A study on the application of the grey wolf optimizer for find the parameter of photovoltaic model

Preeti Saini[1], Ashok Kumar Bunker[1], Ankit Kumar Sharma[1], Bhanu Pratap Soni[2]

[1]Department of Electrical Engineering, University of Engineering & Management, Jaipur, India

[2]Department of Electrical Engineering, Fiji National University, Fiji

1. Abstract.

Modeling the PV cell is crucial for many photovoltaic PV applications. However, the model parameters are typically absent from the datasheet that the manufacturers supply and they alter as a result of degradation. The dwindling supply of fossil fuels and the carbon emissions that cause global warming and climate change have caused power producers to turn their attention away from traditional energy sources and toward sustainable energy alternatives. The most popular solution to these issues is solar cells. To obtain high efficiency, it is crucial to estimate solar cell parameters precisely before installation. Applications of several optimization techniques for solar cell parameter estimation have been investigated in recent years. The intelligent grey wolf optimizer (IGWO), an improved version of the grey wolf optimizer (GWO), has recently been introduced. It incorporates opposition-based learning and a sinusoidal truncated function as a bridging mechanism. Voltage and current measurements are taken at three crucial moments for estimating the PV cell parameter values. There are three points(open circuit, short circuit and maximum power point) for the single diode model and the double diode model . On these two models and for three films, the findings of IGWO are contrasted with those of other GWO variations. Keywords: Photovoltaic (PV) module, grey wolf optimization algorithm, model parameters I.

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2. INTRODUCTION

For PV systems, various models have been put forth in the literature. The most well-known models in literature are thought to be the single diode model (SDM) and double diode model (DDM). A semiconductor PN junction called a PV cell is used to convert solar current into an electrical current. Nonetheless, the main model of the solar cell have to take into the terms of loss of light and current that mainly represented by the diodes. The main model of the solar cell can be basically shown by an ideal current source. More losses are represented by the model with more diodes. One diode in the SDM symbolises the loss in the quasi-neutral zone. Five calculated parameters make to an SDM. By including a second diode in the model, DDM is created to represent the loss in recombination at lower irradiance. Seven factors in total have been estimated for DDM

One (single) diode model and two (double) diode model

A one diode model is favored for its precision, quick convergence, and clarity is The I- V characteristic of a single diode model can be represented numerically as :

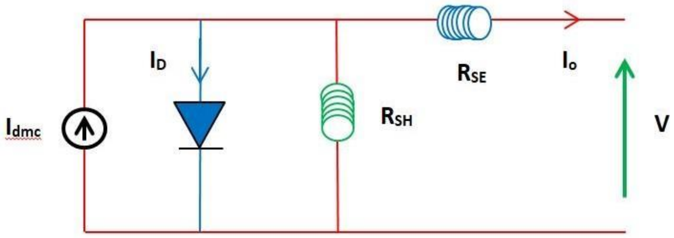

Figure 1. Representive circuit of PV module (one Diode Model)

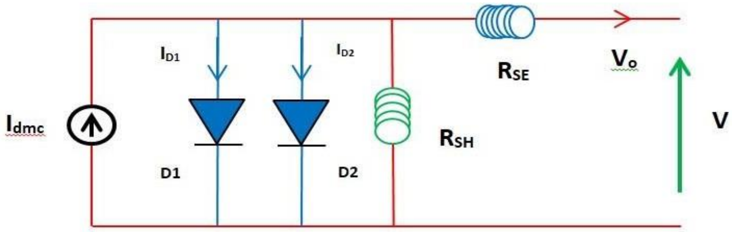

Figure 2. Representive circuit of PV module (two Diode Model)

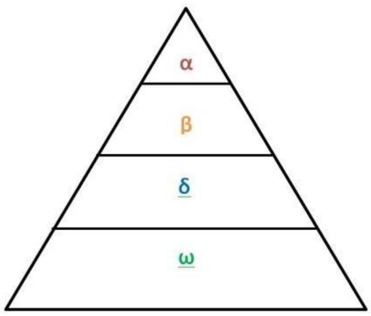

Figure 3. As per dominance up to down hierarchy of Grey Wolves

$$I_O = I_{dmc} - I_{rsc}\left[exp\left(\frac{q(V + IR_{SE})}{\psi KN_S T}\right) - 1 - \left(\frac{V + I_O R_{SE}}{R_{SH}}\right)\right] \quad (1)$$

We need deep understanding of pv cell parameter for design and process of optimization. Here it is 3 case at 3 crucial points.

Case-1 $V = VOC$and $IO = 0$ at open path, then Eq. (1) reduces to:

$$I_{dmc} = I_{rsc}\left[exp\left(\frac{qV_{OC}}{\psi KN_S T}\right)\right] + \frac{V_{OC}}{R_{SH}} \quad (2)$$

Case-2 $V = 0$ and $IO = ISC$ for short circuit path, then from Eq. (1) we find:

$$I_{dmc} = I_{SC} + I_{rsc}\left[exp\left(\frac{qR_{SE}I_{SC}}{\psi KN_S T}\right) - 1\right] + \frac{R_{SE}I_{SC}}{R_{SH}} \quad (3)$$

from Eqs. (2) and (3), we get,

$$I_{rsc} = \frac{I_{SC} + \frac{R_{SE}I_{SC}}{R_{SH}} - \frac{V_{OC}}{R_{SH}}}{exp\left(\frac{qV_{OC}}{\psi KN_S T}\right) - exp\left(\frac{qR_{SE}I_{SC}}{\psi KN_S T}\right)} \quad (4)$$

Substituting equation Eqs 4 into 2:

$$I_{dmc} = \frac{\left(I_{SC} + \frac{R_{SE}I_{SC}}{R_{SH}} - \frac{V_{OC}}{R_{SH}}\right)\left[exp\left(\frac{qV_{OC}}{\psi KN_S T}\right) - 1\right]}{exp\left(\frac{qV_{OC}}{\psi KN_S T}\right) - exp\left(\frac{qR_{SE}I_{SC}}{\psi KN_S T}\right)} + \frac{V_{OC}}{R_{SH}} \quad (5)$$

Case-3 $V = V_{MPP}$ and $I_O = I_{MPP}$ at Maximum Power point,Eq. (1) reduces in:

$$I_{MPP} = I_{dmc} - I_{rsc}\left[\exp\left(\frac{q(V_{MPP} + R_{SE}I_{MPP}}{\psi KN_S T} - 1\right] - \frac{V_{MPP} + R_{SE}I_{MPP}}{R_{SH}} \quad (6)$$

And hence we can get the euation of double diode model too.

3. NUMERICAL DATA

Into Three different types of solar cell modules—monocrystalline, polycrystalline, and thin-film—are taken into consideration in this work. The typical data provided by the designer shown as. It goes without saying to state that the designer provides data for voltage and current at three critical locations under standard test conditions of 1000 W/m2 and 25 °C.

Increasing the number of diodes improved the model's accuracy, but it also made it more complicated. By include a third diode in the model, the 3 diode model (TDM) is made for reflect the leakage in grain bound-arise in Photovoltic systems. Nine parameters in all are estimated for TDM. Increasing the number of diodes improved the model's accuracy, but it also made it more complicated. The difficulty of estimating these models' parametersusing optimization techniques has been covered in numerous earlier studies To estimate the PV parameters of TDM, the Grasshopper Optimization Algorithm was introduced in. As per , to calculate the parameter value of PV panel of SDM and DDM, a quick grey wolf optimizer was initially presented. The goal of the intelligent grey wolf optimizer is to improve the exploration and exploitation stages of the grey wolf optimizer (GWO) by incorporating opposition-based learning.

Table 1 Electrical parameters for PV cells at standard test conditions

Type	Monocrystalline [36]	Polycrystalline [37]	Thin-film [36]
Number of cells in series, N_S	36	54	36
Temperature coefficient (I_{SC},$K_{I,SC}$) (amp/°C)	0.8×10^{-3}	3.18×10^{-3}	0.35×10^{-3}
Temperature coefficient (V_{OC},$K_{V,OC}$ (volt/°C))	− 0.0725	− 0.123	− 0.1
Voltage at maximum power point, V_{MPP} (volt)	17.20	26.3	16.60
Current at maximum power point, I_{MPP} (amp)	4.95	7.61	2.41
Open circuit voltage, V_{OC}	22.20	32.9	23.30
Short circuit current, I_{SC}	5.45	8.21	2.68

4. BRIEF OVERVIEW OF GWO AND DEVELOPMENT OF INTELLIGENT GREY WOLF OPTIMIZER (IGWO)

Grey wolf optimizer A population-based swarm intelligence approach used today. This approach was suggested by and is inspired by grey wolf behaviour. Grey wolves naturally possess a hunting strategy and a hierarchy of leadership, and GWO replicates these benefits. A member of the candidate family is a grey wolf. Grey wolves typically reside in groups of 5 to 12 individuals. In total, there are four groups of wolves: "α wolves" refer to the dominant and most dominating wolves in each of the four subcategories. β wolves are ranked second to alpha wolves in terms of dominance. The β wolves are used to help α wolves when decide judgments or performing other projects. The delta wolves follow the directions given by the alpha and beta wolves. Omega wolves are in the bottom rank in the hierarchy. They serve as the scapegoat for the wolf group. References discuss a few GWO applications. The following are some of the key steps that the algorithm elaborates: prey encircling•

prey encircled mathematical representation by the grey wolves given as:

$$\vec{N} = |\vec{M}.\vec{Y}_P(t) - \vec{Y}(t)| \qquad \text{……….7}$$

$$\vec{Y}(t+1) = \vec{Y}_P(t) - \vec{K}.\vec{N} \qquad \text{…………..8}$$

$$\vec{N}_\alpha = |\vec{M}_1.\vec{Y}_\alpha - \vec{Y}|, \quad \vec{N}_\beta = |\vec{M}_2.\vec{Y}_\beta - \vec{Y}|, \quad \vec{N}_\delta = |\vec{M}_3.\vec{Y}_\delta - \vec{Y}| \qquad \text{……9}$$

$$\vec{Y}_x = \vec{Y}_\alpha - \vec{A}_x.(\vec{D}_\alpha), \quad \vec{Y}_y = \vec{Y}_\beta - \vec{A}_y.(\vec{D}_\beta), \quad \vec{Y}_z = \vec{Y}_\delta - \vec{A}_z.(\vec{D}_\delta) \qquad \text{……10}$$

$$\vec{Y}_{(t+1)} = \frac{\vec{Y}_x + \vec{Y}_y + \vec{Y}}{3} \qquad \text{………..11}$$

here t=current iteration, Y→= position vector of Grey Wolf , coefficient vectors= $\vec{K}$ and $\vec{M}$, and $\vec{Y}$, p= the position vector of the prey. We can calculate the vectors $\vec{K}$ and $\vec{M}$ as follows:

4. Intelligent GWO

A more modern version of GWO is IGWO [10]. Two changes have been made for better exploration and exploitation in order to expand the search capability. The first uses a sinusoidal truncated function to integrate a control parameter for enhanced exploitation and exploration. Opposition-based learning is employed in the 2nd modification to improve exploration.

$\vec{c}$ is varies as a crop sinusoidal function rather than to decrease linearly as per Eqs. (12) and (13). Grey wolves nicely moving after hunting, this step is copy by linear decrement in $\vec{c}$ .During along, the values of $\vec{c}$ are top in 1st half where as in other half values of $\vec{c}$ down very rapidly as compared with the classical GWO which is shown in Fig. 4. .

$$K = \pi * \frac{Current\ Iteration}{Maximum\ Iteration} \qquad \ldots\ldots\ldots\ldots\ldots 12$$

$$C = 2 * [1 - \sin^2(\frac{K}{2})] \qquad \ldots\ldots\ldots\ldots 13$$

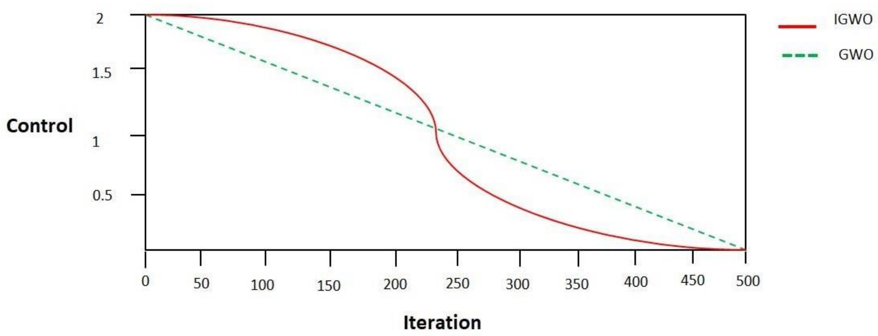

Figure 4. By using sinusoidal truncated function variation of control parameter

Opposition based learning• the search process begins with an educated prediction or a random starting point. Convergence can happen faster if the starting point is close to the ideal solution. On the other hand, convergence takes longer if the chosen initial point is distant from the ideal site

Definition 1: y[a,b] is a real number, then the opposite number of y is defined by:

$$\breve{y} = a + b - y \qquad \ldots\ldots\ldots\ldots 14$$

Definition 2:

Let a point in Q dimensional space is A=($y1$, $y2$, … … … , yQ), where $y\epsilon R$, ∀ $t\epsilon$(1, 2, … … … . .Q) and it is bound by [a,b], the across from points matrix can be given by

$$\tilde{A} = [\tilde{y}_1, \tilde{y}_2, \tilde{y}_3, \dots \dots \dots \dots \dots \dots .. \tilde{y}_Q] \qquad \dots\dots\dots\dots\dots 15$$

Hence, $$\tilde{y}_i = [a_t + b_t - y_t] \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots 16$$

5. DISCUSSION

0 50 100 0 150 200 250 300 350 400 450 500 0.5 1 1.5 2 Control Iteration Figure 5: By using sinusoidal truncated function variation of control parameter IGWO GWO In contrast to forward produce approaches on GWO, the variant IGWO highlights the value of a mechanism for connecting the exploration and exploitation phases . However, the authors of reference have suggested a chaotic method. With these algorithms, the importance of effective bridging between the exploration and exploitation stages has been effectively demonstrated. Additionally, the application of opposition theory has been highlighted. These examples provide sufficient scientific evidence that the optimization capabilities of an algorithm can be significantly improved by an adaptive bridging between the phases of population diversification and intensification as well as some initial population diversification using opposition-based learning

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