Efficient and robust nonlinear control MPPT based on artificial neural network for PV system

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ABSTRACT

The objective of this paper is to optimize the energy generation of a photovoltaic system by proposing an improved maximum power point tracking (MPPT) technique. The proposed method combines an artificial neural network (ANN) with a backstepping controller to enhance the photovoltaic (PV) system's efficiency and precision in diverse climatic conditions, including solar irradiance and temperature. The ANN is used to predict the optimal voltage at maximum power point (MPP) $V_{pv,\ ref}$, and the backstepping controller is used to control the DC/DC converter based on $V_{pv,\ ref}$. The results obtained using this technique are compared with those obtained from the perturbation and observation (P&O) technique. The proposed technique achieves better results than P&O in terms of efficiency, accuracy, stability, and response time. The simulations are performed on MATLAB/Simulink software.

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1. INTRODUCTION

The global energy crisis is caused by the use of traditional generators that use expensive fossil fuels to produce energy in general and electricity in particular. This has led to environmental problems and increased costs for consumers. Over the last two decades, several sectors have been thinking of replacing traditional energy generators with clean or renewable energy sources [1]. Renewable energy sources have emerged as the best option for producing energy in the world, which attracts attention for a number of reasons like it's clean and renewable source of energy, it can reduce reliance on fossil fuels, it's widely available [2].

Photovoltaic energy is a renewable energy source generated by photovoltaic arrays, which consist of photovoltaic cells [3]. These cells are composed of semiconductor materials, such as silicon, that convert sunlight directly into electricity [4]. When sunlight hits a photovoltaic cell, it excites electrons in the semiconductor material, creating an electric current. There are several parameters that influence the output power of a photovoltaic (PV) generator, such as the load connected to the generator and the climatic conditions. Directly connecting a PV array to a load can result in wasted energy due to the load adjusting the operating point. Throughout the day, variations in solar irradiance and temperature cause nonlinear changes in generator output power, as shown in Figure 1. These nonlinear changes in generator output power can affect the total efficiency of the photovoltaic system. Therefore, it is important to implement maximum power point tracking maximum power point tracking (MPPT) techniques to continuously adjust the operating point and maximize energy extraction from the PV generator [5], [6].

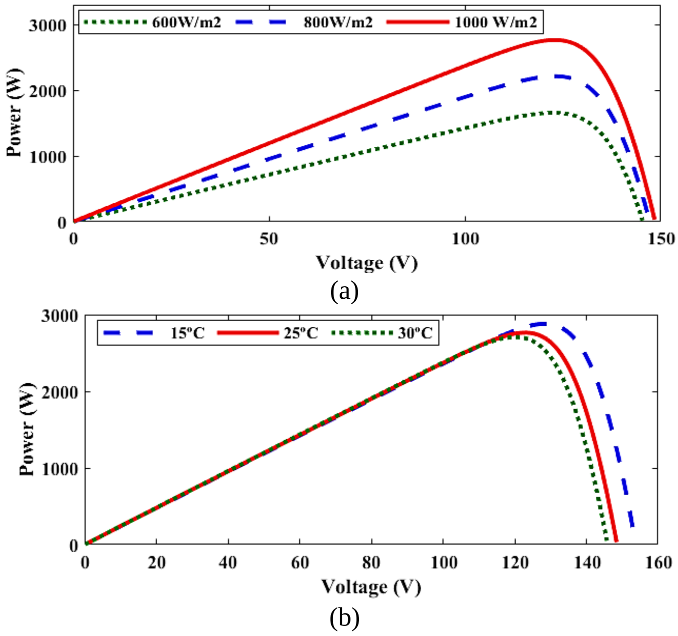


Figure 1. PV characteristic of the PV array (a) at variable solar irradiance and (b) at variable temperature

Researchers have developed several MPPT techniques, [7]-[10] present traditional MPPT techniques. P&O technique described in [7], involves perturbing the operating point and observing the corresponding change in power. Incremental conductance (IC), discussed in [8] which works on the same principle as P&O while hill climbing is covered in [10]. These techniques are widely used due to their ease of implementation, but they have several drawbacks, including slow convergence and tracking under rapidly changing climatic conditions, with oscillations around the MPP and a failure under partial shading conditions (PSC) to track the maximum power point (MPP) [11]. Recently, artificial intelligence (AI)-based MPPT techniques have become more popular due to their ability to track MPP under difficult climatic conditions such as PSC or rapidly changing solar irradiance and temperature. AI techniques can analyze and adapt to these conditions in real time, optimizing the output power of the PV system. MPPT based on artificial neural network (ANN) has been proposed in [6], [12]. Preview study [13], [14] an approach combining ANN and proportional integrator (PI) controllers is used. Fuzzy logic (FL) is applied in [15], [16], and a genetic algorithm (GA) is proposed in [17], [18]. However, there are some disadvantages, for FL technique it can be difficult to find the exact parameters of the system, and for ANN, the problem lies in the database [19]. In nonlinear control, the backstepping technique is discussed in [20], while sliding mode is studied in [21]. Furthermore, in [22]-[25] a hybrid technique that combines two techniques to enhance the overall performance of MPPT is presented.

The primary contribution of this paper is to introduce a hybrid MPPT technique that combines an ANN and a backstepping controller to enhance the accuracy and efficiency of PV systems under changing solar irradiation and temperature. A comparison with the conventional perturbation and observation (P&O) technique was conducted to assess its performance. The paper is structured as: i) Section 2 details the proposed technique; ii) Section 3 presents the simulation results; and iii) The paper concludes with a conclusion.

2. PROPOSED METHOD

2.1. Mathematical model of the system

The photovoltaic system depicted in Figure 2, comprises a photovoltaic array as the primary energy source, which converts sunlight into electrical energy. In order to maximize energy production, a BOOST converter controlled by the MPPT technique is used, which continuously adjusts the operating voltage and current to ensure that the PV array operates at its MPP. This optimization improves the overall efficiency of photovoltaic systems for different types of PV arrays and adapts to changing climatic conditions, such as variations in temperature and solar irradiance. The direct current (DC) charge represents the electrical devices or appliances that consume the energy supplied by the PV system [26].

The system has two operating modes. In mode 1, switch S is open and diode D is forward biased, i.e. conducting. According to Kirchhoff's laws, this gives as (1).

$$\begin{cases} i_{cpv} = i_{pv} - i_l \\ V_L = V_{pv} - V_c \\ i_c = i_L - i_{out} \end{cases} \quad (1)$$

In mode 2, switch S is closed and diode D is reverse-biased, i.e. not conducting, as indicated in (2).

$$\begin{cases} i_{cpv} = i_{pv} - i_l \\ V_L = V_{pv} \\ i_c = -i_{out} \end{cases} \quad (2)$$

According to (1) and (2), we express the mathematical model of our photovoltaic system by (3)-(5).

$$C_{pv} \frac{dV_{pv}}{dt} = i_{pv} - i_L \quad (3)$$

$$L \frac{di_L}{dt} = V_{pv} - (1-D)V_c \quad (4)$$

$$C \frac{dV_c}{dt} = (1-D)i_L - i_{out} \quad (5)$$

The state variables of the system are [V_{pv}, i_L, V_c], representing PV array voltage's, inductor current, and the voltage across the capacitor C, respectively. These variables capture the main dynamic aspects of the system. Additionally, i_{pv} represents PV array output currents. Furthermore, the control of the system D represents the duty cycle of boost converter [27]. The output voltage of a boost converter as in (6).

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

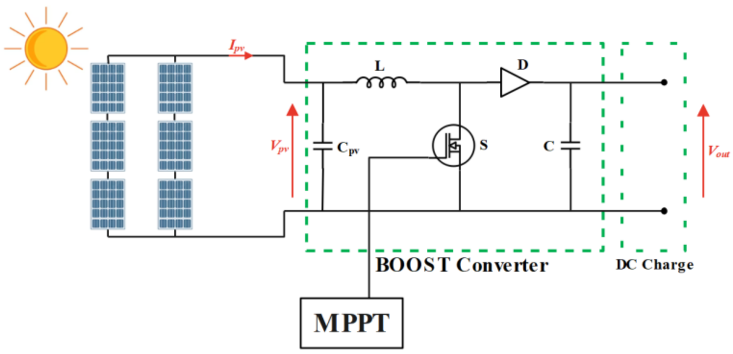


Figure 2. Studied photovoltaic system

2.2. Global control design

This paper presents an improved hybrid MPPT technique that combines the ANN and backstepping controllers. As shown in Figure 3, the ANN predicts the voltage at MPP based on variations in solar irradiance and temperature and the backstepping controller uses the error between the predicted value ($V_{pv,\mathrm{ref}}$) and the photovoltaic voltage (V_{pv}) as input to calculate the duty cycle. This duty cycle (D) is then converted into a control signal via pulse width modulation (PWM) to control the switch (S) in the boost converter, which will force the PV voltage (V_{pv}) to track the predicted value ($V_{pv,\mathrm{ref}}$) and realize the MPPT. By combining these two techniques, the proposed technique aims to enhance the overall efficiency and accuracy of the PV system. Where K_1 and K_2 are the backstepping controller parameters.

2.2.1. Artificial neural network

The artificial neural network is a machine-learning process that uses interconnected neurons in a layered structure similar to the human brain, enabling us to develop high-performance controllers capable of learning and modelling complex, nonlinear relationships [28], [29]. There are several types of ANNs, but this study focuses on feedforward, which is characterized by a unidirectional flow of information, i.e, information flows from the input layer through the hidden layers to the output layer without any feedback connections, as shown in Figure 4 [30], [31]. The choice of ANN type, the number of hidden layers and the number of neurons within each layer depend on several factors, such as the complexity of the problem, the amount of data available, and the desired network performance.

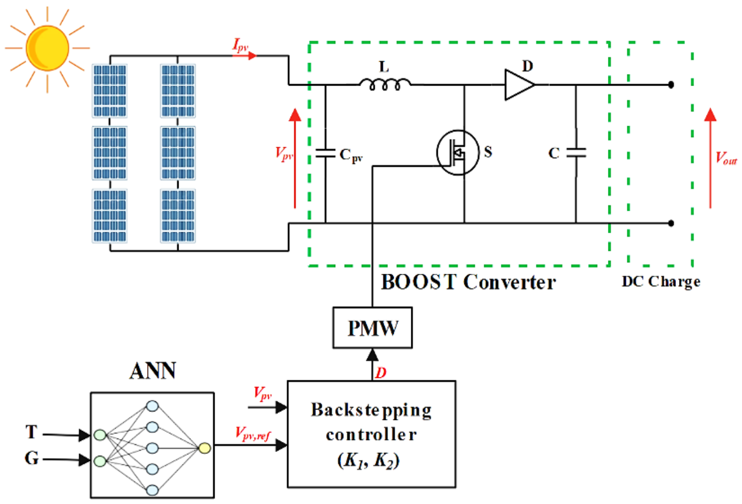


Figure 3. Control design of the system

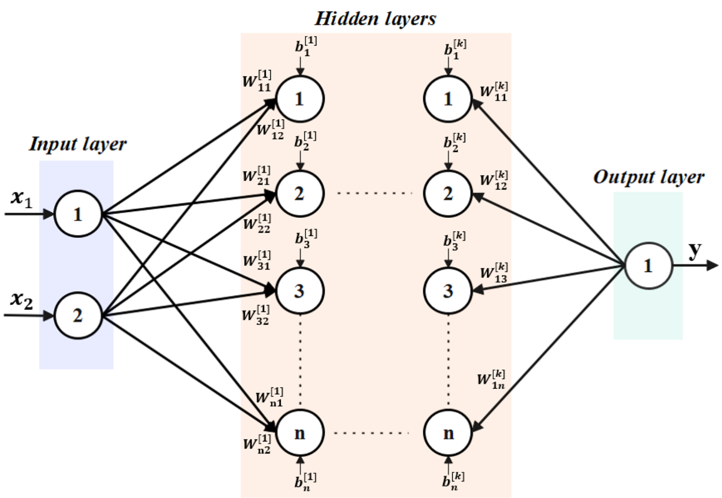


Figure 4. Architecture of the feedforward

The output is equal $y = g(z^{[k]})$,where g is linear activation function. Therefore, as in (7).

$$y = z_1^{[k+1]} = \sum_{j=1}^{n} \omega_{1j}^{[k+1]} A_j^{[k]} \tag{7}$$

Where A_j is a ReLu activation function, as in (8).

$$A_j^{[k]} = \max\,(0, z_j^{[k]}) \tag{8}$$

Where $z_i^{[k]}$ is given in (9).

$$z_i^{[k]} = \sum_{j=1}^{n} w_{ij}^{[k]} A_j^{[k-1]} + b_i^{[k]} \tag{9}$$

In this work, the proposed ANN aims to predict the voltage at the MPP of a PV array. We have used a feedforward network, which contains three layers, as we have shown in Figure 4.
- The input layer consists of two neurons, x_1 and x_2, which represent solar irradiance and temperature.
- There are five hidden layers with 10 neurons each.
- The output layer consists of one neuron y, representing the voltage at the MPP $V_{pv,\ ref}$.

The feedforward network is trained using the allocated database, with 70% for training, 15% for validation, and 15% for testing. In this process, to effectively train a neural network to predict the target variable, the use of a loss function is essential. The loss function is generally defined as the mean square error (MSE), which can be written as (10). It evaluates the accuracy of the network predictions by measuring the mean square difference between the predicted and actual values. By minimizing this difference using the gradient algorithm, the model iteratively refines its parameters, thereby improving its prediction accuracy [14]. Figure 5 illustrates the performance of the ANN network used, which presents an MSE of 1.9407e-09, indicating acceptable results.

$$E_{mse} = \frac{1}{N}\sum_{i=1}^{N}(t_i - y_i)^2 \tag{10}$$

Where N, t_i and y_i respectively represent the total number of samples in the training set, the target for sample i, and the output for sample i, which is $V_{pv,\ ref}$.

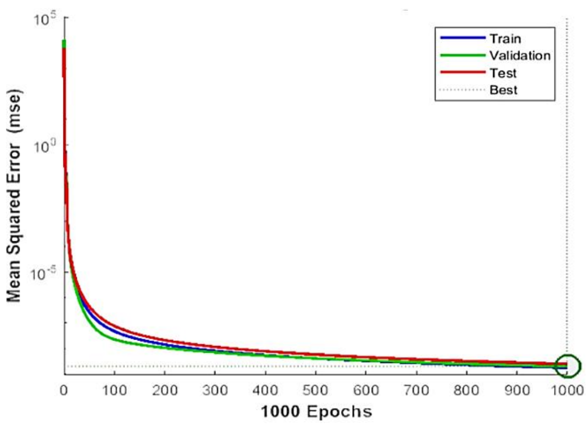


Figure 5. Mean square error

2.2.2. Backstepping controller

Backstepping is a nonlinear control design technique used in high nonlinearity systems, such as photovoltaic systems, to ensure the stable and maximum energy transfer from the photovoltaic array to the DC charge. It involves designing a series of virtual controllers, each responsible for stabilizing a specific part of the system's output. By continuously adjusting the control input, the system ensures operation at MPP of PV arrays across diverse climatic conditions [20], [32]. Our system is defined by (3)-(5).
- Step 1

The error e_1; $e_1 = C_{pv}\left(V_{pv} - V_{pv,ref}\right)$

Using (3), we obtain (11).

$$\dot{e}_1 = i_{pv} - i_L - C_{pv}\,\dot{V}_{pv,ref} = -K_1 e_1 \tag{11}$$

The Lyapunov function is a mathematical tool for analyzing dynamic system stability, ensuring asymptotic stability by maintaining positive energy and a negative time derivative. And its derivative in (12).

$$V_1 = \frac{1}{2}e_1^2 \text{ its derivative } \dot{V}_1 = e_1\dot{e}_1 = -K_1 e_1^2 \tag{12}$$

Where K_1 is a positive constant. By designating i_L as a virtual control input, the stabilizing function is using (13).

$$\alpha_1 = K_1 e_1 + i_{pv} - C_{pv} \dot{V}_{pv,ref} \tag{13}$$

New error as in (14).

$$e_2 = L(i_L - \alpha_1) \tag{14}$$

The (11) becomes (15), using (13) and (14).

$$\dot{e}_1 = -K_1 e_1 - \frac{e_2}{L} \tag{15}$$

Replace (15) in (12), we obtain (16).

$$\dot{V}_1 = -K_1 e_1^2 - \frac{e_1 e_2}{L} \tag{16}$$

- Step 2

Time derivative of e_2, as in (17).

$$\dot{e}_2 = L(\frac{\mathrm{d}i_L}{dt} - \dot{\alpha}_1) \tag{17}$$

Using (4), the (17) becomes (18).

$$\dot{e}_2 = V_{pv} - (1 - D)V_c - L\dot{\alpha}_1 \tag{18}$$

Consider the second Lyapunov function: $V_2 = V_1 + \frac{1}{2}\, e_2^2$. Its derivate: $\dot{V}_2 = \dot{V}_1 + e_2 \dot{e}_2 = -K_1 e_1^2 - \frac{e_1 e_2}{L} + e_2 \dot{e}_2$ $= -K_1 e_1^2 + e_2(\dot{e}_2 - \frac{e_1}{L})$. We put, as in (19).

$$-K_2 e_2 = \dot{e}_2 - \frac{e_1}{L} \tag{19}$$

$$\dot{V}_2 = -K_1 e_1^2 - K_2 e_2^2 < 0$$

Where K_2 is a positive constant, the derivative of the Lyapunov function $\dot{V}_2$ Is negative, and consequently our system is globally asymptotically stable. By combining (18) and (19) we obtain the duty cycle in (20).

$$D = 1 - \frac{K_2 e_2 - \frac{e_1}{L} - L\dot{\alpha}_1 + V_{pv}}{V_c} \tag{20}$$

Using (13) and (20), the duty cycle (D) can be expressed as a function of parameters K_1 and K_2 as (21).

$$D = 1 - \frac{K_2 e_2 - \frac{e_1}{L} - L(\mathrm{K_1 \dot{e}_1} + \frac{\mathrm{di_{pv}}}{dt} - \mathrm{C_{pv} \ddot{v}_{pv,ref}}) + V_{pv}}{V_c} \tag{21}$$

3. RESULTS AND DISCUSSION

Figure 6 illustrates a simulation model of the proposed system implemented in MATLAB/Simulink. The PV array in our system consists of three cells in parallel and four cells in series of the AREi-230W-M6-G polycrystalline model, which generates a maximum output power of 2765 W under standard climatic conditions. Tables 1 and 2 provide the parameters of the PV model and the boost converter, respectively.

The proposed control system is tested under various scenarios of climatic conditions, as shown in Figure 7, to demonstrate the impact of changes in climatic conditions on the proposed technique. In the first scenario time interval [0 s,0.5 s] the PV system is under 800 w/m^2 for solar irradiance and 15 ºC for temperature. In the second scenario time interval [0.5 s,1s] the solar irradiance increases from 800 w/m^2 to 1000 w/m^2 and the temperature increases from 15 ºC to 25 ºC, therefore the system is in standard climatic conditions. In the third scenario time interval [1 s,1.5 s], the solar irradiance decreases from 1000 w/m^2 to 600 w/m^2 and the temperature remains constant. In the last scenario time interval [1.5 s, 2 s], the solar irradiance decreases from 600 w/m^2 to 400 w/m^2 and the temperature decreases from 25 ºC to 20 ºC. Furthermore, a comparison between the proposed MPPT technique and the P&O technique was performed to show its effectiveness.

Table 1. Parameters of the PV model

Parameter	Value
Maximum power P_{max}	230.4 W
Voltage V_{mpp}	30.72 V
Current I_{mpp}	7.5 A
Current of short circuit I_{sc}	8 A
Voltage of open circuit V_{oc}	37.14 V
Temperature coefficient of open-circuit V_{oc}	-0.35339 V/°C
Temperature coefficient of short circuit I_{sc}	0.05535 A/°C
Cells' number	60

Table 2. Parameters of the boost converter

Parameter	Value
C_{pv}	4000µF
L	1mH
C	1000µF
R	50 Ω

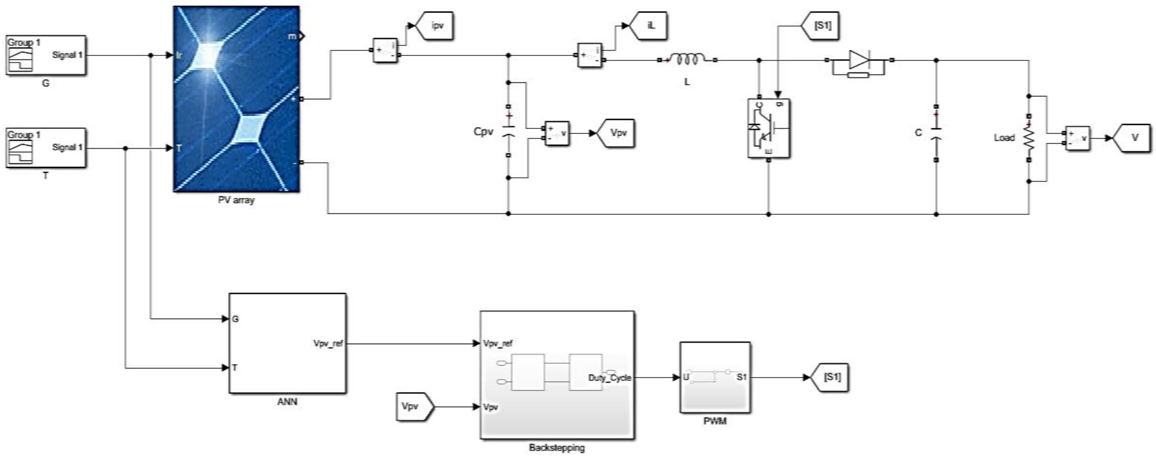
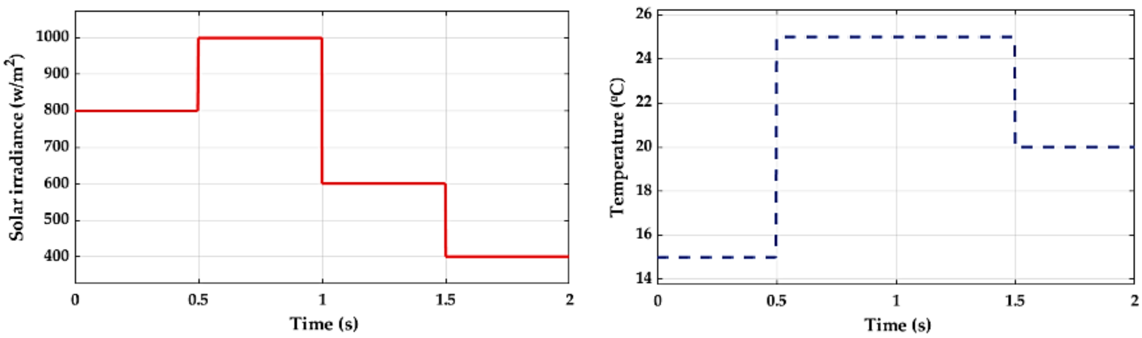


Figure 6. Simulation model of proposed system



(a) (b)

Figure 7. Climatic conditions (a) solar irradiance and (b) temperature

Figure 8 shows the output power results, while Figure 9 shows a zoomed view of these results for the four scenarios. As can be seen, the proposed technique extracts the maximum power in different scenarios compared to P&O. In the first scenario, the ANN backstepping controller shows a faster response time than the P&O technique. The latter shows significant oscillations around the MPP, which may impact the stability of the electrical system it is integrated into, potentially disrupting the operation of sensitive equipment. Therefore, the proposed technique is stable, which maximizes the efficiency of solar energy conversion. In the second scenario, the ANN backstepping controller also shows superior performance by adapting faster to changes in climatic conditions. It maintains stable results with a 0% error rate, indicating reliability in maintaining optimal performance. Conversely, P&O exhibits oscillations, resulting in a reduced system efficiency of 99.31%. In the third scenario, the proposed technique shows improved accuracy in tracking the MPP, resulting in a higher energy yield compared to P&O. The latter's gives a lower power output signifies wastage of energy produced by the PV array. The proposed technique allows rapid convergence to the MPP of 1656 W in 0.001 s, illustrating its effectiveness in terms of accuracy, response time, and stability. In the last scenario, The P&O technique exhibits oscillations around the MPP, thus the proposed technique maintains stability and achieves commendable results with an efficiency of 99.95%. Table 3 summarizes the results obtained.

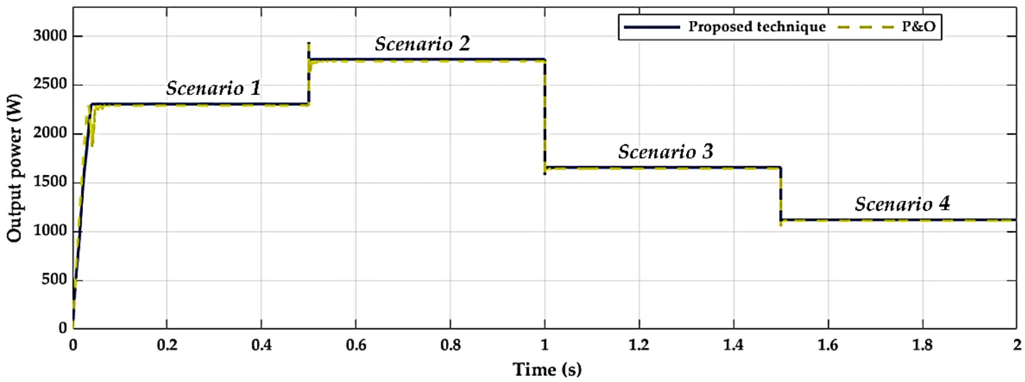


Figure 8. Output power for different scenarios

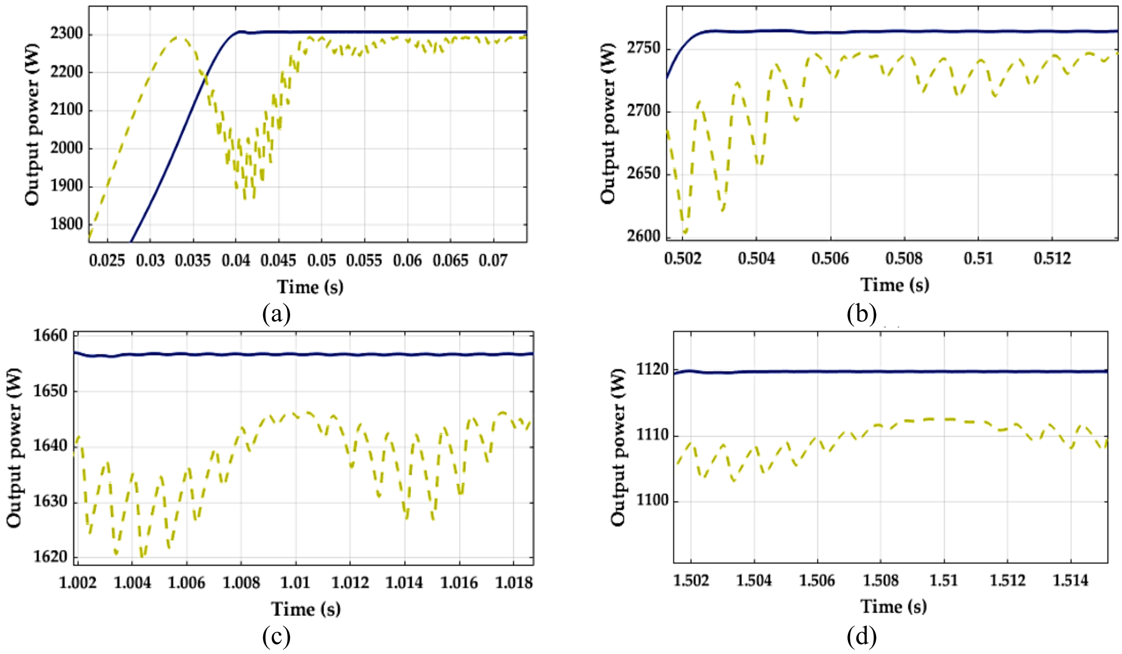


Figure 9. Zoomed view of output power for (a) scenario one, (b) scenario two, (c) scenario three, and (d) scenario four

Table 3. Results of the simulation

Performance	MPPT technique	Scenarios			
		Scenario 1	Scenario 2	Scenario 3	Scenario 4
Maximum power (w)	P&O	2290	2745	1646	1112
	Proposed MPPT	2306	2765	1656	1120
Tracking speed (s)	P&O	0.08	0.018	0.014	0.02
	Proposed MPPT	0.04	0.002	0.001	0.002
Efficiency (%)	P&O	99.26	99.31	99.33	99.24
	Proposed MPPT	99.95	99.99	99.94	99.95
Power oscillation (w)	P&O	20	30	20	5
	Proposed MPPT	0.001	0.0002	0.0001	0.0001

4. CONCLUSION

This paper presents an improved hybrid MPPT technique that combines an ANN and a backstepping controller. In the proposed technique, we use an ANN to predict the optimal voltage at the MPP $V_{pv,\,ref}$ based on the instantaneous solar irradiance and temperature values. This predicted value is then fed to the backstepping controller, which adjusts the DC/DC converter to ensure that the actual voltage follows $V_{pv,\,ref}$. In different scenarios, the proposed technique has an efficiency of 99.4% with a fast response time of 0.001 s. The results show that the neural network-based backstepping controller has better performance in terms of its ability to adapt to variations in climatic conditions and to optimize its control actions in real time than the conventional P&O technique. The proposed technique also demonstrates improved stability and efficiency in the output power of the system.

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