Materials Today: Proceedings 52 (2022) 108–123

Contents lists available at ScienceDirect

Materials Today: Proceedings

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

Multiple learning JAYA algorithm for parameters identifying of photovoltaic models

Driss Saadaoui [a,*], Mustapha Elyaqouti [a], Khalid Assalaou [a], Dris Ben hmamou [b], Souad Lidaighbi [a]

[a] Laboratory of Materials and Renewable Energies, Faculty of Science, Ibn Zohr University, Agadir, Morocoo
[b] Laboratory of Electronics, Signal Processing and Physical, Faculty of Science, Ibn Zohr University, Agadir, Morocoo

ARTICLE INFO

Article history:
Available online 26 November 2021

Keywords:
Parameter extraction
Photovoltaic models
Multiple learning JAYA
Optimization

ABSTRACT

Extracting the optimum parameters of the solar photovoltaic (PV) model based on measured current–voltage data accurately, reliably, and quickly is a vital step to simulating, evaluating, and optimizing the model PV. Although several meta-heuristics have been proposed to extract photovoltaic parameters using experimental data, it suffers from slow convergence and poor efficiency which leads to poor solution quality. In this paper, a multiple learning JAYA (MLJAYA) approach has been proposed to extract the PV parameters under different operating conditions. The main advantage of multiple learning strategies introduced in the MLJAYA proposed is its ability to balance exploration and exploitation capabilities. The chaos perturbation mechanism is employed to improve the quality of the population to escape the local optimum and improve the accuracy of the basic JAYA algorithm. The structure of MLJAYA is very simple and requires only the size of the population and stop criterion. The efficacy of the proposed MLJAYA has been verified by including different PV modules models such as single diode, double diode, and PV module, and the results obtained was compared with different variants of JAYA and other state-of-the-art optimization algorithms. The best results of root mean square error (RMSE), and absolute error generated by MLJAYA are (RMSE = 9.8602E−04, SIAE = 1.781248E−02), and (RMSE = 9.8248E−04, SIAE = 1.76E−02) for RTC solar cell single diode and double diode respectively, and (RMSE = 2.4250748E−03, SIAE = 4.686375E−02) for Photowatt-PWP201. The results show the superior performance in terms of accuracy and reliability. Since, the MLJAYA show is a potential approach for extracting parameters from photovoltaic models.

1. Introduction

Unluckily, fossil fuel energy use has had serious and rising negative environmental impacts, such as CO_2 emissions, global warming, air pollution, and overall global environment degradation [4]. Our future energy needs must be met by a combination of sustainable technologies with minimal environmental impact. Potentially, the majority of these technologies will use solar energy in all its forms [5]. However, solar cells are a major contributor to the production of environmentally friendly electricity. Solar energy is converted into electrical energy using a system of photovoltaic cells that convert the absorbed sunlight into direct electrical current by utilizing the intrinsic properties of semiconductors [6-8]. In general, photovoltaic systems operate in harsh climatic conditions and photovoltaic panels degrade easily, which affects the solar energy utilization efficiency [9]. Therefore, to optimize PV systems, it is important to assess the actual behavior of PV panels in operation using an efficient model based on measured current–voltage data. Several PV models have been used to describe the nonlinear characteristics of PV systems, such as the single diode model, double diode model, and three diode model [10-14]. Overall, the parameters of PV models affect the performance of PV systems, so it is important to extract the parameters of PV models accurately to improve the performance of PV models. Up to now, several approach have been proposed to estimate parameters of PV models, can be broadly classified into deterministic and heuristic methods [15]. The deterministic techniques require a series of model restrictions, including differentiability and convexity, in order to be properly applied. So, numerous meta-heuristic algo-

* Corresponding author.
E-mail address: saadaouidriss@yahoo.fr (D. Saadaoui).

https://doi.org/10.1016/j.matpr.2021.11.106
2214-7853/

rithms have already been in the estimation of single diode model (SDM) and double diode model (DDM). In heuristic algorithms, exploration and exploitation are two very important features to achieve success in solving a particular optimization problem. Exploration refers to the ability of an algorithm to detect a wide range of solutions, located in different areas of the search space. In contrast, exploitation emphasizes the idea of strengthening the research mechanism on solution-rich areas with the aim of finding better solutions or improving existing solutions [16]. Each of the preceding strategies has these advantages: (1) Exploitation strategies are known to improve the speed of convergence towards a global optimum, and also to increase the probability of confinement in local optima. (2) Exploration strategies are known to increase the probability of finding regions in the search space where the global optimum is more favorable to be found, this may influence the speed of convergence of the algorithm [17]. Many meta-heuristic approaches have been used and improved to extract the PV models parameters in the past decade. They are memetic adaptive differential evolution (MADE) [18], teaching–learning-based artificial bee colony (TLABC) algorithm [19], niche particle swarm optimization in parallel computing (NPSOPC) algorithm [20], modified JAYA algorithm [21], genetic algorithm [22], differential evolution with biogeography based optimization (DE/BBO) [23], improved chaotic whale optimization algorithm (CWOA) [24].

However, the performance of these meta-heuristic algorithms depends on the determination of the specific parameters of the algorithm. Any bad parameter will lead to early convergence, reduced optimization accuracy and increased computational load. The competitive swarm optimizer (CSO) [25] is an improved variant of particle swarm optimization (PSO) that gives good results, generally for unimodal optimization problems. On the other hand, it is quickly trapped in local optima when solving complex multimodal optimization problems, due to its poor exploration. Winner-leading competitive swarm optimizer with dynamic Gaussian mutation (WLCSODGM) [26] proposed for extracting the parameters of the PV models. It found that this variant of PSO falls into local minima for complex multimodal optimization problems such as the PV model parameter extraction problem due to its poor exploration capability. Liang, et al. [27] proposed a classified perturbation mutation-based PSO algorithm (CPMPSO), for parameters extraction of PV models. In this approach, the authors divided the individuals into two categories according to the fitness values: The first one has individuals with high quality and is updated using an effective exploitation operator, whereas, in the second, individuals were refreshed based on an effective exploration operator. Its convergence speed still needs improvement. Furthermore, it has a hard time avoiding being trapped in local minima for the DDM. In addition, many meta-heuristic algorithms require additional specific control parameters, such as acceleration factors in PSO, number of mates and mutation control factor in bird mating optimizer (BMO), mutation probability and crossover probability in genetic algorithm (GA). The different algorithms introduced, the modeling type, type of solar cell /panel, performance criteria and results were listed in Table 1.

Recently, JAYA method is among the most recent meta-heuristic algorithms, which was first proposed by Rao [28] for solving different types of optimization problems, it does not require any additional parameters specific [28]. This algorithm has two drawbacks: first, a lack of population diversity leads to poor overall search capacity; second, insufficient exploration capacity leads to an imbalance between exploration and exploitation [29]. In Ref. [30], JAYA is used to extract the unknown parameters of PV models. The obtained results demonstrates JAYA's excellent optimization in relation to other well-known methods such as TLBO [31], CS [32], BLPSO [33], LBSA [34], and NNA [30]. To date, JAYA algorithm is applied in many optimization problems, such as PV system maximum power point (MPP) tracking [35], sizing optimization of a micro-channel heat sink [36], solving constrained mechanical design problems [37], hydro-static thrust bearing and rolling element bearing [37], and other real-world problems [38,39]. In the JAYA algorithm, the solution update is based on the average of the best solution and the worst solution simultaneously, even though the convergence rate is enhanced, does not guarantee diversity of the population, weakening the exploration ability. Therefore, many JAYA modified have been introduced in an attempt to improve the population diversity of the algorithm by implementing other update strategies. Jian and Weng [30] proposed a Logistic Chaotic JAYA (LCJAYA) algorithm for identifying the parameters of PV cell and module models. In this approach, a logistic chaotic map strategy is introduced into the solution updating phase of JAYA algorithm, which improves the population diversity of algorithm. An improved JAYA (IJAYA) optimization algorithm is proposed by Yu et al. [29] to solve the parameters identification of PV models problem. In this approach, a self-adaptive weight is introduced to adjust the tendency to approach the best solution and avoid the worst solution during the different stages of the search, which enables the algorithm to approach the promising area at the early stage and implement the local search at the later stage. The performance improvement of the IJAYA is limited the fact that the elite chaotic learning method used to refine the quality of the best solution at each generation, it did not take into account that different perturbations around the best solution should be attributed to different search stages. Chaotic JAYA (CJAYA) [40], is developed to explore the search space without getting trapped in the regions of local optima. The drawback of CJAYA is the imbalance between exploration and exploitation. Therefore, the performance improvement of CJAYA is bounded and should be improved when solving the parameter estimation problems parameter estimation problems of PV models. Notwithstanding that the previously presented meta-heuristic algorithms can produce accurate results, it is sometimes difficult for them to systematically find a more accurate and consistent global optimal solution. First of all, the estimation of the PV model parameters is a multi-modal problem with many local optima. Following this, these heuristic algorithms, each have their own evolutionary method that is adapted to different types of problems, including mono-modal, multi-modal or complex problems [41]. Moreover, the algorithms each have their own parameters, which require an adjustment to adapt to different phases of evolution and to different problems.

Based on the above considerations, this paper proposes a modified JAYA algorithm namely Multiple Learning JAYA algorithm (MLJAYA) algorithm to extract parameters from PV cell single and double diodes and module models with greater accuracy and reliability. Three main improvements exist in MLJAYA. Firstly, a self-adaptive weight is applied to adjust the matching tendency towards the best solution and to avoid the worst solution. This weight is intended to guide the algorithm to access the potential area at an early stage and to implement the local search at a later stage. Secondly, a multiple learning strategy has been introduced to improve the global search capacity and the balance between exploitation and exploration. Thirdly, to improve the quality of the population, chaos perturbation mechanism is used to escape the local optimal and improves the precision of the basic JAYA algorithm. Moreover, MLJAYA has a very simple design and doesn't add any new parameters to Jaya. The MLJAYA algorithm is validated using single diode model, double diode model, and PV module model. The comparison demonstrates the accuracy of the MLJAYA over well-known algorithms.

To summarize, the main contributions of this study are as follows:

Table 1
Meta-heuristic algorithms used for PV parameter estimation.

Ref.	Year	Used algorithms	Modeling type	Type of solar cell / panel	Performance criteria	Results
[42]	**2020**	grey wolf optimizerand cuckoo search(GWOCS)	**SDM, DDM**	Photowatt-PWP-201 module modelSTM6-40/36 module model	Best RMSEMean RMSEWorst RMSEMedian RMSEStandard deviation (Std. dev.)	• **It is a promising candidate technique for extracting the parameters of solar PV cell models under different operating conditions.** • **The accuracy of solution and convergence speed of global optimization problems show that GWOCS performs better than other algorithms such as GWO, EGWO, and mGWO.**
[43]	**2020**	Transient Search Optimization (TSO)	**Three-diode model (TDM) of the PV module.**	KC-200-GT ; MSX-60 CS6K280M	Extraction timeobjective functionBest fitness	• **The TSO algorithm achieved the best minimum values for the objective function among other algorithms such as GWO, WOA, and SFO** • **The TSO approach and the objective function can be exploited to find the TDM model of all commercial PV cells based on the dataset values of PVs.**
[19]	**2018**	teaching–learning-based artificial bee colony (TLABC)	**SDM; DDM**	RTC France silicon solar cellPhotowatt-PWP-201	Best RMSEMean RMSEWorst RMSEStd. dev.	• **Experimental results demonstrate that TLABC has highly competitive performance in terms of accuracy and reliability** different PV **parameter estimation problems.**
[44]	**2017**	Evaporation Rate based Water Cycle Algorithm (ER-WCA)	**SDM; DDM**	KC-200-GTSX 200 N1STH-235-WH	RMSE ; AEMAE ; REMRE ; NFE	• **In terms of RMSE, MAE and MRE, the ER-WCA is advantageous to NMMPSO, GOTLBO, MABC, CSO, BBO-M methods even under changing irradiation and temperature conditions** • **ER-WCA is a promising optimization technique for PV cell/module identification**.
[34]	**2018**	Multiple learning backtracking search algorithm (MLBSA)	**SDM; DDM**	RTC solar cellPhotowatt-PWP201	Best RMSEMean RMSEWorst RMSEStd. dev.; IAE	• **The experimental and statistical analyses show the superiority of MLBSA to solve the parameters identification problems of different PV compared with other methods in terms of accuracy, reliability, and computational efficiency.** • **The MLBSA can be seen as an efficient method for solving optimization problems in any energy and non-energy system.** • **The performance of MLBSA can be degraded when solving larger or smaller systems compared to other methods.**
[45]	**2020**	Grasshopper Optimization Algorithm (GOA)	**TDM**	KC200GT ; MSX-60	Objective function convergence.AE	• **The GOA approach has been effective in optimizing the parameters of the three-diode model.** • **The GOA is capable of solving other optimization problems in several research areas such as wind energy systems, other renewable energy systems and smart grids.**
[46]	**2021**	Stochastic FractalSearch (SFS)	**SDM; DDM**	R.T.C solar cellSTP6 120/36ESP-160 PPW	Residual auto correlation function (RCAF)AE ; MAE ; RMSE	• **The obtained results by STS method show the superiority, perfectness, and effective modeling concerning various performance parameters.** • **The SFS method can be used as a high valued optimization technique for the extraction of solar PV parameters under any test conditions.** • **The SFS method defines a new error metric (RCAF)**
[47]	**2018**	Differential evolution with whale optimization algorithm (DE/WOA)	**SDM; DDM**	R.T.C solar cellPhotowatt-PWP201	Mean of IAEsPower errorCurrent errorMean ; Std. dev.	• **The DE/WOA algorithm is validation with 13 classical numerical benchmark functions** • **The experimental results demonstrate that DE/WOA can present encouraging results under different irradiances, temperatures, and dynamic weatherconditions, comparing with original DE, WOA, and five advanced variants of them and is highly competitive with some recently-proposed parameter extraction methods.**
[32]	**2019**	biogeography-based heterogeneous cuckoo search (BHCS)	**SDM; DDM**	R.T.C solar cellSTM6-40/36STP6-120/36	Best RMSEMean RMSEWorst RMSEMedian RMSEStd. dev.	• **The best performance of BHCS is due to the combination of two strategies, namely the heterogeneous cuckoo search strategy and the biogeography-based discovery operator.** • **In comparison with CS, BBO and several other *meta*-heuristic algorithms, BHCS has very competitive performances in terms of accuracy and reliability.** • **The BHCS algorithm is an efficient tool for PV parameter estimation.**

Table 1 (*continued*)

Ref.	Year	Used algorithms	Modeling type	Type of solar cell / panel	Performance criteria	Results
[48]	**2021**	gradient-based optimizer (GBO)	**SDM; DDM; TDM**	R.T.C solar cell	AE; RMSE	• **The GBO algorithm has many advantages, including solution accuracy, balance, and convergence speed between analysis and exploitation.** • **The results obtained by the GBO were more accurate than those obtained by most of the ten competitor algorithms.** • **GBO is a good candidate to solve solar cell system optimization problems.**
[49]	**2021**	Reinforcement learning-based differential evolution (RLDE)	**SDM; DDM**	R.T.C solar cell Photowatt-PWP201 STM6-40/36 STP6-120/36	Best RMSE Mean RMSE Worst RMSE Std. dev.	• **The RLDE algorithm essentially applies RL to the selection and adjustment of operators in DE.** • **RLDE can be considered as a very promising approach for parameter extraction of other complex PV models.**
[50]	**2017**	Shuffled complex evolution (SCE)	**DDM**	Known PV cellUnknown PV module	RE; SSE; MAE; MBE ; MAEP ; RMSE	• **Compared with AM, LM, GA, DE, and PSO approach, the results obtained show that SCE has a low convergence computation time and a significant ability to solve all global optimization problems.**
[51]	**2021**	Improved gaining-sharing knowledge (IGSK)	**SDM; DDM**	R.T.C solar cellPhotowatt-PWP201 STM6-40/36STP6-120/36ST40 ; SM55	Best RMSEMean RMSEWorst RMSEMedian RMSEStd. dev	• **The IGSK algorithm will not allow solving multi-objective optimization problems or problems under constraints.** • **Compared with other state-of-the-art algorithms, IGSK has excellent performance in terms of convergence speed and accuracy and reliability of parameter values.**
[52]	**2016**	Differential Evolution and Electro-magnetism like algorithms	**SDM**	KC120-1 multi-crystalline 120 Wp PV	MBE ; RMSECorrelation coefficient R^2CPU execution time	• **The achieved results demonstrate the superiority of the proposed evolutionary method with integrated mutation per iteration and the evaluative algorithm with adaptive mutation per iteration, compared to the electromagnetic type algorithm electromagnetic.** • **These advantages are tied to high estimation accuracy, rapid convergence, and fewer control parameters**
[26]	**2020**	Winner-leading competitive swarm optimizer with dynamic Gaussian Mutation (WLCSODGM)	**SDM; DDM**	R.T.C solar cell Photowatt-PWP201 KC200GT MSX-60	IAE; SIAE; RMSE Best RMSE Mean RMSE Worst RMSE Std. dev.	• **The approach (WLCSODGM) presented performs better in terms of the accuracy of parameters, robustness, convergence, and statistics.** • **Both coefficients of broadening E and narrowing S in the DGM have a significant effect on the performance of the WLCSODGM method.**

- A novel method MLJAYA is developed to extract the unknown parameters of PV cell and module models.
- In MLJAYA, a multiple learning strategy is used to ensure a good balance between exploitation and exploration.
- A chaos perturbation mechanism is proposed to improve the quality of the best solution in each generation.
- The performance of MLJAYA is exhaustively evaluated through parameter identification problems of different PV models.

The remainder of this paper is structured as follows. PV models and mathematical background is presented in Section 2. Section 3 description of the LMJAYA algorithm. Results and discussions are presented in Section 4. Finally, conclusions are presented in Section 5.

2. Photovoltaic models (PV) and mathematical background

2.1. Solar cells

2.1.1. Single diode model

Due to its simplicity, the single diode model (SDM) is usually applied to simulate the characteristic current–voltage of the solar cell. Fig. 1(a) shows the equivalent circuit of SDM [53].

In SDM, the current I and voltage V at the output terminal of the PV panel module are related by the equation [32,54]:

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

where I_{ph} denotes the photo current, I_o indicate the reverse saturation current of the diode, a ideality factor , R_s and R_{sh} denotes series resistance and shunt resistance respectively, $q = 1.60217646 \times 10^{-19}C$ denotes the electron charge, k is the Boltzmann constant ($k = 1.3806503 \times 10^{-23}J/K$) , and T is the temperature in Kelvin (K).

2.1.2. Double diode model

The double diode (DDM) model is more precise, accurate, and better than the single diode (SDM) because in this case, it takes into account the effect of recombination current loss in the depletion region [54-60]. In this model, two diodes are connected in parallel with a shunt resistance and series resistance. Fig. 1(b) shows the equivalent circuit of the DDM. The output current I in the double diode circuit of Fig. 1(b) is given by Eq. (2):

$$I = I_{ph} - I_{01}\left[exp\left(\frac{q(V+R_sI)}{a_1kT}\right) - 1\right] - I_{02}\left[exp\left(\frac{q(V+R_sI)}{a_2kT}\right) - 1\right] - \frac{V+R_sI}{R_{sh}} \tag{2}$$

where I_{01} and I_{02} are the reverse saturation current of the diode D1 and D2 respectively, a_1 denotes the ideality factor of the diode D1 and a_2 is the ideality factor of the diode D2.

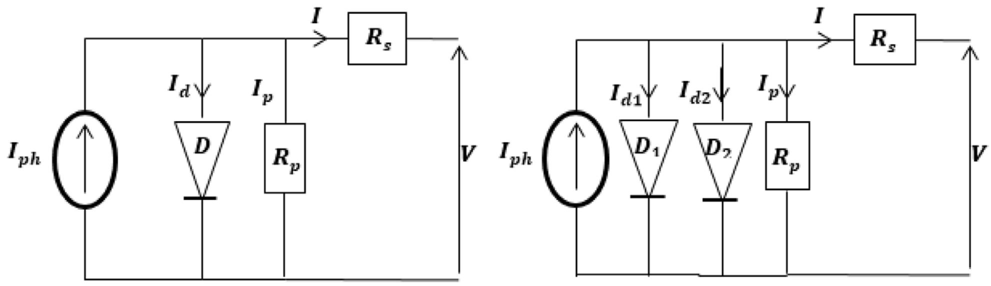


Fig. 1. The equivalent circuit (a) for the single-diode model and (b) for double-diode model.

2.2. Photovoltaic module model

The PV module model contains Ns cells connected in series and Np cells connected in parallel. The equivalent electric circuit of the PV panel module is shown in Fig. 2. Furthermore, the output current of the PV module is expressed as follows [18]:

$$I/N_p = I_{ph} - I_o\left[exp\left(\frac{q(V/N_s + R_sI/N_p)}{akT}\right) - 1\right] - \frac{V/N_s + R_sI/N_p}{R_{sh}} \tag{3}$$

2.3. Objective function

The parameters estimation of the solar PV model is studied as an optimization problem to minimize the difference between measured data and the simulated ones. However, the root mean square error (RMSE) is a widely used objective function to quantify the total error, as shown in Eq. (4) [27,32,42,44,57,58] :

$$RMSE = \sqrt{1/N\sum_{i=1}^{N}(I_{measu} - I_{theor})^2} \tag{4}$$

where, I_{measu} and I_{theor} are the measured and simulated current respectively and N is the number of experimental data.

3. Multiple learning JAYA algorithm (MLJAYA)

3.1. JAYA algorithm

JAYA algorithm is simple and has proved the most effective in solving the optimizing problems with constrained and unconstrained [59]. In this algorithm the initial solutions are randomly generated by respecting the upper and lower bounds of the process variables. The search mechanism of the JAYA algorithm is driven by the current optimal solution and the current worst solution, which can be described as follows.

$$y_{newi,j} = y_{i,j} + \alpha_1 \times (y_{best,j} - |y_{i,j}|) - \alpha_2 \times (y_{worst,j} - |y_{i,j}|) \tag{5}$$

where $y_{i,j}$ denotes the *j-th* variable of the *i-th* candidate solution, $|y_{i,j}|$ is the absolute value of $y_{i,j}$, $y_{best,j}$ and $y_{worst,j}$ respectively denotes the values of the *j-th* variable of the best solution and the worst solution, $y_{newi,j}$ is the update variable of $y_{i,j}$, α_1 and α_2 are two random numbers in [0,1].

In the Jaya algorithm, the solution is updated only using one solution converges to the best solution and another solution diverges from the worst solution simultaneously [28]. Thereby, a good intensification and diversification of the search process attained.

3.2. The proposed MLJAYA

The MLJAYA algorithm is a modified version of the JAYA algorithm for solving the parameters identification problems of different PV models. The solutions in the MLJAYA algorithm are updated in a similar manner as in the JAYA algorithm based on Eq. (5). However, in order to handle complex optimization problems effectively and efficiently, the MLJAYA algorithm is incorporated with self-adaptive weight, multiple learning strategy and a chaos perturbation mechanism. Firstly, a self-adaptive weight is applied to adjust the matching tendency towards the best solution and to avoid the worst solution. Secondly, a multiple learning strategy has been introduced to achieve a good balance between the exploration and exploitation abilities. Thirdly, Chaos perturbation mechanism is used to escape the local optimal and improves the precision of the basic JAYA algorithm [60]

3.2.1. Self-adaptive weight

In the search procedure of JAYA, the population must reach the promising region of the search region at the early stage, and local search should be implemented in promising way to refine the quality of population. For this purpose, the self-adaptive strategy is

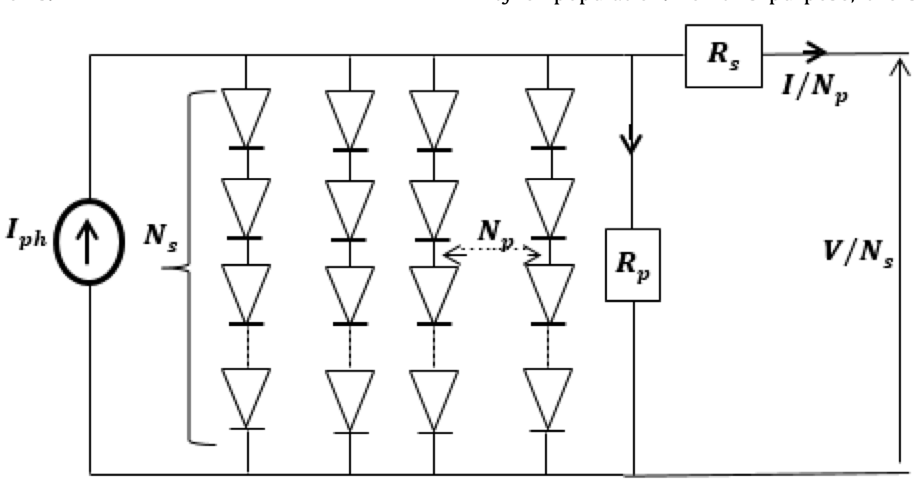


Fig. 2. Equivalent circuit of PV models.

introduced to adjust the degree of avoiding the worst solution and approaching the best solution. For this purpose, Eq. (5) is replaced by Eq. (6):

$$y_{newi,j} = y_{i,j} + \alpha_1 \times (y_{best,j} - |y_{i,j}|) - \Psi.\alpha_2 \times (y_{worst,j} - |y_{i,j}|) \tag{6}$$

The weight Ψ presented in Eq. (7) is given by:

$$\Psi = \begin{cases} \left(\frac{g(y_{best})}{g(y_{worst})}\right)^2 & if \quad y_{worst} \neq 0 \\ 1 & otherwise \end{cases} \tag{7}$$

where $g(y_{best})$ denotes the objective function values of the best solution and $g(y_{worst})$ denotes the objective function values of the worst solution.

It is evident from Eq. (7) that the added weight is self-adaptive, and that its value increases progressively as the difference between the function values of the best and worst solution decreases as the search process proceeds. Thus, taking into account the position of the best solution, the optimal area can be located at the beginning, while the local search in the promising region can be reached at the later stage, because the probability of the best solution being approached and that of avoiding the worst solution are the same.

3.2.2. Multiple learning strategy

In the conventional JAYA algorithm, the best solution and worst solution plays an important role in updating the population, this approach can speed up the convergence rate and increase the exploitation capacity of the algorithm. As a result, the population diversity and exploration capability of the JAYA is quickly deteriorating. Therefore, a multiple learning strategy is introduced to have a good balance between exploitation and exploration. The pre-

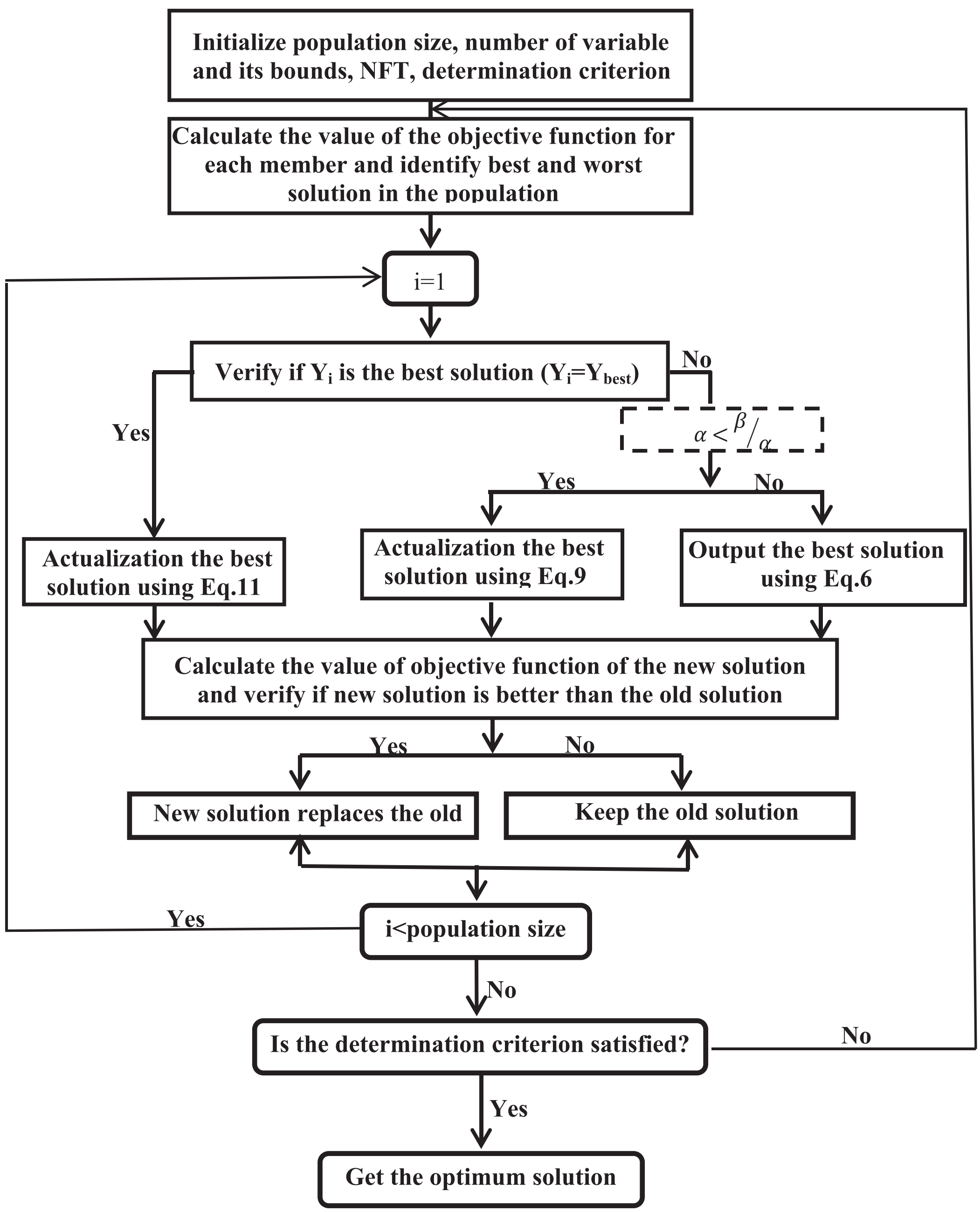


Fig. 3. Flowchart of the MLJAYA algorithm.

Table 2
Parameters boundary of different PV models.

Parameter	RTC solar cell		Photowatt- PWP201	
	Lower bound	Upper bound	Lower bound	Upper bound
$I_{ph}(A)$	0	1	0	2
I_o , I_{o1} , I_{o2} (μA)	0	1	0	50
Rs(Ω)	0	0.5	0	2
Rsh (Ω)	0	100	0	2000
a , a_1 , a_2	1	2	1	50

Table 3
Parameters of the algorithms used.

Algorithm	Parameters	Algorithm	Parameters
PGJAYA	NP = 20	**SATLBO**	NP = 40
IJAYA	NP = 20	**IGHS**	NP = 30, HMCR = 0.95 (ref_askarzadeh2012)
EJADE	NP = 50	**IBSA**	NP =
CLJAYA	NP = 20	**jDE**	NP = 400 when D = 100, F_l = 0.1, F_u = 0.9, τ_1 = τ_2 = 0.1 NP = 100 when D = 30
JAYA	NP = 20	**MLBSA**	NP = 50
DE/BBO	NP = 100, F = rand(0.1, 1), CR = 0.9, E = I = 1, k = 2, $\pi_{max} = 0.005$	**MADE**	NP = 20, ϵ = 0.05 for SDM ϵ = 0.01 for DDM
LBSA	NP = 50, mix rate = 1.	**GWOCS**	NP = 30
GOTLBO	NP = 50, JR = 0.3	**TLBO**	NP = 50
CLPSO	NP = 40, w = 0.9 → 0.4c = 1.49445, m = 7	**MLJAYA**	NP = 30, F = 3.randn

sented multiple learning methods allow some individuals to improve the diversity of the population by learning from both the historical and current population, while other individuals focus on improving the convergence speed by learning from the best individual in the current population. The multiple learning methods are used to generate a new individual, as shown in Eq. (9).

$$y'_{i,j} = \begin{cases} y_{ij} + F \times (y_{worst,j} - y_{i,j}) + (y_{k,j} - y_{i,j}) & if\ (\alpha < \beta/\alpha \sim \Gamma(0,1)) \\ y_{i,j} + rand.(y_{best,j} - y_{i,j})\ otherwise \end{cases} \tag{9}$$

where k is an integer randomly selected from {1, 2, ...,N_P} and satisfies $k \neq i$, so $y_{k,j}$ is the value of the *jth* variable for the individual k of current population. α and β are two uniformly distributed random numbers within [0, 1]. $y_{best,j}$ is the value of the *jth* variable for the best individual of current population.

3.2.3. Chaos perturbation mechanism

The chaos perturbation mechanism is used for preventing the local optimum and thus improving the performance of the algorithm. However, chaos is a nonlinear phenomenon, characterized by its ergodicity, randomness, and high sensitivity to initial conditions [61,62]. We use this randomness and the ergodicity of chaos to avoid the search colliding with a local optimum and to overcome the shortcomings of a traditional optimization algorithm. The chaos system used in this research is the logistic mapping defined by Eq.10. Subsequently, the best solution is updated using equation (11).

$$z_{j,i+1} = \mu_j z_{j,i}(1 - z_{j,i}), z_{j,i} \in [0,1] \quad j = 1 \cdots \mathrm{D}, \quad i = 1, 2 \cdots \tag{10}$$

where $z_{j,i}$ is the *jth* chaotic variable in the *ith* generation, and μ_j is a chaotic attractor. When $\mu_j = 4$, the logistic mapping is considered a full mapping in the range of [0, 1],

The jth learner of the class is expressed by a vector $y_{best,j}$ and the new learner $y'_{best,j}$ generated by the chaotic search in the neighborhood of $y_{best,j}$ is obtained by Eq. (11).

$$y'_{best,j} = y_{best,j} + rand(2Z_{i+1} - 1)\mathrm{if rand} < (1 - \mathrm{NFT/NFT\_max}) \tag{11}$$

where $Z_{i+1} = (z_{1,i+1}, z_{2,i+1}, \cdots\cdots\cdots, z_{D,i+1})$

3.2.4. Pseudo code of MLJAYA

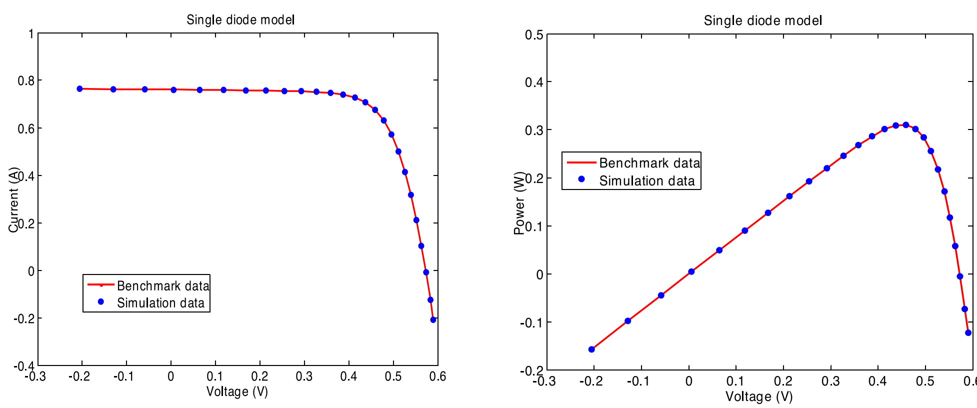
The setups of the proposed MLJAYA is described in algorithm 1, where NFT is the number of function tests and (NFT_max) is the maximum number of function tests, NP is the size of the initial population. In addition, the flowchart of MLJAYA is shown in Fig. 3. It is clear that MLJAYA will stop the search run if the maximum number of generations is achieved.

Algorithm 1: Pseudo code of MLJAYA.

Input: population size (*NP*) and maximum number of function tests (*NFT_max*)
Output: optimal member in the population
Generate an initial population and evaluate fitness of each member in the population
NFT = NP;
While *NFT < NFT_max* **do**
Selected the best member Y_{Best} and the worst member Y_{Worst}
  For $i = 1$ to *NP* **do**
    If *Yi* is not best member //Update the weight by self-adaptive strategy// Calculate the weight by using Eq. (7)
    Uptate the *k-th* variable of the solution *Yi* using Eq.6
    Elseif (α < β/α ~ Γ(0,1))//multiple learning strategy//
    Update the *k-th* variable of the member Y_i using Eq. (9) **Else** // Chaos perturbation mechanism//
Update the k-th variable of the member using Eq.(11)
    End if
  Compute the fitness function value of the new member
    NFT = NFT + 1
Receive new member if it' s better than the worst member ;
  End for
End while

Table 4
The optimal parameters obtained by MLJAYA compared with other state-of-art algorithms for SDM of the solar cell.

Algorithm	$I_{ph}(A)$	I_o (μA)	Rs(Ω)	Rsh(Ω)	a	Best RMSE ($\times 10^{-4}$)	Worst RMSE ($\times 10^{-4}$)	Mean RMSE ($\times 10^{-4}$)
MLJAYA	0.7608	0.32302	0.0364	53.7185	1.4812	**9.8602**	**9.8602**	**9.8602**
PGJAYA [33]	0.7608	0.3230	0.0364	53.7185	1.4812	**9.8602**	9.8603	**9.8602**
IJAYA [29]	0.7608	0.3228	0.0364	53.7595	1.4811	9.8603	9.92	9.92
EJADE [63]	0.7608	0.3230	0.0364	53.7185	1.4812	**9.8602**	**9.8602**	**9.8602**
CLJAYA [68]	0.7608	0.3230	0.0364	53.7185	1.4812	**9.8602**	**9.8602**	**9.8602**
JAYA [68]	0.7608	0.3246	0.0363	52.3754	1.4817	9.9786	14.783	11.617
MADE [18]	0.7608	0.3230	0.0364	53.7185	1.4812	**9.8602**	**9.8602**	**9.8602**
GWOCS [42]	0.76077	0.3219	0.0362	53.6320	1.4808	9.8607	9.9095	9.8874
TLBO [68]	0.76078	0.3271	0.0363	53.9466	1.4824	9.8636	12.3579	10.4761
BBO-M [69]	0.76078	0.31874	0.0364	53.3627	1.4798	9.8630	NA	NA
IGHS [64]	0.76077	0.34351	0.03613	53.2845	1.4874	9.9306	NA	NA
DE/BBO [34]	0.7605	0.32477	0.0364	55.2627	1.4817	9.9922	22.3	12.9
LBSA [34]	0.7606	0.34618	0.0362	59.0978	1.4881	10.143	15.9	12.4
GOTLBO [70]	0.76078	0.33155	0.0362	54.1154	1.4838	9.8744	14.388	10.289
CLPSO [34]	0.7608	0.34302	0.0361	54.1965	1.4873	9.9633	11.8724	10.5871
SATLBO [71]	0.7608	0.3232	0.0363	53.7256	1.4812	**9.8602**	9.9494	9.878



(a) (b)

Fig. 4. Comparison on the (a) I-V and (b) P-V curve between the datasheet and simulated data obtained by MLJAYA algorithm.

Table 5
The individual absolute errors (IAE) of current and power of MLJAYA algorithm on single diode model.

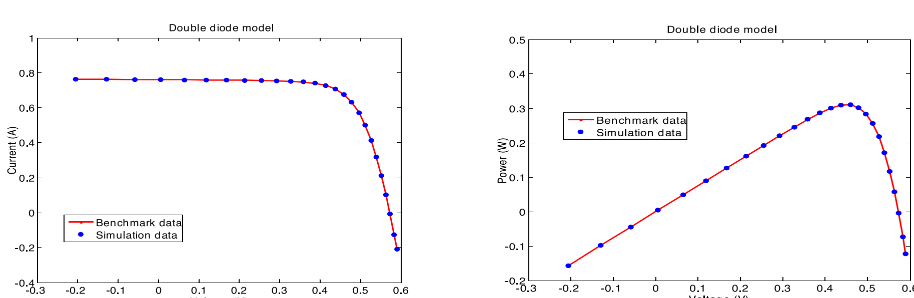
Item	Benchmark data		Simulated current data		Simulated power data	
	V(V)	I(A)	I_{sim}(A)	IAE_C(A)	P_{sim}(W)	IAE_p(W)
1	−0.2057	0.7640	0,764111773510811	0,000111773510810931	−0,15717779	2,29918E-05
2	−0.1291	0.762	0,762686766931466	0,000686766931466409	−0,09846286	8,86616E-05
3	−0.0588	0.7605	0,761378860677928	0,000878860677927529	−0,04476908	5,1677E-05
4	0.0057	0.7605	0,760178372817480	0,000321627182520157	0,00433302	1,83327E-06
5	0.0646	0.760	0,759080063397046	0,000919936602953864	0,04903657	5,94279E-05
6	0.1185	0.759	0,758067128339312	0,000932871660687673	0,08983095	0,000110545
7	0.1678	0.757	0,757115696984078	0,000115696984077651	0,12704401	1,9414E-05
8	0.2132	0.757	0,756166136282915	0,000833863717085048	0,16121462	0,00017778
9	0.2545	0.7555	0,755111281845299	0,000388718154700984	0,19217582	9,89288E-05
10	0.2924	0.754	0,753688167288479	0,000311832711521132	0,22037842	9,11799E-05
11	0.3269	0.7505	0,751411183909163	0,000911183909163449	0,24563632	0,000297866
12	0.3585	0.7465	0,747370311139112	0,000870311139112068	0,26793226	0,000312007
13	0.3873	0.7385	0,740116703841217	**0,00161670384121682**	0,2866472	0,000626149
14	0.4137	0.728	0,727413012461820	0,000586987538179762	0,30093076	0,000242837
15	0.4373	0.7065	0,706964289682593	0,000464289682592489	0,30915548	0,000203034
16	0.4590	0.6755	0,675299187114843	0,000200812885157164	0,30996233	9,21731E-05
17	0.4784	0.632	0,630881679651015	0,00111832034898529	0,3018138	0,000535004
18	0.4960	0.573	0,572074238795868	0,000925761204132125	0,28374882	0,000459178
19	0.5119	0.499	0,499482798110195	0,000482798110194749	0,25568524	0,000247144
20	0.5265	0.413	0,413489887723459	0,000489887723459093	0,21770243	0,000257926
21	0.5398	0.3165	0,317228453575752	0,000728453575752464	0,17123992	0,000393219
22	0.5521	0.212	0,212132620149102	0,000132620149101897	0,11711842	7,32196E-05
23	0.5633	0.1035	0,102778189694791	0,000721810305208528	0,05789495	0,000406596
24	0.5736	−0.01	−0,00915874229842810	0,000841257701571896	−0,00525345	0,000482545
25	0.5833	−0.123	−0,124252477776826	0,00125247777682634	−0,07247647	**0,00073057**
26	0.5900	−0.21	−0,209033140961002	0,000966859038997708	−0,12332955	0,000570447
Total IAE			**0.01781248**		**0,00665235**	

Table 6
Calculated values of IAE_C obtained by MLJAYA and other advanced algorithms SDM.

IAE_C								
Item	Vm(V)	Im(V)	MLJAYA	PGJAYA	IJAYA	CLJAYA	JAYA	GWOCS
1	−0.2057	0.7640	0,00011177	0.00003464	0.00003108	0.00008770	0.00020205	0.00009030
2	−0.1291	0.762	0,00068676	0.00059413	0.00064510	0.00066309	0.00074090	0.00066300
3	−0.0588	0.7605	0,00087886	0.00083513	0.00087259	0.00085531	0.00089959	0.00085299
4	0.0057	0.7605	0,00032162	0.00032210	0.00029691	0.00034601	0.00033252	0.00034934
5	0.0646	0.760	0,00091993	0.00088239	0.00086807	0.00094479	0.00095942	0.00094906
6	0.1185	0.759	0,00093287	0.00086395	0.00085885	0.00095766	0.00099803	0.00096404
7	0.1678	0.757	0,00011569	0.00020632	0.00020437	0.00009165	0.00002770	0.00008313
8	0.2132	0.757	0,00083386	0.00073798	0.00074403	0.00085864	0.00094444	0.00086758
9	0.2545	0.7555	0,00038871	0.00030682	0.00031304	0.00041313	0.00051901	0.00042318
10	0.2924	0.754	0,00031183	0.00026812	0.00026992	0.00033612	0.00046075	0.00034636
11	0.3269	0.7505	0,00091118	0.00089886	0.00090585	0.00089097	0.00074896	0.00087770
12	0.3585	0.7465	0,00087031	0.00078955	0.00080817	0.00085385	0.00069587	0.00083956
13	0.3873	0.7385	0,00161670	0.00148866	0.00151849	0.00161722	0.00144570	0.00159097
14	0.4137	0.728	0,00058698	0.00077985	0.00074326	0.00061778	0.00079846	0.00060496
15	0.4373	0.7065	0,00046428	0.00032714	0.00036230	0.00047265	0.00029052	0.00045663
16	0.4590	0.6755	0,00020081	0.00030107	0.00027606	0.00021985	0.00039164	0.00019848
17	0.4784	0.632	0,00111832	0.00123581	0.00122648	0.00124173	0.00138810	0.00110683
18	0.4960	0.573	0,00092576	0.00098904	0.00099570	0.00107164	0.00117632	0.00090912
19	0.5119	0.499	0,00048279	0.00072822	0.00071050	0.00060702	0.00055795	0.00049840
20	0.5265	0.413	0,00048988	0.00075155	0.00073174	0.00064879	0.00066665	0.00049728
21	0.5398	0.3165	0,00072845	0.00105272	0.00103942	0.00101011	0.00109882	0.00072056
22	0.5521	0.212	0,00013262	0.00011444	0.00011485	0.00015494	0.00031368	0.00010309
23	0.5633	0.1035	0,00072181	0.00135725	0.00134042	0.00124869	0.00102801	0.00077758
24	0.5736	−0.01	0,00084125	0.00119127	0.00121803	0.00128246	0.00154955	0.00075595
25	0.5833	−0.123	0,00125247	0.00255095	0.00251336	0.00250741	0.00220330	0.00137012
26	0.5900	−0.21	0,00096685	0.00165139	0.00168223	0.00152767	0.00184212	0.00082449
Total IAE			0.01781248	0.02125936	0.02129082	0.02152688	0.02228006	**0.0177207**

Table 7
The optimal parameters obtained by MLJAYA compared with other state-of-art algorithms for DDM of the solar cell.

Algorithm	$I_{ph}(A)$	I_{o1} (μA)	I_{o2} (μA)	Rs(Ω)	Rsh(Ω)	a_1	a_2	Best RMSE ($\times 10^{-4}$)	Worst RMSE ($\times 10^{-4}$)	Mean RMSE ($\times 10^{-4}$)
MLJAYA	0.7608	0.82523	0.22021	0.0367	56.2627	1.9988	1.4491	9.8294	14.2102	10.618
PGJAYA [51]	0.76077	0.29500	0.2102	0.03645	54.3036	1.4735	2	9.8443	9.9499	9.8582
IJAYA [29]	0.7601	0.00504	0.75094	0.0376	77.8519	1.2186	1.6247	9.8293	14.055	10.269
EJADE [63]	0.7608	0.21031	0.88534	0.0368	55.8135	1.4450	2	9.8263	**9.8602**	9.8363
CLJAYA [68]	0.76078	0.22605	0.74876	0.03674	55.4859	1.4510	1.9999	**9.8249**	**9.8602**	**9.8308**
JAYA [68]	0.76077	0.28663	0.29702	0.03641	53.5136	1.4712	1.9997	9.9307	14.793	11.767
MADE [18]	0.7608	0.7394	0.22460	0.03680	55.4329	1.9963	1.4505	9.8261	9.8786	9.8608
GWOCS [42]	0.76076	0.53772	0.24855	0.03666	54.7331	2	1.4588	9.8334	10.017	9.9411
TLBO [68]	0.7610	0.67834	0.22954	0.03670	55.8211	1.9803	1.4525	9.8290	15.2057	11.5977
BBO-M [69]	0.76077	0.23260	0.69230	0.03670	55.3582	1.4534	1.9995	9.8251	NA	NA
IGHS [64]	0.76079	0.97310	0.16791	0.03690	56.8368	1.2126	1.42814	9.8635	NA	NA
IBSA [34]	0.7608	0.21507	0.26624	0.0366	51.9008	1.8718	2	9.9663	NA	NA
LBSA [34]	0.7606	0.29814	0.27096	0.0363	60.188	1.4760	1.92202	10.016	17.372	12.728
GOTLBO [70]	0.7608	0.8002	0.2205	0.0368	56.0753	2	1.449	9.8318	13.947	11.475
CLPSO [34]	0.7607	0.25843	0.38615	0.0367	57.9422	1.4625	1.9435	9.9894	11.458	15.494
jDE [51]	0.76078	0.2575	0.49160	0.03659	54.7712	1.4620	1.9999	9.8298	NA	NA



(a) (b)

Fig. 5. Comparison on the (a) I-V and (b) P-V curve between the datasheet and simulated data obtained by MLJAYA algorithm.

Table 8
The individual absolute errors (IAE) of current and power of MLJAYA algorithm on double diode model.

Item	Benchmark data		Simulated current data		Simulated power data	
	V(V)	I(A)	I_{sim}(A)	IAE_C(A)	P_{sim}(W)	IAE_p(W)
1	−0.2057	0.7640	0,763958750706341	4,12E-05	−0,15714631502029	8,48498E-06
2	−0.1291	0.762	0,762598063210525	0,00059806	−0,09845140996047	7,721E-05
3	−0.0588	0.7605	0,761348968505920	0,00084897	−0,04476731934814	4,99193E-05
4	0.0057	0.7605	0,760201803311741	0,0002982	0,004333150278876	1,69972E-06
5	0.0646	0.760	0,759150430695006	0,00084957	0,049041117822897	5,48822E-05
6	0.1185	0.759	0,758176945963568	0,00082305	0,089843968096682	9,75319E-05
7	0.1678	0.757	0,757254260919216	0,00025426	0,127067264982244	4,2665E-05
8	0.2132	0.757	0,756318452213770	0,00068155	0,161247094011976	0,000145306
9	0.2545	0.7555	0,755256979078226	0,00024302	0,192212901175408	6,18488E-05
10	0.2924	0.754	0,753803078522197	0,00019692	0,220412020159890	5,75798E-05
11	0.3269	0.7505	0,751472411078683	0,00097241	0,245656331181622	0,000317881
12	0.3585	0.7465	0,747363961175409	0,00086396	0,267929980081384	0,00030973
13	0.3873	0.7385	0,740047956558985	0,00154796	0,286620573575295	0,000599524
14	0.4137	0.728	0,727311279278660	0,00068872	0,300888676237582	0,000284924
15	0.4373	0.7065	0,706878484766503	0,00037848	0,309117961388392	0,000165511
16	0.4590	0.6755	0,675280195501096	0,0002198	0,309953609735003	0,00010089
17	0.4784	0.632	0,630957787471239	**0,00104221**	0,301850205526241	0,000498594
18	0.4960	0.573	0,572240318087602	0,00075968	0,283831197771450	0,000376802
19	0.5119	0.499	0,499703519654239	0,00070352	0,255798231711005	0,000360132
20	0.5265	0.413	0,413717652861094	0,00071765	0,217822344231366	0,000377844
21	0.5398	0.3165	0,317420496480098	0,0009205	0,171343583999957	0,000496884
22	0.5521	0.212	0,212262012953803	0,00026201	0,117189857351795	0,000144657
23	0.5633	0.1035	0,102838205681634	0,00066179	0,057928761260464	0,000372789
24	0.5736	−0.01	−0,009159327751035	0,00084067	−0,005253790397993	0,00048221
25	0.5833	−0.123	−0,124294949923916	0,00129495	−0,072501244290620	**0,000755344**
26	0.5900	−0.21	−0,209089946913424	0,00091005	−0,123363068678920	0,000536931
Sum of *IAE*			**0.0176**		**0,00677778**	

Table 9
The calculated values of IAE_C obtained by MLJAYA and other advanced algorithms DDM.

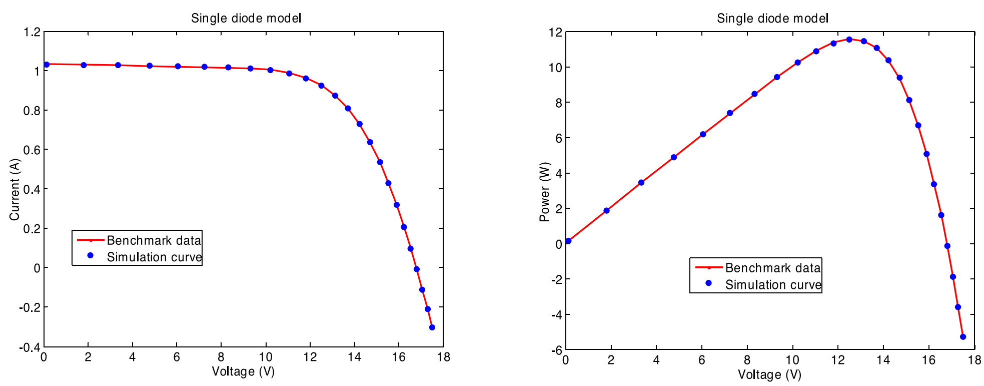
IAE_C								
Item	Vm(V)	Im(V)	MLJAYA	PGJAYA	IJAYA	CLJAYA	JAYA	GWOCS
1	−0.2057	0.7640	4,12E-05	0.00003464	0.00003108	0.00001670	0.00010219	0.00001696
2	−0.1291	0.762	0,00059806	0.00059413	0.00064510	0.00060400	0.00067209	0.00059756
3	−0.0588	0.7605	0,00084897	0.00083513	0.00087259	0.00083761	0.00085919	0.00079481
4	0.0057	0.7605	0,0002982	0.00032210	0.00029691	0.00032628	0.00034705	0.00040087
5	0.0646	0.760	0,00084957	0.00088239	0.00086807	0.00089238	0.00095093	0.00099450
6	0.1185	0.759	0,00082305	0.00086395	0.00085885	0.00087863	0.00096978	0.00100387
7	0.1678	0.757	0,00025426	0.00020632	0.00020437	0.00018858	0.00007141	0.00004849
8	0.2132	0.757	0,00068155	0.00073798	0.00074403	0.00075640	0.00089108	0.00089725
9	0.2545	0.7555	0,00024302	0.00030682	0.00031304	0.00032267	0.00046384	0.00044793
10	0.2924	0.754	0,00019692	0.00026812	0.00026992	0.00027758	0.00041319	0.00036586
11	0.3269	0.7505	0,00097241	0.00089886	0.00090585	0.00089924	0.00077950	0.00086416
12	0.3585	0.7465	0,00086396	0.00078955	0.00080817	0.00080159	0.00070232	0.00083315
13	0.3873	0.7385	0,00154796	0.00148866	0.00151849	0.00151082	0.00142673	0.00159294
14	0.4137	0.728	0,00068872	0.00077985	0.00074326	0.00075292	0.00083681	0.00059386
15	0.4373	0.7065	0,00037848	0.00032714	0.00036230	0.00035036	0.00024621	0.00047596
16	0.4590	0.6755	0,0002198	0.00030107	0.00027606	0.00028950	0.00042731	0.00017357
17	0.4784	0.632	0,00104221	0.00123581	0.00122648	0.00123937	0.00140627	0.00108065
18	0.4960	0.573	0,00075968	0.00098904	0.00099570	0.00100544	0.00117943	0.00088583
19	0.5119	0.499	0,00070352	0.00072822	0.00071050	0.00070598	0.00055478	0.00051674
20	0.5265	0.413	0,00071765	0.00075155	0.00073174	0.00073360	0.00063683	0.00051184
21	0.5398	0.3165	0,0009205	0.00105272	0.00103942	0.00104625	0.00101178	0.00073592
22	0.5521	0.212	0,00026201	0.00011444	0.00011485	0.00012315	0.00013709	0.00012636
23	0.5633	0.1035	0,00066179	0.00135725	0.00134042	0.00133651	0.00132002	0.00073824
24	0.5736	−0.01	0,00084067	0.00119127	0.00121803	0.00120838	0.00113028	0.00081954
25	0.5833	−0.123	0,00129495	0.00255095	0.00251336	0.00254346	0.00277537	0.00127408
26	0.5900	−0.21	0,00091005	0.00165139	0.00168223	0.00162809	0.00116770	0.00094888
Total IAE			**0.0176**	0.02125936	0,02125974	0,02127549	0,02147918	0,01773982

4. Results and discussions

The main goal of this section is tested to appraise the effectiveness of the proposed algorithm by conducting using the benchmarks experimental current–voltage data of single diode, double diode, and PV module. This data are a 57 mm diameter commercial R.T.C. France silicon solar cell operating at an irradiance of 1000 W/m^2 and a temperature of 33 °C, and a solar module named Photowatt-PWP201 contains 36 polycrystalline silicon cells in series operating at an irradiance of 1000 W/m^2 and a temperature of 45 °C. For a fair judgment, the lower and upper bounds for each parameter are adopted as the literature and the detailed descriptions are given in Table 2. The parameters of the algorithms are set in Table 3 [18,35,63,64]. In order to demonstrate the competitive performance of the MLJAYA algorithm in the parameters identification, it was compared with other state-of-the-art algorithms.

Table 10
Comparison MLJAYA with different others algorithms on PV module model.

Algorithm	$I_{ph}(A)$	I_o (μA)	Rs(Ω)	Rsh(Ω)	$A = a \times N_s$	Best RMSE ($\times 10^{-3}$)	Worst RMSE ($\times 10^{-3}$)	Mean RMSE ($\times 10^{-3}$)
MLJAYA	1.0305	3.4823	1.2013	981.9822	48.6428	**2.4250748**	2.49419	2.44395
PGJAYA [33]	1.0305	3.4818	1.2013	981.8545	48.6424	**2.425075**	2.426764	2.425144
IJAYA [29]	1.0305	3.4703	1.2016	977.3752	48.6298	2.4251	2.4389	2.4289
GWO [72]	1.02982	4.3863	1.17573	1186.5926	49.54686	2.526088	NA	NA
CLJAYA [68]	1.030514	3.4822628	1.201271	981.982279	48.64283	**2.425075**	NA	NA
JAYA [68]	1.03038	3.410219	1.204298	972.58408	48.5631	2.4309	2.595873	2.45371
MADE [18]	1.0305	3.4823	1.2013	981.9823	48.6428	**2.4250**	**2.4251**	**2.4251**
GWOCS [42]	1.03049	3.4650	1.2019	982.7566	48.62367	2.4251	2.4275	2.4261
MLBSA [72]	1.030514	3.4823	1.20127	981.9822	48.64283	2.5250748	NA	NA
DE/BBO [34]	1.0303	3.6172	1.1969	1015.1	48.7894	2.428255	2.5256	2.4616
LBSA [34]	1.0304	3.5233	1.2014	1020.4	48.6866	2.4296	2.5344	2.4674
GOTLBO [70]	1.0307	3.5124	1.1995	969.9313	48.8214	2.426583	2.5638	2.4754
CLPSO [34]	1.0304	3.6131	1.1978	1017.0	48.7847	2.4281	2.5433	2.4549
SATLBO [71]	1.0306	3.4715	1.2017	972.9357	48.6313	2.4251	NA	NA



(a) b

Fig. 6. Comparison on the (a) I-V and (b) P-V curve between the datasheet and simulated data obtained by MLJAYA algorithm.

These algorithms are PGJAYA, IJAYA, EJADE, CLJAYA, JAYA, MADE, GWOCS, TLBO, BBO-M, IGHS, DE/BBO, LBSA, GOTLBO, CLPSO, SATLBO, IBSA, jDE, GWO, and MLBSA. The comparisons are conducted on the root mean square error (RMSE) and the individual absolute error (IAE) values to illustrate the accuracy of each algorithm. Then, the convergence curves are analyzed and presented to evaluate the robustness of each algorithm. The simulations are performed using the MATLAB platform under Windows7 64-bit. The MATLAB code runs on an Intel(R) Core (TM) i7 −4600 M CPU @ 2.90 GHz 2.90 GHz HP ZBook 15, 16 GB RAM.

4.1. Case 1: single diode model

The outcomes of the application the MLJAYA and fifteen other methods for the parameter estimation of RTC PV cell with the SDM are recorded in Table 4. It can be noted that MLJAYA, PGJAYA, EJADE, CLJAYA, MADE, and SATLBO obtained the best RMSE value (9.8602E−04), followed by IJAYA (9.8603E−04), GWOCS (9.8607E−04), BBO-M (9.8630E−04), TLBO (9.8636E−04), GOTLBO (9.8744E-04), IGHS (9.9306E-04), CLPSO (9.9633), DE/BBO (9.9922E-04), and LBSA (10.143−04). Even though the RMSE values obtained by the IJAYA, GWOCS, BBO-M, and TLBO algorithms are very close to the value (9.8602E-05), any reduction of the objective function is significant since it leads to an improvement of the knowledge of the real values of the parameters.

As a further analysis, based on the identification parameters of the MLJAYA algorithm, the I-V output curves, and P-V output curves are shown in Fig. 4. As can be clearly seen from Fig. 4, the I-V and P-V curves simulated data are in very good agreement with the benchmark data, which confirm the accuracy of estimated parameters. On the other hand, to show the quality of the results, the individual absolute error (IAE) between the measured data and simulated data on different voltages are recorded, as shown in Table 5 and 6. The current IAE_C and power IAE_P values are not greater than 0.00227392110 and 0.001326378respectively. Additionally, as can be seen in Table. …., the sum of the individual absolute current errors (IAEC) obtained by MLJAYA, PGJAYA, IJAYA, CLJAYA, JAYA, and GWOCS are **0.01781248**, 0.02125936, 0.02129082, 0.02152688, 0.02228006, and **0.0177207**, respectively. It is quite clear that MLJAYA and GWOCS provide the smallest. Although the differences are small, any decrease in the sum IAE value is significant because it indicates an improvement in the accuracy of the parameters. The Fig. 7 illustrates the boxplot of fourteen algorithms for the SDM for the solar cell RTC, which shows the distribution of results obtained by different algorithms in 30 runs. It can be seen that the proposed approach presents excellent performances compared with other compared algorithms in terms of robustness. The error measurements confirm that the estimated currents are in perfect agreement with the measured currents. The individual absolute error values shown in Table 1 are expressed as follows [65-71]:

$$IAE_C = |I_{meas,i} - I_{simu,i}| \quad (12)$$

$$IAE_P = |P_{meas,i} - P_{simu,i}| \quad (13)$$

Table 11
The individual absolute errors (IAE) of current and power of MLJAYA algorithm on PV module model.

Item	Benchmark data		Simulated current data		Simulated power data	
	V(V)	I(A)	I_{sim}(A)	IAE_C(A)	P_{sim}(W)	IAE_p(W)
1	0.1248	1.0315	1.02910483147811	0.00239516852	0.12843228296	0.00029892
2	1.8093	1.0300	1.02736674239367	0.00263325760	1.85881464701	0.00476435
3	3.3511	1.0260	1.02572746353177	0.00027253646	3.43731530304	0.0009133
4	4.7622	1.0220	1.02409281404295	0.00209281404	4.87693479903	0.0099664
5	6.0538	1.0180	1.02227744513878	0.00427744513	6.18866319738	0.0258948
6	7.2364	1.0155	1.01991627774018	0.00441627774	7.38052215223	0.03195795
7	8.3189	1.0140	1.01634860811052	0.00234860811	8.45490243601	0.01953784
8	9.3097	1.0100	1.01048146575136	0.00048146575	9.40727930170	0.0044823
9	10.2163	1.0035	1.00061393548725	0.00288606451	10.2225721491	0.0294849
10	11.0449	0.9880	0.984532752378583	0.00346724762	10.8740657967	0.0382954
11	11.8018	0.9630	0.959505119503797	0.00349488049	11.3238875193	0.04124588
12	12.4929	0.9255	0.922820917609443	0.00267908239	11.5287094416	0.03346951
13	13.1231	0.8725	0.872579994281680	7.9994281e-05	11.4509545229	0.00104977
14	13.6983	0.8075	0.807252422243689	0.00024757775	11.0579858556	0.00339139
15	14.2221	0.7265	0.728312245219096	0.00181224521	10.3581295827	0.02577393
16	14.6995	0.6345	0.637111312228311	0.00261131222	9.36521773410	0.03838498
17	15.1346	0.5345	0.536184041928488	0.00168404192	8.11493100097	0.0254873
18	15.5311	0.4275	0.429480310131995	0.00198031013	6.67030164469	0.03075639
19	15.8929	0.3185	0.318741875604404	0.00024187560	5.06573275479	0.0038441
20	16.2229	0.2085	0.207355818800211	0.00114418119	3.36391271281	0.01856194
21	16.5241	0.1010	0.096132877051555	**0.00486712294**	1.58850927368	**0.08042483**
22	16.7987	−0.008	−0.00835960930196	0.00035960930	−0.1404305687	0.00604097
23	17.0499	−0.111	−0.11097026089431	2.9739105e-05	−1.8920318512	0.00050705
24	17.2793	−0.209	−0.20928021189372	0.00028021189	−3.6162155653	0.00484187
25	17.4885	−0.302	−0.30208067936876	8.0679368e-05	−5.2829379611	0.00141096
Total IAE			**0.04686375**		**0.48078704**	

Table 12
Calculated values of IAE_C obtained by MLJAYA and other advanced algorithms DDM.

IAE_C								
Item	Vm(V)	Im(V)	MLJAYA	PGJAYA	IJAYA	CLJAYA	JAYA	GWOCS
1	0.1248	1.0315	0.00239516852	0.00238036	0.00245607	0.00238084	0.00245607	0.00240597
2	1.8093	1.0300	0.00263325760	0.00261867	0.00262813	0.00261893	0.00262813	0.00264227
3	3.3511	1.0260	0.00027253646	0.00025814	0.00020772	0.00025820	0.00020772	0.00028302
4	4.7622	1.0220	0.00209281404	0.00210704	0.00221094	0.00210715	0.00221094	0.00208051
5	6.0538	1.0180	0.00427744513	0.00429155	0.00444181	0.00429180	0.00444181	0.00426211
6	7.2364	1.0155	0.00441627774	0.00443032	0.00461867	0.00443068	0.00461867	0.00439919
7	8.3189	1.0140	0.00234860811	0.00236269	0.00257921	0.00236311	0.00257921	0.00233705
8	9.3097	1.0100	0.00048146575	0.00049575	0.00072904	0.00049615	0.00072904	0.00048363
9	10.2163	1.0035	0.00288606451	0.00287134	0.00263257	0.00287103	0.00263257	0.00282156
10	11.0449	0.9880	0.00346724762	0.00345177	0.00321631	0.00345162	0.00321631	0.00333714
11	11.8018	0.9630	0.00349488049	0.00347827	0.00324876	0.00347832	0.00324876	0.00328487
12	12.4929	0.9255	0.00267908239	0.00266092	0.00243167	0.00266118	0.00243167	0.00242690
13	13.1231	0.8725	7.9994281e-05	0.00010009	0.00034179	0.00009966	0.00034179	0.00011492
14	13.6983	0.8075	0.00024757775	0.00022523	0.00004717	0.00022574	0.00004717	0.00016575
15	14.2221	0.7265	0.00181224521	0.00183695	0.00215112	0.00183648	0.00215112	0.00147504
16	14.6995	0.6345	0.00261131222	0.00263835	0.00299715	0.00263800	0.00299715	0.00197421
17	15.1346	0.5345	0.00168404192	0.00171321	0.00210668	0.00171306	0.00210668	0.00119493
18	15.5311	0.4275	0.00198031013	0.00201127	0.00241115	0.00201133	0.00241115	0.00130780
19	15.8929	0.3185	0.00024187560	0.00027424	0.00064662	0.00027448	0.00064662	0.00015622
20	16.2229	0.2085	0.00114418119	0.00111086	0.00081061	0.00111049	0.00081061	0.00065583
21	16.5241	0.1010	0.00486712294	0.00483326	0.00464639	0.00483283	0.00464639	0.00265575
22	16.7987	−0.008	0.00035960930	0.00032571	0.00031522	0.00032539	0.00031522	0.00017322
23	17.0499	−0.111	2.9739105e-05	0.00006337	0.00013491	0.00006352	0.00013491	0.00003631
24	17.2793	−0.209	0.00028021189	0.00024715	0.00068793	0.00024727	0.00068793	0.00010220
25	17.4885	−0.302	8.0679368e-05	0.00213691	0.00141908	0.00213641	0.00141908	0.00100513
Total IAE			0,04686375	0,04892342	0,05011672	0,04892367	0,05011672	**0,04178153**

4.2. Case2: double diode model

In this case, seven parameters are needed to be identified. The estimated parameters and the RMSE of several methods are listed in Table 7. The results of the application of the MLJAYA and many other methods for the parameter extraction of RTC PV cell with the DDM show that CLJAYA (9.8249E-0-04), BBO-M (9.8251E-0-04), MADE (9.8261E-0-04), EJADE (9.8263E-0-04), TLBO (9.8290E-0-04), IJAYA (9.8293E-04), MLJAYA (9.8294E-05), jDE (9.8298E-0-04), JAYA (9.8307E-0-04), GWOCS (9.8334E-0-04), PGJAYA (9.8443E-0-04), IGHS (9.8635E-0-04), JAYA (9.9307E-0-04), IBSA (9.9663E-0-04), CLPSO (9.9894E-04), and LBSA (10.016E-0-04). Compared to the RMSE values given in Tables 4 and 7, it can be seen that the two-diode model is generally more accurate than its single-diode counterpart, regardless of the choice of the optimization algorithm.

Furthermore, the extracted parameters of MLJAYA algorithm were used to plot the I-V and P-V curves, which are illustrated in

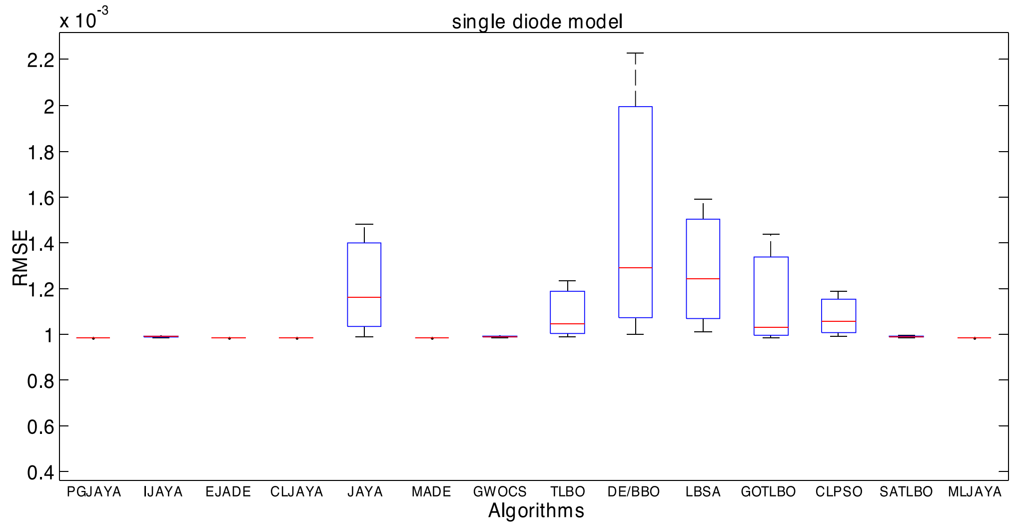


Fig. 7. Best boxplot of different algorithms for the single diode model.

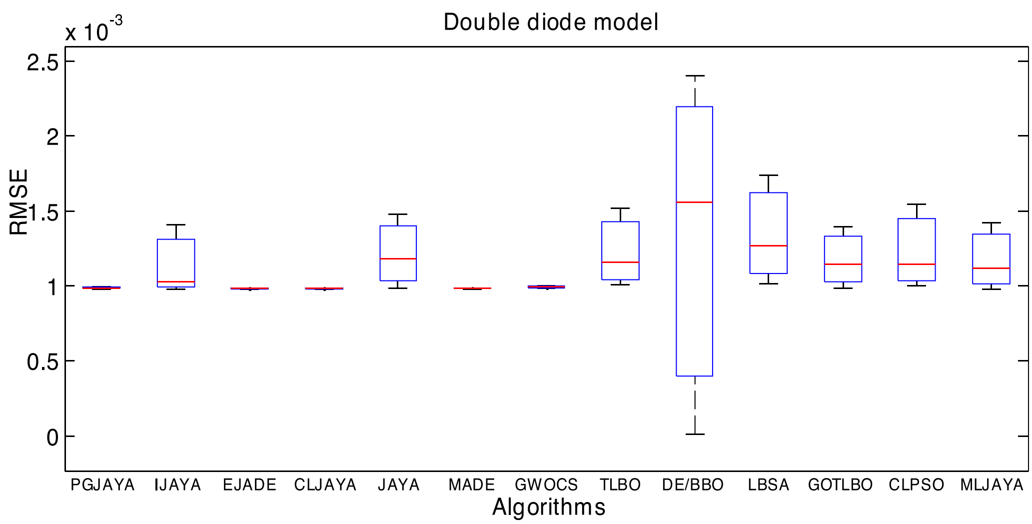


Fig. 8. Best boxplot of different algorithms for the double diode model.

Fig. 5. It is clear that the measured and simulated data obtained by MLJAYA are very coherent for the I-V and P-V curves. In addition, the values of the individual absolute current error (IAE_C) and individual absolute power error (IAE_P) shown in Table 8, it can be seen that all IAE_C values are less than **0,00104221**, and all IAE_P are less than **0,000755344**. According to Table 9, the sum of absolute current errors obtained by MLJAYA, PG JAYA, JAYA, CL JAYA, JAYA, and GWOCS are 0.0176, 0.02125936, 0.02125974, 0.02127549, 0.02127549, and 0.01773982, respectively. Clearly, MLJAYA can achieve the smallest sum of AEI, which means that MLJAYA can provide a solution with higher accuracy.

As per results are shown in boxplots of Fig. 8, it can be observed that the proposed MLJAYA exhibits the best performance compared with CLPSO, LBSA, DE/BBO, TLBO, and JAYA in terms of solution distribution.

4.3. Case 3: PV module

In order to validate the high performance of the MLJAYA algorithm, it was compared to four JAYA variants and ten state-of-the-art meta-heuristics algorithms. The best statistical extracted parameters and their corresponding RMSE results obtained by MLJAYA and the reported algorithms are given in Table 10. It can be noted that the MLJAYA and MLBSA algorithms obtained the best RMSE value (**2.425074E-03**), while MADE, PGJAYA and CLJAYA provided the second best RMSE value (**2.425075E-03**), followed by IJAYA, GWOCS, and SATLBO (2.4251E-03), GOTLBO (2.426583E-03), CLPSO (2.4281E-03), DE/BBO (2.428255E-03), LBSA (2.4296E-03), JAYA (2.4309E-03), MLBSA (2.5250748E-03), and GWO (2.526088E-03). We see that the difference between the first best RMSE value and second-best RMSE values is of the order of 10E-06, it is meaningful for any reduction in the objective function.

To conduct an additional survey on the quality of the parameters obtained by MLJAYA, these parameters were put into the PV model to reconstruct the I-V and P-V characteristics. According to the I–V and P-V characteristics plotted in Fig. 6, we can see that the simulated data obtained by MLJAYA fit the experimental data very well. In addition, the individual absolute error (IAE) between the experimental data and simulated data for MLJAYA and the sum IAE_C values of MLJAYA, PGJAYA, IJAYA, CLJAYA, JAYA, and GWOCS are summarized in Table 11 and Table 12. The obtained results are 0.04686375, 0.04892342, 0.05011672, 0.04892367,

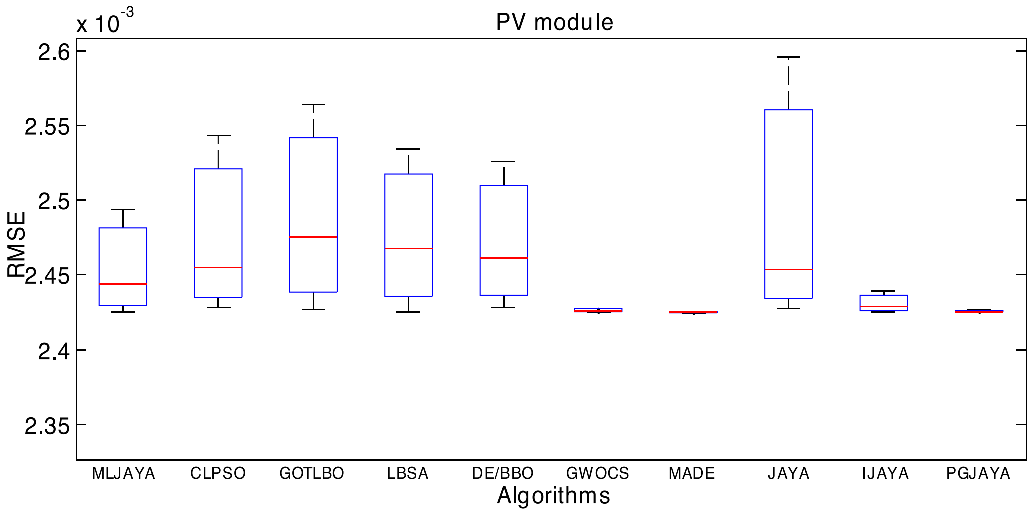


Fig. 9. Best boxplot of different algorithms for PV model.

0.05011672, and 0.04178153. It is obvious that GWOCS can achieve the minimum sum absolute error, followed by MLJAYA which means MLJAYA can offer a higher accuracy solution than PG JAYA, JAYA, CL JAYA, and JAYA.

Fig. 9 presents the boxplot of ten algorithms for Photowatt-PWP201. Based on the comparisons on the solution distribution, it can be achieved that the proposed MLJAYA offers superior performance compared with CLPSO, GOTLBO, LBSA, BE/BBO, and JAYA in terms accuracy and robustness.

5. Conclusion

This paper proposes a multiple learning JAYA (MLJAYA) algorithm for parameter identification different photovoltaic models. In MLJAYA approach three strategy has been used with the aim is avoid the drawback of JAYA algorithm, and therefore achieve good accuracy, convergence and reliability. In the MLJAYA the adaptive weighting consists of helping the algorithm reach the potential search space quickly and perform a local search afterward. The multiple learning strategies are employed to improve the diversity of the population, and a chaos perturbation mechanism is proposed to reinforce the quality of the best solution in each generation. The proposed algorithm is applied to solve three solar PV models, such as the single and double diode models of the benchmark commercial R.T.C France silicon solar cell and the single diode of the benchmark Photowatt-PWP 201 PV module. Based on the experimental results, the conclusions are summarized as follows:

- The accuracy of the double diode model is slightly better than the single diode model.
- The proposed MLJAYA demonstrates the superior performance to that of the original JAYA.
- The experiment results achieved show that the MLJAYA has better performance compared with some variants of JAYA, and other state-of-the-art algorithms in PV models parameters identification.
- As per the solution accuracy results, the I-V and P-V curves, the individual absolute errors (IAE) of current and power, MLJAYA provides superior or similar performance on single diode model, double diode model and PV module.

Therefore, MLJAYA algorithm can be efficiently used and reliable alternative to parameter identification of PV models.

CRediT authorship contribution statement

Driss Saadaoui: Writing – original draft, Writing – review & editing, Software, Visualization, Investigation, Formal analysis, Methodology, Conceptualization. **Mustapha Elyaqouti:** Formal analysis, Visualization, Writing – review & editing, Software, Visualization, Investigation, Formal analysis, Methodology, Conceptualization, Supervision. **Khalid Assalaou:** Formal analysis, Visualization, Writing – review & editing, Software, Visualization, Supervision. **Driss Ben hmamou:** Formal analysis, Visualization, Writing – review & editing. **Souad Lidaighbi:** Formal analysis, Visualization, Writing – review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

References

[4] Y.u. Wang, S. Zhou, H. Huo, Cost and CO2 reductions of solar photovoltaic power generation in China: perspectives for 2020, Renew. Sustain. Energy Rev. 39 (2014) 370–380.
[5] R. Foster, M. Ghassemi, A. Cota. Renewable Energy and the Environment 2010.
[6] A. Yahya-Khotbehsara, A. Shahhoseini, A fast modeling of the double-diode model for PV modules using combined analytical and numerical approach, Sol. Energy 162 (2018) 403–409, https://doi.org/10.1016/j.solener.2018.01.047.
[7] H. Attia, High performance PV system based on artificial neural network MPPT with PI controller for direct current water pump applications, Int. J. Power Electron. Drive Syst. 10 (3) (2019) 1329.
[8] R. Tamrakar, A. Gupta, A review: extraction of solar cell modelling parameters, Int. J. Innov. Res. Electr. Electron. Instrum. Control Eng. 3 (2015) 55–60.
[9] Z. Chen, L. Wu, P. Lin, Y. Wu, S. Cheng, Parameters identification of photovoltaic models using hybrid adaptive Nelder-Mead simplex algorithm based on eagle strategy, Appl. Energy 182 (2016) 47–57.
[10] D.F. Alam, D.A. Yousri, M.B. Eteiba, Flower Pollination Algorithm based solar PV parameter estimation, Energy Convers Manag 101 (2015) 410–422, https://doi.org/10.1016/j.enconman.2015.05.074.
[11] V. Khanna, B.K. Das, D. Bisht, Vandana, P.K. Singh, A three diode model for industrial solar cells and estimation of solar cell parameters using PSO algorithm, Renew. Energy 78 (2015) 105–113, https://doi.org/10.1016/j.renene.2014.12.072.
[12] V. Stornelli, M. Muttillo, T. de Rubeis, I. Nardi, A new simplified five-parameter estimation method for single-diode model of photovoltaic panels, Energies 12 (2019) 4271.
[13] A. Orioli, A. Di Gangi, A procedure to evaluate the seven parameters of the two-diode model for photovoltaic modules, Renew. Energy 139 (2019) 582–599.
[14] M.H. Qais, H.M. Hasanien, S. Alghuwainem, Identification of electrical parameters for three-diode photovoltaic model using analytical and sunflower optimization algorithm, Appl. Energy 250 (2019) 109–117.

[15] D. Oliva, E. Cuevas, G. Pajares, Parameter identification of solar cells using artificial bee colony optimization, Energy 72 (2014) 93–102.
[16] M. Črepinšek, S.-H. Liu, M. Mernik, Exploration and exploitation in evolutionary algorithms: A survey, ACM Comput. Surv. 45 (3) (2013) 1–33.
[17] X.-S. Yang, S. Deb, S. Fong, Metaheuristic algorithms: optimal balance of intensification and diversification, Appl. Math. Inf. Sci. 8 (3) (2014) 977–983.
[18] S. Li, W. Gong, X. Yan, C. Hu, D. Bai, L. Wang, Parameter estimation of photovoltaic models with memetic adaptive differential evolution, Sol. Energy 190 (2019) 465–474.
[19] X. Chen, B. Xu, C. Mei, Y. Ding, K. Li, Teaching–learning–based artificial bee colony for solar photovoltaic parameter estimation, Appl. Energy 212 (2018) 1578–1588, https://doi.org/10.1016/j.apenergy.2017.12.115.
[20] X. Lin, Y. Wu, Parameters identification of photovoltaic models using niche-based particle swarm optimization in parallel computing architecture, Energy 196 (2020) 117054, https://doi.org/10.1016/j.energy.2020.117054.
[21] T.V. Luu, N.S. Nguyen, Parameters extraction of solar cells using modified JAYA algorithm, Optik (Stuttg) 203 (2020) 164034, https://doi.org/10.1016/j.ijleo.2019.164034.
[22] J.D. Bastidas-Rodriguez, G. Petrone, C.A. Ramos-Paja, G. Spagnuolo, A genetic algorithm for identifying the single diode model parameters of a photovoltaic panel, Math. Comput. Simul. 131 (2017) 38–54, https://doi.org/10.1016/j.matcom.2015.10.008.
[23] W. Gong, Z. Cai, C.X. Ling, DE/BBO: a hybrid differential evolution with biogeography-based optimization for global numerical optimization, Soft. Comput. 15 (4) (2010) 645–665.
[24] D. Oliva, M. Abd El Aziz, H.A. Ella, Parameter estimation of photovoltaic cells using an improved chaotic whale optimization algorithm, Appl. Energy 200 (2017) 141–154, https://doi.org/10.1016/j.apenergy.2017.05.029.
[25] R. Cheng, Y. Jin, A competitive swarm optimizer for large scale optimization, IEEE Trans. Cybern. 45 (2014) 191–204.
[26] G. Xiong, J. Zhang, D. Shi, L. Zhu, X. Yuan, Z. Tan, Winner-leading competitive swarm optimizer with dynamic Gaussian mutation for parameter extraction of solar photovoltaic models, Energy Convers. Manage. 206 (2020) 112450.
[27] J. Liang, S. Ge, B. Qu, K. Yu, F. Liu, H. Yang, P. Wei, Z. Li, Classified perturbation mutation based particle swarm optimization algorithm for parameters extraction of photovoltaic models, Energy Convers. Manage. 203 (2020) 112138.
[28] R. Rao, Jaya: a simple and new optimization algorithm for solving constrained and unconstrained optimization problems, Int. J. Ind. Eng. Comput. 7 (2016) 19–34.
[29] K. Yu, J.J. Liang, B.Y. Qu, X. Chen, H. Wang, Parameters identification of photovoltaic models using an improved JAYA optimization algorithm, Energy Convers. Manage. 150 (2017) 742–753, https://doi.org/10.1016/j.enconman.2017.08.063.
[30] X. Jian, Z. Weng, A logistic chaotic JAYA algorithm for parameters identification of photovoltaic cell and module models, Optik (Stuttg) 203 (2020) 164041, https://doi.org/10.1016/j.ijleo.2019.164041.
[31] S. Li, W. Gong, X. Yan, C. Hu, D. Bai, L. Wang, L. Gao, Parameter extraction of photovoltaic models using an improved teaching-learning-based optimization, Energy Convers. Manage. 186 (2019) 293–305.
[32] X. Chen, K. Yu, Hybridizing cuckoo search algorithm with biogeography-based optimization for estimating photovoltaic model parameters, Sol. Energy 180 (2019) 192–206, https://doi.org/10.1016/j.solener.2019.01.025.
[33] K. Yu, B. Qu, C. Yue, S. Ge, X. Chen, J. Liang, A performance-guided JAYA algorithm for parameters identification of photovoltaic cell and module, Appl. Energy 237 (2019) 241–257.
[34] K. Yu, J.J. Liang, B.Y. Qu, Z. Cheng, H. Wang, Multiple learning backtracking search algorithm for estimating parameters of photovoltaic models, Appl. Energy 226 (2018) 408–422.
[35] C. Huang, L. Wang, R.-C. Yeung, Z. Zhang, H.-H. Chung, A. Bensoussan, A prediction model-guided Jaya algorithm for the PV system maximum power point tracking, IEEE Trans. Sustain. Energy 9 (1) (2018) 45–55.
[36] R.V. Rao, K.C. More, J. Taler, P. Ocłoń, Dimensional optimization of a micro-channel heat sink using Jaya algorithm, Appl. Therm. Eng. 103 (2016) 572–582.
[37] R.V. Rao, G.G. Waghmare, A new optimization algorithm for solving complex constrained design optimization problems, Eng. Optim. 49 (1) (2017) 60–83.
[38] S.-H. Wang, P. Phillips, Z.-C. Dong, Y.-D. Zhang, Intelligent facial emotion recognition based on stationary wavelet entropy and Jaya algorithm, Neurocomputing 272 (2018) 668–676.
[39] N. Kumar, I. Hussain, B. Singh, B.K. Panigrahi, Rapid MPPT for uniformly and partial shaded PV system by using JayaDE algorithm in highly fluctuating atmospheric conditions, IEEE Trans. Ind. Inf. 13 (5) (2017) 2406–2416.
[40] J.L. Ravipudi, M. Neebha, Synthesis of linear antenna arrays using jaya, self-adaptive jaya and chaotic jaya algorithms, AEU-Int. J; Electron. Commun. 92 (2018) 54–63.
[41] J. Liang, K. Qiao, M. Yuan, K. Yu, B. Qu, S. Ge, Y. Li, G. Chen, Evolutionary multi-task optimization for parameters extraction of photovoltaic models, Energy Convers. Manage. 207 (2020) 112509, https://doi.org/10.1016/j.enconman.2020.112509.
[42] W. Long, S. Cai, J. Jiao, M. Xu, T. Wu, A new hybrid algorithm based on grey wolf optimizer and cuckoo search for parameter extraction of solar photovoltaic models, Energy Convers. Manage. 203 (2020) 112243, https://doi.org/10.1016/j.enconman.2019.112243.
[43] M.H. Qais, H.M. Hasanien, S. Alghuwainem, Transient search optimization for electrical parameters estimation of photovoltaic module based on datasheet values, Energy Convers. Manage. 214 (2020) 112904, https://doi.org/10.1016/j.enconman.2020.112904.
[44] D. Kler, P. Sharma, A. Banerjee, K.P.S. Rana, V. Kumar, PV cell and module efficient parameters estimation using Evaporation Rate based Water Cycle Algorithm, Swarm Evol. Comput. 35 (2017) 93–110.
[45] O.S. Elazab, H.M. Hasanien, I. Alsaidan, A.Y. Abdelaziz, S.M. Muyeen, Parameter estimation of three diode photovoltaic model using grasshopper optimization algorithm, Energies 13 (2) (2020) 497, https://doi.org/10.3390/en13020497.
[46] H. Rezk, T.S. Babu, M. Al-Dhaifallah, H.A. Ziedan, A robust parameter estimation approach based on stochastic fractal search optimization algorithm applied to solar PV parameters, Energy Rep. 7 (2021) 620–640, https://doi.org/10.1016/j.egyr.2021.01.024.
[47] G. Xiong, J. Zhang, X. Yuan, D. Shi, Y. He, G. Yao, Parameter extraction of solar photovoltaic models by means of a hybrid differential evolution with whale optimization algorithm, Sol. Energy 176 (2018) 742–761, https://doi.org/10.1016/j.solener.2018.10.050.
[48] A.A.K. Ismaeel, E.H. Houssein, D. Oliva, M. Said, Gradient-based optimizer for parameter extraction in photovoltaic models, IEEE Access 9 (2021) 13403–13416, https://doi.org/10.1109/ACCESS.2021.3052153.
[49] Z. Hu, W. Gong, S. Li, Reinforcement learning-based differential evolution for parameters extraction of photovoltaic models, Energy Rep. 7 (2021) 916–928, https://doi.org/10.1016/j.egyr.2021.01.096.
[50] R.C.M. Gomes, M.A. Vitorino, M.B. de Rossiter Correa, D.A. Fernandes, R. Wang, Shuffled complex evolution on photovoltaic parameter extraction: a comparative analysis, IEEE Trans. Sustain. Energy 8 (2) (2017) 805–815.
[51] K.M. Sallam, M.A. Hossain, R.K. Chakrabortty, M.J. Ryan, An improved gaining-sharing knowledge algorithm for parameter extraction of photovoltaic models, Energy Convers. Manage. 237 (2021) 114030, https://doi.org/10.1016/j.enconman.2021.114030.
[52] D.H. Muhsen, A.B. Ghazali, T. Khatib, I.A. Abed, A comparative study of evolutionary algorithms and adapting control parameters for estimating the parameters of a single-diode photovoltaic module's model, Renew. Energy 96 (2016) 377–389.
[53] V. Lo Brano, A. Orioli, G. Ciulla, A. Di Gangi, An improved five-parameter model for photovoltaic modules, Sol. Energy Mater. Sol. Cells 94 (8) (2010) 1358–1370.
[54] W. Gong, Z. Cai, Parameter extraction of solar cell models using repaired adaptive differential evolution, Sol. Energy 94 (2013) 209–220.
[55] P. Sharma, T.S. Bhatti, A review on electrochemical double-layer capacitors, Energy Convers. Manage. 51 (12) (2010) 2901–2912.
[56] A.A. Elbaset, H. Ali, M. Abd El Sattar, New seven parameters model for amorphous silicon and thin film PV modules based on solar irradiance, Sol. Energy 138 (2016) 26–35.
[57] Messaoud R Ben. Extraction of uncertain parameters of single and double diode model of a photovoltaic panel using Salp Swarm algorithm. Measurement 2020;154:107446.
[58] D.H. Muhsen, A.B. Ghazali, T. Khatib, I.A. Abed, Parameters extraction of double diode photovoltaic module's model based on hybrid evolutionary algorithm, Energy Convers. Manage. 105 (2015) 552–561.
[59] R.V. Rao, D.P. Rai, J. Balic, Multi-objective optimization of machining and micro-machining processes using non-dominated sorting teaching–learning-based optimization algorithm, J. Intell. Manuf. 29 (8) (2018) 1715–1737.
[60] K. Yu, X. Wang, Z. Wang, An improved teaching-learning-based optimization algorithm for numerical and engineering optimization problems, J. Intell. Manuf. 27 (4) (2016) 831–843.
[61] L.dos.S. Coelho, T.C. Bora, L. Lebensztajn, A chaotic approach of differential evolution optimization applied to loudspeaker design problem, IEEE Trans. Magn. 48 (2) (2012) 751–754.
[62] B. Alatas, Chaotic bee colony algorithms for global numerical optimization, Expert Syst. Appl. 37 (8) (2010) 5682–5687.
[63] S. Li, Q. Gu, W. Gong, B. Ning, An enhanced adaptive differential evolution algorithm for parameter extraction of photovoltaic models, Energy Convers. Manage. 205 (2020) 112443.
[64] A. Askarzadeh, A. Rezazadeh, Parameter identification for solar cell models using harmony search-based algorithms, Sol. Energy 86 (11) (2012) 3241–3249.
[65] J.P. Ram, T.S. Babu, T. Dragicevic, N. Rajasekar, A new hybrid bee pollinator flower pollination algorithm for solar PV parameter estimation, Energy Convers. Manage. 135 (2017) 463–476, https://doi.org/10.1016/j.enconman.2016.12.082.
[66] A. Babu, A.K. Sao. Unit Selection Using Acoustic Supra-Segmental Cues to Improve Prosody. Recent Adv. Nonlinear Speech Process., Springer; 2016, p. 265–73.
[67] C. Chellaswamy, R. Ramesh, Parameter extraction of solar cell models based on adaptive differential evolution algorithm, Renew. Energy 97 (2016) 823–837.
[68] Y. Zhang, M. Ma, Z. Jin, Comprehensive learning Jaya algorithm for parameter extraction of photovoltaic models, Energy 211 (2020) 118644.
[69] Q. Niu, L. Zhang, K. Li, A biogeography-based optimization algorithm with mutation strategies for model parameter estimation of solar and fuel cells, Energy Convers. Manage. 86 (2014) 1173–1185.
[70] X. Chen, K. Yu, W. Du, W. Zhao, G. Liu, Parameters identification of solar cell models using generalized oppositional teaching learning based optimization, Energy 99 (2016) 170–180, https://doi.org/10.1016/j.energy.2016.01.052.
[71] K. Yu, X. Chen, X. Wang, Z. Wang, Parameters identification of photovoltaic models using self-adaptive teaching-learning-based optimization, Energy Convers. Manage. 145 (2017) 233–246.

[72] J. Liang, K. Qiao, K. Yu, S. Ge, B. Qu, R. Xu, K. Li, Parameters estimation of solar photovoltaic models via a self-adaptive ensemble-based differential evolution, Sol. Energy 207 (2020) 336–346, https://doi.org/10.1016/j.solener.2020.06.100.

Further reading

[1] M. Vafaeipour, S. Hashemkhani Zolfani, M.H. Morshed Varzandeh, A. Derakhti, M. Keshavarz Eshkalag, Assessment of regions priority for implementation of solar projects in Iran: new application of a hybrid multi-criteria decision making approach, Energy Convers. Manag. 86 (2014) 653–663.
[2] S. Mekhilef, R. Saidur, A. Safari, A review on solar energy use in industries, Renew. Sustain. Energy Rev. 15 (4) (2011) 1777–1790.
[3] M. Kumar, A. Kumar, An efficient parameters extraction technique of photovoltaic models for performance assessment, Sol. Energy 158 (2017) 192–206.