Performance analysis of solar PV parameter estimation techniques

Nikita Rawat [a], Padmanabh Thakur [a,*], Asheesh K. Singh [b], R.C. Bansal [c,d]

[a] Department of Electrical Engineering, Graphic Era Deemed to be University, Dehradun, Uttarakhand 248002, India
[b] Department of Electrical Engineering, Motilal Nehru National Institute of Technology Allahabad, Prayagraj, Uttar Pradesh 211004, India
[c] Department of Electrical Engineering, College of Engineering, University of Sharjah, United Arab Emirates
[d] Department of Electrical, Electronic and Computer Engineering, University of Pretoria, Pretoria, South Africa

ARTICLE INFO

Keywords:
Absolute relative maximum power error
Hybrid approach
Iterative technique
Multi-objective function
Overall model error
Photovoltaic cell

ABSTRACT

Firstly, this paper investigates the performances of the three different established parameter estimation techniques, namely multi-objective function, five-point metaheuristic, and hybrid-based approaches. Using these three different techniques, unknown model parameters, such as photovoltaic current (I_{pv}), dark saturation current (I_o), series resistance (R_s), shunt resistance (R_{sh}), and Ideality factor (A), of mono-and poly-crystalline technology-based solar PV modules, are predicted. Afterwards, using the estimated unknown parameters and *P-V & I-V* characteristics curves, two different benchmarks, namely absolute relative maximum power error (*ARMPE*) and overall model error (*OME*), of these modules, are evaluated to reveal their best performances. In addition, various other parameter estimation techniques, such as iterative, analytical, curve-fitting, and metaheuristics-based methods, have also been considered for performance analysis. It is shown that the hybrid-based approach provides a better characterization than the other various established approaches. The value of *%ARMPE* is found almost zero with the hybrid approach for both modules. In addition, the smallest values of *OME* are obtained with the hybrid approach, *i.e.,* 0.002 or 0.003 for poly- and 0.031 for the mono-crystalline technology-based solar PV module. Hence, a hybrid-based parameter estimation technique is suggested to achieve accurate characteristics of solar PV.

1. Introduction

Solar PV systems generate electrical energy, which is very close to the power rating of residential and commercial consumers. This generating ability of solar PV results in a substantial decrease in power losses and also enhances their capability to satisfy the peak load demands [1]. Unfortunately, poor conversion efficiency and high installation cost reduce its competitiveness over conventional energy sources [1–3]. In addition, the performance of solar PV systems is greatly dependent on operating environmental conditions. Therefore, the development of an accurate mathematical model and the selection of a suitable parameter estimation technique is recommended as the most crucial problems before proceeding to the design and installation stage of solar PV systems. Also, precise mathematical modelling and proper selection of parameter estimation techniques play a vital role in the accurate characterization of solar PV [4–6].

In the past decades, several models of solar PV, such as the single diode model (SDM), double diode model (DDM), three diode model, and neural network model were proposed in the research [1–3,5]. The neural network-based model requires a large amount of

* Corresponding author.
E-mail address: tonu_arth@rediffmail.com (P. Thakur).

https://doi.org/10.1016/j.ijleo.2023.170785
Received 2 October 2022; Received in revised form 5 March 2023; Accepted 12 March 2023

Nomenclature

Solar PV	Solar Photovoltaic
R_s	Series Resistance
R_{sh}	Parallel Resistance
I_{pv}	Photon Current
I_o	Reverse Saturation Current
A	Diode Ideality Factor
ARMPE	Absolute relative maximum power error
SDM	Single diode model
NSGA-II	Non-dominated Sorting Genetic Algorithm-II
I_{sc}	Current under SCC
$V_{mpp,\ e}$	Estimated voltage at MPP
SA	Simulated Annealing
OCC	Open circuit condition
EPO	Normalized Root Mean Square Error
Overall model error	OME
MPP	Maximum Power Point
V_{th}	Thermal Voltage
V_{oc}	Voltage under OCC
TRA	Trust-Region Algorithms
TRD	Trust-Region Dogleg
TRR	Trust-Region Reflective
PSO	Particle Swarm Optimization
$I_{mpp,e}$	Estimated current at MPP
$P_{mpp,e}$	Estimated Power at MPP
MHAs	Metaheuristics algorithms
SCC	Short circuit condition

data for the training and hence it is seldom recommended for the characterization of solar PV. However, the DDM and three-diode model are found more accurate than the SDM, especially at lower solar insolation, but it is not adopted broadly due to high computational burden and parameterization difficulty. Therefore, the SDM of solar PV is highly recommended by the research communities for characterization as it offers a good trade-off between simplicity and accuracy [6]. The SDM model of solar PV, consisting of linear as well as non-linear components, is shown in Fig. 1 [7].

The output *P-V* and *I-V* characteristics of SDM are often characterized by a non-linear transcendental equation, as given in (1), that includes five unknown model parameters or variables, *i.e.*, I_{pv}, I_o, R_s, R_{sh}, and A [1,2,7].

$$I = I_{pv} - I_o\left[\exp\left(\frac{V+IR_s}{AV_T}\right) - 1\right] - \left(\frac{V+IR_s}{R_{sh}}\right) \tag{1}$$

Here, V_T (= $N_s\ k\ T/q$) is the thermal voltage, k is Boltzmann's constant, N_s is the number of cells in series, and q is the electron charge. Solar PV's performances and efficiencies are greatly dependent on the accurate prediction of these unknown parameters [2–7]. Although, these unknown variables are mutually coupled to each other, as given in (1), and hence their estimations are found a challenging and tedious task. Considerable amounts of research work, based on numerical, iterative, and analytical techniques, were carried out for the estimation of these unknown model parameters, accurately [8–13]. Usually, numerical methods [8–11] provide

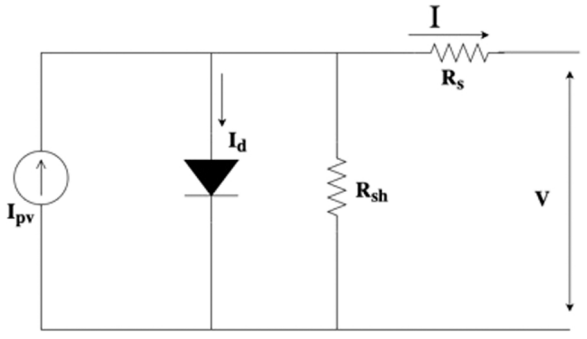


Fig. 1. Equivalent circuit diagram of SDM-R_{sh}.

better characterization than the analytical methods [12,13], but on the other hand, the selection of initial guess and premature convergence are the most challenging issues of the numerical methods for large numbers of unknown model parameters [6,14]. In contrast, analytical methods, with fewer unknown parameters, provide a quick and accurate solution with less computational effort. However, the accuracy of the analytical method is highly subjected to the accuracy of the approximations and the appropriateness of the simplifications [14–18].

Therefore, to resolve the limitations, as discussed in the aforementioned studies, the metaheuristic algorithms (MHAs) based techniques are strongly suggested in the research for the accurate prediction of unknown parameters. Indeed, the MHAs-based techniques are found efficient in solving complex non-linear problems, simple, flexible, derivation-free mechanisms, and local optima avoidance [2,16–21]. Typically, two types of approaches have been considered in MHAs-based techniques. These approaches are as follows:

- In the first approach, error functions are defined using the estimated and experimental *I-V* curve. Afterwards, MHAs are used to minimize the error functions to achieve the best results. The requirement of excessive experimental data is a significant limitation of such a method [16,17].
- In the second approach, the information provided by the manufacturer has been used to design objective functions. Further, by minimizing the objective function, unknown model parameters are estimated [19–21].

Usually, these two approaches are either based on approximation and assumptions or use a five-point single objective function to estimate unknown parameters [16–21]. However, approximation or elimination-based approaches reduce the complexities existing in the modelling but, on the other hand, produce adverse impacts on the overall accuracy of the model [14,22]. Also, the selection of initial guesses for large numbers of unknown parameters is difficult for single objective function-based parameter estimation techniques [14,22]. In addition, premature convergence increased iteration count, and the computational burden is another big challenge of single objective function-based parameter estimations techniques [14,21,22].

Recently, the merits of multi-objective function over single-objective function-based evolutionary algorithms were highlighted in various research [23–25]. Usually, the multi-objective optimization function operates on multiple objectives for optimizing the various constraints, simultaneous [23], [24]. The various attributes of constant handling mechanism design were also highlighted in [23], [24]. Further, the application of constrained Pareto front and unconstrained Pareto front in the designing of multi-objective function has been properly explained [24]. Indeed, the multi-objective function encourages the exploration of different regions and hence maintains a good balance between exploration and exploitation [23–25]. In [25], firstly, multi-objective functions have been developed for the SDM, and then Non-dominated Sorting Genetic Algorithm-II (NSGA-II) has been used to estimate the unknown model parameters. Also, the results, as obtained with the multi-objective function-based method, are compared with the various MHAs, such as Simulated Annealing (SA) [26], Pattern Search [27], Genetic Algorithm [28], Hybrid Flower Pollination Algorithm [29] that use a single-objective function for the parameter estimation. Based on the values of benchmarks, namely absolute relative maximum power error (*ARMPE*) and current absolute errors (*IAE*), superiorities of multi-objective-based parameter estimation over MHAs have been revealed in [25]. However, both single- and multi-objective function-based optimization techniques provide good accuracy but on the other hand increase the computational complexities and number of iterations due to many unknown parameters [6,14,18,22].

Lately, various hybrid techniques have also been developed to avoid the complexities arising due to the five numbers of unknown variables in SDM [6,14,22,30,31]. In [14], firstly, a mathematical model of solar PV has been developed in terms of R_s, and A. These two unknown parameters are determined using SA. The remaining three unknown parameters are estimated with the help of the analytical and numerical technique NRM. In the same way, a mathematical model in terms of R_s, R_{sh}, and A (or thermal voltage) is developed first, and then these three unknown model parameters are estimated with the help of the trust-region algorithm (TRA) and remaining two with the use of the analytical technique in [22]. Though, in [6,30], no mathematical model has been developed for solar PV, instead in this approach the variables, I_{pv} and I_o, are estimated first using the approximation method and then Emperor Penguin Optimization (EPO) method is applied to estimate remaining three unknowns model parameters. Also, these hybrid-based approaches were compared with various metaheuristics approaches, as discussed in [26–29,31–33]. In addition, the hybrid approach, as proposed in [22], is also compared with several numerical, iterative techniques and established hybrid approaches [14,30,31,34–36]. The comparative analysis shows that the hybrid approaches, based on analytical plus iterative, outperform the metaheuristic, numerical, iterative, and other hybrid-based approaches used for the estimation of all five unknown parameters of SDM.

In this work, firstly, the performances of three different parameter techniques, such as five-point single objective function (PSO) [21], multi-objective function (NSGA-II) [25], and hybrid-based approach [22], are evaluated to reveal the best techniques of the parameter estimations among these three. Then, the performances of various other parameter estimation techniques are also investigated. The major contributions of this work are highlighted in the following points:

- The performances of three different parameter estimation techniques, namely the five-point metaheuristics technique (PSO), multi-objective function-based technique (NSGA-II), and hybrid technique, are evaluated through the benchmarks, namely *%ARMPE* and *OME*. It is shown that the hybrid approach provides better characterization than the other two established approaches.
- Also, the performances of the various existing hybrid approaches are evaluated. It is shown that the hybridization of analytical with iterative technique provides better characterization than the other possible hybrid approaches.
- Finally, the performances of various other parameter estimation techniques, such as the five-point single objective, multi-objective function-based approach, iterative, analytical, curve-fitting, error minimization, and metaheuristics-based approach, are also investigated to select the best parameter estimation technique.

2. Parameter estimation techniques

In this section, the basic concept and three different approaches of parameter estimation with their flow diagram are discussed for a better understanding of the performance assessment.

2.1. Five-point metaheuristics technique [21]

In this work, a parameter estimation technique based on a metaheuristic's algorithm, namely PSO has been considered for the comparison of the performance assessment. In the work presented in [21], firstly, a new single objective function, as given in (2), has been developed. Then, using the flow diagram, as shown in Fig. 2, the five unknown parameters are estimated.

$$f'(x) = abs[f_1(x) + f_2(x) + f_3(x) + f_4(x) + f_5(x)] \tag{2}$$

Here,

$$f_1(x) = I_{sc} - I_{pv} + I_0\left[\exp\left(\frac{I_{sc}R_s}{N_sAV_T}\right) - 1\right] + \frac{I_{sc}R_s}{R_{sh}} = 0 \tag{3}$$

$$f_2(x) = I_{pv} - I_0\left[\exp\left(\frac{V_{oc}}{N_sAV_T}\right) - 1\right] + \frac{V_{oc}}{R_{sh}} = 0 \tag{4}$$

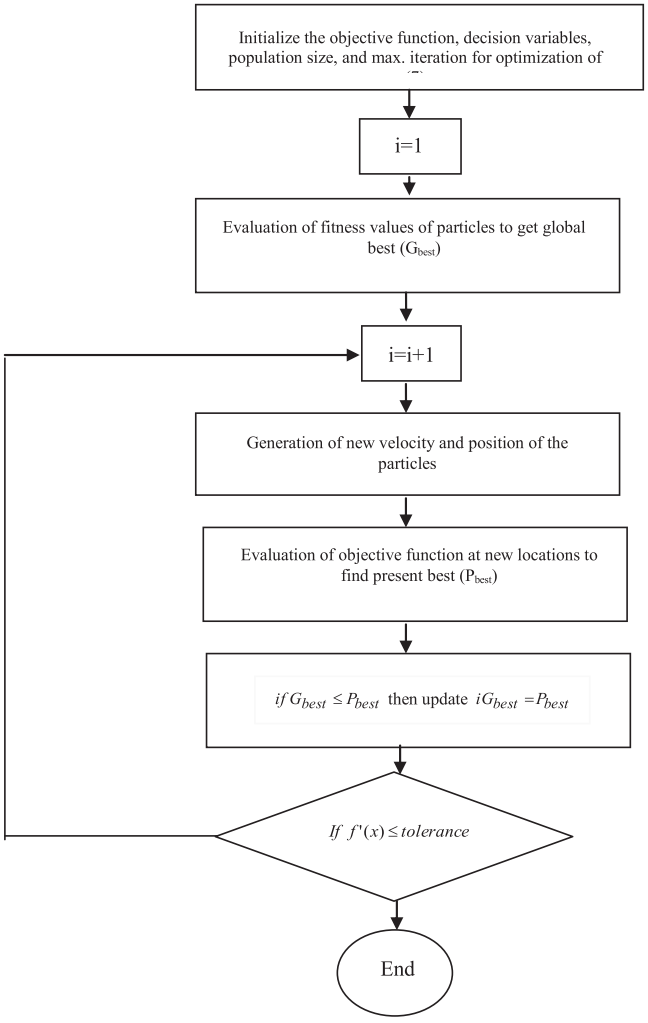


Fig. 2. Flow chart of five-point metaheuristics approach [21].

$$f_3(x) = I_{pv} - I_0\left[\exp\left(\frac{V_{mpp} + I_{mpp}R_s}{N_sAV_T}\right) - 1\right] + \frac{V_{mpp} + I_{mpp}R_s}{R_{sh}} - I_{mpp} = 0 \tag{5}$$

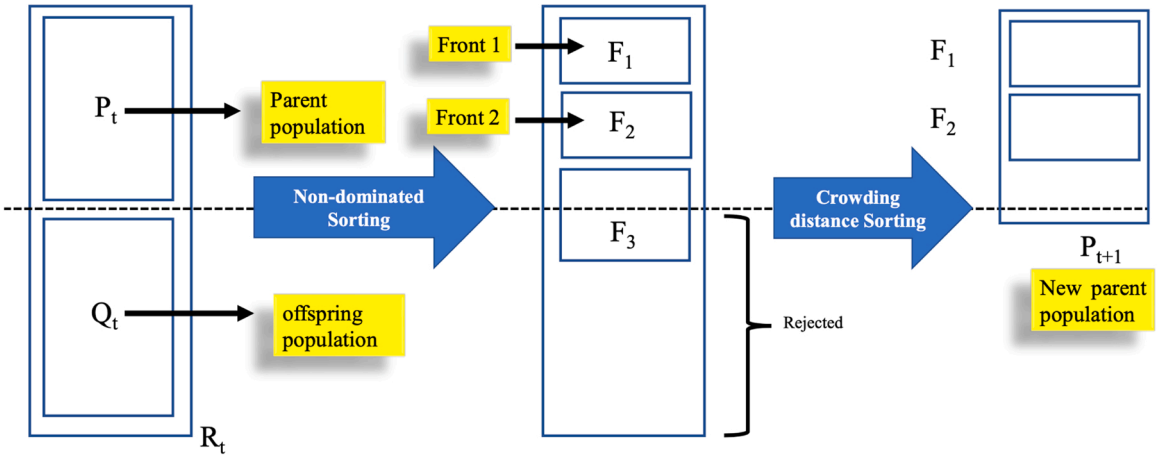
$$f_4(x) = I_{mpp} - \left(V_{mpp} - I_{mpp}R_s\right)\left(\frac{I_o}{N_sAV_T}\left[\exp\left(\frac{V_{mpp} + I_{mpp}R_s}{N_sAV_T}\right)\right] + \frac{1}{R_{sh}} = 0\right. \tag{6}$$

$$f_5(x) = \frac{R_s}{R_{sh}} - \frac{I_o}{N_sAV_T}\left[\exp\left(\frac{I_{sc}R_s}{N_sAV_T}\right)\right]\left(R_{sh} - R_s\right) = 0 \tag{7}$$

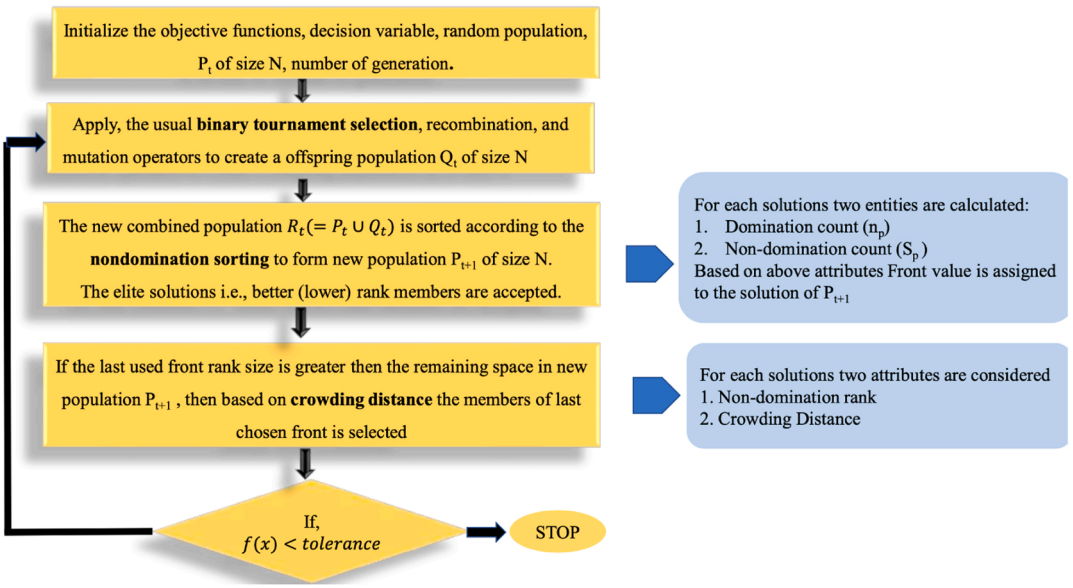
2.2. *Multi-objective function-based metaheuristics technique (NSGA-II) [25]*

In this sub-section, the parameter estimation technique, as suggested in [25], has been considered for the performance assessment. In [25], a multi-objective function, using (3)-(7), has been developed to predict the unknown model parameters of SDM. The multi-objective function, as developed in [25] is given as:

$$\min f(x) = [f_1(x), f_2(x), f_3(x), f_4(x), f_5(x)] \tag{8}$$



(a) Working of NSGA-II.



(b) Flow chart of multi-objective function-based approach.

Fig. 3. Flow chart of multi-objective function-based approach and working of NSGA-II.

Further, an evolutionary optimization algorithm, NSGA-II, has been considered in [25] to minimize the objective function as given in (8). As presented in [25], the flow chart of the method is shown in Fig. 3(a) and (b) [25].

2.3. Hybrid approach

Recently, several hybrid approaches have also been recommended in research to overcome the problems existing due to large numbers of unknown variables in SDM [6,14,22,30,31]. In these studies, usually, two methods are adopted to predict unknown parameters of SDM. In the first approach, a mathematical model of solar PV has been developed either in terms of R_s and A [14] or R_s, R_{sh}, and V_T [22]. Afterwards, either the metaheuristics technique (SA) or numerical technique [14] or iterative technique TRR and TRD [22] has been considered for the estimation of these unknown model parameters. The remaining two or three unknown parameters have been evaluated with the help of analytical techniques [14,22]. In the second approach, firstly, I_L and I_o are estimated through some approximation methods and then, with the help of these two currents and the remaining three unknowns, *i.e.,* R_s, R_{sh}, and A, an objective function is derived [30,31]. Finally, EPO [30] or GWO [31] has been used to determine the unknown model parameters. The objective function, metaheuristics technique or iterative technique, and data used by these hybrid approaches are summarized in Table 1.

In these hybrid approaches, either metaheuristics or iterative technique is hybridized with analytical technique. In this performance analysis study, first, the performance of three different techniques, namely PSO based technique [21], a multi-objective-based technique [25], and a hybrid approach [22], as shown in Fig. 4, are compared to find the most suitable method of the parameter estimation. Then, various other parameter estimation techniques have also been considered for the performance analysis.

The NLS objective function, as developed in [22], is given as:

$$f = f_1^2 + f_2^2 + f_3^2 \tag{9}$$

Here, f is the function of R_s, R_{sh}, and V_T. The details of derivation are presented in [22].

3. Results and discussions

In this section, the effectiveness and accuracy of three different techniques, namely, five-point metaheuristics (PSO), multi-objective (NSGA-II), and hybrid-based approaches for the estimation of the unknown parameter, are compared first and then other established techniques are also considered for the performance assessment. Two different technologies based, namely mono- and poly-crystalline solar PV modules, are considered for the performance assessment. The data given in the manufacturer datasheet for these two modules are summarized in Table 2.

3.1. Estimation of solar PV characteristics

Using the techniques, as suggested in [21,22], and [25], the unknown model parameters are estimated and summarized in Tables 3–4.

summarized in Table 3 and Table 4, *I-V* and *P-V* characteristics curves are drawn for these modules and shown in Figs. 5–12. In the Figs. 5–10, '* ' mark represents the remarkable points (OC, SC and MPP) as given in the manufacturer datasheet, while coordinates, as shown in Figs. 5–12, represent the estimated values.

In Figs. 11 and 12, the '* ' mark represents the actual maximum power point (MPP) given in the manufacturer datasheet. The maximum power, as estimated with these three approaches, and the actual value, given in the manufacturer datasheet, are summarized in Table 5.

Furthermore, using the characteristics, as shown in Figs. 5–10, current at MPP, current in SCC and voltage under OCC are estimated for these modules and are summarized in Table 6.

As summarized in Tables 5 and 6, the estimated data have been used in this study to evaluate the benchmarks, namely, *%ARMPE* and *OME*, for these two modules.

3.2. Estimation of absolute relative maximum power error (ARMPE)

With the help of Eq. (10) and the data given in Table 5, the magnitudes of *%ARMPE* have been evaluated to check the accuracy of these parameter estimation techniques. In (10), $P_{max,\ actual}$ is the actual value of maximum power, provided in the manufacturer

Table 1
Objective function and data used in different hybrid approaches.

S. No.	Hybrid Approach	Objective Function	Techniques	Data used
1	Iterative plus Analytical[22]	Non-linear square function	TRR and TRD	Manufacturer data sheet
2	Metaheuristics plus Analytical[30]	RMSE and MAE	EPO	Experimental
3	Metaheuristics plus Analytical[31]	Non-linear square function	GWO	Experimental
4	Metaheuristics plus Analytical[14]	Nonlinear optimization function	SA	Manufacturer data sheet
5	Metaheuristics plus Numerical[14]	Nonlinear optimisation function	SA	Manufacturer data sheet

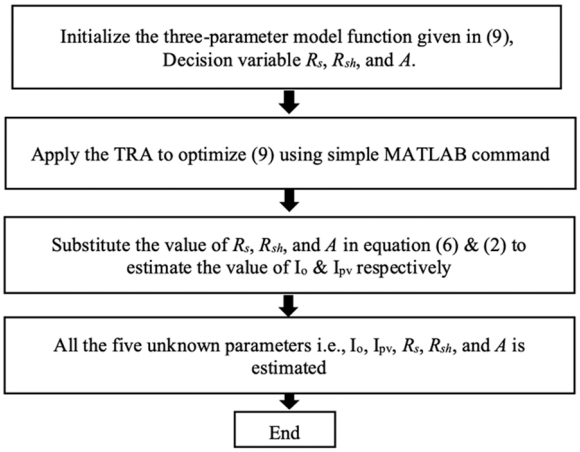


Fig. 4. Flow chart of hybrid approach [22].

Table 2
Manufacturer data for solar PV modules.

Known Parameters	H&T GmbH TS265D60 (Mono)	Solar world Pro.SW255 (Poly)
V_{mpp} (V)	30.9	30.90
I_{mpp} (A)	8.58	8.32
V_{oc} (V)	38.1	38
I_{sc} (A)	9.19	8.88
N_s	60	60
T (°C)	25	25

Table 3
Estimated parameters of mono-crystalline solar PV.

Unknown model Parameters	Five-point single objective (PSO)[21]	Multi-objective Method, NSGA-II[25]	Hybrid Method, Iterative plus Analytical[22]
I_{pv}(A)	9.4878	9.1705	9.1911
I_o(A)	4.40e-09	9.00e-09	$5.8865e^{-8}$
R_s (Ω)	0.3548	0.2348	0.1939
R_{sh} (Ω)	4878	3844.3	1659.4
V_{th} (=N_sAV_T)	1.8399	1.8329	2.022

Table 4
Estimated parameters of poly-crystalline solar PV.

Unknown model Parameters	Five-point single objective (PSO)[21]	Multi-objective Method, NSGA-II[25]	Hybrid Method, Iterative plus Analytical[22]
I_{pv}(A)	8.8565	8.8814	8.8808
I_o(A)	2.311e-08	1.00e-08	$2.8061e^{-8}$
R_s (Ω)	0.2093	0.2277	0.2057
R_{sh} (Ω)	2579.5	3735.8	2357.1
V_{th} (=N_sAV_T)	1.9237	1.8441	1.944

datasheet (Table 2) whereas $P_{max,\ estimated}$ is the maximum power, which is evaluated using hybrid, multi-objective, and five-point metaheuristic-based approaches (Table 5). The statistical analysis of *%ARMPE*, as obtained with three techniques, is shown in Fig. 13.

$$\%ARMPE = \frac{P_{\max,actual} - P_{\max,estimated}}{P_{\max,actual}} \times 100 \tag{10}$$

It is evident from Fig. 13, the hybrid approach, as presented in [22], provides more improved results than the other two existing methods. The values of *%ARMPE*, as estimated with the hybrid technique, are nearly close to zero for both mono- and poly-crystalline solar PV modules. Furthermore, the five-point metaheuristics-based approach provides poorer results than the other two.

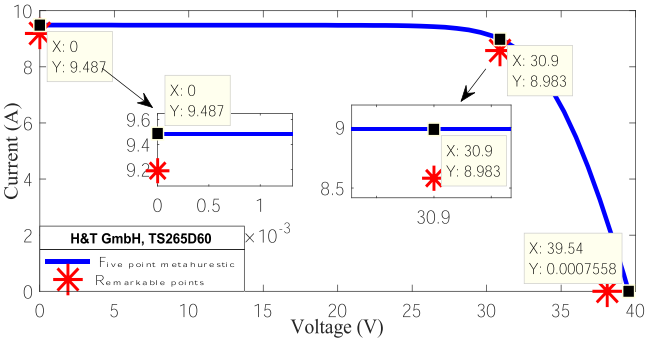


Fig. 5. The *I-V* curve of mono-crystalline solar PV using the five-point metaheuristic method (PSO).

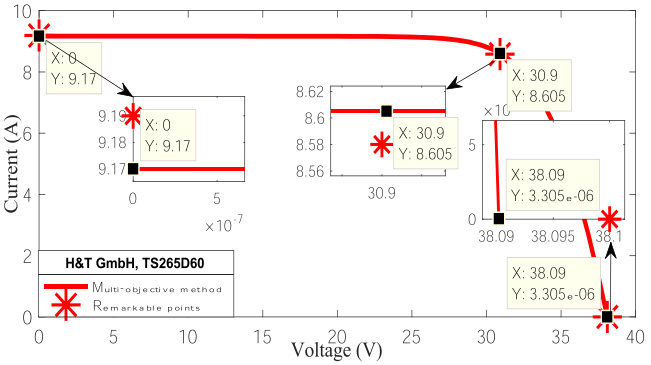


Fig. 6. The *I-V* curve of mono-crystalline solar PV using the multi-objective method.

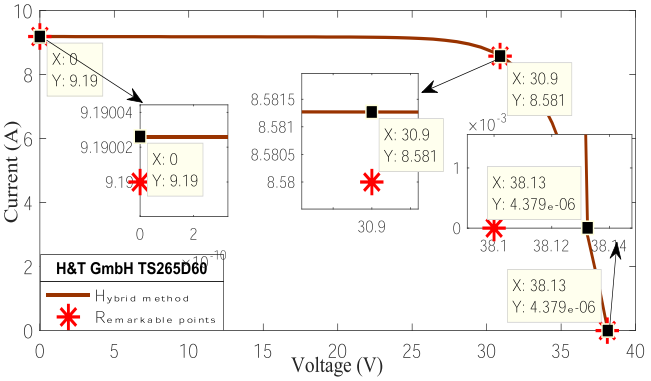


Fig. 7. The *I-V* curve of mono-crystalline solar PV using the hybrid method.

3.3. Estimation of overall model error

Moreover, the overall model error (*OME*) has also been estimated, using (11), to check the effectiveness and accuracy of hybrid, multi-objective, and five-point metaheuristic-based approaches.

$$OME = \Delta\varepsilon = \left|P_{mpp,a} - P_{mpp,e}\right| + \left|I_{mpp,a} - I_{mpp,e}\right| + \left|I_{sc,a} - I_{sc,e}\right| + \left|V_{oc,a} - V_{oc,e}\right| \tag{11}$$

In (11), the suffix '*a*' represents the actual value (provided in the manufacturer datasheet) and '*e*' represents the values estimated through these approaches. The statistical analysis of the model error is shown in Fig. 14.

It is evident from Fig. 14; the hybrid approach again provides better characterization than the other two established approaches. Based on the results, the hybrid approach can be recommended as a better parameter estimation technique than the multi-objective and five-point metaheuristics approach.

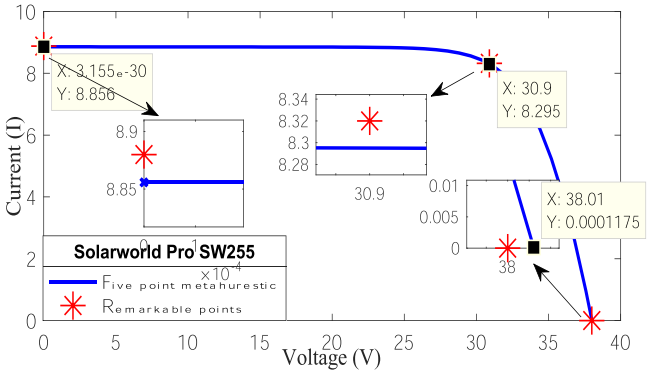


Fig. 8. The *I-V* curve of poly-crystalline solar PV using the five-point metaheuristic method.

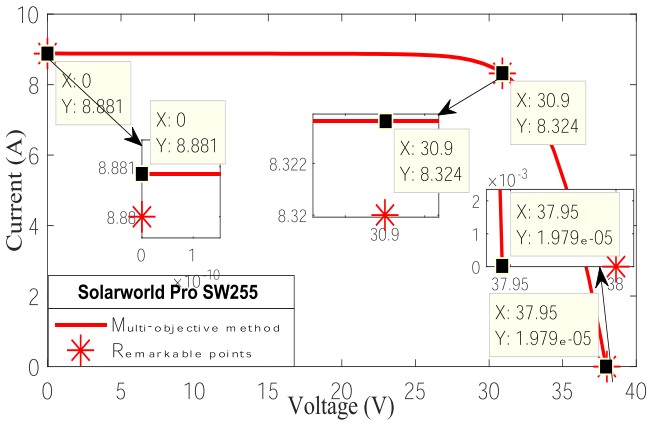


Fig. 9. The *I-V* curve of poly-crystalline solar PV using the multi-objective method.

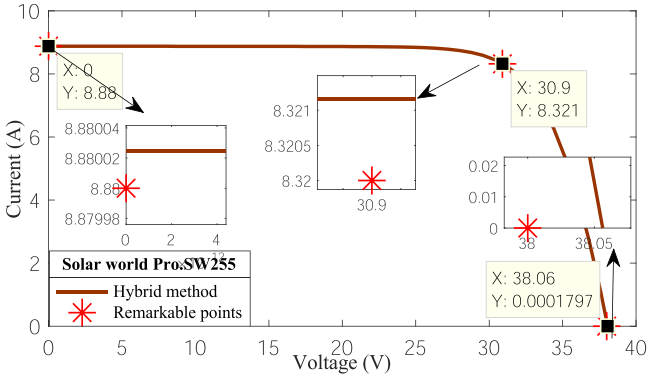


Fig. 10. The *I-V* curve of poly-crystalline solar PV using the hybrid method.

3.4. Comparison of performances of other established techniques of parameter estimation

In this sub-section, the most commonly used poly-crystalline PV module, namely Kyocera KC200GT, is considered to assess the performance of the various other existing parameter evaluation methods. The data available in the manufacture datasheet for this module are summarised in Table 7 [22].

In Table 7, the suffix '*a*' represents the measured or actual values, as given in the manufacturer datasheet. Now, the various parameter estimation techniques, such as analytical technique based on Lambert W function [35], curve fitting method or Villalva method [36], or Accarino method [37], error minimisation between estimated and measured PV curves or Silva method [34], PSO with adaptive mutation strategy [32], HFAPS [2], hybridisation of analytical and SA [14], GWO [31], EPO [30], TRR [22], and TRD [22],

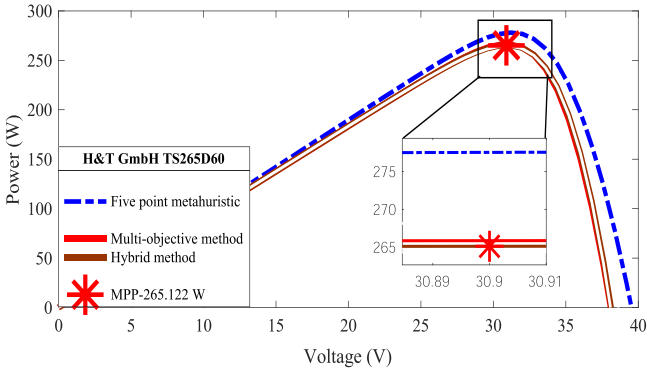


Fig. 11. The *P-V* curve of mono-crystalline solar PV.

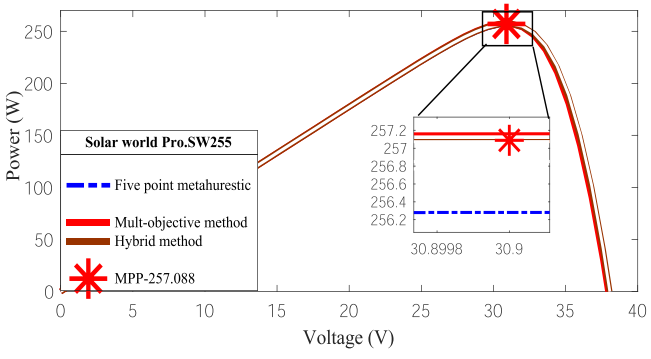


Fig. 12. The *P-V* curve of poly-crystalline solar PV.

Table 5
Estimated and actual values of maximum power.

Estimation method	Mono-Crystalline		Poly- Crystalline	
	Actual (Watt)	Estimated (Watt)	Actual (Watt)	Estimated (Watt)
Hybrid Method	265.122	265.121	257.088	257.086
Multi-objective Method	265.122	265.218	257.088	257.161
Five-point Metaheuristic	265.122	277.53	257.088	256.281

Table 6
Estimated values of current at MPP and SC and voltage under OC.

Mono-Crystalline			
	Hybrid Method	Multi-objective Method	Five-point Metaheuristic
$I_{mpp,\ estimated}$ *(A)*	8.58	8.58	8.98
$I_{sc,\ estimated}$ *(A)*	9.19	9.17	9.48
$V_{oc,estimated}$ *(V)* ε_i	38.13	38.01	39.53
Poly-Crystalline			
	Hybrid Method	Multi-objective Method	Five-point Metaheuristic
$I_{mpp,\ estimated}$ *(A)*	8.32	8.32	8.29
$I_{sc,\ estimated}$ *(A)*	8.88	8.88	8.85
$V_{oc,estimated}$ *(V)*	38.0	37.9	38.0

multi-objective based [25], and PSO based [21], are considered for their performance analysis. The unknown model parameters of SDM of Kyocera KC200GT have been estimated using these techniques and are summarised in Table 8.

Furthermore, with the help of the unknown model parameters, as obtained with these techniques, *P-V* curves are plotted to get the estimated maximum power ($P_{max\ ,\ estimated}$). As obtained with these techniques, the P-V curves are shown in Fig. 15.

Now using (10), the values of *%ARMPE* are estimated for Kyocera KC200GT from these established techniques and are shown in Fig. 16. Similarly, using the estimated parameters, as summarised in Table 8, the values of voltage under OCC, current under SCC,

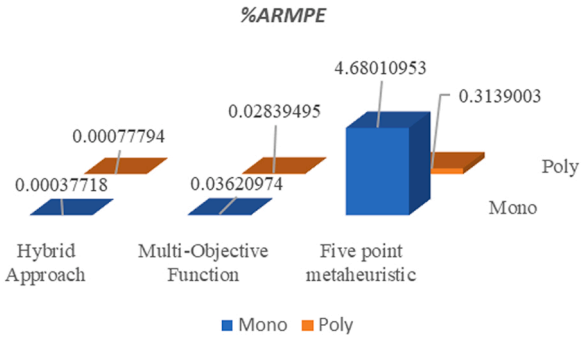


Fig. 13. The *%ARMPE* of mono-and poly-crystalline solar PV modules.

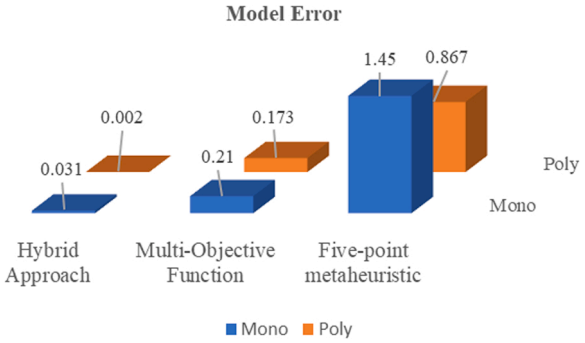


Fig. 14. The overall model error of mono-and poly-crystalline solar PV modules.

Table 7
Manufacturer datasheet of Kyocera KC200GT solar PV model.

S.no.	Module paraments	Magnitude
1	Current under SCC ($I_{sc,\ a}$)	8.21 A
2	Voltage under OCC ($V_{oc,\ a}$)	32.9 V
3	Voltage at MPP ($V_{mpp,\ a}$)	26.3 V
4	Current at MPP ($I_{mpp,\ a}$)	7.61 A
5	Power at MPP ($P_{mpp,\ a}$)	200.14 W
6	Temperature (T)	298.15 K
7	Numbers of series connected cells (n_s)	54

Table 8
Unknown model parameters of SDM obtained with various parameter estimation techniques.

Method	I_{pv} (A)	I_s (A)	R_s (Ω)	R_{sh} (Ω)	V_{th}
Lambert Method[35]	8.21	$2.1954e^{-9}$	0.28405	157.8532	1.491676
Villalva Method[36]	8.214	$9.825\ e^{-8}$	0.221	415.405	1.802625
Silva Method[34]	8.193	$0.3e^{-9}$	0.271	171.2	1.3874
Accarino Method[37]	8.21	$2.1546e^{-9}$	0.2844	157.536	1.4910
MPSO[32]	8.2170821	$2.14017e^{-3}$	0.3448508	753.21483	1.5901367
HFAPS[2]	8.199247	$0.154161e^{-6}$	0.239552	1448.259	2.047205
Hybrid Approach with SA[14]	8.2119	$1.9606\ e^{-6}$	0.21089	895.7971	1.87558
Hybrid approach with GWO Method[31]	8.21	$2.50039\ e^{-7}$	0.2072	1691.575	1.9009134
Hybrid approach with EPO Method[30]	8.194	$2.24925\ e^{-6}$	0.0343	50.018	1.4942306
Hybrid approach with TRR Method[22]	8.21187	$1.71605e^{-7}$	0.217	951.6225	1.862
Hybrid approach TRD Method[22]	8.211872	$1.7108115e^{-7}$	0.21711	951.8898	1.8627
Multi-objective method (NSGA-II)[25]	8.1901	$0.1\ e^{-6}$	0.2382	1166.4	1.8110
Five-point PSO method[21]	8.2138	$6.6473\ e^{-8}$	0.2210	1720.2	1.7542

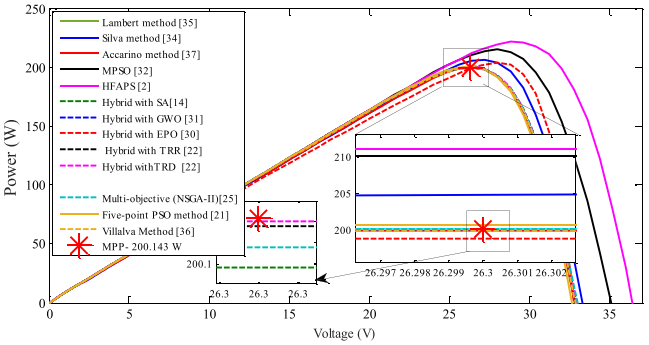


Fig. 15. P-V curves obtained with various parameter estimation techniques.

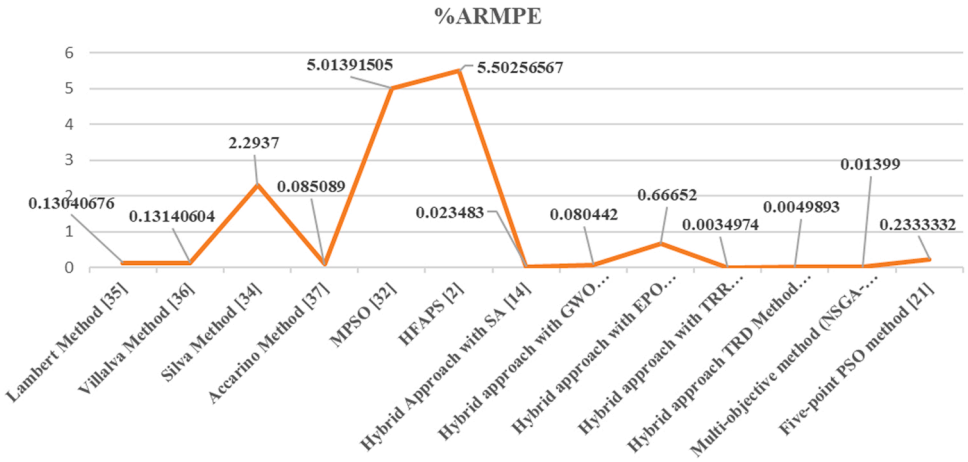


Fig. 16. The values of *%ARMPE* obtained with various parameter estimation techniques.

power at MPP, and current at MPP are estimated and summarised in Table 9. Using the values, as summarised in Table 9, and the equation, as given in (11), the model errors of Kyocera KC200GT have been estimated from the different techniques and are depicted in Fig. 17. Estimated and actual values are considered from Table 9 and Table 7, respectively.

The following observations can be highlighted in Fig. 16 and Fig. 17:

1) The characteristics of solar PV, as obtained with the hybrid approaches, are found better than the analytical method based on Lambert W function [35], curve fitting methods [36,37], metaheuristics algorithm based on five-point single objective function [2, 21,32]. The values of *%ARMPE* in Fig. 16, as obtained with the hybrid approaches, are found smaller than the other existing approaches.

Table 9
The various parameters, required for the estimation of OME, with various techniques.

Extraction methods	$P_{mpp,e}$	$I_{mpp,e}$	$I_{sc,e}$	$V_{oc,e}$
Lambert Method[35]	199.882	7.60	8.19	32.8
Villalva Method[36]	199.88	7.60	8.21	32.8
Silva Method[34]	204.7336	7.78	8.18	33.3
Accarino Method[37]	199.9727	7.61	8.19	32.8
MPSO[32]	210.178	7.99	8.21	35.0
HFAPS[2]	211.156	8.02	8.19	36.4
Hybrid Approach with SA[14]	200.096	7.60	8.20	32.9
Hybrid approach with GWO Method[31]	199.982	7.60	8.20	32.8
Hybrid approach with EPO Method[30]	198.809	7.56	8.20	32.7
Hybrid approach with TRR Method[22]	200.136	7.61	8.21	32.9
Hybrid approach TRD Method[22]	200.142	7.61	8.21	32.9
Multi-objective method (NSGA-II)[25]	200.115	7.61	8.19	32.9
Five-point PSO method[21]	200.61	7.63	8.21	32.7

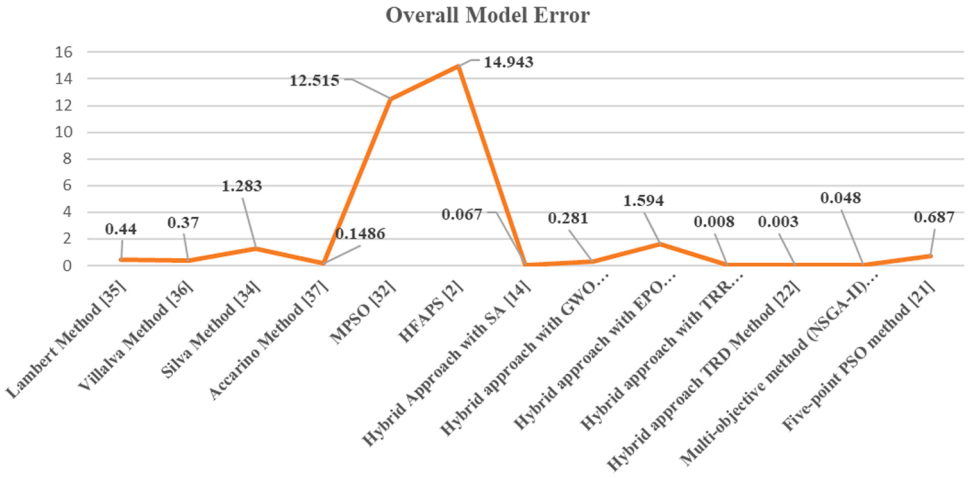


Fig. 17. The values of *OME* obtained with various parameter estimation techniques.

2) Similarly, from Fig. 17, it is evident that the values of *OME*, as evaluated with the hybrid approaches, are much smaller than the other existing techniques.
3) The hybrid approach, based on analytical plus iterative [22], provides smaller values of *%ARMPE* and *OME* than the other existing hybrid approaches [14,30,31], as well as other established iterative, analytical, curve fitting, multi-objective, five-point single objective function-based techniques [2,21,25,32,34–37].
4) Finally, the multi-objective function-based parameter estimation technique is more accurate than the other established iterative, analytical, curve fitting, multi-objective, five-point single objective function-based techniques [2,21,25,32,34–37]. However, its accuracy is smaller than the hybrid approaches [14,22,30,31].

Additionally, it is worth mentioning that in most of the research works, the diode ideality factor (A) is either fixed [36] or estimated through some empirical formula [38]. In the Villalva method [36], the value of 'A' is arbitrarily selected as 1.3 and then unique pair of R_s and R_{sh} is obtained to satisfy MPP power, as provided in the manufacturer datasheet, by increasing the value of R_s. Further, this method assumes photon currents and diode saturation are equal. However, these approximation and assumption reduce the complexity of the model but on the hand enhances the inaccuracy in the characterization. The ideality factor (A) is an index to represent the degree of the ideality of the diode. The proper estimation of 'A' is desirable to get solar PV characteristics closer to the real characteristics [38].

In [36], it is suggested to select any arbitrary value of 'A' initially. Afterwards, modification in the value of 'A' has been recommended to get characteristics closer to the real characteristics. However, this technique makes the model simple but the estimation of the accurate value of 'A' becomes a tedious task. In fact, the value of 'A' is intrinsically associated with 'R_s' and 'R_{sh}' [38,39]. Any increase in the value of R_s results in a reduction in the value of 'A' and 'P_{max}' [38,39]. Therefore, achieving the accurate characteristics of solar PV by changing the values of R_s and keeping 'A' constant results in erroneous characterization. Though, various analytical expressions were developed in the research for the estimation of 'A' but most of the expressions are based on approximation and assumptions [38–40]. For instance, the analytical expression of A, developed in [38], assumes photon currents and current under SCC are equal. Furthermore, the exponential term in this study has been considered as much higher than the unity. Such assumptions and approximations lead to the erroneous characterization of solar PV.

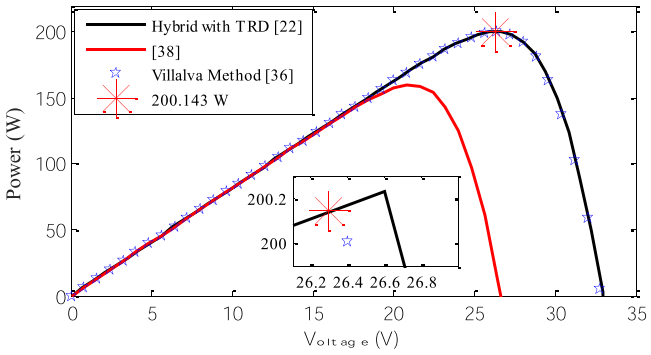


Fig. 18. The PV curves for different values of ideality factor (A).

Finally, the three ideality factors, (i) the Villalva method [36], (ii) estimated with the help of the analytical formula given in [38], and (iii) estimated with a hybrid approach [22] have been considered to reveal the impacts of it on characterization. The PV characteristics curves for these three ideality factors, for the Kyocera KC200GT module, are shown in Fig. 18. In Fig. 18, '* ' mark represents the actual maximum power point (MPP) given in the manufacturer datasheet.

From Fig. 18, it is obvious that the PV curves (Magnified portion), as obtained with the hybrid approach, is exactly passed through the MPP, as provided in the manufacture datasheet. Therefore, instead of fixing or estimating '*A*' analytically through approximate expression, it is advisable to use a hybrid approach for better characterization.

Hence, based on the points, as highlighted in 1–4, and the model sensitivity to the ideality factor, it can be said that the hybridization of analytical technique with iterative method not only provides good accuracy but at the same time, it reduces the model complexity, also. However, the performances of the hybrid approaches are greatly dependent on the following points:

- Techniques which are to be considered in hybrid methods. For instance, the hybridization of analytical with iterative [22] provides better results than the hybridization of metaheuristics technique with analytical [14,30,31].
- Selections of metaheuristics techniques in the hybrid approach play a vital role in determining the accuracy of the techniques. For instance, an almost similar hybridization technique has been applied in [30,31], *i.e.*, hybridization of analytical with metaheuristics technique. It is evident from Figs. 16 and 17 the hybrid approach with the GWO technique [31] provides better results than the EPO technique [30].

Also, the objective function, developed in a hybrid approach, has significant impacts on the overall accuracy of the methods. For instance, the accuracy of the methods, as presented in [14,30,31], differ from each other while these methods use hybridization of metaheuristics with the analytical method. In [30,31], objective function has been developed after the estimation of unknown current, I_{pv}, and $I_{o,}$ while remarkable points are considered in [14]. Therefore, proper selection or development of objective function is highly desirable to get an accurate characterization of solar PV through a hybrid approach. Therefore, in future work, the various possible combinations of hybrid approaches can also be investigated to get the best objective function and suitable methods for hybridization. However, limited research works have been considered in this performance analysis but based on these studies, it is obvious that the hybrid approach that includes analytical and iterative techniques provides better results than the other existing approach.

4. Conclusions

Firstly, the performances of three established parameter estimation techniques of solar PV, namely multi-objective, single objective, and hybrid approach have been investigated. The benchmarks, namely *%ARMPE* and OME of mono- and poly-crystalline solar PV module, have been estimated, using these established techniques. Through the comparative studies of these two benchmarks, it has been revealed that the hybrid approach outperforms both single- and multi-objective function-based approach as the hybrid approach of the parameter estimation has the smaller values of the benchmarks then the other two.

Also, the performances of the various possible combination of hybrid approaches were investigated. It is shown that hybridization of analytical and iterative techniques provides the better characterisation of solar PV than the other existing hybrid approaches. The *% ARMPE* and OME are found smallest for the hybrid approach based on analytical and iterative. Similarly, the hybrid approach comprises analytical and iterative techniques that provide the least value for *OME* for all the modules. Finally, the performances of various numerical, iterative, curve fitting, error minimisation, and analytical-based techniques are also evaluated and compared. It is shown that the hybrid approach, comprised of analytical and iterative techniques, again gives better characterisation than the other existing parameter estimation techniques.

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.

Data Availability

No data was used for the research described in the article.

References

[1] D. Sarkar, A. Kumar, P.K. Sadhu, A survey on development and recent trends of renewable energy generation from BIPV systems, IETE Tech. Rev. 37 (2019) 258–280, https://doi.org/10.1080/02564602.2019.1598294.
[2] A.M. Beigi, A. Maroosi, Parameter identification for solar cells and module using a hybrid firefly and pattern search algorithms, Sol. Energy 171 (2018) 435–446, https://doi.org/10.1016/j.solener.2018.06.092.
[3] A. Mellit, M. Benghanem, S.A. Kalogirou, Modeling and simulation of a stand-alone photovoltaic system using an adaptive artificial neural network: Proposition for a new sizing procedure, Renew. Energy 32 (2007) 285–313, https://doi.org/10.1016/j.renene.2006.01.002.
[4] M.C. Di Piazza, M. Luna, G. Vitale, Dynamic PV model parameter identification by least-squares regression, IEEE J. Photo 3 (2013) 799–806, https://doi.org/10.1109/JPHOTOV.2012.2236146.
[5] A. Hussain, M.M. Garg, M.P. Korukonda, S. Hasan, L. Behera, A parameter estimation based MPPT method for a PV system using Lyapunov control scheme, IEEE Trans. Sustain. Energy 10 (2018) 2123–2132, https://doi.org/10.1109/TSTE.2018.2878924.

[6] Surya Prakash Abhishek Chauhan, Parameter estimation and analysis of photovoltaics through a hybrid emperor penguin optimisation approach under different environmental constraints, IETE J. Res. (2021), https://doi.org/10.1080/03772063.2021.1951378.
[7] V.J. Chin, Z. Salam, K. Ishaque, Cell modelling and model parameters estimation techniques for photovoltaic simulator application: a review, Appl. Energy 154 (2015) 500–519, https://doi.org/10.1016/j.apenergy.2015.05.035.
[8] T.T. Yetayew, T.R. Jyothsna, Parameter extraction of photovoltaic modules using Newton Raphson and simulated annealing techniques, IEEE Proc. Int. Conf. Power, Commun., Inf. Technol., Bhubaneswar (2015), https://doi.org/10.1109/PCITC.2015.7438166.
[9] M. Uoya, H. Koizumi, A calculation method of photovoltaic array's operating point for MPPT evaluation based on one-dimensional Newton–Raphson method, IEEE Trans. Ind. Appl. 51 (2015) 567–575, https://doi.org/10.1109/TIA.2014.2326083.
[10] P. Bharadwaj, K.N. Chaudhury, V. John, Sequential optimisation for PV panel parameter estimation, IEEE J. Photo 6 (2016) 1261–1268, https://doi.org/10.1109/JPHOTOV.2016.2574128.
[11] S. Shongwe, M. Hanif, Gauss-Seidel iteration-based parameter estimation for a single diode model of a PV module, IEEE Proc. Electr. Power Energy Conf., Lond. (2015), https://doi.org/10.1109/EPEC.2015.7379963.
[12] G. Petronea, G. Spagnuolo, M. Vitellib, Analytical model of mismatched photovoltaic fields by means of Lambert W-function, Sol. Energy Mater. Sol. Cells 91 (2007) 1652–1657, https://doi.org/10.1016/j.solmat.2007.05.021.
[13] A. Chatterjee, A. Keyhani, D. Kapoor, Identification of photovoltaic source models, IEEE Trans. Energy Convers. 24 (2011) 883–889, https://doi.org/10.1109/TEC.2011.2159268.
[14] U. Jadli, P. Thakur, R.D. Shukla, A new parameter estimation method of solar photovoltaic, IEEE J. Photo 8 (2018) 239–247, https://doi.org/10.1109/JPHOTOV.2017.2767602.
[15] V.J. Chin, Z. Salam, A new three-point-based approach for the parameter extraction of photovoltaic cells, Appl. Energy 237 (2019) 519–533, https://doi.org/10.1016/j.apenergy.2019.01.009.
[16] K. Sundareswaran, P. Sankar, P.S.R. Nayak, S.P. Simon, S. Palani, Enhanced energy output from a PV system under partial shaded conditions through artificial bee colony, IEEE Trans. Sustain. Energy 6 (2014) 198–209, https://doi.org/10.1109/TSTE.2014.2363521.
[17] H. Wei, J. Cong, X. Lingyun, S. Deyun, Extracting solar cell model parameters based on chaos particle swarm algorithm, IEEE Proc. Int. Conf. Electr. Inf. Control Eng. (2011), https://doi.org/10.1109/ICEICE.2011.5777246.
[18] L. Peng, Y. Sun, Z. Meng, An improved model and parameters extraction for photovoltaic cells using only three state points at standard test condition, J. Power Sources 248 (2014) 621–631, https://doi.org/10.1016/j.jpowsour.2013.07.058.
[19] J.J. Soon, K.S. Low, Photovoltaic model identification using particle swarm optimisation with inverse barrier constraint, IEEE Trans. Power Electron 27 (2012) 3975–3983, https://doi.org/10.1109/TPEL.2012.2188818.
[20] H.M. Hasanien, Shuffled frog leaping algorithm for photovoltaic model identification, IEEE Trans. Sustain. Energy 6 (2015) 509–515, https://doi.org/10.1109/TSTE.2015.2389858.
[21] N. Rawat, P. Thakur, Parameter extraction of PV solar cell: a comparative assessment using newton raphson, simulated annealing and particle swarm optimization, J. Graph. Era Univ. 7 (2019) 119–131. ISSN:0975-1416.
[22] Padmanabh Thakur Nikita Rawat, K.Singh Asheesh, A novel hybrid parameter estimation technique of solar PV, Int. J. Energy Res. 46 (2022) 4919–4934, https://doi.org/10.1002/er.7485.
[23] K. Yu, J. Liang, B. Qu, Y. Luo, C. Yue, Dynamic selection preference-assisted constrained multiobjective differential evolution, IEEE Trans. Syst., Man, Cybern.: Syst. vol. 52 (5) (2022) 2954–2965, https://doi.org/10.1109/TSMC.2021.3061698.
[24] J. Liang et al., "Utilizing the Relationship Between Unconstrained and Constrained Pareto Fronts for Constrained Multiobjective Optimization," IEEE Transactions on Cybernetics, doi: 10.1109/TCYB.2022.3163759.
[25] N. Rawat, P. Thakur, U. Jadli, Solar PV parameter estimation using multi-objective optimisation, Bull. Electr. Eng. Inform. 8 (2019) 1198–1205, https://doi.org/10.11591/eei.v8i4.1312.
[26] K.M. El-Naggar, M.R. AlRashidi, M.F. AlHajri, A.K. Al-Othman, Simulated annealing algorithm for photovoltaic parameters identification, Sol. Energy 86 (2012) 266–274, https://doi.org/10.1016/j.solener.2011.09.032.
[27] M.F. Al Hajri, K.M. El-Naggar, M.R. AlRashidi, A.K. Al-Othman, Optimal extraction of solar cell parameters using pattern search, Renew. Energy 44 (2012) 238–245, https://doi.org/10.1016/j.renene.2012.01.082.
[28] M.R. Al Rashidi, M.F. Al Hajri, K.M. El-Naggar, A.K. Al-Othman, A new estimation approach for determining the I–V characteristics of solar cells, Sol. Energy 85 (2011) 1543–1550, 10.1016/j.solener.2011.04.013.
[29] S. Xu, Y. Wang, Parameter estimation of photovoltaic modules using a hybrid flower pollination algorithm, Energy Convers. Manag. 144 (2017) 53–68, 10.1016/j.enconman.2017.04.042.
[30] A. Chauhan, S. Prakash, A new emperor penguin optimisation-based approach for solar photovoltaic parameter estimation, Int Trans. Electr. Energy Syst. 31 (2021) 1–28, https://doi.org/10.1002/2050-7038.12917.
[31] B. Nayak, A. Mohapatra, K.B. Mohanty, Parameter estimation of single diode PV module based on GWO algorithm, Renew. Energy Focus 30 (2019) 1–12, https://doi.org/10.1016/j.ref.2019.04.003.
[32] M. Merchaoui, A. Sakly, M.F. Mimouni, Particle swarm optimisation with adaptive mutation strategy for photovoltaic solar cell/module parameter extraction, Energy Convers. Manag. 175 (2018) 151–163, https://doi.org/10.1016/j.enconman.2018.08.081.
[33] D. Kler, P. Sharma, A. Banerjee, K.P.S. Rana, V.P.V. Kumar, cell and module efficient parameters estimation using evaporation rate-based water cycle algorithm, Int J. Swarm Evol. Comput. 35 (2017) 93–110, https://doi.org/10.1016/j.swevo.2017.02.005.
[34] E.A. Silva, F. Bradaschia, M.C. Cavalcanti, A.J. Nascimento, Parameter estimation method to improve the accuracy of photovoltaic electrical model, IEEE J. Photo 6 (2016) 278–285, https://doi.org/10.1109/JPHOTOV.2015.2483369.
[35] I.N. Eddine, A. Obbadi, Y. Errami, A. El-Fajri, M. Agunaou, Parameter estimation of photovoltaic modules using iterative method and the Lambert W function: A comparative study, Energy Convers. Manag. 119 (2016) 37–48, https://www.sciencedirect.com/science/journal/01968904.
[36] M.G. Villalva, J.R. Gazoli, E.R. Filho, Comprehensive approach to modeling and simulation of photovoltaic arrays, IEEE Trans. Power Electron 24 (2009) 1198–1208, https://doi.org/10.1109/TPEL.2009.2013862.
[37] J. Accarino, G. Petrone, C.A. Ramos-Paja, G. Spagnuolo, Symbolic algebra for the calculation of the series and parallel resistances in PV module model, IEEE Proc. Int. Conf. Clean. Electr. Power Alghero (2013), https://doi.org/10.1109/ICCEP.2013.6586967.
[38] Caio Meira Amaral da Luz, Fernando Lessa Tofoli, Paula dos Santos Vicente, Eduardo Moreira Vicente, Assessment of the ideality factor on the performance of photovoltaic modules, Energy Convers. Manag. 167 (2018) 63–69, https://doi.org/10.1016/j.enconman.2018.04.084.
[39] Hong-Ki Park, Jaewu Choi, Origin of voltage-dependent high ideality factors in graphene–silicon diodes, Adv. Electron. Mater. 4 (2018) 1700317, https://doi.org/10.1002/aelm.201700317.
[40] W. De Soto, S.A. Klein, W.A. Beckman, Improvement and validation of a model for photovoltaic array performance, Sol. Energy 80 (2006) 78–88, https://doi.org/10.1016/j.solener.2005.06.010.