International Journal on Emerging Technologies **11**(2): 590-594(2020)

ISSN No. (Print): 0975-8364
ISSN No. (Online): 2249-3255

Artificial Neural Network Photovoltaic Generator Maximum Power Point Tracking Method using Synergetic Control Algorithm

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(Received 04 January 2020, Revised 02 March 2020, Accepted 05 March 2020)
(Published by Research Trend, Website: www.researchtrend.net)

ABSTRACT: In this paper, a new approach to find the maximum power point (MPP) of a PV generator based on a hybrid Artificial Neural Networks (ANN)-Synergetic Control Algorithm (SCA) has been proposed. In the first part, the optimal voltage and current of the PV generator are found by using ANN algorithm. The second part deals with the design of a Synergetic Controller Algorithm (SCA) which generates automatically the optimal duty cycle to control the boost converter. The complete PV system is implemented in MATLAB/Simulink software and the results are compared with those obtained using the conventional Perturbation and Observation (P&O) method. Simulation results reveal that the proposed ANN-SCA algorithm is more efficient than the P&O algorithm.

Keywords: PV generator, MPPT, Artificial Neural Network, Synergic control algorithm, P&O method.

I. INTRODUCTION

The photovoltaic solar module is an assembly of several photovoltaic (PV) solar cells. The combination of several PV modules in series / parallel generates a photovoltaic generator that has a nonlinear current-voltage (I-V) characteristic with a maximum power point [1-4]. The characteristics of a solar cell are much related to atmospheric parameters such as temperature and solar irradiation. The latter often varies abruptly, which affects the operating point of the PV generator and then causes power losses in the system [5]. On the other hand, it has been shown that a direct connection of the PV generator to the load does not guarantee the transfer of the maximum power available. The extracted power is often different to the PV generator maximum power point [6-7]. Thus, to ensure the transfer of the maximum available power of the PV generator to the load, an adaptation stage equipped with a maximum power point tracking (MPPT)command and a DC-DC boost converter is required. This command will automatically extract the PV generator maximum power. Several MPPT methods exist in the literature, such as the Perturb and Observe (P&O) command, which is very popular because it is easy to be implemented [8-10]. Another widely method used is the Incremental Conductance (INC) based on the variation of the conductance which is defined as the ratio between the current and the voltage of the PV generator. The advantage of this method over P&O is that theoretically it can find the Maximum Power Point (MPP) and stabilize it [11]. In addition to these two previous methods, the ones based on proportionality relations are been developed such as: open circuit voltage fraction [12], short circuit current fraction [6], ripple correlation control method [13]. Recently, MPPT commands based on artificial intelligence are increasingly used. Among these, fuzzy logic method which does not require mathematical models of great accuracy and can also work with inaccurate inputs. However, the implementation of this type of algorithm is more complex than the previous algorithms [14]. Another method based on artificial intelligence is Artificial Neural Networks (ANN) which is also widely used in many application domains and is adapted to complex systems or random variables. Moreover, this command can operate from a black box that does not require detailed information about the operation of the system. Thus, several research works devoted to the application of this method in the exploration of the MPP are found in the literature [15]. However, despite these numerous commands developed to find the PV generator MPP, accuracy and the searching timestill need to be optimized.

In this paper a new approach that ensures a fast and exact response of ANN using synergetic control algorithm (SCA) was presented. The ANN method takes as input, irradiance (I) and temperature (T) on the PV generator and generates the optimal voltage and current of the PV generator and then the SCA control algorithm based on the outputs of the ANN block, automatically generates the optimal duty cycle for controlling the boost converter.

The complete PV system is implemented in MATLAB/Simulink software and the results are compared with those obtained using the conventional P & O method. The paper is organized as follow: In Section I, the topic and the literature review are presented. Section II deals with the electrical modeling of a solar cell. Section III presents the proposed MPPT command. Section IV presents the results analysis of the proposed MPPT command and Section V concludes the paper.

II. SOLAR CELL EQUIVALENT CIRCUIT

To draw a circuit equivalent of a solar cell it is important to know the electrical characteristics of the elements that compose it [16]. An ideal solar cell is a current source producing a current that is proportional to solar radiation. However, the optical and electrical losses must be taken into account in the practice. Optical losses are considered as the current generator. The recombination losses are modelled by a diode in parallel to the current generator (Fig.1) [17].

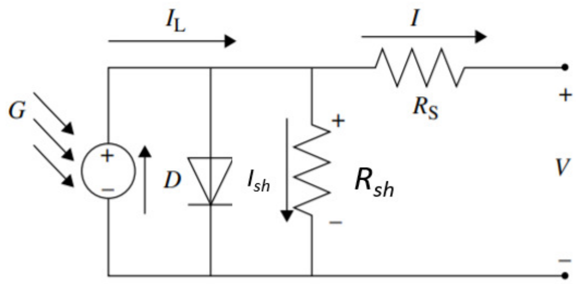

Fig. 1. Electrical diagram of a photovoltaic cell.

The diode D, fixes the I–V characteristics of the cell. R_S represents the Serie resistance, while the shunt resistance R_{Sh} represents the parallel resistance. In an ideal solar cell, it is assumed that R_{Sh}=0 and R_{Sh} =∞. The net current of the cell is defined by [17].

$$I = I_{ph} - I_0\left[\frac{q(V+IR_S)}{nkT} - 1\right] - \frac{V+IR_S}{R_{Sh}} \quad (1)$$

With:

I_{ph} : Photocurrent,
I_0: Saturation current of the diode
n: Ideality factor of the diode
K: The Boltzmann constant
q: Charge of the electron
V: Cell terminal voltage
I: Cell terminal current
T: Absolute temperature of the cell

By considering the R_{sh}= ∞, the previous equation will be:

$$I = I_{ph} - I_0\left[\frac{q(V+IR_S)}{nkT} - 1\right] \quad (2)$$

The expression of the photocurrent is given by the equation below:

$$I_{ph} = [I_{sc} + K_i(T-298)]\frac{\beta}{1000} \quad (3)$$

Where

K=0.0017 A/°C is the cell's short circuit current temperature coefficient
I_{sc}: is the short circuit current of solar cell (A)
β: is the solar irradiation (W/m).

III. ANN-SCA BASED MPPT FOR PV ARRAY

A. Proposed System

Fig. 2 shows the proposed scheme to implement the MPPT method. Firstly, the ANN algorithm estimates the optimal voltage (V_{ref}) and current (I_{ref}) of the PV generator at the maximum power point using irradiance (I) and temperature (T) as inputs on the PV generator. The current of the input capacitor C_{in} is to be negligible ($I_{Cin} \approx 0$) so $I_{PV} \approx I_L$. The Synergetic Control Algorithm (SCA) ensures that the inductance current be equal to the optimal current delivered by the PV generator ($I_{ref} \approx I_L$) and V_0 the output voltage of the DC-DC converter is substantially equal to a certain reference value V_{0ref} and generates an optimal duty cycle.

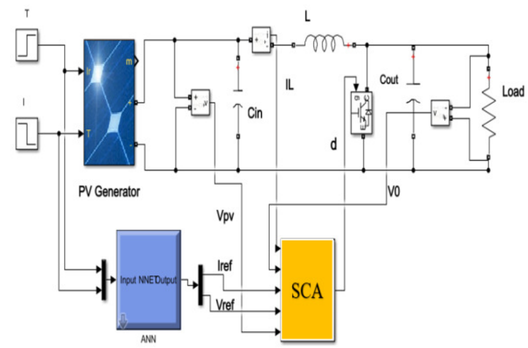

Fig. 2. Proposed schematic system.

B. Artificial Neural Network

The ANN algorithm is represented by Fig. 3. To obtain the neuron network training data, a simulation of the PV generator under Matlab/Simulink was done using the parameters provided by the manufacturer's datasheet. Thus, for each pair of temperature and irradiation values, the corresponding values of the optimal current (I_{ref}) and the optimal voltage (V_{ref}) of the PV generator are generated by the ANN algorithm. The learning of neural networks was done by the Levenberg-Marquardt algorithm. A feed forward based neural network is implemented. It uses two neurons in input layer, five neurons in hidden layer and two in output layer. The algorithm of mean square error method is used to calculate the error [18]. The plot in Fig. 4 shows the performance of the network. Finally using the "gensim" function the ANN block can be generated.

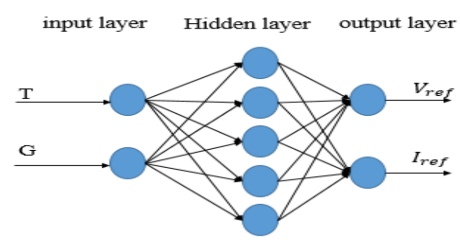

Fig. 3. The ANN configuration.

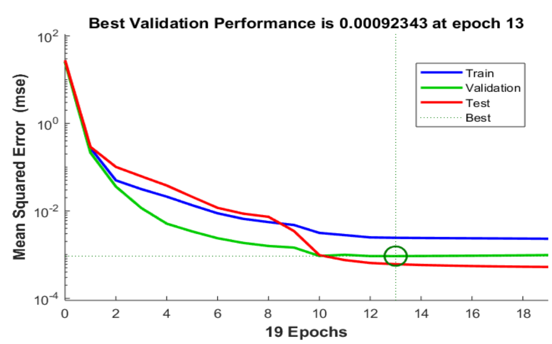

Fig. 4. Performance of the neural network.

C. Synergetic control procedure

The system to be piloted is described by a set of nonlinear equations as follows:

$$\dot{x} = f(x, d, t) \quad (4)$$

Where x is the state vector, d is the controller input vector and t is the time.

As it has been described in [19], the design of the control system consists first of all to choose a macro-variable function:

$$\Psi = \psi\,(x, t) \tag{5}$$

Where Ψ and $\psi\,(x, t)$ designate the designer chosen macro-variable and state variables.

The purpose of the control system is to ensure that the system to be controlled works on the manifold:

$$\Psi = 0 \tag{6}$$

The dynamic evolution of the macro-variables is fixed according to the equation:

$$T\dot{\Psi} + \Psi = 0 \quad (7); \quad T > 0 \tag{7}$$

Where T is a design parameter describing the speed of convergence to the manifold specified by the macro-variable.

According to the rule of the differentiation chain, the derivative of Ψ is given by:

$$\dot{\Psi} = \frac{d\ \Psi}{dx}\dot{x} \tag{8}$$

Finally, by combining Eqns. (4), (7) and (8), the control law is given according to equation (9):

$$T\frac{d\Psi}{dx}f(x,d,t) + \Psi = 0 \tag{9}$$

D. Synergetic Control Law

This part focuses on the application of synergetic control theory to provide the proper duty cycle to control the boost converter.

The dynamic equations that govern a classic boost converter are as follows [20]:

$$\frac{di_L}{dt} = \frac{V_{pv}}{L} - \frac{V_0(1-d)}{L} \tag{10}$$

$$\frac{dV_0}{dt} = \frac{I_L(1-d)}{C} - \frac{V_0}{RC} \tag{11}$$

where V_0 is the DC-DC converter's output voltage, i_L is the inductor current and d ϵ [0 1] the duty cycle.

In steady-state conditions, the optimal current (I_{ref}) is forced to be substantially equal to the inductance current (I_L) and the optimal voltage (V_{ref}) is also forced to be substantially equal to the output voltage (V_0) of the DC-DC converter:

$I_{ref} - I_L \approx 0$ and $V_{0ref} - V_0 \approx 0$

According to the Eqn. (6), the following macro-variable can be chosen:

$$\psi = (I_L - I_{ref}) + (V_0 - V_{0ref}) \tag{12}$$

According to the equation (7):

$$T\left[\frac{\partial I_L}{\partial t} + \frac{\partial V_0}{\partial t}\right] + (I_L - I_{ref}) + (V_0 - V_{0ref}) = 0 \tag{13}$$

By replacing the parameters $\frac{\partial I_L}{\partial t}$ and $\frac{\partial V_0}{\partial t}$ by their expressions d can be expressed by the following equation:

$$d = 1 - \left[\frac{V_{pv}}{L} - \frac{V_0}{RC} + \frac{V_0 - V_{0ref}}{T} + \frac{I_L - I_{ref}}{T}\right] / \left[\frac{V_0}{L} - \frac{I_L}{C}\right] \tag{14}$$

At the maximum power point, to have an optimum duty cycle without using a closed-loop control system, we assume that all unknown parameters in equation d are optimal and that also the efficiency of the boost converter is 100 %. That means:

$$P_{ref} = P_0,\ V_{pv} = V_{ref}, I_L = I_{ref}, V_{0ref} = \sqrt{\frac{P_{ref}}{R}}.$$

Where P_{ref} is the optimum output power of the solar panel and P_0, the output power of the Boost converter.

As a result, the expression of the duty cycle becomes:

$$d = 1 - \left[\frac{V_{Ref}}{L} - \frac{\sqrt{\frac{P_{ref}}{R}}}{RC}\right] / \left[\frac{\sqrt{\frac{P_{ref}}{R}}}{L} - \frac{I_{Ref}}{C}\right] \tag{15}$$

IV. RESULTS ANALYSIS

The PV solar module specifications are given in Table 1.

Table 1: Specifications of solar Module.

Parameter	Value
Open circuit voltage (V_{OC})	44.1 V
Short circuit current (I_{SC})	7.96 A
Voltage at MPP (V_{mpp})	35 V
Current at MPP (I_{mpp})	7.44 A

The system is implemented in MATLAB/Simulink software. As mentioned above, the MPPT control system searches the maximum power of the PV generator. To check the performance of the proposed ANN-SCA command, its results were compared to the classical P & O command under several irradiation and temperature levels, as shown in the Fig. 5 and 6 below:

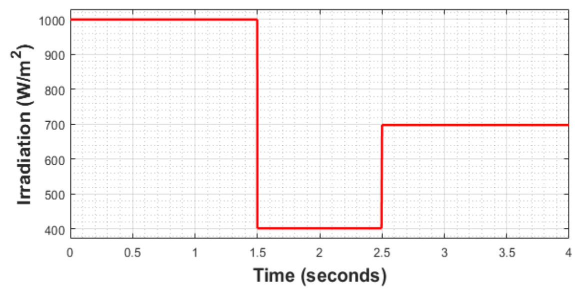

Fig. 5. Irradiation level variations.

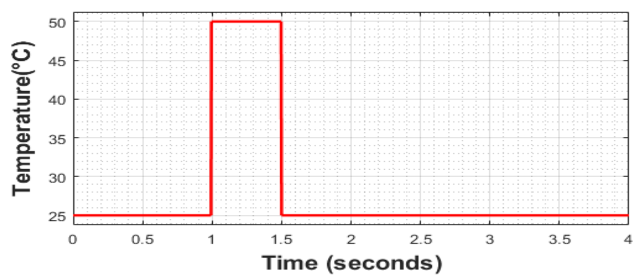

Fig. 6. Temperature level variations.

Fig. 7 shows the evolution of the duty cycle as a function of sudden changes in climatic parameters. It reveals that globally the duty cycle of the P & O method oscillates while the ANN-SCA method is not oscillate. Similarly, during sudden changes of climatic parameters, the P&O takes more time to search the new optimal duty cycle than ANN-SCA. This is also reflected on the evolution curves of the voltage, current and power at the Maximum Power Point (Fig. 8, 9 and 10). In point 1.5 s a considerable variation of the climatic parameters, such as the irradiation drops from 1000 to 400 W / m^2 and the temperature drops from 50 to 25^{o}C led a fall of the duty cycle from 0.53 to approximately 0.2, the V_{mpp} goes from 32 V at 36 V, P_{mpp} goes from 235 to 100 W and the I_{mpp} is almost stable. During this time, the response time of ANN-SCA is almost zero whereas P & O takes about 0.125s to find the new Maximum Power Point. The same scenario takes place in 2.5 s, the temperature remained stable at 25^{o}C and the irradiation climbed from 400 to 700 W/m^2. At this point, the duty cycle is about 0.2 to 0.4, the voltage remains almost stable at 36 V, the current climbs from 3 to 5.2 A and the power from 100 to 170 W. During this period, the ANN-SCA response time is almost zero whereas P & O takes about 0.05s to search the new Maximum Power Point. Based on the results of the interpretations, we can conclude that the ANN-SCA hybrid method is more robust and accurate than the traditional P & O method.

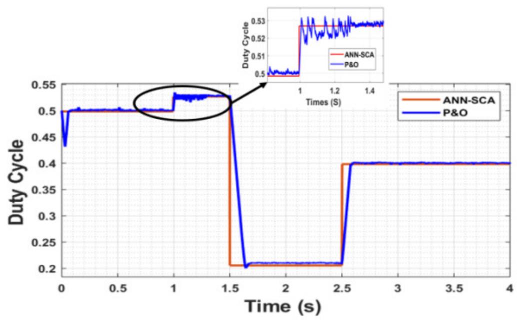

Fig. 7. Duty cycle delivered by P & O and ANN-SCA.

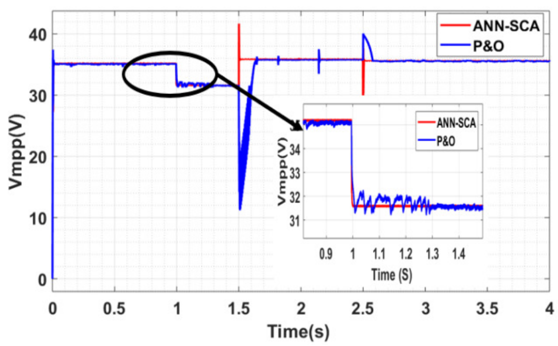

Fig. 8. Voltage delivered at the MPP by P & O and ANN-SCA.

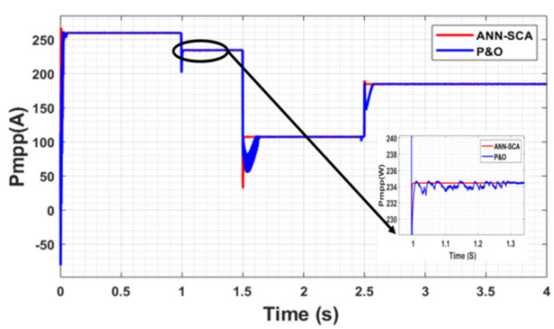

Fig. 9. Power delivered at the maximum power point by P & O and ANN-SCA.

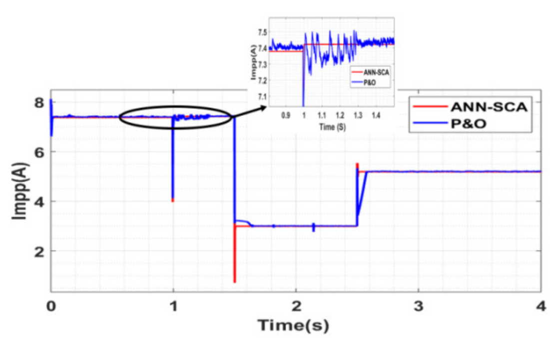

Fig. 10. Current delivered at the maximum power point by P & O and ANN-SCA.

V. CONCLUSION

In this paper, the ANN-SCA hybrid method has been developed to predict the maximum power of the solar photovoltaic module with variable climatic parameters. ANN learning is successfully conducted to achieve a goal of 9.23 e–4. This was done using the database generated by simulation of the solar module. The ANN-SCA hybrid method has been correctly designed. From the simulation results, it can be seen that the pursuit of the maximum power point is well accomplished. The proposed method adapts well to sudden changes in illumination. The results also show that, compared to the conventional P&O method, ANN-SCA is more accurate.

As future work, we foresee an experimental implementation of the proposed method in order to better appreciate its behaviour in a real way.

ACKNOWLEDGEMENTS

The authors acknowledged the support of the African Centre of Excellency in Mathematics, Informatics and TIC (CEA-MITIC) and the Department of Electrical and Computer Engineering of the Université duQuebec à Trois-Rivieres.

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How to cite this article: Akoro, E., Tevi, G. J., Faye, M. E., Doumbia, M. L. and Maiga, A. S. (2020). Artificial Neural Network Photovoltaic Generator Maximum Power Point Tracking Method using Synergetic Control Algorithm. *International Journal on Emerging Technologies*, *11*(2): 590–594.