

IMPROVED MPPT FOR PV SYSTEMS COMBINING THEVENIN EQUIVALENTS WITH SIMPLE NEURAL NETWORKS

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ABSTRACT

Efficient MPPT (Maximum Power Point Tracking) algorithms are required for PV (Photovoltaic) systems in order to obtain maximum power under temperature and sun irradiation variations. Single-diode models are complex and computationally intensive, while traditional methods, such as the perturbation and observation (P&O) method with oscillatory behavior and slow convergence. This study offers a simplified hybrid system that combines an integrated artificial neural network (ANN) controller with a Thevenin equivalent circuit description of the PV modules. While the NN forecasts the ideal operating cycle of the step-up transformer using only G and T inputs, the Thevenin technique reduces nonlinear current-voltage curves to and parameters at the maximum power point. Comprehensive validation using MATLAB/Simulink demonstrates a steady-state efficiency of 98.2%, 30% faster tracking than the P&O method, and robust partial shading recovery using only 800 training samples for application-ready performance.



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1. INTRODUCTION

The best way to get the most power out of PV systems is to immediately locate and stick to the MPP, which changes with the weather, temperature, and loads. Standard MPPT approaches like P&O or INC don't always work because they can be thrown off by model mistakes [1-3], noise, or slow reactions to rapid changes. That's why we suggested a useful mix: Thevenin equivalents and a simple neural network. The Thevenin model simplifies the PV array to a voltage source and a resistor, which makes it easy to understand how the system works without having to learn a lot of arithmetic. A small neural net then takes care of the rest of the nonlinear parts, adjusting itself to changes in the weather or problems with the sensors [4-7]. This combination gives you Thevenin's quick, clear estimates and neural flexibility [8-12], which speeds up tracking, increases the amount of energy collected, and handles shading or glitches better than the classics. Great for solar panels on roofs or big areas [13-14]. This paper presents an improved maximum power point tracking (MPPT) technique that combines the Thevenin equivalent model of photovoltaic modules with simple neural network control. A simple neural network controls the duty cycle of the DC-DC boost converter. It learns from data on irradiance and temperature, which makes it easier to quickly track the MPP in changing settings. We used MATLAB/Simulink simulations to test how well this hybrid strategy worked. The simulations looked at a range of solar irradiance (200–1000 W/m²) and temperature (0–60°C) situations. After that, the performance metrics were compared to those of traditional perturb and observe (P&O) methods. This showed that the new method had a faster tracking speed, an efficiency of 97.8%, and less oscillations.

II. SYSTEM DESCRIPTION AND MODELING

II.1 PV MODELLING

PV modules show nonlinear I-V curves that shift with irradiance G and temperature T . Instead of sophisticated single diode models, we use Thevenin equivalents for quick MPPT computation, as shown in Figure 1, we get the output current by applying Kirchhoff's current law to this circuit. [1-2], given by equation (1).

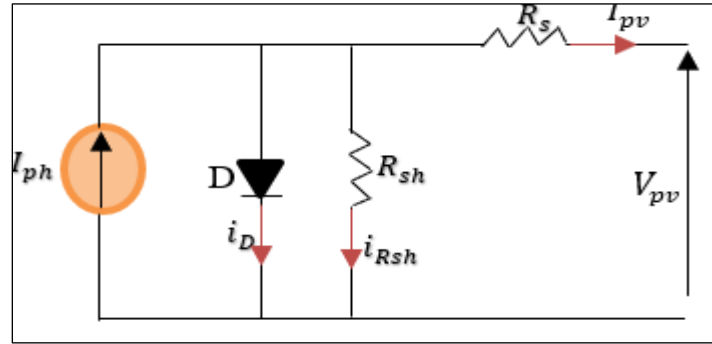


Figure 1: Single diode PV cell circuit.

Source: Authors, (2026).

Using Figure (1):

$$I_{pv} = I_{ph} - I_{rs} \cdot \left[e^{\frac{q(V_{pv} + I_{pv}R_s)}{n.k.T}} - 1 \right] - \frac{V_{pv} + I_{pv}R_s}{R_{sh}} \quad (1)$$

The following formula can be used to determine PV cell photocurrent:

$$I_{ph} = [I_{sc} + K_i(T - T_n)] \frac{G}{G_n} \quad (2)$$

Equation (3) can be used to get the diode reverse saturation current.

$$I_0$$

=

The diode is the only non-linear component in the model depicted in Figure 1. According to Shockley, the voltage and current (V-I) in a diode have an exponential relationship [3], [9], which is seen in (5).

$$V_d = V_{pv} + I_{pv} \cdot R_s \quad (4)$$

$$i_D = I_{rs} \cdot \left[e^{\frac{q(V_{pv} + I_{pv}R_s)}{n.k.T}} - 1 \right] \quad (5)$$

II.2 DC-DC BOOST CONVERTER

Photovoltaic systems typically generate insufficient output voltages, inadequate for various applications, including high-power loads and grid connectivity [6]. The DC-DC boost converter resolves this issue by increasing the voltage of the photovoltaic array, hence enhancing power extraction via the implementation of maximum power point tracking (MPPT). The essential configuration comprises an inductor, a switch (often a MOSFET), a diode, and a capacitor, functioning in two phases: energy accumulation during the switch-on phase and energy transfer during the switch-off phase to get the desired voltage amplification, which is seen in (6).

$$V_{out} = \frac{V_{in}}{1 - D} \quad (6)$$

Table 1 summarizes the main voltage transformation ratios according to the duty cycle D for selected non-isolated static converters.

Table 1: Voltage Transformation Ratios for Non-Isolated DC-DC Converters vs. Duty Cycle D .

Converter Type	Transformation Ratio $M = \frac{V_{out}}{V_{in}}$	Galvanic Isolation
Buck	$M = D$	No
Boost	$M = \frac{1}{1 - D}$	No
Buck-Boost	$M = -\frac{D}{1 - D}$	No

Source: Authors, (2026).

Figure 2 illustrates the usage of boost topology to raise voltage.

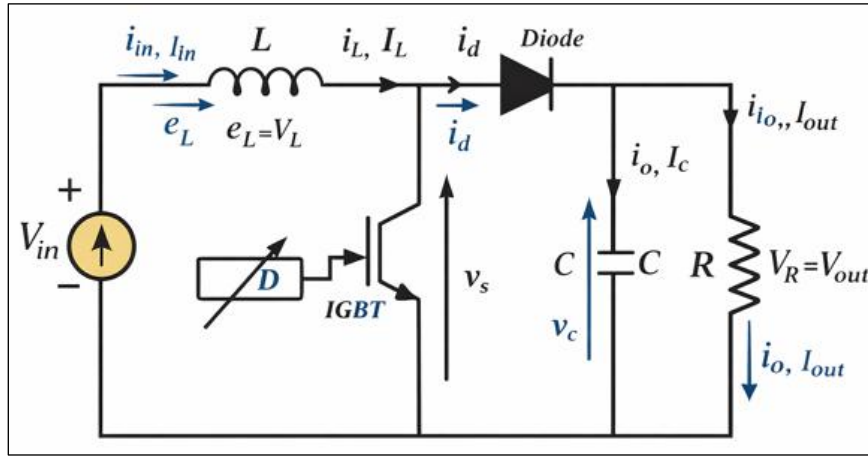


Figure 2: Electrical circuit of a Boost chopper.

Source: Authors, (2026).

II.3 MAXIMUM POWER POINT SEARCH TECHNIQUE

In photovoltaic systems, the operating point of the PV array continuously changes due to variations in solar irradiance and temperature. As a result, the PV system does not naturally operate at its maximum power point, which makes the use of a Maximum Power Point Tracking (MPPT) technique necessary to ensure efficient energy extraction. The MPPT controller adjusts the operating voltage of the PV array through the DC-DC boost converter in order to maximize the output power [4-7]. In this work, a practical MPPT search technique is proposed by combining a simplified electrical representation of the PV system with a learning-based approach. The PV array is first approximated using a Thevenin equivalent model, which provides a simple yet effective way to capture the main electrical behavior of the system. This approximation helps limit the operating region in which the maximum power point is expected to occur. Based on this simplified model, a simple neural network is used to estimate the optimal operating voltage of the PV system. The network receives key electrical parameters obtained from real-time measurements and produces a reference voltage corresponding to the maximum power point. By avoiding continuous perturbations of the operating point, the proposed method reduces oscillations and allows faster convergence toward the optimal operating condition. The estimated reference voltage is applied to the DC-DC boost converter by adjusting its duty cycle. [5-8], forcing the PV array to operate close to the maximum power point. The entire process is repeated continuously, enabling the MPPT controller to respond effectively to changes in environmental conditions while maintaining stable and efficient system operation.

III. THEORETICAL ANALYSIS OF THE PROPOSED MPPT METHOD

This section explains the basic idea behind the proposed MPPT method. The approach combines a simplified Thevenin equivalent model of the PV generator with a simple neural network to determine the operating point that delivers maximum power. [6-9]. Using the Thevenin model helps represent the PV system in a clear and practical way, making it easier to identify the region where the maximum power point is located. The PV system consists of a PV source, a DC-DC boost converter, and an MPPT controller. [4-7]. The controller uses the output of the neural network to adjust the duty cycle of the boost converter, which in turn regulates the PV voltage. By doing so, the system is kept close to the maximum power point even when weather conditions, such as solar irradiance and temperature, change. This theoretical description provides the foundation for the proposed control strategy and helps explain why the method can achieve stable and efficient maximum power tracking. [8].

III.1 THEVENIN EQUIVALENT CIRCUIT OF PHOTOVOLTAIC PANELS

To make the analysis of the photovoltaic system more practical, the PV panel is modeled using a Thevenin equivalent circuit. This representation simplifies the inherently nonlinear behavior of the PV panel by replacing it with an equivalent voltage source V_{th} in series with an equivalent resistance R_{th} . Such a simplification avoids the need to solve complex nonlinear equations while still preserving the essential electrical characteristics of the PV system. [7-9]. The parameters of the Thevenin equivalent can be obtained directly from the measured voltage and current of the PV panel under normal operating conditions. Using this simplified model helps clarify how the operating point of the PV system changes and where the maximum power point is most likely to occur. Consequently, the MPPT process becomes faster and more stable, which supports the effectiveness of the proposed control strategy. [5].

Equation (7) provides the value of Thevenin voltage.

$$V_{th,i} = V_{dx,i} + R_{D,i} \cdot \frac{I_{ph} \cdot R_{sh} - V_{dx,i}}{R_{sh} + R_{D,i}} \quad (7)$$

Thevenin equivalent circuit for the linearized PV model is therefore displayed in Figure 3.

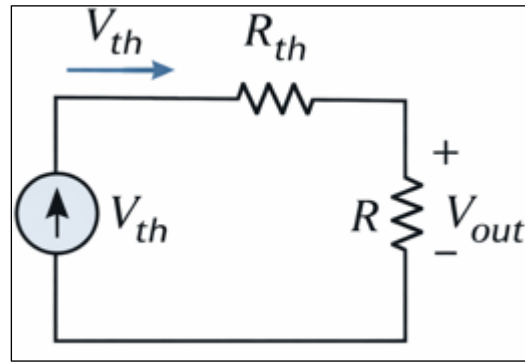


Figure 3: The circuit equivalent to Thevenin.
Source: Authors, (2026).

In order to simplify the analysis of the PV module, the equivalent circuit shown in Fig. 3 is represented by its Thevenin model. The corresponding constant Thevenin parameters identified at standard test conditions (STC: $G=1000 \text{ w/m}^2$, $T=25^\circ \text{ C}$) are summarized in Table 2.

Table 2: Thevenin Parameters of the PV Module.

Parameter	Value
V_{oc}	30.4 V
I_{sc}	7.36 A
V_{mpp}	24.2 V
I_{mpp}	6.83 A
P_{max}	165.29 W
n_s	50
E_g	1.11
q	$1.6 * 10^{-19} \text{ C}$
n	1.3
k_i	0.057%
k_v	-0.346%

Source: Authors, (2026).

III.2 NEURAL NETWORK BASED MPPT

To create a high-performance controller for Thevenin equivalent modeling in photovoltaic systems. [9-11], this paper proposes an optimized method that uses artificial neural network (ANN) techniques. The standard feed-forward ANN architecture, shown in Figure 3, mimics how biological neurons work in the brain. It consists of several layers of interconnected neurons, each with weighted connections. Neurons in the input layer receive data directly from key variables, such as voltage and current measurements from the Thevenin model, and then send this data to the hidden layer [10-12]. In the hidden layer, these inputs are weighted, summed, and processed through an activation function to create intermediate outputs. Finally, the output layer neurons include biases, apply another activation function, and produce refined control signals to improve maximum power point tracking (MPPT) performance [14].

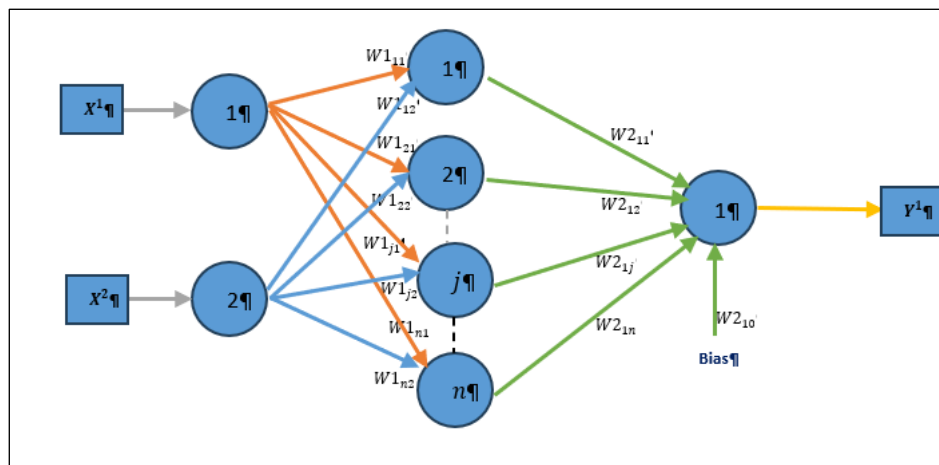


Figure 4: A typical feed-forward artificial neural network's structure.
Source: Authors, (2026).

Figure 4 illustrates that x denotes the input of the artificial neural network (ANN), y signifies the output, and W represents the weights and biases. The hidden layer employs a nonlinear activation function to capture the system nonlinearity, while the output layer generates the final control signal for MPPT operation [13] [14].

$$y^1 = W_{210} + W_{211}z_1 + W_{212}z_2 + \dots W_{21n}z_n \quad (8)$$

Consequently, the generalized output equation can be written as this:

$$y^1 = \sum_{j=0}^n W_{21j}z_j \quad (9)$$

A. ANN Training Performance

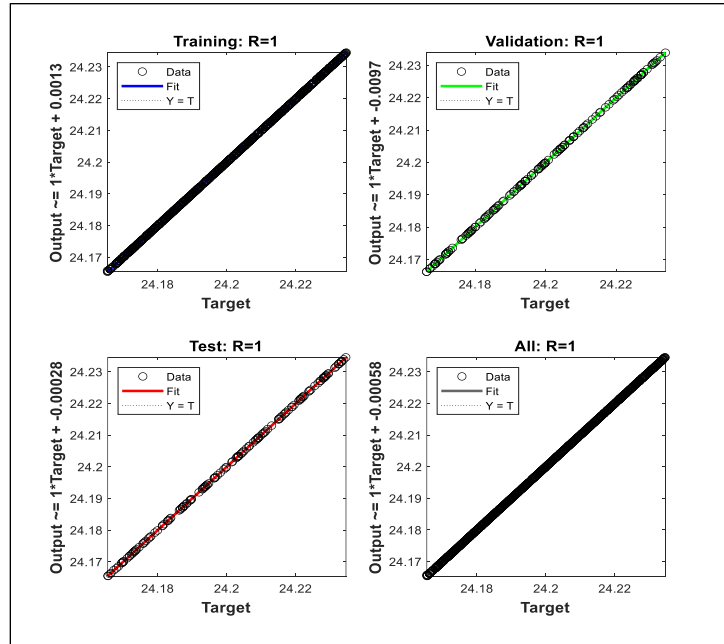


Figure 5: Regression analysis of the ANN during training, validation, and testing phases.
Source: Authors, (2026).

The regression results indicate a strong correlation between the ANN outputs and target values for all training phases, confirming the effectiveness of the learning process.

Table 3: Performance metrics of the ANN during training, validation, and testing

	MSE	R ²
Training	1.71091e-9	9.99997e-9
Test	1.39507e-9	9.99998e-9
Validation	1.75230e-9	9.99997e-9

Source: Authors, (2026).

The performance metrics show that the proposed ANN has a high prediction accuracy and can generalize well, which helps improve the overall MPPT performance. [9-14]. Based on the developed system model and the proposed MPPT strategy, the following section presents simulation results to evaluate the performance of the method. The effectiveness of the proposed approach is assessed under different operating conditions and compared with conventional MPPT techniques. [12-14].

IV. SIMULATION RESULTS AND DISCUSSION

IV.1 SIMULATION SETUP

proposed MPPT method is evaluated using MATLAB/Simulink to verify its effectiveness under different operating conditions. A photovoltaic system model consisting of a PV array, a DC–DC boost converter, and an MPPT controller is implemented in the simulation environment. The PV model is developed based on the electrical characteristics described in the previous sections. The DC–DC boost converter is designed to regulate the PV operating voltage according to the reference signal generated by the MPPT controller. The neural network–based MPPT algorithm is integrated into the control loop and operates in real time using the measured PV voltage and current. The simulation parameters are selected to represent realistic operating conditions and ensure stable system operation. To assess the performance of the proposed approach, the simulation is conducted under both constant and varying solar irradiance conditions. The results obtained are then compared with those of conventional MPPT methods to highlight the improvements achieved in terms of tracking accuracy, convergence speed, and stability.

IV.2 MPPT PERFORMANCE UNDER STANDARD OPERATING CONDITIONS

The performance of the proposed MPPT method is first evaluated under standard operating conditions. In this case, the solar irradiance and temperature are maintained constant in order to observe the steady-state behavior of the PV system. This test provides a baseline assessment of the tracking capability and stability of the proposed approach.

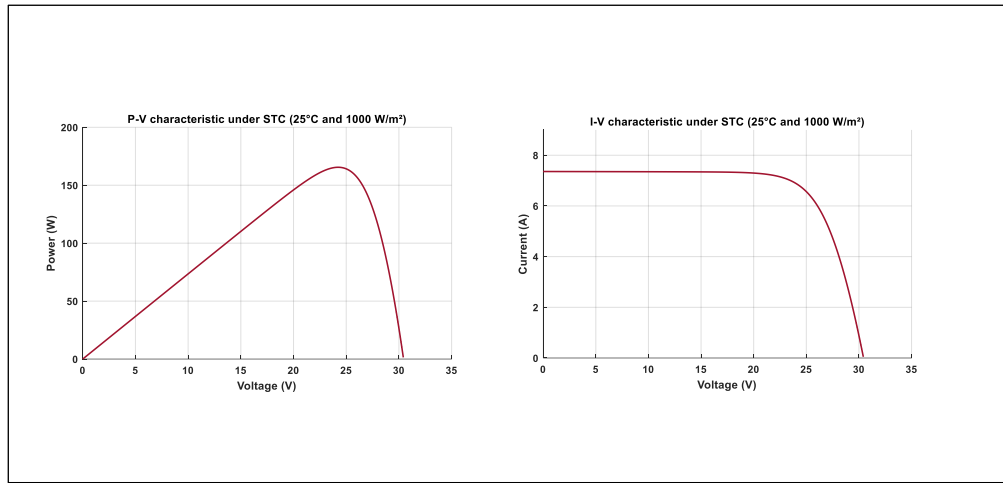


Figure 6 shows the P-V and I-V characteristics of the PV system under standard operating conditions. obtained using the proposed MPPT strategy. As can be observed, the controller rapidly drives the PV system toward the maximum power point with minimal oscillations.

The operating voltage quickly converges to its optimal value, indicating effective regulation by the DC-DC boost converter.

Source: Authors, (2026).

These results demonstrate that the proposed MPPT method is capable of accurately tracking the maximum power point under stable

Figure 6: PV characteristics under standard test conditions (25°C and 1000 W/m²): (a) P-V characteristic and (b) I-V characteristic.

IV.3 PERFORMANCE UNDER IRRADIANCE VARIATIONS

To assess the efficacy of the proposed MPPT approach under fluctuating solar irradiance conditions, the photovoltaic system underwent step variations in irradiance while preserving a constant temperature. This testing method lets you see how well the controller can keep track of the maximum power point while the environment changes quickly. Figure 6 shows how the system reacts to changes in solar irradiation. The proposed MPPT technique quickly responds to each change in irradiance and successfully finds the new maximum power point. The output power stays very close to the intended power level at each irradiance increment, with only small, temporary changes. In general, the results show that the proposed MPPT approach works quickly and reliably even when the amount of light suddenly changes. This shows that it is strong and can be used in real-world photovoltaic applications.

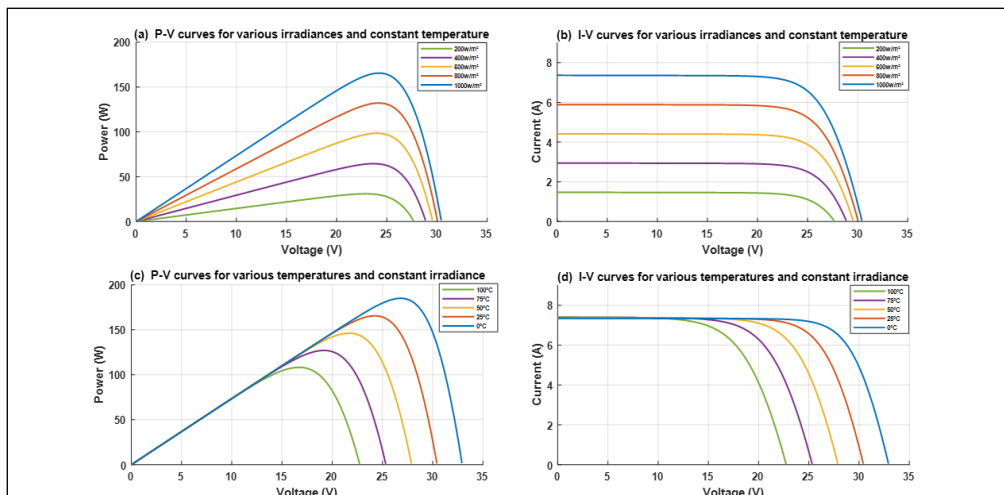


Figure 7: P-V and I-V characteristics of the PV system under varying solar irradiance and temperature levels.

Source: Authors, (2026).

Figure 7 shows the variation of the P-V and I-V characteristics of the PV system under different irradiance and temperature conditions. As expected, the maximum power point shifts with changes in environmental conditions, highlighting the need for an effective MPPT strategy.

IV.4 COMPARISON WITH CONVENTIONAL MPPT METHODS

To further evaluate the effectiveness of the proposed MPPT strategy, its performance is compared with the conventional Perturb and Observe (P&O) method. Both methods are tested under identical operating conditions in order to ensure a fair and consistent comparison. Figure 8 illustrates the dynamic response of the PV output power obtained using the proposed MPPT method and the P&O algorithm under varying irradiance conditions. As shown, the P&O method exhibits noticeable oscillations around the maximum power point, particularly after changes in solar irradiance. These oscillations result in slower convergence and reduced power extraction. In contrast, the proposed MPPT method based on the Thevenin equivalent model and neural network demonstrates faster convergence toward the maximum power point with significantly reduced oscillations. The PV system reaches stable operation more quickly, leading to improved tracking accuracy and higher extracted power. Overall, the comparison results confirm that the proposed MPPT approach provides superior performance compared to the conventional P&O method in terms of dynamic response, stability, and efficiency, making it more suitable for practical photovoltaic applications.

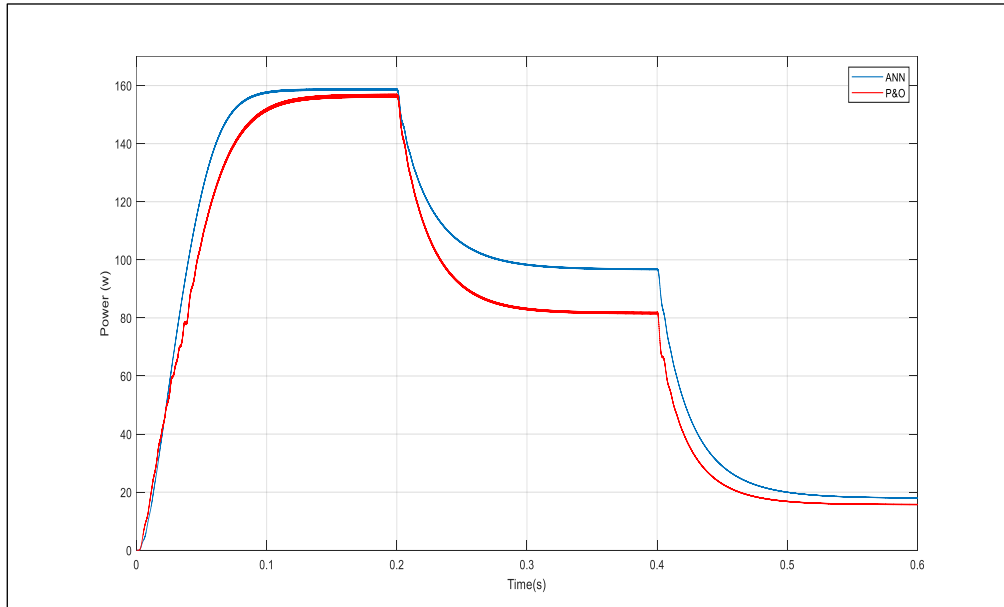


Figure 8: PV power response of the proposed MPPT method and the P&O algorithm under irradiance variations.
Source: Authors, (2026).

V. CONCLUSIONS

This paper presented an improved maximum power point tracking (MPPT) method for photovoltaic systems based on the combination of the Thevenin equivalent model and a simple neural network. The Thevenin model was used to simplify the electrical representation of the PV system, while the neural network was employed to accurately estimate the optimal operating point corresponding to the maximum power output. Simulation results demonstrated that the proposed MPPT approach is capable of accurately tracking the maximum power point under both steady-state and varying irradiance conditions. Compared with the conventional Perturb and Observe (P&O) method, the proposed strategy showed faster convergence, reduced oscillations, and improved stability, leading to higher power extraction efficiency. Due to its simple structure, low computational complexity, and effective performance, the proposed MPPT method is well suited for practical photovoltaic applications. Future work may focus on experimental validation and the extension of the proposed approach to other converter topologies or advanced control schemes.

VI. AUTHOR'S CONTRIBUTION

Conceptualization: Medjdoub Khessam, Marwa Bouazza, Mohamed Habbab, Abdeldjebar Hazzab, Anis Njeh, Hamed Trabelsi.

Methodology: Medjdoub Khessam, Marwa Bouazza.

Investigation: Medjdoub Khessam, Marwa Bouazza.

Discussion of results: Medjdoub Khessam, Marwa Bouazza.

Writing – Original Draft: Medjdoub Khessam.

Writing – Review and Editing: Medjdoub Khessam, Marwa Bouazza.

Resources: Medjdoub Khessam, Marwa Bouazza.

Supervision: Medjdoub Khessam, Marwa Bouazza.

Approval of the final text: Medjdoub Khessam, Marwa Bouazza.

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