MPPT Based On Artificial Neural Networks (ANN) For a Photovoltaic System Under Unstable Environmental Conditions

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Abstract

In this article, an artificial neural networks (ANN) based maximum power point tracking controller (MPPT) was developed to improve the performance of the FL-M-160W solar panel under unstable environmental conditions. To develop and configure the neural controller, a database resulting from experimental tests was built for the training of the proposed model. Then the model was tested and validated under the Matlab / Simulink environment. The optimum voltage obtained at the output of the neural controller is compared to the voltage of the photovoltaic generator and the error is used to modify the duty cycle of the DC-DC boost converter. It is shown after simulations that unlike conventional controllers which are very slow, the neural MPPT controller offers more stable, more accurate output characteristics with very low response time and very low oscillations around the operating point both in transient and steady state, even under varying environmental conditions.

1. Introduction

Fossil fuels represent more than 81% of the energy consumed in the world. These energies generally used in the field of transport, production of electricity and heat as well as for industries are at the origin of the degradation of human survival conditions through the phenomenon of pollution and degradation of the climate that they generate [1, 2]. With the increasing evolution of the population, the International Energy Agency (IEA) estimates in its 2007 reports a world energy demand of about 60% between 2000 and 2030 with an increase of 19% for the 2040 horizon according to the reports published in 2020. However, sub-Saharan Africa indeed has the lowest rate of access to electricity in the world, with an average rate of 32% according to the report of the African Development Bank published in 2010. To increase the rate of people having access to electricity and reduce the rate of degradation of phenomena generated by the consumption of fossil fuels, renewable energies are positioned as alternative energy sources to ensure energy security of the planet [3, 4]. These energies constitute energies with inexhaustible flows, generating little or no waste or polluting emissions. To take advantage of the strong solar potential that prevails in the sub-Saharan region, photovoltaic solar energy appears as an interesting solution [5].

In recent years, photovoltaic solar energy has experienced intense development in Cameroon because in addition to the objective of reduce pollution produced during the process of transformation of fossil fuels into electricity, Cameroon also aspires to move closer to its energy independence. Today, we are witnessing the disappearance of traditional electric lamps in favor of solar lamps for the lighting of public spaces as well as an interest of people for the electricity supply of homes in photovoltaic (PV) energy.

Although these PV systems are now installed, they present many malfunctions due mostly to the inadequacy of the MPP tracking algorithms of the adaptation stage on the one hand and sudden variations in environmental conditions. There is a problematic of non-mastery of maximum power point technology (MPP). To extract at any time and whatever the weather conditions and / or state of the load supplied, the maximum power at the output of the PV panel, the voltage at the terminals of the panel

must continuously been regulated to its optimum value through the adaptation stage. This operation is called the maximum power point tracking (MPPT).

Many algorithms have been used to track the MPP in a PV generator [6, 7, 8]. Although these algorithms have proved their worth, the fact remains that they still have limits in terms of stability, response times and significant presence of oscillations [9, 10], especially for sub-Saharan conditions where environmental conditions are very changeable and have a considerable impact on the efficiency of the solar generator. Since the I-V and P-V characteristic of the PV generator is strongly nonlinear, it has been proven that the neural network gives excellent prediction accuracy for the control of a nonlinear system. Unlike conventional controllers, neural MPPT control has proven to be a very effective solution in terms of precision and increasing the stability of the maximum power point.

In this work, a maximum power point tracking (MPPT) controller based on artificial neural networks (ANN) is proposed to extract the maximum power at the output of the FL-M-160W PV module under stable weather conditions and in case of permanent variation of atmospheric conditions.

To achieve this goal, a data acquisition device has been associated with a pyranometer to record and extract the data during the testing phase. These data served as a learning base for the configuration and development of neural controllers. This controller uses irradiance and temperature as input parameters and voltage as output parameters. The proposed model is used to control the boost converter associated with the PV module. To evaluate the precision, the recovery time and the stability, the developed controller was simulated and tested under Matlab / Simulink in different atmospheric conditions and a comparison is made with the conventional methods.

This document is structured into five sections. Section 1 presents the topic introduction and the generality on PV systems is developed in section 2. A review of MPPT commands used for maximum power point tracking is presented in section 3 and section 4 is used to develop and model the neural MPPT controller. Finally, after modeling and simulation, results and discussion are presented in section 5.

2. Modeling Of The Of The Photovoltaic System

Figure 1 illustrates the overall block diagram of the proposed system. It is a standalone PV system that includes a PV array use as a power generation source. This PV array is connected to the DC-DC boost converter that use ANN algorithm as maximum power point tracking technique to ensure the adaptation between the panel output voltage and the load.

2.1. Electrical Modeling of the Solar Panel

The electrical model of a PV cell is shown in figure 2. The electrical circuit of an ideal solar cell includes an I_{ph} current source generated by light in parallel with a single diode. But in practice, no solar cell is ideal. Therefore, the shunt and serie resistors are added to the model to consider all the phenomena

present during the conversion of light energy. In practice, the maximum current is delivered to the load when the series resistance R_s is very low and the shunt resistance R_{sh} is very large.

A solar cell produces generally a very low power output. To increase the output power of solar PV systems, solar cells are connected in series and parallel configurations to form PV modules whose equivalent model is described in figure 3.

The current-voltage nonlinearity relationship of the PV module can be described mathematically using the basic equations 1, 2, 3, 4, 5 and 6.

Saturation current:

$$I_S = I_{rs}^* \left(\frac{T}{T_n} \right)^3 \exp \left[\frac{qE_{g0}}{kn} \left(\frac{1}{T_n} - \frac{1}{T} \right) \right]$$

1

Reverse saturation current:

$$I_{rs} = \frac{I_{sc}}{\exp \left(\frac{V_{OC}}{nV_T} \right) - 1}$$

2

Photocurrent:

$$I_{ph} = \frac{G}{G_n} (I_{sc} + K_i \Delta T)$$

3

Current through the shunt resistance:

$$I_{sh} = \frac{V_d}{R_{sh}} = \frac{V + R_s \cdot I}{R_{sh}}$$

4

Output Current of a solar cell:

$$I = I_{ph} - I_S \left[\exp \left(\frac{(V + IR_s)}{nV_T} \right) - 1 \right] - \left[\frac{V + IR_s}{R_p} \right]$$

5

$$V_T = \frac{kT}{q}$$

6

The output current of the considered PV module is given by:

$$I_{PV} = n_P I_{ph} - n_P I_s \left[\exp \left(q \cdot \frac{V + R_S I}{n_s k T n} \right) - 1 \right] - \left[\frac{V + R_S I}{R_{sh}} \right]$$

7

where R_s is the series resistance of the solar cell and

V is the output voltage of the cell and n_P is the number of cells in parallel.

At the standard test condition, AM = 1.5, G = 1KW / m² and Tc = 25°C. Then, the FL-M-160W PV module characteristics are given in table 1.

Tableau 1: Characteristics of the FL-M-160W solar module.

Parameters	Values
Production tolerance	+/-3%
Maximum power (Pmpp)	160W
Maximum power voltage (Vmpp)	18.20V
Maximum power current (Impp)	8.80A
Short-circuit current (Isc)	9.33A
Open circuit voltage (Voc)	21.84V
Number of cells in series (Ns)	36
Number of cells in parallel (Np)	1

2.2. Analysis of PV Module Characteristics

The FL-M-160W solar module output characteristics are shown in Figure 4, 5 and 6.

Figure 4 describes the non-linearity relationship of the P (V) and I (V) output characteristics of the PV array. On the P (V) curve, a point where the power is maximum is observed. This is the maximum power point (MPP). As shown in Figures 5 and 6, the characteristics I (V) and P (V) besides being non-linear also change with illumination and temperature [11]. A decrease in the irradiation G causes a decrease in the current followed by a very slight decrease in the voltage Voc and therefore a shift of the maximum power (Pmax) of the solar panel towards lower powers. As the temperature rises, the open circuit voltage Voc

decreases dramatically while the current is virtually unchanged. The immediate consequence of varying environmental conditions is to vary the maximum output power of the PV generator.

2.3. DC-DC Boost Converter

To always extract the maximum power available at the terminals of the PV generator and to transfer it to the load, to ensure that the energy transfer is always possible and that it can be carried out under conditions of operation for the PV source and the load, a DC-DC converter is used [12]. Boost regulator is strongly recommended to follow the MPP because of its advantages over the buck converter. This switching power supply enables a higher value variable DC voltage source to be fabricated from a fixed input DC voltage source. The principle is to change the duty cycle of a rectangular signal to create a variable average voltage called Pulse Width Modulation (PWM). Figure 7 illustrates the boost converter model produced on Simulink, the specifications of which are contained in table 2. The output voltage V_s is given by equation 8.

$$V_s = \frac{V_e}{1 - \alpha}$$

8
With α the duty cycle such that $0 < \alpha < 1$.

Tableau 2: DC-DC boost converter parameters

Parameters	Values
Switching frequency (khz)	20
Inductance L (μH)	10694.10 ^{e-8}
Input voltage (V)	18.20
Capacitors C and Ce (μF)	31575.10 ^{e-8}

3. Maximum Power Point Tracking

In a PV system, the MPPT command can be defined as an algorithm which associated with an adaptation stage allows the system to operate in its optimal operating point and this whatever the atmospheric conditions (temperature and global sunshine) and of load value [1, 13]. Various control laws suitable for permanent MPPT research exist in the literature. Although these techniques are used to follow the MPP with exactitude, the difference is generally observed in the complexity of implementation, the cost, the range of efficiency, the speed of convergence, the correct follow-up of the point of maximum power, the required sensors, the material necessary for the physical implementation and above all the behavior in the event of sudden changes in irradiation and / or temperature

3.1. Perturb & Observe (P&O) MPPT Command

The principle of the P&O command consists in performing a disturbance of the operating point of the PV generator by varying the voltage V_{pv} by a constant value ΔV , called the increment value or disturbance value, and to observe its effect on the resulting P_{pv} power. If the power increases ($\Delta P > 0$), we are therefore in the right direction, we continue the disturbance in the same direction otherwise ($\Delta P < 0$), so we move away from the MPP, we reverse the disturbance. Figure 8 gives the flowchart of this algorithm [14, 10]

The P&O algorithm is a classical algorithm widely used for its simplicity and ease of implementation, its precision, and its speed of reaction [15]. However, in case of rapidly variations of environmental condition, the P&O algorithm presents a poor convergence [10]. This algorithm also presents some problems related to the oscillations around the MPP that it generates in steady state because the MPP search procedure must be repeated periodically, forcing the system to constantly oscillate around the MPP, once the latter is reached. These oscillations can be minimized by reducing the value of the disturbance variable. However, a low increment value slows down the search for MPP, so you have to find a compromise between precision and speed when choosing this update step that makes this command difficult to optimize.

3.2. Incremental conductance (InC) MPPT Command

The Incremental Conductance (InC) method is used to address the problem of divergence encountered by the P&O method in the case of a rapid change in sunlight. To calculate the MPP, the algorithm compares the conductance G with the incremental conductance ΔG , and this by looking for the point of cancellation of the derivative of the power [16, 17]. The evolution of the power of the PV generator relative to the voltage gives the position of the operating point relative to the MPP. When the power derivative is zero, it means that operating point is on the MPP, if it is positive the operating point is to the left of the MPP, when it is negative, it is to the right. A schematic description of this algorithm is shown in Figure 9 [18, 19].

The accuracy and speed with which the algorithm tracks the MPP depends on the size of the reference voltage increment or the duty cycle reference. Two main handicaps are reconciled with this method. The first is the oscillation of the operating point around the steady state MPP, the second is that the algorithm can easily lose track of the MPP if the solar radiation changes rapidly. When the irradiation varies instantly over time, the monitoring of the MPP evolves correctly. But, if the irradiation changes at a slope, the tracking will be poor. The algorithm is unable to determine whether the change in power is due to the voltage disturbance or the change in solar radiation. To verify the performance of this method, several authors choose an irradiation profile of different shapes for the simulations.

3.3. Hill Climbing (HC) MPPT Command

The principle of the Hill Climbing (HC) algorithm is to give a disturbance on the duty cycle which results in a displacement of the operating point along the power-duty cycle characteristic of the photovoltaic generator. The perturbation is applied for several iterations on the parameter α by incrementing or

decrementing it by $\Delta\alpha$ until the derivative is zero. Theoretically, when the maximum power point is reached, the search should stop. The Hill Climbing algorithm is developed in Figure 10 diagram [20, 21].

This technique is easy to implement, but its main limitations are oscillations around the MPP in steady state and an occasional loss of the search for MPP during rapid change in weather conditions.

To remedy the various problems associated with the various classical algorithms, artificial intelligence techniques such as fuzzy logic and neural networks have been introduced.

3.4. Artificial Neural Network

An artificial neural network (ANN) is an information processing system made up of a number of simple, highly interconnected processors called neurons, similar to biological brain cells [22, 23]. These neurons are interconnected by numerous weighted links, over which signals can pass. Each neuron receives many signals on its incoming connections and produces a single outgoing response. These networks have exceptional pattern recognition and learning capacities [23]. Recent ANN applications have shown that they have enormous potential to overcome the difficult tasks of processing and interpreting data. The use of the neural network in the synthesis of the MPPT controller for the optimization of the power of the photovoltaic panels has proven to be a very effective solution in terms of precision and increasing the stability of the maximum power point compared to conventional techniques (P&O, InC, HC) [13]. In this work, a multilayer perceptron neural network is used to extract the maximum output power from the FL-M-160W PV module.

4. Neural Modeling Of The Pv Generator

4.1. *Experimental test*

the construction and configuration of the neuronal MPPT controller involves the establishment of a database for the training of the network. The recording of real data during the test phase made it possible to build this database. Figures 11 and 12 represent the experimental setup used for data acquisition. This device includes an acquisition card used for recording voltage and current data, a Benning Sun 2 pyranometer and a Felicity Solar photovoltaic panel connected to the boost converter. The pyranometer measures solar irradiance, panel surface temperature and ambient temperature. It also determines the orientation and inclination of the panel according to the latitude of the site.

After this test phase, the recorded data will be optimized to approximate the output of the neural model and estimate the maximum output power of the PV panel based on the variation in illumination and temperature. Figure 13 illustrates the network developed to estimate the MPP. It is a multilayer perceptron (MLP) consisting of an input layer with two neurons that correspond to the two input variables, namely the illumination G , the temperature T_{pv} , a hidden layer of 10 neurons and a layer of output with a single neuron representing the target (an output variable) to approach the desired output which is the optimum voltage. this network uses the sigmoid-type activation function for the hidden layer and a linear function

for the output layer. To adjust the weights and biases in order to satisfy the optimization criterion, the backpropagation algorithm is used as a supervised learning method.

4.2. Development of the ANN model on Matlab

The data issued from experimental tests were divided into two categories (training data and test data) to develop and configure the ANN model. Each type of data is an input (Irradiance, Temperature) / output (voltage) pair. 1159 items were used for training and 194 items for testing. Figure 14 illustrates the Matlab model of the neural network with two neurons in the input layer, 10 neurons in the hidden layer and one neuron in the output layer.

The developed network training performance curve shown in Figure 15 displays a mean square error (MSE) of 0.05271 typically achieved after 998 epochs. This network is then used to perform some tests. Figure 16 shows that the outputs of the neural model correspond substantially to the target values.

After a test carried out on 21 target points including Vppm. A comparison is made between the real voltage output values and the neural output values. Table 3 shows that the neural outputs are close to the target values according to the graphs in Figure 17. The neuronal output provides an optimal voltage Vopt close to the real data. This can lead to conclude on the interest of the synthesis of the neural controller in the MPPT command.

The developed neural controller is shown in Figure 18. In this model, the irradiance G and the panel surface temperature Tpv are the input variables while the network output is the optimal voltage Vopt. This voltage is then compared to the reference voltage Vpv of the PV generator and the error is given to generate operating signals. The generated PWM signals manage the duty cycle of the DC - DC converter to adjust the operating point of the PV module.

Tableau 3: Actual output data and Vmpp neural network from irradiance and temperature data

N°	Test point	Irradiance G (W/m ²)	Temperature T _{pv} (°C)	V _{pv} (V)	V _{opt} (V)
1	[1000,25]	1000	25	18,20	18,21
2	[354,36]	354	36	15,85	15,0642
3	[400,35]	400	35	17,77	16,1392
4	[250,35]	250	35	12,27	11,0636
5	[740,37]	740	37	18,51	17,8196
6	[670,41]	670	41	18,62	17,4532
7	[1019,41]	1019	41	18,72	17,7355
8	[1103,42]	1103	42	18,76	17,8025
9	[1010,43]	1010	43	18,62	17,5235
10	[930,45]	930	45	18,16	17,5235
11	[804,45]	804	45	18,23	17,1583
12	[820,41]	820	41	18,37	17,6144
13	[614,41]	614	41	18,23	17,2957
14	[950,42]	950	42	18,44	17,5954
15	[850,42]	850	42	18,51	17,5318
16	[210,33]	210	33	10,14	9,3559
17	[154,31]	154	31	9,15	8,1387
18	[711,42]	711	42	18,08	17,4536
19	[460,37]	460	37	17,98	17,2223
20	[507,38]	507	38	18,55	17,3415
21	[317,35]	317	35	14,43	13,4759

5. Results And Discussion

Figure 19 describes the model of the stand-alone PV system developed in Simulink. It consists of a PV panel, a DC-DC boost converter and a load. the developed ANN MPPT controller is used to drive the converter in order to run the generator at its maximum power point.

The Felicity Solar PV FL-M-160W module used for the simulation produces 160W of power under standard test conditions. To validate the efficiency and robustness of the ANN MPPT controllers,

simulations are carried out under standard environmental conditions and in the case of rapidly change of environmental conditions.

5.1. standard environmental conditions

Under standard environmental conditions, the simulations are carried out under fixed conditions of illumination $G = 1000 \text{ w / m}^2$ and temperature $T = 25^\circ \text{ C}$. The output characteristics of the neural controller are illustrated by figures 18, 19 and 20.

As shown in Figure 20, the output power of the neural MPPT is very stable with a very low response time of around 0.015s. However, there are weak oscillations that remain because this power varies between 154.5 and 155.8W. The output current is relatively low while the output voltage is very high, which is more stable, which makes it possible to have a better efficiency of the power of the output panel.

Figure 23 compares neural and conventional controllers. The ANN controller can accurately track the maximum power point of the PV generator. It provides more stable power output and closer to MPP compared to conventional MPPT and converges quickly to the new MPP. Conversely, although the P&O, InC and HC controls follow the MPP perfectly, they are slower and only arrive at the MPP after a delay. The recovery time is approximately 0.02s for these techniques.

5.2. Rapidly change of environmental conditions

Under rapidly change conditions, there are sharp variations in irradiance and / or temperature. However, the variation in temperature has little influence on the output power compared to the variation in sunlight. simulations are realized with a constant temperature equal to 25°C for a solar irradiation which suddenly deviates from 1000 to 700 W / m^2 then from 700 to 1200 W / m^2 and this for 1s. Figure 24 illustrates the output power of the generator in unstable conditions.

To evaluate the robustness, the rapidity, the precision and the speed of convergence of the neuronal technique developed as well as its capacity to follow the MPP under the conditions of sudden variation of the environmental conditions, a comparison is made with the classical methods (Figure 25, 26 and 27).

During rapid changes in climatic conditions, the output characteristics (maximum power, voltage and current) provided by the PV generator varies proportionally with irradiation as shown in Figures 23, 24 and 25. When irradiation is 1000 W / m^2 , the maximum power supplied by the PV generator stabilizes around 156 W for the different MPP tracking techniques. When the sun goes from 1000 to 700 W / m^2 , this maximum power is 108W for ANN, 99W for P&O, 88W for InC and finally 85W for HC. Finally, when going from 700 to 1200 W / m^2 , P_{max} becomes equal to 188W for ANN, 170W for P&O and InC and 178W for HC. There are significant oscillations of conventional techniques compared to ANN first in transient and steady state as well. The sudden variation in sunlight greatly disturbs conventional controllers. In our case, for low irradiation, the HC controller is less cost effective compared to other conventional techniques, but it becomes better when the irradiation becomes greater. These results show that MPPT controls allow adaptation of PV generator and load to MPP with optimal transfer of PV power.

Conclusion

In this work devoted to the neuronal modeling of the MPPT command for a PV generator in disturbed conditions, the PV system elements have been modeled in Matlab / Simulink. Subsequently, a review on MPPT commands was developed and allowed to highlight the difficulties of classical MPPT commands in the search for MPP and to give particular interest in the use of neural networks in the pursuit of maximum power point. From the experimental tests carried out on site, a database was created and made it possible to develop the neural MPPT controller. After learning, testing and verification phases the block was inserted into the system to regulate the adaptation stage. Then, simulation of the behavior of the PV system under stable and disturbed environmental conditions has been done to analyze the characteristics obtained at the output of the panel. A comparative study between the neural MPPT controller and conventional algorithms reveals robustness, high stability and very low response time compared to conventional methods.

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Figures

Figure 1

Overall block diagram of the PV system proposed.

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Figure 4

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Figure 5

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Figure 18

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Figure 21

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Figure 25

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Figure 26

Comparison of output voltages in unstable conditions

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Comparison of output currents in unstable conditions