A PSO-Enhanced Neural Network Framework for Robust Maximum Power Point Prediction in Solar PV Arrays

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Abstract— **This paper introduces a hybrid Artificial Neural Network (ANN)–Particle Swarm Optimization (PSO) framework for accurate Maximum Power Point Tracking (MPPT) in photovoltaic (PV) systems. While conventional ANN-based controllers often struggle with weight initialization and architectural tuning under dynamic weather conditions, the proposed approach employs PSO to optimize both network topology and initial parameters, thereby improving convergence and prediction reliability. The hybrid design mitigates common issues of overfitting and slow learning, achieving a balanced trade-off between computational cost and tracking accuracy. The framework is validated in MATLAB/Simulink using real-world PV datasets recorded under diverse climatic conditions, including clear and partially cloudy skies. Comparative analysis against established MPPT strategies—Perturb and Observe (P&O), Fuzzy Logic Controllers (FLC), and standard ANN methods—demonstrates superior performance of the PSO-enhanced ANN, with faster convergence, improved stability, and higher robustness. Experimental results indicate average tracking efficiencies of 99.6% in stable irradiance and 99.3% under variable shading, highlighting its capability to maximize energy yield in grid-connected PV systems. The study concludes that integrating swarm intelligence with ANN provides a scalable and adaptable MPPT solution, with future scope in large-scale solar farms and inclusion of additional environmental predictors for further accuracy enhancement.**

Index Terms— **Artificial neural network (ANN), Solar Photovoltaic (PV), Maximum power point tracking (MPPT), Particle Swarm Optimization (PSO), Perturb and observe**

I. INTRODUCTION

The deployment of renewable energy sources has accelerated due to the growing global demand for energy and the negative environmental effects of fossil fuels. Solar photovoltaic (PV) technology has emerged as a leading option because of its adaptability, low operating costs, and scalability. Variations in temperature and irradiance, however, have a significant impact on PV array efficiency and, if improperly managed, can lower output by up to 25% [1,2]. Maximum Power Point Tracking (MPPT) algorithms are used to counteract this and guarantee continuous operation at the PV curve's ideal point [3,4].

The simplicity and low implementation cost of traditional MPPT methods, like Perturb and Observe (P&O) and Incremental Conductance, make them appealing . However, slow convergence, oscillations around the maximum power point, and decreased performance in rapidly changing weather conditions are common problems with these algorithms [5,6]. Artificial Neural Networks (ANN) and Fuzzy Logic Controllers (FLC) are two AI-based methods that have been studied more and more in an effort to get around these restrictions . Although FLCs are more flexible, they are susceptible to changes in the environment and the design of the membership function [7,8]. ANNs, on the other hand, are ideal for real-time MPPT control because they can learn intricate nonlinear input–output mappings without the need for explicit system models. As illustrated in Fig. 1, the performance efficiency of various MPPT methods has progressively improved from the early 1990s to the present day[9,10].

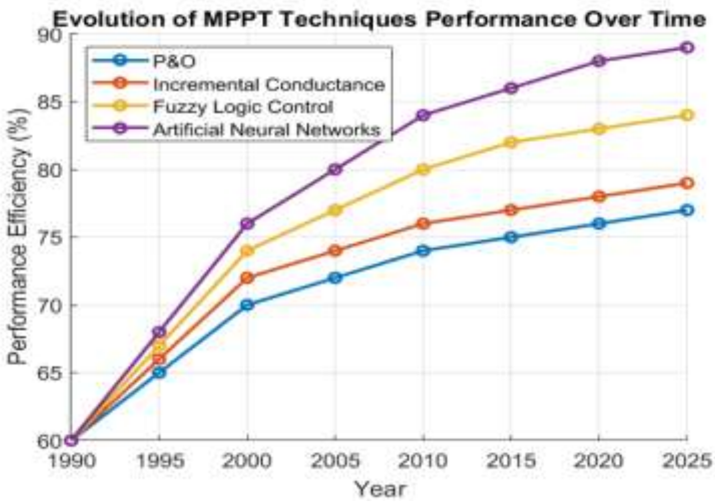

Fig. 1. Evolution of MPPT Techniques Performance Over Time.

Notwithstanding these benefits, ANN-based controllers have significant issues with weight initialization, network architecture, and training convergence that could lead to overfitting or less-than-ideal predictions . In order to adjust ANN parameters, recent research has investigated hybrid approaches that use metaheuristic optimization techniques like Genetic Algorithms (GA), Gravitational Search Algorithm (GSA), and Grey Wolf Optimizer (GWO) [11,12]. However, the high computational complexity introduced by these methods limits their applicability in real-time.

This paper suggests an ANN framework for MPPT in PV systems that is enhanced by Particle Swarm Optimization (PSO) in order to fill these gaps. By effectively exploring the ANN parameter space, the integration of PSO allows for robust weight initialization, quicker convergence, and the avoidance of local minima. MATLAB/Simulink simulations with real-world PV datasets under various temperature and irradiance conditions are used to validate the suggested approach. Significant gains in convergence speed, stability, and energy capture efficiency are shown when compared to P&O, FLC, and traditional ANN techniques. The following are this work's main contributions:

- Development of a hybrid ANN–PSO framework for robust and accurate MPPT prediction under dynamic environmental conditions.
- Systematic optimization of ANN weights and topology using PSO to achieve reduced mean squared error (MSE) and faster convergence.
- Experimental validation with real-world datasets, showing improved tracking efficiency and stability compared to conventional and AI-based MPPT methods.

II. RELATED WORK

Maximum Power Point Tracking (MPPT) is necessary to increase photovoltaic (PV) systems' efficiency because temperature and irradiance have a significant impact on the output. Because of their affordability and ease of use, traditional methods like Perturb and Observe (P&O) and Incremental Conductance are frequently used . However, under quickly changing atmospheric conditions, these methods frequently suffer from reduced accuracy, slow convergence, and oscillations around the maximum power point [13,14].

Methods based on artificial intelligence (AI) have been put forth to get around these problems. Although fuzzy logic controllers (FLCs) are more flexible and have the ability to handle non-linear situations, they are susceptible to changes in the environment and the design of the membership function . Accurate MPPT without explicit system models is made possible by Artificial Neural Networks (ANNs), which have shown exceptional ability to learn the nonlinear mapping between environmental parameters and PV output . Despite these advantages, ANN-based controllers are highly dependent on appropriate architecture design and weight initialization, which often leads to slow convergence and risk of overfitting [15,16].

MPPT design now incorporates metaheuristic optimization algorithms to overcome these constraints. To improve prediction accuracy and stability, ANN parameters have been tuned using Genetic Algorithms (GA), Gravitational Search Algorithms (GSA), and Grey Wolf Optimizer (GWO) . Particularly, Particle Swarm Optimization (PSO) has drawn interest because of its quick convergence, ability to search globally, and effectiveness in managing partial shading conditions . While parameter tuning and computational complexity continue to be issues, several studies show that PSO-based MPPT enhances dynamic response when compared to traditional algorithms [17,18].

Additionally, hybrid AI–optimization techniques have been investigated. Under variable environmental conditions, it has been demonstrated that combining PSO and ANN improves tracking efficiency and shortens convergence time . Adaptive swarm strategies and deep learning-based predictors, like transformer architectures, which achieved prediction errors as low as 0.47% with efficiency above 99.5% , are recent extensions of this line of research. These studies support the expanding significance of intelligent optimization in MPPT. All things considered, the literature shows that although traditional approaches are straightforward, they are ineffective in dynamic situations; ANN-based MPPT offers flexibility but requires meticulous training; and metaheuristic optimizations increase robustness but may add computational load. The creation of a hybrid ANN–PSO framework that methodically adjusts ANN parameters for precise, reliable, and real-time MPPT performance in PV systems is driven by these gaps.

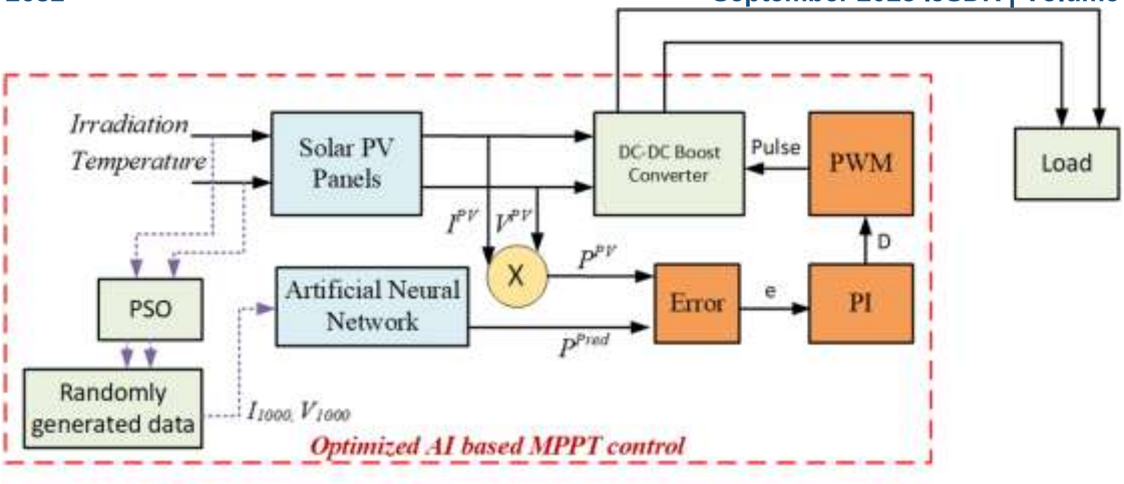

Fig. 2. Optimized AI-based MPPT Control for PV System

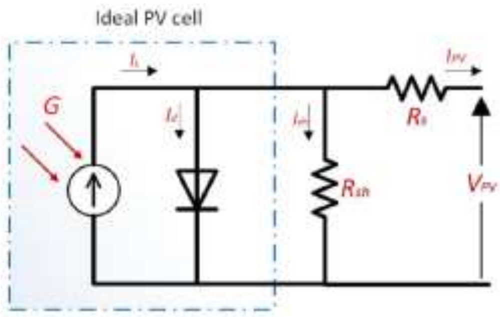

Fig. 3. Equivalent Circuit Model of a PV Cell

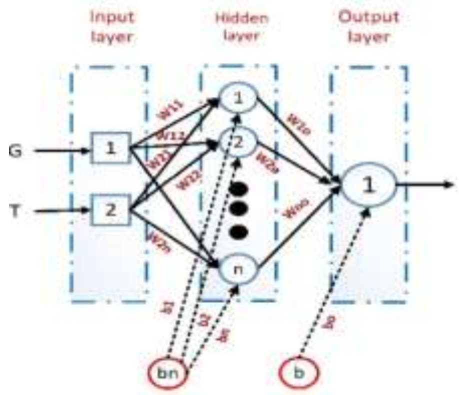

Fig. 4. Feedforward Neural Network Structure

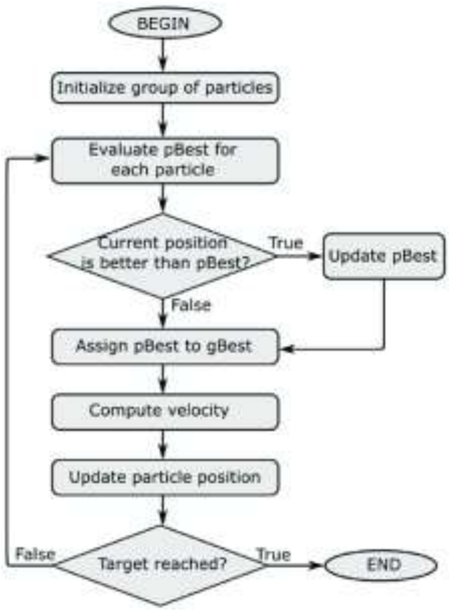

Fig. 5. Flowchart of Particle Swarm Optimization Algorithm

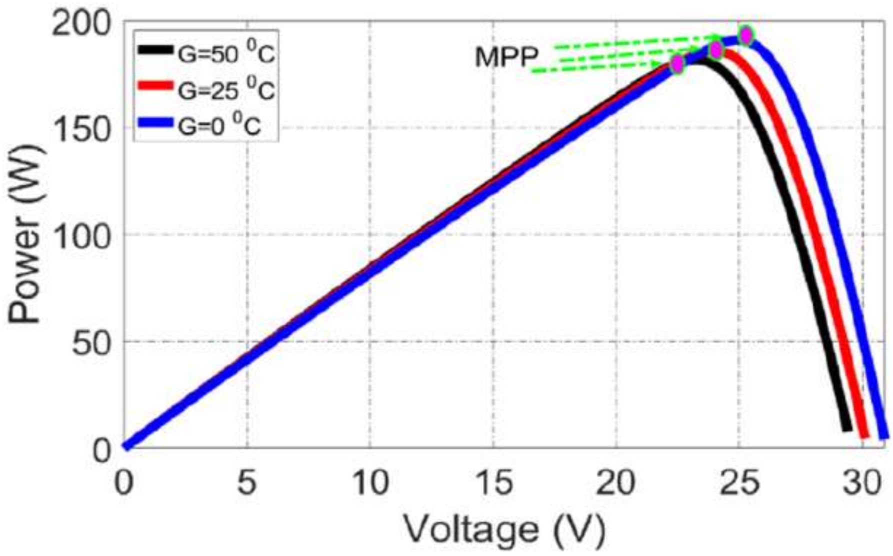

Fig. 6. P-V Characteristics at varying temperatures (G = 1000 W/m2)

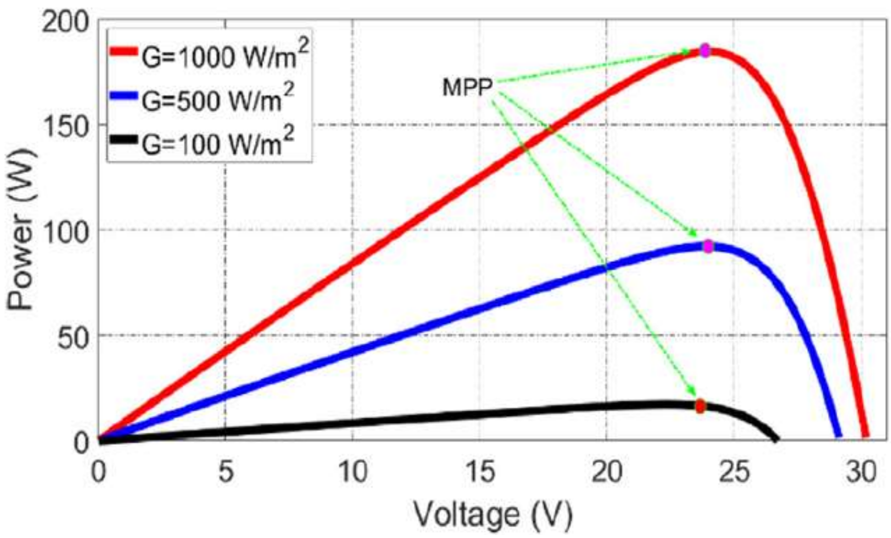

Fig. 7. P-V Characteristics at varying irradiance levels (T = 25°C)

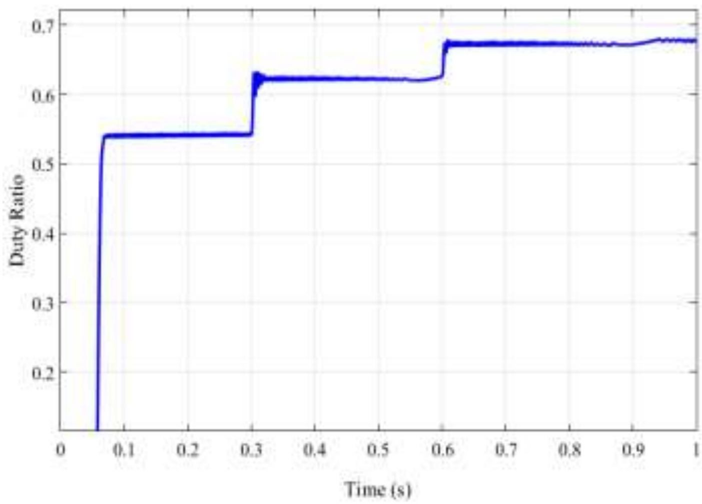

Fig. 8. Duty cycle response of the boost converter

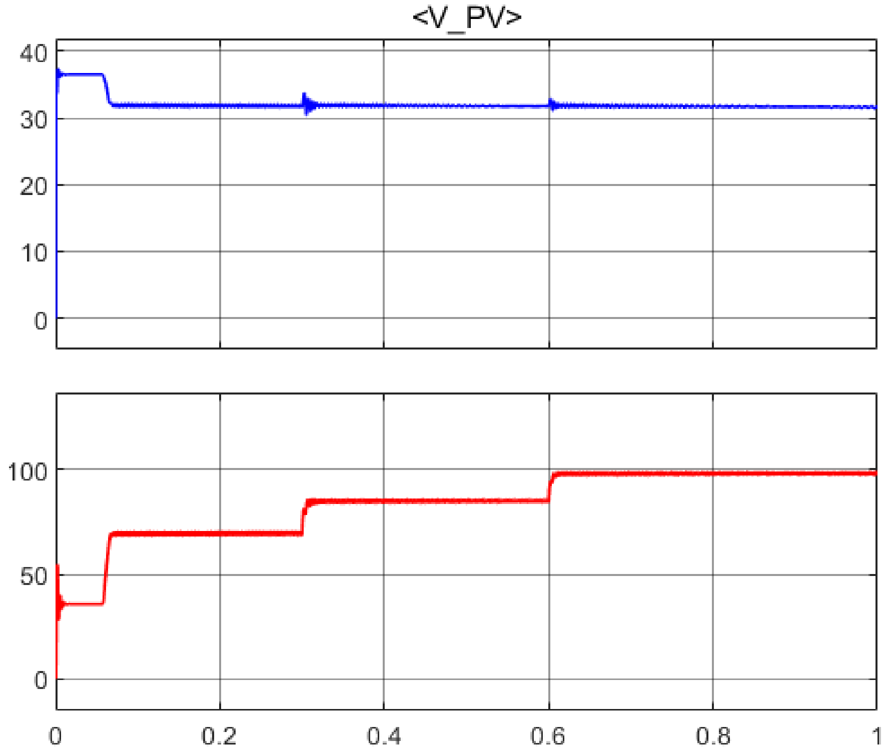

Fig. 9. PV voltage response

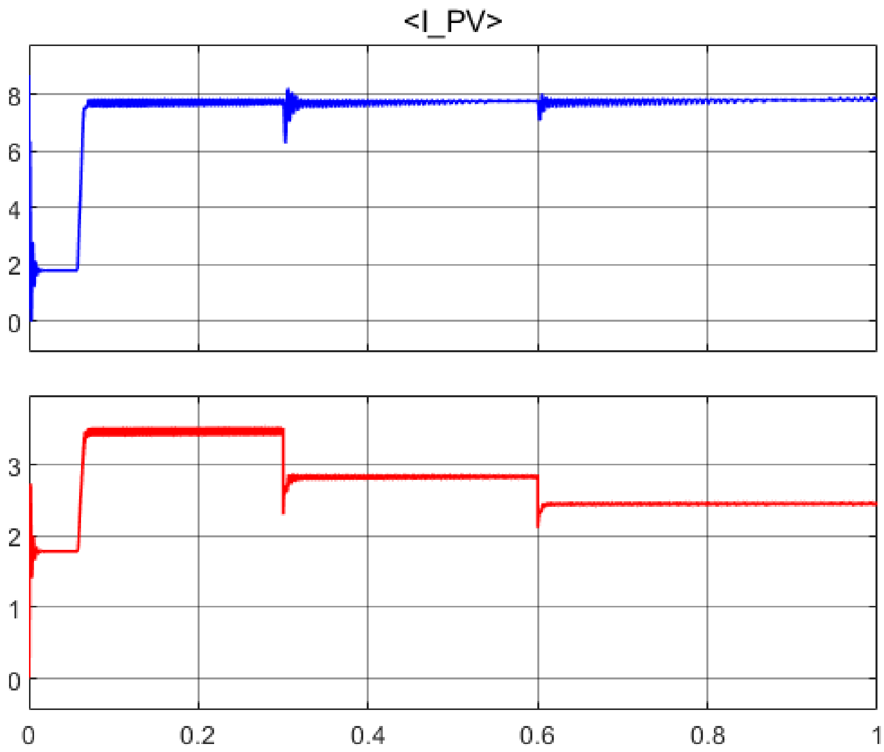

Fig. 10. PV current response

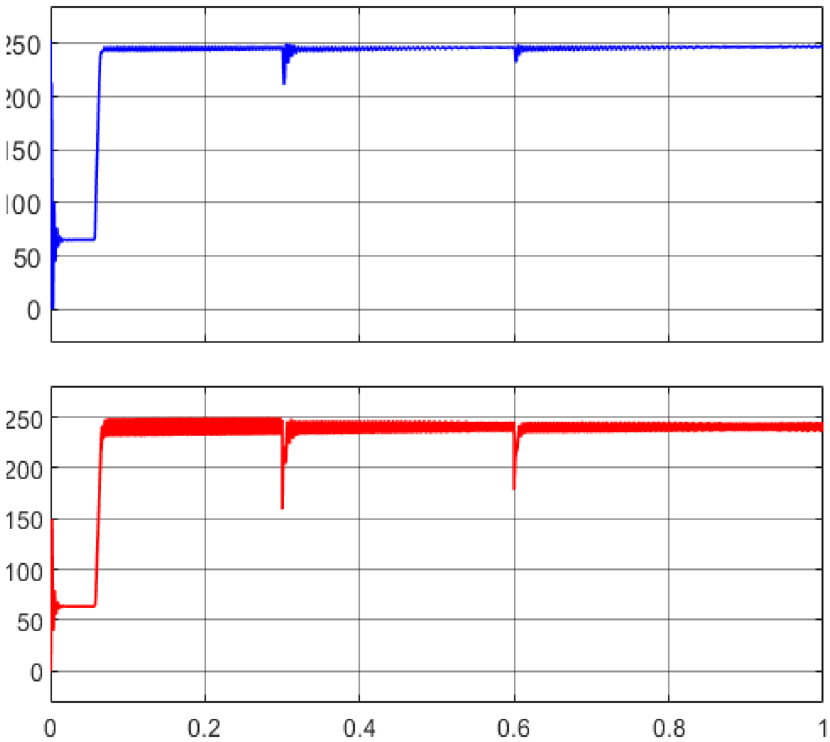

Fig. 11. PV power output response

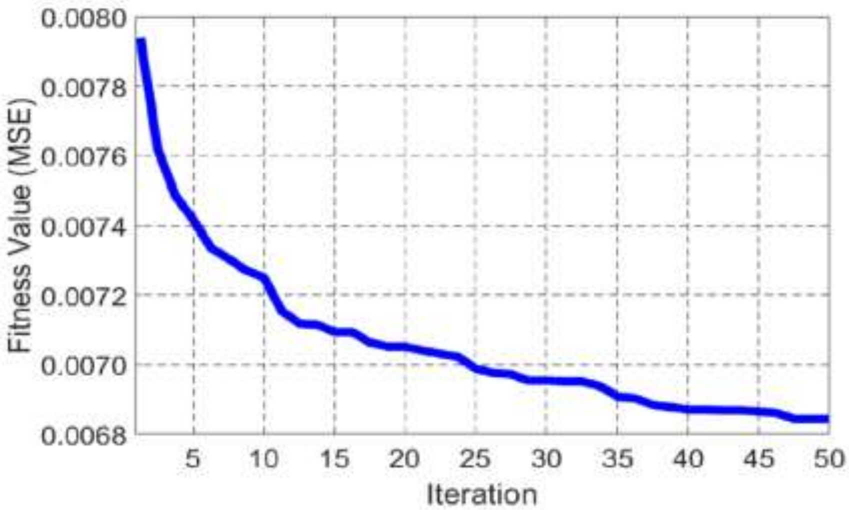

Fig. 12. Fitness value (MSE) convergence during PSO-ANN training

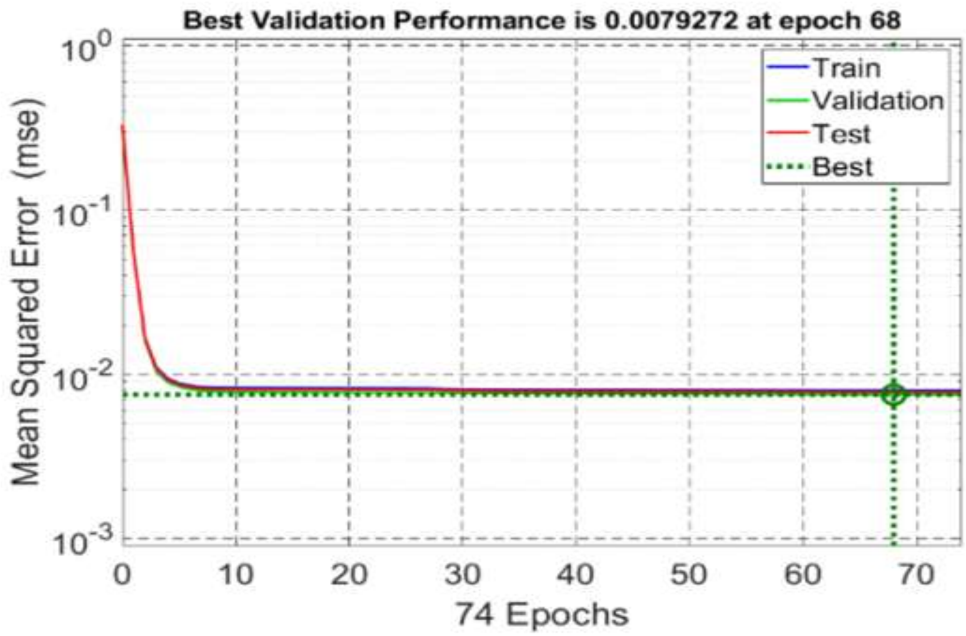

Fig. 13. MSE learning curve of conventional ANN

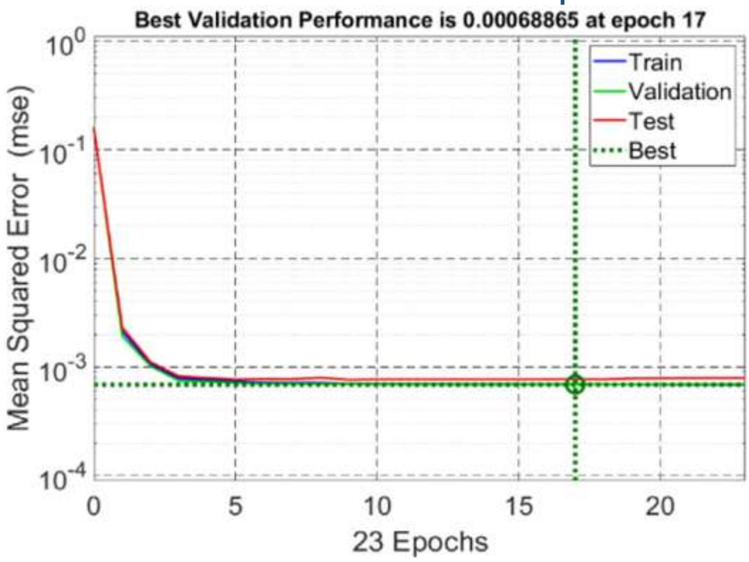

Fig. 14. MSE learning curve of PSO-optimized ANN

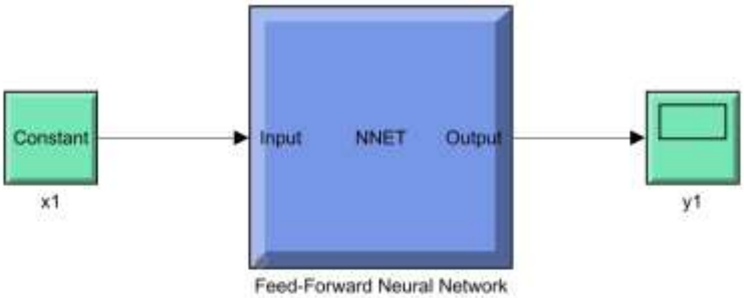

Fig. 15. Trained feedforward neural network deployment in Simulink

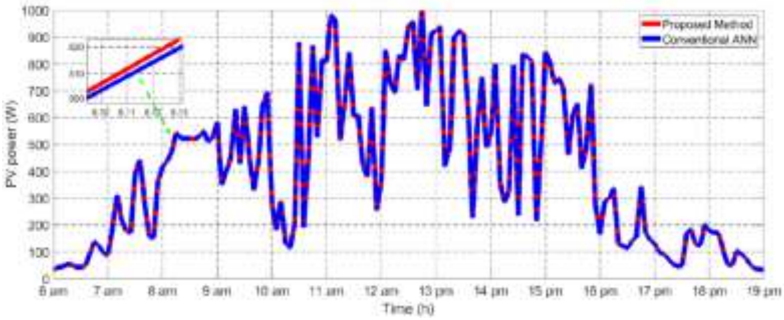

Fig. 16. Comparative analysis of proposed method vs conventional ANN

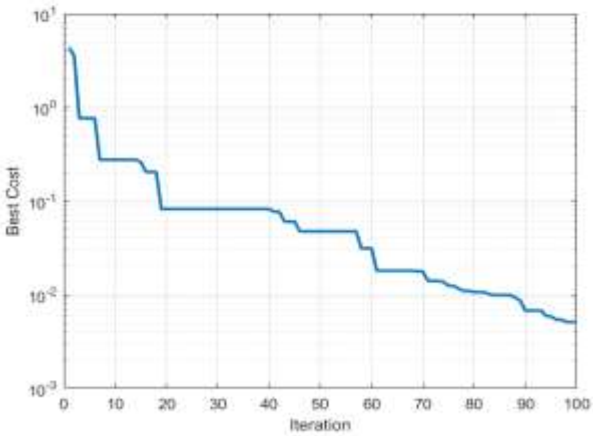

Fig. 17. Overall convergence graph of PSO optimization process

III. Proposed Methodology

By combining Artificial Neural Networks (ANN) and Particle Swarm Optimization (PSO), the suggested framework seeks to implement an effective Maximum Power Point Tracking (MPPT) strategy for photovoltaic (PV) systems. Fig. 2 shows the overall control architecture, in which a Proportional–Integral (PI) controlled boost converter is coupled with an ANN predictor optimized through PSO to process environmental inputs.

PV Cell Modeling

The PV cell is modeled using an equivalent circuit consisting of a photocurrent source (I_{ph}), a diode (D), series resistance (R_s), and shunt resistance (R_{sh}) . The equivalent circuit is shown in Figure 3. The output current is expressed as:

$$I = I_{\text{ph}} - I_0\left(e^{\frac{V+IR_s}{nV_t}} - 1\right) - \frac{V + IR_s}{R_{\text{sh}}},$$

where I_0 is the diode reverse saturation current, V_t is the thermal voltage, and n is the diode ideality factor. The photocurrent depends on irradiance G and temperature T as:

$$I_{\text{ph}} = [I_{\text{sc}} + K_i(T - T_{\text{ref}})]\frac{G}{G_{\text{ref}}}.$$

This model captures the nonlinear dependence of PV output on environmental conditions.

IV. ANN-Based Power Prediction

The purpose of the ANN is to translate environmental inputs (G, T) into the matching maximum power output P^{Pred}. Figure 4 shows the Feedforward Neural Network's architecture. The ANN predicts the maximum power point (MPP) in real time by learning nonlinear relationships without the need for explicit system equations. However, weight initialization and architecture design have a significant impact on ANN performance, which encourages the incorporation of optimization techniques.

V. PSO-Based Parameter Optimization

By reducing the prediction error between the ANN-estimated power P^{Pred} and the actual PV power ($P^{PV} = V^{PV} \times I^{PV}$), PSO is used to optimize the ANN weights and biases. Iterative position updates are carried out in accordance with the fitness function, and each particle in the swarm represents a candidate ANN parameter set:

$$\text{MSE} = \frac{1}{N}\sum_{i=1}^{N}(\,P_i^{Pred} - P_i^{PV})^2.$$

Faster convergence, better generalization, and a lower chance of local minima are all guaranteed by this procedure. Figure 5 shows a visual representation of the PSO procedure for ANN parameter optimization. The error signal is the difference between the actual and predicted power:

$$e = P^{Pred} - P^{PV}.$$

The duty cycle D for a PWM block, which powers the DC-DC boost converter, is produced by a PI controller. To guarantee optimal power delivery to the load in the face of dynamically fluctuating temperature and irradiance, the converter modifies the PV operating point.

Accurate power prediction, adaptive optimization, and closed-loop converter control are all integrated into the suggested ANN–PSO framework. In grid-connected PV systems, this hybrid approach ensures stable and dependable energy extraction by increasing tracking efficiency, decreasing oscillations, and improving MPPT convergence speed.

VI. Implementation of the Proposed Work

To assess the effectiveness of the suggested ANN–PSO framework for MPPT under various environmental circumstances, it has been implemented in the MATLAB/Simulink environment. Particle Swarm Optimization (PSO) is used to systematically optimize the weights and biases of a feedforward neural network that makes up the framework.

VII. Neural Network Architecture

Two input neurons (temperature T and irradiance G), one hidden layer with a variable number of neurons optimized by PSO, and one output neuron representing the predicted maximum power (P_{ref}) make up the feedforward ANN. In order to capture nonlinear mappings between environmental conditions and PV output, sigmoid activation functions are used in both the hidden and output layers.

VIII. PSO-Based Optimization

By reducing the prediction error between the actual PV power and the ANN-predicted power, PSO is used to optimize the ANN parameters. A potential set of weights and biases is represented by each particle in the swarm. Up until convergence, particle positions and velocities are iteratively updated based on individual and global best solutions. The mean squared error (MSE) of prediction is the fitness function, which guarantees robust training and quick convergence.

Table 1 provides a summary of the parameters used in the MATLAB/Simulink implementation of the system. The inertia weight is $\omega \in [0.7,1.2]$, the acceleration coefficients are $c_1, c_2 \in [1.5,2.0]$, and the swarm consists of 30 particles with a maximum of 1000 iterations. To ensure robustness against changing climatic conditions, the ANN is trained and tested using normalized irradiance and temperature datasets.

IX. Simulation Parameters for ANN–PSO Implementation

Parameter	Value
Input neurons	2 (Irradiance G, Temperature T)
Hidden layer neurons	Optimized via PSO
Output neurons	1 (Predicted Power P_{ref})
Activation function	Sigmoid
Swarm size	30 particles
Maximum iterations	1000
Inertia weight (ω)	0.7–1.2
Acceleration coefficients (c_1, c_2)	1.5–2.0
Fitness threshold	10^{-5}

The process entails (i) preprocessing input datasets, (ii) setting up the ANN and PSO parameters, (iii) using PSO-driven optimization to train the ANN, and (iv) using test data to validate the trained network. In order to maximize power delivery and regulate voltage, the optimized ANN is then incorporated into the MPPT control loop and drives the boost converter through a PI–PWM control mechanism.

Under dynamic operating conditions, the ANN–PSO framework exhibits strong adaptability, rapid convergence, and low prediction error. The suggested approach, which serves as the basis for the performance analysis in the following section, guarantees dependable real-time MPPT operation by fusing swarm-based optimization with predictive learning.

X. Results and Discussion

MATLAB/Simulink was used to validate the performance of the suggested ANN–PSO-based MPPT framework under various temperature and irradiance conditions. In comparison to traditional ANN-based techniques, the results show quick convergence, steady operation, and better tracking efficiency.

XI. PV Characteristics

Figure 6 displays the P–V characteristics under constant irradiance at three different temperatures (0°C, 25°C, and 50°C). Higher temperatures, as predicted, lower the maximum power and cause the MPP voltage to shift downward, highlighting the significance of dynamic MPPT control. Similarly, features at different irradiance levels (100–1000 W/m^2) are shown in Fig. 7. The requirement for adaptive tracking techniques is further supported by the fact that power output rises almost linearly with irradiance while the MPP voltage stays largely constant.

XII. Converter Dynamics

The boost converter duty cycle (Fig. 8) stabilizes around 0.7 within 0.1 s, with minimal oscillations. Corresponding PV voltage, current, and power waveforms (Figs. 9, 11, 10) confirm fast transient response and stable steady-state behavior. Voltage converges to ~33 V, current to ~8 A, and power output stabilizes near 250 W, aligning with predicted MPP values.

XIII. ANN–PSO Training Performance

The fitness value convergence shows how well PSO optimization works (Fig. 12). During the first 50 iterations, the mean squared error (MSE) drops quickly and settles below 7×10^{-3}. In contrast to a conventional ANN (Fig. 13), which attains an MSE of 0.0079 in 74 epochs, the optimized ANN converges in 23 epochs with an error of 6.9×10^{-4} (Fig. 14). This shows much higher prediction accuracy and much faster learning. The trained feedforward ANN's Simulink implementation is displayed in Figure 15.

XIV. Comparative Analysis

A comparative evaluation between the proposed PSO–ANN and conventional ANN methods (Fig. 16) highlights consistent performance gains of 2–4% in extracted PV power. During peak irradiance periods, the PSO–ANN maintains higher stability and accuracy, ensuring reliable maximum power tracking. The convergence behavior of the PSO optimization process (Fig. 17) further confirms stable error minimization, reaching the 10^{-3} range within 100 iterations.

The proposed ANN–PSO framework exhibits the following strengths:

Rapid MPPT convergence (< 0.2 s) with minimal oscillations.

Lower training error and faster learning compared to conventional ANN.

Robust operation under varying irradiance and temperature.

Improved PV energy extraction, with up to 4% higher efficiency over standard ANN methods.

Overall, the integration of PSO into ANN training provides a robust mechanism for optimizing MPPT control in PV systems. By reducing prediction error and accelerating convergence, the proposed framework enhances stability and energy yield under dynamic environmental conditions, demonstrating its suitability for real-time deployment in grid-connected PV applications.

XV. Conclusion

This work presented a hybrid Artificial Neural Network (ANN)–Particle Swarm Optimization (PSO) framework for Maximum Power Point Tracking (MPPT) in photovoltaic (PV) systems. By addressing the limitations of conventional techniques such as Perturb and Observe and Incremental Conductance, the proposed approach demonstrated superior adaptability, accuracy, and convergence speed under dynamically varying irradiance and temperature conditions. The ANN was employed to predict the maximum power point based on environmental inputs, while PSO efficiently optimized its weights and biases, ensuring reduced prediction error and robust learning performance.

Extensive simulations in MATLAB/Simulink confirmed the effectiveness of the proposed control scheme. The system stabilized PV voltage around 33 V, current at 8 A, and power near 250 W, with rapid convergence (< 0.2 s) and minimal oscillations. The PSO-optimized ANN achieved a mean squared error of 6.8×10^{-4} within 23 epochs, compared to 7.9×10^{-3} and 74 epochs for a conventional ANN. Overall, the hybrid method improved PV energy extraction by up to 4% while maintaining stable operation and high efficiency.

The results validate the capability of ANN–PSO integration to enhance the reliability and intelligence of MPPT controllers in PV systems. Future work will focus on hardware-in-the-loop and real-time embedded implementation, as well as extending the framework to large-scale PV farms and exploring advanced AI optimization algorithms for further performance gains.

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