Optimizing Photovoltaic Array Performance Using a Hybrid PSO–ANN MPPT Algorithm

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ABSTRACT

In this study, we present a novel method for increasing the performance of photovoltaic (PV) arrays by utilizing a hybrid optimization algorithm involving Particle Swarm Optimization and Artificial Neural Networks (PSO-ANN) to track maximum power points. Increasing global energy challenges have resulted in an increase in demand for efficient solar energy conversion techniques. The proposed hybrid MPPT algorithm combines the strengths of both PSO and ANN to overcome the limitations of traditional MPPT methods, which often have difficulty adapting to changing environments. As a result of this research, PV systems will yield significantly more energy, leading to more sustainable and reliable renewable energy generation.

I. Introduction

As electrical energy becomes increasingly important in sustaining modern lifestyles, its demand has increased significantly. It is mainly generated with the use of fossil fuels. This source, however, contributes to air pollution and exacerbates global warming because of its emissions of greenhouse gases. Sunlight, wind, and swift water are used to generate energy as part of these resources by photovoltaic (PV) arrays, wind turbines, and hydropower stations, respectively. As an alternative to other renewable energy sources, PV systems boast a competitive cost. Additionally, their adaptability to installation across different locations and capacities makes them particularly attractive [1].

Various studies have demonstrated that the Earth's surface receives significant solar radiation. This amount of energy significantly surpasses the global demand for electrical power [2]. However, Photovoltaic (PV) systems are primarily inefficient, posing a primary challenge [3]. A maximum power point tracker (MPPT) technique has been developed to enhance the performance of PV systems, as illustrated in Figure 1. MPPTs are designed to generate optimal power regardless of atmospheric conditions.

MPPT refers to delivering a duty cycle (D) to a power conversion system, such as a DC-DC converter, based on the PV module's output and input parameters. MPPT bolsters PV power generation stability and dependability when integrated with a grid and improves efficiency. A variety of techniques can be classified into two main types: classical methods, such as perturbation and observation (P&O), and artificial intelligence (AI), such as fuzzy logic controllers (FLCs) or artificial neural networks (ANNs) [4][5][6].

Conventional techniques like the P&O algorithm are extensively employed for PV-MPPT controllers due to their straightforward design and cost-effectiveness [7]. However, these controllers exhibit drawbacks such as sluggish tracking speed, pronounced fluctuation, and drifting issues [6]. As a remedy, AI-based techniques have been put forth to address these concerns [8]. These AI techniques prevent the need for intricate mathematics and precise parameters in managing application systems. Among them, the Fuzzy Logic Controller (FLC) method is an attractive MPPT approach for PV systems due to its swifter tracking speed and reduced oscillation compared to classical MPPT methods. Nevertheless, it shares a drawback with traditional methods: susceptibility to the drift phenomenon caused by abrupt shifts in irradiance levels (G) and operating temperatures (T). This stems from the requirement of a solid understanding of PV systems to accurately define membership functions within the FLC model [9].

Recently, the issue with the conventional FLC-MPPT has been tackled using an Artificial Neural Network (ANN) technique, introducing heuristic output functions via numerical quantified data. Consequently, in designing the optimized MPPT controller, in-depth knowledge of PV parameters becomes unnecessary. However, a significant drawback of ANN lies in its training strategy when utilized as a prediction model [10].

In this study, a feedforward ANN technique is harnessed to forecast a PV array's Maximum Power Point (MPP), employing a comprehensive real-world training dataset sourced from experimental trials on a PV array. The Particle Swarm Optimization (PSO) algorithm enhances the ANN model's training strategy. This approach is bifurcated into two segments: first, determining the optimal topology, and subsequently, fine-tuning the initial weights of the feedforward ANN model. This addresses the trade-off between computational time and the optimal regression fit of ANN nodes' distribution in the first part and pursues the global minimum training error of the ANN model in the second. Consequently, the predictive capability of the proposed ANN method is elevated across diverse weather conditions. Atmospheric conditions' G and T values are inputs for the proposed ANN model, while the predictive power (Pref.) is the output. This, in turn, governs the duty cycle (D) of a DC–DC boost converter. A Proportional–Integral (PI) controller compares it with the actual power (Pact.) of the PV and converts D into the DC–DC converter signal using Pulse-Width Modulation (PWM) to regulate the operational MPP of the PV array, as depicted in Figure 1.

Due to the increasing demand for optimized solar energy conversion techniques, this research paper introduces a groundbreaking approach using a Hybrid Particle Swarm Optimization-Artificial Neural Network (PSO-ANN) algorithm to track maximum power points (MPPT). As a result of dynamically changing environmental conditions, traditional MPPT methods often fail to extract optimal amounts of energy. In addition to effectively exploring the solution space, Particle Swarm Optimization quickly converges upon the global maximum power point. Using historical data to predict future optimal MPPs, Artificial Neural Networks simultaneously act as dynamic predictors. In contrast to conventional MPPT techniques, this integration leverages the real-time adaptability of ANNs. Using these two robust methodologies, the hybrid PSO-ANN MPPT algorithm enables more efficient solar energy conversion and strengthens the prospects for renewable energy integration.

The subsequent sections of this paper are structured as follows: Section One elaborates on the methodology, Section Two introduces the PV system modeling, Section Three outlines the proposed method, Section Four presents the results, and Section 5 concludes the study. Development.

II. System Design

The Proposed System Design involves combining Particle Swarm Optimization (PSO) and Artificial Neural Networks (ANNs) to enhance Maximum Power Point Tracking (MPPT) in a photovoltaic array, optimizing energy extraction.

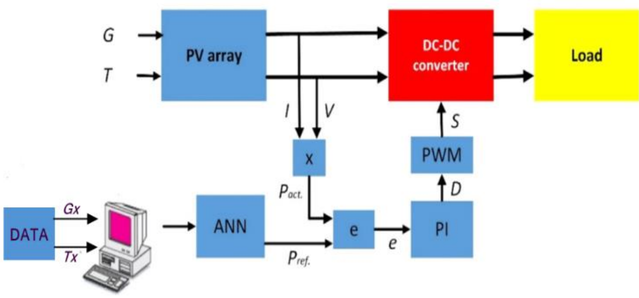

Figure 1. System Schematic.

II.1. Photovoltaic PV System

Solar photovoltaic (PV) panels convert sunlight into electrical energy using the photon-voltage phenomenon. Ideal solar cells don't possess series and shunt resistances, but in real-world scenarios, these are associated with the PV diode, as illustrated in Fig. 2. These resistances come into play due to the inherent resistance of the PV semiconductor and the suboptimal performance of the PN junction diode. Consequently, series and shunt resistances are integrated.

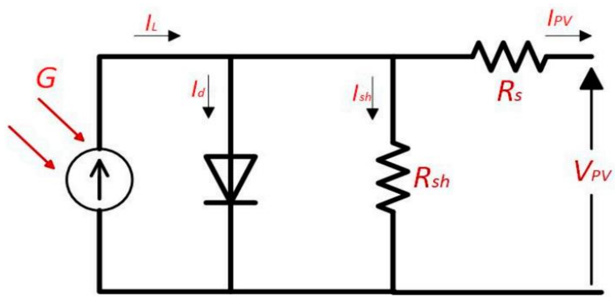

Figure 2. Equivalent circuit of PV solar cell.

The output current of the solar PV cell can be described using Kirchhoff's law (1).

$$I_{PV} = I_L - I_d - I_{sh} \tag{1}$$

Equation (2) gives the current generating diode, I_L:

$$I_L = G\{I_{SC}[1 + ka(T - T_{STC})]\} \tag{2}$$

Where, I_{SC} represents the short circuit current of the PV cell's circuit, ka is the temperature coefficient, T_{STC} denotes the temperature during operation under standard test conditions, and I_d stands for the revised current in the PV diode circuit as determined by Shockley's (3):

$$I_d = I_0\{\exp\left(\frac{qV_d}{nkT}\right) - 1\} \tag{3}$$

In this context, I_0 represents the saturation current of the PV diode circuit, V_d signifies the voltage across the diode, q stands for the elementary charge (1.69 × 10−19 C), k denotes Boltzmann's constant (1.38 × 10−23 J/K), and n represents the conventional factor for the PV diode.

Equation (4) universally defines the current-voltage behavior of the PV cell circuit:

$$I_{PV} = I_L - I_0\left[\exp\left(\frac{q(V_{PV}+IR_S)}{nkT}\right) - 1\right] - [\frac{V_{PV}+IR_S}{R_{sh}}] \tag{4}$$

Where I_{PV} and V_{PV} are the output PV current and voltage.

The PV module used in this study has a maximum power output equivalent to 250 W when measured under standard temperature conditions (STC). STC, T = Tref = 25 degrees Celsius, Solar irradiation Gref = 1000 watts per square meter.

The following is a listing of the electrical properties of this module that can be found in Table 1:

Table 1. Electrical characteristics of PV module.

Solar Photovoltaic Array	
Maximum power (Pmax)	250 W
Voltage, Vmpp	30.7 V
current, Impp	8.15 A
Modules number at series, Ns	1
Modules number at parallel, Np	1

The I-V and P-V characteristics against different radiation levels through simulation are shown in Fig. 3:

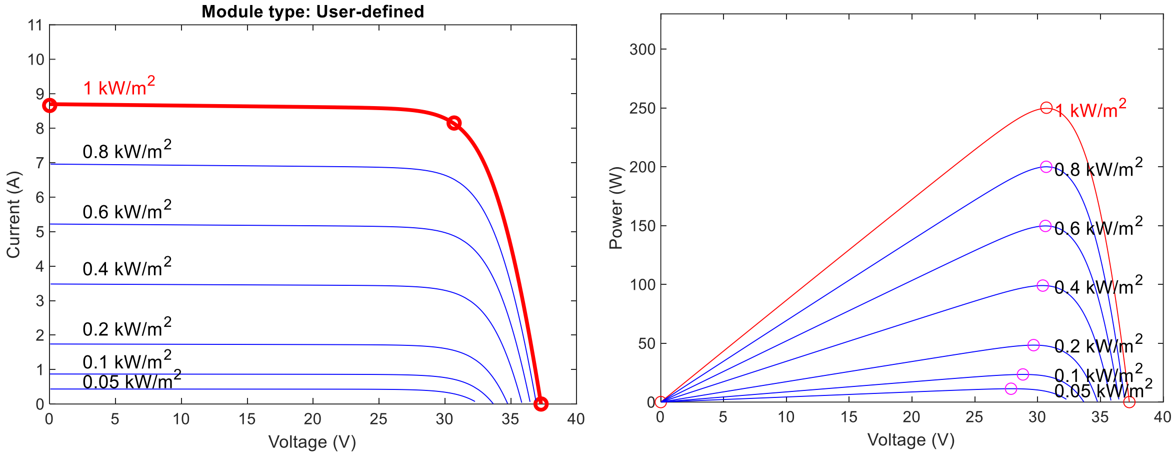

Figure 3. I-V and P-V of PV module.

II.2. DC-DC Boost Converter Design

Between the PV array and the inverter is a regulator called a DC-DC boost converter. The MPPT control [11] determines the duty cycle (α) of the converter, which in turn determines how much of the input DC voltage (V_{pv}) is transformed into the output DC voltage (V_{dc}).

Continuous Conduction Mode (CCM) should be used to determine the boost converter parameters, L_{pv}, and C_{dc}. Where the boost converter's duty cycle is calculated according to the equation below [12]:

$$\alpha = \frac{V_{dc} - V_{mppv}}{V_{dc}} \tag{5}$$

The boost converter inductor can be determined as follows:

$$L = \frac{V_{mppv}\ \alpha}{\Delta I f_S} \tag{6}$$

Where: f_S is the switching frequency, and ΔI is the current ripple.

Table 2. Values for the boost converter's parameters

Parameter	Value
Vdc_refrence	70 V
C	100 uF
L	0.33 mH
α	0.55

Equation (7) can determine the DC bus voltage (V_{dc}) at the input inverter.

$$V_{dc} = \frac{2\sqrt{2} \times V_{LL}}{\sqrt{3}} \tag{7}$$

Where, V_{LL} represents the RMS line voltage of the IM.

The VSI DC Link Capacitor is calculated by (8):

$$C_{dc} = \frac{6\alpha\, V_{LL}\, I_L t}{\sqrt{3}(V_{dc}^{*2} - V_{dc}^{2})} \tag{8}$$

Where, V^*_{dc} is the DC bus voltage reference, V_{dc} is the DC bus voltage measurement, t is the time in seconds that the DC-link voltage must be changed, α is the boost converter's duty cycle, and I_L is the IM line current. The boost converter's input and output parameters are listed in Table 2 designations.

III. MPPT Algorithm

III.1. The proposed PSO-Neural Network Controller (PSO-NNC)

The proposed method introduces an innovative strategy for enhancing the efficiency and accuracy of Maximum Power Point Tracking (MPPT) in solar photovoltaic systems. By synergistically combining the Particle Swarm Optimization (PSO) algorithm and Artificial Neural Networks (ANNs), this method aims to improve the performance of MPPT. The hybrid approach involves initializing a swarm of particles, each representing a set of parameters governing the solar panel's operating point. These parameters are continually adjusted based on evaluations performed using a trained ANN, which predicts the optimal power point using solar irradiance and temperature as inputs. The PSO component orchestrates the swarm's movement through parameter space, directing particles toward optimal configurations. Through this integration of PSO's optimization capabilities and ANN's predictive strengths, the proposed method endeavors to achieve more accurate and adaptable MPPT, thereby enhancing solar energy harvesting efficiency. Fig. 4 shows the PSO–ANN algorithm's training technique schematically.

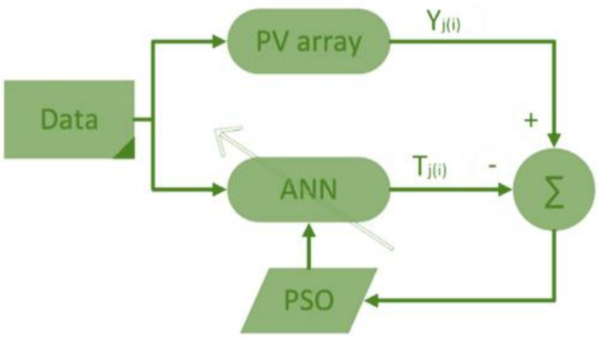

Figure 4. Training technique schematic.

IV. MPPT Algorithm

IV.1. Changing Load Condition

Figures 5(a), 6(a), and 7(a) vividly depict the optimal voltage, current, and power extracted from the solar cell under ideal irradiation conditions of 1000 W/m². These figures showcase the algorithm's efficiency in quickly adapting to ensure optimal energy conversion.

Figures 5(b) and 7(b) illustrate the impact of the change in load on the system by showing an increase in load voltage and a decrease in load current. This sensitivity analysis provides valuable insights into how the system responds to external factors, contributing to a better understanding of its robustness and adaptability.
Despite variations induced by the load, Figure 6(b) reveals that the load power remains remarkably stable. This stability is a crucial indicator of the algorithm's proficiency in swiftly adjusting system parameters to accommodate fluctuating load conditions. It suggests that the algorithm can maintain a consistent power output level even in the face of abrupt changes in load. The overall outcomes underscore the algorithm's rapid response and unwavering stability. These characteristics ensure photovoltaic systems' reliable and efficient operation, particularly in dynamic and unpredictable environments. The Hybrid PSO-ANN MPPT algorithm effectively addresses challenges associated with varying load conditions. The demonstrated efficiency, adaptability, and stability suggest its potential for practical applications in enhancing the performance of photovoltaic systems.

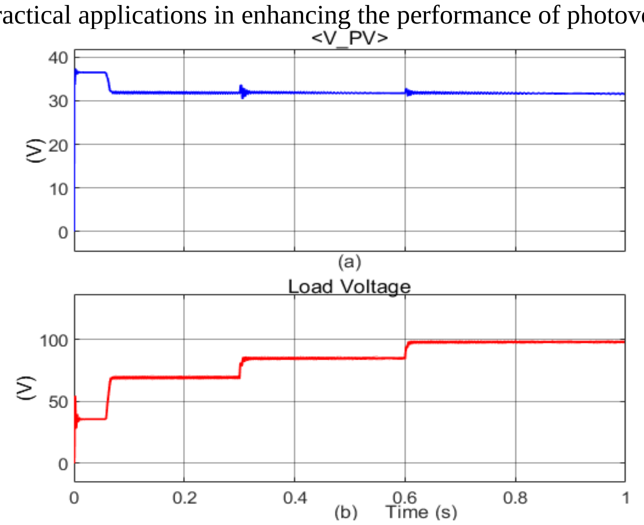

Figure 5. PV voltage and load voltage under changing load conditions.

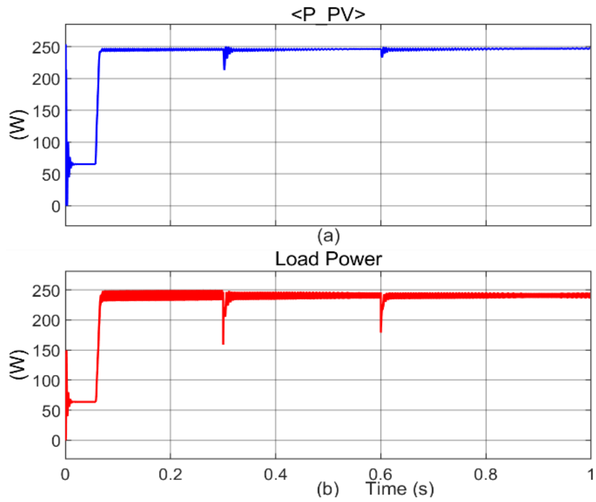

Figure 6. PV current and load current under changing load conditions.

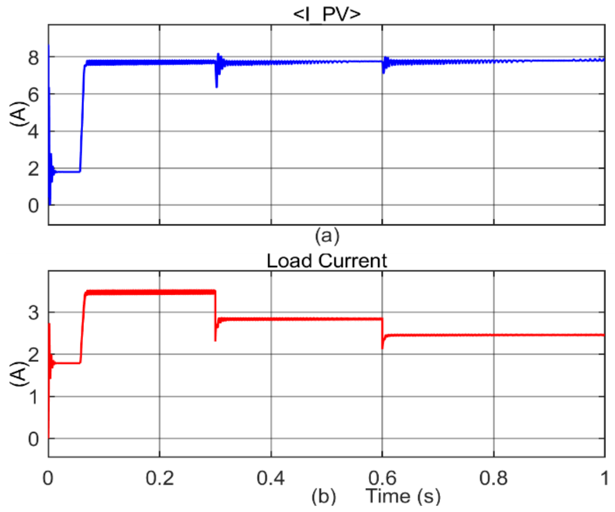

Figure 7. PV power and load power under changing load conditions.

IV.2. Keep The Load Steady

The results of the Hybrid Particle Swarm Optimization-Artificial Neural Network (PSO-ANN) Maximum Power Point Tracking (MPPT) algorithm, demonstrated in the described scenario, shed light on its effectiveness in dynamically adjusting to changing irradiance levels for enhanced photovoltaic performance. The system aims to optimize energy conversion under varying irradiance conditions, spanning from 1000 W/m² down to 200 W/m² at intervals of 0.2 seconds while maintaining a constant temperature of 25 degrees Celsius. Figures 8(a), 9(a), and 10(a) showcase the algorithm's ability to rapidly adapt to shifting irradiance levels, with optimal voltage, current, and power outputs evolving in line with changing solar radiation. Figures 9(a) and 10(a) reveal a direct correlation between solar cell current, power output, and irradiance. As a result of diminished radiation, there has been a decrease in the flow of electric current and a decline in power. Impressively, despite these variations, the system exhibits prompt response dynamics. Figures 8(b), 9(b), and 10(b) offer insight into the applied load's behavior, underscoring its direct link to cell current and energy. Reductions in radiation levels prompt parallel decreases in load voltage, current, and power, consistent with the cell's behavior. These results underscore the algorithm's robust adaptability and stability, even in the face of rapid shifts in irradiance levels. This adaptive capability reinforces its potential to enhance photovoltaic system performance across various environmental conditions, ultimately contributing to more efficient and reliable solar energy utilization.

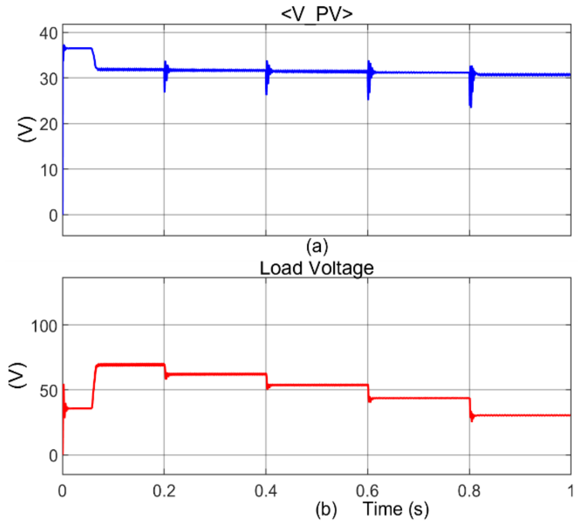

Figure 8. PV module voltage and load voltage under varying radiation.

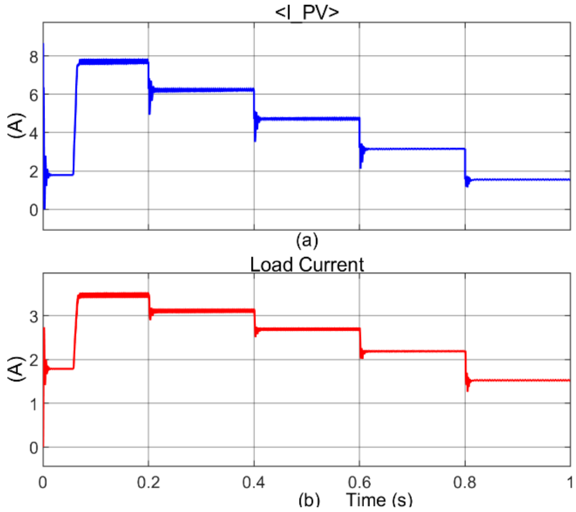

Figure 9. PV module current and load current under varying radiation.

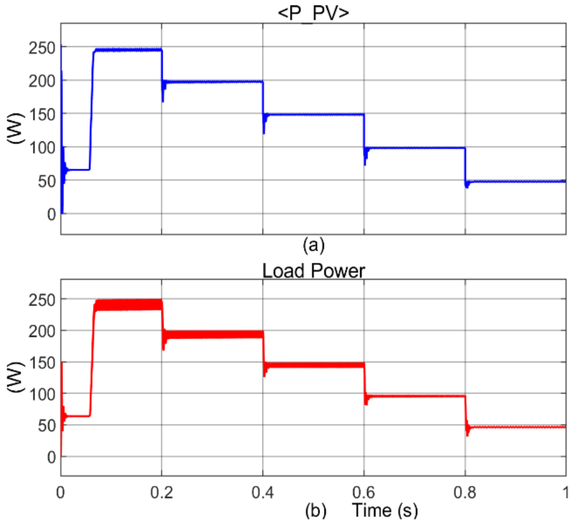

Figure 10. PV power and load power under varying radiation.

V. Conclusion

This research presents an innovative approach to enhance the efficiency of solar energy harvesting. The study introduces a method that combines the Particle Swarm Optimization (PSO) algorithm and Artificial Neural Networks (ANNs) to improve Maximum Power Point Tracking (MPPT) in photovoltaic arrays. By synergizing PSO's optimization capabilities with ANNs' predictive strengths, the proposed algorithm dynamically adjusts the array's operating point to maximize power output under varying environmental conditions. The hybrid approach demonstrates superior accuracy and adaptability compared to conventional MPPT methods, leading to optimized energy extraction from photovoltaic arrays. The results reinforce the algorithm's potential to enhance overall photovoltaic system performance. Its ability to adapt to varying conditions, track the maximum power point, and maintain stability in load power positions it as a promising tool for improving the efficiency and reliability of solar energy utilization.

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