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# ELECTRICAL PARAMETERS ESTIMATION OF SINGLE DIODE PV MODULE MODEL USING HYBRID METAHEURISTIC ALGORIHM

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**Abstract:** In this paper, an improved hybrid algorithm called differential evolution with integrated mutation per iteration (DEIM) is proposed to extract five parameters of single-diode PV module model obtained by combining differential evolution (DE) algorithm and electromagnetic-like (EML) algorithm. The EML algorithm's attraction-repulsion idea is employed in DEIM in order to enhance the mutation process of DE. The proposed algorithm is validated with other methods using experimental I-V data. The results of presented method reveal that simulated I-V characteristics have a high degree of agreement with experimental ones. The proposed model has an average root mean square error of 0.062A, an absolute error of 0.0452A, a mean bias error of 0.006A, a coefficient of determination of 0.992, a standard test deviation around 0.04540, and 15.33sec as execution time. The results demonstrate that the proposed method is better in terms of the accuracy and execution time (convergence) when compared with other methods where provide less errors.

**Keywords**: *DEIM, single diode model, DE, parameter estimation, photovoltaic system.*

## 1. Introduction

In the future, solar energy is expected to be a significant source of energy. Because of its near-zero emissions, low cost, abundant energy supply, and advances in semiconductor and power electronic devices [1]. The photovoltaic (PV) power systems, which convert solar energy into electricity, are becoming increasingly common as a renewable energy source. It is critical to choose a model that closely simulates the characteristics of solar modules [2]. There are some models introduced over recent years. The electrical equivalent models are most commonly used in PV applications. The widely used models are single diode model [3] and double diode model [4]. The important obstacle of using these models is accurate parameter estimating to estimate exactly the productivity of PV system. For the purpose of parameter estimation of the PV module, there are several proposed techniques. In general, these techniques can be categorized into two approaches (1) analytical [5,6] and (2) numerical [7]. The analytical method is only utilizes selected points of the I-V characteristic curve, such as i) the open-circuit and short-circuit points ii) the slopes at strategic portions [5]. This method is often fast and simple to determine parameters, but not sufficient accurate. On the other hand, the numerical method offers more accurate parameter estimation because it utilizes all points belong to I-V curve characteristics [8]. In the literature, several numerical estimation techniques are introduced to estimate parameters of solar cells,

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such as the Newton-Raphson (NR) method [9] and numerical methods based on artificial neural network (ANN) [10–14]. Recently the use of evolutionary algorithms to extract parameters of PV modules has become widespread [15,16] such as Genetic Algorithms (GAs) [3, 8, 17, 18], Particle Swarm Optimization (PSO) [7, 19], Flower Pollination Algorithm (FPA) [20], Artificial Bee Colony (ABC) [21], The modified flower algorithm (MFA) [22], Bee Pollinator Flower Pollination Algorithm (BPFPA) [23] and differential evolution (DE) [24]. Ishaque et al. [25] proposed a method for extracting the parameters of solar PV modules called the penalty differential evolution (PDE) algorithm. According to [25], the results showed that PDE provides better performance than simulated annealing (SA), GA, and PSO algorithms. Moreover, Jiang et al. [1] developed a new version of DE algorithm is called improved adaptive differential evolution (IADE), which includes a new formula to adapt the mutation and crossover stages control parameters in order to extract the parameters of a PV module. According to [1], the proposed IADE offers an estimation with fast convergence and better accuracy than GA, PSO and conventional DE. In [26], an electromagnetism-like algorithm (EMLA) is proposed to estimate the parameters of double-diode PV module model under various operating condition using many sets of experimental I-V curves. EMLA offered acceptance results in term of accuracy, but it was slow in term of convergence to optimal estimated parameters. In the same context, the authors of [27] used electromagnetism-like algorithm to extract the parameters of single diode PV module model using an experimental I-V data. An improved electromagnetism-like (IEM) algorithm is proposed by [28] to estimate the five parameters of a single-diode PV module's model. A nonlinear formula is proposed by [28] to adjust the length of the particle for each iteration in IEM algorithm. Hussein et al. [29] proposed an enhanced version of LSHADE method is called ELSHADE to extract the parameters of triple diode PV module model. According to [29], the proposed ELSHADE offers robust and stable results, and presents high-quality and accurate parameters.

This paper presents differential evolution with integrated mutation per iteration (DEIM) algorithm to extract five parameters of the single diode PV module model. A novel formula is developed to adjust the mutation and crossover stages control parameters of DEIM algorithm. The formula based on sigmoid function of the best values of fitness function of the previous and current iterations. Many statistical criteria are used to measure the deviation between the computed and experimental currents over all I-V curve points under various operation conditions. Compared to other methods mentioned in the literature, the proposed PV modeling method that it is believed estimates the five parameters of the PV module's model with less error, fast convergence, and fewer control parameters. The proposed formula for adjusted control parameters of DEIM is help to overcome the complexity of setting fixed values.

## 2. PV Model

The PV model based on single diode circuit of the solar cell is depicted in Fig. 1, which comprises of a diode used to represent the output voltage connected in parallel with the current source used for representing photocurrent ($I_{ph}$) primarily depending on solar irradiance and ambient temperature, shunt resistance ($R_p$) is utilized to present the saturation current and series resistance ($R_s$) which represent the resistive losses within the cell. The output current equation of solar cell can be written as follows:

$$I = I_{ph} - I_o \left[ exp\left(\frac{V+IR_s}{V_t}\right) - 1\right] - \frac{V+IR_s}{R_p}, \qquad (1)$$

where $V$ and $I$ are respectively refer to the output voltage (v) and current (A); $I_{ph}$ refers to photocurrent (A); $I_o$ refers to the diode reverse saturation current (A); $R_s$ refers to series resistance (Ω); $R_p$ refers to parallel resistance (Ω); and thermal voltage ($V_t$) of diode; which can be expressed by;

$$Vt = \frac{aKBTc}{q}, \qquad (2)$$

where $a$ represents the diode ideality factor, $KB$ is the Boltzmann constant (1,3806503E-23 J/K), $Tc$ is the temperature of the solar cell in kelvin, and $q$ is the change of electron (1.60217646E-19 C).

Several authors proposed modifying the single diode model by adding an extra diode called a two diode model [24]. In comparison to the single diode model, this model is more complex and needs for more computation efforts for estimating its parameters. Therefore, Numerous authors have used the single diode model because it strikes a strong balance between simplicity and accuracy [24].

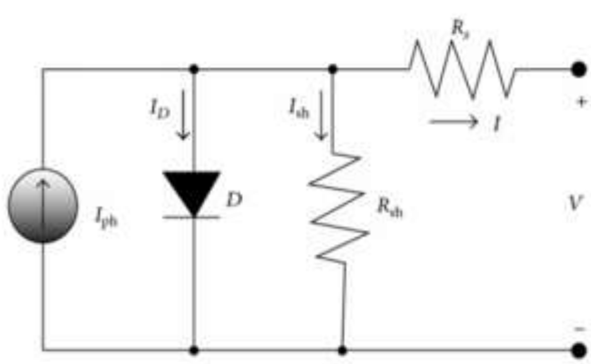



**Figure 1.** Single diode circuit model of a solar cell.

### 2.1. Optimization Problem Formulation

The optimization process aims to extract the optimal values of the five unknown parameters $I_{ph}$, $I_o$, $R_s$, $R_p$, and $a$ of single diode model by minimizing the objective function [1]. Root mean square error (RMSE) between the computed and experimental currents over $n$ data points is represented as objective function that should be as possible as minimized. The objective function can be formulated as follows:

$$f(\delta) = \sqrt{\frac{1}{n}\sum_{i=1}^{n} P(V_e, I_e, \delta)^2}, \qquad (3)$$

where;

$$P(V_e, I_e, \delta) = I_e - I_{ph} + I_o \left[ exp\left(\frac{V_e+I_pR_s}{V_t}\right) - 1\right] + \frac{V_e+I_pR_s}{R_p}, \qquad (4)$$

Where $I_e, V_e$ are the experimental output current (A) and voltage (v), respectively, $\delta = [\, I_{ph}, I_o, R_s, R_p, a]$ refers to the vector of five parameters that would be extracted, and $n$ refers to the number of the measured I-V curve points.

## 3. Proposed DEIM Algorithm

DEIM is a random search optimization algorithm. There are four phases in DEIM, namely, initialization, mutation, crossover, and selection. Like the other evolutionary algorithms, DEIM also works on population, $S^G$ of candidate solutions. These candidate solutions are known as the individuals of the population. The population comprises $NP$ $D$-dimensional real-values vectors as described below.

$$S^G = [X_1^G, X_2^G, \dots, X_{NP}^G] = [X_i^G], \qquad (5)$$

where;

$$X_i = [X_{1,i}, X_{2,i}, \dots, X_{D,i}] = [X_{j,i}], \qquad (6)$$

where $X_i$ refers to the target vector, and $i$ refers to the number of individuals belong to the population (where $i = 1, 2, .., NP$), $j$ is the dimension (number of decision variables) of the individual vector ($j = 1,2,..,D$), and $G$ is the generation index ($G = 1,2,..,G_{max}$), $G_{max}$ refers to maximum number of generations. The four phases of DEIM will be discussed in details as follows.

- **Initialization**

The first step in the optimization process is to create an initial population, $S^G = [X_i^G]$ in which $G$ =0. The $D$ parameters' initial values are generated using Eq. 7 randomly, and distributed uniformly within the range of $[XL_j, XH_j]$, where $XH_j$ and $XL_j$ refer to the upper and lower bounds of the search space region, respectively.

$$X_{j,i}^0 = XL_{j,i} + R\left(XH_{j,i} - XL_{j,i}\right), \quad (7)$$

where $R$ refer to a random number belongs to [0, 1] period.

- **Mutation**

For each iteration, DEIM utilizes both $M_d$ and $M_e$ operations. The following criteria is utilized to switch between the two types of mutation methods.

$$Mutation\ operation = \begin{cases} Me & if\ \sigma_l^G < \varepsilon_1 \sigma_l^0 \\ Md & otherwise \end{cases}, \quad (8)$$

where $\sigma_l^0$ and $\sigma_l^G$ are the values of standard deviation vectors of the row vectors of $S$ population of initial and $G$ generations, respectively; $l$ refers to a random number selected randomly within $[1, D]$, and $\varepsilon_1$ is a control parameter has constant value that dominate how frequently $Me$ operations are used over the population, $\varepsilon_1 \in [0,1]$. The mutation vector $X_i^G$ of $Md$ operation is computed by:

$$X_i^G = X_\alpha^G + MF\left(X_\beta^G - X_\gamma^G\right), \quad (9)$$

where $X_\alpha^G, X_\beta^G$ and $X_\gamma^G$ are randomly chosen from population; $\alpha, \beta$ and $\gamma$ are distinct indices within $[1, NP]$ period, and $MF$ is the mutation factor chosen from the range [0.5,1] [1]. It should be noted that $\alpha, \beta$ and $\gamma$ indices do not equal to the current index, $i$, of individual vector.

Meanwhile, $M_e$ operation is using the total force exerted on $X_\alpha^G$ by $X_\beta^G$ and $X_\gamma^G$ which is computed using the charges between the vectors in the same way as in EML algorithm as follows;

$$q_{\alpha\beta}^G = \frac{f(X_\alpha^G) - f\left(X_\beta^G\right)}{f(X_w^G) - f(X_b^G)}, \quad (10)$$

$$q_{\alpha\gamma}^G = \frac{f(X_\alpha^G) - f(X_\gamma^G)}{f(X_w^G) - f(X_b^G)}, \quad (11)$$

where $f(X)$ refers to the value of objective function of individual vector X; $X_w^G$ and $X_b^G$ refer to the worst and best individual vectors which expresses the worst and best objective function values for $G^{th}$ generation, respectively. The force exerted on $X_\alpha^G\ by\ X_\beta^G\ and\ X_\gamma^G$ are described as follows:

$$F_{\alpha\beta}^G = \left(X_\beta^G - X_\alpha^G\right) q_{\alpha\beta}^G, \quad (12)$$

$$F_{\alpha\gamma}^G = \left(X_\gamma^G - X_\alpha^G\right) q_{\alpha\gamma}^G, \quad (13)$$

After that, the resultant exerted force on $X_\alpha^G$ by both $X_\beta^G$ and $X_\gamma^G$ is computed as follows;

$$F_\alpha^G = F_{\alpha\beta}^G + F_{\alpha\gamma}^G, \quad (14)$$

Afterward, the mutant vector, which is created by $M_e$ operation can be formulated as follows:

$$X_i^G = X_\alpha^G + F_\alpha^G, \quad (15)$$

- **Crossover**

The trial vector $y_{j,i}^G$ is generated by using the corresponding target vector $X_i^G$ and the mutation vector $X_i^G$ as follows:

$$y_{j,i}^G = \begin{cases} X_{j,i}^G & if\ R \le CR\ or\ j = I_i \\ X_{j,i}^G & otherwise \end{cases} \quad (16)$$

where $R$ refers to a random number chosen randomly from the range (0, 1), $I_i$ refers to an index number, where randomly chosen from $[1, D]$ and $CR$ refers to the crossover rate parameter belonging to the range [0.5, 1] [1].

The estimated parameter values have to ensure that are physical values. Thus, the trial vector's elements should be verified if any one lie beyond the allowable search space. The parameter will be replaced with a new value if it overcomes the search space permissible limits as follows:

$$y_{j,i}^{G} = X_{j,L,i} + rand(X_{j,H,i} - X_{j,L,i}), \qquad (17)$$

- **Selection**

The selection operation utilizes both target and trial vectors. The objective function value of the trial vector if is lower, it swaps the target vector in the next generation. Otherwise, the target vector remains in the population, which can be described as follows:

$$X_i^{G+1} = \begin{cases} y_i^G & if\ f(y_i^G) < f(X_i^G) \\ X_i^G & otherwise \end{cases}, \qquad (18)$$

### 3.1. Proposed Formula for Adjusting the Mutation Factor and Crossover Rate

The crossover rate and mutation scaling factor values are typically set constant in the traditional DE. It is worth to mention that when the DE method is incorrectly set, it may take a prolong time to execute and perhaps it fails to converge to a global optimal result. As a result, a trial-and-error approach is often employed to tune the control parameters; however, this approach is neither acceptable nor optimum and frequently results in the requirement for many laborious optimization attempts. Some authors earlier suggested adjusting the control parameters during the search process using various methods. Jiang et al. [1] presented IADE, with a basic structure that allows the control parameters to be automatically adjusted depending on the fitness values during the optimization is underway using an exponential function to adapt $MF$ and $CR$ in the range [0.5, 1]. Similarly, a simplified and accurate approach for adjusting control parameters for each generation within the range [0.5, 1] using a logistic sigmoid function is proposed in this paper as following:

$$g(x) = \frac{L}{1+\exp(-K(\omega-\omega_o))}, \qquad (19)$$

The curve's maximum value ($L$) is chosen 1, the steepness of the curve is represented by $K$, and $\omega_o$ is the x-sigmoid axis's midpoint ($\omega_o = 0$). As described in Eq. 20, the parameter $\omega$ represents the difference between the values of best objective function of previous and current generation's, multiplied by a random number $R$.

$$\omega = [f(X_{best}^{G}) - f(X_{best}^{G-1})] * R, \qquad (20)$$

where $X_{best}^{G}$ refers to the best vector of $G$ generation, while $X_{best}^{G-1}$ refers to the best vector for $G-1$ generation and $R$ refers to a random number chosen from [0, 1] interval, which is randomly selected.

The $MF$ and $CR$ may be expressed as follows:

$$MF, CR = d\left(\frac{L}{1+exp(-K(\omega-\omega_O))} + b\right), \qquad (21)$$

where $d$ and $b$ are constants selected to keep $MF$ and $CR$ inside the [0.5, 1] range, where d set to be 0.5 and b equals to 1.

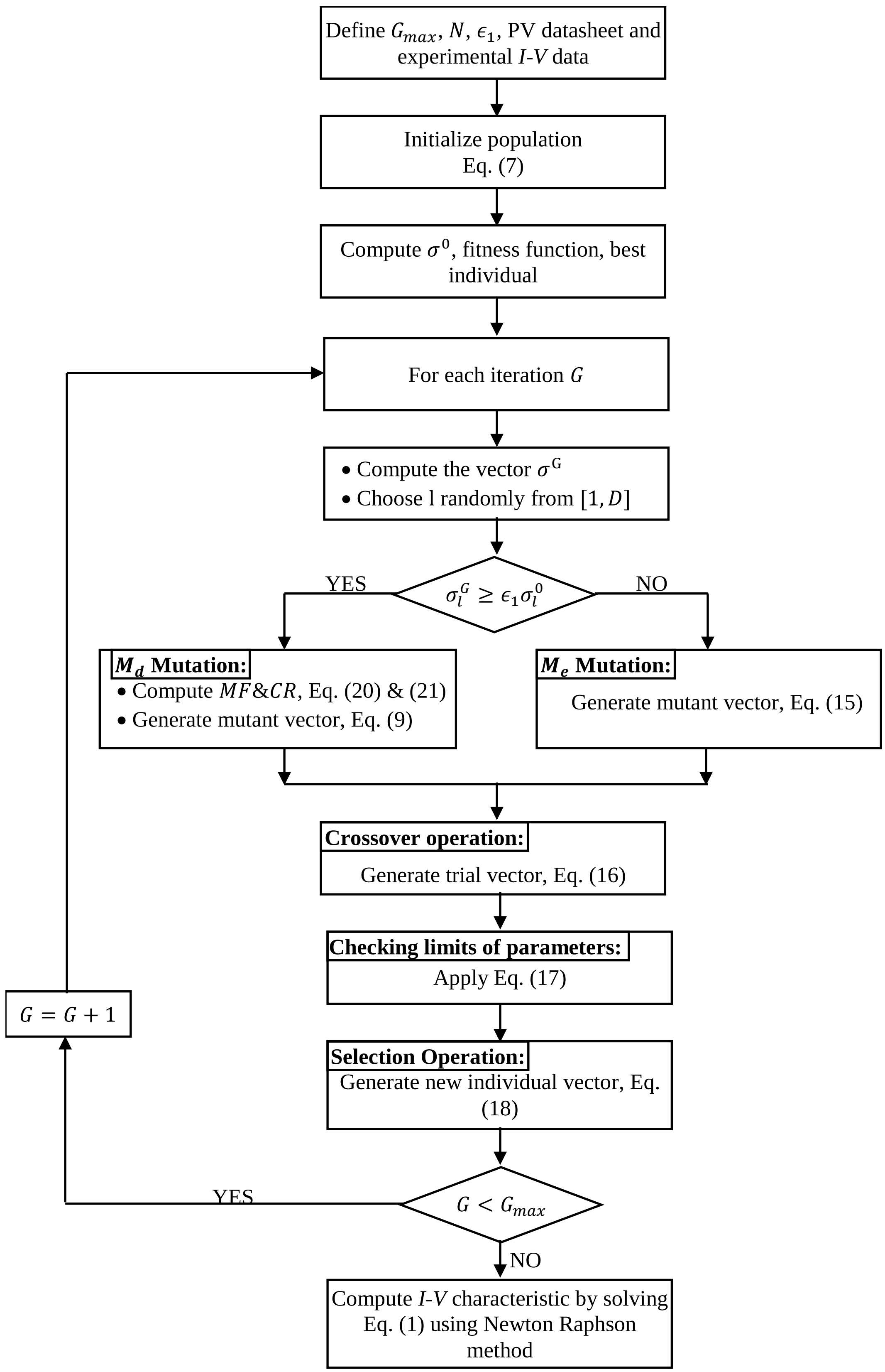



**Figure 2.** Flow chat of DEIM algorithm.

### 3.2. Evaluation Criteria for the Proposed Method

The performance evaluation criteria for the proposed method include: absolute error (AE) criterion, root mean square error (RMSE) criterion, mean bias error (MBE) criterion, coefficient of determination ($R^2$) criterion, deviation of RMSE for each solar radiation level ($d_i$) criterion and standard test deviation of RMSE ($STD$) criterion.

- **AE**: An absolute error refers to the absolute difference between the experimental and calculated currents in a particular voltage in the presence of certain solar radiation and ambient temperature, and it is defined as;

$$AE = |I_p - I_e|, \tag{22}$$

where $I_p$ and $I_e$ refer to the calculated and experimental currents (A), respectively.

- **RMSE**: The RMSE refers to the standard deviation value used to describe the difference between calculated and experimental currents over $n$ data sample points as follows;

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(I_p - I_e\right)^2}, \tag{23}$$

Where $n$ refers to the number of the measured experimental I-V curve points.

- **MBE**: It is utilized to evaluate the proposed model's performance as described below.

$$MBE = \frac{1}{n}\left(\sum_{i=1}^{n}\left(I_p - I_e\right)\right), \tag{24}$$

- $\boldsymbol{R^2}$: is used to measure the model's prediction performance and accuracy. The experiment's findings and the simulation are in close agreement when $R^2$ is close to 1, which means consistency between the two. $R^2$ is given by;

$$R^2 = 1 - \frac{\sum_{i=1}^{n}\left(I_p - I_e\right)^2}{\sum_{i=1}^{n}(I_e - \overline{I_e})^2}, \tag{25}$$

where $\overline{I_e}$ represent the arithmetic mean of experimental ($\overline{I_e}=\frac{1}{n}\sum_{i=1}^{n} I_e$).

- $\boldsymbol{d_i}$: The RMSE deviation of $i^{th}$ solar radiation level is the difference between an $i^{th}$ RMSE and the value of mean RMSE of all solar radiation levels.$d_i$ is given by;

$$d_i = RMSE_i - \overline{RMSE}, \tag{26}$$

where $\overline{RMSE}$ represent the arithmetic mean of RMSE of all levels of solar radiation ($\overline{RMSE} = \frac{1}{m}\sum_{i=1}^{m} RMSE$), $i$ represent a certain level of solar radiation (where $i = 1,2,\dots,m$), and m refers to the total number levels of different solar radiation. In this work, m equals to 7, which is the total number of various operation conditions.

- $\boldsymbol{STD}$: The standard test deviation of the RMSE is used to measure the performance of the proposed models. $STD$ is calculated by;

$$STD = \sqrt{\frac{1}{(n-1)}\sum_{i=1}^{n} {d_i}^2}, \tag{27}$$

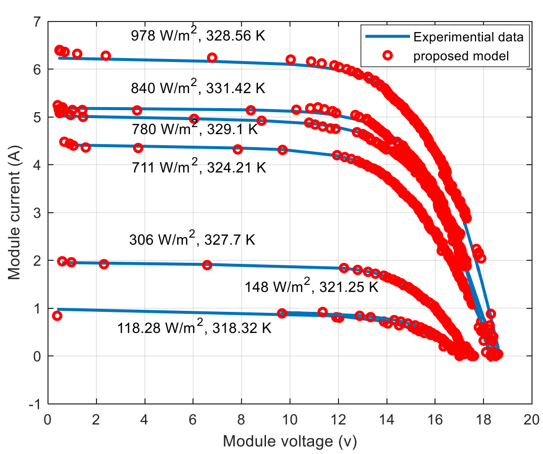
## 4. Result and Discussion

In order to verify the accuracy of the proposed method, the results have been compared with other previous methods mentioned in the literature. The methods used for comparison are PDE algorithm [25], IADE algorithm [1], EML algorithm [30],WOA [31] ,and PSO [31]. Seven different levels of solar radiation and solar cell temperature were used in the comparison, which are (118.28, 148, 306,711,780,840, and 978W/m$^2$) with (318.32, 321.25, 327.7, 324.21, 329.1, 331.42 and 328.56 K), respectively [32]. The search range of $I_{ph}$, $I_o$, a, $R_s$, and $R_p$ are chosen to be within [1,8]A, [1E-12,1E-5]A, [1,2], [0.1,2]Ω and [100,5000]Ω intervals, respectively [9] [25].

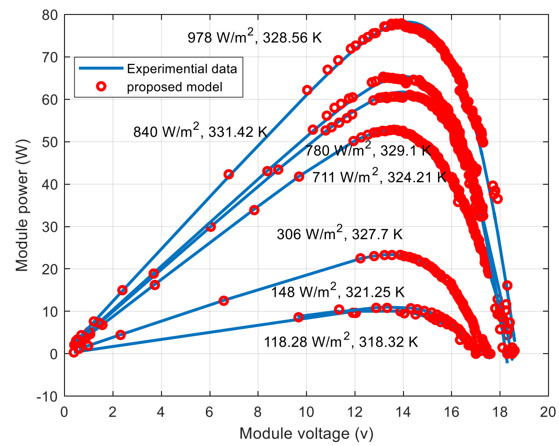
For DEIM implementation, the problem dimension is chosen to be 5 because we have five PV module parameters: a, $R_s$, $R_p$, $I_{ph}$, and $I_o$. The population size is assumed to be $10D$ the parameter $\varepsilon_1$ is set to 0.28 using trial and error strategy to get optimal value. The maximum number of generations is set 500, where the change in fitness function value is found not significant within 500 generations. The mutation factor ($MF$) and the crossover rate ($CR$) are adjusted for each individual vector per generation. On the other hand, $MF$ and $CR$ in PDE algorithm are set to be 0.8 and 1, respectively [25].

Finally, in IADE, both $MF$ and $CR$ are adaptive for each generation [1]. It is worth to mention that the DE/best/1/bin strategy is adopted for IADE, PDE, and also DEIM.

The graphs in Fig. 3a and Fig. 3b illustrate the I-V and P-V characteristics curves for PV module design that is calculated using the estimated parameters by DEIM algorithm under various operation conditions. It is clear the consistency between the experimental and computed curves under various operation conditions as illustrated in Fig. 3. It is noted that many of the present deviations occur in the area of the MPP, particularly under high solar irradiation due to asymmetry of experimental data points.




(a)




(b)

**Figure 3.** Photovoltaic characteristics under seven weather conditions (a) I-V curve (b) P-V curves.

The comparison of the degree of convergence for objective function values is created under seven weather conditions, as shown in Fig. 4. The proposed DEIM algorithm achieves the best and fastest convergence to optimal parameter values in low solar radiation levels for the first 50 generations compared with high solar radiation levels. This is because increasing the number of data points with the increase in solar radiation levels.

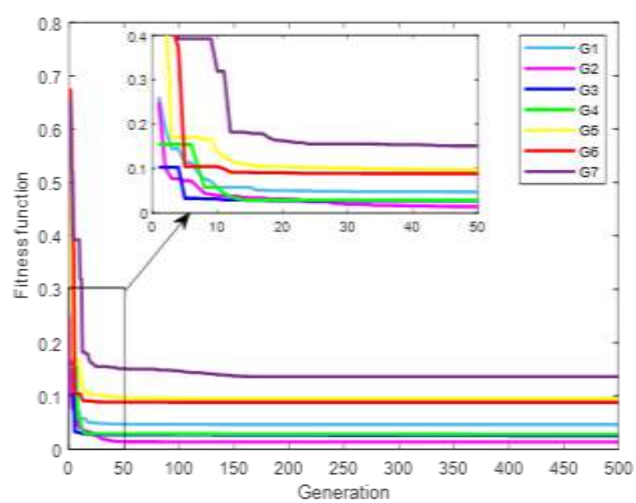



**Figure 4.** Fitness function values Progress of DEIM algorithms under various weather conditions

The superiority of DEIM in terms of accuracy appears when comparing it with other models IADE, PDE, EML, WOA, and PSO under various weather conditions. The average values of the five PV module parameters that extracted using various methods namely PDE, IADE, EML, WOA, PSO and DEIM, are illustrated in Table 1. Table 2 presents the mean values of absolute error of various estimating methods under seven operating conditions. The DEIM provided the minimum mean value of 0.0452 as compared to IADE, PDE, and EML with 0.053. On the other hand, the highest absolute error values of average were recorded for WOA, and PSO which are 0.0740 , and 0.2481, respectively. According to Table 2, it can note that AE values increased with increasing solar radiation due to the increasing in number of data points of I-V curve.

Table 3. offers RMSE, MBE, and $R^2$ and execution time of many methods under seven different operating conditions. The DEIM outperforms other methods with average value of $RMSE$, $MBE$ and $R^2$ were around 0.062, 0.006, and 0.992, followed by IADE, PDE, EML, WOA, and PSO, respectively. DEIM achieves other superiority compared to other methods by requiring less execution time with an average CPU time of 15.33 Sec. Table 4. shows $di$ and $STD$ values of various methods under seven operation conditions. DEIM has the lowest $di$ and $STD$ values, where the $STD$ value is 0.0454, and $di$ values corresponding for seven operation conditions are -0.01549, -0.04816, -0.03653, -0.0338, 0.0332, 0.02638, 0.07439, respectively. Finally, it can be perceived that the DEIM is always able to outperform other models. The lowest mean of average and minimum fitness values are 0.06551 and 0.06186, respectively, as demonstrated in Table 5.

**Table 1.** Extracted Parameter of PV module using various EA and weather conditions.

| **parameter** | **IADE** | **PDE** | **EM** | **DEIM** |
|---|---|---|---|---|
| **G1=118.28 W/m2 , Tc=318.32 K** | | | | |
| a | 1.193 | 1.326 | 1.508 | **1.077** |
| $R_s$ | 1.789 | 1.551 | 1.181 | **1.999** |
| $R_P$ | 100.0 | 100.2 | 183.9 | **100.0** |
| $I_{ph}$ | 1.000 | 1.000 | 0.929 | **1.000** |
| Io | 3.3E-7 | 1.5E-06 | 7.4E-6 | **6.7E-08** |
| **G2=148 W/m2 , Tc=321.25 K** | | | | |
| a | 1.225 | 1.362 | 1.401 | **1.237** |
| $R_s$ | 0.571 | 0.380 | 0.395 | **0.426** |
| $R_p$ | 117.8 | 125.2 | 139.2 | **113.9** |
| $I_{ph}$ | 1.001 | 1.002 | 1.000 | **1.000** |
| $I_o$ | 7.1E-7 | 2.9E-06 | 4.2E-6 | **8.3E-07** |
| **G3=306 W/m2, Tc=327.7 K** | | | | |
| a | 1.085 | 1.186 | 1.359 | **1.008** |

| | | | | |
|---|---|---|---|---|
| $R_s$ | 0.762 | 0.727 | 0.592 | **0.776** |
| $R_p$ | 245.8 | 1868.1 | 5000.0 | **152.7** |
| $I_{ph}$ | 1.954 | 1.937 | 1.952 | **1.967** |
| $I_o$ | 2.4E-7 | 9.3E-07 | 6.0E-6 | **7.1E-08** |
| **G4=711 W/m2, Tc=324.21 K** | | | | |
| a | 1.213 | 1.301 | 1.290 | **1.211** |
| $R_s$ | 0.548 | 0.525 | 0.530 | **0.553** |
| $R_p$ | 120.0 | 209.9 | 403.1 | **119.9** |
| $I_{ph}$ | 4.426 | 4.412 | 4.386 | **4.439** |
| $I_o$ | 1.1E-6 | 3.1E-06 | 2.8E-6 | **1.1E-06** |
| **G5=780 W/m2 , Tc=329.1 K** | | | | |
| a | 1.381 | 1.381 | 1.380 | **1.381** |
| $R_s$ | 0.266 | 0.266 | 0.266 | **0.270** |
| $R_p$ | 100.0 | 100.0 | 100.0 | **100.0** |
| $I_{ph}$ | 5.031 | 5.031 | 5.031 | **5.037** |
| $I_o$ | 1.0E-5 | 1.0E-05 | 9.9E-06 | **1E-05** |
| **G6=840 W/m2 , Tc=331.42 K** | | | | |
| a | 1.348 | 1.348 | 1.317 | **1.349** |
| $R_s$ | 0.209 | 0.209 | 0.220 | **0.198** |
| $R_p$ | 100.0 | 100.0 | 100.0 | **309.1** |
| $I_{ph}$ | 5.373 | 5.373 | 5.364 | **5.186** |
| $I_o$ | 1E-05 | 1.0E-05 | 7.3E-06 | **1E-05** |
| **G7=978 W/m2 , Tc=328.56 K** | | | | |
| a | 1.375 | 1.375 | 1.363 | **1.376** |
| $R_s$ | 0.215 | 0.215 | 0.218 | **0.217** |
| $R_p$ | 100.0 | 100.0 | 100.0 | **100.0** |
| $I_{ph}$ | 6.249 | 6.249 | 6.247 | **6.246** |
| $I_o$ | 1.0E-05 | 1.0E-05 | 8.9E-06 | **1E-05** |

**Table 2.** Comparison of different Average AE among different methods under seven operation conditions.

| Solar radiation | $IADE$ | PDE | EML | WOA | PSO | DEIM |
|---|---|---|---|---|---|---|
| G1 | 0.0389 | 0.0387 | 0.034 | 0.0248 | 0.0436 | **0.0339** |
| G2 | 0.0137 | 0.0150 | 0.015 | 0.0273 | 0.0149 | **0.0095** |

| | | | | | | |
|---|---|---|---|---|---|---|
| G3 | 0.0238 | 0.0261 | 0.028 | 0.0321 | 0.0431 | **0.0170** |
| G4 | 0.0265 | 0.0268 | 0.026 | 0.1395 | 0.254 | **0.0200** |
| G5 | 0.0705 | 0.0705 | 0.071 | 0.0920 | 0.0867 | **0.0667** |
| G6 | 0.0844 | 0.0844 | 0.086 | 0.0891 | 0.7111 | **0.0646** |
| G7 | 0.1104 | 0.1104 | 0.111 | 0.1131 | 0.5832 | **0.1050** |
| Mean | **0.053** | **0.053** | **0.053** | **0.0740** | **0.2481** | **0.0452** |

**Table 3.** $RMSE$, $MBE$, $R^2$, and execution time values of various estimation methods under seven operational conditions.

| **Tool** | **Method** | **G1** | **G2** | **G3** | **G4** | **G5** | **G6** | **G7** | **Average** |
|---|---|---|---|---|---|---|---|---|---|
| | IADE | 0.053 | 0.017 | 0.034 | 0.037 | 0.105 | 0.110 | 0.148 | 0.073 |
| | PDE | 0.054 | 0.018 | 0.035 | 0.038 | 0.105 | 0.110 | 0.148 | 0.072 |
| RMSE | EM | 0.047 | 0.019 | 0.037 | 0.038 | 0.105 | 0.112 | 0.149 | 0.073 |
| | WOA | 0.036 | 0.033 | 0.039 | 0.166 | 0.119 | 0.109 | 0.154 | 0.094 |
| | PSO | 0.059 | 0.018 | 0.059 | 0.298 | 0.117 | 0.807 | 0.805 | 0.309 |
| | DEIM | **0.046** | **0.014** | **0.025** | **0.028** | **0.095** | **0.088** | **0.136** | **0.062** |
| | IADE | 0.003 | 0.000 | 0.001 | 0.001 | 0.011 | 0.012 | 0.022 | 0.007 |
| | PDE | 0.003 | 0.000 | 0.001 | 0.001 | 0.011 | 0.012 | 0.022 | 0.007 |
| MBE | EM | 0.002 | 0.000 | 0.001 | 0.001 | 0.011 | 0.013 | 0.022 | 0.007 |
| | WOA | 0.001 | 0.001 | 0.001 | 0.027 | 0.014 | 0.012 | 0.024 | 0.012 |
| | PSO | 0.003 | 0.000 | 0.003 | 0.089 | 0.014 | 0.651 | 0.649 | 0.201 |
| | DEIM | **0.002** | **0.000** | **0.001** | **0.001** | **0.009** | **0.008** | **0.019** | **0.006** |
| | IADE | 0.957 | 0.996 | 0.997 | 0.999 | 0.993 | 0.993 | 0.991 | 0.989 |
| | PDE | 0.956 | 0.996 | 0.997 | 0.999 | 0.993 | 0.993 | 0.991 | 0.989 |
| $R2$ | EM | 0.966 | 0.996 | 0.996 | 0.999 | 0.993 | 0.993 | 0.991 | 0.990 |
| | WOA | 0.981 | 0.986 | 0.996 | 0.978 | 0.991 | 0.993 | 0.989 | 0.988 |
| | PSO | 0.947 | 0.996 | 0.989 | 0.927 | 0.992 | 0.772 | 0.722 | 0.899 |
| | DEIM | **0.967** | **0.998** | **0.998** | **0.999** | **0.994** | **0.995** | **0.992** | **0.992** |
| | IADE | 19.64 | 18.74 | 20.39 | 20.89 | 20.14 | 21.23 | 21.23 | 20.45 |
| Exe.ti | PDE | 19.88 | 18.71 | 19.88 | 21.29 | 20.59 | 21.67 | 21.11 | 20.32 |
| me(s) | EM | 2465 | 2412 | 2471 | 2677 | 2448 | 2585 | 2588 | 2521 |
| | PSO | 14.17 | 14.22 | 12.86 | 13.69 | 12.61 | 17.22 | 67.08 | 21.69 |
| | DEIM | **14.19** | **14.52** | **15.61** | **16.23** | **16.25** | **15.09** | **15.39** | **15.33** |

**Table 4**. $di$ and $STD$ values of various EA under seven operation conditions.

| Solar radiation | IADE | PDE | EM | WOA | PSO | DEIM |
|---|---|---|---|---|---|---|
| G1 | -0.01882 | -0.01904 | -0.02510 | -0.0580 | -0.2498 | **-0.01549** |
| G2 | -0.05489 | -0.05440 | -0.05385 | -0.0605 | -0.2910 | **-0.04816** |
| G3 | -0.03852 | -0.03775 | -0.03544 | -0.0550 | -0.2499 | **-0.03653** |
| G4 | -0.03553 | -0.03493 | -0.03469 | 0.0720 | -0.1129 | **-0.03380** |
| G5 | 0.03317 | 0.03263 | 0.03269 | 0.0252 | -0.1916 | **0.03320** |
| G6 | 0.03845 | 0.03791 | 0.03984 | 0.0161 | 0.4975 | **0.02638** |
| G7 | 0.07613 | 0.07558 | 0.07655 | 0.0601 | 0.4962 | **0.07439** |
| STD | 0.04914 | 0.04862 | 0.04917 | 0.0032 | 0.1233 | **0.04540** |

**Table 5.** Max, Min, and average values of fitness function for various EA under seven operation conditions.

| Operation condition | Fitness value | IADE | PDE | EM | DEIM |
|---|---|---|---|---|---|
| | Max | 0.34639 | 0.28963 | 0.39097 | **0.26139** |
| G1 | Min | 0.05317 | 0.05349 | 0.04738 | **0.04638** |
| | Average | 0.05883 | 0.05861 | 0.04945 | **0.04831** |
| | Max | 0.42046 | 0.50404 | 0.31271 | **0.25036** |
| G2 | Min | 0.0171 | 0.01813 | 0.01863 | **0.01371** |
| | Average | 0.02408 | 0.02430 | 0.03311 | **0.01597** |
| | Max | 0.4557 | 0.14225 | 0.40918 | **0.10282** |
| G3 | Min | 0.03346 | 0.03478 | 0.03704 | **0.02534** |
| | Average | 0.03849 | 0.03815 | 0.05465 | **0.02711** |
| | Max | 0.41445 | 0.21688 | 0.51200 | **0.15408** |
| G4 | Min | 0.03645 | 0.03760 | 0.03779 | **0.02806** |
| | Average | 0.04292 | 0.04707 | 0.20683 | **0.03044** |
| | Max | 0.59895 | 0.47755 | 0.58153 | **0.47280** |
| G5 | Min | 0.10516 | 0.10516 | 0.10517 | **0.09506** |
| | Average | 0.11332 | 0.11560 | 0.26259 | **0.09838** |
| | Max | 0.37149 | 0.44513 | 0.35345 | **0.67596** |
| G6 | Min | 0.11044 | 0.11044 | 0.11232 | **0.08824** |
| | average | 0.11894 | 0.12115 | 0.14844 | **0.09199** |
| | Max | 0.67832 | 0.59269 | 0.73617 | **0.65534** |
| G7 | Min | 0.14811 | 0.14811 | 0.14903 | **0.13626** |
| | average | 0.15633 | 0.16044 | 0.22584 | **0.14635** |
| | Max | 0.46940 | 0.38117 | 0.28399 | **0.36754** |
| Mean | Min | 0.07198 | 0.07253 | 0.07431 | **0.06186** |
| | Average | 0.07899 | 0.08076 | 0.08471 | **0.06551** |

## 5. Conclusion

In this paper, a differential evolution with integrated mutation per iteration (DEIM) algorithm is proposed to extract unknown five parameters of a single diode model of PV module. The proposed DEIM method mix between the mutation stages of conventional DE and EML algorithms in order to activate the mutation process. Furthermore, a new and effective formula based on sigmoid function is adopted in DEIM algorithm to adjust the mutation factor and crossover rate control parameters. Thus, the control parameters of conventional DE algorithm is reduced by two in DEIM. The suitability of the proposed method has been validated by the experimental data and other previous methods that proposed in literature. The results show that the proposed method exhibits better performance than other methods regarding accuracy and Convergence rapid. In addition, less control parameters as compared to DE and EML algorithms.

### Conflict of Interest

The authors confirm that the publication of this article causes no conflict of interest.

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