Neural network for modeling solar panel

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Abstract — In this paper, we present the results of the characterization and modeling of the electrical current-voltage and power-voltage of the photovoltaic (PV) panel BP 3160W, using a new approach based on artificial intelligence. We analyze the electrical parameters of solar cells and electrical parameters of the optimal PV panel (current, voltage and power) according to changes in weather (temperature, irradiation...) by the simulation programs carried out in MATLAB. These simulation results were compared with experimental data to be validated.

Index terms — One diode model, Modeling and behavior, Photovoltaic panel, neural network.

I. INTRODUCTION

RENEWABLE energy resources will be an increasingly important part of power generation in the new millennium [1].

Solar energy conversions has various advantages such as short time duration of installation and long life of exploitation, circuit simplicity, no need of moving part and realize a salient, safe, not pollutant an renewable source of electricity. The wide acceptance and utilization of the photovoltaic (PV) generation of electric power depends on reducing the cost of the power generated and improving the energy efficiency of PV systems. In recent years, it has been shown that artificial neural networks (ANN) have been successfully employed in solving complex problems in various fields of applications including pattern recognition, identification, classification, speech, vision, prediction and control systems [2].

The Number of electronic applications using artificial neural network-based solutions has increased considerably in the last few years. However, their applications in photovoltaic systems are very limited [3].

In this work, we will implement the model to a single diode in the MATLAB environment, then we will modulate and simulate the behavior of solar panel BP 160W by currentvoltage characteristics I(V) and power-voltage P(V) for a wide range of variation of sunlight and temperature. Simulation results were compared with experimental data (and validated. The work was completed by a comparison with results

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obtained using artificial neural networks.

II. PHOTOVOLTAIC MODULES

A solar cell or photovoltaic cell consists of a p-n junction fabricated in a thin wafer or layer of semiconductor. The I-V output characteristics of a solar cell have an exponential characteristic similar to that of a diode in the dark. If exposed to light, an electron-hole pair is created when photons with energy greater than the band gap energy of the semiconductor are absorbed. The current thus produced when these carriers are swept apart under the influence of the internal electric fields of the p-n junction is proportional to the incident radiation. In general a single cell has a relatively low voltage handling capability on the order of 0.6 V. In order to package solar cells as a more practical device most manufacturers produce solar modules; a group of solar cells connected in series and parallel with the additional components of blocking and bypass diodes in order to increase the voltage and current handling capability. Assemblies of solar cells are used to make solar modules, which may in turn be linked in photovoltaic arrays. A photovoltaic array is composed of series and parallel connections of solar modules [4] [5].

A. Choice of photovoltaic module

The BP 3160 photovoltaic module is chosen for a MATLAB simulation model, the module is made of 72 multicrystalline silicon solar cells in series and provides 160 watts of nominal maximum power [6]. Table 1 shows its electrical specification.

TABLE I: ELECTRICAL CHARACTERISTICS DATA OF PV MODULE TAKEN FROM THE DATASHEET

Maximum Power (P _{max})	160W
Voltage at P _{max} (V _{mp})	34.5V
Current at P _{max} (I _{mp})	4.55A
Open-circuit voltage (Voc)	4.8A
Short-circuit current (Isc)	44.2V
Temperature coefficient of Isc	(0.065±0.015)%/°C
Temperature coefficient of V_{oc}	-(160±20)mV/°C
Temperature coefficient of power	-(0.5±0.05)%/°C

In Figure 1, we presented two curves representing the solar illumination and the temperature versus time of BP 3160

photovoltaic panel.

These measurements were made it during a day with high radiation changes, and extracted at the Unit of Applied Research in Renewable Energy "Ghardaïa" (URAERG), in Algeria.

The Measurements (current, voltage, solar illumination and temperature) are collected in an Excel file on one hundred points in the I-V curve that can be processed by the program that has developed in the MATLAB environment.



Fig.1 the curves of temperature and irradiance versus time

B. Modeling a PV Module by MATLAB

The strategy of modeling a PV module is no different from modeling a PV cell. It uses the same PV cell model. The parameters are the all same, but only a voltage parameter (such as the open-circuit voltage) is different and must be divided by the number of cells.

Several electrical models are used to simulate and modeling the cells (panel) PV. We will exploit the study done Walker [7] of University of Queensland, Australia, uses the electric model with moderate complexity, shown in Figure 2.



Fig. 2 the circuit diagram of the PV model.

The model consists of a current source (I_{ph}) , a diode (D), and a series resistance (R_s) . The effect of parallel resistance (R_p) is very small in a single module, thus the model does not include it. To make a better model, it also includes temperature effects on the short-circuit current (I_{sc}) and the reverse saturation current of diode (I_s) . It uses a single diode with the diode ideality factor (n) set to achieve the best I-V curve match.

I

The output current supplied by the solar cell is obtained by applying Kirchhoff's law, in the equivalent circuit above:

$$=I_{ph}-I_d-I_p \tag{1}$$

Where: I is the cell current. I_{ph} : the photocurrent generated by the current source.

 $I_d = I_s (e^{q(V+IR_s)/nkT} - 1)$: is the current shunted through the intrinsic diode.

$$I_p = \frac{V + IR_s}{R_p}$$
: The current delivered by the parallel

resistance.

From these equations we can deduce the expression of the current delivered by the photovoltaic cell:

$$I = I_{ph} - I_s (e^{q(V + IR_s)/nkT} - 1) - \frac{V + IR_s}{R_p}$$
(2)

Where:

I: is the cell current (the same as the module current),

V: is the cell voltage = {module voltage} ÷ {# of cells in series},

 I_s : the saturation current of the diode.

T: is the cell temperature in Kelvin (K).

q : is the electron charge $(1.602 \times 10^{-19} \text{ C})$,

K: is the Boltzmann's constant $(1.381 \times 10^{-23} \text{ J/K})$,

T: is the junction temperature in Kelvin (K).

The simplest model of a PV cell is shown as an equivalent circuit below that consists of an ideal current source in parallel with an ideal diode. The current source represents the current generated by photons (I_{ph}), and its output is constant under constant temperature and constant incident radiation of light.

There are two key parameters frequently used to characterize a PV cell. Shorting together the terminals of the cell, the photon generated current will follow out of the cell as a short-circuit current (I_{sc}). Thus,

$$I_{ph} = I_{sc} \tag{3}$$

When there is no connection to the PV cell (open-circuit), the photon generated current is shunted internally by the intrinsic p-n junction diode. This gives the open circuit voltage (V_{oc}) . The PV module or cell manufacturers usually provide the values of these parameters in their datasheets.

Using the equality (3), the equation (2) becomes:

$$I = I_{sc} - I_{s} \left(e^{q(V + IR_{s})/nkT} - 1 \right) - \frac{V + IR_{s}}{R_{p}}$$
(4)

The effect of parallel resistance (R_p) is very small in a single module, thus the model does not include it, Then $(R_p = \infty)$, equation (4) becomes:

$$I = I_{sc} - I_s \left(e^{q(V + IR_s)/nkT} - 1 \right)$$
(5)

Using the values obtained from the BP 3160 manufactures' curves; a value of total panel series resistance Rs $\approx 5 \text{ m}\Omega$ was calculated.

Finally, it is possible to solve the equation of I-V

characteristics 5. It is, however, complex because the solution of current is recursive by inclusion of a series resistance in the model. Although it may be possible to find the answer by simple iterations, the Newton's method is chosen for rapid convergence of the answer [7]. The Newton's method is described as:

$$x_{n+1} = x_n - \frac{f(x_n)}{f'(x_n)}$$
(6)

Where: f'(x) is the derivative of the function, f(x) = 0, x_n is a present value, and x_{n+1} is a next value.

Rewriting the equation 5 gives the following function:

$$f(I) = I_{sc} - I - I_s \left[e^{q \left(\frac{V + I \cdot R_s}{nKT} \right)} - 1 \right] = 0$$
(7)

Plugging this into the equation 6 gives a following recursive equation, and the output current (I) is computed iteratively.

$$I_{n+1} = I_n - \frac{I_{sc} - I_n - I_s \left[e^{q \left(\frac{V + I_n \cdot R_s}{nKT} \right)} - 1 \right]}{-1 - I_s \left(\frac{q \cdot R_s}{nKT} \right) e^{q \left(\frac{V + I_n \cdot R_s}{nKT} \right)}}$$
(8)

III. RESULTS OF MATLAB PV MODULE MODEL

A. Electrical characteristics of the BP 3160 photovoltaic panel

The electrical characteristic of the largest solar module BP 3160 is presented by the curves (current-voltage) and IV (power-voltage) PV, which are nonlinear, as shown in Figures 3 and 4, respectively.

The IV curve describes the dependence of the photocurrent (I) generated by the light and the voltage (V) of a panel. In order to produce electrical power, the photovoltaic panel must create a voltage and current and the product between the two being power.



Fig. 3 I-V Curve of PV panel



Fig. 4 P-V Curve of PV panel

B. Parameters influencing the behavior of the PV panel

To compare our model a more to reality, it is necessary to study how certain parameters such as ideality factor, the resistance R_s , the received radiation or temperature, will influence the IV and PV characteristics.

1. Influence of the ideality factor n

Figure 5 shows the effect of the varying ideality factor, the diode ideality factor (n) is unknown and must be estimated. It takes a value between one and two; the value of n=1 (for the ideal diode) is, however, used until the more accurate value is estimated later by curve fitting.



Fig. 5 Effect of diode ideality factor (1000W/m², 25C°)

2. Influence of the resistance R_s

The series resistance (R_s) of the PV module has a large impact on the slope of the I-V curve near the open-circuit voltage (V_{oc}), as shown in Figure 6, hence the value of R_s is calculated by evaluating the slope dV/dI of the I-V curve at the V_{oc} ,

The calculation using the slope measurement of the I-V curve published on the BP 3160 datasheet gives a value of the series resistance per cell, $R_s = 5.0 \text{ m}\Omega$



Fig. 6 Effect of series resistances (1000W/m², 25C°)

3. Influence of temperature

To characterize PV cells, we used the model of one diode, presented above -, to provide the values of voltage (V), current product (I) and the power generated (P).

We present the IV and PV characteristics in Figures 7 and 8 respectively of BP 3160 PV panel, for $G = 1000W/m^2$ given, and for different values of temperature.

If the temperature of the photovoltaic panel increases, the short circuit current I_{sc} increased slightly, to be near 0.1 A at 25°C, while the open circuit voltage V_{oc} decreases, the temperature increase is also reflected in the decrease of the maximum power supplies.

The temperature increase is also reflected by the decrease of the maximum power.



Fig. 7 Simulate I-V curves of PV module influenced by temperature



Fig. 8 Power versus voltage curves influence by temperature

4. Influence of illumination

Now, we present the I-V and P-V characteristics in Figures 9 and 10 respectively of the BP 3160 photovoltaic module at a given temperature T = 25 ° C for different solar illumination levels.



Fig. 9 Simulated I-V curves of PV module influenced by solar illumination



Fig. 10 Power versus voltage curves influence by the solar illumination

IV. VALIDATION OF RESULTS

I-V and P-V characteristics data in Figures 11 and 12 respectively, are obtained for the illumination levels measured (330, 525 and 698 W/m²), at temperatures (38.1°, 43.8° and 48.2° C), at any moment during a same day (for 8 hours). The illumination will change this feature, not in its general form, but the values of I_{sc} , V_{oc} , and the product of curves I_{max} . V_{max}.



Fig. 11 Simulated I-V curves of PV module, (model results with experimental measurements), for different values of illumination and temperature.



Fig. 12 Simulated P-V curves of PV module, (model results with experimental measurements), for different values of illumination and temperature.

V. THE NEURAL 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 artificial neural network are determined by its architecture that has different kinds. And the simpler architecture contains three layers as shown in figure 13. The input layer receives the extern data. The second layer, hidden layer, contains several hidden neurons which receive data from the input layer and send them to the third layer, output layer, this latter responds to the system [8].

We can conclude unlimited neural network architectures. The more several hidden layers and neurons in each layer are added; the more complex they become. The realization of the back propagation network is based on two main points: learning and knowledge. This research was applied by the use of sigmoid function as an activation function in order to calculate the hidden layer output and the linear function to calculate the output [9]. X_i is applied to the input vector which consists of n variable.



Fig. 13 The neural network.

Always, we are with the BP 3160 photovoltaic panel, the technique chosen for the modeling of solar cells is the method

of artificial neural networks, which consists of three steps, we will apply it to approximate the desired output,

A. Choice of neuronal structure

The neural model used in our study is a network of nonrecurring type having:

• An input layer with three neurons whose inputs are the lighting, temperature and voltage. The intervals of variation of these variables are:

 $(200 \le G \le 1000)$

 $\left\{ 0 \le T \le 75 \right\}$

 $0 \le V \le 50$

- The activation function of the input layer is sigmoid type.
- Two hidden layers, one of 20 neurons and the second 30 neuron.
- An output layer with one neuron representing the target to approximate the output current.

B. Learning

Two tests are applied to stop the learning algorithm.

- Error = 10^{-10} , When the distance (in the sense of a standard) is less than the specified error.
- The maximum number of iterations = 1000.

C. Validation

This step ensures that the neural network after learning is actually able to predict the desired output values for input data not used in learning. We always compare the real output of neural networks with the model of photovoltaic cells, which remains our benchmark for comparison. For this we study two cases:

1) Case 1. Voltage and Solar illumination are constants and the temperature varies.

In this case, the input values of the network are:

 $\begin{cases} G = 1000 \\ T = [0 \quad 25 \quad 50 \quad 75] \\ 0 \le V \le 50 \end{cases}$

I-V and P-V curves of PV module are shown in Figures 14 and 16, respectively.

As a validation criterion, we used the relative error (ΔE) is defined as follows:



The percentage error between the desired outputs calculated by the model of photovoltaic cell and the outputs of RNA are shown in Figures 15 and 17.

The absolute value of percentage error in the current is less than 0.5%, while the error in the power of less than 3.5%.



Fig. 14 Simulated I-V curves of PV module, (the model results with the results of RNA), for different values of temperature at $G=1000W/m^2$



Fig. 15 The percentage of relative error in the output current of the Fig. 14



Fig. 16 Simulated P-V curves of PV module, (the model results with the results of RNA), for different values of temperature at $G=1000W/m^2$



Fig. 17 The percentage of relative error in the output power of the Fig. 16

2) Case 2. Voltage and temperature are constants and the Solar illumination varies.

In this case, the input values of the network are:

 $\begin{cases} G = \begin{bmatrix} 200 & 400 & 600 & 800 & 1000 \end{bmatrix} \\ T = 25 \\ 0 \le V \le 50 \end{cases}$

I-V and P-V curves of PV module are shown in Figures 18 and 20, respectively.

The percentage error between the desired outputs calculated by the model of photovoltaic cell and the outputs of RNA are shown in Figures 19 and 21.

The absolute value of percentage error in the current is less than 0,0906 %, while the error in the power of less than 0,209 %.



Fig. 18 Simulated I-V curves of PV module, (the model results with the results of RNA), for different values of the solar illumination at $T=25^{\circ}C$.



Fig. 19 The percentage of relative error in the output current of the Fig. 18



Fig. 20 Simulated P-V curves of PV module, (the model results with the results of RNA), for different values of the solar illumination at $T=25^{\circ}C$.



Fig. 21 The percentage of relative error in the output power of the fig. 20.

VI. CONCLUSION

In this paper, we used artificial intelligence as a tool for modeling of photovoltaic panel BP 3160W.

The analysis of various results, we found that the current of a solar cell is proportional to the solar illumination, it increases slightly with temperature, the open circuit voltage of a solar panel varies slightly with the solar illumination and decrease with increasing temperature.

Moreover, the optimal power increases mainly with increasing illumination and decreases rapidly with increasing temperature.

The simulation results were validated by comparison with experimental measurements, these characteristics don't differ much experimental characteristics of simulation, and the small difference is due to small variations in temperature at the time of testing.

A very good agreement is obtained between the model of the PV panel and the neural technique. A relative error of about 0.1% is found, indicating the effectiveness of artificial neural networks.

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