Indonesian Journal of Electrical Engineering and Computer Science
Vol. 28, No. 3, December 2022, pp. 1276~1285
ISSN: 2502-4752, DOI: 10.11591/ijeecs.v28.i3.pp1276-1285

Integration of an optimized neural network in a photovoltaic system to improve maximum power point tracking efficiency

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Article Info

Article history:

Received Jun 29, 2022
Revised Aug 27, 2022
Accepted Sep 7, 2022

Keywords:

Artificial neural network
DC/DC converter
Multi layer perceptron
Maximum power point tracking
Photovoltaic system
Perturbation and observation

ABSTRACT

Due to the variability of weather conditions and equipment properties the maximum power point tracking (MPPT) performance is influenced. MPPT controllers are widely used to improve photovoltaic (PV) efficiency because MPPT can produce maximum power under various weather conditions. Among the most used techniques and representing a satisfactory efficiency are those based on artificial intelligence. Since the use of neural networks requires resources at the implementation level, the optimization of these systems is an important phase. This work represents an optimized system for tracking the maximum power point, the latter based on a multi-layer neural network. The optimized multi layer perceptron (MLP) will ensure a fast convergence to the maximum power point with a low oscillation compared to the classical method.

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1. INTRODUCTION

The recently, renewable energy systems have become very important and photovoltaic (PV) technology production has grown exponentially around the world. Among these renewable energy sources, the most known and widespread systems in the world are the solar photovoltaic energy and wind energy sources [1], [2]. Photovoltaic panels produce electricity by converting sunlight into electricity through the photovoltaic effect of semiconductors. Among the advantages and the strong points that encourage the use of these renewable sources other than the conventional or traditional energy sources (fossil energy) are the following: the renewable energy sources are nearly inexhaustible, clean, green and do not represent a danger to the environment [3]. Due to the availability of PV modules, solar PV has seen considerable growth compared to other renewable energy technologies.

The PV modules are recognized by their non-linear behavior and the non-linear current versus voltage curve. This means that the production of energy with maximum efficiency is not an easy task, since the maximum power points are unique and reaching their specific techniques is important. All these techniques are collectively called maximum power point tracking (MPPT) techniques or algorithms. These algorithms make the PV system function at about its maximum power point by adapting the impedance of the load and the PV source. As a result of their nonlinear characteristics, MPPT techniques are fundamental to any PV system.

There are dozens of methods that have been reported in the literature to track the maximum power point [4], [5]. Among the most widely used methods and techniques used by researchers cited by [6], [7], are the following: fractional open circuit voltage, perturbation and observation (P&O), fractional short circuit current and incremental conductance (IncCon). The research and development communities are continuously striving to improve the existing methods with the addition of artificial intelligence (AI) based systems such as fuzzy logic, neuronal networks and ANFIS [8], [9].

This paper represents a maximum power point tracking system of a photovoltaic system based on artificial neural networks (MLP). The objective of this work is to improve the efficiency of MPPT search by integrating the optimized MLP model. The Figure 1 illustrates the main components of the system under study.

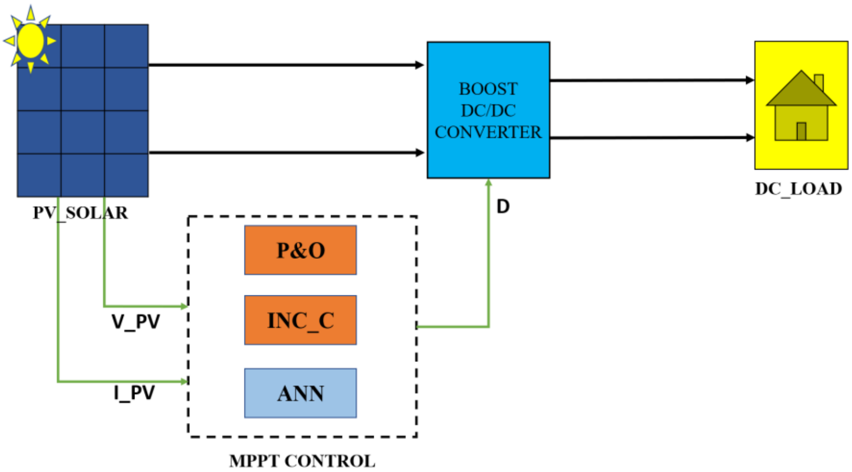


Figure 1. The studied system architecture

2. EQUIVALENT MODULE OF A PHOTOVOLTAIC SOLAR CELL

A solar or photovoltaic cell is in fact a source of current that is produced when sunlight is incident on the surface of the cell. The process of transforming light into electricity is known as the "photovoltaic effect". In order to show the characteristics of voltage, current and power under different operating conditions, the mathematical model of the PV cell is necessary for the simulation. Figure 2 shows a simplified equivalent model of a PV device. As illustrated in Figure 2, photovoltaic cell model consists mainly of a series resistor (Rs), this latter connected with a parallel shunt resistor combination (Rsh) in series, exponential diode (D) and cell photo-current (Iph) [10]. Vpv, and Ipv are respectively corresponding to the current voltage of the PV cell.

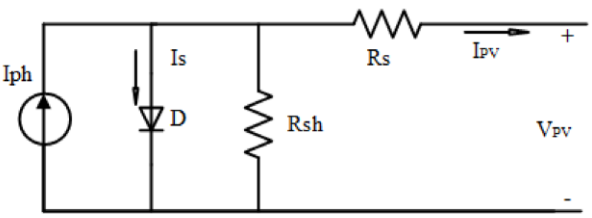


Figure 2. The equivalent model of a PV cell

In (1) and (2) representing the current generated by the solar cell:

$$\mathrm{I_{pv}} = \mathrm{I_{ph}} - \mathrm{I_d} - \mathrm{I_{sh}} \tag{1}$$

$$\mathrm{I_{pv}} = \mathrm{I_{ph}} - \mathrm{I_0}.(\mathrm{e}^{\frac{q(V_{pv}+I_{pv}.R_S)}{nKT}} - 1) - \frac{\mathrm{V_{pv}+I_{pv}.R_S}}{\mathrm{Rsh}} \tag{2}$$

where I_{ph}, I_s, q, K, n and T represent respectively the solar current indued, the saturation current of the diode, the charge of the electrons ($1.6e^{-19}$C), the Boltzmann constant ($1.38e^{-23}$J/K), the Ideality factor of the PN junction (1~ 2) and the Temperature (K). Table 1, demonstrates the main electrical characteristics of the solar panel used in this study. As mentioned in the table, the maximum power that can be produced by this photovoltaic generator is 220 watts.

Table 1. The electrical characteristics of the used photovoltaic array

Parameters and symbol	Value
Rated power P_{MP}	220W
Open circuit voltage V_{OC}	54V
Voltage at maximum power V_{MP}	44.63V
Short circuit current I_{SC}	5.52A
Current at maximum power I_{MP}	4.94A

3. DC/DC CONVERTER

A DC/DC converter is used to convert the DC voltage delivered by the PV array into a DC voltage that is suitable for supplying DC voltage to consumers. In this study, a DC-DC boost converter is used to realize the MPPT power stage due to its high reliability, reduced implementation costs and reduced number of components [11], [12]. The Figure 3 demonstrates the electrical model of boost converter used in this study.

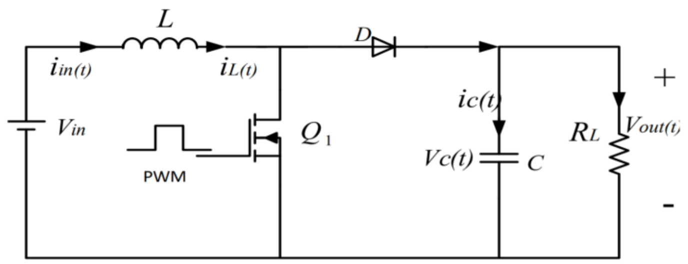


Figure 3. The equivalent circuit of a DC-DC boost converter

by :

$$D = 1 - \frac{V_{in}}{V_{out}}$$

the peak-to-peak inductance current ripple magnitude ΔL is represented by:

$$\Delta L = \frac{V_{in}.D}{f_s.L}$$

and, the voltage ripple of the output capacitor ΔV is represented by:

$$\Delta V = \frac{I_0.D}{f_s.C}$$

4. THE MPPT OPTIMISATION TECHNIQUES

4.1. Perturbation and observation technique

The P&O algorithm is one of the most widely used and well-known MPPT technique in the literature. The flowchart in Figure 4 represents the mechanism of the P&O technique [13], [14]. The principle of this algorithm is to perturb the voltage (by the variation of the duty cycle) in one direction, and if the power value continues to increase in the same direction as the perturbation of the voltage, the algorithm will continue to perturb in the same direction. If the new power value is lower than the last value, the voltage is perturbed in the reverse direction. When this algorithm attains the MPP, it continues to oscillate in the vicinity of the MPP. Moreover, this algorithm tends to malfunction when the meteorological conditions change rapidly [15].

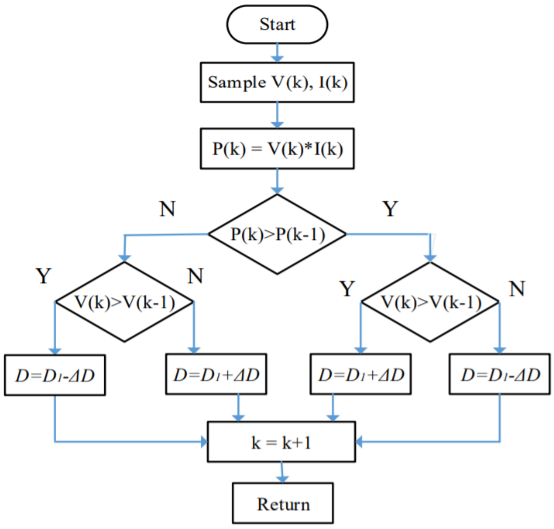


Figure 4. The mechanism of the P&O algorithm

4.2. Incremental conductance technique

One of the techniques that is frequently found in the literature is the incremental conductance technique (IncCon). The algorithm of this technique is based on the tracking of the slope of the photovoltaic module power curve (P-V). Figure 5 illustrates the flow chart of this method [15]-[17]. The basic idea of this algorithm is very simple: in the position where there is the maximum power point, the slope of the curve will be equal to zero. At the left side of the MPP, the slope is negative while it is positive at the other side.

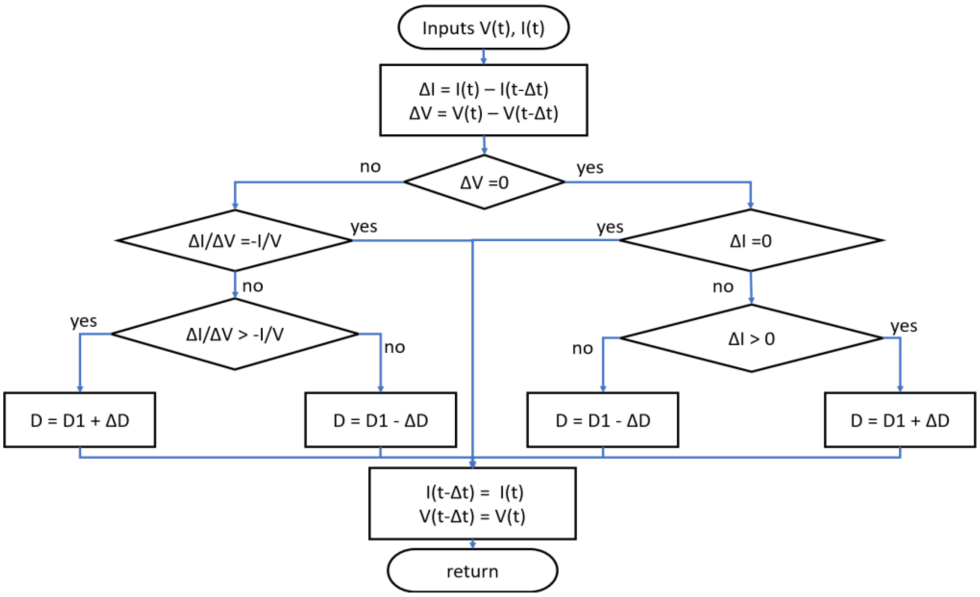


Figure 5. The diagram of Incremental conductance algorithm

4.3. The ANN technique

As a definition to the artificial neural network (ANN), we find that ANN is an imitation of the human nervous system. The ANN learns from its environment in a similar way to humans in order to process tasks with a reasoning close to humans. In this work, we opted to implement the multilayer perceptron (MLP) model.

In order to obtain an optimized architecture (maximum performance with a minimum of layers and a minimum of neurons per layer). We have chosen to use two of the most widely used and effective statistical indicators in this type of problem which is the mean square error (MSE) and the correlation coefficient (R)

[18]. In order to determine the most optimized architecture of the MLP model to be used, we have several training tests in which we have varied the number of hidden layers, the transfer functions, the number of neurons in a hidden layer, the number of iterations and the learning algorithms [19]. Tables 2, 3, 4 and 5, representing the main results obtained using the different algorithms. The first algorithm based on variable learning rate gradient descent, the second is Levenberg-Marquardt algorithm, the third based on the resilient backpropagation algorithm and the fourth algorithm is gradient descent with momentum.

Table 2. Variable learning rate gradient descent

Activation function in HL	Activation function of OL	R square	MSE ($x10^{-4}$)	Number of epochs	MLP model structure
Logsig	Logsig	0.79	905	46	[2-3-1]
Logsig	Tansig	0.976	1350	200	[2-3-1]
Logsig	Purelin	0.978	101	82	[2-3-1]
Purelin	Purelin	0.987	1340	632	[2-3-1]
Purelin	**Logsig**	**0.996**	**10.2**	**130**	**[2-3-1]**
Purelin	Tansig	0.985	56.99	218	[2-3-1]
Tansig	Tansig	0.990	46.5	621	[2-3-1]
Tansig	Purelin	0.981	87.8	191	[2-3-1]
Tansig	Logsig	0.996	1330	271	[2-3-1]

Table 3. Levenberg-Marquardt

Activation function in HL	Activation function of OL	R square	MSE ($x10^{-4}$)	Number of epochs	MLP model structure
Logsig	Logsig	0.887	38.32	32	[2-3-1]
Logsig	Tansig	0.999	0.017	14	[2-3-1]
Logsig	Purelin	0.999	0.0187	22	[2-3-1]
Purelin	Purelin	0.998	0.213	3	[2-3-1]
Purelin	Logsig	0.869	34.70	5	[2-3-1]
Purelin	Tansig	0.999	0.5431	8	[2-3-1]
Tansig	Tansig	0.999	0.208	1000	[2-3-1]
Tansig	**Purelin**	**0.999**	**0.01307**	**261**	**[2-3-1]**
Tansig	Logsig	0.988	3.742	318	[2-3-1]

Table 4. Gradient descent with momentum

Activation function in HL	Activation function of OL	R square	MSE ($x10^{-4}$)	Number of epochs	MLP model structure
Logsig	Logsig	0.901	90.85	1000	[2-3-1]
Logsig	Tansig	0.961	17.44	1000	[2-3-1]
Logsig	Purelin	0.987	12.84	1000	[2-3-1]
Purelin	Purelin	0.997	1.250	1000	[2-3-1]
Purelin	Logsig	0.990	70.42	1000	[2-3-1]
Purelin	**Tansig**	**0.997**	**0.609**	**1000**	**[2-3-1]**
Tansig	Tansig	0.930	270.1	1000	[2-3-1]
Tansig	Purelin	0.987	250.8	1000	[2-3-1]
Tansig	Logsig	0.981	133.0	1000	[2-3-1]

Table 5. The resilient backpropagation algorithm

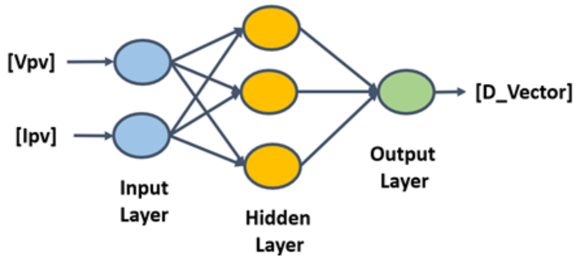
Activation function in HL	Activation function of OL	R square	MSE ($x10^{-4}$)	Number of epochs	MLP model structure
Logsig	Logsig	0.945	0.1050	67	[2-3-1]
Logsig	Tansig	0.997	0.0783	1000	[2-3-1]
Logsig	**Purelin**	**0.998**	**0.0227**	**52**	**[2-3-1]**
Purelin	Purelin	0.998	0.243	25	[2-3-1]
Purelin	Logsig	0.864	34.09	24	[2-3-1]
Purelin	Tansig	0.985	0.488	15	[2-3-1]
Tansig	Tansig	0.990	0.0615	350	[2-3-1]
Tansig	Purelin	0.999	0.0938	187	[2-3-1]
Tansig	Logsig	0.886	35.32	158	[2-3-1]

With, HL represents the hidden layer and OL represents the output layer. Table 6 represents the better results obtained in the four learning algorithms cases. We can conclude from the table that the learning in the case where we used the algorithm of Levenberg-Marquardt we have achieved very good results of the R coefficient and the mean square error. where the value of the R coefficient equals 0.999 (≈ 1) which means that we have a high degree of correlation and the mse has reached in this case the value of $0.01307x10^{-4}$ to 261 iterations.

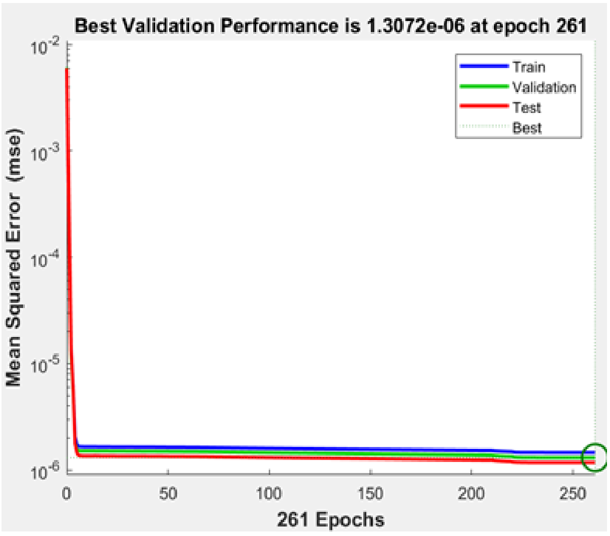
Table 6. Comparison of the best results obtained in the four cases

Algorithms	Labels	Architecture	R factor	MSE (x10-4)
Levenberg-Marquardt	**Tansig-Purelin**	**[2-3-1]**	**0.999**	**0.01307**
Resilient backpropagation	Logsig- Purelin	[2-3-1]	0.998	0.0227
Gradient descent with momentum	Purelin- Tansig	[2-3-1]	0.996	0.609
Variable learning rate gradient descent	Purelin- Logsig	[2-3-1]	0.996	10.2

The Figure 6 represents the chosen MLP and the training results of the latter. The Figure 6(a) shows the architecture of the adopted MLP model, which consists with an input layer with two neurons, a hidden layer with three neurons and an output layer with one neuron. The Figure 6(b) shows that the mean square errors (MSE) corresponding to training, testing and validation converge to the same value of 0.01307×10^{-4}. This shows that the training of the network is done successfully, and the MLP the output converges perfectly to the target output values [20]-[22].



(a)



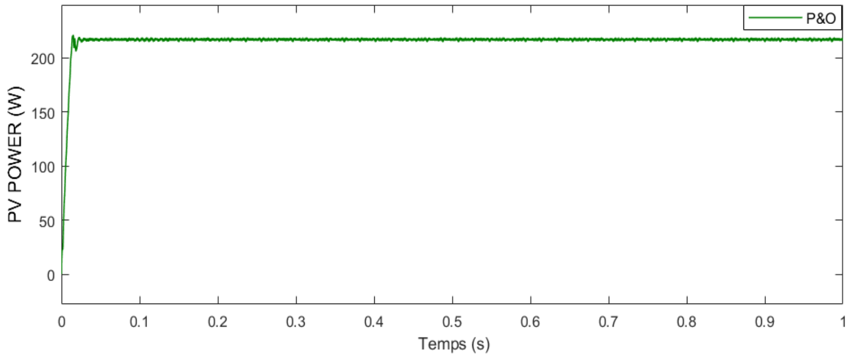
(b)

Figure 6. The ANN structure and training result (a) the ANN architecture and (b) the MSE in training, test and validation phases

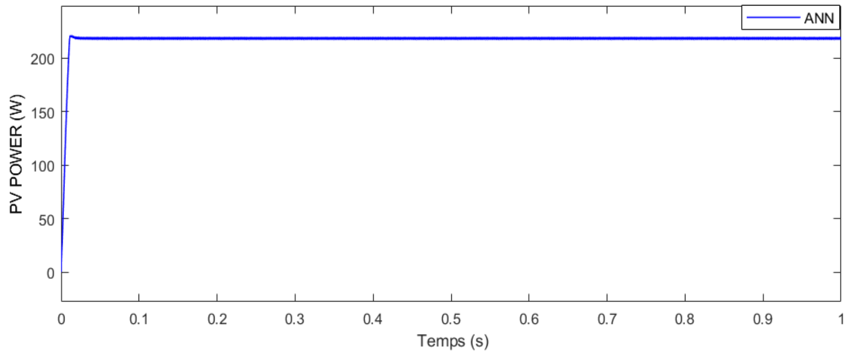
5. DISCUSSIONS OF THE OBTAINED RESULTS

5.1. The first test

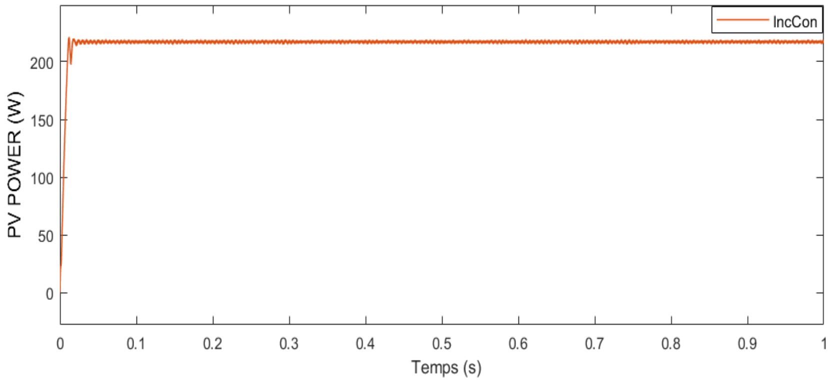
In this part we will try to verify and analyze the performance of the maximum power point tracking techniques in a stable condition (Temperature equal to 25° and irradiation equal to 1000 kw/m²). Figure 7 represents the results obtained by the different techniques used. The Figures 7(a)-(c) aggregate respectively the power generated by the PV model system by using the MPPT P&O, IncCon and ANN techniques. Figure 7(d) shows that all MPPT controllers collect the power produced by the PV systems and which is very close to their maximum power. The efficiency of all methods is excellent (over of 98%). As shown in Table 7, the MPPT technique based on ANN represents the excellent results with a Tracking speed of 0.011s, a very high efficiency reaching 99.36% of the used photovoltaic panel power and a low oscillation [23]-[26].



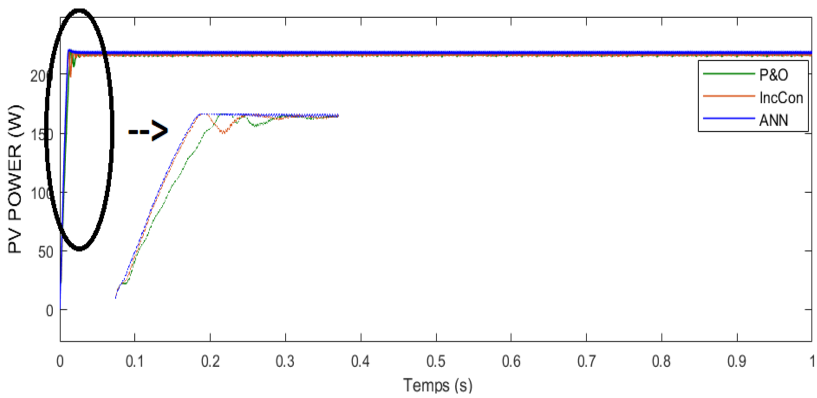
(a)



(b)



(c)



(d)

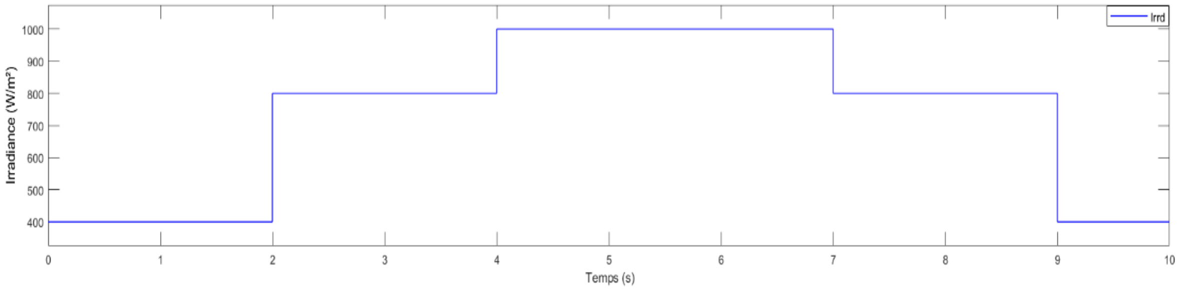
Figure 7. P&O, IncCon and ANN generator output power (a) perturb and observe, (b) incremental conductance, (c) ANN, and (d) P&O, IncCon and ANN

Table 7. P&O, IncCond and ANN (MLP) MPPT performances

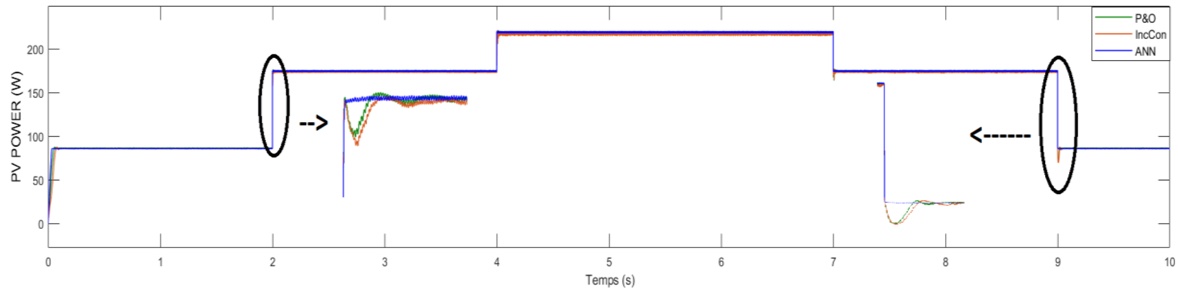
MPPT Technique	Tracking speed (S)	Average power (W)	Efficiency (%)	Oscillations
P&O	0.022	215.7	98.04	High
IncCon	0.017	217.2	98.72	Medium
The optimized MLP	0.011	218.6	99.36	Very Low

5.2. The second test

In this phase, we kept the temperature at 25° with a variable solar irradiance. The Figure 8 shows the results in the case where the test condition is variable. The Figure 8(a) represents the variable solar irradiation and the Figure 8(b) represents the MPP tracking results. In the presence of variable irradiation, all MPPT controllers collect the power produced by the PV systems, which is very close to their maximum power. The use of the ANN technique in tracking the MPP resulted in excellent speed and low ripple in the power curve.



(a)



(b)

Figure 8. PV power and Solar irradiance variation (a) solar irradiance variation and (b) PV power variation

6. CONCLUSION

This paper discusses maximum power point tracking using a multi-layer perceptron with an optimization phase. By using a variety of learning algorithms, an ANN model with a minimum number of layers and a minimum number of neurons per layer was generated after multiple tests. The results of the simulation in MATLAB/Simulink show that the convergence of the ANN model to the desired output is achieved in a perfect way when using the Levenberg-Marquardt algorithm. The developed MLP model provides very satisfactory results for tracking the maximum power point in constant and in variable operating conditions.

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