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Research Article

Estimation and Analysis of the Characteristic Parameters of Photovoltaic Cells by Mayfly Algorithm

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Abstract

In recent years, renewable energy sources such as solar energy have been increasing their importance in energy production day by day. Various studies have been carried out in the literature for the effective performance and control of solar cells that generate energy from the sun. Various solar cell models, such as single diode and double diode models, have been developed to improve performance and control. However, the main problem in these studies is the estimation of characteristic parameters accurately and efficiently. In the last decade, this problem has been tried to be solved by using metaheuristic algorithms in the literature. In this study, for the first time, the Mayfly algorithm (MA) is used for characteristic parameter estimation of photovoltaic models. In order to analyze the estimation performance of the proposed approach, frequently used solar cells and diode models are examined. The results were compared with literature studies. Current-voltage and Power-voltage graphs used to find the maximum point were created using the estimated parameters. The results obtained and the graphs drawn show that the proposed approach is correct and effective in parameter estimation of photovoltaic cells.

Keywords: Mayfly Algorithm, Photovoltaic, Parameter Estimation, Optimization.

Fotovoltaik Hücrelerin Karakteristik Parametrelerinin Mayıs Sineği Algoritması ile Kestirimi ve İncelemesi

Öz

Son yıllarda Güneş enerjisi gibi yenilenebilir enerji kaynakları enerji üretimindeki önemini gün geçtikçe artırmaktadır. Literatürde güneşten enerji üreten güneş pillerinin etkin performansı ve kontrolü için çeşitli çalışmalar yapılmaktadır. Tek diyot ve çift diyot modelleri gibi çeşitli güneş pili modelleri performansı ve kontrolü artırmak için geliştirilmiştir. Ancak bu çalışmalarda asıl problem doğru ve verimli bir şekilde karakteristik parametrelerin kestirimidir. Son on yılda literatürde metasezgisel algoritmalar kullanılarak bu problem çözülmeye çalışılmıştır. Bu çalışmada, ilk kez, Mayıs sineği algoritması (MA) fotovoltaik modellerin karakteristik parametre kestirimi için kullanılmıştır. Önerilen yaklaşımın kestirim performansını analiz etmek amacıyla sık kullanılan güneş pilleri ve diyot modelleri incelenmiştir. Sonuçlar literatür çalışmaları ile karşılaştırılmıştır. Maksimum noktanın bulunmasında kullanılan akım-gerilim ve güç-gerilim grafikleri kestirilen parametreler kullanılarak oluşturulmuştur. Elde edilen sonuçlar ve çizilen grafikler, fotovoltaik hücrelerin parametre kestiriminde önerilen yaklaşımın doğru ve etkili olduğunu göstermektedir.

Anahtar Kelimeler: Mayıs Sineği Algoritması, Parametre Kestirimi, Fotovoltaik, Optimizasyon.

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1. Introduction

In recent years, the usage of carbon-based resources in vehicles and energy production has caused global warming problems and caused climate changes in many places around the world, especially in the poles. For this reason, the idea of using renewable and clean energy sources in daily life, vehicles and energy production has been adopted by many researchers and practitioners. So, the interest in renewable resources such as solar, wind, wave and geothermal is increasing day by day. In particular, the ability of solar energy to be used as an energy source both in the world and in space increases its importance (Ayala et al., 2015).

The main systems that provide energy production from the sun are photovoltaic (PV) systems (Olivia et al., 2014). Because, they can be directly convert solar energy into electric energy, PV systems have been setup and applied worldwide and in space, such as Mars explorer systems, satellites and energy harvesting fields. Although PV systems provided great advantages in energy generation, they had some weaknesses that had to be overcome (Brano & Ciulla, 2013). While PV systems provided great advantages in energy generation, they had some weaknesses to overcome, such as temperature, irradiance, micro defects, and partial shading. Therefore, to solve the problems mentioned above, it is necessary to develop an accurate and effective model of the PV system. The current-voltage (I-V) characteristic of solar (PV) system is nonlinear because of its parameters and it is important to recommend an accurate model using measured current-voltage data (Parida et al., 2011, Nassar-Eddine et al., 2016). In literature, to optimize and simulate PV system, single (SD) and double (DD) diode models has been proposed (Askarzadeh & Rezazadeh, 2012). In these models, there are five and seven unknown parameters, respectively. The accurate and effective estimation of unknown parameters from measured I-V data is an important for modelling, simulating and evaluating of the PV systems.

In literature, analytical, deterministic and meta-heuristic methods have been employed for characteristic parameter estimation of PV models from measured I-V data.

In the beginning, analytical methods including simple and fast solutions using mathematical equations were tried to be developed. However, the assumptions made in the initial state negatively affected the accuracy of the model (Chan & Phang, 1987; Ortiz-Conde et al., 2006; Saleem & Karmalkar, 2009).

Deterministic methods have been proposed to solve the problems encountered by analytical methods, but nonlinearity and multimodality have hampered the solution effectiveness of deterministic approaches (Easwarakhanthan et al., 1986; Tong et al., 2015).

Meta-heuristic algorithms provided sufficiently good solution for multimodal, multidimensional, constrained and constrained, linear and nonlinear optimization problems and inspired by natural phenomenon such as swarm behaviors, evolutionary stages and natural events. Recently, to overcome the disadvantages mentioned above, meta-heuristic methods have been applied for parameter extraction of PV model.

Genetic algorithm (GA) was applied to parameter extraction of fuel cells and three types PVs simulated with MATLAB/Simulink (Balasubramanian et al., 2015; İsmail et al., 2013). Particle swarm optimization (PSO) algorithm, and its variant (enhanced leader PSO, chaotic heterogeneous comprehensive learning PSO) were employed for parameter determining of static and dynamic PV models. (Jordehi, 2018; Nunes et al., 2018; Yousri et al., 2019). Penalty based differential evolution (DE), repaired adaptive DE and memetic adaptive DE algorithms were proposed for different PV models such as thin film, mono- and multi crystalline (Ishaque et al., 2012; Gong & Zhihua, 2013; Li et al., 2019). Cuckoo search (CS) algorithm was hybridized with biogeography-based optimization for different PV models (Chen et al., 2019). Artificial bee colony (ABC) algorithm and its teaching–learning–based version were compared with other suggested methods for PV parameters estimation (Olivia et al., 2014; Chen et al., 2018). Bacterial foraging optimization (BFO) algorithm and its modified approaches were proposed for parameter estimator design from nameplate data of solar cells (Rajasekar et al., 2013; Subudhi & Pradhan, 2018; Awadallah, 2016). Biogeography-based optimization (BBO) algorithm was improved with mutation strategies and hybridization for estimating solar and fuel cells parameters at different models (Chen & Yu, 2019; Niu et al., 2014). Flower pollination algorithm (FPA) and its hybrids were used for different types PV modules at different irradiance (Alam et al., 2015; Xu & Wang, 2017; Olivia et al.,2019). The improved and basic versions of Jaya optimization (JAYA) algorithms were successively applied for estimation and a comprehensive comparison has been made. (Yu et al., 2017; Yu et al., 2019). The parameter estimations of salp swarm (SSA) algorithm and bird mating (BMO) optimization algorithm were realized at different operating (Abbassi et al., 2019; Askarzadeh & Coelho, 2015). Teaching-leaning-based optimization (TLBO) and its improved and hybridized versions were employed and compared for parameter identification (Chen et al., 2018; Li et al., 2019; Patel et al., 2014; Yu et al., 2017; Chen et al.,2016]. Also, Backtracking search algorithm (BSA) was improved with multiple learning strategy and suggested for determining parameters of single diode (SD), double diode (DD) and PV module (Yu et al., 2018). Improved chaotic whale optimization algorithm was performed for comparisons of experimental results (WOA) (Olivia et al., 2017). Sine cosine algorithm (SCA) was developed with opposition-based learning strategy and tested PV parameter identification (Chen et al., 2019). Imperialist competitive algorithm was applied to estimation for mono-, poly- and amorphous modules (ICA) (Fathy & Rezk, 2017). Multi-verse optimizer (MVO) algorithm was analyzed for estimation at varying sun irradiance and temperature cases (Ali et al., 2016), Improved ant lion (ALO) optimizer algorithm and cat swarm (CSO) optimization algorithm were employed parameter estimation of PV modules (Wu et al., 2017; Guo et al., 2016).

Also, parameters extraction of different structure PV models have been analyzed using grouping-based global, innovative global and basic harmony search algorithm (HS) (Askarzadeh & Rezazadeh, 2012), hybrid firefly (FA) algorithm and pattern search algorithm (Beigi & Maroosi, 2018), modified simplified swarm optimization algorithm (SSO) (Lin et al., 2017), moth-flame (MFO) optimization (Allam et al., 2016), eagle (ES) strategy (Chen eet al., (2016), water cycle (WCA) algorithm (Kler et al., 2017; Rezk & Fathy, 2017), shuffled frog leaping algorithm (SFL) (Hasanien, 2015), hybrid grew wolf (GWO) algorithm (Long et al., 2020) at varying irradiance and room temperature.

According to the literature review mentioned above, parameter extraction of PV models from the I-V data is an important real world problem for researcher and practitioners in energy area. Especially, to realize accurate and fast estimation, we need optimization algorithms with high exploration and exploitation capabilities. Of course, with these capabilities, the optimization algorithm should be easy and simple to use for real time application.

In 2020, unlike many well-known meta-heuristic algorithms, Mayfly algorithm (MA) that has a fast and robustness convergence behavior in both the local and the global search space was proposed as a swarm based algorithm (Zervoudakis & Tsafarakis, 2020). MA is inspired by flight and mating behavior of male and female mayflies. It is analyzed for single- and multi-objective optimization tasks and benchmarked in well-known literature test problems such as CEC2017 and flow-shop scheduling. Also, MA is tested for continuous and discrete real engineering problems. The results show that MA has a good solution performance compared with the other algorithms such as PSO, FA, DE, HS, invasive weed optimization (IWO) and bees (BA) algorithms. The successful rise of the MA algorithm in the literature has attracted the attention of researchers and practitioners and this algorithm has been applied in the solutions of new developed and old optimization problems.

For the aforementioned purpose, in this paper, Mayfly algorithm (MA) was applied to extract the characteristic parameter of single diode, double diode and PV modules. To the best of our knowledge, there is no paper in literature about parameter determination of PV models using MA. The motivations and contributions of this paper are given as follows:

- For characteristic parameter estimation of PV cells, MA algorithm was firstly applied in literature.

- The current-voltage data of Photowatt-PWP-201 and R.T.C France PV cells were used to connect the study to the real world problem.

- The estimation performance of MA algorithm was extensively compared with those of the state-of-algorithms in literature. Also, using estimated parameters, P-V and I-V curves were obtained and compared with those of the measured data curves of PV cells.

- The results demonstrate that MA algorithm has a significant performance for parameter determination of PV models and it can be used an alternative method.

This paper is explained in 5 sections. In section 2, the problem of parameter estimation of PV models is explained. MA algorithm is proposed in Section 3. Results and analysis are represented in detail and the comparisons with other algorithms are made in Section 4. Lastly, Section 5 includes conclusions.

2. Mathematical Modelling of PV Cell

In literature, SD and DD models are the most preferred reference designs for PV cell parameter estimation. Also, using reference designs, several parallel or series connected diodes are used to model the PV panel modules. The simplified circuit designs of SD, DD and PV panel models are shown in Figure 1.

In this section, firstly, single diode and double diode models are explained in detail with basic diode parameters definitions. Secondly, it was explained how PV panel modules are modeled using diode models. Finally, it is discussed how aforementioned models are embedded in the objective functions to be used for parameter estimation in optimization algorithms.

2.1. Mathematical Model of Single Diode

The SD model is mathematically expressed as:

$$I = I_{ph} - I_{sd}\left[\exp\left(\frac{q(V + I\cdot R_s)}{n\cdot k\cdot T}\right) - 1\right] - \frac{V + I\cdot R_s}{R_{sh}} \qquad (1)$$

where I, I_{ph} and I_{sd} are cell output, photo and reverse saturation currents. Also, V is output voltage, R_s represents series resistance, R_{sh} shows shunt resistance, n is ideality factor, k denotes Boltzmann constant, T shows cell temperature (Kelvin) and electron charge is q. I_{sd}, I_{ph}, R_s, R_{sh} and n are main characteristic parameter of SD model and they are estimated using optimization algorithms.

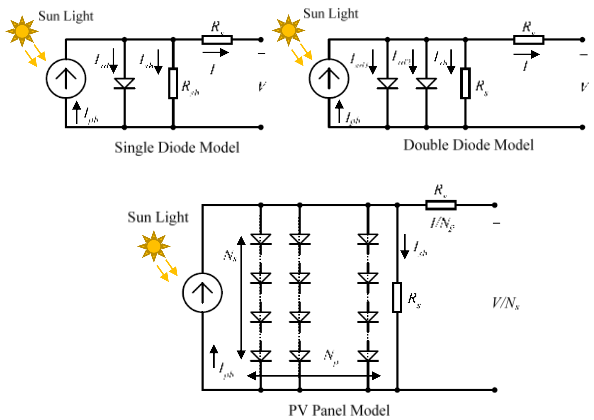

Figure 1. Simplified circuit designs of SD, DD and PV panel models

2.2. Mathematical Model of Double Diode

Using SD model, mathematical model of DD is given as:

$$\begin{aligned} I = I_{ph} - I_{sd1}\left[\exp\left(\frac{q(V + I\cdot R_s)}{n_1\cdot k\cdot T}\right) - 1\right] - \ldots \\ I_{sd2}\left[\exp\left(\frac{q(V + I\cdot R_s)}{n_2\cdot k\cdot T}\right) - 1\right] - \frac{V + I\cdot R_s}{R_{sh}} \end{aligned} \qquad (2)$$

where I_{sd1} and I_{sd2} are reverse saturation currents of first and second diodes while n_1 and n_2 are the ideality factors. I_{ph}, I_{sd1}, I_{sd2} R_s, R_{sh}, n_1 and n_2 are the main characteristic parameter of double diode model and they are estimated using optimization algorithms.

2.3. Mathematical Model of PV Panel

The output current of PV panel is represented as

$$\begin{aligned} I/N_p = I_{ph} - I_{sd}\left[\exp\left(\frac{q(V/N_s + R_s\cdot I/N_p)}{n\cdot k\cdot T}\right) - 1\right] \ldots \\ - \frac{V/N_s + R_s\cdot I/N_p}{R_{sh}} \end{aligned} \qquad (3)$$

where N_p and N_s show the number of series or parallel connected solar cells in PV panel. The aforementioned model is constructed using single diode model and the unknown parameters (I_{ph}, I_{sd}, R_s, R_{sh}, n) are the same as in that model. Generally in practice, the solar cells in PV panel are connected in series, hence N_p is determined as 1.

2.4. Objective Functions of Parameter Estimation Problem

In this paper, to optimize the characteristic parameters estimation of SDM, DDM and PV panel models, three objective function were applied using aforementioned models. The objective functions of SD, DD and PV panel model are formulated in Equation 4, respectively.

$$\begin{cases} f(V,I,x) = I - \left(I_{ph} - I_{sd}\left[\exp\left(\dfrac{q(V+I\cdot R_s)}{n\cdot k\cdot T} \right) - 1 \right] - \dfrac{V+I\cdot R_s}{R_{sh}} \right) \\ x = \{ I_{ph}, I_{sd}, R_s, R_{sh}, n \} \\ f(V,I,x) = I - \begin{pmatrix} I_{ph} - I_{sd1}\left[\exp\left(\dfrac{q(V+I\cdot R_s)}{n_1\cdot k\cdot T} \right) - 1 \right] - ... \\ I_{sd2}\left[\exp\left(\dfrac{q(V+I\cdot R_s)}{n_2\cdot k\cdot T} \right) - 1 \right] ... \\ -\dfrac{V+I\cdot R_s}{R_{sh}} \end{pmatrix} \\ x = \{ I_{ph}, I_{sd1}, I_{sd2}, R_s, R_{sh}, n_1, n_2 \} \\ f(V,I,x) = \left(I/N_p \right) - \begin{pmatrix} I_{ph} - I_{sd}\left[\exp\left(\dfrac{q(V/N_s + R_s\cdot I/N_p)}{n\cdot k\cdot T} \right) - 1 \right] ... \\ -\dfrac{V/N_s + R_s\cdot I/N_p}{R_{sh}} \end{pmatrix} \\ x = \{ I_{ph}, I_{sd}, R_s, R_{sh}, n \} \end{cases} \tag{4}$$

For all three objective functions given above, the root mean square error (RMSE) as suggested in literature is the error function. RMSE is calculated between measured and calculated data and it is suggested as follow:

$$RMSE(x) = \sqrt{\frac{1}{K}\sum_{k=1}^{K} f_k(V_k, I_k, x)^2} \tag{5}$$

where K is the number of real-time measured data. The optimization algorithm tries to converge the RMSE value to zero as much as possible, thus the error between measured and simulated data is reduced and the accuracy of the estimated characteristic parameters is increased.

3. Mayfly Algorithm

Mayfly Algorithm (MA) is a swarm based optimization algorithm and proposed by Zervoudakis and Tsafarakis in 2020 (Zervoudakis & Tsafarakis, 2020). Mayflies are a type of insect that lives in nature. The mating and flight behaviours of mayflies are simulated by this algorithm. MA is developed for the solutions of continuos and discrete problems and performs well compared to other well-known algorithms. Especially, exploration and explotation process are improved and balanced with nuptial dance and random flight mechanisms. The pseudo-code structure of the MA algorithm is given in Algorithm 1:

Algorithm 1: Pseudo-code of Mayfly Algorithm

1: Setup control parameter, problem dimensions and bounds

2: Generate the male mayflies population $y_i (i = 1, 2, ...M)$ and their velocities v_{mi}

3: Generate the female mayflies population $x_i (i = 1, 2, ...N)$ and their velocities v_{fi}

4: Evaluate solutions applying predefined objective functions.

5: Calculate global best (gbest) and personal best (pbest)

6: **while (stopping criteria)**

7: Update velocities and position of males and females mayflies according to velocity and position limits

8: Evaluate solutions applying predefined objective functions

9: Rank mayflies population

10: Mate mayflies population

11: Evaluate offspring

12: Separate randomly the offspring to male and female

13: Replace worst solutions with the best new solutions

14: Update pbest and gbest

15: **end while**

16: Save best solution population

In Mayfly Algorithm, important optimization phases are movements of male and female mayflies, crossover and mutation. Especially, crossover and mutation form the mating phase of mayflies. The position of male mayflies is formulated as

$$x_i^{t+1} = x_i^t + v_i^{t+1} \tag{6}$$

where x_i^t and x_i^{t+1} are current and new position, respectively. v_i^{t+1} shows the velocity. The velocity is given as

$$v_{ij}^{t+1} = vij + a_1 \times e^{-\beta r_p^2} \times (pbest_{ij} - x_{ij}^t) + a_2 \times e^{-\beta r_g^2} \times (gbest_j - x_{ij}^t) \tag{7}$$

where a_1 and a_2 are positive social and cognitive constant. x_{ij}^t shows the position of particle i in dimension j when v_{ij}^t shows the velocity. Also, pbest and gbest demonstrate the personal and global best solution. $pbest_{ij}$ is given as

$$pbest_i = \begin{cases} x_i^{t+1}, & if\ f(x_i^{t+1}) < f(pbest_i) \\ is\,saved\,same, & otherwise \end{cases} \tag{8}$$

gbest is the best solution of pbest. r_p (between x_i and $pbest_i$) and r_g (between x_i and $gbest$) are the Cartesian distance and β is the fixed visibility coefficient. The nuptial dance is an important scene for best mayfly and change the velocity that is given as

$$v_{ij}^{t+1} = v_{ij}^t + d \times r \tag{9}$$

where d and r are the coefficient of nuptial dance and random value between -1 and 1.

The position of female mayflies is formulated as

$$y_i^{t+1} = y_i^t + v_i^{t+1} \tag{10}$$

where y_i^t and y_i^{t+1} are current and new position, respectively. v_i^{t+1} is the velocity. The velocity is demonstrated as

$$v_{ij}^{t+1} = \begin{cases} v_{ij}^t + a_2 \times e^{-\beta r_{mf}^2}(x_{ij}^t - y_{ij}^t), if\ f(y_i) > f(x_i) \\ v_{ij}^t + fl \times r, if\ f(y_i) \le f(x_i) \end{cases} \tag{11}$$

where v_{ij}^t is the velocity of female particle i in dimension j. a2, β, rmf and fl are positive attraction value, fixed visibility constant, Cartesian distance and random walk value respectively.

The mating phase is realized using crossover and mutation mechanism. They are formulated as

$$\begin{aligned} &Crossover \begin{cases} offspring1 = L \times male + (1-L) \times female \\ offspring2 = L \times female + (1-L) \times male \end{cases} \\ &Mutation \{ offspring_n^{'} = offspring_n + rand\ value \end{aligned} \tag{12}$$

where *L* is specified random value.

3.1. Proposed Approach based MA

Characteristic parameter estimation of SD, DD and PV panel models was realized using Mayfly Algorithm. MA minimized aforementioned objective functions of three models using RMSE function and obtained the best parameter of the desired model from the measured I-V data. In Figure 2, the flowchart of the proposed method based MA is shown.

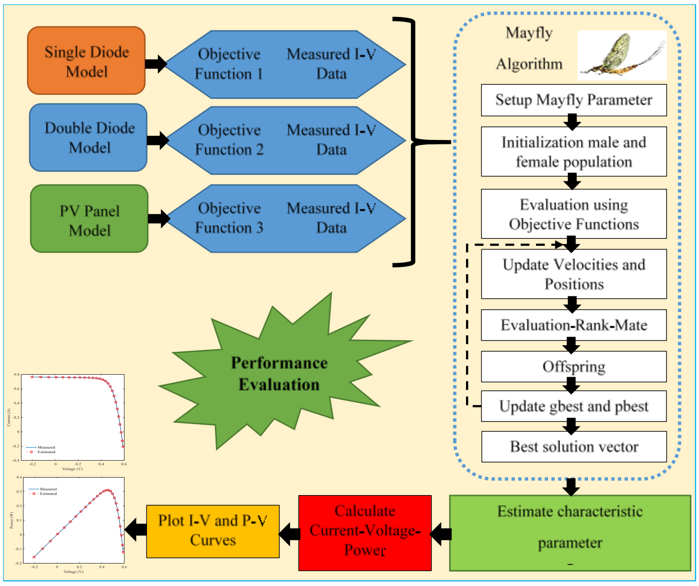

Figure 2. Flowchart of the method based MA for characteristic parameter determination of PV

4. Analysis and Results

In this paper, to analyze performance comparison of the proposed method based MA, the measured I-V data of silicon R.T.C. France solar cell (irradiance: 1000 W/m2, temperature: 33 Celsius), poly-crystalline Photowatt-PWP-201 (36 poly-crystalline, irradiance: 1000 W/m2, temperature: 45 Celsius) are used for characteristic parameter estimation of aforementioned models (Easwarakhanthan et al., 1986; Long et al., 2020).

For a fairly comparison, the search space of the characteristic parameters is selected as in the estimation studies suggested in literature. In Table 1, the lower (LB) and upper (UB) bounds are shown. Also, maximum number of function evaluations (Max_FES) of competitor algorithms is chosen as 50000. But, for MA, Max_FES is set 10000 unlike other competitor algorithms. In this paper, to demonstrate the accurate and robust prediction performance of the MA, several well-known algorithms and their improved versions are compared in the same optimization conditions. For the proposed method by MA, 30 runs with a different initial point are realized and the achieved results are tabulated.

Table 1. Search space of the characteristic parameters

Parameters/ Models	**Single and double diode models**		**Photowatt-PWP-201**	
	LB	**UB**	**LB**	**UB**
I_{ph} (A)	0	1	0	2
I_{sd}, I_{sd1}, I_{sd2} (μA)	0	1	0	50
R_S (Ω)	0	0.5	0	2
R_{sh} (Ω)	0	100	0	2000
n, n_1, n_2	1	2	1	50

4.1. Analysis of Single Diode Model

For SD model, the performance of MA is compared with those of the HISA (Kler et al., 2019), MADE (Li et al., 2019), CS (Chen & Yu, 2019), CS-BBO (Chen & Yu, 2019), ABC (Olivia et al., 2014), TLBO-ABC (Chen et al., 2018), BBO-M (Niu et al., 2014), BLPSO (Yu et al., 2019), CLPSO (Yu et al., 2019), BMO (Askarzadeh & Coelho, 2015), GOTLBO (Chen et al., 2016), IBSA (Yu et al., 2018), LBSA (Yu et al., 2018), DE/BBO (Yu et al., 2018),CWOA (Olivia et al., 2017),ISCA (Chen et al., 2019), IGHS (Askarzadeh & Rezazadeh, 2012), GGHS (Askarzadeh & Rezazadeh, 2012), PSO-WOA (Xiong et al., 2018), SA (El-Naggar et al., 2012), GWO (Long et al., 2020), mGWO (Long et al., 2020), EGWO (Long et al., 2020), AgGWO (Long et al., 2020), SCA (Long et al., 2020), WOA (Long et al., 2020) and GWOCS (Long et al., 2020) algorithms.

In Table 2, the best obtained diode parameters and the minimum values of RMSE of competitor algorithms for single diode model are shown. As seen Table 2, MADE, CS-BBO, TLO-ABC, BMO, CWOA, ISCA and MA algorithms converge to 9.8602E-04 and it is the best value of RMSE.

Table 2. The best obtained diode parameters and RMSE values of competitor algorithms for single diode model.

Algorithm	RMSE	I_{ph}	I_{sd}	R_S	R_{sh}	*n*
ABC (Olivia et al., 2014)	9.8620E−04	0.7608	0.3251	0.0364	53.6433	1.4817
AgGWO (Long et al., 2020)	6.7762E−03	0.769897	0.42945	0.03306	16.8530	1.51294
BBO-M (Niu et al., 2014)	9.8634E−04	0.76078	0.31874	0.03642	53.36277	1.47984
BLPSO (Yu et al., 2019)	1.0272E−03	0.7607	0.36620	0.0359	60.2845	1.4939
BMO (Askarzadeh & Coelho, 2015)	**9.8602E−04**	**0.76077**	**0.32479**	**0.03636**	**53.8716**	**1.48173**
CLPSO (Yu et al., 2019)	9.9633E−04	0.7608	0.34302	0.0361	54.1965	1.4873
CS (Chen & Yu, 2019)	2.0119E−03	0.76048	0.36015	0.03492	43.84232	1.4929
CS-BBO (Chen & Yu, 2019)	**9.8602E−04**	**0.76078**	**0.32302**	**0.03638**	**53.71852**	**1.48118**
CWOA (Olivia et al., 2017)	**9.8602E−04**	**0.76077**	**0.3239**	**0.03636**	**53.7987**	**1.4812**
DE/BBO (Yu et al., 2018)	9.9922E−04	0.7605	0.32477	0.0364	55.2627	1.4817
EGWO (Long et al., 2020)	2.1121E−03	0.763117	0.42126	0.034838	36.1165	1.5091
GGHS (Askarzadeh & Rezazadeh, 2012)	9.9097E−04	0.76092	0.32620	0.03631	53.0647	1.48217
GOTLBO (Chen et al., 2016)	9.8744E−04	0.76078	0.331552	0.036265	54.115426	1.48382
GWO (Long et al., 2020)	7.5011E−03	0.769969	0.91215	0.02928	18.1030	1.596658
GWOCS (Long et al., 2020)	9.8607E−04	0.760773	0.32192	0.03639	53.6320	1.4808
HISA (Kler et al., 2019)	2.0166E−03	1.032368	2.67736	1.23178	748.4507	47.6575
IBSA (Yu et al., 2018)	1.0092E−03	0.7607	0.35502	0.0361	58.2012	1.4907
IGHS (Askarzadeh & Rezazadeh, 2012)	9.9306E−04	0.76077	0.34351	0.03613	53.2845	1.48740
IGWO (Long et al., 2020)	2.3038E−03	0.762763	0.23878	0.036472	30.5388	1.452148
ISCA (Chen et al., 2019)	**9.8602E−04**	**0.760778**	**0.323017**	**0.03638**	**53.7182**	**1.4812**
LBSA (Yu et al., 2018)	1.0143E−03	0.7606	0.34618	0.0362	59.0978	1.4881
MADE (Li et al., 2019)	**9.8602E−04**	**0.7608**	**0.3230**	**0.0364**	**53.7185**	**1.4812**
mGWO (Long et al., 2020)	1.1278E−03	0.760595	0.38534	0.035654	64.6624	1.49911
Proposed	**9.8602E-04**	**0.7608**	**0.32302**	**0.0364**	**53.7185**	**1.4812**
PSO-WOA (Xiong et al., 2018)	1.0710E−03	0.760563	0.340158	0.036124	59.323133	1.486399
SA (El-Naggar et al., 2012)	1.7000E−03	0.7620	0.4798	0.0345	43.1034	1.5172
SCA (Long et al., 2020)	4.1410E−02	0.7852	1.00000	0	6.25833	1.61597
TLBO-ABC (Chen et al., 2018)	**9.8602E−04**	**0.76078**	**0.32302**	**0.03638**	**53.71636**	**1.48118**
WOA (Long et al., 2020)	3.2001E−03	0.7598	0.073481	0.0421	42.77218	1.3453

Table 3. The calculated current, power and IAEs values achieved with MA for the SD model

V (V)	I (A)	Calculated I (A)	IAE (I)	P (W)	Calculated P (W)	IAE (P)
−0.2057	0.7640	0.764087704897160	0.000087704897160	−0.1571548	-0.157172840897346	0.000018040897346
−0.1291	0.7620	0.762663087090251	0.000663087090251	−0.0983742	-0.098459804543351	0.000085604543351
−0.0588	0.7605	0.761355307921703	0.000855307921703	−0.0447174	-0.044767692105796	0.000050292105796
0.0057	0.7605	0.760153991638703	0.000346008361297	0.00433485	0.004332877752341	0.000001972247659
0.0646	0.7600	0.759055209383934	0.000944790616066	0.04909600	0.049034966526202	0.000061033473798
0.1185	0.7590	0.758042345619050	0.000957654380950	0.08994150	0.089828017955857	0.000113482044143
0.1678	0.7570	0.757091654254763	0.000091654254763	0.12702460	0.127039979583949	0.000015379583949
0.2132	0.7570	0.756141365011120	0.000858634988880	0.16139240	0.161209339020371	0.000183060979629
0.2545	0.7555	0.755086872878871	0.000413127121129	0.19227475	0.192169609147673	0.000105140852327
0.2924	0.7540	0.753663878335808	0.000336121664192	0.22046960	0.220371318025390	0.000098281974610
0.3269	0.7505	0.751390966587659	0.000890966587659	0.24533845	0.245629706977506	0.000291256977506
0.3585	0.7465	0.747353851448388	0.000853851448388	0.26762025	0.267926355744247	0.000306105744247
0.3873	0.7385	0.740117221955217	0.001617221955217	0.28602105	0.286647400063256	0.000626350063256
0.4137	0.7280	0.727382224955978	0.000617775044022	0.30117360	0.300918026464288	0.000255573535712
0.4373	0.7065	0.706972651226130	0.000472651226130	0.30895245	0.309159140381187	0.000206690381187
0.4590	0.6755	0.675280151186212	0.000219848813788	0.31005450	0.309953589394471	0.000100910605529
0.4784	0.6320	0.630758271967074	0.001241728032926	0.30234880	0.301754757309048	0.000594042690952
0.4960	0.5730	0.571928357736496	0.001071642263504	0.28420800	0.283676465437302	0.000531534562698
0.5119	0.4990	0.499607017977832	0.000607017977832	0.25543810	0.255748832502852	0.000310732502852
0.5365	0.4130	0.413648791425570	0.000648791425570	0.21744450	0.217786088685563	0.000341588685563
0.5398	0.3165	0.317510108816846	0.001010108816846	0.17084670	0.171391956739333	0.000545256739333

0.5521	0.2120	0.212154938458203	0.000154938458203	0.11704520	0.117130741522774	0.000085541522774
0.5633	0.1035	0.102251311341269	0.001248688658731	0.05830155	0.057598163678537	0.000703386321463
0.5736	−0.0100	-0.00871754175614925	0.001282458243851	−0.0057360	-0.005000381951327	0.000735618048673
0.5833	−0.1230	-0.125507412310708	0.002507412310708	−0.0717459	-0.073208473600836	0.001462573600836
0.5900	−0.2100	-0.208472325535473	0.001527674464527	−0.1239000	-0.122998672065929	0.000901327934071

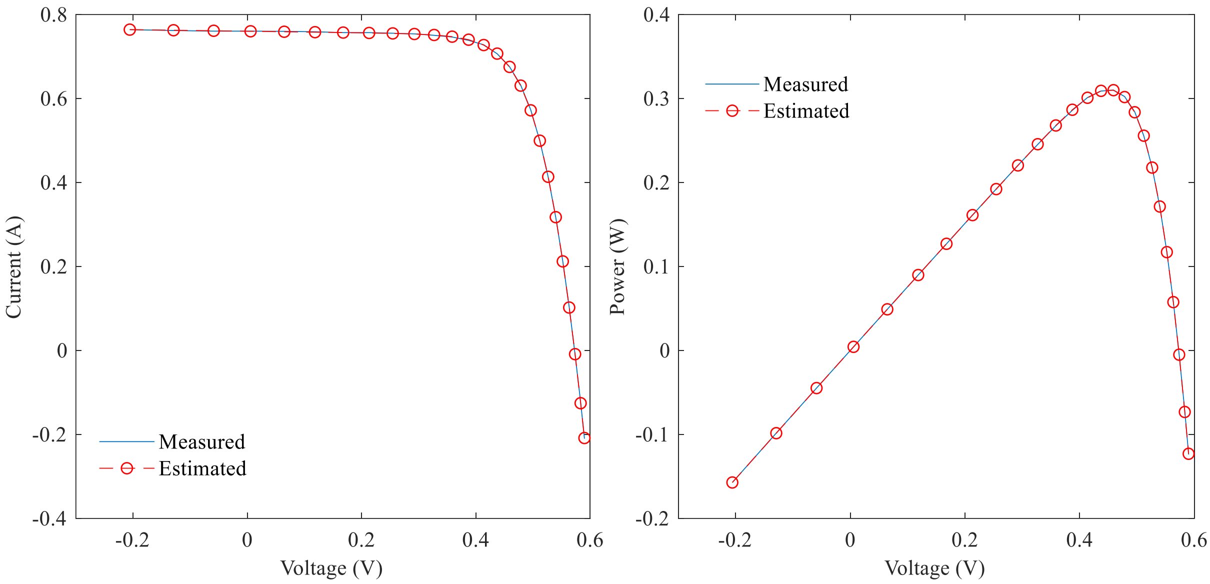

Figure 3. Comparisons between measured data and estimated data achieved by MA for SD model

The calculated values of current, power and individual absolute errors (IAE) achieved with MA for the single diode model are reported in Table 3. Also, using calculated values, P-V and I-V characteristics for SD model are shown in Figure 3. As seen Figure 3, the alignment between the measured and calculated values by MA is quite perfect.

4.2. Analysis of Double Diode Model

For DD model, the performance of MA is compared with those of the TLBO (Li et al., 2019), HISA (Kler et al., 2019), MADE (Li et al., 2019), CS (Chen & Yu, 2019), CS-BBO (Chen & Yu, 2019), ABC (Olivia et al., 2014), TLBO-ABC (Chen et al., 2018), BLPSO (Yu et al., 2019), BMO (Askarzadeh & Coelho, 2015), LBSA (Yu et al., 2018), CWOA (Olivia et al., 2017), ISCA (Chen et al., 2019), IGHS (Askarzadeh & Rezazadeh, 2012), PSO-WOA (Xiong et al., 2018), SA (El-Naggar et al., 2012), GWO (Long et al., 2020), mGWO (Long et al., 2020), EGWO (Long et al., 2020), AgGWO (Long et al., 2020), SCA (Long et al., 2020), WOA (Long et al., 2020) and GWOCS (Long et al., 2020) algorithms.

In Table 4, the best estimated diode parameters and RMSE values of competitor algorithms for double diode model are reported. As reported in Table 4, the best value 9.8237E-04 of RMSE is achieved by ISCA and the second best algorithm is MA with RMSE value 9.8248E-04.

Table 4. The best obtained diode parameters and RMSE values of competitor algorithms for DD model.

Algorithm	**RMSE**	I_{ph}	I_{sd1}	I_{sd2}	R_S	R_{sh}	n_1	n_2
ABC (Olivia et al., 2014)	9.8956E−04	0.76071	0.14623	0.24605	0.03654	55.36509	1.68023	1.46226
AgGWO (Long et al., 2020)	1.1646E−03	0.76003	0.30993	0.071708	0.03643	67.6033	1.4778	1.8839
BLPSO (Yu et al., 2019)	1.1042E−03	0.76056	0.17895	0.31560	0.03553	64.79937	1.69574	1.48789
BMO (Askarzadeh & Coelho, 2015)	9.8262E−04	0.76078	0.21110	0.87688	0.03682	55.8081	1.44533	1.99997
CS (Chen & Yu, 2019)	2.4440E−03	0.76223	0.02732	0.50832	0.03530	97.73242	1.70274	1.52893
CS-BBO (Chen & Yu, 2019)	9.8249E−04	0.76078	0.74935	0.22597	0.03674	55.48544	2	1.45102
CWOA (Olivia et al., 2017)	9.8272E−04	0.76077	0.24150	0.6	0.03666	55.2016	1.45651	1.9899
EGWO (Long et al., 2020)	1.8062E−03	0.76251	0.20856	0.12109	0.03837	32.8813	1.6971	1.3982
GWO (Long et al., 2020)	2.2124E−03	0.761668	0.40302	0.45338	0.03265	72.52775	1.6460	1.5527
GWOCS (Long et al., 2020)	9.8334E−04	0.76076	0.53772	0.24855	0.03666	54.7331	2	1.4588
HISA (Kler et al., 2019)	2.0166E−03	1.032368	2.64194	1.00E−09	1.23178	748.4507	47.6574	47.6325
IGHS (Askarzadeh & Rezazadeh, 2012)	9.8635E−04	0.76079	0.97310	0.16791	0.03690	56.8368	1.92126	1.42814
IGWO (Long et al., 2020)	1.7576E−03	0.760725	0.52878	0.23949	0.03330	80.84466	1.5420	1.74057
ISCA (Chen et al., 2019)	**9.8237E−04**	**0.76078**	**0.74935**	**0.22597**	**0.03674**	**55.48543**	**2**	**1.45102**
LBSA (Yu et al., 2018)	1.0165E−03	0.7606	0.29814	0.27096	0.0363	60.1880	1.4760	1.9202
MADE (Li et al., 2019)	9.8261E−04	0.7608	0.7394	0.2246	0.03680	55.4329	1.9963	1.4505

mGWO (Long et al., 2020)	1.3163E−03	0.76088	0.49333	0.17345	0.034646	62.17868	1.52522	1.94264
Proposed	**9.8248E-04**	0.7608	0.22641	0.74563	0.0367	55.4777	1.4512	2
PSO-WOA (Xiong et al., 2018)	1.6700E−03	0.761091	0.20123	0.93611	0.034223	82.82299	1.463324	1.773674
SA (El-Naggar et al., 2012)	1.9000E−02	0.7623	0.4767	0.01	0.0345	43.1034	1.5172	2
SCA (Long et al., 2020)	4.0585E−02	0.750912	0	0.94825	0	7.374536	1	1.6156
TLBO (Li et al., 2019)	1.0069E−03	0.7610	0.2947	0.1373	0.0366	53.1210	1.4730	1.9938
TLBO-ABC (Chen et al., 2018)	9.8415E−04	0.76081	0.42394	0.24011	0.03667	54.66797	1.90750	1.45671
WOA (Long et al., 2020)	3.1312E−03	0.761631	0.37996	0.98043	0.029896	69.8988	1.876598	1.609125

The calculated current, power and IAEs values achieved with MA for the DD model are tabulated in Table 5. I-V and P-V characteristics obtained by MA for DD model are shown in Figure 4.

The low IEA values shown in Table 5 and the overlapping of measured and calculated data in Figure 4 show the prediction accuracy and efficiency of the MA algorithm.

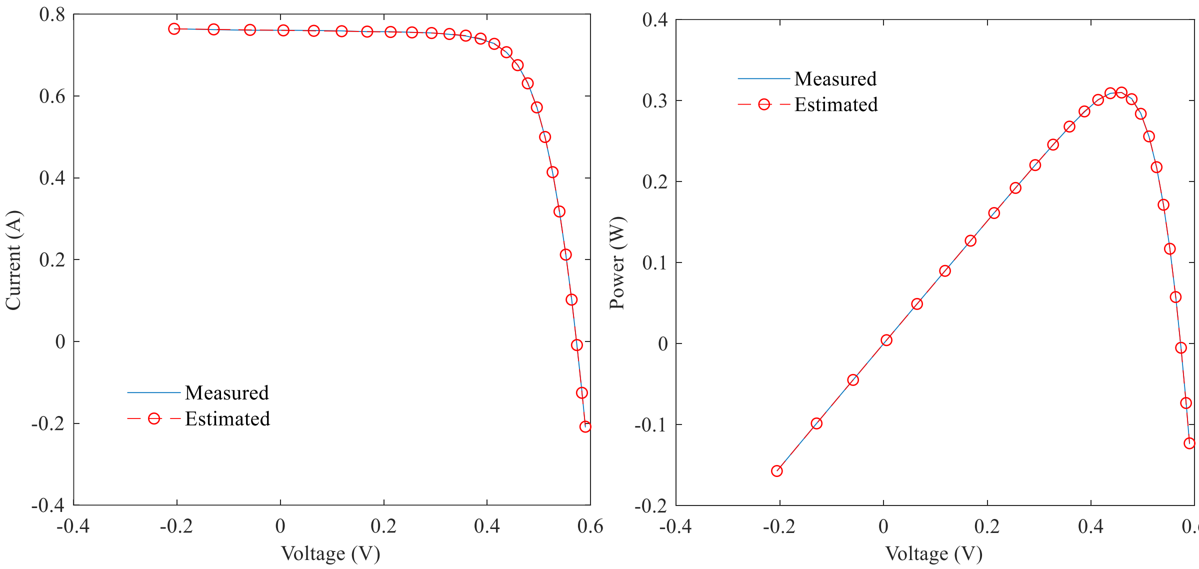

Figure 4. Comparisons between measured data and estimated data achieved by MA for DD model

Table 5. The calculated current, power and IAEs values achieved with MA for the DD model.

V (V)	I (A)	Calculated I (A)	IAE (I)	P (W)	Calculated P (W)	IAE (P)
−0.2057	0.7640	0.763983771266760	0.000016228733240	−0.1571548	-0.157151461749573	0.000003338250427
−0.1291	0.7620	0.762604263115149	0.000604263115149	−0.0983742	-0.098452210368166	0.000078010368166
−0.0588	0.7605	0.761337690239598	0.000837690239598	−0.0447174	-0.044766656186088	0.000049256186088
0.0057	0.7605	0.760173622040099	0.000326377959901	0.00433485	0.004332989645629	0.000001860354371
0.0646	0.7600	0.759107377820958	0.000892622179042	0.04909600	0.049038336607234	0.000057663392766
0.1185	0.7590	0.758121009380292	0.000878990619708	0.08994150	0.089837339611565	0.000104160388435
0.1678	0.7570	0.757188137450428	0.000188137450428	0.12702460	0.127056169464182	0.000031569464182
0.2132	0.7570	0.756243127853974	0.000756872146026	0.16139240	0.161231034858467	0.000161365141533
0.2545	0.7555	0.755176905587466	0.000323094412534	0.19227475	0.192192522472010	0.000082227527990
0.2924	0.7540	0.753722142366433	0.000277857633567	0.22046960	0.220388354427945	0.000081245572055
0.3269	0.7505	0.751399198721574	0.000899198721575	0.24533845	0.245632398062083	0.000293948062083
0.3585	0.7465	0.747301829752872	0.000801829752872	0.26762025	0.267907705966405	0.000287455966405
0.3873	0.7385	0.740011324679151	0.001511324679151	0.28602105	0.286606386048235	0.000585336048235
0.4137	0.7280	0.727247747002051	0.000752252997949	0.30117360	0.300862392934749	0.000311207065251
0.4373	0.7065	0.706850991411476	0.000350991411476	0.30895245	0.309105938544238	0.000153488544238
0.4590	0.6755	0.675210919040362	0.000289080959638	0.31005450	0.309921811839526	0.000132688160474
0.4784	0.6320	0.630760720624882	0.001239279375118	0.30234880	0.301755928746944	0.000592871253056
0.4960	0.5730	0.571994341340495	0.001005658659505	0.28420800	0.283709193304886	0.000498806695114
0.5119	0.4990	0.499705573500788	0.000705573500788	0.25543810	0.255799283075053	0.000361183075053
0.5365	0.4130	0.413733208249973	0.000733208249973	0.21744450	0.217830534143611	0.000386034143611
0.5398	0.3165	0.317546025847281	0.001046025847281	0.17084670	0.171411344752362	0.000564644752362

0.5521	0.2120	0.212123193219821	0.000123193219821	0.11704520	0.117113214976663	0.000068014976663
0.5633	0.1035	0.102163759194494	0.001336240805506	0.05830155	0.057548845554258	0.000752704445742
0.5736	−0.0100	-0.008791410321428	0.001208589678572	−0.0057360	-0.005042752960371	0.000693247039629
0.5833	−0.1230	-0.125543404541762	0.002543404541762	−0.0717459	-0.073229467869210	0.001483567869210
0.5900	−0.2100	-0.208372428076835	0.001627571923165	−0.1239000	-0.122939732565333	0.000960267434667

4.3. Analysis of PV Panel Model

For Photowatt-PWP-201 model, the performance of MA is compared with those of the MADE (Li et al., 2019), TLBO-ABC (Chen et al., 2018), FPA (Alam et al., 2015), CPSO (Xu & Wang, 2017), CLPSO (Yu et al., 2019), JAYA (Yu et al., 2019), LBSA (Yu et al., 2018), MLBSA (Yu et al., 2018), CWOA (Olivia et al., 2017), ISCA (Chen et al., 2019), PSO-WOA (Xiong et al., 2018), SA (El-Naggar et al., 2012), GWO (Long et al., 2020), mGWO (Long et al., 2020), EGWO (Long et al., 2020), AgGWO (Long et al., 2020), SCA (Long et al., 2020), WOA (Long et al., 2020) and GWOCS (Long et al., 2020) algorithms.

In Table 6, the best obtained diode parameters and RMSE values of competitor algorithms for Photowatt-PWP-201 model are tabulated. When the estimation results in Table 6 are compared, the best RMSE value 2.4250E-03 is achieved by MA.

The calculated current, power and IAEs values achieved with MA for Photowatt-PWP-201 model are mentioned in Table 7. The calculated values of current, power values are employed to plot P-V and I-V characteristics of Photowatt-PWP-201 model and they are shown in Figure 5. It is easily understood that the success of the MA algorithm continues because of the low error values (RMSE and IAE) in the tables and the graphical coherence between measured and calculated data.

Table 6. The best obtained diode parameters and RMSE values of competitor algorithms for Photowatt-PWP-201 model.

Algorithm	**RMSE**	I_{ph}	I_{sd}	R_S	R_{sh}	n
AgGWO (Long et al., 2020)	2.6145E−03	1.02808	4.9187	1.16459	1728.7773	50
CLPSO (Yu et al., 2019)	2.4281E−03	1.0304	3.6131	1.1978	1017.0	48.7847
CPSO (Xu & Wang, 2017)	3.5000E−03	1.0286	8.3010	1.0755	1850.1	52.2430
CWOA (Olivia et al., 2017)	2.6417E−03	1.029962	3.847725	1.201407	1172.121142	49.023217
EGWO (Long et al., 2020)	2.6448E−03	1.02984	4.9105	1.16042	1268.9149	50
FPA (Alam et al., 2015)	2.7425E−03	1.032091	3.047538	1.217583	811.3721	48.13128
GWO (Long et al., 2020)	2.6749E−03	1.03038	4.9068	1.15926	1173.7966	50
GWOCS (Long et al., 2020)	2.4251E−03	1.03049	3.4650	1.2019	982.7566	48.62367
IGWO (Long et al., 2020)	2.6228E−03	1.0277	4.9210	1.16582	1895.9042	49.9986
ISCA (Chen et al., 2019)	2.4251E−03	1.030514201	3.4822623	1.201271659	981.9966	48.64283
JAYA (Yu et al., 2019)	2.4278E−03	1.0302	3.4931	1.2014	1022.5	48.6531
LBSA (Yu et al., 2018)	2.4296E−03	1.0304	3.5233	1.2014	1020.4	48.6866
MADE (Li et al., 2019)	2.4251E−03	1.0305	3.4823	1.2013	981.9823	48.6428
mGWO (Long et al., 2020)	2.6034E−03	1.02952	4.6005	1.17284	1261.0638	49.7338
MLBSA (Yu et al., 2018)	2.4251E−03	1.0305	3.4823	1.2013	981.9823	48.6428
Proposed	**2.4250E-03**	**1.0305**	**3.4823**	**1.2013**	**981.9870**	**48.6428**
PSO-WOA (Xiong et al., 2018)	2.6242E−03	1.033772	3.340338	1.205482	776.330261	48.48701
SA (El-Naggar et al., 2012)	2.7000E−03	1.0331	3.6642	1.1989	833.3333	48.8211
SCA (Long et al., 2020)	3.1103E−02	1.0722	5.2254	1.27171	2000	50
TLBO-ABC (Chen et al., 2018)	2.4251E−03	1.0305	3.4826	1.2013	982.1815	48.6432
WOA (Long et al., 2020)	3.6253E−03	1.03265	2.1278	1.22796	624.58027	46.8347

Table 7. The calculated current, power and IAEs values achieved with MA for the Photowatt-PWP-201 model.

V (V)	**I (A)**	**Calculated I (A)**	**IAE (I)**	**P (W)**	**Calculated P (W)**	**IAE (P)**
0.1248	1.0315	1.029119159571656	0.002380840428344	0.1287312	0.128434071114543	0.000297128885457
1.8093	1.0300	1.027381071767876	0.002618928232125	1.8635790	1.858840573149617	0.004738426850383
3.3511	1.0260	1.025741795860399	0.000258204139601	3.4382286	3.437363332107783	0.000865267892217
4.7622	1.0220	1.024107154017180	0.002107154017180	4.8669684	4.877003088860617	0.010034688860617
6.0538	1.0180	1.022291804049050	0.004291804049050	6.1627684	6.188750123352136	0.025981723352136
7.2364	1.0155	1.019930680571695	0.004430680571695	7.3485642	7.380626376889014	0.032062176889013
8.3189	1.0140	1.016363105520908	0.002363105520908	8.4353646	8.455023038517878	0.019658438517878
9.3097	1.0100	1.010496151251689	0.000496151251689	9.4027970	9.407416019307844	0.004619019307844
10.2163	1.0035	1.000628969664897	0.002871030335103	10.252057	10.222725742787487	0.029331307212514

11.0449	0.9880	0.984548378375851	0.003451621624149	10.912361	10.874238384323434	0.038122815676566
11.8018	0.9630	0.959521675878379	0.003478324121621	11.365133	11.324082914381457	0.041050485618543
12.4929	0.9255	0.922838817701344	0.002661182298656	11.562179	11.528933065661123	0.033245884338877
13.1231	0.8725	0.872599662395507	0.000099662395507	11.449905	11.451212629582480	0.001307879582479
13.6983	0.8075	0.807274263265701	0.000225736734299	11.061377	11.058285040492549	0.003092209507450
14.2221	0.7265	0.728336477684136	0.001836477684136	10.332355	10.358474219271551	0.026118569271551
14.6995	0.6345	0.637137999872465	0.002637999872465	9.3268327	9.365610029125293	0.038777279125293
15.1346	0.5345	0.536213063203068	0.001713063203068	8.0894437	8.115370226353159	0.025926526353159
15.5311	0.4275	0.429511325125178	0.002011325125178	6.6395452	6.670783341651655	0.031238091651654
15.8929	0.3185	0.318774483107432	0.000274483107432	5.0618886	5.066250982578100	0.004362332578100
16.2229	0.2085	0.207389507018174	0.001110492981826	3.3824746	3.364459233405143	0.018015416594857
16.5241	0.1010	0.096167172050621	0.004832827949379	1.6689341	1.589075967681673	0.079858132318327
16.7987	−0.008	-0.008325386101837	0.000325386101837	−0.134390	-0.139855663508923	0.005466063508923
17.0499	−0.111	-0.110936483014156	0.000063516985844	−1.892539	-1.891455941743056	0.001082958256944
17.2793	−0.209	-0.209247266603263	0.000247266603263	−3.611374	-3.615646293817758	0.004272593817759
17.4885	−0.303	-0.300863588123880	0.002136411876120	−5.299016	-5.261652860904483	0.037362639095516

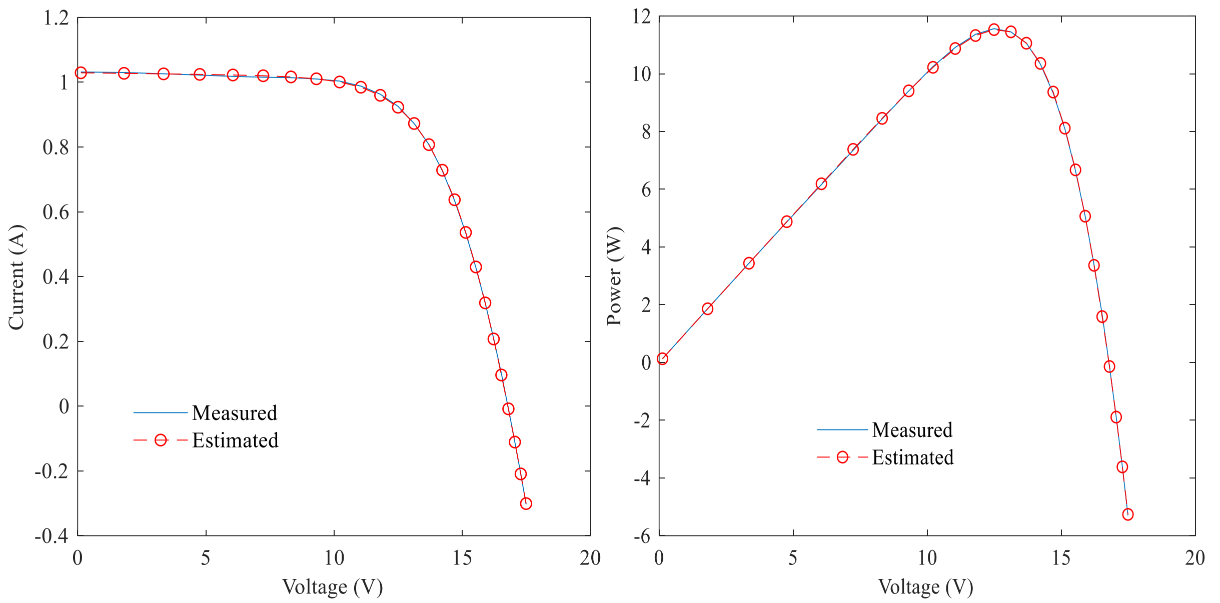

Figure 5. Comparisons between measured data and estimated data achieved by MA for Photowatt-PWP-201 model

4.4. Performance Summary of MA

In table 8, the robustness results of RMSE achieved by MA for single diode, double diode and Photowatt-PWP-201 models are summarized. As seen Table 8, standard deviations are very small for all models. Also, compared with the other algorithms, MA is obtained minimum RMSE values for single diode and Photowatt-PWP-201 models. For double diode model, second minimum value is converged by MA.

Table 8. The robustness results of RMSE achieved by MA for SD, DD and Photowatt-PWP-201 models.

Model	Min	Mean	Max	SD
SD model	9.8602E-04	9.8602E-04	9.8602E-04	6.8856E-15
DD model	9.8248E-04	9.8282E-04	9.8332E-04	2.7878E-07
Photowatt-PWP-201 module model	2.4250E-03	2.4272E-03	2.4383E-03	3.0873E-06

5. Conclusion

In this paper, Mayfly algorithm is applied to estimate the characteristic parameter of aforementioned photovoltaic models, such as single and double diodes. Especially, to analyze the accuracy and robustness of the proposed approach, real-time devices such as R.T.C France, Photowatt-PWP-201 and STM-40/36 are measured and output current and voltage values are used for estimation. Estimated parameters and RMSE values of MA are compared with well-known literature algorithms. Also, current, voltage and their IAEs are calculated and I-V and P-V characteristics are plotted.

Outstanding conclusions of this paper can be declared as follows:

- When the Max_FES is set 50000 for competitor algorithms suggested in literature, MA is realized estimation process for 10000 evaluations. But despite this important factor, MA shows good performance for characteristic parameter estimation of PV models than the other literature algorithms.
- Although several algorithms are improved with strategies and mechanisms in literature, the performance of basic Mayfly algorithm has been demonstrated for four models.
- The robustness and efficiency of MA are quite satisfactory according to achieved statistical results.

I-V and P-V curves are plotted using estimated parameters by MA for all aforementioned models. The alignment between measured and calculated data concludes that the semiconductor models for PV are done correctly and MA algorithm performs characteristic parameter estimation with high precision.

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