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ARTIFICIAL NEURAL NETWORK MODELLING AND EXPERIMENTAL VERIFICATION OF FLEXIBLE ORGANIC TANDEM SOLAR CELL MODULES

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Artificial neural networks have proved useful to model the electrical characteristics of photovoltaic cells. They have many advantages of such an approach as well as the resulting accuracy, robustness and speed. Neural networks have been used to model the characteristics of traditional silicon-based photovoltaic modules, and in this work, we have investigated a model for new generation organic tandem solar cell. Silicon-based photovoltaic cells were generally modeled by a simple circuital parameter sets; however, for organic cells the process is generally impervious. For this reason, we show that the application of artificial neural networks (ANN) has resulted advantageous to modeling. We have used such networks together with an algorithmic solution to automatically parametrize the Voltage-Current and the Voltage-power characteristics of organic photovoltaic modules. The cell also exhibited a photovoltaic characteristic with a power conversion efficiency(η) superior then 4%.In all cases studied, we compared our obtained functions produced by the ANN technique with the corresponding experimental data obtained in Sahara Algeria site and the excellent matching was so clear.

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Keywords: Artificial neural network modelling; Modelling photovoltaic cells; Organic cells; Generation organic tandem solar cell, Sahara Algeria site.

1. Introduction

The photovoltaic (PV) cells fabrication process and implementation is a very complex process. In order to enhance the effectiveness of such process it is often useful to obtain an accurate model of the manufactured cells characteristics. However, the study and verification of mathematical models require a huge amount of resources and has a negative impact on the production timetable [1].

Moreover, for the newly developed technology, namely the organic solar cells of last generation, it has important significant because they have very interesting properties and many advantages [1,2], including the cell flexibility and the ability to be exploited in large areas, the low costs of materials and the low fabrication cost [3,4]. However, their stability and efficiency must be considerably improved compared to their current state. But it is very difficult to obtain an analytical model starting from a priori assumptions, due to the complex nature of the material itself [1]. On the contrary, a model-independent technique is paramount to automatically extract model parameters for the characteristics of this new kinds of cells.

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In the photovoltaic field, the manufacturers provide notations for modules regular minutes to conditions STC (Standard Test Conditions). However, these conditions are not always obvious, occurring seldom outside, because they are mainly carried out under conditions of laboratory by using a solar simulator. Consequently, to carry out a characterization appropriate to the behavior of electric modules regular minutes (obtaining curve I-V), recently, several authors [5-6] use intelligence artificial (AI) such as logic rooks (fuzzy logic) [5,] and artificial neurons networks (ANN) [2,6,7] to model curve I-V. This approach is logical if one were to consider the dependence of the solar cell to the various variations of the environment.

In what precedes, we approached a modeling of OPV modules by using a digital method basing on an electric representation of organic photovoltaic solar cell [8] Well- determinant; during this work, we will test a modeling method using the artificial neuronal networks (ANN) for the characterization of the photovoltaic modules organic [7].

For this purpose, this article is organized as follows: the First section is devoted for the a solar field study of Saharan site(Adrar) .In the second section a presentation of the artificial neurons network structure used to obtain curves I-V and P-V of the organic solar cells flexible tandem modules in STC . In the third section a presentation of organic photovoltaic (OPV) [9] module used in this neurons networks modeling is carried out, by specifying the database used in this training. Finally the curve I-V in STC is deduced and results got with this method are explained thus that comparison with the experimental data.

2. The ADRAR site solar potential

However, the solar system design and dimensioning are subordinated to the knowledge of the solar layer available [10]. This part must lead us to precisely evaluate, the natural energy until one can wait of the solar radiation in a place, particularly the zone of the ADRAR station , and for an installation given. After the presentation, the weather data determine the supplied energy for the horizontal plane and the tilted plan of the sensors, by taking account of various disturbing effects such as the horizon, the reflections of the ground and the shades of possible close objects.

In the photovoltaic system, to estimate the sunshine, we will consult the sunshine map of our region. Always choose the time of the least sunny year (the month when the maximum sunshine and the lowest) in order to obtain the required electricity production during this period. Sunlight is usually expressed in kWh / m^2_day or in full sunshine hours (hours_1000W / m^2).

Any solar application requires knowledge of the sun apparent motion at a given point on the earth's surface, characterized by its latitude (positive for the northern hemisphere) and its longitude (defined in relation to the Greenwich meridian, positively to the east). (for ADRAR region latitude is 27.53°).

Sunlight corresponds to the solar radiation intensity [11, 12] of received on a plane at a time given . It is usually expressed in watts per square meter (W / m^2) [10], it quantified, for various locations, mainly by meteorological measurements. In the Saharan environment, pyranometers are used Fig. 1.

Fig. 1 .The pyranometer

From the results obtained by the measuring apparatus. Fig. 2 shows the variation of global irradiation (GHI), direct irradiation (DNI) values and diffuse irradiation (DHI) values [13,14] for day 10/01/2017 (day with clear sky) incident on a Horizontal plane , and are south oriented .

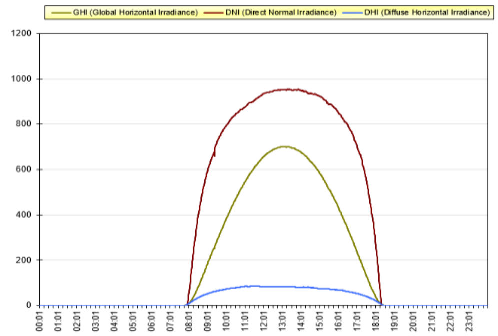

Fig. 2 .The global hourly irradiations variation for the day 10/01/2017

Fig. 3 shows the ambient hourly temperatures values and the humidity's values during the day 10/01/2017.

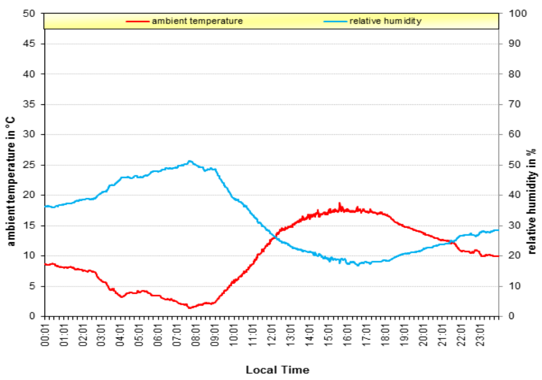

Fig. 3. The ambient temperature and humidity values for the day 10/01/2017

3. Characterization of the Infinity-OPV tandem module with artificial neural networks (ANN)

ANN are considered adequate technology for solving estimation and prediction problems, ANN are used to expand the range of potential applications in different domains due to the neural network black box functionality .

The objective of this article is to create a model based ANN in order to faithfully reproduce the response of a OPV module, this choice is to focus on a flexible organic tandem solar cell modules in series each cell Contains 14 layer fig. 4.[9]

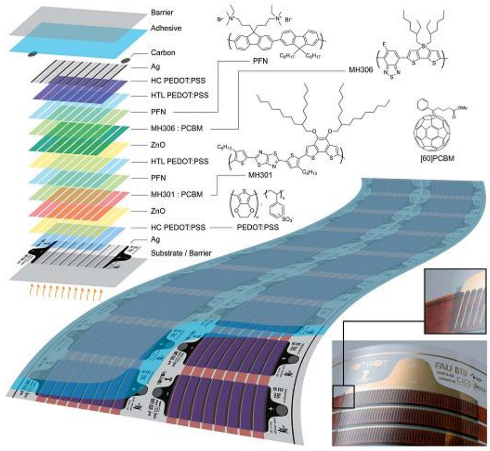

Fig. 4.The complete 14-layer tandem stack (upper left) along with structural formulae and names for the different materials involved (top right).The outline of the printed web is shown (middle) along with an actual photograph of a module (lower right). In the close-up photograph, the differently coloured active materials (red colour from MH301, green colour from MH306 and blue colour from PEDOT:PSS) are seen representing the wide band gap and low band gap semiconductor junctions and the hole transport layer[9].

The procedure for an ANN designing can be summarized in these steps [7]:
• The collection of a database characterized in our case by the input parameters which are the irradiance G (w/m^2) and the temperature T(C°), for each pair (G,T) have an output represented by a curve I-V.
• Separation of the database into three subsets (training bases, validation basis and test basis)
• The choice of neural network architecture (choice of inputs, outputs, number of layers hidden, number of neurons per layer, activations functions used, ...)
• Training of the neural network on the training and validation bases.
• Measurement of the neural network performance on the test basis.

3.1. Database Collection

The objective of this step is to gather a sufficient number of data to build a data base representative, which will be used with the ANN training and test. This database includes the neural network inputs as well as the associated outputs, and consequently it determines the network size (and therefore the simulation time) and its performance.

The electrical specifications of the OPV module used in this study are summarized in Table 1.

Table 1. Electrical characteristics of the PVO module

Infinity-PV organic solar cell module Surface: 0.008 m^2 and weight = 0.1kg	
P_{max} (W)	0.375
I_{sc} (mA)	110
V_{oc} (V)	6.92
I_{max} (mA)	78
V_{max} (V)	4.79
Ƞ (%)	4.7
FF	0.5
Number of cells in series Ns	8

Fig. 5.Shows an experimental characterization bench of the tandem organic photovoltaic module to determine the deferent climatic parameter (G,T) influence on the current-voltage (I-V) and power-voltage (P-V) characteristics.

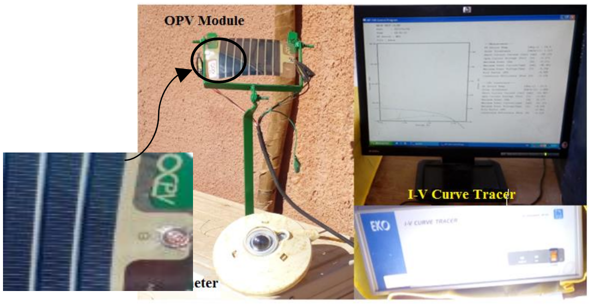

Fig.5. Experimental characterization Bench of the OPV module

For this training, we used 15 different curves, associating each value of G (w/m^2) and T (C°) a curve V-I and V-P (table 2).

Table 2. G and T values for the 15 curves used

Curve	G (w/m^2)	T(C°)
01	683.25	18
02	744	20.1
03	706.77	16.7
04	718.05	17.3
05	773	24.3
06	781	22.3
07	785	19
08	803	22.4
09	793	23.2
10	802	23
11	808	20.6
12	811	21.4
13	809	28.4
14	810	35.9
15	1000	25

Here is a sample curves extracted experimentally in STC condition (G = 1000 w / m^2 and T = 25 °C) by curve plotter device I-V fig.6.

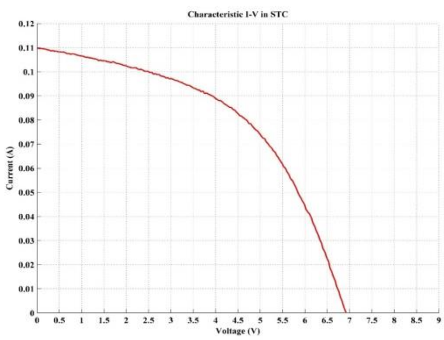

Fig. 6. I-V module characteristic in STC

The database must cover this value set of the 15 curves used. Based on the various parameters values, this database will have 15360 elements separated in 03 under base: A training base, a validation base and a test base.

It should be noted here that there are no specific rules for this separation; however, in general, the training base must include a considerable percentage of the database that can exceed 60%. For the validation base, it represents between 20% and 30% of the database and finally the test database represents between 10% and 25% of the database, according to the problem studied.

The training base is composed of 10752 elements (70%), the validation base is composed of 3072 elements (20%),while at the test base it is composed of 1536 elements (10%). This base is reserved only for the final performance measurement. In other words, In other words, it is used to check if the neural network has a good performance on the examples that it has not learned (test basis).

3.2. Choice of network architecture

The network architecture definition is paramount to obtain a system perform. That consists in making a compromise between the complexity of the network by reducing of the hidden unit number and the neurons number for each layer. [15].

As we mentioned previously, the network structure depend narrowly to the database, made up of inputs/outputs couple, chosen. The entries and outputs nodes number, are generally forced by the function to be approximated.

We tested the following working hypothesis:

$$I = f\ (G, T, V) \tag{1}$$

The neurons network will be able to find the relations wished between these values (provided that they exist), just by approaching the function f.

Once the bringing together is carried out, the desired values can be calculated.

The neural network structure (fig.7) ,is composed the following layers: the input layer has three neurons or nodes (G, T and V),three hidden layers , with the number NC1 for the first hidden layer, NC2 For the second hidden layer and NC3 for the third hidden layer, finally the last layer (output layer) has only one node(values of 1)[16].

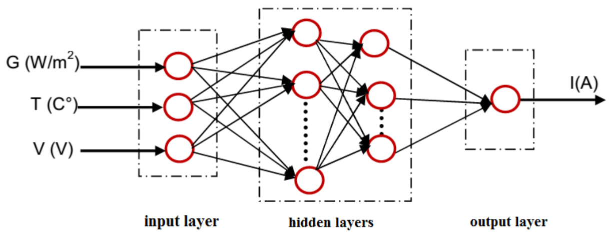

Fig.7. MLP architecture associated with Eq. 1 [15]

We will retain the architecture, which gives the minimum error on the test basis, in order to avoid the training problem.
Thus, we obtain the following table 3:

Table 3. Best Performance of Architecture Parameters

Architecture						MSE On the Training Base
N°	Number of input layer neurons	Number of hidden layer neurons			Number of output layer neurons	
		1st layer NC1	2st layer NC2	3st layer NC3		
01	03	02	15	10	01	$5.99*10^{-06}$
02	03	19	15	10	01	$4.1093*10^{-06}$
03	03	15	10	02	01	$7.19*10^{-6}$
04	03	20	15	15	01	$8.08*10^{-06}$
05	03	05	30	18	01	$5.13*10^{-06}$
06	03	10	02	10	01	$1.15*10^{-05}$

The mean quadratic error is represented on fig.8. After 10000 iterations, the ANN mean squared error reaches a very low value, which is equal to 3.9822×10^{-8}. Network learning error is shown in Fig. 9, where the error is almost zero, the training (approximately 10^{-7}); this proves the ANN training reliability.

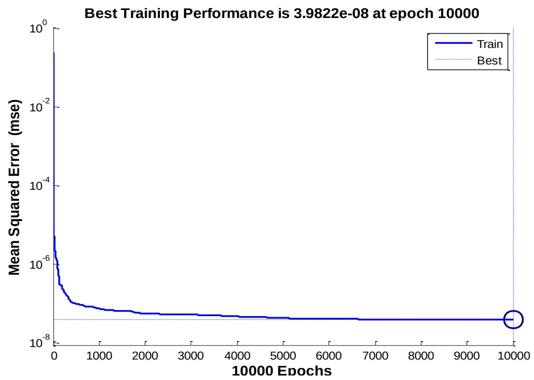

Fig.8. Training mean squared errors for the OPV model

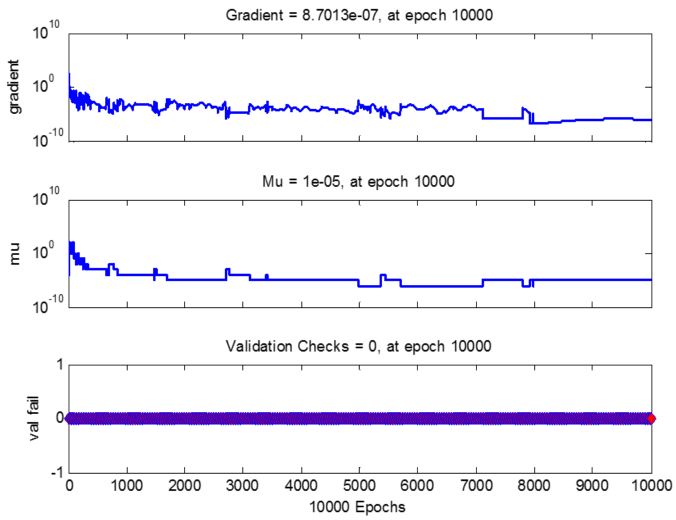

Fig. 9. Output errors of the ANN for the OPV model during learning.

Table 4. Summarizes all the parameters used to optimize our ANN model

Table 4. Optimized parameters of our neural network

Parameter	Optimized value			
Architecture	Feed-Forward MLP(Perceptron Multi-Layers)			
Hidden Layer	03			
Learning Rule	errors Backward propagation (Back propagation)			
Neurons number	Input Layer	03		
	1^{st} hidden layer	19		
	2^{st} hidden layer	15		
	3^{st} hidden layer	10		
	Output Layer	1		
Transfer function	1^{st} Hidden Layer	Logsig		
	2^{st} Hidden Layer	linéaire		
	3^{st} Hidden Layer	linéaire		
	Output Layer	linéaire		
entries Definition		$G(W/m^2)$	T(C°)	V(V)
	Min	683.25	16.7	0
	Max	1000	35.9	6.92
Output Definition		I(mA)		
	Min	0		
	Max	110		
MSE Learning	$4.1093*10^{-06}$			
Database	Learning base	10750		
	Validation base	3072		
	Test base	1536		

3.3. Test phase and performance measurement of the ANN model

Once the network training has been completed, it is always necessary to carry out tests to estimate its generalization quality, by presenting to it a database different from those used for learning or validation. The comparison between the initial database and that obtained after the training under different climatic conditions, indicates that our model accurately expresses the infinity-PVO module behavior . The fig.10 show the ANN model performance obtained for the 8 curves used:

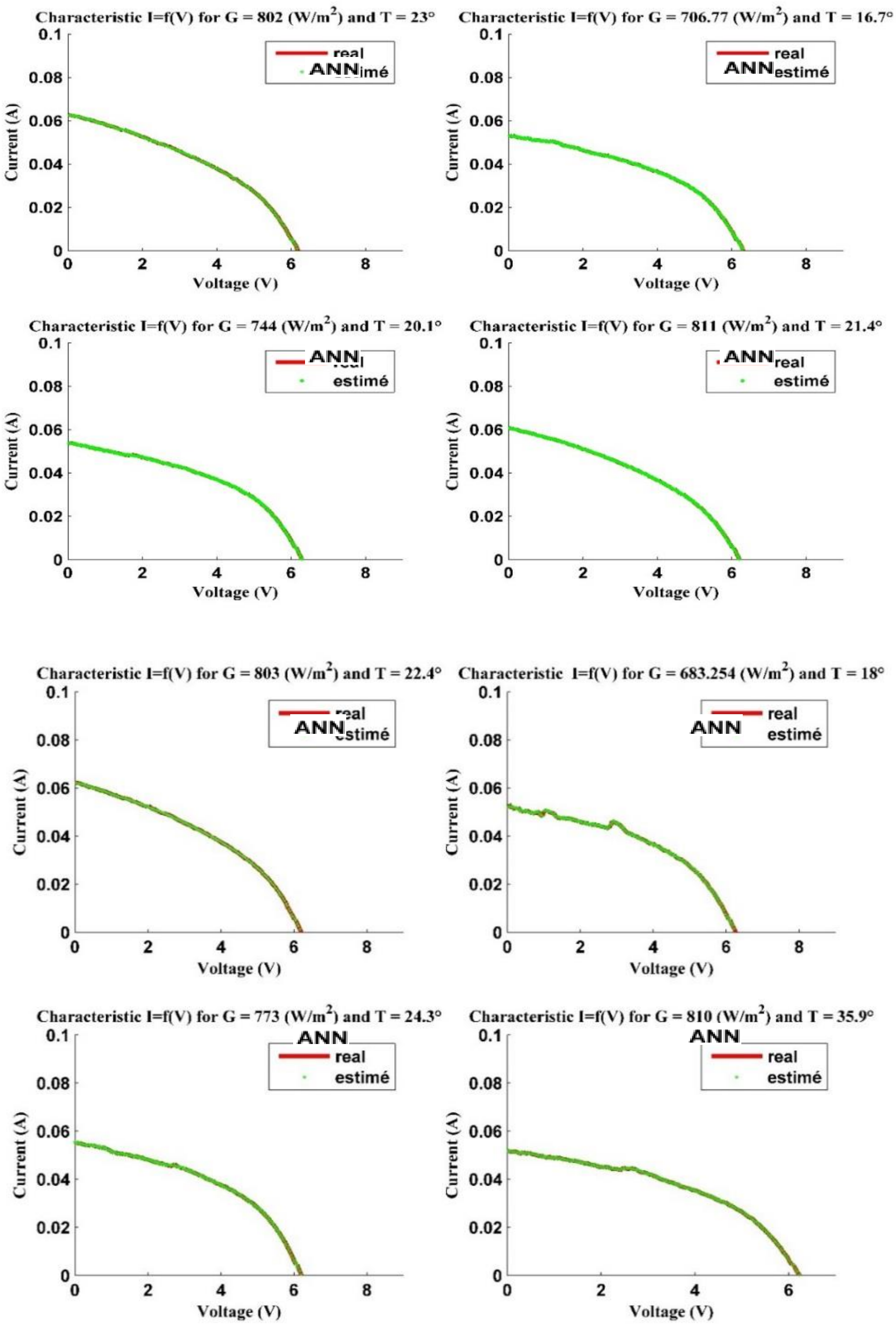

Fig.10. ANN model Performance obtained for the different training curves

3.4. Obtaining the I-V and P-V curves in STC with the ANN model

Once the validity of the proposed method for the flexible organic tandem solar cell modules has been verified, this methodology has been used to obtain the I-V curves of the OPV module in STC, which is the aim of this article. Our MLP (Multilayer Perceptron) [17] has been correctly formed, it tends to give reasonable responses (curve I-V and P-V in STC) when presented to entries that have never been seen, as shown in Fig.11.

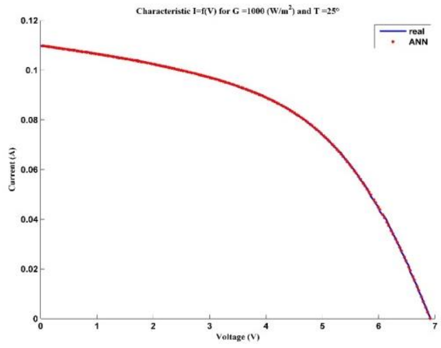

Fig.11. ANN model Performance obtained in STC

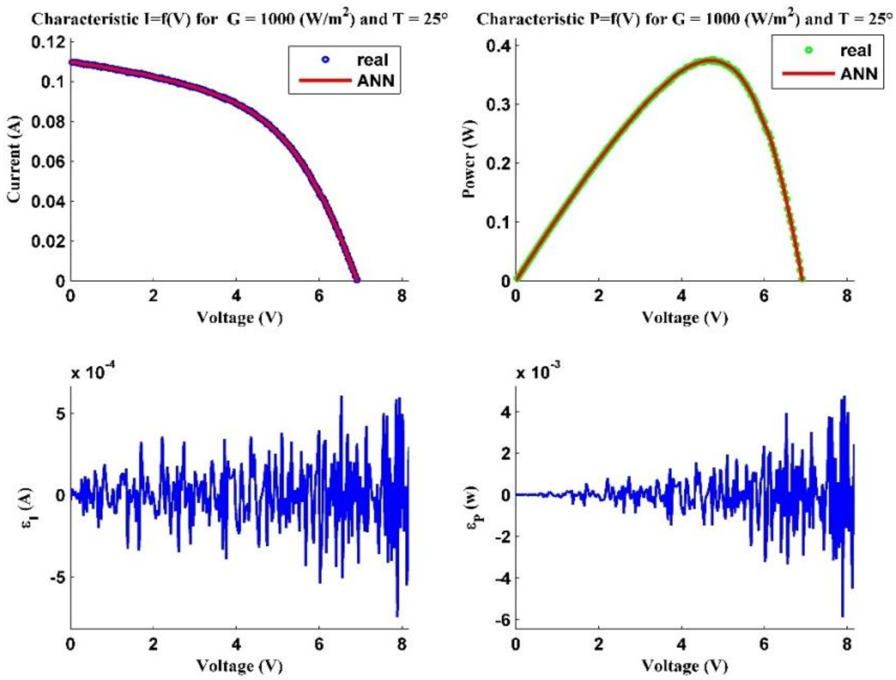

Fig.12. I-V and P-V characteristics of OPV module in STC with error functions

A comparison between the I-V curve extrapolated to the STC conditions by the MLP (ANN model) and the experimental data given by the data sheet was carried out. Fig.12 shows the I-V and P-V characteristics obtained with the ANN model and the experimental results. The current ε_I values and power ε_P errors, deduce that the data obtained by the MLP are very similar to those provided by the experimental tests.

3.5. Obtention des courbes I-V et P-V en défèrent condition avec le modèle ANN

Fig.13 shows the characteristics I-V, P-V and the errors obtained with the ANN model, the results. It can be deduced that the data obtained by the MLP are very similar to those provided by the designer.

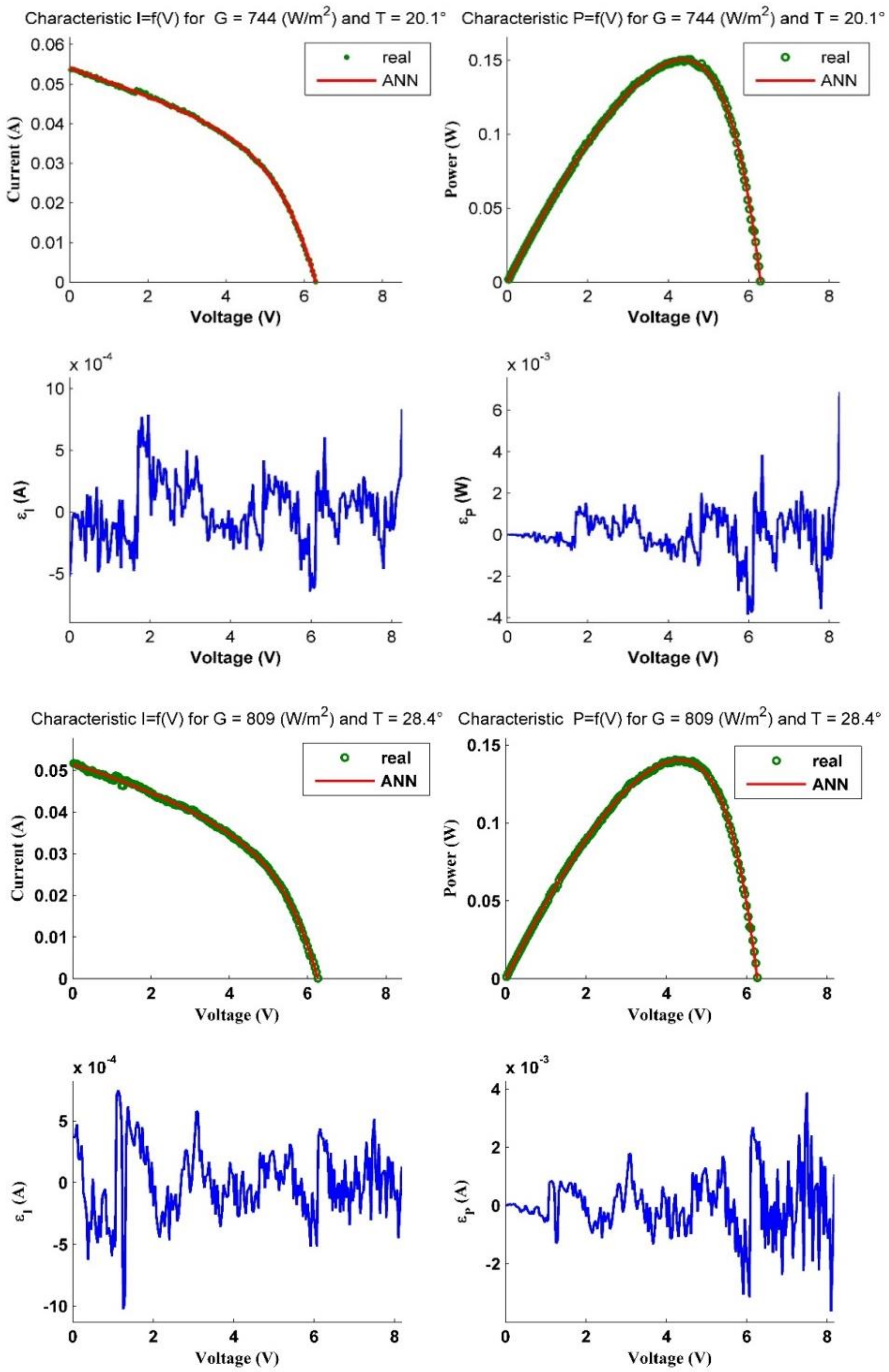

Fig.13. I-V and P-V characteristics with error functions of the OPV module

4. Conclusions

In this paper, we have constructed a model that present the behavior of the flexible organic tandem solar cell modules under different climatic conditions using the neural networks design.

Firstly, a good selection of the database is necessary, the irradiance ranges have been selected from 683.25W / m^2 to 1000 W / m^2 and temperature ranges from 16.7C° to 35.9C°, for the voltage it varies from 0V to V_{oc} V. It is necessary to note that the all training is very important; it must represent a rather broad whole of the behavior of module PV so that our MLP is well formed. The training was stopped when the error arrive the lowest value. Once all the stages of training are carried out, our MLP is formed and the measurements of performance compared to the data of training are necessary in order to test the reliability of our ANN model.

Secondly, the performance of this ANN model is tested for an input, which was not confronted with our system at the training time to give the answer in STC. The results show that the proposed artificial neural networks give a precise prediction for the I-V curve of the OPV modules compared with the measured values.

It is very important to remember that, this method is capable to generate the V-I curve of the module infinity-OPV tested in this article for the different conditions, to this effect this method will be very useful tool for the designers of photovoltaic systems because it could be applied before carrying out a photovoltaic installation, providing an appropriate value of the power supplied by the system in STC.

The proposed methodology exploits the possibility of using the information associated with this problem without knowing the relations between the different variables and information sources , namely it has no a priori model and provides values of the parameters (Pmp, V_{oc}, I_{sc}) that are acceptable with respect to the values given by the designer; It can be deduced that the ANN model compromises simplicity and precision. the proposed ANN an effective improvement of the existing approaches due to the low computational complexity and complete automatism.

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Nomenclature

η	Efficiency of the photovoltaic conversion (%)
P_{max}	Maximum power (W)
I_{sc}	Short circuit current (A)
V_{oc}	Open circuit voltage (V)
ANN	Artificial neural network
G	Illumination incident (W/m^2)
T	Temperature (°C)
OPV	Organic Photovoltaic
STC	Standard Test Conditions
GHI	Global Horizontal Irradiation
DNI	Direct Horizontal Irradiation
DHI	Diffuse Horizontal Irradiation
MSE	Mean Square Error
MLP	Multilayer Perceptron
ε_I	Current Error (A)
ε_P	Power Error (W)