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Estimation of Solar Cell Equivalent Circuit Parameters for Photovoltaic Module Using Differential Evolution Algorithm

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ABSTRACT

The accurate estimation of solar module parameters is crucial for predicting the energy production of photovoltaic modules under different environmental conditions. In this paper, we present an approach for estimating the optimum parameters of a one-diode model using the Differential Evolution (DE) algorithm implemented in MATLAB. Our system enables the determination of these parameters at any solar irradiance and module temperature conditions, making it easy to apply the model for predicting the energy production of a photovoltaic module. The results demonstrate that the DE algorithm can estimate the parameters accurately. The numerical estimation technique based on a mathematical algorithm approximately fits all the points on the I-V curve at various environmental conditions. This work is a valuable tool for improving solar cells' performance and efficiency and applies to many photovoltaic applications.

تخمين المعاملات المثلى لدائرة مكافئة للخلية الشمسية باستخدام خوارزمية التطور التفاضلي (DE)

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الملخص

يعد التقدير الدقيق لمعاملات الوحدات الشمسية أمرًا بالغ الأهمية للتنبؤ بإنتاج الطاقة للوحدات الكهروضوئية في ظل ظروف بيئية مختلفة. في هذه الورقة، نقدم نهجًا لتقدير المعلمات المثلى لنموذج ثنائي مفرد باستخدام خوارزمية التطور حيث يتيح نظامنا تحديد هذه المعلمات في أي ظروف إشعاع شمسي ودرجة حرارة الوحدة، مما يجعل من السهل تطبيق النموذج للتنبؤ بإنتاج الطاقة لوحدة كهروضوئية. توضح النتائج أن خوارزمية التطور التفاضلي يمكنها تقدير المعلمات التفاضلي (DE) بدقة عالية . حيث تعتبر تقنية التقدير العددي المبنية على هذه الخوارزمية الرياضية تحقق تقريبًا جميع النقاط الموجودة على منحنى الجهد والتيار-I V في ظروف بيئية مختلفة. بشكل عام، يعد هذا العمل أداة قيمة لتحسين أداء وكفاءة الخلايا الشمسية واسضا يمكن ان ينطبق على مجموعة واسعة من التطبيقات الكهروضوئية.

Introduction

Renewables, such as solar and wind technologies, have become increasingly popular because of their sustainability, profitability, and potential to reduce global environmental challenges, including CO_2 emissions [1]. Solar photovoltaic (PV) generation uses solar cells to convert sunlight into electricity, and the performance of a solar cell depends on various factors, including solar irradiance, cell temperature, and the quality of the materials used [1].

Solar energy has gained significant attention in recent years as a promising solution for the world's growing energy demands and to mitigate the impact of climate change.

Harnessing the full potential of solar energy requires the development of efficient and reliable solar cell technologies capable of efficiently converting sunlight into electricity. Accurate modeling of solar cells is critical for predicting their performance under different environmental conditions and optimizing their efficiency [2-3].

PV modules are photovoltaic solar cells connected in series-parallel configurations, and their performance is dependent on the values of the solar cell equivalent circuit parameters, in addition to solar irradiance (G) and cell temperature (T) [3].

As the use of PV systems continues to increase, researchers are exploring ways to reduce costs and improve efficiency [2]. The performance of renewable energy systems is affected by meteorological data, and accurate estimation of the solar cell equivalent circuit parameters is crucial for simulating PV sources. The single-diode equivalent circuit model is widely used for studying the behavior of solar cells. Various numerical methods, including the

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Newton-Raphson (NR) method [4] and heuristic techniques like differential evolution (DE) [5] have been proposed for estimating the equivalent circuit parameters.

DE is a population-based optimization algorithm with great potential in solving complex optimization problems, including solar cell equivalent circuit parameter estimation. Compared to other evolutionary algorithms, DE has fewer control parameters and requires fewer computational resources. The objective of this study is to use the DE algorithm combined with the NR method [6] to estimate the single-diode equivalent circuit parameters of a solar module based on field-testing meteorological data.

The primary performance metrics used in this paper are the root mean square error (RMSE) and mean bias error (MBE) between the actual measured and simulated module current data [7]. The accuracy of estimating the solar cell equivalent circuit parameters using the DE algorithm compared to traditional methods, including the NR algorithms.

2 PV model

PV systems are considered static electricity generators. They create electricity directly from sunlight without any moving parts. The system's voltage and current increased by adding more modules, either in series or in parallel.

The PV module consists of PV cells. They are semiconductor materials. It can select from an expensive mono-crystalline or polycrystalline silicon.

It can also be the least efficient and cheapest thin film non-crystalline semiconductor materials like amorphous silicon. PV cell's voltage and current relationship can be derived from an equivalent lumped circuit model, shown in Fig. 1.

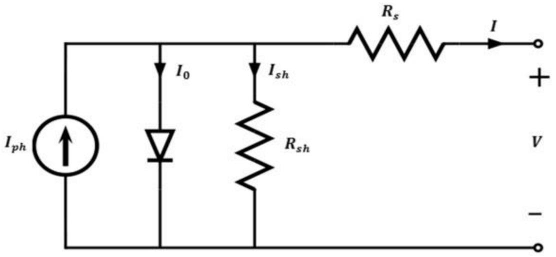

Fig. 1: The equivalent circuit of the solar cell

where R_s is a very small series resistance, and $R_{s,h}$ is a large shunt resistance. *Iph* is expressed as the photocurrent source produced proportionately by *G* and *T*. *Vpv*, and *Ipv* represents the PV cell's output voltage and Output current [3].

PV cell characteristics are given with nonlinear functions derived from Fig 1:

$$I = I_{ph} - I_o\left[e^{\frac{q(V+IR_S)}{aKT}} - 1\right] - \frac{V+IR_S}{R_{sh}} \qquad (1)$$

Where *a*, is the diode ideality constant, *q* is the electron charge, *k* is Boltzmann's constant, and *T* is the temperature of the P-N junction in Kelvin's [8].

I_{pv} is the photovoltaic current and can be expressed by:

$$I_{pv} = (I_{STC} + K_i\Delta T)\left(\frac{G}{G_{STC}}\right) \qquad (2)$$

I_o is the reverse leakage current of the diode and can be calculated from the following:

$$I_o = \frac{I_{sc}+K_i\Delta T}{e^{\frac{q(V_{sc}+K_p\Delta T)}{aKT}}-1} \qquad (3)$$

The I_{STC} is the generated current at 1KW/m^2, 25 ^{o}C. K_i, K_v are the current and voltage temperature coefficients, respectively, and *G* is the radiance. G_{STC} is the radiance at STC conditions, I_{sc}, V_{oc} are the short circuit current and open circuit voltage, respectively at STC, ΔT is the difference between the actual and the nominal temperatures in Kelvin's [4]. Actual cell temperature *T* is calculated as

$$T = T_a + (NOCT - 25)\left(\frac{G}{G_{STC}}\right) \qquad (4)$$

where T_a the ambient temperature and NOCT nominal operating cell temperature [4].

Different methods can measure the current-voltage (I-V) curve of photovoltaic (PV) modules. Some of these methods are a variable resistor provides a simple approach limited to low-power modules, and a capacitive load method requires precise components and timing to obtain accurate I-V curves. In addition, an electronic load uses transistors to control current flow, allowing faster measurements but limited to medium power. A bipolar power amplifier dissipates most of the module's power, restricting use to medium power [9].

A four-quadrant power supply explores the entire I-V curve, including non-first quadrant regions that aid diagnostics. DC-DC converters can emulate a resistor to trace the I-V curve but induce a current ripple that requires mitigation techniques. [9].

These methods aim to characterize PV module performance across operating conditions despite differences fully.

3 Differential evolution Algorithm

DE is a stochastic population-based optimization algorithm developed by R. Storn and K. Price in 1997 [10]. In addition to using real numbers as solution strings, it is significantly faster and more robust for solving numerical optimization problems [9].

The main stages are shown in Fig 2. It begins with the initialization, where a population of *n* solution vectors is initially generated of a random population $\boldsymbol{x}_i$ with *D* parameters, which is then improved using mutation, crossover, and selection. The mutation is for each vector $\boldsymbol{x}_i$.

, firstly randomly choose differential weight parameter F and three distinct vectors $\boldsymbol{x}_p$, $\boldsymbol{x}_q$, and $\boldsymbol{x}_r$, then generate a so-called donor vector $\boldsymbol{v}^{t+1}$. Crossover is controlled by a crossover parameter *Cr* controlling the rate or probability of crossover. The binomial crossover generates a uniformly distributed random number *RI*. If the *RI* is less than or equal to *Cr*, the trial parameter is inherited from the mutant ***VI***; otherwise, the parameter is copied from the vector $\boldsymbol{x}_i$. The selection stage of the differential evolution algorithm chooses the best individuals from the current population to be carried over to the next generation. The offspring are generated using mutation and crossover, and they are compared to the target vectors. If the offspring have a better fitness value than the target vectors, they replace them in the population. This process is repeated until the ending condition is met, such as a satisfactory fitness value or a maximum number of generations.

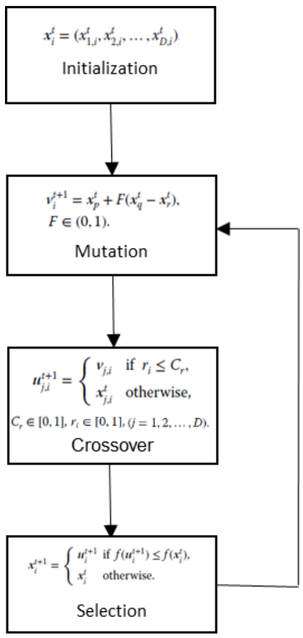

Fig. 2: Main Stages of DE

3.1 Objective Function

The objective function can be, Root Mean Square Error (RMSE). This is a commonly used metric for evaluating the accuracy of a predictive model. The RMSE is calculated by taking the square root of the average of the squared differences between the predicted values *Ie* and the actual values *Ip* of a dependent variable (in this case, current). A smaller value of RMSE indicates a better fit between the predicted and actual values.[11].

RMSE is calculated using the following equation:

$$RMSE = f = \sqrt{\frac{1}{n}\sum_{i=1}^{n} P(V_m, I_m, x)^2} \quad (5)$$

where:

$$P(V_m, I_m, x) = I_m - I_{ph} + I_o\left[e^{\frac{q(V_m+I_pR_s)}{aKT}} - 1\right] + \frac{V_m+I_pR_s}{R_{sh}}, \quad (6)$$

$$x = (I_{ph}, I_o, R_s, R_{sh}, a), \quad (7)$$

vi_m, Im, are the experimental values of the PV module's voltage and current, respectively, and n is the length of the data [8].

MBE (Mean Bias Error): This is a measure of the average difference between the predicted values *Ie* and the actual values *Ip* of a dependent variable without considering the direction of the difference. A smaller value of MBE indicates a better fit between the predicted and actual values. MBE is calculated using the following equation:

$$MBE = \frac{1}{n}\left(\sum_{i=1}^{n} (I_p - I_e)\right) \quad (8)$$

Where n is the vector of voltage measurements, *Ip* is the vector of actual current measurements, and *Ie* is the vector of estimated current values [12].

Both RMSE and MBE are non-dimensional and usually expressed as a percentage error.

Regression R-Squared (RR), is a measure of the goodness of fit in a linear regression model. It is calculated by dividing the sum of the squared differences between the predicted values *Ie* and the actual values *Ip* by the sum of the squared differences between the actual values *Ie* and the mean of the actual values *Ieex*. A value of 1 for RR indicates a perfect fit between the predicted and actual values, while a value of 0 indicates no correlation between them. RR is calculated using the following equation:

$$R^2 = 1 - \frac{\sum_{i=1}^{n} (I_p - I_e)^2}{\sum_{i=1}^{n} (I_e - \bar{I_e})^2} \quad (9)$$

Where *Ip* is the vector of actual current measurements, *Ie* is the vector of estimated current values, and $\bar{I_e}$ is the vector of expected current values.

These objective functions are used to evaluate the accuracy and performance of models and algorithms used for predicting the output of a solar cell or module [12].

4 Results and discussion

A typical *I –V* characteristic of a PV module consists of 36 solar cells connected in series at a specific *G* and fixed cell temperature *T* as shown in Fig 3. In the dark (with no sunlight), the solar cell acts as a diode in reverse mode. Under solar radiation, the solar cell generates DC current.

The system operating point moves along the I_{pv}-V_{pv} characteristic curves of the PV panel.

The maximum power operating point is shown in Fig 3. At this point, The maximum output power is represented by the area under the I-V characteristic curve.

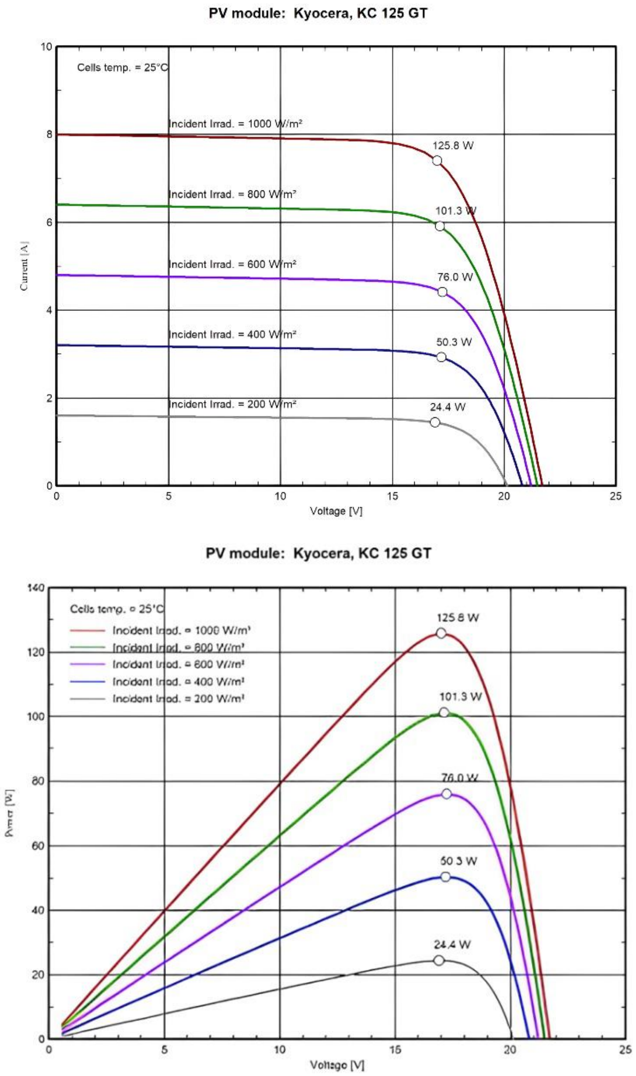

Fig. 3. (a) I-V characteristics of PV module, (b) P-V characteristics of PV module

The proposed method's solar module parameter extraction is evaluated against the synthetic data obtained. Using these values, the synthetic I–V curve is generated. The population size NP is chosen to be 70. A typical value of NP ranges between 50 and 100. The maximum generation number Gmax is set to 1000W/m2. Even though P-DE can converge with much less than 1000 iterations, this value is selected to be consistent.

Additionally, the boundary values for equivalent circuit Parameters shown in Table 1.

Figure 4 shows the P-V Output characteristic curves DE Methods of extraction for the module. The proposed model takes sunlight irradiance and cell temperature as input parameters and outputs the P-V characteristics under various conditions. This method can improve the

Accuracy of the estimated values has been implemented.

It is based on formulating the parameter estimation

Problem as a search and optimization one

Table 1: Boundary of parameters.

Parameters	Minimum value	Maximum value
I_{ph}	1	10
I_o	$1 * 10^{-12}$	$1 * 10^{-5}$
R_s	0.1	2
R_{sh}	100	5000
a	1	2

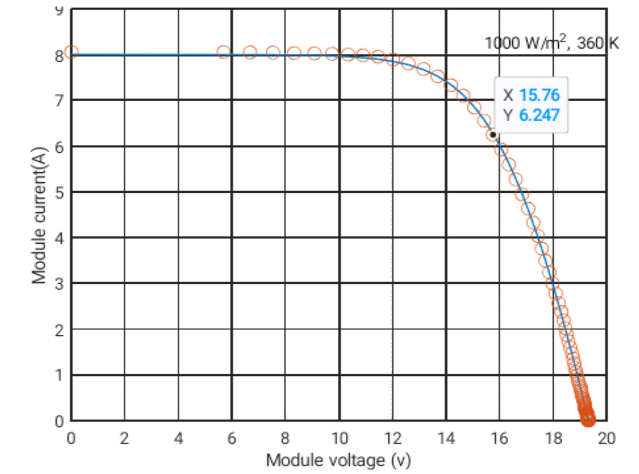

Fig. 4 I-V characteristics of PV module with solar radiation and ambient temperature standard

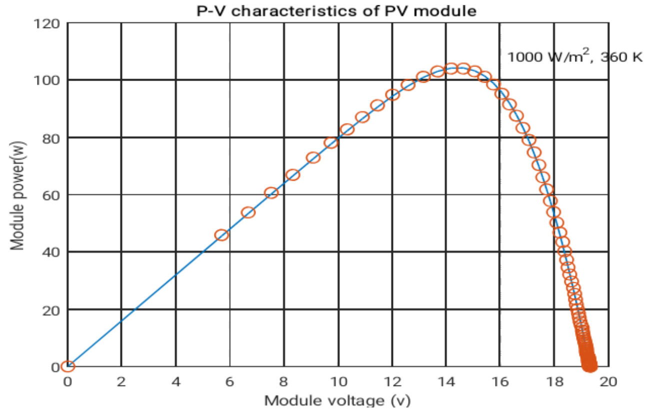

Fig. 5 P-V characteristics of PV module with solar radiation and ambient temperature standard

The model parameters compared to the ones obtained from measurement shown in Table 2. The photo current, reverse saturation current, ideality factor of the diode, series and shunt resistances are obtained by fitting the current-voltage curve obtained from the one-diode model to the current-voltage curve.

Table 2: Estimated parameters for the KYOCERA KC125GT solar panel, obtained through DE algorithm

Code	$I_{ph}(A)$	$I_0(\mu A)$	a	$R_s(m\Omega)$	$R_{sh}(\Omega)$
Present study	8.0648	9.692	1.1571	0.2259	6.3448

Comparing results shown in Table 3 obtained to ensure the study's quality and logical feasibility, it's crucial to establish clear parameters within the scope of the research. Table 3:

Table 3: Comparing Results.

	KYOCERA KC125GT solar PV module	
	Newton-Raphson method [10].	DE algorithm method
RMSE	0.3822	0.0312
RR	0.998	0.999
MBE	-	$7.0068 * 10^{-04}$
SSE	3.7744	0.0695

Based on our analysis, it was determined that the differential evolution algorithm yields more accurate and superior results when compared to the analytical approach.

5 Conclusion

The study presents an approach for estimating the optimum parameters of a one-diode model using the Differential Evolution algorithm. Compared to the methods previously studied by researchers, differential evolution algorithms are preferable in the results compared to the Newton-Raphson method. The proposed method can accurately estimate the parameters and be applied to predict the energy production of photovoltaic modules under different environmental conditions. The study provides a valuable tool for improving the performance and efficiency of solar cells and can be applied to a wide range of photovoltaic applications.

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