



PARAMETER EXTRACTION OF SINGLE-DIODE PV-MODULE MODEL USING ELECTROMAGNETISM-LIKE ALGORITHM

*Dr. Dhiaa Halboot Muhsen¹, Dr. Haider Tarish Haider¹, Dr. Haider Ismael Shahadi²

1) Lecturer, Department of Computer Engineering, University of Al-Mustansiriyah, Baghdad, Iraq.

2) Assist. Prof., Department of Electrical and Electronic Engineering, University of Kerbala, Karbala, Iraq.

Abstract: The performance of photovoltaic (PV) module mainly depends on the parameters of electrical equivalent circuit of module. The parameters are unknown and sensitive to meteorological condition of PV location. Thus, an accurate estimation method should be used to extract the parameters. In this paper, an evolutionary algorithm proposed to optimize the parameters under various operation conditions. The root mean square error between the computed current based estimated parameters and experimental PV output current is proposed as a fitness function to obtain the optimal solution. The results are verified by seven different experimental I-V sets under various meteorological conditions. Furthermore, the results are verified by another work, which based on analytical method that proposed in literature. The results refer to high consistency with realistic data. In addition to that, the proposed method offers an average root mean square error and average absolute error under seven operation conditions were 0.07248 and 0.05316, respectively.

Keywords: *Electromagnetism-like, Photovoltaic, Single diode model, evolutionary algorithm, PV-module.*

استخراج معاملات لموديل احادي الدايدود للوح كهروضوئي بأستخدام نظرية شبه الكهرومغناطيسية

الخلاصة: ان أداء الألواح الشمسية يعتمد بالدرجة الأساس على قيم الدائرة الكهربائية المكافئة لها. وهذه القيم تكون غير معرفة وهي تتأثر بالموقع الجغرافي لوجود الألواح الشمسية. ولهذا اختيار الطريقة الأكثر دقة في تخمين هذه القيم مهم جداً ويجب ان يستخدم في ايجاد هذه القيم. في هذا البحث تم استخدام طريقة الخوارزمية التطورية في ايجاد افضل قيم ضمن ظروف متعددة. وتم استخدام معدل الجذر التربيعي للخطأ بين القيم التي يتم احتسابها للتيار حسب القيم المخزنة وبين القيم العملية لتيار الاخراج للألواح الشمسية كمعادلة تقييم لاعتماد افضل القيم المخزنة. النتائج التي تم الحصول عليها تم التحقق منها من خلال استخدام سبع نماذج عملية وضمن ظروف مختلفة للموقع الجغرافي. بالإضافة الى ان النتائج تم مقارنتها مع اعمال اخرى تم نشرها ضمن قائمة البحوث المماثلة. كذلك تشير النتائج الى تقارب عالي للنتائج الحقيقية بالإضافة الى ان الطريقة المقترحة اعطت معدل الجذر التربيعي للخطأ وكذلك معدل المطلق للخطأ ضمن السبع شروط المعتمدة كانت قيمها 0.07248 و 0.05316، على التوالي.

1. Introduction

The electrical energy (EE) is one of the most important factor for development any society in the world. Therefore, the EE demand is increasing for realizing the requirements of modern life [1, 2].

*Corresponding Author deia_muhsen@yahoo.com

In the fact, the conventional EE resources comprise many disadvantages such as, environmental pollution and fluctuation of fuel prices worldwide. Furthermore, the fuel resources are gradually being lead to depletion [3]. Thus, the researchers are focusing on clean, environmental friendly, renewable and sustainable resources for electrical energy. Solar energy is represented one of the most popular source for generating electrical energy using photovoltaic (PV) technology. However, the modeling of PV array/module plays an essential role in the performance and productivity of PV systems. The modeling of PV module can be considered by estimating the parameters of the electrical equivalent circuit of PV module.

In general, there are three main PV modeling methods namely; analytical, numerical, and artificial intelligent (AI) methods. In analytical method, the parameters of PV module under real operating condition is derived in terms of them under standard test condition (STC) based on manufacturer data [4] It is worth to mention that some key points that belong to I-V curve are used in analytical methods. The advantages of analytical method are simple and it needs to less computation time as compared to other methods [5]. The inaccurate parameter estimation is represented the main drawback of analytical method, because the PV performance is influenced by environmental conditions [6]. Moreover, the accuracy of estimation is strongly dependent on the key points of I-V curve. A simple PV module model based on the correlation that correlated the parameters of PV module and meteorological variables (ambient temperature and solar irradiance) proposed by Tamer et al. in [7]. An analytical method proposed by Lim et al. [8] to estimate the parameters of single diode PV module model using I-V curve and extensive computation.

On the other hand, another method such as numerical has been proposed by [9-13] to overcome the drawback of analytical method. The numerical method is more accurate than analytical method, because it utilized all the I-V curve points. The Newton Raphson and Levenberg-Marquardt algorithms are widely used in PV module modeling as numerical methods [9, 10, 12-14]. The main drawbacks of numerical method that it needs to extensive computation as well as the accuracy of estimation depends on the type of fitting algorithm, the cost function, and the initial values of the extracted parameters. A compound methods proposed by [15, 16], these methods combine between analytical and numerical methods to estimate the parameters of PV module. The drawbacks of both analytical and numerical methods are presence in compound method as well as to the complexity of method.

In the last decade, the AI is widely used for extracting the parameters of PV module model. Artificial neural network (ANN) based method used for estimation the parameters, but it is still as a black box as well as it needs for a huge I-V points for training the network. Due to the high reliability and efficiency of evolutionary algorithms (EA), the last used for modeling PV module [17-19]. The reliability of EA can be defined by the ability to candidate the optimal values of PV parameters. Meanwhile, the efficiency of EA refers to the ability to optimize the PV parameters with less computation time compared with numerical method. The EA can handle nonlinear functions without need for derivative information. Furthermore, EA can deal with multi-modal objective functions.

In this paper, a robust evolutionary algorithm is called electromagnetism-like (EM) algorithm is used to extract the optimal parameters of PV module based on experimental data. Experimental I-V data for seven different meteorological conditions used to validate the results of the proposed model. In addition, the results verified with another model that proposed in literature based on many statistical tools.

2. Optimization of PV module model's parameters

As aforementioned, the modeling of PV module affects on the designing and planning of PV systems productivity. Thus, accurate modeling is important target for researchers those work in PV field. However, accurate estimation of PV module parameters leads to accurate module modeling. It is worth to mention that the PV module parameters are sensitive to solar cell temperature and solar irradiance

2.1 Single Diode PV Module Model

The electrical equivalent circuit of single diode PV module model is illustrated in Fig. 1. The output current of PV module can be depicted by;

$$I_m = I_{Ph} - I_o \left[\exp \left(\frac{V + I_m R_S}{V_t} \right) - 1 \right] - \frac{V + I_m R_S}{R_P}, \quad (1)$$

where; V and I_m are the output voltage (V) and the current (A) of PV module, respectively, I_o and I_{Ph} are the diode saturation current (A) and photocurrent (A), respectively, R_S and R_P are the series and parallel resistances (Ω), respectively, and V_t is the diode thermal voltage and expressed by;

$$V_t = \frac{aBT_C}{q}, \quad (2)$$

where; a is the diode ideality factor, B is the Boltzmann's constant ($1.3806503E-23$ J/K), T_C is the cell temperature (K) and q is the electron charge ($1.60217646E-19$ C). According to eqn (1) and (2), the five parameters (a , R_S , R_P , I_o , and I_{Ph}) affects on the productivity of PV module. The single diode model is used in this paper, because it offers simple computation with satisfactory level of accuracy.

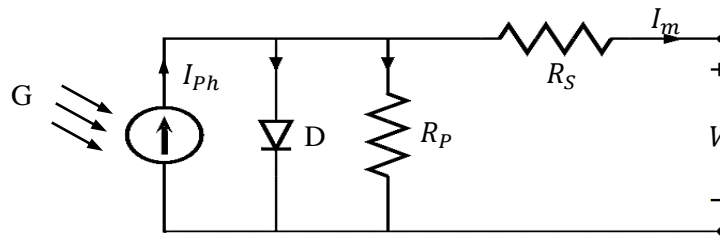


Fig. 1: Electrical equivalent circuit of single diode PV module model.

2.2 Formulating the Parameters estimation problem

The parameters of PV module are unknown and variable with solar cell temperature and solar irradiance. Thus, the parameter estimation problem can be represented as optimization problem, where an evolutionary algorithm is used to find the optimal parameter values. The root mean square error between the computed PV module current and experimental current over n data set of I-V points is represented as objective function of optimization problem. The objective function that utilized to optimize the parameters of single diode PV module model is formulated as,

$$f = \sqrt{\frac{1}{n} \sum_{i=1}^n \left(I_{e_i} - I_{Ph} + I_o \left[\exp \left(\frac{V_{e_i} + I_{m_i} R_s}{V_t} \right) - 1 \right] + \frac{V_{e_i} + I_{m_i} R_s}{R_p} \right)^2} \quad (3)$$

where; f is the objective function, I_e and V_e are the experimental PV module output current (A) and voltage (V), respectively, and n is the length of the I-V data points.

3. EM Algorithm For Optimizing PV Module Model's Parameters

In this paper, electromagnetism-Like algorithms is utilized to model a PV module. Electromagnetism-Like (EM) algorithm is a population-based search algorithm utilizes the attraction and repulsion mechanism to move the D-dimensional individual vectors toward the global optimal values. EM comprises four stages namely, initialization, local search strategy, calculation of exerted force, and new population generation [20].

3.1 Initialization

The first step of EM algorithm is the generation of a population randomly. This population consists of N individual vectors while each vector comprises D parameters that are required to be optimized. The D -dimensional individual vectors are initialized to be distributed uniformly between the corresponding upper ($X_{j,H}$) and lower ($X_{j,L}$) limits of the search domain as depicted in Eq. 4.

$$X_{j,i}^0 = X_{j,L,i} + \text{rand}(X_{j,H,i} - X_{j,L,i}) \quad (4)$$

where rand is a random number within $[0, 1]$ interval.

As shown in Eq. 4, the initial population is described as $S^G = [X_i^G]$, $G = 0$. Where $X_i = [X_{j,i}]$, i is the index of the individual vector in population S ($i = 1, 2, \dots, N$), j is the index of the parameter in the individual vector ($j = 1, 2, \dots, D$), and G is the number of generation ($G = 1, 2, \dots, G_{\max}$). The objective function value for each individual vector in the population is calculated and then the best function value is specified.

3.2 Local Search

The local search procedure is used to explore the neighborhood of the D -parameter of the individual vector [21]. Two control parameters are used in the local search strategy namely LSITER and δ . The LSITER is the number of the iteration that the local search repeats and δ is a multiplier factor for the neighborhood search. The local search of EM algorithm can be described as follows;

The maximum step length for each parameter of the individual vector is calculated first by subtracting the corresponding lower limits from the upper limits. After that, δ is used to weight the difference.

Secondly, each individual vector is improved by searching the coordinates, whereas the individual vector X_i^G is stored in a temporary vector y_j and the last vector is moved by adding the random step length to the initial value of y_j .

After that, the individual vector X_i^G is replaced by y_j if the objective function value of y_j is less than X_i^G vector within the iteration of local search.

Eventually, the neighborhood search for the individual vector i ends and the new best individual and its objective function value are updated.

3.3 Calculation of Exerted Force

In this stage, the total force exerted on each D -dimensional individual vector by all other $D - 1$ -dimensional individual vectors in the population is calculated. Here, each D -dimensional individual vector will have $N - 1$ D -dimensional individual vectors exerting force on it. The force exerted on an individual vector X_i^G by another individual vector X_j^G that is calculated based on the charges of these vectors [22]. The charge of i individual vector X_i^G is computed by,

$$q_i^G = \exp \left[-D \left(\frac{f(X_i^G) - f(X_b^G)}{\sum_{k=1}^N [f(X_k^G) - f(X_b^G)]} \right) \right], i = 1, 2, \dots, N \text{ and } G = 1, 2, \dots, \text{MAXITER} \quad (5)$$

Where X_b^G is the current best individual vector for G generation, $f(X)$ is the objective function value for individual vector X and MAXITER is the maximum number of generation. The D -dimensional force vector F_{ij}^G exerted on the individual vector X_i^G by an individual vector X_j^G that is computed by,

$$F_{ij}^G = \begin{cases} (X_j^G - X_i^G) \frac{q_i^G q_j^G}{\|X_j^G - X_i^G\|^2} & \text{if } f(X_j^G) < f(X_i^G) \\ (X_i^G - X_j^G) \frac{q_i^G q_j^G}{\|X_j^G - X_i^G\|^2} & \text{if } f(X_j^G) \geq f(X_i^G) \end{cases} \quad (6)$$

If the objective function value of the individual vector X_j^G is better than the individual vector X_i^G , then X_j^G will attract X_i^G , otherwise it will repel X_i^G . Therefore, individual vectors with relatively good objective function values attract other individual vectors. Meanwhile the individual vectors with worse objective function values repel the others. The total force F_i^G exerted on the individual vector X_i^G by all other individual vectors in the population is calculated by,

$$F_i^G = \sum_{k=1, k \neq i}^N F_{ik}^G, i = 1, 2, \dots, N \quad (7)$$

3.4 Generating new population

After the total force exerted on, an individual vector X_i^G is computed, the new D -parameters individual vector is generated, as in Eq. (8), by moving X_i^G along the direction of F_i^G by a magnitude that is randomly selected from the range $[0, 1]$.

$$X^i = X^i + \lambda \frac{F^i}{\|F^i\|} R \quad i = 1, 2, \dots, N \quad (8)$$

The R is a vector has components refer to the allowed feasible movement towards the lower or upper limit of the j th parameter of individual vector based on the j th value of the total force vector which is greater or less than zero [21].

The last three stages of EM algorithm are repeated until the maximum number of iteration (MAXITER) is reached or a good fitness value is obtained. Fig. 2 shows the flow chart of EM-algorithm.

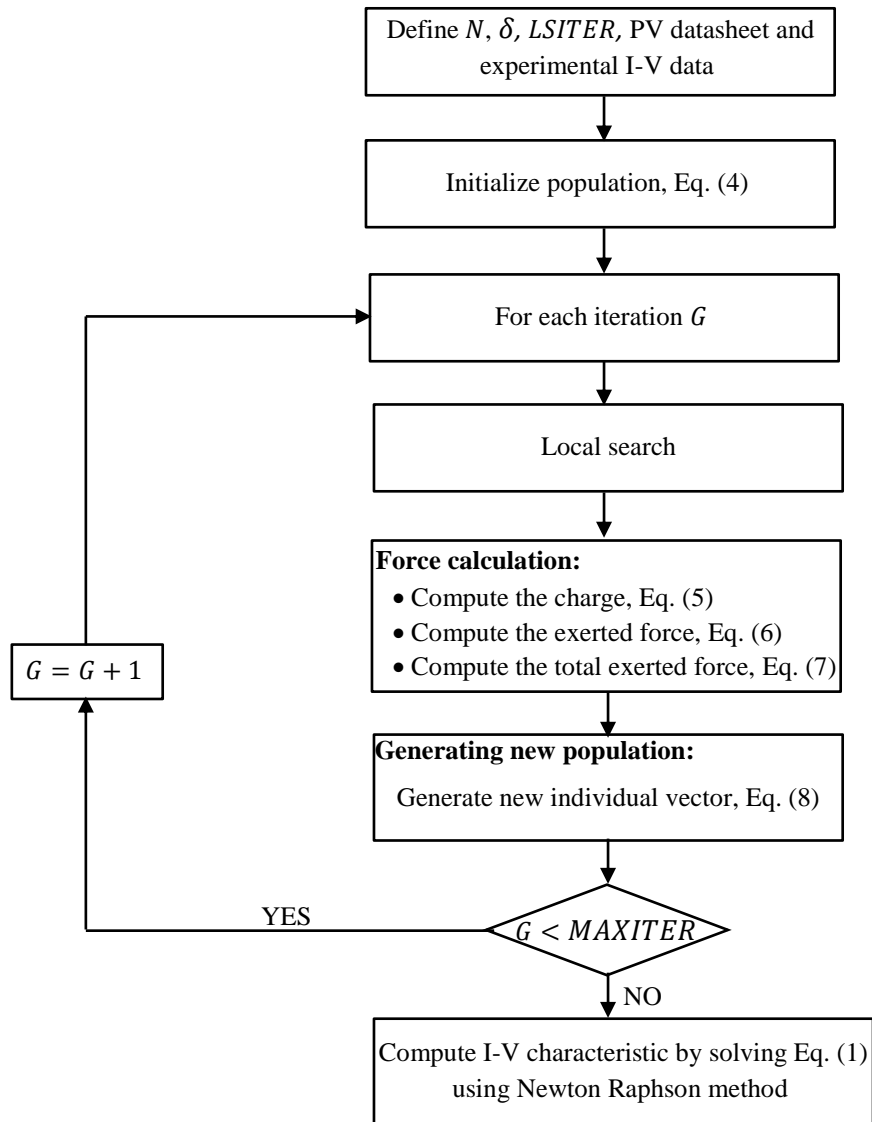


Fig. 2. Flow chart of estimating PV module's model parameters based on EM-algorithm

4. Results

An experimental I-V data performance of a multicrystalline Kyocera KC 120-1 photovoltaic module is used in this research. The manufacturer specification of PV module are illustrated in Table 1.

The typical design space of series resistance (R_s), parallel resistance (R_p), ideality factor of diode (a), saturation current of diode (I_0), and photocurrent are chosen to be within the range $\{0.01, 2\} \Omega$, $\{100, 5000\} \Omega$, $\{1, 2\}$, $\{1e-12, 1e-5\} A$, and $\{1, 8\} A$, respectively [23, 24].

The effectiveness and results accuracy of the proposed modeling method is verified by comparing the results with experimental I-V data and another analytical model that proposed in the literature in [7]. The comparison is achieved under seven various operational conditions

with solar irradiance levels were 118.28, 148, 306, 711, 780, 840, and 978 W/m² with corresponding PV cell temperature 318.32, 321.25, 327.7, 324.21, 329.1, 331.42, and 328.56 K [7]. The data collected at Subang meteorological station in Subang Jaya, Klang Vally, Kuala Lumpur, Malaysia with latitude 3.12° north and longitude 101.6° east.

Four statistical tools used as evaluation criteria in the comparison; the criteria are root mean square error (RMSE), mean bias error (MBE), coefficient of determination (R²), and absolute error (AE). The RMSE refers to the standard deviation between the experimental and computed currents for a given voltage value in the I-V curve under a specific operational conditions as follows:

$$RMSE = \sqrt{\frac{1}{n} (\sum_{i=1}^n (I_c - I_e)^2)} \quad (9)$$

Where, I_c is the computed PV module current by the proposed model (A), I_e is the experimental PV module current (A), and n is the length of the data set of I-V points. The MBE is another evaluation criteria that used to evaluate the performance of the proposed model under n-data set of I-V points. The MBE is defined by;

$$MBE = \frac{1}{n} (\sum_{i=1}^n (I_c - I_e)) \quad (10)$$

The third criterion is R² that reflects the level of variation in the experimental I-V data. The high consistency between the experimental and simulation results leads to R² value close to 1. R² can be formulated by;

$$R^2 = 1 - \frac{\sum_{i=1}^n (I_c - I_e)^2}{\sum_{i=1}^n (I_c - \bar{I}_e)^2} \quad (11)$$

Where \bar{I}_e is the arithmetic mean value of experimental current under n-data set of I-V points and it is calculated by;

$$\bar{I}_e = \frac{1}{n} \sum_{i=1}^n I_e \quad (12)$$

The last criteria used for evaluation the results is AE which is the absolute difference between the experimental and computed current for a given voltage value belong to I-V curve under a specific operation condition. Therefore the AE can be formulated by;

$$AE = |I_c - I_e| \quad (13)$$

The unknown PV module model parameters are R_s, R_p, α, I_p, and I_o. Thus, the dimension of the current optimization problem is chosen to be five as the parameters of PV module. In the meanwhile, the population size (N) and maximum number of iteration (MAXITER) are set to be 10D and 500, respectively. The control parameters S and LSITER are assumed 0.01 and 30, respectively to obtain better results according to many attempts of running the algorithm. The five extracted parameters of single diode PV module's model based on EM algorithm under various operational conditions are tabulated in Table 2.

The I-V and P-V curve under seven operation conditions are shown in Fig. 3 and Fig. 4, respectively. According to Fig. 3, the results of the proposed model are more close to experiment data. Thus, the proposed modeling method is effectiveness to extract the parameters of single diode PV module's model.

A detailed comparison between the proposed modeling method and the method proposed by Tamer et al. in [7] is illustrated in Table 3. According to Table 3, the RMSE, MBE, and AE values of the proposed method are always less than those offered by [7]. The proposed method exhibits average value of RMSE, MBE, and AE around 0.072, 0.007, and 0.053, respectively. On the other hand, the method proposed by [7] offered 0.381, -0.042, and 0.188 for average RMSE, MBE, and AE, respectively. Furthermore, the R^2 values offered by the proposed method is greater than and more close to 1 than obtained from the method proposed by [7] under various operation conditions. The average R^2 of the proposed method and [7] are 0.990 and 0.909, respectively.

Fig. 5 shows the evolution of fitness function over the generation number for seven operation conditions that denominated from G1 to G7. The proposed algorithm to estimate the parameter is fast and offered low final fitness function value, especially for low irradiance cases, because these cases has less I-V points.

Table 1 The key specifications of the PV module.

Characteristics	Value
Maximum power at STC (P_{max})	120 WP
Open-circuit voltage (V_{oc})	21.5 V
Short-circuit current (I_{sc})	7.45 A
Voltage at maximum power point (V_{mp})	16.9 V
Current at maximum power point (I_{mp})	7.1 A
Number of cells connected in series	36
Temperature coefficient of I_{sc} (α)	1.325 mA/K
Temperature coefficient of V_{oc} (β)	-77.5 mV/K

Table 1: Five extracted parameters of single diode PV module model under various operation conditions.

Solar Radiation (W/m^2)	Cell Temperature (K)	a	R_S	R_P	I_{Ph}	I_o
118.28	318.32	1.50820	1.18128	183.89179	0.92907	7.42E-06
148	321.25	1.40056	0.39518	139.23065	1.00000	4.2E-06
306	327.7	1.35890	0.59146	5000	1.95218	6.04E-06
711	324.21	1.28946	0.53042	403.12163	4.38625	2.76E-06
780	329.1	1.38019	0.26630	100	5.03144	9.92E-06
840	331.42	1.31699	0.21956	100	5.36415	7.31E-06
978	328.56	1.36288	0.21769	100	6.24685	8.88E-06

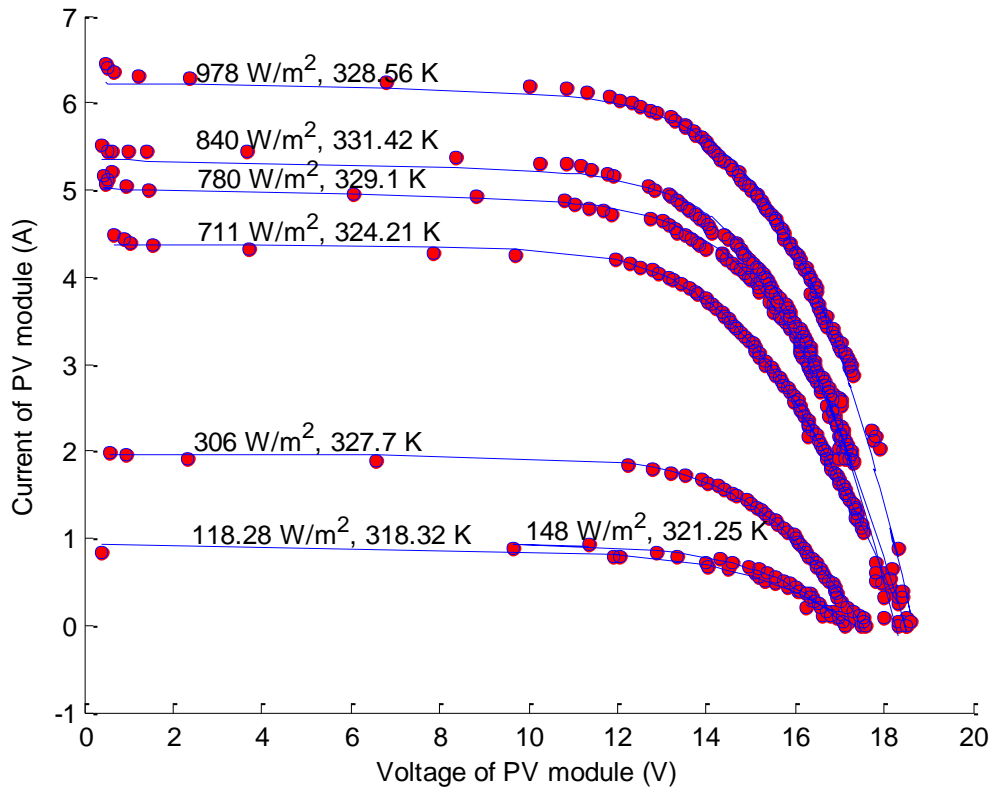


Fig. 3. I-V curve of PV module under various operating conditions.

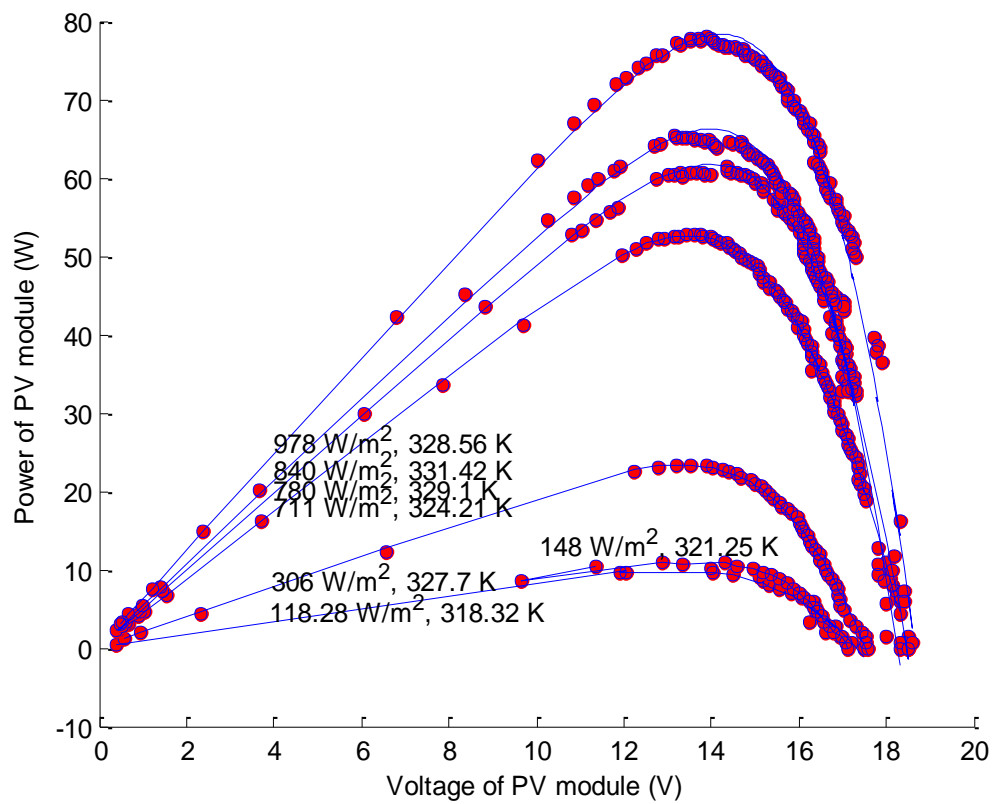


Fig. 4. P-V curve of PV module under various operating conditions.

Table 2: RMSE, MBE, R2, and average error of the proposed and Tamer's models under various operation conditions,

Solar Radiation (W/m ²)	EM-Model				Tamer-Model [7]			
	RMSE	MBE	R ²	Average of AE	RMSE	MBE	R ²	Average AE
118.28	0.04738	0.00224	0.96566	0.03433	0.07009	0.04244	0.92485	0.04780
148	0.01863	0.00035	0.99547	0.01541	0.13896	0.12083	0.74812	0.12157
306	0.03704	0.00137	0.99598	0.02769	1.17084	-1.01480	0.96186	0.09778
711	0.03779	0.00143	0.99883	0.02638	0.17704	-0.00784	0.97429	0.13203
780	0.10517	0.01106	0.99319	0.07061	0.34138	-0.06938	0.92826	0.25034
840	0.11232	0.01262	0.99322	0.08622	0.14513	0.08737	0.98868	0.10011
978	0.14903	0.02221	0.99052	0.11145	0.62289	0.54534	0.83446	0.56613
Average	0.07248	0.00733	0.99041	0.05316	0.38090	-0.04229	0.90865	0.18796

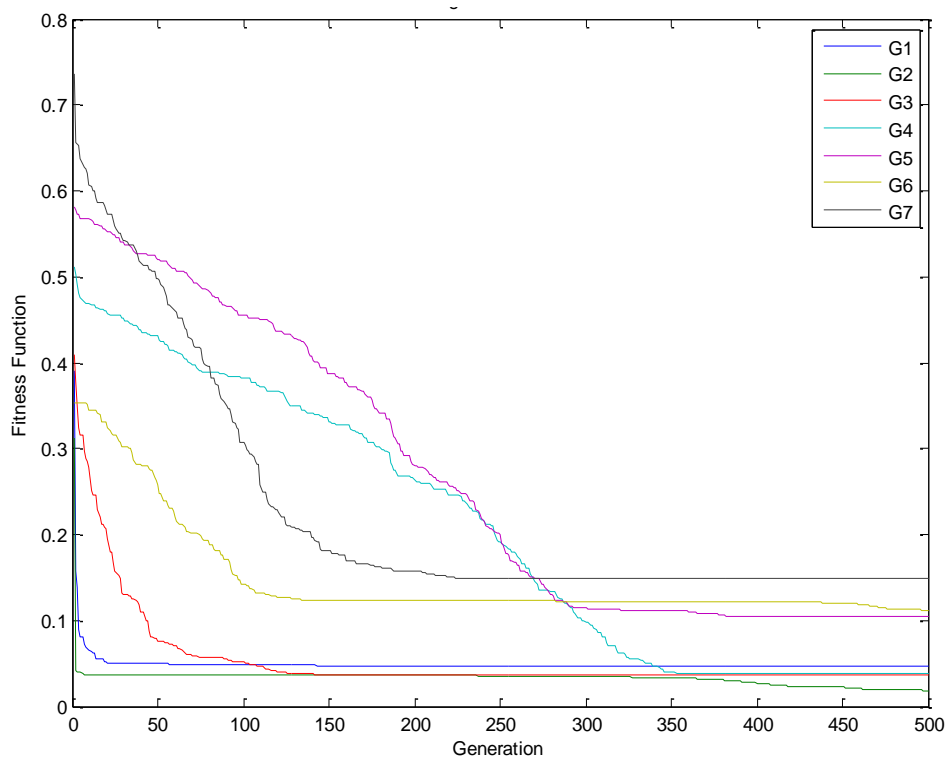


Fig. 5. Evolution of fitness function of various operation conditions over the generations.

5. Conclusions

An electromagnetism-like algorithm is used to estimate the parameters of PV module as a single diode model under various meteorological conditions. Five decision variables (a , R_s , R_p , I_{ph} , and I_o) are optimized based on objective function that represented as the root mean square error between the experimental and computed PV output current for a realistic set of I-V data points. Experimental I-V data under seven different levels of solar irradiance and ambient temperature are used. The proposed method offers I-V characteristics more close to experimental values than other methods that proposed in literature. The proposed method exhibits an average mean bias error and coefficient of correlation under seven different operation conditions were 0.00733 and 0.99041, respectively.

5. References

1. D. H. Muhsen, A. B. Ghazali, T. Khatib, and T. E. Abdulabbas. 2017, "*Techno-economic study and optimal sizing of a stand-alone photovoltaic water pumping system.*" International Transactions on Electrical Energy Systems 27, no. 9.
2. E. O. U.S. Energy Information Administration. (September 2011). China and India account for half of global energy growth through 2035. Available: <http://www.eia.gov/todayinenergy/detail.cfm?id=3130>
3. Haider HT, See OH, Elmenreich W. 2016, "*Residential demand response scheme based on adaptive consumption level pricing*". Energy;113:301–8. doi:10.1016/j.energy.2016.07.052..
4. D. H. Muhsen, A. B. Ghazali, T. Khatib, and I. A. Abed, 2015, "*Extraction of photovoltaic module model's parameters using an improved hybrid differential evolution/electromagnetism-like algorithm,*" Solar Energy, vol. 119, pp. 286-297, 9//.
5. T. Ma, H. Yang, and L. Lu, 2014, "*Solar photovoltaic system modeling and performance prediction,*" Renewable and Sustainable Energy Reviews, vol. 36, pp. 304-315, 8//.
6. D. H. Muhsen, A. B. Ghazali, and T. Khatib, 2015, "*Parameter extraction of photovoltaic module using hybrid evolutionary algorithm,*" in 2015 IEEE Student Conference on Research and Development (SCORED), pp. 533-538.
7. T. Khatib, K. Sopian, and H. A. Kazem, 2013, "*Actual performance and characteristic of a grid connected photovoltaic power system in the tropics: A short term evaluation,*" Energy Conversion and Management, vol. 71, pp. 115-119, 7//.
8. L. H. I. Lim, Z. Ye, J. Ye, D. Yang, and H. Du, 2015, "*A Linear Identification of Diode Models from Single-Characteristics of PV Panels,*" Industrial Electronics, IEEE Transactions on, vol. 62, pp. 4181-4193,.
9. T. Easwarakhanthan, J. Bottin, I. Bouhouch, and C. Boutrit, 1986, "*Nonlinear minimization algorithm for determining the solar cell parameters with microcomputers,*" International journal of solar energy, vol. 4, pp. 1-12,.
10. M. G. Villalva, J. R. Gazoli, and E. R. Filho, 2009, "*Comprehensive Approach to Modeling and Simulation of Photovoltaic Arrays,*" Power Electronics, IEEE Transactions on, vol. 24, pp. 1198-1208.
11. T. Ma, H. Yang, and L. Lu, 2014, "*Development of a model to simulate the performance characteristics of crystalline silicon photovoltaic modules/strings/arrays,*" Solar Energy, vol. 100, pp. 31-41, 2//.
12. K. Ishaque, Z. Salam, and H. Taheri, 2011, "*Simple, fast and accurate two-diode model for photovoltaic modules,*" Solar Energy Materials and Solar Cells, vol. 95, pp. 586-594, 2//.
13. K. Ishaque, Z. Salam, and Syafaruddin, 2011, "*A comprehensive MATLAB Simulink PV system simulator with partial shading capability based on two-diode model,*" Solar Energy, vol. 85, pp. 2217-2227, 9//.
14. K. Tossa, Y. M. Soro, Y. Azoumah, and D. Yamegueu, 2014, "*A new approach to estimate the performance and energy productivity of photovoltaic modules in real operating conditions,*" Solar Energy, vol. 110, pp. 543-560, 12//.

15. R. Navabi, S. Abedi, S. H. Hosseinian, and R. Pal, 2015, "*On the fast convergence modeling and accurate calculation of PV output energy for operation and planning studies*," Energy Conversion and Management, vol. 89, pp. 497-506, 1/1/.
16. S. Lineykin, M. Averbukh, and A. Kuperman, 2014, "*An improved approach to extract the single-diode equivalent circuit parameters of a photovoltaic cell/panel*," Renewable and Sustainable Energy Reviews, vol. 30, pp. 282-289, 2//.
17. N. Sharma, Varun, and Siddhartha, 2012, "*Stochastic techniques used for optimization in solar systems: A review*," Renewable and Sustainable Energy Reviews, vol. 16, pp. 1399-1411, 4//.
18. Khare and S. Rangnekar, 2013, "*A review of particle swarm optimization and its applications in Solar Photovoltaic system*," Applied Soft Computing, vol. 13, pp. 2997-3006, 5//.
19. P. Wei, Z. Yun, G. Hao, L. Yong-qing, Y. Yong-hong, and H. Wei, 2013 "*Evolutionary algorithm and parameters extraction for dye-sensitised solar cells one-diode equivalent circuit model*," Micro & Nano Letters, IET, vol. 8, pp. 86-89.
20. Issa Ahmed Abed, S.P. Koh, K.S.M. Sahari, S.K. Tiong and Nadia M.L Tan, 2014, "*Solving the Inverse Kinematics for Robot Manipulators using Modified Electromagnetism-like Algorithm with Record to Record Travel*,". Research Journal of Applied Sciences, Engineering and Technology 7(19): 3986-3994.
21. Ş. İ. Birbil and S.-C. Fang, 2003, "*An electromagnetism-like mechanism for global optimization*," Journal of global optimization, vol. 25, pp. 263-282.
22. A. Abed, S. Koh, K. S. M. Sahari, P. Jagadeesh, and S. Tiong, 2014, "*Optimization of the Time of Task Scheduling for Dual Manipulators using a Modified Electromagnetism-Like Algorithm and Genetic Algorithm*," Arabian Journal for Science and Engineering, vol. 39, pp. 6269-6285.
23. D. H. Muhsen, A. B. Ghazali, T. Khatib, and I. A. Abed, 2016, "*A comparative study of evolutionary algorithms and adapting control parameters for estimating the parameters of a single-diode photovoltaic module's model*." Renewable energy vol. 96, pp. 377-389.
24. D. H. Muhsen, A. B. Ghazali, T. Khatib, and I. A. Abed, 2015, "*Parameters extraction of double diode photovoltaic module's model based on hybrid evolutionary algorithm*". Energy Conversion and Management, vol. 105, pp.552-561.