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Article

Implementation of Neural Network-Based MPPT Algorithm for Enhanced Solar PV System Performance

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Abstract:

The effective extraction of maximum power from solar photovoltaic (PV) systems is critical for improving energy efficiency in renewable power generation. This paper presents a neural network-based Maximum Power Point Tracking (MPPT) algorithm implemented using MATLAB for a solar PV system. The proposed method utilizes two key inputs—solar irradiation and temperature—to predict the optimal voltage at the maximum power point (Vmp) in real-time. A multi-layer neural network model is trained using data collected from a solar PV array, where the network is designed to map temperature and irradiation levels to the corresponding maximum power point voltage. After training, the network is integrated into a Simulink model for system simulation, where the MPPT controller adjusts the duty cycle of a DC-DC converter to extract maximum power from the PV system. The performance of the proposed algorithm is tested under varying irradiation and load conditions, demonstrating its effectiveness in tracking maximum power and ensuring optimal energy extraction from the system. Results show that the neural network-based MPPT algorithm adapts well to dynamic environmental changes, offering a robust solution for enhancing the efficiency of solar PV systems. The proposed approach is validated through simulation, highlighting its potential for real-world applications in solar energy harvesting and sustainable power generation.

Keywords: Maximum Power Point Tracking, Neural Network, Solar PV System, Photovoltaic Systems, Power Optimization

1. Introduction

Solar energy has emerged as one of the most promising sources of renewable power, but maximizing its efficiency remains a challenge due to the variability in environmental conditions such as sunlight intensity and temperature. Photovoltaic (PV) systems, while highly effective, require sophisticated algorithms to ensure they operate at their maximum potential by continuously tracking the maximum power point (MPP). MPPT (Maximum Power Point Tracking) is a technique employed to achieve this, but traditional methods often struggle to adapt efficiently to rapidly changing environmental conditions.

This paper explores a neural network-based MPPT algorithm designed to address these challenges. Unlike conventional MPPT techniques, which rely on fixed algorithms or complex calculations, a neural network model is trained to predict the optimal voltage at the MPP based on real-time temperature and irradiation data. The model is trained using a data set derived from the solar PV system's performance under different environmental conditions. Once trained, the network is integrated with a Simulink model to simulate real-world conditions, and the performance of the system is evaluated under varying levels of irradiation and load resistance. The results demonstrate that the neural network-based approach offers superior adaptability and precision in tracking the maximum power point, enhancing the overall efficiency of the solar PV system. This work contributes to the development of more reliable and effective MPPT algorithms for solar energy applications.

2. Literature Review

Jyothy and Sindhu (2018) proposed an ANN-based MPPT algorithm specifically tailored for PV systems. Their findings demonstrate that ANN can predict the optimal operating point under varying environmental conditions, improving energy efficiency. However, the study's scalability to larger systems or different geographic regions and its limited performance evaluation metrics raise concerns about the generalizability of the results [1]. Villegas-Mier et al. (2021) reviewed ANN applications in MPPT for PV systems. They emphasized ANN's adaptability and efficiency in tracking maximum power points under dynamic conditions and categorized various ANN architectures for MPPT applications. Nevertheless, the lack of empirical data and comprehensive analysis of ANN-based MPPT limitations were identified as shortcomings of the review [2].

Elobaid et al. (2015) conducted a survey on ANN-based MPPT techniques, detailing their methodologies, advantages, and limitations. The study underscored the role of ANNs in improving PV system efficiency and provided a comparative analysis of existing techniques. However, it did not cover the latest advancements in the field due to its publication date and exhibited potential bias toward widely studied techniques [3]. Roy et al. (2021) performed a comparative analysis of different ANN algorithms for energy harvesting in solar PV systems. They evaluated the efficiency and effectiveness of various configurations under varying conditions. Despite its insights, the study did not account for the effects of external factors such as temperature and irradiance variations and focused on a limited set of algorithms, restricting its applicability [4].

Yap et al. (2020) reviewed AI-based MPPT techniques, including ANNs, highlighting their evolution and potential in optimizing energy extraction. They provided a comprehensive overview of AI approaches and their effectiveness in MPPT applications. However, the review lacked an in-depth discussion of real-world implementation challenges and the limitations of AI approaches, such as the need for extensive training data and computational resources [5]. Fathi and Parian (2021) proposed a hybrid approach combining fuzzy logic, ANNs, and evolutionary algorithms for MPPT optimization in PV systems. Their method demonstrated improved efficiency and faster convergence compared to traditional MPPT techniques, adapting effectively to varying environmental conditions. However, the complexity of the algorithm and its reliance on simulation results limit its practical applicability in real-time systems [6].

Singh et al. (2014) explored the application of ANNs to optimize MPPT control in standalone PV systems. Their findings highlighted the capability of ANN-based methods to enhance energy efficiency under varying irradiance and temperature conditions. Nonetheless, the study's focus on standalone systems and dependence on high-quality training data restrict its applicability to other scenarios, such as grid-connected systems [7]. Ali (2018) introduced an improved ANN design for MPPT in grid-connected PV systems. The results demonstrated superior tracking efficiency and response time compared to traditional methods, making the design suitable for dynamic grid conditions. However, the potential impact of grid disturbances and the need for extensive tuning before deployment were noted as limitations [8].

Kaushik et al. (2021) developed a modified neural network algorithm for controlling grid-connected PV systems. The proposed scheme improved power quality, response time, and energy conversion efficiency under varying load conditions. Despite its advantages, the complexity of the algorithm and reliance on simulation data limit its implementation in smaller-scale systems [9]. Chao et al. (2011) presented an incremental MPPT method utilizing an extended neural network approach. Their findings indicated reduced oscillations and improved tracking speed, making it suitable for real-time applications. However, the method's performance under rapidly changing environmental conditions and its reliance on extensive training data were identified as challenges [10].

3. Block Diagram of Neural Network MPPT

This block diagram illustrates the operation of a solar PV system using an Artificial Neural Network (ANN)-based Maximum Power Point Tracking (MPPT) algorithm. Here's an explanation of each component:

1. PV Panel: Converts solar energy into electrical energy. The output depends on environmental factors like irradiance and temperature.
2. ANN MPPT: This block uses an artificial neural network to track the maximum power point (MPP) of the PV panel. It adjusts the system to operate at optimal conditions for maximum efficiency.
3. Boost Converter: Increases the DC voltage from the PV panel to the required level for the load. It is controlled by the signal generated by the PWM generator.
4. PWM Generator: Produces the Pulse Width Modulation (PWM) signal to control the boost converter. The duty cycle of the PWM signal is adjusted based on input from the ANN MPPT.
5. Load: Represents the electrical device or system that consumes the power generated by the PV system. The load receives stable and optimized power output.

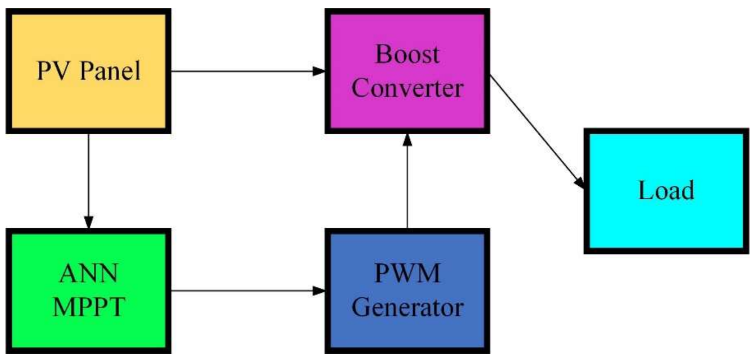


Figure 1. Block Diagram of Neural Network MPPT

Solar PV Panel (250 W)

The PV panel generates DC electricity when exposed to solar irradiance.

Input parameters:

- Irradiance (W/m^2): Determines the power output of the panel.
- Temperature (°C): Affects the efficiency of the PV panel.

Output:

- Voltage (V_{pv}): Voltage produced by the PV panel.
- Current (I_{pv}): Current produced by the PV panel.

Boost Converter

A DC-DC converter boosts the lower voltage from the PV panel to a higher level suitable for the load.

Components:

- **Inductor (L):** Stores energy during the ON state of the switch.
- **Capacitors (C1, C2):** Smooth out voltage fluctuations.
- **Diode (D):** Ensures unidirectional current flow.
- **Switch (controlled by PWM):** Controls the ON/OFF state.

Equation for the boost converter: $V_o = V_{in}/(1-D)$

V_o: Output voltage.
V_{in}: Input voltage.
D: Duty cycle.

Neural Network MPPT Algorithm

This component calculates the optimal **duty cycle (D)** to operate the PV panel at its **maximum power point (MPP)**.

Input:

- Measured PV voltage (V_{pv}).

- o Measured PV current (Ipv).

Output:

- o Optimal duty cycle (DDD).

Working:

- o The neural network is trained on various PV panel parameters to predict the duty cycle for maximum power output under varying environmental conditions (irradiance and temperature).

PWM Generator

Converts the duty cycle (DDD) from the MPPT algorithm into pulse-width modulated signals.

These signals control the switching of the MOSFET in the boost converter to regulate the output voltage.

Parameters measured:

Load Voltage (Vload): Voltage across the load.

Load Current (Iload): Current supplied to the load.

Load Power (Pload): Power consumed by the load, given by: Pload=Vload×Iload

4. Simulation Results and Discussion

The diagram represents a solar photovoltaic (PV) system using a neural network-based maximum power point tracking (MPPT) algorithm. The system starts with an irradiance block, which provides input solar energy under varying sunlight conditions. This energy is fed into a 250 W PV panel, which converts sunlight into electrical energy. The panel is connected to a manual switch, allowing the user to simulate on/off conditions for the system. The output from the PV panel is monitored using a measurement block that tracks the voltage and current generated by the panel.

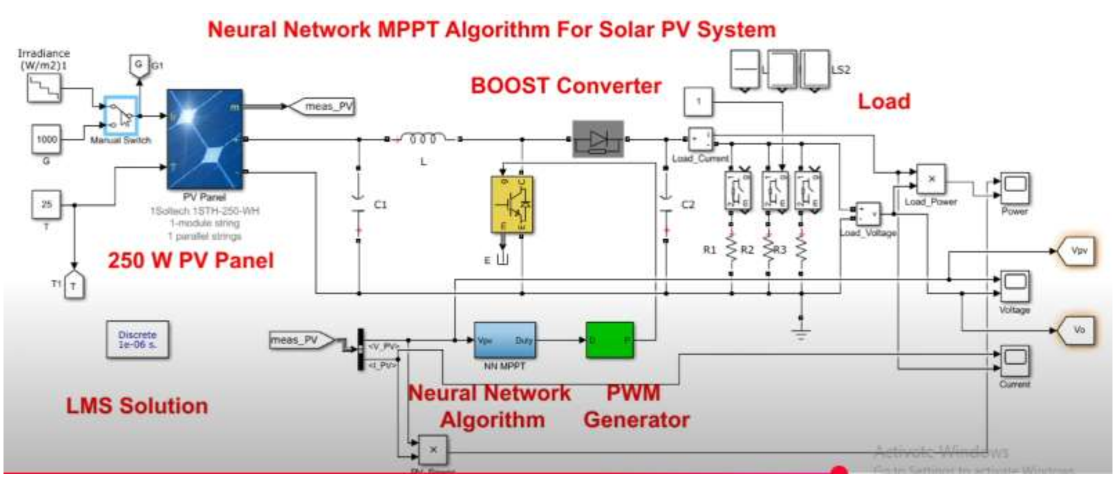
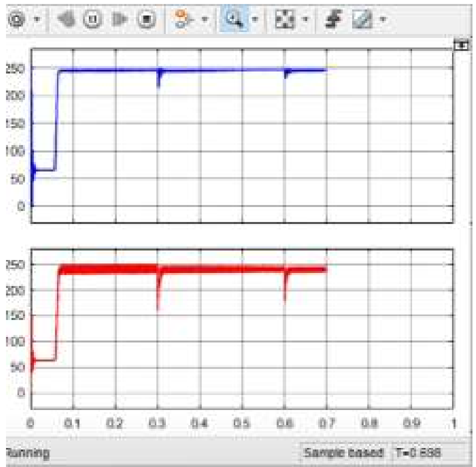


Figure 2. Simulation Diagram of ANN MPPT Solar PV System

A boost converter is integrated into the system to step up the voltage from the PV panel to match the load requirements. The boost converter consists of essential components like an inductor, capacitor, and switching elements. To ensure that the PV panel operates at maximum efficiency, a neural network-based MPPT algorithm is used. This algorithm dynamically tracks the maximum power point (MPP) by analyzing the voltage and current from the PV panel and adjusts the duty cycle accordingly.

The adjusted duty cycle is sent to a pulse width modulation (PWM) generator, which produces the necessary control signals to operate the switching element of the boost converter. The electrical energy from the boost converter is delivered to a load, which consists of resistive elements. The load block measures the voltage, current, and power consumed by the load, providing feedback on system performance.



The graphs represent the performance of a solar PV system with a neural network-based MPPT algorithm. The top graph (blue curve) shows the PV panel's output power, which starts at zero, rapidly increases, and stabilizes around 250 W, demonstrating successful tracking of the maximum power point (MPP). Minor dips in power occur due to adjustments made by the MPPT algorithm in response to changing environmental conditions. The bottom graph (red curve) represents the load power, following a similar pattern as the PV output, starting at zero, stabilizing near 250 W, and reflecting the dips observed in the PV power. This indicates efficient power transfer from the PV panel to the load via the boost converter. Overall, the system quickly stabilizes at the MPP and ensures optimal power delivery, with minor dips reflecting normal real-time adjustments by the MPPT algorithm.

The yellow curve represents the duty cycle, which starts at zero and rapidly increases as the MPPT algorithm begins operating. The duty cycle stabilizes at different levels during distinct intervals, indicating the system's response to changing environmental conditions, such as variations in solar irradiance or temperature. Around t=0.5t = 0.5t=0.5 and t=0.7t = 0.7t=0.7, the duty cycle undergoes small adjustments or steps. This is likely due to the neural network making fine-tuned changes to maintain maximum power tracking as conditions fluctuate.

5. Conclusion

The proposed neural network-based Maximum Power Point Tracking (MPPT) algorithm offers a highly effective solution for maximizing the energy output of solar photovoltaic (PV) systems under dynamic environmental conditions. By utilizing real-time inputs of solar irradiation and temperature, the trained neural network accurately predicts the optimal voltage at the maximum power point (Vmp), enabling the MPPT controller to adjust the duty cycle of the DC-DC converter efficiently. The simulation results demonstrate that the algorithm adapts quickly and effectively to variations in irradiation and load resistance, ensuring optimal power extraction even under rapidly changing conditions.

Compared to conventional MPPT techniques, the neural network-based approach exhibits superior adaptability, robustness, and precision, highlighting its potential for real-world implementation in solar energy harvesting systems. This research validates the algorithm's capability to enhance the overall efficiency of solar PV systems, paving the way for its application in sustainable power generation and renewable energy technologies.

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