NEURAL NETWORK APPLIED ON A SOLAR ENERGY SYSTEM

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ABSTRACT
In this context, the optimization of photovoltaic energy production is studied and presented. In order to extract the maximum available power delivered by the photovoltaic generators (GPV), the technique using an adaptation stage between the generator and the load is chosen. This stage acts as an interface between the two elements by ensuring, through a control action, the transfer of the maximum power supplied so that it is as close as possible to the maximum power. For this purpose, we have been particularly interested in the application of the algorithm based on the neural network in the control of this adaptation stage associated with the photovoltaic generator to ensure its operation at its point of maximum power. Simulation results show that this system adapts to variations in external disturbances and has a relatively small peak at transient state and a uniform steady-state speed. The controller gives satisfactory results and shows their effectiveness not only in tracking the point of maximum power but also in response time.

KEYWORDS: MPPT, PV, neural network, intelligent control technology, optimization.

INTRODUCTION
The conventionally techniques used for input control loops consist in associating to the adaptation stage a control called MPPT (Maximum Power Point Tracking) which performs a permanent search of the MPP (Maximum Power Point). Tracking 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 neural network-based algorithm in the control of DC-DC converters.

OPTIMAL VALUES TO EXTRACT
The reference voltage is obtained from the relationship between $\mathbf{V_{opt}}$ and $\mathbf{V_{oc}}$ of the module PV:

$$\mathbf{V_{opt}} = \mathbf{k_v} \times \mathbf{V_{oc}} \quad (1)$$

Where $\mathbf{k_v}$ is a voltage factor that depends on the GPV used and the operating temperature Generally, for GPVs in Si,

$0,71 < k_v < 0,78$.

The optimum power is calculated by the following relationship:

$$\mathbf{I_{opt}} = \mathbf{k_i} \times \mathbf{I_{cc}} \quad (1)$$

Where $\mathbf{k_i}$ is the current factor which depends on the GPV used, generally between 0.78 and 0.92.

MPPT CONTROL BY NEURAL NETWORK

For the implementation of the neural network then, we need to:

- Determine the relevant inputs, i.e. the quantities that have a significant influence on the phenomenon we want to model.
- Collect the data necessary for learning and evaluating the performance of the neural network.
- Find the number of hidden neurons needed to obtain a satisfactory approximation.
- Estimate the values of the parameters corresponding to a minimum of the function for learning (maximum desired error, error gradient...).
- Evaluate the performance of the neural network at the end of the learning process.

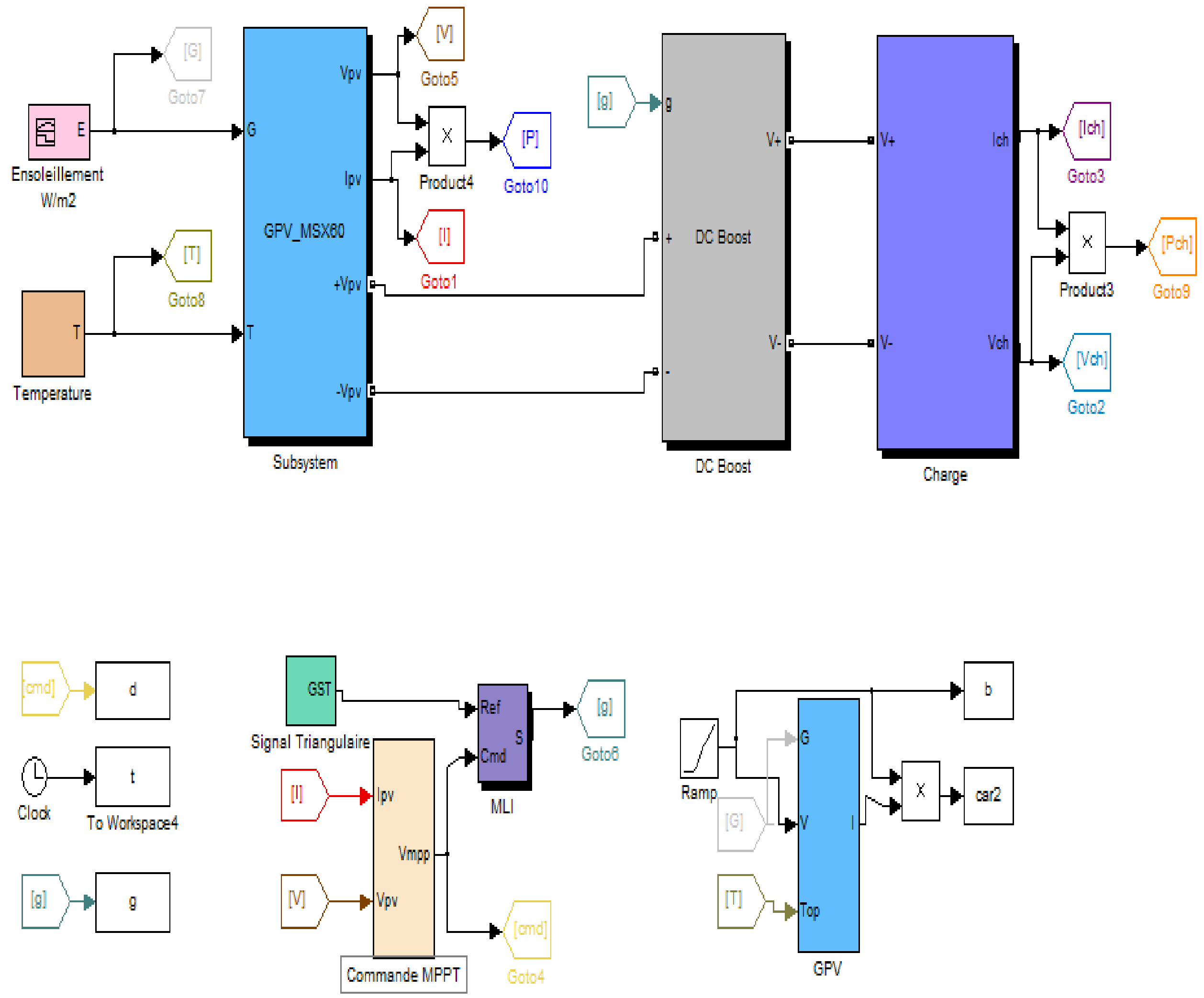

Figure 1– Block diagram of a photovoltaic module

3.1 Choice of Neural Structure

In the neural network implementation, the chosen input variable is the torque (V_{pv},I_{pv}) according to solar radiance (G) and temperature (T) and the output is the reference voltage that will be used in the pulse width modulation. For these variables are relevant to the variation of the output. In our work then, we built a multilayer neural network with:

- Two inputs: V_{pv} and I_{pv}
- A hidden layer with ten neurons (after several experimental trials).
- A single-neuron output layer, corresponding to the reference voltage.

For the transfer function, the sigmoid function was used for the intermediate layers and the linear function for the output layer.

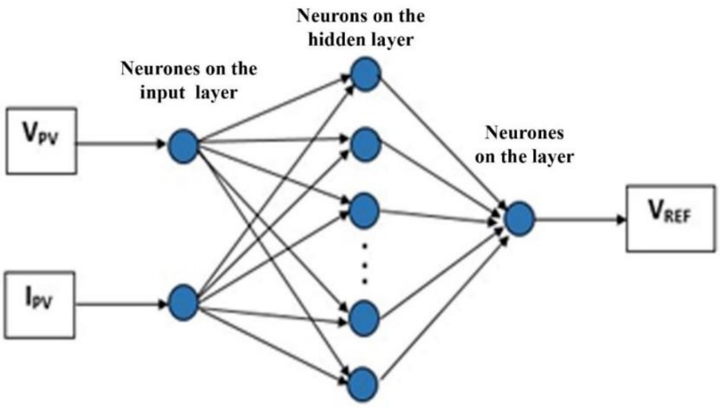

Figure 2 - Neural structure for MPPT control

3.2 Data Collection for Learning

In order to create our neural network, we need a prepared learning base (as shown later, the results obtained by the fuzzy logic MPPT command are much better compared to those of the "perturb and observe" MPPT command). We are going to build our base by the data coming from the fuzzy command.
From these data, we can then perform the learning of our network.

3.3 Neural Network

After launching the simulation of the fuzzy command, we can acquire the data (inputs: V_p 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:

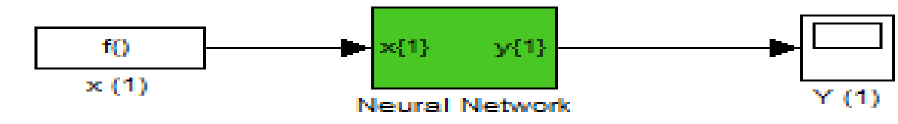

Figure 3 - Neural Network Simulink Block

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

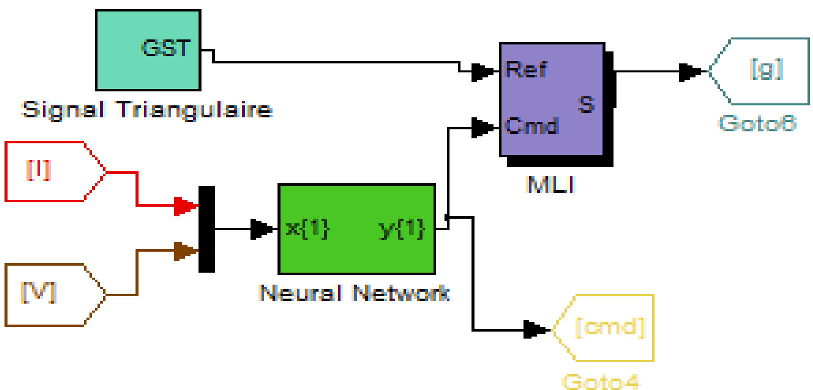

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Figure 4 - Control block

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

SIMULATION RESULTS

4.1 Characteristics of the Photovoltaic Panel

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

- **Reference :**

Table 1 - Characteristics of the photovoltaic panel

Maximum power (Pmax)	58W
Voltage at Pmax (Vmax)	16.46V
Current at Pmax (Imax)	3.5
Open-circuit voltage (Voc)	21.1
Short-circuit current (Isc)	3.8
Temperature coefficient of Isc (Ki)	0.002
Temperature coefficient of Voc (Kv)	0.073
Number of serial cells	36
Number of serial modules	1
Number of parallel branches	1

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

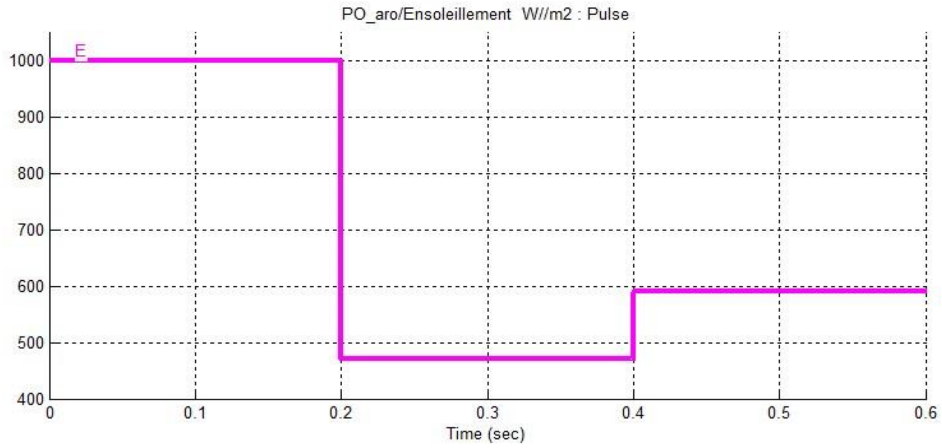

Figure 5 - The variation of the insolation

4.2 Voltage

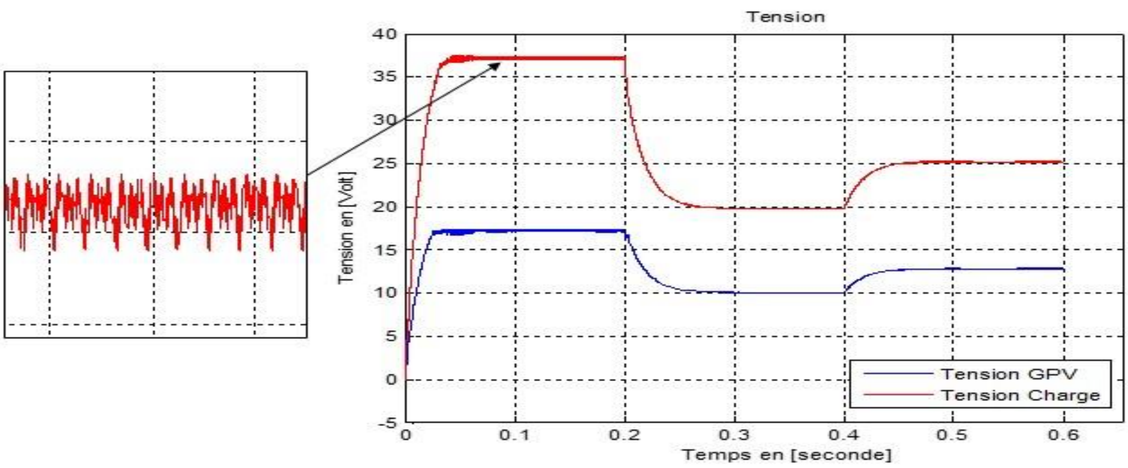

Figure 6 - Voltage: through neural network control

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 be applied 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: accuracy, 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.

4.3 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

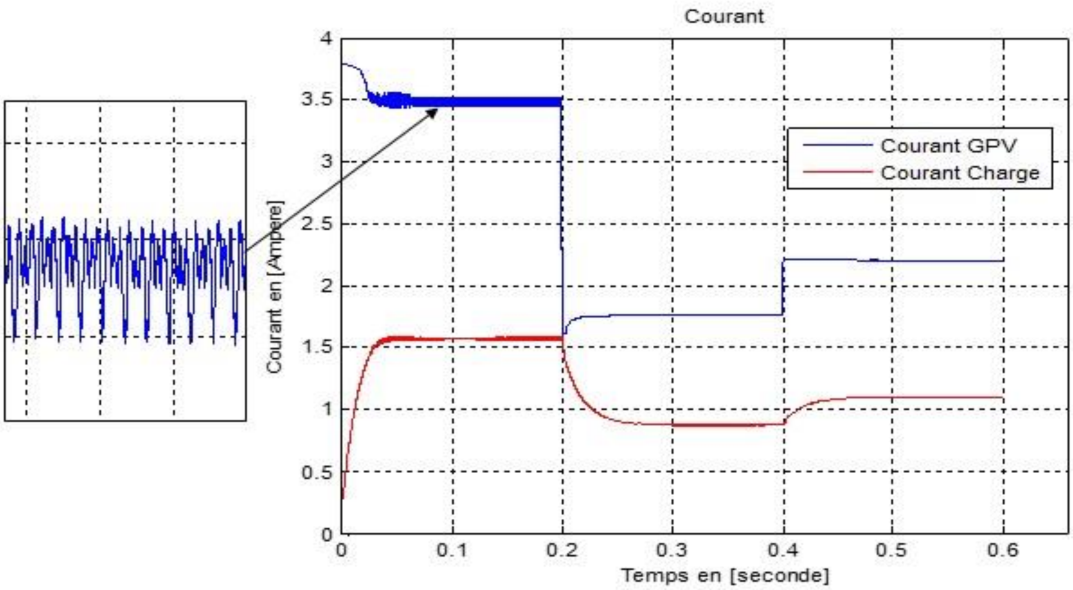

Figure 7 - Current: through neural network control

4.4 Power

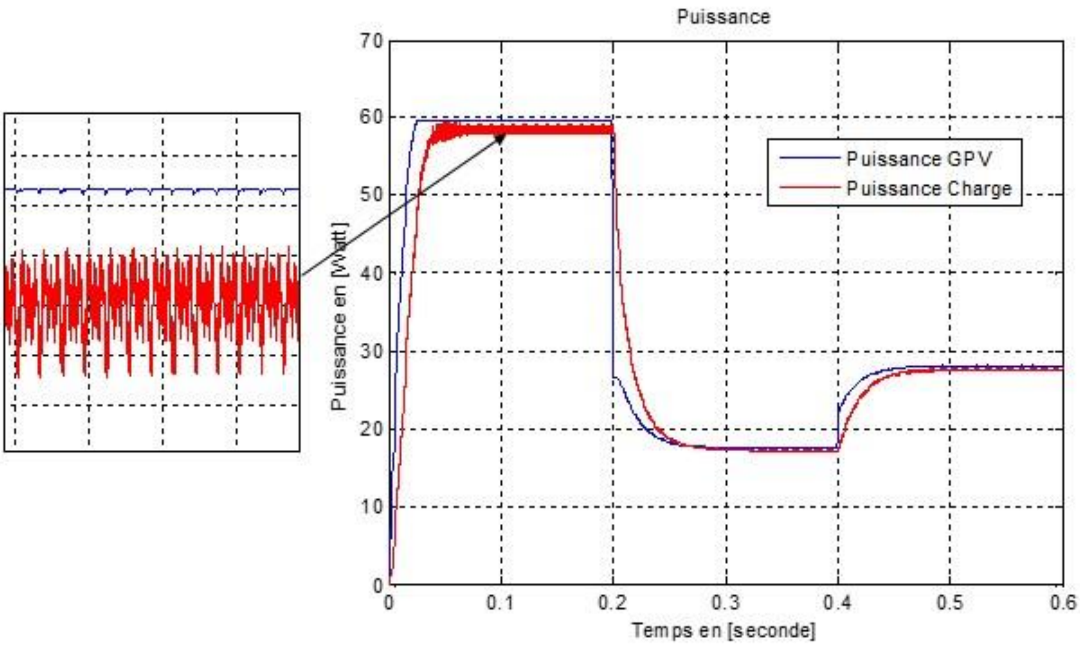

Figure 8 - Power: through neural network control

After a transient state lasting 0.06 s (figure 4.8), the MPPT controls reach the maximum power point for the first level of insolation (25◦C ,1000W/m^2). 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/m^2. During the second change in insolation, the system also converges to the PPM corresponding to 590W/m^2 in 0.08 s. Simulation results prove that this system can reach the point of maximum operating power for external disturbance variations.

CONCLUSION

In the context of a PV solar energy system, the problem is usually a non-optimal exploitation of the system. Then an adaptation is necessary to maximize the system's performance. There has been a very significant variation in the duty cycle of the inverter when illuminance and temperature vary. In order to solve this problem, some algorithms based on artificial intelligence have been presented to always extract the maximum power. For this method, first some theories were defined and then the neural network was created. Simulation results show that this system adapts to variations in external perturbations and has a relatively small peak in the transient state, and a uniform steady-state speed. It can be concluded that neural network control shows a good compromise between characterization and computational efficiency. Its robustness, speed and accuracy of its outputs allow it to give correct decisions and to avoid cases of indecision. Moreover, the controller gives satisfactory results and shows its efficiency not only for the tracking of the point of maximum power but also for the response time. It can also be deduced that the obtained output signals present the reliability of MPPT control and the simulation results of the algorithms show the performance of the neural network algorithm.

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