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Performances of a Photovoltaic System Using PV Model Based on Nonlinear Components

***Abstract**. Several research laboratories have focused their research on the development of mathematical models of PV cells/modules based on equivalent circuits, which contain linear resistors. However, the accuracy of the model and the output power delivered remain insufficient outside the Standard Test Condition STC. In this context, the development of a model providing these requirements remains a challenge for researchers. Contemplating this problem, a new single diode PV model is proposed, the constant shunt and series resistors are replaced by nonlinear resistors (variable with temperature) to highlight the effect of temperature on the PV module performance. In addition, the parameters of the proposed PV model are tuned by the Particle Swarm Optimization algorithm PSO, in which a fitness function is well minimized. This later, is given by discrepancy values between the measured output currents of the SW 85 poly RNA PV module and the predicted output currents, which are computed using the Newton Raphson method. A comparison has been made between standard PV model and the proposed PV model with nonlinear Rs and Rsh on the basis of the Maximum Power Point (MPP) values of the P-V and I-V curves under different operating conditions. Based on the obtained results, it has been proved that the nonlinear character of the resistances improves the maximum power output generated by the PV module. All the tasks performed in this work such as: modeling, simulation and treatment of experimental data were carried out under the MATLAB environment.*

Streszczenie.** Kilka laboratoriów badawczych skupiło swoje badania na opracowaniu modeli matematycznych ogniw/modułów fotowoltaicznych opartych na obwodach zastępczych, które zawierają rezystory liniowe. Jednakże dokładność modelu i dostarczona moc wyjściowa pozostają niewystarczające poza standardowymi warunkami testowymi STC. W tym kontekście opracowanie modelu spełniającego te wymagania pozostaje wyzwaniem dla badaczy. Biorąc pod uwagę ten problem, zaproponowano nowy model fotowoltaiczny z pojedynczą diodą, w którym rezystory bocznikowe i szeregowe zostały zastąpione rezystorami nieliniowymi (zmiennymi w zależności od temperatury), aby podkreślić wpływ temperatury na wydajność modułu fotowoltaicznego. Dodatkowo parametry proponowanego modelu PV dostraja się za pomocą algorytmu Particle Swarm Optimization PSO, w którym funkcja przystosowania jest dobrze zminimalizowana. To później wynika z wartości rozbieżności między zmierzonymi prądami wyjściowymi modułu PV poli RNA SW 85 a przewidywanymi prądami wyjściowymi, które są obliczane przy użyciu metody Newtona Raphsona. Dokonano porównania pomiędzy standardowym modelem fotowoltaicznym a proponowanym modelem fotowoltaicznym z nieliniowymi Rs i Rsh na podstawie wartości maksymalnego punktu mocy (MPP) krzywych P-V i I-V w różnych warunkach pracy. Na podstawie uzyskanych wyników wykazano, że nieliniowy charakter rezystancji poprawia maksymalną moc generowaną przez moduł PV. Wszystkie zadania realizowane w tej pracy, takie jak: modelowanie, symulacja i obróbka danych eksperymentalnych, zostały wykonane w środowisku MATLAB. (Wydajność systemu fotowoltaicznego przy użyciu modelu PV opartego na składnikach nieliniowych**)

Keywords: Solar cell, Nonlinear resistors, Mathematical models, Output power, Particle Swarm Optimization algorithm, Newton-Raphson
Słowa kluczowe: *Ogniwo słoneczne, Rezystory nieliniowe, Modele matematyczne, Moc wyjściowa, Algorytm optymalizacji roju cząstek, Newton-Raphson.*

Introduction

The Nowadays, renewable energies are an actual and urgent need for humanity due to problems related to the consumption of fossil resources, such as global warming and air pollution. Among the existing renewable energy sources, solar energy is the most relevant, because it is clean, free and widely available.

The photovoltaic panels or cells are subject to continuous technological advances in various fields of application due to the efficiency of photovoltaic cells, the reduction of their production costs and their high-energy efficiency [1].

In this context, the major objective of the researchers and the industry is to improve the quality of the energy supplied by PV modules [2-3]. Therefore, it is very important to design a specific and comprehensive mathematical model of a photovoltaic module, which is mainly to express the actual behavior of the PV module or solar cell under variable climatic conditions.

According to the literature, the single diode five parameter model has frequently been used since it offers a good compromise between simplicity and accuracy [4-5]. In addition, the estimation of physical parameter values for PV modules or solar cells is very important in performance assessment and in simulation studies [6].

A survey of the literature reveals several techniques proposed by various author dedicate to the calculus of the five-parameter model using the information provided in the manufacturer's datasheet or experimental measures. Indeed, this topic can be discussed by applying different methods, which are classified into three categories namely analytic, iterative, and evolutionary methods [7]. References [8-9] give details of these methods applied to PV modules at STC as well as under changing environmental conditions.

It should be noted that the accuracy of the PV model depends on several factors, namely: the type of fitness function to be minimized, the number of measurements recorded during the experiment and the variation range of the absolute temperature and the solar irradiation.

Literatures **[**2],[3],[6],[10] have shown that the accuracy of the simulations in reproducing the real behavior of the PV system is evaluated by means of the results obtained from different parameter extraction techniques used. Because improper parameter identification leads to abnormal current-voltage characteristic and an inaccurate PV model outside the nominal climatic conditions.

Nonlinear phenomena, loss mechanisms and parameter sensitivities to temperature considerably affect the behavior of the solar cell by decreasing its electricity production capacity, increasing its operating temperature and reducing its efficiency, especially outside the standard test conditions (STC). In this context, our main objective is to deeply control the dynamics of PV cells and optimize the output of the cell and the PV module.

Motivated by all these observations, in this work we replace the two linear resistances Rs and Rsh of the model by nonlinear resistances (depending directly on the temperature) in order to analyze their effects on the PV cell performances, especially the maximum power generated by the cell. We carry out theoretical investigations which aim to propose a nonlinear model for the PV cell which could improve the existing characteristics of the cell and the PV module.

Experimental tests were carried out over several arbitrary days during the month of May of the year 2022, generating current and voltage measurements under different climatic conditions.

Using the PSO algorithm led to obtain an optimized set of parameters by solving the optimization problem, while taking into account the defined nonlinear constraints. This approach contributes to improving the accuracy of the model.

The rest of this paper is structured as follows. In Section 2, the problem of solar module modeling defined, and the theory of the proposed model is built. Section 3 describes the implementation of PSO to determine the parameters for the PV module. Experimental and Simulation Results are discussed in Section 4. Finally, conclusions are detailed in Section 5.

Modeling procedure

The crucial phase preceding the identification step of any actual PV module is the modeling process which consists in representing the nonlinear behavior of a photovoltaic module by an equivalent electrical circuit. With this model, we can estimate the I-V and P-V characteristics and predict their behavior at all operating points for various applications. Indeed, many equivalent circuit models have been proposed during the last decade. The single diode PV model is commonly used to model the solar cell under specific environmental conditions due to its simplicity [11].

Single diode model of photovoltaic module

The equivalent electric circuit representation of the PV module is depicted in Figure 1. It consists of current source in parallel with a diode and a shunt resistor and a parallel resistor.

In practice, the constant series resistance R_s presents the effects of the internal resistance and environmental contact with the cell. On the other hand, the constant shunt resistance R_{sh} is related to the p-n junction leakage current at the cell's level. Mathematically, to link the current delivered by the PV module with the voltage on its terminal, we use the following equation: [12],[13]

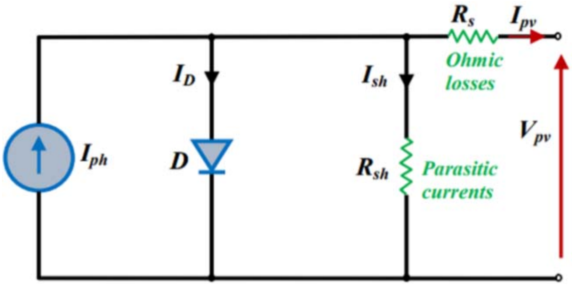

Fig.1. Single diode electrical model for PV module

(1) $$I_{pv} = I_{ph} - I_D - I_{sh}$$

Where I_{ph} , I_D and I_{sh} denote, respectively, the current generated by the incident light, the current provided by the diode D and the current flowing through the shunt resistance R_{sh}. Using the Shockley equation for the diode current and substituting the shunt resistance current, Eq. (1) is rewritten as:

(2) $$I_{pv} = I_{ph} - I_0\left(-1 + e^{\frac{V_{pv}+R_s\ I_{pv}}{N_s\ n.V_t}}\right) - \frac{V_{pv}+R_s\ I_{pv}}{R_{sh}}$$

Where n denotes the diode quality factor of the P-N junction, V_{pv} is the predicted output voltage by the PV panel model. Moreover, the electrical performances of the PV module depend on five model parameters which are: I_{ph} , I_0 , V_t , R_s and R_{sh}.

In fact, the first three parameters are related to the two environmental conditions, which are the current irradiance intensity G as well as the current temperature T. Consequently, the thermal voltage V_t subjected to any temperature T, is defined by the following equation:

(3) $$V_t = \frac{k.T}{q}$$

Where q and k denote, respectively, the electron charge and Boltzmann constant. In addition, the reverse saturation current I_0 of the diodes D can be found using the information from the datasheet given by:

(4) $$I_0 = I_{0,n}\left(\frac{T}{T_n}\right)^{\frac{3}{n}} e^{\frac{qE_g}{n.k}\left(\frac{1}{T_n}-\frac{1}{T}\right)}$$

Where E_g denotes the band-gap energy in the solar cell. $I_{0,n}$ is the diode saturation current given at STC. It can be found using the following equation:

(5) $$I_{0,n} = \frac{I_{sc,n}}{-1+e^{\frac{V_{oc}+K_V(T-T_n)}{n\,N_s\,V_t}}}$$

Here, V_{oc} denotes the solar module open-circuit voltage, $I_{sc,n}$ is the solar module short-circuits current at STC and K_V is the open-circuit voltage temperature coefficient in (V/°C).

The photo generated current given in Eq. (1), can be evaluated for different radiation levels and different temperatures, by using the following equation:

(6) $$I_{ph} = \frac{G}{G_n}\left(I_{sc,n} + K_I(T - T_n)\right)$$

Where $I_{sc,n}$ is the solar panel short circuit current at STC (i.e., $T_n = 25\,°C,\ G_n = 1000\ W/m^2$ and AM1.5) and K_I is the short-circuit current temperature coefficient of the solar panel in (A/°C). In this work, the actual PV panel is built by N_s series PV cells connected series.

Furthermore, according to Eq. (2) the standard PV model has five degrees of freedom, in which its parameter identification is established by the decision variables: n,R_s,R_{sh},I_{ph} and I_0

Proposed model of photovoltaic module

In this work we adopt a new modelling approach of the solar module which introduces the temperature effect in the model parameters. Motivated by this positive effect of non-linearity, our approach consists of replacing the resistances of the equivalent model of the PV panel by non-linear resistances expressed as a quadratic function of the temperature. Because it is well known that any conductor through which a current pass is the seat of the Joule effect, which is generally neglected. Here, we focus on the nonlinear character of the resistance to minimize this effect and improve the behaviour of our solar module.

Concerning our analysis of the nonlinear behavior of the solar panel, we experience the use of a resistor expressed as a function of temperature which is given as follows:

For $T \geq 0$°C:

(7) $$R_{NL}(T) = R_o(1 + aT + bT^2)$$

Where R_o is the resistance of $R_{NL}(T)$ at a standard temperature Tn (usually 25°C). $\boldsymbol{a}$ *and* $\boldsymbol{b}$ are the temperature coefficients of resistance. There values are estimated using the PSO algorithm methods.

According to the above hypothesis, in the representative diagram of the photovoltaic module the two resistances Rs and Rsh of the classic model are replaced by those depending on the temperature, T as shown in Figure 2. In order to find the effect of these resistances, we substitute Eq. (7) in Eq. (2).

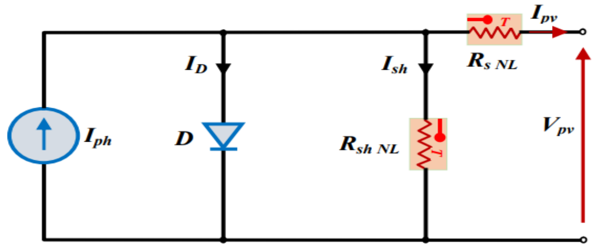

Fig. 2. Equivalent circuit of photovoltaic module based on nonlinear resistors

Thus, we obtain the new output current of the proposed PV panel model, which is expressed as follow:

(8)

$$I_{pv} = I_{ph} - I_0\left[exp\left(\frac{qV_{PV} + R_{S0}(1 + aT + bT^2)I_{PV}}{nN_skT}\right) - 1\right] - \frac{V_{pv} + R_{so}(1 + aT + bT^2)I_{pv}}{R_{sho}(1 + aT + bT^2)}$$

According to Eq. (8), the proposed PV model has seven degrees of freedom that are concatenated in the decision vector $x = \left(n, R_{s_0}, R_{sh_0}, a, b, I_{ph}, I_0\right)^T$.

The desired PV model is given by optimizing the decision vector x. This step is ensured by the particle swarm optimization algorithm where its fitness function is given from comparing two output current vectors.

The components of the first vector $I_{pv\,e}$ are measured from the SW 85 poly RNA module and the components of the second vector I_{pv} are given from solving the following transcendental equation:

(9) $$f\left(I_{pv}\right) = I_{ph} - I_{pv} - I_0\left(-1 + e^{\frac{V_{pv} + I_{pv}\,R_{S\,NL}(T)}{N_S.n.V_t}}\right) - \frac{V_{pv} + I_{pv}\,R_{S\,NL}(T)}{R_{sh\,NL}(T)}$$

When the design stage of the proposed PV model requires great precision in all weather conditions, the exact solution of Eq. (9) becomes indispensable during the optimization process. This solution can be ensured using the Newton-Raphson method which is written as [14]:

(10) $$x_{n+1} = x_n - \frac{f(x_n)}{f'(x_n)}$$

With $f(x_n)$is the function, $f'(x_n)$ is the derivate of the function. We have $f(x_n) = 0$, x_n is the first value, x_{n+1} is the next value. Rewriting the equation (9) gives the following function:

(11) $$f\left(I_{pv}\right) = I_{ph} - I_0\left(-1 + e^{\frac{V_{pv} + I_{pv}\,R_{S\,NL}(T)}{N_S.n.V_t}}\right) - \frac{V_{pv} + I_{pv}\,R_{S\,NL}(T)}{R_{sh\,NL}(T)} - I_{pv} = 0$$

The Newton-Raphson iterative expression also requires the derivative of equation (11) with respect to panel current, Ipv. This is expressed in (12):

(12) $$f'\left(I_{pv}\right) = -I_0\frac{R_{S\,NL}(T)}{N_S.n.V_t}\left(e^{\frac{V_{pv} + I_{pv_n}R_{S\,NL}(T)}{N_S.n.V_t}} - 1\right) - \frac{R_{S\,NL}(T)}{R_{sh\,NL}(T)} - 1$$

We obtain the output current I_{pv} which is computed iteratively by:

(13)

$$I_{pv_{n+1}} = I_{pv_n} - \frac{I_{ph} - I_0\left(-1 + e^{\frac{V_{pv} + I_{pv_n}R_{S\,NL}(T)}{N_S.n.V_t}}\right) - \frac{V_{pv} + I_{pv_n}R_{S\,NL}(T)}{R_{sh\,NL}(T)} - I_{pv_n}}{-I_0\frac{R_{S\,NL}(T)}{N_S.n.V_t}\left(e^{\frac{V_{pv} + I_{pv_n}R_{S\,Nl}(T)}{N_S.n.V_t}} - 1\right) - \frac{R_{S\,NL}(T)}{R_{sh\,NL}(T)} - 1}$$

The equation (13) permits us to calculate the theoretical current at different voltage values and using the extracted parameters.

Particle swarm optimization

To identify the parameters of the actual PV panel using a set of experimental data related to different operating conditions, we suggest applying a metaheuristic optimization algorithm such as particle swarm optimization (PSO) [15],[16],[17].

PSO is a well-established algorithm and widely applied to solve efficiently complicate nonlinear problems and is often cited in the literature. PSO search possible solution in a search space by adjusting the trajectories of particles. Each particle is characterized by the velocity (v_i^{t+1}) and position (X_i^{t+1}) vectors which are evaluated and updated by using Equations (14) and (15), respectively [16]:

(14) $$v_i^{t+1} = \omega \cdot v_i^t + c_1 \cdot \varepsilon_1 \cdot (pbest_i^t - X_i^t) + c_2 \cdot \varepsilon_2 \cdot (gbest^t - X_i^t)$$

(15) $$X_i^{t+1} = X_i^t + v_i^{t+1}$$

Where; $pbest_i$ represents the personal best position reached up to the current iteration for the ith particle, $gbest$ denotes the best global position obtained so far by all the particles, ω design the inertia weight it is considered constant and set equal to 0.9. c_1 and c_2 represent the acceleration coefficients being used and are generally within the values of 0 to 4. ε_1 and ε_2 notify the random vectors which are in the range [0, 1].

Recall that, the steps to find the optimum value using the PSO algorithm are summarized as:

Step1: initialize control parameters: ω, c_1, c_2;

Step2: initialize population of particles: Position, Velocity;

Step3: Evaluate the position of each particle by the objective function;

Step4: Find particle $pbest_i$;

Step5: Find global $gbest$;

Step6: Update Velocity;

Step7: Update Position;

Step8: Evaluate;

Step9: Repeat Step3 to 8 until a stopping criterion is met;

The under mentioned lower and upper boundaries are set to ensure that particles are within the predetermined range:

(16) $$\begin{cases} n_{min} \le n \le n_{max} \\ R_{s_{0min}} \le R_{s_0} \le R_{s_{0max}} \\ R_{sh_{0min}} \le R_{sh_0} \le R_{sh_{0max}} \\ a_{min} \le a \le a_{max} \\ b_{min} \le b \le b_{max} \\ I_{ph_{min}} \le I_{ph} \le I_{ph_{max}} \\ I_{0_{min}} \le I_0 \le I_{0_{max}} \end{cases}$$

As it is mentioned above, the PSO will continue to search for better solutions until it meets the stopping criterion. As a result, we obtain the desired PV model with five unknown variables, which are regrouped in the following design vector:

(17) $$X = \left(n, R_{so}, R_{po}, a, b, I_{ph}\ , I_0\right)^T$$

Fitness function

PSO algorithm requires the fitness function to evaluate each particle and it is defined as Mean Square Error (MSE) of the error between model prediction and actual measurement.

Therefore, the optimal vector X_{opt} is determined from minimizing the MSE criterion, in which the fitness function for one sampled point k is:

(18) $$M_k(X) = I_{pv}(k) - I_{pv\ e}(k)$$

Where, $\hat{I}_{pv}(k)$ is the predicted load current, which is determined from Eq. (8), $I_{pve}(k)$ is the sampled load current given through actual PV system at sampling time k.

Furthermore, the fitness function of one set of PV parameters for N sampled points is:

(19) $$M(X) = \frac{1}{N}\sum_{k=1}^{N}[\ M_k(X)]^2$$

Finally, the parameter extraction of the proposed PV model is ensured by solving the above optimization problem using Particle swarm optimization algorithm, which is available in the Matlab® function PSO. It is executed until function $\boldsymbol{M}(\boldsymbol{X})$, given by Eq. (19), is minimized.

It should be noted that the proposed nonlinear constraints present the key of the success to enhance the PV model accuracy.

Experimental and Simulation Results

The afore mentioned solar systems are positioned on the building roof of the department of Electrical Engineering and Automatic, for the University 8 May 1945 of Guelma, Algeria. Furthermore, they are inclined by an angle equal to the latitude of the area (36, 45°) and has the two instruments. The first one is the K-type thermocouple-based Campbell CS215 instrument, which is used to measure the temperature of PV panel. Nevertheless, the second one is a solar power meter SM206, which is used to measure total solar irradiance. It gives an output in the range of 0.1 to 1999.9W/m2 with a temperature error of ±0.38 W/m2/°C.

The Current and voltage measuring devices are used along with a variable resistor to record the measured values of current and voltage of the PV panel with high accuracy. The experimental systems are shown in Figure3.

Fig.3. Experimental prototype of PV panel

The dimensional of PV panel are $958\ mm \times 680\ mm \times 34\ mm$. The datasheet values of these solar systems are shown in Table 1:

Table 1. Datasheet values of SW 85 poly RNA module.

Electrical characteristics	Datasheet values
Maximum Power Pmax	85 W
Maximum Current Imax	4.76 A
Maximum Voltage Vmax	17.90 V
Open circuit voltage Voc	22.1 V
Short circuit current Isc	5.02 A
Cells per module Ns	36

I(V) and P(V) measurements are performed on the SW 85 poly RNA photovoltaic solar module which comprises 36 polycrystalline cells. For this reason, the experimental data are recorded in four tests (J=4) on days chosen arbitrarily during the month of May 2022, which allows sweeping the possible variations of the meteorological conditions.

The measured voltage and measured current were recorded in different weather conditions, which are summarized in Table 2.

Figure 4 shows the measured I-V and P-V characteristics recorded through actual PV panel under different weather conditions summarized before.

Table 2. Absolute temperature and total solar irradiance recorded during May of the year 2021.

Day	G(W/m^2)	T(°C)
1	681.27	35.21
2	516.45	32.53
3	705.38	24.15
4	982.95	37.96

Also, Figure 4 proves that there is only one point which can deliver the maximum power. As a fact, this operating point strongly depends on the metrological data. Therefore, changing solar radiation and ambient temperature affect the PV module capability to produce the maximum power.

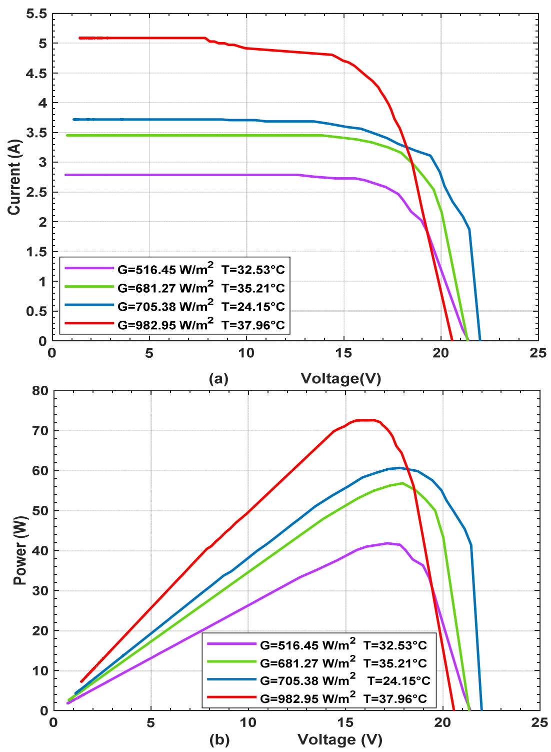

Fig. 4. Measured I-V and P-V curves recorded through PV panel under varying solar radiation and temperature.

To overcome this problem, we suggest using nonlinear resistors in the mathematical model of the PV module, to obtain a behavior similar to reality and improve its maximum power. So, in this work three models are considered under study: standard PV model, PV model with nonlinear R_s and PV model with nonlinear R_s and R_{sh}.

To evaluate and validate the studied models, first the unknown parameters of each model are extracted from the model using the parameter extraction technique described in Section 3. All the estimated parameters are tabulated in Tables 3-6 for PSO algorithm.

Table 3. Extracted parameters of PV models at irradiation: 516.46 W/m^2, ambient temperature: 32.53°C

Parameters	Linear R_s and R_{sh}	Nonlinear R_s	Nonlinear R_s and R_{sh}
n	1.5757	0.9900	1.5163
I_{ph} [A]	2.7483	2.7975	2.7485
I_o [A]	4.0049×10^{-6}	1.000×10^{-10}	2.33629×10^{-6}
R_s [Ω]	0.1583	-	-
R_{sh} [Ω]	1.450×10^{3}	1.450×10^{3}	-
$R_{s\,Nl}$ [Ω]	-	2.5789	0.2290
$R_{sh\,Nl}$ [Ω]	-	-	1.90082×10^{3}
a	-	0.0616	0.0011
b	-	-9.247×10^{-7}	-4.1177×10^{-7}
MSE	0.000416659	0.00146344	0.000384171

Moreover, it can be observed from Table 3 that parameter's values of the PV models under study are in the range of the different parameters: between 0.99 and 1.51 for the diode ideality factor n; 2.74A and 2.79A for the photocurrent Iph; 1.0000×10-10A and 2.33629×10-6A for the saturation current I0; 0.1583Ω and 2.5789Ω for serial resistance Rs; and between 1.450×103Ω and 1.90082×103Ω for the shunt resistance Rsh.

Table 4. Extracted parameters of PV models at irradiation: 681.27 W/m2, ambient temperature: 35.21°C

Parameters	Linear R_s and R_{sh}	Nonlinear R_s	Nonlinear R_s and R_{sh}
n	1.2457	0.9900	1.1387
I_{ph} [A]	3.3996	3.4082	3.3993
I_o [A]	5.2628×10^{-8}	5.5713×10^{-9}	9.4305×10^{-9}
R_s [Ω]	0.1015	-	-
R_{sh} [Ω]	1.4475×10^{3}	1.3744×10^{3}	-
$R_{s\,Nl}$ [Ω]	-	3.7032	3.6865
$R_{sh\,Nl}$ [Ω]	-	-	1.6065×10^{3}
a	-	0.0999	9.8130×10^{-4}
b	-	-4.388×10^{-7}	-7.0291×10^{-7}
MSE	0.000245296	0.00285528	0.00285363

Table 5. Extracted parameters of PV models at irradiation: 705.38W/m2, ambient temperature: 24.15°C

Parameters	Linear R_s and R_{sh}	Nonlinear R_s	Nonlinear R_s and R_{sh}
n	1.4950	1.3690	1.7992
I_{ph} [A]	3.4953	3.4947	3.4929
I_o [A]	1.6863×10^{-7}	3.5696×10^{-8}	2.9088×10^{-6}
R_s [Ω]	0.7018	-	-
R_{sh} [Ω]	1.0195×10^{3}	1.0790×10^{3}	-
$R_{s\,Nl}$ [Ω]	-	0.97392	0.37038
$R_{sh\,Nl}$ [Ω]	-	-	1.8460×10^{3}
a	-	0.0299	0.0014
b	-	-1.0000×10^{-6}	-7.6308×10^{-7}
MSE	0.000504583	0.000465196	0.000628046

In addition, the results show that the temperature coefficients a and b of Eq. (7) vary with PV model type. This means assigning constant temperature coefficients limit the modeling accuracy and results in incompatible values of R_s and R_{sh}.

Also, it can be seen that the results illustrated in the above Tables prove the effectiveness of the PSO algorithm to extract with good accuracy the parameters of the models. So, it can be clearly seen that mean squared error (MSE) between the theoretical and experimental characteristics is very close to zero for the three models.

Table 6. Extracted parameters of PV models at irradiation: 982.95 W/m^2, ambient temperature: 37.96°C

Parameters	Linear R_s and R_{sh}	Nonlinear R_s	Nonlinear R_s and R_{sh}
n	1.5822	1.6133	1.5988
I_{ph} [A]	5.0200	5.0200	5.0200
I_o [A]	7.2988×10^{-6}	9.4747×10^{-6}	$8.\ 340\times10^{-6}$
R_s [Ω]	0.2980	-	-
R_{sh} [Ω]	1.4499×10^{3}	1.4500×10^{3}	-
$R_{s\,Nl}$ [Ω]	-	0.27725	0.29946
$R_{sh\,Nl}$ [Ω]	-	-	1.3690×10^{3}
a	-	3.0000×10^{-4}	0.0067
b	-	-4.0542×10^{-7}	-7.8969×10^{-7}
MSE	0.00447638	0.00446976	0.00423198

Figs. 5, 6, 7 and 8 show the generated three model's I-V and P-V characteristics using the parameters obtained by extracted method. These characteristics are compared with experimental data recorded from SW 85 poly RNA photovoltaic solar module, in different weather conditions (fig.4).

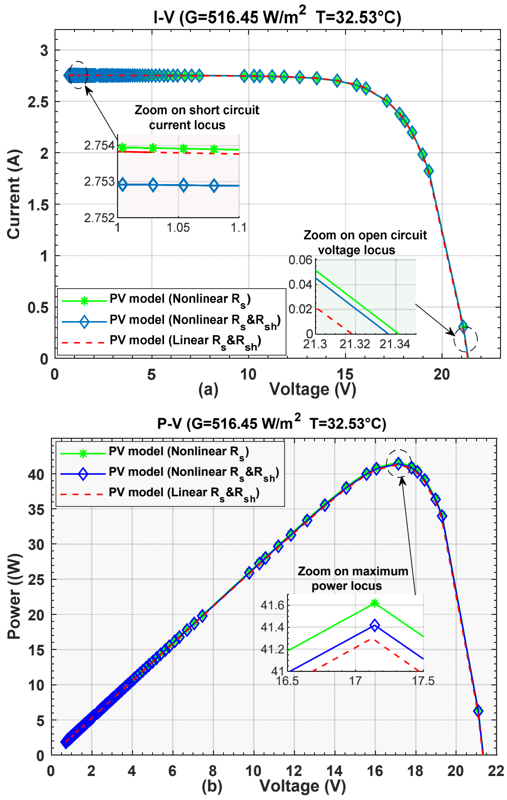

Fig. 5. Obtained I-V and P-V characteristics by PV models at irradiation: 516.45 W/m^2, ambient temperature: 32.53°C.

According to obtained figures, it is easy to see that the experimental measured I-V and P-V characteristics (Figure 4) are closely matched those determined through the three studied models for used extraction method (Figures 5-8). This similarity is due to taking into consideration of nonlinear phenomena of series and shunt resistances in the proposed model.

From the Figure 5 it can be observed that the maximal power P_m provided by the conventional PV model with linear R_s and R_{sh} is $41.30\,W$. In contrast, we record an improvement in the P_m delivered by PV model with nonlinear R_s and R_{sh} which attains $41.42\ W$. In addition, the obtained power energy is enhanced by the PV model with nonlinear R_s where its maximal value attains $41.62\ W$.

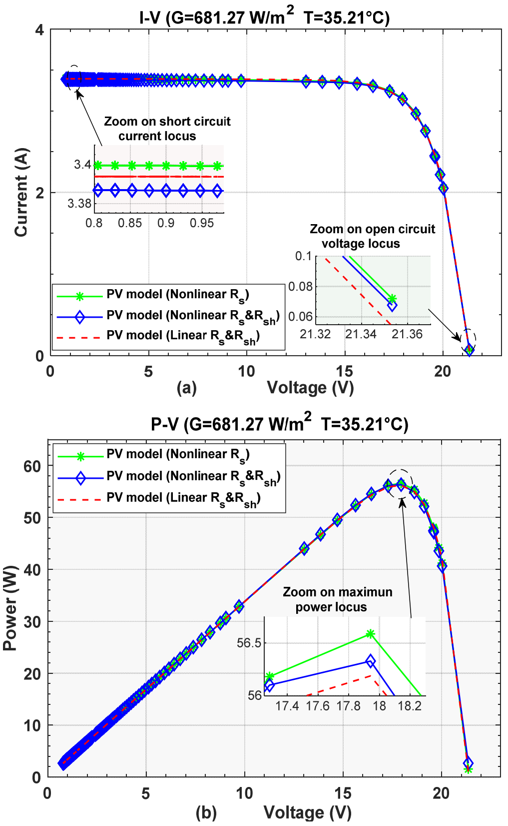

Fig. 6. Comparison of I-V and P-V curves obtained from PV models at irradiation: 681.27 W/m^2, ambient temperature: 35.21°C.

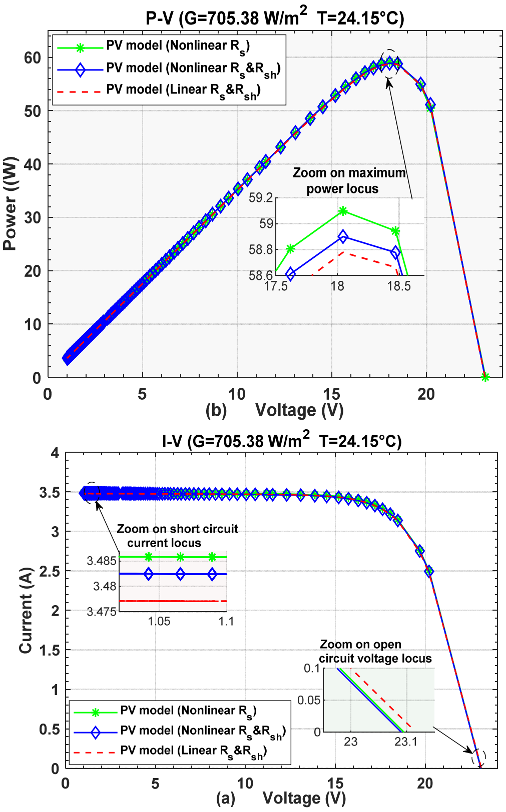

Fig. 7. Comparison of I-V and P-V curves obtained from PV models at irradiation: 705.38 W/m2, ambient temperature: 24.15°C.

Figure 6 gives the simulation results when the irradiation augment from 165 W/m^2 and the temperature increase from 3°C.

Also, from this case it can be seen that the short circuit current I_{sc} provided by the PV model with linear resistors is lower than the value obtained for the other two PV models.

In figure 7, the PV model with nonlinear R_s provide the best results against the maximum power, when the irradiation attaint 705.38 W/m^2 and the temperature is near 25°C.

Note that this comparison remains the same when the environmental conditions change, as the following figures will show.

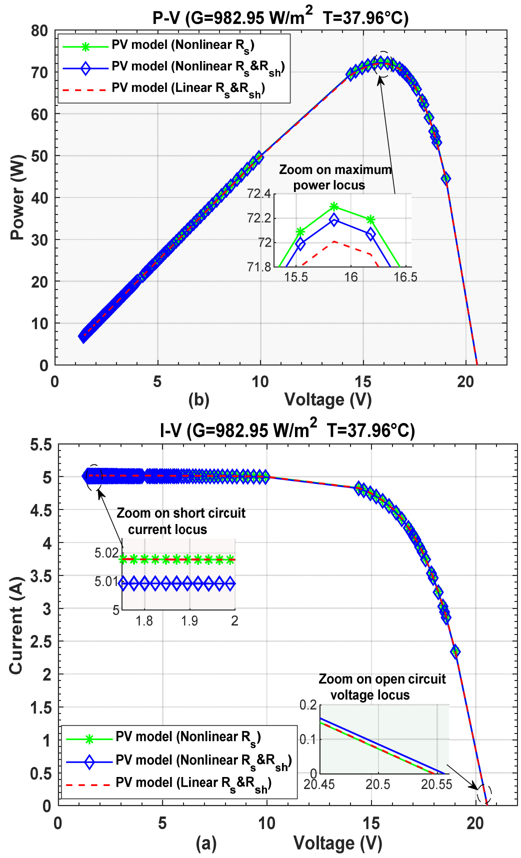

Fig. 8. Comparison of I-V and P-V curves obtained from PV models at irradiation: 982.95 W/m2, ambient temperature: 37.96°C.

From the above results, we can conclude that the open circuit current values and the maximum power obtained for the standard PV model are lower against the two other models despite the changes in climatic conditions.

The maximum power point (MPP) of the P-V characteristics of Figures 5-8 are selected and respectively projected on the I-V characteristics. Table 7 gives the obtained *(I_m, V_m)* coordinates of the MPP for the four considered cases.

Table 7. MPP coordinates of PV models under different weather.

Parameters	PV model with nonlinear R_s			
G[W/m^2]	516.45	681.27	705.38	982.95
T [°C]	32.53	35.21	24.15	37.96
V_m [V]	17.14	17.94	18.25	15.85
I_m[A]	2.428	3.154	3.313	4.561
P_m[W]	41.62	56.59	60.47	72.30
Parameters	PV model with nonlinear R_s R_{sh}			
G[W/m^2]	516.45	681.27	705.38	982.95
T [°C]	32.53	35.21	24.15	37.96
V_m [V]	17.14	17.94	18.25	15.85
I_m[A]	2.416	3.140	3.304	4.555

P_m[W]	41.42	56.33	60.33	72.19
Parameters	PV model with linear R_s R_{sh}			
G[W/m^2]	516.45	681.27	705.38	982.95
T [°C]	32.53	35.21	24.15	37.96
V_m [V]	17.12	17.94	18.25	15.85
I_m[A]	2.412	3.132	3.295	4.543
P_m[W]	41.30	56.19	60.15	72.01
Parameters	Actual PV panel			
G[W/m^2]	516.45	681.27	705.38	982.95
T [°C]	32.53	35.21	24.15	37.96
V_m [V]	17.14	17.94	17.80	16.46
I_m[A]	2.582	3.158	3.407	4.365
P_m[W]	41.82	56.83	60.65	72.57

The results of Table 7 clearly show that the most accurate model is obtained by using the single diode model including R_s nonlinear.

According to the above figures, the given maximal power histograms for both PV systems are presented according to absolute temperature and solar irradiance variations in figure 9.

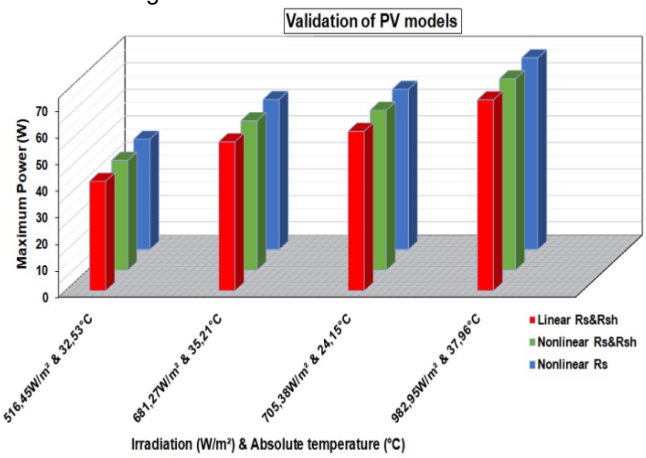

Fig. 9. Maximal power histograms for PV models at different atmospheric conditions.

In addition, the P-V characteristics obtained from the PV models of listed method are compared with the experimental ones. In this case, the experimentally obtained maximum power $P_{m\,exp}$ for the actual PV panel is compared with models calculated maximum powers $P_{m\,cal}$. This is performed by calculating the absolute percentage error [$E_r(\%)$] to measure the accuracy of PV models as given in Table 8. The $E_r(\%)$ is calculated by:

$$E_r(\%) = \left|\frac{P_{m\,exp} - P_{m\,cal}}{P_{m\,exp}}\right| \times 100 \quad (20)$$

Table 8. Comparison between simulated values and experimental values for PV models under different weather conditions.

Parameters	PV model with nonlinear R_s			
G[W/m^2]	516.45	681.27	705.38	982.95
T [°C]	32.53	35.21	24.15	37.96
P_m[W]	41.62	56.59	60.47	72.30
E_r [%]	0.4782	0.4223	0.2967	0.3720
Parameters	PV model with nonlinear R_s R_{sh}			
G[W/m^2]	516.45	681.27	705.38	982.95
T [°C]	32.53	35.21	24.15	37.96
P_m[W]	41.42	56.33	60.33	72.19
E_r [%]	0.9564	0.8798	0.5276	0.5236
Parameters	PV model with linear R_s R_{sh}			
G[W/m^2]	516.45	681.27	705.38	982.95
T [°C]	32.53	35.21	24.15	37.96
P_m[W]	41.42	56.33	60.33	72.19
E_r [%]	1.2434	1.1261	0.8244	0.7716

As can be seen from Tables 8, the absolute percentage error $E_r(\%)$ obtained by proposed single-diode PV model with nonlinear Rs are less than the two other model (between 0.2967 and 0.4782), which prove its accuracy and ability to deliver the maximum power. The models based on nonlinear Rs and Rsh have the best performances compared to standard model, especially at maximum power point because consideration of the temperature effect from the Rs and Rsh resistances. Consequently, we deduce that the operating point of the PV system depends on the characteristics of solar panel and especially of the climate and thermal parameters.

Conclusion

In this paper, we have proposed the temperature dependence PV system, which is modelled by the single diode PV model based on nonlinear resistances. Its optimal model parameters are identified through experiment data using both evolutionary optimization algorithms such as PSO. It is proved that the obtained actual electrical characteristics such as current-voltage and power-voltage are closely matched with those determined through corresponding models.

The electrical characteristics such as current-voltage and power-voltage given through conventional single diode model PV model are compared by those given by the two proposed PV models with nonlinear resistors where temperature and solar irradiance variations are considered. From the obtained results under varying environmental conditions, it's shown an enhancement in the maximal power provided by the proposed PV models.

Finally, we think that the results obtained in this work can be useful for researchers and manufacturers of PV systems, especially in terms of improving the production capacity.

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