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Hybrid ANN-PSO MPPT with high-gain boost converter for standalone photovoltaic systems

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ABSTRACT

Standalone photovoltaic (SPV) systems play a critical role in delivering clean energy to remote areas; however, maintaining consistent maximum power point tracking (MPPT) under dynamic environmental conditions remains a significant challenge. This paper proposes a hybrid artificial neural network–particle swarm optimization (ANN-PSO) based MPPT algorithm, integrated with a high-gain boost converter (HGBC), to overcome these limitations. The hybrid approach leverages the predictive capacity of ANN and the global optimization strength of PSO to achieve accurate and rapid tracking of the maximum power point under fluctuating irradiance. In addition, the high-gain converter improves voltage amplification and reduces power losses, improving overall system efficiency. The simulation results in MATLAB/Simulink confirm that the proposed system achieves a 99.7% tracking efficiency, faster convergence than conventional MPPT techniques, and significantly reduced power ripple. These results indicate that the proposed strategy can improve energy harvesting and operational stability in SPV applications. In addition, it offers a scalable and cost-effective solution suitable for off-grid electrification, particularly in rural and underdeveloped regions, contributing to global renewable energy goals.

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1. INTRODUCTION

Standalone photovoltaic systems (SPV) play a crucial role in providing clean and reliable energy to remote areas and off-grid applications, thus contributing significantly to global sustainable energy initiatives [1]. By reducing reliance on fossil fuel-based generators, SPV systems reduce carbon emissions and promote energy independence [2]. However, their performance is highly sensitive to the variability of solar irradiance and temperature [3], making efficient maximum power point tracking (MPPT) strategies essential to maximize energy extraction [4].

Traditional MPPT techniques, such as perturb and observe (P&O) [5] and incremental conductance (INC) [6], have gained widespread adoption due to their simplicity and low implementation cost [7]. P&O operates by perturbing the operating point and observing the change in output power [8], while INC estimates the MPP by analyzing the slope of the power-voltage curve [9]. Despite their ease of implementation, these algorithms often suffer from slow convergence, oscillations around the MPP, and poor tracking performance under rapidly changing environmental conditions, particularly under partial shading [10].

To overcome these limitations, artificial intelligence (AI)-based MPPT techniques have been explored [11]. Artificial neural networks (ANN) have demonstrated the ability to model the non-linear behavior of photovoltaic (PV) arrays, offering rapid adaptation to dynamic irradiance conditions [12]. However, ANN methods can be computationally intensive and depend on extensive training datasets for optimal performance [13]. Particle swarm optimization (PSO), inspired by the social behavior of organisms, has also been applied to MPPT because of its robustness against local minima and fast convergence properties [14]. However, PSO is sensitive to parameter tuning and can exhibit suboptimal behavior without proper calibration [15].

Recent advances have led to the development of hybrid MPPT strategies that combine the strengths of multiple techniques to enhance tracking performance [16]. Hybrid approaches such as ANN-P&O [17] and PSO-INC [18] integrate AI adaptability with conventional algorithmic simplicity, improving both convergence speed and stability. Furthermore, hybrid AI-based algorithms such as ANN-GA [19] and fuzzy-PSO [20] have been proposed, offering promising results in terms of global search capability and tracking accuracy. However, these methods often face challenges related to computational overhead and parameter optimization [21].

In this context, the hybrid ANN-PSO technique has emerged as a compelling solution that takes advantage of ANN's learning capabilities for the initial prediction of the reference voltage and utilizing PSO for the real-time optimization of the network parameters [22]. This synergy enables faster and more accurate convergence to the MPP under fluctuating environmental conditions while maintaining computational efficiency [23].

Beyond MPPT strategies, the choice of DC-DC converter topology is equally critical in enhancing the performance of the SPV system. Conventional boost converters (BC), though simple and cost-effective, are limited by their voltage gain, particularly at high duty cycles, resulting in increased conduction losses and reduced efficiency [24]. High-gain boost converter (HGBC) architectures, such as cascaded converters [25], switched capacitor designs [26], and coupled inductor configurations [27], have been introduced to address these challenges by offering superior voltage conversion ratios and reduced switching stresses.

Furthermore, advanced topologies such as quasi-Z source converters [28], interleaved BC [29], and switched-inductor BC [30] have been explored for PV applications, focusing on improving system efficiency and dynamic response. However, many of these designs increase the complexity of the circuit, requiring multiple active switches and sophisticated control schemes.

This paper proposes a novel standalone SPV system that integrates a hybrid ANN-PSO MPPT controller with a transformer-less HGBC topology. The proposed approach leverages the real-time adaptability of ANN, the global optimization capability of PSO, and the high voltage gain efficiency of the HGBC to enhance the overall performance of SPV systems under dynamic environmental conditions.

2. SYSTEM CONFIGURATION

The architecture of the proposed SPV system is illustrated in Figure 1. It integrates a PV array, a HGBC, and a hybrid ANN-PSO MPPT controller. Unlike traditional BC topologies, HGBCs minimize voltage limitations while improving overall system efficiency [31]. The MPPT controller, central to adaptive system control, combines the learning capability of ANN with the global optimization strengths of PSO to achieve rapid and precise MPP tracking under dynamic environmental conditions. The following subsections describe each component in detail.

2.1. Solar photovoltaic array

The PV system serves as the primary energy source, converting solar irradiance into direct current (DC) electrical power [32]. A JKM275PP-60 solar PV module is used, with its specifications summarized in Table 1. This module delivers a maximum power output of 275 W, with a corresponding voltage of 32.0 V and current of 8.61 A under standard test conditions (STC). The nonlinear relationship between current, voltage, and power is depicted in the P-V and I-V characteristic curves shown in Figures 2(a) and (b). The output voltage and current are continuously monitored and used as inputs to the hybrid ANN-PSO MPPT controller to enable real-time tracking of the MPP under varying environmental conditions.

2.2. High-gain DC-DC boost converter

To increase the low output voltage of the PV array and meet the higher voltage requirements of the downstream components, a DC-DC boost stage is necessary. Conventional BCs are simple and cost-effective, but suffer significant efficiency losses in high duty cycles, where voltage stress and conduction losses become pronounced [33].

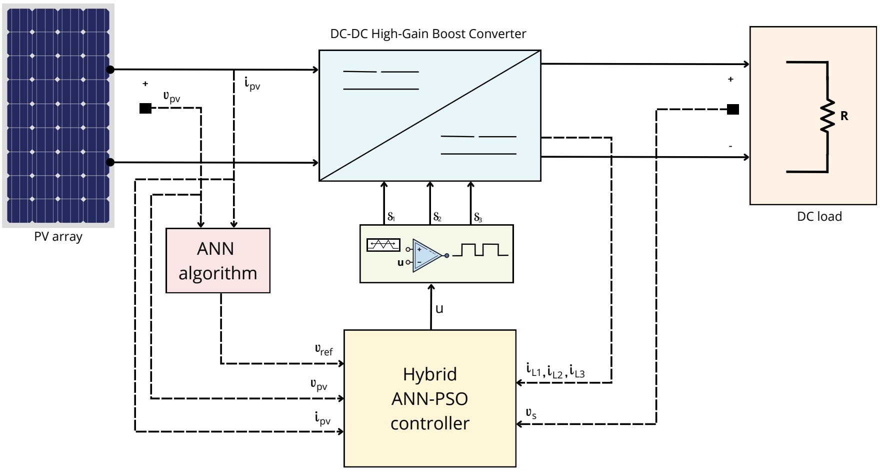
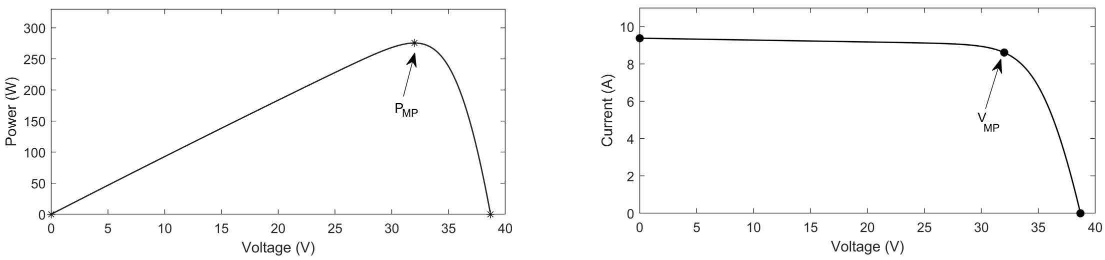


Figure 1. Synoptic diagram of the proposed SPV system

Table 1. Specifications of the JKM275PP-60 solar PV module

Parameter	P_{max}	V_{mp}	I_{mp}	V_{oc}	I_{sc}
Value	275 W	32.0 V	8.61 A	38.7 V	9.38 A



(a) (b)

Figure 2. Characteristic curves of the JKM275PP-60 PV module at STC; (a) P-V and (b) I-V

To address these limitations, the system adopts a transformerless HGBC topology, illustrated in Figure 3. This converter uses three inductors, two diodes, and two capacitors to achieve higher voltage amplification with reduced component stress [34].

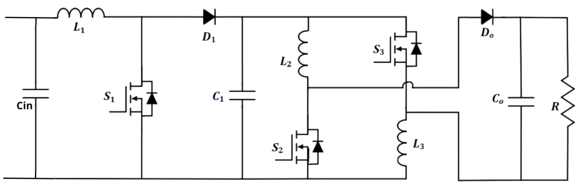


Figure 3. Circuit diagram of the proposed HGBC

The voltage gain M of the HGBC is described by (1):

$$M = \frac{1+D}{(1-D)^2} \tag{1}$$

where D is the duty cycle. This quadratic dependency enables significantly higher voltage gains compared to conventional BCs, especially at elevated duty cycles. In addition, the HGBC distributes current and voltage stresses between multiple components, minimizing ripple and improving system stability.

According to Ahmed *et al.* [34], the HGBC operates in two distinct modes. In Mode 1, all switches are ON, allowing the inductors to store energy while the output capacitor supplies the load. In Mode 2, all switches are OFF, and the inductors discharge their stored energy to recharge the output capacitor and sustain the load. The duty cycle is dynamically adjusted by the MPPT controller to maximize energy harvesting.

The performance comparison among various DC-DC converter topologies is presented in Table 2 and the corresponding boost factors are illustrated in Figure 4. The proposed HGBC achieves superior voltage amplification with a moderate number of components. In contrast, other topologies often introduce higher circuit complexity, require multiple active switches, or suffer from increased conduction losses. Consequently, the HGBC offers an advantageous trade-off between high voltage gain, reduced system complexity, and improved overall efficiency, making it well-suited for SPV applications.

Table 2. Performance comparison of various converter topologies

Converter topology	Voltage gain	Switches	Diodes	Inductors	Capacitors
Conventional BC	$\frac{1}{1-D}$	1	1	1	1
Converter in [35]	$\frac{1+D}{1-D}$	1	1	2	3
Converter in [36]	$\frac{1+D}{1-D}$	2	3	2	4
Converter in [37]	$\frac{2-D}{1-D}$	1	2	1	2
Converter in [38]	$\frac{1+3D}{1-D}$	1	3	4	4
Proposed HGBC	$\frac{1+D}{(1-D)^2}$	3	2	3	2

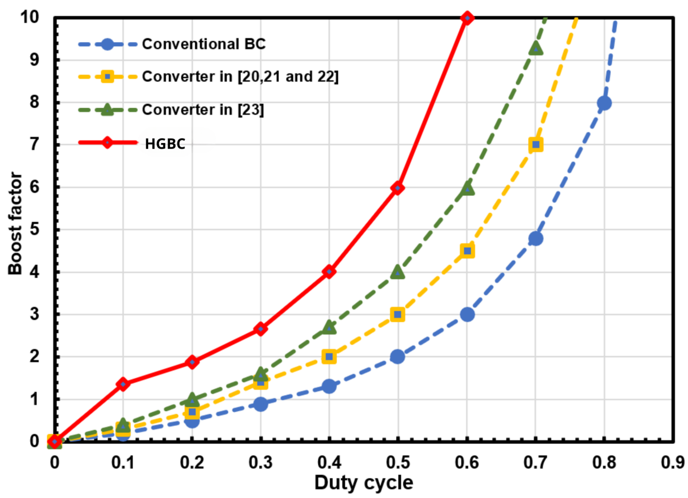


Figure 4. Boost factors for different DC-DC converter topologies

2.3. Hybrid artificial neural network–particle swarm optimization maximum power point tracking controller

The hybrid ANN-PSO MPPT controller is designed to maximize energy extraction by adaptively tracking the MPP of the PV array under variable environmental conditions. Conventional MPPT techniques, such as P&O and INC, often suffer from oscillations and slow convergence, particularly under rapidly changing irradiance levels [39]. To address these limitations, the proposed controller combines the predictive capabilities of ANN with the global optimization capabilities of PSO.

Figure 5 illustrates the architecture of the hybrid ANN-PSO MPPT system where the ANN predicts the optimal reference voltage (V_{ref}) based on real-time measurements of PV voltage (V_{PV}) and current (I_{PV}). The predicted V_{ref} is then fine-tuned by the PSO algorithm to ensure precise tracking of the MPP.

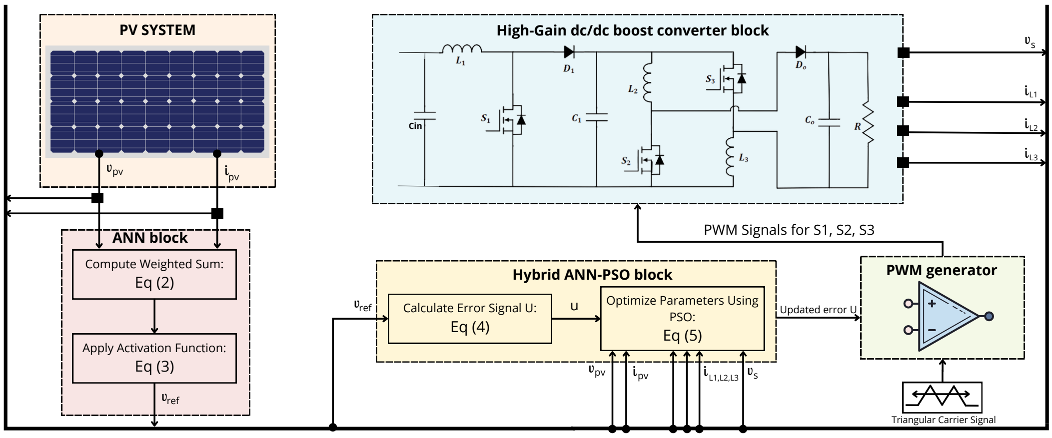


Figure 5. Synoptic diagram of the hybrid ANN-PSO MPPT controller

The ANN adopts a multilayer perceptron (MLP) structure comprising two input neurons (for V_{PV} and I_{PV}), one hidden layer with ten neurons, and one output neuron providing V_{ref}. A sigmoid activation function is employed for the hidden layer to capture the nonlinear relationship between input variables and the optimal operating point.

The ANN was trained offline using a supervised learning approach. A synthetic data set consisting of 5,000 samples was generated from the PV model under varying irradiance levels (200 W/m^2 to 1000 W/m^2) and temperature ranges (15 °C to 45 °C). The mean squared error (MSE) was utilized as the loss function, and weight updates were performed using the backpropagation algorithm with a learning rate of 0.01. The convergence behavior during training is shown in Figure 6, where the MSE decreases significantly after approximately 150 epochs, indicating effective learning and generalization.

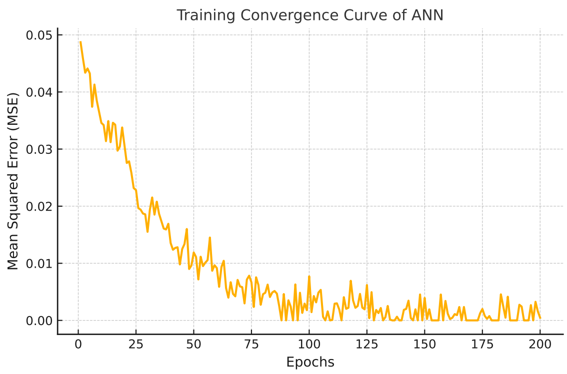


Figure 6. Training convergence curve of the ANN (MSE vs. epochs)

In parallel, the PSO algorithm optimizes the ANN's weights and biases in real time during system operation. Each particle in the swarm represents a candidate solution in the search space, characterized by its position (x_i) and velocity (v_i). These parameters are updated iteratively as (2) and (3):

$$v_i(t+1) = w \cdot v_i(t) + c_1 r_1 (pbest_i - x_i(t)) + c_2 r_2 (gbest - x_i(t)) \tag{2}$$

$$x_i(t+1) = x_i(t) + v_i(t+1) \tag{3}$$

where $w = 0.7$ is the inertia weight, $c_1 = c_2 = 1.5$ are the cognitive and social coefficients, respectively, and r_1, r_2 are random numbers uniformly distributed between 0 and 1. A swarm size of 20 particles was selected to balance convergence speed and computational load, with the optimization process typically converging within 50 iterations.

The error signal (U) used for PWM generation is calculated as (4):

$$U = V_{\text{ref}} - V_{\text{PV}} \tag{4}$$

the PWM signals generated on the basis of U control the switching of the HGB, ensuring that the operating point remains at the MPP.

To ensure real-world deployability, the computational complexity of the hybrid ANN-PSO controller was evaluated. The low dimensionality of the ANN (two inputs, one hidden layer) combined with the moderate number of PSO particles ensures that the controller can be implemented on mid-range microcontrollers, such as the STM32 series, without significant processing delays or memory bottlenecks.

In summary, by integrating ANN-based prediction and PSO-based optimization, the proposed hybrid controller achieves superior tracking performance characterized by fast convergence, reduced steady-state oscillations, and high tracking efficiency, making it well-suited for dynamic PV environments.

3. RESULTS AND DISCUSSION

The performance of the proposed SPV system, which integrates a HGBC and a hybrid ANN-PSO MPPT controller, was evaluated through detailed simulations in the MATLAB/Simulink environment. A dynamic irradiance profile, illustrated in Figure 7, was applied while maintaining a constant ambient temperature of 25 °C. The objective is to validate the dynamic tracking capability, voltage regulation, and overall energy extraction efficiency of the system under realistic and rapidly changing environmental conditions. The HGBC specifications, selected to ensure stable and efficient operation in a wide input range, are summarized in Table 3.

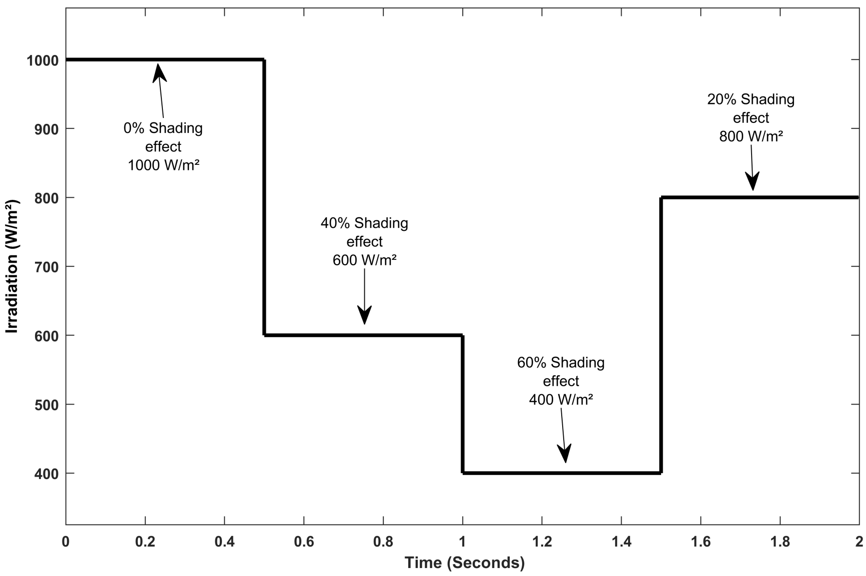


Figure 7. Dynamic irradiance profile simulating real-world shading scenarios for MPPT evaluation

Table 3. Specifications of the HGBC for stable and efficient operation

Component	Value	Description
Inductors L_1, L_2, L_3	3 mH	Input inductors
Input capacitor C_{in}	260 μF	Smoothing capacitor
Parallel capacitor C_1	260 μF	Filtering capacitor
Output capacitor C_0	260 μF	Stabilizing capacitor
Switching frequency	25 kHz	Operating frequency

The dynamic irradiance profile involved abrupt transitions between 1000 W/m^2, 600 W/m^2, 400 W/m^2, and 800 W/m^2, emulating realistic shading effects and challenging the MPPT controller's tracking speed and stability. A resistive DC load was employed to ensure consistent operating conditions across all irradiance levels, enabling isolated analysis of the MPPT strategy's performance.

The voltage regulation and boosting capability of the HGBC under different MPPT techniques were first evaluated. As shown in Figure 8, the hybrid ANN-PSO controller achieved an output voltage of 234.3 V, corresponding to a boost factor of approximately 7.32. Standalone ANN and P&O controllers achieved output voltages of 228.1 V and 223.4 V, respectively. The higher voltage gain achieved by the hybrid controller can be attributed to its ability to maintain the system precisely at the MPP, thus optimizing the duty cycle for maximum voltage amplification, while conventional methods suffered from oscillations and slower adaptation.

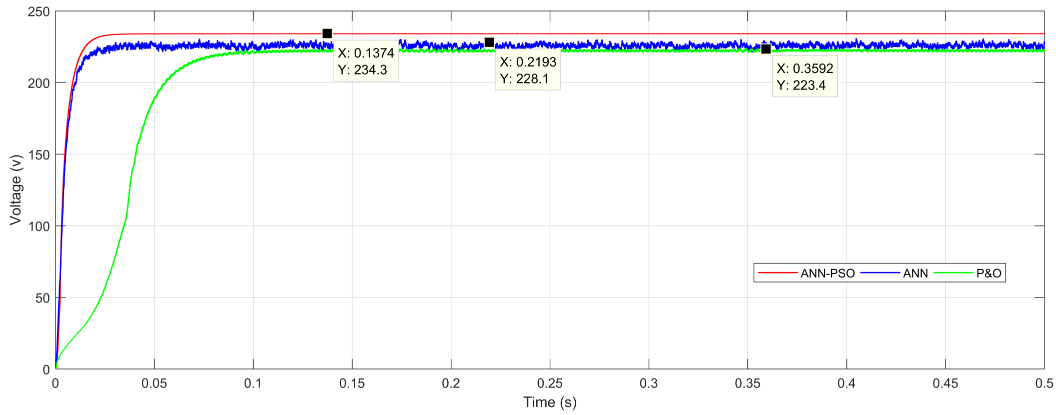


Figure 8. Output voltage of the HGBC using different MPPT techniques

The output power profiles under the dynamic irradiance profile are depicted in Figure 9. It can be observed that the hybrid ANN-PSO controller consistently achieved higher output power and faster response times during irradiance transitions compared to conventional ANN and P&O. This superior performance is attributed to the hybridization mechanism, where the ANN predicts near-optimal reference voltages while the PSO fine-tunes these estimates in real-time, leading to faster and more robust MPP convergence.

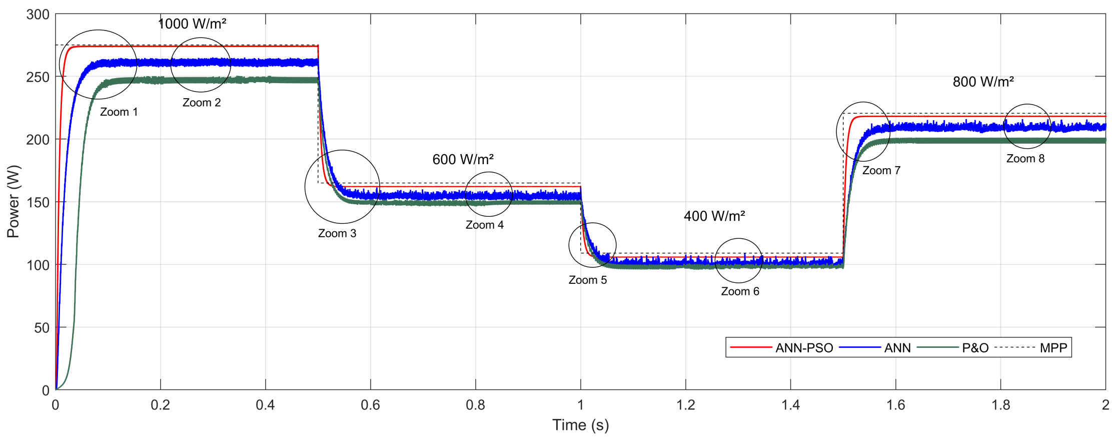


Figure 9. Output power of the HGBC under varying irradiance levels for different MPPT techniques

A detailed transient and steady-state analysis further reinforces these observations. At 1000 W/m^2, as illustrated in Figure 10, the hybrid ANN-PSO reached the MPP within 39.95 ms, outperforming the standalone ANN (80.1 ms) and P&O (119.6 ms). In steady-state conditions (Figure 11), it maintained minimal power ripple of 0.6 W, corresponding to only 0.2% of the output power, compared to 5 W for ANN and 3.7 W for P&O. These results indicate that the hybrid ANN-PSO significantly enhances transient response and reduces steady-state oscillations, directly improving energy capture during both stable and disturbed conditions.

Similarly, when irradiance dropped to 600 W/m^2, the hybrid controller adjusted to the new MPP within 47.2 ms (Figure 12), compared to 81.8 ms for ANN and 85.7 ms for P&O. The ripple analysis in Figure 13 again confirmed lower ripple for the hybrid method (0.5 W) compared to ANN (4.3 W) and P&O (3.9 W).

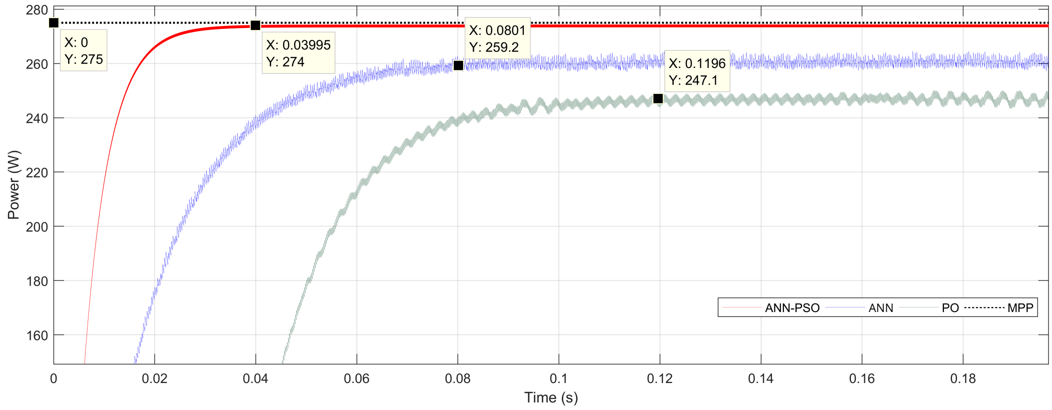


Figure 10. Transient performance of the MPPT controllers at 1000 W/m^2

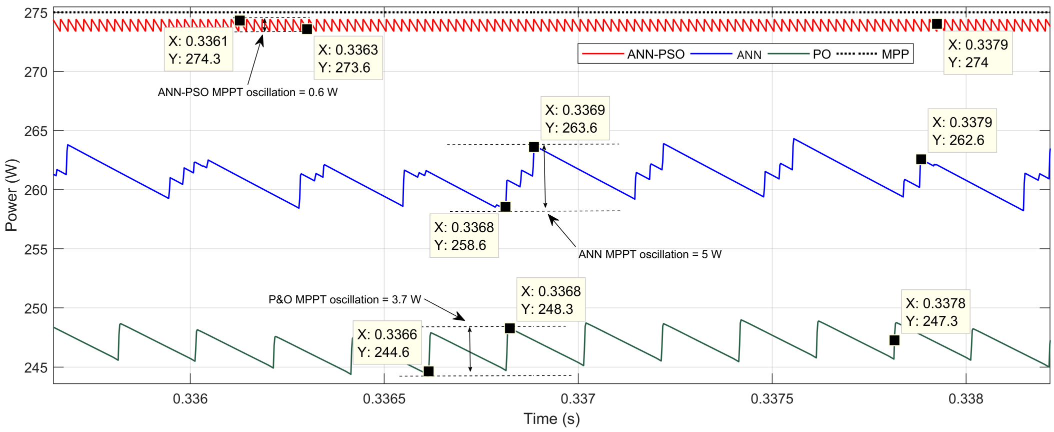


Figure 11. Steady-state performance of the MPPT controllers at 1000 W/m^2

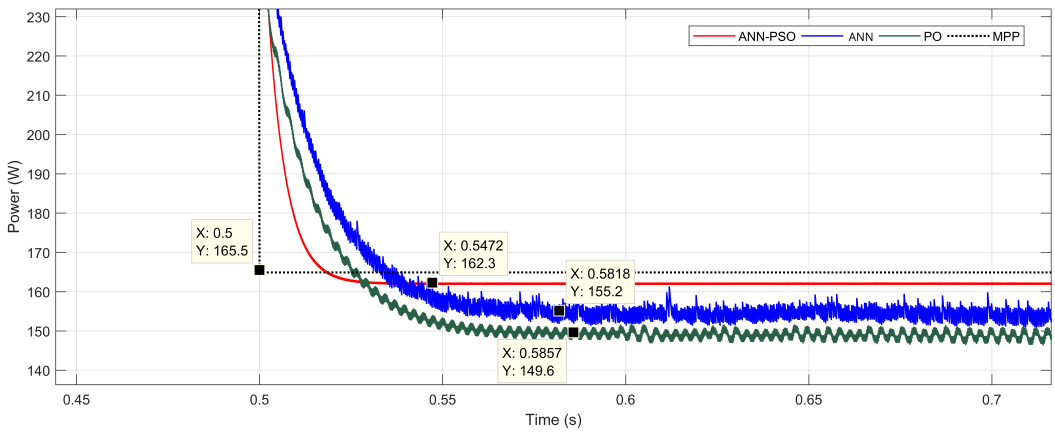


Figure 12. Transition response of the MPPT controllers at 600 W/m^2

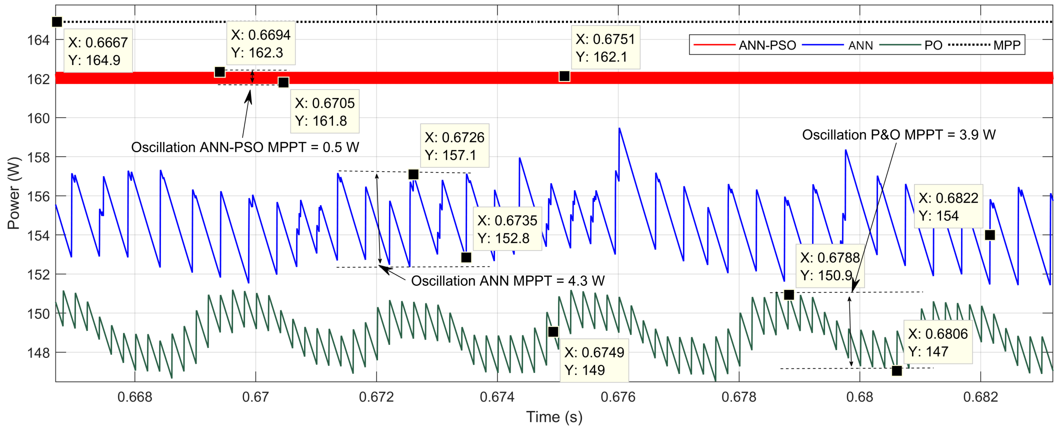


Figure 13. Ripple analysis at steady state for 600 W/m^2

At lower irradiance levels (400 W/m^2), the hybrid controller stabilized at the new MPP within 39 ms (Figure 14), achieving a minimal ripple of 0.2 W (Figure 15), far outperforming both comparison methods. Finally, during a sudden irradiance increase to 800 W/m^2, the hybrid controller adapted in 40 ms with minimal ripple (0.6 W), as illustrated in Figures 16 and 17, outperforming ANN and P&O once again.

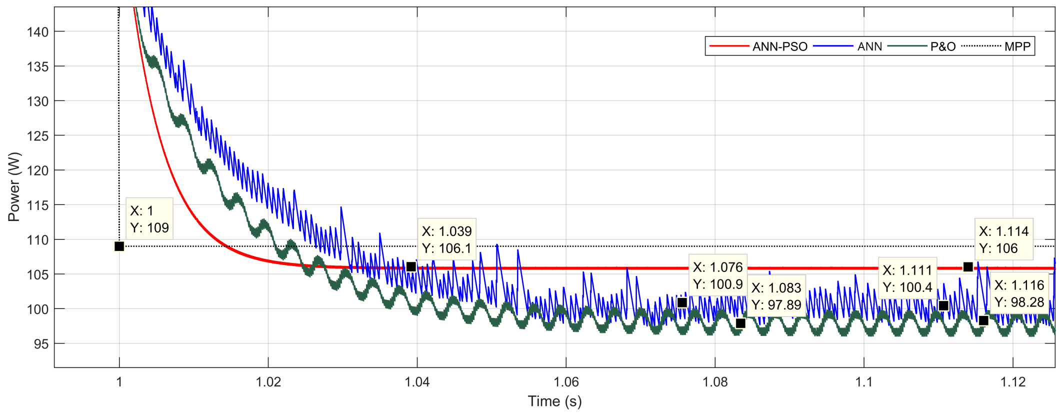


Figure 14. Controller adaptation during irradiance decrease to 400 W/m^2

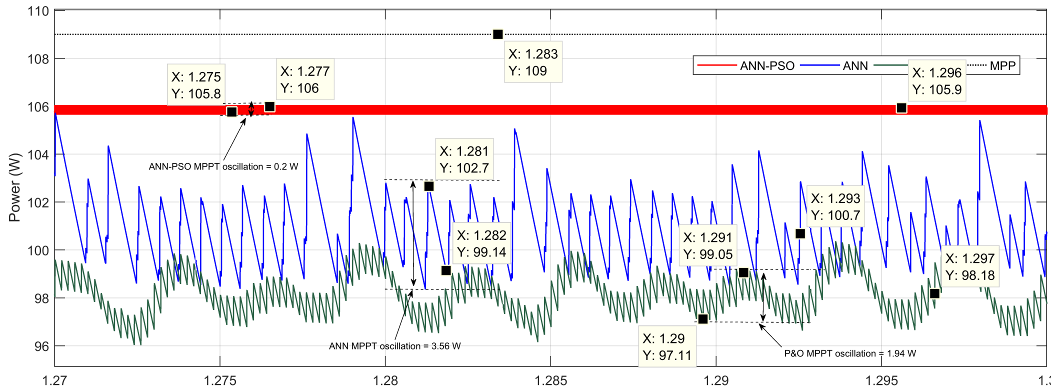


Figure 15. Steady-state power tracking for 400 W/m^2

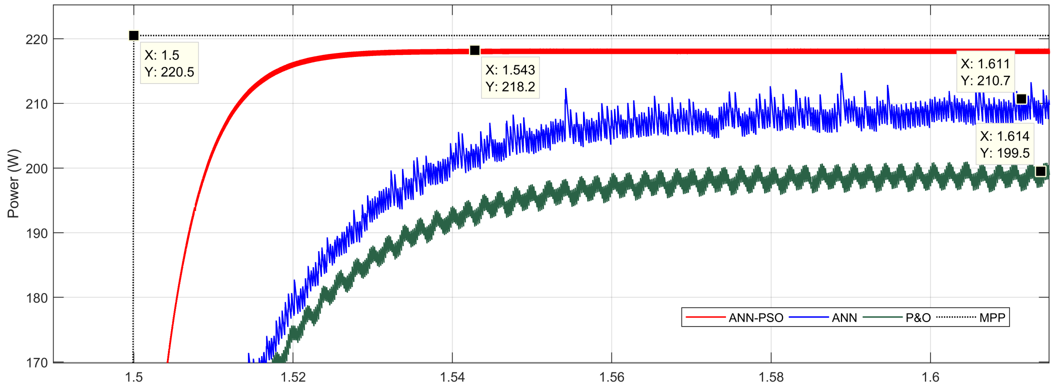


Figure 16. Transient response during irradiance increase to 800 W/m^2

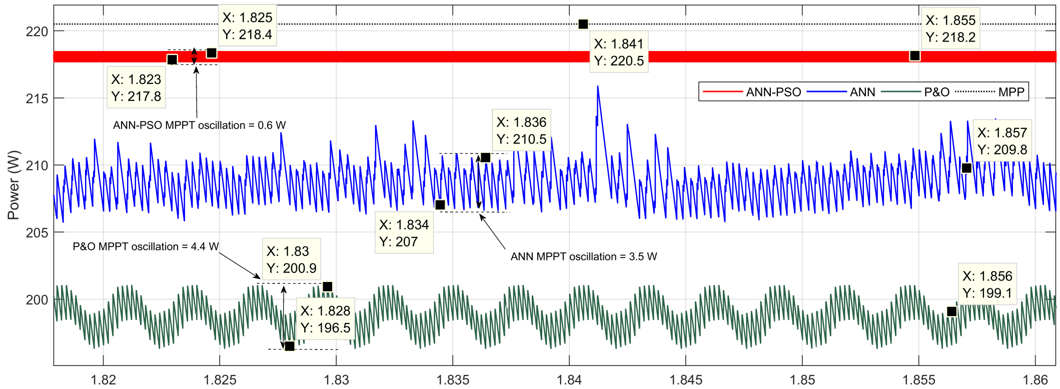


Figure 17. Steady-state performance for 800 W/m^2 irradiance

The cumulative efficiency performance is summarized in Table 4, showing that the hybrid ANN-PSO consistently achieved the highest energy extraction efficiencies across all conditions, exceeding 97% even at low irradiance levels. This improved efficiency directly translates into higher daily energy yields, improved financial return, and greater system resilience to partial shading and environmental variability.

Table 4. Summary of MPPT controller performance across irradiance levels

Controller	Efficiency at 1000 W/m^2	Efficiency at 800 W/m^2	Efficiency at 600 W/m^2	Efficiency at 400 W/m^2
P&O	90.3%	91.2%	91.1%	90.8%
ANN	95.9%	95.5%	95.0%	94.3%
Hybrid ANN-PSO	99.7%	99.0%	98.0%	97.2%

To further contextualize the effectiveness of the proposed hybrid ANN-PSO MPPT approach, it is noteworthy to compare it with other hybrid AI-based methods reported in the literature. Approaches such as ANN-GA [19] and fuzzy-PSO [20] have demonstrated improvements over conventional MPPT techniques, but often suffer from higher computational complexity, slower convergence, or less stable steady-state performance. For instance, ANN-GA methods require extensive tuning of genetic parameters and exhibit longer adaptation times, while fuzzy-PSO systems, although flexible, may introduce oscillatory behavior under rapid irradiance changes. In contrast, the ANN-PSO method presented in this work achieves both rapid convergence and low ripple with a relatively lightweight computational structure, making it more suitable for real-time embedded deployment in dynamic PV environments.

4. CONCLUSION

This paper proposed a SPV system that integrates a HGBC with a hybrid ANN-PSO-based MPPT controller. Simulation results demonstrated that the proposed hybrid approach consistently outperforms conventional standalone ANN and P&O methods by achieving faster convergence, lower steady-state ripple, and tracking efficiencies exceeding 97% across dynamic irradiance scenarios. The incorporation of the HGBC further enhanced system performance by enabling higher voltage gains and improved voltage stability.

The study confirms that combining predictive learning models with real-time optimization significantly improves SPV system adaptability and energy harvesting under fluctuating environmental conditions. However, real-time hardware implementation may introduce constraints related to processing delays, memory usage, and sampling accuracy, especially when deployed on low-cost embedded platforms. These challenges necessitate further algorithmic optimization and efficient coding practices to ensure practical deployment. Future work will address these implementation barriers.

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AUTHOR CONTRIBUTIONS STATEMENT

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Mohcine Byar	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓		✓	✓
Ghizlane Chbirik						✓				✓				
Abdennabi Brahmi						✓				✓				
Abdelouahed Abounada	✓	✓		✓			✓			✓	✓	✓	✓	

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 supporting the findings of this study are available from the corresponding author, M.B., upon reasonable request.

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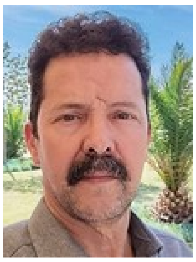

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