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Estimation of Solar PV Models Parameters using WDO Algorithm

Derick Mathew[1], Chinnappa Naidu Rani[2]
[1]Research Scholar, VIT University, Vellore, India, derickmathew1@gmail.com
[2]Associate Professor, VIT University, Vellore, India, crani@vit.ac.in

ABSTRACT

The interest in the generation of solar photovoltaic (PV) power increased worldwide because of climate change and fossil fuel depletion. A detailed simulation of the system with different environmental conditions is important to improve the performance of the solar PV system. Since solar PV has nonlinear characteristics, the optimization technique is the most suitable method to define the solar PV model parameters. The study states a modern approach for the detection of Solar PV parameters through Wind Driven Optimization (WDO). Three data sets are used to check that the process is reliable, timely and dynamic. The first set is the experimental data for Kyocera – KC200GT, while the second set is the experimental data for RTC France and Photo watt – PWP201. The third set is the data provided by the manufacturers in the data sheets. Solar PV models are measured with single diode and double diode parameters. In order to verify the suggested optimization methods, the findings obtained by means of the WDO optimization method are compared with the results reported in recent literature. So, this proposal for the calculation of solar PV parameters is the best optimization algorithm

Key words : Double diode model, Kyocera – KC200GT, Photowatt-PWP201, RTC France, Single diode model, Wind Driven Optimization.

1. INTRODUCTION

Today, the usage of renewables and inexhaustible energy sources is steadily growing as a consequence of climate change and the ongoing depletion of fossil fuels. The strongest choice for solar energy seems to be. In India the usage of solar energy at energy cost is expected to rise at 140%, 80% of which in the state's Tamil Nadu, Telangana and Karnataka. Moreover, the Indian government has agreed to update the National Solar Mission plan to raise the solar energy grid capacity by 2021-22 from 20,000 MW to 100,000 MW [1]. As a result, large-scale PV electricity storage projects are used. But, because of its large initial capital cost and low panel performance, it doesn't impact middle class communities.

The solar photovoltaic array was planned for analyze and study the realistic usage prior to its launch. The detailed design and simulation of the solar PV panel will do this. Solar PV modeling is usually performed using analogous diode models that explain the relationships between current-voltage (I-V) across a broad wide range of climatic conditions. Two different types of diode models are widely used to describe the I-V properties of solar PVs: (a) single diode model, (b) double diode model [2-4]. At the one side, the single diode model is very simple in simulation, and several researchers have tested its precision by analyzing and testing its five unidentified parameters. The double diode model, on the other side, offers more accuracy but is very complex, with an expanded number of parameters.

We will rely in this analysis on the Solar PV configuration with single and double diodes. Solar PV parameters differ by temperature and radiation. Precise parameter estimation was thus needed to model the Solar PV efficiently. Popular approaches in parameter estimation are categorized as analytical technology [5], numerical extraction [6-9] and evolutionary algorithm techniques [10-14].

Mathematical equations are used in the analytical method for determining the parameters. Most of the equation values are not shown in the manufacturer datasheet. This method is still not considered to be precise [4]. The numeric extraction strategy is focused on the fitting of the curves. Nevertheless, it is very challenging to apply curve fitting to the nonlinear diode equation as a result of computational extraction methods [8]. On the other side, artificial intelligence approaches [11] are recognized in nonlinear algorithms as being excellent. Specific optimization techniques have recently been developed for estimating parameters of solar module; notably, the Pattern Search (PS) optimization [13], Genetic Algorithm (GA) [10], [12], Bacterial Foraging Algorithm (BFA) [16], Artificial Immune System (AIS) [14], [15], Differential Evaluation (DE) [18], Simulated Annealing (SA) [17], Differential Evaluation (DE) [18], Flower Pollination Algorithm (FPA) [23], Mutative-scale Parallel Chaos Optimization (MPCOA) [19], Levenberb – Marquard Algorithm with Simulated Annealing (LMSA) [24], Artificial Bee Swarm Optimization (ABSO) algorithm [21], Harmony Search (HS) algorithm [20], Artificial Bee Colony Optimization (ABSO) [22], and Cuckoo Search (CS) [25]. However, these algorithms still require modifications to find the most optimized parameter for various solar PV modules[23]. A more efficient algorithm is still needed to find optimized values for Solar PV parameters.

We have proposed a new optimization technique in this work, called the Wind Driven Optimization (WDO) algorithm. It is used to find optimized parameters for Solar PV models with single diode and double diode. Zikri Bayraktar develops the idea of WDO for application in electromagnetics [3]. A population-driven heuristic framework for multidimensional challenges focused on regional optimization. The WDO inspiration was focused on the flow of microscopic air parcels in a multidimensional space. The algorithm includes four constants. The covariance matrix adaptation evolution strategy (CMAES) technique produces such constants of optimizable meaning. This was widely used because it does not include details other than population size [3]. To use with WDO that provides ideal prices, CMAES is appropriate.

For the parameter estimation of solar PV the WDO algorithm will be verified by comparing its results with three data sets as follows:

1. Multi-crystalline Kyocera experimental data-KC200GT 215 [2].
2. The results obtained from recent optimization techniques (FPA [23], MPCOA [19], ABSO [21], ABC [22], LMSA [24], CS [25], HS [20], Newton [3]) for experimental data of RTC France and Photowatt – PWP201 [3].
3. Manufacture data sheet values of mono-crystalline (SM55) and thin-film (ST40) solar PV module.

The accuracy of the proposed optimization technique is calculated using RMSE. Convergence is calculated according to the period needed to reach the optimal value for the proposed process. In various environmental situations, the durability of the proposed system can be checked by testing the RMSE performance of various Solar PV modules. All these studies also show that the proposed parameter estimation algorithm for solar PV is reliable, time-to-converge and scalable

2. MATHEMATICAL MODELLING

Several researchers have proposed and built several models in which the Solar PV parameters can be accurately estimated [3]. For others, single diode and double diode versions are among those most popular and commonly embraced. In this study, the activity trends of solar PV modules are seen using single diode and double diode layout. The facts were explained:

2.1 Single Diode Model

Single diode model, due to its less complexity, is commonly used to represent solar PV. Figure 1 demonstrates the corresponding circuit of a single diode Solar PV device.

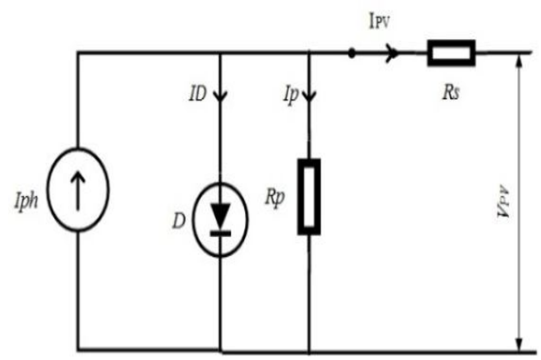

Figure 1: Single – diode solar PV equivalent circuit.

By using Kirchhoff's current law (KCL), one can check that as,

$$I_{PV} = I_{ph} - I_D - I_p \quad (1)$$

Here, I_{PV} is solar PV current, I_{ph} is the photon current generated by the incident light, I_D is the diode current and I_p is the current flowing through parallel resistance [32, 33].

$$I_p = \frac{V_{PV}+(I_{PV}R_S)}{Rp} \quad (2)$$

$$I_D = I_o(exp\left(\frac{V_{PV}+I_{PV}R_S}{N_s V_t}\right) - 1) \quad (3)$$

$$I_o = \frac{I_{SC-S}+K_I(T-T_S)}{\exp\left(\frac{V_{OC-S}+K_V(T-T_S)}{N_S V_t}\right)-1} \quad (4)$$

Here $I_o$is the reverse saturation current of diode, R_p is the parallel resistance, that exist mainly due to the leakage current of P-N junction and depends on the fabrication methods of the solar PV cell, R_s is the series resistance symbolizes the contact resistance of the metal with P and N layers, V_{OC-S} is the open circuit voltage at standard test condition, K_V is open circuit voltage temperature coefficient, N_s is number of series cell per module and V_t is the thermal voltage of diode which depends on junction temperature, and it is represented by:

$$V_t = a\frac{KT}{q} \quad (5)$$

Here, a denotes the ideality factor of diode. T expresses junction temperature in Kelvin (K), q is electron charge (1.6021765 $\times 10^{-19}$ C) and K is the Boltzmann constant ($1.38065 \times 10^{-23} J/K$). The photon current I_{ph} can be expressed as follows:

$$I_{ph} = \left(I_{ph-S} + K_I(T - T_S)\right)\frac{G}{G_S} \quad (6)$$

I_{ph-S} is the photon current at standard test condition, the temperature at standard test condition $T_S = 25^0 c$, solar radiation at standard test condition $G_S = 1000 W/m^2$ and K_I is the short circuit current temperature coefficient.

The photon current at standard test conditions is given by:

$$I_{ph-S} = I_{SC-S}\frac{R_P+R_S}{R_P} \quad (7)$$

Here I_{SC-S} is the short circuit current at standard test conditions.

$$I_{PV} = I_{ph} - I_o\left(exp\left(\frac{V_{PV}+I_{PV}R_S}{N_s * a\frac{KT}{q}}\right) - 1\right) - \frac{V_{PV}+(I_{PV}R_S)}{Rp} \quad (8)$$

From (8), we require optimum values of five parameters such as I_{ph}, I_o, Rp,R_s, and a. So that the single diode model of solar PV module generates I-V characteristic curve same as experimentally obtained curve.

2.2 Double Diode Model

Two diodes are paired in a double diode configuration parallel to the current source of the photons. The second diode represents the Space Charging region recombination. Figure 2 shows the equivalent double diode model circuit.

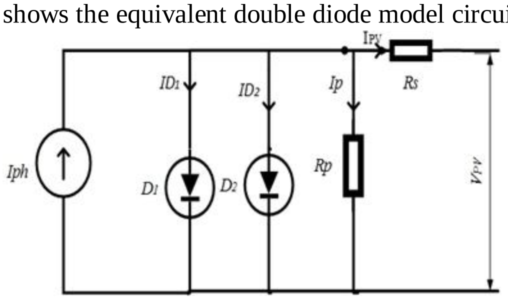

Figure 2: Double – diode solar PV equivalent circuit.

By using KCL

$$I_{PV} = I_{ph} - I_{D1} - I_{D2} - I_p \quad (9)$$

$$I_{D1} = I_{o1}(exp\left(\frac{V_{PV}+I_{PV}R_S}{N_s V_{t1}}\right) - 1) \quad (10)$$

$$I_{D2} = I_{o2}(exp\left(\frac{V_{PV}+I_{PV}R_S}{N_s V_{t2}}\right) - 1) \quad (11)$$

Here I_{o1} and I_{o2} are the reverse saturation current and V_{t1} and V_{t2} are thermal voltage of diode 1 and diode 2 respectively. I_{ph} can determined using the (6)

$$V_{t1} = a_1 \frac{KT}{q} \quad (12)$$

$$V_{t2} = a_2 \frac{KT}{q} \quad (13)$$

a_1 and a_2 denotes the ideality factor of diode 1 and diode 2 respectively. So, the mathematical expression for double diode can be written as follows:

$$I_{PV} = I_{ph} - I_{o1}\left(exp\left(\frac{V_{PV}+I_{PV}R_S}{N_s V_{t1}}\right) - 1\right) - I_{o2}\left(exp\left(\frac{V_{PV}+I_{PV}R_S}{N_s V_{t2}}\right) - 1\right) - \frac{V_{PV}+(I_{PV}R_S)}{Rp} \quad (14)$$

From (14), it is clear that, the optimum values of seven parameters such as I_{ph}, I_{o1}, I_{o2}, Rp,R_s, a_1 and a_2 gives the accurate double diode model of solar PV.

3. PROBLEM FORMULATION

Using the single diode and double diode model, any Solar PV module can be modelled. This modeling 's main objective is to allow the Solar PV model to predict the PV module's I-V characteristics. The optimized parameters of the solar PV model have to be found to minimize the error between predicted and actual I-V characteristics of the PV module. Using optimisation algorithms can do this.As described above, Solar PV model models with single diode and double diode have five and seven parameters, respectively. There are two methods, the first approach is to use the optimisation algorithm to find all these parameters. Second method is the resolution of the resistance idealsRp,R_s and ideality factor a using algorithm and I_{ph}, I_o using (4) - (6) and (10). In our work, we used first approaches to calculate the solar PV parameters.

The Root Mean Square Error (RMSE) objective function is. The objective function aggregates the absolute error and gives predictive strength measurement. Individual Absolute Error (IAE), is the absolute value of the difference between measured and estimated output current. The error function is given in (15) and (16) respectively for single diode and double diode model. The function IAE and Sum of Squared Error (SSE), respectively, is given in (17) and (18).

$$f_i(V_{PV(m)}, I_{PV(m),}X) = abs\left(I_{PV(m)} - \left(I_{ph} - I_D - \frac{V_{PV(m)}+I_{PV(m)}R_S}{R_p}\right)\right) \quad (15)$$

$$f_i(V_{PV(m)}, I_{PV(m),}X) = abs\left(I_{PV(m)} - \left(I_{ph} - I_{D1} - I_{D2} - \frac{V_{PV(m)}+I_{PV(m)}R_S}{R_p}\right)\right) \quad (16)$$

$$\text{IAE} = f_i(V_{PV(m)}, I_{PV(m),}X) \quad (17)$$

$$\text{SSE} = \sum_{i=1}^{N} IAE^2 \quad (18)$$

In (15) and (16) vector X represents the model parameters, for single and double diode model of solar PV respectively and N is the number of experimental data.
The RMSE function is defined as follows:

$$\text{RMSE} = \sqrt{\frac{1}{N}\, SSE} \quad (19)$$

The proposed WDO algorithm finds the optimized solar PV model parameter by minimizing the objective function.

4. WIND DRIVEN OPTIMIZATION

Wind driven optimisation is a technique of optimization that is inspired by modern nature. The idea had been developed for electromagnetic application by Zikri Bayraktar. The motivation for the WDO algorithm was based on microscopic air parcels being moved in a multidimensional space. The solar radiation in Earth's troposphere varies depending on the location. So heating the earth's surface varies by location, region type (water body, soil, cloudy), and earth rotation[3]. At low temperature area the air pressure will be high than the high temperature area. So the difference in air pressure contributes to horizontal air movement. The pressure shift is called the pressure gradient[3] and is given as follows:

$$\nabla P = \left(\frac{\partial P}{\partial x}, \frac{\partial P}{\partial y}, \frac{\partial P}{\partial z}\right) \quad (20)$$

By assuming air has finite volume (δV), the force due to pressure gradient (F_{PG}) can be expressed as,

$$\overrightarrow{F_{PG}} = -\nabla P.\, \delta \text{V} \quad (21)$$

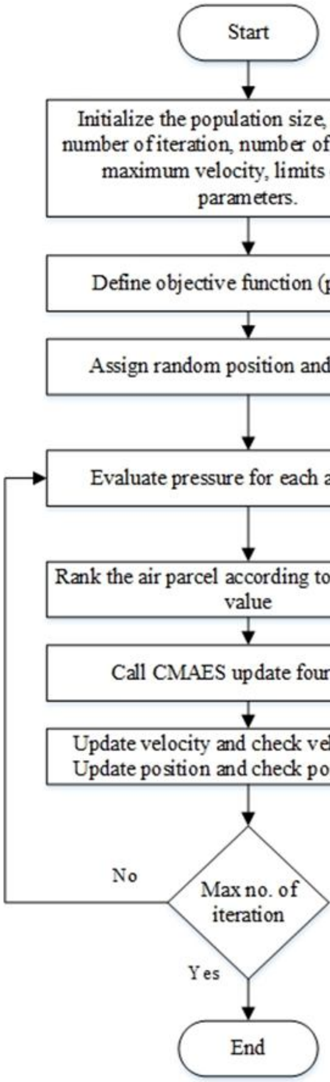

Figure 3: Flowchart of Wind driven optimization.

Here air parcel is assumed to be dimensionless and weightless to reduce the computational complexity.

Newton's second law states that total force (F_t) applied on air parcel causes the air parcel to accelerate with an acceleration a in the same direction of the force.

$$\rho . \vec{a} = \sum \overrightarrow{F_t} \tag{22}$$

Here ρ is the air density of a small air parcel.

In addition to the pressure gradient force there are three other forces, that play a role in the movement of air parcel. They are frictional force, gravitational force and coriolis force. Friction force opposes the air parcel motion started by F_{PG}. It can be expressed as follows:

$$\overrightarrow{F_F} = -\rho\alpha\vec{u}$$

(23)

Here α is frictional coefficient and $\vec{u}$ wind velocity vector.

Gravitational force is the force which pulls the system to the centre of the coordinate system. This force causes vertical motion and expressed as follows:

$$\overrightarrow{F_G} = \rho . \delta V . g \tag{24}$$

Here g is the gravitational constant.

The next force acting on the motion of air parcel is due to the rotation of the earth and named as Coriolis force. This force will generate a deflection in the motion of air parcel. It can be expressed as,

$$\overrightarrow{F_C} = -2\theta \times \vec{u} \tag{25}$$

Here θ represents the rotation of earth. So, by including these forces and ideal gas equation in (20). It can be rewritten as,

$$\nabla\vec{u} = g + \left(-\nabla P . \frac{RT}{P_{cur}}\right) + (-\alpha\vec{u}) + \left(-\frac{2\theta \times \vec{u} RT}{P_{cur}}\right)$$

(26)

In WDO the velocity and position of air parcel changes in all iteration to reach to minimum pressure region. So, in (26) LHS can written as,

$$\nabla\vec{u} = \overrightarrow{u_{new}} - \overrightarrow{u_{cur}} \tag{27}$$

Here $\overrightarrow{u_{new}}$ is the velocity of next iteration and $\overrightarrow{u_{cur}}$ is the velocity of current iteration.

The frictional force can occur in all dimensions of search space. But gravitational force and pressure gradient force can act only in one dimension of search space, it is given as x. Pressure gradient, is the difference in pressure between optimal pressure (P_{opt}) and current pressure (P_{cur}). Therefore (26) can be rewritten as,

$$\overrightarrow{u_{new}} = (1-\alpha)\vec{u}_{cur} - g x_{cur} + \left(\left|P_{opt} - P_{cur}\right| . (x_{opt} - x_{cur}) \frac{RT}{P_{cur}}\right) + \left(\frac{c . \vec{u}_{otherdirection}}{P_{cur}}\right)$$

(28)

Here $c = -2RT$, and $\vec{u}_{otherdirection} = \overrightarrow{F_C}$

The pitfall of (28) is that the velocity gets changed impractically as the pressure value increases. Thus, the (28) is adjusted according to the pressure level. After each iteration, the parcels of air are graded in descending order based on their pressure values. If I'm the Air Parcel category. Use the (29) and (30), respectively, the air parcel velocity and location are changed. Figure 3 displays the flow chart of the wind powered optimisation algorithm.

$$\overrightarrow{u_{new}} = (1-\alpha)\vec{u}_{cur} - g x_{cur} + \left(\left|1 - \frac{1}{i}\right| . (x_{opt} - x_{cur}) RT\right) + \left(\frac{c . \vec{u}_{otherdirection}}{i}\right)$$

(29)

$$\overrightarrow{x_{new}} = \overrightarrow{x_{old}} + \overrightarrow{u_{new}} \tag{30}$$

For each dimension the WDO allows air parcel to travel in a bound of [-1, 1]. The actual maximum and minimum limits of problem is normalized to [-1, 1]. To obtain the optimized objective function value, the coefficients α, g, RT, c in (29) play an important role. In order to find the optimized values of these constants Covariance Matrix Adaptation Evolution Strategy (CMAES) technique is used. It does not require parameter tuning, and hence it does not require any inputs other than population size [3]. CMAES is suitable for WDO application which gives out the optimum values of four constants.

5. SIMULATION AND RESULTS

Wind Driven Optimization algorithm is used to find the optimized parameters for the solar model with single diode and double diode. To verify the accuracy of the proposed optimization algorithm the algorithm's outcome is compared with three separate data sources.

5.1 Results of WDO is compared with the experimental data of Kyocera – KC200GT 215

MATLAB / Simulink creates a single diode and double diode model of solar PV to test the proposed optimisation algorithm. The objective function is found using the experimental data of the multi-crystal PV module Kyocera-KC200GT 215 given in [2]. The objective function is calculated on the basis of experimental data set 18. The ideality factors a has a value of 1 to 2 here.The series resistance R_s generally has lower value, and the range is between 0.01Ω to 0.5Ω, whereas the parallel resistance R_p has higher values between 100Ω and 1000Ω. $I_{ph}$and $I_o$has a value between (5 to 10) and (0.1×10^{-6} to 10×10^{-6}) respectively. The data sheet values of Kyocera – KC200GT 215 module is given in table 1.

Table 1: Datasheet values of Kyocera – KC200GT 215 module.

Maximum power (P_{max})	200W (+10% / -5%)
Voltage at maximum power point (V_{mpp})	26.3 V
Current at maximum power point (I_{mpp})	7.61 A
Open circuit voltage (V_{OC})	32.9 V
Short circuit current (I_{SC})	8.21 A
Temperature coefficient of V_{OC}	-1.23× 10^{-1}
Temperature Coefficient of I_{SC}	3.18× 10^{-3}
Number of modules (N_s)	54

A. Case study 1: Single diode model

In this section, the validity of the proposed method is tested for single diode model. Table 2 indicates the values of a, R_s,R_p,I_{ph}, I_o, RMSE, SSEand IAE for WDO optimization techniques at standard test condition. It clearly shows that the WDO gives much less value for RMSE. Figure 4 demonstrates the features of WDO convergence. It is evident from the convergence feature that the best fitness function value for WDO is 0.0008401, with a smaller number of iterations. This clearly reveals that in terms of accuracy and computation time the WDO algorithm performs well.

The experimental data in [2] give solar PV voltage and current at different temperature and irradiance values. The Kyocera – KC200GT 215 Solar PV module is plotted for 1000w / m^2, 800w / m^2, 600w / m^2, 400w / m^2 and 200w / m^2 in figure 5 using experimental data and calculated device I-V characteristics from WDO. Similarly, I-V characteristics are plotted in figure 6 for different temperatures of 25^{0}C, 50^{0}C, and 75^{0}C. Both figures reflect the fact that the estimated values of the WDO algorithm give an accurate I-V characteristic that accurately replicates the experimental data.

B. Case study 1: Double diode model

In this section, double diode model is used to represent the solar PV. The optimized values of parameters such as $a_1, a_2, R_s, R_p I_{ph}$, I_o , RMSE, SSE, and IAE at standard test condition is presented in table 3. The characteristic I-V is plotted in figure 7 and figure 8, respectively, at various irradiance and temperature. The I-V characteristic curves clearly reveal that, in all irradiance and temperature conditions, the parameter values obtained through WDO produce the exact curve with insignificant RMSE value for the entire voltage range. So, both of these cases clearly show that, with minimum computation time, the WDO technique can generate more accurate results for all weather conditions.

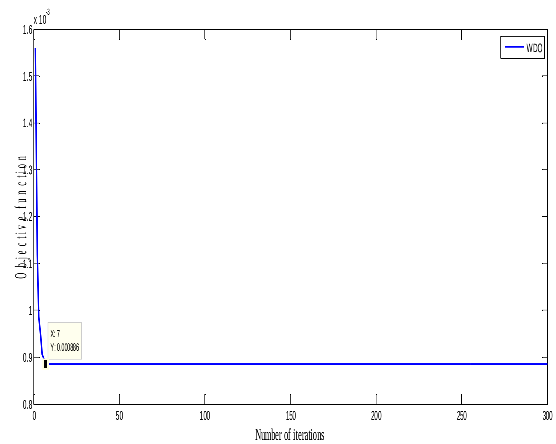

Figure 4: Convergence characteristics of WDO.

Table 2: Estimated parameters of Kyocera – KC200GT 215 module for single diode model by WDO.

a	R_s (Ω)	R_p (Ω)	I_{ph} (A)	I_o (μA)	RMSE	SSE10^{-5}	$\sum IAE$ 10^{-3}
1.42	0.11	747	8.181	0.442	0.0001	1.27	3.5637

Table 3: Estimated parameters of Kyocera – KC200GT 215 module for double diode model by WDO.

a_1	a_2	R_s (Ω)	R_p (Ω)	I_{ph} (A)	I_{o1} (μA)	I_{o2} (μA)	RMSE	SSE 10^{-4}	$\sum IAE$ 10^{-3}
2	1	0.99	784.	8.1	4.7	1.6	0.001	0.20	4.4

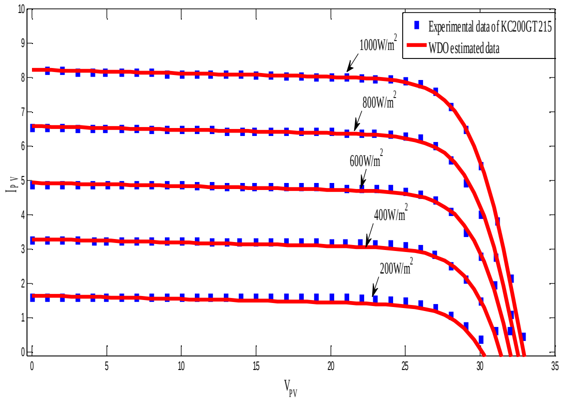

Figure 5: Comparison of experimental data and WDO estimated data of Kyocera – KC200GT 215 module at different irradiance (single diode model).

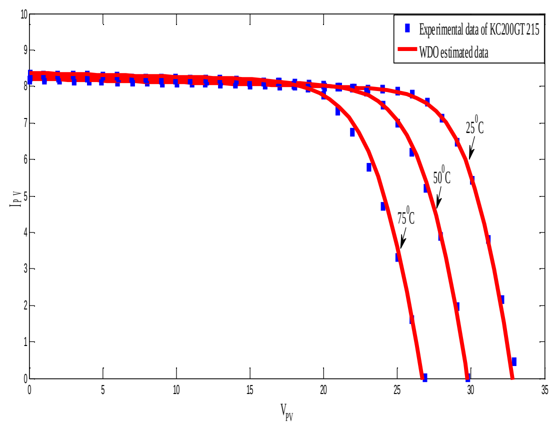

Figure 6: Comparison of experimental data and WDO estimated data of Kyocera – KC200GT 215 module at different temperature (single diode model).

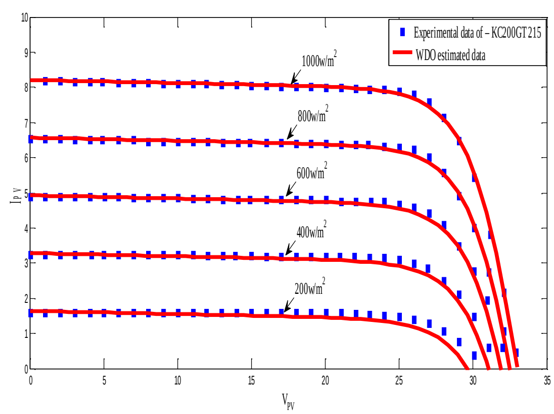

Figure 7: Comparison of experimental data and WDO estimated data of Kyocera – KC200GT 215 module at different irradiance (double diode model).

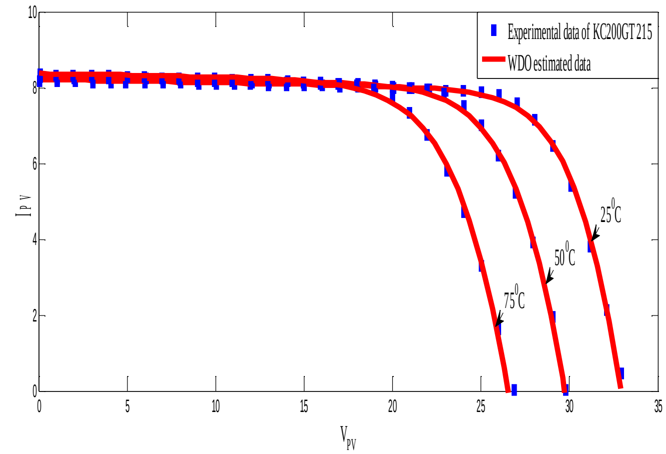

Figure 8: Comparison of experimental data and WDO estimated data of Kyocera – KC200GT 215 module at different temperature (double diode model).

5.2 Results of WDO is compared with data obtained from previous literatures

In order to further verify the performance of the WDO algorithm, it is examined with the experimental data of 57 mm dia RTC France silicon solar cell at 1000W/m^2 irradiance and 33^{0}C temperature presented in [3]. The parameters of single diode and double diode model of the cell is estimated through WDO algorithm. The lower and upper boundaries of a, R_s,R_p,$I_{ph}$and I_o are assigned as (1 to 2), (0.01 to 0.08), (25 to 75), (0.01 to 0.5) and (0.1×10^{-6} to 0.5×10^{-6}) respectively. The optimized values of solar PV parameters along with RMSE, SSE, IAE for single diode and double diode model is presented in table 4 and table 5 respectively. It shows the comparison of results obtained through the optimization techniques presented in recent research papers such as FPA [23], MPCOA [19], ABSO [21], ABC [22], LMSA [24], CS [25], HS [20], Newton [3] with WDO algorithm. In order to verify the accuracy of WDO determined parameter values the I-V characteristics at 1000W/m2 and 33^{0}C for single diode model and double diode model of solar PV is plotted in figure 9 and figure 10 respectively.

Tables 4 and 5 show that, compared with other recent optimization techniques used for parameter estimation of solar PV, the WDO algorithm provides the least RMSE value. Figure 9 and figure 10 clearly reveal that the curve obtained through WDO replicates the experimental data provided in [3] with precision.

WDO 's convergence curve for single-diode and double-diode model is shown respectively in figure 11 and figure 12. They show that, WDO 's convergence period is much less. After 383 iterations WDO achieves an RMSE value of 0.00056691 in parameter estimation of single diode model of RTC France solar cell. Whereas, for the same environmental conditions, FPA and MPCOA took over 400 to get RMSE values of 0.00077301 and 0.00094457, respectively. Similarly, for the double diode model of the RTC France solar cell, the WDO algorithm achieved an RMSE value of 0.00019347 after 252 iterations, while after 800 and 1000 iterations, FPA and MPCOA achieved 0.00078425 and 0.00092163 respectively.

Photwatt-PWP 201 solar PV single-diode model parameters are defined at 1000W / m^2 irradiance and 45^0C temperature via the proposed WDO algorithm. The results obtained by the proposed algorithm are compared with the results obtained for the recent optimization techniques and tabled in table 6. As above, with respect to other optimization methods, the RMSE value is comparatively much less. Figure 13 shows comparison of I-V characteristics of experimental data with estimated data from WDO. It became apparent that the model calculated by the proposed WDO algorithm matched the experimental data accurately.

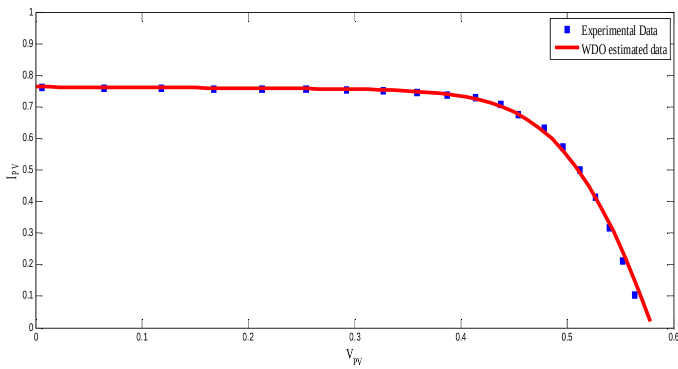

Figure 9: Comparison of experimental data and WDO estimated data of RTC France solar cell at 1000W/m2 and 330C and (single diode model).

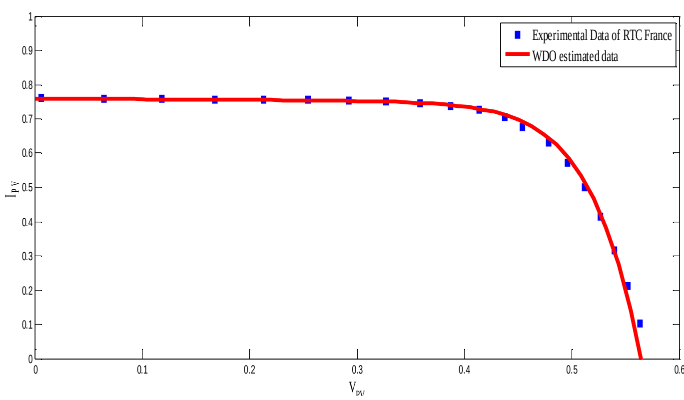

Figure 10: Comparison of experimental data and WDO estimated data of RTC France solar cell at 1000W/m2 and 330C and (double diode model).

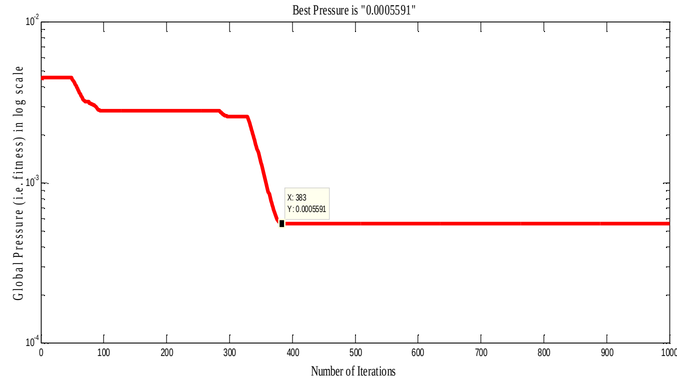

Figure 11: Convergence curve of WDO for single diode model of RTC France.

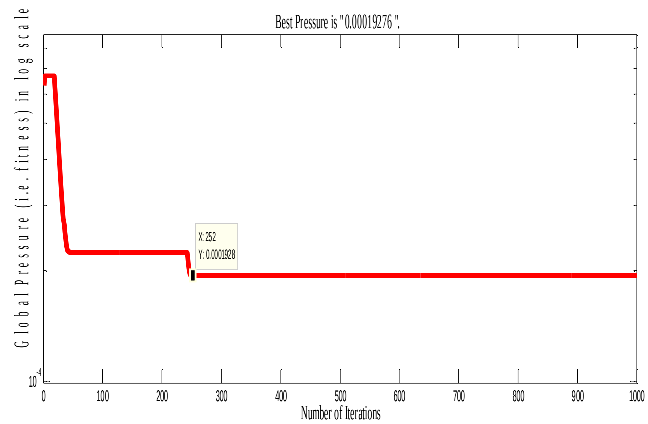

Figure 12: Convergence curve of WDO for double diode model of RTC France.

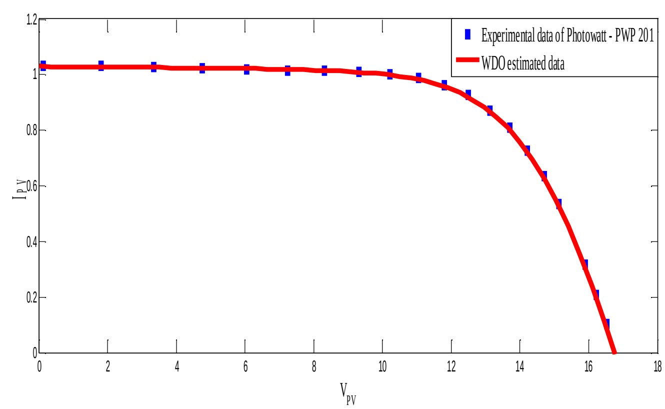

Figure 13: Comparison of experimental data and WDO estimated data of Photowatt – PWP 201 at 1000W/m^2 and 330C and (single diode model).

Table 4: Comparison between estimated single diode model parameters of RTC France using WDO and other recent optimization techniques.

	WDO	**FPA [23]**	**MPCOA [19]**	**ABSO [21]**	**ABC [22]**	**LMSA [24]**	**CS [25]**
a	1.432661	1.47707	1.48168	1.47583	1.4817	1.47976	1.4812
$R_s(\Omega)$	0.038961	0.0365466	0.03635	0.03659	0.0364	0.03643	0.0364
$R_p(\Omega)$	53.86914	52.8771	54.3635	52.2903	53.6433	53.32644	53.7185
$I_{ph}\ (A)$	0.7608	0.76079	0.76073	0.7608	0.7608	0.76078	0.7608
$I_o\ (\mu A)$	0.3223	0.3106	0.3265	0.3062	0.325	0.31879	0.323
RMSE ($\times 10^{-4}$)	5.6691	7.7301	9.4457	9.9124	9.8262	9.864	10
SSE$\times 10^{-5}$	0.7713	0.5182	2.5297				
$\sum IAE$	2.777×10^{-3}	0.015971	0.02151				

Table 5: Comparison between estimated double diode model parameters of RTC France using WDO and other recent optimization techniques.

	WDO	**FPA [23]**	**MPCOA [19]**	**ABSO [21]**	**HS [20]**
a_1	1.56269	1.4777	1.47844	1.46512	1.49439
a_2	1.569	2	1.76078	1.98152	1.49439
$R_s(\Omega)$	0.04453	0.0363342	0.03635	0.03657	0.03545
$R_p(\Omega)$	52.3436	52.3475	54.2531	54.6219	46.82696
$I_{ph}\ (A)$	0.75947	0.760795	0.76078	0.76078	0.76176
$I_{o1}\ (\mu A)$	0.28837	0.3008	0.31259	0.26713	0.12545
$I_{o2}\ (\mu A)$	0.61995	0.166157	0.04528	0.38191	0.2547
RMSE ($\times 10^{-4}$)	1.928	7.8425	9.2163	9.8344	12.6
SSE	2.29232×10^{-7}	1.68739×10^{-5}	5.79×10^{-5}		
$\sum IAE$	4.7878×10^{-4}	0.0172977	0.0234		

5.3 WDO results obtained for different types of solar modules

The preceding subsections show the accuracy and speed of WDO algorithm convergence for application parameter estimation. WDO results were estimated for various types of solar cells such as multi-crystalline (KC200GT), mono-crystalline (SM55), and thin film (ST40) to substantiate the flexibility of the proposed algorithm. Parameter estimation of the multi-cristalline single diode model (KC200GT) was mentioned in section 5.1. So, that's not shown in this section. Single diode model parameters for other two types of solar modules have been estimated.The boundaries of a, R_s, R_p, , $I_{ph}$and I_o are assigned as (300 to 500), (0.1 to 0.5), and (1 to 1.5), (1 to 5) and (0.01×10^{-6} to 0.5×10^{-6}) respectively for mono-crystalline SM55 solar PV module. For thin-film ST40 boundaries of a, R_s, R_p, $I_{ph}$and I_o are assigned as (100 to 400), (1 to 1.5), (1 to 1.8), (1 to 5) and (0.1×10^{-6} to 1×10^{-6}) respectively. The I-V characteristic data of both modules are calculated using the data given in data sheets and the following equations.

$$I_{SC}(G,T) = I_{SC-S} * \frac{G}{G_S} + K_I(T - T_S)$$

$$I_{MPP}(G,T) = I_{MPP-S} * \frac{G}{G_S}$$

$$V_{OC}(G,T) = V_{OC-S} - K_V(T - T_S) + \frac{aKT}{q} * ln\frac{G}{G_S}$$

$$V_{MPP}(G,T) = V_{MPP-S} - K_V(T - T_S)$$

The parameters of single diode model of both solar PV modules at different temperature (25^{0}C, 30^{0}C, 40^{0}C, 50^{0}C) and irradiance (1000 W/m^2, 800 W/m^2, 600 W/m^2, 400 W/m^2) level estimated by WDO and their RMSE values are tabulated in the table 7 and 8 respectively. It can be notice that RMSE values at all temperature and irradiance levels are low. It obviously reflects that WDO algorithm is flexible to all types of PV modules at all ranges of temperature and irradiance.

Table 7: Single diode model parameters estimated by WDO for SM55 and ST40 Solar PV module at different temperature.

G=1000w/m^2	Mono-crystalline (SM55)	Thin-film (ST40)
25^{0}C		
a	1.3731	1.4028
$R_s(\Omega)$	0.32582	1.001302
$R_p(\Omega)$	476.709	345.99831
I_{ph} (A)	3.4524	2.597495
I_o (μA)	0.13102	0.53168
RMSE	1.957×10^{-6}	4.9538×10^{-5}
30^{0}C		
a	1.3523	1.402251
$R_s(\Omega)$	0.3358	1.0067
$R_p(\Omega)$	490.014	387.789
I_{ph} (A)	3.4583	2.598023
I_o (μA)	0.18195	0.958942
RMSE	1.474×10^{-6}	0.00011874
40^{0}C		
a	1.361183	1.4
$R_s(\Omega)$	0.30922	1.0028
$R_p(\Omega)$	451.6096	346.852
I_{ph} (A)	3.4704	2.601388
I_o (μA)	0.16202035	2.9174
RMSE	2.442×10^{-6}	0.00064491
50^{0}C		
a	1.27076	1.4107763
$R_s(\Omega)$	0.36476	1.009417
$R_p(\Omega)$	449.234	393.8844
I_{ph} (A)	3.48201	2.603137
I_o (μA)	0.163105	9.3309
RMSE	4.2705×10^{-6}	0.00172

Table 8: Single diode model parameters estimated by WDO for SM55 and ST40 Solar PV module at different irradiance.

T=25^{0}C	Mono-crystalline (SM55)	Thin-film (ST40)
1000W/m^2		
a	1.3731	1.4028
$R_s(\Omega)$	0.32582	1.001302
$R_p(\Omega)$	476.709	345.99831
I_{ph} (A)	3.4524	2.597495
I_o (μA)	0.13102	0.53168
RMSE	1.957×10^{-6}	4.9538×10^{-5}
800W/m^2		
a	1.287419	1.4094067
$R_s(\Omega)$	0.358696	1.0349217
$R_p(\Omega)$	446.60892	356.89639
I_{ph} (A)	2.7622167	2.078
I_o (μA)	0.0420242	0.571478
RMSE	3.0189×10^{-6}	3.0716×10^{-5}
600W/m^2		
a	1.361183	1.428115364
$R_s(\Omega)$	0.30922	1.000541551
$R_p(\Omega)$	451.6096	397.4796491
I_{ph} (A)	2.07152	1.557911
I_o (μA)	0.0210362	0.698552
RMSE	1.9987×10^{-6}	3.3307×10^{-5}
400W/m^2		
a	1.22351	1.4170608349
$R_s(\Omega)$	0.20834	1.019317797
$R_p(\Omega)$	461.10046	385.90886
I_{ph} (A)	1.3806235	1.0387364
I_o (μA)	0.0162219	0.620801
RMSE	0.0001599	0.00054773

6. CONCLUSION

Detailed solar photovoltaic modeling is required until the whole PV system is installed. Optimized parameter estimation plays a significant part in detailed simulation. This paper provided an optimization algorithm WDO for calculation of solar PV parameters. Using this method, the parameters of single and double diode models of different solar PV types were designed. The WDO methodology has been checked by applying its findings to three separate sets of data. Firstly, with experimental data from Kyocera – KC200GT 215 Additionally, with the findings of recent optimization strategies available in the literature, and thirdly, with the information provided by manufacturing data sheets. It is observed that the WDO algorithm achieves very small RMSE values with less iterations for all types of Solar PV (KC200GT 215, RTC France, Photowatt-PWP201, SM55 and ST40). Moreover, the algorithm is really user friendly and quick. Thus, the WDO algorithm is suggested as the accurate, quickest and flexible optimization algorithm for the estimation of solar PV modules parameters.

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