energies

Review

A Critical Review on the Estimation Techniques of the Solar PV Cell's Unknown Parameters

Papul Changmai [1], Sunil Deka [1], Shashank Kumar [2], Thanikanti Sudhakar Babu [3], Belqasem Aljafari [4] and Benedetto Nastasi [5,*]

1 Electrical and Electronics Engineering Department, Assam Don Bosco University, Guwahati 781039, India
2 Electronics and Electrical Engineering Department, Indian Institute of Technology Guwahati (IIT), Guwahati 781017, India
3 Department of Electrical and Electronics Engineering, Chaitanya Bharathi Institute of Technology (CBIT), Hyderabad 500075, India
4 Department of Electrical Engineering, College of Engineering, Najran University, Najran 11001, Saudi Arabia
5 Department of Planning, Design and Technology of Architecture, Sapienza University of Rome, 00196 Rome, Italy
* Correspondence: benedetto.nastasi@outlook.com

Abstract: To meet the exponentially growing demand for clean and green energy, the solar photovoltaic (PV) system's importance is increasing day by day, for which PV modeling is considered to be one of the most important work in the current state-of-the-art methods. To effectively model a PV system, accurate PV parameter estimation is of the utmost importance. In line with this, although the values of some of the parameters are provided in the manufacturer's datasheet, the values of unknown parameters, such as shunt resistance, series resistance, the diode ideality factor, photogenerated current and diode saturation current, are not provided. To estimate these values a lot of algorithms are already reported in the literature. After careful observation of all the reported algorithms, a few best-reported algorithms are identified and their performances are compared with respect to accuracy, convergence issues, computational complexity and thermal stability. All kind of algorithms, such as numerical, analytical and evolutionary algorithms, are considered in this study, and only the best reported algorithms are considered for the comparison.

Keywords: solar photovoltaic; parameter estimation; single-diode model; double-diode model

Citation: Changmai, P.; Deka, S.; Kumar, S.; Babu, T.S.; Aljafari, B.; Nastasi, B. A Critical Review on the Estimation Techniques of the Solar PV Cell's Unknown Parameters. *Energies* **2022**, *15*, 7212. https://doi.org/10.3390/en15197212

Academic Editor: Elżbieta Szymańska

Received: 20 August 2022
Accepted: 25 September 2022
Published: 30 September 2022

1. Introduction

Solar photovoltaic (PV) technology is one of the leading renewable energy technologies. It has the potential to meet the global energy demand without harming the environment. According to [1], the global solar PV installed capacity is increasing exponentially, and the total installed capacity had reached 629 GW by 2019. Unlike conventional energy sources, such as coal, oil, petrol, etc., solar PV has fewer harmful effects on the environment during operation and maintenance. Again due to the reduction in its cost, solar PV is gaining a new horizon in the energy industry. As a result, PV is considered one of the highest power-producing technologies across the globe. Although the solar PV has manifold advantages compared to all other energy sources, it has a number of demerits too. The power generation from a PV plant depends on the solar irradiance, which is not reliable. Moreover, if a part of the PV module or array is shaded (partial shading condition), the performance of a PV plant decreases drastically. When a solar cell is shaded, it acts as a reverse biased diode, and it affects the performance of the PV module. In such a condition, the short-circuit current (I_{sc}) and fill factor (FF) change [2], which in turn affects the output power of the PV system. Again, to analyse the behaviour of current, voltage and FF in different atmospheric conditions, it is integral to know the different parameters of the PV cell/module.

To optimise the performance, efficiency, size and cost of the PV systems extensive studies have been carried out which help the researchers in efficiently modelling a PV module. For the accurate modelling of a PV cell/module, accurately estimating the PV system's parameters is very important. In line with that, although several parameters are available in the manufacturer's datasheet, a set of parameters are normally not available. It creates difficulty in accurately modelling a PV module. Accordingly, the accurate measurement of modelling parameters, such as diode saturation current (I_0), series resistance (R_s), diode ideality factor (n), shunt resistance (R_{sh}) and photo-genated current (I_{ph}), are essential. To estimate those unknown parameters, several algorithms are proposed in the literature, which have been reviewed and analysed carefully in this paper, along with critical reasoning for all the best-reported models. The existing algorithms can be broadly divided into three categories: analytical algorithms, non-analytical algorithms and meta-heuristic approaches. Analytical algorithms comparatively take less time for computation, and there is no convergence failure problem, whereas numerical or non-analytical methods consume more time for computation and suffer from convergence issues. However, to solve a non-linear PV system equation, an analytical algorithm cannot be used singly. Therefore, in many algorithms, a combination of both analytical and numerical algorithms is used to optimise the computational time and convergence issues. In the current state of art, meta-heuristic approaches are also gaining importance among the PV researchers because of their flexibility in computation time and convergence. However, sometimes, the meta-heuristic algorithms get stuck at local maxima or local minima, and as a result, they do not converse [3,4]. In the case of evolutionary algorithms, if the fitness function is not derived properly, there is a high chance of obtaining the wrong output.

Many reviews on PV parameter estimation have already been published in the literature. However, after carefully observing the last 5 years of publications, it is noticed that some critical points are yet to be highlighted precisely. A few observations are given below:

1. The combination of both analytical and numerical techniques (combined technique) are observed to be less time-consuming compared to other techniques that are used for parameter estimation of solar PV systems;
2. The combined technique has the highest accuracy compared to others in the existing literature;
3. In analytical algorithms, the number of non-linear exponential terms can be reduced by four times compared to the existing literature. Hence, the combined technique is computationally efficient;
4. The shunt resistance (R_{sh}) should be considered as one of the iteration parameters, which makes the approach more realistic;
5. The application of the nominal operating cell temperature (NOCT) value in the PV parameter estimation strengthens the accuracy in varying temperatures and irradiance conditions. It is noticed that, on average, a 10% performance degradation (PD) is present in the MPP obtained at T_{cell} compared to T_{amb}.

Solar PV modelling is discussed in the second part of the paper, in which a single-diode model, double-diode model and three-diode model are discussed with suitable diagrams and relevant mathematical equations. The algorithms reported so far for the estimation of PV parameters are discussed in the third part, in which analytical algorithms, non-analytical algorithms and meta-heuristic algorithms are discussed with suitable examples. The performance analysis of the reported algorithms are discussed in part four of the paper. Here, the effect of temperature and radiance on the PV system are discussed with neat diagrams provided. Finally, the conclusion is written in part five of this paper.

2. Solar PV Modelling

The performance of a PV module depends on the value of irradiance (G) and temperature (T) at which the module operates. To simulate a solar PV module, accurately modelling the solar PV cell is very important. Based on the semiconductor PN junction physics, the equivalent circuit of a solar PV cell is designed, in which there may be one cell, two cells or more than two cells. According to the number of diodes present, the nomenclature of the models are given. In the equivalent circuit, if one diode is present, it is called a single-diode model (SDM). Accordingly, based on the presence of diodes, they are called a double-diode model (DDM), three-diode model and so on.

2.1. Single-Diode Model

The equivalent circuit diagram of a single-diode model solar PV cell is shown in Figure 1. The terminal current (I) of the PV cell is calculated with Equation (1).

$$I = I_P - I_D - \frac{V + IR_S}{R_{SH}} \tag{1}$$

where I_P and I_D are the photo-generated current and diode current, respectively; V is the terminal voltage; R_S and R_{SH} are the series and shunt resistances, respectively. I_D can be expressed as given in Equation (2).

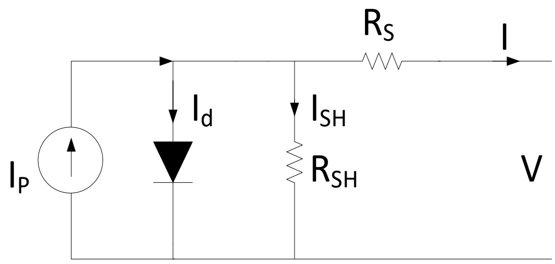


Figure 1. Single-diode model PV system: (i) equivalent circuit diagram; (ii) symbolic diagram.

$$I_D = I_0 \left\{ e^{\frac{V+IR_S}{V_T}} - 1 \right\} \tag{2}$$

where V_T $(= \frac{nkT}{q})$ is the junction thermal voltage. Here n, k, T and q are the diode ideality factor, Boltzmann's constant, cell temperature in °C and electron charge in coulomb, respectively. Combining Equations (1) and (2), we can write Equation (3).

$$I = I_P - I_0 \left\{ e^{\frac{V+IR_S}{V_T}} - 1 \right\} - \frac{V + IR_S}{R_{SH}} \tag{3}$$

For the calculation of the terminal current, it is of the utmost importance to estimate all the parameters involved in Equations (1) and (2). Although the information related to the open-circuit voltage, short-circuit current and maximum power point is provided in the manufacturer's datasheet, the value of the five parameters, namely I_P, I_0, n, R_S and R_{SH}, are normally not provided in the manufacturer's datasheet. Therefore, several algorithms are developed in the literature to estimate those unknown parameters. A comparative review was presented in [5] and included almost all the then best-reported algorithms. After this, a lot of algorithms were developed to estimate the unknown parameters of a PV cell, which are comparatively better in terms of accuracy, computational complexity, convergence issues and many other aspects. By analysing all the best-reported algorithms, a critical review is provided, and the same is reported in this paper.

2.2. Double-Diode Model

The diode ideality factor 'n' mainly depends on the voltage between the two terminals of the device. The value of n approaches 1 when the recombination is dominated by the bulk region and the surfaces. However, if recombination is the dominant parameter, n approaches 2, which happens at lower voltages. To introduce this phenomenon, a second diode is connected in parallel with the diode present in the single-diode model's equivalent circuit, and this model is named the double-diode model (DDM) of the PV system. The equivalent circuit of the DDM PV system is shown in Figure 2, and the expression for the generated current using DDM of a PV system is given in Equation (4).

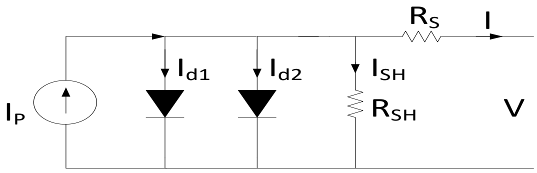


Figure 2. Equivalent circuit of double-diode model PV system.

$$I = I_P - I_{0_1}\left\{e^{\frac{(V+IR_S)q}{n_1kT}} - 1\right\} - I_{0_2}\left\{e^{\frac{(V+IR_S)q}{n_2kT}} - 1\right\} - \frac{V+IR_S}{R_{SH}} \tag{4}$$

From Equation (4), it is seen that there are a total of seven unknown parameters whose values are not provided in the manufacturer's datasheet. These seven parameters are I_P, I_{0_1},I_{0_2}, n_1, n_2, R_S and R_{SH}. The equations during open-circuit and short-circuit conditions in the case of DDM are given in Equations (5) and (6):

$$I = I_P - I_{0_1}\left\{e^{\frac{(IR_S)q}{n_1kT}} - 1\right\} - I_{0_2}\left\{e^{\frac{(IR_S)q}{n_2kT}} - 1\right\} - \frac{IR_S}{R_{SH}} \tag{5}$$

$$0 = I_P - I_{0_1}\left\{e^{\frac{Vq}{n_1kT}} - 1\right\} - I_{0_2}\left\{e^{\frac{(V)q}{n_2kT}} - 1\right\} - \frac{V}{R_{SH}} \tag{6}$$

2.3. Three-Diode Model

To address the effects of leakage current and grain boundaries, a three-diode model of the PV system is introduced. The equivalent diagram of the same is shown in Figure 3, and the expression for generated current using DDM of a PV system is given in Equation (7).

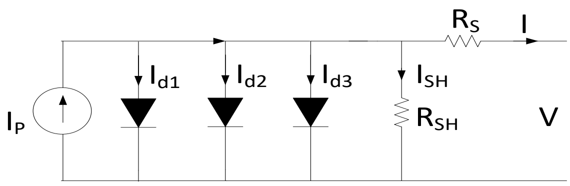


Figure 3. Equivalent circuit of the three-diode model PV system.

$$I = I_P - I_{0_1}\left\{e^{\frac{(V+IR_S)q}{n_1kT}} - 1\right\} - I_{0_2}\left\{e^{\frac{(V+IR_S)q}{n_2kT}} - 1\right\} - I_{0_3}\left\{e^{\frac{(V+IR_S)q}{n_3kT}} - 1\right\} - \frac{V+IR_S}{R_{SH}} \tag{7}$$

From Equation (7), it is seen that there are a total of nine unknown parameters whose values are not provided in the manufactures datasheet. These nine parameters are I_P, I_{0_1},I_{0_2}, I_{0_3}, n_1, n_2, n_3, R_S and R_{SH}.

3. Algorithms Reported So Far

3.1. Analytical Algorithms

Whenever the number of diodes increases in PV modelling, the unknown parameters also increase accordingly. With the increase in every diode, at least two unknown parameters increase. Hence, in the already reported literature, it is observed that the researchers mainly opt for SDM and DDM for parameter estimation work. Again, in SDM, five unknown parameters need to be calculated, whereas, in DDM, seven unknown parameters are present; as a result, the DDM algorithm suffers from more computational complexities [6–8]. In some reported algorithms such as [9,10], DDM is used for parameter estimation, where the computation is carried out for seven unknown parameters without much improvement in accuracy. Therefore, the SDM reported model is analysed critically, and the same is reported below.

To estimate the unknown parameters, several analytical algorithms (AAs) have been reported. In almost all of the algorithms, the mathematical modelling is conducted with the help of three strategic points of the *I*–*V* characteristics. These points are the open-circuit point (V_{OC},0), short-circuit point (0,I_{SC}) and maximum power point (V_{MP},I_{MP}), as shown in Figure 4.

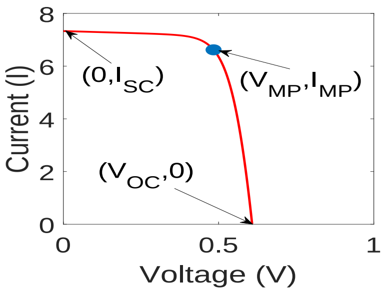


Figure 4. *I*–*V* characteristic of a PV system.

As the value of voltage in short-circuit point is 0 (i.e., $V = 0$), the current is therefore calculated as Equation (8). In Equation (8), the short-circuit current is denoted by I_{SC}.

$$I_{SC} = I_P - I_0\left\{e^{\frac{I_{SC}R_S}{NV_T}} - 1\right\} - \frac{I_{SC}R_S}{R_{SH}} \tag{8}$$

Similarly, the generated current at the open-circuit point is 0 (i.e., $I = 0$) expressions is written as Equation (9).

$$0 = I_P - I_0\left\{e^{\frac{I_{SC}R_S}{NV_T}} - 1\right\} - \frac{V_{OC}}{R_{SH}} \tag{9}$$

Simplifying Equation (9) for I_P, we obtain

$$I_P = I_0\left\{e^{\frac{I_{SC}R_S}{NV_T}} - 1\right\} + \frac{V_{OC}}{R_{SH}} \tag{10}$$

At (V_{MP}, I_{MP}), by putting $I = I_{MP}$ and $V = V_{MP}$ in Equation (2), we obtain Equation (11).

$$I_{MP} = I_P - I_0\left\{e^{\frac{V_{MP}+I_{MP}R_S}{NV_T}} - 1\right\} - \frac{V_{MP}+I_{MP}R_S}{R_{SH}} \tag{11}$$

After simplifying Equation (8) with the help of Equation (10), we obtain

$$I_{SC} = I_0\left\{e^{\frac{I_{SC}R_S}{NV_T}} - 1\right\} - I_0 e^{\frac{I_{SC}R_S}{NV_T}} - \frac{I_{SC}R_S}{R_{SH}} \tag{12}$$

Further simplifying Equation (12) for I_0, we obtain Equation (13),

$$I_0 = \frac{I_{SC} - \left\{\frac{V_{OC}-I_{SC}R_S}{R_{SH}}\right\}}{e^{\frac{V_{OC}}{NV_T}} - e^{\frac{I_{SC}R_S}{NV_T}}} \tag{13}$$

Simplifying I_P and I_0 in Equation (11) using the corresponding expression from Equations (10) and (13), respectively, we obtain Equation (14):

$$I_{MP} = I_0\left\{e^{\frac{I_{SC}R_S}{NV_T}} - 1\right\} + \frac{V_{OC}}{R_{SH}} - \frac{I_{SC} - \left\{\frac{V_{OC}-I_{SC}R_S}{R_{SH}}\right\}}{e^{\frac{V_{OC}}{NV_T}} - e^{\frac{I_{SC}R_S}{NV_T}}}\left\{e^{\frac{V_{MP}+I_{MP}R_S}{NV_T}} - 1\right\} - \frac{V_{MP}+I_{MP}R_S}{R_{SH}} \tag{14}$$

Equation (14) is used for the estimation of unknown parameters in many of the existing algorithms [11]. However, Equation (14) comprises four numbers of exponential terms, and accordingly, it increases non-linearly. Therefore, Equation (14) is not used in the reported models, such as [12]. Therefore, by neglecting the less significant terms, a different approach is introduced, which is explained below.

In the case of the PV systems that are made of silicon, the value of NV_T is smaller than $(V + IR_S)$. Therefore, $e^{\frac{V+IR_S}{NV_T}} \gg 1$. Hence, for simplicity, '-1' is neglected and rewritten as Equations (3), (8) and (10), as given in Equations (15)–(17), respectively.

$$I = I_P - I_0 e^{\frac{V+IR_S}{V_T}} - \frac{V+IR_S}{R_{SH}} \tag{15}$$

$$I_{SC} = I_P - I_0 e^{\frac{I_{SC}R_S}{NV_T}} - \frac{I_{SC}R_S}{R_{SH}} \tag{16}$$

$$I_P = I_0 e^{\frac{I_{SC}R_S}{NV_T}} + \frac{V_{OC}}{R_{SH}} \tag{17}$$

Incorporating Equation (17) into Equation (16) and eliminating the term $e^{\frac{I_{SC}R_S}{NV_T}}$ (as $e^{\frac{V_{OC}}{NV_T}} \gg e^{\frac{I_{SC}R_S}{NV_T}}$), we obtain Equation (18).

$$I_{SC} = I_0 e^{\frac{I_{SC}R_S}{NV_T}} + \frac{V_{OC} - I_{SC}R_S}{R_{SH}} \tag{18}$$

Further resolving Equation (18), we obtain an expression for I_0 as given in Equation (19).

$$I_0 = \left\{I_{SC} - \frac{V_{OC} - I_{SC}R_S}{R_{SH}}\right\}e^{-\frac{V_{OC}}{NV_T}} \tag{19}$$

In Equation (11), I_P and I_0 are replaced by the corresponding expressions of Equations (10) and (19), respectively, which results in Equation (20).

$$I_{SC} = I_{MP} + \frac{V_{MP} + I_{MP}R_S - I_{SC}R_S}{R_{SH}} + \left\{I_{SC} - \frac{V_{OC} - I_{SC}R_S}{R_{SH}}\right\}e^{\frac{V_{MP}+I_{MP}R_S-V_{OC}}{NV_T}} \tag{20}$$

For estimating the unknown parameters, Equation (20) is used, in which only one non-linear term is present. Therefore, it decreases the issues related to non-linearity and accordingly minimises the computational complexity.

Except for R_S, R_{SH} and V_T, the values of all the other parameters in Equation (20) are provided in the manufacturer's datasheet. The estimation of these three unknown parameters helps in obtaining the values of I_0 and I_P using Equations (19) and (10), respectively. As reported by [13,14], the initial values of shunt (R_{SH0}) and series resistance (R_{S0}) can be measured from the I–V curve using Equations (21) and (22).

$$R_{S0} = -\left.\frac{dV}{dI}\right|_{V=V_{OC}} \tag{21}$$

$$R_{SH0} = -\left.\frac{dV}{dI}\right|_{I=I_{SC}} \tag{22}$$

Following the same procedure described in [15], the analytical expressions for V_T, R_S and R_{SH} are derived, which are mentioned in Equations (23) and (24).

$$V_T = \frac{V_{MP}+R_{S0}I_{MP}-V_{OC}}{ln\left\{I_{SC}-\frac{V_{MP}}{R_{SH0}}-I_{mpp(s)}\right\}-ln\left\{I_{SC}-\frac{V_{OC}}{R_{SH}}\right\}+\frac{I_{MP}}{I_{SC}-\left\{\frac{V_{OC}}{R_{SH0}}\right\}}} \tag{23}$$

$$\begin{cases} R_S = R_{S0} - \frac{V_T}{I_0}e^{\frac{-V_{OC}}{V_T}} \\ R_{SH} = \left\{\frac{1}{R_{SH0}-R_S} - \frac{I_0}{V_T}e^{\frac{I_{SC}R_S}{V_T}}\right\}^{-1} \end{cases} \tag{24}$$

By solving Equations (20), (23) and (24), all three unknown parameters—R_S, R_{SH} and V_T—can be obtained. To solve these equations, several algorithms are adopted in the existing literature, such as non-linear optimisation algorithms or numerical algorithms (NAs), evolutionary algorithms (EAs), etc.

3.2. Non-Analytical Algorithms

For parameter estimation, several non-linear optimisation algorithms or EAs are developed in the existing literature, out of which some of the best-reported algorithms are highlighted in [5]. Here, it is observed that the result of some of the reported algorithms, such as [16–19], are very significant. After these, a number of algorithms such as [20–30] are reported. From the critical observation of all the reported algorithms, it is noticed that, although a number of reported algorithms are found to be efficient, they show poor performance in some cases. Again, a comparison of these algorithms is also a tedious job. In the literature, it is seen that, for the purposes of comparison, the authors have validated the algorithms with a common PV system. To check the cell level [31] parameter estimation, they have considered a RTC France silicon solar cell (57 mm diameter) at 1000 W/m^2 irradiance and a temperature of 33 °C (Case Study 1), and for the module level, they have considered a solar module comprised of 36 series connected cells (Photowatt-PWP 201) at 1000 W/m^2 irradiance and a temperature of 45 °C (Case Study 2). In [32]. Finally, 26 data points are considered from the experimentally obtained *I–V* characteristics. The same is implemented in the developed algorithms, and the corresponding values of the estimated current (I_{estd_j}; here, j changes from 1 to 26) are calculated. To check the accuracy, the root mean square error (RMSE), mean absolute error (MAE), deviation, normalised sum of squared error (NSSE) and mean absolute error in power (MAEP) are calculated, as given in Equations (25)–(29), respectively.

$$RMSE = \sqrt{\frac{\sum_{j=1}^{p}(I_{estd_j} - I_j)^2}{p}} \tag{25}$$

$$\text{MAE} = \frac{\sum_{j=1}^{p}(I_{estd_j} - I_j)}{p} \tag{26}$$

$$\text{Deviation }(\%) = \left(\frac{I_{estd_j}}{I_j} - 1\right) \times 100 \tag{27}$$

$$\text{NSSE}(\%) = \frac{\sum_{j=1}^{p}(I_j - I_{estd_j})^2}{\sum_{j=1}^{p}(I_I)^2} \tag{28}$$

$$\text{MAEP} = \frac{\sum_{j=1}^{p}|P_j - P_{estd_j}|}{p} \tag{29}$$

Parameter estimation is carried out for both case studies (Case Study 1 and Case Study 2), and the reported results are given in Tables 1 and 2, respectively, as they appeared in their articles. Recently,a set of algorithms, such as differential algorithm (DE) [33], success-history based adaptive DE with linear population size reduction (LSHADE) [34], iLSHADE [35], LSHADE-EpSin [36], LSHADE-SPACMA [37], jSO [38], Gaussian EDA (GEDA) [39], covariance matrix adaptation evolution strategy (CMA-ES) [40], nuclear reaction optimisation (NRO) [41], etc., have been developed. According to [37], LSHADE is quite competitive compared to state-of-the-art EA.

Table 1. Comparison of the parameters obtained in Case Study 1.

Literature	Year	Algorithm	I_{ph} (A)	I_0 (µA)	R_{sh} (Ω)	R_s (Ω)	n	No. of Steps	RMSE
[42]	2019	EA	0.76080000	0.32230000	53.76340000	0.036400000	1.48370000000	-	1.0072×10^{-2}
[43]	2018	NA	0.76074014	0.31285196	55.90738000	0.036615485	1.477729500	-	7.7301×10^{-4}
[44]	2020	EA	0.76038466	0.23082625	53.67788300	0.037991668	1.447929015	-	9.7505×10^{-4}
[45]	2019	EA	0.76080000	0.32300000	53.71850000	0.036400000	1.481200000	-	9.8602×10^{-4}
[46]	2017	EA	0.76080000	0.32280000	53.75950000	0.036400000	1.481100000	-	9.8603×10^{-4}
[47]	2020	EA	0.76077600	0.32302100	53.71852000	0.036377000	1.481184000	-	9.8602×10^{-4}
[48]	2019	NA + EA	0.76078797	0.31068450	52.88979426	0.036546950	1.477267780	-	7.7301×10^{-4}
[49]	2019	EA	0.76077552	0.32302000	53.71852000	0.036370000	1.481108170	-	9.8602×10^{-4}
[50]	2019	EA	0.76079000	0.31062000	52.88500000	0.036548000	1.477100000	-	7.7300×10^{-4}
[51]	2019	EA	0.76080000	0.32300000	53.71850000	0.036400000	1.481200000	-	9.8602×10^{-4}
[52]	2019	EA	0.76077562	0.32301700	53.71821748	0.036377160	1.481182200	-	9.8602×10^{-4}
[53]	2019	EA	0.76078000	0.32302000	53.71852000	0.036380000	1.481180000	-	9.8602×10^{-4}
[54]	2019	EA	0.76080000	0.32300000	53.71850000	0.036400000	1.481200000	-	9.8602×10^{-4}
[55]	2019	EA	0.76077500	0.32302100	53.71867900	0.036377000	1.481108000	-	9.8602×10^{-4}
[56]	2019	EA	0.76077450	0.32300180	53.73000000	0.036377500	1.481177400	-	9.8602×10^{-4}
[57]	2019	EA	0.76078000	0.32302000	53.71852000	0.036380000	1.481180000	-	9.8602×10^{-4}
[58]	2020	EA	0.76076000	0.32314000	53.71489000	0.036370000	1.481140000	-	9.8482×10^{-4}
[59]	2018	EA	0.76077000	0.32320000	53.68360000	0.036300000	1.520800000	-	9.8600×10^{-5}
[60]	2018	EA	0.76078700	0.31068300	52.88971000	0.036546000	1.475262000	-	7.7301×10^{-4}
[61]	2018	EA	0.76077700	0.32262200	53.67840000	0.036381900	1.481060000	-	9.8602×10^{-4}
[62]	2018	EA	0.76077553	0.32302083	53.71852771	0.036377090	1.481183600	-	9.8602×10^{-4}
[63]	2018	EA	0.76069712	0.43244110	53.40180803	0.033410590	1.452456660	-	5.1382×10^{-4}
[64]	2018	EA	0.76078000	0.32302000	53.71636000	0.036380000	1.481180000	-	9.8602×10^{-4}
[65]	2020	NA	0.76870000	9.9414E-07	100.0000000	0.030966000	1.602000000	26	2.7756×10^{-17}
[66]	2017	NA	0.76072000	0.31911000	54.19241000	0.036290000	1.479860000	-	8.1291×10^{-4}
[67]	2018	EA	0.76077600	0.32302100	53.71852400	0.036377000	1.481718000	-	9.8602×10^{-4}
[68]	2019	EA	0.76078000	0.33971000	54.43370000	0.036160000	1.486290000	-	9.9185×10^{-4}

Table 2. Comparison of the parameters obtained in Case Study 2.

Literature	Algorithm	I_{ph} (A)	I_0 (µA)	R_{sh} (Ω)	R_s (Ω)	n	No. of Steps	RMSE	MAE
[69]	AA + NA	1.032377	2.517957	745.7122	1.239060	1.3173635	27	2.0465456×10^{-3}	1.6925284×10^{-3}
[43]	AA + NA	1.0323823	2.5129059	744.71302	1.3001512	1.3171591	6	2.0465347×10^{-3}	1.6923215×10^{-3}
[70]	AA + NA	1	2.3	830	1.3	1.3056	-	3.26×10^{-2}	-
[6]	AA + NA	1.033285	1.82	850.7068	1.357607	1.2857	-	5.181×10^{-3}	-
[15]	AA + NA	1.0323729	2.5129158	744.713061	1.2456174	1.3248753	4	2.046479×10^{-3}	3.423077×10^{-4}
[44]	EA	1.0263	9.5710	6842.2	0.0298	1.5255	-	3.819492×10^{-3}	-
[65]	NA	1.0285	4.9614×10^{-6}	1632.5	1.1638	-	-	2.6174×10^{-3}	-

3.3. Meta-Heuristic Approach

In order to attain the accurate modelling of the advance photovoltaic solar cell and module, it is pertinent to identify the optimal value of the corresponding parameters. Among the various methods to estimate the parameters of the photovoltaic cell model, meta-heuristic algorithms appear to be a sensible deterministic approach. In order to find the required parameters to enhance the performance of a solar cell, a range of meta-heuristics techniques are considered, such as particle swarm optimisation, the gravitational search algorithm, the flower pollination algorithm, wind-driven optimisation, whale optimisation, the artificial bee colony algorithm, differential evolution, genetic algorithms and cat swarm optimisation. Based on the literature of meta-heuristic optimisation techniques, there are of four types, namely, evolutionary algorithms wherein the genetic algorithm, differential evolution and shuffled complex evolution are involved; physics-based algorithms wherein wind-driven optimisation, the flower pollination algorithm and the gravitational search algorithm are involved; swarm-based algorithms wherein artificial bee colony and particle swarm optimisation is involved; and human-based algorithms wherein harmony search is involved. The documented reports on gradient-based methods [71,72] suggest that the meta-heuristic algorithms have an edge over parameters, such as accuracy, computational time and the avoidance of local minima trap. The optimisation function of the PV array using the meta-heuristic methods is adopted because it uses simple mathematical derivatives. In the evaluation of the state-of-the-art PV cell design, the non-linearity of the current–voltage (IV) curves is an evident consideration, which can be satisfied with meta-heuristic algorithms. The Deterministic methods, including analytical and iterative methods [73], do not support non-linear equations as the complexity increases with the increase in the number of unknown parameters in the proposed model. Moreover, in the iterative method, an erroneous choice during the trial-and-error approach may cause trapping in local optima. A meta-heuristic method [74] was adopted based on the way a group of hawks would approach a prey. Here, Harris hawks are considered for their remarkable behaviour of hunting cooperatively in packs. There exist various stages of chase where the hawks will adopt different strategies based on the dynamic location and credible escape route of the prey. The Harris hawks optimisation (HHO) algorithm emulates the chasing strategies of the Harris hawks using a dynamic pattern. However, it has been observed by Chen, H. (2020 [75]) that in order to obtain the global optimum solution, the HHO algorithm gets stuck in local minima.

In order to estimate the model parameter in the single-diode model (SDM), double-diode model (DDM) and three-diode model (TDM), in 2021, S. Maryam et al. [76] proposed an efficient optimisation algorithm, namely whippy Harris hawks optimisation (WHHO), which is an improved version of the HHO algorithm. Whippy Harris hawks optimisation (WHHO) has higher global search capability, convergence speed and robustness over the original algorithm.

The inability to derive accurate parameters under the non-linear condition [77] is the cause for the inaccurate modelling of the solar photovoltaic cell and module. Based on the documented literature [78], in general, there exist three types of algorithms under non-linear conditions, namely analytical approaches, numerical methods and evolutionary algorithms. The analytical approach is not preferred for non-linear conditions as the complexity increases as the parameters of the advanced model of the PV solar cell and module design increase. Under the various diode-based models [79], to achieve the characteristics of a PV cell, it has been observed that the unknown parameters increase with the increase in the numbers of diodes in the model. This results in a compromise between model accuracy and model simplicity [80]. Another advanced meta-heuristic algorithm [81] adopts the tunicate swarm optimisation (TSA) to accurately identify the model parameter of a PV cell and modules. This algorithm is based on the iterative process where the tunicate is randomly selected within the search area and locates the best tunicate position. The approach helps in improving the exploring capability and averts premature convergence. Analytical methods cannot solve non-linear equations as multiple unknowns result in unacceptable assumptions and produce erroneous results. To devise the unknown parameters in analytical approaches, it is necessary to manipulate model equations mathematically [82].

Due to existence of various characteristic types ranging from multi-modality, non-linearity and multi-variability in the voltage current curve of the photovoltaic cell, meta-heuristic algorithms are the finest approach. Sofiane et al. [83] came up with a hummingbird's optimisation method termed as artificial hummingbird algorithm (AHA). AHA is a meta-heuristic bio-inspired optimisation algorithm in which populations of n humming birds are randomly initialised and placed on n food tables, as in Equation (30).

$$x_i = l + r(u - l) \tag{30}$$

where $i = 1, 2, \ldots, n$;
x_i is the position of the ith foodTable;
l is the lower boundary;
u is the upper boundary;
r is the random vector in (0,1).

The initialisation of the visit table of food sources is given by Equation (31).

$$Vt_{i,j} = \begin{cases} 0\ ;\ if\ i \neq j \\ null\ ;\ if\ i = j \end{cases} \tag{31}$$

There exist two conditions: if $i \neq j$, then ith humming bird obtains the jth food table, whereas if $i = j$, then the humming bird obtains its corresponding food table. A guided foraging behaviour is adopted to obtain direction control in d-dimensional space where the food source is given by Equation (32).

$$v_i(t+1) = x_{i,tar}(t) + \alpha D(x_i(t) - x_{i,tar}(t))\ \ ;\alpha \to N(0,1) \tag{32}$$

where α is the guided factor to reach the desired location, and $x_{i,tar}(t)$ is the target location of the food table where the ith humming bird is supposed to visit. The cluster probability of α ranging from 0 to 1 is represented by $\alpha \to N(0,1)$.

The new position of the ith food source is given by Equation (33).

$$x_i(t+1) = \begin{cases} x_i(t)\ ;\ \ f(x_i(t)) \leq f(v_i(t+1)) \\ v_i(t+1)\ ;\ \ f(x_i(t)) > f(v_i(t+1)) \end{cases} \tag{33}$$

In territorial foraging, only specific food sources will be available for the humming birds in the local search corresponding to Equation (34).

$$v(t+1) = x_i(t) + bD(x_i(t))\ \ ;b \to N(0,1) \tag{34}$$

where 'b' represents the territorial factor corresponding to the normal distribution N (0,1).

The migration foraging of a humming bird from the source corresponding to the worst nectar-refilling rate to a randomly produced new one can be expressed by Equation (35).

$$x_{wor}(t+1) = L + r(U-L) \tag{35}$$

where x_{wor} represents the food source corresponding to the worst nectar-refilling rate.

Various meta-heuristic techniques, including CPMPSO [47], EHHO [84], EJADE [85], ELBA [86], NMSOLMFO [87], GBO [88], RUN [89], GSK [90], RLGBO [91], DSCSE [92], IMPA [93], CCNMHHO [94], SEDE [95], WLCSODGM [96], SGDE [97], EABOA [98], MTLBO [99] and WHHO [76], were compared in [83] based on squared statistical error (SSE), standard deviation (StD) and Root mean square error (RMSE). Based on the following performance indicator, the proposed AHA stands out as an effective parameter-extraction algorithm. The AHA results in a satisfactory RMSE under limited iterations compared to other meta-heuristic techniques, with close matches regarding the experimental dataset.

Another improved algorithm based on flower pollination by [100] has been proposed for determining the unknown parameters of PV cells and module models. Yang [101] proposed the flower pollination algorithm (FPA) wherein the concept of cross-pollination and self-pollination is adopted for pollen transfer and abiotic and biotic pollination for carriers of pollens. In the conventional PFA, the probability factor was the only controlling parameter to determine the local or global process of pollination. Under the improved variant, double exponential based dynamic switch probability is adopted to maintain equilibrium between the local and global searches, and a dynamic step size function is used to avoid premature convergence and local optima stagnation by tuning the search speed.

To study the efficacy of the improved algorithm, an objective function has to be deduced as the root mean square error (RMSE) in Equation (36).

$$RMSE(X) = \sqrt{\frac{1}{M}\sum_{d=1}^{M}(error\ function)} \tag{36}$$

where 'X' is the unknown parameter of the model, and 'M' is the number of measured I–V data. The error function of V_L and I_L denote the measured I–V data acquired from the PV cell.

In order to attain the global pollination process, the pollinators should fly with biotic pollination and cross-pollination mechanisms obeying levy flight. Moreover, the rule based on the probability of reproduction on the percentage of correspondence between the involved flowers is stated as Equation (37).

$$X_i{}^{t+1} = X_i{}^t + L(X_i{}^t - g^*) \tag{37}$$

where $X_i{}^t$ represents the X_i solution at iteration number t, L mimics the Levy flight distribution feature, g^* represents the best solution from the present population and S represents the step size of a Levy flight. Using the Mantegna algorithm, the value of L is identified as Equation (38).

$$L = \frac{\lambda\Gamma(\lambda)sin(\Pi\lambda/2)}{\Pi}\frac{1}{S^{1+\lambda}}\ ;\ (S >> S_0 > 0) \tag{38}$$

To attain the local pollination process, the abiotic and self-pollination mechanism is obeyed. Here, the rule based on the probability of reproduction on the percentage of correspondence between the involved flowers is stated as Equation (39).

$$X_i{}^{t+1} = X_i{}^t + \epsilon(X_j{}^t - X_k{}^t) \tag{39}$$

where $X_j{}^t$ and $X_k{}^t$ are two random chosen solutions from a given set of solutions, and ϵ is a random number varies from 0 to 1.

The conventional FPA does not support the searching agents to gather around the optimal value as the value of probability 'p' will decide the value of search agents towards the local and global pollination equation. The higher values of 'p', i.e., towards 1, will update the search agents using the global pollination equation, which in turn is affected by the Levy fight distribution mechanism. Furthermore, the search agents will be updated by local pollination if the value of 'p' is towards 0, which traps the solution in the local optimum. This detrimental effect is mitigated by creating a balance between the local and global pollination models with the advancement of the convergence rate using the dynamic step function search capability.

In general, the estimation of the model parameter for a photovoltaic cells and modules do not embrace degradation due to environmental effects. The actual working conditions should include the changes in the PV cell's characteristics due to ageing, faults, maintenance and degradation [102]. With the support of string currents, voltages, irradiance and temperature data, the model parameters are estimated using an adaptive module string model. In [103], it is stated that this method supports the estimation of complex module string parameters. In the estimation algorithm, the four standard test condition parameters are reset to the initial values based on the module datasheet. The previous value error will be set to infinity before performing the following steps for each cell and subsequently the substring: minimise the error by searching the STC parameters and set the minimum value as E_{min}. The algorithm is sufficed if the condition $E_{min} < \epsilon$ holds, where ϵ is 0.1. Under this condition, if $max((1-\delta)E_{min,err}, E_{min,err} - \Delta) \leq E_{min}$ is not sufficient to achieve minimum value of error, it is the end of the algorithm. The present parameters are considered as the estimation result with $E_{min,err} = E_{min}$.

There are a few methods, such as Kohno's [104], Harrou's [105] and Mansouri's [106] methods, to detect the presence of shading conditions. Ref. [103] has proposed a method that will exhibit higher detecting accuracy for areas covered by cells larger than four in number using the true-positive rate (TPR) and the false-positive rate (FPR) [105] conditions. However, Mansouri's method is preferred for a module to estimate partial shade detection accuracy.

The existence of non-linear voltage–current characteristics is evidence for considering the organic solar photovoltaic cell modelling. This would lead to the estimation of unknown parameters under a dynamic irradiation profile pattern. Ref. [107] proposed an adaptive wind-driven optimisation (WDO) algorithm for a three-diode electrical equivalent model of an organic solar photovoltaic cell that could emulate the kink effect [108].

In order to test the quality of the solution in the WDO algorithm, the root mean square error via curve fitting is considered. As per the initial procedure of testing, the absolute error (actual data – simulated data) of individual datum is formulated as the function of individual absolute error using Equation (40).

$$f_i(V_m, I_m, x) = abs(I_{act} - I_{sim}) \tag{40}$$

where I_{act} is experimental data, and I_{sim} is estimated values from simulation. x is the function of all nine dimensions (two parallel resistance + three diode reverse saturation currents + three diode ideality factors + initial photon current) of the three-diode PV model. The sum of the squared error is written as Equation (41).

$$Sum\ of\ squared\ error = \sum_{n=1}^{N} (Individual\ absolute\ error)^2 \tag{41}$$

where N is the individual data in the I–V curve. Finally, the root mean square error (RMSE) is given by Equation (42).

$$RMSE = \sqrt{\frac{1}{M}(Sum\ of\ squared\ error)} \tag{42}$$

The WDO algorithm has four velocity update processes that prevent convergence to local optima. Hence, the parameter estimation process is more precise. The WDO algorithm is based on the horizontal imbalance of air pressure in our atmosphere due to various factors, such as topography, temperature variation and suspended air particles. Under the Lagrangian function, the mathematical depiction of force acting on the air parcel is represented as Equation (43).

$$\rho\vec{\alpha} = \sum \vec{F_t} \tag{43}$$

where $\vec{F_t}$ is the algebraic sum of applied force (which includes pressure gradient force, frictional force, gravitational force and Coriolis force), $\vec{\alpha}$ is the acceleration in air parcel and ρ is the air density. It is difficult to devise an accurate model of an organic solar photovoltaic cell as the manufacturer uses various active materials and inter-layers that are reactive to changes in the environment. The adaptive wind-driven optimisation algorithm is a meta-heuristic optimisation technique that utilises four various velocity update processes for a single particle [109] for fast computation. This provides control tuning of the model parameter to obtain the global optimal region using adaptive velocity generation strategy.

4. Performance Analysis of the Reported Algorithms

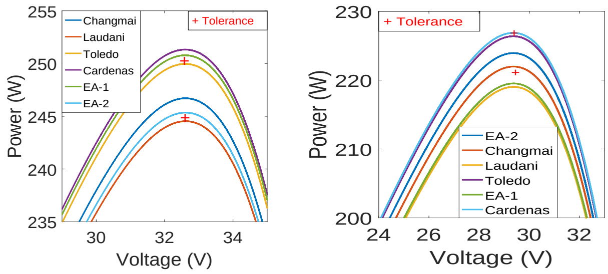
Although analytical algorithms are very much powerful for estimating any unknown parameter, it has limited use for non-linear equations. Again, numerical methods have the potential to solve non-linear equations, but their precision is less, and they suffer from convergence failure. Compared to the analytical and numerical algorithms, evolutionary algorithms are observed to be more precise. Keeping that in view, a number of evolutionary algorithms are developed and reported in the existing literature. However, from our careful observation, it is noticed that the reported algorithms show poor performance in some of the vital points, despite showing better performance in some other criteria. Less than ±5% error is observed in [110], where the genetic algorithm (GA) is used. The artificial immune system (AIS) algorithm is used in [5] to estimate the parameter of the DDM PV module and observed that AIS performs better compared to the GA and particle swarm optimisation (PSO) techniques in terms of convergence speed. In line with the short convergence time, the pattern search (PS) algorithm is also very useful, which is reported in [27,61]. The bacterial foraging algorithm (BFA) [5] is useful for high precision, faster convergence speed and reliable output compared to GA and AIS. However, the computation of BFA is a bit challenging. DDM PV module parameter estimation is carried out in [111] using the differential evaluation (DE) technique, which is also used for thin-film technologies. However, finding the control parameter in DE is a difficult job. The simulated annealing (SA) [65,112] technique gives better accuracy compared to other optimisation algorithms, but accommodating the temperature effect is tough in SA. To overcome the problem of premature outcome, the fireworks algorithm (FA) shows good performance, as reported in [113]. However, the computational time is high in the case of FA. For less convergence time, the flower pollination algorithm (FPA) [114] is a useful algorithm, but accurately determining the fitness function is a difficult job in FPA. The hybrid flower pollination algorithm (HFPA) [115,116] shows good performance in convergence speed and reliability, but it has less precision. The harmony search (HS) [117,118] algorithm shows better accuracy compared to the PS and SA techniques. HS has better convergence speed compared to FA. The artificial bee colony (ABC) [64,119,120] algorithm shows better accuracy and convergence speed compared to HS, GA, BFA and PSO. However, it shows convergence failure in the case of repeated progression. On the other hand, for fast computation, PSO [121–123] shows better performance compared to the other EAs. However, the selection of an initial value of the parameters in PSO is a difficult job.

Effect of Temperature and Irradiance

By applying the estimated values of the unknown parameters, PV modelling is conducted in [15]. Now, to check the performance of the newly modelled PV module, the same is tested at different temperatures. In much of the literature, it is observed that, although the reported algorithms work well within a certain ambient temperature range, the performance deteriorates in some other range of ambient temperatures. In line with this, applying a set of best-reported algorithm simulations are performed for a PV module (datasheet is given in Table 3). The simulated voltage–power (V–P) characteristics of the reported models are shown in Figure 5 at temperatures of 25 °C and 45 °C. For the simulation, irradiance is considered as 888 W/m^2 at air-mass 1.5 gobal (AM1.5g). From Figure 5, it is observed that, although the performance of [124] (mentioned as EA-1 in Figure 5) is near the tolerance limit at 25 °C ambient temperature, it deteriorates at 45 °C. On the other hand, the performance of [58] (mentioned as EA-2 in Figure 5) is good at 45 °C , but it degrades at 25 °C. Similarly, the performance of the algorithms reported by Toledo [43], Laudani [125], Changmai [15] and Cardenas [69] are shown in Figure 5, from which it can be stated that the performance pattern is not linear with the change in temperature. Based on our careful observation, it is noticed that the nominal operating cell temperature (NOCT) is a vital component that affects the performance of a PV module. The effect of NOCT in the PV cell's temperature is given in Equation (44). As reported by [15], there may be around a 10% performance error if the NOCT is not considered for comparison purposes. The specifications of 315 Wp PV modules is presented in Table 3.

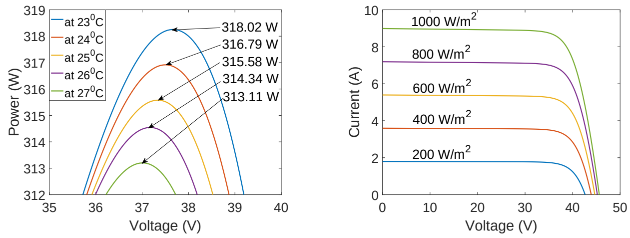
$$T_{cell} = T_{amb} + G \cdot \frac{\mathrm{NOCT} - 20^{\circ}}{800\ \mathrm{W/m^2}} \tag{44}$$

When the irradiance increases, the current generation in the PV module also increases. Moreover, from the voltage and power relationship of a PV module at different irradiance levels, it is seen that as irradiance increases, the module is able to generate more power represented by higher peaks on the V–P curve. The effect of temperature and irradiance (G) in the PV cell are shown in Figure 6a,b, respectively.



(**a**) (**b**)

Figure 5. V–P characteristics of 315 Wp PV module applying different algorithms (**a**) at 25 °C and (**b**) 45 °C.



(**a**) (**b**)

Figure 6. (**a**) *V–P* characteristics when temperature changes at 1000 W/m^2 irradiance. (**b**) *V–I* characteristic when irradiance changes at 25 °C [15].

Temperature is a vital factor in deciding the efficiency of a photovoltaic cell. Moreover, the rate of degradation is prominent on the PV panel under higher temperatures. Various cooling techniques are adopted to improve the efficiency of the solar panel. The force air stream technique [126,127] and the adoption of phase change materials (PCM) [128] are some of the latest methods known to cool off the PV module. With the advancement of composite PCM material embedded with nanoparticles, it has been observed that the efficiency of the photovoltaic module increases by about 13% [129]. Some of the recent active cooling systems adopted are based on the surface water cooling and aluminium heat sink [130]; M.S chips and thermal grease [131,132]; saturated zeolite with water [133]; and the use of palm wax [134] to regulate the temperature of the PV panel to the desired value. An approach for cooling the PV module on both the front and rear surface using a cotton wick mesh has been developed [135–137]. Based on the capillary action, water is allowed to spread along the cotton wick mesh throughout the rear surface of the panel. A perforated aluminium sheet is designed along the back of the PV panel to trap the evading vapour. An overall improvement of 10.89% in voltage is observed in the PV module considering the mentioned arrangement. This results in an enhancement of 11.9% in the efficiency of the suggested cooled panel. Agyekum et al. [138] assessed the viability of combining aluminium fins and paraffin wax to cool a PV module. A combination of both active and passive cooling was adopted [138] to cool a PV system wherein an ultrasonic humidifier was considered for producing a humid environment to cool off along with the aluminium fins.

Table 3. Datasheet values of a 315 Wp PV module.

Parameter	Symbol	Value
Maximum power	P_{MP}	315 W
Short-circuit current	I_{SC}	8.95 A
Open-circuit voltage	V_{OC}	45.6 V
Current at Maximum power	I_{MP}	8.45 A
Voltage at Maximum power	V_{MP}	37.3 V
Co-efficient of current	K_I	0.05%/°C
Co-efficient of voltage	K_V	−0.35%/°C
Co-efficient of power	K_P	−0.40%/°C
Nominal operating cell temperature	NOCT	45 ± 2 °C

5. Conclusions

Parameter estimation of a solar photovoltaic system is a vital in PV modelling. A number of algorithms have been reported to estimate the unknown parameters of the PV cell/module across the globe in the last decade. Based on the observation of all the reported algorithms, a few recent best-reported algorithms were selected for this review in terms of accuracy, computational complexity and convergence issues. To strengthen the review, all types of algorithms, including analytical, numerical and evolutionary algorithms, were considered, and the outcome was reported in a tabular manner. Simulations were performed for a few of the best-reported models, and the performance was checked at various temperatures. In this study, it is observed that the combination of both analytical and numerical techniques (combined technique) are less time-consuming compared to other techniques that are used for parameter estimation of solar PV systems. The combined technique has the highest accuracy compared to the other existing literature. In analytical algorithms, the number of non-linear exponential terms can be reduced by 4 times compared to the existing literature. Hence, the combined technique is computationally efficient. The shunt resistance (R_{sh}) should be considered as one of the iteration parameters, which makes the approach more realistic. The application of the NOCT value in the PV parameter estimation strengthens the accuracy in varying temperatures and irradiance conditions. Based on our careful observations, it is noticed that, on average, 10% performance degradation is present in the MPP obtained at T_{cell} compared to T_{amb}.

Author Contributions: Data curation, P.C.; Formal analysis, S.D. and S.K.; Funding acquisition, B.A. and B.N.; Methodology, S.D. and T.S.B.; Project administration, T.S.B. and B.N.; Resources, S.K., B.A. and B.N.; Supervision, T.S.B.; Writing—original draft, P.C. and S.K. All authors have read and agreed to the published version of the manuscript.

Funding: This work was funded by the All India Council for Technical Education, Govt. of India under Research Promotion Scheme for the North East Region under File No. 8-14/FDC/RPS(NER)/POLICY-1/2020-21 dated 10 March 2021.

Data Availability Statement: Not applicable.

Conflicts of Interest: The authors declare no conflict of interest.

References

1. International, E.A. *Photovoltaic Power Systems Programme*; Snapshot: Paris, France, 2020. Available online: https://iea-pvps.org/snapshot-reports/snapshot-2020/ (accessed on 16 April 2022).
2. Herrmann, W.; Wiesner, W. Modelling of PV modules—The effects of non-uniform irradiance on performance measurements with solar simulators. In Proceedings of the 16th European Photovoltaic Solar Energy Conference, Glasgow, UK, 1–5 May 2000; pp. 2338–2341.
3. Goswami, A.; Sadhu, P.K. Nature inspired evolutionary algorithm integrated performance assessment of floating solar photovoltaic module for low-carbon clean energy generation. *Sustain. Oper. Comput.* **2022**, *3*, 67–82. [CrossRef]
4. Yu, Y.; Wang, K.; Zhang, T.; Wang, Y.; Peng, C.; Gao, S. A population diversity-controlled differential evolution for parameter estimation of solar photovoltaic models. *Sustain. Energy Technol. Assess.* **2022**, *51*, 101938. [CrossRef]
5. Venkateswari, R.; Rajasekar, N. Review on parameter estimation techniques of solar photovoltaic systems. *Int. Trans. Electr. Energy Syst.* **2021**, *31*, e13113. [CrossRef]

6. Mehta, H.K.; Warke, H.; Kukadiya, K.; Panchal, A.K. Accurate Expressions for Single-Diode-Model Solar Cell Parameterization. *IEEE J. Photovol.* **2019**, *9*, 803–810. [CrossRef]
7. Moshksar, E.; Ghanbari, T. Constrained optimisation approach for parameter estimation of PV modules with single-diode equivalent model. *IET Renew. Power Gener.* **2018**, *12*, 1398–1404. [CrossRef]
8. Arabshahi, M.; Torkaman, H.; Keyhani, A. A method for hybrid extraction of single-diode model parameters of photovoltaics. *Renew. Energy* **2020**, *158*, 236–252. [CrossRef]
9. Ridha, H.M.; Hizam, H.; Mirjalili, S.; Othman, M.L.; Ya'acob, M.E.; Abualigah, L. A novel theoretical and practical methodology for extracting the parameters of the single and double diode photovoltaic models. *IEEE Access* **2022**, *10*, 11110–11137. [CrossRef]
10. Yahya-Khotbehsara, A.; Shahhoseini, A. A fast modeling of the double-diode model for PV modules using combined analytical and numerical approach. *Sol. Energy* **2018**, *162*, 403–409. [CrossRef]
11. Gnetchejo, P.J.; Essiane, S.N.; Ele, P.; Wamkeue, R.; Wapet, D.M.; Ngoffe, S.P. Important notes on parameter estimation of solar photovoltaic cell. *Energy Convers. Manag.* **2019**, *197*, 111870. [CrossRef]
12. Sinha, A.; Gopalakrishna, H.; Subramaniyan, A.B.; Jain, D.; Oh, J.; Jordan, D.; TamizhMani, G. Prediction of Climate-Specific Degradation Rate for Photovoltaic Encapsulant Discoloration. *IEEE J. Photovolt.* **2020**, *10*, 1093–1101. [CrossRef]
13. Chan, D.S.; Phang, J.C. Analytical methods for the extraction of solar-cell single-and double-diode model parameters from IV characteristics. *IEEE Trans. Electron Devices* **1987**, *34*, 286–293. [CrossRef]
14. Phang, J.; Chan, D.; Phillips, J. Accurate analytical method for the extraction of solar cell model parameters. *Electron. Lett. IET* **1984**, *20*, 406–408. [CrossRef]
15. Changmai, P.; Nayak, S.K.; Metya, S.K. Estimation of PV module parameters from the manufacturer's datasheet for MPP estimation. *IET Renew. Power Gener.* **2020**, *14*, 1988–1996. [CrossRef]
16. Hsieh, Y.C.; Yu, L.R.; Chang, T.C.; Liu, W.C.; Wu, T.H.; Moo, C.S. Parameter Identification of One-Diode Dynamic Equivalent Circuit Model for Photovoltaic Panel. *IEEE J. Photovolt.* **2019**, *10*, 219–225. [CrossRef]
17. Huang, Y.C.; Huang, C.M.; Chen, S.J.; Yang, S.P. Optimization of Module Parameters for PV Power Estimation Using a Hybrid Algorithm. *IEEE Trans. Sustain. Energy* **2019**, *11*, 2210–2219. [CrossRef]
18. Bradaschia, F.; Cavalcanti, M.C.; do Nascimento, A.J.; da Silva, E.A.; de Souza Azevedo, G.M. Parameter Identification for PV Modules Based on an Environment-Dependent Double-Diode Model. *IEEE J. Photovolt.* **2019**, *9*, 1388–1397. [CrossRef]
19. Zhang, Z.; Hu, G.; Chen, Q.; Yan, Z. Correntropy-based parameter estimation for photovoltaic array model considering partial shading condition. *IET Renew. Power Gener.* **2019**, *13*, 1309–1316. [CrossRef]
20. Guo, S.; Abbassi, R.; Jerbi, H.; Rezvani, A.; Suzuki, K. Efficient maximum power point tracking for a photovoltaic using hybrid shuffled frog-leaping and pattern search algorithm under changing environmental conditions. *J. Clean. Prod.* **2021**, *297*, 126573. [CrossRef]
21. Fathy, A.; Abd Elaziz, M.; Sayed, E.T.; Olabi, A.; Rezk, H. Optimal parameter identification of triple-junction photovoltaic panel based on enhanced moth search algorithm. *Energy* **2019**, *188*, 116025. [CrossRef]
22. Tang, S.; Jiang, M.; Abbassi, R.; Jerbi, H.; Latifi, M. A cost-oriented resource scheduling of a solar-powered microgrid by using the hybrid crow and pattern search algorithm. *J. Clean. Prod.* **2021**, *313*, 127853. [CrossRef]
23. Ye, X.; Liu, W.; Li, H.; Wang, M.; Chi, C.; Liang, G.; Chen, H.; Huang, H. Modified whale optimization algorithm for solar cell and PV module parameter identification. *Complexity* **2021**, *2021*, 8878686. [CrossRef]
24. Eslami, M.; Akbari, E.; Seyed Sadr, S.T.; Ibrahim, B.F. A novel hybrid algorithm based on rat swarm optimization and pattern search for parameter extraction of solar photovoltaic models. *Energy Sci. Eng.* **2022**. [CrossRef]
25. Xiong, G.; Zhang, J.; Yuan, X.; Shi, D.; He, Y. Application of symbiotic organisms search algorithm for parameter extraction of solar cell models. *Appl. Sci.* **2018**, *8*, 2155. [CrossRef]
26. Sharma, A.; Dasgotra, A.; Tiwari, S.K.; Sharma, A.; Jately, V.; Azzopardi, B. Parameter extraction of photovoltaic module using tunicate swarm algorithm. *Electronics* **2021**, *10*, 878. [CrossRef]
27. Sharma, A.; Sharma, A.; Moshe, A.; Raj, N.; Pachauri, R.K. An effective method for parameter estimation of solar PV cell using Grey-wolf optimization technique. *Int. J. Math. Eng. Manag. Sci.* **2021**, *6*, 911. [CrossRef]
28. Gude, S.; Jana, K.C. Parameter extraction of photovoltaic cell using an improved cuckoo search optimization. *Sol. Energy* **2020**, *204*, 280–293. [CrossRef]
29. Prasanth Ram, J.; Pillai, D.S.; Rajasekar, N.; Kumar Chinnaiyan, V. Flower pollination based solar PV parameter extraction for double diode model. In *Intelligent Computing Techniques for Smart Energy Systems*; Springer: Berlin, Germany, 2020; pp. 303–312.
30. Zhen, Z.; Pang, S.; Wang, F.; Li, K.; Li, Z.; Ren, H.; Shafie-khah, M.; Catalão, J.P. Pattern classification and PSO optimal weights based sky images cloud motion speed calculation method for solar PV power forecasting. *IEEE Trans. Ind. Appl.* **2019**, *55*, 3331–3342. [CrossRef]
31. Changmai, P.; Kumar, S.; Nayak, S.K.; Metya, S.K. Maximum Power Estimation of Total Cross-Tied Connected PV Cells in different Shading Conditions for High Current Application. *IEEE J. Emerg. Sel. Top. Power Electron.* **2021**, *10*, 3883–3894. [CrossRef]
32. Easwarakhanthan, T.; Bottin, J.; Bouhouch, I.; Boutrit, C. Nonlinear minimization algorithm for determining the solar cell parameters with microcomputers. *Int. J. Sol. Energy* **1986**, *4*, 1–12. [CrossRef]
33. Gao, S.; Wang, K.; Tao, S.; Jin, T.; Dai, H.; Cheng, J. A state-of-the-art differential evolution algorithm for parameter estimation of solar photovoltaic models. *Energy Convers. Manag.* **2021**, *230*, 113784. [CrossRef]

34. Tran, T.H.; Nguyen, H.; Nhat-Duc, H.; Nguyen, T.-D. A success history-based adaptive differential evolution optimized support vector regression for estimating plastic viscosity of fresh concrete. *Eng. Comput.* **2021**, *37*, 1485–1498.
35. Yeh, J.F.; Chen, T.Y.; Chiang, T.C. Modified l-shade for single objective real-parameter optimization. In Proceedings of the 2019 IEEE Congress on Evolutionary Computation (CEC), Wellington, New Zealand, 10–13 June 2019; pp. 381–386.
36. Biswas, P.P.; Suganthan, P.N. Large initial population and neighborhood search incorporated in lshade to solve cec2020 benchmark problems. In Proceedings of the 2020 IEEE Congress on Evolutionary Computation (CEC), Glasgow, UK, 19–24 July 2020; pp. 1–7.
37. Refaat, M.M.; Aleem, S.H.A.; Atia, Y.; Ali, Z.M.; El-Shahat, A.; Sayed, M.M. A mathematical approach to simultaneously plan generation and transmission expansion based on fault current limiters and reliability constraints. *Mathematics* **2021**, *9*, 2771. [CrossRef]
38. Wang, X.; Zhao, H.; Han, T.; Wei, Z.; Liang, Y.; Li, Y. A Gaussian estimation of distribution algorithm with random walk strategies and its application in optimal missile guidance handover for multi-UCAV in over-the-horizon air combat. *IEEE Access* **2019**, *7*, 43298–43317. [CrossRef]
39. Mohamed, A.W.; Hadi, A.A.; Jambi, K.M. Novel mutation strategy for enhancing SHADE and LSHADE algorithms for global numerical optimization. *Swarm Evol. Comput.* **2019**, *50*, 100455. [CrossRef]
40. Chen, H.; Cheng, R.; Wen, J.; Li, H.; Weng, J. Solving large-scale many-objective optimization problems by covariance matrix adaptation evolution strategy with scalable small subpopulations. *Inf. Sci.* **2020**, *509*, 457–469. [CrossRef]
41. Wei, Z.; Huang, C.; Wang, X.; Zhang, H. Parameters identification of photovoltaic models using a novel algorithm inspired from nuclear reaction. In Proceedings of the 2019 IEEE Congress on Evolutionary Computation (CEC), Wellington, New Zealand, 10–13 June 2019; pp. 210–218.
42. Nunes, H.; Pombo, J.; Bento, P.; Mariano, S.; Calado, M. Collaborative swarm intelligence to estimate PV parameters. *Energy Convers. Manag.* **2019**, *185*, 866–890. [CrossRef]
43. Toledo, F.J.; Blanes, J.M.; Galiano, V. Two-step linear least-squares method for photovoltaic single-diode model parameters extraction. *IEEE Trans. Ind. Electron.* **2018**, *65*, 6301–6308. [CrossRef]
44. Diab, A.A.Z.; Sultan, H.M.; Aljendy, R.; Al-Sumaiti, A.S.; Shoyama, M.; Ali, Z.M. Tree Growth Based Optimization Algorithm for Parameter Extraction of Different Models of Photovoltaic Cells and Modules. *IEEE Access* **2020**, *8*, 119668–119687. [CrossRef]
45. Yu, K.; Qu, B.; Yue, C.; Ge, S.; Chen, X.; Liang, J. A performance-guided JAYA algorithm for parameters identification of photovoltaic cell and module. *Appl. Energy* **2019**, *237*, 241–257. [CrossRef]
46. Yu, K.; Liang, J.; Qu, B.; Chen, X.; Wang, H. Parameters identification of photovoltaic models using an improved JAYA optimization algorithm. *Energy Convers. Manag.* **2017**, *150*, 742–753. [CrossRef]
47. Liang, J.; Ge, S.; Qu, B.; Yu, K.; Liu, F.; Yang, H.; Wei, P.; Li, Z. Classified perturbation mutation based particle swarm optimization algorithm for parameters extraction of photovoltaic models. *Energy Convers. Manag.* **2020**, *203*, 112138. [CrossRef]
48. Kler, D.; Goswami, Y.; Rana, K.; Kumar, V. A novel approach to parameter estimation of photovoltaic systems using hybridized optimizer. *Energy Convers. Manag.* **2019**, *187*, 486–511. [CrossRef]
49. Ebrahimi, S.M.; Salahshour, E.; Malekzadeh, M.; Gordillo, F. Parameters identification of PV solar cells and modules using flexible particle swarm optimization algorithm. *Energy* **2019**, *179*, 358–372. [CrossRef]
50. Yousri, D.; Allam, D.; Eteiba, M.; Suganthan, P.N. Static and dynamic photovoltaic models' parameters identification using Chaotic Heterogeneous Comprehensive Learning Particle Swarm Optimizer variants. *Energy Convers. Manag.* **2019**, *182*, 546–563. [CrossRef]
51. Li, S.; Gong, W.; Yan, X.; Hu, C.; Bai, D.; Wang, L.; Gao, L. Parameter extraction of photovoltaic models using an improved teaching-learning-based optimization. *Energy Convers. Manag.* **2019**, *186*, 293–305. [CrossRef]
52. Chen, H.; Jiao, S.; Heidari, A.A.; Wang, M.; Chen, X.; Zhao, X. An opposition-based sine cosine approach with local search for parameter estimation of photovoltaic models. *Energy Convers. Manag.* **2019**, *195*, 927–942. [CrossRef]
53. Chen, X.; Yue, H.; Yu, K. Perturbed stochastic fractal search for solar PV parameter estimation. *Energy* **2019**, *189*, 116247. [CrossRef]
54. Li, S.; Gong, W.; Yan, X.; Hu, C.; Bai, D.; Wang, L. Parameter estimation of photovoltaic models with memetic adaptive differential evolution. *Solar Energy* **2019**, *190*, 465–474. [CrossRef]
55. Pourmousa, N.; Ebrahimi, S.M.; Malekzadeh, M.; Alizadeh, M. Parameter estimation of photovoltaic cells using improved Lozi map based chaotic optimization Algorithm. *Sol. Energy* **2019**, *180*, 180–191. [CrossRef]
56. Ćalasan, M.; Jovanović, D.; Rubežić, V.; Mujović, S.; Đukanović, S. Estimation of Single-Diode and Two-Diode Solar Cell Parameters by Using a Chaotic Optimization Approach. *Energies* **2019**, *12*, 4209. [CrossRef]
57. Chen, X.; Yu, K. Hybridizing cuckoo search algorithm with biogeography-based optimization for estimating photovoltaic model parameters. *Sol. Energy* **2019**, *180*, 192–206. [CrossRef]
58. Kumar, C.; Raj, T.D.; Premkumar, M.; Raj, T.D. A new stochastic slime mould optimization algorithm for the estimation of solar photovoltaic cell parameters. *Optik* **2020**, *223*, 165277. [CrossRef]
59. Abd Elaziz, M.; Oliva, D. Parameter estimation of solar cells diode models by an improved opposition-based whale optimization algorithm. *Energy Convers. Manag.* **2018**, *171*, 1843–1859. [CrossRef]
60. Merchaoui, M.; Sakly, A.; Mimouni, M.F. Particle swarm optimisation with adaptive mutation strategy for photovoltaic solar cell/module parameter extraction. *Energy Convers. Manag.* **2018**, *175*, 151–163. [CrossRef]

61. Beigi, A.M.; Maroosi, A. Parameter identification for solar cells and module using a Hybrid Firefly and Pattern Search Algorithms. *Solar Energy* **2018**, *171*, 435–446. [CrossRef]
62. Gao, X.; Cui, Y.; Hu, J.; Xu, G.; Wang, Z.; Qu, J.; Wang, H. Parameter extraction of solar cell models using improved shuffled complex evolution algorithm. *Energy Convers. Manag.* **2018**, *157*, 460–479. [CrossRef]
63. Louzazni, M.; Khouya, A.; Amechnoue, K.; Gandelli, A.; Mussetta, M.; Crăciunescu, A. Metaheuristic algorithm for photovoltaic parameters: Comparative study and prediction with a firefly algorithm. *Appl. Sci.* **2018**, *8*, 339. [CrossRef]
64. Chen, X.; Xu, B.; Mei, C.; Ding, Y.; Li, K. Teaching–learning–based artificial bee colony for solar photovoltaic parameter estimation. *Appl. Energy* **2018**, *212*, 1578–1588. [CrossRef]
65. Messaoud, R.B. Extraction of uncertain parameters of single-diode model of a photovoltaic panel using simulated annealing optimization. *Energy Rep.* **2020**, *6*, 350–357. [CrossRef]
66. Chin, V.J.; Salam, Z.; Ishaque, K. An accurate and fast computational algorithm for the two-diode model of PV module based on a hybrid method. *IEEE Trans. Ind. Electron.* **2017**, *64*, 6212–6222. [CrossRef]
67. Kang, T.; Yao, J.; Jin, M.; Yang, S.; Duong, T. A novel improved cuckoo search algorithm for parameter estimation of photovoltaic (PV) models. *Energies* **2018**, *11*, 1060. [CrossRef]
68. Bendaoud, R.; Amiry, H.; Benhmida, M.; Zohal, B.; Yadir, S.; Bounouar, S.; Hajjaj, C.; Baghaz, E.; El Aydi, M. New method for extracting physical parameters of PV generators combining an implemented genetic algorithm and the simulated annealing algorithm. *Sol. Energy* **2019**, *194*, 239–247. [CrossRef]
69. Cárdenas, A.A.; Carrasco, M.; Mancilla-David, F.; Street, A.; Cárdenas, R. Experimental parameter extraction in the single-diode photovoltaic model via a reduced-space search. *IEEE Trans. Ind. Electron.* **2016**, *64*, 1468–1476. [CrossRef]
70. Ishibashi, K.i.; Kimura, Y.; Niwano, M. An extensively valid and stable method for derivation of all parameters of a solar cell from a single current-voltage characteristic. *J. Appl. Phys.* **2008**, *103*, 094507. [CrossRef]
71. Shaheen, A.M.; Spea, S.R.; Farrag, S.M.; Abido, M.A. A review of meta-heuristic algorithms for reactive power planning problem. *Ain Shams Eng. J.* **2018**, *9*, 215–231. [CrossRef]
72. Abd Elaziz, M.; Elsheikh, A.H.; Sharshir, S.W. Improved prediction of oscillatory heat transfer coefficient for a thermoacoustic heat exchanger using modified adaptive neuro-fuzzy inference system. *Int. J. Refrig.* **2019**, *102*, 47–54. [CrossRef]
73. Waly, H.M.; Azazi, H.Z.; Osheba, D.S.; El-Sabbe, A.E. Parameters extraction of photovoltaic sources based on experimental data. *IET Renew. Power Gener.* **2019**, *13*, 1466–1473. [CrossRef]
74. Chen, H.; Jiao, S.; Wang, M.; Heidari, A.A.; Zhao, X. Parameters identification of photovoltaic cells and modules using diversification-enriched Harris hawks optimization with chaotic drifts. *J. Clean. Prod.* **2020**, *244*, 118778. [CrossRef]
75. Chen, H.; Heidari, A.A.; Chen, H.; Wang, M.; Pan, Z.; Gandomi, A.H. Multi-population differential evolution-assisted Harris hawks optimization: Framework and case studies. *Future Gener. Comput. Syst.* **2020**, *111*, 175–198. [CrossRef]
76. Naeijian, M.; Rahimnejad, A.; Ebrahimi, S.M.; Pourmousa, N.; Gadsden, S.A. Parameter estimation of PV solar cells and modules using Whippy Harris Hawks Optimization Algorithm. *Energy Rep.* **2021**, *7*, 4047–4063. [CrossRef]
77. Yousri, D.; Thanikanti, S.B.; Allam, D.; Ramachandaramurthy, V.K.; Eteiba, M. Fractional chaotic ensemble particle swarm optimizer for identifying the single, double, and three diode photovoltaic models' parameters. *Energy* **2020**, *195*, 116979. [CrossRef]
78. Duman, S.; Kahraman, H.T.; Sonmez, Y.; Guvenc, U.; Kati, M.; Aras, S. A powerful meta-heuristic search algorithm for solving global optimization and real-world solar photovoltaic parameter estimation problems. *Eng. Appl. Artif. Intell.* **2022**, *111*, 104763. [CrossRef]
79. Chenche, L.E.P.; Mendoza, O.S.H.; Bandarra Filho, E.P. Comparison of four methods for parameter estimation of mono-and multi-junction photovoltaic devices using experimental data. *Renew. Sustain. Energy Rev.* **2018**, *81*, 2823–2838. [CrossRef]
80. Ibrahim, I.A.; Hossain, M.; Duck, B.C.; Nadarajah, M. An improved wind driven optimization algorithm for parameters identification of a triple-diode photovoltaic cell model. *Energy Convers. Manag.* **2020**, *213*, 112872. [CrossRef]
81. Arandian, B.; Eslami, M.; Khalid, S.A.; Khan, B.; Sheikh, U.U.; Akbari, E.; Mohammed, A.H. An Effective Optimization Algorithm for Parameters Identification of Photovoltaic Models. *IEEE Access* **2022**, *10*, 34069–34084. [CrossRef]
82. Franco, R.; Vieira, F. Analytical method for extraction of the single-diode model parameters for photovoltaic panels from datasheet data. *Electron. Lett.* **2018**, *54*, 519–521. [CrossRef]
83. Haddad, S.; Lekouaghet, B.; Benghanem, M.; Soukkou, A.; Rabhi, A. Parameter Estimation of Solar Modules Operating Under Outdoor Operational Conditions Using Artificial Hummingbird Algorithm. *IEEE Access* **2022**, *10*, 51299–51314. [CrossRef]
84. Jiao, S.; Chong, G.; Huang, C.; Hu, H.; Wang, M.; Heidari, A.A.; Chen, H.; Zhao, X. Orthogonally adapted Harris hawks optimization for parameter estimation of photovoltaic models. *Energy* **2020**, *203*, 117804. [CrossRef]
85. Li, S.; Gu, Q.; Gong, W.; Ning, B. An enhanced adaptive differential evolution algorithm for parameter extraction of photovoltaic models. *Energy Convers. Manag.* **2020**, *205*, 112443. [CrossRef]
86. Deotti, L.M.P.; Pereira, J.L.R.; da Silva Junior, I.C. Parameter extraction of photovoltaic models using an enhanced Lévy flight bat algorithm. *Energy Convers. Manag.* **2020**, *221*, 113114. [CrossRef]
87. Zhang, H.; Heidari, A.A.; Wang, M.; Zhang, L.; Chen, H.; Li, C. Orthogonal Nelder-Mead moth flame method for parameters identification of photovoltaic modules. *Energy Convers. Manag.* **2020**, *211*, 112764. [CrossRef]
88. Ismaeel, A.A.; Houssein, E.H.; Oliva, D.; Said, M. Gradient-based optimizer for parameter extraction in photovoltaic models. *IEEE Access* **2021**, *9*, 13403–13416. [CrossRef]

89. Shaban, H.; Houssein, E.H.; Pérez-Cisneros, M.; Oliva, D.; Hassan, A.Y.; Ismaeel, A.A.; AbdElminaam, D.S.; Deb, S.; Said, M. Identification of parameters in photovoltaic models through a runge kutta optimizer. *Mathematics* **2021**, *9*, 2313. [CrossRef]
90. Xiong, G.; Li, L.; Mohamed, A.W.; Yuan, X.; Zhang, J. A new method for parameter extraction of solar photovoltaic models using gaining–sharing knowledge based algorithm. *Energy Rep.* **2021**, *7*, 3286–3301. [CrossRef]
91. Zhou, W.; Wang, P.; Heidari, A.A.; Zhao, X.; Turabieh, H.; Chen, H. Random learning gradient based optimization for efficient design of photovoltaic models. *Energy Convers. Manag.* **2021**, *230*, 113751. [CrossRef]
92. Zhou, W.; Wang, P.; Heidari, A.A.; Zhao, X.; Turabieh, H.; Mafarja, M.; Chen, H. Metaphor-free dynamic spherical evolution for parameter estimation of photovoltaic modules. *Energy Rep.* **2021**, *7*, 5175–5202. [CrossRef]
93. Abdel-Basset, M.; El-Shahat, D.; Chakrabortty, R.K.; Ryan, M. Parameter estimation of photovoltaic models using an improved marine predators algorithm. *Energy Convers. Manag.* **2021**, *227*, 113491. [CrossRef]
94. Liu, Y.; Chong, G.; Heidari, A.A.; Chen, H.; Liang, G.; Ye, X.; Cai, Z.; Wang, M. Horizontal and vertical crossover of Harris hawk optimizer with Nelder-Mead simplex for parameter estimation of photovoltaic models. *Energy Convers. Manag.* **2020**, *223*, 113211. [CrossRef]
95. Liang, J.; Qiao, K.; Yu, K.; Ge, S.; Qu, B.; Xu, R.; Li, K. Parameters estimation of solar photovoltaic models via a self-adaptive ensemble-based differential evolution. *Sol. Energy* **2020**, *207*, 336–346. [CrossRef]
96. Xiong, G.; Zhang, J.; Shi, D.; Zhu, L.; Yuan, X.; Tan, Z. Winner-leading competitive swarm optimizer with dynamic Gaussian mutation for parameter extraction of solar photovoltaic models. *Energy Convers. Manag.* **2020**, *206*, 112450. [CrossRef]
97. Liang, J.; Qiao, K.; Yuan, M.; Yu, K.; Qu, B.; Ge, S.; Li, Y.; Chen, G. Evolutionary multi-task optimization for parameters extraction of photovoltaic models. *Energy Convers. Manag.* **2020**, *207*, 112509. [CrossRef]
98. Long, W.; Wu, T.; Xu, M.; Tang, M.; Cai, S. Parameters identification of photovoltaic models by using an enhanced adaptive butterfly optimization algorithm. *Energy* **2021**, *229*, 120750. [CrossRef]
99. Abdel-Basset, M.; Mohamed, R.; Chakrabortty, R.K.; Sallam, K.; Ryan, M.J. An efficient teaching-learning-based optimization algorithm for parameters identification of photovoltaic models: Analysis and validations. *Energy Convers. Manag.* **2021**, *227*, 113614. [CrossRef]
100. Khursheed, M.-U.-N.; Alghamdi, M.A.; Khan, M.F.N.; Khan, A.K.; Khan, I.; Ahmed, A.; Kiani, A.T.; Khan, M.A. PV model parameter estimation using modified FPA with dynamic switch probability and step size function. *IEEE Access* **2021**, *9*, 42027–42044.
101. Yang, X.S. Flower pollination algorithm for global optimization. In *International Conference on Unconventional Computing and Natural Computation*; Springer: Berlin, Germany, 2012; pp. 240–249.
102. Jordan, D.C.; Marion, B.; Deline, C.; Barnes, T.; Bolinger, M. PV field reliability status—Analysis of 100 000 solar systems. *Prog. Photovolt. Res. Appl.* **2020**, *28*, 739–754. [CrossRef]
103. Hara, S.; Douzono, H.; Imamura, M.; Yoshioka, T. Estimation of Photovoltaic Cell Parameters Using Measurement Data of Photovoltaic Module String Currents and Voltages. *IEEE J. Photovolt.* **2022**, *12*, 540–545. [CrossRef]
104. Kohno, T.; Gokita, K.; Shitanishi, H.; Toyosaki, M.; Nakamura, T.; Morikawa, K.; Hatano, M. Fault-diagnosis architecture for large-scale photovoltaic power plants that does not require additional sensors. *IEEE J. Photovolt.* **2019**, *9*, 780–789. [CrossRef]
105. Harrou, F.; Saidi, A.; Sun, Y.; Khadraoui, S. Monitoring of photovoltaic systems using improved kernel-based learning schemes. *IEEE J. Photovolt.* **2021**, *11*, 806–818. [CrossRef]
106. Mansouri, M.M.; Hadjeri, S.; Brahami, M. New method of detection, identification, and elimination of photovoltaic system faults in real time based on the adaptive Neuro-fuzzy system. *IEEE J. Photovolt.* **2021**, *11*, 797–805. [CrossRef]
107. Mathew, D.; Ram, J.P.; Pillai, D.S.; Kim, Y.J.; Elangovan, D.; Laudani, A.; Mahmud, A. Parameter Estimation of Organic Photovoltaic Cells–A Three-Diode Approach Using Wind-Driven Optimization Algorithm. *IEEE J. Photovolt.* **2021**, *12*, 327–336. [CrossRef]
108. Huang, G.; Liang, Y.; Sun, X.; Xu, C.; Yu, F. Analyzing S-Shaped I–V characteristics of solar cells by solving three-diode lumped-parameter equivalent circuit model explicitly. *Energy* **2020**, *212*, 118702. [CrossRef]
109. Mathew, D.; Rani, C.; Kumar, M.R.; Wang, Y.; Binns, R.; Busawon, K. Wind-driven optimization technique for estimation of solar photovoltaic parameters. *IEEE J. Photovolt.* **2017**, *8*, 248–256. [CrossRef]
110. Restrepo-Cuestas, B.J.; Montano, J.; Ramos-Paja, C.A.; Trejos-Grisales, L.A.; Orozco-Gutierrez, M.L. Parameter estimation of the bishop photovoltaic model using a genetic algorithm. *Appl. Sci.* **2022**, *12*, 2927. [CrossRef]
111. Abido, M.; Khalid, M.S. Seven-parameter PV model estimation using Differential Evolution. *Electr. Eng.* **2018**, *100*, 971–981. [CrossRef]
112. Kiani, A.T.; Nadeem, M.F.; Ahmed, A.; Sajjad, I.A.; Haris, M.S.; Martirano, L. Optimal parameter estimation of solar cell using simulated annealing inertia weight particle swarm optimization (SAIW-PSO). In Proceedings of the 2020 IEEE International Conference on Environment and Electrical Engineering and 2020 IEEE Industrial and Commercial Power Systems Europe (EEEIC/I&CPS Europe), Madrid, Spain, 9–12 June 2020; pp. 1–6.
113. Shankar, N.; Saravanakumar, N.; Kumar, C.; Kamatchi Kannan, V.; Indu Rani, B. Opposition-based equilibrium optimizer algorithm for identification of equivalent circuit parameters of various photovoltaic models. *J. Comput. Electron.* **2021**, *20*, 1560–1587. [CrossRef]
114. Khursheed, M.-U.-N.; Nadeem, M.F.; Khalil, A.; Sajjad, I.; Raza, A.; Iqbal, M.Q.; Bo, R.; ur Rehman, W. Review of flower pollination algorithm: Applications and variants. In Proceedings of the 2020 International Conference on Engineering and Emerging Technologies (ICEET), Lahore, Pakistan, 22–23 February 2020; pp. 1–6.

115. Alyasseri, Z.A.A.; Khader, A.T.; Al-Betar, M.A.; Awadallah, M.A.; Yang, X.S. Variants of the flower pollination algorithm: A review. *Nat.-Inspired Algorithms Appl. Optim.* **2018**, *744*, 91–118.
116. Niu, P.; Li, J.; Chang, L.; Zhang, X.; Wang, R.; Li, G. A novel flower pollination algorithm for modeling the boiler thermal efficiency. *Neural Process. Lett.* **2019**, *49*, 737–759. [CrossRef]
117. Alshammari, N.; Asumadu, J. Optimum unit sizing of hybrid renewable energy system utilizing harmony search, Jaya and particle swarm optimization algorithms. *Sustain. Cities Soc.* **2020**, *60*, 102255. [CrossRef]
118. Maleki, A.; Nazari, M.A.; Pourfayaz, F. Harmony search optimization for optimum sizing of hybrid solar schemes based on battery storage unit. *Energy Rep.* **2020**, *6*, 102–111. [CrossRef]
119. Huynh, D.C.; Ho, L.D.; Dunnigan, M.W. Parameter estimation of solar photovoltaic cells using an improved artificial bee colony algorithm. In *International Conference on Green Technology and Sustainable Development*; Springer: Berlin, Germany, 2020; pp. 281–292.
120. Tefek, M.F. Artificial bee colony algorithm based on a new local search approach for parameter estimation of photovoltaic systems. *J. Comput. Electron.* **2021**, *20*, 2530–2562. [CrossRef]
121. Kiani, A.T.; Nadeem, M.F.; Ahmed, A.; Sajjad, I.A.; Raza, A.; Khan, I.A. Chaotic inertia weight particle swarm optimization (CIWPSO): An efficient technique for solar cell parameter estimation. In Proceedings of the 2020 3rd International Conference on Computing, Mathematics and Engineering Technologies (iCoMET), Sukkur, Pakistan, 29–30 January 2020; pp. 1–6.
122. Rezk, H.; Arfaoui, J.; Gomaa, M.R. Optimal parameter estimation of solar PV panel based on hybrid particle swarm and grey wolf optimization algorithms. *Int. J. Interact. Multimed. Artif. Intell.* 2021, *in press*. [CrossRef]
123. Bisht, R.; Sikander, A. A New Soft Computing-Based Parameter Estimation of Solar Photovoltaic System. *Arab. J. Sci. Eng.* **2022**, *47*, 3341–3353. [CrossRef]
124. Hao, Q.; Zhou, Z.; Wei, Z.; Chen, G. Parameters Identification of Photovoltaic Models Using a Multi-Strategy Success-History-Based Adaptive Differential Evolution. *IEEE Access* **2020**, *8*, 35979–35994. [CrossRef]
125. Laudani, A.; Fulginei, F.R.; Salvini, A. High performing extraction procedure for the one-diode model of a photovoltaic panel from experimental I–V curves by using reduced forms. *Sol. Energy* **2014**, *103*, 316–326. [CrossRef]
126. Alwan, N.T.; Majeed, M.H.; Shcheklein, S.E.; Ali, O.M.; PraveenKumar, S. Experimental study of a tilt single slope solar still integrated with aluminum condensate plate. *Inventions* **2021**, *6*, 77. [CrossRef]
127. Praveenkumar, S.; Gulakhmadov, A.; Agyekum, E.B.; T Alwan, N.; Velkin, V.I.; Sharipov, P.; Safaraliev, M.; Chen, X. Experimental Study on Performance Enhancement of a Photovoltaic Module Incorporated with CPU Heat Pipe—A 5E Analysis. *Sensors* **2022**, *22*, 6367. [CrossRef]
128. Chavan, S.V.; Devaprakasam, D. Improving the performance of solar photovoltaic thermal system using phase change material. *Mater. Today Proc.* **2021**, *46*, 5036–5041. [CrossRef]
129. Nada, S.; El-Nagar, D.; Hussein, H. Improving the thermal regulation and efficiency enhancement of PCM-Integrated PV modules using nano particles. *Energy Convers. Manag.* **2018**, *166*, 735–743. [CrossRef]
130. Idoko, L.; Anaya-Lara, O.; McDonald, A. Enhancing PV modules efficiency and power output using multi-concept cooling technique. *Energy Rep.* **2018**, *4*, 357–369. [CrossRef]
131. Deokar, V.H.; Bindu, R.S.; Potdar, S. Active cooling system for efficiency improvement of PV panel and utilization of waste-recovered heat for hygienic drying of onion flakes. *J. Mater. Sci. Mater. Electron.* **2021**, *32*, 2088–2102. [CrossRef]
132. PraveenKumar, S.; Agyekum, E.B.; Velkin, V.I.; Yaqoob, S.J.; Adebayo, T.S. Thermal management of solar photovoltaic module to enhance output performance: An experimental passive cooling approach using discontinuous aluminum heat sink. *Int. J. Renew. Energy Res. (IJRER)* **2021**, *11*, 1700–1712.
133. Abdallah, S.R.; Saidani-Scott, H.; Benedi, J. Experimental study for thermal regulation of photovoltaic panels using saturated zeolite with water. *Sol. Energy* **2019**, *188*, 464–474. [CrossRef]
134. Wongwuttanasatian, T.; Sarikarin, T.; Suksri, A. Performance enhancement of a photovoltaic module by passive cooling using phase change material in a finned container heat sink. *Sol. Energy* **2020**, *195*, 47–53. [CrossRef]
135. Agyekum, E.B.; PraveenKumar, S.; Eliseev, A.; Velkin, V.I. Design and construction of a novel simple and low-cost test bench point-absorber wave energy converter emulator system. *Inventions* **2021**, *6*, 20. [CrossRef]
136. Agyekum, E.B.; PraveenKumar, S.; Alwan, N.T.; Velkin, V.I.; Adebayo, T.S. Experimental Study on Performance Enhancement of a Photovoltaic Module Using a Combination of Phase Change Material and Aluminum Fins—Exergy, Energy and Economic (3E) Analysis. *Inventions* **2021**, *6*, 69. [CrossRef]
137. Agyekum, E.B.; PraveenKumar, S.; Alwan, N.T.; Velkin, V.I.; Shcheklein, S.E.; Yaqoob, S.J. Experimental investigation of the effect of a combination of active and passive cooling mechanism on the thermal characteristics and efficiency of solar PV module. *Inventions* **2021**, *6*, 63. [CrossRef]
138. Agyekum, E.B.; Adebayo, T.S.; Bekun, F.V.; Kumar, N.M.; Panjwani, M.K. Effect of two different heat transfer fluids on the performance of solar tower csp by comparing recompression supercritical CO_2 and rankine power cycles, China. *Energies* **2021**, *14*, 3426. [CrossRef]