Electromagnetism-Like Algorithm-Based Parameters Estimation of Double-Diode PV-Module Model

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Abstract: An accurate parameters extraction of photovoltaic (PV) module is necessary as it plays an essential role in determining the performance of PV system. Therefore, an electromagnetism-like algorithm (EMLA) is proposed to optimally estimate associated parameters of double-diode PV module model. The parameters are optimized based on a proposed fitness function, which depends on the root mean square error between the experimental and computed PV output current. Seven different experimental data sets of I-V curve are utilized to verify the presented approach under various operation conditions. The results show there is a high fitness between the estimated and realistic I-V curves under different weather conditions. Furthermore, the results are validated with another model that proposed in literature under different statistical indices. Finally, the proposed PV modeling method exhibits under all operation conditions an average root mean square error, average mean bias error and average determination coefficient under all operation conditions were 0.0799, 0.0088, and 0.9863, respectively.

Keywords: Photovoltaic, evolutionary algorithm, electromagnetism-like algorithm, I-V curve, double-diode model.

1. Introduction
The increasing in the world population and comfort level led to high energy demand [1]. Adding a traditional energy capacity for serving this demand, led to produce high pollutions to the environment which is considered as an unsophisticated solution [2]. Furthermore, depletion of fossil fuel and critical political situation in the one of the most important fossil fuel sources region, Arab gulf, are other factors that stimulate the utilization of renewable generation resources to balance the required demand. One of the significant renewable energy sources is photovoltaic (PV), which converts the sun light to energy. The parameters of equivalent electrical circuit of PV module have a direct effect on performance of the whole PV- system. The available methods used to estimate these parameters are analytical, numerical, and artificial intelligent (AI) which all seeking for optimal PV model. The main advantages of analytical method are the simplicity and less computation requirements as relative to others methods [3]. However, the main disadvantage of this method is the inaccurate parameters.
estimation process, since it is more dependent on the key points of I-V curve [4], as well as the environmental conditions are affecting on the performance of PV module. There are many contributions based on analytical method, Tamer et al in [5] used a set of correlation to estimate the PV module model’s parameters using meteorological variables as; solar irradiance and ambient temperature. In [6], Lim et al. used the analytical method to estimate single diode PV model parameters based on extensive computation and I-V curve.

To overcome these drawbacks of the analytical method, there are many works proposed the numerical method such that in [7-11]. The numerical method exploited all points of I-V curve. The Newton Raphson and Levenberg-Marquardt algorithms are commonly used as numerical methods in [7, 8, 10-12] for modeling PV module. This method needs more computation process and relies on the cost function, types of fitting algorithm and the preliminary values of extracted parameters. The analytical and numerical methods are compound together to estimate PV model in [13-14]. The compound methods still infected by the original drawbacks of both methods as well as the complexity of work.

Artifcial intelligent (AI) is widely depended in the parameters estimation process of PV module model. Due to the huge number of points need to train artificial neural network (ANN) and the complexity of internal process of ANN, which are considered as a black box, the focus is directed to evolutionary algorithms (EA). As a result of the high reliability and efficiency incurred by evolutionary algorithms (EA), it has been depended for modeling PV module as in [15-17]. In addition, the EA can deal with objective functions that have multi-modal. Moreover, EA has ability to handle nonlinear functions regardless the availability of derivative information.

In this paper, an evolutionary algorithm, namely the electromagnetism-like algorithm (EMLA) is presented to extract the optimal PV module’s parameters using an experimental data. Experimental I-V curve data of seven different operating conditions are utilized to validate the proposed model’s results. Furthermore, the results are verified with other methods based on various statistical criteria.

2. Parameters optimization of PV module model

The model of PV is an essential part in the modeling of whole PV system. Modeling of PV module plays a crucial role in the productivity of PV-systems. The PV module model’s parameters are influenced by the solar radiation and ambient temperature. Thus, a robust method is necessary to extract the PV module’s parameters.

2.1 Double diode PV module model

The electrical equivalent circuit of the double diode PV module model is illustrated in Figure 1. The output current of module can be formulated as [10];

\[ I_m = I_{Ph} - I_{d1} - I_{d2} - \frac{V_m + I_m R_s}{R_p}, \]  

(1)

where;

\[ I_{d1} = I_{o1} \left[ \exp \left( \frac{V_m + I_m R_s}{V_{t1}} \right) - 1 \right], \]  

(2)

\[ I_{d2} = I_{o2} \left[ \exp \left( \frac{V_m + I_m R_s}{V_{t2}} \right) - 1 \right], \]  

(3)

where; \( V_m \) and \( I_m \) are the output voltage (V) and current (A) of double diode PV module, respectively, \( I_{o1,2} \) and \( I_{Ph} \) are the diodes saturation currents (A) and photocurrent (A), respectively. In the meantime, \( R_s \) and \( R_p \) are the series and parallel resistances (\( \Omega \)), respectively, and \( V_{t1} \) and \( V_{t2} \) are the first and second diodes thermal voltages and expressed by;

\[ V_{t1} = \frac{a_1 B T_c}{q}, \]  

(4)
\[ V_{t2} = \frac{\alpha_2}{q} B T_C, \]  

where; \( \alpha_1 \) and \( \alpha_2 \) are the first and second diodes ideality factors, respectively, \( B \) is the constant of Boltzmann which is \( (1.3806503E-23 \text{ J/K}) \), \( q \) is the charge of electron \( (1.60217646E-19 \text{ C}) \), and \( T_C \) is the cell temperature \( (\text{K}) \). According to Eq. (1-5), the seven parameters that have direct effects on the productivity of PV module are \((a_{1,2}, R_S, R_P, I_{o1,2}, \text{and } I_{ph})\).

\[ \text{ff} = \frac{1}{\sqrt{n}} \sum_{i=1}^{n} (I_{e_i} - I_{c_i})^2, \]  

where;

\[ I_c = I_{ph} - I_{o1} \left[ \exp \left( \frac{V_m + I_c R_S}{V_{t1}} \right) - 1 \right] - I_{o2} \left[ \exp \left( \frac{V_m + I_c R_S}{V_{t2}} \right) - 1 \right] - \frac{V_m + I_c R_S}{R_P}, \]  

where; \( \text{ff} \) is the fitness function, \( I_e \) and \( I_c \) are the experimental and computed PV module output current \( (\text{A}) \), respectively, and \( n \) is the number of the utilized I-V data points.

2.2 Formulating the Parameters estimation problem

The PV module’s parameters under real operating condition are unknown as well as their values are sensitive to ambient temperature and solar radiation \([18]\). Based on the above, an evolutionary technique is essential to anticipate the parameters by representing the estimation process as an optimization problem. The optimization problem needs a fitness function to evaluate the estimated parameters. In this work, the root means square error between the computed and experimental PV currents according to \( n \)-points of I-V curve. Therefore, the formula of the fitness function that is used to determine the optimal values of double diode PV module’s parameters can be represented by \([18]\);

\[ \text{ff} = \frac{1}{\sqrt{n}} \sum_{i=1}^{n} (I_{e_i} - I_{c_i})^2, \]  

where;

\[ I_c = I_{ph} - I_{o1} \left[ \exp \left( \frac{V_m + I_c R_S}{V_{t1}} \right) - 1 \right] - I_{o2} \left[ \exp \left( \frac{V_m + I_c R_S}{V_{t2}} \right) - 1 \right] - \frac{V_m + I_c R_S}{R_P}, \]  

where; \( \text{ff} \) is the fitness function, \( I_e \) and \( I_c \) are the experimental and computed PV module output current \( (\text{A}) \), respectively, and \( n \) is the number of the utilized I-V data points.

3. EMLA for optimizing PV parameters

The seven of PV module’s parameters are estimated with regards to EMLA in this work. EMLA is an evolutionary algorithm based on \( D \)-dimensional individual vectors as a population. The algorithm depends on the attraction-repulsion mechanism to converge decision variables (seven parameters) toward their optimal values. In general, the algorithm includes the following main stages, which are described in the following subsections \([19]\).

3.1 Initialization

In this stage, a random population is generated for starting the optimization process. The generated population includes \( N \)-individual vectors; each vector consists of \( D \) decision variables (7 parameters). The initial values of decision variables are initiated uniformly within the search (design) space of each parameter as follows:

\[ X^0_{i,j} = X_{L,j} + \text{rand}(X_{H,j} - X_{L,j}) \]
where \( X_{L,i,j} \) and \( X_{H,i,j} \) are the lower and upper limits of design space for \( j \)th decision variable that belongs to \( i \)th individual vector, respectively, and \( \text{rand} \) is a random number belongs to the range \([0, 1] \). In the present work, \( j = 1, 2, \ldots, 7 \) and \( i = 1, 2, \ldots, N \), where \( N \) is the overall counts of individual vectors of population (S).

### 3.2 Local search

As it stated earlier, the D-decision variables of each individual vector are initiated in the initial stage. Then, the neighborhood of each decision variable is explored by using a simple local search algorithm [20]. In the local search algorithm, there are two control parameters (LSITER and \( \delta \)) which are used to control the process of local searching. LSITER is a control parameter referring to the number of iterations to repeat the local search. In the meanwhile, \( \delta \) is a neighborhood search multiplier factor for weighting the maximum step length that represents the difference between the upper and lower limits of each decision variable. The original \( i \)th individual vector \((X^G_i)\) for \( G \) generation is stored in a temporary vector, which is called \( Y^G_i \). After that, the vector \( Y^G_i \) is moved by adding/subtracting the weighted random step length to the initial value of vector \( Y^G_i \). Then, a comparison between the fitness function values of \( X^G_i \) and new \( Y^G_i \) within the local search iteration is occurred. If \( Y^G_i \) has a fitness function value less (in minimization case) than that of \( X^G_i \), then \( X^G_i \) is replaced by \( Y^G_i \) and the fitness function value is updated and the local search for \( i \)th individual vector is finished. Otherwise, the local search iteration is moving on to the next iteration.

### 3.3 Calculation of exerted force

The forces on \( i \)th individual vector that exerted by other vectors in population are calculated in this stage. After that, the total exerted force on \( i \)th individual vector is computed. The exerted force by \( X^G_k \) on the vector \( X^G_i \) is computed by using the charge of both vectors [21]. The charge of \( X^G_i \) individual vector is formulated as:

\[
q^G_i = \exp\left[-D \left( \frac{f(X^G_i)-f(X^G)}{\sum_{r=1}^{N}[f(X^G_i)-f(X^G_r)"]} \right)\right], \quad i = 1, 2, \ldots, N \text{ and } G = 1, 2, \ldots, G_{\text{max}}
\]

(9)

Where \( q^G_i \) is the charge of \( i \)th individual vector in \( G \)th generation, \( G_{\text{max}} \) is the maximum number of generations, \( X^G_i \) is the best individual vector for generation \( G \), \( f(X) \) refers to the value of objective function for \( X \) individual vector. The exerting force on the individual vector \( X^G_i \) exerts by \( X^G_k \) vector can be calculated by,

\[
F^G_{ik} = \begin{cases} 
(X^G_k - X^G_i) - \frac{q^G_i q^G_k}{\|X^G_k - X^G_i\|^2} & \text{if } f(X^G_k) < f(X^G_i) \\
(X^G_i - X^G_k) - \frac{q^G_i q^G_k}{\|X^G_k - X^G_i\|^2} & \text{if } f(X^G_k) \geq f(X^G_i) 
\end{cases}
\]

(10)

According to Eq. (10), vector \( X^G_k \) will attract \( X^G_i \) iff the objective function of \( X^G_k \), \( f(X^G_k) \), is less (in minimization case) than \( f(X^G_i) \), otherwise \( X^G_k \) will repel \( X^G_i \). Finally, the total force exerted on \( X^G_i \) by all other individual vectors in \( G \)th generation is computed by,

\[
F^G_i = \sum_{r=1, r \neq i}^{N} F^G_{ir}, \quad i = 1, 2, \ldots, N
\]

(11)
3.4 Generating new population

In the last stage of EMLA, the new \(D\)-dimensional individual vector is created as described in Eq. (12). The new individual vector is computed by moving \(X_i^G\) along the direction of \(F_i^G\) by a random magnitude that is selected from the interval [0, 1].

\[
X_i^G = X_i^G + \lambda \frac{F_i^G}{\|F_i^G\|} R \quad i = 1, 2, \ldots, N
\]

where:

\[
R = \begin{cases} 
X_{ji}^G - l_j & \text{if } F_{ji}^G > 0 \\
X_{ji}^G - X_{ji} & \text{otherwise} 
\end{cases} \quad i = 1, 2, \ldots, N \text{ and } j = 1, 2, \ldots, 7
\]

where \(R\) is a vector has elements refer to the allowed feasible movement towards the upper and lower limit of the \(j\)th parameter of \(i\)th individual vector, that is based on the \(j\)th total force value [20].

The local search, exerted force calculation, and creating new population stages are repeated until the stop criteria is achieved. Figure 2 shows the flow chart of estimating PV module double diode model parameters using EMLA.

![Flow Chart](image)

**Figure 2.** EMLA-based estimation of PV module’s model parameters flow chart.
4. Evaluation criteria

In this research, six statistical evaluation criteria are used to evaluate the performance of the proposed approach as compared to experimental I-V data and other PV-modeling methods that proposed in literature. The criteria are standard test deviation (STD), mean bias error (MBE), absolute error (AE), coefficient of determination ($R^2$), root mean square error (RMSE) and the deviation of RMSE over every solar radiation ($D_j$). The MBE criterion is utilized to assess the outcomes of the proposed PV-modeling method over $n$-data set of I-V curve points. The MBE can be defined as:

$$MBE = \frac{1}{n} \left( \sum_{i=1}^{n} (I_{ci} - I_{ei}) \right),$$

(14)

The AE presents the absolute deviation between the experimental and computed currents over $n$-data set of I-V curve points for each operation condition. Thus, AE criterion can be presented by:

$$AE = |I_c - I_e|,$$

(15)

The standard variation among the experimental and computed currents over $n$-data set of I-V curve refers to the RMSE criterion, which is formulated by:

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (I_{ci} - I_{ei})^2},$$

(16)

The $R^2$ criterion determines the level of dissimilarity in the experimental I-V data. High symmetry between the computed and experimental currents yields a value of $R^2$ close to 1. The $R^2$ criterion can be presented by:

$$R^2 = 1 - \frac{\sum_{i=1}^{n} (I_p - I_e)^2}{\sum_{i=1}^{n} (I_e - \bar{I}_e)^2},$$

(17)

where,

$$\bar{I}_e = \frac{1}{n} \sum_{i=1}^{n} I_e,$$

(18)

The fifth utilized criteria in this paper for evaluating the proposed method is $D_j$. The $D_j$ value illustrates the ability of the modeling method to determine the optimum value of parameters over various operating conditions. The method exhibits better parameters estimation when $D_j$ values are small and close to zero. $D_j$ can be calculated by:

$$D_j = RMSE_j - \bar{RMSE},$$

(19)

where,

$$\bar{RMSE} = \frac{1}{m} \sum_{j=1}^{m} RMSE_j,$$

(20)

where $m$ refers to the number of operating conditions, in this research work $m = 5$. The sixth and last criterion is STD of RMSE, which expresses the RMSE deviation of the proposed PV-modeling method over all operating conditions. The STD criterion can be presented as follows:

$$STD = \sqrt{\frac{1}{(m-1)} \sum_{j=1}^{m} d_j^2},$$

(21)

5. Results

A multicrystalline Kyocera KC-120-1 PV module is used in this paper with manufacturer standard test condition (STD) specifications that are illustrated in Table 1. The $a_{1,2}$, $R_S$, $R_P$, $I_{01,2}$, and $I_{Ph}$ are seven unknown parameters of PV module. Thus, the decision variables of EMLA in this research work are seven. The number of individual vectors of population is chosen 10 times the number of decision variables. According to several attempts of EMLA running, it is found to get better results with control
parameters of algorithm $\delta$, LSITER, and maximum number of iteration (MAXITER) are chosen to be, 0.01, 30, and 500, respectively.

### Table 1. The STC specifications of Kyocera KC120-1 PV module.

| Characteristics                        | Value   |
|----------------------------------------|---------|
| Maximum power at STC ($P_{max}$)       | 120 Wp  |
| Open-circuit voltage ($V_{oc}$)        | 21.5 V  |
| Maximum power point’s voltage ($V_{mp}$)| 16.9 V  |
| Current of short-circuit ($I_{sc}$)    | 7.45 A  |
| Maximum power point’s current ($I_{mp}$)| 7.1 A   |
| Counts of connected cells in series    | 36      |
| Temperature coefficient of $I_{sc}$ ($\alpha$) | 1.325 mA/K |
| Temperature coefficient of $V_{oc}$ ($\beta$) | -77.5 mV/K |

According to [22, 23], the typical search space of $a_{1,2}, R_S, R_P, I_{01,2},$ and $I_{ph}$ are assumed belonging to the following ranges: [1, 2], [0.01, 2]$\Omega$, [100, 5000]$\Omega$, [1e-12, 1e-5]$A$, and [1, 8]$A$, respectively. Five different operating conditions (G1 to G5) with various solar radiation and PV cell temperature are utilized to estimate the seven parameters, as summarized in Table 2. It should be noted that the data are collected by a meteorological station in Subang Jaya, Klang Vally, Kuala Lumpur, Malaysia with longitude 101.6° east and latitude 3.12° north. Based on Table 2, the length of I-V data points ($n$) is different for each operating condition. However, the seven estimated parameters of the electrical equivalent circuit of double-diode PV module model are tabulated in Table 3 under various operating conditions. In the meanwhile, the I-V and P-V curves of PV module model with regards to seven estimated parameters for different operating conditions are shown in Figure 3 and Figure 4, respectively. According to Figure 3, the estimated I-V curves are closer to experimental I-V curves. Based on Figure 4, the computed P-V curves are more diverge from experimental P-V curves at high solar radiation (840 and 978 W/m2). This is due to the degradation in the PV module performance when the PV cell temperature is elevated. On the contrary, the computed P-V curves are very close to experimental curves at low solar radiation.

### Table 2. Solar radiation and cell temperature of various operating conditions.

| Operating condition | Solar radiation (W/m²) | Cell temperature (K) | Length of data ($n$) |
|---------------------|------------------------|----------------------|----------------------|
| $G_1$               | 118.28                 | 318.32               | 22                   |
| $G_2$               | 306                    | 327.7                | 50                   |
| $G_3$               | 711                    | 324.21               | 91                   |
| $G_4$               | 840                    | 331.42               | 101                  |
| $G_5$               | 978                    | 328.56               | 102                  |
Table 3. Double diode PV model module’s parameters using EMLA under various operating conditions.

| Operating condition | \(a_1\) | \(a_2\) | \(I_{o_1}\) | \(I_{o_2}\) | \(R_s\) | \(R_p\) | \(I_{ph}\) |
|---------------------|--------|--------|--------|--------|---------|---------|--------|
| G1                  | 1.00000 | 1.54072| 1.0000E-12 | 9.59439E-06 | 1.33837 | 120.96029 | 1.00000 |
| G2                  | 1.15333 | 2.00000 | 6.14889E-07 | 1.0000E-12 | 0.73146 | 467.34831 | 1.95062 |
| G3                  | 1.31127 | 1.40122 | 1.41330E-06 | 5.33536E-06 | 0.48539 | 359.18180 | 4.38943 |
| G4                  | 1.37737 | 1.50684 | 0.00001 | 0.00001 | 0.19735 | 100.00000 | 5.40445 |
| G5                  | 1.30601 | 1.14486 | 1.27300E-06 | 4.81647E-07 | 0.27761 | 100.00000 | 6.21710 |

Figure 3. Experimental and estimated I-V curves of PV module under various operating conditions.
Figure 4. Experimental and estimated P-V curves of PV module under various operating conditions.

Figure 5 and Figure 6 show the absolute error between the computed and experimental currents with module output voltage as function of solar radiation and PV cell temperature, respectively. It is noticed, $AE$ is increased when the PV cell temperature and solar radiation are increased, as well as the number of $n$-points of I-V curve is increased. The evolution of fitness function of EMLA for five different meteorological operating conditions is shown in Figure 7. The proposed algorithm can reduce the fitness function value significantly in the first 50 generations. However, the proposed algorithm has presented high fitness function values under high solar radiation levels. Therefore, it can be concluded that the proposed algorithm is more effective with low and moderate solar radiation.
Figure 5. $AE$ related to PV module output voltage and solar radiation under various operating conditions.

Figure 6. $AE$ related to PV module output voltage and cell temperature under various operating conditions.
The accuracy of results and the effectiveness of EMLA-based PV modeling method is verified and evaluated by collating the outcomes with other modeling methods, which proposed in literature by [10, 5, 24]. The evaluation is achieved by using experimental I-V data under five different operating conditions. The MBE and $R^2$ of the proposed and other modeling methods presented by [5], [10], and [24] under various operating conditions are tabulated in Table 4. According to Table 4, the EMLA-based double diode PV model offers MBE less than [5] and [10] models over whole operation conditions. Thus, the average MBE of the proposed method is significantly less than [5] and [10] models. The proposed and [24] methods offered consistent average MBE. Moreover, the MBE and $R^2$ values of EMLA are less than those offered by [24] in G2 and G4. The average $R^2$ values of [24] and EMLA are also better than other models based on Table 4.

**Table 4.** MBE and $R^2$ of various PV modeling methods under various weather conditions.

| Parameter | Method             | Operating condition | Average |
|-----------|--------------------|---------------------|---------|
|           |                    | G1      | G2      | G3      | G4      | G5      |
| MBE (A)   | Dhiaa et al. model | 0.0022  | 0.0014  | 0.0014  | 0.0126  | 0.0222  | 0.0080  |
|           | Tamer et al. model | 0.0424  | -1.0148 | -0.0078 | 0.0874  | 0.5453  | -0.0695 |
|           | Ishaque et al. model | 0.0095  | 0.3521  | 4.3311  | 3.6990  | 4.8363  | 2.6456  |
|           | EM – based model   | 0.0030  | 0.0012  | 0.0016  | 0.0115  | 0.0268  | 0.0088  |
| $R^2$     | Dhiaa et al. model | 0.9657  | 0.9960  | 0.9988  | 0.9932  | 0.9905  | 0.9888  |
|           | Tamer et al. model | 0.9249  | 0.9619  | 0.9743  | 0.9887  | 0.8345  | 0.9369  |
|           | Ishaque et al. model | 0.8548  | -0.0325 | -2.5522 | -0.9872 | -1.0635 | -0.7561 |
|           | EM – based model   | 0.9539  | 0.9966  | 0.9987  | 0.9938  | 0.9886  | 0.9863  |
Figure 8 shows the $RMSE$ of the proposed PV model and other models. According to Figure 8, the proposed and [24] models exhibited the lowest $RMSE$ values among other models. In addition, the proposed PV model presents low average $AE$ values under various operation conditions as compared to [5] and [10] models, and close to [24] model as illustrated in Figure 9. The deviation of $RMSE$ over each solar radiation is shown in Figure 10. As a result of Figure 10, the $D_t$ values of the proposed and [24] method are the lowest as compared to other models.

**Figure 8.** $RMSE$ of various PV models under various operating conditions.

**Figure 9.** Average $AE$ of various PV models under various operating conditions.
Finally, the average $RMSE$, mean of average $AE$, and $STD$ of various PV models are tabulated in Table 5. The proposed and [24] model offers the best results according to Table 5. It is noted that $RMSE$ and $AE$ values are increased when solar radiation is increased, since the number of $n$-points of $I-V$ curve is increased.

Table 5. Average $RMSE$, mean of average $AE$, and $STD$ of $RMSE$ for various PV models.

| Model                  | RMSE (A) | Average AE (A) | STD     |
|------------------------|----------|----------------|---------|
| Dhiaa et al. model     | 0.0767   | 0.05722        | 0.05109 |
| Tamer et al. model     | 0.4372   | 0.18876        | 0.46380 |
| Ishaque et al. model   | 1.3789   | 1.31276        | 0.96457 |
| EM – based model       | 0.0799   | 0.0594         | 0.05502 |

6. Conclusion
The seven parameters of electrical equivalent circuit of double diode PV module model are estimated using electromagnetism-like algorithm. The parameters are extracted under five different operating conditions to explain the effectiveness of the proposed method. The root mean square error between computed and experimental PV output currents is utilized as an objective function to optimize the seven parameters. The results offer high consistency between the computed and experimental of $I-V$ and $P-V$ curves for different operating conditions. As a result, the proposed model exhibits an average $MBE$, average $RMSE$, and average $R^2$ are 0.0088, 0.0799, and 0.9863, respectively. Furthermore, the outcomes of the presented approach are verified and evaluated with other methods that proposed in literature to show the superiority of EMLA for estimating the parameters. According to results, the proposed model offers notability than other methods and consistence with single diode PV module model based on EMLA.
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**Acknowledgments**

The authors would like to thank Mustansiriyah University (www.uomustansiriyah.edu.iq) Baghdad-Iraq for its support in the present work.