Study of neural controller based MPPT in comparison with P&O for PV systems

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Article Info

Article history:

Received Oct 1, 2025
Revised Dec 23, 2025
Accepted Feb 10, 2026

Keywords:

Artificial neural networks
Maximum power point tracking
Simulink
P&O
Photovoltaic

ABSTRACT

This study investigated the performance of two prominent maximum power point tracking (MPPT) strategies: the established perturb and observe (P&O) technique and an artificial neural network (ANN)-based controller. Through simulations conducted in MATLAB/Simulink, a 50 W photovoltaic (PV) array was evaluated under dynamic irradiance and temperature variations. Notably, data generated by the P&O system served as the training dataset for the ANN model. The simulation results indicate that the ANN controller effectively and accurately identifies the PV system's optimal operating point even amidst fluctuating environmental conditions. When compared to the conventional P&O method, the ANN approach demonstrated superior characteristics, including a significantly faster response, diminished oscillations around the maximum power point, and enhanced tracking accuracy during rapid environmental shifts. These findings underscore the substantial potential of ANN-based MPPT strategies for improving both the efficiency and operational stability of photovoltaic power systems.

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1. INTRODUCTION

The global demand for electrical energy has surged due to industrial growth, population increase, and concerns over fossil fuel depletion and environmental sustainability. Renewable energy technologies have gained significant attention, with solar energy being one of the most promising sources because of its abundance, sustainability, and environmentally friendly nature [1], [2]. Despite these advantages, photovoltaic (PV) systems face two main technical challenges. First, their energy conversion efficiency is still relatively low. Second, the operating point of a PV module is highly affected by load conditions and environmental factors such as irradiance and temperature. These variations cause nonlinear changes in the current-voltage (I-V) and power-voltage (P-V) characteristics, complicating the maintenance of operation at the maximum power point (MPP) [3]. To maximize energy extraction under fluctuating environmental conditions, maximum power point tracking (MPPT) controllers are used. MPPT algorithms adjust the operating parameters of the power converter to ensure continuous operation of the PV array at its MPP, thus improving overall system efficiency [4], [5]. Among various MPPT techniques, the perturb and observe (P&O) method is widely used because of its simplicity and ease of implementation. However, it inherently causes steady-state oscillations around the MPP and may have reduced effectiveness under rapidly changing environmental conditions. [6]. To overcome these limitations, intelligent control methods such as artificial neural networks (ANN), fuzzy logic systems, and genetic algorithms have been proposed. These approaches offer improved adaptability and robustness in nonlinear environments [7]-[9].

In recent years, significant attention has been devoted to the development of MPPT techniques aimed at maximizing the energy extracted from PV systems. The primary function of these methods is to ensure optimal power transfer from the PV array to the load or grid by dynamically regulating the duty cycle of the associated power converter under changing environmental conditions. A wide range of MPPT strategies has been developed to maximize photovoltaic system efficiency. Among conventional methods, the P&O technique is widely used due to its simple implementation and decent performance in stable conditions. However, P&O causes steady-state oscillations around the MPP and performs poorly when irradiance or temperature changes rapidly, leading to energy losses [10]-[13]. To address these drawbacks, intelligent MPPT methods using artificial intelligence—such as fuzzy logic control, artificial neural networks (ANN), and genetic algorithms—have been introduced. These AI-based approaches provide better adaptability and accuracy under nonlinear and time-varying conditions, enhancing overall system efficiency [14]-[18]. The study compared a traditional P&O-based controller to an ANN-based MPPT controller using simulations in MATLAB/Simulink with a PV module and DC–DC boost converter. Results showed that the ANN method offers faster dynamic response and superior power tracking than the P&O algorithm. In summary, while P&O remains popular for its simplicity, ANN-driven MPPT techniques demonstrate clear advantages in accuracy and adaptability, especially under fluctuating environmental conditions.

2. PV SYSTEM MODEL

2.1. Solar cell model

The PV module functions as a technology that converts sunlight into electrical energy. Essentially, when a PV module is exposed to solar radiation, it generates direct current without producing noise or causing environmental harm. In this study, we began by designing a 50 W photovoltaic array using the equivalent circuit representation of PV cells. The standard model of a PV cell used in this work is illustrated in Figure 1 [19], [20].

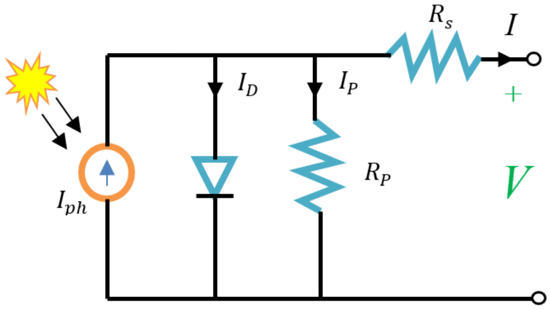

Figure 1. Mathematical modeling of PV module

The equations for the output current and voltage are given by (1)-(4).

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

$$I_{ph} = \frac{G}{G_{ref}}\left(I_{ph,ref} + \mu_{sc} * \Delta T\right) \tag{2}$$

$$I_d = I_0\left[exp\left(\frac{V_{pv}+I_{pv}*R_s}{q}\right) - 1\right] \tag{3}$$

$$I_{sh} = \frac{V_{pv}+I_{pv}*R_s}{R_{sh}} \tag{4}$$

By substituting the (2), (3), and (4) in the first equation, the characteristic equation of a photovoltaic cell linking the parameters of the solar cell to the output current and voltage is given as (5).

$$I_{pv} = I_{ph} - I_0\left[exp\left(\frac{V_{pv}+I_{pv}*R_s}{q}\right) - 1\right] - \frac{V_{pv}+I_{pv}*R_s}{R_{sh}} \tag{5}$$

I_{pv} represents the output current from the photovoltaic panel, while I_{ph} is the light-generated current that varies proportionally with solar irradiation. Id refers to the diode current, also known as the dark current, which is associated with the reverse saturation current. I_{sh} corresponds to the shunt current. The resistances R_{sh} and R_s denote the parallel and series resistances within the solar cell, respectively. K is the Boltzmann constant, q stands for the electron charge, and V_{pv} indicates the output voltage at the terminals. Temperature difference ΔT is calculated as the actual cell temperature Tc minus the reference cell temperature Tc,ref, measured in Kelvin. G defines the irradiance in watts per square meter with a reference value G_{ref} of 1000 W/m², and Tc,ref is set at 298 K. $T_{c,ref} = 298$ K, $\mu_{sc}$is the temperature coefficient of the short circuit current, and $I_{ph,ref}$is the photocurrent measured under standard test conditions (STC). The study uses the 50M photovoltaic module, whose electrical specifications at STC (G = 1000 W/m², T = 25°C) are detailed in Table 1. The PV system was modeled in MATLAB Simulink, with the simulation framework illustrated in Figure 2 based on equations (1) to (5). The simulation output from the PV model closely matches the P-V characteristics of the 50M (36) module. Figures 3 and 4 demonstrate that as solar irradiance increases, both power and current rise. Conversely, Figures 5 and 6 show that increasing the cell temperature results in a decrease in both power and voltage.

Table 1. Electrical characteristics of 50M (36) PV panel

Parameters	Value
Voltage at maximum power Vmpp	17.98 V
Current at maximum power Impp	2.78 A
Maximum power Pmax	50 W
Short-circuit current Isc	3.04 A
Open-circuit voltage Voc	21.87 V

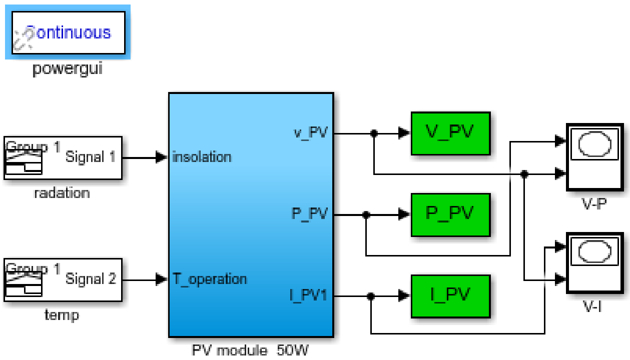

Figure 2. Simulink model of the 50 M (36) PV array

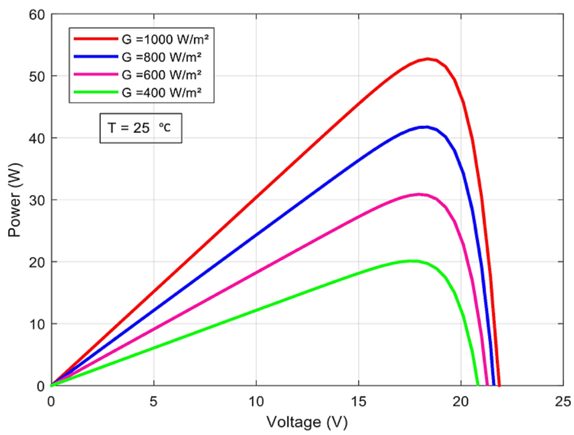

Figure 3. Irradiance variation of PV under test

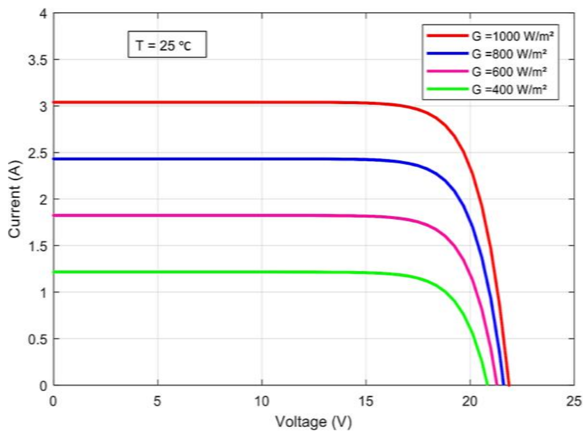

Figure 4. Irradiance variation of model under testing

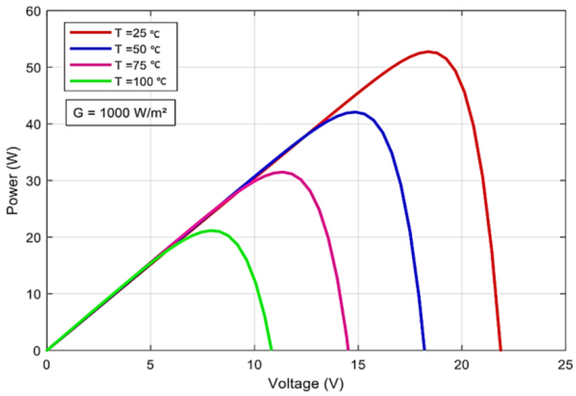

Figure 5. Temperature variations of the model under testing

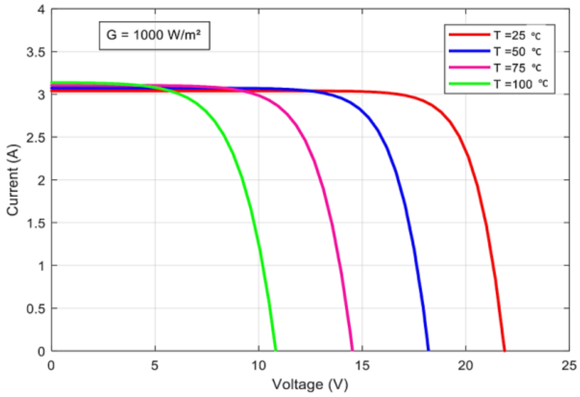

Figure 6. Temperature variations of PV module

2.2. Modeling of the boost converter

The MPPT is implemented by placing a DC/DC boost converter between the photovoltaic (PV) array and the load. To ensure the system tracks the maximum power point (MPP), the converter must operate with the precise duty cycle corresponding to that point. As shown in Figure 7, the specific converter used is a boost converter, which has an output voltage higher than its input voltage, described by (6). [21]. Table 2 illustrates the different parameters of PV.

$$V_{out} = \frac{V_{in}}{1-a_{pv}} \tag{6}$$

The differential equations of Kirchhoff's voltage and current laws are expressed as (7) and (8).

$$V_{pv} = L_{pv}\frac{di_{L_{pv}}}{dt} + (1-a_{pv})V_s \tag{7}$$

$$C_s\frac{dV_s}{dt} + \frac{V_s}{R} = (1-a_{pv})i_{L_{pv}} \tag{8}$$

Table 2. Values of boost converter elements

Parameters	Value
Inductance L_{pv}	18 mH
Intput capacitor C_e	2200 µF
Output capacitor C_s	2200 µF
Switching frequency of the MOSFT F	1 KHz
Load R	22 Ohm

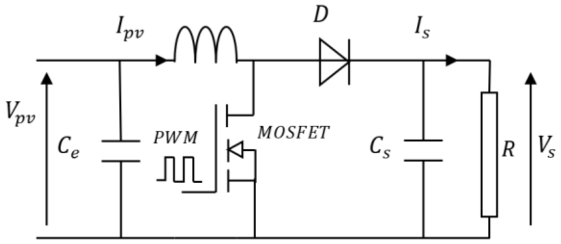

Figure 7. The boost converter scheme

3. THE MPPT METHODS

3.1. Classical P&O algorithm

The P&O method remains widely used for maximizing power extraction from photovoltaic systems due to its simplicity and low computational demand. This technique works by making slight adjustments to the PV module's operating voltage and monitoring the effect on output power. If a change results in increased power, the adjustment continues in that direction; if power drops, the direction reverses. This iterative process moves the system toward the MPP. However, because the method constantly perturbs the voltage, it naturally causes small fluctuations around the MPP once that point is reached. The working steps of the P&O method are visualized in Figures 8 and 9 [22], [23].

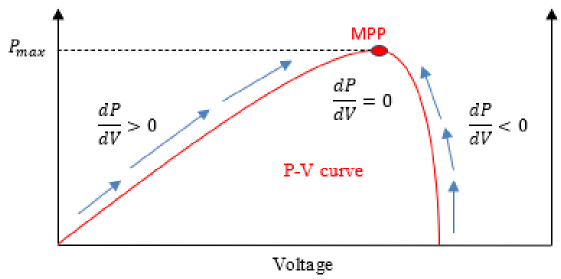

Figure 8. P &O method

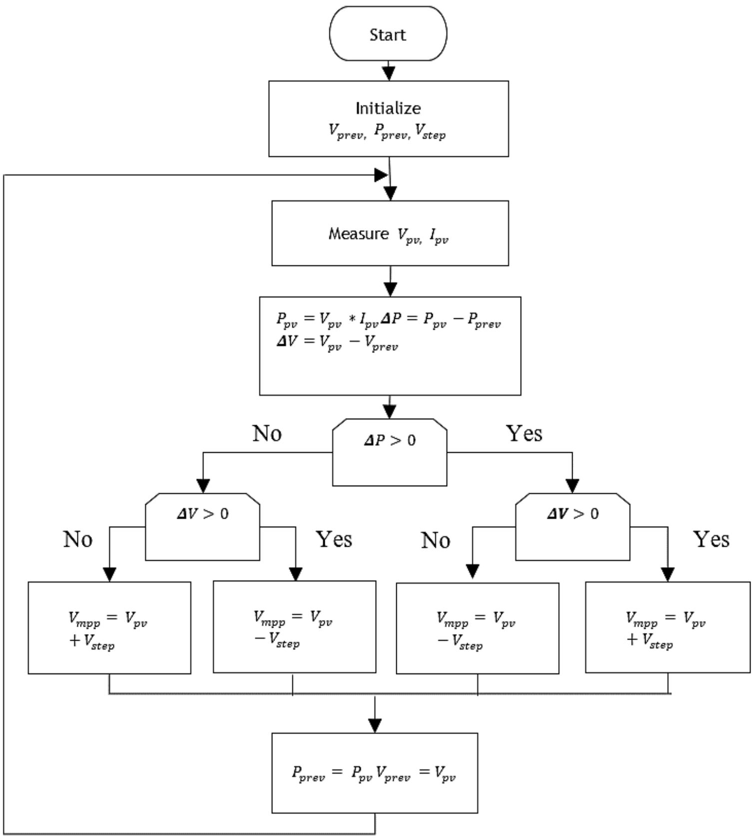

Figure 9. P&O MPPT algorithm

3.2. Neural network-based MPPT

In this study, an artificial neural network is employed to estimate and track the MPP for a 50 W photovoltaic array. Given the nonlinear relationship between environmental conditions and PV electrical characteristics, ANN-based control provides a suitable alternative for improving tracking accuracy. To facilitate network training, data generated using the P&O method within a MATLAB-based simulation environment were utilized. This approach enables the ANN to learn the nonlinear mapping between system inputs and the corresponding optimal operating conditions (Figures 10-12) [24].

3.2.1. Selecting network structure

The structure of the neural network determines how the input signals are processed to generate the control output. In this case, the network receives three inputs: the PV current, voltage, and power. Its output layer produces a single value — the duty cycle needed for the DC–DC boost converter. To capture the nonlinear dependencies between inputs and outputs, a single hidden layer is included. Because the PV system cannot be accurately modeled with linear equations, the neurons in this hidden layer use a tangent sigmoid activation function. Meanwhile, the output layer applies a linear activation function to provide a smooth, continuous duty cycle signal [25].

3.2.2. Collecting data

Simulation of the PV array in MATLAB/Simulink was conducted across a range of operating conditions. This was done to determine the corresponding optimal duty cycle values for the boost converter. The process produced a dataset consisting of 104 operating points linking electrical measurements to the required control actions.

3.2.3. Training the network

Out of the total dataset, 94 samples were used to train the neural network. During training, these input-output pairs allowed the network to learn between PV operating parameters. The necessary conditions for maximum power extraction.

3.2.4. Testing the network

Following the training phase, the remaining 10 samples were reserved for testing purposes. The resulting prediction error was then analyzed. This analysis was used to further refine the network's accuracy.

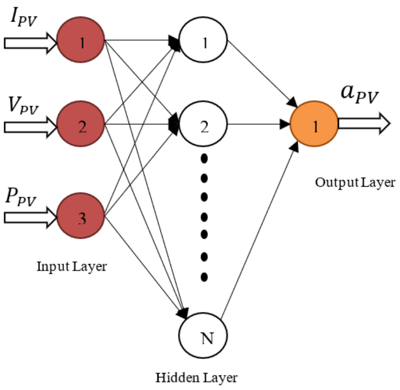

Figure 10. Neural network structure

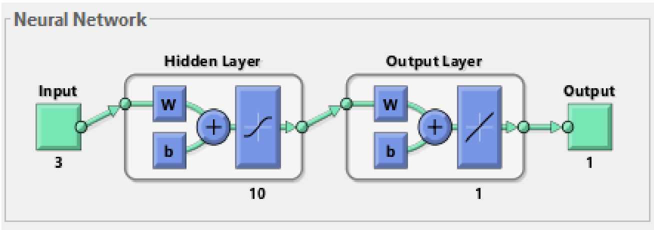

Figure 11. Neural network training with MATLAB toolbox

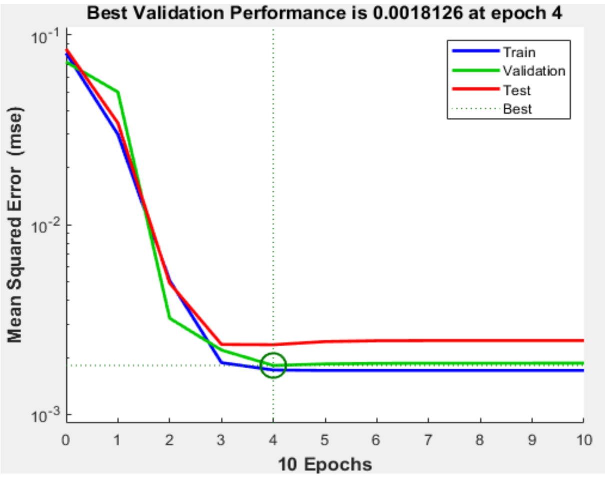

Figure 12. Training performance curve

4. RESULTS AND DISCUSSION

The photovoltaic system was created and tested within the MATLAB/Simulink platform (refer to Figures 13 and 14). Its design consists of three main components: a mathematical representation of the PV module, a DC–DC boost converter, and an MPPT controller that utilizes an artificial neural network. The PV module's behavior was simulated based on the analytical model described in Section 2, while the boost converter was set up following the circuit design shown in Figure 7. The neural network was initially trained using datasets representing PV voltage, current, and corresponding maximum power point (MPP) values. Once the training process was completed and the network weights were obtained, the ANN model was embedded into the control framework within Simulink. During operation, the controller receives real-time inputs ofI_{pv}, V_{pv}, and P_{pv} as inputs, the ANN automatically and determines the optimal duty cycle required to drive the boost converter toward maximum power extraction.

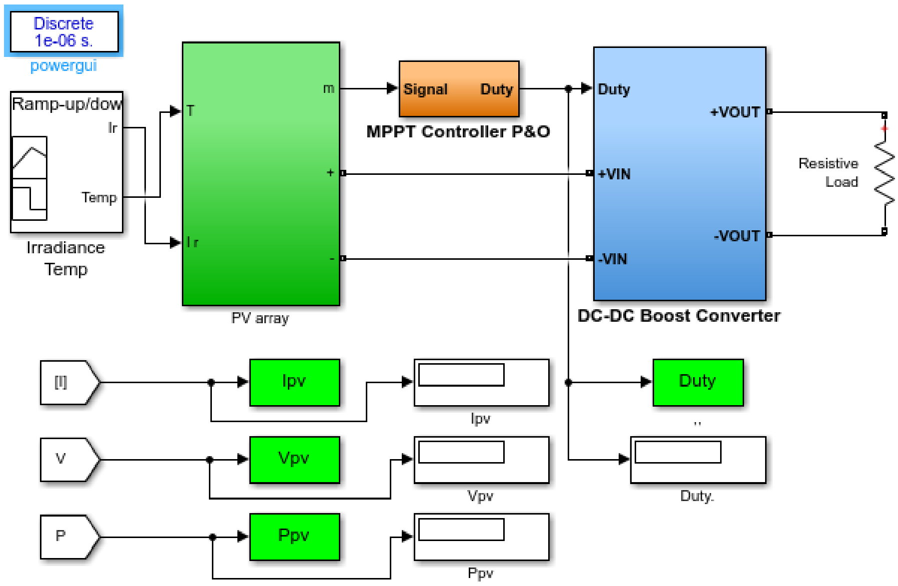

Figure 13. The modelling of P&O MPPT

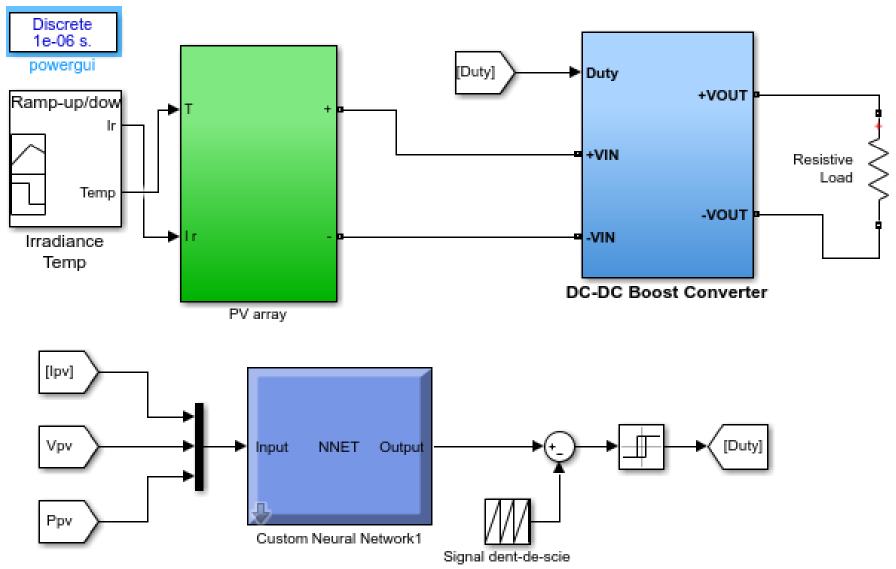

Figure 14. Simulink model of neural network controller MPPT with DC-DC boost converter

The simulations experiment at (G = 1000 W/m², T = 25°C), illustrated in Figures 15–17 through a comparison with the P&O. The ANN-based controller exhibits quicker convergence to the MPP, reduced steady-state fluctuations, and improved tracking capability. Quantitative evaluation shows that the neural network method achieves a tracking efficiency of 99.2%, exceeding the 97.6% obtained with P&O. In addition, the settling time is shortened from 0.08 s to 0.04 s, while power ripple is reduced by approximately 35%. These outcomes highlight the enhanced stability and responsiveness of the ANN-driven controller under nominal operating conditions. Furthermore, testing under identical standard conditions confirmed its ability to sustain consistent power output and high tracking precision across different operating intervals. Over the evaluation period, the ANN-based strategy yielded greater harvested energy than the conventional technique, indicating superior adaptability for practical deployment.

To further assess system performance, additional simulations were carried out under variable irradiance levels of 800 W/m², 900 W/m², and 1000 W/m². The results are shown in the following figures, emphasizing the ANN controller's capacity to adapt efficiently to varying irradiance levels while ensuring stable power delivery and precise tracking performance. In the second scenario, the system's effectiveness was tested through simulations conducted at different solar irradiance intensities (800 W/m², 900 W/m², and 1000 W/m²) with a fixed temperature of 25 °C. The outcomes confirm that the neural network controller can adjust promptly to fluctuations in solar input, maintaining consistent power output and accurately tracking the maximum power point.

In the third test case, the impact of rapid temperature fluctuations on system performance was examined while maintaining a G = 1000 W/m². The PV temperature was varied between 25 °C, 37.5 °C, and 50 °C, as depicted in the corresponding Figures 18-23. The obtained results indicate that the ANN-based MPPT controller preserves stable power delivery and consistently achieves accurate MPPT despite thermal disturbances.

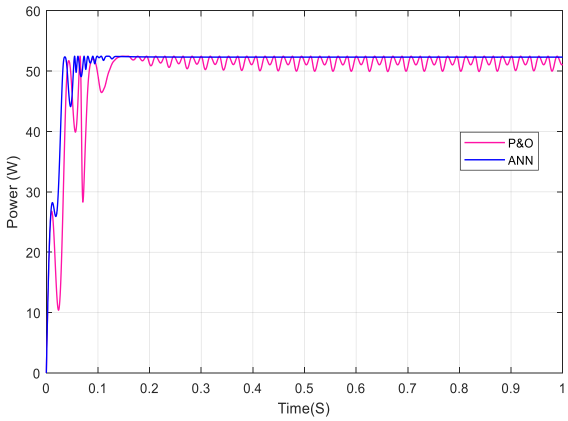

Figure 15. Output results at standard conditions with ANN and P&O

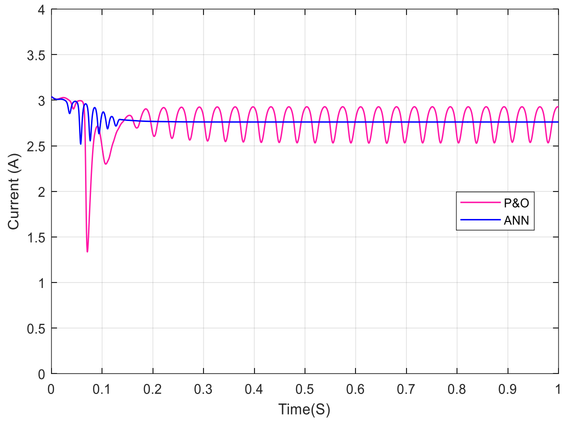

Figure 16. Current output under typical circumstances using ANN and P&O

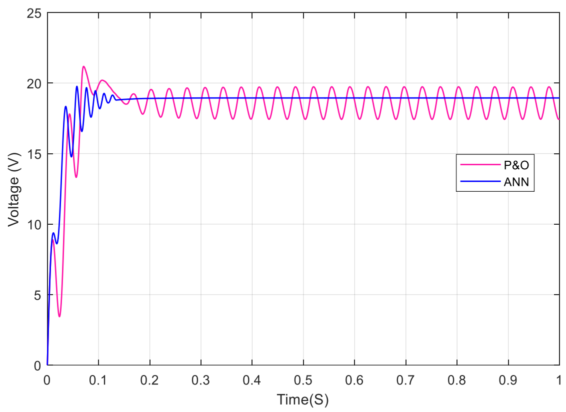

Figure 17. Voltage output under typical circumstances using ANN and P&O

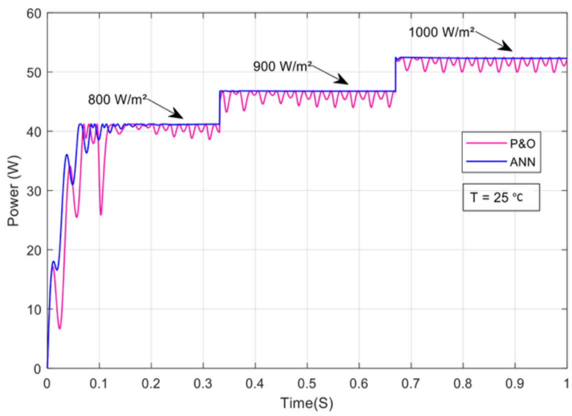

Figure 18. Variations in output power with ANN and P&O under varying irradiation and a constant temperature of 25 °C

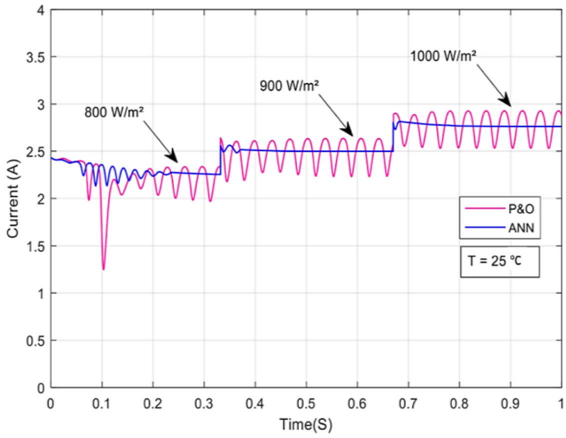

Figure 19. Variations in output current with ANN and P&O under varying irradiation and a constant temperature of 25 °C

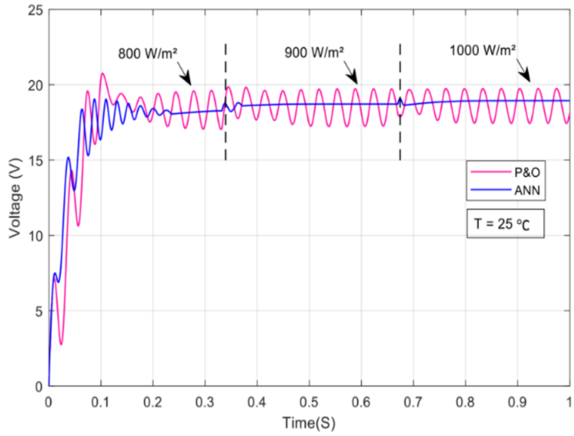

Figure 20. Variations in output voltage with ANN and P&O under varying irradiation and a constant temperature of 25 °C

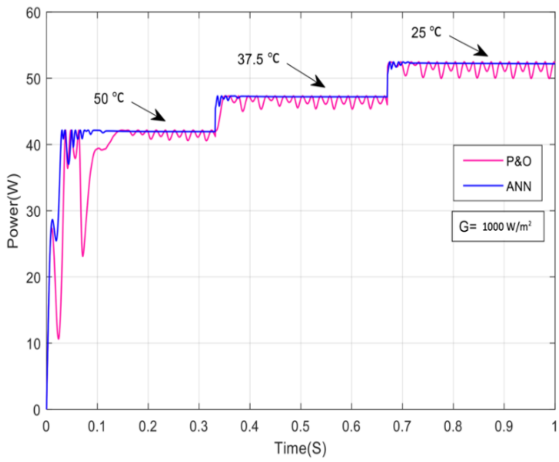

Figure 21. Variations in output power with ANN and P&O under varying temperatures

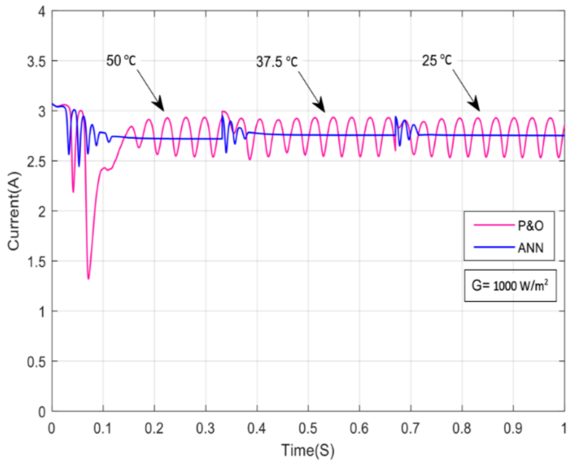

Figure 22. Variations in output current with ANN and P&O under varying temperatures

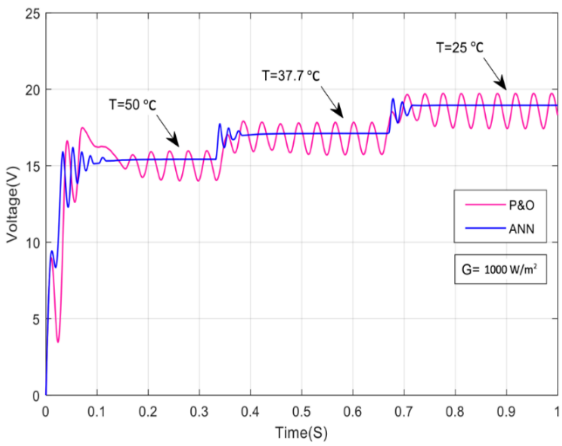

Figure 23. Variations in output voltage with ANN and P&O under varying temperature

Overall, the findings demonstrate that the ANN-driven MPPT strategy effectively adapts to changing environmental conditions. By comparing the P&O method with the neural-network-based controller exhibits faster transient behavior, enhanced tracking capability, and significantly reduced steady-state oscillations, highlighting its practical applicability in real photovoltaic systems.

5. CONCLUSION

This study presents an artificial neural network-based MPPT technique aimed at enhancing both the dynamic response and energy harvesting efficiency of photovoltaic systems. The PV module was represented through a single-diode model that reflects the electrical behavior of its equivalent circuit. To implement the ANN tracking, a DC–DC boost converter was combined with the PV model. The converter's operation was analytically detailed to define how the duty cycle, load variations, and input impedance seen by the PV array are interconnected. This system setup was then built and tested using MATLAB/Simulink simulations. Results from the simulations demonstrate that the ANN-based MPPT method outperforms the conventional perturb and observe (P&O) technique. It achieves quicker tracking of the maximum power point, offers better stability during operation, and minimizes power output fluctuations under changing conditions.

FUNDING INFORMATION

Authors state no funding involved.

AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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Mourad Tiar	✓		✓	✓	✓		✓			✓	✓		✓	✓
Abir Boucetta		✓		✓		✓			✓					
Ikram Boucetta	✓		✓		✓		✓			✓		✓		✓
Ahmed Ibrahim	✓	✓	✓		✓			✓		✓	✓			✓

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

The authors confirm that the data supporting the findings of this study are available within the article.

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