Maximum Power Point Tracking Method Based on Perturb and Observe Coupled with a Neural Network for Photovoltaic Systems Operating Under Fast Changing Environments

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ABSTRACT

The output power of Photovoltaic (PV) arrays presents a nonlinear behavior. Its maximum power point varies with the cell's temperature and solar radiation. It is due to this situation that Maximum Power Point Tracking (MPPT) methods have been proposed and used in order to maximize the PV array output power. This paper presents an artificial neural network (ANN) combined with the classic Perturbation and Observation (P&O) algorithm to accelerate the search of such Maximum Power Point. Simulations generated using Matlab/Simulink show the improvement compared to the P&O alone and the hardware implementation, using a 16-bit microcontroller corroborates these findings.

Keywords: Neural Network, Photovoltaic, Perturbation and Observation, Maximum Power Point Tracking.

1. INTRODUCTION

With diminishing costs, the use of PV systems for generating electrical power is expanding all over the world, even though PV panels are low-energy conversion efficient. They convert solar radiation into electrical energy, and optimizing them to its maximum output, using MPPT systems, becomes an essential task.

Besides varying by the cell's temperature and solar radiation, the MPP changes as a function of the voltage presented at the cell's output. A DC-to-DC converter is used by an MPPT system in order to change the cell's output voltage and it is this feature that allows tracking the MPP. There are different methods presented in the literature to achieve maximum power. The most prevalent methods are: perturb and observe (P&O), incremental conductance (IC), fractional short-circuit current, fractional open-circuit voltage, fuzzy logic, and ANN.

P&O and IC are well tested methods, simple algorithms with low cost implementation. However, on situations where the irradiation changes rapidly due to changing atmospheric conditions, such as clouds, the overall tracking efficiency of these methods may drop noticeably. They even present a fluctuation of output power around the MPP even under steady irradiation, which results in the loss of available solar energy.

For fast changing atmospheric conditions, many MPPT algorithms have been proposed. In (1), a current-based and a voltage-base, MPPT techniques, are presented. Both methods are simple and fast. However, they present poor tracking efficiencies for low irradiation levels. In (2), MPPT control rules are created based on a prediction line that relates the MPP and the optimum current. There is a trade-off between steady-state performance and speed of tracking, hence, several techniques have been proposed, like parabolic prediction, variable step-size, steepest descent and fuzzy logic control-based (3-8). These techniques present faster dynamic response and a smoother steady state than the traditional P&O and IC methods, however, all utilize two output power samples corresponding to two steady-state operating points to determine the incremental value of the control variable. Hence, when the operating point is adjusted, they need to wait for all transients to settle before recording information.

In this paper, a simple approach for improving the MPP tracking time using the classic P&O method is proposed. An ANN is built and trained to generate the locus of the MPP on changing atmospheric conditions. This locus is used by the P&O method to find the new MPP without doing an extensive tracking process.

The paper is organized as follows: A description of a PV system is presented in section 2. In section 3 the P&O is described. The ANN is detailed in section 4, and in section 5 the results are presented.

2. PHOTOVOLTAIC CELL MODEL

A photovoltaic (PV) cell is an electric device that transforms light energy (photons) into electric energy (free electrons flux). It operates similar to a common diode. There are several mathematical models to simulate a PV cell and are derived from the Shockley equation

$$I_D = I_0\left(e^{\frac{V_D}{nV_t}} - 1\right) \tag{2.1}$$

$$\mathrm{V_t} = \frac{\mathrm{kT}}{\mathrm{q}} \tag{2.2}$$

In these equations I_D is the diode current, V_D is the diode voltage, I_0 is the diode reverse saturation current, V_t is the thermal voltage, *n* is de ideality factor for a p-n junction, *k* is the Boltzmann constant (1.3806503x10-23 J/K), *T* (in Kelvin) is the temperature of the p-n junction, and *q* is the electron charge. For this work it was used the standard model of five parameters, see Figure 1 and Equation 2.3

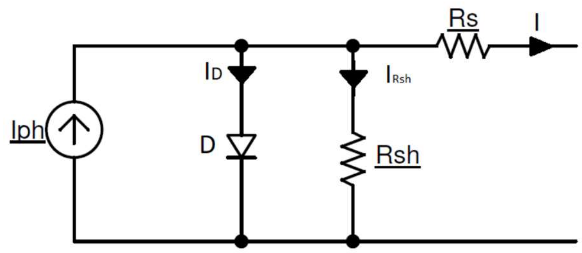

Fig. 1. 5-parameter PV cell model

$$I = I_{ph} - I_0\left(e^{\frac{V+IR_S}{V_t}} - 1\right) - \frac{V+IR_S}{R_{sh}} \quad (2.3)$$

where, *I* is the output current, *V* is the output voltage, I_{ph} is the generated current under a given radiation, R_s is the series loss resistance, and R_{sh} is the shunt loss resistance. Here, the unknown parameters are I_{ph}, I_o, R_s, R_{sh}, and V_t. The processes to find these variables are described in (9, 10) where there are known parameters: I_{sc}, V_{oc}, I_{mpp}, V_{mpp}, given by the manufacturer of the PV cell for standard conditions.

3. PERTURB AND OBSERVE (P&O)

This algorithm uses a simple feedback arrangement and scant measured parameters. The PV cell voltage is periodically given a perturbation and the corresponding output power is compared with that of the previous perturbing cycle. In this algorithm, if a perturbation is introduced to the system (e.g. a variation in irradiance), it causes a variation of the power output of the PV cell. If the power increases due to the perturbation ($\Delta P \geq 0$) then if the variation of voltage is positive, the duty cycle is decreased, otherwise, the duty cycle is increased, see Figure 2.

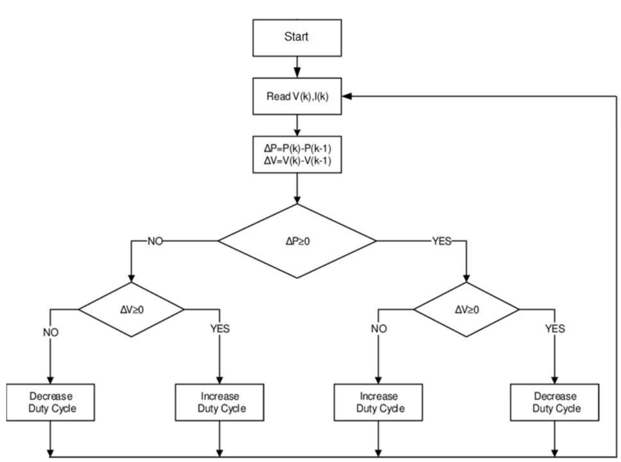

Fig. 2. Perturb and Observe Algorithm

When the stable condition is reached ($\Delta P = 0$), the algorithm oscillates around the peak power point. In order to maintain the power variation small, the variation of the duty cycle should be very small. But the trade-off is that a very small variation of the duty cycle increases the time for reaching the stable condition. Nevertheless, this algorithm is very popular due to its simplicity. The duty cycle is the pulse in a pulse width modulation output used in a buck converter (DC-DC). This electric circuit varies the output voltage, hence allows finding the MPP for the PV solar panel where it is applied. A buck converter was developed in order to comply with the parameter requirement of the PV solar panel used and to be able to measure each point for validation purposes

4. ARTIFICIAL NEURAL NETWORK (ANN)

ANN can be thought of as a black box device fed with inputs and produces outputs (11), and they are appropriate for the modeling (approximation) of nonlinear systems. In this work, an ANN is used to give an initial estimate of the optimum voltage, which corresponds to the MPP, for any given solar radiation. For that purpose, there were tested feedforward neural networks (FNN) as well as recurrent neural networks. The best results were obtained with an RNN with the structure presented in Figure 3

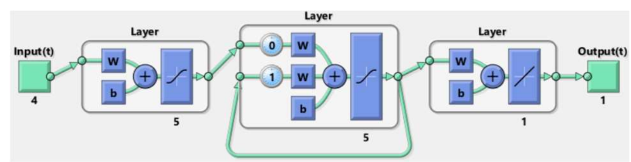

Fig. 3. Recurrent Neural Network

This RNN has four inputs, five neurons in its two hidden layers and with feedback in the second hidden layer. The four-input data are two values, each from current and voltage measurements from the PV cell array, one set of values is from the last measurement and the other set is from a previous measurement, which is calculated by the system according to the sample frequency employed. In this work, with a sample frequency of 1 minute between samples, the immediate previous measurement was the value selected. The ANN output is the voltage value for the MPP and this value is then used by the P&0 algorithm to start tracking its own MPP.

5. SIMULATIONS AND EXPERIMENTAL RESULTS

To design the algorithms for the MPPT system, it was needed a model of a photovoltaic array as precise as possible as a real one. The 5-parameter PV cell model described in section 2 was adapted to simulate the PV solar module Shell PowerMax Ultra SQ85P with the following features: 32 cells in series, Pmpp (power at the MPP) = 85W, Vmpp (voltage at the MPP) = 17.2V, Impp (current at the MPP)= 4.95A, Voc (voltage at open circuit) = 22.2V, Isc (current at short circuit)= 5.45A. It was used the “solar cell” block from Matlab/Simulink for simulation. It was possible to plot voltage vs power for the real panel at controlled irradiance levels and compare it to the plot generated by Matlab/Simulink. The difference at the MPP was 0.54%. The two plots are shown in Figures 4 and 5.

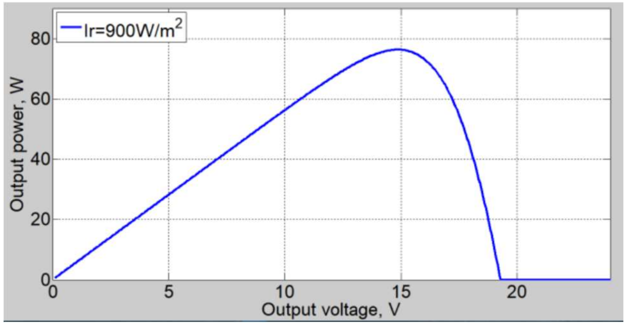

Fig. 4. Voltage vs Power generated using Matlab/Simulink

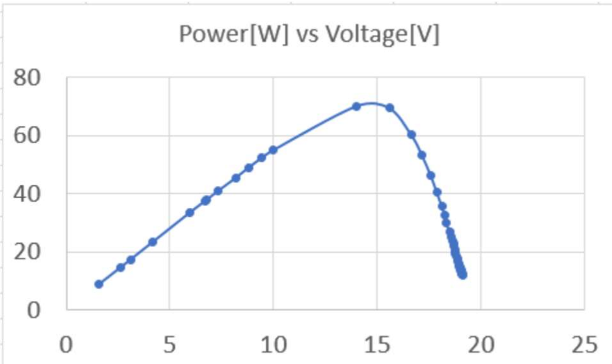

Fig. 5. Voltage vs Power from the PV solar panel

For training the ANN data from (12) was used. Data was arranged on sets (current and voltage generated by the PV solar module and the voltage for the MPP), measured once per minute from 05:00 to 19:00. There were two sets, named Data1 for a day with low variations and irradiance on the whole panel, Data2, Data3 and Data4 were selected from days with high variation on irradiance level and partial irradiance on some of the cells, see Figure 6. For validation it was selected a day in which there were present two differentiated intervals, one with low variations and another with high variations.

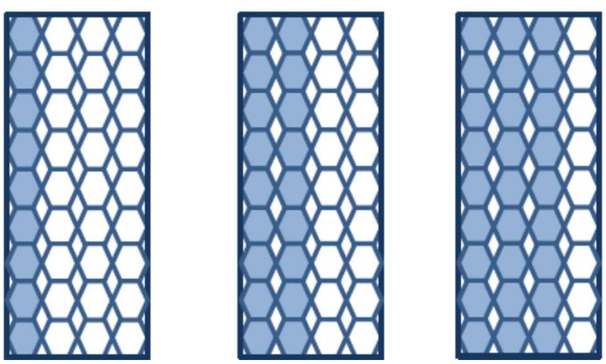

Fig. 6. Panel with partial irradiance. Shaded cells have variable irradiance. White cells have 1000W/m2.

Once it was trained, the output of the ANN was used as a starting point for the P&O algorithm, which allowed it to escape local maxima as well as to have a small step for the duty cycle of the PWM used in the buck circuit.

The scheme used in this work is showed in Figure 7.

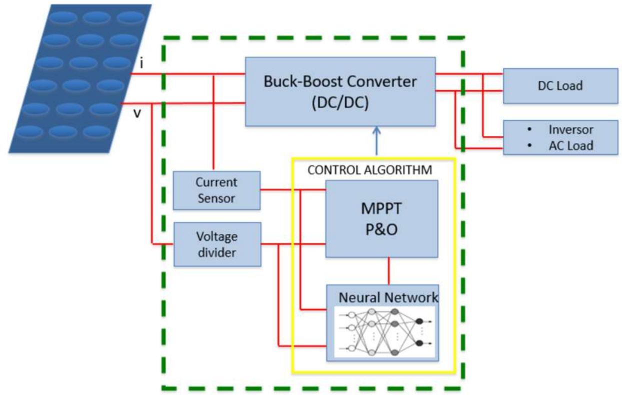

Fig. 7. Scheme using ANN coupled with P&O for MPPT.

The system was tested first without the ANN in order to verify the response by the P&O. It must be noted that several step sizes were used to get the best response in terms of response time and power output. This test was conducted with two levels of irradiance, 1000W/m2 for half the panel and the other part with 500W/m2. The response is shown in Figure 8:

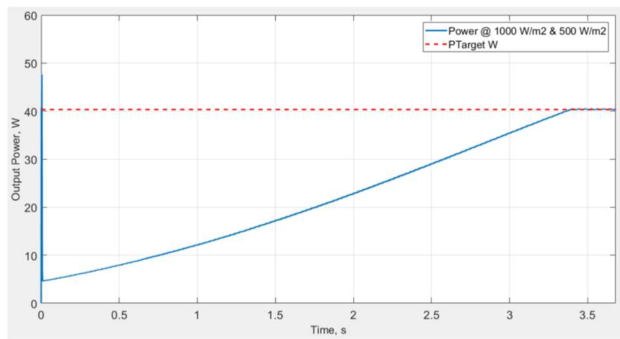

Fig. 8. System response using only P&O.

Enabling the ANN and under the same conditions, the response is presented in Figure 9.

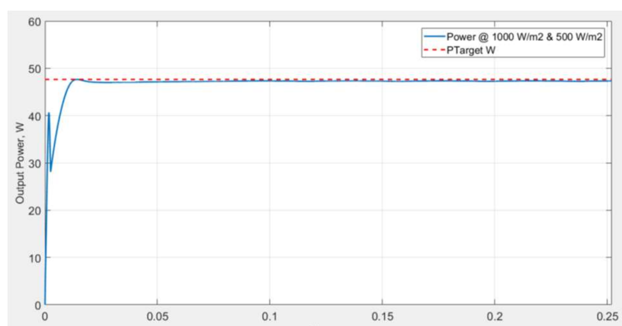

Fig. 9. System response using ANN and P&O.

It is a clear improvement in response by using, as a starting voltage point for the P&O algorithm, the output generated by the ANN. The response time to reach a steady state went from 3.4 seconds to 0.03 seconds.

6. CONCLUSIONS

There are several advantages to consider from this proposed method:
Time reduction for MPPT.
Ripple reduction for output voltage once the MPP is found. This

is thanks to the reduced search for the MPP.

Reliability in finding the global maximum because the ANN already generates a voltage value in the vicinity of the MPP.

It does not necessarily imply an additional cost in hardware, because in most cases the ANN algorithm can be embedded in the microcontrollers already used in controllers or inverters where the MPPT control is already implemented. The processing time does not have to be affected because, between each iteration of the P&O, there must be a minimum time to reach a steady state, which is larger than the time required by the ANN algorithm to generate its output.

And there is too, a disadvantage:

In order to implement the ANN algorithm, there must be a training stage offline, and it requires data, real or synthetic, and once the ANN is trained, the weights must be downloaded to the microcontroller. This training and the corresponding data are unique for each system, according to its characteristics and array distribution.

In order to address this issue, it could be developed an app for a smart phone where the final user can introduce the parameters concerning his or her PV solar panels and, once the ANN is trained using the capabilities of any actual smart phone, the weights generated can be downloaded via a wired or wireless connection to the microcontroller.

7. REFERENCES

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