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Neural Network Modeling and Experimental Evaluation of Organic Solar Panel Performance in Algerian Sahara

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ABSTRACT

In this paper, the characterization and modeling results of the electrical parameters of the tendem organic photovoltaic cells (infinityPV) are presented. The electrical performances of this organic cell's module (I-V and P-V) are characterized and analyzed in the weather condition of southwest Algeria (Adrar site). A program in MATLAB language is developed locally for modeling the organic cell, using artificial intelligence. The multilayer feed forward perception type ANN is used for extraction of the organic photovoltaic model performances, and the back-propagation algorithm is used for the program training. The ANN obtained results by the simulation showed a good conformity with the results obtained experimentally in the saharan climate (MAPE:0.68%, MBE:4.5018e-09 A and RMSE:1.8062e-04 A).

1. INTRODUCTION

Solar photovoltaic cells have experienced rapid development because they represent a key field in the cleaner electrical energy production. Those who grapple with solar photovoltaic science and technology devoted themselves to the study of novel materials and fabrication methods and device configurations for the next generation of solar cells, which must be efficient, low cost, lightweight and flexible [1].

Moreover, for the newly developed technology, namely the organic solar cells of last generation, it has important significance 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 organic cells fabrication [3-4]. However, the improvement of efficiency and stability must be considerably compared to their current state. But it is very difficult to obtain an matimatical model starting from a priori assumptions, due to the complex nature of the material of OPV itself [1]. On the contrary, an independent model technique is paramount to automatically extract model parameters for the electrical characteristics of this new kinds of photovoltaic cells.

In the photovoltaic field, the manufacturers provide the electical parameters for modules in conditions STC. However, these conditions are not always obvious, occurring seldom outside, because they are mainly carried out under conditions of the laboratory by using a solar simulator matirials. Consequently, to carry out a characterization appropriate to the behavior of electric modules regular minutes (obtaining curves I-V and P-V), recently, several authors [5-6] are used the artificial intelligence technics such as the fuzzy logic [5-7] and the artificial neuron networks (ANN) [2, 6-13] to modeling OPV cells. This approach is logical if one were to consider the dependence of the solar cell to any variations conditions of the environment [8]. Galphade [14] has presented a review paper of the photovoltaic module characterizations that using artificial neural networks (ANN). Celik [15] has presented a mode of mono-crystalline photovoltaic modules that based on artificial neural network methods. An artificial neural network based-model (ANN) have introduced by Mekki et al. [16], to detect the partial shading losses in the photovoltaic (PV) panel. Gotleyb [17] have proposed an ANN model for new generation organic solar cells to extract the electrical parameters of the studied organic photovoltaic modules. Riede et al. [18] have presented an optimization of organic (small molecules) tandem solar cells.

In this article, the electrical parameters of flexible tandem OPV module (current-voltage and current-power) are characterized and analyzed in the desert weather condition in the southwest Algeria (Adrar city). In addition, OPV module modeling is approache by using a numerical method basing on an electrical representation of the OPV solar cell. The obtained results by the ANN simulation methods showed a good conformity with the results obtained experimentally.

2. EXPERIMENTATION

The experiments are realized in the southwest of Algeria in Adrar city. This region of the Algerian Sahara has one of the greatest solar deposits in the world. The number of sunshine hours amounts almost 3500 hours/year [19]. The mean annual of the daily global irradiance measured on the tilted surface exceeds the value of 7kWh/m.sq/day [20]. The curves presented in Figure 1 give some examples of the GHI, DNI and DHI (data source: New Energy Algeria meteorological station URER-MS Adrar, Algeria). However, this Saharan region is characterized by important differences in the temperature over the year. In summer, the daily average of ambient temperature exceeds 42 °C (the maximum almost reaches 50°) while in winter the daily average is around 7 °C (the minimum is nearly 0 °C) Figure 2. The annual average measured relative humidity in the year 2017 is near 35 %.

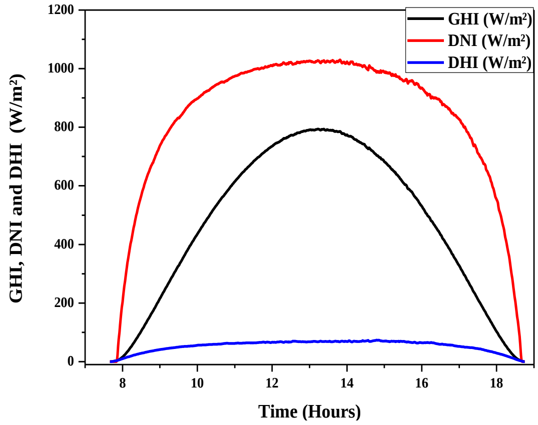


Figure 1. GHI, DNI and DHI variations. Day: 10/01/2017

To testing OPV module performance, we useing the experimental platform installed in URERMS field consists of a computer station, MP-160 I-V tracer (figure 3a), irradiance and temperature sensors and photovoltaic modules consist eight flexible organic tandem solar cells connected in series figure 3b.

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

In figure 4 a, sample curve is extracted experimentally in STC condition (G = 1000 W / m2 and T = 25 °C) by MP-160 I-V tracer.

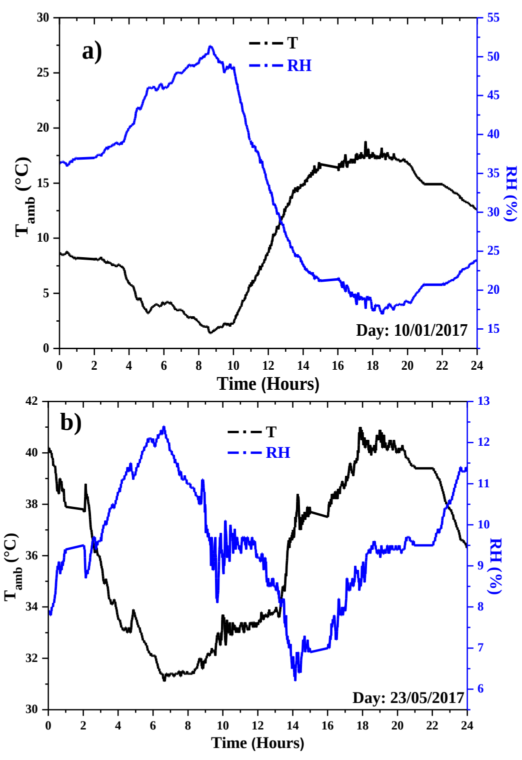
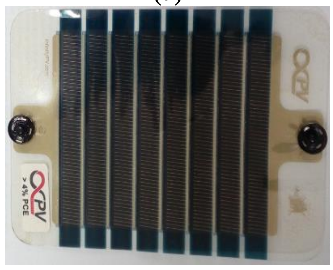


Figure 2. The humidity values and ambient temperature. a) Day: 23/05/2017, b) Day: 10/01/2017

(a)



(b)

Figure 3. Experimental platform: a) computer station and MP-160 I-V tracer, b) Organic module

Table 1. Electrical characteristics of the OPV module

Infinity-PV organic module Surface: 0.008 m² and weight = 0.1kg	
P_m (W)	0.375
I_{sc} (mA)	110
V_{oc} (V)	6.92
I_{max} (mA)	78
V_{max} (V)	4.79
η (%)	4.7
FF	0.5
Number of cells in series Ns	8

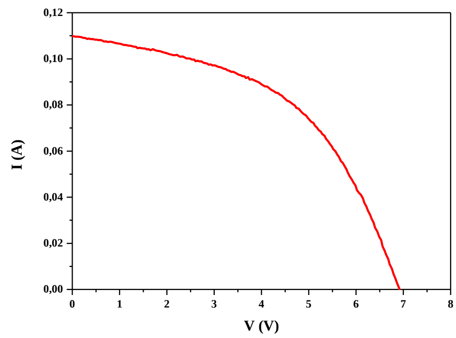


Figure 4. I-V module characteristic in STC

3. THE ANN APPROACH

Neural network is specified in finding the appropriate solution for the non-linear and complex systems or the random variable ones. Among its types, there is the back-propagation network, which is more widespread, important and useful. The function and results of the ANN programe are determined by its architecture that has different kinds. The simplest architecture of ANN contains three layers (input layer, hidden layer, and the output layer) [21] Figure 5.

In this technic, can conclude unlimited neural network architectures. The more several hidden layers and neurons in each layer are added to the network; the more complex they become. The realization of the back-propagation network is based on bowth main points (learning and knowledge). This research was utilized by the sigmoid function as an activation function to calculate the hidden layer output and the linear function to calculate the output [8, 22].

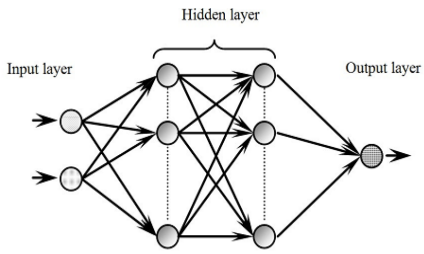


Figure 5. The used neural network

The technic chosen for the modeling of solar cells is the technic of ANN method, which consists of three steps; the choice of neuronal structure, learning and validation. [13, 22]. Table 2. Collected all the used parameters to optimize the ANN model.

The mean quadratic error of our ANN is represented in Figure 6. After 10000 iterations, the ANN mean squared error reaches a very low value (3.9822×10^{-8}) this proves the reliability of the ANN training.

Table 2. ANN parameters

Parameter	Optimized value			
Architecture	Feed-Forward MLP (Perceptron Multi-Layers)			
Hidden Layer	03			
Learning Rule	Errors Backward propagation (Back propagation)			
Neurons layer	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		Linear	
	3^{ird} hidden layer		Linear	
	Output Layer		Linear	
Entries		G(W/m²)	Tc(°C)	V(V)
	Min	584	7.4	0
	Max	1000	50.5	6.92
Output			I(mA)	
	Min		0	
	Max		110	
MSE Learning	$4.1093*10^{-06}$			
Data bases	Learning		10750	
	Validation		3072	
	Test		1536	

4. ANN MODEL VALIDATION

Once MLP (Multilayer Perceptron) is formed, it tends to give graphical responses (curve I-V and P-V in STC) when presented to entries that have never been seen. The objective of this step is ensured that the learning of the neural network is actually reliable and it is able to predict the desired output values for input data not used in learning of the ANN. For this, the output results that obtained by the ANN model must be compared with the experimentally obtained results.

Once the validity of the proposed method for the flexible organic tandem solar cell modules has been verified, we proceed to use this methodology to obtain the I-V and P-V curves of the OPV module in STC, which is the aim of this article Figure 7.

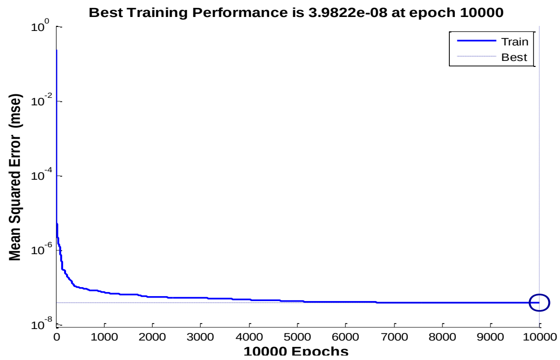


Figure 6. ANN mean quadratic error

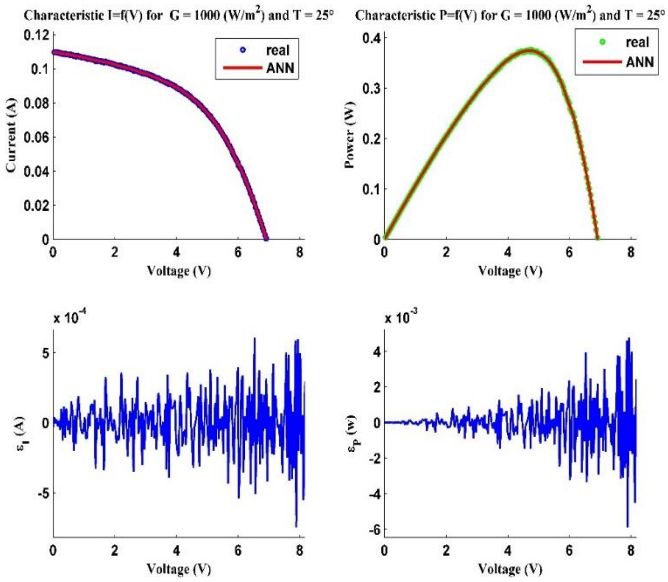


Figure 7. I-V and P-V characteristics of OPV module in STC with error functions

The aforementioned prediction model performances are evaluated in terms of mean absolute percentage error (MAPE), mean bias error (MBE) and root mean square error (RMSE). [23].

The mean absolute error is calculated by the following equation:

$$MAPE = \frac{1}{N}\sum_{i=1}^{N}\left(\left|\frac{D_{ie}-D_{im}}{D_{im}}\right|\right) \quad (1)$$

The mean absolute error (MAPE) is equal to 0.68%.

The mean bias error (MBE) is calculated by the following equation:

$$MBE = \sum_{i=1}^{N}\left(\frac{D_{ie}-D_{im}}{N}\right) \quad (2)$$

The mean bias error (MBE) is equal to $4.5018e^{-09}$ A

The root means square error (RMSE) is given by the following equation:

$$RMSE = \sqrt{\sum_{i=1}^{N}\frac{(D_{ie}-D_{im})^2}{N}} \quad (3)$$

The root means square error (RMSE) is equal to $1.8062e^{-04}$ A.

Where *Die* is the estimated value, *Dim* is the measured value and *N* is the the number of observations.

The real and simulated curves of the current and power obtained for the studied organic solar module for the day 10/05/2017 are shown in the figs.8 and 9. Where the day (10/05/2017) is a normal day with the sun and clouds in the southwest of Algeria (Adrar city). The error between the obtained results (real and simulated of the current and power of the OPV panel) during to the daytime is very acceptable.

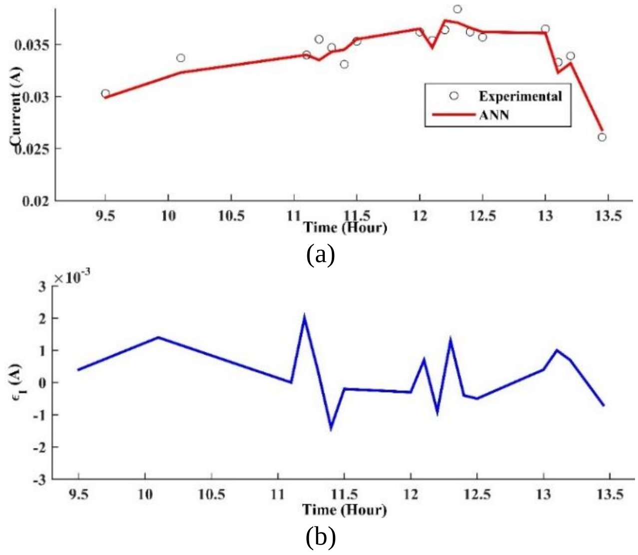


Figure 8. Current values of the PVO module for the day 10/05/2017. a) Power, b) Error

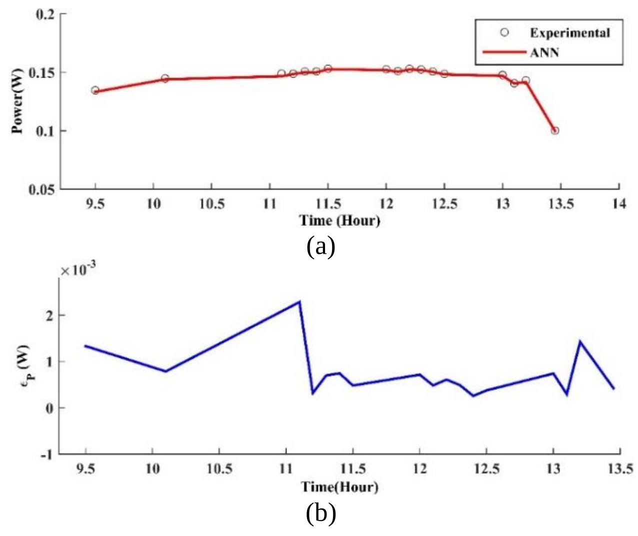


Figure 9. Power values of the PVO module for the day 10/05/2017. a) Power, b) Error

5. CONCLUSION

In this paper, an organic photovoltaic module study is presented. The characterization and modeling results of the electrical current-voltage and power-voltage of the organic photovoltaic (PV) panel are obtained. The electrical parameters of organic flexible tandem solar cell module (current, voltage and power) are characterized and analyzed in the weather condition of southwest Algeria in Adrar city (temperature, irradiation...). A model that present the behavior of the flexible organic tandem solar cell modules under different climatic conditions using the neural networks design is constructed in MATLAB. A good selection of the database is elaborate, the irradiance ranges have been selected from $584W / m^2$ to $1000 W / m^2$, the cell temperature varied between 7.4 to 50.5 °C and the voltage varies from 0 to V_{oc}. The back-propagation algorithm is used for the ANN training. The obtained results by the simulation of the ANN program showed a good agreement with the results obtained experimentally in the saharan climate (MAPE:0.68 %, MBE: $4.5018e^{-09}$ A and RMSE: $1.8062e^{-04}$ A).

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NOMENCLATURE

STC	Standard Test Conditions
GHI	Global Horizontal Irradiation
DNI	Direct Horizontal Irradiation
DHI	Diffuse Horizontal Irradiation
MSE	Mean Square Error
MLP	Multilayer Perceptron
ƐI	Current Error (A)
ƐP	Power Error (W)
FF	Factor of Form
η	photovoltaic conversion efficiency (%)
Pm	Maximum power (W)
T	Temperature (°C)
TC	Cell Temperature (°C)
Isc	Short circuit current (A)
Voc	Open circuit voltage (V)
ANN	Artificial neural network
G	illumination (W/m2)