Photovoltaic parameters estimation of poly-crystalline and mono-crystalline modules using an improved population dynamic differential evolution algorithm

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ABSTRACT

Photovoltaic (PV) parameters estimation from the experimental current and voltage data of PV modules is vital for monitoring and evaluating the performance of PV power generation systems. Moreover, the PV parameters can be used to predict current-voltage (I-V) behavior to control the power output of the PV modules. This paper aimed to propose an improved differential evolution (DE) integrated with a dynamic population sizing strategy to estimate the PV module model parameters accurately. This study used two popular PV module technologies, i.e., poly-crystalline and mono-crystalline. The optimized PV parameters were validated with the measured data and compared with other recent meta-heuristic algorithms. The proposed population dynamic differential evolution (PDDE) algorithm demonstrated high accuracy in estimating PV parameters and provided perfect approximations of the measured I-V and power-voltage (P-V) data from real PV modules. The PDDE obtained the best and the mean RMSE value of 2.4251E-03 on the poly-crystalline Photowatt-PWP201, while the best and the mean RMSE value on the mono-crystalline STM6-40/36 was 1.7298E-03. The PDDE algorithm showed outstanding accuracy performance and was competitive with the conventional DE and the existing algorithms in the literature.

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1. INTRODUCTION

The solar photovoltaic (PV) industry is currently experiencing rapid growth, which is indicated by the ability to mass-produce modules at low prices [1] and their applications for residential and utility-scale PV power generations. The use of PV modules for power generations is increasingly in demand and will increase in the future [2], [3] due to the availability of solar irradiation, which is naturally abundant, eco-friendly, and independent from fossil fuels. Moreover, the PV power generations have the advantages such as sustainability, long project lifespan, and less maintenance during operation. It is crucial to know the actual dynamic behavior of the PV modules in order to control, monitor, and evaluate the operation of the PV systems [4]. Therefore, it is necessary to find accurate PV parameters referring to the measured voltage and current data. The PV parameters can be used to predict the current-voltage (I-V) and power-voltage (P-V) characteristics of the PV modules. The current-voltage curve describes the output voltage and current generated by the PV modules when operating under certain solar irradiance and temperature conditions. From the power-voltage curve, the most efficient output voltage operating at maximum power can be traced.

Several computational attempts have been made to estimate the parameters of PV models. Evolutionary algorithms are widely adopted to predict PV parameters from the measured data because of their flexibility, efficiency, and reliability [5]. Among the evolutionary algorithms, there are three popular algorithms *i.e*., genetic algorithm (GA), particle swarm optimization (PSO), and differential evolution (DE).

Zagrouba *et al.* [6] used the GA to estimate PV parameters of the poly-crystalline PV cell and module to find the maximum power point (MPP). The GA was also implemented to search the maximum power point of the Conergy PowerPlus 214P PV panel through the P-V characteristics [7]. The PSO was applied to extract PV parameters of 30XLS and 30XLS1 modules as reported in [8]. Wang [9] developed an enhanced PSO to identify PV parameters of the Radiotechnique Compelec (RTC) France silicon PV cell and the Photowatt-PWP201 PV module. In studies [10], [11], the poly-crystalline, mono-crystalline, and thin-film PV module optimum parameters were estimated using the DE algorithm.

In the literature, several works on PV parameter estimations have been carried out using DE variants. Cárdenas-Bravo *et al.* [12] reported that the DE integrated with parameter boundaries adaptation successfully calculated the PV parameters of the poly-crystalline KC200GT PV module. Li *et al*. [13] developed a memetic adaptive DE (MADE), the combination of success-history based adaptive DE (SHADE) and Nelder-Mead simplex method (NMM), to estimate PV parameters of the RTC France silicon PV cell and three PV modules such as Photowatt-PWP201, STM6-40/36, and STP6-120/36. Song *et al*. [14] proposed an enhanced SHADE (EBLSHADE), which used the less and more greedy mutation strategy and the linear population size reduction strategy to optimize the parameters of PV models. Liao *et al*. [15] improved DE by reusing the successful difference vectors in DE with an adaptive mutation strategy (DVADE) to extract the unknown parameters of different PV models. Yu *et al*. [16] hybridized an adaptive algorithm based on JAYA and DE (HAJAYADE) to identify PV parameters. Wang *et al*. [17] presented a heterogeneous DE algorithm (HDE) to extract the parameters of PV models.

The DE algorithms are population-based optimization algorithms. Population size is one of the essential parameters that must be determined to achieve high accuracy results [18]. In DE, an initial population is created in the first step. The population is then evaluated to find the best individuals. The new population is generated repeatedly for each step of the DE algorithm process until the best criteria are met.

Most DE variants used a fixed population sizing scheme. In this scheme, the search process runs with a fixed population size. However, a variable population sizing scheme improved the DE performance and yielded better results, as shown in [14], [17]. This study aimed to propose an improved DE algorithm to estimate the PV parameters of the poly-crystalline and mono-crystalline PV modules. A dynamic population strategy was applied to dynamically change the size of the population during the DE algorithm process to find accurate PV parameters. Finally, the results were cross-checked using experimental data to ensure a high level of accuracy.

2. RESEARCH METHOD

In this study, the measured current and voltage data sets are obtained from the poly-crystalline Photowatt-PWP201 and mono-crystalline STM6-40/36 modules. The Photowatt-PWP201 PV module has 36 series-connected poly-crystalline silicon cells, while the STM6-40/36 has 36 mono-crystalline silicon cells joined together in series. An improved DE algorithm integrated with a dynamic population strategy (PDDE) is constructed to accurately estimate the PV parameters from the data sets.

2.1. Photovoltaic parameters

A PV module is made up of PV cells connected in series and parallel. Series-connected PV cells increase the output voltage of the PV module, while parallel PV cells produce more output current. The PV module equivalent circuit can be represented by using a current source, series-parallel connected diodes, one resistor connected in series, and the other resistor connected in parallel [19], as seen in Figure 1.

When the solar irradiation hits the PV module, the PV cells generate the photo-current. The photo-current depends on the proportion of the solar irradiation. According to the equivalent circuit as shown in Figure 1, the I-V characteristics of the PV module can be mathematically described as (1):

$$I = N_P I_{PV} - N_P I_O \left\{ \exp\left[\frac{(V + IR_S(N_S/N_P))}{AV_{th}N_S}\right] - 1 \right\} - \frac{V + IR_S(N_S/N_P)}{R_P(N_S/N_P)} \tag{1}$$

where I_{PV} is the photo-current, I_O is the reverse saturation current of the diode, N_S is the number of series-connected diodes, N_P is the number of diodes connected in parallel, R_S is the series resistance, R_P is the parallel resistance, A is the diode ideality factor, I is the PV output current, V is the PV output voltage, and V_{TH} is the PV module thermal voltage, which can be calculated with

$$V_{TH} = N_S kT/q \tag{2}$$

where k is the Boltzmann constant (in J/K), q is the charge of an electron (in Coulomb), and T is the photovoltaic cell temperature (in Kelvin).

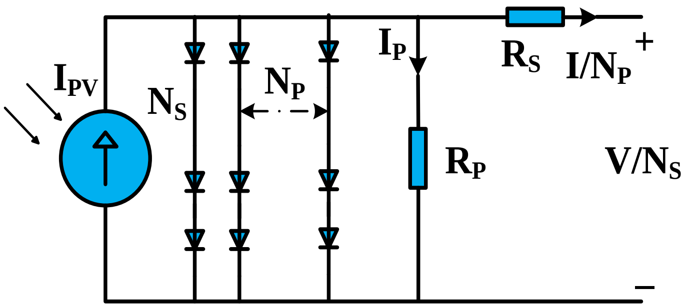

Figure 1. Equivalent circuit of the PV module

The PV module has five PV parameters to be computed, i.e., I_{PVM}, I_{OM}, A_M, R_{SM}, and R_{PM}. Considering (1), I_{PVM}=$N_P I_{PV}$, I_{OM}=$N_P I_O$, R_{SM}=$(N_S/N_P)R_S$, R_{PM}=$(N_S/N_P)R_P$, and A_M=$N_S A$, therefore:

$$I = I_{PVM} - I_{OM}\left\{\exp\left[\frac{(V+IR_{SM})}{A_M V_{TH}}\right] - 1\right\} - \frac{V+IR_{SM}}{R_{PM}} \tag{3}$$

In addition, the P-V characteristics of the PV module can be found by multiplying (3) and the output voltage of the PV module.

2.2. Optimization problem

The estimation of PV module parameters is an optimization problem to predict the I-V and P-V characteristics. The optimal parameters are found by minimizing the error between the measured and estimated data. The PV module model has five unknown parameters, which are written in the design vector as in (4).

$$X = (I_{PVM}, I_{OM}, A_M, R_{SM}, R_{PM}) \tag{4}$$

The absolute accuracy error (AAE) between the measured and estimated current is defined as in (5).

$$AAE(V, I, X) = \left|I - \left(I_{PVM} - I_{OM}\left\{\exp\left[\frac{(V+IR_{SM})}{A_M V_{TH}}\right] - 1\right\} - \frac{V+IR_{SM}}{R_{PM}}\right)\right| = |I - I_{est}| \tag{5}$$

In this study, the optimal parameters (I_{PVM}, I_{OM}, A_M, R_{SM}, and R_{PM}) are determined by minimizing the root mean square error (RMSE) [20] of the fitness function for N measured data as described by (6).

$$RMSE = \min\left\{\sqrt{\frac{1}{N}\sum_{j=1}^{N}\left[AAE\left(V_j, I_j, X\right)\right]^2}\right\} \tag{6}$$

2.3. Optimization algorithm

In the proposed approach, a DE algorithm [21]–[23] with a population dynamic method is used to solve the optimization problem for the PV modules. The DE algorithm is started by creating a population size of PV parameters, and then the PV parameters will evolve with an adequate population size to find the best PV parameters in the search space. The method will dynamically change the population size during the search process to enhance the convergence speed and find accurate results. The flowchart of the optimization algorithm, including the DE process, is given in Figure 2. The DE algorithm in this study is adopted from the reference [21] with *DE/rand/2* mutation strategy.

The population dynamic method is a deterministic method based on the variable population sizing scheme, which is proposed in [24], and the bisection method. The population size is reduced monotonically as the DE runs. In this method, the population size is continuously decreased according to the number of function evaluations as (7):

$$NP^{(G+1)} = round\left[\left(\frac{NP_{min}-NP^{(G)}}{NFE_{max}}\right).NFE + NP^{(G)}\right] \quad (7)$$

where $NP^{(G+1)}$ is the next-generation population size, $NP^{(G)}$ is the previous-generation population size, NP_{min} is the smallest population size, *NFE* is the number of function evaluations, and NFE_{max} is the maximum *NFE* value. The population size in each generation is produced at the beginning of the DE algorithm. The next-generation population is created after the best PV parameters are selected based on the previous-generation population. Furthermore, during the DE process, if $NP^{(G+1)} < NP^{(G)}$, then ($NP^{(G)}$ - $NP^{(G+1)}$) PV parameter members that give the worse RMSE values will be removed from the population. The mutation variant applied in this method is the *DE/rand/2* [21], which requires five individuals so that NP_{min}=5. The maximum population size used in this study is 100. The maximum population size refers to the population size at generation *G*=0 or $NP^{(G=0)}$. The large population size in the first stage is used to generate extensive exploration in the search space. Meanwhile, as the population size decreases as long as the DE is running, the exploitation process will reach DE convergence.

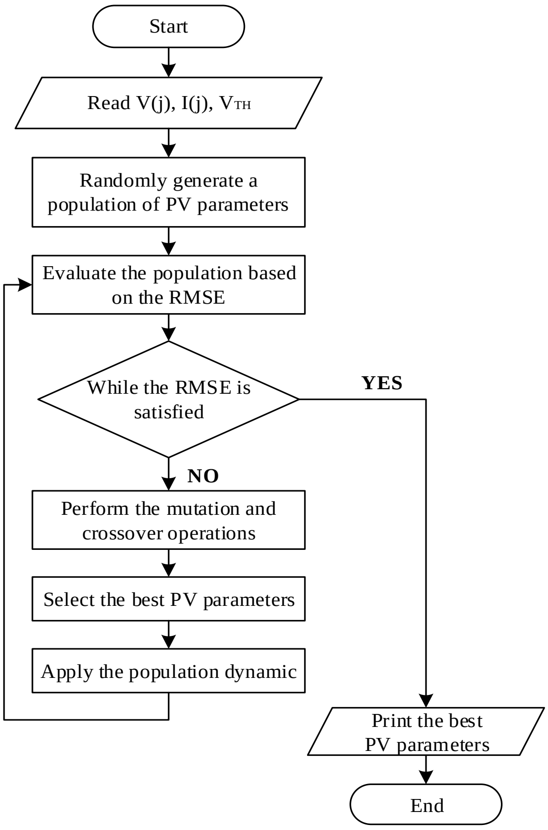

Figure 2. The population dynamic differential evolution algorithm flowchart

3. RESULTS AND DISCUSSION

In this section, the PDDE algorithm is applied to estimate the unknown photovoltaic parameters of the Photowatt-PWP201 and STM6-40/36 PV modules. The accuracy of the proposed PDDE algorithm is compared with other recent algorithms according to the RMSE values. The PDDE algorithm uses the same parameter search intervals as the competing algorithms in order to get a fair comparison. The measured voltages and currents of 25 data points for the Photowatt-PWP201 module under 1 kW/m^2 at 45 °C are presented in Table 1. Table 1 also contains a group of 20 voltage and current measurement data points of the STM6-40/36 module under 1 kW/m^2 at 51 °C.

Table 1. Experimental data of PV modules

j	Photowatt-PWP201		STM-40/36	
	V_j (V)	I_j (A)	V_j (V)	I_j (A)
1	0.1248	1.0315	0.0000	1.6630
2	1.8093	1.0300	0.1180	1.6630
3	3.3511	1.0260	2.2370	1.6610
4	4.7622	1.0220	5.4340	1.6530
5	6.0538	1.0180	7.2600	1.6500
6	7.2364	1.0155	9.6800	1.6450
7	8.3189	1.0140	11.5900	1.6400
8	9.3097	1.0100	12.6000	1.6360
9	10.2163	1.0035	13.3700	1.6290
10	11.0449	0.9880	14.0900	1.6190
11	11.8018	0.9630	14.8800	1.5970
12	12.4929	0.9255	15.5900	1.5810
13	13.1231	0.8725	16.4000	1.5420
14	13.6983	0.8075	16.7100	1.5240
15	14.2221	0.7265	16.9800	1.5000
16	14.6995	0.6345	17.1300	1.4850
17	15.1346	0.5345	17.3200	1.4650
18	15.5311	0.4275	17.9100	1.3880
19	15.8929	0.3185	19.0800	1.1180
20	16.2229	0.2085	21.0200	0.0000
21	16.5241	0.1010	-	-
22	16.7987	-0.0080	-	-
23	17.0499	-0.1110	-	-
24	17.2793	-0.2090	-	-
25	17.4885	-0.3030	-	-

3.1. Estimating parameters of Photowatt-PWP201 module

According to the photovoltaic module model, there are five unknown parameters to be estimated, i.e., I_{PV}, I_O, A, R_S, and R_P. The search intervals of the related parameters are tabulated in Table 2. The results of the five unknown parameters, along with the RMSE values for the Photowatt-PWP201 module estimated by different algorithms, are shown in Table 3. In this case, the proposed PDDE algorithm is compared with other algorithms such as: DE, MADE, adaptive differential evolution (JADE), SHADE, EBLSHADE, DVADE, HAJAYADE, HDE, triple-phase teaching-learning-based optimization (TPTLBO), grey wolf optimizer and cuckoo search (GWOCS), improved teaching-learning-based optimization (ITLBO), performance-guided JAYA (PGJAYA), improved sine cosine algorithm (ISCA), symbiotic organisms search (SOS), teaching-learning-based artificial bee colony (TLABC), improved cuckoo search algorithm (ImCSA), improved JAYA (IJAYA), self-adaptive teaching-learning-based optimization (SATLBO), and hybrid adaptive Nelder-Mead simplex algorithm based on eagle strategy (EHA-NMS).

Table 3 shows photovoltaic parameters and RMSE values with the varying decimal place limit found by different algorithms. It can be observed that all algorithms provide their best RMSE values. The best RMSE value means the smallest RMSE found because no exact RMSE is available. Table 3 also shows a significant difference in the R_{PM} value given by each algorithm. The HAJAYADE gives an RMSE of 2.4251E-03, but the parameter I_{OM} is 0.34823. The HDE reports an RMSE of 2.4250749E-03, but the parameters A_M, R_{SM}, and R_{PM} are very distinct from the other algorithms. To clarify such cases, the RMSE values obtained by all algorithms can be validated using the PV parameters and the objective function as suggested by Gnetchejo *et al*. [25]. Calasan *et al*. [26] also investigated these issues, and they found that the RMSE values would be incorrect if the exact expression of the PV output current data were not used correctly.

The photovoltaic parameter values obtained by PDDE *i.e*., I_{PVM}=1.03051430 A, I_{OM}=3.48226301E-06 A, A_M=48.64283497, R_{SM}=1.20127101 Ω, R_{PM}=981.98228397 Ω, and measured data (as shown in Table 1) are substituted into the objective function as:

$$RMSE = \sqrt{\frac{1}{25}\sum_{j=1}^{25}\left[I_j - \left(I_{PVM} - I_O\left\{\exp\left[\frac{\left(V_j + I_j R_{SM}\right)}{A_M V_{TH}}\right] - 1\right\} - \frac{V_j + I_j R_{SM}}{R_{PM}}\right)\right]^2}$$

As a result, the RMSE value is 2.42507487E-03, and this value matches the RMSE found by the PDDE algorithm (RMSE=2.425075E-03).

Further confirmation of the accuracy of the PDDE algorithm, the I-V and P-V curves of both measured and estimated data are plotted as presented in Figure 3. The measured and estimated current data match very well, as shown in the I-V curve. The P-V curve also indicates that the power measurement data fits the power estimation data perfectly.

The difference between the measured and estimated data can be determined by observing the absolute accuracy error of current (AAEI) and power (AAEP), as presented in Figure 4. According to the AAE of current, the differences between the measured and estimated current are less than 0.004 A for all ranges of voltage. The smallest AAE of current is 0.00006 A, and it is found at the voltage point of 17.05 V. The AAE of power data shows that most AAE values are smaller than 0.04 W. The highest AAE of power is 0.08 W at the voltage point of 16.52 V. This finding indicates that the PDDE algorithm can accurately estimate the photovoltaic parameters of the Photowatt-PWP201 module.

Table 2. Parameter search intervals on the Photowatt-PWP201 module

Parameter	I_{PVM}	I_{OM}	A_M	R_{SM}	R_{PM}
Search Interval	[0, 2] A	[0, 50] μA	[1, 50]	[0, 2] Ω	[0, 2000] Ω

Table 3. Photovoltaic parameters and RMSE values for the Photowatt-PWP201 module

Ref.	Algorithm	I_{PVM} (A)	I_{OM} (μA)	A_M	R_{SM} (Ω)	R_{PM} (Ω)	RMSE
-	PDDE	1.03051430	3.48226301	48.64283497	1.20127101	981.98228397	2.425075E-03
[11]	DE	1.0305	3.4823	48.6428	1.2013	981.9819	2.4251E-03
[12]	MADE	1.0305	3.4823	48.6428	1.2013	981.9823	2.425E-03
[14]	JADE	1.0305	3.4823	48.6238	1.2012	982.3236	2.4343E-03
[14]	SHADE	1.0305	3.4823	48.6428	1.2013	981.9822	2.4251E-03
[14]	EBLSHADE	1.0305	3.4823	48.6428	1.2013	981.9825	2.4251E-03
[15]	DVADE	1.0305	3.4823	48.6428	1.2013	981.9824	2.4251E-03
[16]	HAJAYADE	1.0305	0.34823	48.6428	1.2013	981.9824	2.4251E-03
[17]	HDE	1.03051430	3.48226262	1.35118985	0.03336864	27.27728467	2.4250749E-03
[27]	TPTLBO	1.0305	3.4823	48.6428	1.2013	981.9822	2.4251E-03
[28]	GWOCS	1.03049	3.4650	48.62367	1.2019	982.7566	2.4251E-03
[29]	ITLBO	1.0305	3.4823	48.6428	1.2013	981.9823	2.4251E-03
[30]	PGJAYA	1.0305	3.4818	48.6424	1.2013	981.8545	2.425075E-03
[31]	ISCA	1.030514201	3.4822623	48.64283	1.201271659	981.9966	2.4251E-03
[32]	SOS	1.0303	3.5616	48.7291	1.1991	1017.7000	2.4251E-03
[33]	TLABC	1.03056	3.4715	48.63131	1.20165	972.93567	2.42507E-03
[34]	ImCSA	1.030514	3.482263	48.660397	1.201271	981.982233	2.425E-03
[35]	IJAYA	1.0305	3.4703	48.6298	1.2016	977.3752	2.425129E-03
[36]	SATLBO	1.030511	3.48271	48.6433077	1.201263	982.40376	2.425E-03
[37]	EHA-NMS	1.030514	3.482263	48.642835	1.201271	981.982256	2.4250E-03

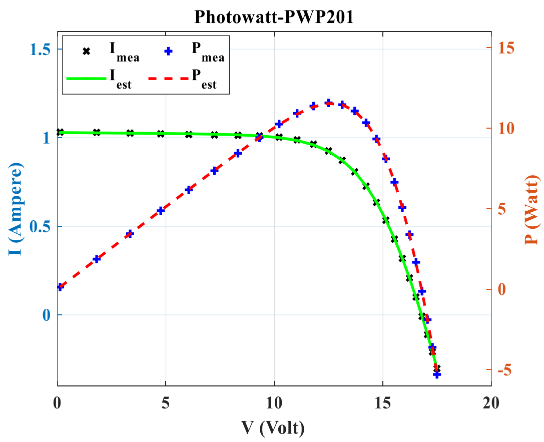

Figure 3. Measured and estimated I-V/P-V of the Photowatt-PWP201 module

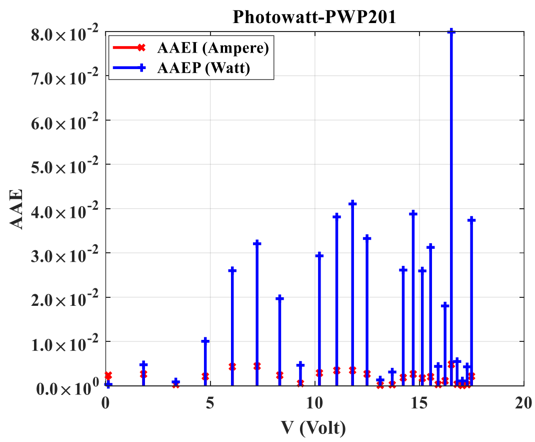

Figure 4. Absolute accuracy error of current and power of the Photowatt-PWP201 module

3.2. Estimating parameters of STM6-40/36 module

The five unknown parameters to be estimated, i.e., I_{PVM}, I_{OM}, A_M, R_{SM}, and R_{PM}, and the search intervals of related parameters are presented in Table 4. The five unknown parameters and the RMSE values estimated by different algorithms on the STM6-40/36 module are shown in Table 5. In this case, the algorithms compared are PDDE, DE, MADE, JADE, SHADE, EBLSHADE, DVADE, HAJAYADE, HDE, TPTLBO, GWOCS, ITLBO, ImCSA, cuckoo search algorithm with biogeography-based optimization (CS-BBO), enhanced leader particle swarm optimization (ELPSO), and chaotic improved artificial bee colony (CIABC).

Table 4. Parameter search intervals on the STM6-40/36 module

Parameter	I_{PVM}	I_{OM}	A_M	R_{SM}	R_{PM}
Search Interval	[0, 2] A	[0, 50] μA	[1, 60]	[0, 0.36] Ω	[0, 1000] Ω

Table 5. Photovoltaic parameters and RMSE values for STM6-40/36 module

Ref.	Algorithm	I_{PVM} (A)	I_{OM} (μA)	A_M	R_{SM} (Ω)	R_{PM} (Ω)	RMSE
-	PDDE	1.66390478	1.73865691	1.52030292	0.00427377	15.92829413	1.729814E-03
[11]	DE	1.6630	2.3342	1.5534	0.0033	17.6907	1.8669E-03
[12]	MADE	1.6639	1.7387	1.5203	0.0043	15.9283	1.7298E-03
[14]	JADE	1.6638	1.7946	1.5238	0.0042	16.0190	2.1308E-03
[14]	SHADE	1.6639	1.7386	1.5203	0.0043	15.9282	1.7306E-03
[14]	EBLSHADE	1.6639	1.7387	1.5203	0.0043	15.9283	1.7298E-03
[15]	DVADE	1.6639	1.7387	1.5203	0.0043	15.9283	1.7298E-03
[16]	HAJAYADE	7.4725	2.3351	1.2601	0.0045946	22.2199	1.6601E-02
[17]	HDE	1.66390478	1.73865689	1.52030292	0.00427377	15.92829411	1.72981371E-03
[27]	TPTLBO	1.6639	1.7387	1.5203	0.0043	15.9283	1.7298E-03
[28]	GWOCS	1.6641	1.7449	1.5207	0.00424	15.7326	1.7337E-03
[29]	ITLBO	1.6639	1.7387	1.5203	0.0043	15.9283	1.7298E-03
[34]	ImCSA	1.663971	2.0000	1.533499	2.913631	15.840511	1.79436329E-03
[38]	CS-BBO	1.6639	1.73866	1.5203	0.00427	15.92829	1.7298E-03
[39]	ELPSO	1.666268	0.4596141	50.458643	0.5	497.747315	2.1803E-03
[40]	CIABC	1.6642	1.676	1.4976	4.40	15.617	1.819E-03

The accuracy of the comparison algorithms in estimating the five photovoltaic unknown parameters on the STM6-40/36 module can be observed from the RMSE results, as seen in Table 5. It is seen that the PDDE algorithm is as accurate as MADE, EBLSHADE, DVADE, HDE, TPTLBO, ITLBO, and CS-BBO algorithms. The JADE, HAJAYADE, ImCSA, and ELPSO obtain larger RMSE values than other algorithms. The HAJAYADE, ImCSA, and ELPSO also give the photovoltaic parameters with very different values from other comparison algorithms. The RMSE values found can be validated to ensure their accuracy [25], [26].

To crosscheck the accuracy results obtained by the PDDE algorithm on the STM6-40/36 module, the parameters, i.e., I_{PVM}=1.66390478 A, I_{OM}=1.73865691E-06 A, A_M=1.52030292, R_{SM}=0.00427377 Ω, R_{PM}=15.92829413 Ω, and measured data from Table 1 are substituted into the following objective function:

$$RMSE = \sqrt{\frac{1}{20}\sum_{j=1}^{20}\left[I_j - \left(I_{PVM} - I_{\mathrm{OM}}\left\{\exp\left[\frac{\left(V_j + I_j R_{SM}\right)}{A_M V_{TH}}\right] - 1\right\} - \frac{V_j + I_j R_{SM}}{R_{PM}}\right)\right]^2}$$

The computational RMSE is 1.72981371E-03, and this result is in agreement with the estimated value (RMSE=1.729814E-03).

Additionally, the I-V and P-V curves of both measured and estimated data on the STM6-40/36 module are shown in Figure 5. It is seen that the estimated currents and powers closely match the measured data. The AAEI and AAEP between the measured and estimated data on the STM6-40/36 module are shown in Figure 6. It can be noticed that the AAEI values are smaller than 0.002 A, except at the voltage point of 14.88 V. The AAEI at the voltage point of 14.88 V is 0.006 A, and this value is relatively small compared to the measured current (1.597 A). As shown in Figure 6, most of the AAEP value is less than 0.01 W. The largest AAEP from the estimated power of 0.09 W occurs at a measured voltage of 14.88 V and a measured power of 23.76 W. From the AAEI and AAEP values, it is evident that the PDDE has excellent accuracy in estimating the photovoltaic parameter of the STM6-40/36 module.

Further, the PDDE performance is compared to the conventional DE and the results are presented in Table 6. The results are obtainable after 30 independent experiments. It is noted that the smaller the RMSE value means the more accurate the estimation results. The small standard deviation (SD) value specifies the good reliability, while the mean RMSE determines the average accuracy of the algorithm. According to Table 6, both PDDE and DE obtain the best and the mean RMSE of 2.4251E-03 on the Photowatt-PWP201. Meanwhile, on STM6-40/36, the PDDE is able to achieve the best and the mean RMSE of 1.7298E-03, which is more accurate than the DE (RMSE=1.8669E-03). In terms of the SD and the worst RMSE, the PDDE outperforms the DE algorithm on both Photowatt-PWP201 and STM6-40/36.

Finally, the performances of the PDDE algorithm working on the poly-crystalline Photowatt-PWP201 and mono-crystalline STM6-40/36 modules are compared. According to the aforementioned results, the PDDE algorithm can estimate PV parameters on the mono-crystalline module (RMSE=1.729814E-03) more accurately than on the poly-crystalline module (RMSE=2.425075E-03). However, in terms of convergence speed, the estimation of PV parameters on the poly-crystalline module is faster than on the mono-crystalline module, as shown in Figure 7. For the Photowatt-PWP201 module, the minimum value of the RMSE is reached before the 6,000 number of function evaluations, but for the STM6-40/36 module, the algorithm consumes more than the 30,000 number of function evaluations to reach the minimum value of the RMSE.

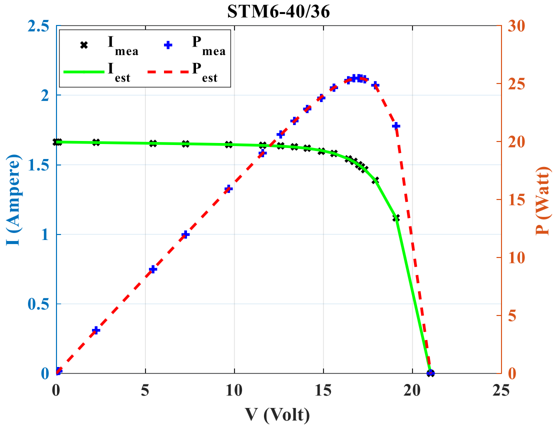

Figure 5. Measured and estimated I-V/P-V of the STM6-40/36 module

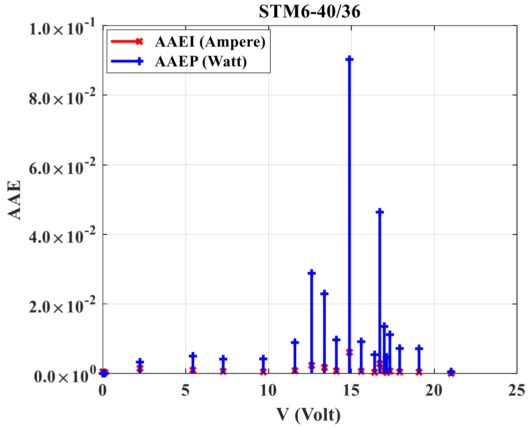

Figure 6. Absolute accuracy error of current and power of the STM6-40/36 module

Table 6. Comparison between PDDE and DE

	Photowatt-PWP201		STM6-40/36	
	DE	PDDE	DE	PDDE
I_{PVM} (A)	1.0305	1.0305	1.6630	1.6639
I_{OM} (μA)	3.44823	3.4823	2.3342	1.7387
R_{SM} (Ω)	1.2013	1.2013	0.0033	0.0043
R_{PM} (Ω)	981.9819	981.9819	17.6907	15.9283
A_M	48.6428	48.6428	1.5534	1.5203
the best RMSE	2.4251E-03	2.4251E-03	1.8669E-03	1.7298E-03
the worst RMSE	2.4384E-03	2.4268E-03	1.8984E-03	1.7332E-03
the mean RMSE	2.4251E-03	2.4251E-03	1.8669E-03	1.7298E-03
standard deviation (SD)	2.7000E-06	5.2004E-07	4.3531E-06	6.5879E-07

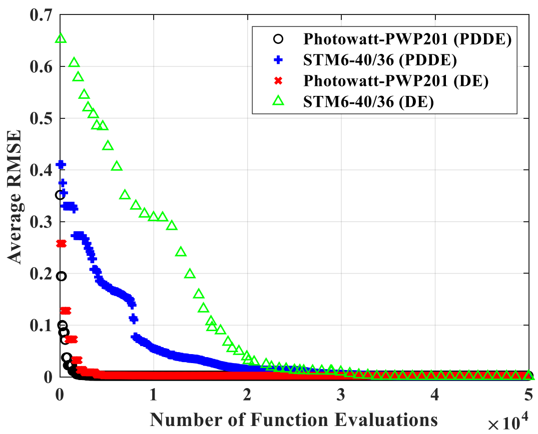

Figure 7. The convergence speed performance of the PDDE algorithm

4. CONCLUSION

A PDDE algorithm was applied to estimate the five unknown PV parameters on both poly-crystalline and mono-crystalline modules. It revealed that the proposed algorithm had the ability to accurately estimate PV parameters, which was indicated by the small RMSE and AAE values between the measured data and the estimated data. The characteristics of the I-V and P-V results also showed that the proposed algorithm had a very competitive accuracy compared to the results reported in the literature. Results indicated that the proposed algorithm was a potential tool for estimating both poly-crystalline Photowatt-PWP201 and mono-crystalline STM-40/36 PV modules parameters. Nevertheless, the PDDE algorithm estimated the PV parameters on the mono-crystalline module more accurately than on the poly-crystalline module. The PDDE obtained the best and mean RMSE value of 2.4251E-03 with a standard deviation of 5.2004E-07 on the Photowatt-PWP201. In another case, the proposed algorithm achieved the best and mean RMSE value of 2.4251E-03 with a standard deviation of 6.5879E-07 on the STM-40/36. On the other hand, the PDDE algorithm converged faster with a smaller standard deviation when working on the poly-crystalline Photowatt-PWP201 module than on the mono-crystalline STM-40/36 module.

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