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Solar PV parameter estimation using multi-objective optimisation

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ABSTRACT

The estimation of the electrical model parameters of solar PV, such as light-induced current, diode dark saturation current, thermal voltage, series resistance, and shunt resistance, is indispensable to predict the actual electrical performance of solar photovoltaic (PV) under changing environmental conditions. Therefore, this paper first considers the various methods of parameter estimation of solar PV to highlight their shortfalls. Thereafter, a new parameter estimation method, based on multi-objective optimisation, namely, Non-dominated Sorting Genetic Algorithm-II (NSGA-II), is proposed. Furthermore, to check the effectiveness and accuracy of the proposed method, conventional methods, such as, 'Newton-Raphson', 'Particle Swarm Optimisation, Search Algorithm, was tested on four solar PV modules of polycrystalline and monocrystalline materials. Finally, a solar PV module photowatt PWP201 has been considered and compared with six different state of art methods. The estimated performance indices such as current absolute error matrics, absolute relative power error, mean absolute error, and P-V characteristics curve were compared. The results depict the close proximity of the characteristic curve obtained with the proposed NSGA-II method to the curve obtained by the manufacturer's datasheet.

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1. INTRODUCTION

Among all the available inexhaustible energy sources, solar PV systems have received utmost attention throughout the world because of their abundance, lack of pollution, zero noise, and less maintenance characteristics and their wide acceptance in integration with modern power grids [1]. Though, solar energy is being considered as the most accessible renewable energy resources with huge potential of electricity generation, unfortunately, it is often characterized by low power density, low conversion efficiency and high installation costs [2]. Therefore, there is need to explore the research in the area that could be supportive in enhancement of optimal capturing capacity of available solar energy. Over the years, myriad of works have been carried out to ensure improved performance of the solar PV. Among all of the existing research areas the parameter estimations and modeling of solar PV have received utmost attentions by the researchers.

The accurate estimation of electrical model parameters, such as, light-induced current (I_{Ph}), diode dark saturation current (I_o), thermal voltage (V_T), series resistance (R_s), and shunt resistance (R_p), of solar PV is necessary for accomplishing the following motives:

a. To improve the overall efficiency of PV systems [3].
b. To predict expected power output in varying environmental condition [4].

c. To obtain accurate design specification of the power conditioning equipment connected with the solar PV, and [5].
d. To simulate maximum power tracking algorithm, precisely.

Generally, existing methods were divided into three categories in the research, such as: Analytical methods, Numerical methods, and Metaheuristics methods.
Usually, the manufacturer provides the remarkable points, such as, 'voltage at the maximum power point (V_{MP})', 'current at the maximum power point (I_{MP})', 'short-circuit current (I_{SC}), and 'open-circuit voltage (V_{OC})' in their data sheet [6]. The accuracy of parameter estimation through analytical methods relies heavily on the accurate emplacement of these remarkable points or known parameters on solar PV output characteristics [3, 7].

Among the various existing numerical methods, Newton-Raphson (NR) method [8], Lambert W function [9], and Gauss-Seidel (GS) method [10], were frequently considered in estimation of accurate electrical parameters of solar PV. Though these numerical methods have a higher level of accuracy than the analytical methods, these methods suffer from extensive computation time for the convergence also they converge to local maxima instead of global in case of wrong selection of initial values especially in NR and GS methods [8, 11].

Although Metaheuristics Algorithms based approaches play a vital role in the extraction of electrical model parameters of solar PV, unfortunately, the speed of convergence is found to be low in genetic algorithm (GA) [3]. Also, the GA based approach is found to be unsuitable for highly interactive fitness function [3]. The swap between the initial temperature and cooling schedule is a major issue in simulating annealing (SA) [12]. Though particle swarm optimization (PSO) outperforms SA and GA [13], at the same time it is found inept to track accurate characteristics as provided in manufacturer's datasheet. Also, the uniformity of estimated electrical model parameter cannot be assured through PSO [3, 13-15].

Besides the shortfalls as discussed above, most of the aforementioned methods consider the task of parameter estimations as a single objective optimisation i.e., the error between the real and estimated or predicted current at a known voltage is considered as the objective function. Indeed, parameter estimation of solar PV is a multi-objective optimisation (MOO) task, wherein, accurate values of all five parameters, such as I_{Ph}, I_o, V_T, R_s, and R_p are highly desirable to achieve characteristics exactly in tune with the real characteristics of solar PV. Unfortunately, in most of the research works, all of these five unknown parameters were not considered to reduce computational complexities.

Therefore, to rectify the inconsistencies prevailing in these methods, the present study proposes an accurate method of parameters extraction based on MOO [16], to accurately describe the solar PV output characteristics.

2. THE SOLAR PV CELL MODEL

The single diode model or R_p-model of solar PV is shown in Figure 1 which has been used in the present work to investigate the performance of solar PV. Although, there are two and three diode models of solar PV but these models have simultaneously increased the computational complexity due to a large number of unknown parameters. Also, a significant trade-off between accuracy and computational simplicity is achieved in R_p-model [11].

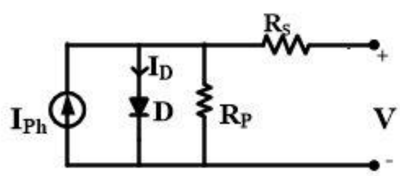

Figure 1. Single-diode solar PV model

The characteristic equation of R_p-model, as given in (1), provides the relation between the output voltage (V) and current (I) in terms of unknown parameters.

$$I = I_{Ph} - I_o \left[\exp\left(\frac{V + R_s I}{V_T} \right) - 1 \right] - \frac{V - R_s I}{R_p} \quad (1)$$

Where, $V_T=(\alpha KTN_s)/e$ is in terms of diode ideality factor (α), electron charge (e), Boltzmann's constant (K), number of solar PV cell in series (N_s), and temperature (T).

3. PROPOSED OBJECTIVE FUNCTION

The output characteristic of a PV cell relies on five parameters, namely, I_{Ph}, I_o, V_T, R_s, and R_p, as given in (1). To estimate these unknown parameters, five equations, as given in (2), (3), (4), (6), and (8), can be derived from (1) as [17]:

a. Under short circuit condition, i.e., when V=0, I=I_{SC}, the relation, as given in (1), can be written as:

$$f_1(x) = I_{SC} - I_{Ph} + I_o\left(\exp\left(\frac{I_{SC}R_S}{V_T}\right)-1\right) + \frac{I_{SC}R_S}{R_P} \tag{2}$$

b. Under open circuit condition, i.e., when I=0, V=V_{OC}, the relation as given in (1), can be derived as:

$$f_2(x) = I_{Ph} - I_o\left(\exp\left(\frac{V_{OC}}{V_T}\right)-1\right) - \frac{V_{OC}}{R_p} \tag{3}$$

c. At maximum power point (MPP), i.e., when I=I_{MP}, V=V_{MP}, the relation, as given in (1), can be written as:

$$f_3(x) = I_{MP} - I_{Ph} + I_o\left(\exp\left(\frac{V_{MP}+I_{MP}R_s}{V_T}\right)-1\right) + \frac{(V_{MP}+I_{MP}R_S)}{R_P} \tag{4}$$

d. The slope at MPP on P-V curve will be parallel to the voltage axis and hence it is found that

$$\left.\frac{dI}{dV}\right|_{MPP} = -\frac{I_{MP}}{V_{MP}} \tag{5}$$

On solving (5) the forth equation can be derived as:

$$f_4(x) = I_{MP} - (V_{MP} - I_{MP}R_s)\left(\frac{I_o}{V_T}\exp\left(\frac{V_{MP}+I_{MP}R_s}{V_T}\right) + \frac{1}{R_P}\right) \tag{6}$$

e. The final equation is derived by calculating the slope of the I-V characteristic curve. The slope of the I-V characteristic curve is derived by differentiating the output current with respect to the output voltage under short circuit condition.

$$\left.\frac{dI}{dV}\right|_{I=I_{SC}} = -\frac{1}{R_p} \tag{7}$$

On solving (7) the fifth equation can be derived as:

$$f_5(x) = \frac{R_s}{R_p} - \frac{I_o}{V_T}\exp\left(\frac{I_{SC}R_s}{V_T}\right)\left(R_p - R_s\right) \tag{8}$$

The (2), (3), (4), (6), and (8), have been combined to define objective function, $f(x)$, as:

$$f(x) = \left[\, f_1(x),\, f_2(x),\, f_3(x),\, f_4(x), f_5(x)\right] \tag{9}$$

Now, the MOO problem is formulated as:

$$min(\, f_1(x),\, f_2(x),\, f_3(x),\, f_4(x),\, f_5(x)) \tag{10}$$

Here, x is the array of decision variables $\{x_1, x_2, x_3, x_4, x_5\}$. In the proposed work x_1, x_2, x_3, x_4, and x_5 represents I_{Ph}, I_o, R_s, R_p and V_T, respectively.

3.1. Proposed parameter estimation method

Various MOO methods generated from GA, such as the Vector-Evaluated Genetic Algorithm, Strength Pareto Metaheuristics Algorithm, Pareto Archived Evolution Strategy, classical non-dominated sorting-based multi-objective evolutionary algorithm, and NSGA-II, were tested and verified. Among these Methods, NSGA-II is considered to be one of the best methods due to its lower computation time and non-elitism approach. Therefore the present work considers NSGA-II, to evaluate the electrical model parameters of solar PV [16]. The following steps have been used in the proposed NSGA-II:

a. *Initialisation*: objective function $f(x)$, as given in (9), main population D, and the input variable and their ranges are initialized.
b. *Non-Domination Sort*: NSGA-II uses non-domination sort to sort the initialized main population D. Each individual p in the main population D has two sets. The set S_p contains the individuals which are dominated by p whereas set n_p contains those individuals which are dominated to p. If the individual p has zero individuals in its set n_p, then p is assigned to front one (F_1) and ranked one.
c. *Crowding Distance*: As the fitness value or rank is achieved, the next step is to assign the crowding distance $F_i(d_j)$, where F_i is the i^{th} front counter and d_j is the crowding distance of the j^{th} individual in front F_i. The crowding distance is the distance between two individuals.
d. *Tournament Selection*: The selection of the individual is dependent on its individual rank and crowding distance. The rank of the individual has been checked and the individual with the smallest rank is selected. In case of similar rank of two individuals, the crowding distance is considered for the selection. In this case, the individual with larger values of crowding distance, i.e., $F_i(d_j)$, is selected.
e. *Genetic Operators*: Offspring population is created using the genetic operator's binary crossover and mutation.
f. *Recombination*: The parent population is united with the offspring population and sorted again using non-domination sorting. The unfit individuals are replaced by the fit one and the original size of the population is maintained.

4. RESULTS AND DISCUSSION

4.1. Estimation of performance indices for polycrystalline and monocrystalline PV modules

Three polycrystalline and monocrystalline PV module with specifications as given in Tong NT et al [18] were considered. For proposed method and PSO, similar lower and upper bound values were taken, while for the NR method, different initial values were used. The electrical model parameters value for the PV modules found by the proposed method, NR, PSO, and search algorithm is summarised in Table 1. Figure 2-5 shows the *P-V* characteristic of the PV modules. It is evident that the *P-V* curve obtained by the proposed method for both type of PV cell modules were closest to the MPP. Also, it was observed that NR was the second best among the other methods but the accuracy of NR method is very much subjected to the selection of initial values which is evident from Table 1. Table 2 summarises the ARPE calculated for PV modules. The ARPE for all the PV modules using the proposed method were calculated to be very less. Thus, from the analysis of all the results it is evident that proposed method outperforms NR, PSO, and search algorithm in the case of polycrystalline as well as monocrystalline PV modules.

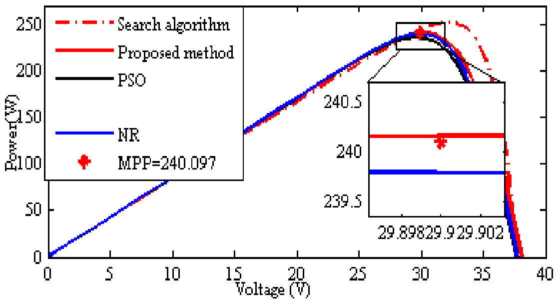

Figure 2. *P-V* characteristics for WW energy, AS240-6P30 module

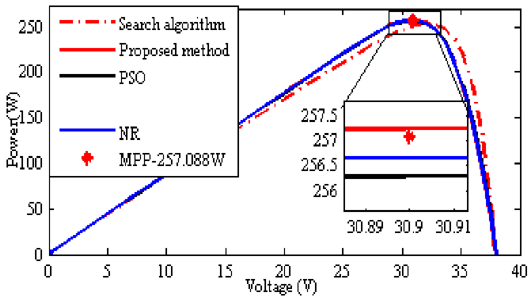

Figure 3. *P-V* characteristics for Solarworld, Pro. SW255 module

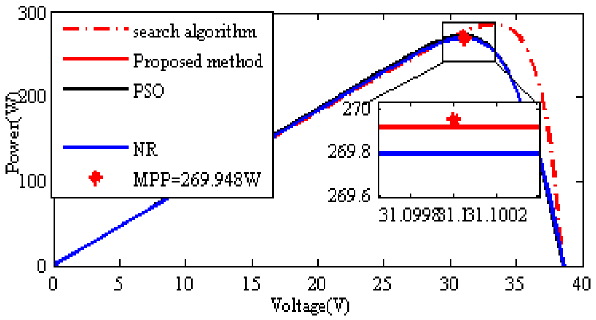

Figure 4. *P-V* characteristics for Nemy, JP270M60 module

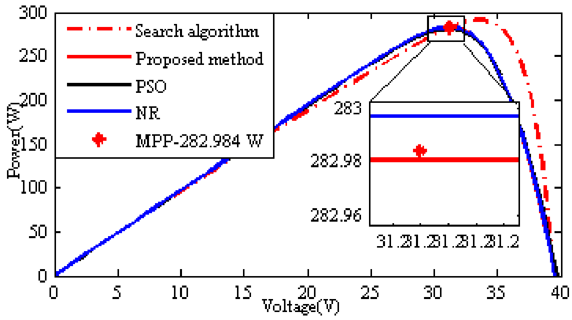

Figure 5. *P-V* characteristics for Solarworld, Plus SW280 module

Table 1. Extracted parameters for polycrystalline and monocrystalline PV modules by the proposed and existing methods

PV modules	ParameterExtracted	Search algorithm [18]	NR Initial value	NR Estimated value	Lower Bound	Upper Bound	PSO	Proposed method
Polycrystalline								
WW Energy AS240-6P30	*IPh (A)*	8.5705	8.5	8.5707	8	8.6	8.5568	8.5108
	Io (A)	0.0074E-6	1E-8	6.83E-9	7E-10	1E-7	3.488E-8	1E-8
	Rs (Ω)	5.79E-3	0.3	0.3490	0.1	0.5	0.3450	0.343
	Rp (Ω)	94.87	2000	4175.46	50	5000	2047.8	3500.6
	VT	*α*=1.1725	1.6	1.7997	0.1	2	1.9489	1.8509
Solarworld, Pro. SW255	*IPh (A)*	8.8805	8	8.8807	8	9	8.8565	8.8814
	Io (A)	0.026E-6	1E-6	2.317E-8	10E-10	1E-6	2.311E-8	0.1E-7
	Rs (Ω)	3.457E-3	0.1	0.21	0.1	0.5	0.2093	0.2277
	Rp (Ω)	57.40	2000	2570.3	50	5000	2579.5	3735.8
	VT	*α*=1.2554	1	1.9228	0.1	2	1.9237	1.8422
Monocrystalline								
Solarworld, Plus SW280	I_{Ph} *(A)*	9.7109	9.7	9.7112	9	10	9.6748	9.6945
	I_o *(A)*	0.019E-6	1E-8	1.735E-8	1E-10	1E-7	1.844E-8	0.9E-8
	R_s *(Ω)*	5.357E-3	0.2	0.3235	0	0.5	0.3447	0.3371
	R_p *(Ω)*	61.07	2000	2714.3	50	1000	2591.2	3563.3
	V_T	*α*=1.2793	1.8	1.9612	0.1	2	1.9746	1.8991
Nemy, JP270M60	I_{Ph} *(A)*	9.2002	9	9.2003	9	10	9.3243	9.2035
	I_o *(A)*	0.001E-6	1E-9	1.197E-9	1E-10	1E-7	1.069E-9	1E-9
	R_s *(Ω)*	5.01E-3	0.3	0.3015	0.1	0.5	0.2981	0.3061
	R_p *(Ω)*	207.73	9000	9120.8	1000	10000	9393.7	9838.8
	V_T	*α*=1.1027	1.6	1.6958	0.1	2	1.6826	1.6827

Table 2. Absolute relative power error for polycrystalline modules

PV module	Extraction methods	Actual Maximum Power P_{actual} *(W)*	Calculated maximum *power* P_{cal} *(W)*	Absolute Relative Power Error $ARPE = \left\lvert \frac{P_{actual} - P_{cal}}{P_{actual}} \right\rvert \times 100(\%)$
WW Energy AS240-6P30	NR	240.097	239.8	1.2370×10^{-1}
	PSO	240.097	235.64	0.0185×10^{2}
	Search algorithm	240.097	243.3	0.0133×10^{2}
	Proposed Method	240.097	240.15	2.2074×10^{-2}
Solarworld, Pro. SW255	NR	257.088	256.76	1.2758×10^{-1}
	PSO	257.088	256.280	3.1428×10^{-1}
	Search algorithm	257.088	250.68	0.0249×10^{2}
	Proposed Method	257.088	257.15	2.4116×10^{-2}
Solarworld, Plus SW280	NR	282.984	282.99	2.1202×10^{-3}
	PSO	282.984	281.24	6.1628×10^{-1}
	Search Algorithm	282.984	282.52	1.6396×10^{-1}
	Proposed Method	282.984	282.980	1.4135×10^{-3}
Nemy, JP270M60	NR	269.948	269.793	5.7418×10^{-2}
	PSO	269.948	272.94	0.0110×10^{2}
	Search Algorithm	269.948	277.8	0.029×10^{2}
	Proposed Method	269.948	269.913	1.2965×10^{-2}

4.2. Estimation of performance indices for photowatt PWP201 module

The unknown parameters of Photowatt PWP201 comprising of 36 polycrystalline silicon series connected cells at T=45˚C [18], is calculated with the proposed method (NSGA-II), NR, GA, PS, SA, (MPCOA), and (GOFPANM) are outlined in Table 3. Figure 6 shows the *P-V* curve of the PV module. The *P-V* curve obtained by the proposed method is close to the experimental data, in particular at the MPP point. Further, the values of MPP and ARPE, as estimated with these existing and the proposed method, have been summarised in Table 4. The ARPE is smaller for the proposed method. Table 5 shows the IAE matrics for each experimentally measured I-V points. The MAE calculated for the proposed method is 0.1875%, which is the lowest followed by the MAE calculated by the MPCOA and GOFPANM methods.

The convergence process of the proposed method is shown in Figure 7. The proposed method is incomplex and does not have parameters that need to be tuned as in the case of PSO, SA, PS, MPCOA, and GOFPANM methods.

Table 3. Photowatt PWP201 module parameters extracted by the proposed method and compared with various methods

Parameters Extracted	SA [12]	NR [8]	PS [19]	GA [20]	MPCOA [21]	GOFPANM [22]	Proposed method
$I_{Ph}(A)$	1.0331	1.0318	1.0313	1.0441	1.03188	1.0305143	1.0301
$I_o(\mu A)$	3.6642	3.2875	3.1756	3.436	3.3737	3.4822631	0.79851
$R_s(\Omega)$	1.1989	1.2057	1.2053	1.1968	1.20295	1.2012710	1.4944
$R_p(\Omega)$	8333.333	555.56	714.29	555.556	849.693	981.98232	785.1624
$N_s\alpha$	48.8211	48.45	48.289	48.5862	48.5065	48.6428351	43.583919 (V_T=1.1949)

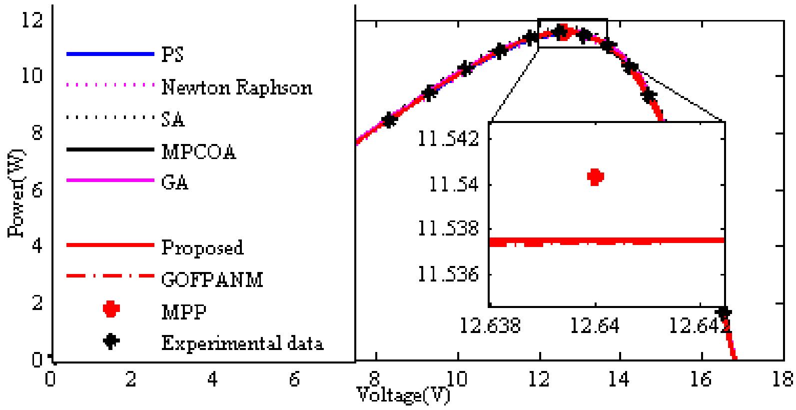

Figure 6. The P-V curve of the reference module Photowatt PWP201 by the proposed method and eight other existing method

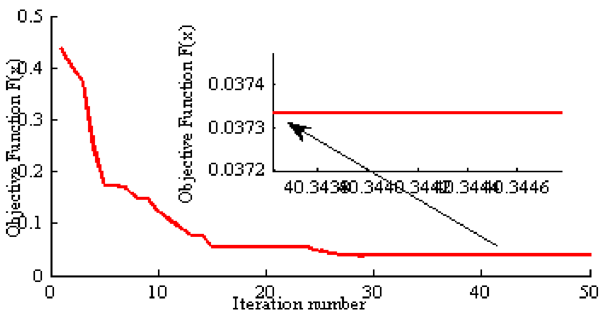

Figure 7. The convergence curve of Photowatt PWP201 by the proposed method (f(x)=0.0373 at 50 generation and 5000 population)

Table 4. Absolute relative power error for Photowatt PWP201 module

Methods	$*P_{actual}$	$**P_{cal}$	ARPE
SA	11.5403	11.6958	0.01347×10^{2}
NR	11.5403	11.4441	8.60462×10^{-1}
PS	11.5403	11.5025	3.27547×10^{-1}
GA	11.5403	11.5752	3.02418×10^{-1}
MPCOA	11.5403	11.5293	9.53181×10^{-2}
GOFPANM	11.5403	11.5374	2.51293×10^{-2}
Proposed method	11.5403	11.5375	2.42628×10^{-2}

*Actual Maximum Power, P_{actual} *(W)*
**Calculated maximum power, P_{cal} *(W)*

Table 5. The error matrics measurement by the proposed method and other existing methods for Photowatt PWP201 module

	Measured value		Calculated I(A)	Current Absolute Error (IAE%) matrics						
	V (V)	I (A)	Proposed Method	Proposed method	GOFPANM [20]	MPCOA [18]	GA [22]	PS [19]	NR [8]	SA [12]
1	0.1248	1.0315	1.028	0.340467	0.233213488	0.119	0.988	0.207	0.213	0.006
2	1.8093	1.03	1.0269	0.301879	0.253065992	0.168	0.845	0.294	0.367	0.062
3	3.3511	1.026	1.0258	0.019497	0.029248318	0.037	0.966	0.123	0.258	0.137
4	4.7622	1.022	1.0219	0.009786	0.2050581	0.247	1.099	0.055	0.138	0.341
5	6.0538	1.018	1.02	0.196078	0.42062017	0.443	1.224	0.222	0.023	0.531
6	7.2364	1.0155	1.0177	0.216174	0.431414845	0.440	1.155	0.196	0.099	0.521
7	8.3189	1.014	1.0142	0.01972	0.226311129	0.223	0.876	0.041	0.383	0.292
8	9.3097	1.01	1.0099	0.009902	0.049480455	0.029	0.626	0.250	0.636	0.082
9	10.2163	1.0035	1.0006	0.289826	0.289826104	0.307	0.237	0.600	1.028	0.281
10	11.0449	0.988	0.9855	0.253678	0.345317896	0.368	0.135	0.668	1.139	0.374
11	11.8018	0.963	0.9609	0.218545	0.354314298	0.371	0.102	0.675	1.189	0.418
12	12.4929	0.9255	0.9237	0.194868	0.249133449	0.288	0.174	0.587	1.144	0.378
13	13.1231	0.8725	0.8712	0.149219	0.068720651	0.008	0.495	0.269	0.867	0.115
14	13.6983	0.8075	0.8023	0.648137	0.061881188	0.035	0.505	0.286	0.919	0.188
15	14.2221	0.7265	0.7227	0.525806	0.137457045	0.194	0.868	0.016	0.648	0.061
16	14.6995	0.6345	0.6339	0.094652	0.188768287	0.309	1.154	0.198	0.487	0.192
17	15.1346	0.5345	0.5342	0.056159	0.037404152	0.226	1.240	0.115	0.575	0.067
18	15.5311	0.4275	0.427	0.117096	0.11682243	0.311	1.666	0.270	0.405	0.187
19	15.8929	0.3185	0.3184	0.031407	-0.031407035	0.057	1.738	0.122	0.735	0.232
20	16.2229	0.2085	0.2083	0.096015	0.143678161	0.302	2.030	0.775	1.222	0.906
21	16.5241	0.101	0.1009	0.099108	0.296150049	0.990	0.520	5.153	5.002	5.287
Total IAE%				3.888021	4.10647917	5.481	18.648	11.13	21.63	5.775
MAE (%)				0.185144	0.195546	0.261	0.888	0.530	1.030	0.275
MAE of 3 points near MPP (%)				0.1875	0.22405	0.2223	0.257	0.510	1.0666	0.3036

5. CONCLUSION

The present investigation has considered MOO algorithm NSGA-II for estimating the electrical model parameters of solar PV modules. In comparison to the existing methods such as NR, GA, PSO, PS, SA, MPCOA, and GOFPANM, the proposed NSGA-II method outperformed and provided a better *P-V* and *I-V* curve, as well as a lesser value of ARPE and MAE. Henceforth, it is inferred that the MOO-based approach can be recommended as one of the most accurate tools for the parameters estimation of solar PV.

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