Comparative analysis for various control strategies based MPPT technique of photovoltaic system using DC-DC boost converter

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***Abstract*—The present research investigates a comparative analysis for various strategies based on Maximum Power Point Tracking (MPPT) technique dedicated for PV systems. The different strategies adjust the duty cycle so as to provide maximum power to the load via a DC-DC boost converter. The two first methods refer to the traditional approach where as the Perturb and Observe (P&O) and the Incremental Conductance (INC) methods. The third and fourth one, based on the artificial intelligence approach, are respectively Fuzzy Logic (FL) and Radial Basis Function Neural Network (RBFNN). The suggested MPPT strategies are tested and validated by using Matlab/Simulink simulation for varying weather conditions. Some concluded remarks are given allowing a best choice of the adequate strategy for a given application, referring to the desired performances and taking into account the required real-time implementation cost.**

***Keywords*—PV system; MPPT; DC-DC Boost converter; Perturb & Observe; Incremental Conductance; Fuzzy Logic; Neural Network.**

I. INTRODUCTION

Photovoltaic (PV) systems are an attractive subject of technical technology; it seems clean, silent and inexhaustible producers of energy. However, the challenges still remain especially in terms of output power and efficiency which are mainly affected by solar irradiance and temperature. Therefore, the Maximum power point tracking technique (MPPT) is widely adopted in order to extract the maximum power under variable environmental conditions [1, 2].

So far, many strategies based MPPT methods have been approached for tracking MPP in different ways [3, 4, 5, 6]. Among conventional MPPT techniques, the algorithms Perturb and Observe (P&O) and Incremental conductance (INC) have been firstly developed and continuously improved [7, 8].
These methods are often used because they are rather simple to implement and they have a good convergence speed. However, they have a major drawback during the steady state which is the oscillations around the MPP. This behavior reduces considerably the efficiency due to power losses.
Several attempts were performed by means of decreasing the perturbation step size but this will affect the tracking speed [9]. Lately, P&O and INC methods with variable step size have been suggested to overcome this compromise [10, 11].

Recently, novel approaches using the artificial intelligent techniques are proposed such as Neural Network (NN) and Fuzzy Logic (FL) [12]. These soft computing controls, which need to have prior knowledge of system operation, have attracted a great interest. Studies have proved their fast response to extract the MPP under irradiance variations with a good reduction of the perturbations step size [13, 14, 15]. The FL based methods is usually known that there isn't a systematic method for identifying the input and output membership functions and the rules base, they are usually determined intuitively. With regards to NN based methods, they are known to suffer from a long training time [4]. However, Radial Basic Function Neural Network (RBFNN) is a typical local approximation neural network that has a simpler structure and a faster convergence than the Back-propagation neural network (BPNN) [16].
This paper suggests a comparative study of the different tracking strategies of the MPP based on P&O, INC, FL and NN techniques. The above cited techniques vary in complexity, effectiveness, time response, cost and sensors required. The objectives attempted to be achieved are: first the optimization of the control parameters and the manner of their adjustment conducing to the improvement of the performances of these techniques under different irradiance and temperature and with respect to power loss reduction. The second objective is to propose a guideline approach that allows an optimal utilization of the presented control strategies.

The paper is organized as follows: section II exhibits the modeling of the adopted solar system; section III details four ameliorated control strategies based MPPT techniques dedicated to a PV system. Section IV includes simulation results and comparative studies where some concluded Remarks will be addressed.

II. PV SYSTEM DESCRIPTION AND MODELLING

The design of the PV system can be divided into two parts: the PV array modelling and the MPPT boost DC-DC converter modelling illustrated by fig1.
By changing the boost converter duty cycle (D), the load impedance as seen by the source is changed and adapted at the peak power point of the source in order to transfer the maximum power.

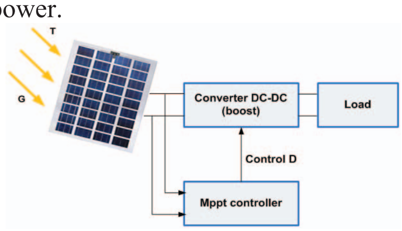

Figure1: PV system

A. PV panel model

To design the PV model, we must first focus on the research of the electrical equivalent to that source.
PV cells are electrically connected in parallel (N_p) and/or series (N_s) to produce higher power; it is basically a P-N junction semiconductor that converts solar energy into electric power, therefore, the PV cell can be represented by fig.2; it consists by a light produced current source I_{ph}, one diode(D), parallel and series resistances: ($R_{sh,}$ R_s.).

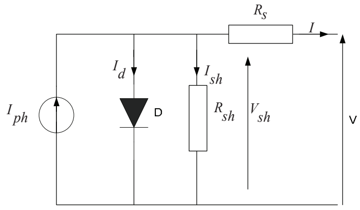

Figure 2: equivalent circuit of PV cell

The equivalent mathematical model for the current and voltage of a PV module is given by [17]:

$$I_{pv} = N_p I_{ph} - N_p I_0 \left\{ \exp\left(\frac{q\left(\frac{V_{pv}}{N_S} + R_S \frac{I_{pv}}{N_p}\right)}{AKT} \right) - 1 \right\} - \frac{\frac{N_p}{N_S} V_{pv} + R_S I_{pv}}{R_{sh}} \quad (1)$$

Such as:

V_{pv} : voltage output
I_{pv} : current output
I_0 : reverse saturation current
A : ideality factor
q : electron charge, ($1.602.10^{-19}\,C$)
N_s , N_p : numbers of cells connected respectively in series and in parallel
T : cell temperature
K : Boltzman constant, ($1.381.10^{-23}\,J/K$)

The parameters of the PV module which is simulated are given in appendix 1.
Usually, the performance of a PV module is presented by its P(V) curve, which is depends on the irradiance and temperature, fig. 3 shows the output characteristics P(V). For various irradiance (G) and temperature (T) levels, it is shown on the curve that there is a single point at which the generated power is maximum.

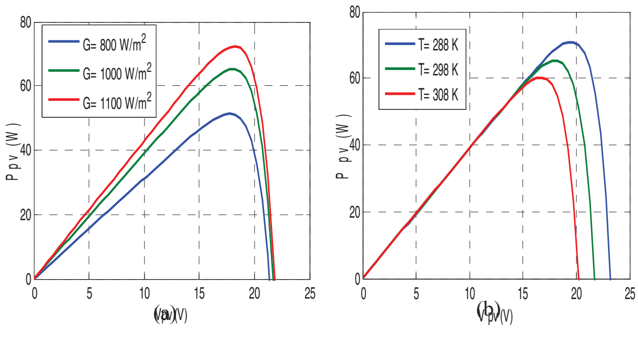

Figure 3: (a).Irradiance effect under a constant temperature on PV array. (b) Temperature effect under a constant irradiance on PV array.

We can see that the output characteristic is nonlinear and highly affected by the temperature and solar irradiance. In order to generate the maximum power, it must be activated at the unique point specific with determined current and voltage values. To achieve this aim, distinct power converter circuits are adopted and associated with several control strategies. In our case, a DC-DC boost converter is considered and will be developed in the next paragraph.

B. DC-DC boost converter

In fig.4, a boost converter basic circuit is shown; it is composed of two switches (K: MOFSET transistor, D: diode), output filter capacitor C_2, inductor L, input capacitor $C_1$and load resistor R.
In the boost converter modeling, it is supposed that all components are ideal and the converter runs in continuous conduction mode.

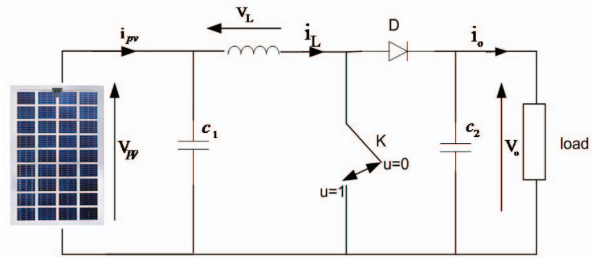

Figure 4: Boost converter model

K is either on or off depending on switching position, it induces two synthetic circuits.
- K is on and D is reverse biased, the output voltage V_0 and the inductor current i_L are given by eq (2), (3) and (4):

$$\frac{di_L}{dt} = \frac{V_{pv}}{L} \quad (2)$$

$$\frac{dV_o}{dt} = -\frac{V_o}{R C_2} \quad (3)$$

$$i_{pv} = i_L + C_1 \frac{dV_{pv}}{dt} \quad (4)$$

- K is off and D is forward, the evolution of V_0 and i_L is described by eq (5) and (6):

$$\frac{di_L}{dt} = \frac{V_{pv}}{L} - \frac{V_o}{L} \quad (5)$$

$$\frac{dV_o}{dt} = \frac{i_L}{C_2} - \frac{V_o}{R C_2} \quad (6)$$

Once the equation development of PV system associated with the boost DC-DC converter is completed, we can aborded the presentation of different control strategies.

III. CONTROL STRATEGIES BASED MPPT TECHNIQUE

As explained above, using MPPT techniques is strongly required to extract the maximum power of the PV system regardless of climatic conditions. In the following, four control strategies based MPPT technique will be presented and investigated.

A. Perturb and Observe technique (P&O)

P&O technique has been broadly used due to its simplicity and its ease of implementation; it is based on the insertion of perturbation to the system actual operating point and the observing of the system behaviors. Accordingly and in order to attract the MPP, a decision, increasing or decreasing the PV system output voltage, is taken, then executed by acting immediately on the duty cycle. Fig.5 shows the flowchart of this technique, it can be detailed by the following steps:

- If V_{pv} and P_{pv} variations are both positives or negatives, then the duty cycle D will be increased by a step size of ΔD ,
- If V_{pv} and P_{pv} variations have opposite sign, then the algorithm will work vice versa.

This process is repeated periodically to achieve the MPPT.
In fact, considering a big ΔD insures a fast dynamic performance and causes non neglected oscillations in steady state. While, a small ΔD implies little oscillations at steady state and slow dynamic response [14].
So, the principal limitation of the P&O method is a compromise, between reduced oscillations at steady state and a fast dynamic response, there needs to be established. This is not always easy to done because no algebraic criteria exists to fulfill this compromise.

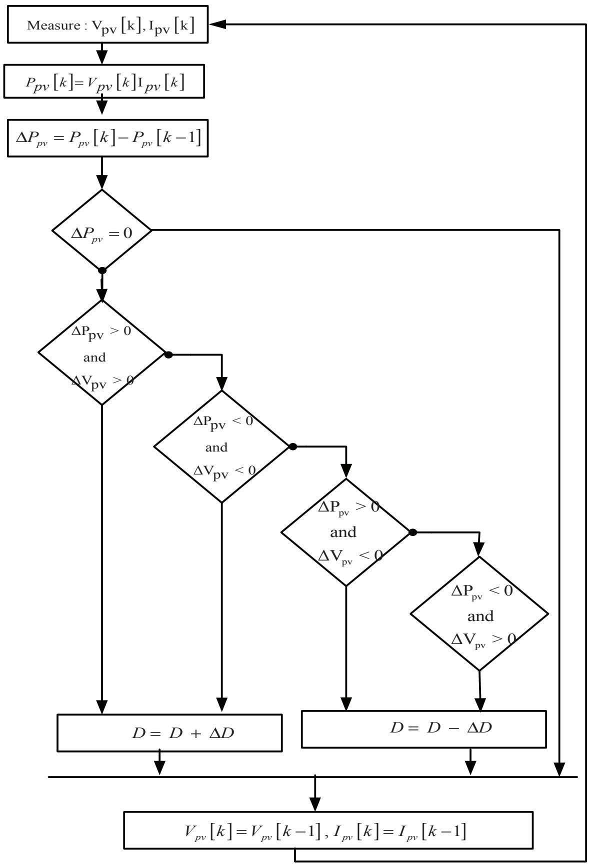

Figure 5: P&O algorithm flowchart

B. *Incremental Conductance technique (INC)*

In contrast to P&O method, this method is not oscillating around the steady point (MPP), it requires the voltage and current instantaneous to find the desired point [18], and fig.6 shows its algorithm flowchart. The partial derivative dP_{pv}/dV_{pv} is in the form:

$$\left(\frac{dP_{pv}}{dV_{pv}}\right) = I_{pv} + V_{pv}\left(\frac{dI_{pv}}{dV_{pv}}\right) \quad (7)$$

From the P(V) curve of PV array shown in fig 3, it is quite clear that the slope is set to zero at MPP, so the power variation is written as follows:

$$\left(\frac{dI_{pv}}{dV_{pv}}\right)_{MPP} = -\frac{I_{pv}}{V_{pv}} = -G \quad (9)$$

Where G is called the instantaneous conductance.
We define the incremental conductance as follows:

$$\Delta G = \frac{\Delta I_{pv}}{\Delta V_{pv}} \quad (10)$$

The MPP tracking is based on the comparison between the instantaneous and the incremental conductance. This method is based on the following equations.

$\Delta G \prec -G$ right of MPP (10)

$\Delta G = -G$ at MPP (11)

$\Delta G \succ -G$ left of MPP (12)

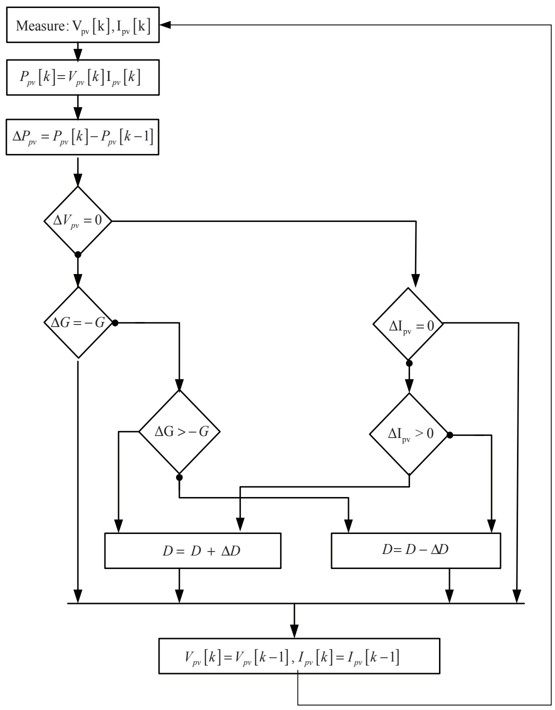

Figure.6: INC algorithm flowchart

C. *Fuzzy logic based MPPT technique*

Recently, the Fuzzy logic control was used in the tracking of the MPP of PV system. This technique has the advantage to work with imprecise inputs and not requiring a specific mathematical model and operation nonlinearity [14, 19]. The design of a FLC requires the elaboration of four components: fuzzification, fuzzy inference, rules base and defuzzification, which are briefly presented below. A conventional fuzzy controller contains two inputs such as the error E and the variation of this error ΔE at sample time K_t, They are defined by the relationships (13) and (14).The output variable is the boost converter duty cycle ΔD .

$$E(K_t) = \frac{P_{pv}(k_t) - P_{pv}(k_t - 1)}{I_{pv}(k_t) - I_{pv}(k_t - 1)} \quad (13)$$

$$\Delta E(K_t) = E(K_t) - E(K_t - 1) \quad (14)$$

The following figure shows the fuzzy logic controller, we introduce normalization gains: K_E , $K_{\Delta E}$ and $K_{\Delta D}$.

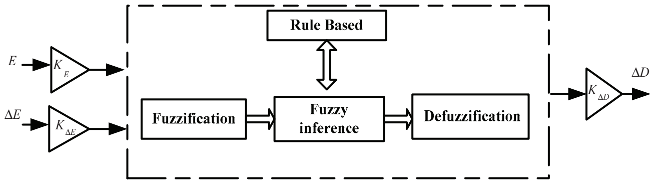

Figure 7: Basic structure of conventional fuzzy logic control MPPT.

1. Fuzzification:

A preliminary step consists to convert each numeric variable that describes the control rules into linguistic variables on the basis of the membership functions. In this work, we define the universe and the membership functions of the input and output variables by five fuzzy sets as follows: Z (Zero), NS (Negative Small), NB (Negative Big), PS (Positive Small) and PB (Positive Big). Fuzzy inference and rules base:

This step is the fuzzy logic control core, where decisions are made. Indeed, we formulate logical relationships between inputs and output by setting the membership rules. From that, we summarized, in table I, the reasoning mechanism as a set of fuzzy {if.., then} rules.

Table I. Fuzzy control rules

E \ ΔE	NB	NS	Z	PS	PB
NB	Z	Z	PB	PB	PB
NS	Z	Z	PS	PS	PS
Z	PS	Z	Z	Z	N
PS	NS	NS	NS	Z	Z
PB	NB	NB	NB	Z	Z

2. Defuzzification:

The fuzzy sets outputs are converted into numeric value.

The proposed MPPT uses a fuzzy logic Mamdani controller so that the operating point tracking MPP, while, the centre of gravity is proposed for computing the output.

D. Artificial Neural Networks based MPPT technique

The Artificial Neural Networks has provided recently new profits in PV systems; they are commonly agreed as a technology, giving an alternative way for solving complex problems.

The greatest benefit of the ANN relative to others modeling techniques is their ability to model nonlinear, complex process without knowing relationships between input and output data. This technique is conceived to imitate the human brain structure and its reasoning. Indeed, ANN is composed by a connection of processors called neurons analogous to the biological brain cells, these neurons are interconnected by many weighted links for transmitting signals [13].

In particular, Radial Basis Function Neural Network (RBFNN), suggested by C.Darken and J.Moody in the late 1980s, is a typical artificial network with a simple structure [16]. It was served in a broad range of applications; it has the ability to approximate any function with faster convergence than other networks [16]. Then, the following part has introduced technical MPPT based on RBFNN.

1. RBFNN basic model

RBFNN has a specific structure; it has only one hidden layer using a conversion function as the Gaussian function.

Numerous controllers based on RBFNN are adopted to generate the duty cycle relative to a DC-DC boost converter. Three layers are used for implementing this controller type, which are shown in fig 8, input layer such that inputs are temperature and irradiance, one hidden layer and output layer which the output is duty cycle D.

The hidden units represented as $\{C_1, C_2,..C_h\}$, give a set of functions that consists an arbitrary basis of the input forms.

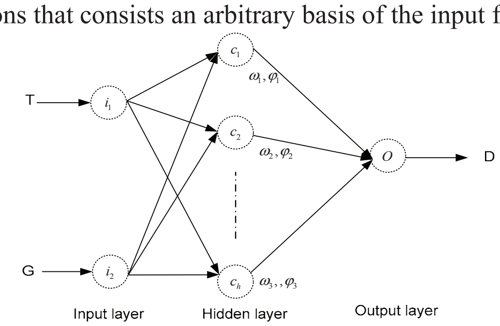

Figure 8: RBFNN structure

Indeed, an input vector $\{i_1, i_2\}$, which is in the receiver field for center c_j , has to activate c_j and by suitable choice of weights, the desired output is obtained. The output is written as follows:

$$O = \sum_{j=1}^{h} \omega_j \varphi_j \quad (15)$$

Where

ω_j is the weight of j^{th} centre, $\varphi_j = \Phi\left(\left\| i - c_j \right\|\right)$ and Φ is a Gaussian radial function, its graph is represented by fig.9, that is used for activation and given by [20]:

$$\Phi(y) = e^{\frac{-y^2}{2\sigma^2}} \quad (16)$$

Where

$$y = \left\| x - c_j \right\| \quad (17)$$

And σ is the width of the center.

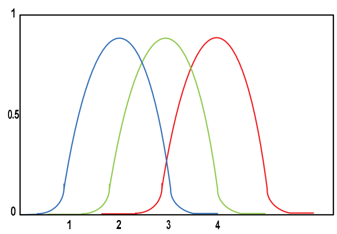

Figure 9: Gaussian radial functions of the same width, which their centers are 2, 3 and 4 respectively.

2. RBFNN training

Let

$$\begin{cases} C=\left\{c_{kj},\left(k=1,\dots,h\right),(j=1,2)\right\} \\ \Theta=\left\{\sigma_{kj},k=\left(1,\dots,h\right),(j=1,2)\right\} \\ W=\left\{\omega_{kj},k=\left(1,\dots,h\right),(j=1,2)\right\} \end{cases} \quad (18)$$

RBFNN training involves updating $\left\{C,\Theta,W\right\}$ in order to minimize the error E; indeed, it is required to define a minimum value of h of RBF with best value of $\left\{C,\Theta,W\right\}$. We are required to have a set of data samples (training set) for that outputs are known.

c_{kj}, σ_{kj}, ω_{kj} are adjusted as follows [13]:

$$\begin{cases} c_{kj}(t+1)=c_{kj}(t)-\eta_1\dfrac{\partial E}{\partial c_{kj}} \\ \sigma_{kj}(t+1)=\sigma_{kj}(t)-\eta_2\dfrac{\partial E}{\partial \sigma_{kj}} \\ \omega_{kj}(t+1)=\omega_{kj}(t)-\eta_3\dfrac{\partial E}{\partial \omega_{kj}} \end{cases} \quad (19)$$

Where

η_1,η_2,η_3 are training rates and $E=\dfrac{1}{2}\Sigma\left(O^d-O\right)^2$, O^d is the actual duty cycle.

IV. Simulations results and discussions

The algorithms described previously have been applied to control the DC-DC boost converter coupled to a PV system composed from 10 PV modules which are connected in parallel. The PV module parameters are shown in appendix I. Three cases are considered to ensure the comparison between these algorithms in terms of their robustness, accuracy and stability of the MPP.

The first case consists in comparing the performance of studied controllers under standard conditions: (G=1000W/m^2, T= 25°C).

Second case, a rapid variation of irradiance is considered.

Third case, the four controllers are subject to a rapid variation of temperature. The variation versus time of the irradiance and temperature are given by fig. (10).

The obtained results are shown in fig. (11), fig. (12) and fig. (13).

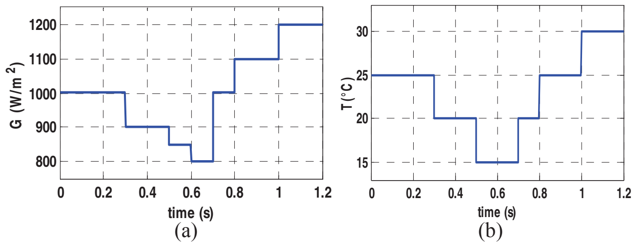

Figure 10: (a) Irradiance scenario changes

(b)Temperature scenario changes

A. Simulation results under standard conditions

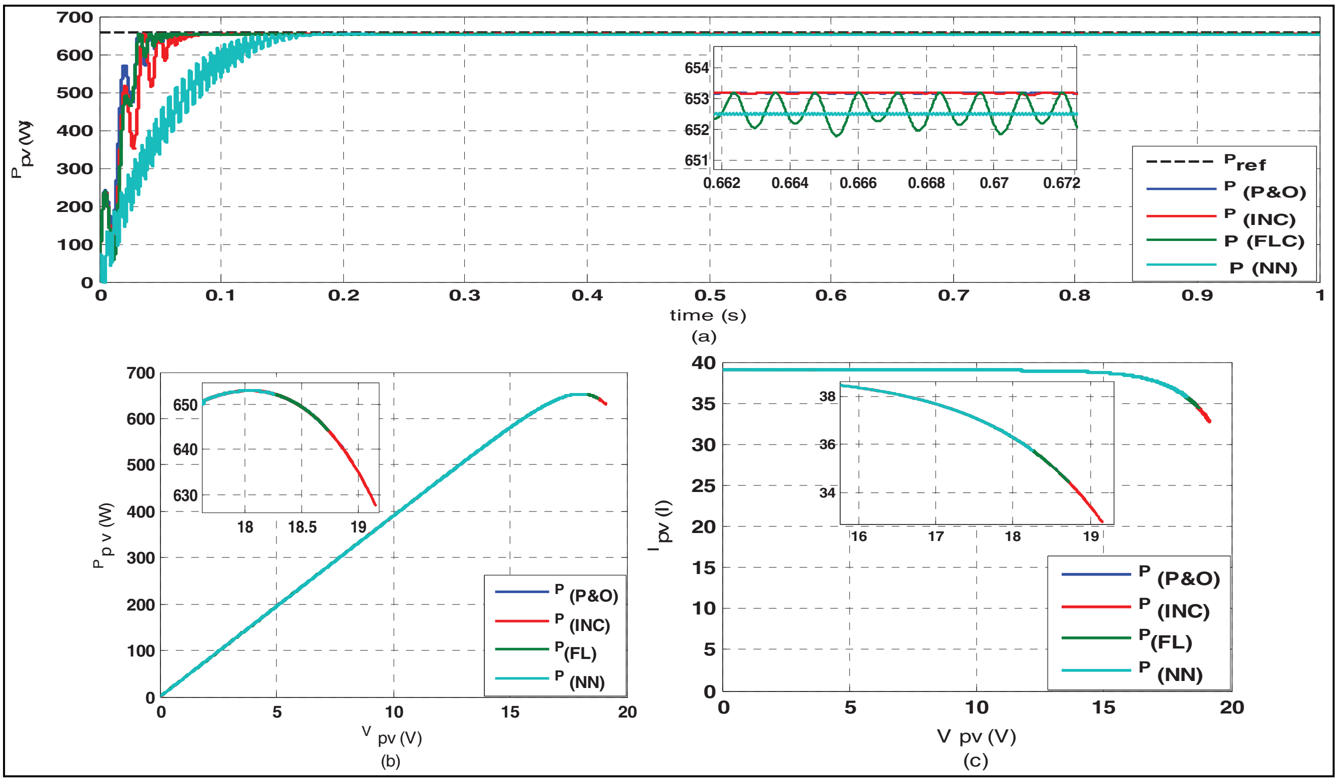

Figure11: Result simulations under standard conditions of P&O, INC, FL and NN techniques: (a). Power outputs P_{pv}, (b). output characteristics $P_{pv}\left(V_{pv}\right)$ and (c). Output characteristics $I_{pv}\left(V_{pv}\right)$

B. Simulation results under irradiance variation

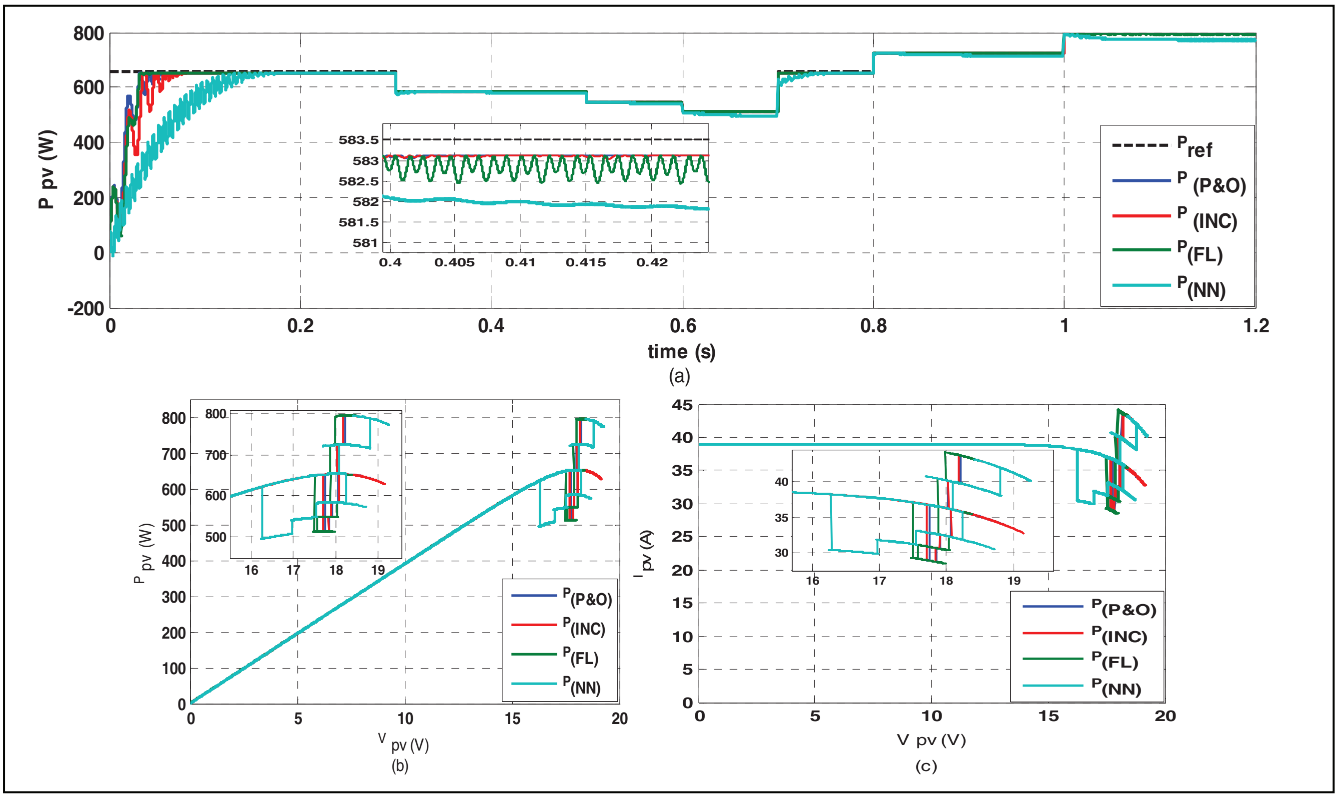

Figure12: Result simulations under variation of irradiance of P&O, INC, FL and NN techniques: (a). Power outputs P_{pv} , (b). Output characteristics $P_{pv}\left(V_{pv}\right)$ and (c). Output characteristics $I_{pv}\left(V_{pv}\right)$

C. Simulation results under temperature variation

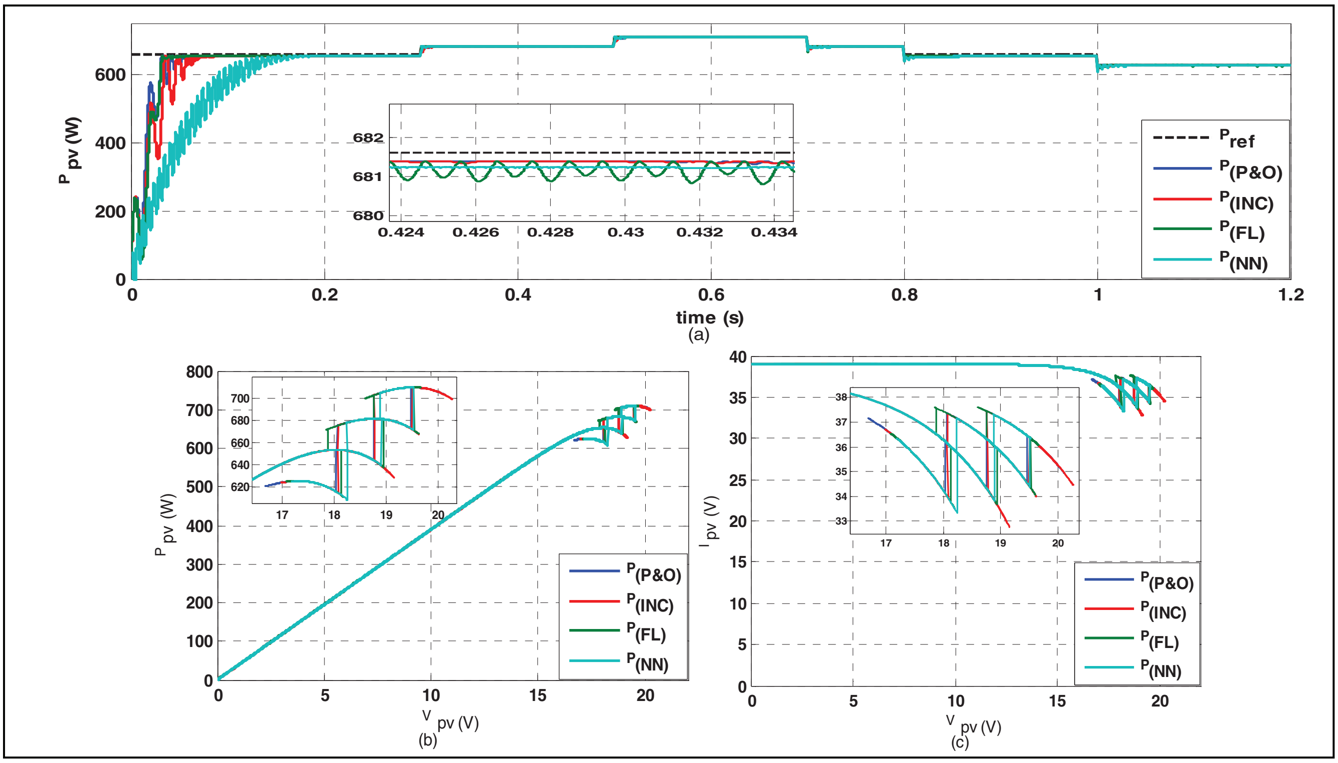

Figure 13: Result simulations under variation of temperature of P&O, INC, FL and NN techniques: (a). Power outputs P_{pv} , (b). Output characteristics $P_{pv}\left(V_{pv}\right)$ and (c). Output characteristics $I_{pv}\left(V_{pv}\right)$

As shown in fig.11:
The P&O technique tracks the MPP in 0.034 s; its output power curve is smooth, nearly without oscillations.
The INC technique tracks the MPP in 0.037 s, it is noted that its output power curve coincides with that achieved by the P&O technique at the steady state.
The FL technique tracks the MPP in 0.032 s, at steady state a slight oscillations with a magnitude of 1.2 W are registered.
The NN technique tracks the MPP but after 0.18 s, the output power curve presents oscillations at transient response. But once it reaches the MPP, the oscillations vanished. A neglected steady error around 0.5 W is registered.
At MPP, the system delivers a current of 36.5 A, at a voltage of 18 V, this is in parfait adequation with PV system parameters.
As shown in fig.12 and fig.13, P&O and INC techniques respond efficiently to all sudden changes in atmospheric conditions, they also track the MPP closely, same for the FL method, but, this latest, presents slight oscillations. The NN method can track quickly the MPP for small variations of temperature and irradiance.
Furthermore, methods studied have an accurate MPP tracking; we conclude that the fuzzy method is the fastest, it reaches the MPP before the other methods, but it takes relatively a high computation time. However, the use of a reduced fuzzy set can significantly reduces the calculation time control. Thus and in real time implementation, a compromise would be made between the desired performances and the computation time.
The NN method has the largest response time especially during high variations in climatic conditions, nevertheless, the advantage of this method is to not set the initial value of delta D which leads to a compromise between accuracy and convergence speed unlike the other methods.
The power curves achieved with P&O, INC and NN are smoother and more stable at steady state compared to FL technique that provides more Power loss.
At last, to evaluate the performance of these methods, the simulation results are summarized in Table II in terms of relative error, steady error and tracking time.

$$\varepsilon_r = \frac{P_{MPPT} - P_{pv}}{P_{MPPT}} 100 \quad \text{and} \quad \varepsilon_s = P_{MPPT} - P_{pv,final} \tag{20}$$

Where P_{MPPT} refers to the maximum power provided theoretically by the PV array, $P_{pv,final}$ refers to the power at steady state and P_{pv} is the maximum power for each method.

Table II Comparison between performance controllers

	P&O	INC	FLC	NN
Relative error	0.57%.	0.58%	0.6%	0.65%.
Steady error (w)	3.8	3.82	4	4.3
Response time (s)	0.034	0.037	0.032	0.16s
Sensors required	Voltage and current	Voltage and current	Voltage and current	Temperature and irradiance

V. CONCLUSION

In this paper, P&O, INC, FL and NN based MPPT techniques, to control a PV system associated with DC-DC Boost converter, are presented and their specificities and performances are discussed. On the basis of the simulation results, it is verified that the all cited control strategies insure satisfactory performances during the irradiance and temperature variations. The NN technique holds the longer response time and this is to the required learning phase, where the FL technique has the best transit response by means of faster tracking speed and oscillations magnitude. The P&O and INC techniques have shown very similar behaviors. With regarded to simplicity implementation the P&O technique is considered as more favorite. In all cases and in order to minimize the power loss, a compromise should be established between the adopted step variation, the desired speed convergence and the tolerated oscillation degree. Furthermore, the substitution of required sensors with an estimator or observer in the real implementation of any of these control strategies should be taken in consideration.

APPENDIX-I

Table III PV module parameters

PARAMETERS	Value
N_s	36
N_p	1
ideality factor	1.5
Maximum power	65.7 W
Voltage at maximum power	18 V
Current at maximum power	3.65 A
Open circuit voltage	21.7 V
Short circuit current	3.9 A

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