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An improved optimization technique for estimation of solar photovoltaic parameters

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ABSTRACT

The nonlinear current vs voltage (I-V) characteristics of solar PV make its modelling difficult. Optimization techniques are the best tool for identifying the parameters of nonlinear models. Even though, there are different optimization techniques used for parameter estimation of solar PV, still the best optimized results are not achieved to date. In this paper, Wind Driven Optimization (WDO) technique is proposed as the new method for identifying the parameters of solar PV. The accuracy and convergence time of the proposed method is compared with results of Pattern Search (PS), Genetic Algorithm (GA), and Simulated Annealing (SA) for single diode and double diode models of solar PV. Furthermore, for performance validation, the parameters obtained through WDO are compared with hybrid Bee Pollinator Flower Pollination Algorithm (BPFPA), Flower Pollination Algorithm (FPA), Generalized Oppositional Teaching Learning Based Optimization (GOTLBO), Artificial Bee Swarm Optimization (ABSO), and Harmony Search (HS). The obtained results clearly reveal that WDO algorithm can provide accurate optimized values with less number of iterations at different environmental conditions. Therefore, the WDO can be recommended as the best optimization algorithm for parameter estimation of solar PV.

1. Introduction

Today, due to the necessity of clean energy sources, the application of renewable and inexhaustible energy sources is gradually increasing. Among them, solar energy source seems to constitutes one of the best alternative solutions for energy provision. However, for this purpose, precise modeling of solar PV is required as it must be employ to predict the characteristic curves of solar PV at different weather condition of a particular area. This, in turn, is necessary for designing the corresponding inverter with high efficiency that is suitable for the given location. In addition to that, it will be beneficial to identify any mismatch in the PV array due to dust in the solar PV module by calculating the difference in real power generated by the module and predicted power by the model. This will enable to carry out maintenance at the right time (Babu et al., 2016).

The modeling of solar PV is generally derived using equivalent diode models. The current vs voltage (I-V) characteristics of solar PVs are mostly described using two types of diode models: single diode model and double diode model (Farivar and Asaei, 2011; Barth et al., 2016; Rezaee Jordehi, 2016). In this work, we focus on both single diode and double diode models of the solar PV. The parameters of the solar PV model vary with temperature and irradiance. Hence, precise estimation of the parameters is required to model the solar PV accurately. The popular approaches employed for parameter estimations are broadly categorized as analytical techniques (Chan and Phang, 1987), numerical extraction (Wolf and Benda, 2013; Ishaque et al., 2011, 2012; Barukcic et al., 2015) and evolutionary algorithm techniques (Ismail et al., 2013; Ma et al., 2016; Moldovan et al., 2009; Derick et al., 2016; Rajasekar et al., 2014).

In the analytical technique, mathematical equations are used to find the parameters. Most of the values in the equations are not provided in the manufacturer datasheet. As a result, this method is not deemed accurate (Rezaee Jordehi, 2016). Numerical extraction technique is based on curve fitting. However, the application of curve fitting to the nonlinear equation of diode is quite difficult. Consequently, numerical extraction approach is not so popular

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either (Ishaque et al., 2012). On the other hand, artificial intelligence techniques (Ma et al., 2016) are considered as excellent in dealing with nonlinear equations. In recent years, different optimization techniques have been introduced to estimate the parameters of solar PV; namely, the Genetic Algorithm (GA) (Ismail et al., 2013; Moldovan et al., 2009), Pattern Search (PS) optimization (Derick et al., 2016), Artificial Immune System (AIS) (Xiaoping et al., 2003), Bacterial Foraging Algorithm (BFA) (Rajesekar et al., 2013), Simulated Annealing (SA) (El-Naggar et al., 2012), Differential Evaluation (DE) (da Costa et al., 2010), Mutative-scale Parallel Chaos Optimization (MPCOA) (Yuan et al., 2014), Harmony Search (HS) based algorithm (Askarzadeh and Rezazadeh, 2012), Artificial Bee Swarm Optimization (ABSO) algorithm (Askarzadeh and Rezazadeh, 2013), Artificial Bee Colony (ABSO) optimization (Oliva et al., 2014), Flower Pollination Algorithm (FPA) (Alam et al., 2015), Levenberb – Marquard Algorithm with Simulated Annealing (LMSA) (Dkhichi et al., 2014), Cuckoo Search (CS) (Ma et al., 2013), Bee Pollinator Flower Pollination Algorithm (BPFPA) (Ram et al., 2017), Fireworks Algorithm (FA) (Babu et al., 2016) and Generalized Oppositional Teaching Learning Based Optimization (GOTLBO) (Chen et al., 2016). However, these algorithms still require some modifications to find the most optimized parameter for different solar PV modules (Alam et al., 2015). The most efficient algorithm for finding the optimized value of solar PV parameters are yet to be found.

In this work, we proposed Wind Driven Optimization (WDO) algorithm to optimize parameters of a single diode and double diode models of solar PV. The idea of WDO is developed by Zikri Bayraktar for electromagnetic application (Bayraktar et al., 2010). It is a population based heuristic global optimization technique for multidimensional problems. The algorithm contains four constants. Optimized values of these constants are generated using Covariance Matrix Adaptation Evolution Strategy (CMAES) technique (Bhandari et al., 2014).

The accuracy of the proposed optimization technique is measured using the value of Root Mean Square Error (RMSE). Convergence time is evaluated by the time required for the proposed method to reach the optimized value. In order to display the potential of the WDO algorithm, its accuracy and convergence time is compared with PS, GA, and SA available in the MATLAB optimization toolbox. In addition, the parameters obtained through WDO is compared with results obtained in recent literature like BPFPA (Ram et al., 2017), FPA (Alam et al., 2015), ABSO (Askarzadeh and Rezazadeh, 2013), HS (Askarzadeh and Rezazadeh, 2012). All these investigations provide an evaluation on the accuracy and time of convergence of the proposed algorithm for parameter estimation of solar PV.

An outline of the paper is as follows: The mathematical modeling of solar PV is presented in next section. Section 3 presents the problem formulation. The WDO is explained in detail for solar PV parameter estimation in Section 4. This is followed by the discussion of results in Section 5. Finally, conclusions are presented in Section 6.

2. Mathematical modeling

Many models have been proposed and developed by several researchers to estimate the solar PV parameters accurately (Barth et al., 2016). Among them, the most popular and universally adopted models are the single diode and double diode models. In our work, both diode models are used to represent the behavior of solar PV module. In what follows, a description of both models is given.

2.1. Single diode model

Single diode model is commonly used to represent solar PV, because of its reduced complexity (VIllalva and Gazoli, 2009; Chatterjee et al., 2011). The equivalent circuit of single diode model of solar PV is shown in Fig. 1.

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

$$I = I_{ph} - I_D - I_p \tag{1}$$

Here, I 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 (Chatterjee et al., 2011; Bayraktar, 2011).

$$I = I_{ph} - I_o\left(\exp\left(\frac{V + I\,R_s}{N_s * a\frac{KT}{q}}\right) - 1\right) - \frac{V + I\,R_s}{Rp} \tag{2}$$

$$I_o = \frac{I_{SC-S} + K_I(T - T_S)}{\exp\left(\frac{V_{OC-S} + K_V(T - T_S)}{N_s V_t}\right) - 1} \tag{3}$$

$$I_{ph} = (I_{ph-S} + K_I(T - T_S))\frac{G}{G_S} \tag{4}$$

Here I_o is the reverse saturation current of diode, V is solar PV voltage, R_p is the parallel resistance, R_s is the series resistance, V_{OC-S} is the open circuit voltage at standard test condition, K_V is open circuit voltage temperature coefficient, N_s is the number of series cell per module, the temperature at standard test condition $T_S = 25^0c$, solar radiation at standard test condition $G_S = 1000\ \mathrm{W/m^2}$, K_I is the short circuit current temperature coefficient, V_t is the thermal voltage of diode which depends on junction temperature and is given by:

$$V_t = a\frac{K\,T}{q} \tag{5}$$

where a denotes the ideality factor of diode. T expresses the junction temperature in Kelvin (K), q is the electron charge ($1.6021765 \times 10^{-19}$ C) and K is the Boltzmann constant ($1.38065 \times 10^{-23} J/K$).

I_{ph-S} is the photon current at standard test condition, and it is given by

$$I_{ph-S} = I_{SC-S}\left(\frac{R_P + R_S}{R_P}\right) \tag{6}$$

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

From Eq. (2), one can see that we require optimum values of five parameters I_{ph}, I_o, R_p,R_s, and a in order to be able to generate the same I-V characteristic curve as obtained experimentally. Finally, it is important to note that Eq. (2) is an implicit equation in I.

2.2. Double diode model

In double diode model, two diodes are connected in parallel to the photon current source. The second diode represents the recombination in the space charge region. The equivalent circuit of double diode model is shown in the Fig. 2.

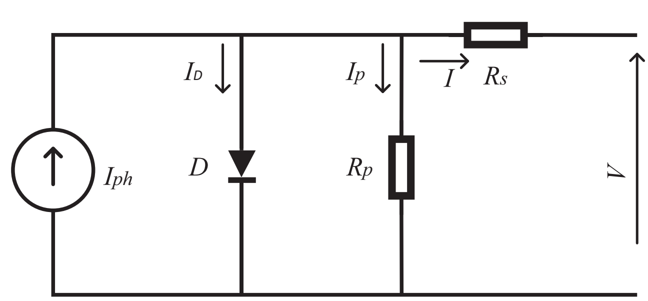

Fig. 1. Single – diode model of solar PV.

By using KCL

$$I = I_{ph} - I_{D1} - I_{D2} - I_p \tag{7}$$

$$I = I_{ph} - I_{o1}\left(\exp\left(\frac{V + I\,R_s}{N_s V_{t1}}\right) - 1\right) - I_{o2}\left(\exp\left(\frac{V + I\,R_s}{N_s V_{t2}}\right) - 1\right) - \frac{V + I\,R_s}{Rp} \tag{8}$$

Here I_{o1} and I_{o2} are the reverse saturation currents and V_{t1} and V_{t2} are thermal voltages of diode 1 and diode 2 respectively. I_{ph} can determined using the Eq. (4)

$$V_{t1} = a_1 \frac{KT}{q} \tag{9}$$

$$V_{t2} = a_2 \frac{KT}{q} \tag{10}$$

where a_1 and a_2 denotes the ideality factor of diode 1 and diode 2 respectively.

From Eq. (8), it is clear that it is necessary to obtain optimized values of the seven parameters I_{ph}, I_{o1}, I_{o2}, Rp, R_s, a_1 and a_2 in order to have an accurate double diode model of solar PV.

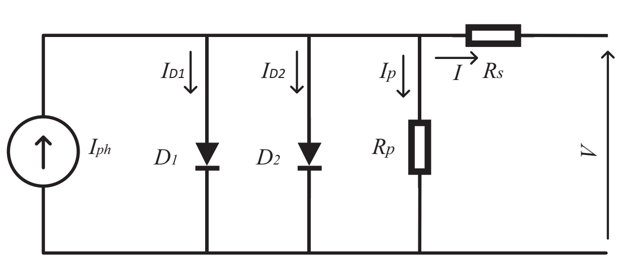

Fig. 2. Double – diode model of solar PV.

3. Problem formulation

Any solar PV module can be modeled by using the single diode or double diode models. The main objective of this modeling is to enable the solar PV model to predict the I-V characteristics of the PV module. In order to minimize the error between predicted and actual I-V characteristics of PV module, one has to find the optimized parameters of the solar PV model. This can be done by using optimization algorithms.

As mentioned above single diode and double diode models of solar PV model have five and seven parameters respectively. In this paper, the values of resistances R_p, R_s and ideality factor a are determined using the proposed algorithm where as I_{ph} and I_o using Eqs. (3) and (4) in order to reduce the computational complexity.

The objective function is Root Mean Square Error (RMSE) between the measured and estimated current. The objective function will aggregate the absolute error and gives the measure of predictive power. The absolute difference between measured and estimated output current is the Individual Absolute Error (IAE). The error function of a single diode and double diode model is given in Eqs. (11) and (12) respectively. The Sum of Squared Error (SSE) function is given in Eq. (13).

$$f_s(V_{(m)}, I_{(m)}, X) = IAE = abs\left(I_{(m)} - (I_{ph} - I_{D(m)} - I_{p(m)})\right) \tag{11}$$

$$f_d(V_{(m)}, I_{(m)}, X) = IAE = abs\left(I_{(m)} - (I_{ph} - I_{D1(m)} - I_{D2(m)} - I_{p(m)})\right) \tag{12}$$

$$SSE = \sum_{i=1}^{N} IAE^2 \tag{13}$$

In Eqs. (11) and (12) the 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:

$$\text{RMSE} = \sqrt{\frac{1}{N} SSE} \tag{14}$$

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

4. Wind driven optimization

Wind driven optimization is a new nature inspired optimization technique (Bayraktar, 2011). The idea was developed by Zikri Bayraktar for electromagnetics application (Bayraktar et al., 2010). The motivation for WDO algorithm was based on the motion of microscopic air parcels in a multidimensional space. In earth's troposphere, the solar radiation varies based on the location. So, heating the surface of the earth varies according to the location, type of the region (water body, soil, cloudy), and rotation of earth (Bhandari et al., 2014). The air pressure will be high at low-temperature area than high-temperature area. This difference in air pressure leads horizontal motion of air. The change in pressure is the pressure gradient (Bayraktar, 2011), and is given as follows:

$$\nabla P = \left(\frac{\partial P}{\partial x}, \frac{\partial P}{\partial y}, \frac{\partial P}{\partial z}\right) \tag{15}$$

Here the 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:

$$\rho.\vec{a} = \sum \vec{F_t} \tag{16}$$

The four forces that create movement of air parcel are pressure gradient force (F_{PG}), frictional force (F_F), gravitational force (F_G) and Coriolis force (F_C).

Assuming that air has finite volume (δV), the force due to pressure gradient can be expressed as Eq. (17). The friction force opposes the air parcel motion started by F_{PG}. The gravitational force pulls the air parcel to the center of the coordinate system from all dimensions. The rotation of the earth causes deflection in the motion of air parcel and named as Coriolis force. This force will work in such a way that velocity in one direction is influenced by velocity in another direction. All these forces can be expressed as:

$$\overrightarrow{F_{PG}} = -\nabla P \cdot \delta V \tag{17}$$

$$\overrightarrow{F_F} = -\rho\alpha\vec{u} \tag{18}$$

$$\overrightarrow{F_G} = \rho \cdot \delta V \cdot g \tag{19}$$

$$\overrightarrow{F_C} = -2\theta \times \vec{u} \tag{20}$$

Here ρ is the air density of a small air parcel, α is frictional coefficient, $\vec{u}$ wind velocity vector, g is the gravitational constant, θ represents the rotation of earth.

So, by including F_{PG}, F_F, F_G, F_C and ideal gas equation in total force Eq. (16), the latter can be rewritten as:

$$\overrightarrow{\nabla u} = g + \left(-\nabla P \cdot \frac{RT}{P_{cur}}\right) + (-\alpha\vec{u}) + \left(-\frac{2\theta \times \vec{u}RT}{P_{cur}}\right) \tag{21}$$

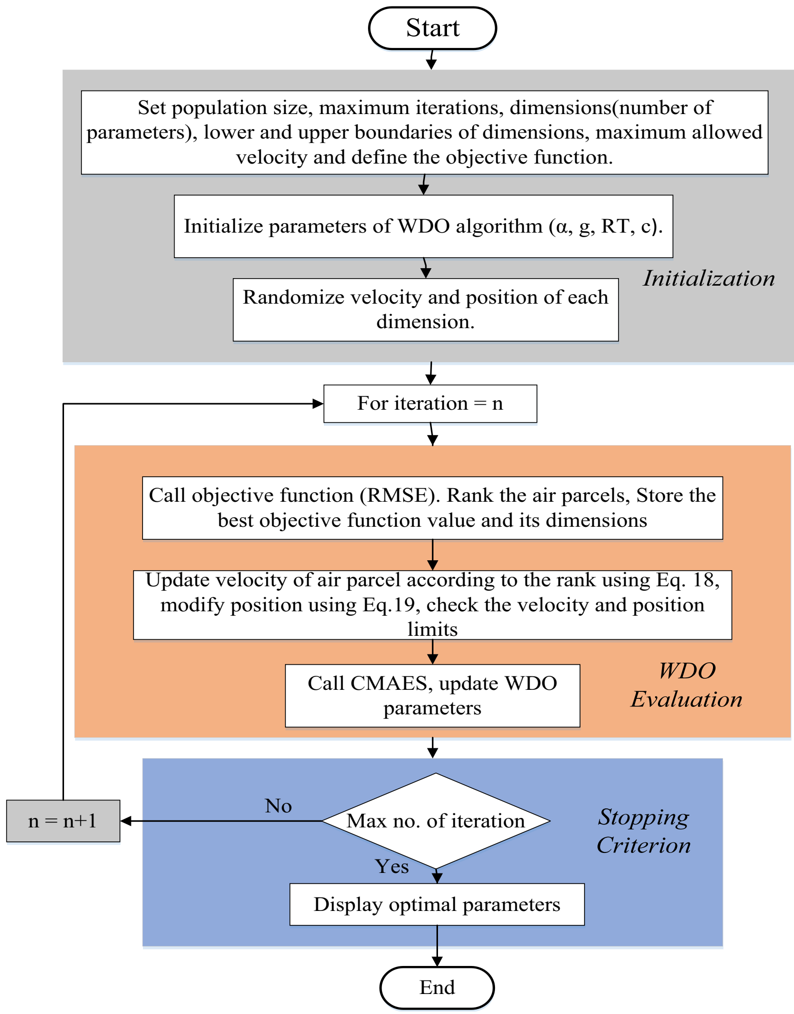

Fig. 3. Flowchart of wind driven optimization.

In Eq. (21) velocity of air parcel depends on pressure value. Consequently, if pressure value increases the velocity gets updated impractically. For that, Eq. (21) is modified based on the rank of the pressure. After every iteration, the air parcels are ranked in descending order based on their pressure values. If i is the rank of the air parcel, velocity and position will be updated using the Eqs. (22) and (23) respectively.

$$\overrightarrow{u_{new}} = (1-\alpha)\vec{u}_{cur} - gx_{cur} + \left(\left|1-\frac{1}{i}\right| \cdot (x_{opt} - x_{cur})RT\right) + \left(\frac{c \cdot \vec{u}_{otherdirection}}{i}\right) \tag{22}$$

$$\overrightarrow{x_{new}} = \overrightarrow{x_{old}} + \overrightarrow{u_{new}} \tag{23}$$

Here $\overrightarrow{u_{new}}$ is the velocity of next iteration, $\overrightarrow{u_{cur}}$ is the velocity of current iteration, x is the position of the air parcel in search space, x_{opt} is optimal position, x_{cur} = current position,$c = -2RT$, and $\vec{u}_{otherdirection} = \overrightarrow{F_C}$.

In this parameter estimation problem, each dimension of an air parcel is the parameters of solar PV. So, in single diode model, the air parcel is in a three-dimensional space whereas, in the double diode model it is in four-dimensional space. The pressure of air parcels in a search space is evaluated using the objective function. Next, air parcels are ranked based on their objective function value. So, the velocity of air parcels is modified using their ranks and move to another position with that velocity. The air parcels continue their movement to find the lowest objective function value. The last step is to find the air parcel with lowest objective function value and their corresponding parameters.

For each dimension the WDO allows air parcel to travel in a bound of $[-1, 1]$. The actual maximum and minimum limits of the problem are normalized to $[-1, 1]$. To obtain the optimized objective function value, the coefficients α, g, RT, c in Eq. (22) 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 any inputs other than population size (Bayraktar et al., 2010). Hence, CMAES is easy to implement for WDO application. The flow chart of wind the driven optimization algorithm is shown in Fig. 3.

5. Results and discussion

5.1. Results of WDO is compared with PS, GA, and SA

Wind Driven Optimization algorithm is used to find the optimized parameters of a single diode and double diode solar model. In order to validate the accuracy of the proposed optimization algorithm, the result of WDO is compared with results obtained from PS, GA, and SA available in MATLAB optimization tool box.

Table 1
Datasheet values of Kyocera – KC200GT 215 module.

Maximum power (P_{max})	200 W (+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 cells (N_s)	54

Table 2
Estimated single diode model parameters of Kyocera – KC200GT 215 module.

	WDO	PS	GA	SA
a	1.4172	1.7	1.4819	1.6118
R_s (Ω)	0.1132	0.0339	0.1067	0.0796
R_p Ω)	747.41	624.382	728.58	713.110
$I_{ph}(A)$	8.1812	8.2104	8.2112	8.2109
$I_o(\mu A)$	0.4423	7.1836	0.9220	3.3484
RMSE	0.00084	0.001796	0.00188	0.001875

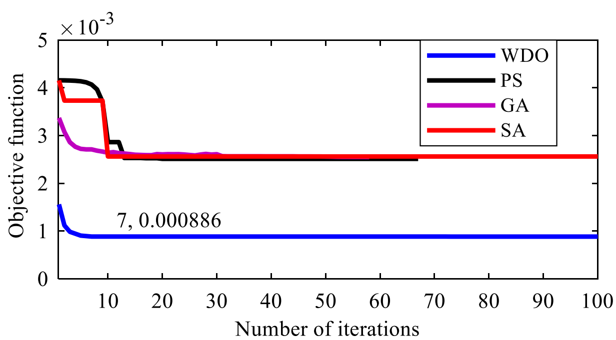

Fig. 4. Convergence characteristics of WDO, PS, GA, and SA.

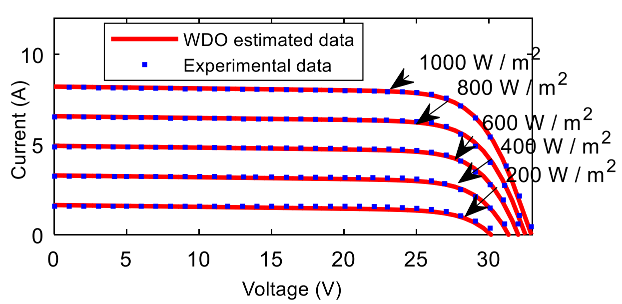

Fig. 5. Comparison of experimental data and WDO estimated data of Kyocera – KC200GT 215 module at different irradiance (single diode model).

Single diode and double diode models of solar PV is developed in MATLAB/Simulink to test the optimization techniques. The results obtained through PS, GA, and SA are compared with the proposed WDO algorithm results. The experimental data of multi-crystal PV module Kyocera – KC200GT 215 given in Pauls (2014) is used to find the objective function. The objective function is calculated based on the 18 set of experimental data.

Here the ideality factor a has a value between 1 and 2. The value of series resistance R_s is between 0.01Ω to 0.5Ω, whereas the parallel resistance R_p has value between 100Ω and 1000Ω. The I_{ph} and I_o values are calculated using Eqs. (3) and (4). The data sheet values of Kyocera – KC200GT 215 module is given in Table 1.

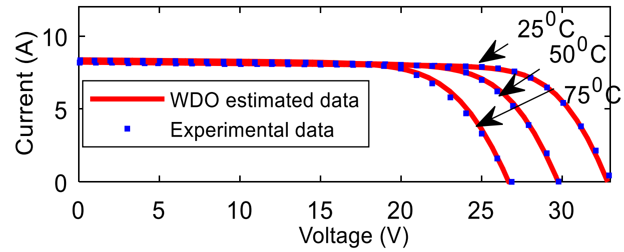

Fig. 6. Comparison of experimental data and WDO estimated data of Kyocera – KC200GT 215 module at different temperature (single diode model).

Table 3
Estimated double diode model parameters of Kyocera – KC200GT 215 module.

	WDO	PS	GA	SA
a_1	1.9667	1.01	1.17	1.12
a_2	1.5370	1.9	1.4324	1.5631
R_s Ω)	0.99	0.031	0.0691	0.01783
R_p Ω)	784.4062	793.215	763.3564	862.97
$I_{ph}(A)$	8.1914	8.2107	8.2103	8.2102
$I_{o1}(A)$	4.746×10^{-5}	5.22×10^{-10}	1.29×10^{-11}	5.24×10^{-9}
$I_{o2}(A)$	1.632×10^{-6}	3.12×10^{-10}	5.3×10^{-7}	2.12×10^{-9}
RMSE	0.00106	0.0029	0.0029	0.003

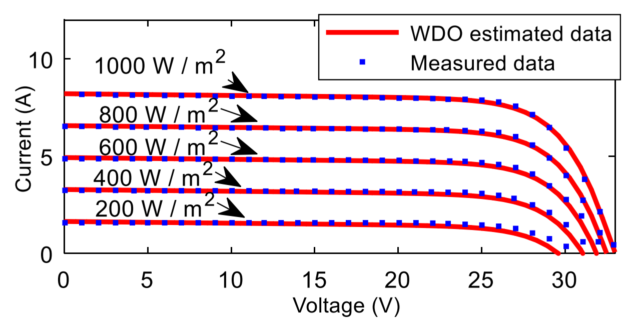

Fig. 7. Comparison of experimental data and WDO estimated data of Kyocera – KC200GT 215 module at different irradiance (double diode model).

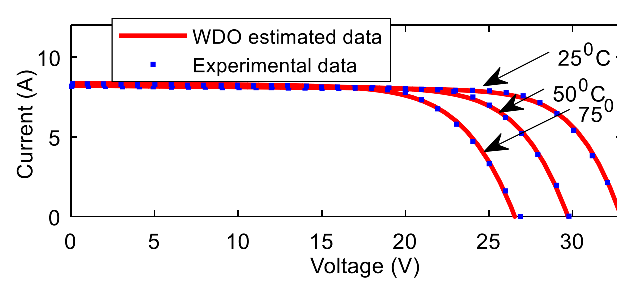

Fig. 8. Comparison of experimental data and WDO estimated data of Kyocera – KC200GT 215 module at different temperature (double diode model).

5.1.1. Case study1: 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 and RMSE WDO, PS, GA, and SA optimization techniques at standard test condition. It clearly exhibits that, the WDO gives very less RMSE value compared to other techniques. So, in terms of accuracy WDO is the best technique.

The Fig. 4 shows the convergence characteristics of four optimization techniques. From the fitness function curve, it is evident

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

	WDO	BPFPA (Ram et al., 2017)	GOTLBO (Chen et al., 2016)	FPA (Alam et al., 2015)	ABSO (Askarzadeh and Rezazadeh, 2013)	HS (Askarzadeh and Rezazadeh, 2012)
a	1.4808	1.4774	1.48382	1.47707	1.47583	1.47538
R_s Ω)	0.036768	0.03666	0.036265	0.0365466	0.03659	0.03663
R_p Ω)	57.74614	57.7156	54.115426	52.8771	52.2903	53.5946
$I_{ph}(A)$	0.7608	0.76	0.76078	0.76079	0.7608	0.7607
$I_o(\mu A)$	0.3223	0.3106	0.3315	0.3106	0.3062	0.30495
RMSE ($\times 10^{-4}$)	0.08664	7.27	9.8744	7.7301	9.9124	9.951

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

	WDO	BPFPA (Ram et al., 2017)	GOTLBO (Chen et al., 2016)	FPA (Alam et al., 2015)	ABSO (Askarzadeh and Rezazadeh, 2013)	HS (Askarzadeh and Rezazadeh, 2012)
a_1	1.51162	1.4793	1.99973	1.4777	1.46512	1.49439
a_2	1.38434	2.00	1.448974	2	1.98152	1.49439
R_s Ω)	0.037433	0.0364	0.036783	0.0363342	0.03657	0.03545
R_p Ω)	52.6608	59.624	56.075304	52.3475	54.6219	46.82696
$I_{ph}(A)$	0.7606	0.7600	0.7607	0.760795	0.76078	0.76176
$I_{o1}(\mu A)$	0.2531	0.3211	0.800195	0.3008	0.26713	0.12545
$I_{o2}(\mu A)$	0.04827	0.04528	0.220462	0.166157	0.38191	0.2547
RMSE ($\times 10^{-4}$)	0.065237	7.23	9.83177	7.8425	9.8344	12.6

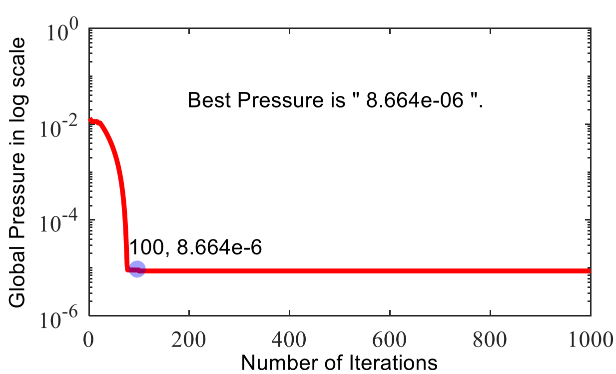

Fig. 9. Convergence curve of WDO algorithm for optimizing the parameters of single diode model.

that the best fitness function value of 0.0008401 is obtained for WDO with less number of iterations. This clearly reveals that WDO algorithm performs well in terms of accuracy and computation time. The time required for the WDO to find the optimized values is 5.6 ms while PS and GA are 0.8 ms whereas SA required 0.02 s.

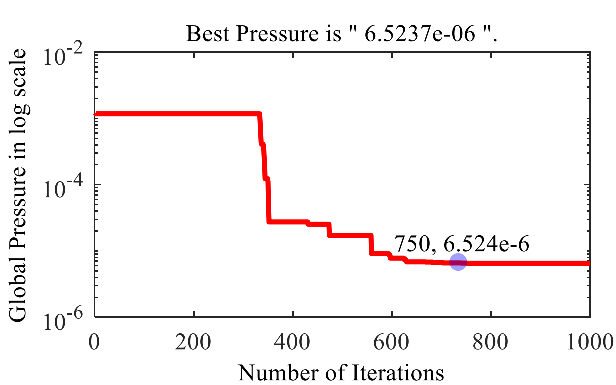

Fig. 10. Convergence curve of WDO algorithm for optimizing the parameters of double diode model.

The experimental data in Pauls (2014) gives solar PV voltage and current at different irradiance and temperature values. Using the experimental data and WDO estimated data I-V characteristics of Kyocera – KC200GT 215 Solar PV module is plotted for 1000 W/m^2, 800 W/m^2, 600 W/m^2, 400 W/m^2 and 200 W/m^2 in Fig. 5. Similarly, I-V characteristics for different temperature 25 °C, 50 °C and 75 °C is plotted in Fig. 6. Both Figures reflects the fact that the values estimated by the WDO algorithm give out accurate I-V characteristics which exactly replicate the experimental data.

5.1.2. Case study2: 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, and the derived values of I_{ph}, I_o, RMSE at standard test condition is presented in Table 3. The I-V characteristic at different irradiance and temperature are plotted in Figs. 7 and 8 respectively.

From I-V characteristics curves it is observable that the parameter values obtained through WDO produce the accurate curve with insignificant RMSE value for an entire range of voltage in all irradiance and temperature conditions. Hence, both these case studies clearly substantiate that, the WDO technique can generate more accurate results in all weather conditions with a minimal time of computation.

5.2. Results of WDO is compared with recent literature

In order to further verify the performance of the WDO algorithm, the latter is examined with the experimental data of 57 mm dia RTC France silicon solar cell at 1000 W/m^2 irradiance and 33 °C temperature presented in Easwarakhanthan et al. (1986). The parameters of a single diode and double diode model of the cell is estimated through WDO algorithm. The lower and upper boundaries of a, R_s, and R_p are assigned as (1–2), (0.01–0.08) Ω, and (25–75) Ω respectively. The optimized values of solar

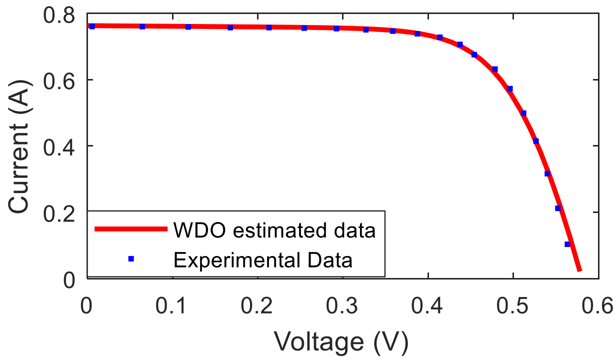

Fig. 11. Comparison of experimental data and WDO estimated data of RTC France solar cell at 1000 W/m^2 and 33 °C for single diode model.

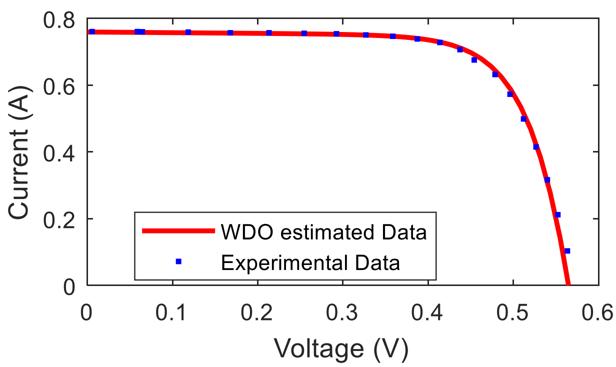

Fig. 12. Comparison of experimental data and WDO estimated data of RTC France solar cell at 1000 W/m^2 and 33 °C for double diode model.

PV parameters along with RMSE for single diode and double diode models are presented in Tables 4 and 5. It shows the comparison of results obtained through the optimization techniques presented in recent research papers such as BPFPA (Ram et al., 2017), GOTLBO (Chen et al., 2016), FPA (Alam et al., 2015), ABSO (Askarzadeh and Rezazadeh, 2013), HS (Askarzadeh and Rezazadeh, 2012) with WDO algorithm. From Tables 4 and 5 it is clear that WDO algorithm provides the least RMSE value (0.08664×10^{-4} and 0.065237×10^{-4}) while comparing with other optimization techniques.

The convergence curve of WDO algorithm for the single diode and double diode model is shown in Figs. 9 and 10 respectively. They prove that convergence time for WDO is very less. In parameter estimation of single diode model, WDO reaches a RMSE value of 8.664e−6 after 100 iterations. Whereas, BPFPA and FPA took more than 500 iterations to obtain RMSE values of 8.456e−4 for same environmental conditions. Similarly, for double diode model, WDO algorithm reached a RMSE value of 6.5237e−6 after 750 iterations, whereas BPFPA and FPA reach 7.917e−4 after 500 iterations.

In order to verify the accuracy of WDO determined parameter values, the I-V characteristics at 1000 W/m2 and 33 °C for single diode model and double diode model of solar PV are plotted in Figs. 11 and 12 respectively. They clearly show that the I-V characteristic curve accurately replicates the experimental data provided in Easwarakhanthan et al. (1986). In order to validate the accuracy of curve fit between measured and estimated values, error analysis is used. So, Relative Error (RE) between measured and estimated values of PV current for the single diode and double diode models are calculated using the below mentioned formula.

$$RE = \frac{I_{measured} - I_{estimated}}{I_{measured}}$$

The RE value obtained using WDO for the single diode and double diode is compared with BPFPA (Ram et al., 2017), and HS (Askarzadeh and Rezazadeh, 2012) and tabulated in Table 6 and 7. From Tables, it is obvious that relative error for WDO is low while comparing the other optimization techniques considered for comparison.

Table 6
The comparison of relative error values of WDO, BPFPA, HS for single diode model.

Data	Vmeasured	Imeasured	**WDO**		BPFPA (Ram et al., 2017)		HS (Askarzadeh and Rezazadeh, 2012)	
			Iestimated	**RE**	Iestimated	RE	Iestimated	RE
1	−0.2057	0.764	**0.764**	**0.00016**	0.764	0.00012	0.764	−0.00036
2	−0.1291	0.762	**0.763**	**−0.00072**	0.762	0.00032	0.762	−0.00109
3	−0.0588	0.761	**0.761**	**−0.00109**	0.761	−4.9e−5	0.761	−0.00133
4	0.0057	0.760	**0.760**	**0.00037**	0.759	0.00142	0.760	0.000272
5	0.0646	0.760	**0.759**	**0.00106**	0.758	0.00210	0.759	0.001078
6	0.1185	0.759	**0.758**	**0.00098**	0.757	0.00203	0.758	0.001113
7	0.1678	0.757	**0.757**	**−0.00048**	0.757	0.00057	0.757	−0.00025
8	0.2132	0.757	**0.756**	**0.00069**	0.755	0.00174	0.756	0.001015
9	0.2545	0.755	**0.755**	**4.08e−5**	0.754	0.00108	0.755	0.000441
10	0.2924	0.754	**0.754**	**−0.00011**	0.753	0.00090	0.753	0.000353
11	0.3209	0.750	**0.751**	**−0.0017**	0.751	−0.000	0.751	−0.00126
12	0.3585	0.746	**0.747**	**−0.0017**	0.747	0.0008	0.747	−0.0012
13	0.3873	0.738	**0.740**	**−0.0028**	0.739	−0.0019	0.740	−0.00221
14	0.4137	0.728	**0.727**	**0.0003**	0.727	0.00090	0.727	0.000802
15	0.4373	0.706	**0.707**	**−0.0010**	0.706	−0.0006	0.706	−0.00066
16	0.459	0.675	**0.675**	**0.00024**	0.675	0.00014	0.675	0.000293
17	0.4784	0.632	**0.630**	**0.00231**	0.631	0.00150	0.630	0.001744
18	0.490	0.573	**0.571**	**0.0028**	0.572	0.00126	0.572	0.001553
19	0.5119	0.499	**0.498**	**0.00051**	0.499	0–0.0013	0.499	−0.00108
20	0.5265	0.413	**0.412**	**0.0011**	0.413	−0.00171	0.413	−0.00134
21	0.5398	0.316	**0.316**	**0.00070**	0.317	−0.00302	0.317	−0.00248
22	0.5521	0.212	**0.210**	**0.0047**	0.212	−0.00183	0.212	−0.00076
23	0.5633	0.103	**0.102**	**0.01047**	0.103	0.003957	0.102	0.007188
24	0.5736	−0.010	**−0.009**	**0.01**	−0.008	0.12410	−0.009	0.075
25	0.5833	−0.123	**−0.124**	**−0.00821**	−0.123	−0.00596	−0.124	−0.01171
26	0.59	−0.210	**−0.209**	**0.003904**	−0.208	0.007587	−0.209	0.003333

Table 7
The comparison of relative error values of WDO, BPFPA, HS for double diode model.

Data.	Vmeasured	Imeasured	**WDO**		BPFPA (Ram et al., 2017)		HS (Askarzadeh and Rezazadeh, 2012)	
			Iestimated	**RE**	Iestimated	RE	Iestimated	RE
1	−0.2057	0.764	**0.764**	**3.912e−5**	0.764	9.65e−5	0.764	0.00011
2	−0.1291	0.762	**0.762**	**−0.00067**	0.762	0.000361	0.762	0.0007
3	−0.0588	0.761	**0.761**	**−0.00089**	0.760	−3.9e−5	0.761	0.001
4	0.0057	0.760	**0.759**	**0.00071**	0.759	0.0014	0.760	0.0004
5	0.0646	0.760	**0.758**	**0.00153**	0.758	0.002	0.759	0.0011
6	0.1185	0.759	**0.757**	**0.001575**	0.757	0.0019	0.758	0.00107
7	0.1678	0.757	**0.756**	**0.000214**	0.756	0.0004	0.757	0.0003
8	0.2132	0.757	**0.755**	**0.00148**	0.755	0.0016	0.756	0.0008
9	0.2545	0.755	**0.754**	**0.00089**	0.754	0.00098	0.755	0.0003
10	0.2924	0.754	**0.753**	**0.00077**	0.753	0.0008	0.753	0.0002
11	0.3209	0.750	**0.751**	**−0.00094**	0.751	−0.0008	0.751	0.0012
12	0.3585	0.746	**0.747**	**−0.00104**	0.747	−0.0008	0.747	0.0010
13	0.3873	0.738	**0.740**	**−0.00233**	0.739	−0.0019	0.739	0.0019
14	0.4137	0.728	**0.727**	**0.00036**	0.727	0.0010	0.727	0.0011
15	0.4373	0.706	**0.707**	**−0.0015**	0.706	−0.0045	0.706	0.0002
16	0.459	0.675	**0.676**	**−0.00095**	0.675	0.0004	0.675	0.0005
17	0.4784	0.632	**0.631**	**0.00041**	0.630	0.0016	0.630	0.00186
18	0.490	0.573	**0.572**	**0.00026**	0.572	0.0016	0.572	0.00157
19	0.5119	0.499	**0.500**	**−0.00257**	0.499	−0.0010	0.499	0.0011
20	0.5265	0.413	**0.413**	**0.00413**	0.413	−0.00137	0.413	0.0014
21	0.5398	0.316	**0.317**	**−0.00283**	0.317	−0.00266	0.317	0.0024
22	0.5521	0.212	**0.211**	**0.00424**	0.212	−0.00126	0.212	0.0005
23	0.5633	0.103	**0.102**	**0.0073**	0.102	0.00560	0.102	0.0078
24	0.5736	−0.010	**−0.009**	**0.0100**	−0.009	0.09727	0.009	0.0706
25	0.5833	−0.123	**−0.125**	**−0.0020**	−0.124	−0.00932	0.124	0.011
26	0.59	−0.210	**−0.208**	**0.0095**	−0.208	0.004979	0.209	0.0040

6. Conclusion

Accurate modeling of solar PV is necessary before designing the entire PV system. The optimized parameter of single and double diode models plays an important role for accurate modeling. This paper presented a new Wind Driven Optimization algorithm for parameter estimation of solar PV. The performance of WDO algorithm was verified by comparing its results with PS, GA, and SA algorithms using MATLAB optimization tool box. Results of WDO clearly shows a better performance in terms of accuracy and convergence. In addition, in order to further validate the proposed algorithm, the WDO is compared with the optimization techniques presented in recent literature. Compared to recent optimization algorithms presented in literature such as Bee Pollinator Flower Pollination Algorithm, Flower Pollination Algorithm, Generalized Oppositional Teaching Learning Based Optimization, Artificial Bee Swarm Optimization, and Harmony Search, the WDO shows better results. As a result, WDO algorithm is recommended as the accurate and fastest optimization algorithm for parameter estimation of solar PV modules.

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