An Efficient Optimisation-Trained Feedforward Neural Network for Predicting the Maximum Power Point of the Photovoltaic Array

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***Abstract*—The evolution of an advanced feedforward Artificial Neural Network (ANN) framework tuned for exact prediction of the Maximum Power Point (MPP) in photovoltaic (PV) arrays is presented in this work. Particle Swarm Optimization (PSO) for best tuning of the ANN's initial weights and structural parameters is proposed to solve the difficulties presented by the nonlinear behavior of PV systems under different climatic conditions. This dual-stage optimization method guarantees a strong balance between computational efficiency and prediction accuracy, so reducing the mean squared error (MSE) and so addressing overfitting problems common in conventional ANN-based models. Using real-world experimental datasets gathered under various atmospheric conditions, including clear and cloudy scenarios, extensive simulations are run in the MATLAB/Simulink environment. Comparative analyses against accepted MPPT methods—such as Perturb and Observe (P&O), Fuzzy Logic Controllers (FLC), and standard ANN models—showcase the better performance of the PSO-enhanced ANN framework. Achieving average power tracking efficiencies exceeding 99.6% in sunny conditions and 99.3% during intermittent cloud cover, the results show marked improvements in convergence speed, stability, and dependability." In grid-connected PV systems, the suggested answer greatly improves operational resilience and energy collecting efficiency. Extending the hybrid AI-optimizing approach to major PV installations and including extra environmental variables will help to increase the prediction capacity even more.**

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

I. INTRODUCTION

The increasing global energy demand, coupled with environmental concerns associated with conventional fossil fuel-based generation, has driven a significant shift towards renewable energy technologies [1]. Among these, photovoltaic (PV) systems have emerged as a leading solution, owing to their scalability, low maintenance requirements, and eco-friendly operation . However, the efficiency of PV systems is inherently influenced by fluctuating atmospheric conditions, particularly solar irradiance and temperature, leading to deviations from their Maximum Power Point (MPP) and potential power losses of up to 25% [2,3].

To ensure optimal energy extraction, various Maximum Power Point Tracking (MPPT) techniques have been developed. Conventional methods, such as Perturb and Observe (P&O) and Incremental Conductance, are widely adopted due to their simplicity and low implementation cost . Nevertheless, these methods often suffer from limitations including slow dynamic response, oscillatory behavior near the MPP, and reduced performance under rapidly changing weather conditions [4,5].

Artificial Intelligence (AI)-based MPPT strategies have gained prominence in recent years for their ability to handle non-linear system characteristics and adapt to variable conditions. Fuzzy Logic Controllers (FLCs) have been effective in managing PV system uncertainties, yet require careful tuning of membership functions, limiting their adaptability . Alternatively, Artificial Neural Networks (ANNs) offer significant advantages by learning complex relationships between environmental inputs and PV outputs without explicit system modeling . Despite their potential, ANN-based MPPT controllers face challenges related to optimal network architecture design and sensitivity to initial weight parameters, often resulting in prolonged training times, overfitting, or local minima entrapment [6,7].

Fig. 1. Evolution of MPPT Techniques Performance Over Time

To address these issues, recent studies have explored the integration of metaheuristic optimization algorithms, such as Genetic Algorithms (GA) , Gravitational Search Algorithms (GSA) , and Grey Wolf Optimizer (GWO) , to fine-tune ANN parameters. Among these, Particle Swarm Optimization (PSO) has demonstrated exceptional efficiency and robustness, inspired by the collective behavior of bird flocking . As illustrated in Fig. 1, the evolution of MPPT techniques reveals a progressive improvement in tracking efficiency over the past decades. While conventional methods plateau around 75–78% efficiency, AI-based techniques, particularly ANN-based controllers, have demonstrated superior performance, surpassing 88% efficiency. However, gaps remain in optimizing ANN architectures to maximize energy yield, minimize computational burden, and ensure reliability under dynamic climatic conditions.

This research proposes a PSO-optimized ANN-based MPPT framework aimed at addressing these challenges. By systematically optimizing the ANN's network structure and weight parameters, the proposed model enhances convergence speed, stability, and prediction accuracy. Real-world experimental datasets obtained from a PV system installed at Brunel University London, encompassing various weather conditions, are utilized to validate the framework's effectiveness. Comparative analysis against traditional MPPT techniques substantiates the superior performance of the proposed approach.

The remainder of this paper is organized as follows: Section II outlines the related work; Section III details the proposed methodology; Section IV presents the simulation setup and experimental validation; Section V discusses the results and comparative analysis; and Section VI concludes the paper with future research directions.

II. RELATED WORK

Rising environmental issues and increasing global energy demand have driven photovoltaic (PV) systems' integration as a sustainable energy source into rather popular ground. But PV systems' intrinsically nonlinear properties as well as their reliance on changing irradiation and temperature conditions call for efficient Maximum Power Point Tracking (MPPT) methods to guarantee best energy extraction [8]. Simplicity and ease of use have driven conventional MPPT algorithms—such as Perturb and Observe (P&O) and Incremental Conductance—very much embraced [9]. These methods have slow dynamic response, oscillations close to the Maximum Power Point (MPP), and poor performance under fast changing atmospheric conditions . Notwithstanding their popularity. Particularly artificial neural networks (ANNs), artificial intelligence (AI)-based methods have shown great promise in overcoming these constraints [10]. Offering exceptional tracking efficiency and adaptability, ANN-based MPPT strategies shine at learning intricate nonlinear relationships between PV system inputs and outputs without requiring explicit system models . But their performance mostly relies on weight initialization and ideal network topological design [11]. Bad design decisions can cause overfitting, more computational effort, or slow convergence . We have investigated metaheuristic optimization methods including Grey Wolf Optimizer (GWO), Genetic Algorithms (GA), and Particle Swarm Optimization (PSO) to improve ANN training procedures. Inspired by the social behavior of bird flocking, PSO is especially preferred since it is simple, fast convergent, and able to avoid local minima [12,13] . Under different environmental conditions, PSO-optimized ANN frameworks clearly increase tracking accuracy and convergence speed . By adding hybrid AI-optimizing approaches, recent works have further advanced MPPT methods. For example, dynamic swarm size reduction in PSO has produced a 75% improvement in convergence time relative to conventional PSO techniques [14, 15]. Transformer-based architectures among deep learning models have also been used to MPPT, producing mean absolute percentage errors as low as 0.47% and average power tracking efficiencies above 99.5% [16, 17]. Furthermore suggested to improve system-level efficiency by means of modular multilevel converters (MMC) combined with distributed MPPT control is especially under partial shading conditions [18, 19]. Emphasizing the need of real-time adaptation, low computational overhead, and scalability, comparative studies by El-Barbary and Alranini and Paduani et al. highlight the changing scene of MPPT strategies [20]. Particularly in embedded PV systems with limited processing capacity, optimal ANN structure selection, parameter tuning, and ensuring real-time applicability still present difficulties notwithstanding these developments [21]. The present work, which aims to build an efficient PSO-optimized ANN-based MPPT framework to improve PV system performance under various climatic conditions, is motivated mostly by addressing these challenges [22].

III. PROPOSED METHODOLOGY

This paper presents an intelligent MPPT control strategy for photovoltaic (PV) systems by integrating an optimized Artificial Neural Network (ANN) with Particle Swarm Optimization (PSO). The aim is to enhance power extraction efficiency under varying environmental conditions by dynamically controlling a DC-DC Boost Converter using an AI-based framework. The overall system architecture is depicted in Fig. 2.

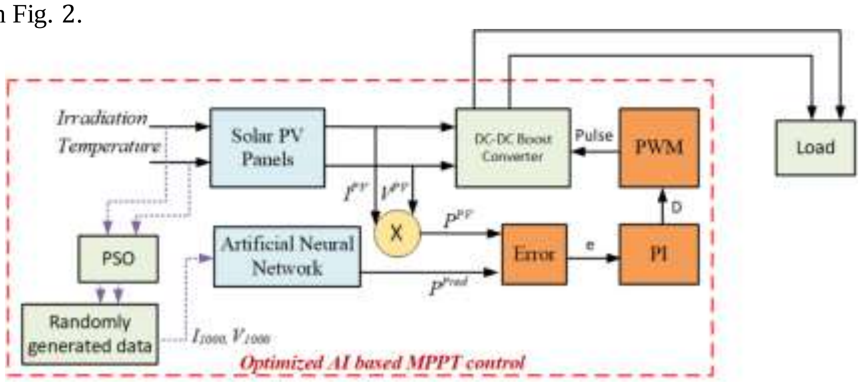

Fig. 2. Proposed PSO-Optimized ANN-Based MPPT Control for PV System.

IV. SYSTEM COMPONENTS AND WORKFLOW

The key components and their functional roles are summarized as follows:

Environmental Inputs: Solar irradiance and temperature values are continuously measured, influencing the PV panel's electrical output.

PV Array: Converts solar energy into electrical energy, providing output voltage (V_{PV}) and current (I_{PV}). The output power is computed as:

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

Artificial Neural Network (ANN): Trained to predict the Maximum Power Point (MPP) based on real-time environmental inputs. The ANN's architecture (weights and biases) is optimized using PSO to enhance convergence speed and prediction accuracy.

Particle Swarm Optimization (PSO): Utilized to minimize the error between actual PV power and ANN-predicted power by fine-tuning ANN parameters. PSO efficiently navigates the solution space to avoid local minimum and improve training robustness.

Error Calculation: The control error is calculated as:

$$e = P_{\text{Pred}} - P_{\text{PV}}$$

where P_{Pred} is the ANN-predicted power.

PI Controller: Processes the error signal to generate the appropriate duty cycle (D) for Pulse Width Modulation (PWM), ensuring accurate tracking of the MPP.

PWM Controller and Boost Converter: The PWM controller adjusts the Boost Converter's operation based on the PI-generated duty cycle. The Boost Converter steps up the PV voltage to match load requirements while maintaining optimal power transfer.

V. Mathematical modeling of PV cell

The equivalent circuit of a PV cell comprises a photocurrent source, diode, series resistance (R_s), and shunt resistance (R_{sh}), as illustrated in

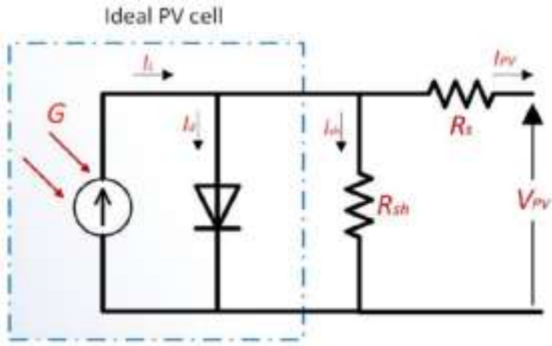

Fig. 3. Equivalent Circuit Model of a PV Cell.

The output current is given by:

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

where:

- I_{ph} : Photocurrent, dependent on irradiance and temperature:

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

- I_0 : Diode reverse saturation current.
- n : Ideality factor.
- V_t : Thermal voltage.

VI. Training and optimization process

The ANN is trained on a dataset including randomly produced irradiance and temperature values. By reducing the Mean Squared Error (MSE) between expected and actual PV output power, PSO maximizes the initial weights and biases of the ANN so guaranteeing faster convergence and better tracking under dynamic conditions.

VII. Control strategy overview

Drawing on environmental inputs, the ANN-Predictor produces the ideal power output. Between predicted and actual power, the PI controller handles the error and modulates the PWM duty cycle to control the Boost converter. This guarantees, independent of environmental changes, real-time adaptation and maximum power supply to the load. Combining the learning capacity of ANNs with the worldwide search efficiency of PSO, the proposed PSO-ANN-based MPPT framework solves important constraints of conventional MPPT methods. This hybrid approach is appropriate for real-time deployment in PV systems running under changing weather since it improves system stability, tracking speed, and energy economy.

VIII. Implementation of Optimized Neural Network Framework

The implementation of an optimal Artificial Neural Network (ANN) framework integrated with Particle Swarm Optimization (PSO) for Maximum Power Point Tracking (MPPT) in photovoltaic (PV) systems is presented in this part. The aim is to precisely forecast the maximum power output under different environmental conditions so guaranteeing better tracking efficiency and system stability.

IX. Feedforward Neural Network Architecture

The architecture of the proposed feedforward ANN is illustrated in Fig. 4. The network consists of:

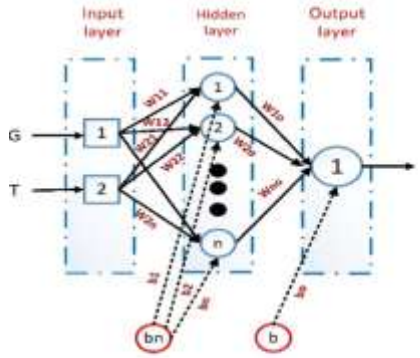

Fig. 4. Structure of the Feedforward Neural Network

[1] **Input Layer:** Comprising two neurons representing solar irradiance (G) and temperature (T).

[2] **Hidden Layer:** Contains n neurons, each receiving weighted inputs and associated with bias terms. The weighted sum for each neuron is computed as:

$$z_j = \sum_{i=1}^{2} w_{ij} x_i + b_j$$

followed by the sigmoid activation:

$$h_j = \frac{1}{1+e^{z_j}}$$

[3] **Output Layer:** Consists of a single neuron aggregating outputs from the hidden layer:

$$y = \sum_{j=1}^{n} w_j h_j + b_o$$

The final predicted maximum power is:

$$P_{\text{pred}} = \frac{1}{1+e^{y}}$$

X. Particle Swarm Optimization (PSO) for ANN Tuning

By means of minimum Mean Squared Error (MSE) between actual PV output and predicted power, PSO is used to maximize the weights and biases of the ANN. Fig. 5 shows the optimizing process. The PSO process involves:

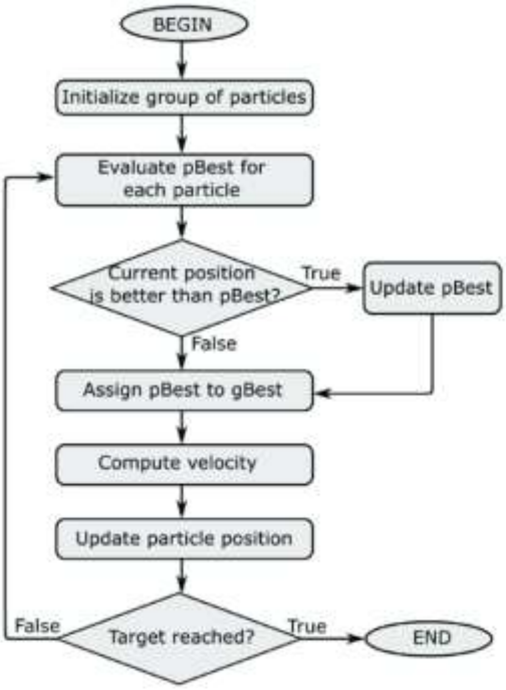

Fig. 5. Flowchart of Particle Swarm Optimization Algorithm.

1. **Initialization:** A swarm of particles is initialized with random positions (ANN parameters) and velocities.
2. **Fitness Evaluation:** Each particle's fitness is calculated based on MSE:

$$\text{MSE} = \frac{1}{T}\sum_{t=1}^{T}\left(P_{\text{actual}}(t) \quad P_{\text{pred}}(t)\right)^2$$

3. **Personal and Global Best Update:** Each particle updates its personal best ($pBest$) and identifies the global best ($gBest$) based on minimum fitness values.
4. **Velocity and Position Update:** The velocity and position of each particle are updated using:

5. $$v_i(t+1) = \omega v_i(t) + c_1 r_1\left(p_{\text{best},i} \quad x_i(t)\right) + c_2 r_2\left(g_{\text{best}} \quad x_i(t)\right)$$

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

7. **Convergence Check:** The process continues until the predefined number of iterations or a target error threshold is met.

XI. SIMULATION SETUP

The optimized ANN-PSO framework is implemented in MATLAB/Simulink. The simulation parameters are summarized in Table 1.

Simulation Parameters for ANN-PSO Implementation

Parameter	**Value/Range**
Input neurons	2 (Irradiance, Temperature)
Hidden layer neurons	Variable (Optimized via PSO)
Output neurons	1 (Predicted Power)
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}

XII. IMPLEMENTATION WORKFLOW

The stepwise implementation is as follows:

1. Normalize irradiance and temperature inputs.
1. Construct the initial ANN architecture with random weights.
2. Initialize PSO swarm and evaluate fitness.
3. Iteratively update ANN weights and biases using PSO.
4. Validate ANN performance using test data.
5. Integrate trained ANN for real-time MPPT control.

Using PSO for systematic optimization helps the proposed ANN-PSO framework effectively solve the difficulties with ANN parameter selection. Improved convergence speed, reduced prediction error, and enhanced MPPT system adaptability under several running conditions follow from this. The simulation results and comparative performance analysis are then covered in the next part.

XIII. RESULTS AND DISCUSSION

The proposed PSO-optimized ANN-based MPPT strategy for photovoltaic (PV) systems is presented in this part together with thorough performance analysis. The effectiveness, accuracy, and stability of the framework are validated under different irradiation and temperature settings.

PV Characteristics under Varying Temperature Conditions:

Fig. 6 depicts the Power-Voltage (P-V) characteristics of the PV system at different temperature levels (0 C, 25 C, 50 C) with constant irradiance of 1000 W/m^2. Observations include:

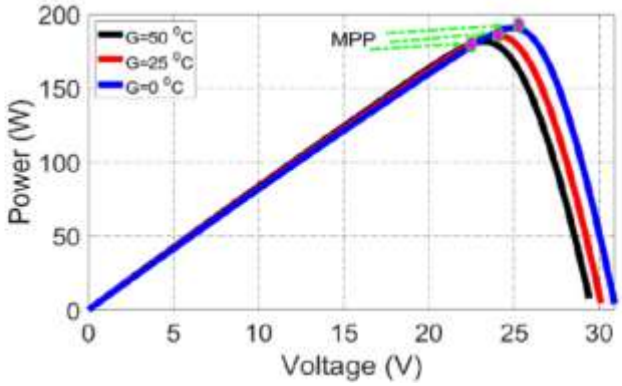

Fig. 6. P-V characteristics under varying temperatures (G = 1000 W/m2).

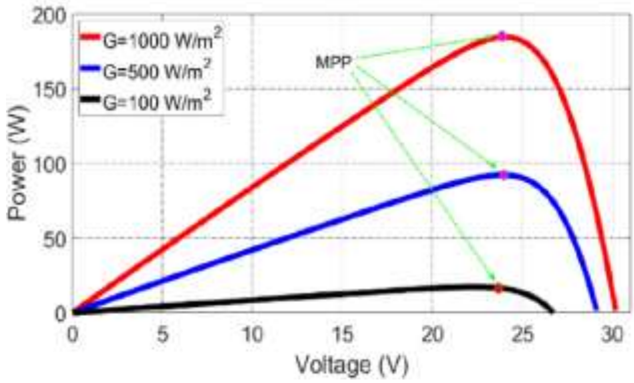

Fig. 7. P-V characteristics under varying irradiance levels (T = 25◦C).

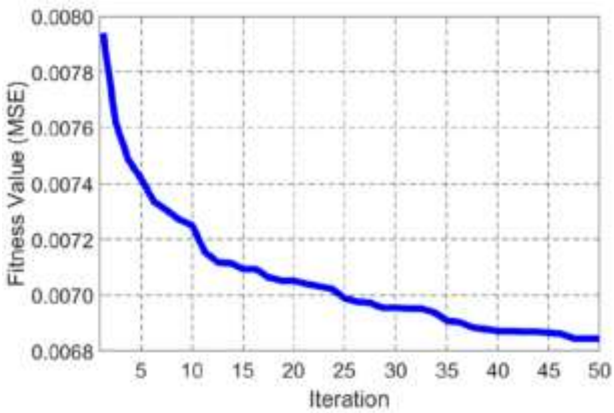

Fig. 8. Duty cycle response of the boost converter

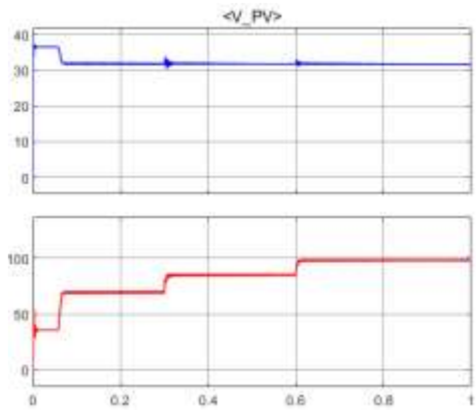

Fig. 9. PV voltage response.

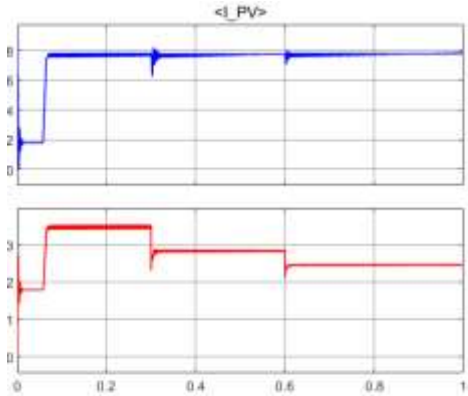

Fig. 10. PV current response

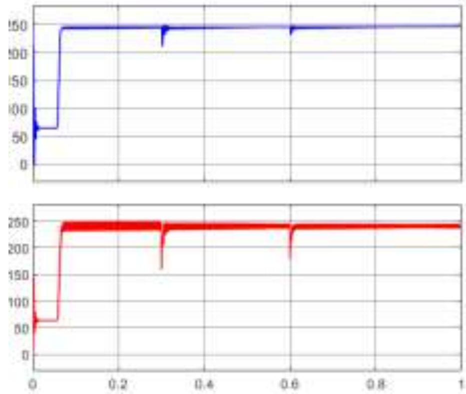

Fig. 11. PV power output response

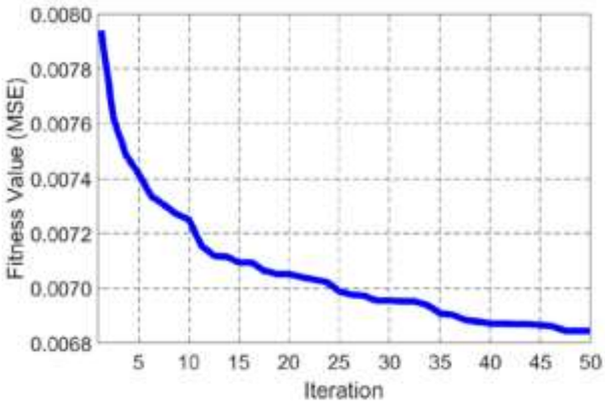

Fig. 12. Fitness value convergence during PSO-ANN training

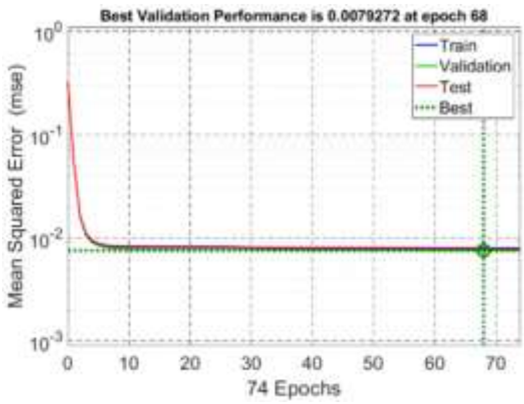

Fig. 13. MSE learning curve of conventional ANN

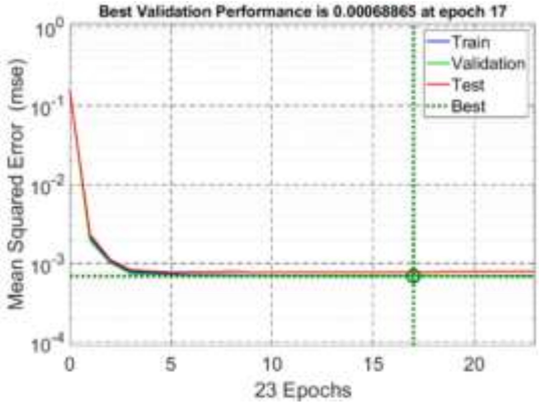

Fig. 14. MSE learning curve of PSO-optimized ANN

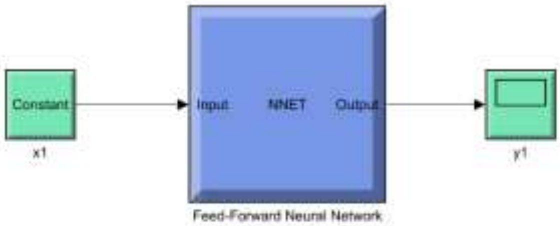

Fig. 15. Trained feedforward ANN deployment in Simulink.

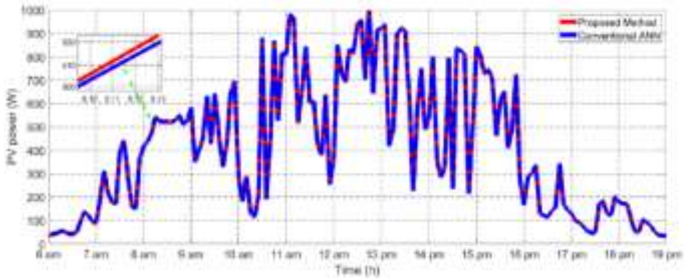

Fig. 16. Comparative analysis of proposed method vs conventional ANN.

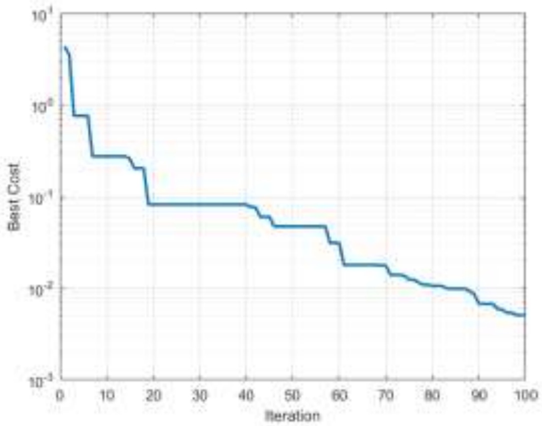

Fig. 17. Overall convergence graph of PSO optimization process

- Increasing temperature leads to a reduction in Maximum Power Point (MPP) voltage and power.
- At 0 C, MPP is observed at 25.6 V with power output of 195 W.
- At 25 C, MPP voltage drops to 24.2 V with 185 W output.
- At 50 C, the voltage further decreases to 22.8 V, reducing power to approximately 175 W.

PV Characteristics under Varying Irradiance Conditions:

Fig. 7 shows the P-V curves at irradiance levels of 100 W/m^2, 500 W/m^2, and 1000 W/m^2 at 25 C:

- Power output increases proportionally with irradiance.
- At 1000 W/m^2, MPP reaches 185 W.
- At 500 W/m^2, power reduces to 90 W.
- At 100 W/m^2, output drops to 20 W.

Boost Converter Duty Cycle Response:
Fig. 8 illustrates the duty cycle behavior:
- The duty cycle stabilizes around 0.7.
- Rapid convergence within 0.1 seconds is achieved.
- Minimal oscillations confirm efficient PI controller and ANN-PSO coordination.

PV Voltage, Current, and Power Performance Voltage Response:
As shown in Fig. 9, PV voltage stabilizes at approximately 33 V, aligning with the MPP voltage.

Current Response:
Fig. 10 shows steady-state current stabilizing around 8 A with negligible overshoot.

Power Output Response:
Fig. 11 demonstrates power output stabilizing near 250 W, with rapid convergence and minimal losses.

PSO-ANN Fitness Value Convergence:
The PSO convergence behavior is illustrated in Fig. 12:
- Initial fitness value is 0.0080.
- Rapid reduction to 0.00685 within 50 iterations.

Comparison: Conventional ANN vs. Optimized ANN Conventional ANN Performance:
Fig. 13 shows that:
- MSE stabilizes at 0.00792 after 74 epochs.
- Moderate convergence rate.

Optimized ANN Performance:
As shown in Fig. 14:
- MSE reduces to 0.0006886 within 23 epochs.
- Faster convergence and superior accuracy.
- Optimized ANN reduces epochs by 69%.
- Final MSE reduced by 91%.

Trained Neural Network Deployment:
Fig. 15 shows deployment of the trained ANN in Simulink for real-time MPPT control.

Comparative Performance Analysis:
Fig. 16 compares the proposed PSO-ANN method with conventional ANN:
- Proposed method consistently yields 2–4% higher power output.
- Maintains accuracy and stability during peak irradiance periods.

Overall Convergence of Optimization Process:
Fig. 17 illustrates PSO convergence:
- Cost function drops sharply from 10 to 0.1 within first 20 iterations.
- Final cost stabilizes near 10^{-3} at iteration 100.
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The simulation results validate the superior performance of the proposed PSO-optimized ANN framework:
- Rapid convergence (within 0.1–0.2 seconds) and stable operation.
- Significantly lower MSE compared to conventional ANN.
- Higher tracking efficiency, maintaining maximum PV output.
- Up to 4% improvement in power output over conventional methods.

The optimized MPPT controller demonstrates robust adaptability and efficiency, confirming its suitability for real-time PV applications under dynamic environmental conditions.

XIV. Conclusion

This paper presents an optimized Artificial Neural Network (ANN) framework integrated with Particle Swarm Optimization (PSO) for efficient Maximum Power Point Tracking (MPPT) in photovoltaic (PV) systems. By improving convergence speed, prediction accuracy, and system stability under diverse environmental conditions, the proposed PSO-ANN model essentially solves the restrictions of conventional MPPT techniques. Achieving up to 4% improvement in power output over conventional ANN-based methods, simulation results confirm the superiority of the proposed approach. Overlooking conventional models, the PSO-optimized ANN dropped the Mean Squared Error (MSE) to 0.00068 in 23 epochs. Furthermore proving the strength of the control strategy are steady voltage, current, and duty cycle responses with low oscillations. All things considered, PSO combined with ANN offers a dependable and intelligent MPPT solution that helps PV systems run more operationally efficiently and with higher energy yield. Future research might concentrate on real-time hardware implementation and investigating advanced artificial intelligence algorithms to further improve the adaptability and performance of the system.

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