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Extraction of the PV modules parameters with MPP estimation using the modified flower algorithm

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ABSTRACT

Modeling of photovoltaic (PV) module remains a serious issue for a lot of applications such as monitoring system or fault detection system. Therefore, several equivalents models of the PV cell have been proposed, the famous proposed models are called the single diode model (SDM) and double diode model (DDM). Each model possesses unknown parameters values which must be defined. In the present paper, two electrical models equivalent to PV cell are proposed, these models have an unknowns parameters which must be identified. The modified flower algorithm (MFA) is an optimization algorithm inspired from the nature, this algorithm is used to extract the optimal parameters values for both models. The proposed algorithm mimics the pathways of pollen transfer to help produce plants in nature, in other words, there are a lot of ways that the pollen can be travel to reproduce the plants these ways can be developed to a powerful optimization algorithm. In order to assess the proposed algorithm, several experimental data are used, these data are acquired in outdoors conditions and contains various I-V curves, these I-V curves are taken from three kind of PV cell technologies which namely Monocrystalline, Polycrystalline and Amorphous. In addition, the simulation results are compared with experimental data for both models. Moreover, the identified SDM parameters are applied to predict the current, the voltage and the power at the maximum power point (MPP) which was then compared to the MPP obtained from real data of grid connected photovoltaic system (GCPVS).

1. Introduction

In recent years, the use of renewable energy is grown due to the great development that touched this area. The most popular source is the solar energy. Several electrical systems are realized depending on this source, and among these systems regulations relating to the electricity grid and hybrid system. The main part of these systems is the PV module.

Several factors must be confirmed to guarantee the benefits of the PV system, among these factors one must chose a correct sizing which is requires a rigorous study, find a best location to install the system. In order to accomplish the righteous choice, the best performances and the lowest cost, the preliminary study is depending on the manufacturing data; nonetheless, the given data by the manufacturers of PV modules help just to make an approximate sizing of the PV system [1]. The purpose of this paper is to extract the best parameters values of the PV module for several cell PV technologies and using these parameters for the MPP estimation which guarantee a correct PV system sizing. Moreover, the predicted MPP value can be exploited for monitoring system in real time and to oversight the power losses of the GCPVS.

Moreover, several contributions have been used for PV cell modeling, these contributions follow two different paths; the first path is based on the PV module data to build a non-parametric model and this due by the machine learning algorithms. Where, its attributes are the input and the output of the systems modeled namely in our case the I-V PV cell [2]. Authors in Ref. [3] Propose hybrid neuro-fuzzy algorithm to build a non-parametric model which is based on few old measured PV cell data, the obtained model predicted a short-circuit current and an open circuit voltage of the PV cell. The results getting by this model are more accurate than the conventional PV cell model.

Furthermore, an intelligent model is performed to estimate the PV module parameters, this model obtain by a training process

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using the neural network [4], the developed model inputs are the weather conditions such as temperature and solar irradiation, and the model outputs are the five parameters of the SDM which found without going through the iterative research that used an optimization algorithm. The training process is done using experimental data recorded before; these data contain the current, the voltage and the estimated parameters of the SDM. The obtained model is assess by an measured data, the results given by the model are very close to the experimental data which also shows that predicted curve have a good matching to the measured curve.

The second path uses a parametric model, in this path several models are proposed in the literature [5]. However, the most popular equivalent models are called single and double diode models respectively [6]. Each model possesses unknown values parameters, therefore an identification process must be executed in purpose to find the best parameters. As a result, different optimization algorithms have been intended to extract the parameter from the PV cell.

In addition, the optimization algorithms are divided into several ones, the well-used is stochastic techniques, among these techniques are heuristic and meta-heuristic contributions, generally, these later has inspired from the nature, among them namely: Genetic Algorithm (GA) [7], Particle Swarm Optimization (PSO) [8], Harmony Search (HS) [9], Pattern Search (PS) [10], Moth-Flame Optimization Algorithm (MFOA) [11], Simulated Annealing (SA) [12], Artificial Bee Colony (ABC) [13], Cat Swarm Optimization (CSO) [14], Differential Evolution Technique (DET) [15], Chaotic Particle Swarm Optimization (CPSO) [16], Firefly Algorithm (FA) [17], Bird Mating Optimizer (BMO) [18], Cuckoo Search (CS) [19], Artificial Fish Swarm Algorithm (AFSA) [20], Biogeography Based Optimization Algorithm with Mutation (BBO-M) [21], Artificial Immune System (AIS) [22], Multiple Learning Backtracking Search Algorithm (MLBSA) [23], Ant Lion Optimizer (ALO) [24], these algorithms seek to solve the parameters extraction problem of PV module with artificial intelligence approaches.

In this work, a modified flower algorithm (MFA) is proposed, this algorithm have the basic rules of flower algorithm. Furthermore, the MFA is applied to identify the unknown parameters of SDM and DDM, this algorithm mimics the moving ways of the pollen in the nature to reproduce the plants [25–27]. Therefore, four main rules summarized the pollen moving process, these rules are converted into an optimization algorithm. This algorithm provides a good solution with a minimum number of iteration as well a minimum rate of convergence for both models and for several PV modules manufacturing with different type of PV cell [28,29]. In addition, the extracted parameters of the SDM are used to estimate the MPP and give good results in terms of matching with experimental data of GCPVS.

This paper is divided 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 part of this section, the optimization problem is defined. The second section is reserved for the basic steps of the MFA 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.

2. Problem formulation

In this section, the PV cell models used in this paper are described with a closely look. As good as, these models are the single diode model and the double diode model which these models possess five unknown variables and seven unknown variables respectively.

2.1. Single diode model (SDM)

The PV cell have a several equivalent models and the one of the most used in the literature is called single diode model, this model consist of four electrical elements which are current generator, diode and two resistors as represented in Fig. 1. The model is formed by connected generator of current, a diode and the resistor R_{sh} in parallel and these last are in series with another resistor R_s. Although, the forming model is tied with electrical behavior of the PV cell such as the generator of current represents the current generated by radiation wave, both parallel and series resistor serve as the losses energy in the PV cell [30].

Mathematically, the SDM circuit can be converted to a mathematical equation by applied the Kirchhoff's law as expressed in equation (1). Additionally, the approximate function get from this model have a nonlinear variation, which represents the generated current by the PV cell depending on the output voltage as described in the equation (4), where the generated current is named I. Furthermore, the model have other current that is called photocurrent I_{ph}, as well as the diode current I_d and it possesses a shunt current I_{sh}. Moreover, the model contains two constants namely: the electric charge and the Boltzmann's constant which are called q and K respectively. T_c is the value of cell temperature. The ideality factor of the diode is named n; I_0 is the saturation current due to diffusion and recombination.

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

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

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

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

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

The equation (4) contains five unknowns variables that must be identified using an optimization algorithm, these variables are I_{ph}, I_0, R_s, R_{sh} and n. The SDM is considered good and easy for the simulation of the I-V curve; however, this model have miss the

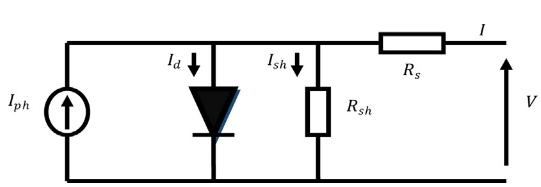


Fig. 1. Equivalent electrical circuit of Single diode model for solar cell.

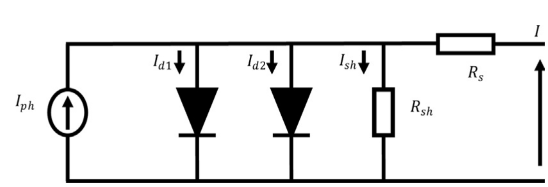


Fig. 2. Equivalent electrical circuit of Double diode model for solar cell.

phenomena of the recombination effect in the diode, because of this, it is not the most accurate model, while for study of solar cell characteristics at critical points, DDM is more complicated and more enhanced, so is preferable to including it in this study.

2.2. Double diode model (DDM)

The DDM is considered more accurate and complicate compared to the single diode model; this model is included in our study. This model comprises two diodes instead one diode as the SDM mentioned previously. Therefore, the recombination current passed across these diodes is divided into two currents named I_{01} and I_{02}, related to 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 described in the Fig. 2 with n = 2 in the schematic of the single diode model [2].

$$I = I_{ph} - I_{01}\left[\exp\left(\frac{q(V+R_sI)}{n_1KT_c}\right) - 1\right] - I_{02}\left[\exp\left(\frac{q(V+R_sI)}{n_2KT_c}\right) - 1\right] - \frac{V+R_sI}{R_{sh}} \tag{5}$$

This model have seven unknowns variables which are I_{01}, I_{02}, I_{ph}, n_1, n_2, R_s and R_{sh} and are called the currents of saturation, the photo generated current, ideality factors of the two diodes and both resistors series and parallel respectively.

3. Objective function

The aim of this paper is to find the best values of these unknown variables for both models. Based on the optimization of the root mean square error (RMSE) obtained by the subtraction between the data of the model with identified variables and the experimental data, the flowchart of the optimization process is represented in Fig. 3. Consequently, each model have an own unknowns variables, therefore each model possess its own cost function. The function of the error is expressed in the equation (6) taken as the objective function in our work. Thus, the error resulting from the measured data of the current and the simulated data by the equation (7) or (8) is minimized too.

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

I_m and V_m are the measured current and voltage respectively, K is the number of samples contained in the measured data set; the best solution found can be represented by a vector X, on one hand, the model of single diode $X = [I_{ph}, I_0, n, R_s, R_{sh}]$, on other hand, the model of double diode $X = [I_{ph}, I_{01}, I_{02}, n_1, n_2, R_s, R_{sh}]$ as defined in equations (7) and (8)

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

$$f(I_m, V_m, X) = I_{ph} - I_{01}\left[\exp\left(\frac{q(V_m+R_sI_m)}{n_1KT_c}\right) - 1\right] - I_{02}\left[\exp\left(\frac{q(V_m+R_sI_m)}{n_2KT_c}\right) - 1\right] - \frac{V_m+R_sI_m}{R_{sh}} - I_m \tag{8}$$

4. Modified flower algorithm (MFA)

The flower algorithm (FA) is one of the metaheuristic algorithms created by Yang [31], this algorithm is imitative of the behavior in the plants pollination. The plants continue survive by the pollination process that can be considered as an optimization method, therefore this process enable to use for solve the optimization problems. In addition, the pollination process is done by the flowering plants, where each flower can transfer its own pollen from one to another for helping the plants in reproduction while this can be achieved by several ways. Generally, these ways can be divided into two manners which are biotic and abiotic way. The biotic pollination can be performed by insects, animals or birds that move between the flowers and these are called pollinators. On other hand, the abiotic pollination can be realized by rain, wind or gravity. Besides, each way itself can be occurred by two possibilities, either the pollen moves from a blossom to another in different tree, and this is called cross pollination, otherwise in the same tree, the pollen moves from blossom to another or the pollen transferred from the male side to the female side in the same flower, and this is called fertilization. Consequently, the pollen able to move for a long distance or even in the tree itself, mathematically those represent global pollination or local pollination respectively. Based on these hypotheses, the pollination process has four main rules which can aid to describe the flower algorithm.

- Global pollination can be due by the biotic and the cross-pollination as well as the pollinators is taking the pollen following the Lévy flights behavior (first rule);
- Both abiotic pollination and self-pollination are classified as local pollination (second rule);
- Introduce a factor named flower constancy which can be expressed by a reproduction probability while this latter is a

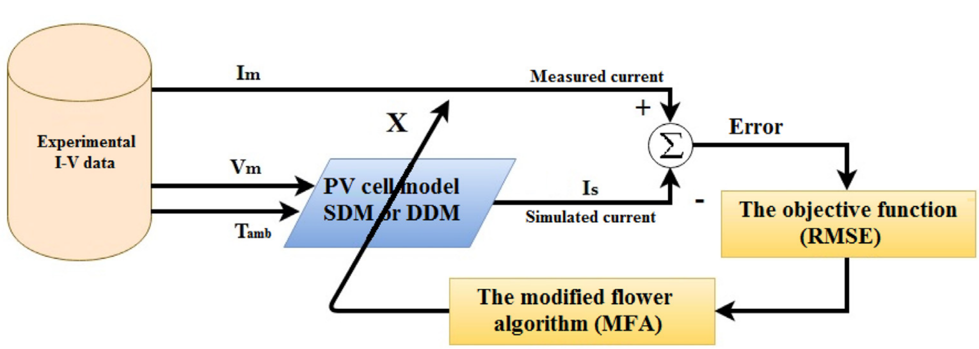


Fig. 3. The synoptic diagram of the optimization process.

proportional to the similarity among two working flowers (third rule);

- Introduce a switching factor that allowing to pass from the local pollination to the global pollination or vice versa which can be represented by a switching probability called p, where $p \in [0,1]$ (forth rule);

The first and the third rule can be expressed in equation (9):

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

x_i^t is the solution vector x_i at iteration t or the pollen i, g_* is the vector of the optimal solution which is corresponding to the best solution. L is a parameter of the Lévy flight which is tied with the walking step size. Therefore, this parameter is homogeneous with the pollination strength. The insects have a various walking step because they have a different characteristics like size of body, type, wings, which is meaning they can displaced with a different distance. The Lévy flight can be used to imitate efficiently this characteristic while this is get from a Lévy distribution. As well as, L is expressed in the equation (10). Where $\Gamma(\lambda)$ is the standard gamma function, this distribution is valid for large steps $s > 0$.

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

The second rule is represented by the equation (11):

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

Both x_i^t and x_k^t represent the pollen that comes from different flowers in the same plant species. Therefore, the flower constancy is in a restricted space for the possibility that the two pollen x_i^t and x_k^t are coming from the same plant species or they are chosen from the same population. The shown equation (11) becomes a local random walk, if we draw ε from a uniform distribution in [0, 1], as well as the new best solution will be not far from last best solution.

In this paper, a new modified flower algorithm is proposed, this

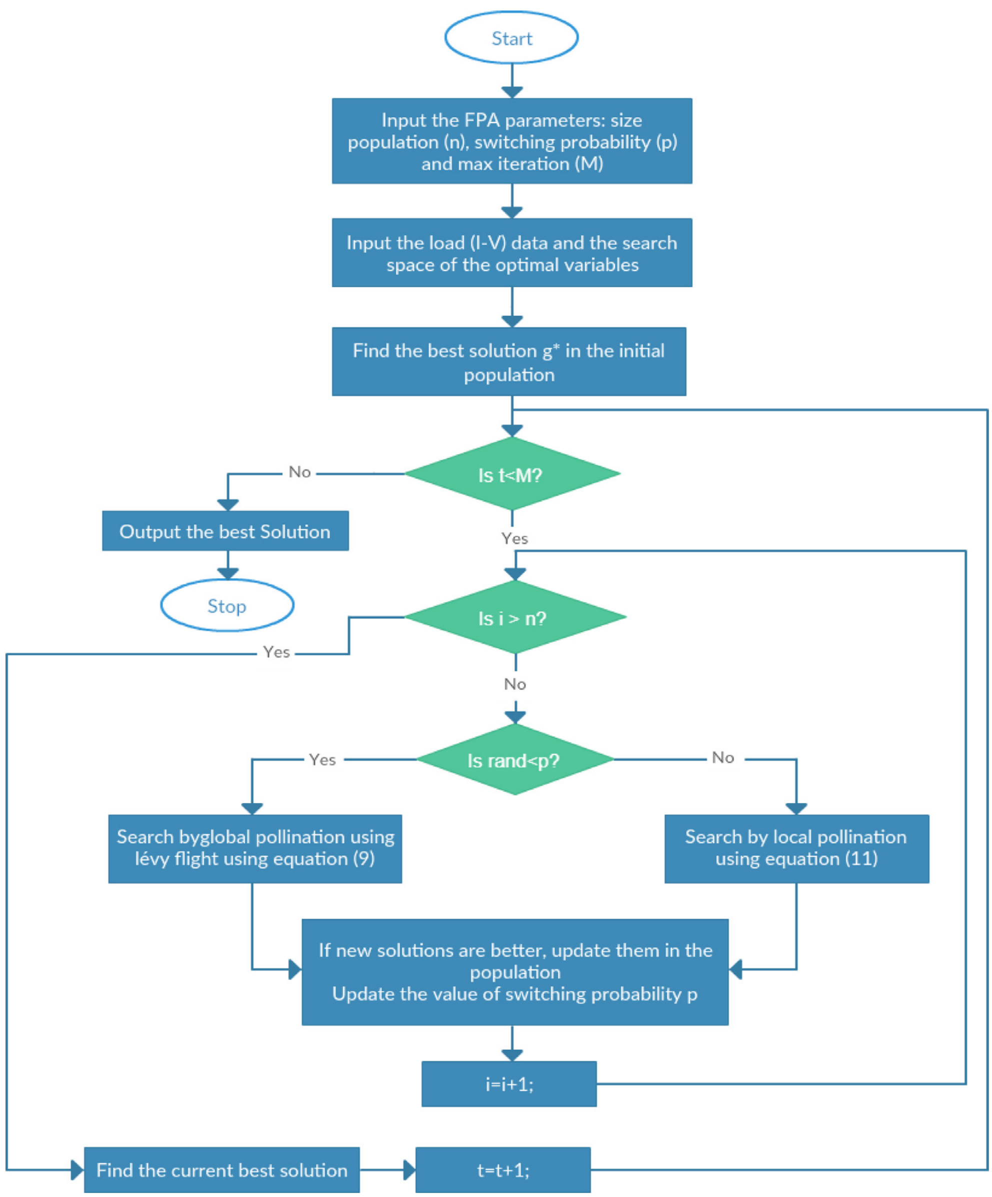


Fig. 4. The flowchart of modified flower algorithm.

Table 1
The search space (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}
$\boldsymbol{n}1$	0	120
$\boldsymbol{n}2$	0	120

Table 2
Characteristics parameters of the MFA.

MFA parameter	Value
Population size (n)	25
Switch probability (p)	0.7
Max iteration (M)	1000

algorithm has the same fundamental rules of the FA expect the four rule is modified in such a way that the switching probability is changed at each iteration [36]. The main idea in this algorithm is to change the value of the switching probability in order to increase the accuracy of the solution so that the solution found will be close to the global solution. In addition, instead algorithm is working with a fixed probability and which already selected in the initial conditions, the probability becomes variable in this new algorithm at each iteration. The flowchart describes the main rules of the modified flower algorithm is shown in Fig. 4.

In order to find the best solution vector, the MFA is used to search the optimal mean square error that get from the error between the experimental data and the estimated one. The simulated data is getting from the equation (4) in case of a SDM which contains five unknown variables, and as expressed in the equation (5) in case of a DDM which has seven unknown variables. To can run the optimization process for each model, some parameters must be provided in advance such as the search space of the solution and the characteristics parameters of the MFA. Consequently, the upper and the lower bound of the search space are represented in Table 1 that represents the vector of the search space for the ISOFOTON PV module; each other PV module has its own vector. Moreover, the Table 2 contains the parameters values of MFA such as the number of population, the initial switching probability and the maximum of iteration.

5. Maximum power point

Each I-V curve of the PV module can be represented by a nonlinear function such as the obtained function from the SDM; this function has a maximum power point (MPP). In addition, each I-V curve has its own point, and this point can be represented by their coordinates of voltage and current which are named V_{Pmax} and I_{Pmax} respectively, and the power at the maximum is named P_{Pmax}. Furthermore, turning from the static I-V curve to the dynamic variation of the current and the voltage is based on the estimation method [32]. This method uses the data of the PV module manufacturing and the extracted parameters of the SDM, the equations (12)–(14) are used to calculate the current I_{Pmax}, the voltage V_{Pmax} and the power P_{Pmax}:

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

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

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

where: G_0 and T_{j0} are the irradiation and temperature respectively in the standard test condition (STC), also the values of the G_0 is equal 1000 W/m^2 and T_{j0} is equal 25 °C. R_s is the series resistor of the SDM, C_T is the power temperature coefficient, while the value of T_j is calculated by the equation (15):

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

In the equation (15), NOCT represents the relation between the temperature of the PV cell and the temperature of the PV cell at the

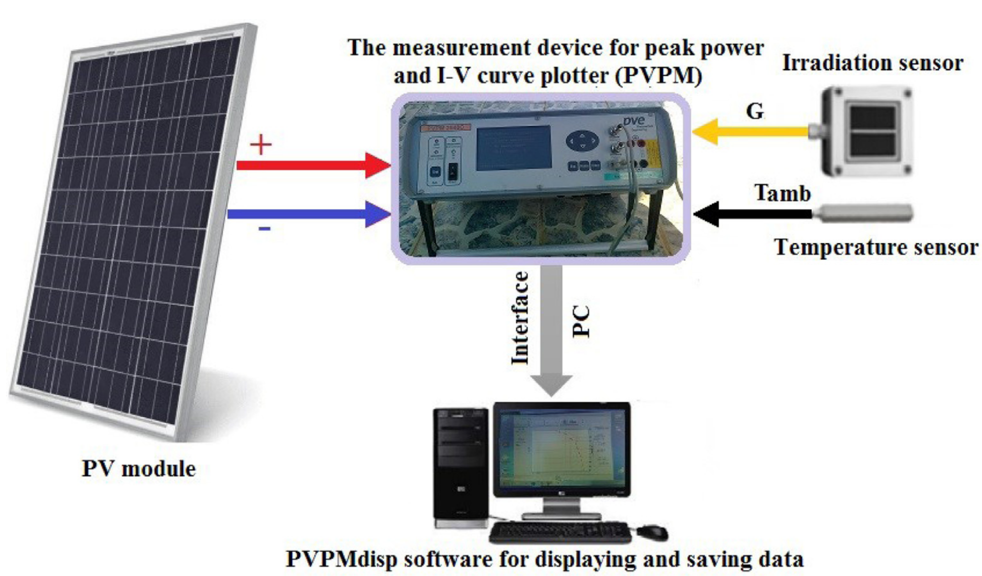
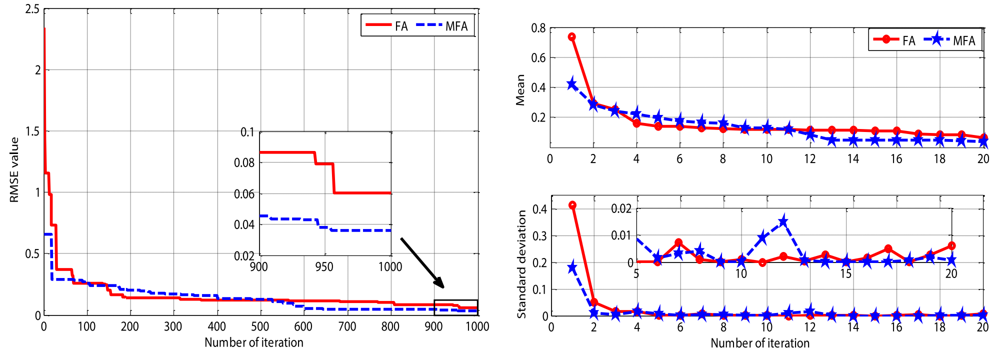
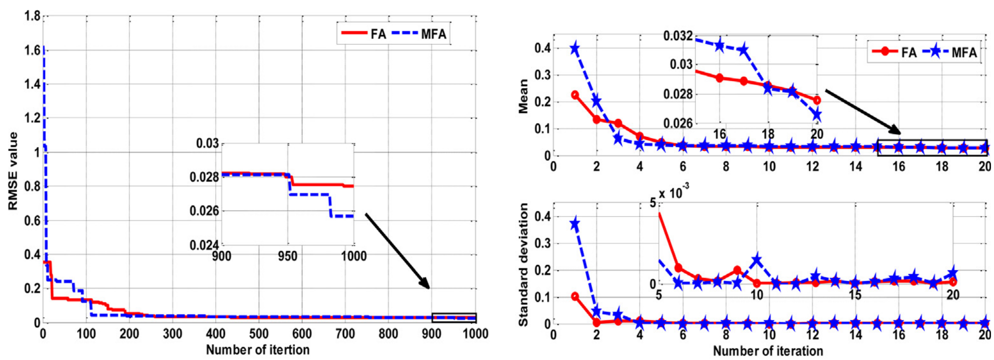


Fig. 5. Synoptic diagram for data acquisition of I-V characteristics.



(a) (b)

Fig. 6. The curves of error variation during the extraction parameters process for SDM obtained from FA or MFA (a) RMSE (b) Mean and Standard deviation for each 50 iterations.



(a) (b)

Fig. 7. The curves of error variation during the extraction parameters process for DDM obtained from FA or MFA (a) RMSE (b) Mean and Standard deviation for each 50 iterations.

nominal operating conditions and this value can be find in the manufacturing data, we find that NOCT = 48 °C. The G_N and T_{ambN} are irradiation and temperature ambient at normal operating conditions and their values are 800 W/m^2 and 20 °C respectively, these values are used for the evaluation of the NOCT. V_T is called the thermal voltage and is expressed by equation (16):

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

Moreover, V_{Pmax0} and I_{Pmax0} are the voltage and the current at the MPP in nominal conditions and these values are given by the PV module manufacturer.

6. Simulation and experimental results

In the present section, the results of the optimization process are demonstrated for both SDM and DDM models, so the FA is applied to find the best solution along for the I-V experimental data of the selected modules (Table 4). Experimental data consisting of three different kinds of PV cell technologies; these technologies are Mono-crystalline silicon, Polycrystalline silicon and Amorphous, where the optimal parameters of both electrical models are extracted for each type. The peak measuring device tracer (PVPM 2540C) is the instrument used for data acquisition that provides I-V measured curve of 101 samples in a period of 30 s [33]. This data gives a real I-V curve tracing of the chosen PV module. The Fig. 5 shows the synoptic diagram the acquisition platform system.

The study provides a test of FA for several PV manufacturing with various meteorological conditions. Where, data of two Amorphous, three Poly-crystalline silicon and three Mono-crystalline silicon PV modules are used for the test. Moreover, a comparison with three other algorithms namely: Generalized evolutionary walker algorithm (GEWA) [31], Simulated Annealing

Table 3
PV module manufacturer data.

PV modules technology	Manufacturer	Pmp (W)	Isc (A)	Imp (A)	Voc (V)	Vmp (V)
Monocrystalline silicon	SANYO	180	3.65	3.33	66.4	54
	CONDOR	155	9.02	8.4	22.45	18.85
	ISOFOTON	100	3.27	2.87	43.2	34.8
Polycrystalline silicon	CONDOR	150	8.59	8.11	22.9	18.5
	KYOCERA	125	8	7.2	21.7	17.4
	SCHOTT SOLAR	105	4.92	4.47	29.5	23.5
Amorphous	INVENTUX	125	1.22	1.01	168	127
	UNISOLAR	64	5.1	4.1	21.3	15.6

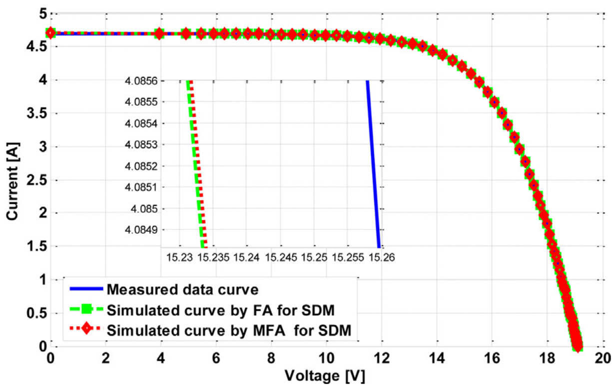


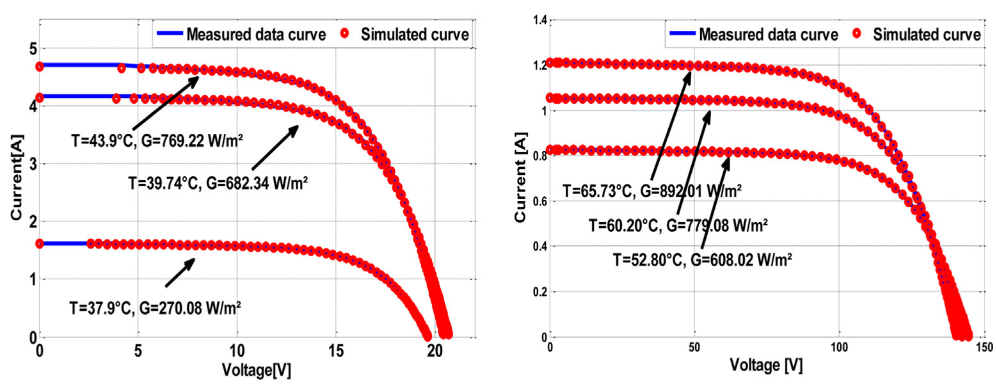
Fig. 8. Comparison between I-V curves (measured, simulated by FA and simulated by MFA) for SDM with $T_{amb} = 46.08\,^{\circ}C$ and $G = 723.37\ W/m^2$.

(SA) [34] and Lightning Search Algorithm (LSA) is carried out [35]. In addition, a test of convergence efficiency was done by the running of the process 20 times for each algorithm and calculating the average of STD of the errors, this test is performed of both models (SDM and DDM).

To assess the new proposed algorithm, the MFA is compared with FA, therefore, these algorithms are run with the same initial conditions which is indicated in Tables 1 and 2.

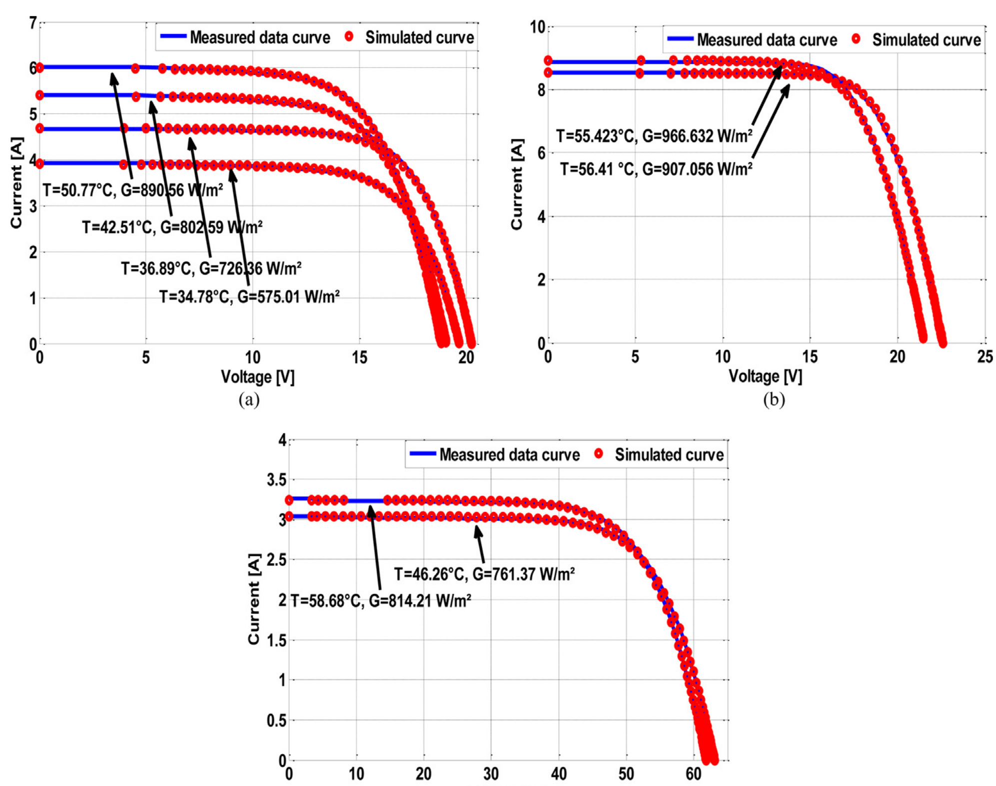
The variation of the error during the extraction parameters process for SDM using the FA and MFA is plotted in the Fig. 6, the two Fig. (6.a) and (6.b) show the evolution of error related to the SDM and mean & standard deviation for every 50 successive iterations respectively, this figure demonstrates that the MFA converge to the minimal error lower than the obtained one from the FA which means the solution gives by the MFA is better than the FA.

For the DDM, the curves of the error variation are illustrated in



(a) (b)

Fig. 9. Comparison between measured and simulated I-V curves based on SDM for Amorphous PV module technology (a) UNISOLAR and (b) INVENTUX.



(a) (b) (c)

Fig. 10. Comparison between measured and simulated I-V curves based on SDM for Monocrystalline PV module technology (a) ISOFOTON, (b) CONDOR and (c) SANYO.

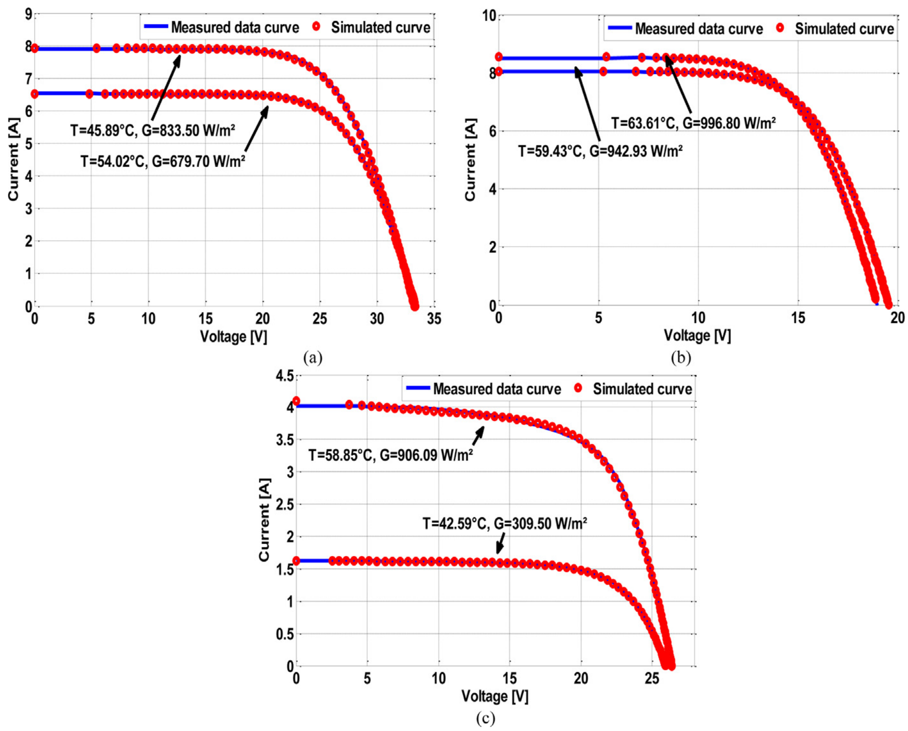


Fig. 11. Comparison between measured and simulated I-V curves based on SDM for Polycrystalline PV module technology (a) CONDOR, (b) KYOCERA and (c) SCHOTT SOLAR.

Fig. 7 resulting from the optimization process by FA and MFA. In addition, the Fig. (7.a) and (7.b) represent the evolution of error that is tied with the DDM and mean & standard deviation for every 50 successive iterations respectively, this figure proves that the MFA converge to the minimal error better than the obtained one from the FA.

Consequently, the proposed modification in the FA shown that MFA is an improved version of FA for the two PV cell models.

6.1. Single diode model

For this case, five parameters were included in this identification. The process consists of the minimization of the cost function given in equation (7) using both MFA. Figs. 9–11 show the matching between the measured and the simulated with the obtained parameters I-V curves for different solar cell technology. To evaluate the proposed algorithm with various PV module technologies, eight PV modules are selected with different output power, as presented in the Table 3.

A convergence efficiency test is required, therefore, 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/m^2 as shown in the Fig. 8. The Table 4 summarizes the results of comparison.

As can be seen from the Table 4, it is very clear that the MFA is the one that gives better results for the same range of search space. This is expressed by an RMSE of 0.02 and a MEAN of 0.022 and a STD equal to 1.052E-6.

In addition, the weakness factor of MFA compared to FA is the speed of convergence to the optimal solution, the time of convergence to best solution by MFA is 36 s while the FA took 28 s to converge. Whereas, the other algorithms take a different elapsed time, for the SA algorithm 1 s, for the GEWA algorithm 2 s, for the LSA algorithm 240 s. Moreover, taking into account the RMSE of the four algorithms, the MFA is one more accurate among them according to the other algorithms results as is highlighted in the Table 4.

From the Table 4, the optimal value of R_{sh} extracted using the FA is 400 Ohm and this value is the same value of the upper bound of

Table 4
Comparative results between MFA, FA, GEWA, SA and LSA algorithms for SDM.

Parameter	SA	GEWA	FA	LSA	MFA
$R_s (\Omega)$	0.064	0.090	0.238	0.1517	0.2382
$R_{sh} (\Omega)$	348.805	305.859	400	111.295	399.828
$I_{ph} (A)$	4.841	4.763	4.710	4.771	4.711
$I_0 (A)$	0.0002	1.602 E-4	5.171E-6	0.0076	5.207E-06
n	71.172	67.456	50.643	50.915	50,668
RMSE	0.064	0.046	0.022	0.0224	0.02
MEAN	0.087	0.050	0.0223	0.023	0.022
STD	0.037	0.002	1.051E-6	0.002	1.052E-6

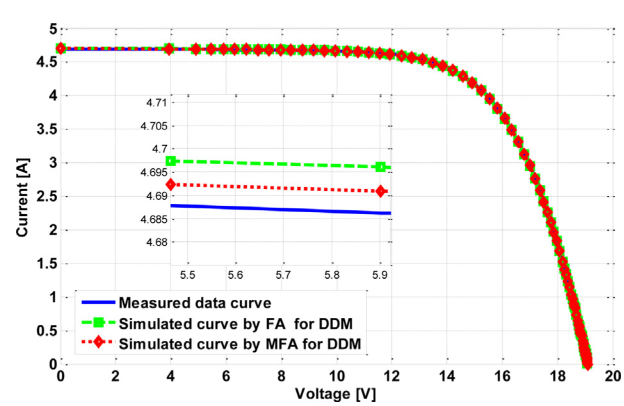


Fig. 12. Comparison between I-V curves (measured, simulated by FA and simulated by MFA) for DDM with $T_{amb} = 46.08$ °C and G = 723.37 W/m^2.

Table 5
Comparative results between MFA, FA, GEWA, SA and LSA algorithms for DDM.

Parameter	SA	GEWA	FA	LSA	MFA
$R_s(\Omega)$	0.022	0.034	0.166	0.0424	0.1769
$R_{sh}(\Omega)$	259.958	186.770	395.010	106.332	396.914
$I_{ph}(A)$	4.775	4.763	4.674	4.7903	4.7297
$I_{01}(A)$	0.0001	1.60E-4	1.072E-6	5.99E-6	2.9121e-05
$I_{02}(A)$	0.0017	6.464 E-4	1.743E-6	5.139E-4	5.8516e-06
n_1	73.155	79.219	77.007	100.3724	57.9186
n_2	106.507	111.304	51.249	75.4107	111.97
RMSE	0.062	0.0842	0.0186	0.0556	0.0181
MEAN	0.099	0.1572	0.0224	0.0603	0.0222
STD	0.037	0.0512	0.0038	0.0033	0.0038

search space. So the algorithm can be fall in a local solution which provides local optimal parameters. Therefore, to avoid the local solution is better to update the switching probability in the population. Moreover, the MFA ensured the search of the optimal parameters in all search space. Furthermore, it increases the probability that the algorithms converge to the global optimum.

Figs. 9–11 show the I-V curves of both experimental data and the simulated curve for Amorphous, Mono-crystalline and Polycrystalline cell technology respectively.

The Figs. 9–11 show a comparison between the experimental curves and the calculated ones for PV modules at different meteorological conditions (temperature and irradiation). Figs. 9 and 11 show clearly the effectiveness of the MFA in modeling of the PV modules at different test conditions.

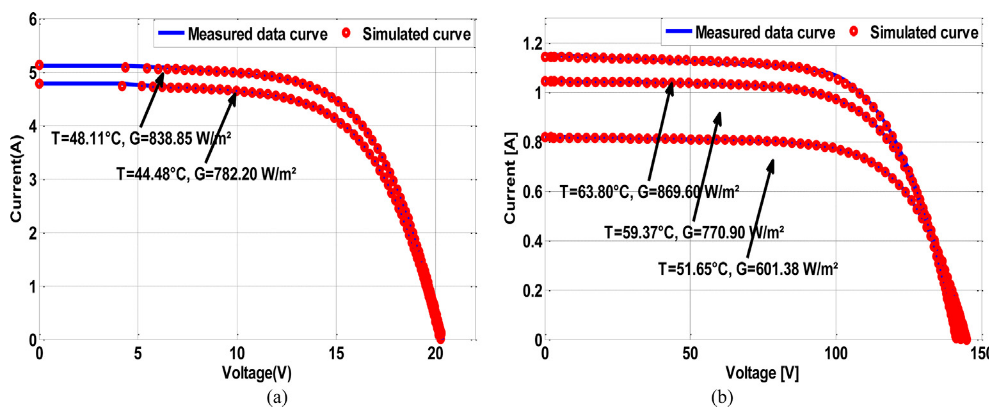


Fig. 13. Comparison between measured and simulated I-V curves based on DDM for amorphous PV module technology (a) UNISOLAR and (b) INVENTUX.

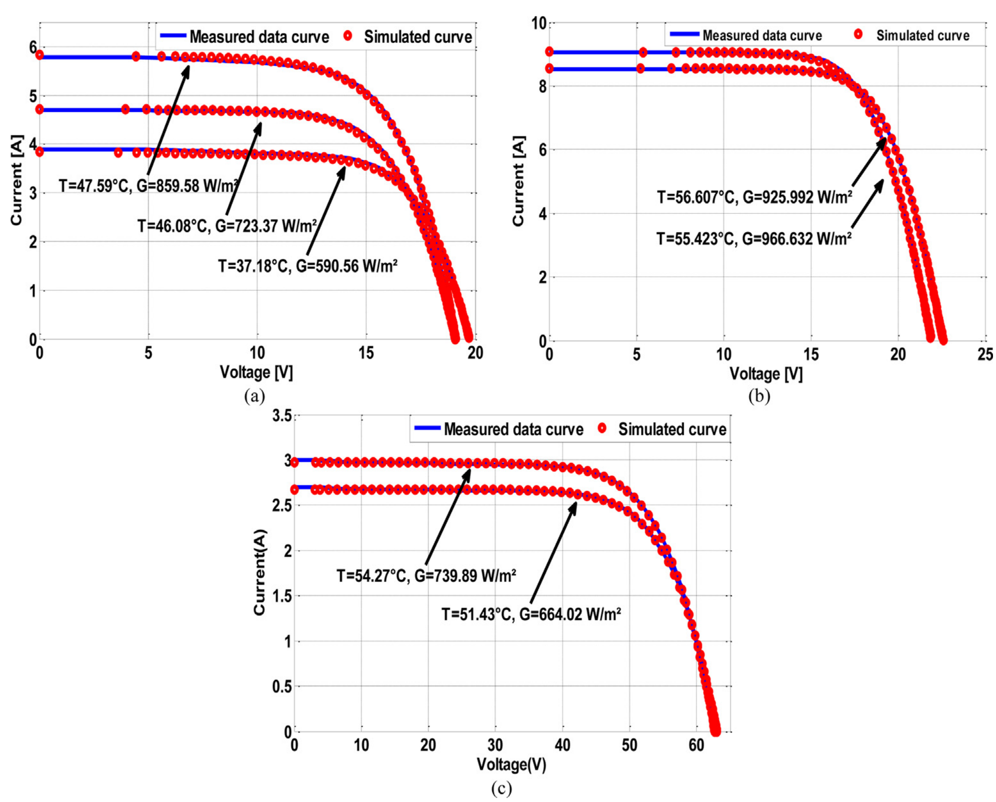


Fig. 14. Comparison between measured and simulated I-V curves based on DDM for Monocrystalline PV module technology (a) ISOFOTON, (b) CONDOR and (c) SANYO.

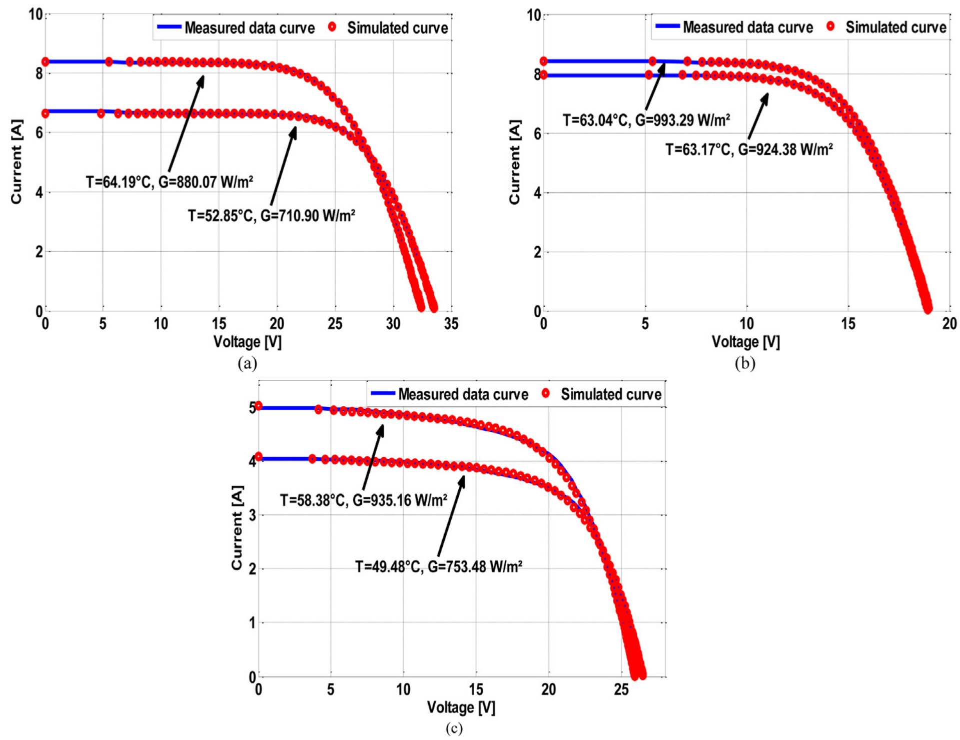


Fig. 15. Comparison between measured and simulated I-V curves based on DDM for Polycrystalline PV module technology (a) CONDOR, (b) KYOCERA and (c) SCHOTTSOLAR.

From the Figs. 9–11, we notice that the curve obtained from the simulation of the SDM with the extracted parameters give a good matching with the experimental data of the three cell technology and under many irradiation values.

6.2. Double diode model

To ensure and to validate the effectiveness of the algorithm convergence, the MFA is tested in a more complex problem to extract the seven parameters of the DDM following the same steps as for the SDM, the Fig. 12 represented the comparison between the experimental I-V curve and the one obtained from identified parameters by MFA and FA. From Table 5, it's clear that, for the same initial conditions, the MFA gives better results compared to the old FA and the three other algorithms. The displayed time of the convergence using MFA algorithm is equal to 48 s, which is slowly compared to the elapsed time of the FA that take 34 s to converge. Whereas, the three other algorithms take these times, for the GEWA algorithm 4 s, for the SA algorithm 2 s and for LSA takes 322 s. On the one hand, based on the elapsed time value of these algorithms, we notice that the MFA is slowly to find the best solution compared with the FA, the SA and GEWA algorithm, on the other hand the solution found by the MFA is more accurate than the others algorithms. Furthermore, the LSA takes more time than the MFA, compared the minimal error between these two algorithms, the MFA give better results.

Figs. 13–15 show also a comparison between the experimental curves got in outdoor condition with various values of irradiation and temperature, and the simulated curve for each ones for the three types of cell technologies.

From the figures, we concluded that the MFA is an effectiveness algorithm used for find the optimal parameters for more

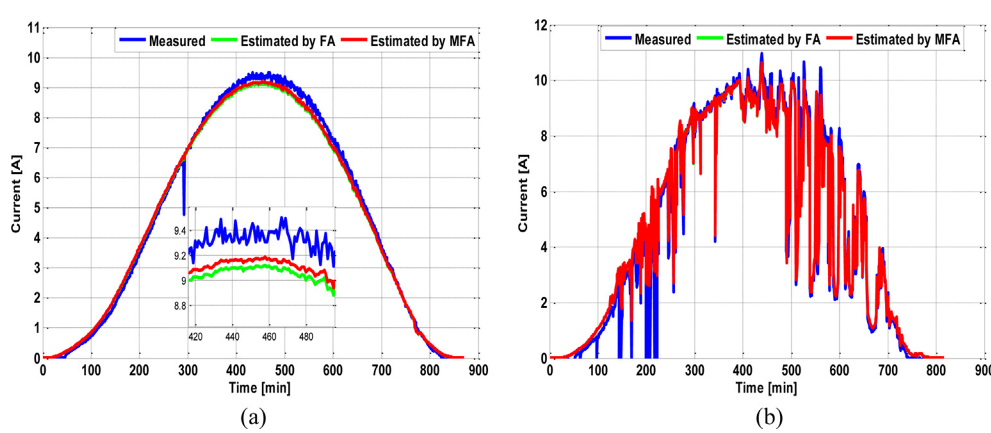
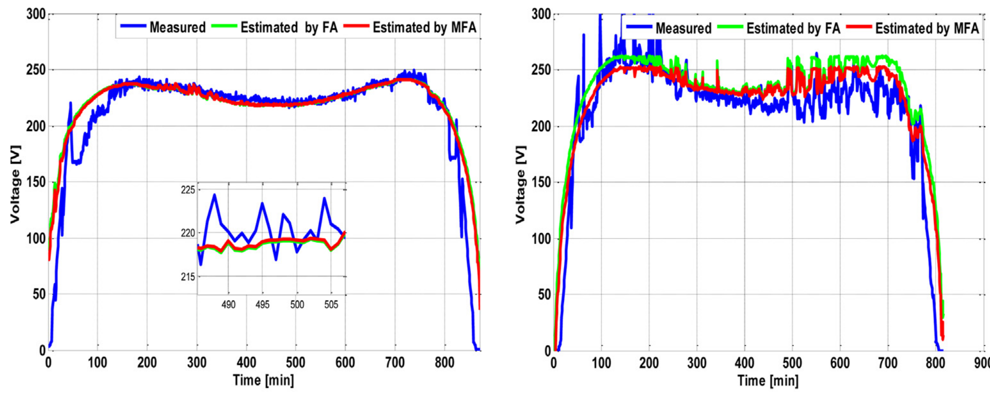


Fig. 16. Comparison between measured and estimated values of current at MPP for both FA and MFA solutions (a) clean sky day (b) cloudy sky day.



(a) (b)

Fig. 17. Comparison between measured and estimated values of voltage at MPP for both FA and MFA solutions (a) clean sky day (b) cloudy sky day.

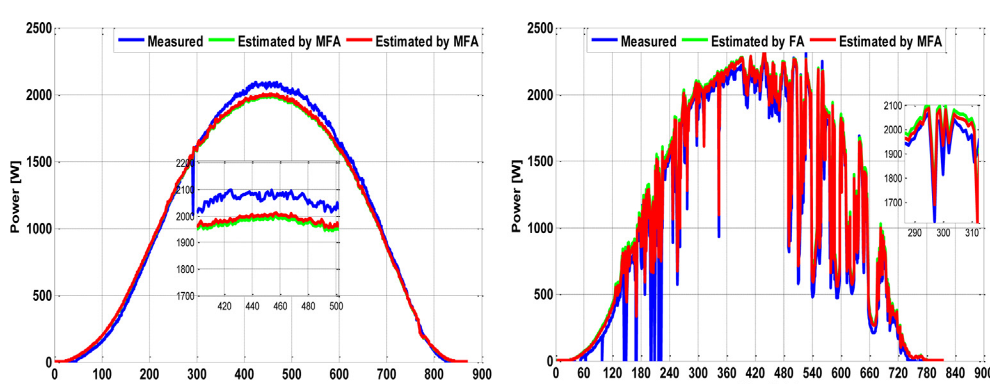
complicated model that have more unknowns parameters, for the case of DDM model seven unknowns parameters must be identified. From the Figs. 13–15, it can be concluded that the parameters extracted by the MFA give a good results for the DDM with different cell technology under several metrological conditions (from the low to the high irradiation).

6.3. Maximum power point

The parameters values of the SDM which are found previously enable to predict the MPP with using the equations (12) and (13) as mentioned before, the used data are obtained from two days, these days are characterized by different weather conditions (clear sky and cloudy sky). In addition, the experimental data are collected from a grid connected PV system (GCPVS) that installed in CDER in Algiers [37]. The system generates a power equal to 3.18 KW from array contains a 30 PV modules that structured by two strings, each one has 15 modules in series and the type of module in this system is ISOFOTON. Therefore, the results of the optimization process of this later are used. In order to assess the obtained results, the prediction values and the experimental ones are plotted in the below Figs. (16–18). These figures show the curves of the dynamic variation for the three variables such as current, voltage and power at MPP which are referred as I_{Pmax}, V_{Pmax}, and P_{Pmax} respectively, and each variable have two values one predicted and the other is measured from the GCPVS which are plotted in the same figure to able evaluate the extracted parameters. A comparison is carried out for both clear and cloudy sky. The figures have shown that the estimated curve by MFA and measured curve have a good matching that better than FA, therefore the extracted SDM parameters by the MFA are obviously had a good accuracy compared to FA.

7. Conclusion

In the present work, two models of PV cell have been proposed, these models are namely SDM and DDM, and each model has its unknown's parameters. The MFA is a metaheuristic algorithm inspired from the transfer of the pollen to produce the plants, the MFA has been applied to identify the optimal parameters values which has a minimum RMSE for both models. Several PV modules data were used. These data also contain three types of PV cells that are amorphous cell, monocrystalline silicon cell and polycrystalline silicon cell. In addition, the experimental data are recorded outside in several meteorological conditions, in other words for each temperature and irradiation, an I-V curve is generated. In addition, three optimization algorithms, called simulated annealing algorithm, generalized evolutionary walker algorithm and flash search algorithm, are used to compare its results with the results of FA, as well as the same initial conditions are used in these algorithms to make a fair comparison. The assessment of the FA shows a high accuracy compared to the three other algorithms which also have better optimization performances such as the fast convergence, minimum iterations and lower error, therefore the identified parameters by FA are more accurate than the one obtained from other algorithms. In order to predict the current, the voltage and the power at the MPP, the parameters of the SDM that has been



(a) (b)

Fig. 18. Comparison between measured and estimated values of power at MPP for both FA and MFA solutions (a) clean sky day (b) cloudy sky day.

identified are used for this purpose, the offered results show the effectiveness of prediction in both features days, and a high matching between the measured MPP values and the predicted one is achieved.

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