Parameters Extraction of a Photovoltaic Cell Model Using a Co-evolutionary Heterogeneous Hybrid Algorithm

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***Abstract*—This paper proposes a new hybrid algorithm with a combination between the wind driven optimization (WDO) algorithm and the differential evolution with integrated mutation per iteration (DEIM) algorithm. The proposed algorithm, a wind driven optimization based on differential evolution with integrated mutation per iteration (WDO-based on DEIM) algorithm, is utilized to extract the unknown parameters in both of a single-diode photovoltaic (PV) cell model and a double-diode PV cell model. To show the effectiveness of the proposed model, its performance is validated internally by comparing the generated current-voltage (I-V) characteristic curves by the proposed algorithm with the actual I-V characteristic curves, and externally with those obtained by the WDO and DEIM algorithms. The results show the superiority of the proposed model. According to the normalized-root-mean-square error (nRMSE), the mean absolute percentage error (MAPE) and the coefficient of determination (R^2) of the achieved results, the proposed WDO-based on DEIM algorithm outperforms the aforementioned algorithms. Finally, the average efficiency of the WDO-based on DEIM algorithm is 95.31%, while it is 81.08% for the WDO algorithm and 88.37% for DEIM algorithm in the single-diode PV cell model. While, it is 96.78% based on WDO-based on DEIM algorithm and it is 92.30% for the WDO algorithm and 91.42% for DEIM algorithm in the double-diode PV cell model.**

***Index Terms*—Photovoltaic (PV), I-V characteristic curve, parameter extraction, WDO algorithm, DEIM algorithm**

I. Introduction

The renewable energy installation is expanded worldwide to overcome the limitations of the availability of fossil fuel sources. The usage of solar energy is increased sharply because of it considers as a secure, clean and environmentally friendly source. Hence, solar photovoltaic (PV) systems are considered as an active solar energy source. The high initial cost of the PV systems is one of the drawbacks that limited its efficient use. To increase the efficiency of PV systems, a maximum capture of the available solar radiation should be ensured. To do so, an accurate and reliable model of a PV cell/module should be provided to optimize the performance of the PV systems during the design phase [1].

Several mathematical models are utilized in the literature to express the nonlinear behaviour of a PV cell/module [2]. The most utilized models are the single-diode PV cell model as well as the double-diode PV cell model. Accordingly, two main approaches are used to extract the unknown parameters of these models. These approaches are deterministic and stochastic approaches [3]. Deterministic approaches are successfully applied to solve the unimodal optimization problems. In contrast, those approaches require a long computational time and they cannot handle any optimization problem with a discontinuity objective function. A nonlinear least-squares based algorithm with Levenberg parameter is used to extract the unknown parameters in a single-diode PV cell model [4]. This algorithm has a strong dependency on the initial values. Moreover, Newton Raphson method is applied in [5] to extract the unknown parameters in a double-diode PV cell model. The results show a large deviation value between the experimental and generated current-voltage (I–V) characteristic curves.

Alternatively, stochastic approaches are applied to overcome the limitations of the deterministic approaches as they have the ability to solve the multi-modal, complex and nonlinear optimization problems independently without any previous information about the initial values. Some of stochastic approaches that utilized to extract the unknown parameters in a single-diode PV cell model and a double-diode PV cell model are the simulated annealing (SA) algorithm [6], pattern search (PS) algorithm [7], harmony search (HS) algorithm [8], artificial bee swarm optimization (ABSO) algorithm [9], mutative-scale parallel chaos optimization (MPCO) algorithm

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[10] and evolutionary algorithm (EA) [11]. Most of the aforementioned algorithms were not converged before 2000 iterations and their results have slightly large values of errors [12]. Therefore, a more capable algorithm is needed to overcome these limitations to extract the unknown parameters for PV modules optimally with a smaller number of iterations and an acceptable range of error.

Hybrid algorithms are the alternative for the standard stochastic approaches which are a combination between two or more of stochastic algorithms. These algorithms mostly have the ability to reach the global optimum faster than standard stochastic algorithms [13]. Several hybrid algorithms have been proposed in literature to overcome the aforementioned limitations of the single stochastic algorithms. Those algorithms are the hybrid firefly algorithm and pattern search (HFAPS) [14] and hybrid PSO and SA [15]. The aim of these algorithms is reducing the probability of the standard stochastic algorithms in trapping at the local optimum.

In this paper, a new hybrid algorithm, a wind driven optimization based on differential evolution with integrated mutation per iteration (WDO-based on DEIM) algorithm, is proposed to enhance the efficiency of the standard stochastic algorithms in extracting the unknown parameters in a single-diode PV cell model as well as a double-diode PV cell model. Actual performance data are utilized, which is recorded for 3 years at 15-minitue intervals by Commonwealth Scientific and Industrial Research Organisation (CSIRO), NSW, Australia. Here, the JAM6-60-260W PV module is utilized to extract its unknown parameters using both of a single-diode PV cell model and a double-diode PV cell model under different operating conditions.

The structure of this paper is organized as follows: the mathematical models for both of a single-diode PV cell model and a double-diode PV cell model as well as the formulation of the optimization problem are described in Section II. The WDO-based on DEIM algorithm is proposed in Section III. In section IV, the simulation results, validation and related discussions are provided. Finally, the main conclusions are summarized in Section V.

II. PV Cell Models and Problem Formulation

In this section, the mathematical modeling of a single-diode PV cell model and a double-diode PV cell model as well as their problem formulations are briefly described.

A. Single-diode PV cell model

The single-diode PV cell model equivalent circuit is illustrated in Fig. 1. It considers as a simply model in terms of complexity after the ideal PV cell model. The output current of the PV cell (I) in Fig. 1 can be mathematically formulated as [16]:

$$I = I_{Ph} - I_0 \left[exp\left(\frac{q\,(V + IR_s)}{ak_bT_c} \right) - 1 \right] - \frac{V + IR_s}{R_{sh}} \quad (1)$$

where I_{Ph} is the photocurrent, I_0 represents the diode saturation current, q is the electron's charge, V is the output voltage

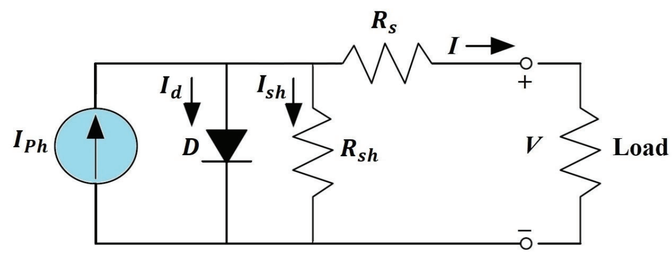

Fig. 1. The equivalent electrical circuit for a single-diode PV cell model

of the PV cell, R_s stands for the series resistance, a is the diode's ideality factor, k_b stands for Boltzmann's constant, T_c is the cell temperature (K) and R_{sh} denotes the shunt resistance.

B. Double-diode PV cell model

The double-diode PV cell model is more accurate than the single-diode PV cell model in characterizing the nonlinear behavior of a PV cell, but it is more complex. The double-diode PV cell model is depicted in Fig. 2. The output current

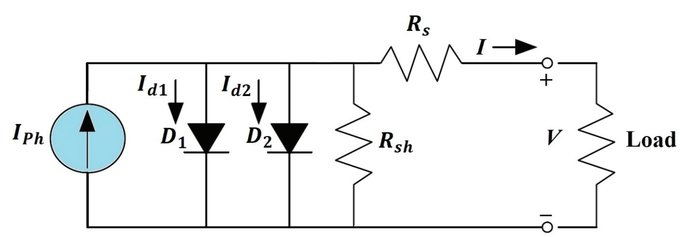

Fig. 2. The equivalent electrical circuit for a double-diode PV cell model

of the PV cell (I) in Fig. 2 can be given as [17]:

$$I = I_{Ph} - I_{0_1} \left[exp\left(\frac{q\,(V + IR_s)}{a_1k_bT} \right) - 1 \right] - I_{0_2} \left[exp\left(\frac{q\,(V + IR_s)}{a_2k_bT} \right) - 1 \right] - \frac{V + IR_s}{R_{sh}} \quad (2)$$

where I_{0_1} and I_{0_1} are the saturation currents for the first and the second diodes respectively, and a_1 and a_2 denote the ideality factors for the first and the second diodes respectively.

C. Problem formulation

Each of the above described models has several unknown parameters which must be optimally determined to secure the higher efficiency and effectiveness of the mathematical model. Therefore, extracting the unknown paraments for each model can be considered as a multi-modal optimization problem. Accordingly, an objective function should be set for each optimization problem. In this research, the objective function aims to minimize the deference between the experimental data and the generated one. Here, the root-mean-square-error

(RMSE) is selected to represent the objective function. The RMSE is given as:

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N} f_i\left(V_a, I_a, \theta\right)} \tag{3}$$

where N represnts the lenght of thr dataset, $f\left(V_a, I_a, \theta\right)$ is the error function, V_a and I_a represnt the actual values of the PV output voltage and current respectively and θ stands for a vector of the unknown parameters. For the single-diode PV cell model, $\theta = \left(I_{Ph}, I_0, R_s, R_{sh}, a\right)$ and for double-diode PV cell model, $\theta = \left(I_{Ph}, I_{0_1}, I_{0_2}, R_s, R_{sh}, a_1, a_2\right)$. The error function for the single-diode PV cell model can be represented as:

$$f\left(V_a, I_a, \theta\right) = I_a - I_{Ph} + I_0\left[exp\left(\frac{q\left(V + IR_s\right)}{ak_bT_c}\right) - 1\right] + \frac{V + IR_s}{R_{sh}} \tag{4}$$

Simultaneously, the error function for the double-diode PV cell model can be given by:

$$f\left(V_a, I_a, \theta\right) = I_a - I_{Ph} + I_{0_1}\left[exp\left(\frac{q\left(V + IR_s\right)}{a_1k_bT}\right) - 1\right] + I_{0_2}\left[exp\left(\frac{q\left(V + IR_s\right)}{a_2k_bT}\right) - 1\right] + \frac{V + IR_s}{R_{sh}} \tag{5}$$

In this work, a new algorithm, a WDO-based on DEIM algorithm, is proposed to minimize the RMSE in order to extract the global values of the unknown parameters in the single-diode PV cell model and the double-diode PV cell model.

III. Proposed WDO-based on DEIM Algorithm

A new hybrid algorithm, wind driven optimization based on differential evolution with integrated mutation per iteration (WDO-based on DEIM) algorithm, is proposed tto enhance the efficiency of the standard stochastic algorithms for extracting the unknown parameters in a single-diode PV cell model and a double-diode PV cell model.

The WDO algorithm is proposed in [18]. The mechanism of the WDO algorithm is inspired by the movement of the wind. This algorithm has been successfully used to extract the unknown parameters in a double-diode PV cell model [17]. This algorithm has four hyper-parameters which should be tuned optimally to get the highest accuracy of the optimized results. The WDO algorithm has four hyper-parameters which represent its physical characteristic. The optimal values of these hyper-parameters will improve the ability of the WDO algorithm in finding the global optimum. Therefore, these hyper-parameters should be optimized. To do so, the DEIM algorithm is utilized. The DEIM algorithm is proposed in [19]. The DEIM algorithm is a simple and accurate algorithm which aims to adjust the mutation and crossover rate parameters automatically to optimize the hyper-parameters of the WDO algorithm. The DEIM algorithm is successfully used to find the optimal values of the unknown parameters in a double-diode PV cell model.

The main idea of the WDO-based on DEIM algorithm is to combine the ability of WDO algorithm in finding the global optimum and the speed of the DEIM in localizing the values. The procedure of solving the optimization problems in the WDO-based on DEIM algorithm can be summarized as illustrated in Fig. 3.

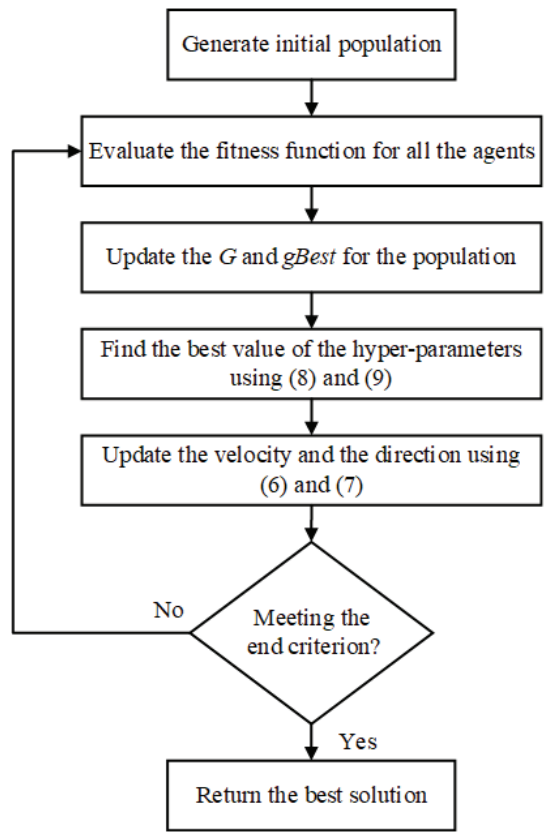

Fig. 3. Steps of the WDO-based on DEIM algorithm

Firstly, all agents in WDO-based on DEIM algorithm are randomly initialized. After the initialization, the hyper-parameters of the WDO algorithm (α, g, c and RT) are randomly selected to start the first optimization iteration. Based on these values, the velocity and the direction of each air parcel are calculated using:

$$u^i_{new} = (1-\alpha)u^i_{cur} - gx^i_{cur} + \left(RT\left|\frac{1}{r} - 1\right|\left(x_{opt} - x^i_{cur}\right)\right) + \left[\frac{cu^{other\ dim}_{cur}}{r}\right] \tag{6}$$

$$x^i_{new} = x^i_{cur} + u^i_{new} \tag{7}$$

where i refers to the air parcel number, u^i_{cur} represents the velocity at the current iteration, u^i_{new} represents the velocity at the next iteration, x_{opt} stands for the global best position, x^i_{cur} represents the position at the current iteration, x^i_{new} represents the position at the next iteration, r stands for the air-parcel ranking, and (α, g, c and RT) are hyper-parameters which reflect the physical model.

Accordingly, the population is evaluated using the fitness function which is the RMSE of the optimization problem. Meanwhile, the pressure values are ranked and the solution which has the minimum value of RMSE is used to update the velocity and the direction of each air parcel. In each iteration, the hyper-parameters of the WDO algorithm are optimized using the DEIM algorithm. The optimization function in DEIM algorithm also aims to minimize the RMSE of the optimization problem by optimizing the hyper-parameters of the WDO algorithm. This optimization is carried out using:

$$\omega = \left[f(X^{G}_{best}) - f(X^{G-1}_{best})\right] \times R \tag{8}$$

where X^{G}_{best} and X^{G-1}_{best} represent the vectors which contain the best values of the hyper-parameters for G and $G-1$ respectively, and R represents a random number between 0 and 1.

According to the value of ω, the values of the mutation factor (F) and crossover rate (CR) are updated by:

$$F, CR = A\left(\frac{L}{1+exp(-k(\omega-\omega_0))} + B\right) \tag{9}$$

where A and B are constants in the range of $[0.5, 1]$. In this paper, $A = 0.5$ and $B = 1$.

The hyper-parameters that have a minimum value of the RMSE are used in the next iteration. This process will be repeated until the iteration number reaches the maximum number of iterations. The efficient of the proposed algorithm are remarked as follows: i) the minimum value of RMSE is considered in the updating procedure for the hyper-parameters in DEIM algorithm and the final values of the extracted unknown parameters in WDO algorithm; ii) the agents which have the minimum value of RMSE are exploring the search space by attracting the other agents to their position; and iii) the best agents are helping the other agents to exploit the global best.

IV. Experimental Results

To show the superiority of the proposed algorithm a mono-crystalline JAM6-60-260W PV module is used. Actual data are used for extracting the unknown parameters for the single-diode PV cell model as well as the double-diode PV cell model. The dataset is measured by the Commonwealth Scientific and Industrial Research Organisation (CSIRO), NSW, Australia (Latitude: -32.883889, Longitude: 151.728889). The dataset for JAM6-60-260W module is recorded for 3 years at 15-minute intervals and it contains 61730 I-V characteristic curves.

The superior performance of the WDO-based on DEIM algorithm is verified using the experimental I-V characteristic curves and compared with that obtained by the WDO and DEIM algorithms. The unknown parameters are extracted for the single-diode PV cell model and the double-diode PV cell model. The hyper-parameters for WDO, α, g, c and RT, are initially set as 0.4, 0.2, 0.4 and 3, respectively. In addition, the hyper-parameter for DEIM, a switching parameter which is used to switch between the mutation operation of differential evolution algorithm and the mutation operation of electromagnetism-like algorithm (ϵ_1), is set to be 0.28.

A. Single-diode PV cell model

In the single-diode PV cell model, five parameters are unknown. Accordingly, the dimensions of the optimization problem are set to be 5. The population size is usually calculated by multiplying the dimensions of the optimization problem by 10, which is 50, in case of the single-diode PV cell model. In addition, 500 iterations are assumed as a value of the maximum number of iterations. The search space for each of the unknown parameters, I_{Ph}, I_0, R_s, R_{sh}, a are in the ranges of $[1, 8]$ A, $[1E-12, 1E-5]$ A, $[0.1, 2]$ Ω, $[100, 5000]$ Ω and $[1, 2]$, respectively. Each of the unknown parameters is extracted for each I-V characteristic curve in the dataset, which means 61730 values for each unknown parameter. To generalize these values for each parameter, the average value is calculated. Accordingly, the average values of the extracted parameters using the WDO, DEIM and WDO-based on DEIM algorithms are shown in Table I.

TABLE I
THE AVERAGE EXTRACTED VALUES OF THE 5 UNKNOWN PARAMETERS IN THE SINGLE-DIODE PV CELL MODEL

Parameter (Average value of 61730)	**Model**		
	WDO	***DEIM***	***Proposed model***
$I_{Ph}(A)$	4.5210	3.5221	3.9822
$I_0(A)$	4.3320E-6	1.2251E-6	2.3055E-6
a	1.8152	1.4995	1.5211
$R_s(\Omega)$	1.1009	1.5321	1.6529
$R_{sh}(\Omega)$	3.2250E+3	2.9981E+3	3.1107E+3

Fig. 4 shows a sample of the I-V characteristic curves that obtained based on the WDO-based on DEIM algorithm in the single-diode PV cell model.

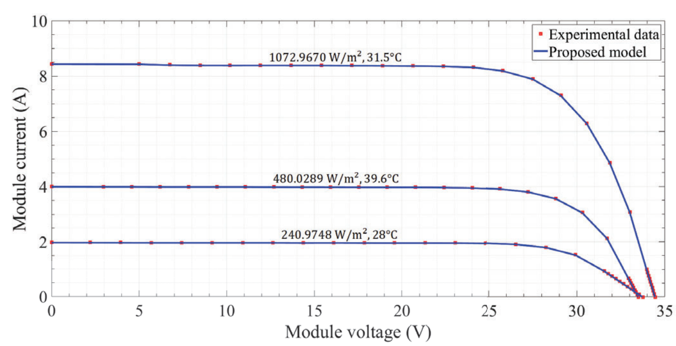

Fig. 4. Experimental and computed I-V characteristic curves of the single-diode PV cell model using the WDO-based on DEIM algorithm under various weather conditions

Visually, it is obvious from Fig. 4 that the I-V characteristic curves which are obtained based on the WDO-based on DEIM algorithm are close to the measured I-V characteristic curves. To proof that statistically, three error terms, such as the normalized-root-mean-square error (nRMSE), the mean absolute percentage error (MAPE) and the coefficient of determination (R^2) are used. The nRMSE, MAPE and R^2 can be mathematically formulated as:

$$nRMSE = \frac{\sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(I_{c_i} - I_{a_i}\right)^2}}{mean(I_a)} \tag{10}$$

$$MAPE = \frac{100}{N}\sum_{i=1}^{N}\left|\frac{I_{c_i} - I_{a_i}}{I_a}\right| \tag{11}$$

$$R^2 = 1 - \frac{Var\left(I_c - I_a\right)}{Var\left(I_a\right)} \tag{12}$$

where I_c stands for the calculated PV current, I_a stands for the actual PV current and Var represents the variance.

Table II shows the values of the statistical error terms for the proposed model as well as the WDO and DEIM models.

TABLE II
THE AVERAGE VALUES OF THE STATISTICAL PERFORMANCE INDICES FOR THE USED PARAMETERS EXTRACTION MODELS IN THE SINGLE-DIODE PV CELL MODEL

Performance index (Average value of 61730)	Model		
	WDO	*DEIM*	*Proposed model*
Avg. nRMSE (%)	5.22	3.66	**1.99**
Avg. MAPE (%)	18.92	11.63	**4.69**
Avg. R^2 (%)	89.11	91.01	**96.32**

From Table II, it is clear that the obtained results by the proposed model is more accurate than those obtained by WDO and DEIM models in terms of nRMSE, MAPE and R^2. Therefore, the proposed model is the better choice to extract the five unknown parameters in the single-diode PV cell model.

B. Double-diode PV cell model

In the double-diode PV cell model, seven parameters are unknown. Therefore, the dimensions of the optimization problem are set to be 7. Accordingly, the population size is set to be 70. Moreover, the maximum number of iterations is assumed to be 500. The search space for I_{Ph}, I_{0_1}, I_{0_2}, R_s, R_{sh}, a_1, a_2 are in the ranges of $[1, 8]$ A, $[1E-12, 1E-5]$ A, $[1E-12, 1E-5]$ A, $[0.1, 2]$ Ω, $[100, 5000]$ Ω and $[1, 2]$, respectively. Table III shows the average values of the extracted seven parameters using the WDO, DEIM and WDO-based on DEIM algorithms are shown in Table III.

Fig. 5 shows a sample of the I-V characteristic curves that obtained based on the WDO-based on DEIM algorithm in the double-diode PV cell model.

From Fig. 5, the I-V characteristic curves which are obtained by the WDO-based on DEIM algorithm are close to the measured I-V characteristic curves. To show the superiority of the proposed model in extracting the seven unknown parameters, its performance is compared to other models using the nRMSE, MAPE and R^2.

TABLE III
THE AVERAGE EXTRACTED VALUES OF THE 7 UNKNOWN PARAMETERS IN THE DOUBLE-DIODE PV CELL MODEL

Parameter (Average value of 61730)	Model		
	WDO	*DEIM*	*Proposed model*
$I_{Ph}(A)$	4.5482	4.0910	4.3809
$I_{0_1}(A)$	5.0505E-6	4.7226E-6	2.8812E-6
$I_{0_2}(A)$	5.0512E-6	4.7292E-6	3.8821E-6
a_1	1.5101	1.3182	1.4933
a_2	1.5101	1.3179	1.6992
$R_s(\Omega)$	1.0209	1.8830	1.8851
$R_{sh}(\Omega)$	2.5640E+3	2.5531E+3	2.5441E+3

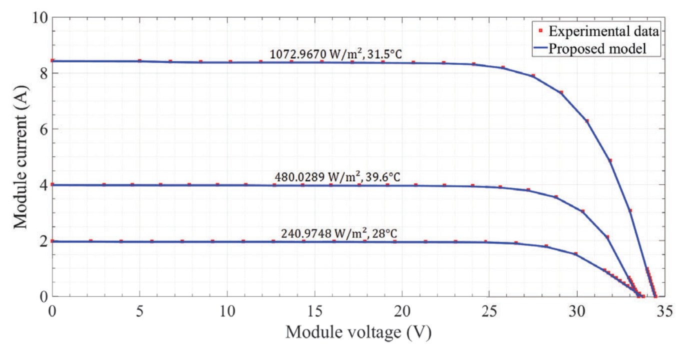

Fig. 5. Experimental and computed I-V characteristic curves of the double-diode PV cell model using the WDO-based on DEIM algorithm under various weather conditions

Accordingly, Table IV shows the results of the comparison in terms of the average values of the nRMSE, MAPE and R^2.

TABLE IV
THE AVERAGE VALUES OF THE STATISTICAL PERFORMANCE INDICES FOR THE USED PARAMETERS EXTRACTION MODELS IN THE DOUBLE-DIODE PV CELL MODEL

Performance index (Average value of 61730)	Model		
	WDO	*DEIM*	*Proposed model*
Avg. nRMSE (%)	2.37	4.65	**1.22**
Avg. MAPE (%)	7.70	8.58	**3.22**
Avg. R^2 (%)	94.99	92.69	**98.37**

From Table IV, it is clear that the obtained results by the proposed model is more accurate than those obtained by WDO and DEIM models in terms of the statistical error terms. Therefore, the proposed model is also the better choice to extract the seven unknown parameters in the double-diode PV cell model.

V. CONCLUSIONS

In this paper, a new hybrid algorithm is proposed by utilizing the strengths of the WDO and DEIM algorithms. The main idea is to combine the ability of WDO algorithm in finding the global optimum and the speed of the DEIM in localizing the values. The proposed algorithm is used to extract the unknown parameters of a single-diode cell model and a double-diode PV cell model. The JAM6-60-260W PV module is used in this research as well as actual recorded data for 3 years at 15-minitue intervals. The performance of the proposed model is validated by comparing the generated I-V characteristic curves with the experimental records. In order to show the superiority of the proposed model, the performance of the proposed model is compared with the performance of the WDO and DEIM algorithms based on nRMSE, MAPE and R^2. The average values of the nRMSE, MAPE and R^2 for the proposed model are 1.99%, 4.69% and 96.32% for the single-diode PV cell model respectively, and they are 1.22%, 3.22% and 98.37% for the double-diode PV cell model, respectively. The results show that the proposed model performs better than the WDO and DEIM algorithms. As a result, the proposed model is recommended to extract the unknown parameters of the PV cell models. Therefore, the proposed model can be used to track the maximum power point in the PV modules to secure the optimal installation of the PV systems.

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