Comparative Study of MPPT Techniques For Solar Photovoltaic System

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Abstract: **Several MPPT algorithms are proposed for photovoltaic system. In this work, various algorithms have been presented such as P&O so-called conventional, MPPT based on fuzzy logic, and the method using the artificial neural network. The aim is to compare the results of the above mentioned methods after performing the simulation with the Simulink Matlab software. Simulation results show that the artificial neural network leads to good performances.**

Keywords: **Artificiel neural network, MPPT, PV, P&O, fuzzy logic**

I. INTRODUCTION

The techniques conventionally used for input control loops consist in associating a control called MPPT (Maximum Power Point Tracking) to the adaptation stage, which performs a permanent search of the PPM (Maximum Power Point). The tracking of this maximum power point is necessary to extract the maximum power from the PV module. For this purpose, we were particularly interested in the application of the four algorithms: namely the disturbance and observation-based algorithm, increment control, fuzzy logic control, and the neural network-based algorithm in the control of DC-DC converters.

A. Conventional MPPT control: P&O

The principle of any tracking method is to move the operating point by increasing V_{pv}, when dP_{pv} / dV_{pv} is positive or by decreasing V_{pv} when dP_{pv} / dV_{pv} is negative. During transient or steady state, these commands shall estimate and compare the power with that of the previous instant. Their performances are related to the speed with which the MPP is reached, the way to oscillate around this same point, but also to the robustness to avoid divergence during sudden changes in insolation or load..

1) Principle

The "P&O" disturbance and observation method is the most widespread in the industrial environment, because its algorithm is easy to implement. This process works by disturbing the system by increasing or decreasing the operating voltage of the module and observing its effect on the output power of the row.

To do this, the voltage V and the current I are measured to calculate the actual output power P(k) of the row. This value is compared to the P(k-1) value of the last measurement. If the output power has increased, the disturbance will decrease in the same direction. If the power has decreased since the last measurement, the output voltage disturbance will be reversed in the opposite direction of the last cycle.

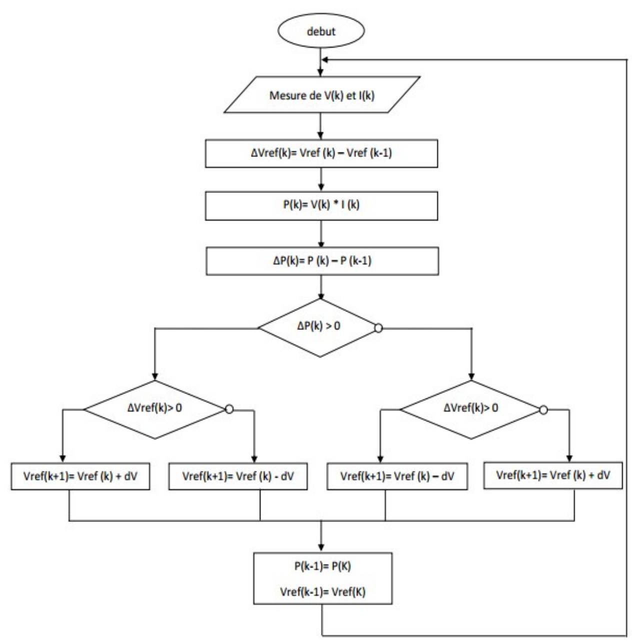
2) Algorithm

With the following algorithm, the operating voltage V is disturbed at each cycle of the MPPT. As soon as MPP is reached, V will oscillate around the ideal operating voltage V_mp. This causes a power disturbance that depends on the step width of a positive increment (dv) of the voltage Vpv.

The choice of dv is the result of a logical experiment because :

If dv is large, the MPPT algorithm will respond quickly to sudden changes in operating conditions, but losses will be increased under stable or slightly changing conditions.
If dv is very small, losses under stable or slowly changing conditions will be reduced, but the system will no longer be able to keep up with rapid changes of temperature or insolation.

Figure 1 : The P & O control algorithm.



B. Fuzzy MPPT control

Fuzzy logic is emerging as an operational technique. Used alongside other advanced control techniques, it makes a quiet but appreciated entry into industrial control automation. Fuzzy logic does not necessarily replace conventional control systems, but is complementary to them.

Fuzzy logic is a very powerful technique derived from fuzzy set theory, to fill the gap between the precision of conventional logic and the imprecision of the real world. Its fundamental characteristic is the use of linguistic variables instead of numerical variables in fuzzy conditional situations.

1) Use for control

Fuzzy logic is well known to automation engineers for its applications in process control, commonly referred to as "fuzzy control". Just like a conventional controller, the fuzzy controller is inserted in the control loop and calculates the command to be applied to the process according to one or more setpoints and one or more measurements carried out on the process. This controller is broken down into three blocks: fuzzification, inference and defuzzification.

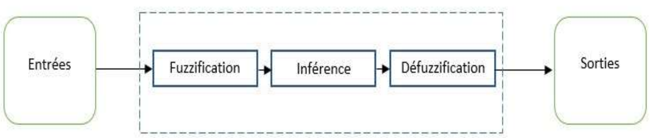


Figure 2 : Fuzzy controller

2) The fuzzification

This part transforms the digital inputs into fuzzy sizes. The inputs are transformed into linguistic variables described by membership functions. Our fuzzy controller uses trapezoidal and triangular membership functions. These are the simplest forms, composed of pieces of straight lines. We choose n=5 the number of membership functions which will result in 25 inference rules. The input variable, its variation and the output variable are subdivided into five classes.

- NG : Negative Large
- NP : Negative Small
- Z : Zero
- PP : Positive Small
- PG : Positive Large

MAMDANI's method of inference requires that we find the center of gravity of a two-dimensional shape by integrating through a continuous variable function. This process is usually not very emotional. SUGENO therefore suggested using a singleton. Instead of a fuzzy set for MAMDAMI, we then use a mathematical function of the variable input of type:

If [(x is A) and (y is B) then s [z is C]

Since we are going to work on the power and voltage of the photovoltaic generator, two input variables are used in this system, the first input of the fuzzy controller E represents the slope of the P-V characteristic curve:

$$E_k = \frac{P_{(k+1)} - P_{(k)}}{V_{(k+1)} - V_{(k)}} \quad (1)$$

The second entry ΔE is given by :

$$\Delta E = E(k+1) - E(k) \quad (2)$$

The membership functions of the input variables are of the triangular and trapezoidal type. Their arrangement is symmetrical and equidistant:

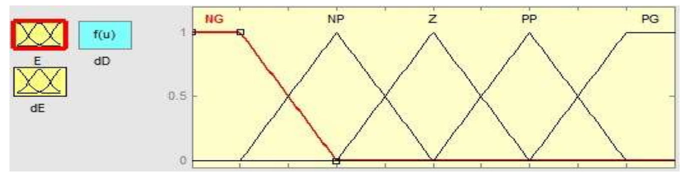


Figure 3 : E Membership Functions

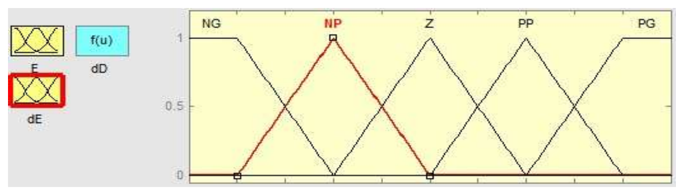


Figure 4 *:* dE Membership Functions

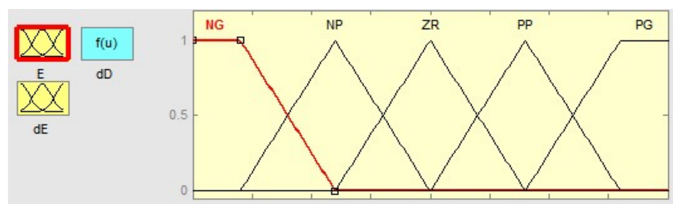


Figure 5 : Dd Membership Functions

3) Inference method

The value of the static converter pilot output variable to search for PPM (Maximum Power Point) is determined using a truth table and the evolution of the input parameters. This output variable depends on the combination of the inputs E and ΔE.

Let's take the following inference table as an example: If E is ΔE Z : this means that the output (operating point) is far away from the setpoint (maximum power point). This therefore leads to a decrease in the value of d_α (duty cycle), d_α is NG.

Table 1: Inference Table

E/ΔE	NG	NP	Z	PP	PG
NG	Z	Z	PG	PG	PG
NP	Z	Z	PP	PP	PP
Z	PP	Z	Z	Z	NP
PG	NP	NP	NP	Z	Z
PG	NG	NP	NP	Z	Z

For our application therefore, the fuzzy inference method chosen is Sugéno's method with the operator SOMME-PROD, which consists in using :

For the condition: OR in SUM; AND in Poduct

For the conclusion: THEN in Product

For linking rules: OR in sum

The output is directly given by real numbers.

4) Defuzzification

Once the fuzzy regulation is done, it is necessary to convert the linguistic variable of the output $d\alpha$ into a digital variable in order to be able to drive the power converter. The value assigned to the duty cycle $d\alpha$ will be governed by the expression :

$$d_{\alpha} = \frac{\sum U_{\alpha i} \times \alpha_i}{\sum U(\alpha_i).} \qquad (3)$$

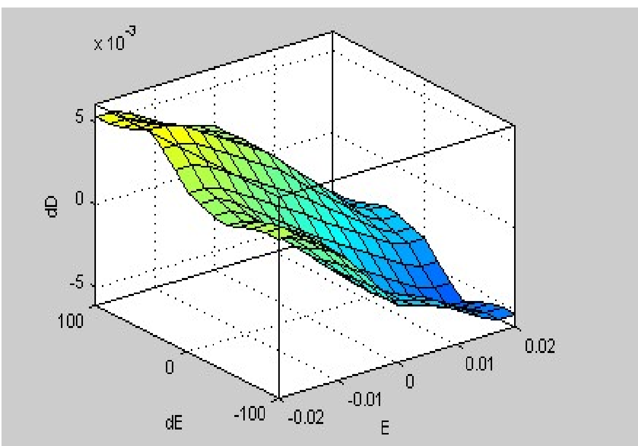


Figure 1 : FLC rules on the surface

C. MPPT control by neural network

After starting the simulation of the fuzzy command, the data can be acquired (inputs:V_{pv} and I_{pv} ; the target output: d).

Having the input and output data, we can proceed to the creation of the network by launching the ".m file " which contains the functions of the Matlab toolbox for neural networks in order to carry out the training. At the end of the learning, thanks to the command «gensim(net)», we obtain the following block :

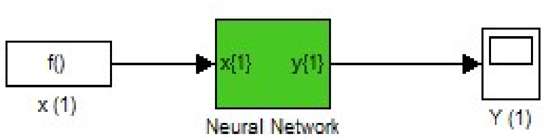


Figure 2 : Simulink block of the neural network

By introducing this block into the control system for the converter we have this:

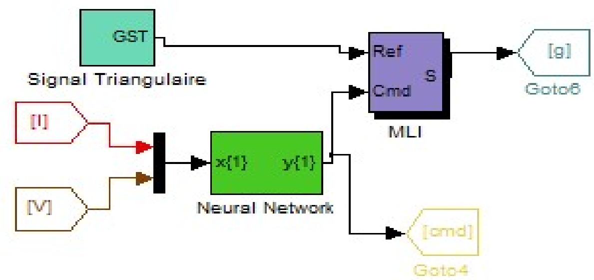


Figure 9 : Control block

- V is the voltage and I is the current from the PV generator.
- g is therefore the switching command of the booster converter.

D) Simulation results

1) Characteristics of the photovoltaic panel

For the simulation, the characteristics of the photovoltaic panel are illustrated in the following table:

Reference :

Table II :Characteristics of the photovoltaic panel

Parameters	Values
Maximum power	58 W
Maximum power voltage	16.46 V
Maximum power current	3.5 A
Open circuit voltage	21.1 V
Short circuit current	3.8 A
Temperature coefficient of Isc (Ki)	0.002
Temperature coefficient of Voc (Kv)	0.073
Number of cells in series	36
Number of modules in series	1
Number of parallel branches	1

The following figure shows the voltage output values for a data pair of temperature and insolation equal to (25◦C,1000W/m^2) for each of the commands.

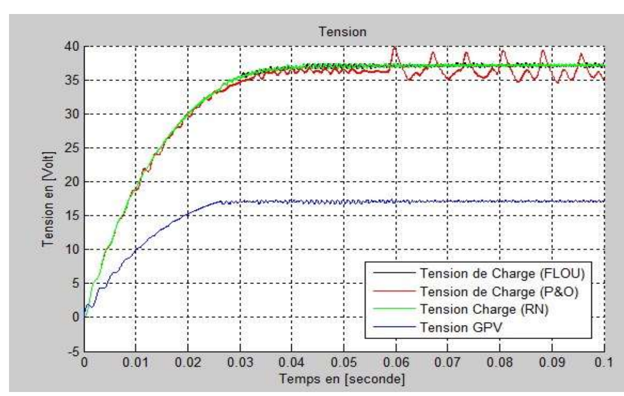
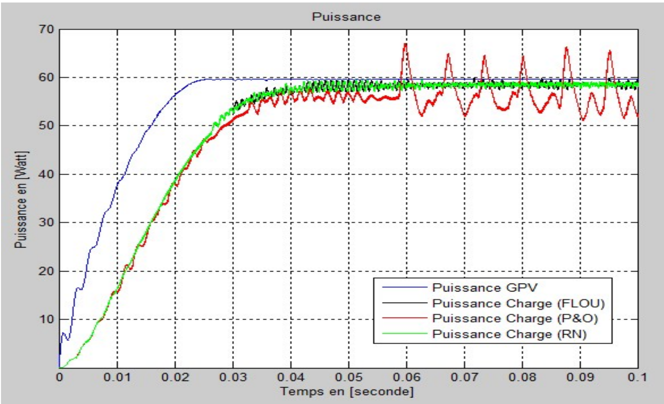


Figure 3 : Output voltage

The curves in the figure below show the power output values for a data pair of temperature and insolation equal to (25◦C,1000W/m^2).



The two previous simulation figures actually show that the photovoltaic system with each of the controls converges towards the maximum values.

2) The variation of insolation

In order to be able to clearly demonstrate the tracking capability of the algorithms, the following variations of insolation are considered.

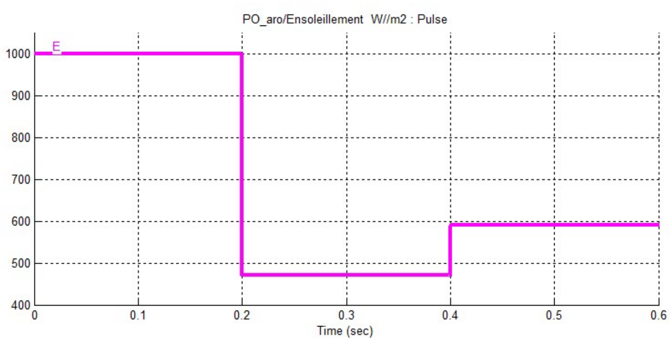


Figure 4 : Variations of insolation

3) Voltage

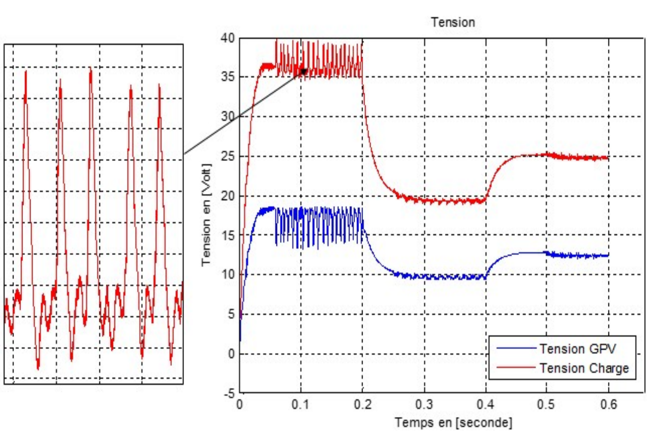


Figure 5 : Voltage: by the P&O control

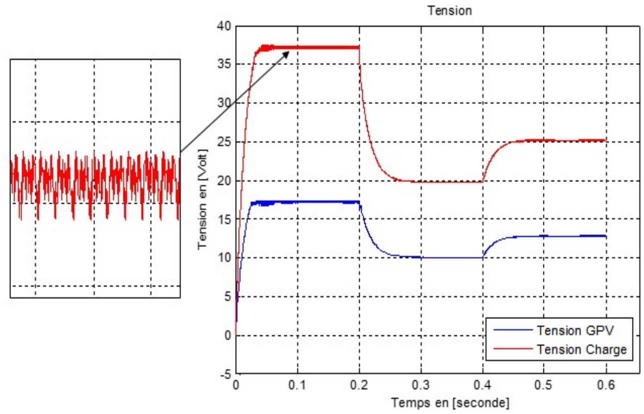


Figure 14 : - Voltage: by the Fuzzy control

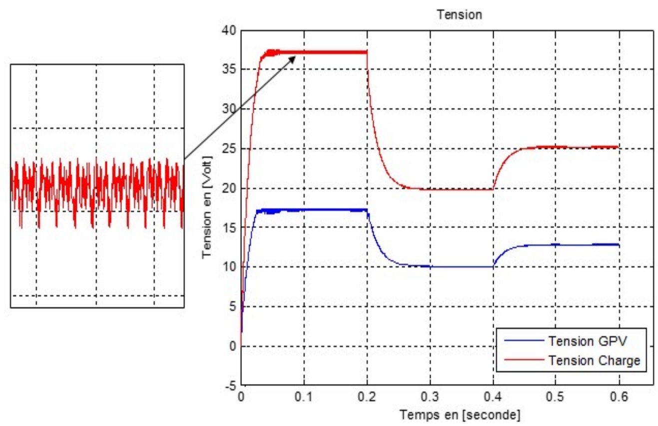


Figure 6 : Voltage: by neural network control

We find that the algorithm-controlled chopper provides a voltage at its output that is higher than that provided by the photovoltaic generator. However, the P&O control has an oscillation around the PPM, as well as for slightly changing conditions. It is then important to carefully evaluate the positive increment to apply to the reference voltage in order to limit these oscillations as much as possible. In the case of fuzzy logic, the servo has a good performance: precision, speed and stability as well as good tracking capability. Then there is a clear improvement of the tracking response by applying neural network control. The choice of the example (that of fuzzy logic) that we made obviously helped in the learning process.

4) Current

The current varies inversely to the voltage so that their product always gives the maximum power desired. As well as the voltage curves, we can see the improvements in the results obtained by neural network control compared to the other two algorithms. The following figures show these variations:

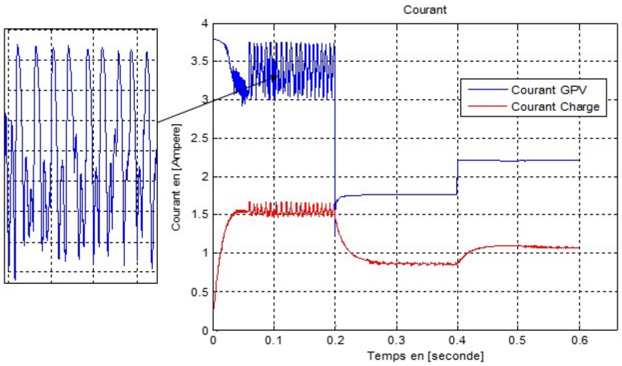


Figure 16 : The current: by the P&O control

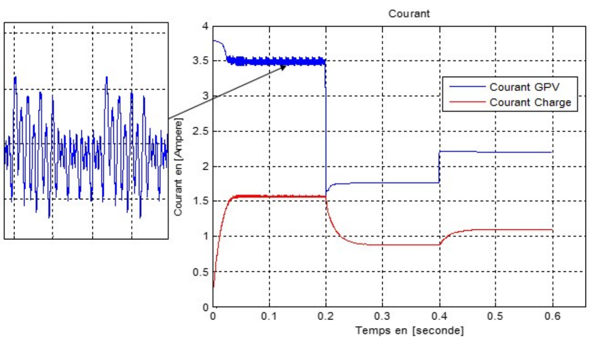


Figure 17 : The current: by the Fuzzy control

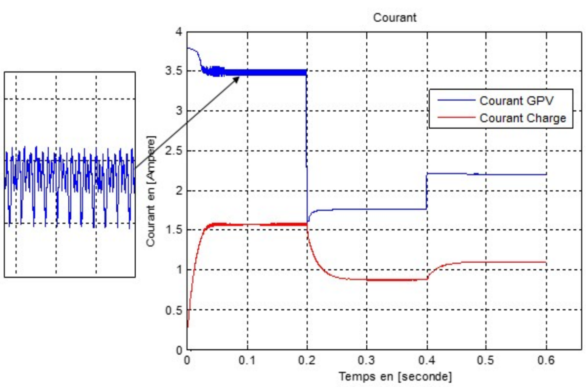


Figure 7 : The current: by neural network control

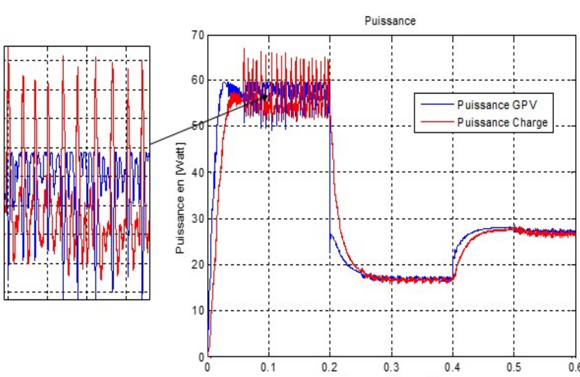


Figure 8 : Power: by P&O control

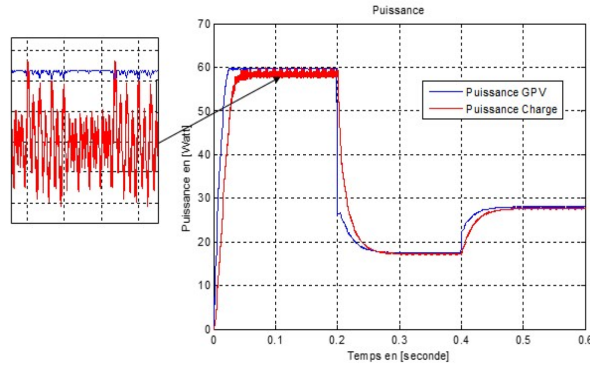


Figure 20 : Power: by the Fuzzy control

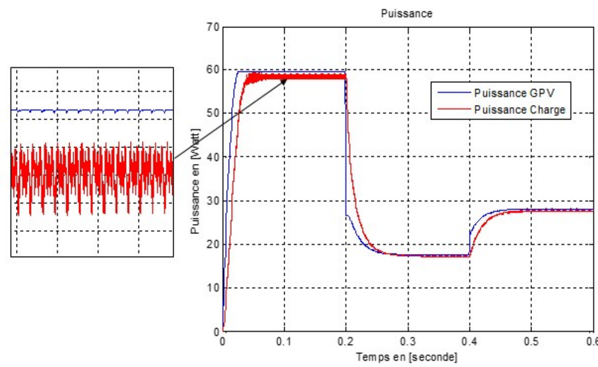


Figure 9 : Power: by neural network control

After a transient regime lasting 0.06 s (figure 4.8) , the MPPT controls reach the maximum power point for the first level of insolation (25◦C ,1000W/m2). In the first case of a change in sunlight intensity, it appears that the system converges to the new PPM in 0.08 s, this state corresponds to an imposed illuminance of 470W/m2. During the second change in sunlight intensity, the system also converges to the PPM corresponding to 590W/m2 in 0.08 s. Simulation results prove that this system can reach the point of maximum operating power for external disturbance variations.

II. CONCLUSIONS

The P&O method is frequently used although it presents problems of oscillations around the PPM because the research must be repeated periodically to force the system to oscillate around the PPM. In addition, for abrupt variations in weather conditions and/or load, this method sometimes presents misinterpretations in the direction that must be followed to reach the MPP. Fuzzy control, on the other hand, is necessary to bridge the gap between the accuracy of classical logic and the imprecision of the real world, especially in situations where there are large uncertainties and unknown variations in the system settings and structure. Moreover, we can clearly see an improvement of the curve regarding the control by the P&O algorithm. Finally the neural network, this result is obtained from many tests by varying the number of hidden layers but also by varying the number of neurons in these layers. We can see that the curves become more refined. With their ability to adapt to unknown situations through learning, we can see that neural network control shows a good compromise between characterization and computational efficiency. Its robustness, its speed and the accuracy of its outputs allow it to make correct decisions and avoid cases of indecision.

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