Research on Neural Network MPPT Algorithm Based on DE and Dichotomy

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Abstract. Aiming at the shortcomings of traditional MPPT method, such as slow tracking speed and oscillation at maximum power point, this paper combines neural network with dichotomy to propose a new maximum power point tracking method for photovoltaic power generation system. And the traditional neural network uses the gradient descent method to solve the problem that the parameters are easy to enter the local optimal solution. In this paper, the improved differential evolution method is used to solve the global optimal solution. The neural network is used to track the vicinity of the maximum power point, and then the dichotomy is used to further approach the maximum power point. The simulation results show that compared with the traditional MPPT method, BP neural network and dichotomy can track the maximum power point faster, avoid the oscillation phenomenon, and have faster tracking speed and higher tracking accuracy.

1. Introduction

Solar energy has the most abundant reserves and the most widely distributed advantages. However, its investment cost is high, conversion efficiency is low, and it is susceptible to environmental changes. Therefore, photovoltaic power supply must be operated in the maximum power point mode [1] to maximize economic benefits.

At present, the traditional maximum power point tracking algorithms mainly include constant voltage method, observation disturbance method and conductance increment method [2-4]. Among them, the disturbance observation method and the conductance increment method are widely used for their high tracking accuracy. However, both methods are gradually approaching the maximum power point by a fixed step loop iterative calculation. The step size is too small, the tracking speed is slow, and the real-time performance is degraded; the step size is too large, and the maximum power point oscillates nearby. In order to make up for the shortcomings of the traditional methods, the literature [5] also added corresponding improvement methods based on these traditional algorithms, such as the function of adaptive step size, so that the tracking speed and accuracy have been greatly improved. With the rise of artificial intelligence control methods, some scholars have introduced neural network method [6-8] and fuzzy control method [9-10] to the maximum power point prediction of photovoltaic power generation. The neural network model is used to approximate the maximum power point of the photovoltaic system, which effectively improves the influence of environmental factors on the photovoltaic array. However, the neural network algorithm can only predict to track the vicinity of the maximum power point and oscillate near its maximum power point, causing partial power loss.

Therefore, this paper proposes an BP neural network combined with dichotomy [11-12] for MPPT tracking algorithm, that is, the BP neural network algorithm is used in the startup process of the PV
system to make the PV operating point quickly track near the maximum power point, and then The dichotomy method is used to further search for the tracking maximum power point. This combined approach enables fast searching and tracking of the maximum power point and can effectively reduce the power loss caused by searching for areas far from the maximum power point during startup.

2. Equivalent model of photovoltaic cells
Photovoltaic cells convert solar energy into electrical energy through photochemical effects. The equivalent circuit is shown in Figure 1 [13].

\[
I = I_{ph} - I_d \left( \exp \left[ \frac{q(U + RI)}{AKT} \right] - 1 \right) - \frac{U + IR_{sh}}{R_s}
\]

(1)

Where, \(I_{ph}\) is photocurrent; \(I_d\) is the current flowing into the diode; \(I\) is the output current of the photovoltaic cell; \(U\) is the load terminal voltage; \(R_{sh}\) and \(R_s\) are equivalent series-parallel resistances, respectively.

Photovoltaic cells are a kind of non-linear DC source. Figure 2 shows the output characteristics of photovoltaic cells under different temperatures and different illumination conditions.

3. Photovoltaic power generation MPPT method

3.1. Neural network MPPT algorithm
BP neural network is the most common and widely used multi-layer feed-forward neural network model. The network model is trained according to the error back propagation algorithm, including the forward transmission of the input signal and the back propagation of the error signal. The main idea is to use gradient search technology to adjust and change the connection weight among neurons in each layer so as to control the mean square error between the actual output and the expected output of the network within the given interval.

The BP neural network is applied to the maximum power point tracking of photovoltaic systems. The basic idea is to establish a neural network model to predict the maximum power point voltage of the PV system in real time based on ambient temperature and illumination intensity. Therefore, the input layer of the model contains two neuron nodes, which represent the ambient temperature and light intensity received by the PV array. The output layer contains one neuron node, which is the maximum power point voltage of the PV array in a specific environment. The number of nodes in the hidden layer is determined by repeated trial and error with the reference formula. The optimal number of
nodes with the smallest error rate is 5. The topology diagram of the BP neural network is shown in Figure 3.

The BP neural network algorithm has the disadvantage of being easily trapped in the local optimum during the training process. When the training sample has a large amount of data and the input-output mapping relationship is complex, the convergence speed of the network will be significantly reduced. In order to improve the above problems and reduce the prediction error and improve the accuracy of BP neural network, the absolute value of the error between the predicted output and the expected output was taken as the fitness value, and the threshold and weight of BP neural network were optimized by differential evolution algorithm.

3.2. Improved differential evolution (DE) algorithm
Differential evolution is characterized by simple mechanism and superior performance. In addition, the algorithm has parallel ability and can search cooperatively. Therefore, differential evolution is adopted to achieve the speed and simplicity of the optimization objective function.

The optimization effect of the standard DE algorithm will be affected by the values of the population size \( N_p \), the mutation operator \( F \) and the crossover operator \( CR \), and will also be affected by the mutation strategy. In this paper, the standard DE algorithm is optimized from the \( F \) value of the mutation operator, the value of the crossover operator \( CR \) and the improvement of the mutation strategy.

(1) Improved mutation operator.
In the standard DE algorithm, the value of the mutation operator \( F \) is a constant, and it is impossible to balance the global search ability and convergence speed. According to the previous analysis, in order to make the algorithm have better global convergence ability and convergence speed, the value of \( F \) needs to be larger in the early stage and then gradually decreased.

\[
F = e^{-2 \left( \frac{t}{T} \right)^3}
\]  

Where \( t \) represents the current evolutionary algebra and \( T \) stands for the largest evolutionary algebra of the algorithm.

(2) Improve the crossover operator.
In order to prevent falling into local optimum in the early stage, it is necessary to maintain the diversity of the population. In order to accelerate the convergence in the later stage, it is necessary to enhance the local convergence ability of the algorithm. Therefore, the adaptive crossover operator proposed in this paper.

\[
CR = 0.8(1 - F)
\]  

Where \( F \) is the mutation operator and its expression is as shown in equation (2). It can be seen from equation (3) that the value of the crossover algorithm \( CR \) is opposite to that of the mutation operator \( F \), which is monotonically increasing, and its value range is \([0, 0.8]\).

(3) Improve the mutation strategy.
In this paper, the \( \text{DE} / \text{rand} / 1 \) strategy is improved, adding a random perturbation to the two parent individuals of the differential operation, and replacing the fixed step size with the random step size, so that the algorithm can not only achieve global optimization but also accelerate the convergence speed. The improved mutation strategy is as follows:

\[
S_{i+1}^{t+1} = X_{i1}^t + F(\text{rand} \times X_{i2}^t - \text{randn} \times X_{i3}^t)
\]  

Figure 3. Neural network topology
Where rand is a random number between 0 and 1, rand n is a normally distributed random number with a mean of 0 and a variance of 1.

3.3. MPPT algorithm based on dichotomy

Since the neural network method can only track the vicinity of the maximum power point, in order to further accurately track the maximum power point, the idea of the dichotomy can be applied to the photovoltaic MPPT control algorithm. The specific dichotomy steps are as follows:

(1) The power \( P_{\text{max}} \) and voltage \( U_{\text{max}} \) of the maximum power point under the current environment are calculated according to the neural network. The power at the current moment is \( P(k) \) and the voltage is \( U(k) \).

(2) Determine the size of \( dP(k)/dU(k) \). If \( dP(k)/dU(k) \) is smaller than zero, the reference voltage \( U_{\text{ref}} \) at the next moment of the controller is calculated according to formula (5), where \( Du = 2|U(k) - U_{\text{max}}| \) and the minimum value of \( Du \) is \( \delta \). If it is greater than zero, the reference voltage \( U_{\text{ref}} \) at the next moment of the controller is calculated according to formula (6)

\[
U_{\text{ref}} = U(k) - Du
\]

(5)

\[
U_{\text{ref}} = U(k) + Du
\]

(6)

(3) Determine the value of \( dP(k)^* dP(k+1)/dU(k)^*dU(k+1) \) at the next moment. If the value is greater than 0, the first and the second moments are on the same side of the PV curve and repeat step (2). If it is less than 0, the front and rear moments are on different sides of PV curve, and the maximum power point is in the middle of the front and rear moments, entering step (4).

(4) The maximum power point is in the front and rear intervals, so dichotomy is adopted in this section. The midpoint \( U_{\text{ref}} = (U(k) + U(k+1))/2 \).

(5) Judging \( |U_{\text{ref}} - U(k+1)| < \xi \). If it is less than 0, it jumps out of the loop, and the maximum power point of the system is \( U_{\text{ref}} \); otherwise, it goes to step (2).

4. Simulation and results

The PV array parameters are shown in Table 1.

| Parameters                        | Value |
|-----------------------------------|-------|
| open circuit voltage /V           | 740   |
| short circuit current /A          | 907.2 |
| Maximum power point voltage /V    | 590   |
| Maximum power point current /A    | 842.4 |
| Maximum power point power /kW     | 500   |
In this section, the performance of the control strategy of photovoltaic power generation system proposed in this paper is tested by simulating the disturbance of abrupt natural conditions, such as the change of irradiance.

A total of 300 groups of data were collected, 100 groups of data were randomly selected as test samples, and the remaining 200 groups of data were used as training samples. The weights and thresholds of the BP neural network need to be optimized. The BP neural network algorithm parameters are set as follows: the hidden layer and the output layer transfer function are \textit{tansig} and \textit{purelin} respectively, the training function is \textit{trainlm}, and the systematic training error is $10^{-5}$. The maximum number of training is 1000 times. The differential evolution parameters are set as follows: the population size is 50, the maximum number of iterations is 50, and the random initialization interval of the population position is $[-5, 5]$.

\textbf{Figure 5.} Convergence curve

In order to verify the effectiveness of the improved differential evolution algorithm, the gradient descent (GD) method is also used to optimize the weight and threshold parameters of BP neural network, and then the optimization effects of the two methods are compared and analyzed. The convergence curves and prediction error plots of the two algorithms are shown in Figures 5 and 6.

It can be seen from Figure 5 that the basic DE is close to convergence when the number of iterations exceeds 30, and the gradient descent method does not converge until the 150th generation. In addition, the average relative error of DE is 0.3%, and the average relative error of GD is 1.5%. In summary, DE is superior to the basic GD in convergence speed and solution accuracy, which also proves the feasibility and effectiveness of the improved algorithm.

As shown in Figure 7, a comparison diagram of the output power curve of the photovoltaic array using the classical perturbation observation method, the neural network combined with the disturbance observation method and the neural network combined with the dichotomy method is presented. Initial conditions for $G = 1000 \text{W/m}^2$, $T = 25^\circ \text{C}$, compared with the traditional method, the neural network can rapidly track the maximum power point. When the number of simulation steps is 100, the illumination intensity is $G=300 \text{W/m}^2$, and the temperature is $T=40^\circ \text{C}$. At this time, the neural network method quickly tracks the maximum power point, and the oscillation near the maximum power point is avoided when combined with the dichotomy.

\textbf{Figure 6.} Relative error curve

\textbf{Figure 7.} Effect of sudden changes in working conditions on PV array output power
For the classical fixed-step perturbation observation method, although the response time after the sudden change of working conditions can be reduced by increasing the step size, the static stability of the system can be reduced accordingly. The combination of the classical neural network and the perturbation observation method can reduce the response time after the mutation of working conditions, but the static stability of the system is not improved. Compared with the photovoltaic output control strategy combined with the neural network and the dichotomy, both the response speed and the static stability characteristics are significantly improved.

5. Conclusion
Based on the illumination and temperature affecting the output characteristics of photovoltaic system, a BP neural network based on DE is designed to track the maximum power point of the photovoltaic system, and then the dichotomy is used to further improve the static stability of the maximum power point tracking. The simulation results show that, compared with the traditional MPPT method, the proposed method can quickly and accurately track the maximum power point and effectively avoid power loss, and it has a faster convergence speed, higher precision and smooth static stability.

References
[1] Carrasco J M, Franquelo L G, Bialasiewicz J T 2006 Power-Electronic Systems for the Grid Integration of Renewable Energy Sources: A Survey IEEE Transactions on Industrial Electronics 53(4) 1002-1016.
[2] Lin Zhou, Jian Wu, Qiuhua Li 2008 Survey of Maximum Power Point Tracking Techniques for Photovoltaic Array High Voltage Engineering 34(6) 1145-1154.
[3] Wei Xi, Jing Hui 2011 Study on New Strategy for Enhancing Efficiency of PV System Computer Simulation 28(11) 288-292.
[4] Subudhi B, Pradhan R 2013 A comparative study on maximum power point tracking techniques for photovoltaic power systems IEEE Transactions on Sustainable Energy 4(11) 89—98.
[5] Yaai Chen, Jinghua Zhou, Jin Li, Lingling Zhou 2014 Application of Gradient Variable Step Size MPPT Algorithm in Photovoltaic System Proceedings of the CSEE 34(19) 3156-3161.
[6] Liang Zhang, Haoyue Sun, Xiaolu Sun 2014 Self-adaption BP neural network application in photovoltaic maximum-power-point tracking Chinese Journal of Power Sources 38(6):1090-1091.
[7] Chenxu Lü 2018 Design of neural network based MPPT control algorithm for photovoltaic system Modern Electronics Technique 41(3).
[8] Shuai Li 2016 Study on photovoltaic array mppt control based on BP Neural Network Northeast Electric Power University.
[9] Tianyang Li, Binhua Su, Xiaofeng Zhang, Ning Yin 2018 MPPT Control Method for Photovoltaic Power Generation Based on Fuzzy Control Electric Drive 48(4) 53-57.
[10] Hao Fu, Yixin Su, Jialei Gao 2017 Research on the fuzzy control based MPPT of voltage sensor-less photovoltaic system Renewable Energy Resources 35(1) 26-31.
[11] Xing Zhang, Songsen Yu, Lulin Yin 2018 P&O MPPT algorithm with variable step size based on dichotomy Chinese Journal of Power Sources 42(4) 536-539.
[12] Ke Li 2016 Application Research of Interpolation Method in Photovoltaic Power System MPPT Xi'an University of Technology.
[13] Xing Zhang, Renxian Cao 2010 Solar photovoltaic grid-connected power generation and its inverter control (Beijing: Mechanical Industry Press) p 42.