Optimisation of a GPV by an Artificial Intelligence Technical

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Abstract- This paper present two approaches for improving intelligence and performance optimization control of a photovoltaic system, the method further maximum power point tracking (MPPT) based on fuzzy logic method and artificial neural networks.The MPPT controller based neural networks, is developed and compared to the fuzzy logic algorithm. The results obtained under different operating conditions show that the system of control by fuzzy logic MPPT PV system is faster compared to the algorithm for neural networks against the latter is more stable than fuzzy logic.

Keywords- GPV, MPPT. Fuzzy logic Control. Artificial neural network.

1. Introduction

During operation of a PV generator adapted by energy converters, the maximum power point MPP can be degraded in response to changing weather conditions or load. The fit between the source and the load takes place by varying the duty cycle of. In fact, research from this point of maximum power must be done automatically. It is quite possible by adopting an adaptation approaches known as orders MPPT (Maximum Power Point Tracking). In this article we will give two methods of intelligent pursuit of maximum power point Method neuron network method and fuzzy sets.

Among the intelligent methods that exist, we will be interested in this work, the method of fuzzy logic and that of neural network.

2. Modeling of Photovoltaic System

The photovoltaic module is represented by its equivalent circuit diagram "Fig.1" Which consists of a current source model the luminous flux, the losses are modeled by two resistors, a shunt resistor R_{sh}, a series resistor R_s and two diodes for the polarization of the cell and the phenomenon of minority carrier recombination[1].

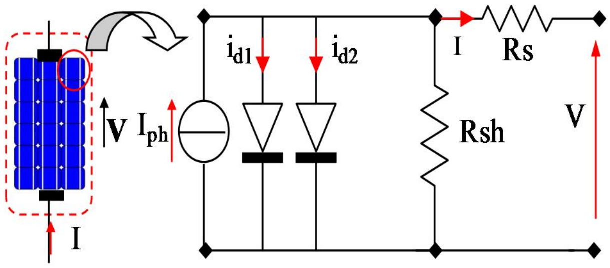


Fig. 1. Model of a photovoltaic cell to two diodes

The term of the current-voltage characteristic of a GPV for a given temperature and illumination can be written as follows

$$I = I_{ph} - I_{s1}\left[\exp\left(\frac{q(V+R_sI)}{A_1kT}\right)-1\right] - I_{s2}\left[\exp\left(\frac{q(V+R_sI)}{A_2kT}\right)-1\right] - \frac{(V+R_sI)}{R_p} \quad (1)$$

"Figure 2" shows respectively the (I-V) characteristics and (P-V), for standard conditions. To determine the behavior of the PV generator deal with various climate changes, we perform the simulation using the software "MATLAB/ SIMULINK". For this, we used as a first step, a standard solar module of 36 cells in series.We implemented the model of the PV generator and got the characteristics (I-V) and (P-V).

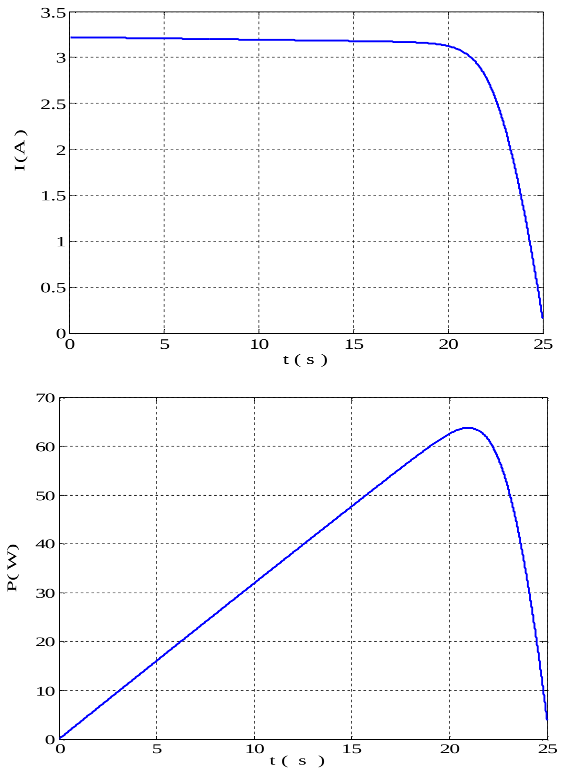
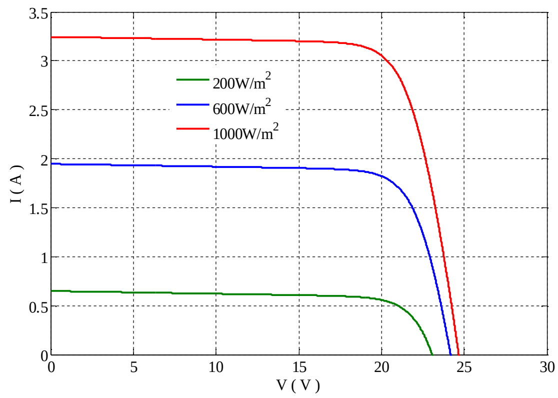


Fig. 2. Characteristics I=f(V) and P=f(V) of a cell MSX-83 at 25°C and E=1000W/m^2

The electrical characteristics of a GPV vary depending on the temperature and lighting. We simulated the behavior of the generator subject to various constraints. These notions are indeed necessary to understand the behavior of a GPV in order to optimize the operation of a GPV.

Concerning the variation of illumination, we note that for a temperature 25°C, the increase in irradiance leads to an increase in maximum power and a slight increase in open circuit voltage. The short circuit current increases dramatically with increasing illumination. This implies that the optimum power of the generator is substantially proportional to the illuminance and the maximum power points are approximately the same voltage.

The influence of temperature is significant on the operation of the generator. By varying the temperature between 0°C and 50°C under an irradiance of 1000W/m^2, we can see the influence of temperature on the characteristics I=f(V) and P=f(V).



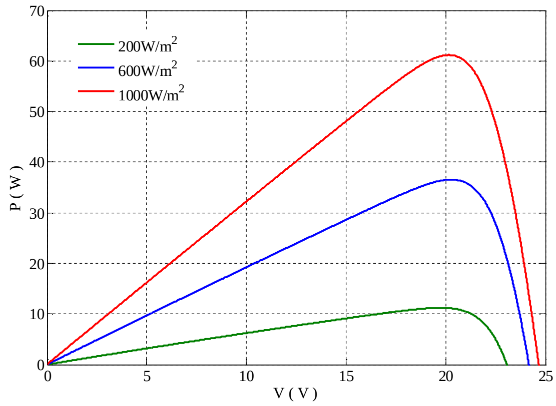


Fig. 3. Characteristics (I-V) and (P-V) for different values of radiation at 25°C

The open circuit voltage decreases significantly with increasing temperature even for the maximum power. By against, we notice a slight increase in short circuit current with increasing temperature.

For a temperature change, we deduce that the voltage changes significantly while the current remains constant. “Figure 4” shows the influence of temperature on the current-voltage characteristics and power-voltage of the photovoltaic module for a given illumination (E=1kW/m^2).

Note that when the temperature increases, the open circuit voltage V_{oc} decreases while the short-circuit current I_{sc} increases. Note that the variation of illumination clearly affects the short circuit current and the low open circuit voltage, therefore the variation of PPM is proportional to the illumination.

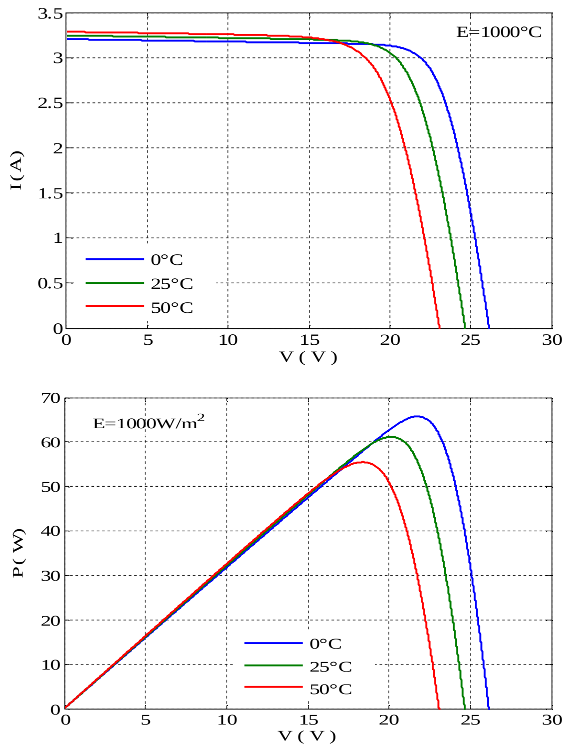


Fig. 4. Characteristics I(V) and P(V) for different temperature values to 1000W/m^2

3. Controller Maximum Power Point

The follower of maximum power point tracking (MPPT) allows the photovoltaic module to operate at its maximum power point. It is usually designed with a converter that regulates the power drawn from the solar panel. By changing the order of switches, the energy transferred by the converter can be precisely controlled. The maximum power point (MPP) is usually controlled by two control variables. The voltage or power is measured each time is used again in a loop to determine if the solar module is at maximum power point.

The intercalation of a static converter DC/DC, as shown in figure 5, changes the operating point of the panel through an external control law in order to maximize the energy transferred permanently.

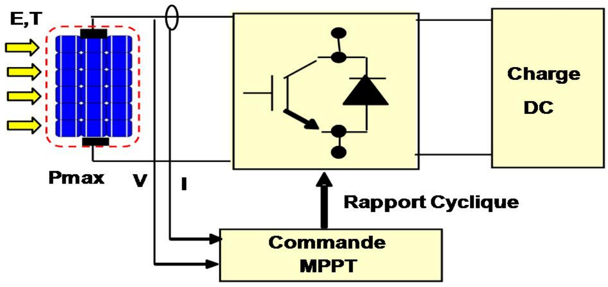


Fig. 5. Line of the photovoltaic conversion

The electrical circuit of buck-boost converter is represented in figure 6.

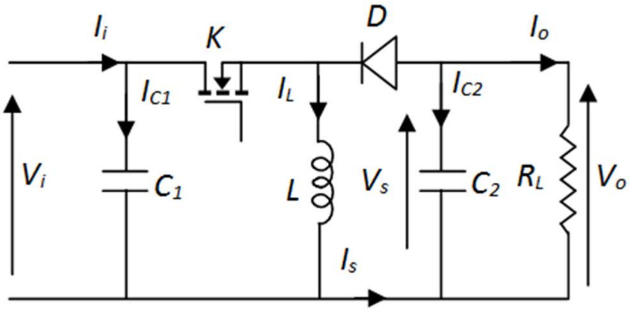


Fig. 6. DC-DC Buck-Boost converter

The dynamic model of the Buck-Boost converter is given by:

$$\begin{cases} i_L = \dfrac{1}{D}\left(i_i - C_1 \dfrac{dv_i}{dt}\right) \\ i_o = -(1-D)\, i_L - C_2 \dfrac{dv_o}{dt} \\ v_i = \dfrac{1}{D}\left(-(1-D)\, v_o + R_L\, i_L + L \dfrac{di_L}{dt}\right) \end{cases} \tag{2}$$

The conversion report V_0/V_i is given by the following expression

$$M(d) = \frac{V_o}{V_i} = \eta \frac{-d}{1-d} \tag{3}$$

Where:

$$\eta = \frac{1}{1 + \dfrac{R_L I_0}{(1-\delta)^2 V_0}} \tag{4}$$

The variation of M as shown in in figure 7.

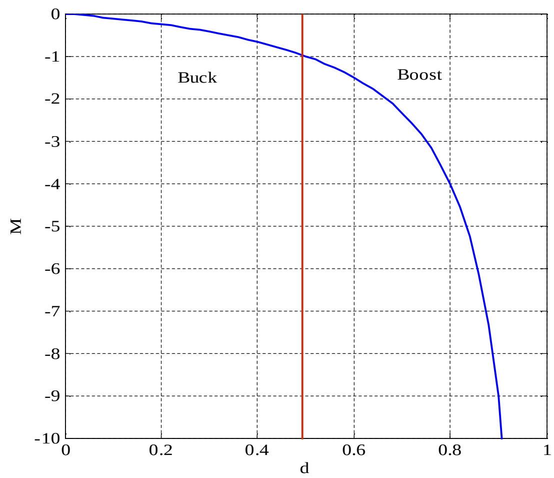


Fig.7. Conversion report M as a function of the duty cycle

Most methods of tracking maximum power point based on the power-voltage characteristic of photovoltaic energy [3]. Different control algorithms exist, we present in this paper a comparative study between different numerical method of MPPT, namely fuzzy logic (FLC) and artificial neural networks (ANN).

3.1. MPPT Control by the Algorithm Based on Fuzzy Logic

Ease of use of fuzzy logic on any application, allowed to adapt to the field of renewable energy which includes photovoltaic. Several researchers have studied this type of algorithm, especially for its application in research and the pursuit of maximum power point tracking (MPPT). This method uses a controller based on fuzzy logic applied to a DC-DC converter [2, 3].

Fuzzy logic controllers have the advantage of being robust and relatively simple to design because they do not require knowledge of the exact model. On the other hand they require perfect knowledge and complete photovoltaic system by the operator for the establishment of rules of inference.

The fuzzy controller proposed MPPT has two inputs and one output. The two input variables of the controller are the error E and the error variation CE sampled at each sampling step k. These two variables are defined by:

$$\begin{cases} E(k) = \dfrac{P(k) - P\,(k-1)}{V(k) - V(k-1)} \\ CE(k) = E(k) - E(k-1) \end{cases} \tag{5}$$

Where P (k) and V (k) are respectively: the power and voltage of GPV.

The value of E (k) shows the positioning of the operating point for the load at time k relative to the maximum power point. The value CE (k), it expresses the direction of movement of this point.

The method chosen for inference, in our work is that of Mamdani. As for the defuzzification is the center of gravity method for calculating the output, the duty cycle of DC-DC converter, which was preferred:

$$d = \frac{\sum_{j=1}^{n} \mu(d_j) - dj}{\sum_{j=1}^{n} \mu(dj)} \tag{6}$$

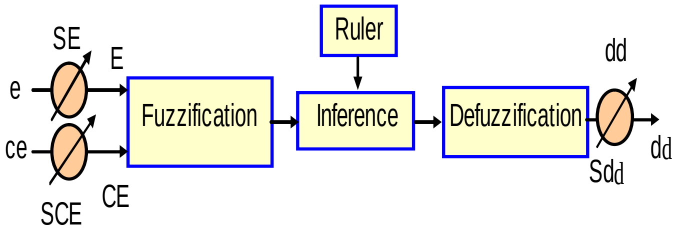


Fig. 8. General structure of a fuzzy logic controller

Generally, a fuzzy logic control consists of three blocks: Fuzzification, inference and eventually block the defuzzification.

The fuzzification itself is to define membership functions for the different variables, making the passage of a physical quantity to a quantity language. The inference rules selected were obtained from general rules applied to any system that can be ordered.

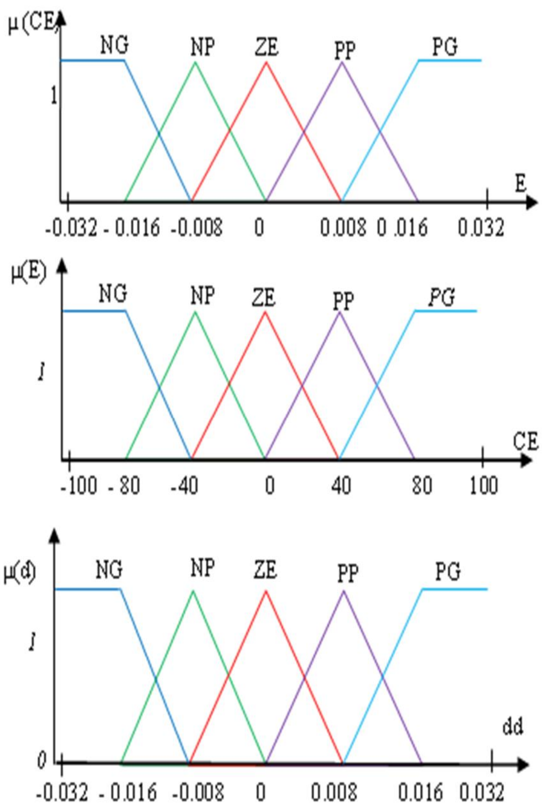


Fig.9. Membership functions of the change in error CE, the error E and the output dd

The "Table 1." shows matrix of inference of the regulator. The five linguistic variables used are: NB (Negative Big), NS (Negative Small), ZE (Zero Approximately), PS (Positive Small), PB (Positive Big) [4]. To define the control law, the fuzzy controller must be accompanied by a defuzzification procedure acts as a converter fuzzy control value in physical condition necessary for such a process. It is to calculate, based on the degrees of belonging to all the fuzzy sets of the output variable, the abscissa corresponding to the value of this output.

Table 1. Fuzzy rule table

Error	Change in error				
	NB	NS	ZE	PS	PB
NB	ZE	ZE	PB	PB	PB
NS	ZE	ZE	PS	PS	PS
ZE	PS	ZE	ZE	ZE	NS
PS	NS	NS	NS	ZE	ZE
PB	NB	NB	NB	ZE	ZE

3.2. Control by Artificial Neural Networks (ANN)

Artificial neural networks differ by the type of neurons they are made of and by the manner of their interconnection. In this paper we use the feed forward Artificial Neural Networks that are organized into cascaded layers of neurons. Feed-forward ANN allow signals to travel one way only; from input to output. There is no feedback (loops). The output of any layer does not affect that same layer. Feed-forward ANNs tend to be straight forward networks that associate inputs with outputs.

The artificial neural network (ANN) models are based electronic neural structure of the brain which is often used for optimization of the MPPT algorithm. Indeed, neural networks can be used to find the position of the maximum power point with a reduced number of iterations to reach the MPP and reduced oscillations around the latter [5][6].

Neural networks commonly have three layers: input, hidden and output layers as shown in figure 10 with two Neurons in the inputs layer, five neurons in the hidden layer and a neuron in the output layer. The numbers of nodes in each layer are variable and dependent on the user. The input variables can be parameters of photovoltaic panels as the open circuit voltage VOC and the short circuit current ISC, the atmospheric data such as irradiance and temperature, or any combination thereof. The output signal is generally one or more reference as a duty cycle signal used to drive the power converter to operate at or near the MPP[7].

The neurons of the input layer of the neural network to obtain the input signals from the illumination measurement room and temperature. The neuron in the hidden layer to receive data from the input layer, to calculate their outputs using the sigmoid activation function, and then pass them to the output layer.

The outputs of neural networks are data values of the neurons of the output layer. The neural network, using the solar radiation and ambient temperature as input, generates control signals to switching DC/DC converters lift. The output of the neural network is a duty cycle; the system adjusts the switching converter.

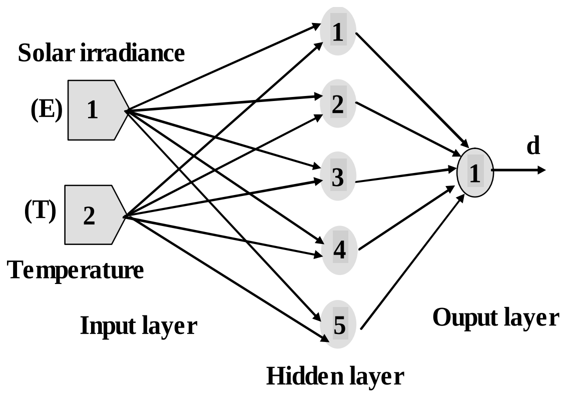
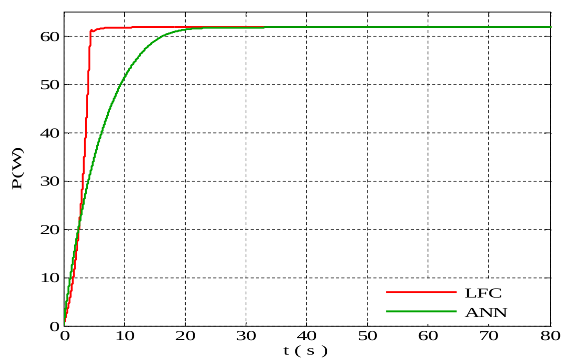


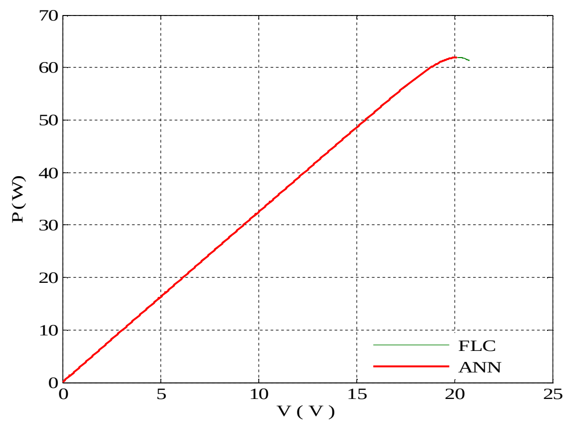
Fig. 10. Architecture of the neural network adopted

4. Simulation Result

"Figure 11" shows the characteristic (PV) in the case of operation under standard atmospheric conditions for both algorithms, fuzzy logic control (FLC) and Artificial neural networks (ANN).

We note that the value of the power of the two controllers oscillates around the value of PPM solar panel for standard conditions (temperature and irradiance). This means that the two algorithms has really taken the point of maximum power and response time of the fuzzy controller is faster than that of neural networks against by the duty cycle d is stable all the time.





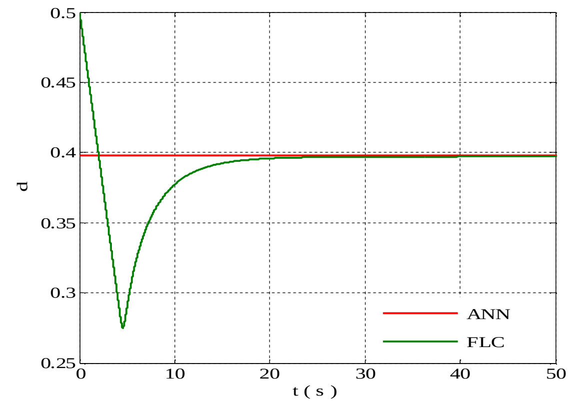
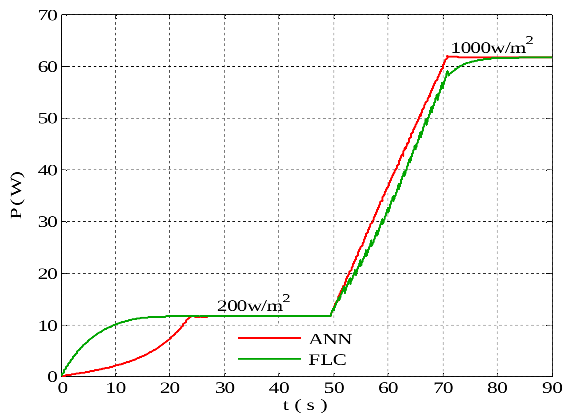


Fig. 11. Power change in standard atmospheric conditions for both algorithms fuzzy

Constant temperatures (T=25°C) increases the illumination of 200W/m^2 to 1000W/m^2 for 30s "Fig.11". We redo the same test in the other direction, by reducing the illumination of 1000W/m^2 at 200W/m^2 during the same period "Fig.12".



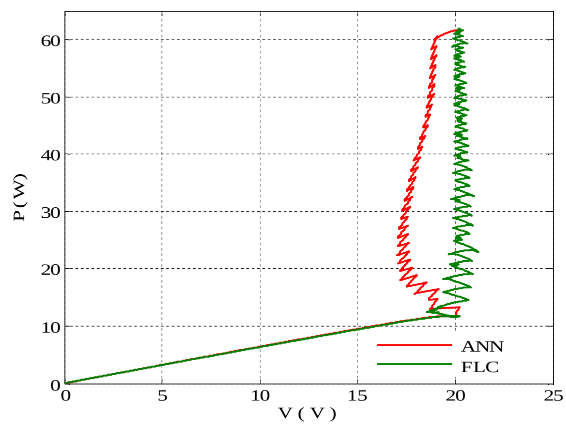


Fig. 12. Variation of the power for variations in illumination algorithms for both FLC and ANN

We note that the decrease of illumination resulted in a decrease in power and thus alters the point of maximum power, and increased sunlight also causes an increase in power. But the system controlled by fuzzy logic is faster compared to the algorithm for a neural network against the latter is more stable than fuzzy logic.

For change in temperature, initially the temperature is 25°C, t=10s augment it up to t=40s and stabilizes at T=50°C for 20s to lower 30s during and after it finally stabilizes at its initial value 25°C

"Figure 13" shows the characteristic (P-V) during simultaneous variation of temperature, sunlight has a fixed 1000W/m^2.

From "Fig 13", it is found that the increase in temperature produces a decrease in the power accompanied by a displacement of MPP and decrease in temperature produces a higher power. But the response time of the order by neural networks is slow compared with fuzzy logic.

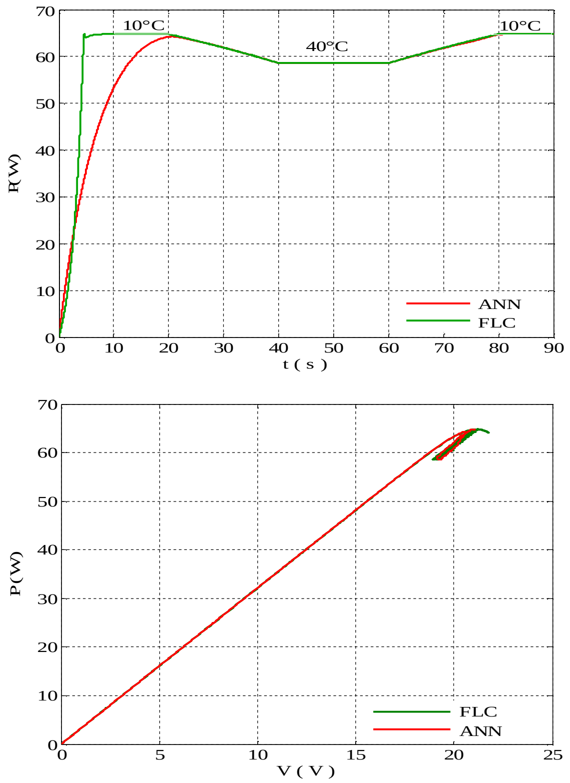


Fig. 13. Variation of the power for variations in temperature for both algorithms

5. Conclusion

To ensure the operation of a photovoltaic generator at its maximum power point, MPPT controllers are often used. These controllers are intended to further PPM and thus minimize the error between the operating power and the power maximum reference variable which is a function of load and climatic conditions. For the same purpose, several techniques have been introduced MPPT control, in this work, we presented two methods smart: neural networks and fuzzy logic to develop a system for controlling and tracking the point of maximum power to extract maximum power. The simulation results show that the system controlled by the neural network adapts to changes in external disturbances, and has a stability system. But the response time is relatively slow compared with fuzzy controller.

Electrical Characteristics of Gpv Smx-83

Number of cells in series	*36*
Maximum power	*83(W)*
Short circuit current	*3.25(A)*
Open circuit voltage	*21.2(V)*
Series resistance	*0.099(Ω)*
Shunt resistance	*200(Ω)*
Temperature coeff. of I_{sc}	*(0.065±0.015)(%/°C)*
Temperature coeff. of V_{co}	*(-80±10) (mV/%)*

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