

Performance Analysis of Three MPPT Controls Under Partial Shading: P&O, PSO and ANN

Mohamed Amine Atillah^{1,}, Hicham Stitou¹, Abdelghani Boudaoud¹ and Mounaim Aqil¹*

¹Engineering and Applied Physics Team (EAPT), Superior School of Technology, Beni Mellal, Morocco

Abstract. Photovoltaic energy has gained an important place among renewable energies. Given its weather-dependent efficiency, Maximum Power Point Tracking (MPPT) techniques are essential to maximize the energy extracted from the panels.

Partial shading is a phenomenon that degrades the efficiency of photovoltaic panels, by distorting the power vs. voltage curve, which consequently has several peaks, one of which is a global maximum.

The aim of this work is to evaluate the ability of MPPT methods to find the global maximum power point in partial shading conditions. To achieve this, the work focuses on simulating and discussing the performance of three MPPT methods, the Perturb and Observe (P&O) command, a command based on particle swarm optimization (PSO), and a command based on artificial neural networks (ANN).

By comparing the results of simulations of the three controllers under different partial conditions, we can see that the P&O controller loses accuracy in partially shaded conditions, while the PSO controller is more accurate but with a very slow response time, and lastly, the ANN-based controller offers the best precision and speed performance.

Keywords. Photovoltaic energy, MPPT techniques, Perturb and Observe, Particle swarm Optimization, Artificial Neural Network, Renewable Energy.

1 Introduction

The efficiency of photovoltaic panels depends directly on irradiation and temperature [1]. A drop in irradiation or an increase in temperature reduces photovoltaic panels' maximum power, which is why we use the MPPT [2].

Its concept is based on algorithms that act on the photovoltaic panel's voltage or current to position the operating point at maximum power [3], enabling the panel to deliver the maximum available power at all times, despite disturbances [1].

The literature presents a variety of MPPT techniques, which differ in terms of speed, stability, precision and complexity.

MPPT techniques can be classified into 3 principal categories [2]:

* Corresponding author: atillah.mohmed.amine@gmail.com

- Conventional MPPT techniques: They are characterized by their simplicity [4]. However, they are limited to uncomplicated applications, especially in partial shading or rapid variations in climatic conditions [5]. There are many traditional controls, but the most frequently used are Hill-Climbing (HC), P&O and Incremental Conductance (InCond).
- Soft computing methods: They are advanced approaches, which include 3 families [6]. Artificial Intelligence (AI)-based methods such as (ANN) and Fuzzy Logic (FL)..., Metaheuristic Algorithms (MA)[7] like (PSO), Bat Algorithm (BA), Grey Wolf Optimiser (GWO), Artificial Bee Colony Algorithm (ABC), Dragonfly Optimization Algorithm (DFO)..., and Chaotic Optimization Algorithms (COA) like Stepped-Up Chaos Optimization (SCO) and Dual-Carrier chaotic Search (DCCS)....
- Hybrid methods: They combine several MPPT methods to take advantage of the various techniques [8]. Some examples of hybrid techniques are: ANN with P&O, ANN with InCond, GWO with P&O, PSO with P&O : ANN with P&O, ANN with InCond, GWO with P&O, PSO with P&O.

Several researchers have contributed to the analysis of MPPT techniques in photovoltaic systems. For example, Murari Lal Azad et al [9] made a comparative study between P&O and InCond. Omorogiuwa Eseosa and Itelema Kingsley [10] dealt with the same techniques. On the other hand, Rudra Sankar Pal and V. Mukherjee [11] studied the performance of two Metaheuristic methods under various conditions. The same goes for Izviye Fatimanur Tepe and Erdal Irmak [12] who analysed PSO, GWO, and DFO, which are also Metaheuristic methods. Most previous research in the field of MPPT has focused on methods belonging to the same category. However, our work is distinguished by its focus on an in-depth comparison of techniques from two distinct families, namely traditional methods and soft computing methods. Hybrid methods will be one of our research perspectives.

The aim of this article is to analyse the performance of the three methods and compare them in terms of accuracy, stability and response time.

The article is structured so that Section 2 presents the methodologies and materials, Section 3 examines the results. The concluding section is in Section 4.

2 Methodologies and materials

This section details the methodology employed to perform an evaluation and comparison of the three MPPT methods under partial shading conditions.

The system used for the simulations is described first, including the characteristics of the panels and the associated DC-DC converter. Then, the three MPPT methods examined in this study are presented in detail.

2.1 Photovoltaic system description

2.1.1 Pv generator

The PV Array block is a five-parameter model that uses a light-generated current source (I_L), a diode, a series resistor (R_s) and a parallel resistor (R_{sh}) [13].

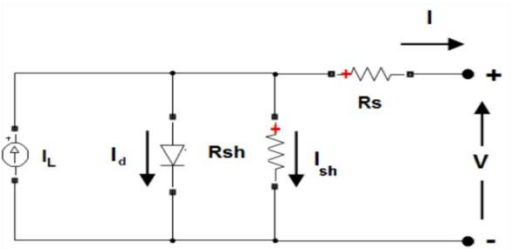


Fig. 1. PV Array model

The equations of the photovoltaic panel model are [14]:

$$I = I_L - I_d - I_{sh} \tag{1}$$

Replacing I_d and I_{sh} by their expressions we obtain [14]:

$$I = I_L - I_0 \left(e^{\frac{q(v+I*Rs)}{nkT}} - 1 \right) - \frac{(v+I*Rs)}{Rsh} \tag{2}$$

Where:

- I_L : The photo current
- I_d : The Diode current
- I_{sh} : The shunt current
- q : Electron charge = 1.6022e-19 C
- k : Boltzman constant = 1.3806e-23 J.K-1
- n : Diode ideality factor
- T : Cell temperature
- I_0 : Diode saturation current
- Rsh : represents P-N junction of photovoltaic diode
- Rs : the bulk resistance of semiconductor material and interconnections

The photovoltaic array used is shown in Fig. 2.

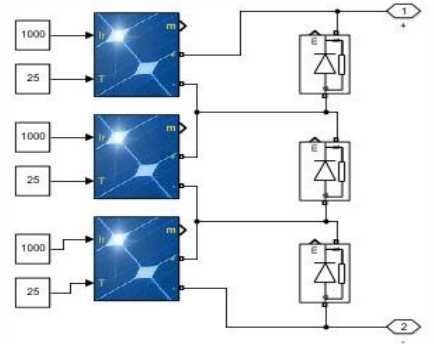


Fig. 2. The photovoltaic arrays employed in the study

The photovoltaic generator used in this study consists of 6 solar panels grouped into 3 groups connected in series, with each group containing 2 panels in parallel. Each solar panel has a maximum power of 213.15 watts, a maximum voltage of 29 volts and a maximum current of 7.35 amperes. This means that the photovoltaic generator has a total maximum output power of 1278 watts.

The characteristics of the photovoltaic array are shown in Fig.3.

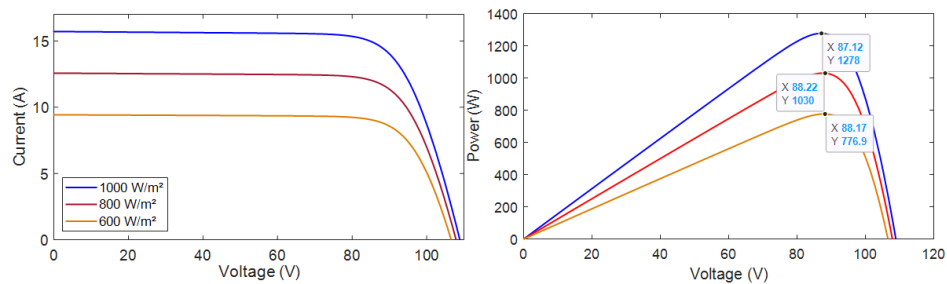


Fig.3. The current-voltage and power-voltage curves of the PV array for different irradiation levels

Power and current curves plotted against voltage at a fixed temperature of 25°C and three distinct irradiance levels: 1000 W/m², 800 W/m² and 600 W/m². These curves show a significant relation between incident irradiance and the maximum power produced. An increase in irradiance is directly correlated with a proportional increase in maximum power, which is clearly illustrated by the evolution of the maximum power point (MPP) on each curve [15].

Partial shading appears when part of the photovoltaic array is exposed to reduced irradiance due to obstacles such as buildings [16], vegetation or other surrounding elements. This phenomenon results in an unequal distribution of solar energy over the panels [17], inducing local variations in irradiance and causing significant changes in the system's electrical characteristics.

The photovoltaic array characteristics for partial shading are shown in Fig.4.

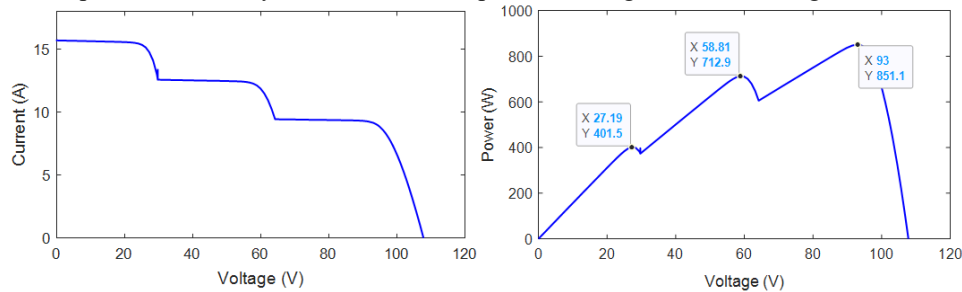


Fig.4. The current-voltage and power-voltage curves of the PV array under partial shading

These curves were produced at a constant temperature of 25°C, while each group of solar panels in series was exposed to a different irradiation. Specifically, the first group was exposed to an irradiance of 1000 W/m², the second to 800 W/m², and the third to 600 W/m².

The power versus voltage curve, under partial shading conditions, shows three different peaks (global peak and two local peaks). In contrast, under uniform irradiation, the same curve shows just one peak [18].

2.1.2 DC-DC converter (Boost)

As photovoltaic modules have a limited output voltage, the DC-DC boost converter is crucial to reducing the need to connect a large number of modules in series [19].

Thus, variations in irradiance and temperature induce photovoltaic panel characteristics specific to each condition. This variability influences maximum power output as a function of climatic conditions [19]. In view of this, the integration of an inverter with a control

system is necessary to guarantee that the photovoltaic array reaches and maintains its optimum operating point. The structure of the boost converter is illustrated in Fig.5 [14].

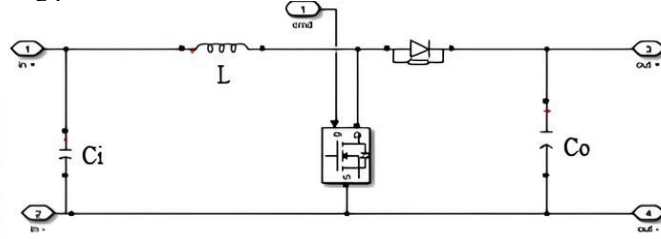


Fig.5. The DC-DC Boost Converter

Essential components include inductor (L), output capacitor (Co), input capacitor (Ci), diode and controlled switch. The values of the inductor and capacitor are calculated using the equations below [14]:

$$C_i = \frac{D \cdot I_o}{f_s \cdot \Delta V_i} \quad (3)$$

$$C_o = \frac{D \cdot I_o}{f_s \cdot \Delta V_o} \quad (4)$$

$$L = \frac{D \cdot V_i}{f_s \cdot \Delta I} \quad (5)$$

Where:

D : Duty cycle.

f_s : Switching frequency.

ΔV_i : Input voltage ripple.

ΔV_o : Output voltage ripple.

ΔI : Current ripple.

The boost output voltage is related to the input voltage by the relationship below [14].

$$V_o = \frac{V_i}{1 - D} \quad (6)$$

The load used at the Boost output is a resistor.

2.2 Mppt control techniques

2.2.1 Perturb and Observe (P&O)

The P&O controller is the most popular MPPT method used in photovoltaic applications [5]. The advantages of this method include its ease of implementation. Its principle is based on the systematic disturbance of the solar generator voltage or current, followed by observation of the direction of the resulting power change [20]. P&O aims to keep the generator close to the MPP by following the slope of the power-voltage curve. When power increases after a disturbance, the controller maintains the same disturbance in that direction. On the other side, if the power decreases, the disturbance is reversed.

The algorithm of the MPPT is given Fig. 6 [21].

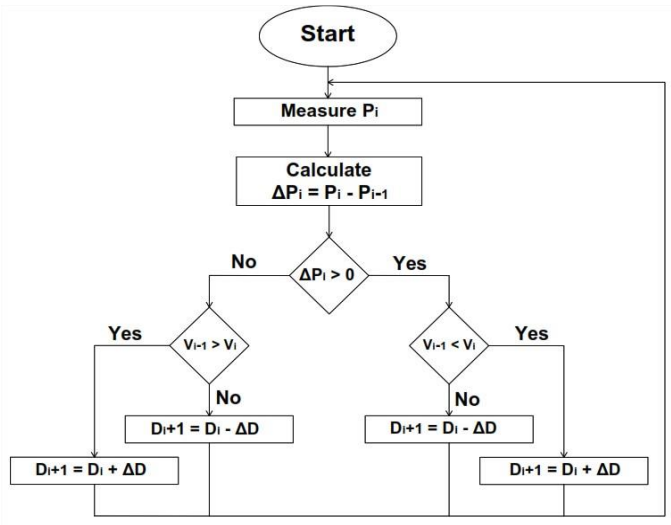


Fig.6. The P&O Algorithm

P_i : Current power value
 V_i : Current voltage value
 D_i : Current duty cycle value
 ΔD : Duty cycle step size

The MPPT (P&O) control was implemented using MATLAB Simulink, based on the system elements presented above, and programming the control algorithm as a MATLAB function.

The system simulation is shown Fig.7.

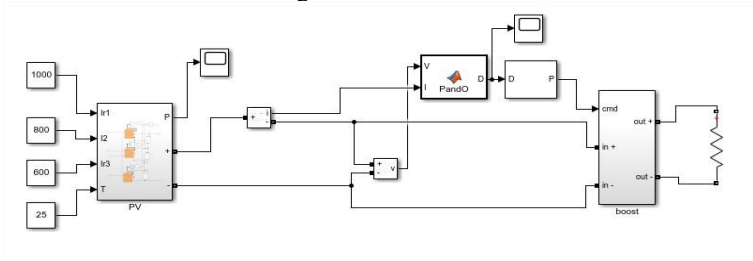


Fig.7. The system simulation with P&O technique

2.2.2 Particle swarm optimization (PSO)

The PSO method is a population-based stochastic optimization, modelled on the social organization of bird flights or fish swarms. The PSO algorithm is started with a random population of solutions [22], representing a swarm of individuals called particles.

The particles move through a search space to find the best solution [23]. Each particle adapts its position depending on its personal experience and that of the other particles in the group. This iterative process eventually leads to convergence on the optimal solution.

Applying this technique to MPPT control, the particle position is defined as the value of the Boost duty cycle, and the objective function is chosen as the power generated by the photovoltaic panels.

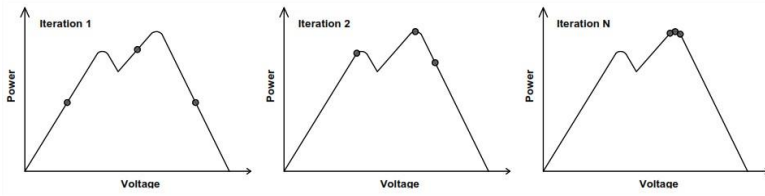


Fig.8. Illustration of PSO-based MPPT Algorithm Searching for Maximum Power Point

To find the point of maximum power, the PSO process is divided into several steps [22]. For the purposes of this study, a configuration with 3 particles is considered, as illustrated in Fig. 8. The following steps describe how the PSO command operates to find the maximum value [22]:

- Particles initialization: At the start of the process, an initial random duty cycle value is set for each particle [17]. These values determine the initial position of the particles in the search space.
- Power measurement: The power values corresponding to each duty cycle are measured for all three particles [24].
- Best Position Update: The duty cycle value equivalent to the higher power is saved [17]. This is the best position found for the moment.
- Update Particle Positions: Particle positions are updated using the values of the best positions found in the previous step [24]. This allows the particles to move towards promising areas in the search space.
- Process repetition: The steps of measuring power, updating best positions and up-dating particle positions are repeated several times [24]. With each iteration the particles gradually converge on the duty cycle values that maximize power.

The PSO technique's parameters play a critical role. These parameters include [17]:

- Number of particles: This defines the number of potential solutions in the search area.
- Velocity components: The velocity of each particle is made up of several elements, including the current velocity, the particle's personal best experience (Pp_{best}) and the group's best experience (G_{best}).
- Acceleration coefficients: $C1$ and $C2$ govern the respective importance of the Pp_{best} and G_{best} components in updating particle velocity.

Updating particle positions and velocities are the fundamental operations governing the operation of the PSO method. The following two equations are used to describe the characteristics of the PSO method [22]:

$$Pp_i(k+1) = Pp_i(k) + Vp_i(k+1) \quad (7)$$

$$Vp_i(k+1) = W Vp_i(k) + C1 R1 (Pp_{best_i}(k) - Pp_i(k)) + C2 R2 (G_{best}(k) - Pp_i(k)) \quad (8)$$

$Pp_i(k)$: Position of the particle i

$Vp_i(k)$: Velocity of the particle i

k : The current iteration

W : Inertia weight

$R1$ and $R2$: Uniformly distributed random values in the range $[0, 1]$.

$C1$: Cognitive coefficient

$C2$: Social coefficient

Pp_{best_i} : Best position of each particle

G_{best} : Best position among all particles

The flowchart illustrates the PSO algorithm [22], as shown in Fig. 9.

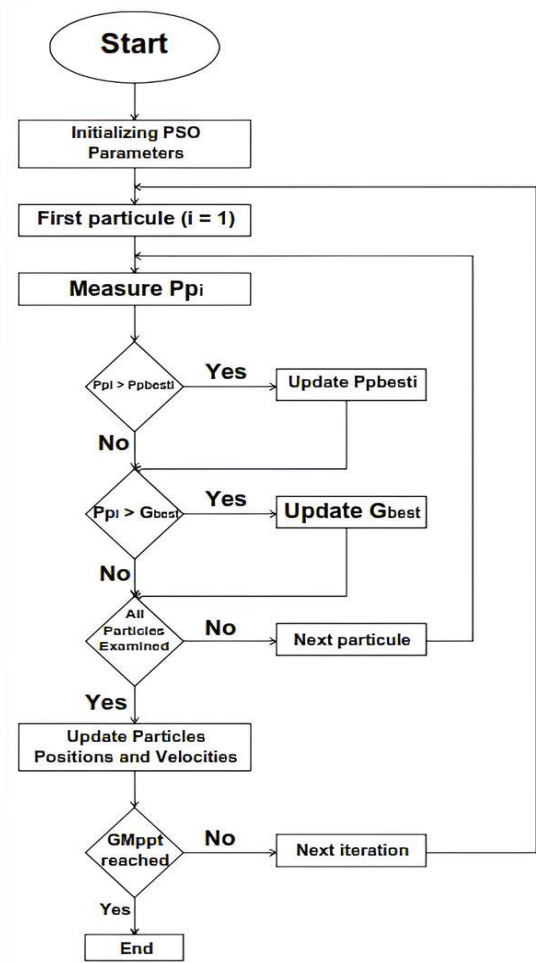


Fig.9. PSO MPPT algorithm

The implementation of the MPPT control based on the PSO method was achieved with MATLAB Simulink, using the system elements presented previously, and programming the control algorithm as a MATLAB function. With a configuration of three particles, an inertia weight $W = 0.4$, and acceleration coefficients $C1 = 1.2$ and $C2 = 2$.

The system simulation is shown in Fig. 10.

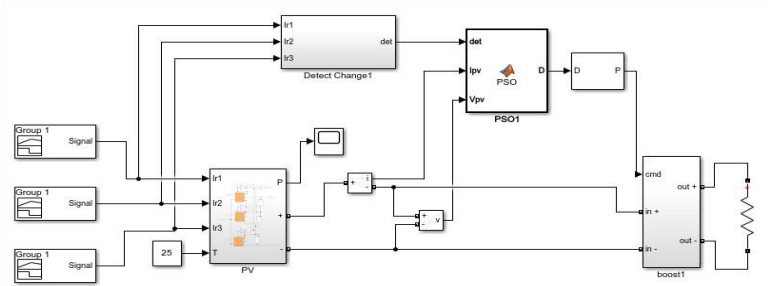


Fig.10. Synopsis of PSO simulation

2.2.3 Artificial neural networks (ANN)

The ANN method is an inspiration for the way biological neurons work [25]. Unlike conventional algorithms, ANNs have the ability to learn from supplied data, and convert it into knowledge in a similar way to the human brain [26]. Architecturally, an ANN is made up of interconnected elementary units called neurons. The configuration of neural networks generally follows a layered structure. The network architecture is characterized by the layer number and the neuron count in each layer. [25].

The creation of a neural network generally involves three main steps [13]:

- Data collection: In this first step, a convenient database is built up by collecting corresponding input and output examples [26]. This database must be representative and varied, covering different conditions.
- Architecture selection: The next step is to select the neural network architecture. This means determining the number of hidden layers [26], the number of neurons in each layer and the appropriate activation methods.
- Training and test/validation: With the architecture defined, the network is trained using the training data. Throughout training, network weights and biases are adjusted to minimize an error metric, such as the root mean square error [26]. After training, the network is evaluated on separate test or validation data to assess its performance in terms of generalization and accuracy.

Fig.11. Illustrates the concept of MPPT based on the ANN. The main feature of this algorithm is the generation of the voltage value that corresponds to the maximum power point based on irradiation and temperature. This voltage is then used as a reference for a PID controller, which adjusts the overall system performance to reach the maximum power point.

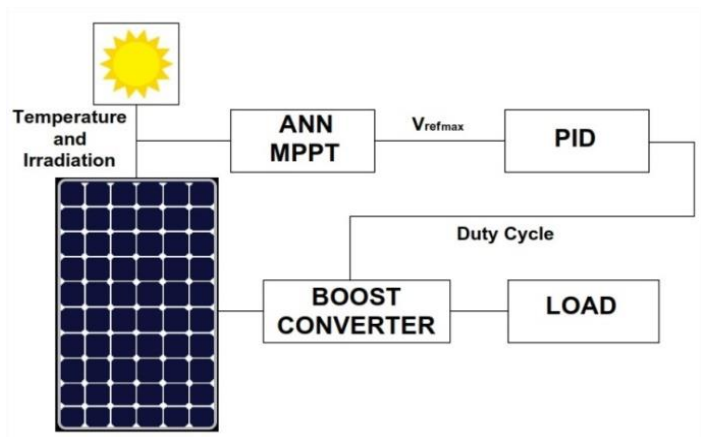


Fig.11. The concept of MPPT based on ANN

The methodology adopted for data collection used a simulation of the solar panel model integrated into MATLAB's Simulink library. A loop program was designed to extract the value of the maximum power point voltage (V_{mp}), while also registering the irradiance levels associated to each group of solar panels. These data were collected for use during the training and test phases. Concerning temperature, a constant value of 25 degrees Celsius was maintained to simplify the study. In total, 27331 values were registered in the table. A selection of these values is shown in Table 1 and Table 2.

Table 1. A selection of training data collected

Irradiation Pv1	Irradiation Pv2	Irradiation Pv3	Voltage of MPP
903.85	452.23	70.68	60.98
241.27	731.86	40.49	28.31
424.52	540.21	953.82	93.65
208.90	116.33	646.22	28.31
108.41	983.49	248.34	28.31
606.35	816.69	830.05	91.47
489.03	760.72	915.10	93.65
900.97	214.23	547.06	60.98
784.70	194.44	746.88	58.80
475.55	583.25	260.54	58.80

Table 2. A selection of test data collected

Irradiation Pv1	Irradiation Pv2	Irradiation Pv3	Voltage of MPP
805.29	562.38	470.07	91.47
359.61	371.77	382.87	87.12
256.30	972.03	660.56	60.98
505.28	198.02	104.38	28.31
888.41	362.95	453.71	93.65
64.79	850.76	279.43	28.31
911.91	59.77	615.96	60.98
563.94	668.26	335.44	58.80
37.79	285.78	931.24	28.31
799.85	331.07	737.41	58.80

The data collected in the previous step will be used to training MPPT system. To this end, the MATLAB integrated "nftool" application will be used [29]. This tool will be used to design the algorithm for determining the maximum power point voltage as a function of irradiation and temperature values.

The artificial neural network architecture is made up of four inputs and one output, structured in three distinct layers: the input layer, the hidden layer containing 200 neurons, and the output layer. Fig. 12. shows the Neural Network Architecture considered in this study.

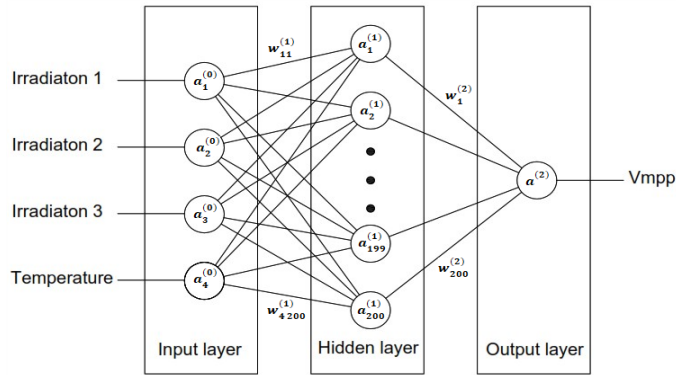


Fig. 12. Neural Network Architecture

$a_j^{(0)}$: the bias associated with jth neuron of the input layer.

$a_j^{(1)}$: the bias associated with jth neuron of the hidden layer.
 $a^{(2)}$: the bias associated with the output layer neuron.
 $w_{ij}^{(1)}$: the weight for the synapse from the ith input to the jth hidden layer neuron.
 $w_j^{(2)}$: the weight from the jth hidden layer neuron to the output layer neuron.

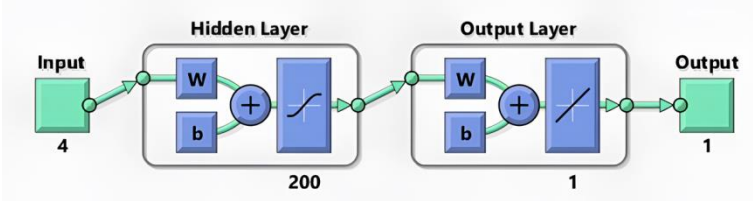


Fig. 13. Neural Network Architecture in Simulink

	Samples	MSE	R
Training:	19131	11.62824e-0	9.87162e-1
Validation:	4100	0.00000e-0	0.00000e-0
Testing:	4100	14.50999e-0	9.84150e-1

Fig. 14. Training Results of the Neural Network

The training stage was performed using the Bayesian regularization algorithm. The data were divided into three distinct sets, with 70% allocated to training data, 15% to validation data and 15% to test data.

The results were promising, with a regression of around 0.98. In addition, evaluation of the model's performance showed a mean square error of around 11.16 in the training stage. During testing, the mean square error increased a little to 14.5, but this level remains acceptable, suggesting a good generalization capability of the model.

The system simulation is shown in Fig. 15.

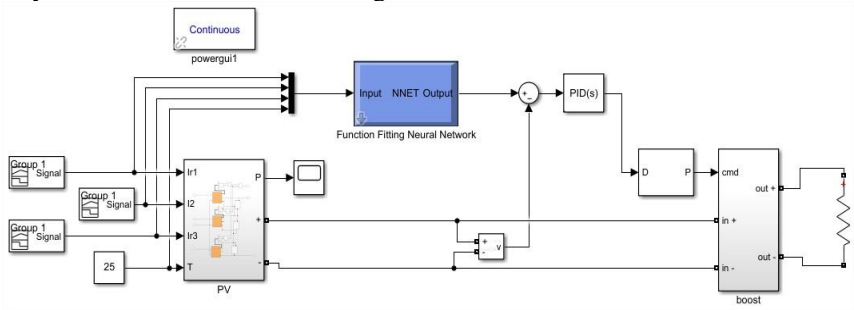


Fig.15. The system simulation with ANN technique

3 Results and discussion

3.1 Results under Uniform Irradiation:

This section focuses on evaluating the performance of the three MPPT control methods presented above under uniform irradiation. The three approaches will be tested using the same irradiation levels: 1000, 800 and 600 W/m².

The solar panel specifications give maximum expected powers of 1278, 1030 and 776.9 W respectively.

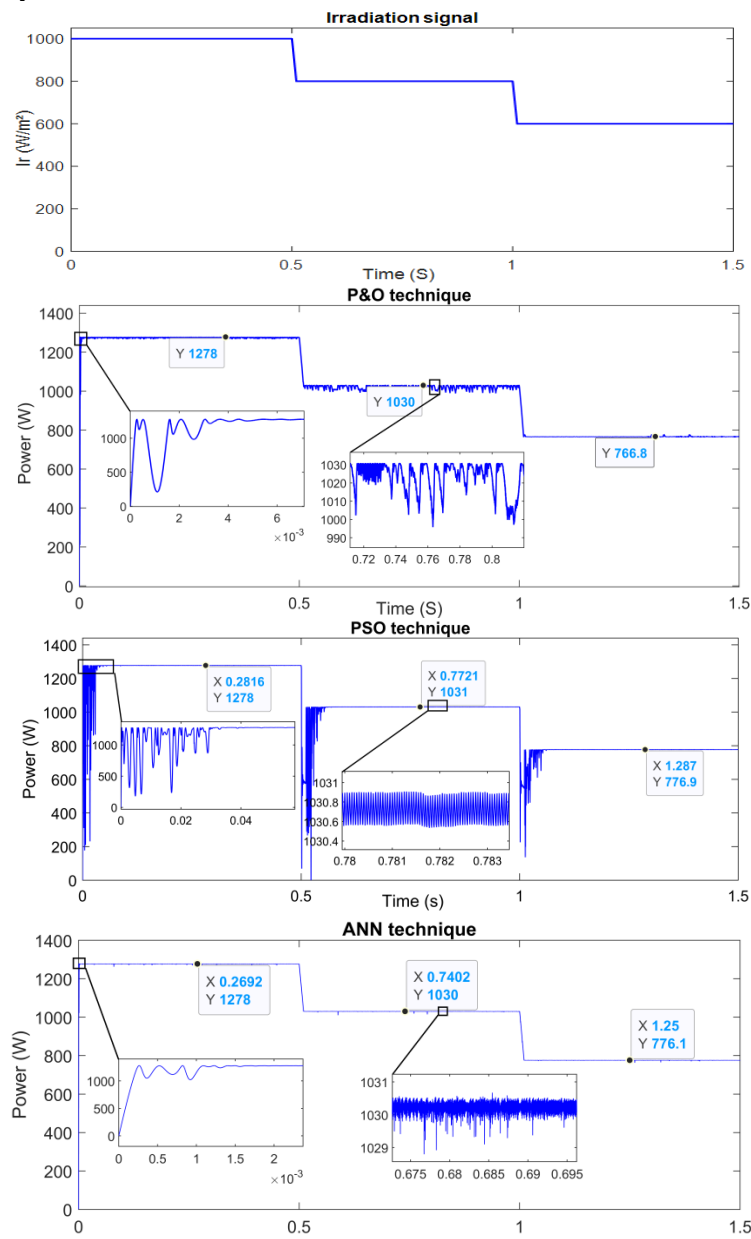


Fig.16. PV power for the three techniques

Fig. 16. , show the power curves generated by the system controlled by the three different MPPT methods.

Table 3. Response time, oscillations, and power discrepancy for the three methods

	P&O technique	PSO technique	ANN technique
Response time	5 ms	40 ms	1.5 ms
Oscillations	30 W	0.3 W	1.5 W
Power discrepancy	0 W	0 W	0 W

Examination of table values reveals that all three methods succeeded in tracking the maximum power point with great accuracy.

In response speed terms, the ANN method had the fastest response time, closely followed by the P&O method, while the PSO method was the slowest.

On the other hand, the P&O method shows significant oscillations around the point of maximum power.

3.2 Results under Partial Irradiation:

To simulate partial shading, each group of solar panels in the three groups will be exposed to different irradiances: 1000, 800 and 600 W/m².

According to the solar panel characteristics presented above Fig. 4. , the maximum power (corresponding to the global peak) to be tracked by the methods is 851.1 W.

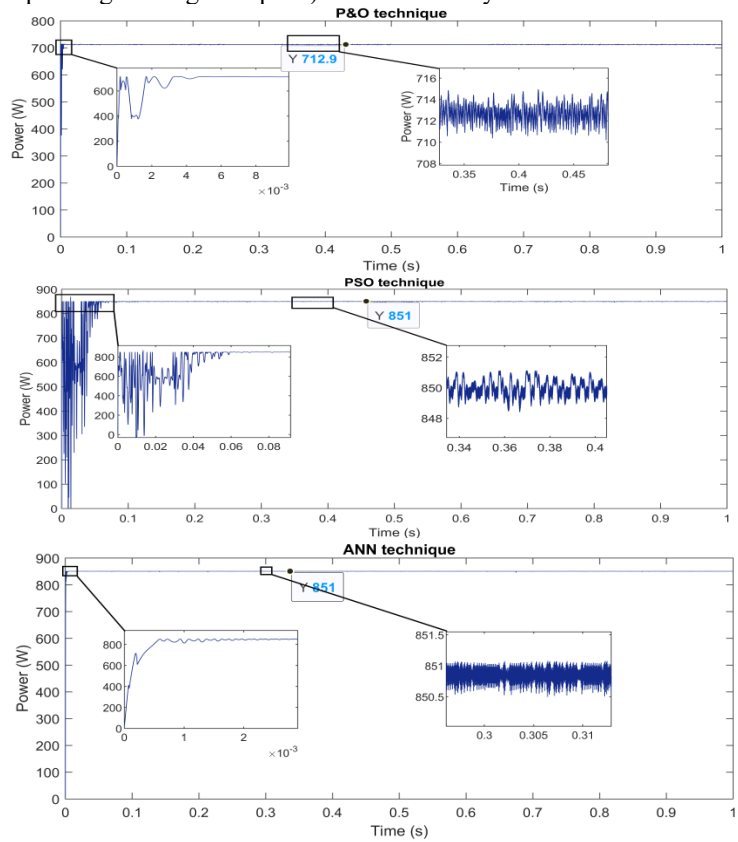


Fig.17. PV power for the three techniques

Fig. 17. , show the power curves generated by the system controlled by the three different MPPT methods.

Table 4. Response time, oscillations, and power discrepancy for the three methods

	P&O technique	PSO technique	ANN technique
Response time	5 ms	60 ms	2 ms
Oscillations	4.5 W	2.5 W	0.5 W
Power discrepancy	138 W	0 W	0 W

Based on the values in **Table 4**. The PSO and ANN methods succeeded in operating the system at the maximum power point with high accuracy. In contrast, the P&O method is trapped by the local peak corresponding to the power of 712.9 W, which results in a decrease in accuracy under partial shading conditions.

In terms of speed, the ANN method stands out as offering a significantly faster response time than the PSO method. Thus, the ANN-based MPPT appears to be the most suitable of the three methods studied, whether in the presence of uniform irradiation or in conditions of partial shading.

4 Conclusion

In conclusion, this study examined in detail three MPPT methods: P&O, PSO and ANN, in contexts of variable climatic conditions. The results obtained revealed that all methods have demonstrated their capability to track the maximal power point with notable accuracy in uniform irradiation conditions.

However, when partial shading was applied, the P&O method showed limitations due to its sensitivity to local peaks. In contrast, the PSO and ANN methods maintained high performance in terms of accuracy and speed of response, with ANN particularly distinguished by its rapid response speed.

Considering all the results, it is clear that the MPPT method based on ANN performed best, being able to handle irradiation variations efficiently and provide a rapid response in the event of disturbances. This method has significant potential for application in real photovoltaic systems subject to variable conditions. Ultimately, this study contributes to the growing body of knowledge on MPPT techniques.

Continuous improvement of MPPT methods is a key priority for optimizing the efficiency of photovoltaic systems. Our future perspectives focus on two main areas:

- Continued study of the ANN-based MPPT method and its application to more complex configurations. This will involve handling a variety of loads, from off-grid systems to grid-connected networks. The aim will be to assess the robustness and performance of MPPT control in a variety of contexts. This in-depth study will also identify possible drawbacks and limitations of this approach.
- Exploring new avenues and new MPPT methods to further maximize the benefits offered by photovoltaic systems. The integration of advanced learning mechanisms and experimentation with hybrid approaches, such as the implementation of a Neuro-fuzzy controller, will represent opportunities to optimize current performance. The ultimate goal is to propose significant improvements in maximum power point tracking, thus contributing to the overall efficiency of photovoltaic systems.

By combining these two lines of research, we aim to broaden the scope of MPPT methods, explore new ones and enhance their applicability in various scenarios.

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