ISSN: 2583-5637 (Online)

International journal of Inventive Research in Science and Technology

Volume 4 Issue 8 August 2025

REVIEW PAPER -2

Neural Network-Driven MPPT for Enhanced Dynamic Response in Solar PV Systems

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ABSTRACT

The increasing global demand for clean energy has positioned solar photovoltaic (PV) systems as a cornerstone of modern power networks. However, the inherent nonlinearity of PV characteristics and their strong dependence on dynamic environmental conditions, such as irradiance and temperature fluctuations, pose significant challenges to efficient power extraction. Maximum Power Point Tracking (MPPT) algorithms are crucial for optimizing energy harvesting from PV panels. While traditional MPPT methods like Perturb and Observe (P&O) and Incremental Conductance (InC) are widely used due to their simplicity, they often suffer from slow response, oscillations around the Maximum Power Point (MPP), and limitations under partial shading conditions (PSC). This review paper comprehensively examines the application of Artificial Neural Networks (ANNs) in MPPT for solar PV-integrated power networks, focusing on their ability to significantly improve dynamic response. ANNs offer a robust and adaptive approach to track the MPP rapidly and accurately, even under highly variable conditions. This paper discusses the principles, methodologies, advantages, recent advancements, challenges, and future directions of ANN-based MPPT, highlighting its potential to enhance the stability, efficiency, and reliability of solar PV systems within the smart grid paradigm.

KEYWORDS

Solar Photovoltaic (PV), Maximum Power Point Tracking (MPPT), Artificial Neural Networks (ANN), Dynamic Response, Irradiance, Temperature, Partial Shading, Power Networks, Machine Learning.

1. INTRODUCTION

The global energy landscape is undergoing a significant transformation, driven by concerns about climate change and the depletion of fossil fuels. Renewable energy sources, particularly solar photovoltaic (PV) systems, are at the forefront of this shift, offering a clean and sustainable alternative for electricity generation [1]. Solar PV systems convert sunlight directly into electricity, and their widespread adoption is crucial for achieving a sustainable energy future.

However, the power output of a PV module is highly dependent on environmental factors, primarily solar irradiance and module temperature. The current-voltage (I-V) and power-voltage (P-V) characteristics of a PV module are nonlinear, and there exists a unique operating point, known as the Maximum Power Point (MPP), at which the module delivers its maximum possible power output [2]. As irradiance and temperature change throughout the day and due to weather variations, the MPP continuously shifts. To ensure optimal energy harvesting from PV systems, a Maximum Power Point Tracking (MPPT) algorithm is indispensable [3].

Conventional MPPT algorithms, such as Perturb and Observe (P&O) and Incremental Conductance (InC), are widely implemented due to their low computational complexity and ease of implementation [4], [5]. Despite their popularity, these methods exhibit certain limitations. P&O, for instance, introduces oscillations around the MPP in steady-state conditions, leading to power losses. Both P&O and InC can struggle to accurately track the global MPP under rapidly changing atmospheric conditions or partial shading, where multiple peaks may appear on the P-V curve [6], [7]. This often results in slow tracking speed and reduced efficiency, particularly in dynamic grid-integrated scenarios where stable and rapid power delivery is crucial.

To overcome these limitations, researchers have increasingly turned to intelligent control techniques, with Artificial Neural Networks (ANNs) emerging as a promising solution. ANNs, inspired by the structure and function of the human brain, possess remarkable capabilities for learning complex nonlinear relationships, pattern recognition, and adaptation to varying conditions [8]. Their ability to approximate any continuous function makes them well-suited for the complex and dynamic nature of PV systems. This paper provides a comprehensive review of ANN-based MPPT techniques, emphasizing their role in improving the dynamic response of solar PV-integrated power networks.

2. LITERATURE REVIEW

The pursuit of efficient MPPT has led to significant research in various methodologies. Early efforts primarily focused on traditional algorithms.

2.1 Conventional MPPT Algorithms

- **Perturb and Observe (P&O):** This method periodically perturbs the operating voltage (or current) of the PV array and observes the change in power [4]. If the power increases, the perturbation continues in the same direction; otherwise, it reverses. While simple, it suffers from oscillations around the MPP and can lose track under rapidly changing conditions.
- **Incremental Conductance (InC):** InC overcomes the oscillation issue of P&O by comparing the instantaneous conductance (dI/dV) with the incremental conductance (I/V) to determine the direction of perturbation [5]. It offers better tracking accuracy and speed than P&O but still faces challenges under partial shading and fast transient conditions [9].
- **Fractional Open Circuit Voltage (FOCV) and Fractional Short Circuit Current (FSCC):** These methods assume a linear relationship between the MPP voltage/current and the open-circuit voltage/short-circuit current, respectively [10]. While simple, their accuracy is limited due

ISSN: 2583-5637 (Online)
International journal of Inventive Research in Science and Technology
Volume 4 Issue 8 August 2025

to the approximation and dependence on empirical constants, making them less robust to varying conditions.

2.2 Advanced MPPT Techniques

To address the shortcomings of conventional methods, researchers have explored various advanced MPPT techniques, including:

- **Fuzzy Logic Controllers (FLC):** FLCs are rule-based systems that can handle imprecise and uncertain data [11]. They offer better performance than traditional methods in dynamic conditions and partial shading, but their effectiveness heavily relies on the experience-based tuning of membership functions and rules [12].
- **Metaheuristic Optimization Algorithms:** Algorithms like Particle Swarm Optimization (PSO), Genetic Algorithms (GA), Ant Colony Optimization (ACO), and Grey Wolf Optimization (GWO) have been applied to MPPT [13], [14]. These algorithms are particularly effective in identifying the Global Maximum Power Point (G_{MPP}) under partial shading by exploring a wider search space. However, they can be computationally intensive and may suffer from slow convergence or oscillations if parameters are not tuned correctly [15].

2.3 Emergence of Neural Network-Based MPPT

The limitations of both conventional and some advanced MPPT techniques in handling the highly nonlinear and dynamic nature of PV systems, especially in scenarios demanding fast and precise tracking, have propelled the development of ANN-based approaches. ANNs offer a data-driven approach, learning the complex relationship between environmental conditions (irradiance, temperature) and the optimal operating point (voltage, current, or duty cycle) directly from training data [8]. This eliminates the need for explicit mathematical models of the PV system or complex rule-sets, offering inherent adaptability and robustness [16], [17]. Recent research has consistently demonstrated that ANN-based MPPT systems can achieve significantly

ISSN: 2583-5637 (Online)
International journal of Inventive Research in Science and Technology
Volume 4 Issue 8 August 2025

improved efficiency and faster response times compared to traditional techniques, particularly under rapid irradiance variations and partial shading [18], [19].

3. METHODS

The implementation of Neural Network-based MPPT typically involves several key stages: data collection, network architecture design, training, and deployment.

3.1 Data Collection

The performance of an ANN is highly dependent on the quality and quantity of its training data. For MPPT applications, this data typically includes:

- **Input Parameters:** Solar irradiance (G) and module temperature (T). Some advanced ANNs may also include previous voltage, current, or power values as inputs to capture dynamic trends [20].
- **Output Parameters:** The corresponding Maximum Power Point (MPP) voltage (V_{MPP}), MPP current (I_{MPP}), or directly the optimal duty cycle (D) for the power converter [21].

Data can be collected through simulations using PV models (e.g., single-diode model) under various environmental conditions, or through experimental measurements from actual PV systems. A comprehensive dataset covering a wide range of irradiance, temperature, and partial shading scenarios is crucial for robust ANN training [19].

3.2 Neural Network Architectures for MPPT

Various ANN architectures have been employed for MPPT, each with its strengths:

- **Feedforward Neural Networks (FNNs):** These are the most common architectures, consisting of an input layer, one or more hidden layers, and an output layer [22]. They are well-suited for mapping nonlinear relationships between inputs (G, T) and outputs (V_{MPP}, I_{MPP}, or D).

- **Radial Basis Function (RBF) Networks:** RBF networks use radial basis functions as activation functions in their hidden layer. They are known for their fast training and good generalization capabilities, particularly for interpolation tasks [23].
- **Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) Networks:** While less common for direct MPPT, RNNs and LSTMs are powerful for sequence prediction and can potentially capture temporal dependencies in weather variations, leading to more predictive MPPT strategies [24].
- **Adaptive Neuro-Fuzzy Inference Systems (ANFIS):** ANFIS combines the learning capabilities of ANNs with the human-like reasoning of fuzzy logic [25]. This hybrid approach can offer improved interpretability and robustness, especially for handling uncertainties.

The choice of architecture, number of hidden layers, and neurons per layer depends on the complexity of the PV system and the desired performance.

3.3 Training and Optimization

The training process involves adjusting the weights and biases of the ANN to minimize the error between its predicted output and the actual target values from the training data. Common training algorithms include:

- **Backpropagation:** A widely used algorithm for training FNNs, where the error is propagated backward through the network to update the weights [26].
- **Levenberg-Marquardt Algorithm:** Often used for its faster convergence compared to standard backpropagation, particularly for smaller to medium-sized networks [27].
- **Bayesian Regularization:** A technique that regularizes the network weights to prevent overfitting, leading to better generalization on unseen data [28].

The training process typically involves splitting the dataset into training, validation, and testing sets to ensure the model's generalization ability.

3.4 Integration with Power Converters

The output of the ANN (e.g., predicted VMPP or D) is then used to control a DC-DC converter (e.g., boost, buck-boost, or SEPIC converter) connected between the PV array and the load/grid [29]. The converter adjusts the operating point of the PV array to match the predicted MPP. This closed-loop control ensures that the PV system continuously operates at its maximum power output.

4. ADVANTAGES

Neural Network-based MPPT offers several significant advantages over conventional and some advanced MPPT techniques, particularly in improving dynamic response:

4.1 Faster Tracking Speed and Reduced Oscillation: ANNs can learn the complex, nonlinear relationship between environmental conditions and the MPP. Once trained, they can directly predict the optimal operating point or duty cycle, eliminating the iterative search process characteristic of P&O and InC [18]. This direct mapping leads to much faster tracking speeds and significantly reduces oscillations around the MPP, resulting in higher energy yield, especially during rapidly changing irradiance conditions [19].

4.2 Enhanced Robustness to Dynamic Conditions: Unlike conventional methods that might lose track or exhibit slow convergence under sudden changes in irradiance or temperature, ANNs, with properly trained datasets, can adapt quickly and maintain stable operation near the MPP [30]. They are less prone to being trapped in local maxima under these dynamic scenarios.

4.3 Superior Performance under Partial Shading Conditions (PSC): PSCs are a major challenge for traditional MPPT methods, often leading to multiple peaks in the P-V curve and the system getting stuck at a local maximum [31]. ANNs, especially those trained with diverse PSC data, can effectively identify and track the Global Maximum Power Point (GMPP) due to their pattern recognition capabilities, leading to higher power output in shaded conditions [32].

4.4 Model-Free Operation: ANNs do not require a precise mathematical model of the PV panel, which can be complex and vary with different PV technologies. They learn the system's behavior directly from data, making them highly adaptable to various PV modules and configurations [16].

4.5 Adaptability and Generalization: Once trained on a sufficiently diverse dataset, an ANN-based MPPT controller can generalize well to unseen environmental conditions and even to

ISSN: 2583-5637 (Online)

International journal of Inventive Research in Science and Technology

Volume 4 Issue 8 August 2025

slightly different PV modules within the same technology, offering a robust and scalable solution [19].

4.6 Reduced Sensor Requirements (in some configurations): Some ANN approaches can be trained to infer the MPP using fewer sensors than traditional methods that might require both voltage and current measurements [6]. For instance, an ANN might be trained to predict the optimal duty cycle directly from irradiance and temperature data, potentially simplifying hardware.

5. RECENT CHALLENGES

Despite the notable advantages, the widespread adoption of Neural Network-based MPPT faces several challenges:

5.1 Data Acquisition and Training Complexity:

- **Large and Diverse Datasets:** Training robust ANNs requires extensive and diverse datasets covering a wide range of irradiance, temperature, and partial shading conditions [19]. Generating or collecting such data can be time-consuming and resource-intensive, especially for real-world scenarios.
- **Computational Cost of Training:** The training process for complex ANNs can be computationally demanding, requiring powerful hardware and significant time, particularly for deep learning architectures [33].
- **Generalization to Unforeseen Conditions:** While ANNs offer good generalization, their performance can degrade when exposed to entirely new or unforeseen environmental patterns not present in the training data.

5.2 Real-Time Implementation and Hardware Limitations:

- **Computational Burden for Microcontrollers:** Deploying complex ANN models on low-cost microcontrollers for real-time MPPT in embedded systems can be challenging due to limited processing power and memory [34]. This necessitates optimizing network architectures for efficiency.
- **Sampling Rate and Latency:** For fast dynamic response, the ANN needs to process inputs and generate outputs at a high sampling rate. Any latency in computation can hinder accurate tracking, especially during rapid changes.

5.3 Optimal Architecture Design and Hyperparameter Tuning:

- **Trial and Error:** Determining the optimal ANN architecture (number of layers, neurons per layer) and hyperparameters (learning rate, activation functions) for a specific PV system often involves extensive trial and error, requiring expert knowledge [35].
- **Overfitting:** A common challenge where the ANN learns the training data too well, leading to poor performance on new, unseen data [28]. Effective regularization techniques are crucial to mitigate this.

5.4 Sensor Reliability and Noise Sensitivity:

- **Input Data Quality:** The accuracy of ANN predictions relies heavily on the quality of input sensor data (irradiance, temperature) [36]. Sensor inaccuracies or noise can directly impact the MPPT performance.
- **Sensor Calibration:** Periodic calibration of sensors is necessary to maintain the accuracy of the input data for the ANN.

5.5 Cost and Complexity of Development:

- **Expertise Requirement:** Designing, training, and deploying ANN-based MPPT systems requires specialized knowledge in machine learning, power electronics, and control systems, which can increase development costs.
- **Maintenance and Retraining:** As PV panels degrade over time or environmental conditions shift significantly, the pre-trained ANN might need periodic retraining or adaptation to maintain optimal performance [37].

6. FUTURE DIRECTIONS

The promising capabilities of Neural Network-based MPPT indicate several exciting avenues for future research and development:

6.1 Development of Lightweight and Efficient ANN Architectures:

- **Edge Computing and On-Device AI:** Future research will focus on developing highly optimized and compact ANN models suitable for deployment on low-power, embedded microcontrollers directly at the PV module level [34]. This involves exploring techniques like model quantization, pruning, and specialized hardware accelerators.
- **Transfer Learning and Pre-trained Models:** Leveraging pre-trained ANN models on large, diverse PV datasets and then fine-tuning them for specific PV module types or regional climates could significantly reduce training time and data requirements.

6.2 Integration with Advanced Control Strategies:

- **Hybrid MPPT Approaches:** Combining the strengths of ANNs with traditional or metaheuristic algorithms could lead to more robust and efficient hybrid MPPT strategies. For instance, an

ANN could provide an initial estimate of the MPP, while a conventional algorithm refines the tracking, or an ANN could act as a supervisory controller for optimal algorithm selection [38].

- **Predictive MPPT using Time-Series Forecasting:** Incorporating time-series forecasting techniques (e.g., LSTMs) to predict future irradiance and temperature could enable proactive MPPT, allowing the system to anticipate MPP changes and react even faster, minimizing power loss during transient conditions [24].

6.3 Enhanced Robustness to Partial Shading and Faults:

- **Deep Learning for Complex Shading Patterns:** Utilizing deeper neural networks and advanced training techniques to better identify and track the GMPP under highly complex and dynamic partial shading patterns, including those caused by moving clouds or surrounding structures [39].
- **Fault Detection and Diagnosis:** Integrating fault detection and diagnosis capabilities within the ANN-based MPPT to identify issues like module degradation, open circuits, or short circuits, thereby improving system reliability and enabling predictive maintenance [40].

6.4 Data-Driven Adaptive Learning and Self-Optimization:

- **Online Learning and Adaptive ANNs:** Developing ANNs that can continuously learn and adapt their parameters in real-time as new data becomes available or as the PV module characteristics change over its lifespan [37]. This would eliminate the need for periodic manual retraining.
- **Reinforcement Learning for MPPT:** Exploring reinforcement learning approaches where the MPPT agent learns optimal control policies through trial and error interactions with the PV system and its environment, potentially leading to truly autonomous and self-optimizing MPPT [41].

6.5 Integration with Smart Grid Functionalities:

- **Grid Support Functions:** Beyond just power maximization, future ANN-based MPPT controllers could incorporate grid support functionalities, such as reactive power compensation, voltage regulation, and participation in demand-side management, thereby contributing to grid stability and reliability [42].
- **Cyber-Physical Security:** Addressing the cyber-physical security aspects of intelligent MPPT systems to protect them from potential cyberattacks that could compromise their performance or stability

7. CONCLUSION

Neural Network-based MPPT represents a significant leap forward in optimizing power extraction from solar PV systems, particularly in enhancing their dynamic response. By leveraging their powerful learning and generalization capabilities, ANNs overcome many limitations of traditional MPPT methods, offering faster tracking speeds, reduced oscillations, and superior performance under dynamic environmental conditions and partial shading. While challenges related to data acquisition, computational complexity, and hardware integration remain, ongoing research in lightweight architectures, hybrid approaches, and online learning is continuously pushing the boundaries. The future of solar PV-integrated power networks will undoubtedly be characterized by increasingly intelligent and autonomous MPPT solutions, with Neural Networks playing a pivotal role in maximizing energy yield, improving system stability, and facilitating the seamless integration of renewable energy into the smart grid.

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