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REVIEW PAPRER-1

Neural Network Based MPPT for Improved Dynamic Response in Solar PV-Integrated Power Networks-A Review

Sakshi Bhoyar [1], Devendra Sharma[2], M.S.Dash[3]

bhoyarsakshi2000@gmail.com[1],devendrasharma798@gmail.com[2],malaya_rec@rediffmail.com[3]

[1]MTech Scholar, Department of Electrical and Electronics Engineering, Technocrats Institute of Technology, Bhopal, India

[2]Assistant Professor, Department of Electrical & Electronics Engineering, Technocrats Institute of Technology, Bhopal, India

[3]Professor, Department of Electrical & Electronics Engineering, Technocrats Institute of Technology, Bhopal, India

ABSTRACT

Solar Photovoltaic (PV) systems are increasingly vital to modern power grids. However, their power output is highly sensitive to fluctuating environmental conditions like solar irradiance and temperature, leading to a non-linear power-voltage (P-V) characteristic with a unique Maximum Power Point (MPP). To maximize energy harvest, Maximum Power Point Tracking (MPPT) algorithms are crucial. Traditional MPPT techniques, such as Perturb and Observe (P&O) and Incremental Conductance (IncCond), often suffer from slow response times, oscillations around the MPP, and limitations under partial shading conditions (PSCs). This review paper comprehensively examines the application of Neural Networks (NNs) in MPPT for solar PV systems, focusing on their ability to significantly enhance dynamic response. We delve into various NN architectures and training methodologies, highlighting their advantages over conventional methods in terms of tracking speed, accuracy, and robustness, particularly under rapidly changing atmospheric conditions and PSCs. A detailed literature review of the last ten years (2015-2025) is presented, followed by a discussion of the methods, advantages, and a comparative analysis. Finally, we address the recent challenges in NN-based MPPT and outline promising future directions for research in this field.

KEYWORDS

Solar PV, Maximum Power Point Tracking (MPPT), Neural Network (NN), Artificial Intelligence (AI), Dynamic Response, Partial Shading Conditions (PSCs), Renewable Energy, Power Networks.

INTRODUCTION

The escalating global energy demand and the pressing need to mitigate climate change have propelled renewable energy sources, especially solar photovoltaic (PV) systems, to the forefront of sustainable development [1]. Solar PV systems convert sunlight directly into electricity, offering a clean and abundant energy supply. However, the inherent variability of solar irradiance and ambient temperature profoundly affects the power output of PV panels, leading to a non-linear power-voltage (P-V) characteristic. To extract the maximum possible power from the PV array under these varying conditions, Maximum Power Point Tracking (MPPT) techniques are indispensable [2], [3].

Conventional MPPT algorithms, such as Perturb and Observe (P&O) and Incremental Conductance (IncCond), are widely adopted due to their simplicity and ease of implementation [4]. Nevertheless, these methods face significant limitations, including slow tracking speed, steady-state oscillations around the MPP, and a susceptibility to getting trapped in local maxima under partial shading conditions (PSCs). PSCs occur when different parts of a PV array receive varying levels of sunlight, resulting in multiple peaks in the P-V curve, making it challenging for traditional algorithms to locate the true Global Maximum Power Point (GMPP) [5].

In recent years, Artificial Intelligence (AI) techniques, particularly Neural Networks (NNs), have emerged as a powerful solution to overcome the limitations of conventional MPPT methods. NNs, with their inherent ability to learn complex non-linear relationships from data, offer a promising avenue for improving the dynamic response, accuracy, and robustness of MPPT controllers [6]. By leveraging historical and real-time environmental and electrical data, NNs can predict and track the MPP more efficiently, even under highly dynamic and challenging conditions. This paper provides a comprehensive review of NN-based MPPT strategies, highlighting their contribution to enhanced dynamic response in solar PV-integrated power networks.

LITERATURE REVIEW OF LAST 10 YEARS (2015-2025)

Over the past decade, research in NN-based MPPT has significantly advanced, demonstrating its potential to overcome the shortcomings of traditional methods.

In the mid-2010s, initial studies focused on basic Artificial Neural Network (ANN) architectures for MPP prediction. For instance, in 2016, a study explored variable step-size ANN MPPT controllers, demonstrating improvements in tracking accuracy, response time, and steady-state ripple compared to fixed step-size approaches [7]. Many early ANN-based MPPT systems typically used environmental inputs like solar irradiance and temperature to estimate the MPP voltage or current [8], [9]. These studies often highlighted the ANN's ability to provide faster and more precise tracking than conventional methods, especially under sudden changes in environmental conditions [10].

As the decade progressed, the focus shifted towards improving the robustness and adaptability of NN-based MPPT, particularly under challenging scenarios like partial shading. Hybrid approaches gained prominence, combining NNs with other intelligent techniques or conventional algorithms. For example, some researchers integrated NNs with Fuzzy Logic (FL) or metaheuristic algorithms to enhance performance under PSCs, aiming for faster convergence to the GMPP and reduced oscillations [11], [12].

More recently (2020-2025), deep learning architectures and advanced training strategies have been explored. Long Short-Term Memory (LSTM) networks, a type of Recurrent Neural

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Network (RNN), have been utilized to leverage the sequential nature of environmental data, leading to superior power tracking accuracy under changing solar conditions [13]. Reinforcement Learning (RL) combined with NNs has also shown promise in dynamically optimizing power flow and energy management in grid-integrated PV systems with battery storage, demonstrating reduced convergence time and lower complexity [14].

Several studies in this period emphasize the significant improvements achieved by ANN-based MPPT systems. A recent study (published in 2025 but accessible in 2024) indicated that ANN-based MPPT systems improved efficiency by up to 15% and achieved a 25% increase in response speed compared to traditional techniques, particularly under partial shading and rapid irradiance variations [15]. Another paper highlighted the use of NNs to dynamically adjust the duty cycle change in P&O algorithms, enabling rapid adjustments to variations in solar irradiance and achieving lower settling times [16]. The development of novel ANN architectures designed to address the non-linear characteristics of solar PV systems has also been reported, leading to improved efficiency and reduced response time, especially under dynamic operating conditions [15].

Overall, the literature clearly demonstrates a trend towards more sophisticated NN architectures, hybrid approaches, and data-driven training methodologies to enhance the dynamic response, accuracy, and robustness of MPPT in increasingly complex solar PV-integrated power networks.

METHODS

Neural Network-based MPPT primarily relies on the learning capabilities of NNs to establish the complex non-linear relationship between environmental parameters (irradiance, temperature) or electrical parameters (voltage, current) and the corresponding Maximum Power Point (MPP) of a PV system. The general methodology involves the following key steps:

1. **Data Collection and Preprocessing:**

- **Data Acquisition:** Real-world or simulated data of PV panel characteristics (voltage, current, power) under varying irradiance and temperature conditions are collected. For robust training, data should encompass a wide range of operating conditions, including partial shading scenarios [15].
- **Feature Selection:** Input features for the NN typically include solar irradiance (G), module temperature (T), PV voltage (VPV), and/or PV current (IPV). The output often includes the optimal voltage (VMPP), optimal current (IMPP), or the duty cycle (D) of the DC-DC converter [10], [13].
- **Normalization:** Input and output data are often normalized to a specific range (e.g., [0, 1]) to improve training stability and convergence speed of the NN.

2. **Neural Network Architecture Design:**

- **Type of NN:**
  - **Feedforward Neural Networks (FNNs) / Multilayer Perceptrons (MLPs):** These are the most common NNs used for MPPT due to their ability to approximate complex non-linear functions. They consist of an input layer, one or more hidden layers, and an output layer [1], [6].
  - **Recurrent Neural Networks (RNNs) / Long Short-Term Memory (LSTM):** LSTMs are particularly useful for handling sequential data and time-series predictions, making them suitable for dynamic and rapidly changing environmental conditions [13].
  - **Radial Basis Function Networks (RBFNs):** RBFNs offer fast learning and good generalization capabilities, often used for their ability to handle non-linear mappings effectively.
- **Number of Layers and Neurons:** The optimal number of hidden layers and neurons depends on the complexity of the problem and the size of the training data. This is often determined through trial and error or optimization techniques.
- **Activation Functions:** Common activation functions include sigmoid, ReLU (Rectified Linear Unit), and tanh, which introduce non-linearity into the network.

3. **Training the Neural Network:**

- **Training Algorithm:**
  - **Backpropagation:** This is the most widely used algorithm for training FNNs, adjusting the network's weights and biases to minimize the error between predicted and actual outputs [9].

- **Metaheuristic Algorithms (e.g., Particle Swarm Optimization (PSO), Genetic Algorithms (GA)):** These optimization algorithms can be used to fine-tune NN parameters (weights, biases, or even network topology) for better accuracy and convergence [12].
- **Reinforcement Learning (RL):** In RL-based MPPT, an agent learns to make optimal decisions (e.g., duty cycle adjustments) by interacting with the PV system environment and receiving rewards for successful power tracking [14].

- **Dataset Splitting:** The collected dataset is typically divided into training, validation, and testing sets to ensure the network's generalization capability and prevent overfitting.

4. **Deployment and Control:**

- Once trained, the NN is implemented as the core of the MPPT controller. The inputs to the NN (e.g., PV voltage and current measurements) are fed, and the output (e.g., optimal duty cycle for a DC-DC converter) is generated in real-time.
- This output then controls a power converter (e.g., boost converter, buck-boost converter) to drive the PV panel to its MPP [6], [17].

5. **Hybrid Approaches:**

- Many recent studies propose hybrid MPPT techniques that combine NNs with conventional methods (e.g., P&O-ANN, IncCond-ANN) or other AI techniques (e.g., Fuzzy-ANN) [11], [16]. These hybrid approaches often aim to leverage the strengths of both methods, such as the fast tracking of NNs and the simplicity or robustness of traditional algorithms. For example, an ANN might be used to provide a good initial estimate of the MPP or to adjust the step size of a P&O algorithm during rapid changes [16].

The effectiveness of NN-based MPPT largely depends on the quality and diversity of the training data, the chosen NN architecture, and the optimization strategy employed during training.

ADVANTAGES

Neural Network-based MPPT offers several significant advantages over conventional techniques, particularly for improving the dynamic response of solar PV-integrated power networks:

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1. **Fast Tracking Speed and Improved Dynamic Response:** NNs, once trained, can provide a rapid and accurate estimation of the MPP. Unlike iterative traditional methods (like P&O or IncCond) that require multiple perturbations to track changes, NNs can directly map input parameters to the optimal operating point, leading to significantly faster convergence, especially under rapidly changing irradiance and temperature conditions [6], [10]. This rapid response is crucial for maximizing energy harvest in dynamic environments [16].
2. **Higher Accuracy and Efficiency:** NNs can learn complex, non-linear relationships within the PV system's characteristics. This allows them to predict the MPP with greater precision compared to conventional methods, which may rely on simplified models or approximations. This enhanced accuracy translates to a higher overall energy yield from the PV system [15], [17].
3. **Robustness under Partial Shading Conditions (PSCs):** One of the most significant advantages of NN-based MPPT is its superior performance under PSCs. Traditional algorithms often get stuck at local maxima on the multi-peaked P-V curve under shading. Trained NNs, however, can learn to identify the global maximum power point (GMPP) by recognizing complex patterns in the input data, leading to more efficient operation even with varying shading patterns [5], [15].
4. **Adaptability and Learning Capability:** NNs are inherently adaptive. Once trained on a diverse dataset, they can generalize and adapt to unseen environmental conditions. This "learning" capability allows them to maintain optimal performance even as external factors fluctuate widely, making them more robust than fixed-logic algorithms [15].
5. **Reduced Oscillations at Steady State:** Unlike P&O which continuously perturbs around the MPP, leading to oscillations and power loss, a well-trained NN can converge directly to the MPP with minimal or no oscillations, improving the steady-state efficiency of the system [1], [5].
6. **Potential for Sensor Reduction:** While many NN models use multiple inputs (irradiance, temperature, voltage, current), some advanced models have shown the potential to track the MPP effectively with fewer sensor inputs, such as solely using current measurements, which can reduce system complexity and cost [16].
7. **Integration with Advanced Control Strategies:** NNs can be easily integrated with other advanced control strategies, such as fuzzy logic controllers or metaheuristic optimization

algorithms, to create powerful hybrid MPPT systems that combine the strengths of different approaches [11], [12].

These advantages collectively position NN-based MPPT as a highly effective solution for improving the performance and reliability of solar PV systems, particularly in grid-integrated applications where dynamic response and efficiency are paramount.

COMPARISON TABLE

Here's a comparison table summarizing the key characteristics of Neural Network (NN) based MPPT versus conventional methods like Perturb and Observe (P&O) and Incremental Conductance (IncCond):

Feature/Method	Perturb and Observe (P&O)	Incremental Conductance (IncCond)	Neural Network (NN) Based MPPT
Principle	Perturbs voltage/current and observes power change.	Compares incremental and instantaneous conductance.	Learns complex non-linear mapping from input to MPP.
Tracking Speed	Slow, especially under rapid changes.	Faster than P&O, but still iterative.	Very fast (once trained), direct estimation of MPP.

Feature/Method	Perturb and Observe (P&O)	Incremental Conductance (IncCond)	Neural Network (NN) Based MPPT
Accuracy	Moderate, oscillations around MPP.	High, reduced oscillations compared to P&O.	Very high, precise tracking.
Dynamic Response	Poor, struggles with rapid irradiance/temperature changes.	Improved over P&O, but can still lag in highly dynamic conditions.	Excellent, highly adaptive to rapid environmental changes.
Partial Shading (PSC) Robustness	Poor, susceptible to local maxima.	Poor, susceptible to local maxima.	Excellent, can identify Global MPP.
Steady-State Oscillations	Significant oscillations around MPP.	Reduced oscillations compared to P&O.	Minimal to none, smooth operation.
Complexity	Low, simple to implement.	Moderate, requires more sensors/computation than P&O.	High (training phase), moderate (real-time operation).

Feature/Method	Perturb and Observe (P&O)	Incremental Conductance (IncCond)	Neural Network (NN) Based MPPT
Sensor Requirements	Voltage, Current.	Voltage, Current.	Typically Voltage, Current, Irradiance, Temperature (can vary).
Computational Overhead	Low.	Low to moderate.	High (training), Low to moderate (inference).
Tuning/Calibration	Minimal, fixed step size.	Moderate, adaptive step size variations exist.	Requires extensive training data and careful tuning of parameters.
Learning Capability	None.	None.	High, can adapt to diverse operating conditions.

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Feature/Method	Perturb and Observe (P&O)	Incremental Conductance (IncCond)	Neural Network (NN) Based MPPT
Initial Conditions Dependency	Can be affected by initial perturbation direction.	Less dependent than P&O.	Less dependent, can quickly converge from any starting point.

This table highlights the superior performance of NN-based MPPT in terms of speed, accuracy, dynamic response, and robustness under partial shading, albeit at the cost of higher initial complexity due to training requirements.

RECENT CHALLENGES

Despite the significant advancements and advantages of Neural Network-based MPPT, several challenges persist that require further research and development:

1. **Data Dependency and Training Complexity:**

- **Large Dataset Requirement:** Training robust NNs for MPPT demands vast and diverse datasets encompassing a wide range of operating conditions, including varying irradiance, temperature, and partial shading scenarios [15]. Acquiring such comprehensive real-world data can be time-consuming and resource-intensive.
- **Data Quality:** The performance of the NN is highly sensitive to the quality and accuracy of the training data. Noisy or incomplete data can lead to poor generalization and inaccurate MPP tracking.

- **Computational Cost of Training:** Training complex deep neural networks can be computationally intensive, requiring significant processing power and time. This can be a barrier for real-time online learning or deployment on low-cost microcontrollers.

2. **Generalization and Adaptability to Unseen Conditions:**

- While NNs are good at generalizing, their performance might degrade significantly if they encounter operating conditions outside the range of their training data (e.g., extreme weather events, unforeseen shading patterns).
- Ensuring the trained NN can effectively handle long-term variations in environmental conditions and PV panel degradation over time remains a challenge [13].

3. **Real-Time Implementation and Hardware Limitations:**

- Deploying complex NN models on embedded systems or low-cost microcontrollers for real-time MPPT can be challenging due to limited computational resources (memory, processing power) [9].
- The trade-off between model complexity (for accuracy) and computational efficiency (for real-time execution) is a critical design consideration.

4. **Optimal Network Architecture and Hyperparameter Tuning:**

- Determining the optimal NN architecture (number of layers, neurons, activation functions) and hyperparameters (learning rate, batch size) for a specific PV system and operating environment is often a trial-and-error process, requiring expert knowledge and extensive experimentation [7].

5. **Robustness Against Sensor Noise and Faults:**

- NN-based MPPT algorithms can be sensitive to sensor noise and measurement inaccuracies. Developing techniques to make them more robust against such disturbances is important for reliable operation.
- Handling sensor failures or drifts gracefully is another critical aspect for practical deployment.

6. **Cybersecurity Concerns in Grid-Integrated Systems:**

- As PV systems become more interconnected and integrate AI, cybersecurity concerns arise, especially in grid-integrated power networks. Protecting the training data and the deployed NN models from malicious attacks or data manipulation is crucial.

7. **Cost-Effectiveness for Small-Scale Applications:**

- While the performance benefits are clear, the initial development and deployment costs of sophisticated NN-based MPPT systems might still be a limiting factor for small-scale residential or off-grid PV applications.

Addressing these challenges is vital for the widespread adoption and successful integration of NN-based MPPT into the next generation of solar PV-integrated power networks.

FUTURE DIRECTIONS

The field of Neural Network-based MPPT for solar PV systems is continuously evolving, with several exciting avenues for future research and development:

1. **Reinforcement Learning (RL) and Adaptive Learning:**

- Further exploration of RL techniques for online, adaptive MPPT. RL agents can learn optimal tracking strategies directly from interaction with the PV system, eliminating the need for extensive pre-collected datasets and allowing the system to adapt to long-term changes and degradation [14], [18].
- Investigating self-learning and self-correcting MPPT algorithms that can continuously improve their performance based on real-time operational data.

2. **Deep Learning for Complex Scenarios:**

- Utilizing more advanced deep learning architectures, such as Convolutional Neural Networks (CNNs) for image-based shading analysis or Graph Neural Networks (GNNs) for multi-array PV systems, to capture intricate spatial and temporal patterns in complex partial shading conditions.
- Exploring deep reinforcement learning (DRL) to handle highly dynamic and uncertain environments, potentially leading to more robust and intelligent MPPT controllers.

3. **Hybrid AI Approaches and Meta-heuristics:**
   - Developing novel hybrid MPPT strategies that combine the strengths of NNs with other AI techniques (e.g., fuzzy logic, genetic algorithms, particle swarm optimization) or even traditional methods in a more sophisticated manner. This could involve using NNs for initial prediction, with other algorithms for fine-tuning or global search under specific conditions [11], [12].
4. **Edge AI and Embedded System Optimization:**
   - Focusing on optimizing NN models for deployment on low-cost, low-power embedded systems (e.g., microcontrollers, FPGAs) at the "edge" of the PV system. This involves techniques like model quantization, pruning, and efficient network architectures to reduce computational and memory requirements without significant performance degradation.
   - Developing specialized hardware accelerators for NN inference in MPPT applications.
5. **Predictive MPPT with Weather Forecasting Integration:**
   - Integrating real-time weather forecasts (irradiance, temperature, cloud cover) as inputs to the NN to enable proactive and predictive MPPT. This could allow the system to anticipate changes and adjust the operating point even before the environmental conditions fully manifest, leading to even faster dynamic response and higher energy yield [4], [18].
6. **Data Augmentation and Synthetic Data Generation:**
   - Research into techniques for generating high-quality synthetic PV data to augment real-world datasets, especially for rare or extreme operating conditions. This can help in training more robust NNs and reducing reliance on extensive physical data collection.
7. **Explainable AI (XAI) for MPPT:**
   - Developing methods to make NN-based MPPT algorithms more "interpretable" or "explainable." Understanding how the NN makes its decisions can help in debugging, improving trust, and validating its behavior in critical power system applications.
8. **Fault Detection and Diagnosis Integration:**

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- Leveraging the pattern recognition capabilities of NNs to integrate fault detection and diagnosis (FDD) functionalities within the MPPT controller. This could enable the system to identify and respond to common PV system faults (e.g., panel degradation, wiring issues) while simultaneously optimizing power extraction.

These future directions suggest a strong emphasis on developing more autonomous, intelligent, and efficient NN-based MPPT solutions that are well-suited for the increasingly complex and dynamic nature of modern solar PV-integrated power networks.

CONCLUSION

Neural Network-based Maximum Power Point Tracking has emerged as a transformative technology for solar PV-integrated power networks, significantly addressing the limitations of conventional MPPT techniques. This review paper has highlighted how NNs, with their inherent ability to learn complex non-linear relationships, offer superior dynamic response, higher tracking accuracy, and enhanced robustness, particularly under rapidly fluctuating environmental conditions and challenging partial shading scenarios. The comprehensive literature review of the past decade underscores the consistent advancements in this field, moving from basic ANN architectures to more sophisticated deep learning and reinforcement learning approaches.

While challenges such as data dependency, training complexity, and real-time implementation on constrained hardware still exist, the ongoing research into adaptive learning, hybrid AI methods, and edge computing promises to overcome these hurdles. The future directions point towards even more intelligent, self-optimizing, and resilient MPPT systems, capable of integrating predictive capabilities and advanced fault diagnostics. As solar PV penetration in power grids continues to grow, the role of sophisticated NN-based MPPT algorithms will become increasingly critical in maximizing energy harvesting, ensuring grid stability, and accelerating the global transition towards sustainable energy.

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