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Maximum Power Point Tracking Control for Photovoltaic Battery Systems using Deep Q Network Algorithm

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Abstract: Currently, many countries around the world have taken specific steps to gradually replace traditional fossil energy sources with renewable energy sources, of which solar energy is an appropriate choice. Power generation using photovoltaic (PV) batteries is becoming increasingly important because this is a renewable energy source with many advantages such as no fuel costs, no environmental pollution, requiring little maintenance, and does not emit noise compared to other energy sources. However, PV modules when working with inappropriate load impedance still have low conversion efficiency, so maximum power point tracking (MPPT) for PV is essential in a PV system. The amount of electricity generated depends on the operating voltage of the PV. On the I(V) and P(V) characteristics of PV, there exists only one maximum power point (MPP), this MPP point changes depending on radiation and environmental temperature. The MPPT's mission is to find and maintain the most efficient working mode. Therefore, many MPPT methods have been studied to determine the optimal working point. In this article, we propose to use the Deep Q Network (DQN) algorithm to maximize the energy from solar panels when there are changes in radiation intensity and environmental temperature. The results have been simulated and verified on MATLAB/SIMULINK, showing the feasibility and quality of the response when applying the new algorithm.

Keywords: *Solar Energy, Deep Reinforcement Learning, Deep Q Network, Maximum Power Point Tracking, Photovoltaic Systems, DC - DC converter*

1. Introduction

Renewable energy is a clean and infinite source of energy that nature has given to humans. For example, sunlight, flowing water, wind, tides, rain... Using PV panels has the disadvantage of a large initial investment. In addition, the system also depends on weather conditions, so the generation of electrical energy will not be continuous during the day, month, and year. Furthermore, the efficiency of converting solar energy from PV panels into electrical energy is not high [1]. This means that to create large power generation capacity, the system needs to use a large area to install PV panels. Therefore, we need to study the MPPT algorithm so that the power converters operate at the MPP of PV panels. The main goal of the MPPT algorithm is to achieve high-quality response, accurate tracking, and minimize fluctuations due to weather effects. In the documents [2-5] the authors did a comparative study on MPPT techniques to find the right direction. Among the various MPPT algorithms, reports focus heavily on the perturb and observe (P&O) method [6-8] and incremental conductance (INC) method [9-13]. In [6], a study and evaluation of the P&O technique, it is shown that the technique suffers from variability, algorithmic complexity, design dependence, and increased computational load. In the P&O technique, the operating point oscillates around the MPP, causing increasing power loss. This oscillation can be minimized by reducing the influence of turbulence, but achieving MPP will take a long time. In the literature [14-16] it was proposed to change the step size in this situation. Although these methods use simple algorithms. However, the results tracking MPP are not fast and accurate. At the same time, the methods do not consider the effects of radiation intensity and environmental temperature. Some proposed methods considering adaptive perturbations are presented in research [17-19]. In document [9], the authors concluded that using the INC method when the radiation intensity changes large and suddenly will give an undesirable response. To overcome these disadvantages, some intelligent control methods are researched such as neural networks [20-29] and fuzzy logic [30-33]. However, the limitation of the method is complex calculation and large data storage requirements. Besides, MPP continuously changes due to the radiation intensity shining on the panels and the environmental temperature changing in real time, so low-cost hardware processors cannot be used for these applications.

Today, Deep Reinforcement Learning (DRL) is an advanced subfield of Artificial Intelligence (AI) and Machine Learning (ML). DRL combines Deep Learning techniques with Reinforcement Learning algorithms to

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create intelligent agents capable of making decisions through trial and error to optimize long-term goals or rewards. This allows agents to continuously learn from interactions with complex, dynamic, and uncertain environments. The core of DRL lies in using neural networks to approximate complex functions and effectively estimate the value of actions or states based on environmental observations. These capabilities have enabled DRL to achieve notable milestones in a variety of applications, such as robotics, natural language processing, autonomous vehicles, and gaming [34-38]. However, the application of DRL techniques to control systems using renewable energy is still limited.

From the $I(V)$ characteristics, it shows that there is a point called MPP, which is the point where when the system operates at that point, the PV output power is the largest. Weather factors greatly affect PV operations. Among them, temperature and solar radiation intensity are typical factors that have the strongest influence on $I(V)$ characteristics, leading to changes in the MPP position of PV. In most applications it is desirable to optimize the output power flow from the PV to the load. To do that requires the system's operating point to be set at the MPP point. There are many algorithms researched and applied in practice. This article introduces the DQN algorithm, develops the algorithm, simulates and evaluates the effectiveness of the algorithm in controlling the maximum power point of the PV array.

2. Mathematical Description of Photovoltaic Cells

The PV battery has an electrical circuit equivalent to a diode connected in parallel with a photogenerated power source. At stable light intensity, the PV battery has a certain working state, the photogenerated current does not change with the working state. Therefore, in the equivalent circuit it can be considered as a steady current source I_{ph}. In fact, during the fabrication of PV batteries, due to the front and back electrode contact, it is also possible that the material itself has a certain resistivity. Therefore, in the equivalent circuit, it is necessary to add a series resistor R_s and a parallel resistor R_{sh} to the load R_L. Thus, the equivalent circuit of a PV battery is shown in Figure 1.

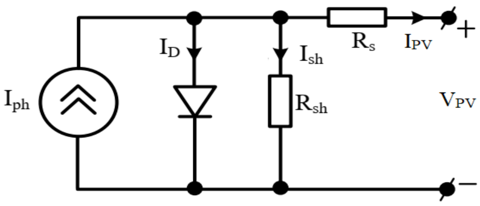

Fig 1. Equivalent circuit diagram of PV

The current through the diode is calculated as the following equation [29,41]:

$$I_D = I_{sh}\left(e^{\frac{qV_D}{nkT}} - 1\right) \quad (1)$$

According to Kirchhoff's law of electric current, we have:

$$I_{ph} - I_D - \frac{V_D}{R_{sh}} - I_{PV} = 0 \quad (2)$$

According to Kirchhoff's law of voltage, we have:

$$V_{PV} = V_D - R_s I_{PV} \quad (3)$$

where: I_D is the current through the diode (A); I_{sh} is the saturation current of the diode (A); q is the charge of the electron ($1.602 \times 10^{-19} C$); k is the Boltzman constant ($1.381 \times 10^{-23} J/K$); T is the contact layer temperature (K); n is the ideal coefficient of the diode; V_D is diode voltage (V); I_{PV} is the PV output current (A).

From equations (1), (2), and (3), deduce the $I(V)$ characteristic equation of a PV cell.

$$I_{PV} = I_{ph} - I_D - I_{sh} = I_{ph} - I_{sh}\left(e^{\frac{q(V_{PV}+R_s I_{PV})}{nkT}} - 1\right) - \left(\frac{V_{PV}+R_s I_{PV}}{R_{sh}}\right) \quad (4)$$

From equations (1), (2), (3), and (4) and from the equivalent diagram of the PV array, we can build a simulation model of the PV array when the temperature and radiation intensity change.

Simulation diagram using PV module A10Green Technology A10J-S72-175 has basic parameters measured under standard conditions (1000W/m^2, 25ºC) as shown in table 1.

Table 1. Technical specifications of PV modules under standard conditions

Parameters	Symbol	Value
Maximum Power	P_{MPP}	175 W
Cells per module	N	72 cells
Open circuit voltage	V_{oc}	43.99 V
Short-circuit current	I_{sc}	5.17 A
Voltage at MPP	V_{MPP}	36.63 V
Current at MPP	I_{MPP}	4.78 A
Temperature coefficient of V_{oc}	K_V	-0.36 V/ºC
Temperature coefficient of I_{sc}	K_I	0.04 A/ºC

Conducting simulations on MATLAB/SIMULINK software, we obtain the $I(V)$ and $P(V)$ relationship curves of PV as shown in Figures 2-5.

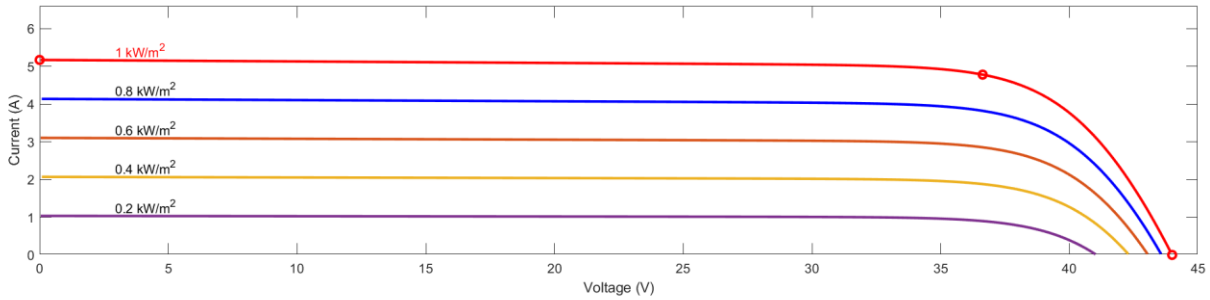

Fig 2. I(V) characteristics of PV when solar radiation changes

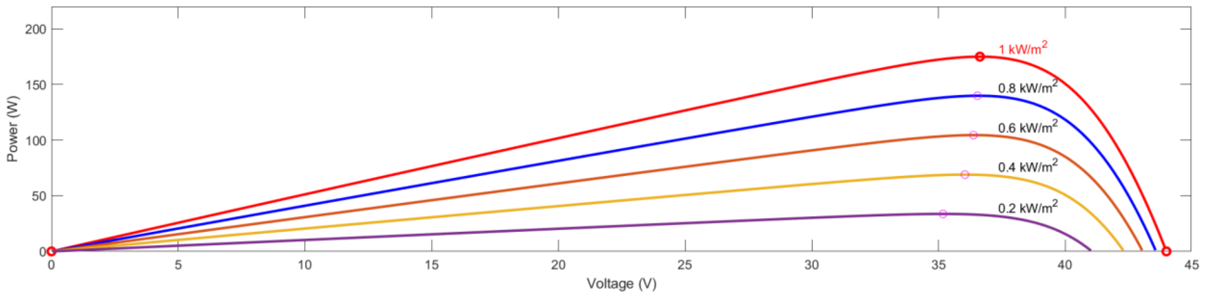

Fig 3. P(V) characteristics of PV when solar radiation changes

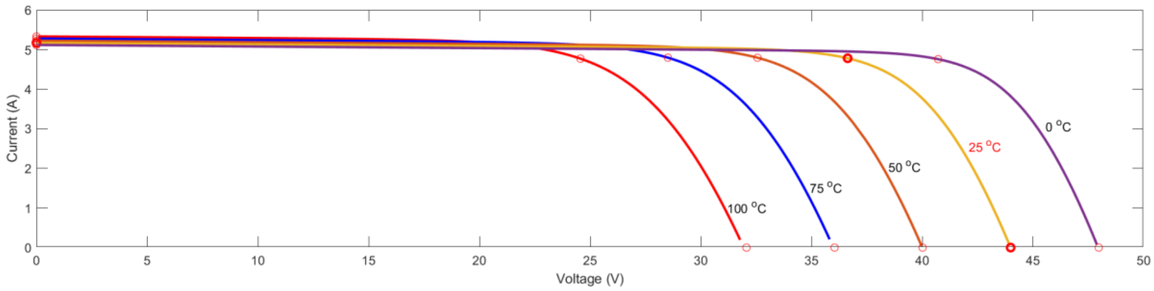

Fig 4. I(V) characteristics of PV when temperature changes

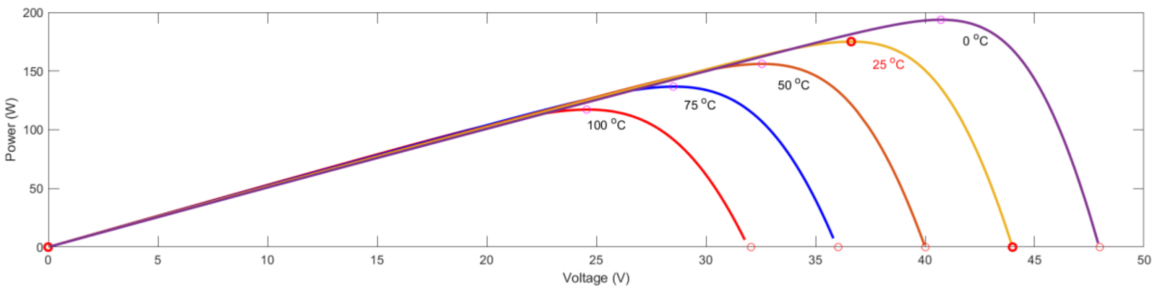

Fig 5. P(V) characteristics of PV when temperature changes

Thus, the position of the MPP point on the characteristic curve is unknown and it always changes depending on radiation conditions and temperature. Therefore, an algorithm is needed to track the MPP point, which is the heart of the MPPT controller.

3. Deep Reinforcement Learning based MPPT Control

3.1. Introduction to DRL techniques

Two key concepts lie at the heart of DRL: Reinforcement Learning (RL) and Deep Learning (DL). RL, which focuses on learning the optimal policy through interaction with the environment and DL, uses artificial neural networks to generalize and represent complex patterns or relationships in data. The combination of these techniques synergistically expands the capabilities of both. Because DL offers scalability and generalization to large state spaces and complex functions. While RL guides the learning process through trade-offs between exploration and exploitation, allowing agents to coherently improve their performance over time.

A DRL framework typically includes the following components: environment, agent, state, action, and reward. Environment represents the contextual surroundings in which the agent operates. The agent is controlled by AI, interacting with its environment through actions and learning to make better decisions based on observed changes in state and rewards it receives while performing perform specific actions. The agent aims to develop an optimal policy that maximizes the cumulative reward (also known as profit) over a period or multiple time steps, considering both the immediate and future value of each take action to achieve better long-term results.

To accomplish this, DRL techniques often use a combination of value-based and policy-based approaches. Value-based methods, such as Q-Learning or Temporal Differential Learning, aim to estimate the value functions associated with each state-action pair. In contrast, policy-based methods, such as Policy Gradient (PG) or Actor-Critic (AC), attempt to learn the optimal policy by explicitly optimizing the objective function with respect to expected profit. Both approaches have their own advantages and challenges, and successful DRL applications often use combined techniques to improve their overall performance and stability.

Effectively training a DRL agent often requires overcoming a number of challenges. For example, the balance between exploration and exploitation is an important aspect of maintaining a balance between gathering new information about the environment and exploiting existing knowledge to optimize benefits. Additionally, learning in large and high-dimensional state spaces, dealing with partial observability, managing confounding or delayed rewards, and transferring learned knowledge across tasks are some of the key challenges that the DRL algorithm needs to address to improve its overall performance and robustness.

3.2. Markov decision process model

To use the DRL technique in MPPT control for PV systems, we define a Markov Decision Process (MDP) model applied to the problem. The Markov decision process is a set of data S, A, T, r. In which: S describes the operating points of the PV system - is a finite set of states; A describes the duty cycle disturbance, applied on the converter to change the operating state of the PV source - which is a finite set of actions; T is the probability that the action executes the next state; r is a reward function that represents the direct reward for performing the action in the current state.

The process of implementing the DRL technique in the PV system is for the agent to receive a reward when determining the correct action, on the contrary, it will receive a penalty when choosing the wrong one. In which the reward function as well as the state and action space are predetermined. This combination includes duty cycle, duty cycle disturbance, PV array current and voltage as shown in the literature [42,43]:

$$S = \{V_{PV}, I_{PV}, D, \Delta D\} \tag{5}$$

The agent causes an action in the perturbed action space of the duty cycle ΔD and is then performed in the environment.

$$A = \{a| + \Delta D, 0, -\Delta D\} \tag{6}$$

Define reward function:

$$r = r_1 + r_2 + r_3 \tag{7}$$

where:

$$r_1 = \begin{cases} 0 \ \ if \ 0 \leq D \leq 1 \\ -1 \ \ otherwise \end{cases} \tag{8}$$

$$r_2 = \begin{cases} \left(\frac{P_{t+1}}{P_{MPP}}\right)^2 & if \ \Delta P \geq -\varepsilon \\ 0 & if \ \Delta P < -\varepsilon \end{cases} \tag{9}$$

$$r_3 = \frac{P_{t+1}}{P_{MPP}} \tag{10}$$

We see that the reward function is the sum of the components r_1, r_2, r_3.

where: function r_1: the agent is penalized if it is outside D; function r_2: Agent gets reward if capacity increases, otherwise no reward; function r_3: The agent receives a higher reward when in the global MPP position than in the local MPP position.

3.3. Deep Q Network algorithm controls MPPT for PV arrays

The Deep Q Network (DQN) algorithm is a variation of Q-Learning. When the association between states and actions is too large, the memory and computation requirements for Q will be very large. To solve that problem, we will turn to a deep learning network Q to approximately calculate the value $Q(s, a)$. With the new approach, we will generalize the approximation of the Q-value function instead of having to record and re-store the solutions. Here, the optimization goal of the model is to reduce bias in one step of updating the value function.

Definition of the loss function:

$$L(w) = \left(Q'(S_t, A_t) - Q(S_t, A_t)\right)^2 \tag{11}$$

where: $Q'(S_t, A_t) = r_t + \alpha max Q'(S_{t+1}, A_{t+1})$ is the target Q value; $Q(S_t, A_t)$ is the Q value estimated from the neural network

The optimization problem in DQN is to find a set of neural network model parameters w_Q that minimizes the loss function.

$$w_Q = argmin\left(L(w)\right) \tag{12}$$

The block diagram of the DQN algorithm controlling MPPT in the PV array is shown in Figure 6.

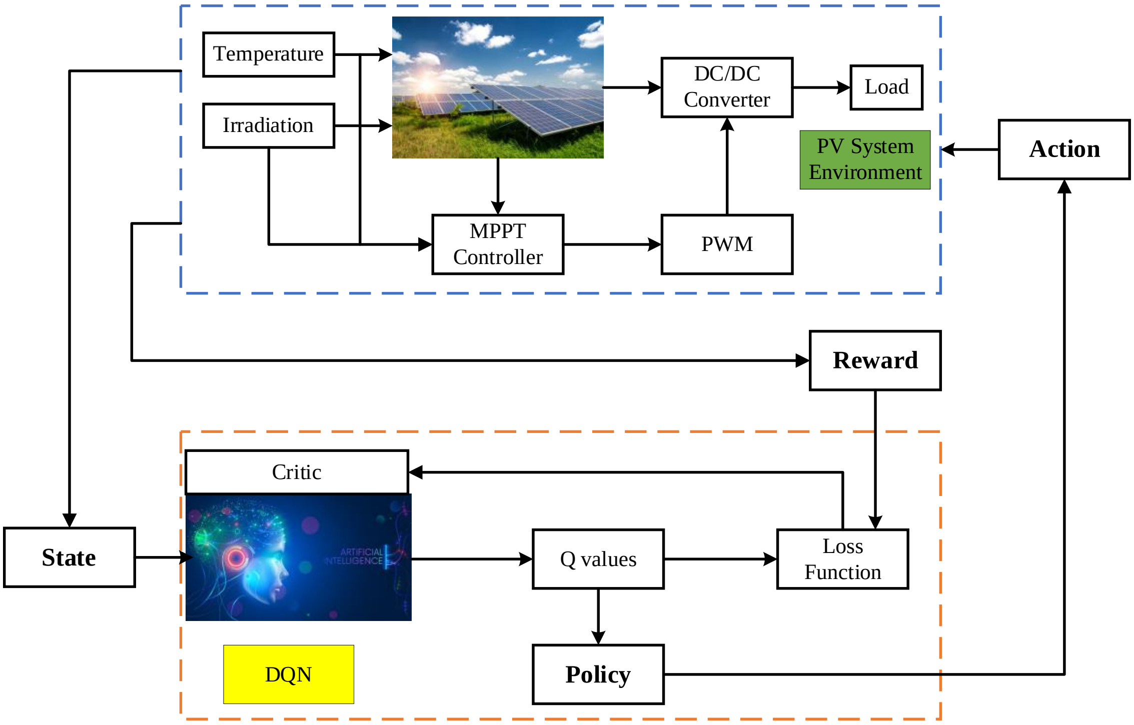

Fig 6. Structure of DQN algorithm to control MPPT for PV systems

The DQN agent is built on MATLAB/SIMULINK software shown in Figure 7.

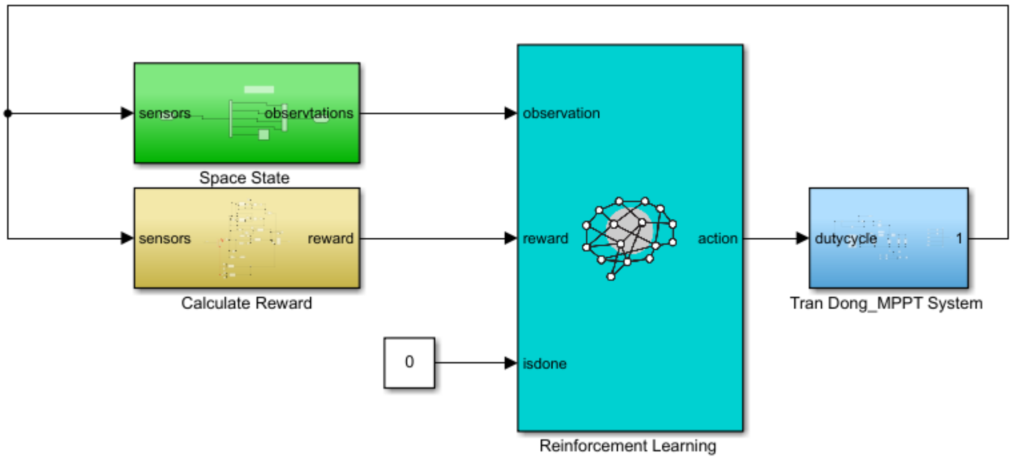

Fig 7. System control block diagram on MATLAB/SIMULINK

4. Simulation Results

Conduct simulations to verify the effectiveness of the DQN algorithm in two different scenarios.

Scenario 1: The PV array is simulated for sudden changes in radiation intensity, assuming a constant ambient temperature of 25 ºC. Initially, the PV array was simulated at I_r = 1000 W/m^2. Then, at time t = 0.5s, the radiation intensity suddenly drops to 850 W/m^2. At time t = 1s, the radiation intensity drops to 650 W/m^2. At time t = 1.5s, the radiation intensity is 450 W/m^2. During t = 2s to 4s, the radiation intensity suddenly increases from 450 W/m^2 to 900 W/m^2. During t = 5s to 7s, the radiation intensity drops to 400 W/m^2.

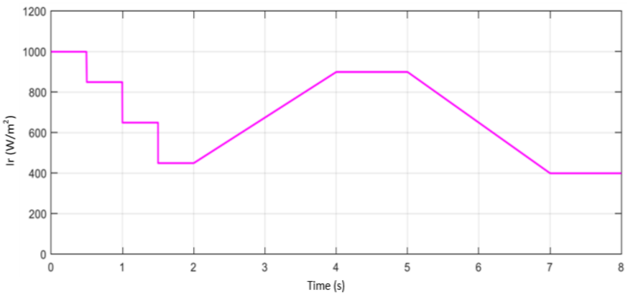

Fig 8. Characteristics showing changes in radiation intensity

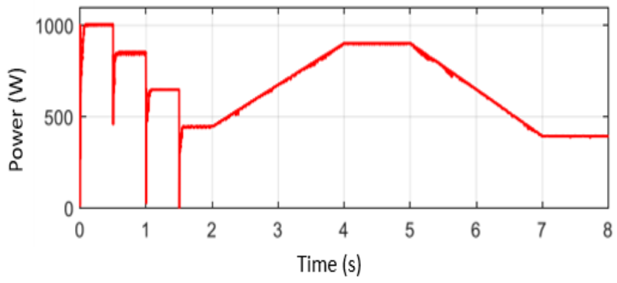

Fig 9. The power of the PV array when the radiation intensity changes

Scenario 2: The PV array is simulated for sudden changes in ambient temperature, assuming a constant radiation intensity of I_r = 1000 W/m^2. Initially, the PV array is simulated at a temperature of T = 25 ºC. Then, at time t = 0.5s the temperature suddenly increases to 35 ºC. At time t = 1s the temperature increases to 45 ºC. At time t = 1.5s, the temperature suddenly drops to 15 ºC. During t = 2s to 4s, the temperature increases from 15 ºC to 40 ºC. During t = 4.5s to 7.5s, the temperature drops to 20 ºC.

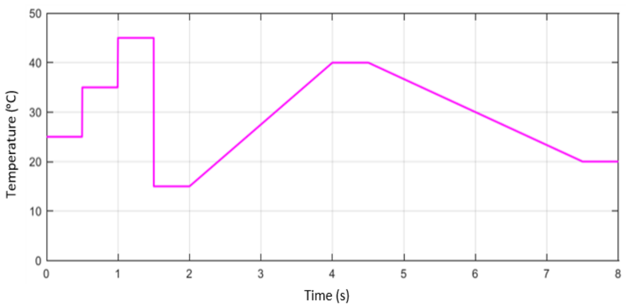

Fig 10. Characteristics showing changes in temperature

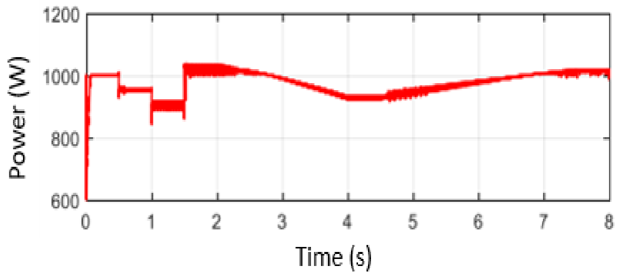

Fig 11. PV array power when temperature changes

From the simulation results of Figure 8-11, it can be seen that when the intensity of solar radiation and environmental temperature change, the PV system can adhere to MPP in a very fast time. We see, MPPT works well with the DQN algorithm, the PV array capacity in this case closely follows the maximum capacity MPP, or in other words the fluctuation range around MPP is small. DQN algorithm during MPPT control, responds quickly and accurately, especially the current and voltage of PV are stable when using this algorithm. Therefore, using the DQN algorithm in MPPT control of an independent power-supplied PV system is very appropriate, ensuring optimal, continuous and stable power supply to the load.

5. Conclusion

The article has built a simulation model of a PV array, investigating the influence of solar radiation intensity and temperature on the generating capacity of a PV array. In a PV system, people always want that regardless of weather conditions, the power flow from the PV array to the load is always maximum, which is the goal of the MPPT control problem. Thereby, the article introduces the DQN algorithm applied in MPPT control of PV arrays. Simulate the MPPT algorithm under changing weather conditions commonly encountered in practice to see the effectiveness of the proposed method. Based on simulation results on MATLAB/SIMULINK, it shows that the MPPT method works well when weather conditions change suddenly, the maximum power point tracking response is very fast, and the over-adjustment is very small. The proposed algorithm has advantages such as: small and narrow fluctuations around the maximum power point; Minimize transmission power loss due to fluctuations around the small maximum power point. Therefore, applying the DQN algorithm in MPPT control for PV systems will give good results.

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Conflicts of interest

The author declare no conflicts of interest.

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