PREDICTION OF THE CHARACTERISTICS OF THE PHOTOVOLTAIC MODULE UNDER THE INFLUENCE OF CLIMATIC CONDITIONS IN MAHAJANGA

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ABSTRACT

This article contributes to the prediction of the electrical power produced by a photovoltaic (PV) module operating under the actual weather conditions of the city of Mahajanga. The Brichambaut Perrin empirical method is adopted for the estimation of the solar energy received by the photovoltaic module. Single diode models (three-parameter model, four-parameter model, five-parameter model), dual diode models (five-parameter model, six-parameter model, seven-parameter model) and artificial neural networks are adopted to model the photovoltaic cell.
The results of the simulation of the approximate mathematical models of the power produced were compared with the results predicted by the neural network under the same operating and climatic environment conditions. A good agreement was reached.

Keyword: *Modeling, Simulation, solar cell, PV module, Single diode model, Dual diode model, Artificial Neural Networks.*

I.INTRODUCTION

Faced with the global issue of climate change, renewable energies have a major role to play in the energy transition and in reducing greenhouse gas (GHG) emissions. In Madagascar, almost all regions receive more than 2800 hours of sunshine per year. The maximum potentials are among the highest in the world and the minimum potentials are on average 3 to 4 times higher than the potential in Western Europe. Among these regions, Mahajanga, which is 575 km northwest of Antananarivo, the capital of Madagascar, enjoys a warm climate, characterized by exceptional sunshine that exceeds ten hours a day for several months, a very high insolation rate (on average 75%) and the annual average global daily radiation measured horizontally exceeds 6000 Wh.m-2. Its geographical location (15°40' South of North latitude, 46°21' East of West longitude and 22m of altitude), favours the development and development of the use of solar energy. This study focuses on the development of renewable energy in Mahajanga using the photovoltaic module as an energy production system. The Brichambaut Perrin empirical method is adopted for the estimation of the solar energy received by the photovoltaic module. Single diode models (three-parameter model, four-parameter model, five-parameter model, dual diode models (five-parameter model, six-parameter model, seven-parameter model) and the artificial intelligence method are used as tools for modelling photovoltaic cells.The reference number should be shown in square bracket [1]. However the authors name can be used along with the reference number in the running text. The order of reference in the running text should match with the list of references at the end of the paper.

II. METHODOLOGIES

2.1- Modelling of the solar potential

The Brichambaut Perrin empirical method is adopted for estimating the solar energy received by any orientation sensor. For a clear sky, the different components of solar radiation, namely the direct component, the diffuse component and the global component received by a collector inclined at an angle β with respect to the horizontal plane and oriented at an angle α with respect to the south, are expressed respectively by the following equations[1]:

$$E_d = \left(\frac{1+cos(\beta)}{2}\right)H_d + \left(\frac{1-cos(\beta)}{2}\right).a\times H_G \qquad (1)$$

$$E_D = A\,cos(i)\,exp\left(-\frac{1}{B\,sin(h+2)}\right) \qquad (2)$$

$$E_G = E_d + E_D \qquad (3)$$

$$H_d = A'.(sin(h))^{0.4} \text{ et } \quad H_G = A''.(sin(h))^{B''} \qquad (4)$$

With :
HD: diffuse illumination received by a horizontal surface.
HG: global illumination received by a horizontal surface.
a: being the albedo of the soil (reflection coefficient of the soil).
A, B, A/, A/, A//, B///: are constants that depend on the state of the atmosphere.

Table 1: Constants characterizing the state of the atmosphere

State of the atmosphere	A	B	A'	A''	B''
Dark blue sky	1300	6	87	1150	1.15
Light blue sky	1230	4	125	1080	1.22
Milky blue sky	1200	2.5	187	990	1.25

2.2-Modelling a photovoltaic cell

The mathematical modeling of each photovoltaic cell involves the determination of the equivalent circuit, the mathematical equations IPV=f(VPV), PPV=f(VPV) and the characteristic curves of IPV=f(VPV) and PPV=f(VPV). Figure 1 shows the tree structure of some models found in the literature:.

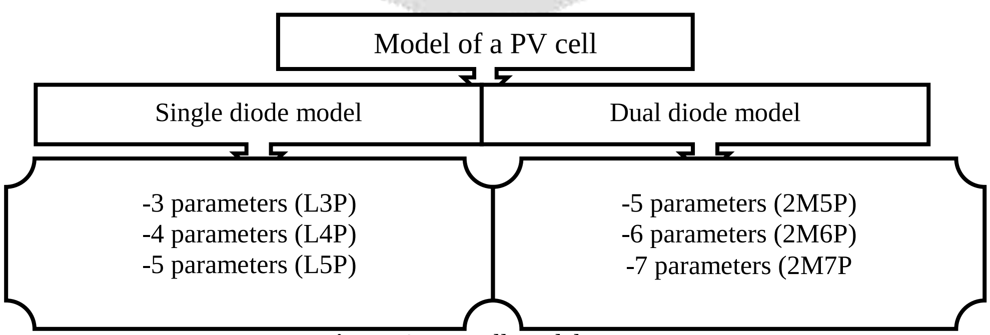
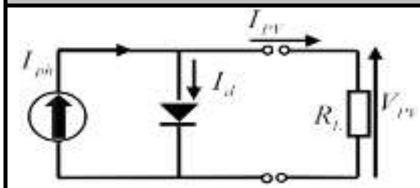
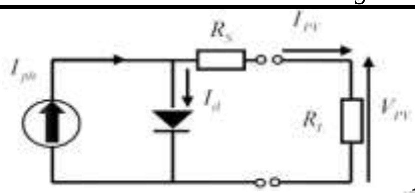
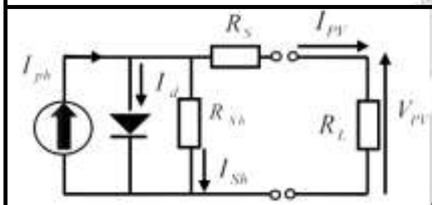
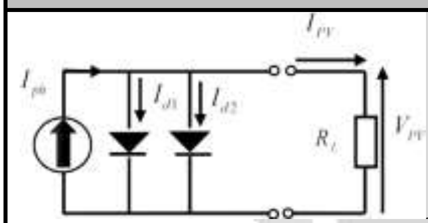
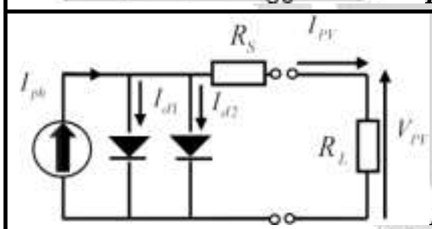
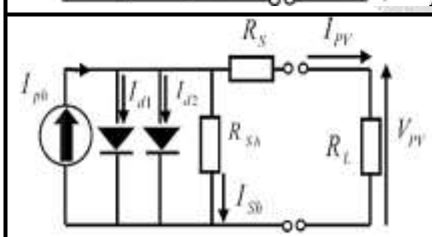


Figure 1: PV cell models

These models are grouped in Table 1.

Table 1: Different electrical models of a photovoltaic cell [2,3,4]

Models with a diode (or simple exponential)	
	$I_{cell} = I_{ph} - I_S \times \left(\exp\left(\frac{V_{cell}}{nV_T} \right) - 1 \right) \quad (1)$ *Figure 2: Model of an ideal photovoltaic cell or three-parameter model*
	$I_{cell} = I_{ph} - I_S \times exp\left(\left(\frac{V_{cell} + I_{cell}R_S}{V_T n} \right) - 1 \right) \quad (2)$ ***Figure 3 :** Ohmic loss model or four-parameter model*
	$I_{cell} = I_{ph} - I_S \times \left(\exp\left(\frac{V_{cell} + I_{cell}R_S}{V_T n} \right) - 1 \right) - \left(\frac{V_{cell} + R_S I_{cell}}{R_{Sh}} \right) (3)$ ***Figure 4 :** Model of a real photovoltaic cell or 5-parameter model*
Dual diode (or double exponential) models	
	$I_{cell} = I_{Ph} - I_{S1}(T_c) \times \left[\exp\left(\frac{V_{cell}}{n_1 V_T} \right) - 1 \right] - I_{S2}(T_c) \times \left[\exp\left(\frac{V_{cell}}{n_2 V_T} \right) - 1 \right] \quad (4)$ ***Figure 5 :** Five-parameter model*
	$I_{cell} = I_{Ph} - I_{S1}(T_c) \times \left[exp\left(\frac{V_{cell} + I_{cell}R_S}{n_1 V_T} \right) - 1 \right] - I_{S2}(T_c) \times \left[exp\left(\frac{V_{cell} + I_{cell}R_S}{n_2 V_T} \right) - 1 \right] (5)$ ***Figure 6 :** Six-parameter model*
	$I_{cell} = I_{Ph} - I_{S1}(T_c) \times \left[exp\left(\frac{V_{cell} + I_{cell}R_S}{n_1 V_T} \right) - 1 \right] - I_{S2}(T_c) \times \left[exp\left(\frac{V_{cell} + I_{cell}R_S}{n_2 V_T} \right) - 1 \right] - \frac{V_{cell} + I_{cell}R_S}{R_{Sh}} (6)$ ***Figure 7 :** Seven-parameter model*

2.3-Modelling a photovoltaic generator

For a GPV of number of modules connected in series in a string and number of branches connected in parallel, the parameters of the GPV (output current, output voltage, equivalent parallel resistance, equivalent serial resistance, output power and efficiency) are linked to those of the module (module current, module voltage, number of modules in parallel and number of modules in series) by the following relationships [5.6]:

$$I_{GPV} = N_p \times I_{MPV} \quad ; \quad V_{GPV} = N_s \times V_{MPV} \quad (7)$$

$$R_{p\_GPV} = \frac{N_s}{N_p} \times R_{p\_\mathrm{MPV}} \quad ; \quad R_{\mathrm{s}\_GPV} = \frac{N_s}{N_p} \times R_{s\_MPV} \quad (8)$$

$$P_{GPV} = \sum_{i=1}^{N_s} V_i \sum_{i=1}^{N_p} I_i \quad ; \quad \mathrm{r}_{\mathrm{GPV}} = \frac{P_{\max}}{P_e} = \frac{I_{GPV\max} V_{GPV\max}}{G N_s N_s S_{GPV}} \quad (9)$$

The characteristic equation of a GPV is derived from the equivalent electrical diagram of a cell, model 1 diode (Table 1).

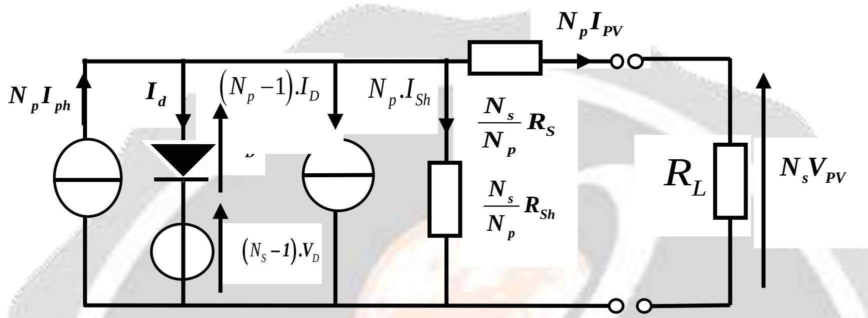


Figure 8: Equivalent circuit diagram of a GPV, model 1 diode

$$I_{GPV} = N_p I_{ph} - N_p I_S \times \left(exp\left(\frac{V_{GPV}}{n N_p V_t} \right) - 1 \right) (3\,p\,model) \quad (10)$$

$$I_{GPV} = N_p I_{ph} - N_p I_S \times \left(exp\left(\frac{V_{GPV} + I_{GPV} R_{GS}}{n N_p V_t} \right) - 1 \right) (4\,p\,model) \quad (11)$$

$$I_{GPV} = N_p I_{ph} - N_p I_S \times \left(exp\left(\frac{V_{GPV} + I_{GPV} R_{GS}}{n N_p V_t} \right) - 1 \right) - \left(\frac{V_{GPV} + R_{GS} I_{GPV}}{R_{GSh}} \right) (5\,p\,model) \quad (12)$$

Figure 9 shows, in relation to Figure 9, the electrical diagram of the Dual Diode Model for a group of panels.

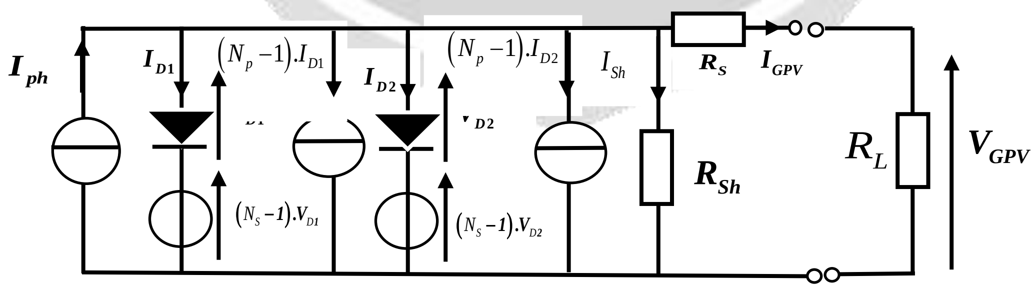


Figure 9: Equivalent circuit diagram of a GPV, model 2 diodes

The modeling of a GPV composed of Ns series modules and Np parallel modules is given by the equation

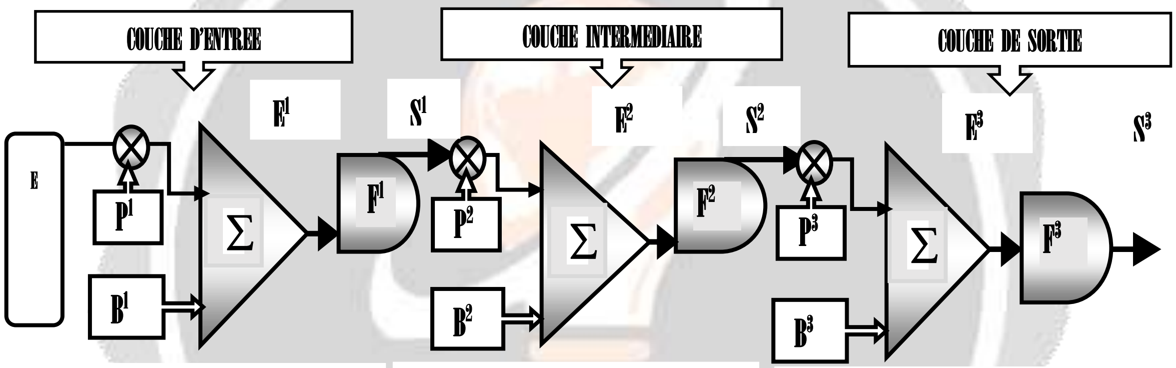
$$I_{GPV} = N_p I_{Ph} - N_p I_{S1}(T_c) \times \left[exp\left(\frac{V_{GPV}}{n_1 N_S V_t} \right) - 1 \right] - N_p I_{S2}(T_c) \times \left[exp\left(\frac{V_{GPV}}{N_S n_2 V_t} \right) - 1 \right] (5P) \qquad (13)$$

$$I_{GPV} = N_p I_{Ph} - N_p I_{S1}(T_c) \times \left[exp\left(\frac{V_{GPV} + I_{GPV} R_{GS}}{N_S n_1 V_t} \right) - 1 \right] - N_p I_{S2}(T_c) \times \left[exp\left(\frac{V_{GPV} + I_{GPV} R_{GS}}{N_S n_2 V_t} \right) - 1 \right] (6P) \qquad (14)$$

$$I_{GPV} = N_p I_{Ph} - N_p I_{S1}(T_c) \times \left[exp\left(\frac{V_{GPV} + I_{GPV} R_{GS}}{N_S n_1 V_t} \right) - 1 \right] - N_p I_{S2}(T_c) \times \left[exp\left(\frac{V_{GPV} + I_{GPV} R_{GS}}{N_S n_2 V_t} \right) - 1 \right] - \frac{V_{GPV} + I_{GPV} R_{GS}}{R_{GSh}} (7P) \qquad (15)$$

2.4- Perceptron Multilayer Artificial Neural Network Model

Artificial neural networks (ANS) are mathematical models inspired by the structure and behaviour of biological neurons. They are composed of interconnected units called formal or artificial neurons capable of performing specific and very specific functions. Multilayer perceptron RNAs allow non-linear relationships to be approached at high degrees of complexity [7].
Figure 10 illustrates the architecture of a 3-layer perceptron network formed by 3 neurons per layer.



$$S^1 = F^1\left(P^1.E + B^1\right) \qquad S^2 = F^2\left(P^2.S^1 + B^2\right) \qquad S^3 = F^3\left(P^3.S^2 + B^3\right)$$

Figure 10: Matrix representation of 3-layer perceptron[7.8]

The final simulation consists in calculating the final value of the actual output of the network, using the actual output returned by the network S3 with the values of P1, P2, P3, B1, B2 and B3 set at the end of the learning process.

$$S^3 = F^3(E^3) = F^3\left[P^3 F^2 \left[P^2 F^1 \left(P^1.E + B^1 \right) + B^2 \right] + B^3 \right] \qquad \mathbf{(16)}$$

$$E = \begin{bmatrix} e_1 & e_2 & e_3 \end{bmatrix}^T \ ; \ B^1 = \begin{bmatrix} b^1_{1,1} & b^1_{1,2} & b^1_{1,3} \end{bmatrix}^T \ ; B^2 = \begin{bmatrix} b^2_{2,1} & b^2_{2,2} & b^2_{2,3} \end{bmatrix}^T \ ; \ B^3 = \begin{bmatrix} b^3_{3,1} & b^3_{3,2} & b^3_{3,3} \end{bmatrix}^T$$

$$P^1 = \begin{bmatrix} p^1_{1,1} & p^1_{1,2} & p^1_{1,3} \\ p^1_{2,1} & p^1_{2,2} & p^1_{2,3} \\ p^1_{3,1} & p^1_{3,2} & p^1_{3,3} \end{bmatrix} ; P^2 = \begin{bmatrix} p^2_{1,1} & p^2_{1,2} & p^2_{1,3} \\ p^2_{2,1} & p^2_{2,2} & p^2_{2,3} \\ p^2_{3,1} & p^2_{3,2} & p^2_{3,3} \end{bmatrix} ; P^3 = \begin{bmatrix} p^3_{1,1} & p^3_{1,2} & p^3_{1,3} \\ p^3_{2,1} & p^3_{2,2} & p^3_{2,3} \\ p^3_{3,1} & p^3_{3,2} & p^3_{3,3} \end{bmatrix} ; S = \begin{bmatrix} S^1 & S^2 & S^3 \end{bmatrix}^T$$

III-RESULTS AND DISCUSSIONS

3.1- Mahajanga site geographical data

The Mahajanga site, located in the northwestern region of Madagascar, is characterized by meteorological data according to Table 1.

Table1: Geographical coordinates of the Mahajanga site

Latitude (°)	Longitude (°)	Altitude (m)	Méridien de référence (°)	Albédo du sol	DEL
15°40'Sud	46°21'Est	22m	40°	0 ,35	0 ,9h

3.2- Characteristics of the adopted photovoltaic panel

The electrical characteristics of the SW 80 mono RHA photovoltaic module under standard conditions (1000 W.m-2, optical mass: AM 1.5, cell temperature: 25 °C) are given in Table 2 below:

Table 2: Electrical characteristics of the SW 80 mono RHA module [8]

Puissance maximale	P_{max}	80 W
Tension à P_{max}	V_{mp}	18,5 V
Courant à P_{max}	I_{mp}	4,35 A
Courant de court-circuit	I_{sc}	4,66 A
Tension à circuit ouvert	V_{oc}	22,5 V
Coefficient de température de courant	K_i	0,044 %/°C
Coefficient de température de tension	K_v	0,30%/°C
Nominal Operating Cell Temperature	NOCT	45+/- 2°C
Nombre de cellule en Série	Ns	36
Nombre de cellule en parallèle	Np	1

3.3-Solar radiation simulation

Through the Brichambaut Perrin formulas, a program under Matlab is developed that calculates the solar flux in Mahajanga with its direct and diffuse components. The script has the following entries: latitude, longitude of the place, day number, angle of inclination and time difference. The calculation code evaluates during true solar time: the time angle, the incidence angle and the height of the sun. With the condition that the height of the sun is positive; it returns the values of the components (diffuse, direct) and the global sunshine. The temporal evolution of the global horizontal and inclined irradiations at the latitude of the place during the sunny day of 21 October 2018 in Mahajanga is shown in Figure 11.

The sunrise time is around 05h 40mn and the sunset time around 17h 58mn, which means an average duration of sunshine per day of 12 hours. The maximum global radiation values, 1258 W.m-2 in the horizontal plane and 1211 W.m-2 in the 15.40° south-facing inclined plane, are at noon solar, respectively.

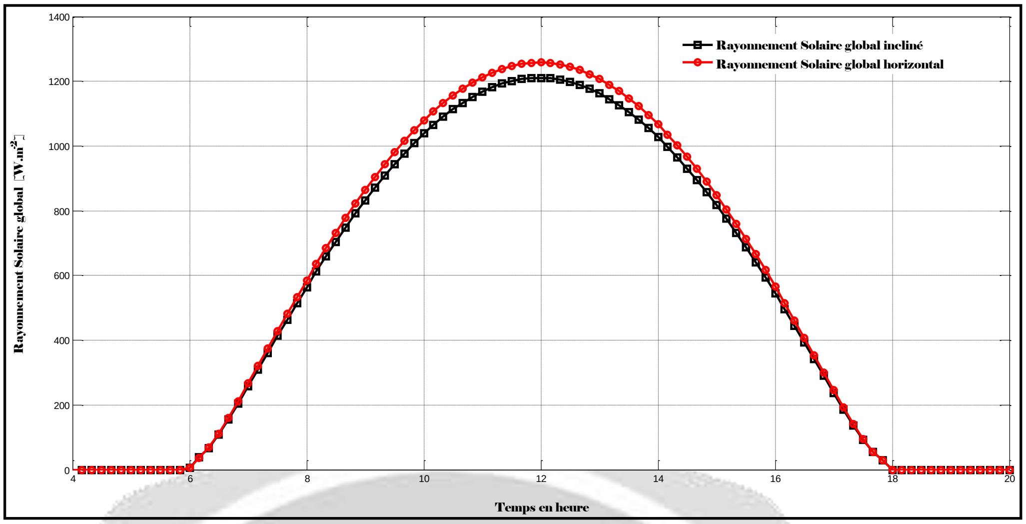


Figure11: Estimated values of hourly global solar irradiations on the horizontal and inclined planes - BRICHAMBAUT PERRIN

3.4-Prediction of the electrical characteristics of the GPV SW 80 mono RHA

The curves presented in Figures 12 and 13 describe the behaviour of the PV module under a fixed illumination of 1000W.m-2, at variable temperatures 25°C, 35°C, 45°C, 55°C and for a fixed temperature T=25°C, at variable illuminances of 400 W.m-2, 600 W.m-2, 800 W.m-2, 1000W.m-2. Depending on the results obtained, 1D and 2D models can be applied accurately to estimate the characteristics of the PV module in practical applications for normal conditions (1000 1000 1000W.m-2 illumination, optical mass: AM 1.5, cell temperature: 25 °C). From a power point of view, the single diode model gives better maximum values than the two diode model, but the main constraint is the high open circuit voltage (Vco) values obtained. On the other hand, the two diode model has lower Vco values and higher quality factors per unit.
However, it is difficult to conclude on the accuracy of a particular model in the absence of reliable experimental data.

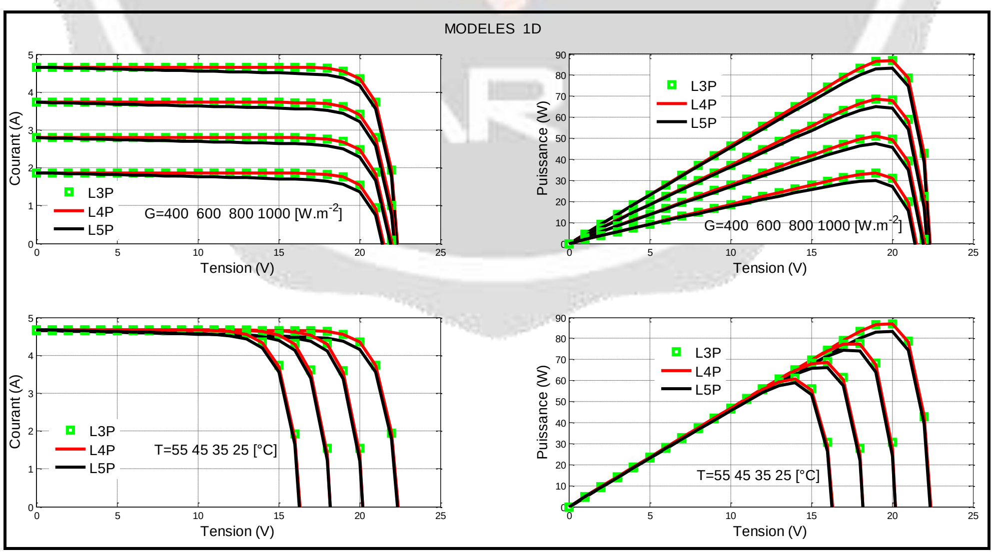


Figure 12: Estimation of the characteristics I(V) and P(V) of the PV module according to the 1D models (L3P, L4P and L5P).

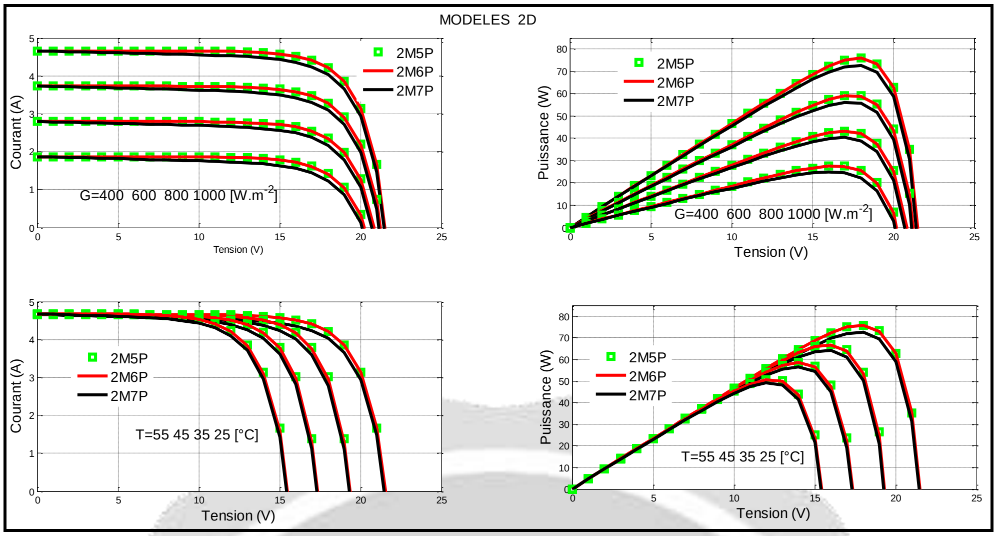


Figure 13: Estimation of the characteristics I(V) and P(V) of the PV module according to the 2D models (2M5P, 2M6P and 2M7P).

3.5-Prediction of the characteristics of the GPV SW 80 mono RHA by RNA

The Perceptron Multilayer Artificial Neuron Network (Muli Layer Perceptron) is adopted for the prediction of the current-voltage and power-voltage characteristics of SW 80 single RHA photovoltaic panels for different sunlight and temperatures.

The proposed MLP neural network has three layers, an input layer composed of three neurons including the three input variables (Temperature T, sunlight G and panel output voltage Vpv); and an output layer with a single neuron representing the target, the only output variable (the panel output current Ipv to be estimated). The variation intervals of these input variables are: The selected architecture is presented in Table 3 below.

Table 3: Architecture of the selected NAS

Architecture	Perceptron multicouches (MLP Feed-forward)		
Learning rule	Back propagation of errors (Back propagation)		
Parameters	Number of layers	Number of neurons	Activation function
Entry layer	1	3	
Hidden layer	2	1st hidden layer: 4	Sigmoids
		2nd hidden layer: 8	
Output layer	1	1	Linear

The curves shown in Figure 14 show, respectively, the comparison between the 2 diode mathematical model and the RNA model of the SW 80 mono RHA photovoltaic panel characteristics I(V) and P(V) for different sunlight and temperatures. For this purpose, two cases are studied:

Case 1: The voltage and temperature are constant and the illumination is variable.

Case 2: The voltage and illumination are constant and the temperature is variable.

The values of the network input are :

The results show that the proposed neural model provides an accurate prediction for

the speed of the current curves provided as a function of the voltage. Thus, the power delivered by the RNA model is very close to that obtained by the mathematical 2 diode model.

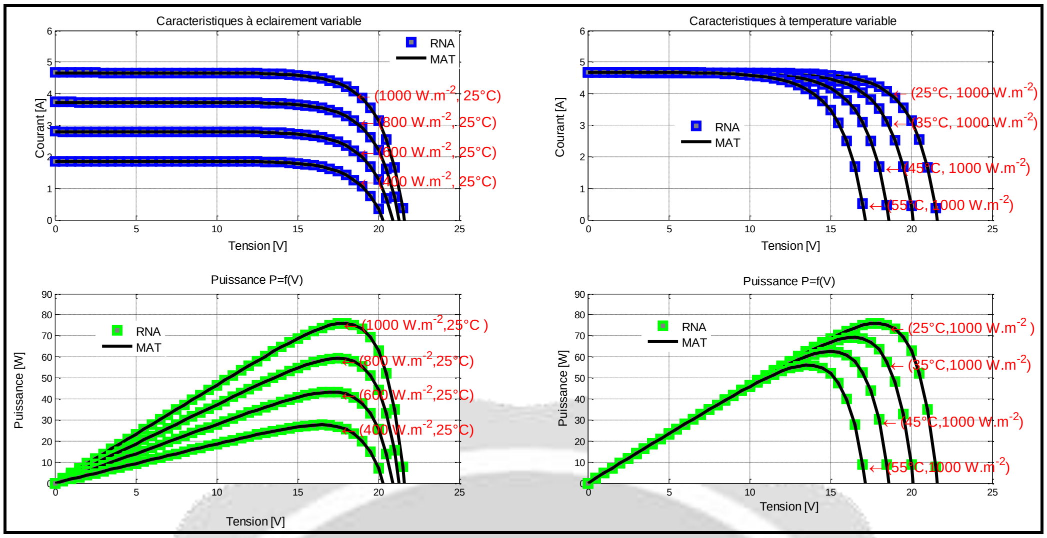


Figure 14: Estimation of the characteristics I(V) and P(V) of the PV module according to the model RNA perceptron with three layers and 2 diodes model

The relative errors of the estimates of the characteristics I(V) and P(V) of the PV module according to the three-layer perceptron RNA model, for different climatic conditions, are shown in Figure 15 below. The relative error is defined as the difference between the simulated values for the 2 diode mathematical models and the RNA of Ipv or Ppv divided by the value of the 2 diode mathematical model.

The relative error of the open circuit voltage for the different illumination values is minimal, especially for an illumination equal to 1000 W.m-².

The relative power error increases when the irradiance is reduced. For a T=25°C, the relative error of the maximum power is large compared to that of the other temperature values, since the 25°C value of the temperature is within the space limit of the database selected for learning.

In any case, the relative power error for different temperature values does not exceed the value 0.03, this confirms the efficiency of the neural model.

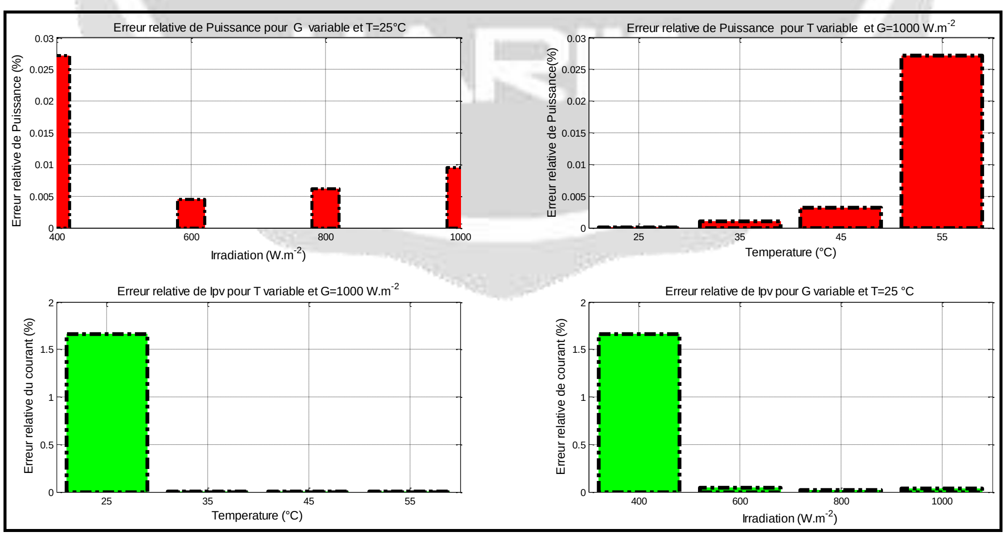


Figure 15: Relative errors of the estimates of the characteristics I(V) and P(V) of the PV module according to the three-layer perceptron RNA model.

III-CONCLUSION

The single diode, dual diode and three-layer perceptron RNA models were processed to simulate the P(V) and I(V) characteristics of the SW 80 mono RHA photovoltaic module for a wide range of illumination (from 400 W.m-2 to 1000 W.m-2) and temperature (from 23°C to 55°C) variation. The results of comparative studies between the three models show a very good agreement with the theoretical and practical results cited in the literature. The results of the proposed three-layer perceptron RNA perceptron model give an accurate prediction of the curves of the current supplied as a function of voltage as well as the power as a function of voltage. The relative power error for different temperature values does not exceed the value 0.03, this confirms the efficiency of the neural model.
In parallel, this study specifies the influence of the main climatic parameters (temperature and sunshine) on the output characteristics of the photovoltaic generator (I-V) and (P-V).

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