Grid-connected PV System with a Modified-Neural Network Control

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Abstract-The integration of solar energy in the field of electricity production is becoming a growing trend, especially photovoltaic grid-connected system because of the high cost of batteries. The simulation of single-phase two-stage photovoltaic grid-connected is highlighted in this study under different climatic conditions to analyse their influence on the output performances. So, for injecting the maximum amount of power in the grid, the photovoltaic (PV) array must extract the maximum solar energy available and operate continuously at the maximum power point (MPP). For that, an efficient maximum power point tracking algorithm (MPPT) should be integrated. MPPT methods are the result of considerable research work and developments, a very large number of those studies classified them in two categories conventional and novel. Conventional techniques as Incremental Conductance (IncCond), Perturb and Observe (P&O) and Open Circuit Voltage (OCV) present several drawbacks, especially in the fast variation of meteorological and solar irradiation conditions. Novel techniques as Particle Swarm Optimisation (PSO) and Neural Network (NN) achieve better results however, they are complex and require high cost of implementation. Two efficient MPPT algorithms based on NN have been performed and simulated. To evaluate the proposed MPPT algorithms and compare them with the conventional MPPT algorithms as IncCond, P&O and OCV a simulation on MATLAB/SIMULINK platform has been done under several temperatures and irradiance. The study covers the stability, time response, oscillation and the overshoot. The simulation results show a high efficiency and small response time with high accuracy for the proposed techniques.

Keywords MPPT algorithms, photovoltaic grid-connected, Neural Network, Solar PV system.

1. Introduction

Nowadays, the involment of solar energy is growing up in the world due to the limitation of fossil fuels and also to participate in the reducing of greenhouse gas emissions. For this reason, the European Union (EU) currently has set objectives to increase the contribution of renewable energies to 32% by 2030 with a 40% decrease in greenhouse gas emissions compared to 1990 levels [1]. However, the major drawback of renewable energies like solar energy their dependency on meteorological conditions, like temperature and irradiance [2].

To avoid that problem, an integration of a storage element as a battery is useful on grid, however, it will strongly increase the installation's cost. Following this, the injection of photovoltaic (PV) energy is expected to increase in the future due to environmental benefit, economic factor and technical [3]. In addition, The Photovoltaic energy can be used as a source to supply a standalone load [4]. or one of different energy sources to provide energy to microgrid [5].

The solar photovoltaic array can be connected to main grid by three phase system [6] or single phase [7], via single stage or two-stage configurations. Actually, the two-stage solar PV system is the most used in which the first stage (dc/dc converter) ensures the maximum power point (MPP) using a maximum power point tracking (MPPT) algorithm and adapt the dc voltage, on the other side, the second stage (inverter) converts dc current to ac current considering the synchronisation between the main grid and PV inverter [8].

In the way of enhancing the overall efficiency of solar PV system, the MPPT algorithms are widely used. They operate to maintain the solar PV array works in the maximum power point to extract the maximum of power available [9].

By reason of nonlinear characteristics of solar PV array, several MPPT algorithms have been investigated in literature for instance Incremental Conductance (IncCond) [10], Perturb and Observe (P&O) [11], Fractional Open Circuit Voltage and Fractional Short Circuit Current methods [12]. Some other intelligent methods have been developed like fuzzy logic [13] and [14], genetic algorithm [15], Neural Networks methods [16].

The most requirement in the MPPT algorithms is to track the maximum power in different environmental conditions with less time of response. The conventional algorithms show several problems, the major issue is the tracking while a fast variation in meteorological conditions. The proposed algorithms in this study are used to control a solar PV array with high output power. Following this, a small variation in the optimal duty cycle causes a huge loss in the produced power. In [17] a partially shaded solar PV array is controlled by a MPPT algorithm based on Fuzzy Logic and Neural Network (NN), the reference voltage is given by the NN and fed the fuzzy logic system. Then, it generates the appropriate control signal for the dc-dc converter. The principal disadvantages of that system are the complexity and the high price of implementation. In [18] an experimental study of five MPPT algorithms (Perturb & Observe and Incremental Conductance, Particle Swarm Optimization, Fuzzy Logic and Kalman Filter) under normal condition and partial shading, as a result of this study, all the tested techniques track MPP with tolerance less than 2%, on the other hand, only Particle Swarm Optimization achieve the global MPP under partial shading. In [19] a review of the most used MPPT algorithms is made, covering direct methods (1), such as Incremental Conductance and Perturb and Observe and, indirect methods (2), such as Fractional Open Circuit Voltage (FOCV) and Fractional Short-Circuit Current (FSCC), and finally, soft computing methods (3) such as Fuzzy Logic Control (FLC), a Kalman Filter, NN and Particle Swarm Optimization (PSO). That work shows also described study of the advantages and drawbacks of each method. Comparing with the last work, this work presents a detailed study of four MPPT algorithms (IncCond, P&O, OCV and NN). Subsequently, development of another MPPT algorithm based on NN. Finally, the simulation of the five MPPT algorithms with detailed comparison between them using the obtained results. The comparison of different MPPT technics is performed based on simulation, under the energy production point of view. On the other hand, the influence of the variation in the environment conditions on the different performances is shown. This paper is organized as follows. In section 2 a modelling of solar PV system components is presented. Following by MPPT algorithms (section 3), the simulation results and discussion (section 4) and finally conclusion (section 5). The solar PV array used in this study contains four solar PV panels connected in series and three parallel strings. The P-V characteristics of the solar PV array is shown in Fig.1.

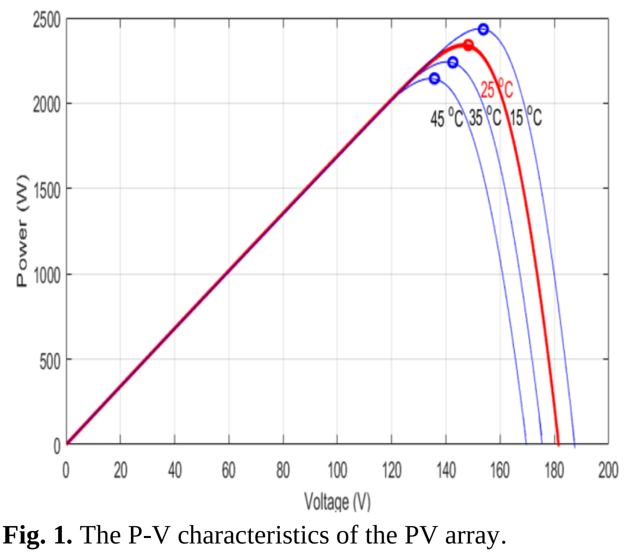

Fig. 1. The P-V characteristics of the PV array.

2. Modelling of PV system components

The single-phase photovoltaic grid-connected is widely used nowadays to avoid the using of batteries. The photovoltaic array can be directly connected to the utility grid through the inverter (single stage) or a dc-dc converter can be integrated between the array and the dc-ac converter (two-stage). In this study a boost converter is used as a dc-dc converter for increasing the PV voltage to a high value. The control of the boost converter is affected by a MPPT algorithm. Dual loops regulator is performed to control the second stage (inverter). A phase-locked loop (PLL) generates the grid voltage phase to make in synchronization the injected current with the voltage of grid. The outer loop commands the dc-link voltage to reach the desired reference. The inner loop (for controlling the current) makes the inverter current follow the current reference. A low-pass output filter (L filter) is introduced with the inverter to eliminate the harmonics around the switching frequency [20]. Fig. 2 shows the simulated system architecture.

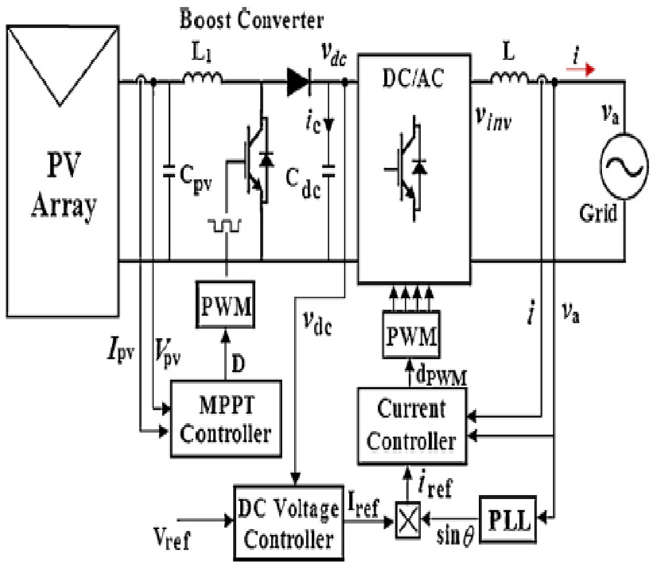

Fig. 2. A single phase two-stage photovoltaic grid connected system [21].

3. MPPT algorithms

The determination of the maximum power is more delicate as it depends of meteorological parameters (temperature and irradiance). As a result, it becomes more difficult to keep the system running at maximum power under different environmental conditions. It is generally based on adjusting the duty cycle of the static converter until it reaches the MPP. Different MPPT algorithms have been published in the literature in the purpose of achieving optimal performance. Some of them are presented in the following sections.

3.1. Incremental Conductance

Incremental Conductance technique is widely used due to its great adaptability and precision, even when there are atmospheric changes conditions [22]. Knowing that the slope of P-V curve equal to zero at the MPP $\left(\frac{dP}{dV}=0\right)$. Hence, using that it seeks for MPP based on the comparison between the conductance $\left(G=\frac{I}{V}\right)$ and conductance increment $\left(G=\frac{\Delta I}{\Delta V}\right)$.

$$\frac{dP}{dV}=\frac{d(VI)}{dV}=I\frac{dV}{dV}+V\frac{dI}{dV}=\mathrm{V}\frac{dI}{dV}+I \qquad (1)$$

Where,

$$\begin{cases} \frac{\Delta I}{\Delta V}=-\frac{I}{V}\ if\ P=MPP \\ \frac{\Delta I}{\Delta V}>-\frac{I}{V}\ if\ P\ in\ the\ right\ of\ MPP \\ \frac{\Delta I}{\Delta V}<-\frac{I}{V}\ if\ Pin\ the\ left\ of\ MPP \end{cases} \qquad (2)$$

The flow chart of this algorithm is shown in Fig. 3.

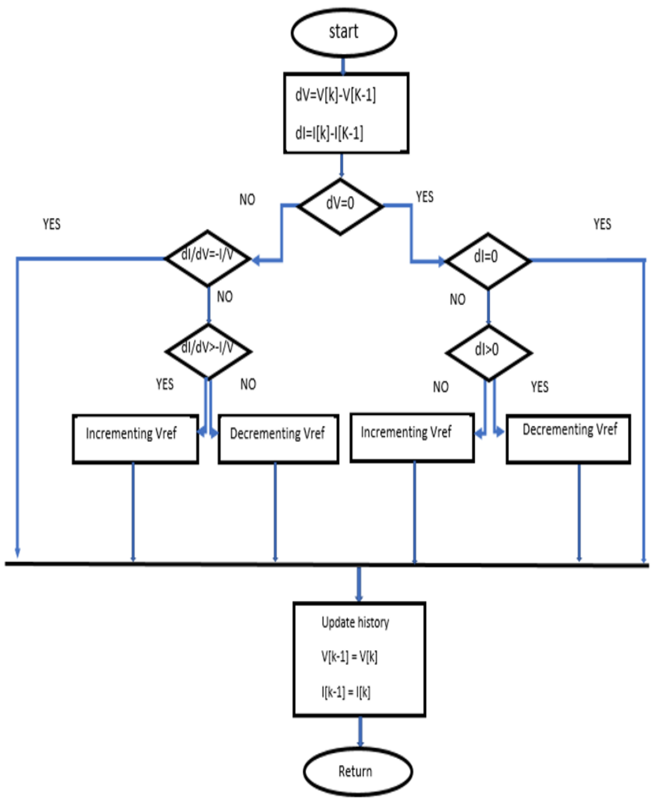

Fig. 3. The flow chart of IncCond method.

3.2. Perturb and Observe

Perturb and Observe (P&O) algorithm is the most popular MPPT algorithm. It's based on the calculation of the photovoltaic voltage and current to get the power. When the perturbation of the operating voltage of PV array is made in a precise direction and $\frac{dP}{dV}>0$ the perturbation moves the operating point toward the MPP [23]. In the other case, if $\frac{dP}{d\,V}<0$ the operating point is then far away from the MPP, and then P&O algorithm changes the direction of the perturbation. Fig. 4 presents the flow chart of P&O algorithm.

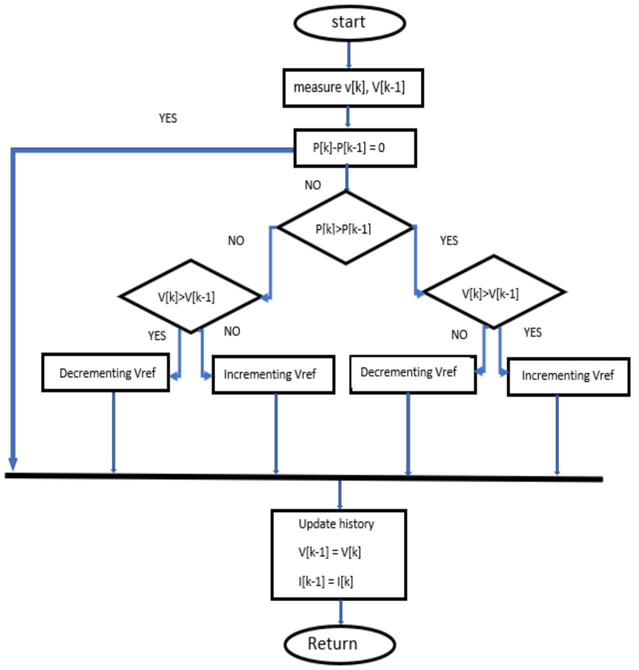

Fig. 4. The flow chart of P&O algorithm.

3.3. *Open Circuit Voltage*

It is based on keeping the solar PV array works around the MPP by the relationship between the voltage at MPP ($VMPP$) and the open circuit voltage of the solar PV array (VOC) ($K=\frac{VMPP}{VOC}$)(from 70 % to 80 %). By varying the intensity of solar radiation VMPP varies a little. In contrary, with the variation on temperature $VMPP$ varies strongly. For this reason, this algorithm must be implemented in region where the temperature varies very little [24]. Fig. 5 indicates the flowchart of OCV algorithm.

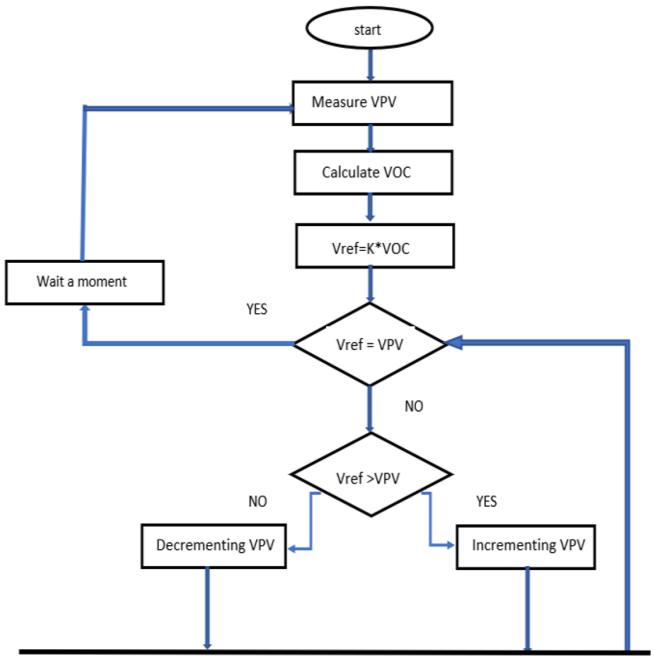

Fig. 5. The flow chart of OCV algorithm.

3.4. Neural Network

The NN is a mathematical model taken from the biological neural networks used to solve a complex problems [25]. The purpose behind it is to predict an output based on the network's training used inputs and targets. For complex problems a multilayer network is needed. This later presents three layers (input, hidden and output layers). The equation 3 is considered to choose the number of hidden neurons [26]:

$$H = O + 0.75 \times L \text{ and } H < 2 \times L \quad (2)$$

where, H: the number of the hidden neurons, L: number of the input neurons and O: the number of output neurons.

Since the boost converter is controlled through the duty cycle, this later can be generated directly by NN or indirectly (modified-NN). In this work the two architectures are presented in which the direct one presents a duty cycle as an output. On the other side, the indirect one shows the reference voltage as an output, this later is compared with the reel photovoltaic array voltage and fed a PI controller which provides the corresponding duty cycle. Both architectures have the temperature and solar irradiance as input. Fig. 6 and Fig. 7 indicate the NN architectures of direct and indirect duty cycle (modified-NN) respectively.

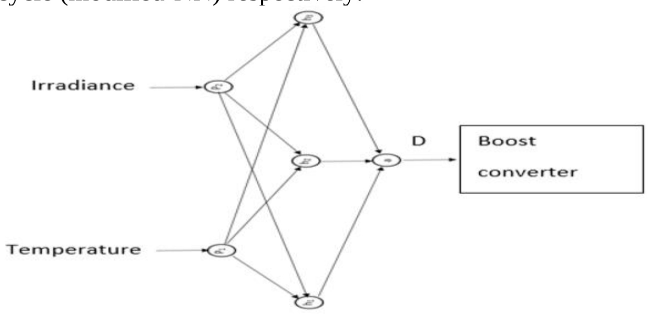

Fig. 6. The NN architecture of direct duty cycle.

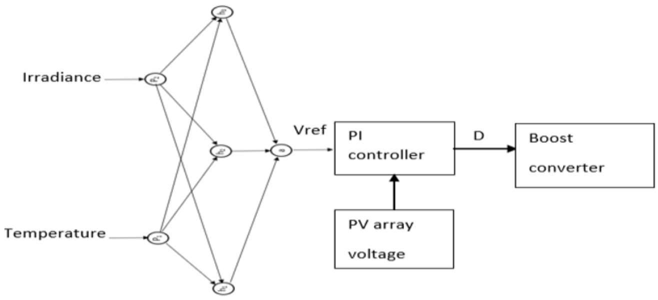

Fig. 7. The architecture of indirect duty cycle (modified NN).

In order to validate the network a high training must be affected. To do that, a number of data samples should be used to obtain a weight corresponding to a small mean squared error (MSE) and perform a supervised training. The equation 4 describes MSE [27].

$$\mathrm{MSE} = \frac{1}{N}\sum_{k=1}^{N}(\mathrm{y(k)} - a(k))^2 \quad (4)$$

Where, N the number of outputs. $\mathrm{y(k)}$: the outpout and $a(k)$: the target.

4. The simulation results and discussion

The platform MATLAB/SIMULINK is used to simulate the single phase two-stage photovoltaic grid connected in which the control of the injected current, dc link voltage and MPP are achieved. Also, the influence of variation in the climatic conditions on the output performance of the system. After that, a simulation of Neural Network MPPT algorithm with analysis covering the stability, time response, oscillation and the overshoot is performed. Fig. 2 shows the single phase two stage photovoltaic grid connected system architecture.

The single-phase two-stage photovoltaic grid-connected system used is modelling as the following. A PV array with capacity of 2341W in standard test conditions (STC) is connected to a boost converter which controlled through an MPPT algorithm. A dc link capacitor is introduced between the boost converter and the inverter to get a constant dc link reduce the harmonics around the switching frequency. A signal builder assures the variation of irradiance and temperature. One MPPT control system with different MPPT algorithms is used to test the proper working around MPP for all the PV panels. In the way of highlighting the features of the simulated MPPT algorithms a huge range of solar irradiances and temperatures are used to test their performances. All the simulations are executed with a step time of $T_s = 5\text{x}10^{-6}$s. Table 1. presents the irradiance and temperature variations in function of time.

Table 1. The changing of the environmental conditions.

Time (s)	0-1	1-2	2-3	3-4	4-5
Irradiance (W/m^2)	1000	1100	800	400	700
Temperature (°C)	25	45	35	5	33

The global configuration of the system is shown in Fig. 8.

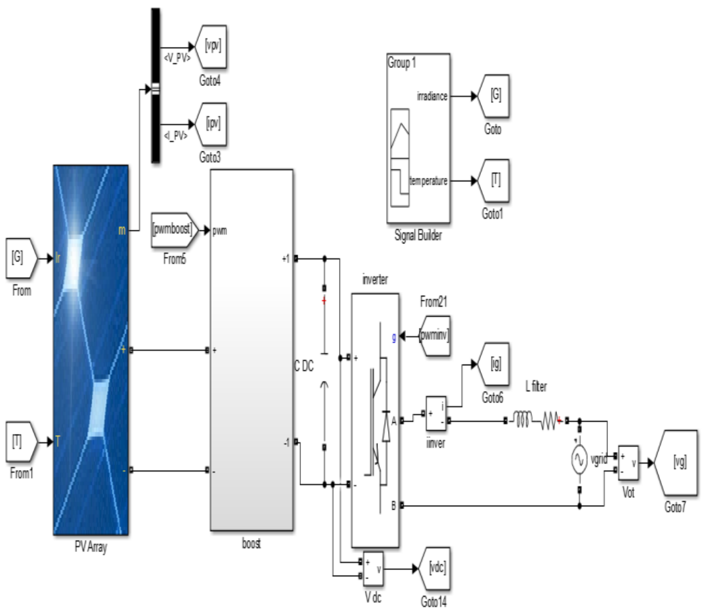

Fig. 8. The configuration of the simulated system.

The used PV array specifications are shown in Table 2.

Table 2. The specifications of the PV array.

Module	STP195-24-Ad
Maximum Power (W)	195.078
Cells per module	72
VOCV (V)	45.4
ISC (A)	5.69
VMPP (V)	36.6
IMPP (A)	5.33
Coefficient of Temperature in VOC (%/°C)	-0.32599
Coefficient of Temperature ISC (%/°C)	0.034007
Number of Parallel strings	3
Number of modules per string	4

The other component's parameters are given in Table 3.

Table 3. The characteristics of the system.

The input capacitor Ci	5 x10^{-5} F
Inductance L	3x10^{-2} H
Switching frequency fsw	5 kHZ
The dc link capacitor Cdc	12 x10^{-3} H
The dc link voltage vdc	400 V
The grid frequency f	50 HZ
The utility grid voltage Vg	220 Vrms
The output L filter Lf	10^{-2} H
The output L filter resistance Rf	0.1 Ω

The inductor of the boost converter [28] and dc link capacitor [29] are calculated respectively by,

$$L = \frac{v_i \times D}{\Delta I \times f_{sw}} \tag{5}$$

Being, v_i: input voltage of boost converter, D: duty cycle and ΔI: ripple current through inductor.

$$C_{dc} = \frac{P_0}{w\Delta v_{dc} \times v_{dc}} \tag{6}$$

Where, P_0: the injected power and Δv_{dc}: dc link voltage ripple.

To present the performances of the system outputs an efficient MPPT algorithm is needed, for this reason, a modified-Neural Network algorithm is performed. In the first part of the simulation the system works under STC using the modified-Neural Network as a MPPT algorithm which has like inputs the solar irradiance and temperature and the reference voltage of PV array represents the output.

The chosen NN algorithm is a multilayer feed-forward network with back propagation algorithm in order to adjust the weights and obtained a reduced mean squared error (MSE). The specification of the network is indicated in Table 4.

Table 4. The characteristic s of the network.

Network's type	Feed-forward
Activation function used in hidden layer	Sigmoid
Activation function used in output Layer	Linear
The used back propagation algorithm	Levenberg-Marquardt
Type of performance	Mean Squared Error (MSE)
Hidden neurons	5
Samples used in offline training	625

The used data samples are achieved by varying the irradiance from 100 W/m^2 to 1100 W/m^2 and temperature from 5°C to 45°C. Those data samples are used for training the network. On the other side, some data are used for the validation of the network. Fig. 8 indicates a small MSE which represent the convergence of output to the desired target with high accuracy of data acquisition which justify validity of samples.

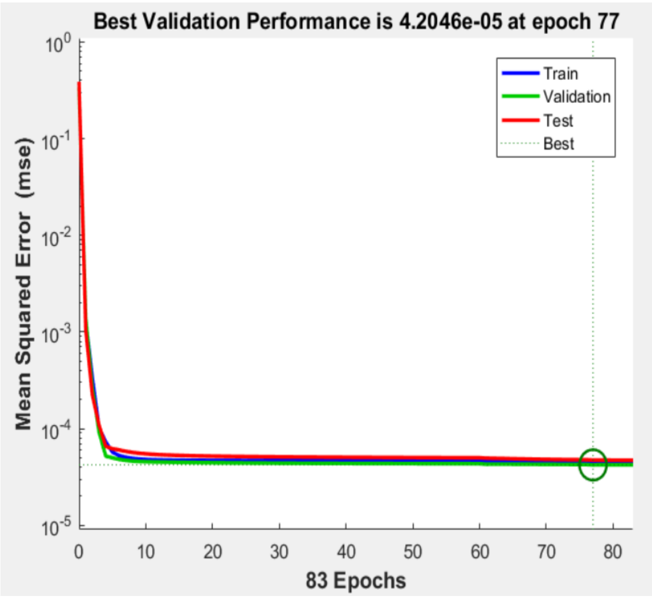

Fig. 8. The Mean Squared Error (MSE) of the NN.

The inverter controller contains two loops, the first one controls the dc link voltage using a PI controller which compares the real dc link voltage to a reference value. The output of this loop is the maximum value of the reference current. The PLL gives the grid voltage phase. A sinusoidal signal is generated and synchronized with the phase of grid voltage and multiplied by the maximum value of the reference current which gives the reference current. The second loop makes the injected current following the reference current via Pr controller. The Pr controller generates the reference signal to the PWM generator to monitor the inverter's switches. The Fig. 9 presents the inverter controller block.

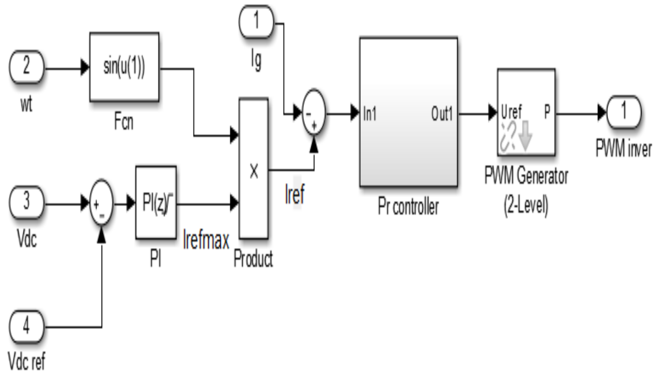

Fig. 9. The inverter controller block diagram.

Using the equation 6 and the characteristics in Table 4, dc link voltage ripple equal to: Δv_{dc}= 1.55V. Fig. 10 shows that the voltage of dc link is following the reference voltage (Vdcref= 400V) with a peak-to-peak voltage ripple of Δv_{dc}= 1.50V, this value represents 0.375% of the reference value and as it seems it's very close to the theoretic value (1.55V).

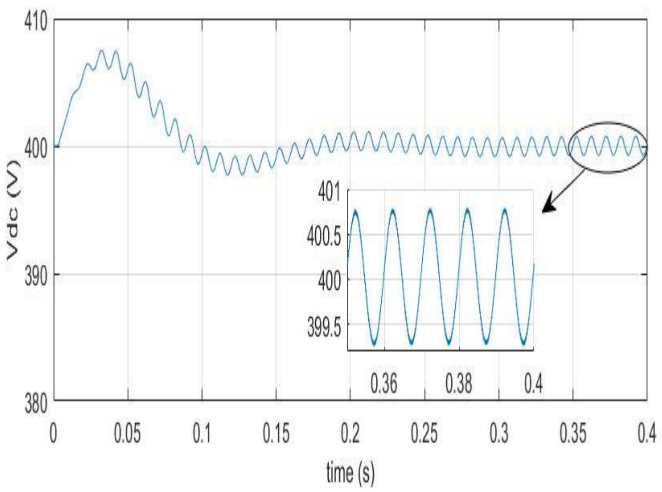

Fig. 10. The dc link voltage.

Fig. 11 indicates the connection between the inverter and the utility grid in which the injected current transformed to sinusoidal form.

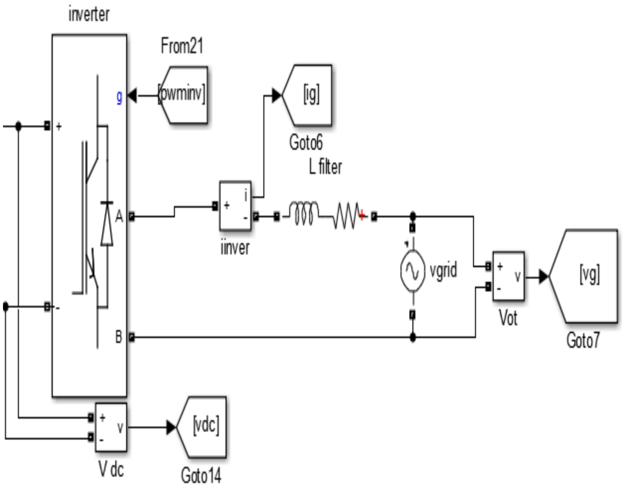

Fig. 11. The inverter-grid connection.

Fig. 12 indicates that the injected current and the grid voltage are in phase and sinusoidal what means a unity power factor is obtained. So then, the validation of the current control loop.

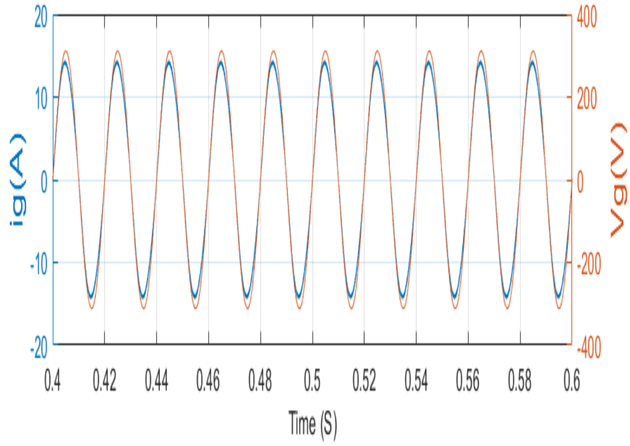

Fig. 12. The grid voltage and the injected current.

Additionally, Fig. 13 shows a total harmonic distortion (THD) of 2.96% < 5%. Consequently, the condition mentioned in [30] is satisfied and the utility of output L filter is reached.

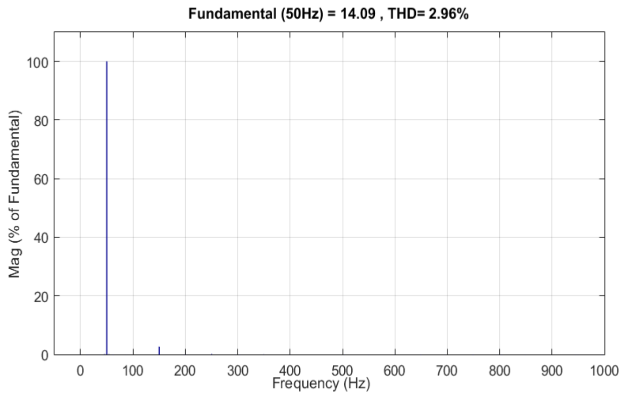

Fig. 13. Total Harmonic Distortion.

Fig. 14 indicates the extracted power from the PV array in STC using modified-Neural Network algorithm.

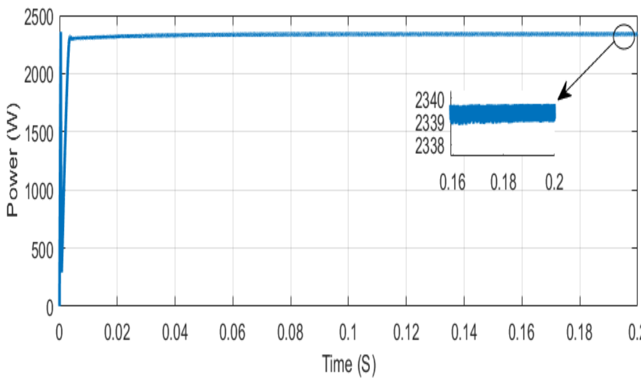

Fig. 14. The extracted PV array power using the modified-NN.

As it seems form Fig. 14 the modified-Neural Network algorithm presents a fast response with a 0.12 s as response time. With a high accuracy of 99.93% from the maximum PV array power.

Fig. 15 shows the active power fed to grid.

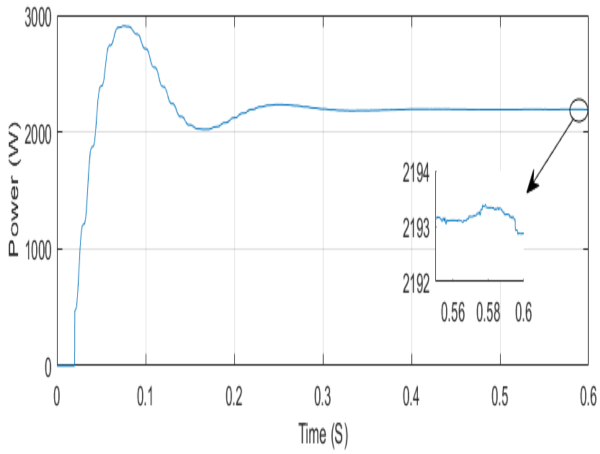

Fig. 15. The active power injected in the grid.

As indicated in Fig. 15 a power of 2193 W is injected which represents 93.68% from the maximum PV array power and 93.73% from the extracted PV array power using the modified-Neural Network algorithm.

In the way of presenting the high performances of the modified-NN algorithm and showing the differences between the modified-NN and the NN algorithm (duty cycle as output) a simulation of the on-grid system as presented in Fig. 7 is made.

Fig. 16 shows the extracted power from the PV array using both of Neural network algorithms.

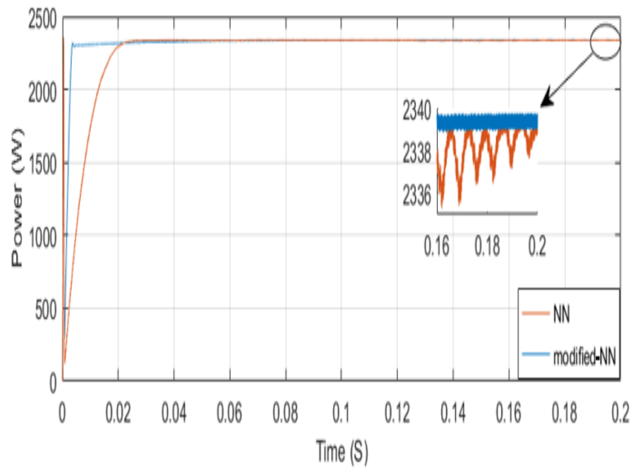

Fig. 16. The extracted power from the PV array using both of NN algorithms.

It is observed from the Fig. 16 that the modified-NN is more efficient than the classic Neural Network by a high precision and stability. While, (ΔP = 2339.8−2339 = 0.8W) for the modified-NN and (ΔP = 2339.6−2335.4 = 4.2W) for the NN. But, this later is quicker than the modified NN by a response time of 0.07 s and 0.12 s for the modified-NN. The delay that presents in the modified-NN due to the time taken by PI controller to converge.

The main difference between the two Neural network algorithms is that the modified-NN has a constant reference voltage with a variable duty cycle. On the contrary, the NN has a constant duty cycle with a variable voltage. As shown in Fig. 10 an oscillation around the dc link voltage with 1.5V peak to peak voltage ripple which represents the output voltage of the boost converter.

$$v_{dc} = \frac{v_{pv}}{1 - D} \tag{7}$$

So, based on the equation 7 in the presence of the output voltage ripple and for making the PV array works in the optimum point voltage a variable duty cycle is needed that's what is present in the modified-NN technique as shown in the Fig. 17.

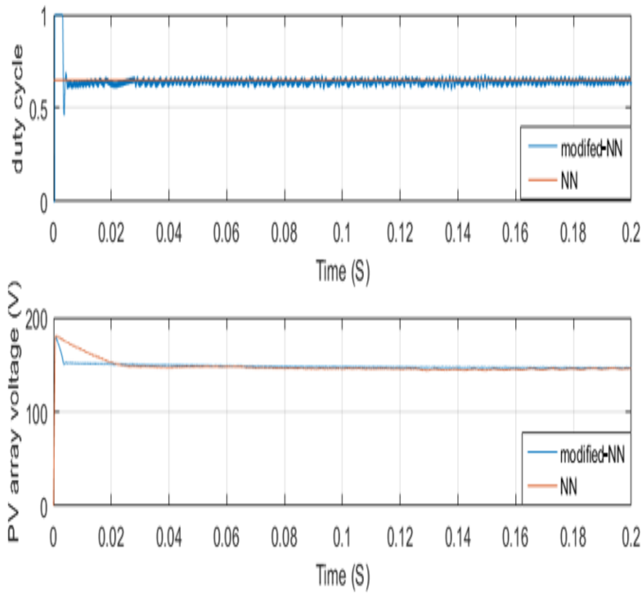

Fig. 17. PV array voltage and duty cycle using both of NN algorithms.

To analyse the influence of the variation in the climatic conditions on the output performance of the system the simulation is performed under different couples of temperatures and solar irradiance as exposed in the Table 1.

Fig. 18 illustrates from top to bottom the extracted power from the PV array and the injected active power in the grid. The subsystem (boost + inverter) has high efficiency with η= 93.15% between 1-2 and η= 97.27% between 5-6. So, with the rising of irradiance both of PV power and losses increase. Between 0-1 and 3-4 the irradiance is constant and the temperature varies. Consequently, as observed the augmentation of temperature has a negative influence on the power. On the other hand, between 0-1 and 1-2 the temperature is constant and the irradiance varies so then, the augmentation of irradiance leads an increasing of power. Following this, the best power is obtained when the irradiance is maximal and temperature is minimal.

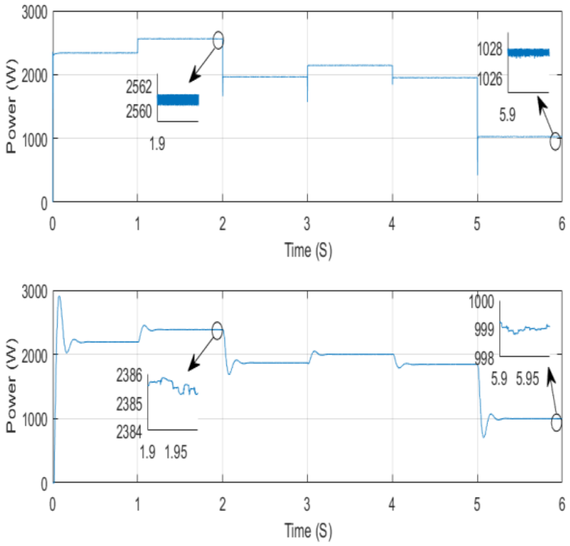

Fig. 18. The extracted power from PV array and active power injected.

Fig. 19 presents from bottom to top the Total Harmonic Distortion (THD) and the dc link voltage. It is noticed that in the preferable meteorological conditions (high irradiance and low temperature) the voltage ripple is high and THD is small. On the contrary, in high temperature and low irradiance the voltage ripple is small and THD is high.

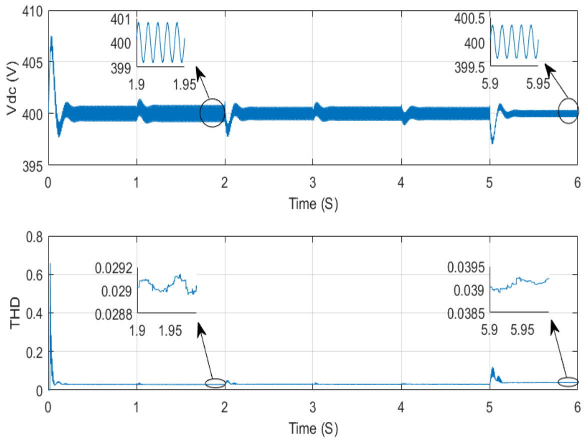

Fig. 19. The dc link voltage and THD.

Fig. 20 indicates the extracted power using modified-NN, NN, P&O, IcnCond and OCV algorithms in STC. NN algorithms present a fast response (tr = 0.07 s for NN and tr = 0.12 s for modified-NN) following by OCV method with tr = 0.31 s after that, we have P&O with tr = 0.32 s and finally, IncCond with tr = 0.35 s.

In steady state, All the algorithms track the maximum power except the OCV which has a high error. The OCV has the highest oscillation and it's far from the theoretical maximum power (by ΔP = 2300-2220 = 80W). Comparing with OCV method, both of IncCond and P&O have less oscillation around MPP (by ΔP = 2339-2333 = 6W for IncCond and ΔP = 2339-2332 = 7W for P&O). NN technique presents small oscillation comparing with the conventional methods (by ΔP = 2339.6-2335.4 = 4.2W for NN). The smoothest response is reached by the modified-NN (by ΔP = 2339.8-2339 = 0.8W for modified-NN).

The modified-NN provides the most effective results, by getting a tracking performance of 99.93%.

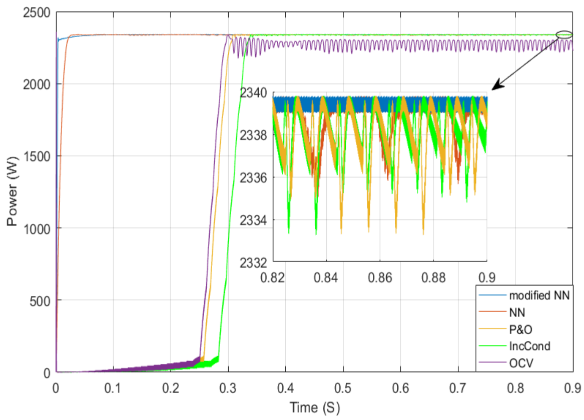

Fig. 20. The extracted power from PV array by applying different MPPT algorithms.

To highlight the performances of the MPPT algorithms under different climatic conditions, the system has been simulated as exposed in Table 1. Fig. 21 presents the extracted power from PV array using different MPPT algorithms under different environmental conditions.

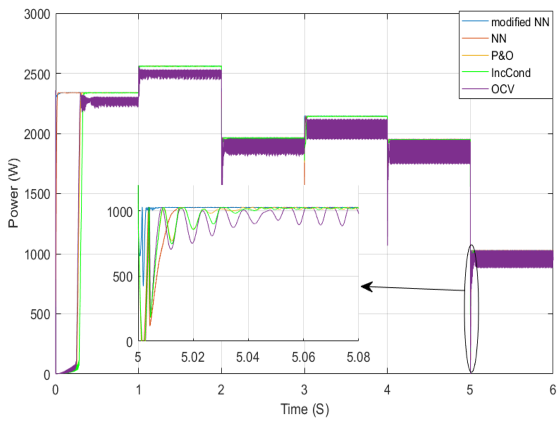

Fig. 21. The extracted power from PV array using different MPPT algorithms under different environmental conditions.

As it seems with the increasing of irradiance and decreasing of temperature the extracted power increases. In the rapidly changing of climatic conditions the OCV method presents the highest overshoot and oscillation. Also, the other algorithms have an overshoot but, less than OCV and after that, they converge to MPP. The smallest overshoot is reached by the modified-NN.

5. Conclusion

The simulation of single phase two-stage photovoltaic grid-connected system through MATLAB/SIMULINK platform presents an excellence performance. This performance justified by high accuracy of control for the dc link voltage, the injected current and the maximum power point (MPP). Hence, a unity power factor is obtained with total harmonic distortion (THD) of 2.96% in the standard test conditions (STC). Under variable climatic conditions the higher power is obtained when the irradiance is maximal and temperature is minimal. On the other side, in high temperature and low irradiance the dc link voltage ripple is small and THD is high. The extraction of MPP is done by different maximum power point algorithms (MPPT). For this, two efficient MPPT algorithms based on Neural Network (NN) have been developed. A high training has been affected using 625 data samples with multilayer network with back-propagation algorithm. Also, a comparison between two types of developed NN algorithms, Incremental Conductance (IncCond), Open Circuit Voltage (OCV) and Perturb and Observe (P&O) is established. The NN algorithms present the fastest response following by OCV method, P&O and finally, IncCond. In steady state, all the algorithms track the maximum power except the OCV which shows high error. The OCV has the highest oscillation and it is far from the theoretical maximum power. NN algorithms present small oscillation around MPP comparing with the conventional methods. The smoothest response is reached by the modified-NN. Finally, in the rapidly changing of climatic conditions the OCV method presents the highest overshoot followed by P&O, IncCond, NN and modified-NN (reference PV voltage).

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