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An Improved Model Combining Evolutionary Algorithm and Neural Networks for PV Maximum Power Point Tracking

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ABSTRACT Aiming at the large error of the traditional constant control method in predicting the maximum power of solar UAV, this paper proposed an improved mind evolutionary algorithm combined with BP neural network (BPNN), in which the improved mind evolutionary algorithm optimizes the BPNN. The optimized model is used to predict the voltage at the maximum power of the panel in the UAV. The constant voltage parameter based on the conventional constant pressure control algorithm is replaced by this value. At the same time, a new control simulation model of constant voltage solar panel maximum power tracking based on the improved mind evolution algorithm optimize BPNN was built. At last, the algorithm was simulated and validated in the MATLAB/Simulink environment. The simulation results show that this algorithm is better than simply using BPNN and genetic algorithm optimize BPNN stability and higher accuracy.

INDEX TERMS Simulation, photovoltaic maximum power tracking, artificial neural networks, mind evolutionary algorithm.

I. INTRODUCTION

As a clean and renewable green energy, solar energy has the incomparable superiority and become a new focus in the field of energy. Photovoltaic cell is the key parts of solar photovoltaic power system, so the PV solar cell becomes an important part in the UAV. Traditional photovoltaic cell homeostasis evaluation model is the mathematical model based on physical characteristics, and through the power flow calculation, achieved real-time control. This model can characterize the photovoltaic cell internal principle [1], [2], but can not effectively reflect the transient changes of photovoltaic cell operating state when the radiation intensity and the ambient temperature changes.

While the photovoltaic battery external characteristics is used in the practical applications, the traditional mathematical model can not meet to the need of engineering [3]–[5]. How to build an effective and accurate solar cell model is very important. In recent year, the maturing neural network technology has good adaptability and flexibility. However, BP neural network is the most widely used neural network which has been widely used in photovoltaic power generation control system [6], [7]. Literature [8], [9] used BP neural network modeling of photovoltaic cells, and achieved better results. But the traditional BP neural network training is easy to fall into the local optimum, the convergence speed is slow, and the efficiency is low. In recent year, the Mind Evolutionary Algorithm (MEA) has been widely used , which is significantly higher than GA in terms of convergence performance and computational efficiency.

II. SOLAR CELL CHARACTERISTIC

A. SOLAR CELL MODEL AND CHARACTERISTICS

Solar cells are a special device that converts solar radiation into electrical energy and are based on the photovoltaic effect of semiconductor components [10]–[12]. The main influencing factors of its performance are the sunlight intensity, temperature and the properties of raw materials. Therefore, it must be an external load and converted into an equivalent circuit to simulate the calculation. Photovoltaic cell equivalent circuit shown in figure 1.

The output power of the solar panels are affected by the light intensity and the outside temperature, therefore, we must establish a photovoltaic panel simulation model to let the maximum solar panels in the UAV to play its photoelectric conversion efficiency. It can more clearly grasp the impact of the external environment on its output power [13]–[17].

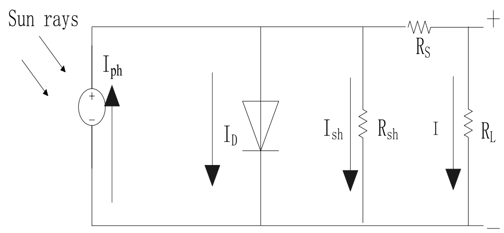

FIGURE 1. **Electrical equivalent circuit model of solar cells.**

The battery's output characteristic equation is as follow.

$$I = I_{ph} - I_0\{\exp[\frac{q(U + IR_S}{AKT}] - 1\} - \frac{U + IR_S}{R_{sh}} \tag{1}$$

Where, I_{ph}-photogenic current (A); I_0-diode Reverse Saturation Current (A); q-electronic charge (1.6 × 10-19C); I-photovoltaic battery operating current (A); R_S -photovoltaic cell series resistance (Ω); R_{sh}-photovoltaic cell parallel resistance (Ω); A-diode quality factor; T-absolute temperature (°C); K-Boltzmann's constant (k = 1.38 × 10-23J/K).

B. SOLAR CELL CHARACTERISTIC CURVE

Figure 2 shows that temperature is 25 °C, light intensity of 400 W/m^2, 600 W/m^2, 800W/m^2, and 1000W/m^2 solar cell U-I characteristic curve family. The change of light intensity has a great influence on the current of solar cell. the short-circuit current of the cell also increases with the light intensity increases from 400 W/m^2 to 1000 W/m^2.The light intensity has little effect on the open circuit voltage of the battery. The open circuit voltage of the battery slightly changes with the light intensity increases. It can be seen from Figure 3, the light intensity has a great influence on the output power of the solar cell. The output power of the battery increases with the light intensity increases from 400 W/m^2 to 1000 W/m^2. The same light intensity corresponds to the only maximum power output point, while maintaining the same temperature of the solar cell. The output power of the battery on the left side of the maximum power point increases with the increase of the output voltage of the photovoltaic cell, the battery

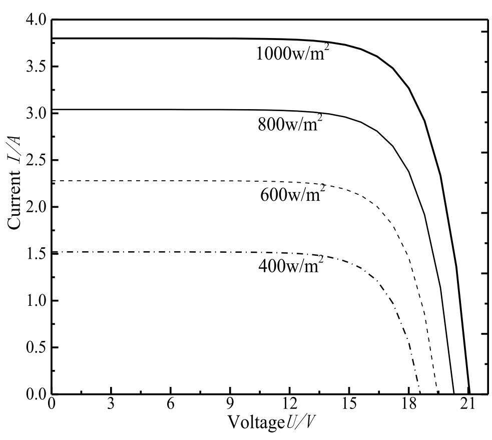

FIGURE 2. ***U-I* characteristic curve.**

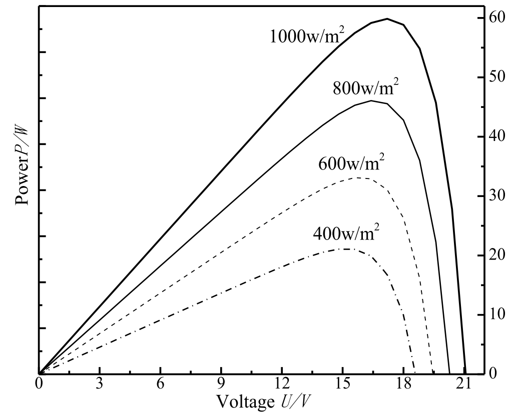

FIGURE 3. ***U-P* characteristic curve.**

output power decreases with the output voltage increases after reaching the maximum power point.

III. MODELING OF PV CELL WITH BP NEURAL NETWORK BASED ON MEA

Mind Evolutionary Algorithm sources to mimic the evolution of human mind evolutionary process. The group is divided into several sub groups, where individuals in the group learn to be the winners and launch a global competition. Two kind of operators "similarity" and "difference" are used to realize the local and global optimization of the entire solution space. Similarity is a process of group competitive learning based on local bulletin board information and tends to be partial optimal solution. Dissmilation refers to the global optimization under the guidance of the global bulletin board. The global bulletin board content is environment information by information extraction system in evolution.

In this paper, using the mind evolutionary algorithm to optimize the training to find the BP neural network connection weights and thresholds. Modeling photovoltaic cells with BP neural network by MEA steps are as follow [18]–[22]:

(1) Date collection: Collecting solar light, temperature and photovoltaic cell output voltage at different time.

(2) Date classification: Date is divided into two parts of training set and test set.

(3) Neural network training: Training neural network with training samples, at same time, the use of MEA parameter optimization, optimization steps are as follows:

1) Get training and test date. The dates include the test parameters of the solar cell, solar intensity and the corresponding weather temperature from am 6 to pm 18.

2) Determine the BP neural network input layer, hidden layer and output layer L = 2m + 1; L = log2n; L is the number of hidden layer nodes, m is the number of input layer nodes, n is the number of output layer nodes. Determine the structure of the neural network is 2-5-1.

3) The initial population of mind evolutionary algorithms is generated and initial populations can be easily generated using the initial population generation function

initpop_generate(). The best subpopulations and temporary subpopulations are generated by the subpopulation production function subpopulation. The size of mind evolutionary algorithm is set 30,the number of best subpopulations and temporary subpopulations are set 5, and the number of iterations is set 30.

4) Subpopulation convergence operation. After the best sub-population and the temporary sub-population are generated, each sub-population first needs to perform the convergence operation. We can easily determine whether the convergence of each sub-population is completed using the mature maturity discriminate function ismature().

5) Subpopulation alienation operation. After completing the convergence operation, we can perform the alien operation and fill in the new subgroups.

6) Solve the best individual. When the iterative stop condition is satisfied, the mind evolutionary algorithm finishes the optimization of the whole process and finds the optimal individual, while the initial weights and initial thresholds of the corresponding BP neural network are obtained.

7) Training BP neural network. The optimized weights and thresholds are taken as the initial values and thresholds of BP neural network, and BP neural network are trained and learned by using training samples. The learning rate of the network is set 0.1, the number of training iterations in 800, the transfer function of the hidden layer and the output layer is selected as the S tangent function 'tansig', and the network training function is 'trainlm'.

A. TEST RESULT ANALYSIS OF MIND EVOLUTION ALGORITHM OPTIMIZATION BP NEURAL NETWORK

According to the solar cell model, it operates under different environments and lights intensities. In this paper, a total of 150 sets of data were collected, then randomly selected 100 sets of data as a network training samples, and the remaining 50 sets of data as a test samples. BP neural network parameters are set as follow, the training number is 800, learning rate is 0.1, and the network error is 0.01. The parameters of the mind evolutionary algorithm are set as follow, the population size is 30, the number of winning sub-population and temporary sub-population is 5, and the number of iterations is 30. The basic parameters of the light intensity of 1000 W/m^2 and ambient temperature of 25°C are shown in table 1.

TABLE 1. Solar cell parameters.

Basic parameters	Short circuit current/A	Open circuit voltage/V	Maximum current/A	Maximum voltage/V
Value	5.95	22	5.55	18

It can be seen from Figure 4 that the after optimization BP neural network voltage prediction error has been significantly with the not optimization BP network optimization. The effectiveness of the algorithm is illustrated, and the prediction error is greatly improved. It can be seen from Figure 5 that the voltage prediction result is more accurate after using the BP neural network optimized by the thought evolutionary algorithm. That MEA-BP neural network can more accurately predict the maximum power at the maximum voltage. That MEA-BP neural network can more accurately predict the maximum power at the maximum voltage.

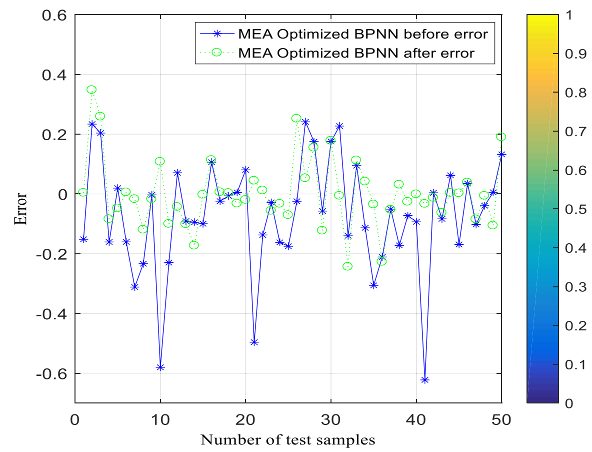

FIGURE 4. MEA optimized BPNN predictive error.

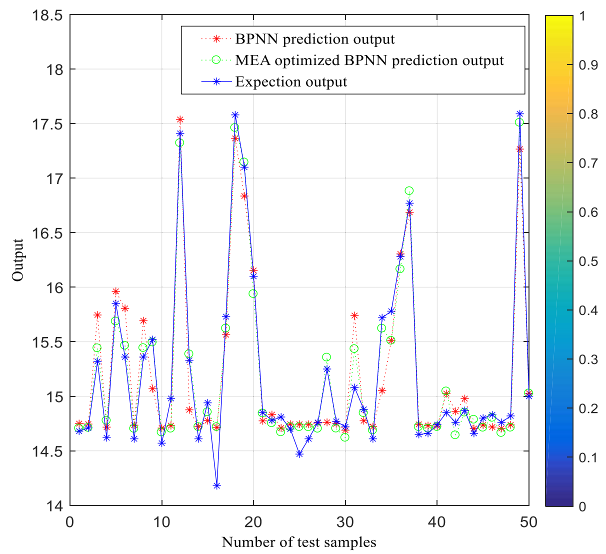

FIGURE 5. MEA optimized BPNN predictive output.

B. MPPT CONTROL STRATEGY OF MIND EVOLUTION ALGORITHM OPTIMIZATION BP NEURAL NETWORK

The main steps of MPPT control based on MEA-BP neural network are as follows:

(1) use the collected solar intensity and ambient temperature as the test set;

(2) pass the data collected in step 1 to the BP neural network with thought evolution, after the forecast corresponding to the environment under the panel maximum power point voltage;

(3) the voltage value in step 2 instead the constant voltage parameter value in the constant voltage method.

IV. SIMULATION RESULTS AND ANALYSIS

In this paper, after the optimization algorithm of mind evolutionary algorithm trained BP neural network using function gensim () to get the Simulink module diagram, This block diagram based on MEA-BPNN solar cell module MPPT schematic and the solar cell module MPPT model based on the constant voltage method are simulated. In MATLAB/Simulink, the ambient temperature is set to 25 °C and the simulation time is 2s. The corresponding light intensities were 1000 W/m^2, 900 W/m^2, 800W/m^2 and 500 W/m^2 at 0 s, 0.5 s, 1 s and 1.5 s, BP neural network control algorithm compared with the new control algorithm proposed in this paper, which gets the simulation characteristic curve shown in Figure 6. Voltage simulation curves based on MEA-BP neural network control algorithm under different illumination intensities in Figure 7.

According to Figure 6, MPPT curve based on the MEA-BP neural network algorithm almost coincides with the theoretical value, which the error is very small and the oscillation is also small at the maximum power point. When the light intensity is abrupt, it can be traced to the vicinity of the maximum power in a hurry and its stability is better. This algorithm improves the drawbacks that BP neural network has great error in the control of MPPT when the ambient temperature is constant and the solar intensity changes. This paper proves the feasibility and effectiveness of this new control algorithm.

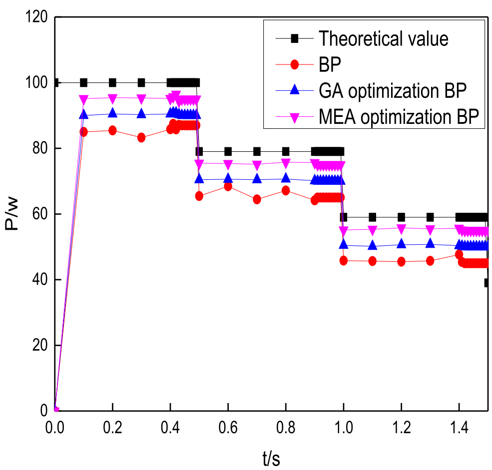

FIGURE 6. **Comparison chart of the MPPT control simulation curves before and after improvement.**

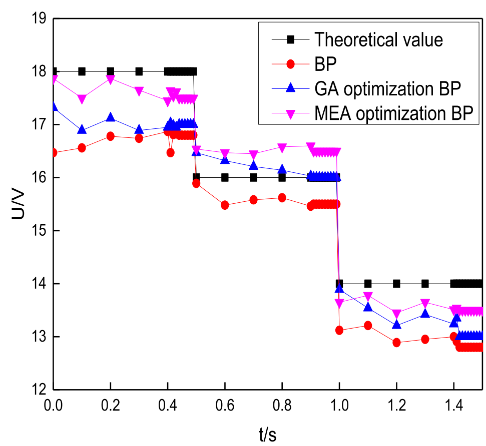

FIGURE 7. **Voltage curves based on the MEA-BPNN algorithm under different conditions.**

It can be seen from Figure 7, the voltage curve predicted by MEA-BP neural network basically agrees with the theoretical value simulation curve, which shows that the prediction error is small. The maximum power tracking control algorithm based on MEA-BPNN proposed in this paper can track the maximum power faster from the analysis of figure 7 and figure 8, which has good stability and high accuracy.

V. CONCLUSIONS

The maximum power tracking of solar PV modules based on BP neural network, which predicts a large error in voltage. In this paper, the evolutionary algorithm is used to optimize the BP neural network algorithm, and then the optimized algorithm model is used to predict the voltage value, which is replaced by the voltage parameter in the constant voltage control algorithm. Finally, the proposed algorithm is validated by Simulink simulation.

(1) BP neural network is optimized by genetic algorithm and thought evolutionary algorithm, which the voltage prediction error is obviously improved. It shows that the algorithm is effective and the prediction error is greatly improved.

(2) The new control algorithm of MPPT based on MEA-BPNN proposed in this paper can quickly track the voltage of solar photovoltaic modules with good stability and high accuracy.

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Authors' photographs and biographies not available at the time of publication.