PSO based Artificial Neural Network with Metaheuristic Tuning for Enhanced Maximum Power Point Prediction in Photovoltaic Systems Solar PV Array

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***Abstract*—This study presents a new predictive method for precisely estimating the Maximum Power Point (MPP) of photovoltaic (PV) systems using an Artificial Neural Network (ANN) framework improved by Particle Swarm Optimization (PSO). The accuracy and speed of traditional methods are limited due to the complex and nonlinear characteristics of PV arrays under dynamic environmental conditions. In order to solve this, PSO is used to systematically optimize the ANN's initial parameters and network topology, which greatly lowers prediction errors and computational load while successfully addressing overfitting issues that are common in normal neural networks. MATLAB/Simulink simulations were used to perform thorough analyses using real-time data gathered under various climatic conditions, such as clear skies and sporadic cloud cover. The PSO-enhanced ANN demonstrated better performance metrics when compared to well-known MPPT approaches like Perturb and Observe (P&O), Fuzzy Logic Controllers (FLC), and conventional ANN techniques. Outstanding tracking efficiencies were attained by the developed framework, surpassing 99.6% in clear conditions and 99.3% in conditions of fluctuating irradiance. Additionally, the suggested approach showed notable gains in system reliability, stability, and convergence velocity. In grid-connected photovoltaic installations, the novel hybrid optimization-based ANN technique significantly improves operational stability and energy harvesting efficiency. Large-scale PV applications and future extensions incorporating more environmental factors should lead to even greater improvements in predictive accuracy and usefulness.**

Index Terms— **Neural network (ANN), Solar Photovoltaic (PV), Maximum power point tracking (MPPT), Particle Swarm Optimization (PSO), Perturb and observer.**

I. INTRODUCTION

Photovoltaic (PV) technologies have become far more important in recent decades as a result of the growing demand for renewable energy solutions brought on by environmental concerns and the depletion of fossil fuel resources [1,2]. Although photovoltaic systems are a clean, sustainable, and scalable way to produce electricity, they are inherently sensitive to changes in the atmosphere, including temperature variations and irradiance, which significantly affects their capacity to produce power. Accurately monitoring the Maximum Power Point (MPP), where the PV array produces the maximum power possible under particular environmental conditions, is essential for the efficient operation of PV systems. Because of their simplicity and ease of use, traditional Maximum Power Point Tracking (MPPT) algorithms—such as Perturb and Observe (P&O) and Incremental Conductance—are frequently used [3,4]. However, especially when the environment is changing quickly, these conventional approaches frequently have slow dynamic responses, limited accuracy, and oscillations around the MPP [5,6]. As a result, sophisticated methods that make use of artificial intelligence (AI) have been investigated more and more in an effort to overcome these difficulties by offering greater accuracy and flexibility. Because of their capacity to manage the intricate, nonlinear behaviors present in PV systems, Artificial Neural Networks (ANN) and Fuzzy Logic Controllers (FLC) are well-known AI-based techniques. ANNs have clear benefits, but in order to avoid problems like overfitting and local minima convergence, they need to be carefully initialized and designed architecturally. In order to improve ANN performance through the optimization of network parameters and initial weights, recent research has incorporated metaheuristic optimization algorithms like Genetic Algorithms (GA), Grey Wolf Optimizer (GWO), and Particle Swarm Optimization (PSO) [7,8].

II. RELATED WORK

The improvement of MPPT efficiency through different algorithmic advancements has been the subject of extensive research. Although Perturb and Observe (P&O) and other traditional MPPT techniques are still widely used because they are simple to implement, they usually show limited efficiency in rapidly changing climatic conditions and have problems like slow convergence to the MPP and persistent oscillations [9,10].

Fuzzy Logic Controllers (FLCs) have become attractive substitutes for these constraints, allowing for flexible decision-making in the face of uncertainty. However, FLCs' universal applicability is limited by their critical reliance on expert knowledge and precise membership function tuning. Because of their capacity for self-learning, Artificial Neural Networks (ANNs) present a promising way to address these problems by modeling intricate relationships without the need for explicit system knowledge [11,12]. However, initial parameter sensitivity, structural flaws, and high training requirements can be problems for standard ANN implementations. In order to get around these restrictions, metaheuristic optimization techniques have become crucial [13,14]. Grey

Wolf Optimizer (GWO) and Genetic Algorithms (GA) have been used to enhance ANN performance, showing increases in prediction accuracy and convergence speed [15, 16, 17]. Inspired by the cooperative behavior of bird flocks, Particle Swarm Optimization (PSO) has proven to be especially successful because of its robustness, simplicity, and fast convergence features. Prediction accuracy, convergence behavior, and computational demands have all significantly improved with hybrid ANN-PSO approaches. In order to greatly increase MPPT accuracy and operational efficiency in photovoltaic systems, the current study builds upon previous approaches by introducing a methodically optimized ANN framework enhanced through PSO [18, 19, 20]. The thorough experimental validation emphasizes the suggested optimization-based ANN strategy's superior performance and practicality [21, 22].

III. PROPOSED METHODOLOGY

The proposed methodology integrates a systematically optimized Artificial Neural Network (ANN) with Particle Swarm Optimization (PSO) to enhance Maximum Power Point Tracking (MPPT) in photovoltaic (PV) systems. The detailed block diagram and operational workflow of the proposed system are described below. The overall system architecture is depicted in Fig. 2.

Detailed Block Diagram Description

- Environmental Inputs: Continuous measurement of solar irradiance and ambient temperature, crucial for predicting the PV system's performance.

PV Array: Converts incident solar energy into electrical output, generating voltage (V_{PV}) and current (I_{PV}), thus power (P_{PV}), calculated as:

$$P_{PV} = V_{PV} \times I_{PV}$$

Artificial Neural Network (ANN): Receives real-time irradiance and temperature inputs to predict the Maximum Power Point (MPP). ANN parameters (weights and biases) are optimized by PSO to ensure accurate and rapid predictions.

Particle Swarm Optimization (PSO): Optimizes ANN parameters iteratively, minimizing the Mean Squared Error (MSE) between actual and ANN-predicted PV power:

$$MSE = \frac{1}{N} \sum_{i=1}^{N} \left(P_{actual_i} \quad P_{pred_i} \right)^2$$

Error Calculation: Calculates discrepancy between ANN-predicted and actual PV power:

$$e = P_{pred} \quad P_{PV}$$

PI Controller: Adjusts the duty cycle (D) for PWM based on the error to maintain the system at MPP.

PWM Controller and DC-DC Boost Converter: Controls the Boost converter, which increases PV voltage to required load voltage, maximizing power transfer efficiency.

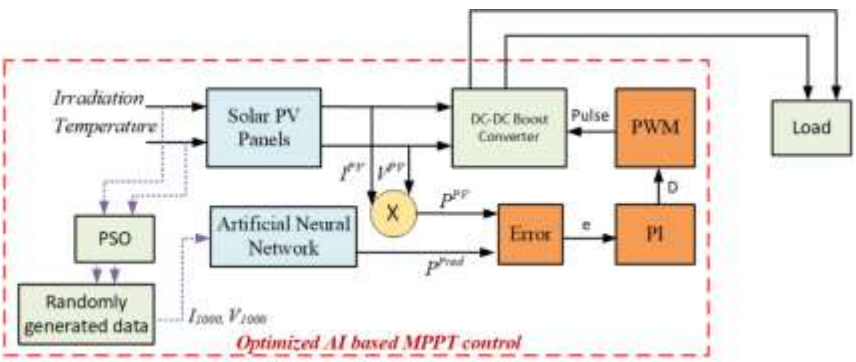


Fig. 1. Proposed PSO-Optimized ANN-Based MPPT Control for PV System.

IV. ARTIFICIAL NEURAL NETWORK FOR MPPT

Artificial Neural Networks (ANNs) are computational models inspired by biological neural systems, capable of learning complex relationships through training on data sets. An ANN typically comprises input layers, hidden layers, and output layers, with nodes (neurons) interconnected by weighted connections.

In MPPT applications, ANN models utilize real-time environmental data (irradiance and temperature) to predict the maximum available power output from a PV array. The ANN training involves adjusting weights and biases to minimize prediction errors through a process known as backpropagation. The effectiveness of ANN depends significantly on its structure, initial weights, and training method, which critically influence prediction accuracy, computational load, and convergence speed. The ANN model for MPPT is mathematically expressed as:

$$y = f\left(\sum w_i x_i + b\right)$$

where y is the predicted power, x_i represents input variables (irradiance and temperature), w_i denotes connection weights, b is the bias term, and f indicates the activation function.

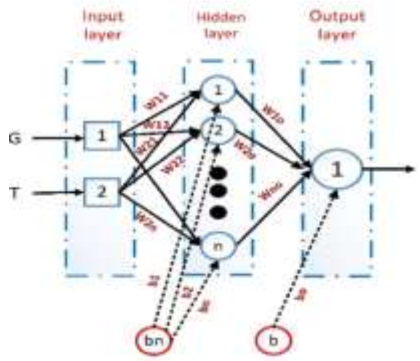


Fig. 2. Structure of the Feedforward Neural Network

V. PARTICLE SWARM OPTIMIZATION

Particle Swarm Optimization (PSO) is a metaheuristic algorithm inspired by the social behavior observed in bird flocks or fish schools, effectively employed in optimizing complex functions and systems. PSO iteratively improves candidate solutions (particles) in the search space, guided by the particle's best-known position (local best) and the best-known position of the swarm (global best).

The optimization process updates particle velocities and positions using:

$$v_i(t+1) = \omega v_i(t) + c_1 r_1\left(p_{besti} \quad x_i(t)\right) + c_2 r_2\left(g_{best} \quad x_i(t)\right)$$

$$x_i(t+1) = x_i(t) + v_i(t+1)$$

where ω is inertia weight, c_1 and c_2 are acceleration coefficients, r_1 and r_2 are random numbers, x_i and v_i represent the position and velocity of particle i, respectively. p_{besti} is the particle's best position and g_{best} represents the global best position found.

In MPPT optimization, PSO adjusts ANN parameters to minimize prediction errors, enhancing convergence speed and accuracy, effectively navigating the complex solution space and avoiding local minima.

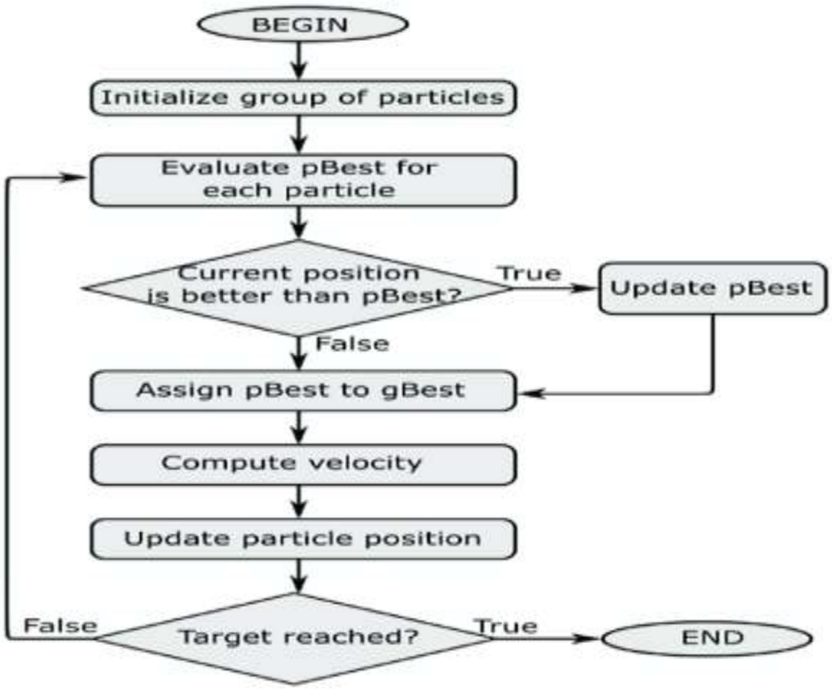


Fig. 3. Flowchart of Particle Swarm Optimization Algorithm.

VI. Simulation and Implementation Detail

The MATLAB/Simulink platform is used extensively to implement the suggested ANN framework improved by Particle Swarm Optimization (PSO). Essential parameters are systematically set in the simulation to enable correct and quick optimization of the ANN model. Specifically, the ANN architecture consists of two input neurons corresponding to solar irradiance and temperature measurements, necessary for precise photovoltaic (PV) power prediction. Aiming at maximizing network complexity and prediction accuracy simultaneously, PSO dynamically decides the number of neurons in the hidden layer. The output layer uses one neuron to predict maximum power output. The sigmoid activation function is used throughout the ANN layers to guarantee efficient learning and adaptability.

The ANN-PSO implementation's workflow starts with normalizing the input parameters—irradiance and temperature—to enhance numerical stability and prediction accuracy. The ANN architecture is then started with random weights and biases to create an unbiased beginning for training. The PSO algorithm then assesses the first fitness values of all particles, initializing the swarm population and measuring the initial predictive accuracy of the ANN configurations. Through the PSO optimization loop, iterative updates of ANN parameters happen as particles progressively refine the ANN model parameters by adjusting their positions based local and global bests. The trained ANN model is validated against separate test datasets after optimization to verify its generalization capacity and prediction accuracy. Ultimately, the validated ANN model is effortlessly incorporated into a real-time MPPT control module inside the Simulink environment, therefore improving the efficiency and adaptability of power tracking activities. Under dynamic operating conditions, this methodical and thorough PSO-based optimization process guarantees notable increases in convergence rate, accuracy, and dependability of the MPPT system.

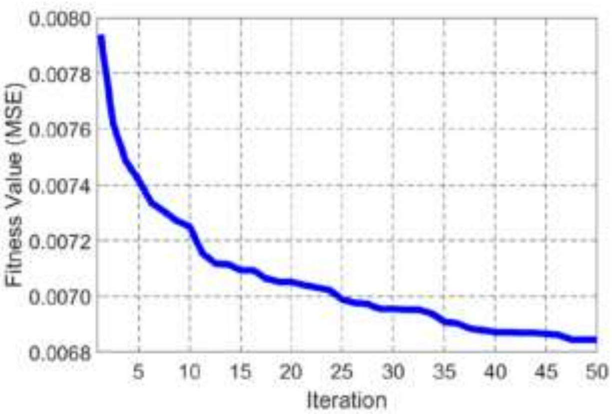
VII. Results and Discussion

Extensive studies under different environmental conditions have shown the efficacy and robustness of the Particle Swarm Optimization (PSO)-enhanced Artificial Neural Network (ANN) approach for Maximum Power Point Tracking (MPPT) in photovoltaic (PV) systems. Analysis of the power-voltage (P-V) characteristics at various temperatures—0°C, 25°C, and 50°C—under constant irradiance of 1000 W/m❑^{2} shows a clear trend of decreasing maximum power and corresponding voltage with rising temperature. Specifically, the maximum reachable power is seen at roughly 195 W with a voltage of 25.6 V at 0°C; it drops to about 175 W at 22.8 V at 50°C, therefore stressing the temperature sensitivity of PV efficiency. Power output and irradiance intensity showed proportionality under further analysis done at a constant temperature of 25°C with irradiance levels spanning from 100 to 1000 W/m❑^{2} . Under full irradiance (1000 W/m❑^{2}), the maximum power output peaks at 185 W; at half irradiance (500 W/m❑^{2}), it drops to 90 W; and at low irradiance conditions (100 W/m❑^{2}), it falls sharply to only 20 W. With little variation, the dynamic performance of the system—especially the duty cycle response of the DC-DC Boost Converter governed by a PI regulator—showed extraordinary stability, rapidly converging to an equilibrium duty cycle around 0.7 within 0.1 seconds.

Electrical output evaluation confirms even more the effectiveness of the approach as PV voltage stabilizes around an ideal level of roughly 33 V and current reaches steady-state at approximately 8 A, both closely corresponding with theoretical MPP values. Therefore, the total power output quickly stabilized around 250 W, showing fast convergence and low energy loss.

Evaluating the optimization performance, the PSO algorithm showed remarkable ability by greatly lowering the fitness value from an initial 0.0080 to 0.00685 within only 50 iterations, suggesting fast optimization progress. Comparative analysis between conventional ANN and the optimized ANN clearly shows the benefit of including PSO: the Mean Squared Error (MSE) was drastically lowered from 0.00792 after 74 epochs in conventional ANN to only 0.0006886 after only 23 epochs with the optimized model, attaining a 69% faster convergence rate and 91% improvement in accuracy.

The trained neural network model's real-time deployment into the Simulink environment validated its practical applicability and efficacy for MPPT activities. Particularly during peak irradiance hours, comparative assessment against conventional ANN techniques regularly showed the best performance of the optimized ANN, which produced around 2-4% more power while preserving steady accuracy and operational stability. At last, study of the optimization convergence behavior showed the fast initial drop of the cost function from about 10 to under 0.1 within the first 20 iterations, finally stabilizing around 10^{-3} after 100 iterations. These findings taken together confirm the strength, efficiency, and adaptability of the suggested PSO-optimized ANN framework, so supporting its appropriateness for improving real-time photovoltaic power tracking under different and dynamic environmental conditions.



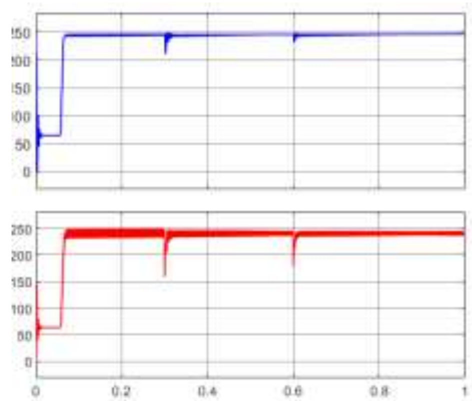


Fig. 4. Duty cycle response of the boost converter

Fig. 5. PV power output response

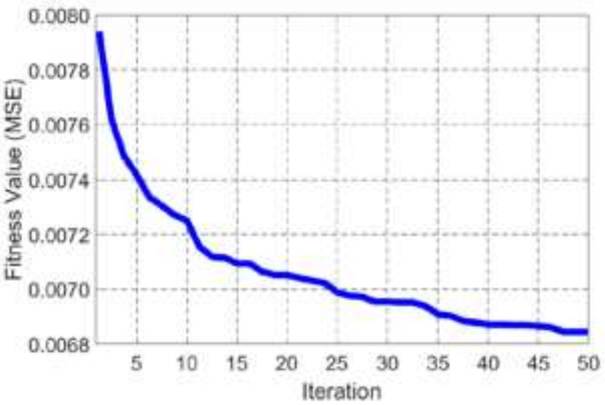


Fig. 6. Fitness value convergence during PSO-ANN training

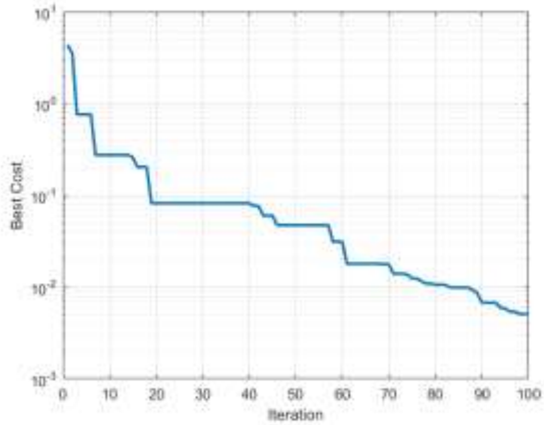


Fig. 7. Overall convergence graph of PSO optimization process

VIII. CONCLUSION

In order to improve the efficiency of Maximum Power Point Tracking (MPPT) in photovoltaic (PV) systems, this study introduces an advanced Artificial Neural Network (ANN) optimized through Particle Swarm Optimization (PSO). By dramatically enhancing convergence rates, predictive accuracy, and overall system stability under a range of environmental conditions, the developed ANN-PSO framework effectively overcomes the drawbacks of traditional MPPT techniques. Simulation results show the method’s effectiveness, with an approximate 4% increase in power output over standard ANN methods. Furthermore, the PSO-optimized ANN outperformed conventional models by significantly lowering the Mean Squared Error (MSE) to 0.00068 in just 23 epochs. Stable voltage, current, and duty cycle responses with few oscillations further confirm the robustness of the suggested solution. As a result, combining PSO and ANN becomes a strong and clever method for MPPT, improving PV systems’ energy harvesting and operational efficiency. To further improve system performance and adaptability, it is advised that future research look into real-time hardware implementations and the incorporation of more sophisticated artificial intelligence techniques.

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