Optimizing Operation of Photovoltaic System Using Neural Network and Fuzzy Logic

N. Drir, L. Barazane, M. Loudini

***Abstract*—**It is well known that photovoltaic (PV) cells are an attractive source of energy. Abundant and ubiquitous, this source is one of the important renewable energy sources that have been increasing worldwide year by year. However, in the V-P characteristic curve of GPV, there is a maximum point called the maximum power point (MPP) which depends closely on the variation of atmospheric conditions and the rotation of the earth. In fact, such characteristics outputs are nonlinear and change with variations of temperature and irradiation, so we need a controller named maximum power point tracker MPPT to extract the maximum power at the terminals of photovoltaic generator. In this context, the authors propose here to study the modeling of a photovoltaic system and to find an appropriate method for optimizing the operation of the PV generator using two intelligent controllers respectively to track this point. The first one is based on artificial neural networks and the second on fuzzy logic. After the conception and the integration of each controller in the global process, the performances are examined and compared through a series of simulation. These two controller have prove by their results good tracking of the MPPT compare with the other method which are proposed up to now.

***Keywords*—**Maximum power point tracking, neural networks, photovoltaic, P&O.

I. Introduction

PHOTOVOLTAIC, system continues to gain wide acceptance as one of the energy solutions in the future. This has necessitated the need for research efforts aimed at improving the performance of such systems. As the photovoltaic power system is a free-fuel source of electric power, tracking the optimal operating point is a very important issue. Many researchers have discussed this in a normal operating condition [1].

In the V-P characteristic curve of GPV, there is a maximum point called the maximum power point (MPP) with the varying atmospheric conditions and because of the rotation of the earth [2]. The irradiation and temperature keeps on changing throughout the day. So, it is a big challenge to operate a PV module consistently on the maximum power point and for which many MPPT algorithms have been developed [3].

In this paper, we propose to study the modeling of a photovoltaic system and to find a method for optimizing the operation of the PV generator using intelligent neural network and fuzzy logic controller.

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II. Photovoltaic Power Generation

The electrical equivalent circuit of solar cell used in this study is show in Fig. 1, which is composed of light-generated current source, two diode, series and parallel resistance.

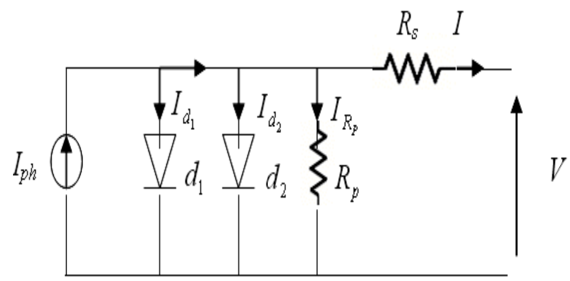

Fig. 1 Equivalent electrical circuit for the PV cell

The equation for the current and voltage of solar cell is given by:

$$I = I_{ph} - I_{s1}\left[e^{\frac{q(V+I.R_s)}{n_1 kT}} - 1\right] - I_{s2}\left[e^{\frac{q(V+I.R_s)}{n_2 kT}} - 1\right] - \frac{V+IR_s}{R_p}. \quad (1)$$

$I_{ph} = S \cdot I_{ph.\max}$, S : Percentage of irradiation,

I_{S1} and I_{S2} : the saturation currents of the diodes,

n_1 and n_2 : purity factors of the diodes,

R_s and R_p are respectively the series resistance and the parallel resistance,

T : Absolute temperature in Kelvin.

The equation also contains the elementary charge constant q $(1{,}602 \cdot 10^{-19}\ C)$ and the Boltzmann constant k $(1{,}380 \cdot 10^{-23}\ J/K)$.

The photovoltaic solar energy comes from the direct conversion of a portion of solar radiation into electrical energy carried through a photovoltaic cell based on physical phenomenon called photovoltaic effect. The role of this latter consists on producing an electromotive force when the surface of the cell is exposed to light [4].

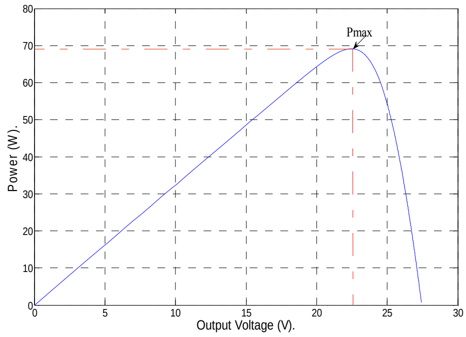

Fig. 2 Power curve under standard condition

Fig. 2 shows the output characteristics P-V of PVG which is non-linear, with an operating point (MPP) depends on the temperature and irradiation level.

In the following, we present the two intelligent controllers, and investigated here performance via numerical simulation.

III. Artificial Neural Networks

The artificial neural network (ANN) is considered as an assembly of elements of identical structure called cells (or neurons) interconnected like cells of the vertebrate nervous system. Each point of connection (called the coefficient or weight) between two cells acts as a synapse, the main element of interaction between neurons. These connections or synaptic weights have a role in the parallel operation and adaptive neural networks where the notion of connectionist [6].

Fig. 3 shows us the schematic representation of a simple artificial network model. The artificial neuron has as an input value the output product of other neurons or, at the initial level, the models input variables (input i, i = 1, 2, . . . input n). These values are then multiplied by a weight Wi and the sum of all these products (P) is fed to an activation function. The activation function alters the signal accordingly and passes the signal to the next neuron(s) until the output of the model is reached [5].

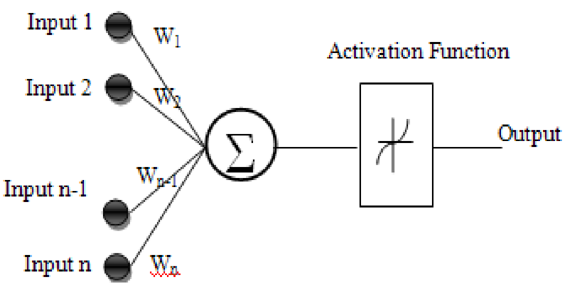

Fig. 3 Artificial neurons network

The greatest advantage of ANNs over other modeling techniques is their capability to model complex, non-linear processes without having to assume the form of the relationship between input and output variables [8].

Learning in ANNs involves adjusting the weights of interconnections to achieve the desired input/output relation of the network.

A. Description and Architecture the Proposed MMPT Neural controller

Fig. 4 shows the architecture of proposed MPPT neural network intended to replace the MPPT controller which is selected as a static, multilayer network.

ANN Controllers it consists of three layers as follows:

- An input layer with two neurons (temperature T and the irradiations S).
- Two hidden layers: the first with 5 neurons and the second with 8 neurons.
- An output layer with one neuron (ratio cyclic D).

In addition, the activation functions are adopted for the hyperbolic sigmoid neurons entered and those of hidden layers whereas corresponding to the output neuron is chosen linear.

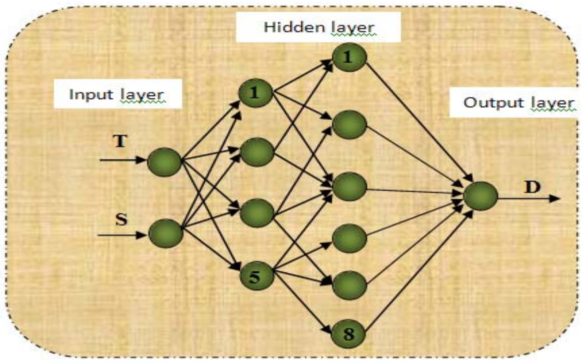

Fig. 4 The proposed neural network architecture

The Tests have shown that the most stable structure is that composed of five neurons in first hidden layer and eight neurons for the second hidden layer. The number of neurons in the hidden layer has been optimized empirically during the learning phase. It is also note worthy that the choice of the function activation of the hidden layer for which we opted not been adopted arbitrarily, but was chosen after several tests which showed that the function sigmoid hyperbolic converges faster by relative to the sigmoid tangential function during phase learning.

IV. Fuzzy Logic

Fig. 5 shows the basic structure of FLC which are briefly presented below:

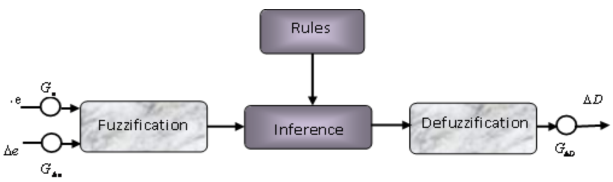

Fig. 5 Basic structure of fuzzy logic control

A. Fuzzification

The system converts the actual inputs values E and CE into linguistic fuzzy sets using fuzzy membership function that can be used in inference engine. These variables are expressed in terms of five linguistic variables (such as PB (positive big), PS (positive small), ZE (zero), NB (negative big), NS (negative small).

B. Inference and Rule Base

The rules base content all rule necessary to control system. The mechanism of inference allows obtaining, by using the membership of every linguistic variable and the rule base the membership function of under fuzzy set solution of the command.

C. Deffuzification

Having obtained under fuzzy set solution of the command, we need a numerical value for the command; the stage of the defuzzification allows obtaining this value.

Fuzzy logic controllers (FLC) have the advantages of working with imprecise inputs, no need to have accurate mathematical model, and it can handle the non linearity [7].

The proposed FLC; it consists of two inputs and one output. The two FLC input variables are the error (E) and change of error (ΔE) that expressed by (2):

$$\begin{cases} E(n) = \dfrac{P(n) - P(n-1)}{V(n) - V(n-1)} \\ \Delta E(n) = E(n) - E(n-1) \end{cases} \quad (2)$$

where E and ΔE are the error and change in error, n is the sampling time, $P(n)$ is the instantaneous power of the PVG, and $V(n)$ is the corresponding instantaneous voltage.

The membership function of the two input variables and the control duty cycle D used in our application are illustrated in Fig. 6.

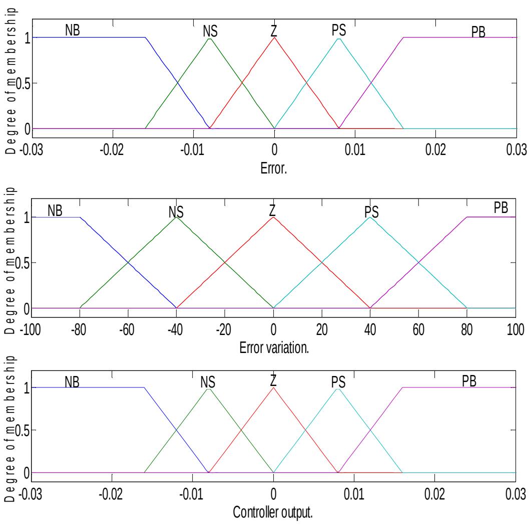

Fig. 6 Membership function of FLC

V. Simulation Study

Once our photovoltaic chain designed, and to verify the ability of our fuzzy controller to improve the performance obtained under the conventional MPPT controller, numerical simulation was performed for different conditions as follows:

The first test consists to compare the performance of this controller in standard condition, solar irradiation =1000w/m^2 and temperature of 25^{0}C. Fig. 7 shows the result of the tracked power by the two controllers.

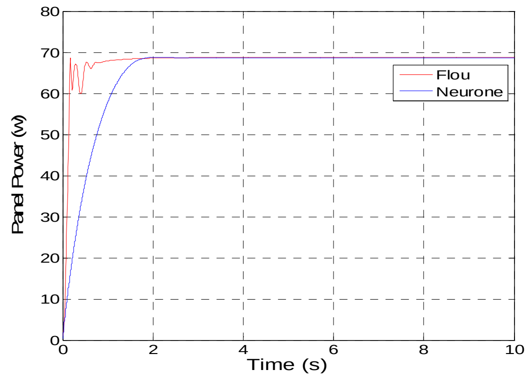

Fig. 7 Provided power from ANN, FLC controller in standard condition

As can be seen, the FLC is faster than the neural tracker, in addition the FLC presents oscillations before achieve the MPP. In standard conditions the two controllers presents no overshoot and the maximum power point is well monitored by the both.

The next simulation is under rapid variation of temperature (increasing the temperature of 25°C to 45°C in 2 s) see Fig. 8.

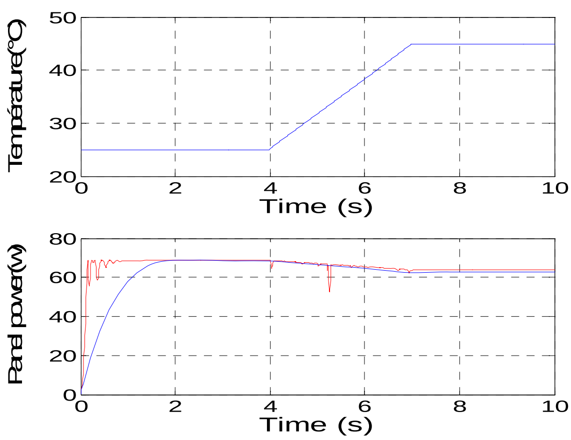

Fig. 8 Output power of PV for different irradiation

Another simulation is under the rapid variation of solar irradiation (from 1000 w/m^2 to 900 w/m^2 through 940 w/m^2); the results are shown in Fig. 9.

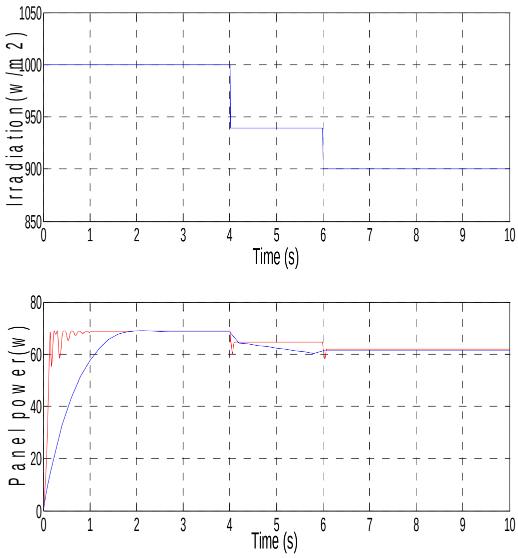

Fig. 9 Output power of PV for different irradiation

According to the tests of variation of temperature and irradiation, we notice that the neural network controller behaves exactly as expected for different variations considered contrary to the FLC with presents some fluctuation.

VI. Conclusion

In this paper we have investigated two intelligent control techniques to control output power of the solar panel in order to obtain the maximum power possible, whatever the solar irradiation and temperature conditions.

The design and simulation of neural network and fuzzy logic based MPPT was present.

According to the obtained results we can say that use of intelligent controller to track the maximum power point in PV systems is very promising. Indeed the two controller have presents good performance: fast responses for FLC, no overshoot in neural network controller and some fluctuations in FLC one.

Ongoing research, and in order to get the fast responses and no presence of fluctuations, the hybridation of the two controllers will be developed.

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