Artificial ecosystem-based optimiser to electrically characterise PV generating systems under various operating conditions reinforced by experimental validations

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Abstract
Efficient modelling of photovoltaic (PV) generating units’ characteristics to investigate their steady-state and dynamic impacts on the performances of power systems and electric drives is essential. The current work aims at developing an effective tool based on artificial ecosystem optimiser (AEO) to define (optimally) the uncertain parameters of PV generating units. The root mean squared deviations (RMSDs) along with the predefined inequality constraints formulate the optimization problem to be solved by the AEO. Initially, two test cases with different PV technologies are demonstrated complete with their relevant discussions and necessary validations. At a later stage, real measurements (followed the procedures of IEC 60904) of a commercial PV module namely Ultra 85-P of Shell Power-Max are made for further experimental validations of the AEO results. Various operating temperatures and sun irradiance levels are investigated among the simulated scenarios. The statistical validations along with predefined indices plus comparisons to other competing methods appraise the results obtained by the AEO. It can be confirmed that the AEO is able to produce best values of unidentified parameters of the PV units with different solar technologies under study with lesser values of RMSDs among other optimisers.

1 INTRODUCTION

At the last decade, many countries have developed strategic plans for diversifications of energy sources to meet the growing demand for energy namely ‘integrated and sustainable energy strategy’. This trend is compulsory due the depletion of conventional energy sources and their destructive effects on environment. Among the fastest growing and promising alternative renewable energy sources (RESs) are the photovoltaic (PV) systems. To quantify the rate of PV installations worldwide, it can be seen that the PV installed capacity is 622 GW by the end of 2019 (almost 115 GW has been installed in 2019), whereas nearly 23 GW was installed in 2009 [1, 2]. In the same context, these strategic future plans of many countries include their committed to deploying renewable energy technologies lead to high penetration of PV systems to existing power systems (EPSs).

With reference to the above-mentioned, high penetration of PV systems to EPSs is considerably influence their performances. Therefore, many researchers are paid their attentions to accurately model the PV generating units (PVGUs) for further analysis in the coming technical studies. Such models used to characterise electrical performances of PVGUs range from simple to sophisticated non-linear models including single, double and triple diodes [3–5]. Needless to say, effective PV modelling is crucial for appropriate control, simulation and evaluation of PV performance. Typically, manufactures of PVGUs announce only three key points on the $I–V$ curve at standard test condition (STC) [6]. These points are: (i) the open circuit voltage ($V_{oc}$), (ii) the short circuit current ($I_{sc}$), and (iii) the voltage and current at maximum power point (MPP) ($V_{mpp}$, $I_{mpp}$), respectively.

Generally speaking, the methods used for parameter estimation of PV models can be classified into: analytical, deterministic and heuristic methods [7, 8]. Analytical methods are fast and simple with some assumptions such as equating the photo generated current ($I_{PV}$) to $I_{sc}$ at STC [9]. These assumptions cause
less accurate model, specially knowing that normal operation of PVGUs is not frequently at STC. On the other hand, deterministic methods solve the non-linear model equations iteratively depending on traditional optimization techniques \cite{7, 9}. Although these methods are accurate, their solutions are very sensitive to the initial guess of model parameters that may make a possible divergence and these methods are straggling with higher number of model unknown parameters.

Nowadays, new trends for PV model parameters extraction are based on meta-heuristic methods. They are derivative-free, can deal effectively with non-linear multimodal functions and with many parameters. However, they are random in nature and have different convergence rates.

Estimating the five uncertain parameters of one diode model (1DM) has been reported by many researchers using different mathematical approaches. Among them, a piecewise curve-fitting method \cite{10}, a successive discretization algorithm \cite{11}, and a concept of shift factors \cite{12, 13}. More investigations on mathematical methods for PV parameters estimation can be found in \cite{14}.

Additional to the aforementioned, number of authors employed a heuristic-based approaches such as genetic algorithm (GA) \cite{15}, bacterial foraging algorithm \cite{16}, flower pollination algorithm (FPA) \cite{17}, multi-verse optimiser \cite{18}, and many versions of differential evolution (DE) \cite{19}. Some other researchers have modified original optimization method with aim of performance improvements such as self-adaptive teaching-learning \cite{8, 20}, an improved Jaya algorithm \cite{21}, and improved shuffled complex evolution algorithm (ISCE) \cite{22}. This led to less errors compared to other algorithms. In addition to that, the whale optimization algorithm is enhanced by modifying the exploration of the search space as reported in \cite{23, 24}.

Further enhancements are proposed via hybridizations of methods for better convergence rate. For example, the FPA is integrated with Nelder–Mead technique \cite{24}, a hybrid DE with integrated mutation per iteration \cite{19}, a hybridised interior search algorithm (HISA) \cite{25}, and a hybrid trust-region reflective deterministic algorithm with the artificial bee colony (ABC) \cite{26}.

Parameters estimation of two diode model (2DM) based on slap swarm algorithm \cite{28}, mine-blast \cite{29}, and particle swarm optimiser (PSO) and GA \cite{30} are addressed. In which, authors have proved the difficulty encountered with estimating these parameters mathematically, especially for the 2DM. In addition to that, difference in convergence rate and solution quality compared with different meta-heuristic methods are illustrated. The published work reported in literature for the three diode model (3DM) is very few compared to that of 1DM and 2DM \cite{12, 13, 15}. This may be due to the sophisticated nature of 3DM and both 1DM and 2DM can reach to a competitive solution. In \cite{31}, Manta-rays foraging optimiser is applied to extract the nine parameters of 3DM depending either on experimental data or the vendor datasheet. In some cases, the solution quality by 3DM is very close to that of 1DM and 2DM.

It can be concluded from the aforementioned literature review that parameter identifications of PVGUs is a hot point of research, and newly developed heuristic-based methods have to be examined for better modelling in regard to reducing errors, smooth convergence, computational burden and fine statistical measures. This is the reason why different methods are still examined in literature for PV parameters estimation, and room for new methods is open intended for more accurate results.

The later mentioned encourages the authors of the current paper to employ a recent population-based algorithm to attain the same namely, Artificial Ecosystem-based Optimiser (AEO). Upon the writing of this paper initial draft, and to the knowledge of the authors after intensive search, this is the first attempt of employing AEO to solve this problem of PV parameter identifications. AEO is a nature-inspired which is motivated from the flow of energy in an ecosystem on the earth. Zaho, Wang and Zhang (2019) \cite{32} developed this novel population-based optimization approach to deal with constrained and unconstrained optimization engineering problems. AEO employed three mechanisms: (i) producer, (ii) consumer, and (iii) decomposer. These three mechanisms are the powerful tools of the AEO algorithm. The first mechanism is applied to balance between exploration and exploitation phases, the second mechanism is used to reinforce the exploration phase, while exploitation phase is promoted by the third mechanism \cite{32}. The performance assessment of AEO has been proved and demonstrated on 31 standard benchmark functions and 8 design problems. It is claimed thru evaluations by comparisons among other competing optimisers plus statistical measures (parametric and non-parametric) that the results of AEO are very convincing and challenging \cite{32}.

In this paper, AEO is employed to generate the best values of the 1DM and 2DM undefined parameters. Three test cases are demonstrated with subsequent analysis and models’ validations. The third case is investigated using real measurements of PV module named Ultra 85-P. Comparisons to other challenging algorithms along with various assessments to appraise the performance of the AEO are made.

The final contributions of this current work can be revealed here as follows: (i) Novel application of AEO to solve the PVGUs parameter definition of both 1DM and 2DM, (ii) Real commercial case studies are used to assess the performance of the AEO including real measurements of Shell PowerMax Ultra 85-P module, and (iii) very competitive results are cropped by the AEO in comparisons to recent results published in the literatures with lesser effort in adjusting its control parameters.

The rest of this article text is organised as follows: Section 2 presents the mathematical models of 1DM and 2DM plus problem statement for parameters identifications. Procedures and motivation of the AEO are publicised in Section 3. However, in Section 4, the best results are realised and summarised after numerous independent runs of the AEO. In addition, the performance assessments of both models along with the comparisons to other some recent methods are decided in Section 4. Lastly, the final recommendations and conclusions along with
future extension of this current work are announced in Section 5.

2 SOLAR PV MODELS AND PROBLEM IDENTIFICATION

Many models for PVGs are developed to illustrate the performance and I–V characteristics such as 1DM, 2DM and 3DM. The 1DM is the popular one because of its simplicity and lesser number of unidentified parameters [18, 23] and 2DM is used to have an accurate modeling of PVGUs [23, 29, 30]. Since, the current research work cares by the first two models (i.e. 1DM and 2DM), their mathematical descriptions are described in the subsequent sections as follows:

2.1 One-diode model

The simplified equivalent circuit of 1DM is shown in Figure 1(a). In which, the output current of the PVGU (I) is computed using the formula depicted in (1) along with the following equations to describe the performance of a PV cell at actual irradiance and temperature.

\[
I = I_{ph} - I_D - I_{sh}.
\]  
(1)

\[
I_D = I_o \exp \left( \frac{q(V_{ph} + IN_J R_s)}{nKT} - 1 \right).
\]  
(2)

\[
I_{sh} = \frac{V + IR_s}{R_{sh}}.
\]  
(3)

For a module of \(N_s\) series connected-cells, the total voltage of the module (\(V_{ph}\)) is equal to \(N_sV\) with the assumption that all connected cells have the same operating conditions, by the substitution in (2) and (3):

\[
I_D = I_o \exp \left( \frac{q(V_{ph} + IN_J R_s)}{nKT} - 1 \right)
\]

\[
= I_o \exp \left( \frac{q(V_{ph} + IR_s)}{nKT} - 1 \right)
\]  
(4)

\[
I_{sh} = \frac{V + IR_s}{R_{sh}} = \frac{V}{R_{sh}} + \frac{IN_J R_s}{R_{sh}},
\]  
(5)

where \(V\) is voltage of PVGU, \(I_o\) and \(I_D\) define the light-generated and the diode reserve saturation currents (\(A\)), respectively, \(R_s\) and \(R_{sh}\) are the series and shunt resistances (\(\Omega\)), respectively, \(n\) is the diode ideality factor, \(q\) is the electron charge (\(1.60217646 \times 10^{-19} \text{C}\)), \(K\) is the Boltzmann’s constant (\(1.3806503 \times 10^{-23} \text{J/K}\)), \(T\) is actual operating temperature of the solar cell (\(K\)), and \(R_{sm}, R_{sh},\) and \(n_m\) denote the overall module series, shunt resistors and ideality factor, respectively. Whereas \(R_{sm} = N_sR_s, R_{sh} = N_sR_{sh},\) and \(n_m = N_s n\).

It can be seen that the above (1)–(3) of 1DM have five unknown parameters \(I_{ph}, I_o, n, R_s,\) and \(R_{sh}\). Thus, it is important to have their best values for further simulations. Manufacturers of PVGUs are given at their datasheets at STC (irradiance \(G_{ref} = 1000 \text{W/m}^2\) and cell temperature of \(T_{ref} = 298.15 \text{K}\)).

In this work, the PV uncertain parameters are extracted using AEO via measuring actual dataset points. The integrity of such defined parameters is validated with the given datasheets by manufacturers at STC such as \((V_{mpv}, I_{mpv}, V_{mpp}, I_{mpp})\), which are performed in Section 4.4.

It is well-known that \(I_{ph}, I_o, R_{sh}, E_{grf}\) and \(R_s\) are dependent of irradiance level \((G)\) and/or temperature \((T)\) which can be corrected based on the formulas’ specified in (6) to (10), respectively [33]. On the other hand, \(n\) is independent of such variations [34, 35].

\[
I_{ph} = \frac{G}{G_{ref}} \left[ I_{phrf} + \alpha \left( T - T_{ref} \right) \right],
\]  
(6)

\[
I_o = I_{srcf} \left( \frac{T}{T_{ref}} \right)^{3} \frac{qgE_{grf}}{nKT} \left[ \frac{1}{T_{ref}} - 1 \right],
\]  
(7)

\[
R_{sh} = \left( \frac{G_{ref}}{G} \right) R_{shr},
\]  
(8)

\[
E_{grf} = E_{grf}\left[ 1 - 2.6677 \times 10^{-4} \left( T - T_{ref} \right) \right],
\]  
(9)

\[
R_s = R_{sr} \left( \frac{T}{T_{ref}} \right) \left[ 1 - 0.217 \ln \left( \frac{G}{G_{ref}} \right) \right],
\]  
(10)

where \(\alpha\) is the cell short-circuit coefficient (\(\text{A/K}\)), \(I_{phrf}, I_{srcf}, R_{sr}, \) and \(R_{shr}\) are the photo-current, diode reserve saturation current, series and shunt resistors at STC, respectively, and \(E_{grf}\)
is the physical energy band-gap (eV) \( E_g = 1.12 \) for mono- and poly-crystalline silicon and \( E_g = 1.7 \) for thin-film at 298.15 K [36].

### 2.2 Two-diode model

It is claimed that the 2DM is more accurate than 1DM because it describes the recombination current losses of depletion region. The equivalent circuit of 2DM is shown in Figure 1(b). The diode D1 simulates the majority charge carrier's diffusion effect within the p-n junction. However, the diode D2 represents the recombination current of minority charge carriers [37, 38]. The I–V characteristics of the PV cell using 2DM can be given within the following expressions:

\[
I = I_{ph} - I_{D1} - I_{D2} - I_{bg}, \quad (11)
\]

\[
I_{D1} = I_{a1} \exp\left(\frac{q(V + IR)}{n_1 k T} - 1\right), \quad (12)
\]

\[
I_{D2} = I_{a2} \exp\left(\frac{q(V + IR)}{n_2 k T} - 1\right). \quad (13)
\]

If the voltage \( V_{ph} \) across a module consists of \( N_s \) series cells is substituted in (12), then

\[
I_{D1} = I_{a1} \exp\left(\frac{q(V_{ph} + IR)}{n_1 k T} - 1\right),
\]

\[
I_{D2} = I_{a2} \exp\left(\frac{q(V_{ph} + IR)}{n_2 k T} - 1\right), \quad (13)
\]

If the voltage \( V_{ph} \) across a module consists of \( N_s \) series cells is substituted in (12), then

\[
I_{D1} = I_{a1} \exp\left(\frac{q(V_{ph} + IR)}{n_1 k T} - 1\right),
\]

\[
I_{D2} = I_{a2} \exp\left(\frac{q(V_{ph} + IR)}{n_2 k T} - 1\right). \quad (13)
\]

Closer look to (11)–(12), it can be realised that the 2DM has seven uncertain parameters such as \( I_{ph}, I_{a1}, I_{a2}, n_1, n_2, R_s \), and \( R_{sh} \). Therefore, this model is alternatively known as seven parameters model. The same for 1DM, module's overall values in terms of \( R_{sh}, R_{s} \), and \( n_s \) are used.

The values of parameters can be converted to reference values using the same expressions depicted in (6)–(10). It is important to emphasise that the reverse saturation current of diode D1 \( (I_{a1}) \) and ideality factor \( (n_1) \) are smaller than or equal to the reverse saturation current of diode D2 \( (I_{a2}) \) and ideality factor \( (n_2) \), respectively [33].

It is well-known that a single PV cell can generate 0.6–0.7 V and a few watts per cell. To have a higher output voltage, numbers of PV cells \( (N_s) \) are wired in series to construct a module. In addition, multiple modules can be arranged together in series/parallel to erect an array to satisfy the load demand [29].

### 2.3 Problem definition

Root mean squared deviation \( (RMSD) \) is widely adopted in the literature to define the fitness value to be minimised. RMSD can be expressed using (14) and the fitness function \( (FF) \) is depicted in (15). In which, the proposed PV-models are assessed by summarizing the deviations among the corresponding actual and estimated values of PV currents. The same \( FF \) is followed in this paper to ensure fair comparisons with others.

\[
RMSD = \sqrt{\frac{\sum (I_{act}(k) - I_{est}(k))^2}{N_w}}, \quad \forall k \in N_w \quad (14)
\]

\[
FF = min(RMSD), \quad (15)
\]

where \( N_w \) denotes the number of measured dataset points, and \( I_{act} \) and \( I_{est} \) define the actual measured and estimated corresponding by proposed models, respectively. It is useful stating that the value of \( I_e \) is obtained for each measured voltage point using Newton–Raphson numerical iterative method [18] by solving (1) and (11) for 1DM and 2DM, respectively.

The depicted \( FF \) in (15) are subjected to number of min/max constraints of the uncertain parameters of the model under investigation. In addition to that, for 2DM, \( I_{a1} \leq I_{a2} \) and \( n_1 \leq n_2 \) are adopted.

### 3 PROCEDURES OF THE AEO

In this smart approach, AEO exhibits three operators: (i) production to boost the balance between exploration and exploitation, (ii) consumption for improving the exploration, and (iii) decomposition for exploitation stage. The next steps illustrate brief mathematical procedures of the AEO. The AEO assumes only one producer and one decomposer among the populations and the rest of agents are consumers [32]. The execution of the AEO starts by creating initial ecosystem agents. In this random initialization, the initial agents are estimated within their min/max limits as depicted in (16).

\[
X_{rand}(i, : ) = \text{rand}(1, \text{Pop}) \cdot \text{HL} + \text{LL}, \quad \forall i \in \text{Dim}, \quad (16)
\]

where \( \text{LL} \) and \( \text{HL} \) define the min/max bounds of the control variables, \( \text{rand}(...) \) represents a random uniform number lies between 0 and 1, \( \text{Pop} \) defines the swarm-size of agents and \( \text{Dim} \) denotes the number of variables (dimension of the optimization problem).

The production operator can be mathematically formulated as depicted in (17). It may be noted from (18) that scaling factor \( (\beta) \) is employed which is updated with iterations increase aiming at improving the exploitation process.

\[
X_{1}^{k+1} = (1 - \beta) X_{best}^{k} + \beta X_{rand}^{k}, \quad (17)
\]

\[
\beta = r_i \left(1 - \frac{k}{Max_I ter}\right), \quad (18)
\]

where \( r_i \) defines random uniform numbers between \( (0, 1) \), \( k \) defines iteration counter, \( X_{rand}^{k} \) is the location of the agent
Define the fitness function and min/max bounds
Set the parameters of the AEO: Pop, and Max Iter
Initialize randomly ecosystem agents ($X_i$) between min/max bounds by (16)
Estimate the fitness values, sort in descending order and register best solutions obtained so far.

$k = 1$: Max Iter
For all agents
Estimate the fitness values
Calculate $C_f$
Update the location of the agent ($X_i$) accordingly as per (17)
Update the location of the agent ($X_2$) accordingly as per (21)

$i = 3$: Pop
Update the locations of the agents based on (21)
Estimate the fitness values, sort in descending order and register best solutions $X_{best}$

$i = 1$: Pop
Calculate $D_i$, $e$ and $h$
Update the locations of the agents based on (23)
Estimate the fitness values, sort in descending order and register best solutions $X_{best}$

A
Stopping?
Record the best/final solutions $X_{best}$ and best score of the fitness value

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**FIGURE 2** The overall procedures of the AEO

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**TABLE 1** RTC France PV cell parameters by AEO and various algorithms

| Model | Method | AEO   | ISCE [22] | pSFS [38] | GCPPO [39] | ABC-DE [40] |
|-------|--------|-------|-----------|-----------|------------|-------------|
| 1DM   | $I_{ph}(A)$ | 0.760787966454727 | 0.7608 | 0.7608 | 0.7608 | 0.76077 |
|       | $I_0(\mu_A)$ | 0.310684606 | 0.3230 | 0.3230 | 0.3106 | 0.3230 |
|       | $n$ | 1.477267789254185 | 1.4812 | 1.4812 | 1.4773 | 1.4798 |
|       | $R_s(\Omega)$ | 0.036546945140114 | 0.0364 | 0.0364 | 0.0365 | 0.0363 |
|       | $R_{sh}(\Omega)$ | 52.889790253866444 | 53.7185 | 53.7185 | 52.8898 | 53.7185 |
|       | RMSD $\times 10^{-4}$ | 7.730062689944642 | 9.8602 | 9.8602 | 7.7301 | 9.8602 |
|       | Average run time (s) | 46.67 | NR | 23.05 | 98.00 | NR |
| 2DM   | $I_{ph}(A)$ | 0.760813075264878 | 0.7608 | 0.7608 | 0.7608 | 0.7608 |
|       | $I_0(\mu_A)$ | 0.310684606 | 0.3230 | 0.3230 | 0.3106 | 0.3230 |
|       | $n_1$ | 1.477267789254185 | 1.4812 | 1.4812 | 1.4773 | 1.4798 |
|       | $R_s(\Omega)$ | 0.036546945140114 | 0.0364 | 0.0364 | 0.0365 | 0.0363 |
|       | $R_{sh}(\Omega)$ | 52.889790253866444 | 53.7185 | 53.7185 | 52.8898 | 53.7185 |
|       | RMSD $\times 10^{-4}$ | 7.730062689944642 | 9.8602 | 9.8602 | 7.7301 | 9.8602 |
|       | Average run time (s) | 53.25 | NR | 23.05 | 98.00 | NR |

NR means not reported

*The RMSD value is infeasible as $n_2$ is beyond the defined upper limit (i.e. 2).
haphazardly generated in the search space using (16), $X^k_{best}$ is the best agent with least fitness value and $MaxIter$ is the maximum number of iterations.

In the exploration stage after production process completed, consumption factor ($C_f$) similar to Lévy flight is followed as demonstrated in (19). This $C_f$ helps each consumer’s agent to hunt for foodstuff, adopting various consumption tactics. These strategies are mathematically exhibited as shown in (21). At the consumption stage, the locations of agents are updated based on their energy levels with the aim of enhancing the exploration mechanism.

$$ C_f = \frac{v_1}{2|v_2|}, $$

(19)

$$ v_1 = \text{randu}(1, Dim), \quad v_2 = \text{randu}(1, Dim) $$

(20)

where $\text{randu}$ is the normally distributed pseudorandom numbers drawn from the standard normal distribution with mean equals 0 and standard deviation is equal to 1.

$$ X^{i+1}_j = \begin{cases} 
X^k_i + C_f \Delta X^k_{i,j} & \forall \text{rand} < \frac{1}{3}, i = 2 \ldots \text{Pop} \\
X^k_i + C_f \Delta X^k_{i,j} & \forall \frac{1}{3} \leq \text{rand} \leq \frac{2}{3}, i = 3 \ldots \text{Pop} \\
X^k_i + C_f : r_2 \Delta X^k_{i,1} + C_f : (1 - r_2) \Delta X^k_{i,j} & \text{else}, i = 3 \ldots \text{Pop} 
\end{cases} $$

(21)

$$ \Delta X^k_{i,j} = X^k_i - X^k_j, \Delta X^k_{i,1} = X^k_i - X^k_1, \quad j = \text{randi}([2 \ldots i - 1]), $$

(22)

where $r_2$ is a random uniform distribution on the open interval (0,1), $\text{randi}$ is pseudorandom integers from a uniform discrete distribution. At the last decomposition stage, the locations of agents are updated as depicted in (23) with the aim of reinforcing the exploitation process.

$$ X^{i+1}_f = X^k_f + D_f \left( e X^k_{best} - h X^k_f \right), \forall i \in \text{Pop} $$

(23)

$$ D_f = 3 \gamma, \gamma \sim \text{Norm}(0, 1), $$

where $r_3$ is a random uniform distribution on the open interval (0,1). It can be seen that the decomposition scaling factor ($D_f$), $\beta$ and $C_f$ are self-adaptive dynamically and no interference from the user which considers an advantageous and also reinforcing the search space to evade from trapping in local minima. Thus, the key advantageous of the AEO are faster rate of convergence pattern and reduction in computational burdens. Similar to other optimisers, proper settings of the AEO controlling parameters are essential to guarantee best performance. The only two settings that require fine-tuning are $Pop$, and $MaxIter$. The flow-chart shown in Figure 2 illustrates the overall procedures of the AEO approach. Moreover, the reader can obtain further detailed descriptions in regard to the AEO’s Pseudocode, inspiration and motivation in [32].
4 | SIMULATIONS, CROPPED RESULTS AND VALIDATIONS

In this section, three test cases of typical commercial PVGUs (1 cell plus 2 modules) are demonstrated to appraise the performance of the AEO in estimating the 5 and 7 uncertain parameters of 1DM and 2DM, respectively. Within the parameters extraction using the AEO, the boundaries of these per cell parameters are: \( I_{ph}(\text{A}) \in [0.9 I_{vo}, 1.1 I_{vo}] \), \( I_{po} (\text{A}) \), \( I_{oa}(\mu \text{A}) \in [10^{-3}, 10] \), \( R_s(\Omega) \in [0, 0.5] \), \( R_{sh}(\Omega) \in [0, 100] \) and \( n, n_1, n_2 \in [1, 2] \).

The adopted final AEO parameters are: Pop equals 50 and MaxIter is equal to 3000, which are valid for the three test cases under study. It is worth mentioning that these control parameters are obtained by trials and errors methodology. Moreover, due to the nature of high randomness of AEO similar to heuristic-based optimisers, the best results are cropped after 100 times of its independent implementations on 1DM and 2DM per each test case. In which, some accuracy assessments are made thru normalised indices along with parametric and non-parametric statistical measures which are offered in Section 4.4. It is worth to mention here that simulation is performed on Intel® core i7-3612QM CPU @ 2.1 GHz and 12 GB RAM Laptop.

### 4.1 Test Case 1: R.T.C. France PV cell

To check the quality of the proposed AEO in parameters determination of PVGUs, a simulation is developed using 1DM and 2DM and the results are compared with other algorithms [22, 38–40].

The AEO is applied to 26 points of I–V experimental data of RTC France silicon (Si) solar cell at 35°C and irradiance of 1000 \( \text{W/m}^2 \) [22]. This RTC PV cell considers as benchmarking in testing the different algorithms for PV parameters estimation. The RMSD between the measured and estimated data is used to measure the quality of the AEO for PV parameters extraction. The results of the AEO are compared with other optimization algorithms such as ISCE [22], perturbed stochastic fractional search (pSFS) [37], guaranteed convergence PSO (GCPSO) [39], and ABC-DE [40] and they are listed in Table 1. It is worth to mention here that, original data in some papers are displayed in long format. Only those of AEO in this paper are displayed in long format, and for others, kindly refer to their original articles. It’s clear from the comparisons that the AEO is the best ever to yield a minimum values of RMSD of 7.7301 × 10^{-4} and 7.3265 × 10^{-4} for 1DM and 2DM, respectively. The performance of RTC France Si PV cell for 1DM and 2DM using the AEO are illustrated in Figure 3. One may note that the performance curves for 1DM is illustrated in Figure 3(b) which is more or less typical to 2DM (not shown here). In addition, the reader can see the maximum biased current error is less than 1.5 mA as indicated in Figure 3(c). The average computational time (out of 100 trials) of 3000 iteration by AEO is 46.67 s for 1DM of RTC France cell and 53.25 s for 2DM. However, computation time and specifications of CPU of other methods are not included in their published work except few papers as they consider this task as offline in nature. More specifically, for GCPSO, the reported mean times are 98.00 s, and 218.00 s for 1DM and 2DM of RTC Silicon PV cell; respectively. Bear in mind, the computing tasks of GCPSO were implemented utilizing MATLAB in a computer with an Intel® Xeon® E5-1620 @3.60 GHz CPU proces-
4.2 Test Case 2: Photowatt PWP201 module

In this study case, the AEO is tested on Photowatt PWP201 module. Experimental data of this module are found in [41], it consists of 26 test points at $1000 \text{ W/m}^2$ and $45^\circ C$. The records of Table 2 give the best cropped results by the AEO together with the results with other some recent algorithms found in literature. Values of RMSDs produced by the AEO are very competitive and challenging other recent algorithms as indicated in Table 2.

In case of PWP201 module, average run time for 1DM is $50.77\text{ s}$ and that of 2DM is $52.18\text{ s}$, while the average CPU times are $111.00\text{ s}$ and $189.00\text{ s}$ for 1DM and 2DM; as indicated in Table 2 for AEO and GCPSO, respectively.

Figure 4(a) illustrates the convergence curve trends for 1DM and 2DM, smooth and stable convergence rate is established using 1DM compared to 2DM case. The $I-V$ and $P-V$ curves are plotted for 1DM case as shown in Figure 4(b), identical figure for the 2DM case can be presented (however, again, to avoid such silly duplications, it is not shown here). Biased errors amongst measured and calculated current points for 1DM and 2DM are demonstrated in Figure 4(c). It can be seen that the maximum biased current error is $4\text{ mA}$.

4.3 Test Case 3: Ultra 85-P with real experimental configurations

In this study case, commercial module namely Ultra 85-P (Manufacturer: Shell PowerMax) is used for further practical validations of the AEO in getting 1DM and 2DM models. The typical nameplate data of this module is shown in Figure 5(a). Ultra 85-P module can generate a maximum power of 85 W at STC with $\pm 5\%$ tolerance and consists of 36 monocrystalline PV cells connected in series. The efficiency of this module is 13.4% and has a fill factor of 70.3%. The dimension of this module is 120.0 cm length $\times$ 52.70 cm width $\times$ 3.40 cm depth weighted 7.5 kg and protected by 20 A series fuse. The temperature coefficients for $P_{max}$, $V_{mp}$, $I_{sc}$ and $V_{oc}$ are $-0.43%/^\circ C$, $-72.5mV/^\circ C$, $0.8mA/^\circ C$, and $-72.5mV/^\circ C$, respectively. Complete datasheet of this module can be obtained from [43].

Outdoor experimental setup is arranged as per the configuration shown in Figure 5(b). The procedures of IEC 60904 [44, 45] is followed for the measurements of $I-V$ characteristics. Initially, a variable load resistance is used to change the module output current and the module output voltage and current are recorded at different temperature and irradiance levels. It may be useful mentioning that the infrared thermometer temperature digital indicator model 5500 (Kyoristu) to measure cell temperature (measuring accuracy is $\pm 2^\circ C$) and sun irradiance is measured by a digital solar power meter type TES 1333 (measuring accuracy $\pm 10\text{ W/m}^2$) are employed in such measurements. Voltage and current are recorded using multi-channel power sensor 68–600. It is a digital multimeter with 1024 sampling length, 12 bits resolution and 512 kHz as a maximum sampling rate. Readings of the multimeter is displayed on Espial software package. Needless to say, that it is well-known that changes in irradiance level produces differences in PV unit temperature that can definitely affect the accuracy of $I-V$ curve measurements. If the irradiance has increased significantly immediately before measurements are made, the PV module temperature may not have stabilised. Variations in irradiance during an $I-V$
curve measurements can dramatically affect the quality and integrity of the I–V curve. So, the I–V curve measurements are made when there is a clear sky and little wind. Nevertheless, typically, each group of measurements was obtained in 2–3 min maximum, slight change within allowable tolerance are noticed. The sample time between each measure is around 2–4 s. The extracted best values of the models unknown parameters are collected in Table 3. In the same context, these AEO results are validated by implementing two other optimisers, namely PSO [46] and lightning attachment procedure optimization (LAPO) [47] complete with best scores of RMSDs as recorded in Table 3. Such validations are made at \( G = 950 \text{W/m}^2 \), and \( T = 48.7^\circ \text{C} \) at which the optimal values of the uncertain PV parameters are cropped. The records of Table 4 summarise the picked readings at three different ambient test condition (ATC) and irradiances \( (G = 950 \text{W/m}^2, \ T = 48.7^\circ \text{C}) \), \( (G = 650 \text{W/m}^2, \ T = 41.4^\circ \text{C}) \), and \( (G = 450 \text{W/m}^2, \ T = 39.7^\circ \text{C}) \) with estimated corresponding values of current by the models.
### Table 4

The experimental and estimated dataset points via 1DM and 2DM (Ultra 85-P module)

|          | Measured | Estimated | Measured | Estimated | Measured | Estimated |
|----------|----------|-----------|----------|-----------|----------|-----------|
|          | 1DM      | 2DM       | 1DM      | 2DM       | 1DM      | 2DM       |
| $V_m$    |          | $L_A$     |          | $L_A$     |          | $L_A$     |
|          |          | $\xi_A$   |          | $\xi_A$   |          | $\xi_A$   |
| $V_e$    |          | $L_e$     |          | $L_e$     |          | $L_e$     |
|          |          | $\xi_e$   |          | $\xi_e$   |          | $\xi_e$   |
| $I_m$    |          | $L_I$     |          | $L_I$     |          | $L_I$     |
|          |          | $\xi_I$   |          | $\xi_I$   |          | $\xi_I$   |
| $I_e$    |          | $L_I$     |          | $L_I$     |          | $L_I$     |
|          |          | $\xi_I$   |          | $\xi_I$   |          | $\xi_I$   |

- $G = 450/\mu_m$, and $T = 41.4^\circ C$
  - $G = 650/\mu_m$, and $T = 48.7^\circ C$
  - $G = 950/\mu_m$, and $T = 39.7^\circ C$
In addition, the error (\( \varepsilon \)) denoting the difference between measured and calculated corresponding current data points are added to Table 4.

Additional demonstrations to check the validities of model’s cropped parameters, the models are tested at two different cases of real experimental data (i.e. at irradiance level and temperature of \((650\text{W}/\text{m}^2\) and \(41.4^\circ\text{C}\)) and \((450\text{W}/\text{m}^2\) and \(39.7^\circ\text{C}\)), respectively). Their performance patterns are illustrated in Figure 6(a)–(d) for both 1DM and 2DM, respectively.

The computed three key points at STC are \( \{0\ V, 5.4683\ A\}, \ (22.3400\ V, 0\ A\}, \ (16.9900\ V, 4.8867\ A\}\) for 1DM and \( \{0\ V, 5.4675\ A\}, \ (22.3400\ V, 0\ A\}, \ (16.9900\ V, 4.8874\ A\}\) for 1DM and 2DM, respectively. The tolerance between the given datasheet at STC of Ultra 85-P module and its corresponding estimated data are insignificant as illustrated before. It is self-explanatory that both generated models can produce maximum power of nearly 83.03 W at STC (bear in mind \( \pm 5\% \) tolerance in the \( P_{mp} \) as reported by the manufacturer) which is near enough to the given datasheet. In addition to that, the calculated fill factor is equal to 68.0% which is again very well-nigh from the given data in this regard.

Three normalised indices are employed to estimate the differences between the estimated key points versus the given corresponding datasheet values of the PV generating system under study at STC. These factors namely; open-circuit, short-circuit and mpp indices can be defined as depicted in (25)–(27).

\[
F_{oc\%} = \sqrt{\left( \frac{V_{oc}|_e}{V_{oc}|_{STC}} - 1 \right)^2} \times 100, \quad (25)
\]

\[
F_{sc\%} = \sqrt{\left( \frac{I_{sc}|_e}{I_{sc}|_{STC}} - 1 \right)^2} \times 100, \quad (26)
\]

\[
F_{mpp\%} = \sqrt{\left( \frac{V_{mpp}|_e}{V_{mpp}|_{STC}} - 1 \right)^2 + \left( \frac{I_{mpp}|_e}{I_{mpp}|_{STC}} - 1 \right)^2} \times 100, \quad (27)
\]

where \( V_{oc}|_e, I_{sc}|_e, V_{mpp}|_{STC} \) and \( I_{mpp}|_{STC} \) define the estimated and given datasheet of \( V_{oc} \) and \( I_{sc} \) by proposed models at STC, respectively, and \( V_{mpp}|_e, I_{mpp}|_e, V_{mpp}|_{STC} \) and \( I_{mpp}|_{STC} \) define the
estimated and given datasheet of $V_{mp}$ and $I_{mp}$ by proposed models at STC, respectively.

The values of $F_{oc}$, $F_{sc}$ and $F_{mpp}$ of Ultra 85-P module under STC based on estimated results in regard to datasheet points are given in Table 5. It is well-known that due to real continuous variations of sun radiance levels and temperatures, the performance of PVGUs are significantly affected. To investigate the impact of such variations on the PVGUs parameters, varied $T$ and $G$ are fed to the models to observe their reactions to such changes. As a result, the variations of Ultra 85-P module performance are revealed in Figures 7(a)–(d) and 8(a)–(d) for 1DM and 2DM, respectively. A closer look to the reported Tables and illustrated Figures, it can be confirmed that good matching between actual experimental and estimated datasets is indicated. In spite of the aforementioned, further validations for the accuracy assessments of the AEO performances for both 1DM and 2DM are revealed in the next section.

4.4 | Accuracy assessments

This sub-section aims at validating the results of the AEO and announces the performance assessments of proposed PV models (i.e. 1DM and 2DM). As long as, mean absolute error ($MAE$) is also regularly used in the literatures to assess proposed PV-models by summarizing the deviations among the corresponding actual and estimated values of PV current. $MAE$ for PV current can be expressed using (28).

$$MAE = \frac{1}{N_m} \sum_{k \in N_m} |I_m(k) - I_e(k)|$$  \hspace{1cm} (28)

It is well-known that $MAE$ has equal flat weight to all deviations, while $RMSD$ gives extra weight to huge errors. Needless to say, the insignificant values of $RMSD$ and $MAE$, indicate better performance of the proposed PV-models. In addition to that, Pearson correlation coefficient ($PCF$) along with $P-values$ with 1% confidence level are employed to statistically appraise the estimated results by AEO analogy to experimental observations. It is worth mentioning that the AEO is implemented 100 independent times per each model and the best results are cropped. The $PCF$ is mathematically expressed using the formula depicted in (29).

$$PCF = \frac{\sum \left(I_m(k) - \bar{I}_m\right) \left(I_e(k) - \bar{I}_e\right)}{\sqrt{\sum (I_m(k) - \bar{I}_m)^2 \cdot \sum (I_e(k) - \bar{I}_e)^2}} \hspace{1cm} k \in N_m$$  \hspace{1cm} (29)
where $\bar{I}_m$ and $\bar{I}_e$ define the arithmetic means of the given experimental current data and estimated current by the model.

The statistical results of the AEO are listed in Table 6 and it can be concluded that the AEO is more robust to attain the best or very close to best solution in each trial. Final minimum value of FF produced by the AEO is attained for most of trials as indicated by the RMSD (mode) value. This indicates noticeably the robustness of the AEO algorithm to reach to the desired solution in spite of its search process randomness. Furthermore, small values of calculated indices are real evidence for the quality of the cropped results generated by the AEO. The values of PCFs are very close to 1 which indicate certainly to the good correlation between actual and estimated dataset points. Intensive performance assessments of the 1DM and 2DM models are performed by comparing their produced I–V characteristics with real measurements at constant and/or changeable irradiance levels and/or cell temperatures. Openly to express the authors’ findings, the outcomes of the study can indicate obviously that the performance of 1DM is well-sufficed for the sake of simulations with less calculation burdens and high precision.
In spite of its simplicity, very competitive RMSDs are cropped with lesser effort in estimating its uncertain parameters and shorter computational elapsed time.

## 5 | CONCLUSIONS

The viability of the AEO algorithm is intensively evaluated by solving 1DM and 2DM parameter identifications of three commercial solar generating systems. Performance assessments of the AEO are made through comprehensive comparisons to some recent optimizers plus other statistical measures over number of independent runs. In addition, it is indicated that AEO results are very promising with reference to the given typical datasets of the studied test cases along with real measurements. It can be concluded that the proposed AEO-based methodology has been tested in handling many types of solar technologies such as RTC France solar cell is mono-crystalline type, PWP201 (polycrystalline silicon cells) module and the module Ultra 85-P of Shell PowerMax which composed 36 connected solar monocrystalline cells. Better convergence and less adjustments for fine-tuning of AEO signify its applicability to real problems. Thus, the accuracy and efficacy of the AEO algorithm are established in tackling the 1DM and 2DM parameters identifications. Further, the various scenarios of changeable operating conditions are demonstrated. In which, precise models of 1DM and 2DM are realized. When 1DM is employed, it can be quantified that the best values of RMSDs that are generated by the AEO are 7.73006268994462e-4, 2.039992273216e-3, and 2.599645862712e-3 for RTC Silicon cell, PWP201 module, and Ultra-85P module; respectively. On the other hand, the best generated RMSD values when 2DM is engaged for the same; are 7.326480062589926e-4, 2.039992273217e-3, and 2.513549300132e-3; which are very competitive to other competing methods reported in the literature. The authors would like to extend this current work to study the performance of triple diode model with further analysis including dynamic modeling.

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