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EXTRACTION OF DOUBLE-DIODE PHOTOVOLTAIC MODULE MODEL'S PARAMETERS USING HYBRID OPTIMIZATION ALGORITHM

*Mawj M. Abbas Dhiaa H. Muhsen

Department of Computer Engineering, College of Engineering, Mustansiriyah University, Baghdad, Iraq

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Abstract: This paper presents seven parameters of double diode model of the photovoltaic module under different weather conditions are extracted using differential development with an integrated mutation per iteration (DEIM) algorithm. The algorithm is produced by integrating of two other algorithms namely, electromagnetism like (EML) and differential evolution (DE) algorithms. DEIM enhances the mutation step of the original DE by using the attraction-repulsion principle found in the EML algorithm. Meanwhile, a novel strategy based on adjusting mutation and crossover rate factors for each iteration is adopted in this paper. The implemented scheme's success is confirmed by comparing its results with those obtained by techniques cited in the literature. Along with the results, the DEIM suggests high closeness with the experimental I–V characteristic. For the proposed algorithm an average Root Mean Square Error ($RMSE$), absolute error (AE), mean bias Error (MBE), and execution time values were 0.0608, 0.044, 0.0053 and 23.333, respectively. The comparisons and evaluations results proved that the DEIM is better in terms of precision and rapid convergence. Furthermore, fewer control parameters are needed in comparison to EML and DE algorithms.

Keywords: *DEIM, Double diode model, differential evolution, parameter estimation, Electromagnetism-like algorithm, solar cell modeling, control parameters, I–V curve.*

1. Introduction

Due to many promising characteristics like renewability, reduced pollution, simplicity of installation, and noise-free operation, photovoltaic power plants that convert solar energy into electricity are called photovoltaic (PV) power plants, have lately gained increased attention [1]. However, because of the high initial cost of such a system, it is necessary to guarantee that the maximum amount of solar energy is captured. As a result, an efficient and accurate photovoltaic modeling should be given in order to improve the system's performance [2]. The term "photovoltaic module modeling" means the process of PV module parameters estimating based on manufacturing and/or experimental data [3]. A model that simulates the behavior of solar modules is important. [4]. In the literature, there are two of the most often used electrical equivalent circuit models of the PV module are the single diode (SD) [5] and double diode [6] models. The single diode model is the simplest, but the double diode model is more accurate,

**Corresponding Author*: egma014@uomustansiriyah.edu.iq

particularly when solar irradiance is low. Several techniques for estimating the parameters of solar cells have been developed in recent years. There are two approaches to these techniques; analytical [7, 8] and numerical [9]. Only nominated data points for I-V characteristic curve are used in the analytical approach. For instance, short circuit and open circuit points, also the slopes of the strategic segments [7]. Oftentimes, this technique is fast and simple in determining the parameters, however, it is not always precise. Moreover, more accurate parameter approximation can be provided by numerical analysis because it takes into account all designated points belonging the to I-V curve [10]. In the previous literatures, Numerous authors have suggested the numerical methods to overcome the analytical method's shortcomings, including the Newton-Raphson method (NR) [11], Artificial Neural Network (ANN) algorithms [12–16] and evolutionary algorithms (EA) [17, 18]. Newly, extracting parameters of (PV) modules utilizing evolutionary algorithms, such as genetic algorithms (GAs), has become widespread [5, 10, 19, 20], particle group optimization -P S O- [9, 21], flower pollination algorithm (FPA) [22], artificial bee colony (ABC) [23], The modified flower algorithm (MFA) [24], bee pollinator flower pollination algorithm (BPFPA) [25] and differential evolution [26]. DE is well-known for its many characteristics, including fast convergence, high accuracy, and the need for fewer control parameters when compared to other EA techniques. Ishaque et al. [2] compared the performance of several evolutionary algorithms used to obtain the values of photovoltaic model. The penalty-based differential evolution (PDE) scheme has a faster convergence to optimal values than simulated annealing (SA, PSO, and GA methods, according to [2]. Gong et al. [27] developed an improved adaptive differential evolution for parameter extraction of solar PV components by means of the crossover rate repairing method besides the ranking-based mutation (Rcr-IJADE) scheme. The results of [27] showed that Rcr-IJADE provides better performance as compared to other methods. Furthermore, Jiang et al. [28] proposed an improved DE algorithm version that was dubbed improved adaptive differential evolution (IADE) that comprises a novel method to change the crossover and mutation phases control parameters so as to excerpt the parameters of PV module. Based on [28], IADE provides more accurate parameter estimation than traditional DE, PSO, and GA algorithms.

A differential evolution with integrated mutation per iteration scheme are utilized to obtain the seven parameters of the double diode model of PV module. The DEIM algorithm's mutation and crossover phases control parameters are adjusted using a new method to eliminate the difficulty of setting fixed values. In a new formula, the best fitness points of sigmoid function is exploited for the previous and current iterations.

2. PV Model

The photovoltaic cell has many mathematical models, the most common of which is the double diode model, which is made up of five electrical components: a two diode, a current source, and two resistors as given in Fig. 1. This model is created by connecting a current source, two diodes, and a resistor R_p in parallel, with the latter being linked in series with another resistor R_s. The output current I of the cell is represented by [29];

$$I = I_{ph} - I_{o1}\left[exp\left(\frac{V+IR_s}{V_{t1}}\right) - 1\right] - I_{o2}\left[exp\left(\frac{V+IR_s}{V_{t2}}\right) - 1\right] - \frac{V+IR_s}{R_p} \quad (1)$$

where V_L denotes the output voltage (V); I_{ph} refers to the solar cell's photocurrent (A); I_{o1} and I_{o2} are respectively refer to the reverse saturation currents of the two diodes (A); R_s and R_{sh} refer to the series and parallel resistances (Ω), respectively. V_{t1} and V_{t2} are thermal voltage of the two diodes (V), which can be expressed by [29]:

$$V_{t1} = \frac{a_1 KBTc}{q} \quad (2)$$

$$V_{t2} = \frac{a_2 KBTc}{q} \quad (3)$$

Where:

Tc is the solar cell temperature in Kelvin;

KB = the Boltzmann constant ($1.3806503E - 23\, J/K$);

a_1 and a_2 are the ideality factors of the 1st and 2nd diodes;

q = the electron charge ($1.60217646E - 19\, C$).

An extra relationship for extra Shockley diode is included in the current equation of double diode model to account the losses due to recombination in the space-charge. It has been demonstrated that the double-diode application implies more truthful representation for solar cell behavior compared to the single-diode application, particularly when low solar irradiance exists, also it requires more computation efforts for calculating its seven parameters, [7].

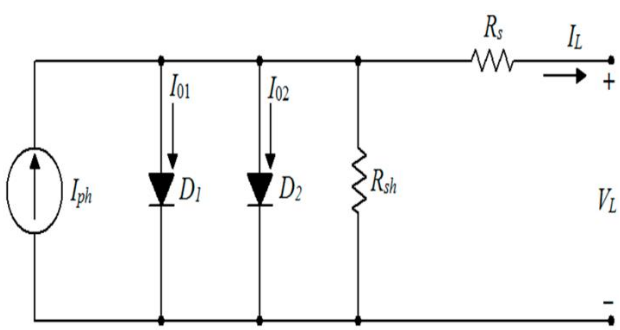


Figure 1. Double diode circuit model of PV cell.

2.1. Formulation of Optimized Problem

The primary goal of the solar cell modeling is to determine the optimum values of the seven unidentified coefficients I_{ph}, I_{o1}, I_{o2}, R_s, R_p, a_1, and a_2 of double diode application by finding the minimum objective function. The root mean square error [RMSE] characterizes the discrepancy between the experimental and computed electric currents over (n) measurement points by the means of an objective function, which to be minimized as possible. Objective function is summarized in the following formula [29]:

$$f(\delta) = \sqrt{\frac{1}{n}\sum_{i=1}^{n} P(V_e, I_e, \delta)^2} \quad (4)$$

where;

$$P(V_e, I_e, \delta) = I_e - I_{ph} + I_{o1}\left[exp\left(\frac{V_e+I_pR_s}{V_{t1}}\right) - 1\right] + I_o\left[exp\left(\frac{V_e+I_pR_s}{V_{t2}}\right) - 1\right] + \frac{V_e+I_pR_s}{R_p} \quad (5)$$

V_e, I_e indicated to the measurable output voltage (V) and current (A) of PV module, respectively; $\delta = [\,I_{ph}, I_{o1},, I_{o2}, R_s, R_p, a_1, a_2]$ represent the vector of seven parameters, which will be applied, and n denotes the points' number of the obtainable current and voltage along I-V curve.

3. Suggested (D.E.I.M) Algorithm

Which is random search optimization algorithm. At D.E.I.M, there four stages, called mutation, crossover, initialization and selection. As in the further evolutionary algorithms; DEIM based on NP of potential resolutions, which entail individuals of population (S^G). The population includes NP of D-dimensional real-values vectors as given in the following equation:

$$S^G = [X_1^G, X_2^G, \dots, X_{NP}^G] = \left[X_i^G\right] \quad (6)$$

where;

$$X_i = [X_{1,i}, X_{2,i}, \dots, X_{D,i}] = [X_{j,i}] \quad (7)$$

X_i represents the vector of the target (individual);

i represents the population number of individuals where $i = 1, 2, .., NP$;

G equals $1,2,..,G_{max}$, and represents the generation index;

G_{max} is the maximum number of generations;

j represents the number of decision variables of each individual vector $(j = 1,2,..,D)$.

In the following subsections discuss deeply the four phases of DEIM.

- **Initialization**

Generating an initial set, $S^G = [X_i^G]$ where $G = 0$ is the first step in the optimization process. Equation 8 is utilized to randomly generate the D parameters' initial value, and to uniformly distribute these values within the range of $[XL_j, XH_j]$, where XH_j and XL_j signifies the upper and lower limits of the examination region, as given below:

$$X_{j,i}^0 = XL_{j,i} + R(XH_{j,i} - XL_{j,i}) \quad (8)$$

where R = an arbitrary number between 0 and 1 interval.

- **Mutation**

For each step iteration, DEIM uses Md and Me mutation process together. Switching between the two different mutation methods is based on the following criteria. $Mutation\ operation =$

$$\begin{cases} Me & if\ \sigma_l^G < \varepsilon_1 \sigma_l^0 \\ Md & otherwise \end{cases} \quad (9)$$

The row vectors σ_l^0 and σ_l^G belong to the (S) datasets of preliminary and G generations, respectively; l denotes an arbitrary random figure that was arbitrarily chosen between [1, D], and ε_1 represents a constant of the control coefficient that determines how often Me operations are performed over the dataset, $\varepsilon_1 \in [0, 1]$ [29]. The mutation vector X_i^G of Md step is calculated using the following formula:

$$X_i^G = X_\alpha^G + MF(X_\beta^G - X_\gamma^G) \quad (10)$$

The coefficients X_α^G, X_β^G and X_γ^G are arbitrarily selected from population; γ, β and α represent the different parameters in period $[1,\ NP]$, then the mutation factor MF is selected to be within the range [0.5, 1] [28]. The parameters α, β and γ indices will not equal the current index, i, of individual vector.

In the meantime, M_e task is utilizing the total applied force on X_α^G by X_β^G and X_γ^G that is calculated from the charges amongst the vectors same as in algorithm of EML as given below:

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

$$q_{\alpha\gamma}^G = \frac{f(X_\alpha^G) - f(X_\gamma^G)}{f(X_w^G) - f(X_b^G)} \quad (12)$$

The each individual vector X, the objective function is given as $f(X)$;

though X_b^G and X_w^G denote the best and worst findings, which define the best and worst results of objective function for generation G^{th}. Thus, the applied forces on X_α^G , X_β^G and X_γ^G can be given as in the following formulas [3]:

$$F_{\alpha\beta}^G = (X_\beta^G - X_\alpha^G) q_{\alpha\beta}^G \quad (13)$$

$$F_{\alpha\gamma}^G = (X_\gamma^G - X_\alpha^G) q_{\alpha\gamma}^G \quad (14)$$

Then, the applied resultant force on X_α^G from X_β^G and X_γ^G is worked out as in the following equation:

$$F_\alpha^G = F_{\alpha\beta}^G + F_{\alpha\gamma}^G \quad (15)$$

So on, the mutant vector obtained by M_e process is summarized in the following expression:

$$X_i^G = X_\alpha^G + F_\alpha^G \quad (16)$$

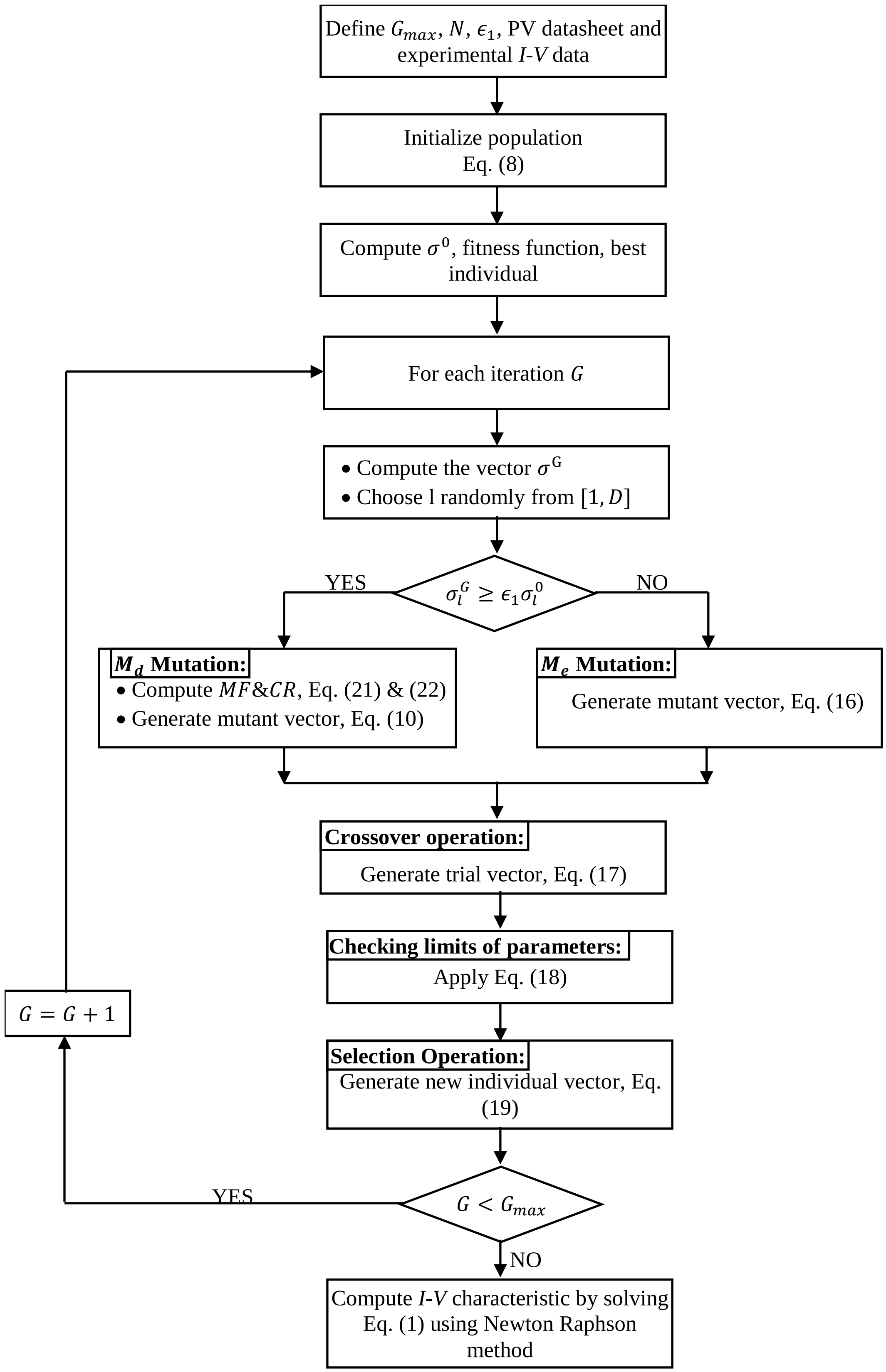


Figure 2. Flow chart of DEIM algorithm.

- **Crossover**

the relevant target vector X_i^G and mutation vector X_i^G were exploited to estimate the trial vector $y_{j,i}^G$ using the following functions [3]:

$$y_{j,i}^G = \begin{cases} X_{j,i}^G & if\ R\ \le CR\ or\ j = I_i \\ X_{j,i}^G & otherwise \end{cases} \tag{17}$$

Where R indicated the number selected in a random way from the interval (0, 1), I_i = an index number, were arbitrarily selected from $[1, D]$ and the crossover CR is the rate parameter in the range [0.5, 1].

The physical value behavior of the estimated parameter must be insured. Therefore, the corresponding allowable search space will be examined to check whether the trial vector's elements exist within the search space or not. A new value parameter of permissible limit will replace the surpassed parameter in the search space region, as shown below [3]:

$$y_{j,i}^G = XL_{j,i} + R\left(XH_{j,i} - XL_{j,i}\right) \tag{18}$$

- **Selection**

The selection procedure uses both the target and the trial vectors. If the trial vector's objective function value is lower than that of the target vector, the target vector's objective function value is lesser. The target vector is swapped in the next generation. Alternatively, the target vector is kept in the original population. Thus, selection between trial and target vectors can be described as follows [3]:

$$X_i^{G+1} = \begin{cases} y_i^G & if\ f(y_i^G) < f(X_i^G) \\ X_i^G & otherwise \end{cases}, \tag{19}$$

3.1. The Suggested Method for Adapting the Mutation and Crossover Rate Factors

In the traditional DE, the values of crossover rate and mutation scaling factors are both fixed values to mention that it takes a longer period to perform and could fail to meet a comprehensive optimal outcome if the control parameters of the DE algorithm are incorrectly set. Consequently, a trial-and-error technique is repeatedly used to adjust the control parameters; nonetheless, this method is not either appropriate not yet beneficial and often necessitates many laborious optimization attempts. Several authors have suggested that by various means, the control parameters be adjusted throughout the search process. a basic structure IADE that permits the control parameters to be repeatedly adjusted based on fitness values during the optimization process was presented by Jiang et al. [28], using an exponential function to adjust MF and CR ranging between [0.5, 1] period. Likewise, a simple and precise technique for adjusting control parameters for individual generation at ranging within the period [0.5, 1] a mathematical-based logistic sigmoid equation is suggested in this research as follows:

$$g(x) = \frac{L}{1+\mathrm{e}^{(-K(\omega-\omega_o))}} \tag{20}$$

The maximum value (L) of the curve is taken 1, and the gradient of the curve is signified by K, and ω_o is the x-sigmoid midpoint of the axis $(\omega_o = 0)$. As described in Eq. 21, the parameter ω signifies the variance between the best values of objective function of previous and current generations, multiplied by a random number R.

$$\omega = [f(X_{best}^G) - f(X_{best}^{G-1})] * R \tag{21}$$

Where X_{best}^G indicated to the best vector of G^{th} generation, while X_{best}^{G-1} indicated to the best vector for $G-1$ generation and R = a random number chosen from [0, 1] interval, which is randomly selected. Then, the MF and CR parameters can be expressed as follows:

$$MF, CR = d\left(\frac{L}{1+e^{(-K(\omega-\omega_o))}} + b\right) \quad (22)$$

Where d and b are constants that selected to keep MF and CR within [0.5, 1], where b equals to 1 and d set to be 0.5.

3.2. Appraisement Criteria for the Proposed Method

The proposed model used six distinct statistical indicators to measure the various algorithms' performance to provide an effective and fair comparison are: mean bias error (MBE) approach, coefficient of determination (R^2) approach, absolute error (AE) approach, root mean square error (RMSE) approach, standard test deviation of RMSE (STD) approach and deviation of RMSE for each solar irradiance level (d_i) approach. The definition of each criterion will be explained as follows:

- **AE**: the absolute error that refers to the discrepancy between the estimated and measured of a specific voltage in the occurrence of definite solar irradiance and ambient temperature, and is given as;

  $$AE = \left|I_p - I_e\right| \quad (23)$$

  Where I_p and I_e are the numerically computed and experimentally measured currents (A), respectively.
- **RMSE**: The root mean square error denotes the discrepancy between standard deviation value of the numerically computed and experimentally measured currents (A) over n points of the dataset as expressed in the following formula:

  $$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(I_p - I_e\right)^2} \quad (24)$$

  where n indicated to to the number of the measured experimental I-V curve points.
- **MBE**: the mean bias error that exploited to estimate the performance of devised model as shown in equation 25:

  $$MBE = \frac{1}{n}\left(\sum_{i=1}^{n}\left(I_p - I_e\right)\right) \quad (25)$$
- $\boldsymbol{R^2}$: has been employed to find the prediction performance model and its accuracy. The findings from the simulation and experiments are in close agreement when R^2 is close to 1 that implicates consistency between the both. R^2 is written as;

  $$R^2 = 1 - \frac{\sum_{i=1}^{n}\left(I_p - I_e\right)^2}{\sum_{i=1}^{n}(I_e - \overline{I_e})^2} \quad (26)$$

  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 irradiance level is the discrepancy between an i^{th} RMSE and the value of mean RMSE of all solar irradiance levels.d_i is given by;

  $$d_i = RMSE_i - \overline{RMSE} \quad (27)$$

  Where: $\overline{RMSE}$ signifies the mathematical mean of RMSE for all levels of solar irradiance ($\overline{RMSE} = \frac{1}{m}\sum_{i=1}^{m} RMSE$), i : signifies a specific level of solar irradiance ($i = 1,2, \dots, m$), and m is the entire levels of various solar irradiance. In this study, the total number of levels (m) is taken as (7), which represents the number of different operation status.
- $\boldsymbol{STD}$: The standard deviation of the RMSE is utilized to evaluate the efficiency of the suggested method. The following formula is used to compute STD; [30]

  $$STD = \sqrt{\frac{1}{(n-1)}\sum_{i=1}^{n} {d_i}^2} \quad (28)$$

3. Outcomes and Discussion

Both computed and experimental results are tested under various irradiance levels in order to validate the efficiency of the suggested approach. Additionally, comparisons with other earlier techniques cited in the literature for estimating PV module parameter are also given for the simulated data, which is produced utilizing double diode photovoltaic cell model. The techniques employed for assessment and evaluation are PDE algorithm [2], IADE algorithm [28], and EML algorithm [31]. Seven different levels (G1-G7) of irradiance as well as 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 [3].

To provide a fair comparison of the four techniques, identical simulation circumstances, such as maximum number of iterations, size of population, and parameters search space ranges, are maintained for all methods.

The problem dimension is set to be 7 since there are seven PV module parameters: a_1, a_2, R_s, R_p, I_{ph}, I_{o1} and I_{o2}. The population size is assumed referring that the DE/best/1/bin strategy is implemented for IADE, PDE, and also DEIM. The term (best) denotes the best vector in the current population, the number (1) denotes the number of variance vectors, and (bin) refers to the binomial crossover method.

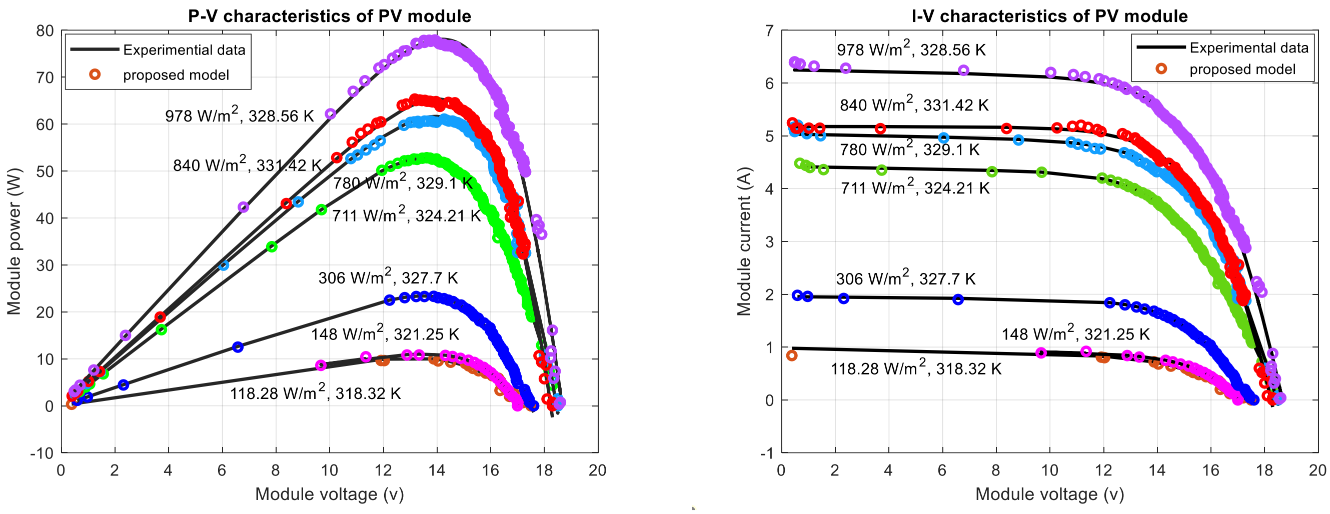
Fig. 3a-b illustrates the I-V and P-V characteristics curves, which produced utilizing the obtainable parameters by DEIM algorithm under numerous operation status.

to be $10D$ because the typical population size values range from $5D$ to $10D$ [29]. The parameter ε_1 is chosen as 0.28 by means of trial and error process so as to find the ideal number. Because of the change in the values of fitness function is obtained insignificant within 500 generations, the total number of generations is taken 500. The search range of the seven parameters I_{ph}, I_{o1}, I_{o2}, a_1, a_2, R_s, and R_p are chosen to be within (1, 8) A for I_{ph}, (1E-12, 1E-5) A for $I_{o1}$and I_{o2}, (1, 2) for a_1 and a_2, (0.1, 2) Ω for R_s, and (100, 5000) Ω for R_p intervals [2, 11].

For DEIM implementation, the mutation factor and the crossover rate are adapted for each solution per generation. On the other hand, MF and CR in PDE are chosen to be 0.8 and 1, respectively [2].

Eventually, in IADE, both MF and CR are adaptive for each generation [28]. It is important

Clearly, the I-V and P-V curves produced by the proposed method are accurate as well as closely match the measured data, particularly under low solar irradiance, as shown in Fig. 3. It can be noted that most of the present deviations occur in the area of the maximum power point (MPP) due to the asymmetry of experimental data points.



(a) (b)

Figure 3. DEIM's photovoltaic characteristics under seven operating conditions (a) I-V curves (b) P-V curves.

A comparison is made between the degrees of convergence of objective function values under seven atmospheric conditions, as shown in Fig. 4. The first 50 generations for low solar radiation levels are compared to high solar radiation levels the proposed DEIM algorithm achieves the best and fastest convergence of the optimal parameter values. And that is because the number of data points increases with increasing levels of solar radiation.,

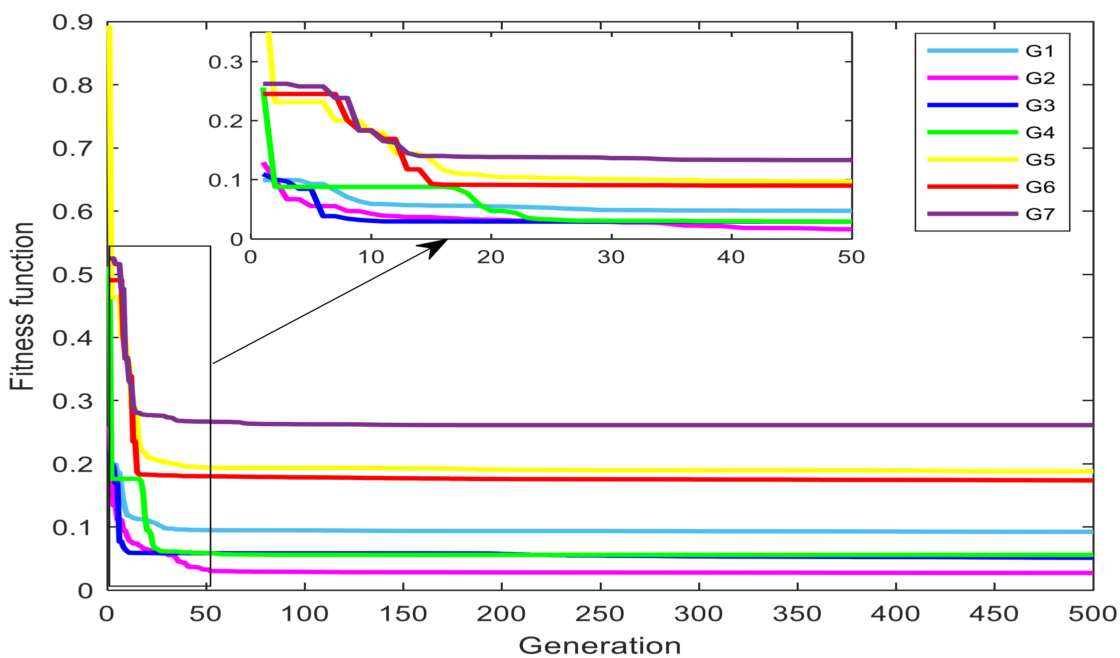


Figure 4. The comparison of the degree convergence using DEIM algorithm under seven weather conditions.

To demonstrate DEIM's superior performance, it is compared with other models IADE, PDE, and EML based on statistical results from various performance criteria. The seven extracted parameters for the PV module's double diode model are shown in Table 1. Table 2 summarizes the mean values of the absolute error of the different modeling methods of the seven status. The DEIM has the lowest absolute error as compared to IADE, PDE, and EML, where the AE value is 0.044. As in Table 2, AE values were increased with the increasing solar irradiance because of the aggregated number points of dataset for the curve (I-V). Table 3 shows that the DEIM outperforms all other methods in terms of performance. DEIM has the lowest RMSE values across all weather conditions, with an average RMSE of 0.0608, followed by PDE in second place with an RMSE of 0.0712. After that, IADE and EML had the worse average RMSE values, 0.0716 and 0.0752, correspondingly. DEIM provides other advantage in comparison to other algorithms by needing fewer consuming time around CPU time of 23.333sec. Moreover, DEIM offers the lowest MBE and highest coefficient of correlation as compared to other methods with 0.0053 and 0.9922 values, respectively, as tabulated in Table 2. Additionally, Table 4 illustrates the statistical criteria for the STD and di rates for different techniques where (7) operation conditions are taken. DEIM has minimum di and STD values, where the STD value is 0.0436, and di values corresponding for (7) operation status are -0.0145, -0.0471, -0.0350, -0.0328, 0.0333, 0.0262, 0.0699, respectively. Lastly, it is perceived that the DEIM outperforms other models. The average and minimum fitness values are 0.06395 and 0.06077, respectively, as shown in Table 5. Compared to other methods cited in the literature, the obtainable results showed that the proposed model assesses the (7) parameters of PV module with insignificant inaccuracy, lower CPU execution time, and fewer control parameters. The superiority of the proposed DEIM, due to that the mutation process of the conventional DE algorithm is boosted by combining the mutation strategy of the EML algorithm with it. Furthermore, the proposed approach for adapting the mutation scaling factor and crossover rate assist DEIM to estimate PV's parameters more convergence to the globally optimal values.

Table 1. Output parameter s of PV module using the proposed DEIM model under various weather conditions.

parameter	Method	Weather conditions							Avg.
		G1	**G2**	**G3**	**G4**	**G5**	**G6**	**G7**	
a_1	IADE	1.393	1.939	1.985	1.915	1.391	1.371	1.472	1.638
	PDE	1.401	1.949	1.897	1.241	1.415	1.455	1.448	1.544
	EM	2.000	1.914	1.419	1.683	1.560	2.000	1.226	1.686
	DEIM	**1.000**	**1.130**	**1.065**	**1.156**	**1.440**	**1.478**	**1.450**	**1.246**
a_2	IADE	1.681	1.375	1.186	1.335	1.592	1.527	1.396	1.441
	PDE	1.796	1.357	1.136	1.809	1.524	1.392	1.450	1.495
	EM	1.518	1.259	1.704	1.336	1.229	1.340	1.472	1.409

	DEIM	**1.311**	**1.305**	**1.937**	**1.180**	**1.478**	**1.386**	**1.450**	**1.435**
R_s	IADE	1.405	0.217	0.669	0.514	0.256	0.185	0.198	0.492
	PDE	1.416	0.325	0.732	0.540	0.245	0.186	0.193	0.519
	EM	1.226	0.429	0.476	0.508	0.304	0.217	0.247	0.487
	DEIM	**1.961**	**0.453**	**0.733**	**0.563**	**0.246**	**0.181**	**0.195**	**0.619**
R_p	IADE	100.863	118.816	1053.62	668.531	102.627	3338.89	110.062	784.773
	PDE	100.779	121.639	378.949	142.451	100.324	100.115	100.090	149.192
	EM	104.054	123.979	4914.11	722.409	100.00	1593.16	100.00	1093.96
	DEIM	**100.003**	**114.933**	**175.068**	**103.949**	**100.009**	**1353.89**	**100.00**	**292.55**
I_{ph}	IADE	1.000	1.005	1.943	4.399	5.049	5.172	6.249	3.545
	PDE	1.000	1.004	1.946	4.426	5.043	5.389	6.266	3.582
	EM	1.000	1.000	1.946	4.381	5.022	5.176	6.241	3.538
	DEIM	**1.000**	**1.000**	**1.966**	**4.446**	**5.052**	**5.178**	**6.263**	**3.558**
I_{o1}	IADE	2.75E-06	2.13E-06	6.33E-06	8.14E-06	9.10E-06	9.88E-06	8.99E-06	6.76E-06
	PDE	2.86E-06	1.42E-06	7.17E-07	1.56E-06	9.81E-06	9.89E-06	9.99E-06	5.18E-06
	EM	1.00E-12	7.67E-08	1.00E-05	6.94E-07	7.97E-06	4.24E-07	1.44E-06	2.94E-06
	DEIM	**1.27E-08**	**1.00E-07**	**1.78E-07**	**1.08E-08**	**9.98E-06**	**9.98E-06**	**1.00E-05**	**4.32E-06**
I_{o2}	IADE	1.82E-07	3.33E-06	9.49E-07	4.37E-06	9.87E-06	9.31E-06	7.71E-06	5.10E-06
	PDE	1.78E-06	2.79E-06	4.84E-07	6.74E-07	9.86E-06	9.72E-06	9.99E-06	5.04E-06
	EM	7.93E-06	1.08E-06	4.43E-06	4.56E-06	1.62E-06	8.99E-06	5.99E-06	4.94E-06
	DEIM	**4.14E-07**	**9.53E-07**	**3.63E-07**	**7.03E-07**	**1.00E-05**	**9.76E-06**	**1.00E-05**	**4.60E-06**

Table 2. The comparison of average AE among different models along seven O.Cs.

Solar irradiance	***IADE***	**PDE**	**EML**	**DEIM**
G1	0.039	0.039	0.040	**0.033**
G2	0.016	0.014	0.017	**0.010**
G3	0.026	0.025	0.025	**0.017**
G4	0.027	0.026	0.028	**0.020**
G5	0.070	0.069	0.071	**0.065**
G6	0.080	0.081	0.080	**0.063**
G7	0.105	0.106	0.124	**0.099**
Mean	**0.052**	**0.051**	**0.055**	**0.044**

Table 3. The comparison among different estimation methods based on various performance criteria under seven operation conditions.

Tool	Method	G1	G2	G3	G4	G5	G6	G7	Average
	IADE	0.0538	0.0188	0.0348	0.0380	0.1051	0.1069	0.1438	0.0716
RMSE	PDE	0.0536	0.0181	0.0341	0.0376	0.1048	0.1074	0.1430	0.0712
	EM	0.0549	0.0213	0.0343	0.0394	0.1057	0.1073	0.1636	0.0752
	DEIM	**0.0463**	**0.0137**	**0.0258**	**0.0280**	**0.0941**	**0.0869**	**0.1307**	**0.0608**
	IADE	0.0029	0.0004	0.0012	0.0014	0.0110	0.0114	0.0207	0.0070
MBE	PDE	0.0029	0.0003	0.0012	0.0014	0.0110	0.0115	0.0204	0.0070
	EM	0.0030	0.0005	0.0012	0.0016	0.0112	0.0115	0.0268	0.0080
	DEIM	**0.0021**	**0.0002**	**0.0007**	**0.0008**	**0.0089**	**0.0076**	**0.0171**	**0.0053**
	IADE	0.9556	0.9954	0.9965	0.9988	0.9932	0.9939	0.9912	0.9556
R^2	PDE	0.9560	0.9957	0.9966	0.9988	0.9932	0.9938	0.9913	0.9560
	EM	0.9539	0.9941	0.9966	0.9987	0.9931	0.9938	0.9886	0.9884
	DEIM	**0.9676**	**0.9976**	**0.9981**	**0.9994**	**0.9946**	**0.9957**	**0.9927**	**0.9922**
	IADE	30.295	30.670	32.105	33.977	33.805	34.055	34.024	32.705
Exe.time(s)	PDE	29.547	29.937	30.997	32.838	32.308	33.634	33.696	31.851
	EM	5924	5742.1	5914.9	6231.1	6107.6	6248.8	6272.9	6063.06
	DEIM	**22.266**	**22.016**	**22.859**	**23.813**	**23.422**	**23.672**	**25.281**	**23.333**

Table 4. standard deviation and d_i values of different methods under seven operation conditions.

Solar irradiance	IADE	PDE	EM	DEIM
G1	-0.01882	-0.01904	-0.02510	**-0.0145**
G2	-0.05489	-0.05440	-0.05385	**-0.0471**
G3	-0.03852	-0.03775	-0.03544	**-0.0350**
G4	-0.03553	-0.03493	-0.03469	**-0.0328**
G5	0.03317	0.03263	0.03269	**0.0333**
G6	0.03845	0.03791	0.03984	**0.0262**
G7	0.07613	0.07558	0.07655	**0.0699**
STD	0.04914	0.04862	0.04917	**0.0436**

Table 5. Average, minimum, and maximum values of objective function of various EA.

fitness-value	IADE	PDE	EM	DEIM
Maximum	0.2944	0.3143	0.20352	**0.22136**
Minimum	0.0716	0.0712	0.07523	**0.06077**
Average	0.0811	0.0802	0.08063	**0.06395**

4. Conclusion

In this paper, a new and effective version of the D.E algorithm, named DEIM, which proposed by combining two algorithms' DE and EML, to extract the seven parameters of PV module by using a double diode model under various environmental conditions. Using the proposed approach, the mutation phases of traditional DE and EML algorithms are combined providing speed up the mutation process. The DEIM method also devotes an improved formula based on the sigmoid function to modify the mutation scaling factor and crossover rate control parameters.

The suggested method's feasibility has been verified by using both I-V measured data and other previous models are inspired from the relevant literature. The results of DEIM algorithm show that the last is capable of accurately calculating the seven parameters of the PV module model. under various meteorological data as compared to other algorithms. The superiority of DEIM model in terms of convergence and accuracy is proven using a variety of statistical criteria with realistic experimental data.

Conflict of interest

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

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