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Simulation and study of maximum power point tracking for rim-driven tidal current energy power generation systems

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Abstract

This paper presents a maximum power point tracking (MPPT) control algorithm based on an intelligent reinforcement learning. The proposed model-free Q-learning algorithm realizes the online learning of the control algorithm of the tidal power generation system by updating the action values stored in the Q-table. By learning the optimal rotor speed-output power curve, the algorithm fits the optimal generator curve and applies the optimal $\mathrm{P_e} - \omega_\mathrm{r}$ curve to the optimal control method of the tidal power generation systems.
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Keywords: Tidal current energy power generation systems; Rim-driven; MPPT; Q-learning

1. Introduction

Tidal power has been extensively developed in the past decades and is expected to become an important source of electricity for clean, renewable and sustainable island power supply in the future. The rim-driven generator studied in this paper comes from the new tidal energy power generation device independently developed by the research group in the early stage, which has been successfully operating in Zhoushan for more than three years, and has shown good performance in terms of reliability and conversion efficiency. The integration of the impeller and the generator is structurally distinct from conventional generators.

It is mainly composed of a deflector cover, stator, rotor and impeller. The deflector hood collects the seawater and increases the speed and supports the entire motor structure; The generator stator is mounted on the inside of the deflector; The generator rotor is integrated at the tip of the impeller and is composed of multiple permanent magnet poles; The impeller is mounted in a deflector and directly drives the rotor to rotate [1].

Compared with the traditional generator, the rim-driven generator integrates the impeller and the generator, and replaces the conventional axial connection method with a radial connection, which reduces the complexity of the

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system and improves the reliability of the system operation due to the cancellation of the transmission device; The air gap of the rim-driven generator adopts an open design, the sea water can flow freely in the air gap, and the stator and rotor are sealed separately by static sealing, which reduces the occurrence of faults such as seal failure and improves the stability of system operation; The rim generator works under the surface of the water, dissipates heat through seawater, has a good heat dissipation environment, and therefore has a strong overload capacity. The rim generator operates at a lower speed, with less noise and a relatively small impact on marine life.

2. Maximum power point tracking

2.1. The principle of maximum power point tracking

The significance of Maximum Power Point Tracking (MPPT)lies in that it can ensure the hydraulic turbine to obtain the maximum power in the case of varying current speed, so as to improve the annual energy output and economic benefit of power generation system.

In the fixed-pitch tidal current energy conversion system, to allow the system to achieve the maximized capture, it is essential to make the revolving speed of the turbine to track the change in current speed, and ensure the tip speed ratio of the turbine to be the optimal value. Therefore the maximum power point tracking of fixed-pitch tidal current power generation system can also be known as variable speed control.

The maximal value of output mechanical power of hydraulic turbine, namely the maximal capture power can be represented by the maximal performance coefficient C_{pmax} and the optimum tip speed ratio λ_{opt} [2] :

$$\mathrm{P} = \frac{1}{2} C_{pmax} \rho S (R\omega/\lambda_{opt})^3 = k_w \omega^3 \tag{1}$$

It can be known from Eq. (1) that, the direct-driven tidal current energy power generation system, the maximal power value of hydraulic turbine capture is directly proportional to the cubic rotating speed of the generator speed. With different speed of tidal current, the output mechanical power of hydraulic turbine varies with the change in rotating speed of the impeller, the maximum output power curve in the case of different current speed is shown in Fig. 1.

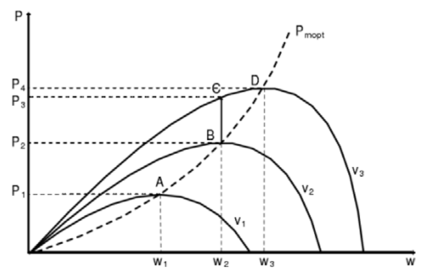

Fig. 1. The output characteristics of hydraulic impeller.

For the fixed-pitch hydraulic turbine, if the pitch angle of impeller β is constant, there will be a maximum power point at the different current speeds, this maximum power point corresponds to the optimum tip speed ratio λ_{opt} at that tidal current speed, at which point the performance coefficient of hydraulic turbine is the maximum value C_{pmax}. The line connecting the maximum power points of hydraulic turbine corresponding to different current speeds is the very maximum power curve. With a fixed tidal current speed, as the rotating speed of hydraulic turbine varies, its performance coefficient will accordingly vary, the output mechanical power of hydraulic turbine will be consequently changed. In order to track the maximum power curve, the change of tidal velocity must be taken into account. By adjusting the rotation speed of the turbine, the tip speed ratio is always kept at the optimal value, so that the turbine operates on the maximum power curve and thus obtains the maximum tidal energy, which is the principle of maximum power point tracking of the turbine.

Many classical MPPT algorithms have been proposed for efficient control in marine current energy power generation systems, such as power signal feedback (PSF), optimal relationship-based (ORB), tip speed ratio (P&O), etc. TSR and PSF conduct the controlling procedure with the control loop's target reference signal based on motor parameters and optimal power curve [3]. Due to the wear and aging of the hydraulic impeller, the reference signal of the control loop will change, which results in a decrease in control accuracy and motor efficiency, whereas P&O has no previous experience in the process of the next search, which will lead to a rather slow response when searching MPP and may affect the control performance of the system. At present, intelligent control such as sliding mode control, fuzzy logic control and neural network control have been studied in wind power generation systems, but there is little research on intelligent control in marine current energy generation systems.

We therefore need a new learning method to adapt MPPT control for tidal current energy power generation system as shown in Fig. 2.

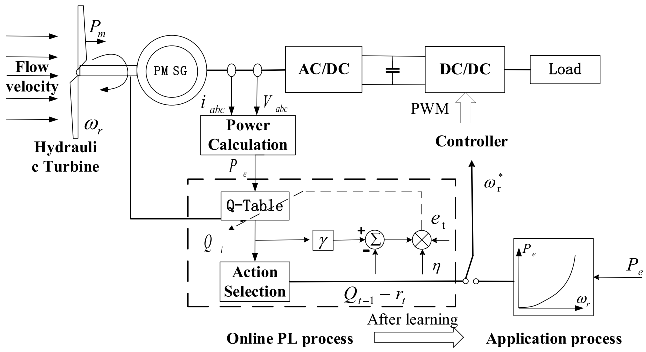

Fig. 2. Block diagram of MPP control based on Q-Learning algorithm.

2.2. MPPT application technology based on Q-learning algorithm

The Q-learning model-free RL algorithm for reinforcement learning with excellent search performance. Reinforcement learning does not require an object model or prior knowledge. The most significant benefit of reinforcement learning in optimal control is that it can ignore problems such as system disturbances, time variation and non-linearity when solving large complex systems and seek the best behavioral strategy through learning. After investigation, the Q-Learning algorithm can improve the problem of maximum power point (MPP) instability caused by machine aging. The following will examine how Q-learning can be applied to MPP. The core idea of Q-learning is to obtain further Q-sheets based on feedback through continuous iteration [4].

Therefore, it is necessary to clarify the iterative process of the algorithm first. The iterative equation is as follows:

$$\mathrm{Q_{t+1}(s_t, a_t) = Q_t(s_t, a_t) + l_t}\left[\mathrm{r_{t+1}} + \gamma^{\mathrm{max}}_{\mathrm{ai}}\mathrm{Q_{t+1}(s_{t+1}, a_i) - Q_t(s_t, a_t)}\right] \tag{2}$$

in this equation, γ is the discount coefficient, and it decides the value of the reward; i is the action's index. $\mathrm{Q_t(s_t, a_t)}$ is a function of the value of the action, and it should be estimated. At each time period, the system observes its current state firstly and chooses to perform the corresponding action nextly. Meanwhile, the value $\mathrm{Q_t(s_t, a_t)}$ has been documented. Then, the subsequent state $\mathrm{s_{t+1}}$ is observed and the feedback $\mathrm{r_{t+1}}$ is immediately obtained, while the maximum Q value corresponding to $\mathrm{s_{t+1}}$, i.e., $\mathrm{Q_{t+1}(s_{t+1}, a_i)}$, is found using the method mentioned below. The recorded will be updated according to (1). The parameter l_{t} is the learning rate, l_{t} decides how far the currently estimated $\mathrm{Q_t(s_t, a_t)}$ is adjusted toward the newly estimated Q value $\mathrm{r_{t+1}} + \gamma$ maxa$_i$ $\mathrm{Q_{t+1}}(\mathrm{s}_{t+1}, a_i)$. It should update all state–actions in order to make sure that the Q-value function converges to the optimal value. In this process, the agent should try all actions in every states in order to find a balance between exploration and exploitation [5,6]. Using Boltzmann exploration strategy can help to achieve this goal. The probability that action a_i in state s will be selected is as follows:

$$p(\mathrm{s, a_i}) = \frac{\mathrm{e}^{\frac{\mathrm{Q(s,a_i)}}{\tau}}}{\sum \mathrm{a^i e}^{\frac{\mathrm{Q(s,a_i)}}{\tau}}} \tag{3}$$

in this equation, τ is a positive parameter that controls the randomness of exploration. A larger τ results in more random action selection, while a lower temperature results in high-value actions being chosen with a better chance. In fact, τ can change over time during the learning process to balance exploration and exploitation [7].

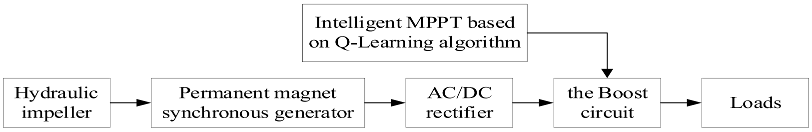

Fig. 3. The entire block diagram of tidal current energy generation system.

3. The simulation model of tidal current energy power generation system

The whole marine current energy generation system consists of several sub-models, including a tidal water velocity model, a turbine model, a permanent magnet synchronous generator model, a three-phase uncontrolled rectifier circuit, and a Boost circuit. In the control algorithm, the Q-Learning based power signal feedback method is used. The whole simulation system is shown in Fig. 3.

3.1. Tidal current speed model

The four-component method of specific wind speed, combined with the characteristics of slow change of tidal water speed and small fluctuation range, tidal water speed can be divided into the following four basic parts: basic water speed, periodic fluctuation, sudden water speed and noise. The time-varying function is shown in the formula.

$$\vartheta = f(\mathrm{t}) = \begin{cases} \vartheta_{avr} + \sin(2\pi f t) + \vartheta_{noize} \ 0 < t < t_1 \\ \vartheta_{avr} + \sin(2\pi f t) + kt + \vartheta_{noize} \ t_1 < t < t_2 \\ \vartheta_{avr} + \sin(2\pi f t) + \vartheta_C + \vartheta_{noize} \ t_2 < t < t_3 \\ \vartheta_{avr} + \sin(2\pi f t) + \vartheta_{noize} \ t_3 < t < t_4 \end{cases} \tag{4}$$

In the formula, ϑ_{avr} is the average tidal water speed, f is the frequency of tidal water speed periodic change, k is the rising rate of the tidal water speed when the spring tide comes, ϑ_{C} is the maximum value of the tidal water speed increase during the spring tide, and $\vartheta_{\mathrm{noize}}$ is the noise of the tidal water speed.

3.2. The model of hydraulic impeller

In general, the functional relationship between the power capture coefficient $C_P(\lambda, \beta)$, the tip speed ratio λ and the propeller angular pitch β can be expressed as:

$$C_p(\lambda, \beta) = 0.5176(\frac{116}{\lambda_1} - 0.4\beta - 5)e^{-\frac{21}{\lambda_1}} + 0.0068\lambda \tag{5}$$

In the Eq. (5), the relationship between $\lambda, \lambda_1, \beta$ is:

$$\frac{1}{\lambda_1} = \frac{1}{\lambda} - \frac{0.035}{\beta^3 + 1} \tag{6}$$

According to the output power equation of the hydraulic impeller:

$$P = \frac{1}{2}\rho S C_p(\lambda, \beta) v^3 \tag{7}$$

The relationship between the output power and output torque is:

$$T = \frac{P}{\omega} \tag{8}$$

It can be seen from the above mentioned relational expression that, the output power of hydraulic impeller is the product of current power and power-capture coefficient, the output torque is the ratio of output power to rotating speed, due to the fact that the hydraulic impeller directly drives the generator to rotate, so the output torque of impeller is completely transferred to the generator.

3.3. The model of permanent magnet synchronous generator

As to the non-salient pole permanent magnet synchronous generator, its mathematic model in the rotating coordinate system is shown in the Eq. (9):

$$\begin{cases} \dfrac{di_d}{dt} = -\dfrac{R_a}{L} i_d + \omega_e i_q + \dfrac{1}{L} u_d \\ \dfrac{di_q}{dt} = -\dfrac{R_a}{L} i_q - \omega_e (i_d + \dfrac{1}{L}\varphi_f) + \dfrac{1}{L} u_q \end{cases} \tag{9}$$

The torque equation is shown in Eq. (10):

$$T_e = 1.5 p \varphi_f i_q \tag{10}$$

The equation of torque balance of generator is shown in formula Eq. (11):

$$T_e - T_m = -J \frac{d\Omega}{dt} \tag{11}$$

It can be seen from Eq. (10) and Eq. (11) that, by controlling the i_q of permanent magnet synchronous generator, the goal of controlling its electromagnetic torque can be achieved.

3.4. Power conversion control module

The DC-DC circuit adopts the Boost circuit. The Boost circuit adjusts the output voltage according to the duty cycle of the input driving square wave signal, and uses the triangular wave to compare with the reference voltage. When the current value of the triangular wave is higher than the constant value, it outputs a high level, and vice versa. The output is low, thereby obtaining a square wave with a controllable duty cycle. The AC-DC module is a three-phase uncontrolled rectifier. Power conversion control module designed in this paper can be obtained by combining the above modules with Matlab/Simulink.

3.5. Control module of Q-learning model

In order to apply Q-learning to MPPT control, the three items, named state space, action space, and feedback, need to be identified. In the tidal current power generation system, the agent can be regarded as the whole power generation system, and the state space is s(ω, P), this space represents all the working points of the power tidal current power generation system, and the discrete control action (a∈A) is selected according to Q-values for all possible actions, extracted from the action space using Boltzmann exploration. The agent then inputs a new action point and will get a feedback in order to renew the result of the action already selected in the previous state. The target of the generation system is to take as much energy as possible from the power flow, and to achieve this target, each time the agent decides to choose an action, it is more likely to choose an action with a higher value [8].

3.6. State space

The total mechanical power that the hydro turbine can derive from the water flow can be calculated by the following formula:

$$\mathrm{P_m} = \frac{1}{2} \rho \mathrm{A} \vartheta_{\omega}^{3} \mathrm{C_P}(\lambda, \beta) \tag{12}$$

As shown in Fig. 2, there are two process in the method:the online learning process and the online application process. In the online learning process, the controller behaves like an agent, which interacts with the environment to obtain Pe and ωr, uses the Q-learning algorithm to learn MPP from its own experience, and continuously improves the action reliability by updating the Q table. The optimal rotor speed-power output curves are then obtained from these MPPs and used in online applications for ORB MPPT control.

3.7. Action space

The action space of an intelligent body can be expressed as

$$A = \{a| + \Delta\omega_r, 0, -\Delta\omega_r\} \tag{13}$$

where $\Delta\omega_r$ represents a change in speed and 0 means that the speed remains constant. The control command update is given by.

$$\omega^*_{r,t+1} = \omega^*_{r,t} + a \tag{14}$$

$\omega^*_{r,t}$ and $\omega^*_{r,t+1}$ are the previous and current control commands respectively.

In each state, the intelligent body has three action options, namely "increment" ($+\Delta\omega_r$), "decrement" ($-\Delta\omega_r$) and "hold" (0). At each time step, the intelligence selects an action from the action space to modify the tacho control command based on the measurement of the state ($\omega_{r,k}$, $P_{e,j}$) and the action selection strategy used.

3.8. Reward

After taking an action, the intelligence is rewarded to evaluate the selected action. the Q-learning reward mechanism in the MPPT application is set as follows.

$$r_{t+1} = \begin{cases} +1, \text{if} P_{e,t+1} - P_{e,t} > \delta 1 \\ 0, \text{if} |P_{e,t+1} - P_{e,t}| \le \delta 1 \\ -1, \text{if} P_{e,t+1} - P_{e,t} < \delta 1 \end{cases} \tag{15}$$

where $P_{e,t+1}$ and $P_{e,t}$ are the output power for two consecutive time steps and $\delta 1$ is a small positive number. If the selected operation P_e leads to an increase, a positive reward will be provided to the intelligence and conversely a negative reward will be provided to indicate a penalty. However, measurement errors may lead to small differences, even when the actual output power is the same for two consecutive time steps, or when the operating point is close to the MPP and it is difficult to detect the difference between $P_{e,t+1}$ and $P_{e,t}$. Therefore, a small positive number $\delta 1$ is used to set the bounds. When the absolute value of the difference between $P_{e,t+1}$ and $P_{e,t}$ is less than a sufficiently small $\delta 1$, then we can assume that the state point has reached the target state point [9].

The proposed intelligent RL-based MPPT algorithm consists of two processes:an online learning process and an online application process, as shown in the following diagram (see Fig. 4).

4. Simulation result of tidal current energy power generation system

The Q-learning algorithm was implemented by code and simulation experiments were carried out on the model already built in simulink, and the waveforms controlled by Q-learning were obtained: as shown in the figure, this is the waveform of the turbine output power at a water speed of 3 m/s, and the number of iterations is 3, 5, 7 and 9, from which it can be seen that the turbine output power is continuously learning in The maximum power point obtained from the tracking can be considered reliable because the maximum output power of the turbine is used as a reference in the model built. In practice, there is no maximum output power as a reference, so more iterations are needed to ensure the reliability of the tracked maximum power point. The output Q table is then looked up to find the corresponding maximum power point. At a constant water speed of 3 m/s and a motor speed of 48.8426 rpm, the turbine can achieve a maximum output power of 5216.3 W (see Fig. 5).

By the same method, the maximum output of the turbine at different water speeds and the corresponding speed of the motor are shown in Table 1.

By allowing the motor to learn this fitted curve, as shown in Fig. 6, real-time control of its motor speed can be achieved so that the turbine reaches its maximum output. The maximum power curve needs to be reacquired when the motor is old, aging etc. in order for the motor to control the turbine to its maximum output in different states.

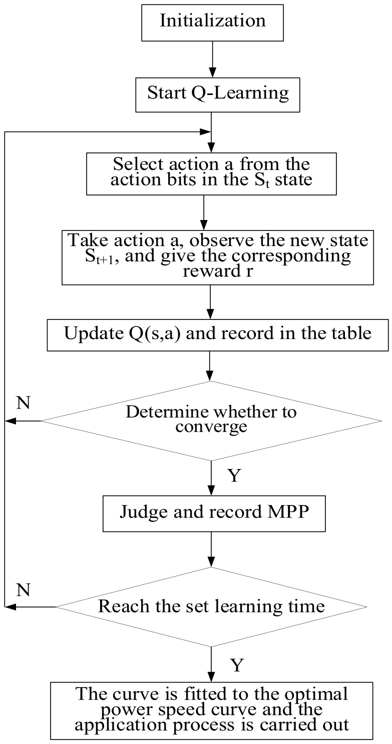

Fig. 4. Flow chart of MPPT intelligent control algorithm based on Q-Learning.

Table 1. Maximum output of the turbine at different water speeds and the corresponding speed of the motor.

Water speed (m/s)	Rator speed (rpm)	Pmax (W)
2	32.3390	1545.7
2.1	34.0908	1789.3
2.3	37.3697	2350.8
2.4	38.7101	2670.8
2.5	41.3270	3015
2.6	42.0902	3395.9
2.7	43.7100	3803.0
2.8	45.1925	4241.2
2.9	46.7926	4712.0
3	48.8426	5216.3
3.1	50.2591	5756.0
3.2	51.7390	6331.1
3.3	53.2021	6943.0
3.4	55.2945	7593.7
3.5	56.8339	8283.9

Using the tidal velocity input in Eq. (4), the system uses a combination of Q-Learning based algorithms and PSF to track the maximum power point. In the simulation experiments, the reference value for the optimal tip speed ratio is set to 8 and the control system is then observed to track the maximum power point in time.

To facilitate the simulation, the period of tidal current speed has been shrunken by many times during the simulation, so as to obtain the simulation result quickly during the simulation and confirm the validity of system. The current speed waveform during the simulation of whole system is shown in Fig. 7.

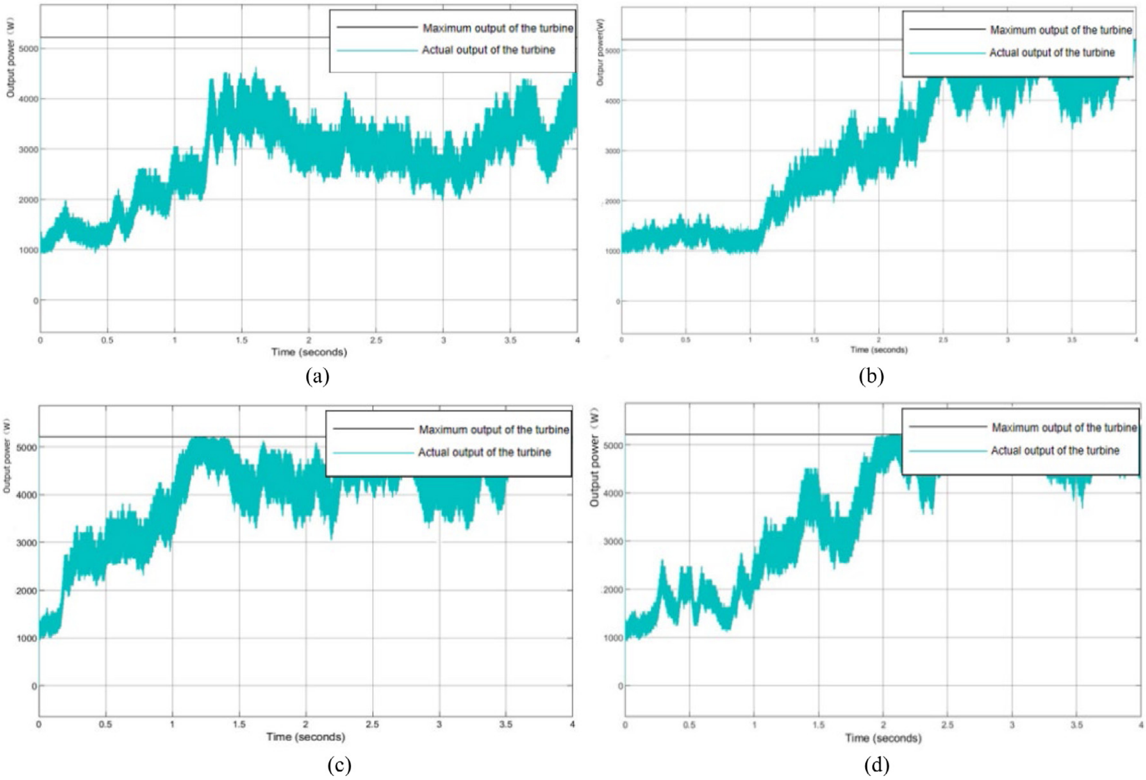

Fig. 5. (a) Third iteration of tracking power simulation results at a constant water velocity of 3 m/s; (b) Fifth iteration of tracking power simulation results at a constant water velocity of 3 m/s; (c) Seventh iteration of tracking power simulation results at a constant water velocity of 3 m/s; (d) Ninth iteration of tracking power simulation results at a constant water velocity of 3 m/s.

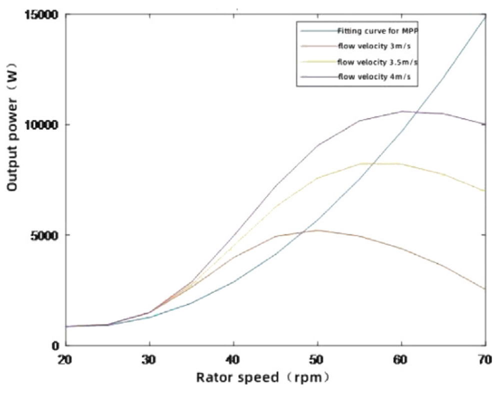

Fig. 6. Maximum power curve fitting results.

The simulation result of the tip speed ratio is shown in Fig. 8:

It can be seen from Fig. 8 that, the region of system tip speed ratio is stable after the simulation has been done, it fluctuates around the place where the optimum tip speed ratio is 8.

The simulation result of performance coefficient C_p of hydraulic turbine is shown in Fig. 9.

It can be seen from Fig. 9 that, the energy-gain coefficient of hydraulic turbine of the system with a control algorithm basically remains at about 0.47 after the system is stable, while as to the system without controller, its performance coefficient fluctuates a lot with a low efficiency.

The simulation result of output power of hydraulic impeller is shown in Fig. 10:

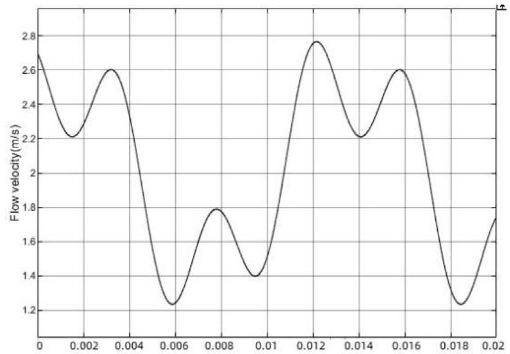

Fig. 7. Flow velocity waveform during the process of system simulation.

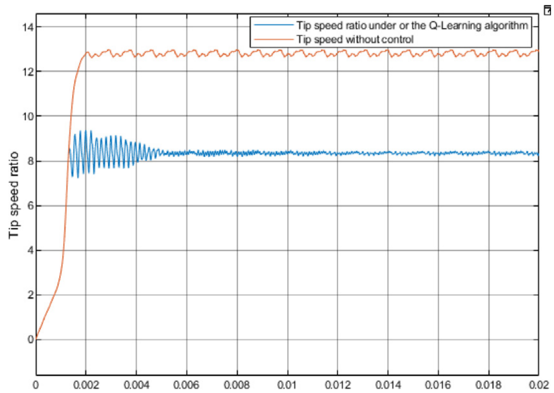

Fig. 8. Curve of the tip speed ratio.

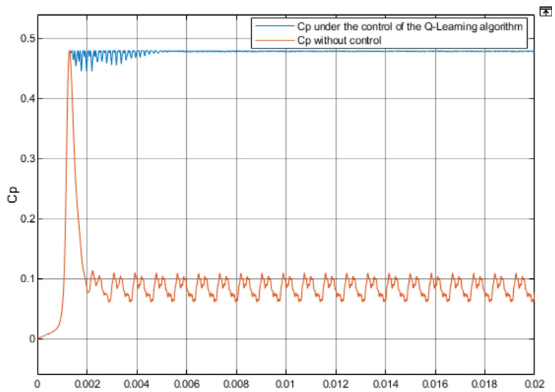

Fig. 9. Curve of the C_p.

According to the waveform shown in Fig. 10, when no control is implemented, the power of the generator rises rapidly but fails to stabilize at the optimum speed point. And when the motor is stable, the output power of the hydraulic impeller is at a low level of around 500 W. However, with the Q-Learning algorithm combined with the improvement of the PSF algorithm, it basically stabilized at the maximum power point at 0.005s. The output power is able to be tracked well. Therefore, this control method has good responsiveness and effectiveness.

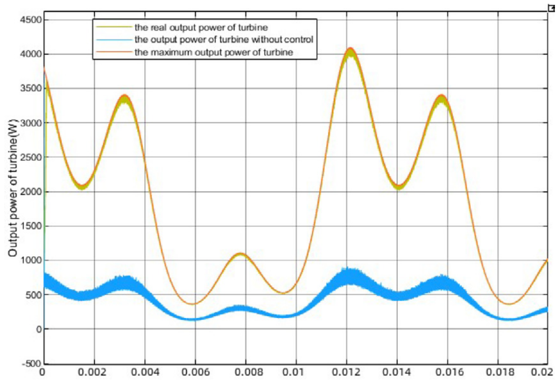

Fig. 10. Output power curve of hydraulic impeller.

5. Summary

In this paper, the MPPT method of tidal power generation system is studied from the aspects of theory and simulation. The experimental MATLAB/Simulink simulation model of the tidal power generation system is developed, which uses a combination of Q-Learning and PSF to simulate the whole system. Compared with the traditional TSR and PSF methods, the proposed MPPT method does not require water velocity sensors or knowledge of previous control system models. When the motor ages and deteriorates, the maximum power curve of the motor can be obtained by re-learning, so that the motor can control the turbine to reach its maximum power output in different states. The simulation results show that the system can track the maximum power point stably and in real-time with the change of the environment.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Yani Ouyang reports financial support was provided by Institute of Electrical Engineering, Chinese Academy of Sciences, China University of Chinese Academy of Sciences, China.

Data availability

The data that has been used is confidential

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