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Contribution for an optimization study of a photovoltaic generator

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Abstract

The good operation of a photovoltaic system depends on weather conditions such as illumination and temperature, because for example in a mobile station powered by a photovoltaic source, power supplied by the photovoltaic generator fluctuates when changing direction or during passage in poorly sunny.

In other words, a good photovoltaic system is where the power delivered by the photovoltaic generator is maximum whatever the conditions.

In the present work, we will precede first time modeling of solar cells by neural networks, then, we will use this approach to track the point of maximum power regardless of the location of use and operating conditions.

Keywords: Photovoltaic array, signal diode model, artificial neural networks, P&O, MPPT;

1. 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].

The model of a single diode in this work will be implemented in the MATLAB environment, and the behavior of the solar panel BP160W will be modulated and simulated by current-voltage characteristics I(V) and power-voltage P(V); for a wide range of variation of sunlight and temperature in one side , and track the point of maximum power in the other side using the artificial neural networks. The simulation results were compared with the experimental data and validated.

2. 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].

2.1. Choice of photovoltaic module

The BP3160 photovoltaic module is chosen for a MATLAB simulation model, the module is made of 72 multi-crystalline silicon solar cells in series and provides 160 watts of nominal maximum power [6]. Table1 shows its electrical specification.

Table 1. 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 (V_{oc})	4.8A
Short-circuit current (I_{sc})	44.2V
Temperature coefficient of I_{sc}	(0.065±0.015)%/°C

2.2. 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 by Walker [7] of University of Queensland, Australia, uses the electric model with moderate complexity, shown in Figure 1.

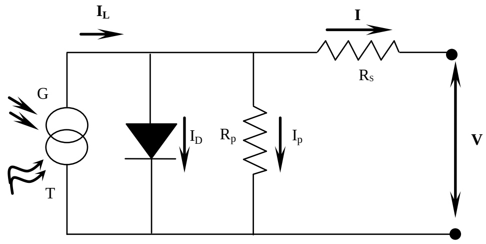

Fig. 1 The circuit diagram of the PV model.

The model consists of a current source (Iph), a diode (D), and a series resistance (Rs). The effect of parallel resistance (Rp) 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 (Isc) and the reverse saturation current of diode (Is). It uses a single diode with the diode ideality factor (n) set to achieve the best I-V curve match.
The output current supplied by the solar cell is obtained by applying Kirchhoff's law, in the equivalent circuit above:

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

Where: I is the cell current.
Iph: 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.
$I_p = \dfrac{V+IR_s}{R_p}$: The current delivered by the parallel resistance.
From these equations we can deduce the expression of the current delivered by the photovoltaic cell:

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

Where:
I: is the cell current (the same as the module current),
V: is the cell voltage = {module voltage} ÷ {# of cells in series},
Is: the saturation current of the diode.
T: is the cell temperature in Kelvin (K).
q :is the electron charge (1.602×10^{-19} C),
K: is the Boltzmann's constant (1.381×10^{-23} J/K),

3. Results of Matlab PV module model

3.1. 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 the received radiation or temperature, will influence the I-V and P-V characteristics.

3.2. Influence of temperature

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

We present the I-V and P-V characteristics in Figures (4 & 5) respectively of BP3160 PV panel, for $G=1000W/m^2$ given, and for different values of temperature.

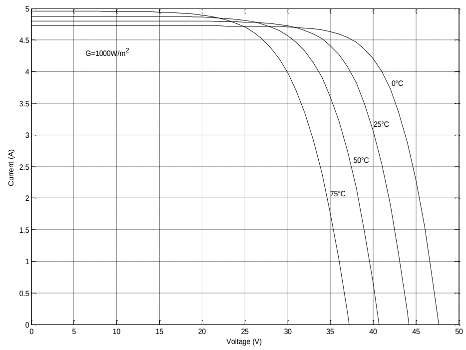

Fig. 4 Simulate I-V curves of PV module influenced the T.

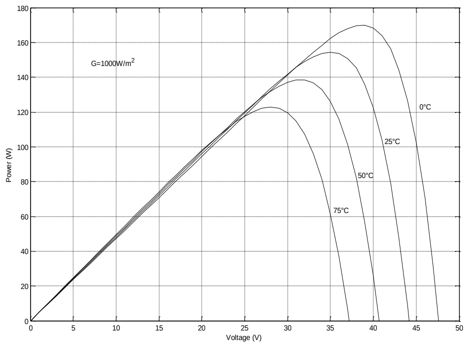

Fig. 5 Power versus voltage curves influence by the T.

3.3. Influence of illumination

Now, we present the I-V and P-V characteristics in Figures (6 & 7) respectively of the BP3160 photovoltaic module at a given temperature T=25°C for different solar illumination levels.

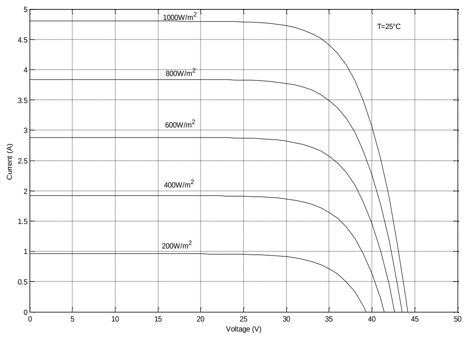

Fig. 6 Simulated I-V curves of PV module influenced solar illumination.

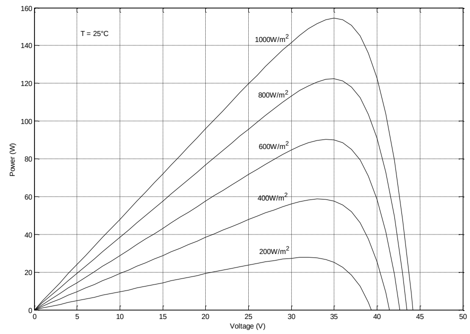

Fig. 7 Power versus voltage curves influence by the solar illumination

4. Validation of results

I-V and P-V characteristics data in Figures (8 & 9) respectively, are obtained for the illumination levels measured (330, 525 and 698 W/m^2), 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 Isc, Voc, and the product of curves $I_{max}.V_{max}$.

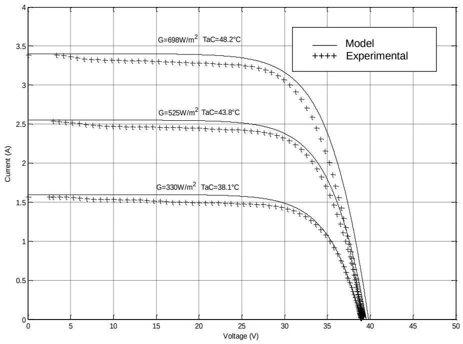

Fig. 8 Simulated I-V curves of PV module, (model results with experimental measurements), for different values of G and T.

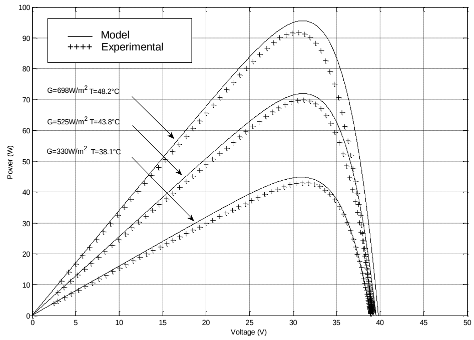

Fig. 9 Simulated P-V curves of PV module, (model results with experimental measurements), for different values of G and T.

5. 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 10. 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]. Xi is applied to the input vector which consists of n variable.

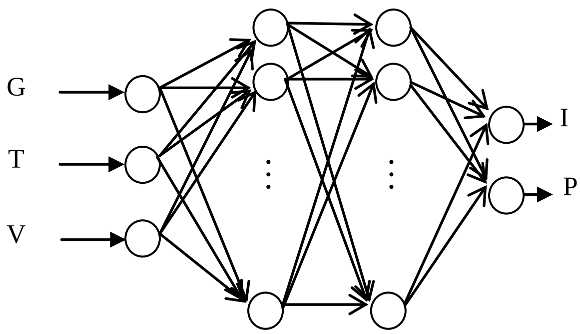

Fig.10. The neural network

Always, we are with the BP3160 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 (Choice of neural structure, learning and validation).

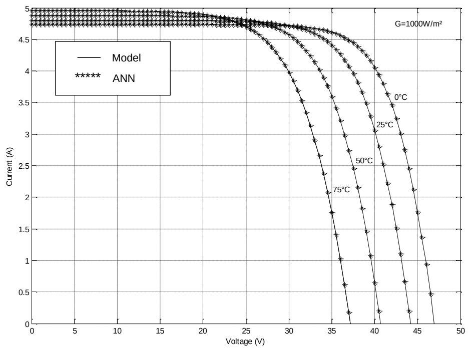

Fig. 11. Simulated I-V curves of PV module, (the model results with the results of RNA), for different values of temperature at G=1000W/m^2.

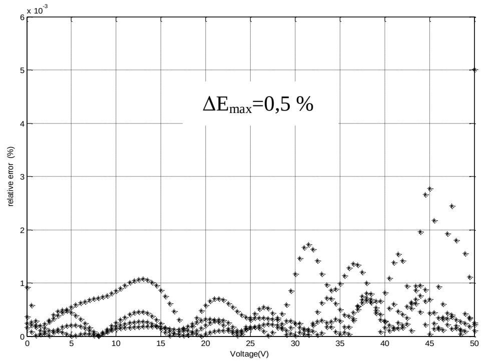

Fig. 12. The percentage of relative error in the output current of the Figure 11.

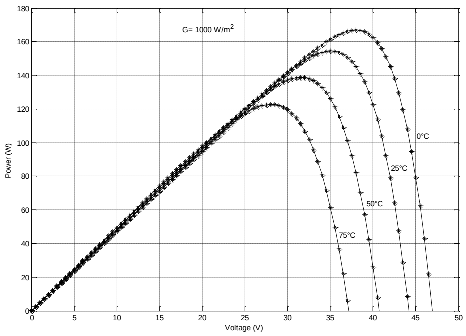

Fig. 13. Simulated P-V curves of PV module, (the model results with the results of RNA), for different values of temperature at G=1000W/m^2.

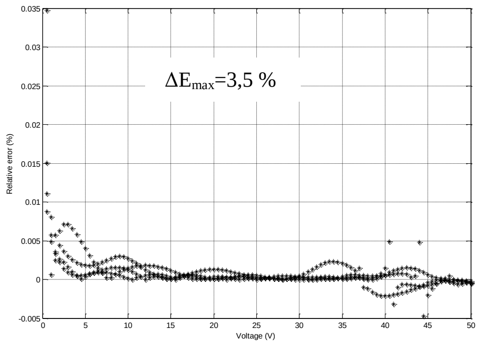

Fig. 14. The percentage of relative error in the output power of the Figure 13.

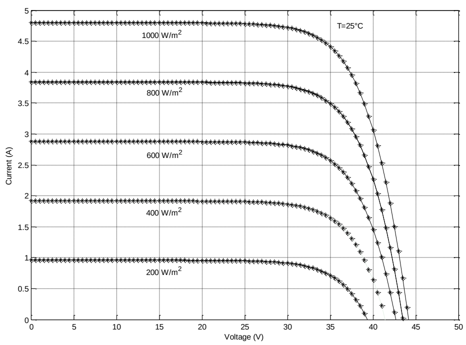

Fig. 15. Simulated I-V curves of PV module, (the model results with the results of RNA), for different values of the solar illumination at T=25°C.

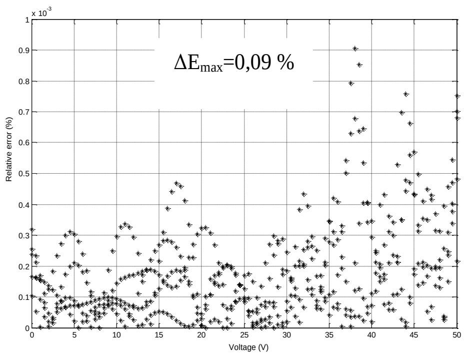

Fig. 16. The percentage of relative error in the output current of the Figure 15.

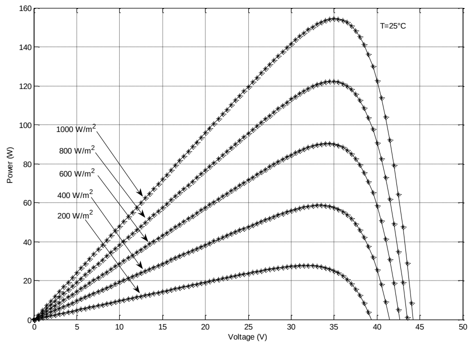

Fig. 17. Simulated P-V curves of PV module, (the model results with the results of ANN), for different values of the solar illumination at T=25°C.

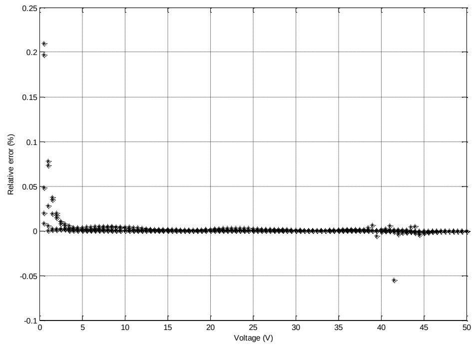

Fig. 18. The percentage of relative error in the output power of the Figure 17.

6. The maximum power point tracking (MPPT)

In order to gain maximum power, MPPT is an essential part of a PV generation system. Because of the nonlinear voltage current characteristics of PV cells, the power versus voltage P-V curve in solar cells has more complicated nonlinear relationship when solar illumination and ambient temperature change, so the MPP is difficult to solve analytically, and therefore numerous techniques have been proposed to realize MPPT. These MPPT methods vary in complexity, sensors required, convergence speed, cost, range of effectiveness, implementation hardware, popularity, and in other respects. Some methods applied in PV system are the constant voltage method, the perturb-and-observe (P&O or hill-climbing, because hill climbing and P&O methods are different ways to envision the same fundamental method.) method, the incremental conductance method, and so on [10].
The figures (19 & 20) represent the characteristic curves I-V and P-V respectively. These figures show the curve of the trajectory of Maximum Power Point (PPT) produced by the model of the photovoltaic module BP 3160. The maximum power that corresponds to the optimum operating point is determined for different illuminations of the illumination.

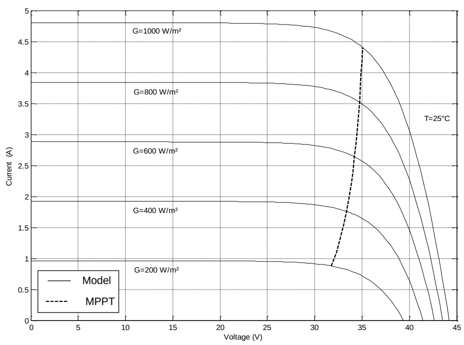

Fig. 19. I-V Characteristic for different values of the illumination, at T = 25°C, and the trajectory of maximum power point (PPM).

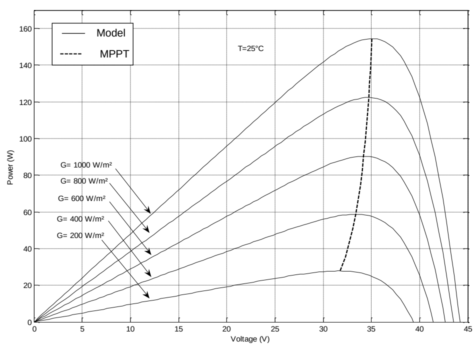

Fig. 20. P-V Characteristic for different values of the illumination, at T = 25°C, and the trajectory of maximum power point (PPM).

Now, the new technique chosen for the maximum power point tracking is the neural method which

consists of three steps; we will apply it to approximate the outputs which are the maximum power (P_{max}), the current, and voltage corresponding to this power. According to the illumination and the temperature's changes, it the tracking of the variation of the maximum power point where our system has to evolve quickly and efficiently.
So, to estimate the MPPT, we will use three neural networks that operate in parallel.

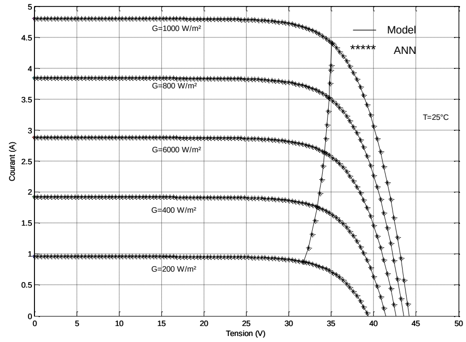

Fig. 21. Simulated I-V curves for different values of illumination at T = 25°C, with the trajectory of MPP. (The results of the model and the results of the ANN).

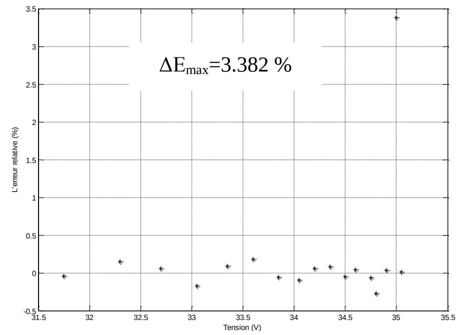

Fig. 22. The percentage of relative error in the output current of the figure 21.

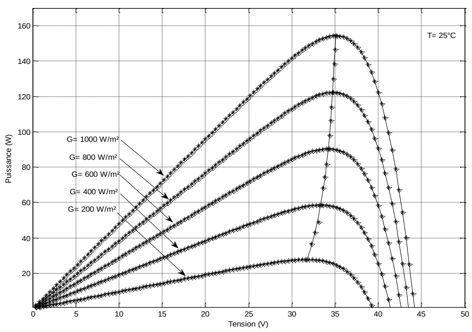

Fig. 23. Simulated P-V curves for different values of illumination at T = 25°C, with the trajectory of MPP. (The results of the model and the results of the ANN).

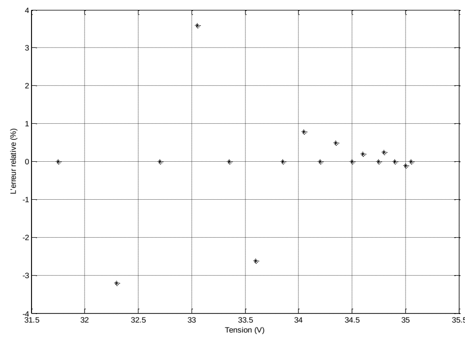

Fig. 24. The percentage of relative error in the output power of the figure 23.

7. Conclusion

We used artificial intelligence as a tool for modeling of photovoltaic cells in one side, and as a method of tracking the maximum power point in another side.
From 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 cell 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 do not differ much from the experimental characteristics of simulation, and the small difference is due to small variations in temperature at the time of testing.

From these results, we show that the measured values are coincident with those calculated by the simulation programs conducted in MATLAB. Also, a very good agreement is obtained in all studied cases between the model of photovoltaic cells and neural technique, a relative error of about 0.1% is found, indicating the effectiveness of artificial neural networks.

Finally, we can say that the artificial neural networks are modeling tools, powerful, and effective, their robustness is the ability to predict the output of the network even if the relationship with the input is not linear or even unknown.

References

[1] L. A. C Lopes and Lienhardt, A.-M. "A simplified nonlinear power source for simulating PV panels". *Power Electronics Specialist*, 2003. PESC'03. IEEE 34th Annual Conference on, Volume 4, pp. 1729- 1734.15-19 June 2003.

[2] S. A. Kalogirou "Artificial neural networks in renewable energy systems applications: a review". *Renewable and Sustainable Energy Reviews*, vol.5, pp.373-401, 2000.

[3] H. Mekki, A. Mellit, H.Salhi, and K. belhout, "Modeling and Simulation of Photovoltaic Panel based on Artificial Neural Networks and VHDL-Language'', 4th *International Conference on Computer Integrated Manufacturing CIP'2007*, 03-04 November 2007.

[4] V. K. Sethi, C.S. Rajeswari, Vinay Thapar, and Navankur Beohar, "Evaluating effect of insolation on pv cell Output using Matlab/Simulink", *Journal of Engineering, Science and Management Education*/Vol. 1, pp. 34-38, 2010.

[5] Huan-Liang Tsai, Ci-Siang Tu, and Yi-Jie Su, "Development of Generalized Photovoltaic Model Using MATLAB/SIMULINK", *Proceedings of the World Congress on Engineering and Computer Science 2008 WCECS 2008*, October 22 - 24, 2008, San Francisco, USA.

[6] BP Solar BP3160-160W Multi-crystalline photovoltaic Module Datasheet.

[7] G. Walker, "Evaluating MPPT converter topologies using a MATLAB PV model", *Journal of Electrical & Electronics Engineering*, Australia, IEAust, vol.21, No. 1, pp.49-56, 2001.

[8] A. Saadi and A. Moussi, "Neural Network Use in the MPPT of Photovoltaic Pumping System", *Rev. Energ. Ren.: ICPWE* (2003) 39-45.

[9] Eduard Mujadi. "ANN Based Peak Power Tracking for PV Supplied DC Motors". *Solar Energy*, Vol. 69, N°.4, 2000, pp343-354.

[10] Jiyong Li, and Honghua Wang, "Maximum Power Point Tracking of Photovoltaic Generation Based on the Fuzzy Control Method" *Sustainable Power Generation and Supply*, 2009. SUPERGEN'09. International Conference on 6-7 April 2009.