Renewable Energy 111 (2017) 307–320

Contents lists available at ScienceDirect

Renewable Energy

journal homepage: www.elsevier.com/locate/renene

Parameter estimation of photovoltaic system using imperialist competitive algorithm

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ARTICLE INFO

Article history:
Received 24 December 2016
Received in revised form
26 February 2017
Accepted 8 April 2017
Available online 12 April 2017

Keywords:
PV parameter estimation
Imperialist competitive algorithm
Single diode model
Double diode model

ABSTRACT

This paper presents a reliable methodology based on imperialist competitive algorithm (ICA) for estimating the optimal parameters of photovoltaic (PV) generating unit. The PV system is simulated by single diode model and double diode model. The proposed constrained objective function is derived from the voltage-power curve of the PV system which has unique maximum power point (MPP). The analysis is performed on different types of PV systems; mono-crystalline, poly-crystalline and amorphous modules. The validation of ICA is investigated for PV cell/module operated under different irradiances and temperatures; the obtained results are compared with experimental data and other reported meta-heuristic optimization algorithms. The results confirm the validity and reliability of ICA in extracting the optimal parameters of the PV generating unit.

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1. Introduction

The main obstacle of fossil fuel is its negative effect on the environment; therefore alternative clean resources are used, renewable energy sources (RESs) gained great attention in the last years. One form of RESs is the solar power in which the electric current is produced by photovoltaic cell. The PV is manufactured from a semiconductor material which may be mono-crystalline, poly-crystalline or amorphous type. The PV module manufacturer's datasheet provides the parameters of open circuit voltage (V_{oc}), short circuit current (I_{sc}), maximum power (P_{mpp}), voltage and current at MPP (V_{mpp} and I_{mpp}) and the temperature coefficients of voltage and current, (K_v and K_i,). However, the model of the PV module requires other parameters such as the photon current (I_{ph}), saturation current (I_o), ideality factor of diode (n), series resistance (R_s) and parallel resistance (R_p), the values of such parameters are not specified in the datasheet. Accordingly; the estimation of such parameters is considered essential issue. Many researchers performed the extraction of the PV module parameters, the reported methods can be classified into two categories; analytical methods [1–13] and evolutionary algorithms based methods [9,14–26]. The analytical methods are based on formulating set of equations be solved to determine the parameters of the PV system. A modified nonlinear optimization approach based on the Newton model is employed for extracting solar cell parameters from measured data [1]. An improved Lambert-W function is used to identify the parameters of PV system [2]. An approach based on analytical 5-point technique that employed to estimate the PV cell parameters has been developed by Ref. [3] and compared with two other techniques which are curve fitting and iterative 5-point method. Analytical solutions for extracting the parameters of single diode model (SDM) and double diode model (DDM) of the PV cell have been introduced in Ref. [4]. In Ref. [5]; the physical parameters of the SE model for various solar cells have been extracted based on analytical method. The intrinsic and extrinsic models' parameters of the PV cell are calculated in Ref. [6] via estimating the co-content function from analytical solution of the voltage-current curve. In Ref. [7]; the parameters of the PV system have been extracted by adjusting the voltage-current curve at three points (V_{oc}, P_{mpp}, I_{sc}). An approach to predict the voltage-current characteristics of the PV system has been presented in Ref. [8]. In Ref. [9]; Newton-Raphson method, Levenberg–Marquardt algorithm and genetic algorithm (GA) are employed in extracting the

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http://dx.doi.org/10.1016/j.renene.2017.04.014
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PV parameters. The parameters of the PV cell have been determined in Ref. [10] via impedance spectroscopy. In Ref. [11]; several conventional approaches for extracting the PV module parameters have been applied. Analytical method based on datasheet values of PV modules is addressed in Ref. [12] for extracting the unknown parameters of PV unit. A review study of cell parameters estimation has been given in Ref. [13]. The defects of the previous reported methods are their dependency on the starting point of the algorithm; furthermore requirement of excessive effort due to large consumed time in simulation and complexity in the mathematical form. In the recent years; many researchers are used meta-heuristic optimization algorithms in extracting the optimal parameters of the PV system. Such algorithms include; artificial immune system [14], pattern search [15,16], repaired adaptive differential evolution [17], simulated annealing [18], harmony search-based algorithms [19], artificial bee colony [20], chaos particle swarm algorithm [21], cuckoo search [22], mine blast algorithm [23], bird mating optimizer [24], mutative-scale parallel chaos optimization algorithm [25] and adaptive differential evolution technique [26]. The aforementioned methods used meta-heuristic algorithm required more computational time and produced larger error between the experimental and calculated data; therefore this work proposes an efficient algorithm endorsed the imperialist competitive algorithm (ICA) to extract the optimal parameters of the PV system. The main objective is to obtain a model which is well-matched with actual one; this can be achieved by minimizing the proposed objective function that derived from the differential of power w.r.t. the PV output voltage. The analysis is performed on different types of PV generating units; mono-crystalline, poly-crystalline and amorphous modules under different irradiances and temperatures. The obtained results show the superiority of the proposed methodology as it achieves less error with acceptable computational time.

2. Mathematical model of PV cell/module

The mathematical model of the PV unit can be presented by two models, SDM [27,28] and DDM [29]. The SDM of the PV cell is shown in Fig. 1.

Referring to Fig. 1; the output current is formulated by the following:

$$I = I_{ph} - I_D - I_p \tag{1}$$

$$I = I_{ph} - I_o\left\{exp\left(\frac{V + IR_s}{nV_T}\right) - 1\right\} - \left\{\frac{V + IR_s}{R_p}\right\} \tag{2}$$

where I_{ph} denotes the photon current, I_o is the diode saturation current, V and I are the cell voltage and current, R_s and R_p are the cell series and parallel resistances, n is the ideality factor of the

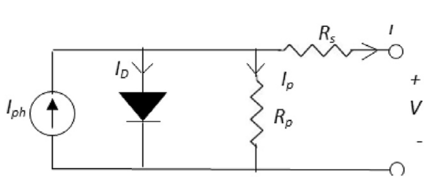


Fig. 1. Single diode model of the PV cell.

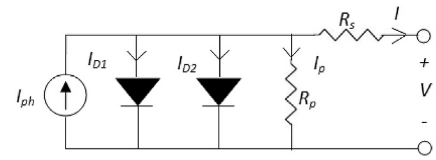


Fig. 2. Double diode model of the PV cell.

diode and V_T denotes the thermal voltage of the diode which is calculated as follows:

$$V_T = \frac{K.T}{q} \tag{3}$$

where K is the Boltzmann constant (1.381*10^{-23} J/K), q is the electron charge (1.602*10^{-19} C) and T is the cell temperature in Kelvin. The short circuit and saturation currents are dependent on the temperature as follows [30]:

$$I_{SC} = [I_{SCr} + K_i(T - T_r)]{*}G \tag{4}$$

$$I_o = I_{or}{*}\left(\frac{T}{T_r}\right)^3{*}exp\left(\frac{qE_g}{nK}\left(\frac{1}{T_r} - \frac{1}{T}\right)\right) \tag{5}$$

where I_{scr} and I_{or} are the short circuit and saturation currents at reference temperature, ($T_r = 298$ K), K_i is the temperature coefficient of short circuit current, G is the irradiance and E_g is the band gap energy which is typically equal to 1.12 eV for silicon and 1.35 eV for germanium semiconductors.

In DDM; an extra diode is connected in parallel with the current source to give more accurate voltage-current characteristic as shown in Fig. 2.

Referring to the circuit shown in Fig. 2; one can get that:

$$I = I_{ph} - I_{D1} - I_{D2} - I_p \tag{6}$$

$$I = I_{ph} - I_{o1}\left\{exp\left(\frac{V + IR_s}{n_1 V_{T1}}\right) - 1\right\} - I_{o2}\left\{exp\left(\frac{V + IR_s}{n_2 V_{T2}}\right) - 1\right\} - \left\{\frac{V + IR_s}{R_p}\right\} \tag{7}$$

where I_{o1} and I_{o2} are the saturation currents of diodes D_1 and D_2, n_1 and n_2 are the ideality factors of D_1 and D_2, V_{T1} and V_{T2} are the thermal voltages of two diodes.

For SDM; the current extracted from the PV module of series cells (N_s) and parallel strings (N_p) can be expressed as follows:

$$I_{mod} = N_p\left\{I_{ph} - I_o\left(exp\left(\frac{\frac{V_{mod}}{N_s} + \frac{I_{mod}.R_s}{N_p}}{nV_T}\right) - 1\right)\right\} - \left\{\frac{\frac{N_p}{N_s}V_{mod} + I_{mod}.R_s}{R_p}\right\} \tag{8}$$

While Eqn. (8) in DDM becomes,

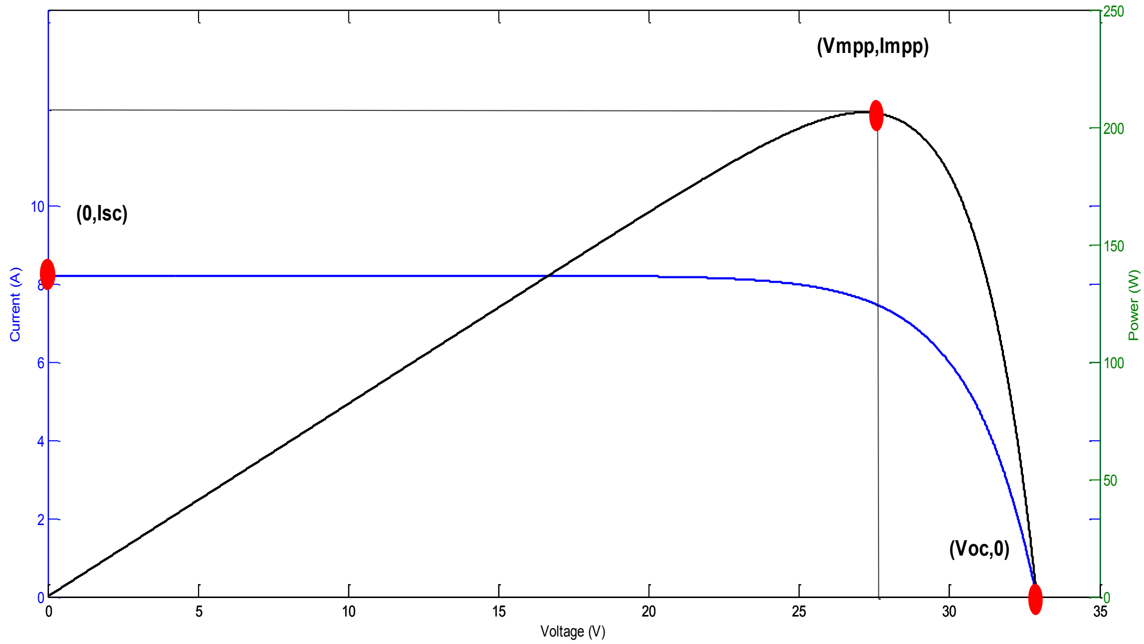


Fig. 3. Typical V-I and V-P curves of PV system.

$$I_{mod} = N_p\left\{I_{ph} - I_{o1}\left(exp\left(\frac{\frac{V_{mod}}{N_s} + \frac{I_{mod}.R_s}{N_p}}{n_1 V_{T1}}\right) - 1\right) - I_{o2}\left(exp\left(\frac{\frac{V_{mod}}{N_s} + \frac{I_{mod}.R_s}{N_p}}{n_2 V_{T2}}\right) - 1\right)\right\} - \left\{\frac{\frac{N_p}{N_s}V_{mod} + I_{mod}R_s}{R_p}\right\} \quad (9)$$

3. Principle of imperialist competitive algorithm

Imperialist competitive algorithm (ICA) has been presented by Gargari in 2007 [31]; the algorithm is motivated from the concept of imperialistic competition process. it starts with initial population of countries divided into two groups; the first one named imperialists which has the best values of fitness function while the second group is called colonies follow the imperialists. The colonies in the initial population share the imperialists according to their powers such that the imperialist with more power has more colonies. The colonies start to change their cultures based on their imperialist; this action is simulated by moving colonies toward their imperialist country, this process named assimilation. In the assimilation process; the colony with large power may be replace the imperialist and vice versa. During the imperialistic competition; the most powerful empires try to increase their powers while the less powerful try to crumble. At the end of ICA algorithm; the solution is concentrated at the most powerful empire. The ICA steps can be explained as follows:

Step 1: Initialization of population.

The population has individuals; in ICA the individuals are countries, each country is represented by N_{var} vector as follows:

$$Country = \left[p_1,\ p_2,\ \ldots, p_j\right] \quad j = 1, 2, \ldots,\ N_{var} \quad (10)$$

The cost of country is calculated by evaluating the objective function (f),

$$Cost = f(Country) = f\left(p_1,\ p_2,\ \ldots, p_j\right) \quad (11)$$

The colonies are divided among the imperialists based on their powers; this process is performed by defining a normalized cost of imperialist as follows:

$$C_n = c_n - max_i(c_i) \quad (12)$$

where c_n is the cost of nth imperialist, the normalized power of each imperialist can be expresses as:

$$p_n = \frac{|C_n|}{\left|\sum_{i=1}^{N_{imp}} C_i\right|} \quad (13)$$

where N_{imp} is the number of imperialists. The initial number of colonies of nth empire is given by:

$$NC_n = round(p_n,\ N_{col}) \quad (14)$$

where N_{col} is the total number of colonies.

Step 2: Movement of colonies towards the imperialist (Assimilation)

This process depends on the distance between the colonies and their imperialists, the new position of the colony is calculated by:

$$x^{k+1} = x^k + \gamma.\delta.d \quad (15)$$

where x^{k+1} is the new position of colony at iteration $k+1$ while x^k is the position of colony at iteration k, γ is the assimilation coefficient, δ is the random value in range [0, 1] and d is a vector represents the distance between colony and its imperialist. After updating the colony position, it may be settled at a position with lower cost than the imperialist, in this case the colony replaces imperialist and vice versa.

Step 3: Evaluating the total cost of the empires.

An empire consists of the imperialist and their colonies;

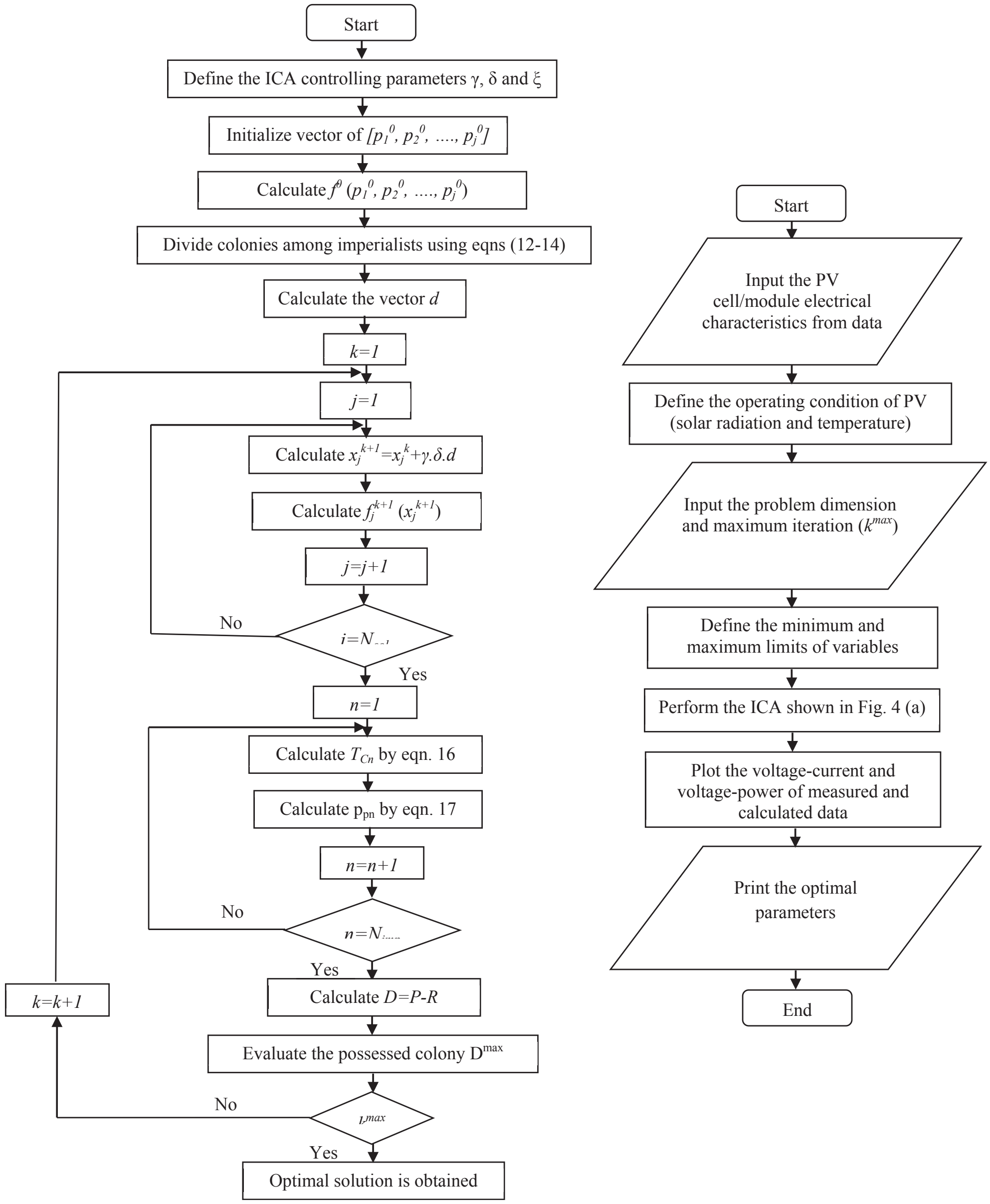


Fig. 4. (a) ICA flowchart, (b) The proposed methodology flowchart.

Table 1
Electrical specification of the PV units.

Parameter	R.T.C France	KC200GT	SQ150-PC	ST40
Type	Poly-crystalline	Poly-crystalline	Mono-crystalline	Thin film
Maximum Power (P_{mpp}) (W)	0.3101	200	150	40
Voltage at MPP(V_{mpp}) (V)	0.4507	26.3	34	16.6
Current at MPP (I_{mpp}) (A)	0.6880	7.61	4.4	2.41
Open Circuit Voltage (V_{oc}) (V)	0.5728	32.9	43.4	23.3
Short Circuit Current (I_{sc}) (A)	0.7603	8.21	4.8	2.68
Temperature Coefficient of I_{sc} (A/°C)	0.035	0.00318	0.0014	0.00035
Number of series cells (N_s)	1	54	72	–
R_s^{max} (Ω)	0.1775	0.8673	2.1364	2.7801
R_p^{min} (Ω)	6.2337	43.8333	85.0000	61.4815

Table 2
Controlling parameters of the proposed ICA.

Parameter	Assigned value
Number of countries	400
Number of initial imperialists	10
Number of all colonies	390
Number of iterations (k^{max})	100
Assimilation coefficient (γ)	2
Δ	0.1
Ξ	0.02

Table 3
Optimal parameters of R.T.C France for both SDM and DDM.

Single diode model						
I_{ph} (A)	I_o (μA)	n	R_s (Ω)	R_p (Ω)		
0.7603	0.14650	1.4421	0.0389	41.1577		
Double diode model						
I_{ph} (A)	I_{s1} (μA)	I_{s2} (μA)	n_1	n_2	R_s (Ω)	R_p (Ω)
0.7605	0.65637	0.00015751	1.5970	1.0000	0.0294	50.0000

therefore the cost of an empire is affected by the cost of all included components:

$$TC_n = f(Imperialist_n) + \xi.mean(f(Colonies\ of\ impires_n)) \tag{16}$$

where TC_n is the total cost of nth empire and ξ is a positive number represents the significance of colonies cost.

Step 4: Performing imperialist competition.

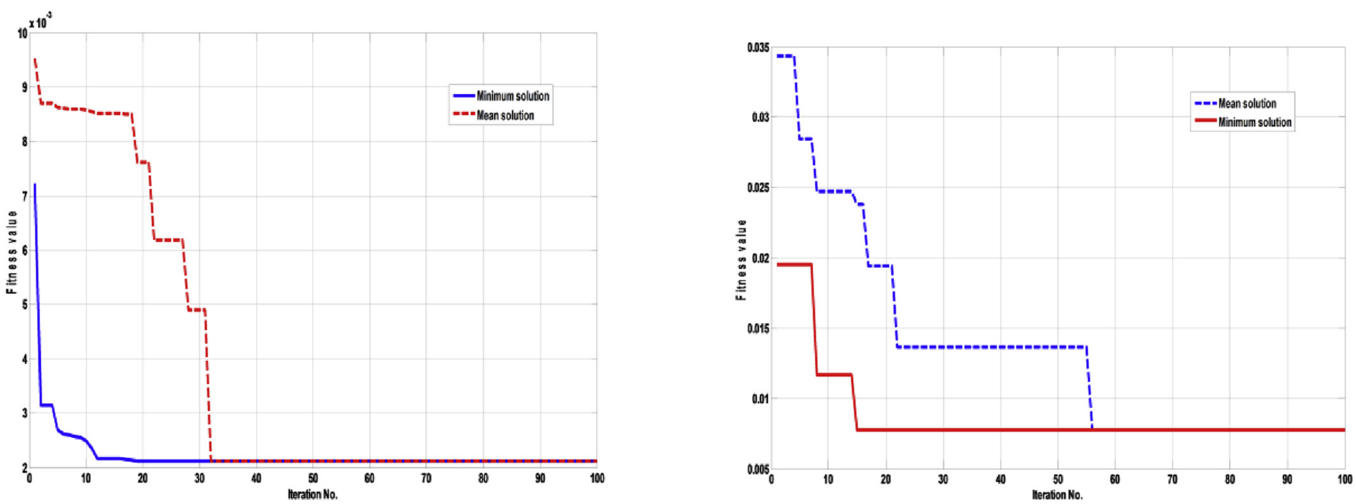
This process includes the competition between imperialists to seize colonies in other imperialists; this is done by selecting the weakest colony from the weakest empire to be disputed among the others. The most powerful empire vanquishes the selected colony; so the normalized cost of nth empire is calculated by:

$$NTC_n = TC_n - max_i(TC_i) \tag{17}$$

The possession probability of each empire is given by:

$$p_{pn} = \frac{|\mathrm{NTC_n}|}{\left|\sum_{i=1}^{N_{imp}} \mathrm{NTC_i}\right|} \tag{18}$$

After calculating the possession probability vector, another



(a) (b)

Fig. 5. (a) ICA response for R.T.C France, (b) ICA response for KC200GT.

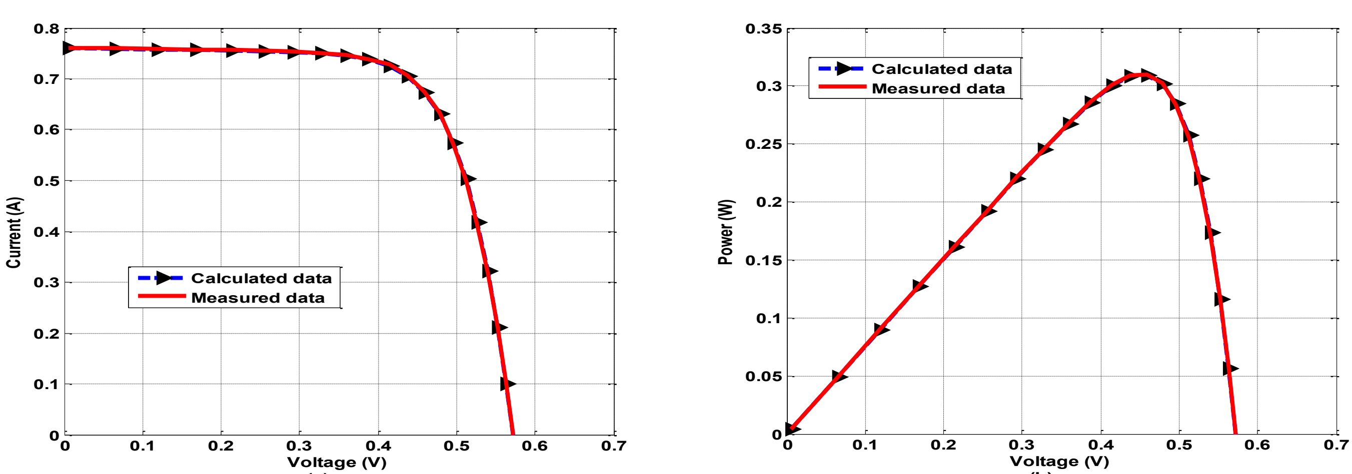


Fig. 6. (a) Voltage-current curve of the PV cell using SDM, (b) Voltage-power curve of the PV cell using DDM.

Table 4
Comparison between the results obtained by proposed ICA and other methods for R.T.C France.

Single diode model						
Method	I_{ph} (A)	I_o (μA)	n	R_s (Ω)	R_p (Ω)	MAE
Method in Ref. [1]	0.7608	0.3223	1.4837	0.0364	53.7634	0.0141
Pattern search [15]	0.7617	0.9980	1.6000	0.0313	64.1026	0.0022
Adaptive differential evolution [17]	0.760776	0.323021	1.481184	0.036377	53.718526	6.8091e-04
Simulated annealing [18]	0.7620	0.4798	1.5172	0.0345	43.1034	0.0022
harmony search algorithm [19]	0.76070	0.30495	1.47538	0.03663	53.5946	6.89346e-4
Artificial bee swarm [20]	0.76080	0.30623	1.47583	0.03659	52.2903	6.82615e-4
chaos particle swarm algorithm [21]	0.7607	0.4000	1.5033	0.0354	59.012	0.005067
Bird mating optimizer [24]	0.76077	0.32479	1.48173	0.03636	53.8716	6.80808e-4
mine blast algorithm [23]	0.7604	0.2348	1.489	0.0388	44.61	0.0012
Proposed ICA	**0.7603**	**0.14650**	**1.4421**	**0.0389**	**41.1577**	**5.66478e-4**

Double diode model								
Method	I_{ph} (A)	I_{o1} (μA)	I_{o2} (μA)	n_1	n_2	R_s (Ω)	R_p (Ω)	MAE
Pattern search [15]	0.7602	0.9889	0.0001	1.6000	1.1920	0.0320	81.3008	0.0019
Adaptive differential evolution [17]	0.760781	0.225974	0.749347	1.451017	2.000000	0.036740	55.485443	6.8113e-04
Simulated annealing [18]	0.7623	0.4767	0.0100	1.5172	2.0000	0.0345	43.1034	0.0014
harmony search algorithm [19]	0.76176	0.12545	0.25470	1.49439	1.49989	0.03545	46.82696	6.66808e-4
Artificial bee swarm [20]	0.76078	0.26713	0.38191	1.46512	1.98152	0.03657	54.6219	6.73e-4
Bird mating optimizer [24]	0.76078	0.21110	0.87688	1.44533	1.99997	0.03682	55.8081	6.64115 e-4
mine blast algorithm [23]	0.7605	0.4513	1.1846	1.592	1.845	0.0314	493.72	0.0013
Proposed ICA	**0.7605**	**0.65637**	**0.00015751**	**1.5970**	**1.0000**	**0.0294**	**50.0000**	**5.26589e-4**

Showing the best results obtained by ICA.

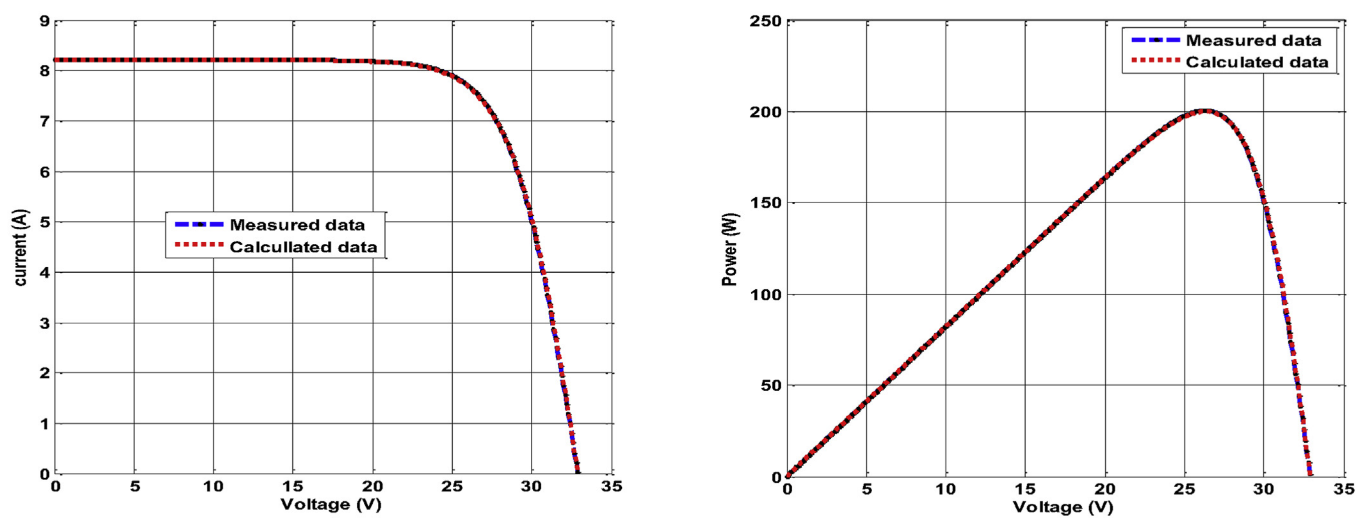


Fig. 7. (a) Voltage-current curve of KC200GT using SDM, (b) Voltage-power curve of KC200GT using DDM.

Table 5
A comparison between the ICA results and other methods for SDM KC200GT and the optimal parameters obtained for DDM KC200GT.

Single diode model					
Parameter	Method in Ref. [7]	Method in Ref. [8]	Cuckoo search [22]	Mine blast algorithm [23]	Proposed ICA
I_{ph} (A)	8.210	8.215	8.173	8.189	8.2100
I_o (μA)	0.09825	0.004812	0.00423	0.01087	0.10946
n	1.300	1.235	1.009	1.317	1.3079
R_s (Ω)	0.00409	0.247	0.00494	0.00360	0.0039
R_p (Ω)	415.41	414.89	140.49	137.81	188.2103

Double Diode Model						
I_{ph} (A)	I_{o1} (μA)	I_{o2} (μA)	n_1	n_2	R_s (Ω)	R_p (Ω)
8.2100	0.14290	0.002643	1.3274	1.0851	0.0038	108.7844

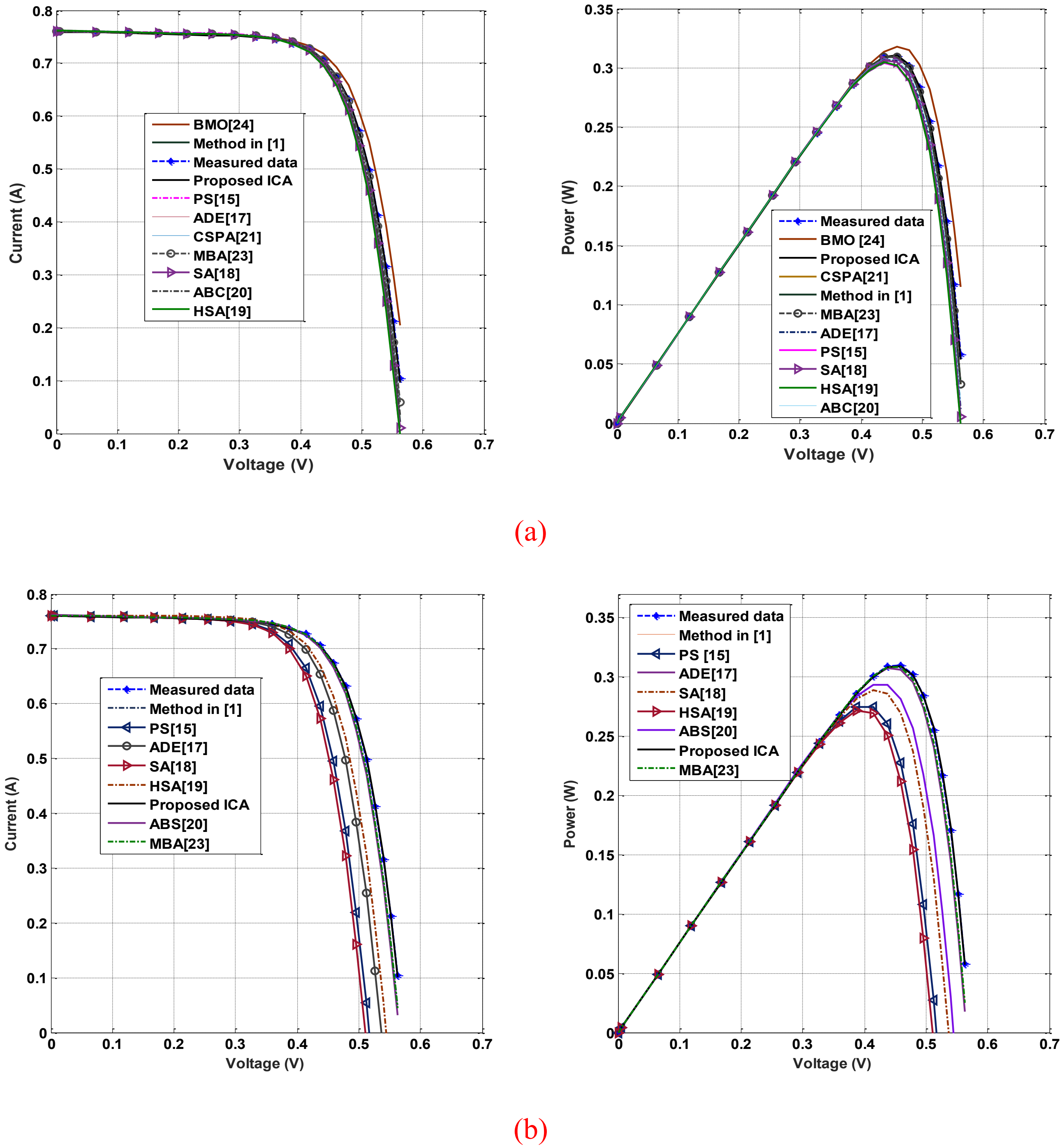


Fig. 8. R.T.C France curves obtained via ICA and other algorithms (a) SDM, (b) DDM.

vector called D with the same size is formulated by subtracting a random vector called R from the possession probability vector ($D = P\text{-}R$), the possessed colony has the maximum value of D.

Step 5: Verification of stopping condition.

The previous steps are repeated until the convergence criterion is achieved; the convergence criterion may be maximum number of iterations or accepted error between the two cascaded iterations. The flowchart of the ICA is given in Fig. 4 (a).

4. Problem formulation

The main objective of this work is to extract the unspecified parameters of PV cell/module such that the voltage-current characteristic of the PV unit is well-matched with the experimental data. The parameters to be determined are the photon current (I_{ph}), the diode saturation current (I_o), the ideality factor (n) and the PV cell series and parallel resistances (R_s and R_p) in SDM while in DDM; the parameters are I_{ph}, I_{o1}, I_{o2}, n_1, n_2, R_s and R_p. The proposed objective function is derived from the typical curves of the PV

Table 6
Optimal parameters of SQ150-PC and ST40 compared to DE [34].

Algorithm	SQ150-PC		ST40	
	DE [34]	ICA	DE [34]	ICA
I_{ph} (A)	4.810	4.8000	2.700	2.6800
I_{o1} (μA)	0.007690	5.4646	0.02110	0.026539
I_{o2} (nA)	40.90	2.1350	29.50	0.0015834
n_1	1.190	1.7145	1.040	1.968483
N_2	1.260	1.08967	2.340	1.288481
R_s (Ω)	0.805	0.74023	1.360	1.508053
R_p (kΩ)	1538.400	8850.2394	266.450	377653.427
MAE	0.018	**0.004**	0.018	**0.0083**

Showing the best results obtained by ICA.

system given in Fig. 3, as there is a unique MPP for the PV panel. The MPP of the obtained curve should be matched with datasheet curve. Referring to Fig. 3, the following equations can be written:

$$P = V.I \tag{19}$$

$$\frac{dP}{dV} = \frac{d(V.I)}{dV} = I + V.\frac{dI}{dV} \tag{20}$$

At MPP; the derivative of power w.r.t. voltage is zero.

$$\frac{dP}{dV} = I_{mpp} + V_{mpp}.\frac{dI}{dV}\Big|_{(V_{mpp},\ I_{mpp})} = 0 \tag{21}$$

By differentiating Eqn. (9), one can get that:

$$\frac{dI}{dV}\Big|_{(V_{mpp},\ I_{mpp})} = N_p\left\{0 - I_{o1}\left(\frac{exp\left(\frac{\frac{V_{mpp}}{N_s}+\frac{I_{mpp}.R_s}{N_p}}{n_1 V_{T1}}\right)}{\frac{1}{N_s.n_1 V_{T1}}}\right) - I_{o2}\left(\frac{exp\left(\frac{\frac{V_{mpp}}{N_s}+\frac{I_{mpp}.R_s}{N_p}}{n_2 V_{T2}}\right)}{\frac{1}{N_s.n_2 V_{T2}}}\right)\right\} - \left\{\frac{N_p}{N_s.R_p}\right\} \tag{22}$$

Therefore, the proposed objective function is given by:

Table 7
Optimal extracted parameters of PV systems under variable irradiance.

	R.T.C France	KC200GT	SQ150-PC	ST40
***G* = 1000 W/m²**				
I_{ph} (A)	0.7605	8.2100	4.8000	2.6800
I_{o1} (μA)	0.65637	0.14290	5.4646	0.026539
I_{o2} (nA)	0.00015751e-3	0.002643	2.1350	0.0015834
N_1	1.5970	1.3274	1.7145	1.968483
N_2	1.0000	1.0851	1.08967	1.288481
R_s (Ω)	0.0294	0.0038	0.74023	1.508053
R_p (Ω)	50.0000	108.7844	8850.2394	377653.427
MAE	**5.26589e-4**	**0.000526**	**0.004**	**0.0083**
***G* = 600 W/m²**				
I_{ph} (A)	0.4562	4.9260	2.8800	1.6080
I_{o1} (μA)	0.52604	0.023441	4.9306	0.00011174
I_{o2} (nA)	1.5151	0.51296	56.227	4.2149e-7
n_1	1.5720	1.2054767	1.70171	1.5179535
n_2	1.1130	1.0093862	1.28484	0.9970198
R_s (Ω)	0.0375	0.1111486	0.901140	2.2806995
R_p (Ω)	72.0979	167.98487	62170.598	893179.405
MAE	**0.0013**	**0.0110**	**1.0935**	**0.5551**
***G* = 200 W/m²**				
I_{ph} (A)	0.1521	1.6420	0.9600	0.5360
I_{o1} (μA)	0.50159	0.018306	0.78236	0.030263
I_{o2} (nA)	0.22779	1.0560	21.217	4.9706
n_1	1.5668	1.1905	1.501284	1.982612
n_2	1.0168	1.0414	1.219751	1.804482
R_s (Ω)	0.0436	0.4738	1.41695	2.394320
R_p (Ω)	50.0646	164.0178	849379.2174	1204070.984
MAE	**4.4563e-04**	**0.0049**	**0.7415**	**0.4054**

Showing the best results obtained by ICA.

$$Minimize\ J(x) = \frac{I_{mpp}}{V_{mpp}} - N_p I_{o1}\left(N_s.n_1 V_{T1}.exp\left(\frac{\frac{V_{mpp}}{N_s}+\frac{I_{mpp}.R_s}{N_p}}{n_1 V_{T1}}\right)\right) - N_p I_{o2}\left(N_s.n_2 V_{T2}.exp\left(\frac{\frac{V_{mpp}}{N_s}+\frac{I_{mpp}.R_s}{N_p}}{n_2 V_{T2}}\right)\right) - \left\{\frac{N_p}{N_s.R_p}\right\} \tag{23}$$

Finally, one can generalize the objective function as follows:

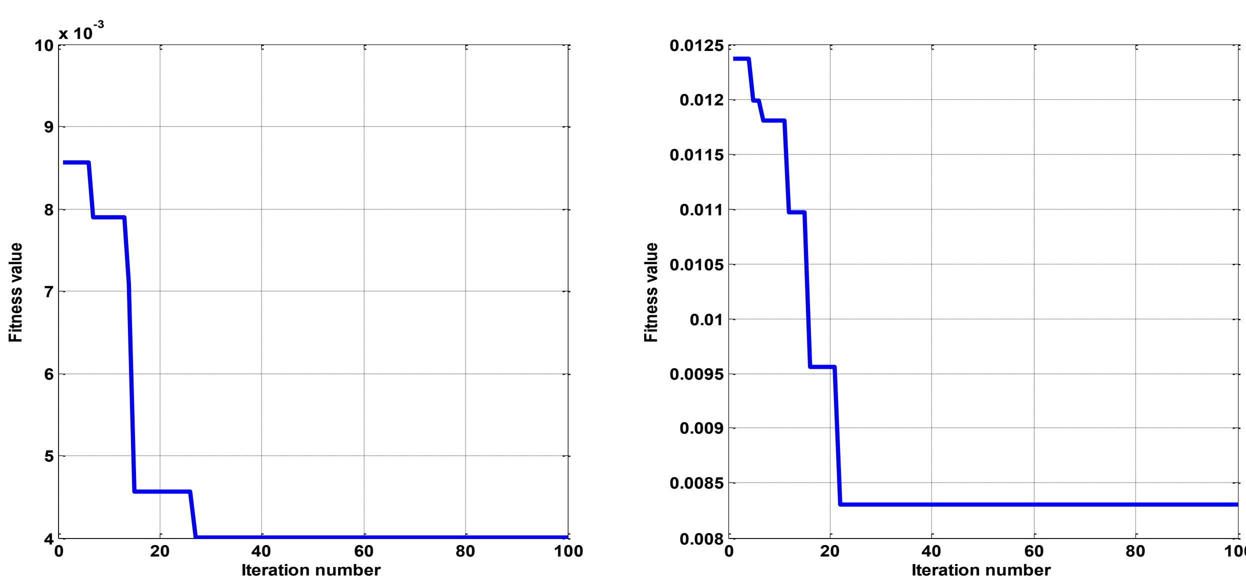


Fig. 9. (a) ICA response for SQ150-PC, (b) ICA response for ST40.

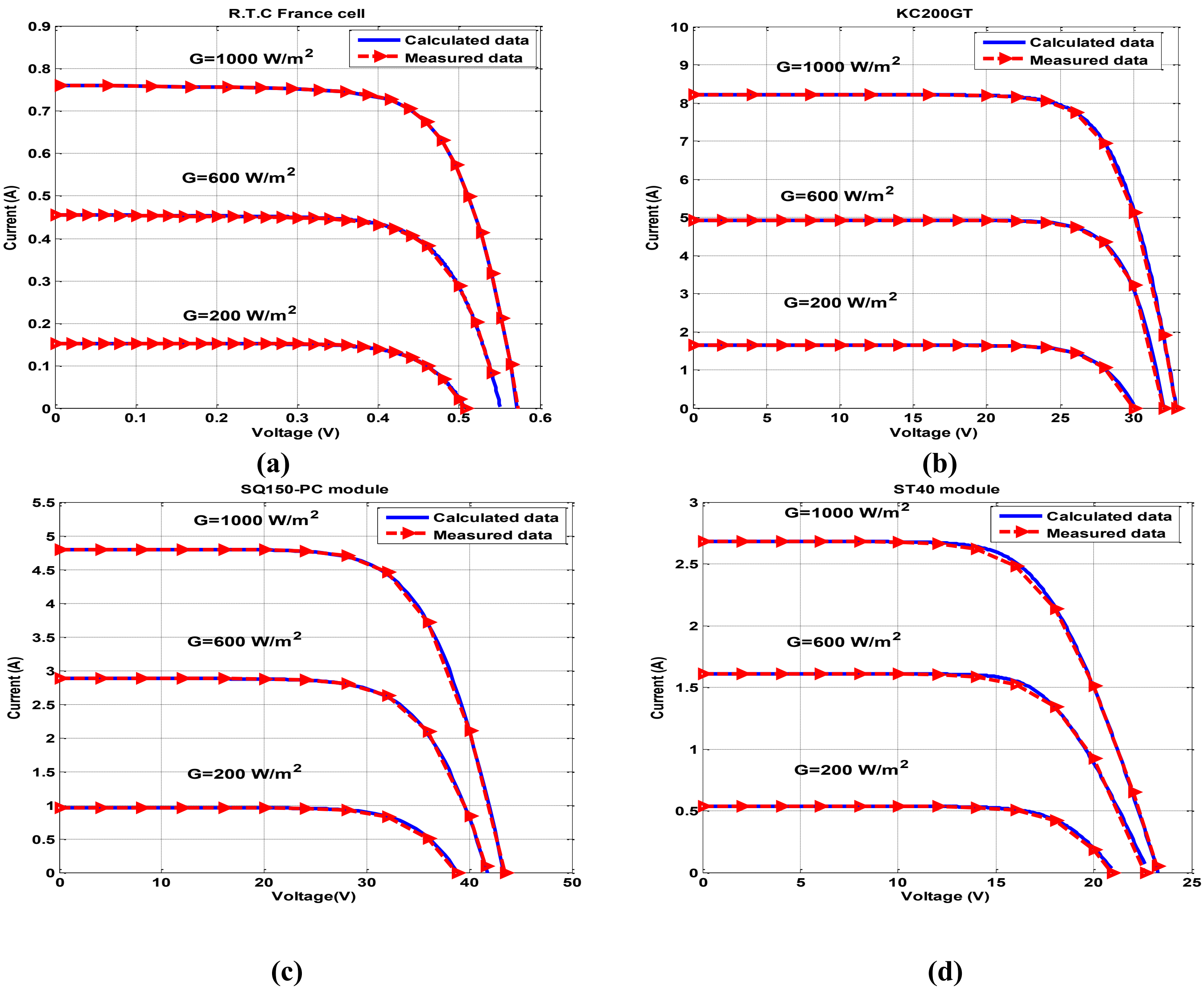


Fig. 10. Voltage-current curves under variable irradiance (a) R.T.C France, (b) KC200GT, (c) SQ150-PC and (d) ST40.

$$\textit{Minimize} \quad J(x) = \xi + \varphi(I_{o1}, n_1, R_s) + \varepsilon(I_{o2}, n_2, R_s) - \gamma(R_p) \tag{24}$$

The objective function presented in Eqn. (24) is representing the difference between the MPP obtained via the established model and that given in the measured data. The proposed equation comprises four functions; the first one depends on the PV generating unit current and voltage at maximum power point while the rest terms are dependent on the parameters to be extracted. In case of SDM; only the term $\varepsilon(I_{o2}, n_2, R_s)$ is equal to zero.

The constraints are:

$$1 \le n_1 \;\; or \;\; n_2 \le 2 \tag{25a}$$

$$0 \le I_{o1} \;\; or \;\; I_{o2} \le 5 \;\; \mu\text{A} \tag{25b}$$

$$0.95 I_{sc} \le I_{ph} \le 1.05 I_{sc} \tag{25c}$$

$$0 \le R_s \le R_s^{max} \tag{25d}$$

$$R_p^{min} \le R_p \le R_p^{max} \tag{25e}$$

The value of maximum series resistance and minimum parallel resistance are selected as given in Ref. [23]:

$$R_s^{\min} = \frac{V_{oc} - V_{mp}}{I_{mp}} \& R_p^{\max} = \frac{V_{mp}}{I_{scr} - I_{mp}} \tag{26}$$

The indicated values are selected as the diode ideality factor is in range [1,2] as in Ref. [4]. The base value of the reverse saturation current used in Ref. [4] is 1 μA; in our analysis this value is extended to be 5 μA to allow global optima, and the photon current is proportional to the solar radiation strikes the module surface; it is assumed that the solar radiation is changed with allowable range of

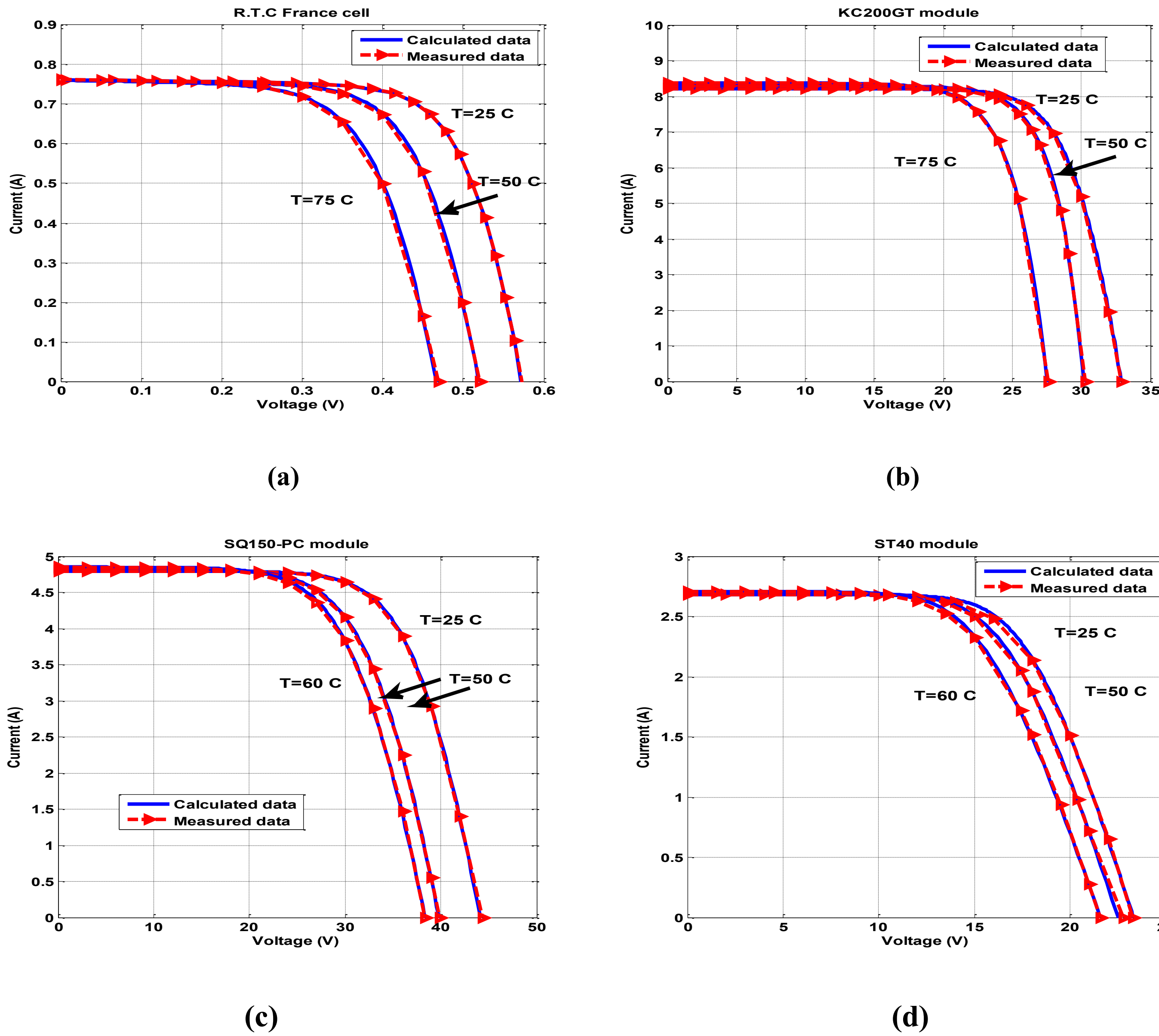


Fig. 11. Voltage-current curves under variable temperature (a) R.T.C France, (b) KC200GT, (c) SQ150-PC and (d) ST40.

±5%. The proposed solution methodology used in this work is given in Fig. 4 (b). After performing the ICA; the mean absolute error (MAE) between the measured current and the PV model calculated current is calculated and compared with other algorithms; the MAE is given by:

$$MAE = \frac{1}{M}\sum_{k=1}^{k=m}\left(\left|I_{measured}(k) - I_{calculated}(k)\right|\right) \tag{27}$$

5. Numerical analysis

The proposed algorithm is applied on different types of PV cell/module; mono-crystalline, poly-crystalline and amorphous modules. The mono-crystalline module used in the analysis is SQ150-PC [32], examples on poly-crystalline are 57 mm diameter commercial silicon solar cell (R.T.C France) given in Ref. [1] and Kyocera module (KC200GT) given in Ref. [33] and the amorphous type is ST40 module given in Ref. [34]. The electrical specifications of these types are given in Table 1. The controlling parameters of the proposed ICA are tabulated in Table 2; the experimental data for all studied PV systems are extracted from their datasheets. The values of ICA controlling parameters have been selected at random; however, they give the preference results after the application of the proposed ICA for 100 runs.

For poly−crystalline type, both models (SDM and DDM) are studied. R.T.C France cell, the optimal parameters of SDM and DDM obtained via the proposed ICA are given in Table 3. The response of ICA is illustrated in Fig. 5 (a). The algorithm catches the global optimum solution after 0.7980 s with acceptable MAE of value 5.66478e-4. Measured and calculated curves are given in Fig. 6.

Table 8
Optimal extracted parameters of PV systems under variable temperature.

	R.T.C France	KC200GT	SQ150-PC	ST40
T = 25 °C				
I_{ph} (A)	0.7605	8.2100	4.8000	2.6800
I_{o1} (μA)	0.65637	0.14290	5.4646	0.026539
I_{o2} (nA)	0.00015751e-3	0.002643	2.1350	0.0015834
n_1	1.5970	1.3274	1.7145	1.968483
n_2	1.0000	1.0851	1.08967	1.288481
R_s (Ω)	0.0294	0.0038	0.74023	1.508053
R_p (Ω)	50.0000	108.7844	8850.2394	377653.427
MAE	**5.26589e-4**	**0.000526**	**0.004**	**0.0083**
T = 50 °C				
I_{ph} (A)	0.7612	8.2895	4.8350	2.6888
I_{o1} (μA)	2.0677	0.80422	32.026	0.20612
I_{o2} (nA)	0.0042486	22.520	4.8342	0.0014304
n_1	1.4578	1.2455	1.665460	1.994058
n_2	0.7814	1.0469	1.02112	1.203239
R_s (Ω)	0.0386	0.0196	0.7853120	1.48863
R_p (Ω)	38.6933	402.1384	7702.1574	6006.8415
MAE	**0.0017**	**0.0200**	**0.0048**	**0.0016**
	T = 75 °C		**T = 60 °C**	
I_{ph} (A)	0.7621	8.3690	4.8490	2.6923
I_{o1} (μA)	22.450	11.327	66.010	0.17391
I_{o2} (nA)	0.62408	168.03	47.830	0.40031
n_1	1.4926	1.2589	1.656989	1.895072
n_2	0.2111	1.0252	1.091626	1.43542
R_s (Ω)	0.0330	0.0373	0.767162	1.544014
R_p (Ω)	27.5978	438.0631	2139.1414	3013.57638
MAE	**0.0022**	**0.0249**	**0.0066**	**0.0039**

Showing the best results obtained by ICA.

Table 9
Statistical parameters of ICA responses under variable temperature.

Temperature	R.T.C France	KC200GT	SQ150-PC	ST40
***T* = 25 °C**				
Best	5.26589e-4	0.000526	0.0040	0.0083
Worst	0.0040	0.03433	0.0149	0.0114
Mean	0.0034	0.01356	0.0081	0.0089
Standard deviations	3.5051e-04	0.007204	0.0025	5.9956e-04
***T* = 50 °C**				
Best	0.0017	0.0200	0.0048	0.0016
Worst	0.0036	0.1427	0.0202	0.0067
Mean	0.0021	0.0546	0.0080	0.0036
Standard deviations	7.5453e-04	0.0523	0.0055	0.0021
	***T* = 75 °C**		***T* = 60 °C**	
Best	0.0022	0.0249	0.0066	0.0039
Worst	0.0046	0.1012	0.0110	0.0059
Mean	0.0026	0.0541	0.0085	0.0049
Standard deviations	6.8839e-04	0.0334	0.0019	9.8928e-04

Comparison with previous methods is tabulated in Table 4; it is obvious that the MAE obtained by the proposed ICA for R.T.C France is the best one compared to the others. In Table 4;

For KC200GT; it is operated at temperature of 25° C and G = 1000 W/m^2. The minimum error between the measured and calculated current is 0.0069 obtained after 0.6300 s. The measured and calculated curves are shown in Fig. 7. A comparison with other methods is tabulated in Table 5. The variation of fitness function with iterations is given in Fig. 5 (b). To confirm the superiority of the obtained results via the proposed ICA; the parameters obtained from the previous algorithms tabulated in Table 4 are used and the corresponding curves are shown in Fig. 8 in comparison with the measured data and the ICA ones. Referring to Fig. 8; the curve obtained via the proposed ICA is closely matching with the measured data which ensures the ICA obtained objective function in Table 4.

For both mono-crystalline and amorphous modules, only the DDM is studied, Table 6 shows the optimal parameters obtained via ICA for SQ150-PC and ST40 compared with differential evolution described in Ref. [34]. The fitness function obtained by the proposed method is the best for both modules. The variation of fitness function with iteration number is given in Fig. 9.

6. Validation of the proposed algorithm

In order to check the validity of the ICA, different operating conditions of both irradiance and temperature are studied for all types stated before. Three different irradiances of values 1000 W/m^2, 600 W/m^2 and 200 W/m^2 are studied with constant temperature at 25 °C. The optimal values are given in Table 7. Fig. 10 shows the measured and calculated data in each studied case. The other important parameter that has impact on the PV module characteristic is the temperature, the effect of temperature is studied and the optimal parameters are obtained in Table 8. Fig. 10 shows the measured and calculated data in each case (see Fig. 11).

It is clear that, the calculated curves are matched with the experimental ones. The statistical parameters (best, worst, mean and standard division) of the ICA responses obtained under varying temperature are calculated and given in Table 9.

It is important to investigate the proposed methodology based on ICA in PV array operated under shadow conditions. The analysis is performed on three KC200GT connected in series, the model given in Ref. [35] is used as shown in Fig. 12. Two different shadow patterns are applied as given in Ref. [26], the first pattern is applying solar radiations of $G = [140, 970, 970]$ W/m^2 while the second one is $G = [500, 930, 700]$ W/m^2, the array is operated at temperature of 27.5 °C. The optimal parameters of this module given in Ref. [26] are used and the corresponding curves are obtained. Figs. 13 and 14 show the PV array curves obtained via ICA compared with the experimental curves those obtained in Ref. [26]. It is clear that; the obtained curves via ICA are the most closer to the measured ones. The error between the current obtained via established model and that measured one is calculated and the corresponding statistical parameters of mean, median, minimum, maximum and standard deviation are calculated and tabulated in Table 10. It is obvious that; the results obtained via the proposed methodology are better than of those obtained via ADE [26].

Finally, one can derive that, ICA has succeeded in extracting the optimal parameters of the PV system operated under variable conditions (irradiance, temperature and show effect) with the best fitness function compared to other reported methods.

7. Conclusion

This paper presents recent optimization approach based on imperialist competitive algorithm (ICA) in extracting the optimal parameters of PV cell/module. Mono-crystalline, poly-crystalline and amorphous PV systems are studied. The PV generating unit is modeled via single diode model (SDM) and double diode model (DDM) and the parameters of each model are determined optimally. The proposed objective function is derived from the voltage-power curve of the PV unit which has unique maximum power point (MPP). Different operating conditions are studied and the ICA extracted the optimal parameters in each case. The PV curves obtained via the proposed ICA are compared to the measured curves and others obtained via other reported meta-heuristic algorithms. The results obtained via the proposed methodology ensure the superiority, efficiency and reliability of the ICA in estimating the PV

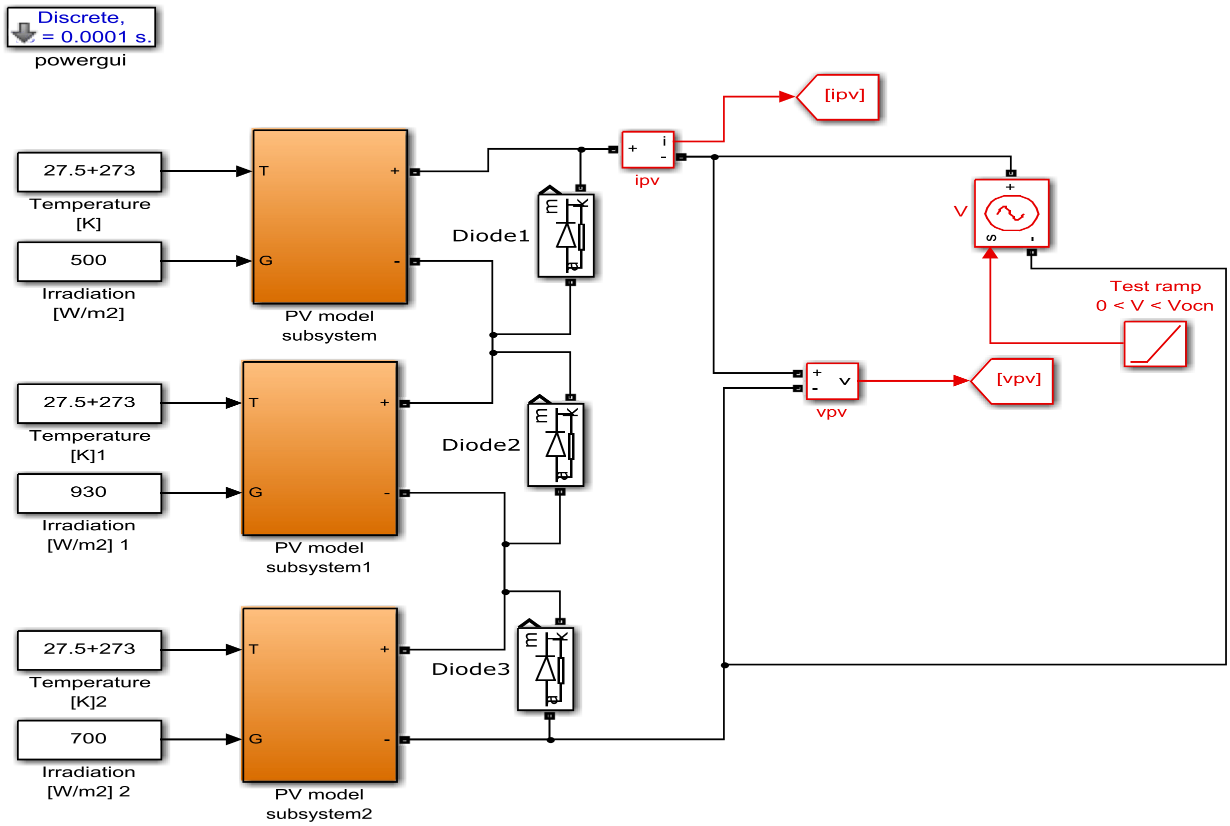


Fig. 12. Simulink model of PV array comprises three KC200GT modules connected in series.

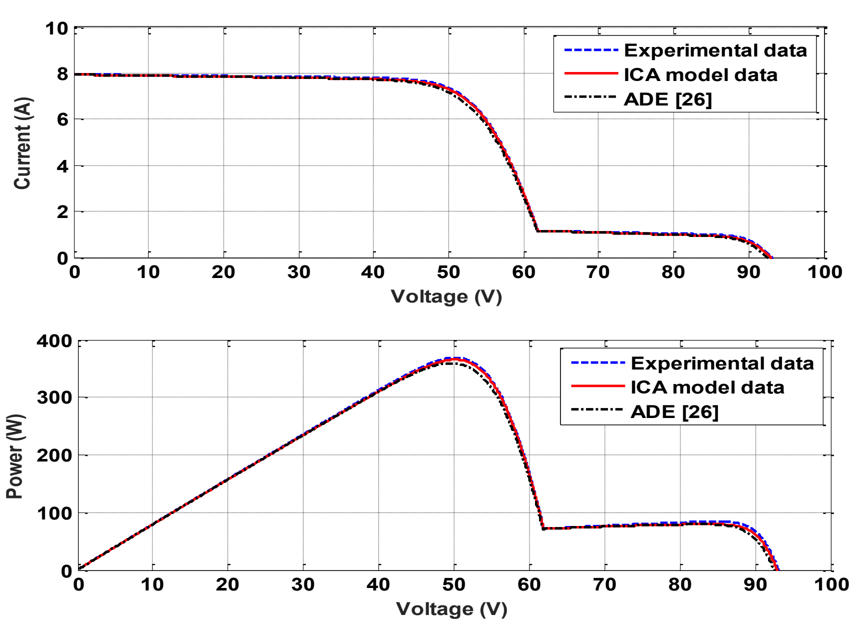


Fig. 13. *I-V* and *P-V* curves of the PV array operated in the first shadow pattern.

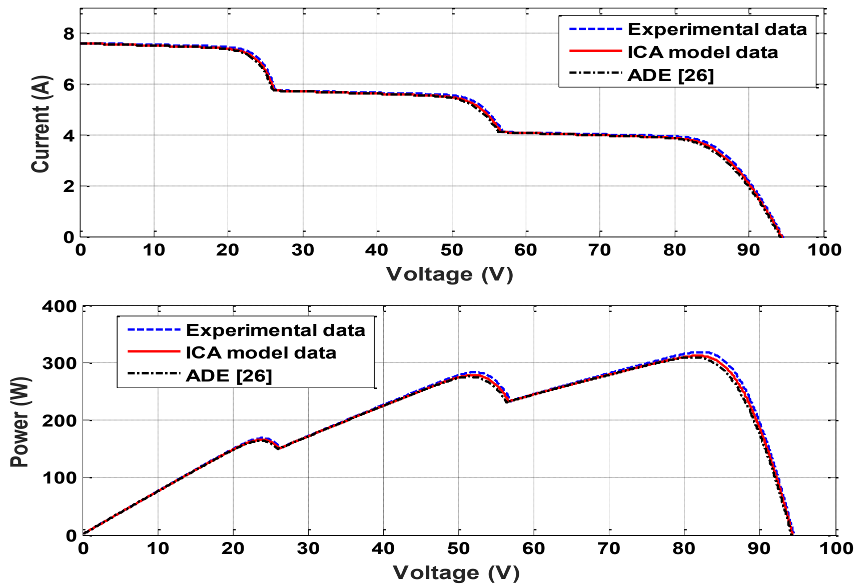


Fig. 14. *I-V* and *P-V* curves of the PV array operated in the second shadow pattern.

Table 10
Comparative analysis of the error obtained via ICA and ADE [26] for both shadow patterns.

Studied case	Case #1		Case #2	
Algorithm	ADE [26]	Proposed ICA	ADE [26]	Proposed ICA
Minimum	4.0471×10^{-6}	2.2152×10^{-6}	0.0055	0.0035
Median	0.0445	0.0411	0.0463	0.0446
Maximum	0.2551	0.0667	0.2558	0.1206
Mean	0.0716	0.0397	0.0770	0.0524
Std. deviation	0.0680	0.0185	0.0717	0.0338
Model GMPP (W)	359.1149	365.5215	309.3535	311.9414
Experimental GMPP (W)	368.8396		318.4836	
% error	2.64%	0.8996%	2.87%	2.05%

cell/module optimal parameters for both SDM and DDM as it obtains the best fitness function with acceptable time.

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