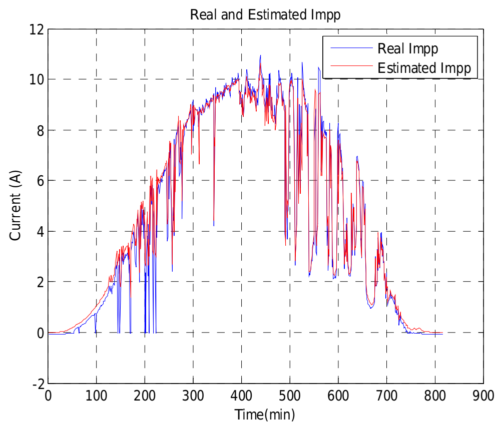


(b)

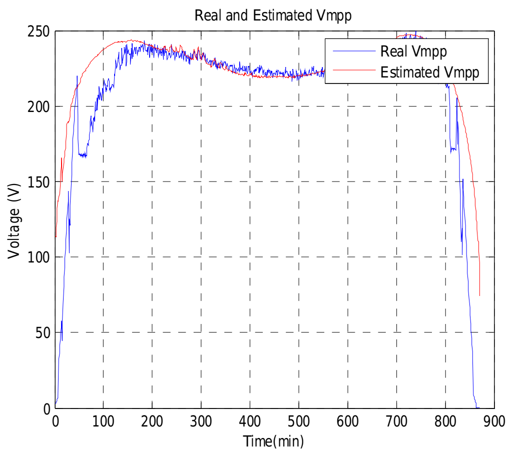
Fig. 7. Comparison between experimental and calculated I-V curves and P-V curves using double diode model for many meteorological conditions for CONDOR 155P module (a) I-V (b) P-V

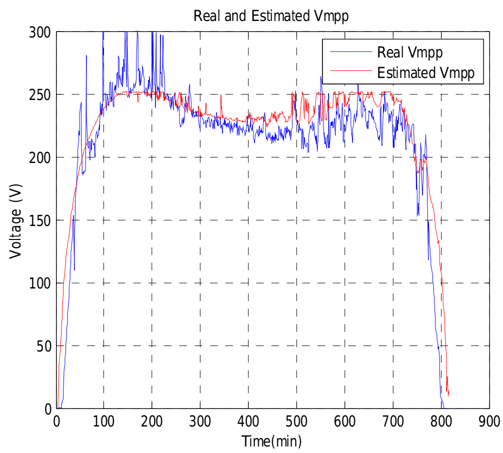




(a) (b)

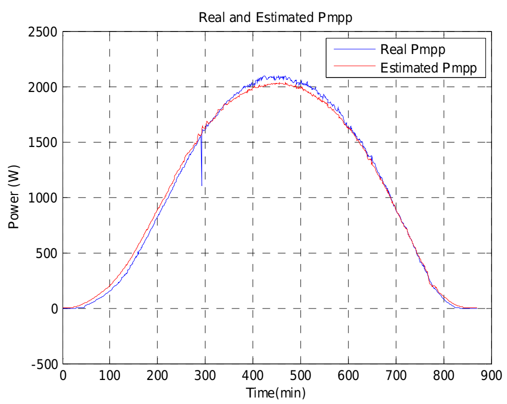
Fig. 9. Comparison between real and estimated values of current at MPP (a) clean sky day (b) cloudy sky day

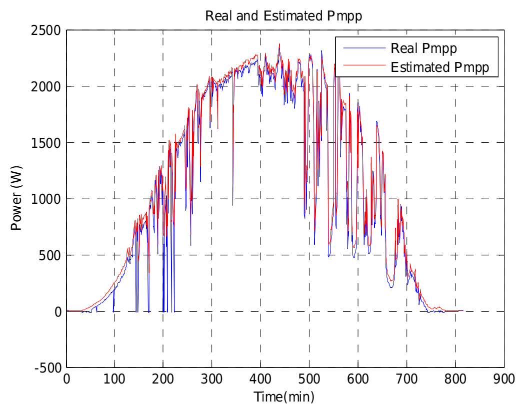




(a) (b)

Fig.10. Comparison between real and estimated values of voltage at MPP (a) clean sky day (b) cloudy sky day





(a) (b)

Fig.11. Comparison between real and estimated values of power at MPP (a) clean sky day (b) cloudy sky day

The figures 6 and 7 show the effectiveness of the FPA technique in extracting the seven parameters of the double diode model.

2. *Maximum power point*

The extracted parameters values of single diode model are used to estimate the MPP for two different profiles. The first day is without shading (clear sky) and the second day is with natural shading (cloudy sky). The photovoltaic panel used for the experiments consists of two parallel groups of 15 ISOFOTON modules connected in series 106/12 PV modules. Figures 9 to 11 show a comparison in the dynamic variation between estimated and acquired data of I_{mpp}, V_{mpp} and P_{mpp}, respectively, the comparison are done for a clear sky day and cloudy sky day

It's show clearly the effectiveness of result given by FPA in dynamic MPP, and also in two different day profiles.

VI. CONCLUSION

In this paper, Flower pollination algorithm has been proposed to extract the parameters of both single and double diode model. The FPA algorithm is used to identify the parameters of two different manufacturers of PV modules.

And also we comparing the result obtained by the FPA with two other algorithms such as firefly algorithm and simulated annealing algorithm, more than, several I-V curves of experimental data are compared with its. The best result between these three algorithms is given by the proposed FPA, therefore, it is clear that the FPA is more effective than the others for extract the optimal parameters of the PV modules. In addition, the parameters extract by FPA are used to estimate the maximum power point and the results have been compared with measured MPP of grid connected photovoltaic system.

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