CENTRAL ASIAN JOURNAL OF THEORETICAL AND APPLIED SCIENCE

CENTRAL ASIAN STUDIES

https://cajotas.centralasianstudies.org/index.php/CAJOTAS

Volume: 06 Issue: 02 | April 2025 ISSN: 2660-5317

Article

Artificial Neural Network-Based Energy Management System for Optimized Solar Photovoltaic Performance

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Abstract: The purpose of this research is to offer an improved maximum power point tracking (MPPT) method that makes use of artificial neural networks (ANN) in order to maximise the effectiveness of photovoltaic (PV) systems. Through the process of estimating and adjusting the duty cycle of the DC-DC converter in order to track the maximum power point, the suggested ANN controller is able to regulate itself in response to climatic circumstances (irradiance and temperature). For the purpose of training the Maximum Power Point Tracking (MPPT) algorithm, measurements from a perturb and observe (P&O) algorithm are recorded under a range of different climatic circumstances. The usefulness of the suggested technique is demonstrated by simulation and experimental findings, which show that the new method is more efficient, has fewer oscillations, and has less overshoot than traditional P&O MPPT methods. The performance of the proposed method has been confirmed by experimental verification using the DC-DC Converter and the supporting platform under steady-state conditions.

Keywords: Traditional and Soft Computing, Maximum Power Point Tracking, Slower Tracking Speeds, Artificial Neural Networks, Perturb and Observe

Citation: Gupta, A. K., Tiwari, S. K. Tomar, S. P. Artificial Neural Network-Based Energy Management System for Optimized Solar Photovoltaic Performance. Central Asian Journal of Theoretical and Applied Science 2025, 6(2), 155-165.

Received: 24th Feb 2025
Revised: 28th Feb 2025
Accepted: 9th Mar 2025
Published: 18th Mar 2025

1. Introduction

Sustainability, environmental benefits, and economic advantages as a clean source of renewable energy are driving the rapid development in the usage of photovoltaic (PV) systems globally. The efficiency of PV technology is still an issue [1]. The development of control approaches like Maximum Power Point Tracking (MPPT) to optimise energy extraction [2] helps to overcome this difficulty. By taking into account different operating conditions and maximising energy output, maximum power point tracking (MPPT) algorithms usually change the DC-DC converter duty cycle to operate the PV system at its maximum power point [3], [4], [5], [6], [7], [8], [9]. Photovoltaic (PV) modules display a non-linear curve that continuously changes with changes in climatic circumstances, like irradiation and temperature. This leads to a maximum power point (MPP) problem that changes over time, so an accurate and fast duty cycle calculation is required in real time. To tackle this problem, researchers have developed a number of maximum power point tracking (MPPT) algorithms, which can be categorised into two main types: traditional and soft computing. In settings of uniform irradiance, traditional maximum power point tracking (MPPT) algorithms such as Perturb and Observe (P&O) [10], Hill Climbing (HC) [11], and Incremental Conductance (InC) [12] are able to track the maximum power point with respectable efficiency and rapid convergence. In steady-state operation, however, these approaches lose a lot of power since they don't keep track of the exact value of the

MPP but instead oscillate around it. Attempts to attenuate the oscillatory behaviour have been made in certain investigations, although this has frequently resulted in slower tracking speeds [13].

Innovative methods based on soft computing have emerged in response to the limitations of classic MPPT algorithms. The latest crop of algorithms makes use of state-of-the-art techniques such as genetic algorithms [14], artificial neural networks [15], fuzzy logic controllers [16], genetic evolution [17], particle swarm optimisation [18], and ant colony optimisation [19]. While these techniques built on top of soft computing do boost efficiency, they come at the cost of additional computational overhead and complexity. Because of this, specialised high-performance microcontrollers are necessary for some of these algorithms, which can add a substantial amount to the final price tag. This research introduces a new Maximum Power Point Tracking (MPPT) approach that uses Artificial Neural Networks (ANNs) to directly predict the duty cycle from weather observations [20], [21], [22], [23]. To do this, a minor duty cycle step is used during the training of the neural network utilising a typical Perturb and Observe (P&O) response in different climates. The suggested tracker is able to eliminate oscillations around the maximum power point [24], [25], [26], [27] by promptly and accurately computing the DC-DC converter duty cycle value. The computational complexity and hardware requirements are further reduced by employing a simpler ANN structure with minimal layers and neurones. The remainder of this paper is organized as follows:

1. Section 2: Mathematical modeling of the photovoltaic (PV) module
2. Section 3: Introduction to the proposed ANN-based MPPT algorithm
3. Section 4: Simulation results comparing the proposed algorithm with the conventional P&O method
4. Section 5: Experimental verification
5. Section 6: Conclusions

2. Materials and Methods

2.1 PV Model and the variation in MPPT

A number of mathematical models can be used to characterise the behaviour of photovoltaic systems, as shown in figure 1 [28]. One popular method for measuring PV system efficiency and creating algorithms to follow the highest power point is the one-diode equivalent circuit model, which is used in this study [29], [30]. Using a photo-current source, a diode, and resistive components, this model depicts the electrical behaviour of the PV system [31]. Environmental variables like sun irradiance and temperature affect the non-linear correlations between current, voltage, and power, and the model correctly captures these relationships [32], [33], [34]. Accurately tracking the maximum power point and optimising PV system performance depend on understanding these relationships [35], [36], [37], [38], [39], [40], [41].

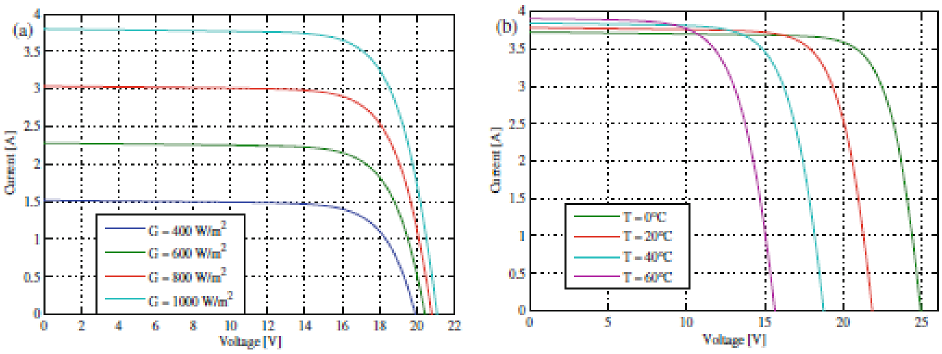

Figure 1. Various operating temperature degrees.

The goal of this research is to create a new kind of Maximum Power Point Tracking (MPPT) controller that can optimise energy harvesting from photovoltaic (PV) systems by using real-time data of operational temperature and sun irradiance [42], [43], [44]. A custom-built ANN algorithm was developed and trained with an extensive dataset produced by a Perturb and Observe (P&O) approach that has been fine-tuned to achieve optimal accuracy [45].

2.2 The Proposed ANN MPPT Controller

2.2.1 The Proposed System Scheme

An array of photovoltaic (PV) components, including a generator, a DC-DC converter, and a resistive load, is utilised in this system. A custom Maximum Power Point Tracking (MPPT) controller controls the transfer of energy from the photovoltaic (PV) generator to the load and is thus the brains of the operation. As shown in Figure 2, the primary goal of the controller is to maximise power extraction by delivering the highest amount of available power to the load.

A photovoltaic (PV) generator transforms sunlight into electricity, and a direct current to direct current (DC-DC) converter modifies the voltage output to suit the needs of the load. An integral part of this process is the maximum power point tracking (MPPT) controller, which keeps an eye on the output of the photovoltaic generator and changes the duty cycle of the DC-DC converter to extract as much power as possible.

Because conventional maximum power point tracking (MPPT) algorithms have trouble keeping up with the dynamic nature of real-world environmental conditions, the suggested MPPT controller is an attempt to address this issue. The proposed controller is able to adapt to different conditions and guarantee optimal power extraction by using advanced control algorithms and real-time data from the PV generator.

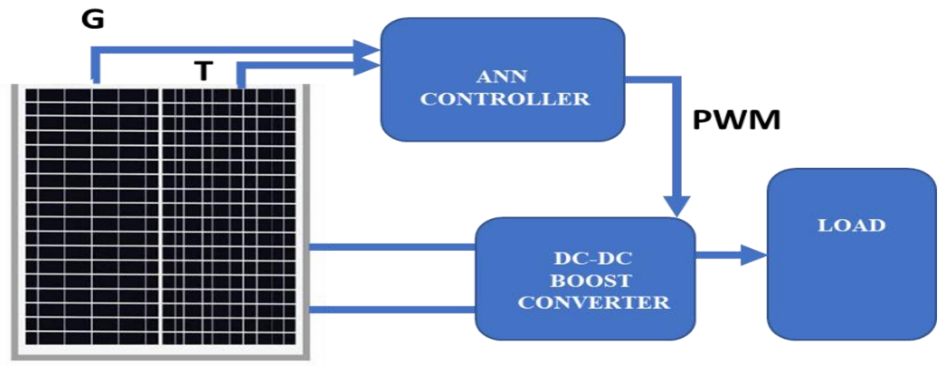

Figure 2. MPPT system.

To maximise the efficiency of the photovoltaic (PV) system, the suggested ANN controller makes use of a state-of-the-art method. To optimise power extraction, the ANN controller uses real-time data on solar irradiance and temperature to dynamically change the DC-DC converter's switching duty cycle. In order to efficiently supply the maximum available power to the load, this intelligent control technique allows the PV system to run at its maximum power point [46], [47], [48], [49]. This research makes use of a boost converter architecture, which for its main switching device is a metal-oxide-semiconductor field-effect transistor (MOSFET). A basic equation describes the link between the duty cycle, the photovoltaic voltage, and the converter's output voltage; this equation provides the basis of the proposed control approach. Equation 1 shows the relationship between output voltage and duty cycle.

$$\frac{V_{OUT}}{V_{PV}} = \frac{1}{1-\alpha} \quad (1)$$

Where,

α (alpha) is the duty cycle,

VOUT is the average output voltage of the DC-DC converter

VPV is the input voltage of the photovoltaic (PV) system.

2.2.2 Artificial Neural Network

By implementing an intelligent control system for Maximum Power Point Tracking (MPPT) using Artificial Neural Networks (ANNs), this study introduces a new way to optimise photovoltaic energy harvesting. The ANN-based MPPT controller precisely forecasts the optimal duty cycle for the DC-DC converter by evaluating real-time data on solar irradiance and module temperature, guaranteeing maximum energy extraction. This groundbreaking controller was painstakingly developed using a three-stage design approach. Here are the steps:

Step 1: Input-Output Variable Selection

In the design of the ANN controller, there is a simplified input layer with two neurones that take in real-time information about solar irradiance (G) and module temperature (T). A single neurone controls the operation of the DC-DC converter by processing the incoming data and producing an expected duty cycle (D) value.

Step 2: Network Architecture Selection

This study's neural network architecture is a three-layer feed-forward design, with two neurones in the input layer, one neurone in the output layer, and eight processing nodes in the hidden layer (Figure 3). The network creates non-linearity in the hidden layer using the tangent sigmoid activation function, and then predicts the duty cycle value in the output layer using the pure linear function.

Step 3: Network Training and Testing

A neural network is fine-tuned for a particular task during the training phase. The training dataset was built by recording the duty cycle values of a boost converter that was linked to a test photovoltaic (PV) panel. The converter was then subjected to several climatic conditions. The duty cycle (D) and input parameters (irradiance, G, and temperature, T) were measured using a standard Perturb and Observe (P&O) technique [50], [51, [52], [53]. After optimising the P&O perturbation step to minimise oscillations around the duty cycle value, the network output was merely the mean value.

The training dataset, created in the MATLAB/SIMULINK environment, covers a temperature range of 0 to 70 °C and an irradiance range of 100 to 1000 W/m² [54], [55], [56]. A thorough training dataset with 700 samples was produced by this methodical procedure. With 80% of the data set aside for training and 20% for testing and validation, the neural network was trained using the Levenberg-Marquardt (LM) algorithm.

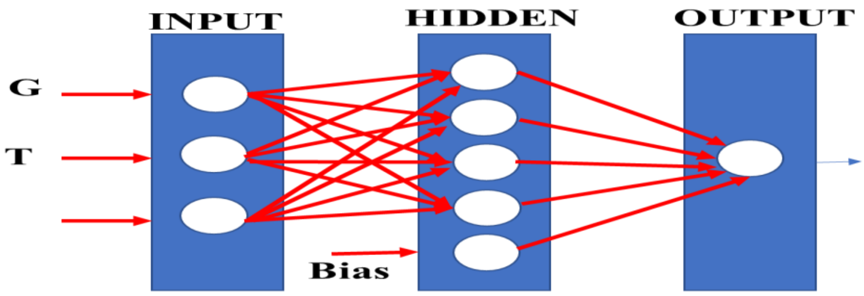

Figure 3. The proposed MPPT system.

2.3 Simulation and Results

2.3.1 ANN Algorithm Training Performance

To make reliable predictions when presented with novel data, a well-trained Artificial Neural Network (ANN) needs strong generalisability capabilities. This requires the network to keep its forecast accuracy at a constant level even when it encounters data that isn't part of the training dataset.

Figure 4 shows the ANN model's performance graphically, and it's clearly effective because the Mean Squared Error (MSE) dropped significantly. Correlation coefficients approaching unity during validation, testing, and training further demonstrate a robust synergy between the network's anticipated outputs and the real target values in the regression plot. This incredible congruence between the intended outcomes and the ANN's outputs demonstrates the model's outstanding predictive power.

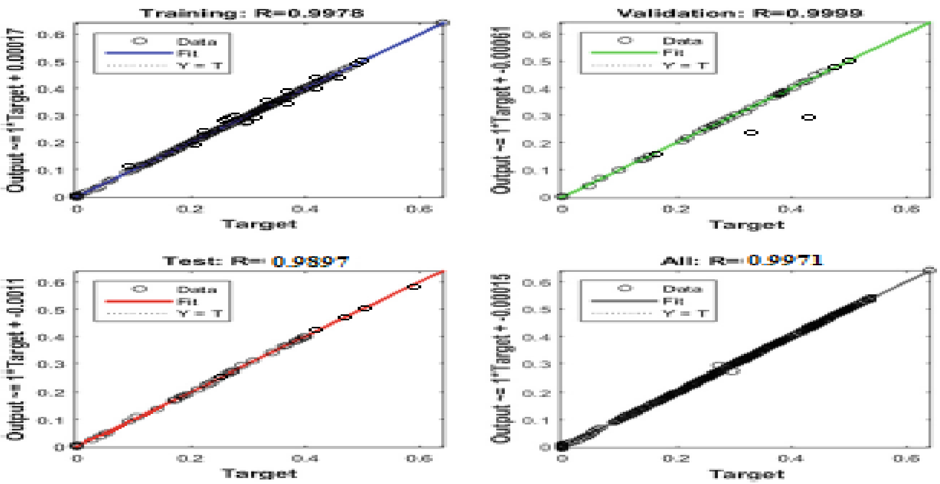

Figure 4. Proficiency through a significant decrease in Mean Squared Error (MSE).

4.2. Effectiveness of the Proposed Tracker

A simulation was carried out using the schematic diagram in Figure 2 to evaluate the efficacy and legitimacy of the suggested method. Using predicted duty cycle and output power as metrics, this simulation aimed to compare the ANN algorithm's performance to that of a traditional Perturb and Observe (P&O) algorithm.

A photovoltaic (PV) module with the specs listed in Table 1 was used as the PV generator in the simulation. In addition, to maintain consistency and realism, the DC-DC converter utilised in the simulation was the same as the boost converter used in the data generating phase.

Table 1. Solar Panel Rating.

Immp:	**2.38A**
Vmmp:	21V
Pmax:	50 W
Isc:	2.7A
Voc:	24.8V
Ns:	42

The duty cycle responses of the standard Perturb and Observe (P&O) controller and the suggested technique are compared in Figure 5, after a sudden shift in solar irradiation. The predicted fast convergence to a stable duty cycle value by the suggested method and the noticeable oscillations around the optimal value by the P&O controller demonstrate the obvious stability and transient response advantages of the former.

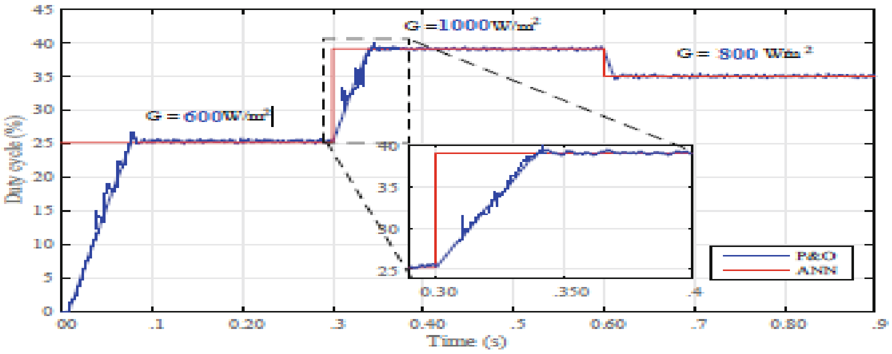

Figure 5. Duty cycle under sudden irradiance variation.

In Figure 6, we can see how the suggested ANN controller stacks up against the tried-and-true P&O algorithm in terms of maximum power extracted under STC. In accordance with the manufacturer-specified maximum power rating of the PV panel (Table 1), the graph shows that both methods accomplish maximum power extraction. In comparison to the P&O technique, the suggested ANN controller converges to maximum power more quickly and with fewer oscillations. The suggested method outperforms the P&O algorithm by a wide margin, with a convergence speed of 0.011 s compared to 0.096 s.

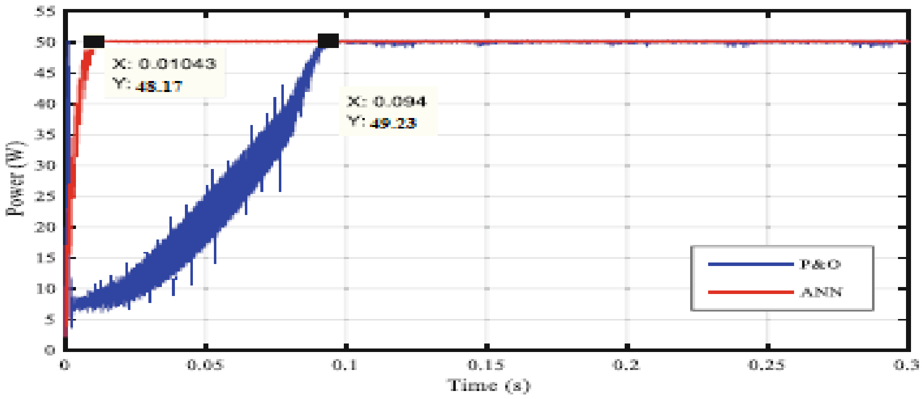

Figure 6. Power tracking of each algorithm under STC.

In Figure 7, we can see how the suggested ANN controller stacks up against the tried-and-true Perturb and Observe (P&O) algorithm in terms of their maximal power extraction capabilities under STC. Both algorithms were able to effectively extract the maximum possible power, which is in line with the manufacturer-specified maximum power output of the photovoltaic (PV) panel, according to the results (Table 1).

But there is a clear difference when looking at the stability and rate of convergence. In comparison to the P&O approach, which takes 0.096 seconds to reach the same milestone, the suggested ANN controller shows a substantially faster convergence rate, reaching maximum power extraction in just 0.011 seconds. The ANN controller is more stable and performs better at maximising power extraction, and it shows less oscillations when it converges.

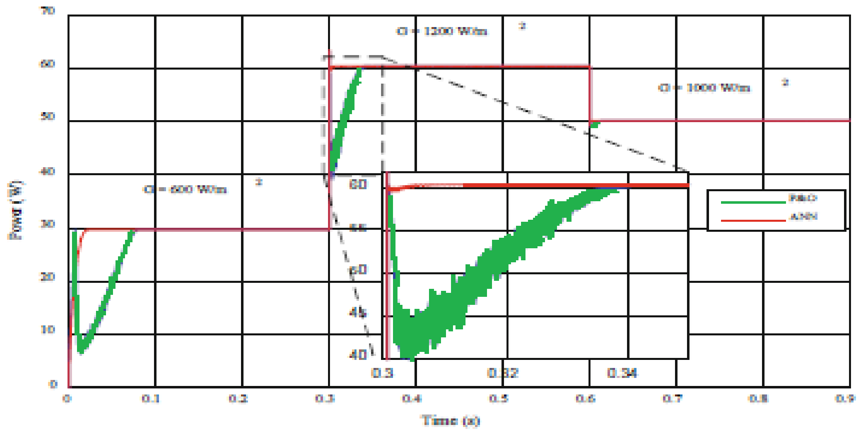

Figure 7. Power tracking of each algorithm under sudden irradiance change.

3. Results and Discussion

A hardware interface was used to physically implement the suggested method, which proved to be effective and perform as expected in the simulated ANN tracker. As shown in Table 1, the experimental setup included a photovoltaic (PV) generator that was identical to the one used in the simulation phase. This ensured that the testing environment was constant and reliable. To ensure a perfect comparison between the simulated and practical results, the boost converter and load configuration were carefully duplicated from the simulation, down to the switching frequency. A complete experimental setup was set up, as shown in Figure 8, which included a photovoltaic (PV) generator, a boost converter linked to the load, and sensors to measure temperature and irradiance.

Figure 8. Experimental setup for testing purposes.

An appropriate strategy for conducting a thorough comparison between the suggested method and the Perturb and Observe (P&O) controller would be to apply both controllers to the same converters and generators under the same conditions. However, a single system was used to enable seamless switching between the two methods in real-time, which mitigated possible inconsistencies between the testing systems. The controller was purposefully intended to work with both ANN-based and P&O trackers, so the comparison would be fair and straightforward. Extracted power, duty cycle variation, and weather conditions for each algorithm are illustrated in Figure 9, which displays the test findings. The ANN algorithm performed as expected, providing accurate and immediate duty cycle estimates in a climate that did not fluctuate. In addition, the ANN estimates showed impressive resistance to temperature and irradiance measurement noise, leading to more precise power extraction, less oscillations, and quicker reaction times. The P&O algorithm's response time was noticeably slower than the ANN controller's because the duty cycle recalculation process was much more time-consuming. This further proves that the suggested ANN-based method is the best option with regard to responsiveness, accuracy, and stability.

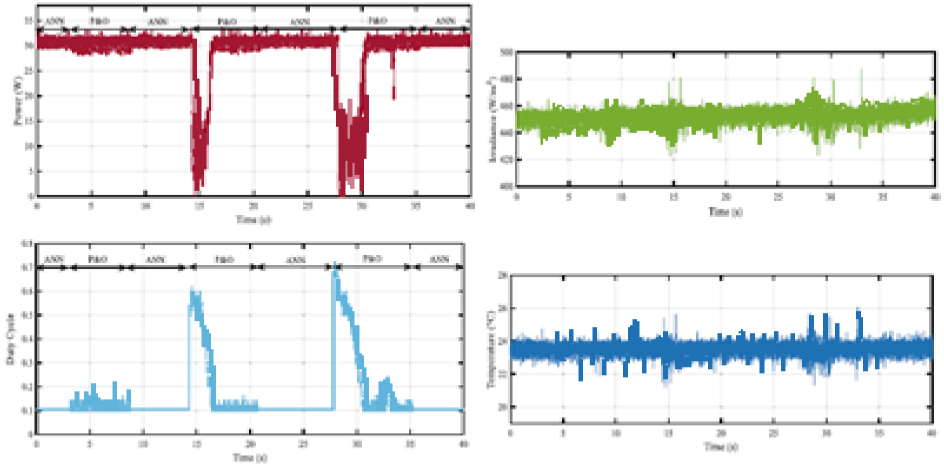

Figure 9. MPPT switching between ANN and P&O.

Overall, the suggested method is superior since it directly estimates the duty cycle using irradiance and temperature readings, which leads to better accuracy and quicker reaction times. Because of this, the suggested method is a good option for improving photovoltaic energy harvesting since it is effective and dependable.

4. Conclusion

This paper presents a neural network-based maximum power point tracker (MPPT) designed to enhance the efficiency of solar photovoltaic (PV) systems. The proposed approach leverages an Artificial Neural Network (ANN) to predict the optimal duty cycle for a DC-DC converter, ensuring the system operates at the Maximum Power Point (MPP) under varying environmental conditions. To generate training data for the ANN, the widely used Perturb and Observe (P&O) algorithm is employed, incorporating key parameters such as irradiance, temperature, and the mean duty cycle value. Simulation results demonstrate that the trained ANN-based tracker effectively estimates the duty cycle based on real-time measurements of irradiance and temperature. This approach offers significant advantages over conventional MPPT techniques, particularly in achieving faster response times and reducing oscillations around the MPP. Unlike the P&O method, which suffers from steady-state oscillations and slower tracking speeds, the ANN-based tracker dynamically adjusts to changing environmental conditions with greater precision. To validate the simulation results, an experimental implementation of the proposed MPPT system was conducted. The experimental findings confirm that the ANN-based tracker exhibits rapid convergence speeds and minimal oscillations near the MPP, highlighting its potential for real-world solar energy applications. The proposed method enhances energy harvesting efficiency and improves system stability, making it a viable alternative to traditional MPPT techniques. This research underscores the potential of neural network-based controllers in advancing renewable energy systems, ensuring optimized power extraction and improved performance in dynamic operating conditions.

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