Maximum Power Point Tracking of Photovoltaic Modules

Comparison of Neuro-Fuzzy "ANFIS" and Artificial Network Controllers Performances

Z. ONS, J. AYMEN, M. MOHAMED NEJIB and C.AURELIAN

Abstract—This paper makes a comparison between two control methods for maximum power point tracking (MPPT) of a photovoltaic (PV) system under varying irradiation and temperature conditions: the Neuro-Fuzzy logic and the Neural Network control. Both techniques have been simulated and analyzed by using Matlab/Simulink software. The power transitions at varying irradiation and temperature conditions have been simulated and the power tracking time realized by the Neuro-Fuzzy logic controller against the Neural Network controller has been evaluated.

Keywords— Photovoltaic Modules; MPPT; Neuro-Fuzzy Logic Control; Neural Network Control; Matlab/Simulink models.

I. Introduction

The power output from a solar photovoltaic system mainly depends on the nature of the connected load because of non-linear I-V characteristics. The PV systems connected directly to the load result in overall poor efficiency as such maximum power point tracking (MPPT) is to be introduced in PV systems to increase the efficiency of the system [1]. Solar irradiation, load impedance and module temperature are the three factors which affect the maximum power extraction from solar PV module. I-V curve of PV module is a function of solar irradiation and the temperature of the cells which affects output current and voltage. The increased temperature decreases the open circuit voltage (V_{oc}) while increased the intensity of solar irradiation increases short circuit current (I_{sc}). Therefore I-V and P-V curve changes according to the operating conditions which alters maximum power point [2]. The concept of MPPT is to continuously monitor the terminal voltage and current and update the control signal accordingly to achieve maximum power point. A DC/DC convertor with MPPT algorithm is used between PV module and load to extract maximum available power [3]. MPPT can be achieved by using a chopper with positive feedback of measurement speed and algorithm for controlling the duty cycle [4-5]. By using highly efficient MPPT with the DC/DC converter to charge batteries from PV modules, the cost of PV power generation reduced by 30% [6]. A lot of research efforts have been made to achieve faster, better and accurate MPPT technique. They are voltage feedback method, perturbation and observation method, linear approximation method, incremental conductance method, hill climbing method, actual measurement method, fuzzy control method and so on [1]-[5].

The authors are: 25 Rue de la jeunesse,5080,Teboulba,Monastir, Zarrad_ons@yahoo.fr

In this paper, intelligent control techniques using neuro-fuzzy logic control and neural network control are associated to an MPPT controller in order to improve energy conversion efficiency. Simulation and analysis in Matlab/Simulink environment of these control techniques are presented, and its performances are evaluated.

This paper is organized as follows. Section 1 is the introduction which includes the background of renewable energy, and the purpose of this paper. Sections 2 and 3 illustrate PV array model, and neuro-fuzzy logic and artificial neural network (ANN) MPPT principles, respectively. Section 4 is dedicated to the modeling, simulation, analysis and discussion concerning the two MPPT compared techniques. The conclusions are given in Section 5.

II. PV Array Model

The PV cell equivalent electric circuit can be represented as in Fig. 1. It consists in an ideal current source (I_{PV}), an ideal diode, a parallel resistor (R_P) and a series resistor (R_S). The current source, I_{PV}, is the light generated current which is directly proportional to the solar irradiation G (measured in W/m^2). The series and the parallel resistances are representative for the voltage loss on the way to the cell terminals and for the cell's leakage current, respectively.

The *I-V* characteristic of a photovoltaic array is given by the following equation:

$$I = I_{PV} - I_0\left[\exp\left(\frac{V + R_S I}{V_T a}\right) - 1\right] - \frac{V + R_S I}{R_P} \qquad (1)$$

Where I_{pv} and I_0 are the photovoltaic and saturation currents of the array and $V_T = N_S kT/q$ is the thermal voltage of the array with N_S cells connected in series. Cells connected in series provide greater output voltages and cells connected in parallel increase the current. T is the temperature of the cell, q is the charge of an electron, k is the Boltzmann constant and a is the ideality factor of the diode.

The array nonlinear power variation curves versus the array voltage is shown in Fig. 2.

The analyzed PV module has the electric specifications given in the TABLE 1.

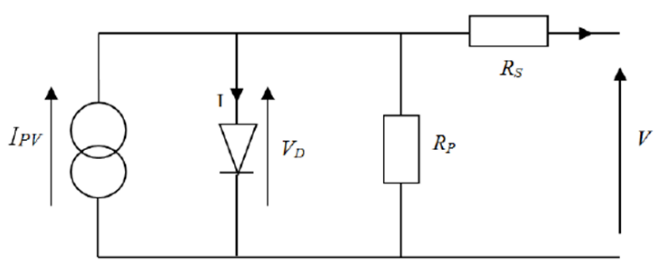

Fig. 1. Electrical equivalent circuit of a PV cell.

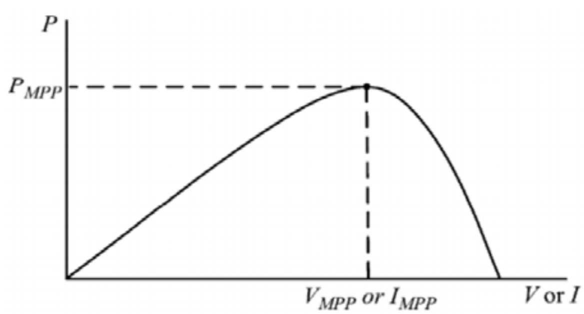

Fig. 2. Power variation curve versus the array voltage for a PV cell.

TABLE I. SPECIFIC DATA OF BPMSX60 PV MODULE

Rated Power	60 Wp
Current at MPP	3.25 A
Voltage at MPP	16.8 V
Short-circuit current	3.56 A
Open circuit voltage	21.6 V
Number of cells in series	36
Number of cells in parallel	1

III. THE MPPT CONTROL

The Maximum Power Point Tracking (MPPT) control is a functional element of the photovoltaic system which allows searching the operating point of the PV generator under variable load and atmospheric conditions. The maximum power point principle is based on the circuit maximum power transfer requirements: it happens when the photovoltaic cell's output impedance and the load impedance are equal[7-8]. In Fig. 3 it is shown the bloc diagram of a PV module equipped with a MPPT controller. The duty factor d of the DC-DC boost converter is controlled, in permanence, to adapt the load to the PV source for the maximum power transfer at variable climate conditions. The voltage transfer function of the considered DC-DC converter is given by the following relation:

$$\frac{V_0}{V_1} = \frac{1}{(1-d)} \tag{2}$$

Where V_0 is the output voltage and V_1 is the input voltage of the boost converter.

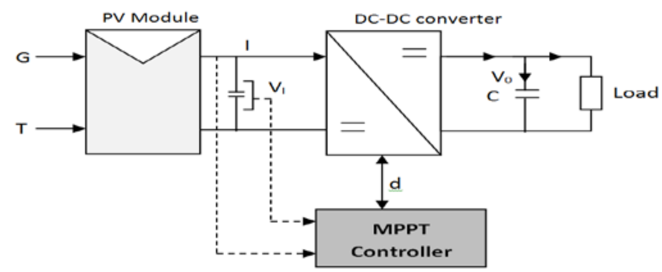

Fig. 3. The block diagram of a PV module with MPPT controller

A. *The MPPT with Neuro-Fuzzy Logic Control*

The neuro-fuzzy inference system (ANFIS) is a combination of Artificial Network Neural (ANN) and fuzzy logic. The ANN identifies the patterns and conforms to them to deal with altering environments. On the other hand, the fuzzy inference systems (FIS) combine the human knowledge and carry out the inference and process of decision making [9]. Tow common fuzzy models, the mamdani and takagi-sugeno(TSK), are defined for FIS.

For the MPPT controller with FIS, the inputs are taken as a change in power and voltage as well. There is a block for calculating the error (E) and the change of the error (dE) at sampling instants' k:

$$E(k) = \frac{dP}{dV} = \frac{P(k) - P(k-1)}{V)k) - V)k-1)} \tag{3}$$

$$dE(k) = E(k) - E(k-1) \tag{4}$$

Where *P(k)* is the power delivered by PV module and *V(k)* is the terminal voltage of the module. Value of the error *E(k)* determines the MPPT controller output according to the sign. By example, if the operating point is located to the left of the MPP of the characteristic *(P-V)*, the sign of the error *E(k)* is positive, and the reported load resistance to the PV terminal has to be increased. As a consequence, the duty factor *d* has to be decreased.

In order to avoid the final oscillations around the MPP, when the change of the error *dE(k)* decreases, the speed of convergence to the operating point has to be reduced. As a consequence, the decreasing increment of the duty factor *d* has to be reduced. This is the way the MPPT controller can decide what will be the variation of the duty cycle that must be imposed on the DC-DC boost converter to approach MPP. Once *E(k)* and *dE(k)* are calculated and converted to the linguistic variables, which is the duty ratio *d* of the power converter.

The ANFIS is only able to use the TSK fuzzy model due to its high calculative efficiency, adaptive techniques and built in optimum. The controller provides smoothness in convergence because of the fuzzy TSK inference and adaptability as a result of ANN back propagation algoritms[10] .The structure of a typical five layer ANFIS system illustrated in Fig4.

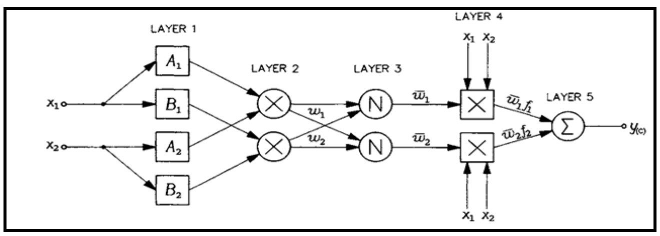

Fig. 4. Structure of a typical five layer ANFIS system

In the first layer, membership function (MF) will be defined for each of inputs. In the second layer, each node via multiplication calculates the firing strength of a rule. The firing strength is normalized in LAYER3. Tow common rules in TSK fuzzy model are defined as

Rule 1: if x_1 is A_1 and x_2 is A_2 then $f_1=a_1x_1+b_1x_2+c_1$

Rule 2: if x_1 is B_1 and x_2 is B_2 then $f_2=a_2x_1+b_2x_2+c_2$

Where a_i,b_i and c_i are design parameters defined in the training plant. Also A_i and B_i are the fuzzy sets intput[11].

B. Matlab/Simulink model of the PV System with MPPT Neuro-Fuzzy Logic Control Algorithm

In Fig. 5 is shown the Matlab/Simulink model of a PV module with MPPT fuzzy logic controller. It contains five main blocks: the climate conditions, the PV generator, the DC/DC converter, the battery and the block with neuro-fuzzy logic control.

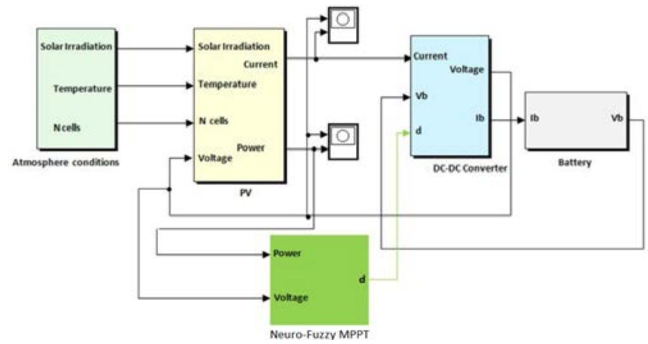

Fig. 5. Simulink model of the PV module with MPPT Neuro-fuzzy logic controller.

Data for the ANFIS inputs are collected from the PV module I-V characteristics. Temperature (T) varies from 280°K to 300°K with the step of 5°K and solar irradiation (G) between 600 to 1000W/m^2 with step equal 100 W/m^2. The database is used for training the network and the remaining are used for checking data. The training is done offline using ANFIS Toolbox and the target error is set 2.9%. The proposed MPPT controller in SIMULINK is shown in fig.6 and the surface of system in fig.7

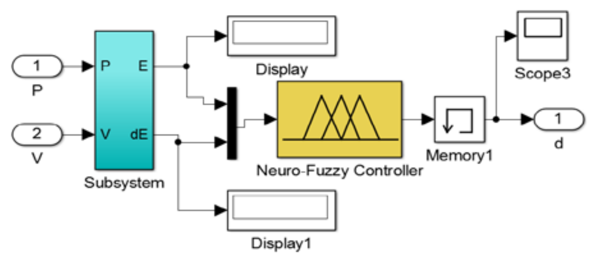

Fig. 6. The proposed MPPT controller in SIMULINK.

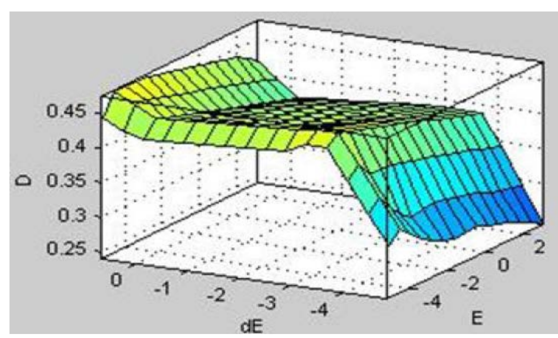

Fig. 7. Surface of the system For ANFIS.

C. The MPPT with Artificial Neural Network Control

Artificial neural network provides a method of deriving nonlinear models of a PV array. Neural networks have a self-adapting capability which makes them well suited to handle the parameter variations[7].

In fig. 8 is shown the architecture of a simple neural network. The artificial neuron consists of input, activation function and output with appropriate weight. In this simple feed forward neural network, the inputs are fed directly to the outputs via a series of weights. The weights of the artificial neuron are adjusted to obtaining the outputs for the specific inputs. The sum of the products of the weights and the inputs is calculated in each hidden node, and if the value is above some threshold (typically 0) the neuron fires and takes the activated value of (typically 1); otherwise, it takes the deactivated value (typically -1).

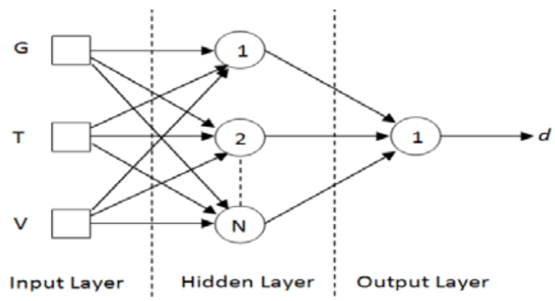

Fig. 8. The neural network basic architecture.

The algorithm used for training of the neural network is back propagation. The back propagation training algorithm needs only inputs and the desired output to adapt the weight. Back propagation training is referred to as supervised training. The neural network was trained using MATLAB software.

D. Matlab/Simulink model of the PV System with MPPT Artificial Neural Network Control Algorithm

In Fig. 9 is shown the general scheme of a PV system with MPPT artificial neural network controller. It is similar with the scheme of Fig. 5, the only difference being the used controller.

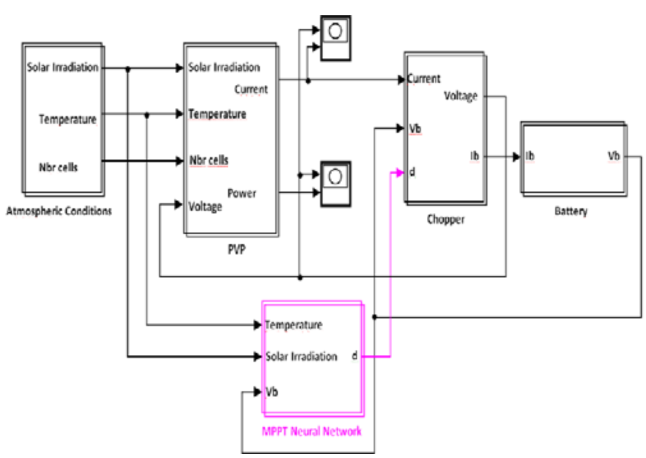

Fig. 9. Simulink model of the PV module with MPPT ANN controller.

IV. The Simulation Results

The comparison of the MPPT performances of the two analyzed control algorithms were made for a solar irradiance of 1000 W/m^2 and for a cells' temperature of 300° K.

The PV MPPT neuro-fuzzy controller was with TSK type inference rules and The structure of a typical 5 layer ANFIS.

For the PV MPPT ANN controller, six structures given in the Table III were chosen.

The simulation results, for the analyzed cases, are given in the following five figures.

TABLE III. The Sturctures of Analyzed ANN Controllers

Controller Type	ANN structure	1st layer	2nd layer	3rd layer
1	***Neuron numbers***	1	1	-
	Activation function	sigmoidal	linear	-
2	***Neuron numbers***	3	1	-
	Activation function	sigmoidal	linear	-
3	***Neuron numbers***	20	1	-
	Activation function	sigmoidal	linear	-
4	***Neuron numbers***	1	1	1
	Activation function	sigmoidal	sigmoidal	sigmoidal
5	***Neuron numbers***	1	1	1
	Activation function	sigmoidal	linear	sigmoidal

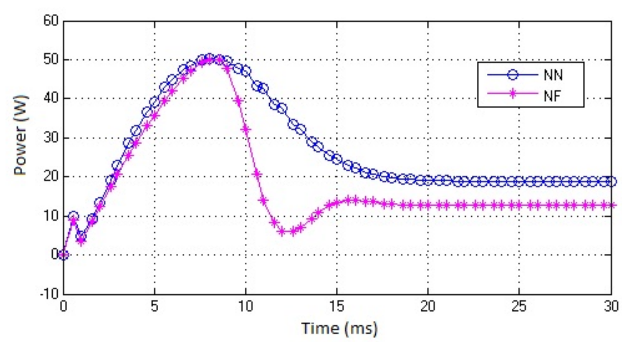

Fig. 10. MPPT performances of Fuzzy Logic Controller and ANN Controller Type number 1.

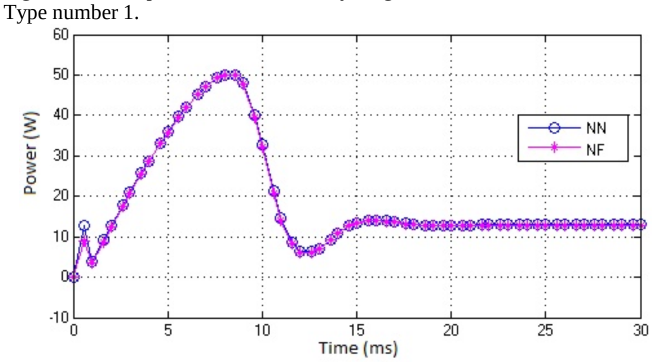

Fig. 11. MPPT performances of Fuzzy Logic Controller and ANN Controller Type number 2.

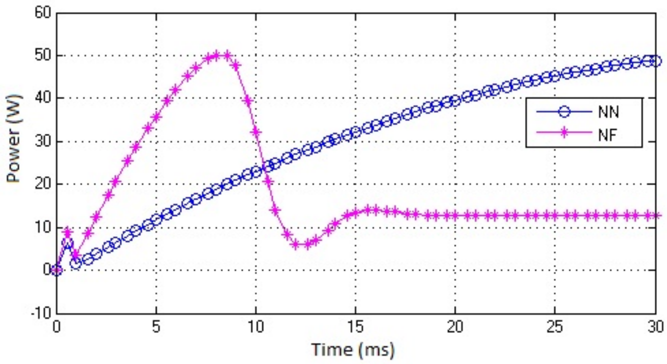

Fig. 12. MPPT performances of Fuzzy Logic Controller and ANN Controller Type number 3.

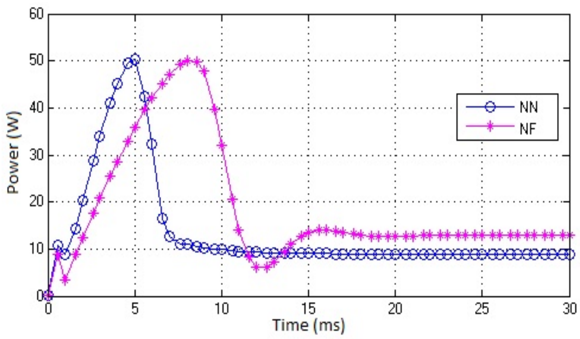

Fig. 13. MPPT performances of Fuzzy Logic Controller and ANN Controller Type number 4.

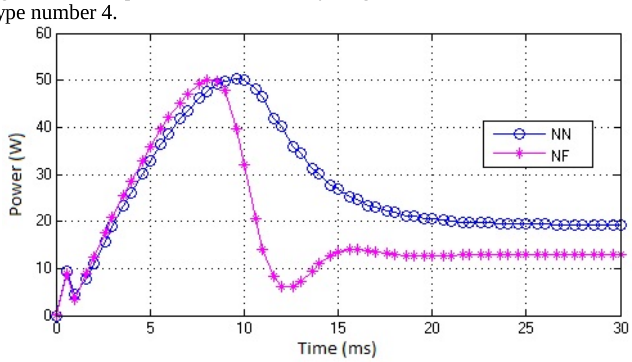

Fig. 14. MPPT performances of Fuzzy Logic Controller and ANN Controller Type number 5.

In the first and 2nd cases MPP achieving time of ANN controller and the achieving time of Neuro-Fuzzy controller are the same.

In the 3rd case achieving time of ANN controller is much more as the achieving time of Neuro-Fuzzy controller.

In the 4th case achieving time of ANN controller is a little bit faster more as the achieving time of Neuro-Fuzzy controller.

In the 5th case achieving time of Neuro-Fuzzy controller is a little bit faster more as the achieving time of ANN controller.

V. Conclusion

Two MPPT control strategies based on Neuro-Fuzzy and ANN have been compared. In general, the MPP achieving time of Neuro-Fuzzy controller is shorter as the achieving time of ANN controller. For the analyzed cases it is about 7,5 ms.

When the ANN Controller is used, the MPP achieving time is a little bit faster only in one of analyzed cases (5 ms, in 4th case).

References

[1] W. Swiegers and J. Enslin, “An integrated maximum power point tacker for photovoltaic panels”, Proceedings of IEEE International Symposium on Industrial Electronic, vol. 1, 1998, pp. 40-44.

[2] A. de Medeiros Torres, F.L.M. Antunes, and F.S. dos Reis, “An artificial neural network-based real time maximum power tracking controller for connecting a PV system to the grid”, Proceeding of IEEE the 24th Annual Conference on Industrial Electronics Society 1998, vol. 1 , pp. 554 -558.

[3] G. Petrone, G. Spagnuolo, R. Teodorescu, M. Veerachary, and M. Vitelli. "Reliability issues in photovoltaic power processing systems", IEEE Trans. On Ind. Electron. vol. 55, pp. 2569-2580, july 2008.

[4] JHR Enslin, MS Wolf, DB Snyman, W Swiegers. Integrated photovoltaic maximum power point tracking converter. IEEE Trans Energy Convers, vol. 44, pp. 769-773, 1997.

[5] M.G. Villalva, J.R. Gazoli, E.R Filho, "Comprehensive approach to modeling and simulation of photovoltaic arrays," Power Electronics, IEEE Transactions on , vol.24, no.5, pp.1l 98-1208, May 2009.

[6] L.M. Elobaid, A.K. Abdelsalam, and E.E. Zakzouk, “Artificial neural network based maximum power point tracking technique for PV systems”, IECON 2012 - 38th Annual Conference on IEEE Industrial Electronics Society, Montreal, QC, 25-28 Oct. 2012, 937 – 942.

[7] Z. Ons, J. Aymen, A. Craciunescu and M. Popescu, “Comparison of Hill-Climbing and Artificial Neural Network Maximum Power Point Tracking Techniques for Photovoltaic Modules”, Proceeding of IEEE the Second International Conference on Mathematics and Computers in Sciences and in Industry (MCSI-2015), 2015, pp. 19-23.

[8] J. Aymen, Z. Ons, A. Craciunescu and M. Popescu, ”Comparison of Fuzzy and Neuro-Fuzzy Controllers for Maximum Power Point Tracking of Photovoltaic Modules” Proceeding of IEEE International Conference on Renewable Energies and Power Quality (ICREPQ-16), 2016, ISSN 2172-038 X, No.14 May 2016.

[9] T. Esram and P. L. Chapman, "Comparison of photovoltaic array maximum power point tracking techniques," IEEE TRANSACTIONS ON ENERGY CONVERSION EC, vol. 22, p. 439, 2007.

[10] C. A. Otieno, G. N. Nyakoe, and C. W. Wekesa, "A neural fuzzy based maximum power point tracker for a photovoltaic system," in AFRICON, 2009. AFRICON'09., 2009, pp. 1-6.

M. A. Denaï, F. Palis, and A. Zeghbib, "Modeling and control of nonlinear systems using soft computing techniques," Applied Soft Computing, vol. 7, pp. 728-738, 2007.