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ANN-based MPPT for photovoltaic systems: performance analysis and comparison with nonlinear and classical control techniques

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ABSTRACT

In photovoltaic energy systems, maximum power point tracking (MPPT) techniques are essential for optimizing power output under changing climatic conditions. Several techniques have been proposed in the literature, including classical techniques such as perturb and observe (P&O) and incremental conductance (INC), nonlinear controllers such as backstepping, and artificial intelligence-based techniques like fuzzy logic. This study compares the performance of an artificial neural network (ANN)-based MPPT approach with these nonlinear and classical MPPT techniques. It analyses the advantages and limitations of the various techniques to evaluate their performance in terms of efficiency, accuracy, and output power stability under changing climatic conditions. The study aims to help researchers select the most effective technique to improve the efficiency of photovoltaic systems. The simulation was carried out using MATLAB/Simulink. The simulation results indicated that the artificial neural network achieved better performance than the other techniques in terms of tracking speed, with an efficiency of up to 99.94%, while maintaining stable output power under changing climatic conditions. The backstepping controller also showed stable output power compared to traditional techniques. Fuzzy logic had a lower efficiency than both the artificial neural network and backstepping. Perturbation and observe and incremental conductance are easy to implement, but they showed oscillations around the maximum power point, which reduces the overall efficiency of the system.

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1. INTRODUCTION

Global solar energy production capacity is growing significantly, reaching a cumulative total of more than 1,000 gigawatts (GW) by 2024. This growth reflects the acceleration of the global energy transition to more sustainable and less polluting energy sources. solar energy offers significant advantages, such as reducing greenhouse gas emissions to combat climate change. Additionally, it promotes energy independence by decreasing reliance on fossil fuels and provides lower operating costs after installation [1]. Its flexibility allows it to be adapted from large power stations to domestic systems, and it can be used to power remote and isolated areas that often have no access to electricity grids, making this energy accessible in a wide range of areas [2], [3].

Solar energy or photovoltaic (PV) energy is generated from sunlight by PV cells connected in series and/or parallel to make up a photovoltaic generator. Each PV generator is characterized by its MPP, which depends on climatic conditions such as solar irradiance and temperature. Connecting this generator directly to a load can result in an operating point that is far from the MPP, making it necessary to use maximum power point tracking (MPPT) techniques to adjust this point and extract maximum power [4].

Researchers have developed several MPPT techniques. [5] proposed the perturbation and observation (P&O) technique, and [6] proposed a modified P&O to reduce oscillation and increase efficiency. [7] discussed the hill climbing (HC) technique. [8] presented the incremental conductance (INC) technique. These traditional techniques are widely used due to their simplicity, low cost, and reliability under stable conditions. However, they suffer from ineffectiveness in rapidly changing climatic conditions, slower convergence to the maximum power point, and potential oscillations around the peak, which can reduce the overall system efficiency. To address these problems, intelligent and nonlinear MPPT methods have been introduced, such as fuzzy logic (FL), which is presented in [9]. The work in [10] proposed an artificial neural network (ANN). Integrating ANN into photovoltaic systems offers a promising solution, potentially increasing efficiency by 2–3%. Partial swarm optimization (PSO) is studied in [11]. In nonlinear controllers [12] proposed a sliding mode controller (SMC) and [13] proposed a backstepping controller. Hybrid techniques aim to improve tracking accuracy, speed, and adaptability by taking advantage of both traditional and advanced techniques. The work [14] presents an optimal fuzzy logic controller-based PSO for a photovoltaic system. [15] proposed an MPPT technique based on artificial neural networks combined with backstepping. In [16], the authors propose a combination of incremental conduction and fuzzy logic.

This paper compares an MPPT technique based on artificial neural networks with several other techniques, both nonlinear and conventional, including fuzzy logic, backstepping, perturbation and observation, and incremental conductance. This comparison aims to evaluate the performance of each technique in terms of speed, efficiency, and stability under constant or variable climatic conditions. This detailed analysis provides a deeper understanding of the strengths and limitations of each technique, giving researchers the information necessary to select the most suitable technique for their photovoltaic system application. This choice should be based on important metrics such as performance, cost, and complexity. The paper is structured as follows: i) Section 2 details the photovoltaic system; ii) Section 3 presents the technique for tracking maximum power points; iii) Section 4 presents the results and discussion; and iv) The paper concludes with a conclusion.

2. PHOTOVOLTAIC SYSTEM

The purpose of the PV system shown in Figure 1 is to maximize the power extracted from the PV array. The control mechanism of the system includes pulse width modulation (PWM), which takes the duty cycle (D) generated by the MPPT technique as input to produce a control signal u that regulates the DC-DC converter switch S (typically a MOSFET or IGBT) [17]. The MPPT technique dynamically adjusts D to maintain the PV array at its MPP, adapting to variations in solar irradiance and temperature [15]. The DC-DC converter modulates voltage V_{pv} and current I_{pv} of the array to match the load requirements, ensuring that the PV array remains at its MPP.

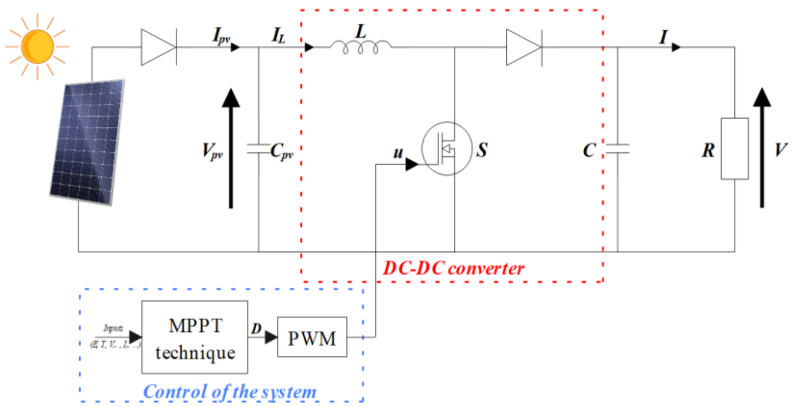

Figure 1. Photovoltaic system

The mathematical model of the system is described by (1)-(3).

$$\begin{cases} C_{pv}\dfrac{dV_{pv}}{dt} = i_{pv} - i_L & (1) \\ L\dfrac{di_L}{dt} = V_{pv} - (1-D)V & (2) \\ C\dfrac{dV}{dt} = (1-D)i_L - i & (3) \end{cases}$$

The output voltage of the DC-DC converter can be expressed as (4):

$$V = \frac{1}{1-D} V_{pv} \tag{4}$$

where D is bounded within the interval [0,1].

3. MAXIMUM POWER POINT TRACKING TECHNIQUE

3.1. ANN-based MPPT technique

An artificial neural network is a type of computational model inspired by the structure and function of biological neurons. It consists of interconnected nodes, called artificial neurons, which are responsible for processing and transmitting information. Integrating ANN into photovoltaic systems has the potential to improve energy efficiency and optimize power output. By analyzing data from various climatic factors, these networks can predict energy production and improve the overall management of PV systems [18], [19]. There are different types of artificial neural network architectures. Figure 2 illustrates the feedforward neural network architecture, which is characterized by its simplicity. In this type of network, data flows directly from the input layer to the output layer without cycles or loops [20]. The interconnected neurons are arranged into layers, with each layer fully connected to the subsequent one. It takes solar irradiance and temperature as inputs and voltage at MPP (V_{mpp}) as output. The error between the V_{mpp} and the actual photovoltaic voltage (V_{pv}) is then calculated. The resulting error signal is fed into a proportional-integral (PI) controller. The PI controller processes the error and generates D used to control the boost converter. By continuously adjusting the duty cycle, the controller ensures that the photovoltaic system operates at its maximum power point, thereby optimizing the efficiency of the energy conversion.

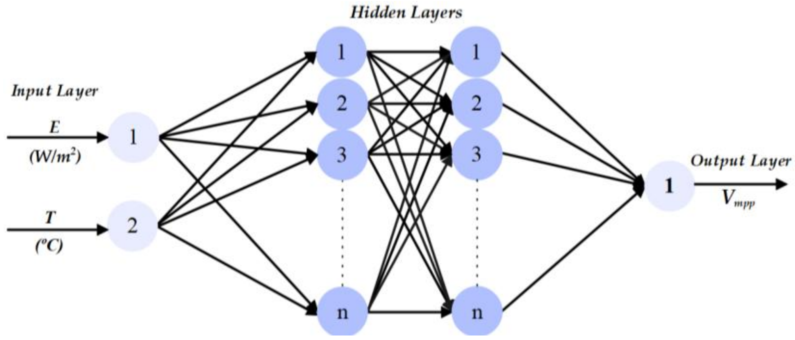

Figure 2. Architecture of the ANN-based MPPT technique for photovoltaic systems

3.2. Fuzzy logic controller

Fuzzy logic is a mathematical framework designed to model the uncertainty and imprecision inherent in human reasoning, allowing for variable degrees of truth between 0 and 1, rather than binary values of 0 or 1 (true or false) [21], [22]. This controller is commonly employed in systems with complex or poorly modeled dynamics, such as PV systems, where it optimizes power output by adjusting parameters to changing climatic conditions [14], [23]. Figure 3 shows the general structure of the *FL* controller.

- Fuzzification: This block receives the error $e = \frac{P_k - P_{k-1}}{V_k - V_{k-1}}$ and the error rate Δe as inputs and converts the crisp input values into fuzzy sets. Membership functions are used to assign degrees of membership to the inputs in predefined fuzzy sets, such as positive big (PB), positive small (PS), zero (Z), negative big (NB), and negative small (NS).

- Inference mechanism: This is the brain of the FL controller. It applies rules from the rule base, as shown in Table 1, to the fuzzy inputs. The rules are in the form of "if-then" statements; for example, if the error is *PS* and the error rate is *PB*, then the output is *NB*.
- Defuzzification: Once the inference mechanism has determined the output fuzzy set based on the rules, this block converts the fuzzy output back into a crisp value, which is the duty cycle rate ΔD.

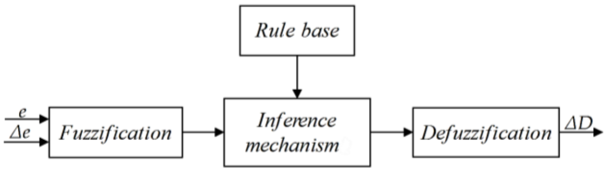

Figure 3. Structure of the FL controller

Table 1. Fuzzy logic rules

Rules		E(K)				
		PS	PB	Z	NB	NS
ΔE	PS	NS	NB	Z	PB	Z
	PB	NB	Z	NS	PB	Z
	Z	NS	NB	Z	PS	PS
	NB	Z	NB	PS	Z	PB
	NS	Z	NB	Z	PB	PS

3.3. Backstepping controller

The backstepping controller, a Lyapunov-based nonlinear control technique, is adopted for photovoltaic systems due to its recursive design methodology that ensures global stability [24]. In the MPPT technique, it adjusts the control input to ensure that the system operates at its MPP while maintaining stability under varying climatic conditions [25], [26]. The design process of the technique is divided into two main steps:

a) Step 1

The first error ε_1 is defined by: $\varepsilon_1 = y - y_{ref}$, where $y = \frac{\partial P}{\partial V}$ and $y_{ref} = 0$ ($\frac{\partial P}{\partial V} = 0$ at *MPP*).

$$\dot{\varepsilon_1} = \frac{\partial}{\partial t}\left(\frac{\partial P}{\partial V}\right) = \frac{\partial V}{\partial t}\frac{\partial}{\partial V}\left(\frac{\partial P}{\partial V}\right) = \frac{\partial V_{pv}}{\partial t}\frac{\partial}{\partial V_{pv}}\left(i_{pv} + V_{pv}\frac{\partial i_{pv}}{\partial V_{pv}}\right) \tag{5}$$

Using (1), (5) becomes (6).

$$\dot{\varepsilon_1} = \frac{1}{C_{pv}}\left(i_{pv} - i_L\right)\left(2\frac{\partial i_{pv}}{\partial V_{pv}} + V_{pv}\frac{\partial^2 i_{pv}}{\partial V_{pv}^2}\right) \tag{6}$$

The Lyapunov function $V_1 = \frac{1}{2}\varepsilon_1^2$ is a mathematical tool for analyzing the stability of dynamic systems, ensuring asymptotic stability by maintaining positive energy and a negative time derivative. The (7) expresses its derivative.

$$\dot{V_1} = \varepsilon_1\dot{\varepsilon_1} = \varepsilon_1\frac{1}{C_{pv}}\left(i_{pv} - i_L\right)\left(2\frac{\partial i_{pv}}{\partial V_{pv}} + V_{pv}\frac{\partial^2 i_{pv}}{\partial V_{pv}^2}\right) \tag{7}$$

The second error is $\varepsilon_2 = i_L - \alpha_1$, where α_1 is a virtual control input that is expressed in (8).

$$\alpha_1 = \frac{C_{pv}K_1\varepsilon_1}{2\frac{\partial i_{pv}}{\partial V_{pv}} + V_{pv}\frac{\partial^2 i_{pv}}{\partial V_{pv}^2}} + i_{pv} \tag{8}$$

The (7) becomes (9) using (8).

$$\dot{V_1} = -K_1\,\varepsilon_1^2 - \frac{1}{C_{pv}}\left(2\frac{\partial i_{pv}}{\partial V_{pv}} + V_{pv}\frac{\partial^2 i_{pv}}{\partial V_{pv}^2}\right)\varepsilon_1\varepsilon_2 \tag{9}$$

Where K_1 is a positive constant. To eliminate the term $\frac{1}{C_{pv}}\left(2\frac{\partial i_{pv}}{\partial V_{pv}} + V_{pv}\frac{\partial^2 i_{pv}}{\partial V_{pv}^2}\right)\varepsilon_1\varepsilon_2$ in (9), we proceed to step 2.

b) Step 2

Based on (2), the second error is expressed in (10).

$$\dot{\varepsilon_2} = \frac{1}{L}\left[V_{pv} - (1-D)V_c\right] - \dot{\alpha}_1 \tag{10}$$

Consider the second Lyapunov function $V_2 = V_1 + \frac{1}{2}\,\varepsilon_2^2$, its derivative is given in (11).

$$\dot{V}_2 = \dot{V}_1 + \varepsilon_2 \dot{\varepsilon}_2 \tag{11}$$

The (11) becomes (12) using (10) and (9).

$$\dot{V}_2 = -K_1\, \varepsilon_1^2 + \left[-\frac{1}{C_{pv}} \left(2\frac{\partial i_{pv}}{\partial V_{pv}} + V_{pv}\frac{\partial^2 i_{pv}}{\partial V_{pv}^2} \right) \varepsilon_1 + \frac{1}{L}(V_{pv} - V_c) + \frac{1}{L} D V_c - \dot{\alpha}_1 \right] \varepsilon_2 \tag{12}$$

The duty cycle for controlling the boost converter is given in (13).

$$D = \frac{L}{V_S}\left(\frac{1}{C_{pv}} \left(2\frac{\partial i_{pv}}{\partial V_{pv}} + V_{pv}\frac{\partial^2 i_{pv}}{\partial V_{pv}^2} \right) \varepsilon_1 - \frac{1}{L}(V_{pv} - V_c) + \dot{\alpha}_1 - K_2 \varepsilon_2 \right) \tag{13}$$

Therefore $\dot{V}_2 = -K_1\, \varepsilon_1^2 - K_2\, \varepsilon_2^2 < 0$, where K_2 is a positive constant; consequently, our system is globally asymptotically stable.

3.4. Perturbation and observation

The perturbation and observation technique is based on continuously adjusting the operating point of the PV array and observing the resulting changes in output power. The technique adjusts D based on the sign of dP and dV [27]. If $\frac{\mathrm{dP}}{\mathrm{dV}} = 0$ it means that the system is at the MPP. If dP and dV have the same sign, the duty cycle is reduced by subtracting the fixed step size ΔD otherwise, the duty cycle is increased to move towards the MPP [4], [28]. Figure 4 shows the flowchart of the P&O technique.

3.5. Incremental conductance

The incremental conductance technique is considered one of the most effective MPPT techniques due to its balance of cost-effectiveness and ease of implementation. It is based on analyzing the slope of the current-voltage curve $\frac{\mathrm{dI}}{\mathrm{dV}}$. If $\frac{\mathrm{dI}}{\mathrm{dV}} = 0$, the system is at the MPP, and the duty cycle remains constant until climatic conditions change. If $\frac{\mathrm{dI}}{\mathrm{dV}} < 0$ the operating point is to the right of the MPP; thus, the duty cycle must be increased [29]. Conversely, if $\frac{\mathrm{dI}}{\mathrm{dV}} > 0$, the duty point is to the left of the MPP, and the duty cycle must be reduced. Figure 5 shows the flowchart of the technique.

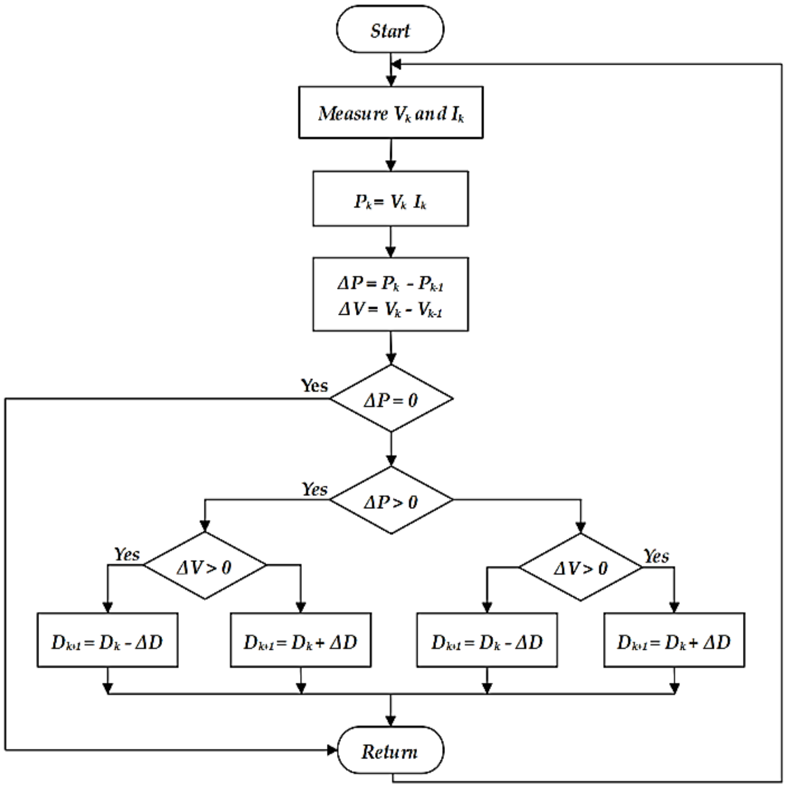

Figure 4. Flowchart of the P&O technique

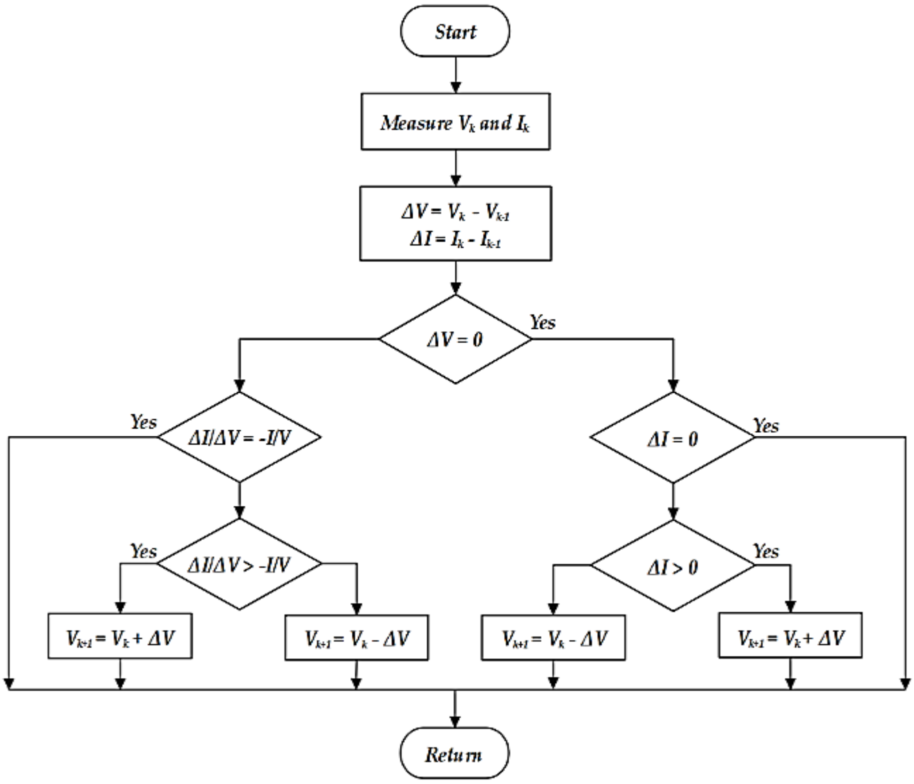

Figure 5. Flowchart of the INC technique

4. RESULTS AND DISCUSSION

The techniques proposed in this paper are tested under both standard and variable climatic conditions to assess their performance and adaptability. The simulation was carried out using MATLAB/Simulink. Figure 6 illustrates the simulated photovoltaic system, which includes a PV generator consisting of three parallel strings, each containing four modules connected in series of the AREi-230W-M6-G module. The detailed parameters of this module are presented in Table 2. The parameters of the boost converter used in the system are C_1 = 4 mF, L = 0.1 mH, C_2 = 10 mF, and R = 20 Ω.

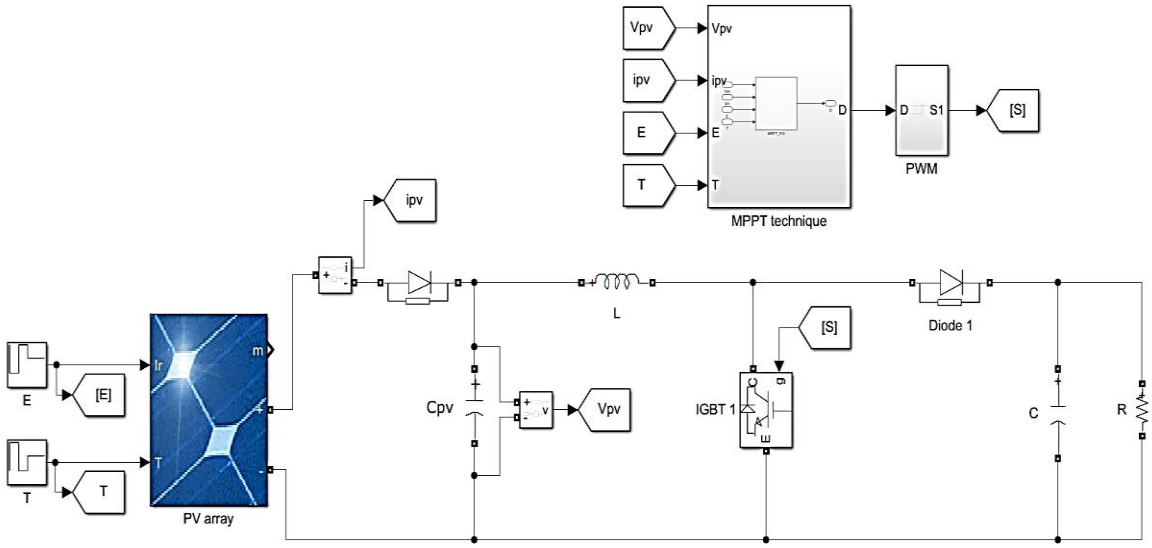

Figure 6. Studied PV system modeled in MATLAB/Simulink

Table 2. AREi-230W-M6-G model parameters

Parameter	Value
Voltage V_{mpp}	30.72 V
Current I_{mpp}	7.5 A
Maximum power P_{max}	230.4 W
Current of short circuit I_{sc}	8 A
Voltage of open circuit V_{oc}	37.14 V
Open circuit temperature coefficient V_{oc}	-0.3533 V/°C
Short circuit temperature coefficient I_{sc}	0.0553 A/°C
Number of cells	60

4.1. Results under standard climatic conditions

The parameters of the ANN-based MPPT technique were trained and optimized using the mean squared error (MSE) metric, which calculates the mean squared difference between predicted and actual values. To achieve this, the dataset was divided into three subsets. The training set, comprising 70% of the data, was used to adjust the weights and biases of the ANN during the training phase. A validation set, consisting of 15% of the data, was used to monitor the model's performance and prevent overfitting. Finally, the test set, also consisting of 15% of the data, was used to evaluate the model's final performance. The results are presented in Figure 7. Figures 8 and 9, respectively, illustrate the PV power and voltage obtained by the MPPT techniques tested under standard climatic conditions, corresponding to solar irradiation of E = 1000 W/m² and a temperature of T = 25 °C.

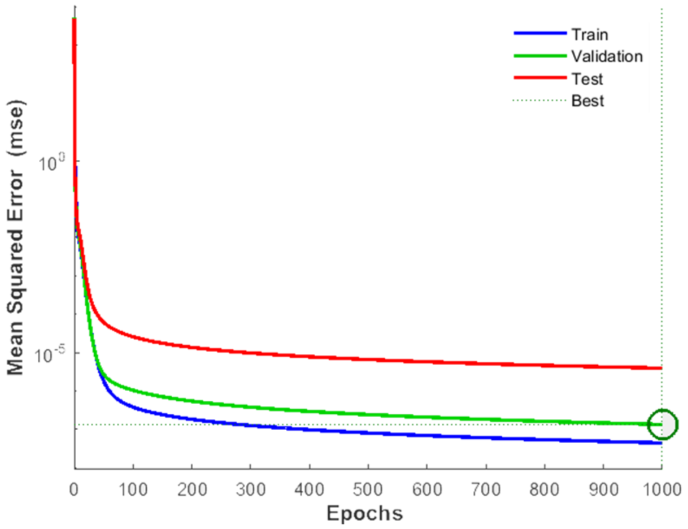

Figure 7. Training performance of the ANN model: mean squared error versus training epochs

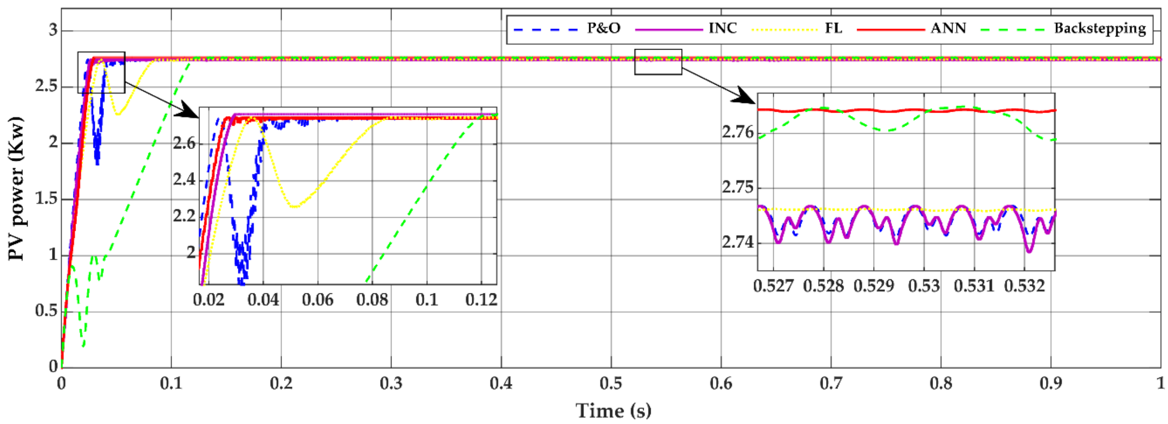

Figure 8. PV power under standard climatic conditions

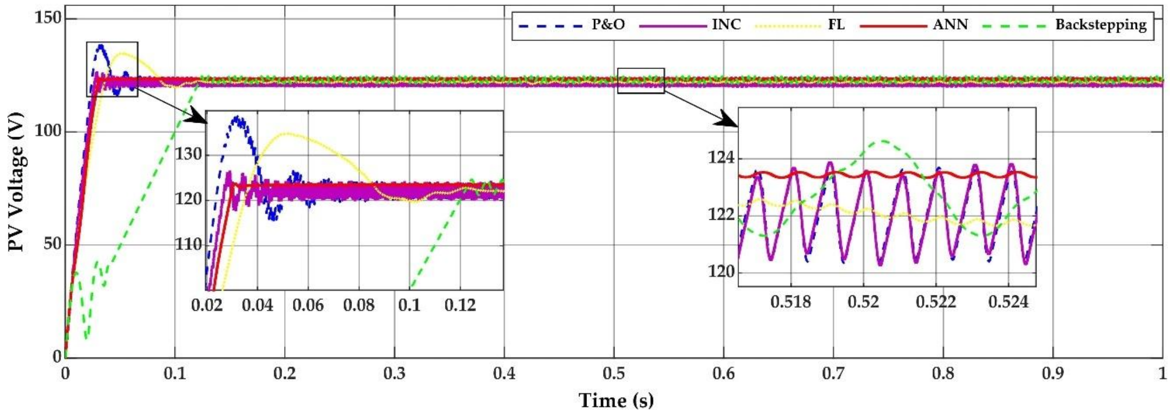

Figure 9. PV voltage under standard climatic conditions

The results show that all MPPT techniques converge to the MPP, each with unique performance characteristics. ANN demonstrates the fastest performance, high accuracy, stable PV power, and an efficiency of 99.97%. FL reaches the MPP quickly but overshoots slightly and stabilizes at 0.08 seconds with an efficiency of 99.32%. Backstepping achieves stable PV power with fewer oscillations than P&O, INC, and FL and has a high efficiency of 99.88%. P&O exhibits the slowest performance, primarily due to initial oscillations, and achieves an efficiency of 99.21%. INC stabilizes faster with fewer oscillations but achieves the same efficiency as P&O.

4.2. Results under variable climatic conditions

The evaluation of MPPT techniques under constant irradiance and temperature is insufficient to reflect their real-world performance. To address this, the techniques are tested under three scenarios with varying climatic conditions, as shown in Figure 10, to assess their ability to track the MPP under rapid environmental changes. The resulting PV power and voltage are presented in Figures 11 and 12, respectively.

The performance of ANN-based MPPT is evaluated under three different scenarios of climatic conditions and compared with other MPPT techniques (P&O, INC, FL and Backstepping) based on their rabidity, stability, and tracking efficiency:

- In scenario 1 [0, 0.5s], the solar irradiance is set to 600 w/m² and the temperature is 30 °C, representing a low solar irradiance condition with relatively lower available maximum power. Under these conditions, the ANN-based MPPT and backstepping controller show excellent adaptability by quickly converging to the MPP. In contrast, P&O and INC take longer to stabilize and show significant oscillations around the MPP due to their iterative perturbation approach. FL achieves acceptable performance but converges slower than ANN and backstepping. ANN's ability to learn and predict the MPP ensures higher tracking efficiency and minimal power dissipation, making it particularly effective in low irradiance conditions.
- In scenario 2 [0.5, 1s], the solar irradiance increases to 1000 W/m² and the temperature decreases to 20°C, resulting in a higher available MPP. This scenario represents a sudden change in climatic conditions. The ANN-based MPPT shows excellent performance, achieving convergence to the MPP while maintaining excellent stability. Backstepping also performs well, with a tracking speed comparable to ANN, but requires precise adjustment of the control parameters for optimal results. In contrast, P&O and INC show significant delays in adapting to the new MPP, along with overshoots and oscillations that reduce the overall efficiency. FL performs better than P&O and INC, providing more stable tracking, but remains slower than ANN due to its rule-based approach. ANN's fast and accurate response to these climatic changes demonstrates its effectiveness and adaptability in tracking the MPP under rapidly changing solar irradiance and temperature.
- In scenario 3 [1, 1.5s], the solar irradiance decreases to 800 W/m² while the temperature increases to 25°C, resulting in a reduced MPP. The ANN-based MPPT adapts smoothly and efficiently to the new MPP, maintaining stable operation and minimizing power loss during the change in climatic conditions. Backstepping also effectively tracks the new MPP, but its performance is less efficient in this scenario. On the other hand, P&O and INC are slower to adapt to the new MPP and show significant oscillations around the MPP, reducing their overall efficiency. FL, although more adaptive than P&O and INC, responds more slowly than ANN, resulting in a low efficiency in tracking the MPP.

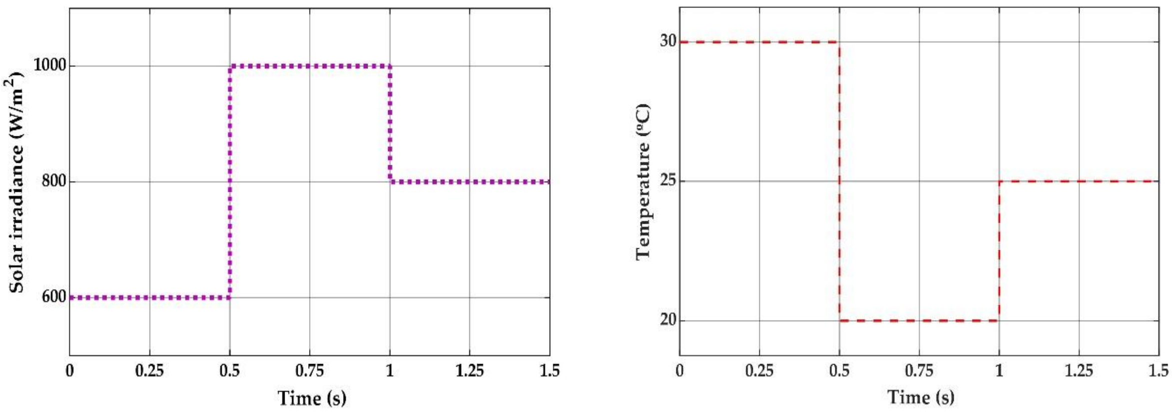

Figure 10. Test scenarios for varying irradiance and temperature conditions

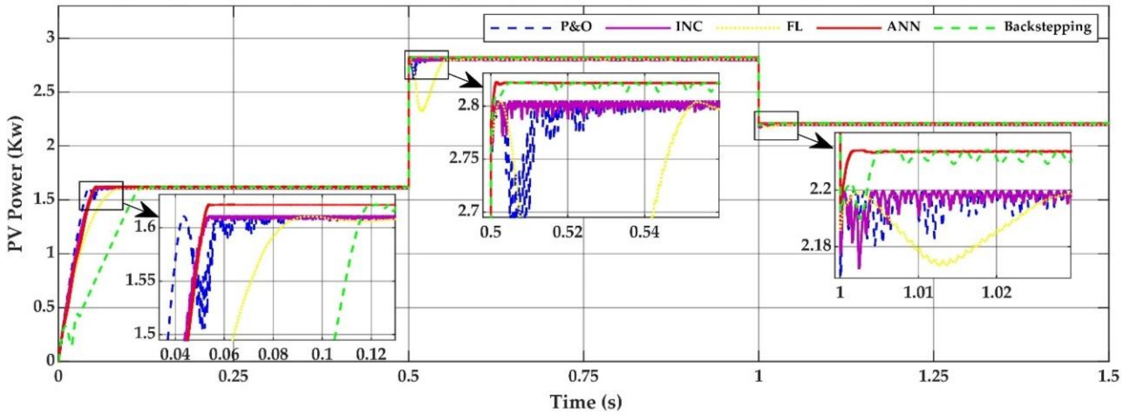

Figure 11. PV power under three different climatic condition scenarios

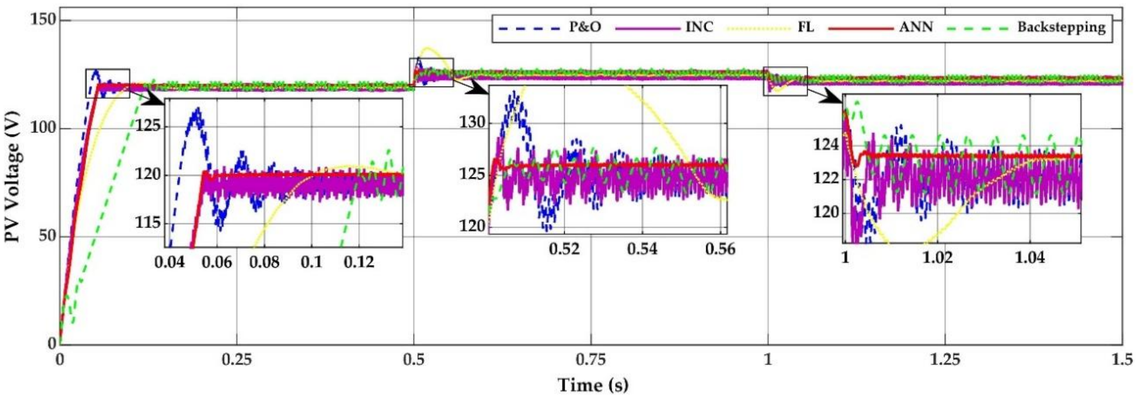

Figure 12. PV voltage under three different climatic condition scenarios

Table 3 summarizes the results obtained from this comparison under both standard climatic conditions and rapidly changing climatic scenarios. The performance of various MPPT techniques, including ANN, FL, backstepping, P&O, and INC, is evaluated based on key metrics such as efficiency, tracking error, tracking speed, and oscillation behavior. The results show that the ANN-based MPPT technique achieves the maximum efficiency, more than 99.96% in all climatic conditions, with negligible error and the fastest response times, as low as 0.001 seconds. In addition, ANN is characterized by stable operation with no oscillations, even under rapidly changing solar irradiance and temperature. This demonstrates its superior adaptability and reliability compared to the other MPPT techniques evaluated.

Table 3. Performance metrics of MPPT techniques

Climatic conditions	G (w/m^2)	1000	600	1000	800
	T (ºC)	25	30	20	25
	P_{max} (W) "Theoretical"	2764.8	16225	2822.27	2214.01
ANN	– Efficiency (%)	99.97	99.96	99.99	99.99
	– Error (%)	0.02	0.03	0.009	0.004
	– Tracking speed (s)	0.03	0.05	0.02	0.001
	– Oscillation	none	none	none	none
FL	– Efficiency (%)	99.32	99.29	99.35	99.32
	– Error (%)	0.67	0.70	0.64	0.67
	– Tracking speed (s)	0.08	0.09	0.06	0.03
	– Oscillation	Low	Low	Medium	Medium
Backstepping	– Efficiency (%)	99.88	99.90	99.95	99.90
	– Error (%)	0.13	0.09	0.04	0.09
	– Tracking speed (s)	0.14	0.12	0.01	0.01
	– Oscillation	Low	Low	Low	Low
P&O	– Efficiency (%)	99.21	99.22	99.24	99.27
	– Error (%)	0.78	0.77	0.75	0.72
	– Tracking speed (s)	0.06	0.08	0.04	0.02
	– Oscillation	High	High	High	Medium
IC	– Efficiency (%)	99.29	99.22	99.28	99.23
	– Error (%)	0.71	0.77	0.71	0.76
	– Tracking speed (s)	0.03	0.05	0.01	0.005
	– Oscillation	Medium	Low	Medium	Medium

5. CONCLUSION

MPPT techniques are essential for optimizing the energy production of photovoltaic systems to ensure that they operate at maximum power even under variable climatic conditions. In this study, the performance of an ANN-based MPPT controller under different scenarios of climatic conditions was evaluated using MATLAB/Simulink and compared with conventional techniques such as perturb and observe, incremental conductance, fuzzy logic controller, and backstepping controller. The simulation results showed that ANN-based MPPT outperformed the other techniques, achieving the highest efficiency (up to 99.94%) with fast tracking and low oscillation. Its robustness under rapidly changing climatic conditions allowed it to maintain stable output power while accurately tracking the MPP.

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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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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 data that support the findings of this study are available from the corresponding author, [AK], upon reasonable request.

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