Postprint: Research on MPPT Control Algorithm for Photovoltaic Systems Based on Binary Ant Colony Fuzzy Neural Network

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Abstract

Maximum Power Point Tracking (MPPT) control enables photovoltaic modules to output power at the maximum level, thus becoming a research hotspot for enhancing the output power of photovoltaic power generation systems. This paper proposes a photovoltaic system maximum power point tracking control strategy based on binary ant colony fuzzy neural network, which utilizes a fuzzy neural network to replace the traditional BP neural network for predicting the maximum power point, thereby addressing the issue of large errors in the constant voltage control method; employs a binary ant colony algorithm to optimize the weights of the fuzzy neural network, overcoming its shortcomings of slow search speed and susceptibility to local minima; and inputs the obtained maximum power point voltage into the constant voltage control algorithm, subsequently tracking the maximum power point through the constant voltage method. In the constructed simulation model, simulation environments with different light intensities and ambient temperatures were simulated, and the results demonstrate that the proposed MPPT control strategy exhibits high accuracy and strong adaptability.

Full Text

Preamble

Research on MPPT Control Algorithm for Photovoltaic Systems Based on Binary Ant Colony Algorithm and Fuzzy Neural Network

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Abstract

Maximum Power Point Tracking (MPPT) control enables photovoltaic modules to output power at their maximum capacity, making it a research hotspot for enhancing the output power of photovoltaic generation systems. This paper proposes an MPPT control strategy for photovoltaic systems based on a Binary Ant Colony Algorithm and Fuzzy Neural Network (BACA-FNN). The strategy employs a Fuzzy Neural Network (FNN) instead of the traditional Backpropagation Neural Network (BPNN) to predict the maximum power point, which solves the problem of large errors inherent in the constant voltage control method. The Binary Ant Colony Algorithm (BACA) is used to optimize the weights of the FNN, overcoming its shortcomings of slow search speed and tendency to fall into local minima. The voltage at the maximum power point obtained from this approach is then input into a constant voltage control algorithm, which tracks the maximum power point through the constant voltage method. Simulation models were constructed to simulate various environmental conditions with different light intensities and ambient temperatures. The results demonstrate that the proposed MPPT control strategy achieves high accuracy and strong adaptability.

Keywords: MPPT, constant voltage control method, BACA, FNN, weight optimization

1 Introduction

Photovoltaic power generation has garnered increasing attention due to its advantages of being pollution-free, zero-noise, and having widely distributed resources. Particularly with the continuous development of AC-DC hybrid microgrids, photovoltaic generation has become an indispensable distributed power source that attracts significant industry attention. However, due to the inherent characteristics of photovoltaic cells and the influence of environmental factors such as temperature and irradiance, it is difficult for photovoltaic systems to consistently operate at their maximum power state. Therefore, Maximum Power Point Tracking (MPPT) control strategies have become a key research focus in photovoltaic power generation systems to ensure maximum energy output.

Currently, commonly used MPPT methods include the constant voltage method, incremental conductance method, perturbation and observation method, and various combinations of intelligent algorithms with conventional approaches. The perturbation and observation method, despite its simple structure and ease of implementation, produces oscillations near the maximum power point and can generate misjudgments when environmental conditions change rapidly, limiting its application scope. Although the incremental conductance method can reduce oscillations by modifying its logical judgment formula, selecting appropriate step sizes and thresholds remains a significant challenge. The constant voltage method is an open-loop MPPT control approach that is easy to implement in both algorithm and hardware, making it widely used in practical engineering applications. However, it often fails to accurately reach the maximum power point under conditions of large external temperature variations.

This paper conducts an in-depth analysis of the limitations of the constant voltage method in MPPT control and proposes a novel MPPT control strategy based on Binary Ant Colony Algorithm and Fuzzy Neural Network (BACA-FNN). First, to address the large prediction errors of traditional BP Neural Networks (BPNN) in forecasting the voltage at maximum power points, a Fuzzy Neural Network (FNN) is employed. The FNN combines the learning and computational capabilities of neural networks with the fuzzy expression functionality of fuzzy rule systems that align with human thinking. Second, the Binary Ant Colony Algorithm is utilized to optimize the weights of the FNN, overcoming its disadvantages of slow search speed and susceptibility to local minima. Finally, the obtained maximum power point voltage is input into the constant voltage control algorithm, solving the problem of inaccurate maximum power point tracking under large external temperature variations. Extensive computational results validate the effectiveness of the proposed MPPT control strategy.

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2 Photovoltaic System Modeling

2.1 Photovoltaic Cell Equivalent Model

[Figure 1: see original paper] shows the equivalent circuit model of standard photovoltaic cell parameters. By deriving this equivalent model, the mathematical model of the photovoltaic cell can be expressed as:

$$I = I_{ph} - I_o \exp\left(\frac{q(V_{pv} + IR_s)}{kTA}\right) - \frac{V_{pv} + IR_s}{R_p}$$

where I_{ph} is the photocurrent, I_o is the diode current, R_p and R_s are the parallel and series resistances respectively, V_{pv} is the cell terminal voltage, q is the elementary charge ($q = 1.6 \times 10^{19}$ C), k is the Boltzmann constant ($k = 1.38 \times 10^{-23}$ J/K), T is the absolute temperature in Kelvin, and A is the ideal factor of the PN junction diode.

2.2 Photovoltaic Array Characteristic Curves

[Figure 2: see original paper] illustrates the U-I characteristic curves of the photovoltaic array under different ambient temperatures at a constant irradiance of 1000 W/m². The results show that as ambient temperature increases, the maximum current of the photovoltaic array gradually increases while the maximum voltage gradually decreases.

[Figure 3: see original paper] presents the U-P characteristic curves of the photovoltaic array under different ambient temperatures at 1000 W/m² irradiance. The results indicate that both the voltage at the maximum power point and the maximum power itself increase as temperature decreases.

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3 Construction of the BACA-FNN System

3.1 Fuzzy Neural Network Controller

This paper combines Neural Network (NN) with Fuzzy Logic System (FS) to create a system that integrates logical reasoning, linguistic computation, distributed processing, and nonlinear dynamics. This hybrid approach leverages both the learning capabilities of neural networks and the fuzzy expression functionality of rule-based systems that align with human reasoning.

The constructed FNN system has two input parameters (ambient temperature and irradiance) and one output parameter U_{MAX} (voltage at the maximum power point). The network topology is shown in [Figure 4: see original paper].

The system structure consists of four layers: 1. **Input Layer**: All input vectors become nodes in this layer, transmitting data to the next layer. 2. **Fuzzification Layer**: This layer fuzzifies the input quantities using three fuzzy linguistic variables {Large (b_i), Medium (m_i), Small (s_i)} (where $i = 1$ represents ambient temperature and $i = 2$ represents irradiance). Gaussian basis functions are employed as membership functions. This layer contains 12 nodes (w_1 to w_{12}). 3. **Fuzzy Rule Layer**: According to the established fuzzy rule base, this layer performs fuzzy inference on the fuzzified input data. All nodes in this layer are rule nodes, each containing one fuzzy rule that matches rule conditions and performs fuzzy "AND" operations to calculate the fitness of each fuzzy rule. The "Π" symbol represents the fuzzy "AND" operation, implemented here using multiplication (*) for fuzzy set intersection. This layer also contains 12 nodes. 4. **Output Layer**: This layer performs defuzzification by calculating the sum of all rule outputs and normalizing the result.

3.2 Binary Ant Colony Algorithm

Although FS and NN complement each other well, their shared disadvantages remain difficult to resolve, such as slow training speed and frequent entrapment in local optima. Compared with traditional continuous-domain ant colony algorithms, the Binary Ant Colony Algorithm offers advantages including smaller memory footprint, lower algorithmic complexity, stronger search capability, and easier coupling with other algorithms. Therefore, this paper employs BACA to optimize all weights of the constructed FNN.

The primary advantage of BACA lies in its binary path selection (only 0 and 1 states), eliminating the need to traverse all paths as in conventional ant colony algorithms, thus significantly improving search speed. [Figure 5: see original paper] shows the traversal path diagram of the BACA.

A directed graph $G = (C, L)$ is defined, where vertex set C represents all path starting vertices v_s, and vertex v_j represents the states of 0 and 1 in the binary string. For $j = 2, 3, \dots, N$, at all vertices of the path, only two directed arcs point to v_{j-1}, representing the allowed next states: 0 and 1. Each ant traverses its own path, and the problem solution is obtained by integrating the solutions from all ants.

Initially, both paths have equal pheromone levels, set as $\tau_{i,j}(0) = C$ (where C is a constant, typically 0.5), and $\Delta\tau_{i,j}(0) = 0$ $(i, j = 1, 2, \dots, n)$. During movement, ant k $(k = 1, 2, \dots, h)$ selects paths based on pheromone levels. The transition probability is given by:

$$p^k_{i,j}(0) = \frac{[\tau_{i,j}(0)]^\alpha \cdot [\eta_{i,j}(0)]^\beta}{[\tau_{i,j}(0)]^\alpha \cdot [\eta_{i,j}(0)]^\beta + [\tau_{i,j}(1)]^\alpha \cdot [\eta_{i,j}(1)]^\beta}$$

$$p^k_{i,j}(1) = 1 - p^k_{i,j}(0)$$

where h is the number of ants in the colony; $p^k_{i,j}$ is the probability of ant k moving from position i to j at time t; α is the relative importance of the pheromone trail $(\alpha \geq 0)$; β is the relative importance of visibility $(\beta \geq 0)$; $\tau_{i,j}(0)$ and $\tau_{i,j}(1)$ are the pheromone levels on edges where j equals 0 and 1 respectively; and $\eta_{i,j}(0)$ and $\eta_{i,j}(1)$ are the visibility values for edges where j equals 0 and 1 respectively.

To improve algorithm efficiency, the Max-Min Ant System (MMAS) approach is adopted. After each iteration, only the ant that found the optimal path can release pheromones. The pheromone update rule is:

$$\tau_{i,j}(0)(t+1) = \rho \cdot \tau_{i,j}(0)(t) + \Delta\tau_{i,j}$$
$$\tau_{i,j}(1)(t+1) = \rho \cdot \tau_{i,j}(1)(t) + \Delta\tau_{i,j}$$

where $\Delta\tau_{i,j} = 1/f(s_{best})$, and $f(s_{best})$ represents either the iteration-best solution (s_{ib}) or the global-best solution (s_{gb}) of each iteration. This method enhances the system' s optimization capability and significantly improves solution speed.

4 Simulation and Analysis

4.1 Computational Model Establishment

The photovoltaic array computational model is established based on the equivalent model shown in [Figure 1: see original paper]. Under environmental conditions of 25°C and 1000 W/m^2 irradiance, the voltage and current at the maximum power point are 14.8 V and 3.9 A respectively, while the open-circuit voltage and short-circuit current are 19.1 V and 4.3 A respectively.

Since the photovoltaic system under study will be applied in an AC-DC hybrid microgrid system, corresponding simulation analysis was conducted for the photovoltaic system within this context. [Figure 6: see original paper] illustrates the structure of the AC-DC hybrid microgrid system constructed for this study, where 1#DG represents the photovoltaic array under investigation. During system operation, the static switch DC-PCC is in the open state while AC-PCC is closed, allowing the DC microgrid to function as a distributed power source connected to the AC microgrid through a bidirectional power flow controller.

4.2 BACA-FNN Training

Based on the constructed system model, the maximum power point voltage values under different environmental temperatures and irradiance conditions were simulated. Sampling was performed at 10 key time points each day, with 30 days per month averaged, resulting in a total of $10 \times 30 \times 12 = 3{,}600$ sample points for the year. According to neural network training standards, 80% of the samples were randomly extracted for system training. [Figure 7: see original paper] shows the error distributions after training for four different neural network approaches.

The results indicate that the BP neural network required 13,058 steps to reach the convergence condition (root mean square error less than 0.001). Through continuous algorithm fusion and optimization, the convergence speed progressively improved. After optimizing the fuzzy neural network weights using the binary ant colony algorithm, the convergence condition was achieved in only 4,598 steps. Since neural network weights are randomly initialized, the convergence steps are highly unstable. However, after optimization using the ant colony algorithm, an optimal set of weights can be provided. Statistics show that the binary ant colony algorithm optimized fuzzy neural network achieved the fewest training steps, enabling the network to find optimal solutions more quickly without falling into local optima.

4.3 BACA-FNN Testing

The trained BACA-FNN-based MPPT control strategy and the BPNN-based MPPT control strategy were respectively implemented in the 1#DC/AC converter shown in [Figure 6: see original paper], and tested under varying external conditions.

First, the ambient temperature was set constant at 25°C, while irradiance levels were changed at 0s, 0.2s, 0.3s, and 0.4s to 1000 W/m², 800 W/m², 600 W/m², and 400 W/m² respectively. To test the response speed under rapid environmental changes, a short-duration cloud shading event lasting 5 ms was introduced at 8 ms.

[Figure 8: see original paper] compares the MPPT control curves of both strategies with the theoretically calculated maximum power curve at constant temperature. The results show that the proposed method' s MPPT curve essentially coincides with the theoretical calculations, achieving an average relative error of 0.982%, which is significantly lower than the 3.891% error of the BPNN method. Moreover, during short-duration cloud shading and irradiance changes, the proposed method requires substantially less response time than the BPNN method.

[Figure 9: see original paper] compares the voltage curves at the maximum power point for both MPPT control strategies with theoretical calculations, showing consistent results with [Figure 8: see original paper].

To evaluate both algorithms under different temperature conditions, the irradiance was set constant at 1000 W/m² while ambient temperatures were changed at 0s, 0.2s, 0.4s, 0.6s, and 0.8s to 15°C, 20°C, 25°C, 30°C, and 35°C respectively.

[Figure 10: see original paper] compares the MPPT control curves of both strategies with theoretical maximum power calculations at constant irradiance. The results demonstrate that the proposed method can rapidly track the maximum power point even under temperature variation conditions where the constant voltage method is most prone to errors. The average relative error is 0.997%, far lower than the 4.577% error of the BPNN method. Additionally, at the instant of temperature change, the BPNN method produces large errors (exceeding 10%), whereas the proposed method maintains errors below 1% with a response time only one-fifth that of the BPNN method.

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5 Conclusion

This paper presents a comprehensive study with the following key findings:

1. Replacing BP neural networks with fuzzy neural networks for maximum power point control significantly reduces the errors associated with the constant voltage method.
2. Optimizing all weights of the fuzzy neural network using the binary ant colony algorithm yields an optimal set of weights, effectively addressing issues such as random initial thresholds and susceptibility to local optima.
3. The proposed MPPT control strategy demonstrates excellent tracking performance for maximum power points, with errors less than 1% compared to theoretical calculations under various temperature and irradiance test conditions.

The results indicate that the proposed method offers high accuracy and strong adaptability, making it suitable for practical engineering applications.

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Note: Figure translations are in progress. See original paper for figures.