INTERNATIONAL JOURNAL FOR INNOVATIVE RESEARCH IN MULTIDISCIPLINARY FIELD
ISSN(O): 2455-0620 [Impact Factor: 7.581]
Monthly, Peer-Reviewed, Refereed, Indexed Journal with IC Value : 86.87
Volume - 9, Issue - 6, June - 2023 Publication Date: 25/06/2023

DOIs:10.2015/IJIRMF/202306012 --:-- Research Paper / Article / Review

Comparative Analysis of MPPT Techniques: Artificial Neural Network and P&O for Photovoltaic Systems

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Abstract: *The demand for renewable energy has surged in recent years due to its perceived cleanliness, lack of harmful emissions, and low maintenance requirements. It is crucial to develop and expand renewable energy production to meet this growing demand. This study presents a comparison of maximum power point tracking (MPPT) control method for photovoltaic systems that utilizes a Neural Network (NN) and Perturb & Observe (P&O). Initially, a standalone PV system linked to a DC boost chopper with MPPT is designed using the perturbation and observation (P&O) technique. Next, a design for MPPT using ANN for the same system is presented, and a comparison is made between the two control methods. The study examines results in both constant and adjustable weather settings, such as irradiation and temperature. The findings reveal that the proposed MPPT by ANN control method can significantly improve the efficiency of the PV array by reducing oscillations around the MPP that occur in the P&O method, thus reducing power losses. It also lowers the overshoot that occurs in the transient response, thereby enhancing the performance of the solar cell.*

Key Words: *Photovoltaic (PV), P&O, MPPT, Artificial Neural Network (ANN).*

1. INTRODUCTION :

In recent decades, the issue of energy scarcity is becoming increasingly severe, leading to intensified exploration and research for alternative energy resources like wind, water, geothermal, and solar power across the globe. Solar power, which is renewable and environmentally friendly, is considered to be a green energy source. Due to its natural advantages, photovoltaic solar energy has been widely utilized for generating electricity from sunlight. A solar photovoltaic device, cell, or module converts solar energy directly into electrical energy. However, solar energy obtained from a solar PV cell is not consistently available. The amount of power generated by a PV system depends on the voltage and current set point of the PV module.

The behavior of photovoltaic arrays is not linear and it alters according to the temperature of the cell and the intensity of the solar radiation. A unique point, known as the maximum power point (MPP), is reached by the array for specific conditions, where the maximum output power is generated. This MPP varies due to changes in cell temperature and the present level of irradiation. A maximum power point tracker (MPPT) is utilized to obtain the maximum power from a photovoltaic array. Among the various MPPT methods, Perturbation and Observation (P&O) is the most commonly used due to its simple implementation (2-4). However, P&O has some drawbacks, including slow response speed, oscillation around the MPP in steady state, and incorrect tracking during rapidly changing atmospheric conditions(2-5).

In this paper, artificial neural network method (ANN) is introduced, which relies on an adaptive algorithm. This algorithm automatically adjusts the reference voltage step size and exploits the capabilities of artificial neural networks to achieve dynamic response and locate the MPP under rapidly changing conditions.

In order to transfer the maximum power from a PV array to a load, a DC-DC boost converter is placed between them, which adjusts the duty cycle of the converter. In this study, Simulink/Matlab is utilized to simulate the Perturbation and Observation (P&O) technique and the artificial neural network (ANN) technique. As a part of this study, an ANN is designed and compared with the P&O technique.

2. MODELLING OF THE PV ARRAY AND BOOST CONVERTER

Figure 1 illustrates the suggested setup comprising of a PV array, DC-DC boost converter, load, and MPPT controller.

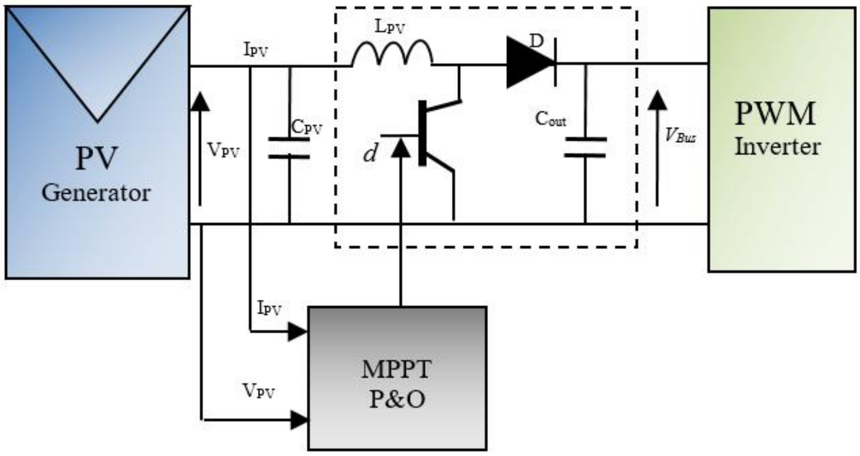


Figure 1 : Schematic diagram

2.1 PV ARRAY

In Figure 2, a solar cell is depicted as having a current source I_{ph}, a reversed diode that is connected in parallel to it, and internal resistances R_s and R_{sh}. This representation is commonly used, as stated in reference (6).

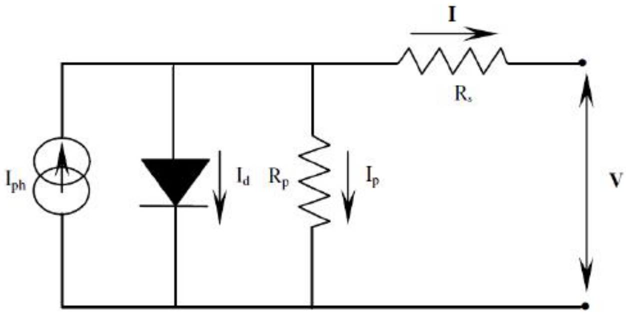


Figure 2: Equivalent circuit of a solar panel

The output current provided by the solar cell is obtained by applying Kirchhoff's law in the equivalent circuit shown above.

$$I = I_{ph} - I_d - I_p \tag{1}$$

$$I_d = I_s(e^{\frac{q(V+IR_s)}{nKT}} - 1) \tag{2}$$

$$I_p = \frac{V + IR_s}{R_p} \tag{3}$$

$$I = I_{ph} - I_s\left(e^{\frac{q(V+IR_s)}{nKT}} - 1\right) - \frac{V + IR_s}{R_p} \tag{4}$$

I: is the current of the PV cell (same as the module current).
V: is the voltage of the PV cell = (module voltage) ÷ (number of series cells).
q: Electron charge (1.602×10^{-19}).
n: Ideality factor of the junction, ranging from 1 to 2.
K: Boltzmann constant (1.381×10^{-23} J/K).
T: is the temperature of the PV cell in Kelvin (K).

In a PV cell, a basic model can be depicted as an equivalent circuit comprising an ideal diode coupled with an ideal current source. The current source signifies the photocurrent produced by photons (I_{ph}). The PV cell can be characterized using two parameters - the short circuit current (I_{sc}) and the open circuit voltage (V_{oc}), which can be determined when the cell is not linked to a load. Since the photocurrent behaves similarly to a short circuit current, I_{sc} can be considered equivalent to I_{ph}.

$$I = I_{sc} - I_s\left(e^{\frac{q(V+IR_s)}{nKT}} - 1\right) - \frac{V + IR_s}{R_p} \tag{5}$$

For the purpose of our research, we selected a specific photovoltaic (PV) array model (refer to table 2 for its characteristics) and simulated it using MATLAB/Simulink. Our simulation results, presented in Figure 3 and 4, showcase the I-V and PV characteristics of the modeled PV array under different temperature and irradiance conditions.

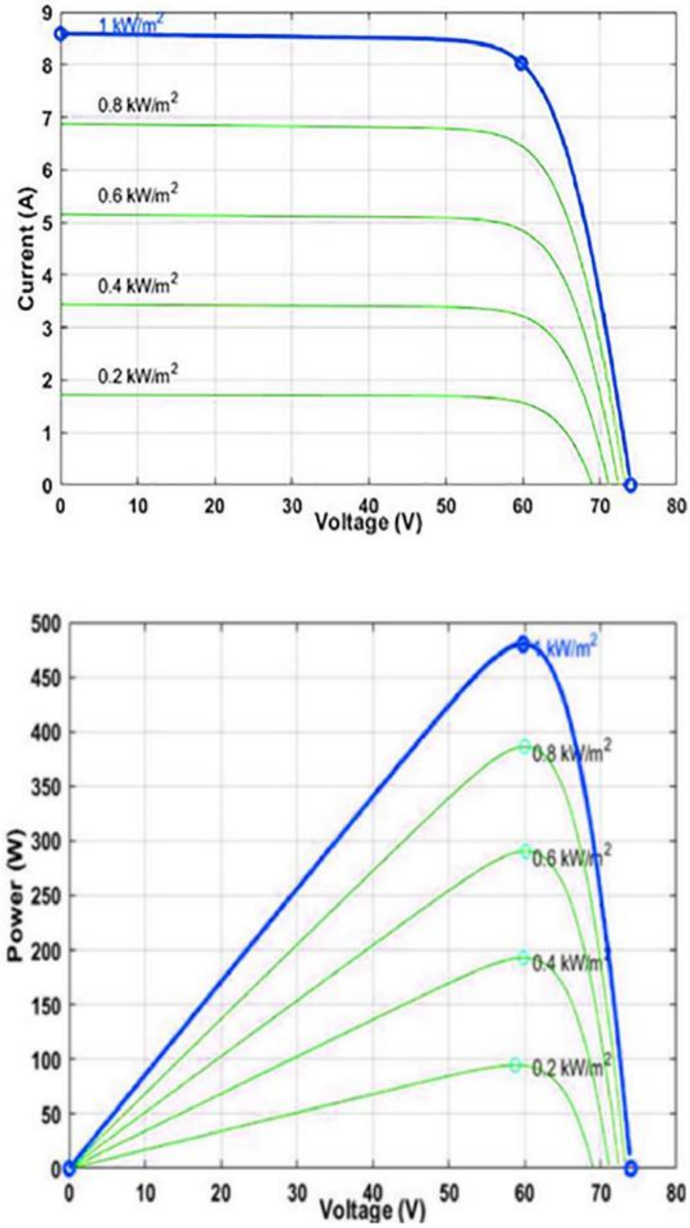
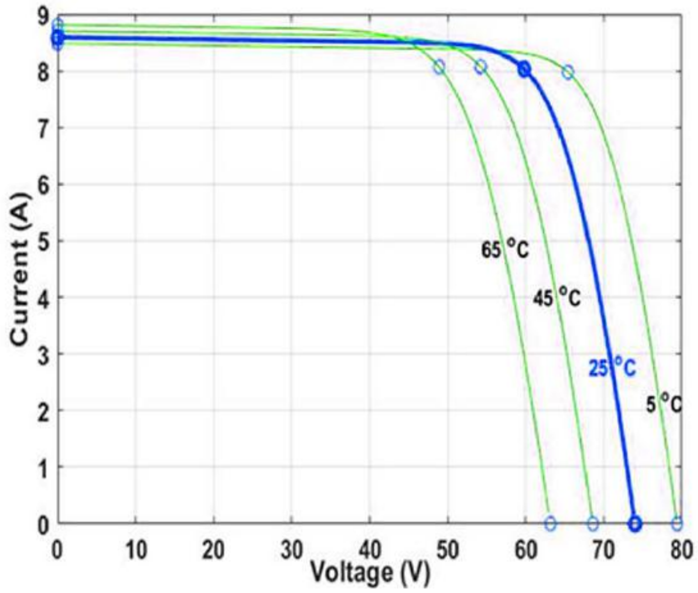


Figure 3: The P–V and I-V characteristics for PV array with



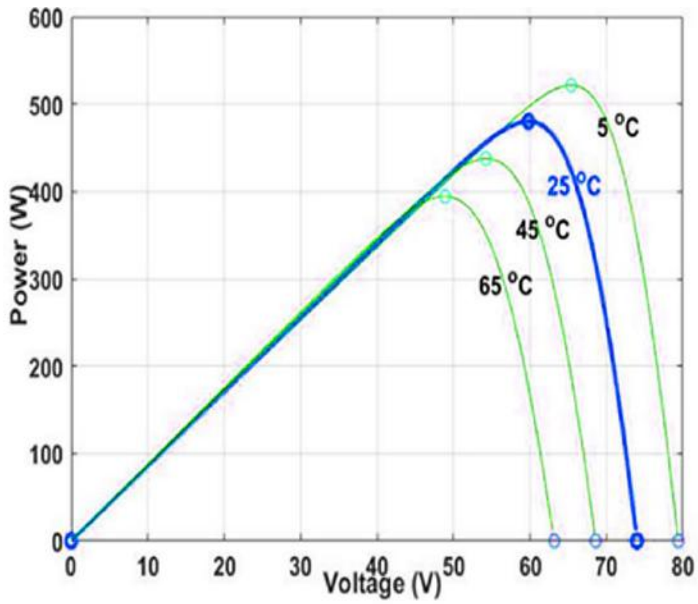


Figure 4: The P–V and I-V characteristics for PV array with

2.2 BOOST CONVERTER

As an input, DC-DC converters are commonly used to control the output voltage and current of the PV module. There are many converters available in the literature that have their own advantages and disadvantages (7). In this article, we are using a boost DC-DC converter.

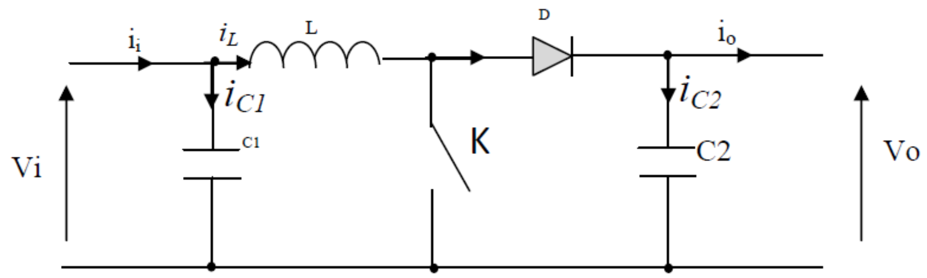


Figure 5; DC/DC boost converter

The equation 6 (8) provides an expression for the voltage conversion ratio of the boost converter.

$$\frac{V0}{Vi} = \frac{1}{1-D} \tag{6}$$

In 7 and 8 (9), Table 1 presents the computed values for the inductor L and capacitor C utilized to limit current and voltage ripple, respectively, in accordance with the boost converter's performance. The duty cycle of the switch PWM signal, denoted as D, and the input voltage, V_{pv}, which is the photovoltaic (PV) voltage, together with the output voltage, VL, are key parameters in this design.

$$C_{out} = \frac{D}{R.\, f_s \frac{\Delta Vl}{Vl}} \tag{7}$$

$$L = \frac{V_{pv}.\, D}{I_{pv}.\, f_s.\, \delta} \tag{8}$$

In this context, δ denotes the proportion of the inductor current ripple, while (ΔVL/VL) represents the proportion of output voltage ripple.

Parameters	Symbols	Values
Input filter capacitor (μF)	C_{in}	390
Output filter capacitor (μF)	C_{out}	470
Boost inductor (mH)	L	10
Resistive load (Ohm)	R	40
Switching frequency (KHz)	f_s	24

Table 1: Parameters of the boost converter

3. MPPT ALGORITHMS :

MPPT procedures are imperative in photovoltaic applications because the maximum power output of a PV cell varies with changes in solar radiation intensity and temperature. Therefore, implementing MPPT systems is crucial for achieving maximum power output from a solar array (10). The basic approach for MPPT control involves determining the voltage and current references that correspond to maximum power output under different levels of sun illumination and temperature by adjusting the load resistance R. Figure 6 illustrates the (I-V) and (P-V) curves, where operational point (OPR1) represents the maximum power point (MPP) value under the condition of irradiation (G1), temperature (T1), and load (R1). If the illumination changes from (G1 to G2) and temperature changes from T1 to T2, the I-V curve shifts from the curve (G1, T1) to the curve (G2, T2), and the load resistance must be varied from R1 to R2 to obtain the MPP at (OPR2) (10). Various algorithms, such as (P&O), (INC), and intelligent techniques like (FL) and (NN), can be used for automatic tracking. Our focus is primarily on the P&O and NN techniques.

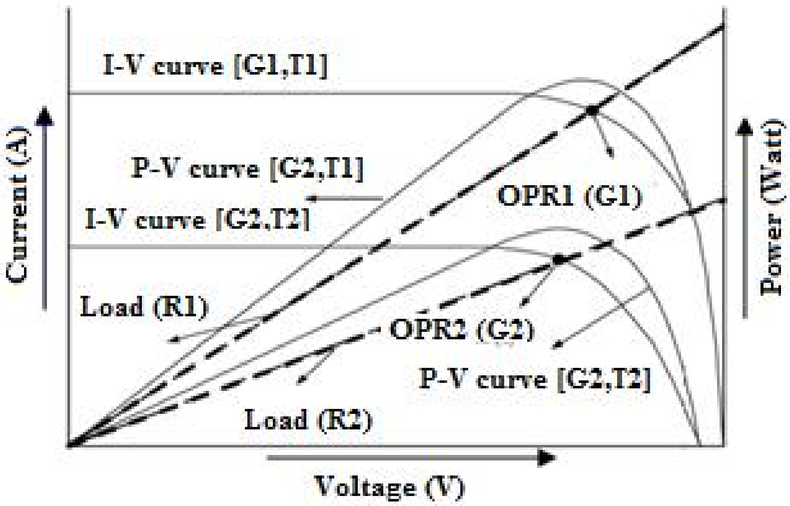


Figure 6: MPPT curve

3.1 PERTURB AND OBSERVE

The Perturbation and Observe Method is an iterative approach employed to determine the maximum power point (MPP) in photovoltaic systems (11), (12). This method involves assessing the characteristics of the PV array and subsequently perturbing its operating point to observe the resulting direction of change. Various adaptations of this method exist, ranging from simplistic to intricate. Figure 7 illustrates the algorithm implemented for MPPT.

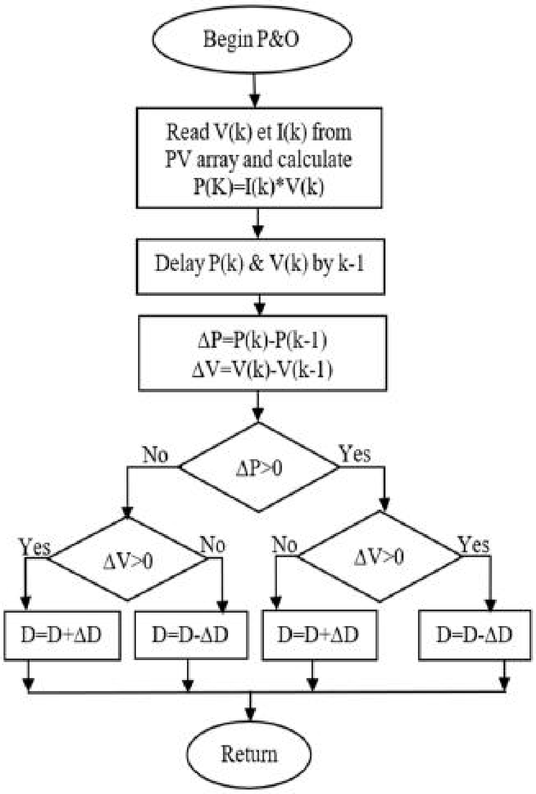


Figure 7: P&O scheme flow chart

In the P&O technique, the PV array terminal voltage is consistently adjusted in small increments or decrements until the maximum power point is attained. This adjustment is then compared to the trend of the output power. If the output power increases, the perturbation is continued in the same direction; however, if the output power decreases, the perturbation direction is reversed. The algorithm follows this iterative process to achieve optimal results.

3.2 MPPT BASED ARTIFICIAL NEURAL NETWORK

Artificial Neural Networks (ANN) are widely acknowledged as tools that offer innovative solutions to complex problems. ANN serves as an accurate model that aims to mimic the structure and functionality of biological neural networks. It acts as a data processing system, consisting of numerous interconnected neurons, which are simple yet highly efficient processors. These neurons form a network with a multitude of weighted connections. Such networks possess remarkable capabilities for pattern recognition and learning. Recent applications of ANN have demonstrated their significant potential in addressing challenging tasks related to data processing and interpretation. Among various types, the multilayered feedforward ANN, specifically the backpropagation (BPN) model, is widely utilized across numerous domains. It comprises an input layer, one or more hidden layers, and an output layer (13) (14).

In this study, the proposed Artificial Neural Network (ANN) is developed with the objective of predicting the maximum power point (MPP) of a photovoltaic (PV) array. The steps involved in designing the ANN for use as an MPPT controller in a PV system can be summarized as follows:

- Step 1: Selecting the structure of the proposed ANN: In this research, a three-layer ANN architecture is chosen. The inputs to the network are the PV current (I_{pv}) and voltage (V_{pv}) recorded under varying temperature and irradiance conditions. The hidden layer consists of ten neurons with a log sigmoid activation function. The proposed ANN architecture is illustrated in Figure 8.
- Step 2: Training the neural network: To train the neural network, input and target example patterns need to be obtained. A PV system with Perturbation and Observe (P&O) control is designed and simulated to generate training data for the ANN and for result comparison. A large number of example patterns are collected under

different temperature and irradiance conditions from the simulated PV system under P&O control. The ANN is trained offline using the error backpropagation method with the Levinberg Marquardt (LM) algorithm in MATLAB, utilizing the NNTOOL command as shown in fig 9. The LM algorithm is chosen for its effectiveness in solving non-linear problems and its robustness compared to other techniques. Figure 10 illustrates the execution of regression analysis to assess the correlation between the target variable and the output variable.

- Step 3: Simulating the proposed ANN: After training the ANN and obtaining the optimized weights, the network is simulated using MATLAB Simulink. It is then integrated with the PV system and a Boost chopper to function as an MPPT controller.

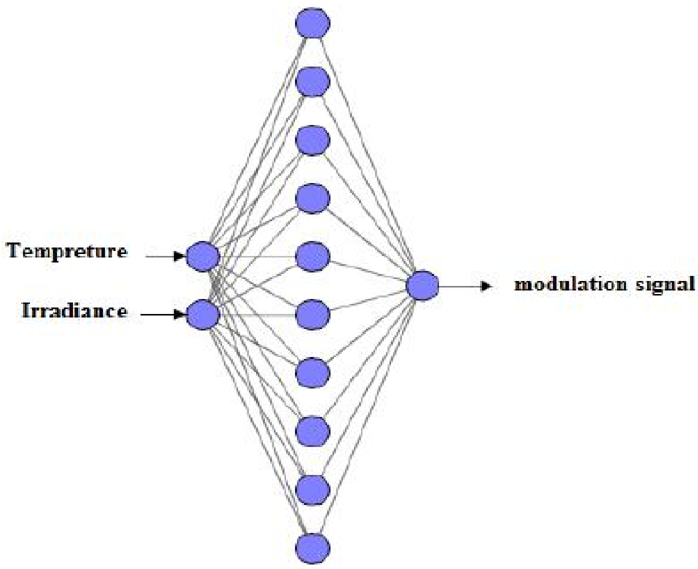


Figure 8: Proposed ANN architecture

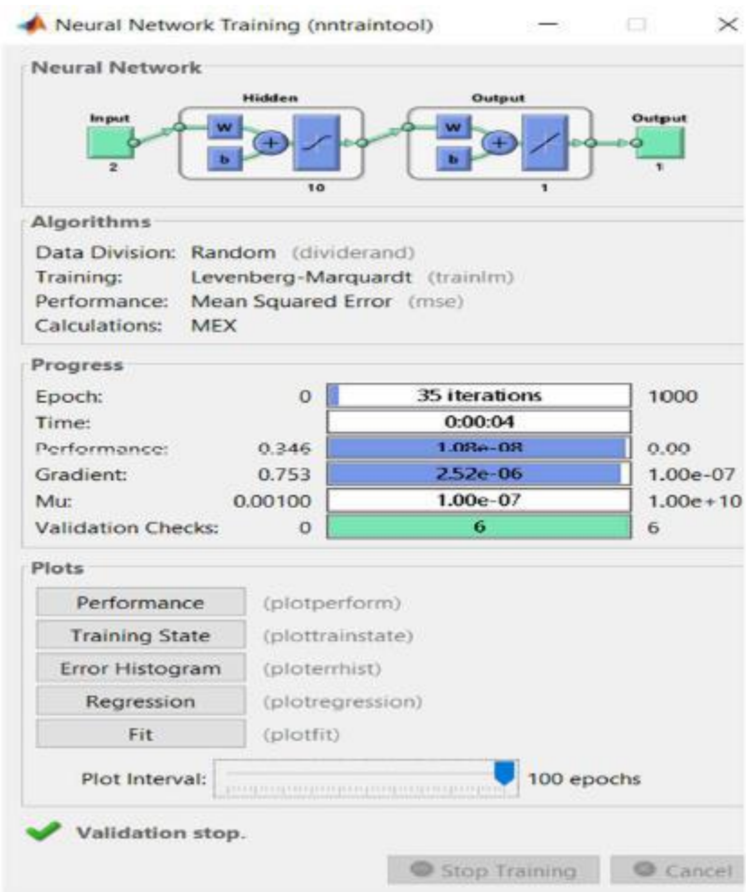


Figure 9: Neural Network training

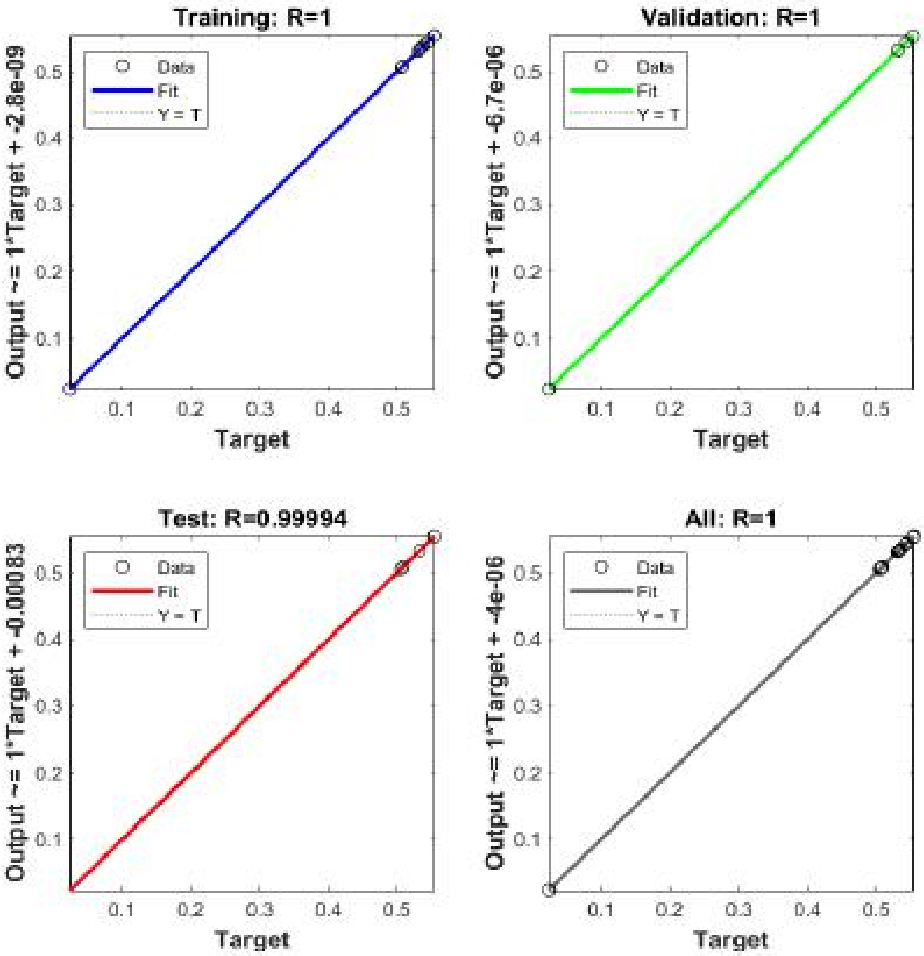


Figure 10: Regression

4. RESULTS AND DISCUSSION :

In this section, we demonstrate the simulation outcomes using the MATLAB/Simulink environment for the proposed system, which comprises PV arrays, a DC-DC converter, an MPPT controller, and a load. The electrical parameters of the PV array are provided in Table 2.

Parameters	Symbols	Values
Maximum power (w)	P_{mpp}	240.097
Maximum power point current (A)	I_{mpp}	8.03
Maximum power point Voltage (V)	V_{mpp}	29.9
Short circuit current (A)	I_{sc}	8.59
Open circuit voltage (V)	V_{oc}	37
Temperature coefficient of I_{sc} (A/K)	K_{sc}	0.0637
Temperature coefficient of V_{oc} (V/K)	K_{oc}	-0.3654
Series cells	N_{sc}	60
Number of parallel modules	N_p	1
Number of series modules	N_s	2

Table 2:Electrical parameters of the Solar

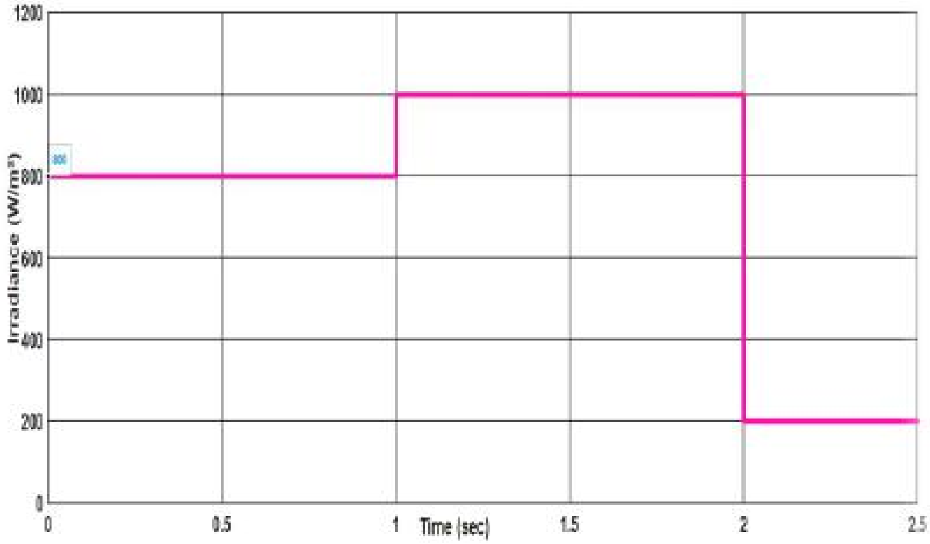


Figure 11: Solar radiation slope

In Figure 11, we can observe a scenario where the irradiation level experiences a sudden increase from 800 W/m² to 1000 W/m², followed by a decrease from 1000 W/m² to 200 W/m², while maintaining a constant temperature of 25°C. The simulation results presented in Figure 12 showcase the generated power of the PV arrays using both the ANN and P&O MPPT techniques. Notably, the ANN method demonstrates swift and effective tracking of the MPP, achieving an impressive efficiency of 97.7%, surpassing the performance of the P&O method.

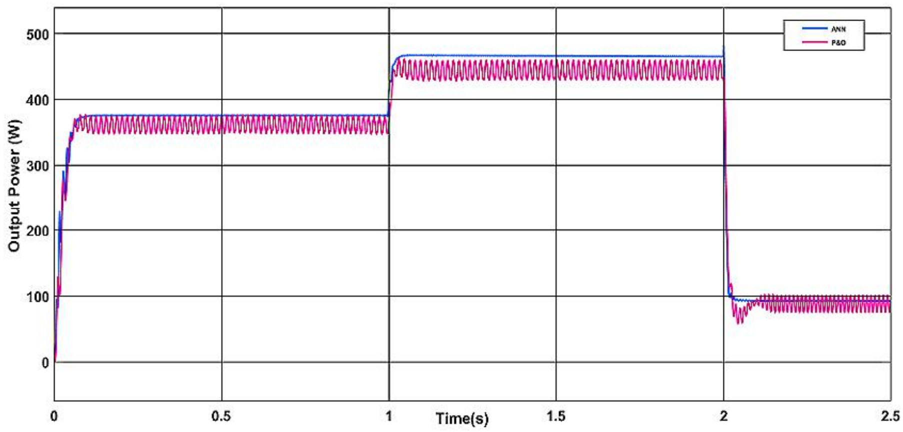


Figure 12: Power output from both methods in response to rapidly changing solar irradiation

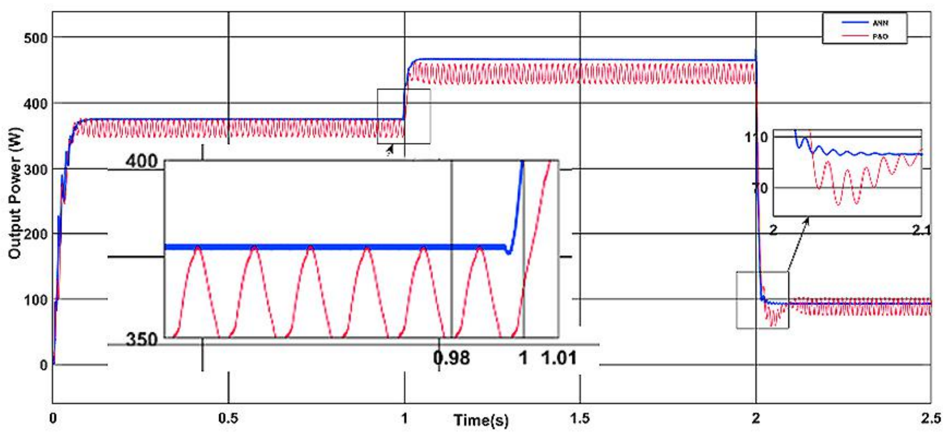


Figure 13: Both methods exhibit power overshoot when confronted with sudden increases or decreases in irradiation levels

As depicted in Figure 13, the comparison between the P&O MPPT controller and the proposed artificial neural network (ANN) MPPT controller reveals distinct overshoot characteristics. The P&O controller demonstrates a larger overshoot during sudden changes in irradiation, whereas the ANN controller exhibits a reduced overshoot. The ANN technique demonstrates its capability to swiftly track the maximum power point (MPP) even in the presence of rapidly changing solar irradiation, whereas the P&O technique struggles to effectively track the MPP under such conditions. Additionally, the ANN technique showcases minimal oscillation around the MPP, whereas the P&O technique shows a higher degree of oscillation in the vicinity of the MPP.

5. CONCLUSION :

This research paper focuses on maximum power point tracking (MPPT) control system for photovoltaic (PV) arrays using artificial neural network (ANN) technology, considering varying atmospheric conditions. A comparative analysis is conducted with the classical perturbation and observation (P&O) method. The first method employs the P&O MPPT strategy, while the second method utilizes the ANN MPPT approach. Through simulations conducted under identical atmospheric settings, the performance of the two MPPT controllers is evaluated and compared. The results reveal that the proposed ANN control system enhances the efficiency of the PV array by reducing oscillation around the maximum power point (MPP), thereby mitigating power losses observed in PV systems using the P&O method. Additionally, the ANN controller exhibits superior transient response compared to the P&O controller, particularly in scenarios involving sudden changes in irradiation or temperature.

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