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doi:10.15199/48.2024.05.29

Artificial Neural Networks technique for Parameters Estimation of Amorphous Silicon Solar Module

***Abstract**. To conduct exact performance investigations and control studies on solar PV systems, it is necessary to extract relevant circuit model characteristics. In this work, we have proposed for the identification of the parameters of the single-diode model of the amorphous PV module, a numerical modeling approach presented by the determinist based on the "Levenberg–Marquardt (LM)" gradient descent, combined with the intelligent method based on artificial neural networks (ANN) taking into account the variation of the solar radiation and the temperature of the cell, in real working conditions.*

***Streszczenie.** Aby przeprowadzić dokładne badania wydajności i badania kontrolne systemów fotowoltaicznych, konieczne jest wyodrębnienie odpowiednich charakterystyk modelu obwodu. W pracy tej zaproponowaliśmy do identyfikacji parametrów modelu jednodiodowego amorficznego modułu PV podejście modelowania numerycznego zaprezentowane przez deterministę w oparciu o opadanie gradientowe „Levenberga-Marquardta (LM)" w połączeniu z inteligentna metoda oparta na sztucznych sieciach neuronowych (ANN) uwzględniająca zmienność promieniowania słonecznego i temperatury ogniwa w rzeczywistych warunkach pracy. (**Technika sztucznych sieci neuronowych do szacowania parametrów modułu słonecznego z amorficznego krzemu**)*

Keywords: Parameters estimation; ANN model; Levenberg–Marquardt method; Performance I–V curves.
Słowa kluczowe: Estymacja parametrów; model ANN; metoda Levenberg-Marquardt; Krzywe wydajności I – V.

Introduction

It is necessary to choose a model that closely simulates the characteristics of solar modules; in which to measure a PV system's performance under different operating conditions [1,2], a mathematical model of the system requires a set of lumped circuit parameters of its PV modules. Unfortunately, PV module manufacturers do not always offer these characteristics directly or completely. As a result, numerous various parameter extraction approaches have been developed and tested in the literature [3-5], with varying degrees of complexity and accuracy. A model is known to be accurate if it fits I-V data measured under all operating conditions. Numerical or analytical methods are used to classify these methods. In most cases, numerical methods generate a set of equations that can be solved using numerical or iterative procedures [6]. Over the years, many models have been introduced - among the most popular are the single diode [7] and the two diode model [8]. The latter, although computationally more comprehensive, is preferable because its I-V characteristics closely resemble the behavior of a physical module [9].

The Newton-Raphson equation can be used to calculated the parameters of the two-diode model. only a few papers are reported to go along this approach, due to the complexity of the two-diode model (which necessitates the solution of seven parameters) [10–13].

The algorithms used to extract the parameter from solar PV models have been compared by certain researchers. For example, Appelbaum and Peled [14] have extracted the single-diode solar cell model's parameters using the experimental I-V characteristics of Si and Multi-junction solar cells. Three distinct optimization techniques were used for the extraction: the Newton-Raphson method, the Levenberg-Marquardt algorithm, and the genetic algorithm. This was done to see which technique provided the best data-to-model fitting. Their findings showed that the Newton-Raphson approach is the most effective for extracting the parameters.

On the other hand, In the absence of a direct mathematical equation between environmental circumstances and electrical parameters, the artificial neural network (ANN) appears to be a suitable way for modeling this implicit nonlinear relationship. The ability of this technology to forecast the outcome of data exploitation is one of its distinguishing features. As a result, the information is carried by weights, which indicate the values of connections between neurons [15]. The ANN's functioning necessitates the use of a learning algorithm to ensure that the error generated at the network output is minimized.

Multilayer Perceptrons (MLP) are the most common type of ANNs in literature, despite being one of the oldest networks [16,17]. An MLP with a single hidden layer may estimate any continuous function [18]. They are typically employed to address problems involving supervised learning, in which they practice on a collection of input-output pairs and learn to model the relationship between those inputs and outputs [19]. Once the ANN has been created and trained using the measured I-V curves, the shape parameters and I-V curve are predicted using only solar irradiance and temperature, without the need to solve any nonlinear implicit equations.

The numerical method described in the first section of this study is straightforward and quick, although it relies on parameters taken from the curve I(V) supplied by the designers of PV modules under standard test conditions (STC) (temperature T = 25 °C and irradiance G = 1000 W/m^2). Data sheets are used to present these statistics. The unavailability of these datasheets is a drawback of the numerical method.

In this research, we proposed the identification of the parameters of the single-diode model of the amorphous PV module, a numerical modeling approach presented by the determinist based on the "Levenberg–Marquardt (LM)" gradient descent, combined with the intelligent method based on artificial neural networks (ANN).

As a result, we used a modeling approach based on artificial intelligence, namely artificial neural networks (ANN), to generate the curve I(V) under STC condition. The ANN model that reproduced the behavior of an amorphous silicon PV module (QS-60DGF) in STC was developed in the second phase of this work.

The suggested work is expected to be particularly valuable for designers of PV systems and developers that require simple, fast, and accurate PV module model simulators.

Materials and Methods

PV module models

An electrical circuit with a single diode (fig.1) is considered as the equivalent photovoltaic cell in the present article.

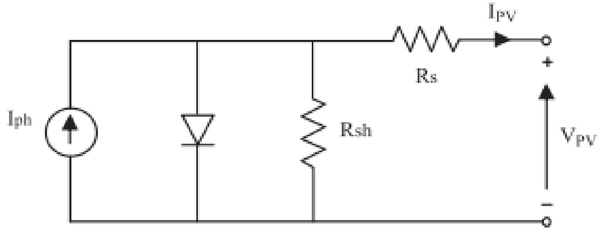


Fig.1. PV-cell equivalent-circuit models: single-diode model.

This model's output current equation for the I-V characteristic is as follows [20]:

$$I_{PV} = I_{ph} - I_s\left[\exp\left(\frac{V_{PV}+I_{PV}Rs}{aV_T}\right)-1\right]-\left[\frac{V_{PV}+I_{PV}Rs}{Rsh}\right] = f(I_{PV}, V_{PV}, \theta) \quad (1)$$

wWhere: I_{ph} – Photocurrent; I_s - Cell saturation current; R_{sh} - Shunt resistance; R_s - Series resistance; a - Ideal factor of the PV diode; V_T - the thermal voltage (V_T=Ns.k.T/q); N_s - Number of cells in series; q - Electron charge (1.60281×10^{-19} C); k - Boltzmann's constant=1.38066×10^{-23} J/K; T - Cell operating temperature

Parameter identification process

Principle of optimization

In order to identify the intrinsic parameters Rs; Rsh; Iph; Is and a of characteristic I(V), we adjusted the model of Equation (1) as well as possible to the experimental data (I_{PV} -V_{PV}), by minimizing the squared errors between the theoretical and experimental curves.

Therefore, the objective function used in the optimization process is the sum of squared errors (SSE), which is given as [20]:

$$g(I_{PV}, V_{PV}, \theta) = \sum_{i=1}^{N}\left[I_{PVmes\ i} - f(I_{PV}, V_{PV}, \theta)_i\right]^2 = \sum_{i=1}^{N}\left[\varepsilon(I_{PV}, V_{PV}, \theta)_i\right]^2 \quad (2)$$

where: $I_{PVmes\ i}$: presents the ith measured value of the I_{PV}, ε: Error between $I_{PVmes\ i}$ and I_{PV} calculated by $f(I_{PV}, V_{PV}, \theta)$ from Equation (1), N: number of measuring points, θ: Vector of the five intrinsic parameters Rs; Rsh; Iph; Is and a.

The minimum of SSE leads to five optimal values of the parameters θ.

The minimization of objective function cannot be performed analytically intuitively due to the strong I_{PV} (V_{PV}) characteristic nonlinearity. Indeed, it will be noted that the solar cell model has a double non-linearity. The first is inherent in Equation (1) itself, while the second is structural parameters Rs and a. Therefore, numerical methods for nonlinear regression based on the principle of least squares are more suitable for minimizing this function.

Levenberg–Marquardt method

The LM method is an iterative technique that locates a local minimum of a multivariate function expressed as the sum of the squares of several real-valued nonlinear functions. It has become a standard technique for nonlinear least squares problems. The LM method can be considered as a combination of the "steepest descent" and "Gauss-Newton" methods [21, 22]. When the current solution is far from a local minimum, the algorithm behaves like a steepest descent method. Then, once the calculated values become in close proximity to the final solution, it behaves like a Gauss-Newton method and exhibits a fast convergence rate [20]. The automatic commutation between the two methods (steepest descent and Gauss-Newton) is ensured by the control parameter λ called "damping factor". Thus, the parameters θ = f (Iph, Is, a, Rs, Rsh) to be identified are updated at each iteration according to the following expression [20]:

$$\theta_{k+1} = \theta_k - \left[\frac{J'\varepsilon}{J'J + \lambda_k I}\right]_{\theta=\theta_k} \quad (3)$$

Where, ε is the error between the measured current and that calculated using Equation (2),

J is the Jacobean matrix $\left[\frac{\partial f(\theta)}{\partial \theta}\right]_{\theta=\theta_k}$ containing the derivatives of the function $f(I_{PV}, V_{PV}, \theta)$ as a function of each parameter of the vector θ and I is the identity matrix.

Results and discussion

Characterization of the amorphous PV module (QS-60DGF) by the Levenberg-Marquardt method

This section presents a method for estimating the parameters of a PV module in its equivalent circuit. The data needed to estimate the parameters are based on weather conditions and electrical parameters estimated by the Levenberg-Marquardt algorithm (LM) method for different radiations and temperatures.

First, the V-I curves are obtained from the exposure to the real condition. For the measurement of the V-I curves, the external measurements of V-I curves of the amorphous PV module (QS-60DGF) were carried out on the ground of the Research Unit in Renewable Energies in the Saharan Environment (URERMS) in the south-west of the Algeria for one year using the software and hardware of EKO instruments (plotter MP-160 I – V) (fig.2).

Fig.2. Software and hardware of EKO instruments (plotter MP-160 I – V).

Our choice is to carry on the PV module amorphe (QS-60DGF) just because of the availability of a database (Table 1).

Table 1 Electrical parameters of the PV module QS-60DGF

Parameters		**Thin-Film a-Si (QS-60DGF)**
Maximum power	Pm (W)	60
Open Circuit Voltage	Voc (V)	80.3
Short Circuit Current	Isc (A)	1.22
Voltage At Maximum Power	Vmp (V)	62.3
Current At Maximum Power	Imp (A)	0.96
PV module dimensions	D (mm)	1404*794*35

To create the LM method we used 36 different curves (Table 2), associating each value of G (w/m^2) and T (°C) a V-I curve. We would like to point out that the number of all data is 2313 practical measurements for all illuminance values used.

Table 2 Database used of G and T for the 36 curves used

***I* (V) Curve**	**G (w/m^2)**	**T(C°)**	***I* (V) Curve**	**G (w/m^2)**	**T(C°)**
1	905	31.2	19	924.5	39.2
2	918.3	31.8	20	1442.4	38.4
3	927.4	34.9	21	1036.4	40.9
4	1101.5	34.6	22	636.2	37.9
5	707.3	36.2	23	1212.6	40.2
6	1341	34.7	24	783.9	38.7
7	506	34.9	25	852.3	37.2
8	615.9	35	26	935.5	37.9
9	515.2	35.7	27	1230.5	40.8
10	1159.8	35.5	28	1018	38.4
11	1100.7	36.9	29	1387	37.1
12	1060	38.1	30	1332.5	38
13	1260.5	35.7	31	939.5	39.7
14	1485.2	37.6	32	746.8	37.3
15	1074 .2	36	33	1157.2	37.5
16	783.7	38.4	34	1081.5	37.7
17	630	38.1	35	679	37.3
18	1364.5	35.7	36	792.5	34.5

It can be deduced that the V-I curves of ML are very similar to the real V-I curves with a very small error (Fig 3). This method is going to be a very useful method for designers of photovoltaic systems.

The results of the estimation of the parameters of amorphous PV module (QS-60DGF) by the proposed LM method at different environmental conditions are shown in Table 3.

A more comprehensive comparison is presented in Table .4, which shows the estimated value and relative error for each significant point for different environmental conditions. The proposed LM method has small relative errors, however, the proposed method has better performance for Isc and Voc parameters.

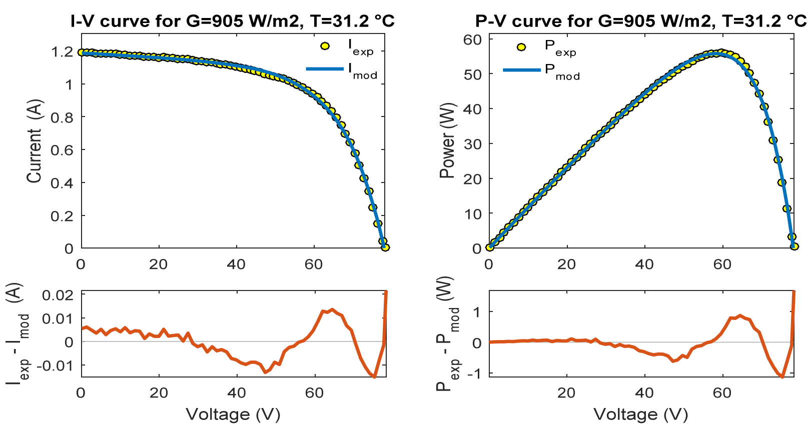
Table 3 Estimated parameters of PV module (QS-60GDF) under different conditions.

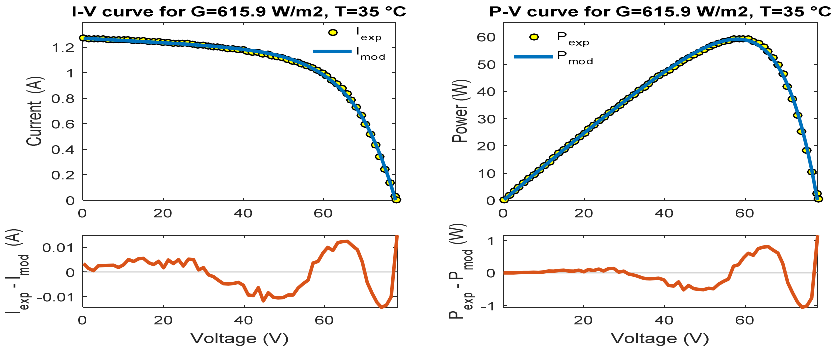
Real condition		**LM Method**				
G (W/m^2)	**T (°C)**	**Iph**	**I_S**	**a**	**Rs**	**Rsh**
905	31.2	1.188	4.6748×10^{-4}	3.8373	0.2182	771.3574
615.9	35	1.271	3.1305×10^{-4}	3.5704	0.9303	625.2568
792.5	34.5	1.231	7.5251×10^{-4}	3.9779	0.8367	986.7084
1036.4	40.9	1.325	6.6614×10^{-4}	3.7737	0.1323	778.9268

Table 4 The estimated significant points of the PV module (QS-60GDF) under different conditions.

		LM Method			
Parameters	**G (W/m^2)**	**615.9**	**792.5**	**905**	**1036.4**
	T (°C)	**35**	**34.5**	**31.2**	**40.9**
Pm	Valeur estimé	59.149	56.575	55.755	61.178
	Erreur relative	0.491	1.097	0.588	0.376
Imp	Valeur estimé	1.015	0.992	0.957	1.066
	Erreur relative	1.601	1.743	2.243	3.595
Vmp	Valeur estimé	58.29	57.03	58.26	57.39
	Erreur relative	2.033	2.795	2.770	3.806
Isc	Valeur estimé	1.268	1.230	1.188	1.325
	Erreur relative	0.078	0.726	0.251	0.450
Voc	Valeur estimé	77.829	77.384	78.045	76.816
	Erreur relative	0.129	0.220	0.177	0.159

(a)





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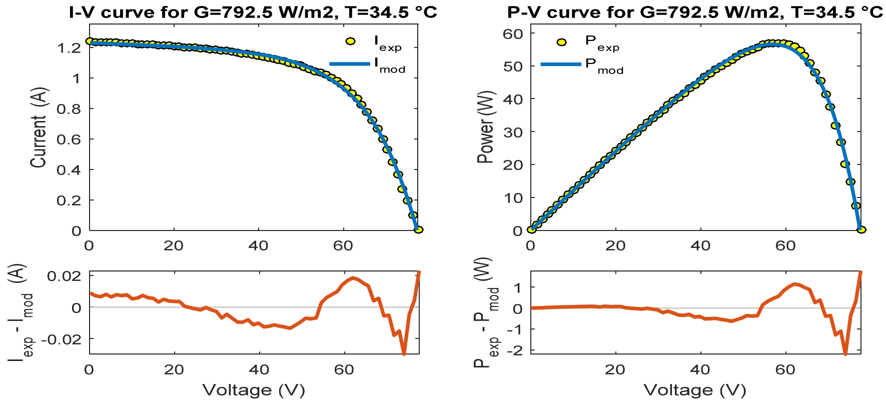

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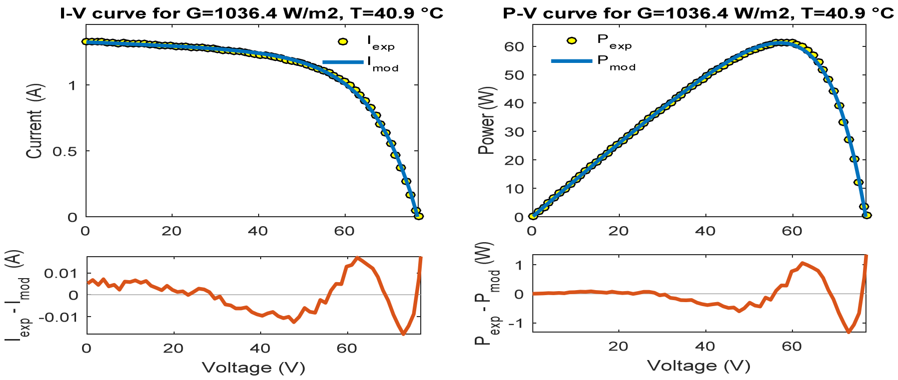

(d)

Fig.3 Performance of the LM method obtained under different operating conditions.

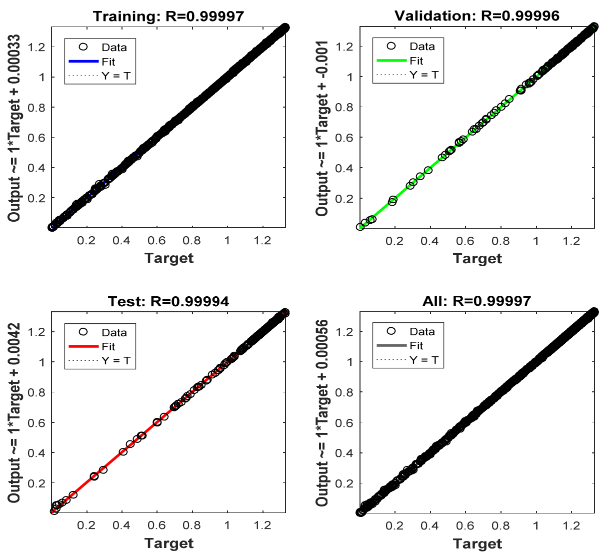

Fig.4. Regression curves of training, validation, and testing data

Of course, the most important thing is to validate the proposed method with experimental data.

An important tool for the validation is a plot of the outputs against the desired outputs, figure 4 represent the plots of the training, validation, and testing of our data.

The solid line represents the best fit linear regression (R) line between outputs and targets. The R value is an indication of the relationship between the outputs and targets. If R = 1, this indicates that there is an exact linear relationship between outputs and targets.

The training , validation, and testing data show R values that greater than 0.9, it can be observed that the proposed method has high accuracy.

Estimation of Parameters of PV Module (QS-60DGF) at STC by ANN Method

This part presents a method to estimate the parameters of a model PV module at standard condition using artificial neural networks; more specifically, the multilayer perceptron concept is used. The data needed to estimate the parameters are based on meteorological conditions and electrical parameters estimated by the LM method for different radiations and temperatures. The MLP (Multi Layer

Perceptron) type neural network with two hidden layers and the learning method chosen was the backpropagation.

The proposed method is illustrated in Figure.5.

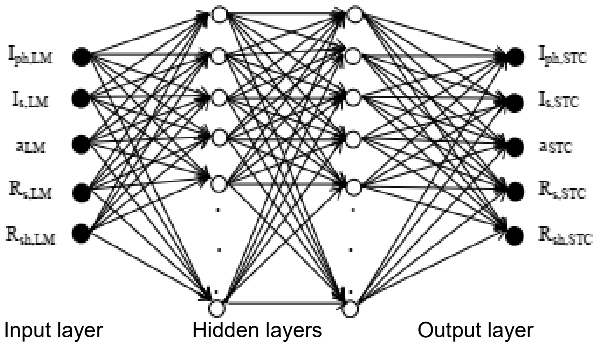

Fig.5. Proposed ANN estimation method.

Proposed ANN method validation

In this section, a comparison of the parameter estimation with two other methods cited in the literator (Villalva and Esram models) [23, 24] based on the one-diode model (1D).This model is based on the assumption that the slope of the I -V curve at Voc and Isc is controlled by the series and shunt resistance, respectively, with further simplifications assuming that Iph is short equivalent to the circuit current and Rs, Rsh and a can be obtained by simultaneously solving the equations [24, 25]. The simultaneous equation can be solved with the Newton-Raphson technique using the symbolic function fsolve.

The results of the parametric estimation of the three models are presented in Table 5, which shows that there is a difference between the parameters obtained.

Table 5 Estimated electrical parameters of PV module (QS-60GDF) by different models under STC condition

parameter	Estimated values		
	1D (Esram) Model	1D (Villalva) Model	Proposed ANN Model
Iph	1.220	1.245	1.1971
I_s	2.6318×10^{-5}	1.0898×10^{-9}	4.4980×10^{-4}
a	2.9101	1.5	3.5451
Rs	0.4523	5.980	0.4922
Rsh	379.855	290.247	594.116

The model validity proposed for the QS-60DGF amorphous PV module was verified by a more exhaustive comparison between the values estimated at different conditions by the ANN model and the two other analytical models cited in the literator with the experimental values.

Figure 6 shows the IV characteristics of the amorphous PV module obtained by the three models after fitting the curve with the curve measured at solar radiation of 1000 W/m^2 and 800W/m^2 and at an ambient temperature of 25 °C

This figure illustrates an excellent agreement between the measurements and the output of the proposed ANN model. On the other hand, the model of Esram provides results very close to the experimental values under standard STC conditions, whereas in low radiation (800 W/m^2), the precision of this model is reduced, as for the model of Villalva, it is less precise in all cases.

Table.6 presents the estimated value and the relative error (RE) for each significant point (the maximum power of the photovoltaic module Pm, the open-circuit voltage Voc and the short-circuit current Isc) obtained with the ANN model and the other two analytical models. For the Villalva and Esram analytical models, the relative errors in the power prediction are approximately 4% and 5.5% respectively at 800 W/m^2. However, the absolute power error by the ANN model is 0.006%. The comparison between the measured values and the simulation results of the PV characteristics showed that the ANN model has a better correlation with the input data and a lower relative error.

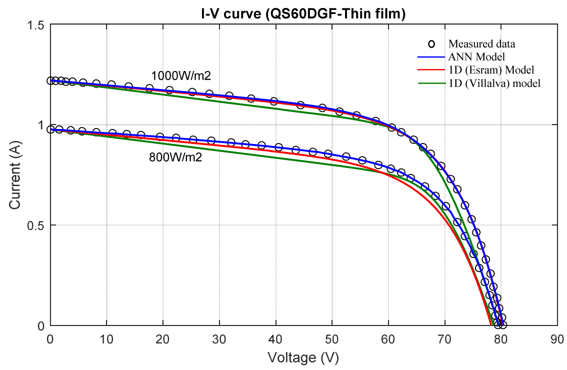

Fig.6. I-V characteristics of the QS-60DGF PV module by the three models for different radiations

Table 6 Relative errors of the characteristics of the QS-60DGF PV module by the three models.

Irradiance at 25°C (W/m^2)	Parameter	1D (Villalva) Model	1D (Esram) Model	ANN Model	RE [%] (Villalva)	RE [%] (Esram)	RE [%] (ANN)
	P_m	59.811	59 .802	60.068	0.315	0.330	0.113
1000	V_{OC}	79.410	80.300	80.300	1.108	0.000	0.000
	I_{SC}	1.220	1.220	1.220	0.000	0.000	0.000
	P_m	45.534	44.875	47.493	4.118	5.506	0.006
800	V_{OC}	78.265	78.229	79.5	1.553	1.598	0.000
	I_{SC}	0.976	0.976	0.977	0.204	0.204	0.102

Conclusion

This paper described the modeling of an amorphous silicon PV module (QS-60DGF) using MLP-type neural networks at the level of the Renewable Energies Research Unit in the Saharan Environment (URERMS) in southern Algeria. for a year and for various values of illumination and temperature to estimate the five parameters of the equivalent model of a diode based on meteorological parameters. G, T, and V are the network inputs, whereas Iph, Is, a, Rs, and Rsh are the estimated parameters.

The combining Levenberg-Marquardt (LM) and neural networks MLP type leads to precise parameters of a single diode model. This high accuracy was revealed after comparing the results obtained with those of other previously reported methods. Moreover, it was confirmed when the fitted I_{PV} (V_{PV}) values matched the experimental data significantly.

The specific values of the five electrical parameters of the solar cell obtained by the Levenberg-Marquardt algorithm are very close to the experimental values, due to the ability of this algorithm to combine the characteristics of the steepest regression algorithm and the Gauss-Newton algorithm, which ensures the maximum minimization of the mean square error. Secondly, the MLP neural networks is implemented to estimate the parameters of the PV module in the standard condition(STC), and, therefore, know its electrical characteristics.The results reveal that neural network modeling agrees well with experimental data, and the curves created are essentially fixed, with low errors (less than 0,01%).

The fundamental superiority of the proposed method is due to the black box's data-based property, and the specific explanation is that we can estimate the output current directly from a new temperature and a new radiation using an ANN formed and constructed from abundant data, where the weight factors and biases are calculated automatically.

On the other hand, a comparison of the parameter estimation with the Esram and Villalva approachs (a model diode) was presented, with the results showing that the ANN method gave greater values for Rsh, a, and that the value of Rs is tiny when compared to the other methods, although Iph's findings for all methods are similar.

As a consequence, this paper can provides researchers, engineers and investors in the related field with an overview of the different solar cell parameters extraction methods; which would be very useful for the future.

ACKNOWLEDGMENT

The authors would like to acknowledge the support provided by the Research Unit in Renewable Energies in the Saharan Medium (URER/MS), Adrar, Algeria for providing the necessary facilities to carry out this work.

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