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Artificial intelligence based approach to improve the frequency control in hybrid power system

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Abstract

Frequency control over networks is done using the frequency droop control technique which has the simplicity advantage although it allows that, in certain situations, frequency control is not very efficient. Artificial intelligence techniques have been increasingly used, so it is justified to explore their viability in electrical networks. The present work analyzes the use of Artificial Intelligence in networks to improve the frequency droop control. In order to realize this, a deep reinforcement learning (DRL)-based agent is proposed to tune the controller parameters for voltage source converter (VSC) in this paper. The DRL-based agent is trained by numerous hybrid grid operation conditions to learn the optimal control policy, which make it achieve a good adaptability to variety of operation conditions. For the purpose of demonstrating this method, a time-domain simulation model of hybrid power system is built with MATLAB/Simulink to act as test system. The simulation results verify the effectiveness of the proposed method.

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Keywords: Frequency support; MTDC; Droop control; Deep reinforcement learning

1. Introduction

The flexible multi-terminal direct current (MTDC) system is one of the most promising method to connect asynchronous AC power systems into a hybrid AC/MTDC grid [1,2]. Fig. 1 shows an example of a hybrid power system. The converter control method is one of the most crucial techniques for the hybrid AC/MTDC grid. In order to make an asynchronous AC power system share its primary frequency control with others, AC frequency and

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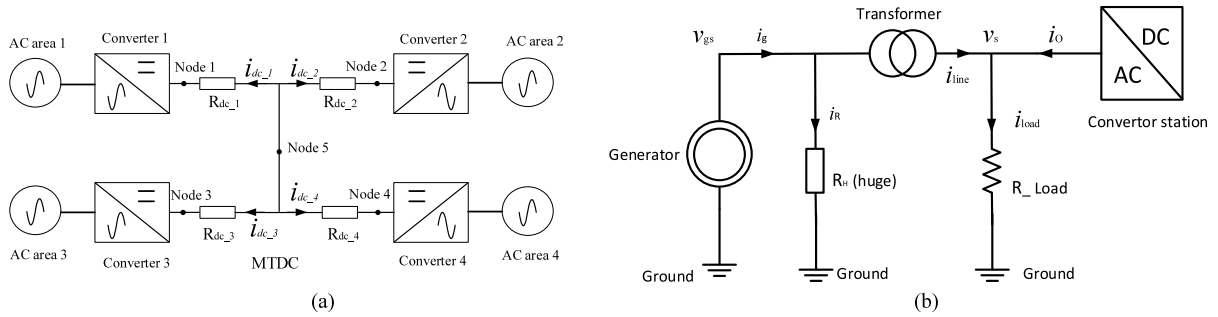


Fig. 1. AC/MTDC hybrid power system. (a) MTDC power system; (b) AC grid.

DC voltage ($F-V_{dc}$) droop control is widely used in voltage source converter (VSC) MTDC [3–6]. While, this method needs to collect the frequency information of AC power system, and may not provide a frequency source to a passive AC system (which has no generator as power source, and is supplied by a DC system). Combined with virtual generator control, another ($V_{dc}-P-f$) droop control method takes AC frequency as its output to realize frequency control [7–9].

Though the ($V_{dc}-P-f$) droop control method can realize frequency support for AC grids, the capacity of frequency support deeply depends on the droop coefficient which is the ratio of AC frequency to DC voltage. Some authors tried to design the droop coefficient basing on ratio of maximum permissible relative power deviation to the maximum permissible relative frequency deviation. It seems reasonable. Nevertheless, this method achieves a good performance only in the case of low transmission power or extremely small DC resistance [7].

A reasonable setting of droop coefficients and DC voltage reference values can improve frequency support performance. However, the ongoing transformation of hybrid AC/MTDC grids results in increased complexity. This calls for a more intelligent and efficient solutions, such as deep reinforcement learning (DRL) method.

With the development of artificial intelligence (AI). In recent years, more and more scholars try to adopt AI based approach to solve the power systems problems. With superior robustness to adjust the controller, machine learning has become a promising technology for electrical engineering. For example, the adjustment of power system stabilizer is realized by Q-learning algorithm [10]. However, when the problem needs a discrete action domain, Q-learning usually loses its merit. To solve this problem, deep neural networks (DNN) is a good choice to approximate the action-value function to form the novel algorithm, named DRL algorithm [11].

Considering numerous operation conditions of power system, this paper adopts DRL method to adjust VSC controllers, to improve the frequency support of hybrid AC/MTDC power system. First, the deep reinforcement learning (DRL) method needs to collect the power system state information. Based on these information, the DRL provides an action, which is droop coefficients and DC voltage reference values. With the action, hybrid AC/MTDC power system responses to a constant values of load change, which is randomly added to only one of the Asynchronous AC grids. The AC frequencies and DC voltages response will be regarded as the rewards of DRL. For the purpose of demonstrating this method, a time-domain simulation model of hybrid AC/MTDC grid is built with MATLAB/Simulink. The simulation results verify the effectiveness of this method.

The rest of this paper is organized as follows. In Section 2, the structure of hybrid AC/MTDC power system and the controller of voltage source converter (VSC) is described. The deep neural networks (DNN) method is given in Section 3. The simulation results are presented to validate the method in Section 4. The conclusions are drawn in Section 5.

2. Structure of hybrid grid and VSC controller

To demonstrate the effectiveness of DNN, a time-domain simulation model of hybrid power system is built. This section illustrates the structure of the AC/MTDC hybrid power system model and the controller of VSC.

2.1. Structure of hybrid

With a radial topology, a MTDC power system is shown in Fig. 1(a), which is used as an example in this work. In the hybrid grid, four asynchronous AC grids are connected to a HVDC grid by VSC stations, which is respectively

marked as Converter 1, 2, 3 and 4. In Fig. 1(a), the 4 VSC stations are connected to the center bus (Node 5) through the four resistances: $R_{dc,1}$, $R_{dc,2}$, $R_{dc,3}$ and $R_{dc,4}$. In the AC side, four nonsynchronous AC systems 1, 2, 3, 4 are connected to DC grid via Converter 1, 2, 3, 4 respectively. Fig. 1(b) depicts the simplified AC power system topology.

2.2. VSC controller

In order to make asynchronous weak AC power system share their primary frequency regulation, generally, the AC frequency droop (P - f) control and DC voltage droop (P - V_{dc}) control will be adopted [11]. The V_{dc} - f droop control is adopted by this paper as shown in Fig. 2. In Fig. 2(a), the reactive power (Q) filter is a first order low pass filter with the time constant K_{Qs} .

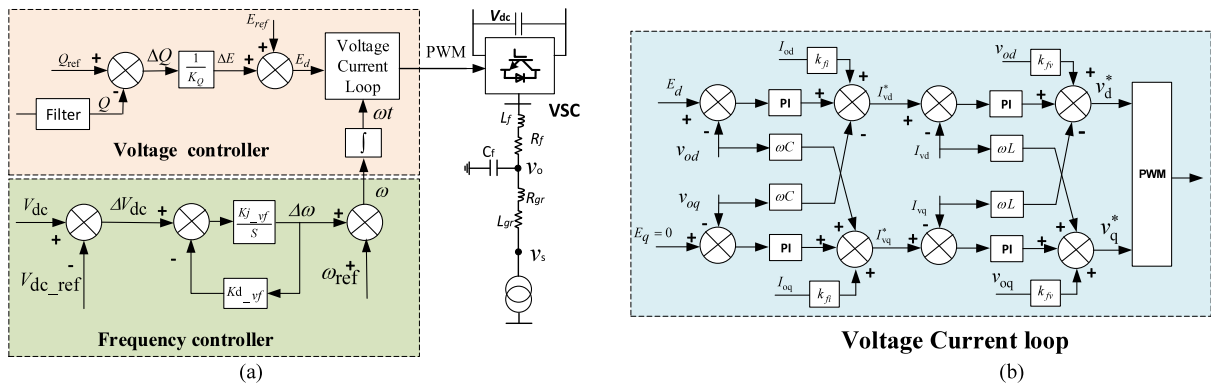


Fig. 2. Diagram of VSC controller. (a) frequency and reactive controller; (b) voltage and current loop.

As Fig. 2(a) shows, in the frequency controller, V_{dc_ref} is the reference value of DC voltage and V_{dc} is the detected DC note voltage. The difference of the DC voltage is used to adjust AC side frequency to realize the droop control between DC voltage and AC frequency [7].

Reasonable design of droop coefficients can improve the frequency support function. Constant droop coefficients will lose the frequency support function when the HVDC in some heavy load conditions, which is demonstrated in the simulation part. Therefore the reasonable coefficient design method should consider all the operation conditions. Considering numerous operation conditions of power system, DRL is a good choice to solve this problem.

3. Deep reinforcement learning method

For the conventional RL algorithm, e.g. Q-learning, which is not suitable for task that has high-dimensional and continuous action domain. Therefore, when it is applied to solve complex problem, the control effect is limited. To solve this problem, deep neural networks (DNN) is employed to approximate the action-value function to form the novel algorithm, named DRL algorithm. The details of DRL algorithm is described as follows:

3.1. Problem formulation

The adjustment of the parameters can be seen as a decision making problem which is connected to an unknown environments. With finite time steps, those problems can be described as a Markov decision process (MDP). Usually, the MDP is illustrated by S , A , P , R .

- S is the set of system state. To describe the complex and unknown power system, some collected electrical parameters (such as generator output powers, AC loads and frequencies) is taken as the system states. $S_j = (M_{1,j} \dots M_{i,j} \dots M_{4,j})$ is used to describe j th step state of the hybrid system. $M_{i,j}$ is defined as the i th AC grid measured electrical parameters in the k th step.

- A is used to describe the action set. The adjustment of VSC controller parameters is defined as action. Therefore, the controller parameters set (such as droop coefficients and DC voltage reference values) is the action set. a_j represents the j th step action.

- P illustrates the environment change probability, from one state s_j to the next s_{j+1} . It is described as $s_{j+1} \sim P(s_j, a_j)$
- R is the function of reward, which is used to just the value of action. In this paper, $r(s_j, a_j)$ is defined as the evaluation of action a_j under j th state s_j .

The overall process can be described by Fig. 3.

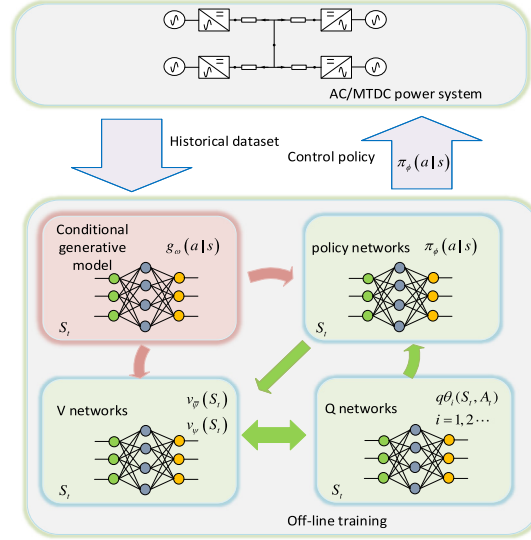


Fig. 3. SAC based DRL Process.

3.2. Soft actor critic

The soft actor critic (SAC) method is an actor-critic structure algorithm. Compared with other DRL algorithms, such as asynchronous advantage Actor critic (A3C) and proximal policy optimization, it can maximize both the entropy of the policy and the expected return, which achieves the better sample-efficient learning.

In SAC, the entropy of the probabilistic policy can be described as follows:

$$H(\pi(\cdot | s_t)) = - \sum_a \pi(a | s_t) \ln \pi(a | s_t) \quad (1)$$

For the value function in the maximum-entropy RL framework, it can be described as follows:

$$\begin{aligned} V_h^\pi(s_t) &= E_{\tau \sim \pi} \left[\sum_{t=0}^T r^t (R_t + \alpha H(\pi(\cdot | s_t))) | s_0 = s \right] \\ Q_h^\pi(s_t, a_t) &= E_{\tau \sim \pi} \left[\sum_{t=0}^T r^t R_t + \alpha \sum_{t=1}^T r^t H(\pi(\cdot | s_t)) | s_0 = s, a_0 = a \right] \end{aligned} \quad (2)$$

Similar with other DRL algorithm, Eq. (9) is satisfied Bellman equation, which can be also rewritten as follows:

$$\begin{aligned} V_h^\pi(s_t) &= E_{s_{t+1} \sim P_r} [R_t + \alpha H(\pi(\cdot | s_t)) + \gamma V_h^\pi(s_{t+1})] \\ Q_h^\pi(s_t, a_t) &= E_{s_{t+1} \sim P_{\gamma}} [R_t + \gamma Q_h^\pi(s_{t+1}, a_{t+1}) + \alpha H(\pi(\cdot | s_{t+1}))] \end{aligned} \quad (3)$$

Moreover, for the both regularized value functions shown in Eq. (10), which satisfies the following constraints:

$$V_h^\pi(s) = E_{a_t \sim \pi} [Q_h^\pi(s, a)] + \alpha H(\pi(\cdot | s_t)) \quad (4)$$

where

$$\pi(\cdot | s_t) = \frac{e^{Q_h^\pi(s, \cdot)/\alpha}}{\sum_a e^{Q_h^\pi(s, \cdot)/\alpha}} \quad (5)$$

In SAC, $V_h^\pi(s_t)$, $Q_\theta^\pi(s_t, a_t)$ and $\pi_\phi(a_t | s_t)$ is approximated by the neural network, which is named V network, Q network and policy network, respectively.

For the V network $V_\psi(s_t)$, it can be parameterized by the ψ and updated by the mean squared error of loss function:

$$J_V(\psi) = E_{s_t \sim D} \left[\frac{1}{2} \left(V_\psi(s_t) - E_{a_t \sim \pi_\phi} [Q_\theta(s_t, a_t) - \log \pi_\phi(a_t | s_t)] \right)^2 \right] \\ \psi \leftarrow \psi - \lambda_V \nabla_\psi J_V(\psi) \quad (6)$$

where λ_V is the learning rate of V network.

For the policy network $\pi_\phi(a_t | s_t)$, it can be parameterized by the ϕ and updated by the Kullback–Leibler divergence loss:

$$J_\pi(\phi) = E_{s_t \sim D} \left[D_{KL}(\pi(\cdot | s_{t+1})) \left\| \frac{\exp(Q_\theta(s_t, \cdot))}{Z_\theta(s_t)} \right\| \right] \\ \phi \leftarrow \phi - \lambda_\pi \nabla_\phi J_\pi(\phi) \quad (7)$$

where λ_π is the learning rate of V network.

For the Q network $Q_\theta^\pi(s_t, a_t)$, it can be parameterized by the θ and updated by the soft Bellman residual:

$$J_Q(\theta) = E_{(s_t, a_t) \sim D} \left[\frac{1}{2} \left(Q_\theta(s_t, a_t) - \widehat{Q}_\theta(s_t, a_t) \right)^2 \right] \\ \theta \leftarrow \theta - \lambda_Q \nabla_{\theta_i} J_Q(\theta_i) \quad (8)$$

where

$$\widehat{Q}_\theta(s_t, a_t) = r(s_t, a_t) + \gamma E_{s_{t+1} \sim p} [V_{\widehat{\psi}}(s_{t+1})] \quad (9)$$

where $V_{\widehat{\psi}}(s_t)$ presents the target network, which can be updated by the following equation:

$$\psi \leftarrow \tau \psi + (1 - \tau) \widehat{\psi} \quad (10)$$

4. Simulation and results

In order to validate the proposed method, a time-domain simulation model is built in MATLAB/Simulink to act as a test system, and the parameters of the test system are listed in Table 1.

One of the major merits of the proposed method is that, the DRL-based agent is trained by numerous operation conditions to continuously improve its decision to cope with variety of power system conditions. After training, the well-trained agent can provide near-optimal parameter settings for VSC in each operation conditions. It makes the decision of the proposed method more adaptive in comparison with other methods. Two cases are illustrated to demonstrate it. The first case simulates the heavy load condition of HVDC, and the second case for light load condition. The initial states of 2 cases are illustrated in Table 2, which is defined as the system state set S in part 3.1. The droop coefficients and DC voltages references are illustrated in Table 3, which is defined as the action set A in part 3.1. The corresponding values of tradition method are listed in Table 4 [7].

Table 1. Parameters of test system.

Variable	Value	Variable	Value	Variable	Value	Variable	Value
S_base (MVA)	600	K_Q	0.1	K_{vp}	0.1	R_{dc_1} (pu)	0.0375
U_base (kV)	110	L_line (pu)	5.1×10^{-4}	K_{vi}	10	R_{dc_2} (pu)	0.015
Vdc_base (kV)	200	R_line (pu)	0.04	K_{cp}	1	R_{dc_3} (pu)	0.0075
R_H	0.0496	K_{qs}	0.05	K_{ci}	100	R_{dc_4} (pu)	0.03
K_{j_vf}	10.9013	L_f	1.4876×10^{-4}	C_f	2.0167×10^{-5}	R_f (pu)	4.735×10^{-4}

Figs. 4 and 5 show the simulation results in Case I. With the traditional method, AC frequencies and DC voltages response curves are plotted in Fig. 4. The Fig. 5 describes the results of DRL method.

At $t = 0$ s, an active power disturbance P_{load_2} (0.1 pu) is added to AC grid 2. In Fig. 4(a), the frequency of AC grid 1 decreases down to 49.77 Hz, which is out of permissible range (49.8 Hz~50.2 Hz). This means that the traditional method is failing in providing frequency support in Case I. In contrast, with the same active power disturbance, all the frequencies in Fig. 5(a) are still in permissible range (50 ± 0.2 Hz) [7]. This means the DRL method helps the MTDC provide better frequency support than conventional method.

Table 2. Initial state of two simulation operating conditions: Case 1- heavy load; Case 2- light load.

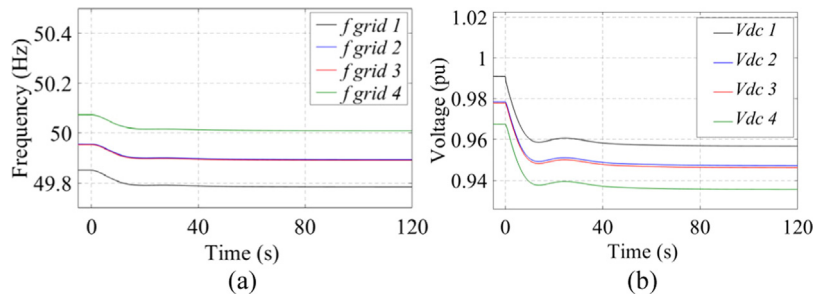
State 1	Value	State 1	Value	State 2	Value	State 2	Value
Generator 1 output (pu)	0.8454	Frequency 1 (Hz)	49.851	Generator 1 output (pu)	0.5953	Frequency 1 (Hz)	49.901
Generator 2 output (pu)	0.8545	Frequency 2 (Hz)	49.950	Generator 1 output (pu)	0.6963	Frequency 2 (Hz)	49.908
Generator 3 output (pu)	0.8448	Frequency 3 (Hz)	49.950	Generator 1 output (pu)	0.8761	Frequency 3 (Hz)	49.911
Generator 4 output (pu)	0.4634	Frequency 4 (Hz)	50.075	Generator 4 output (pu)	0.4755	Frequency 4 (Hz)	49.915
Load 1 (pu)	0.3532	DC voltage 1 (pu)	0.9911	Load 1 (pu)	0.5202	DC voltage 1 (pu)	0.9611
Load 2 (pu)	0.8144	DC voltage 2 (pu)	0.9790	Load 2 (pu)	0.5575	DC voltage 2 (pu)	0.9655
Load 3 (pu)	0.8399	DC voltage 3 (pu)	0.9781	Load 3 (pu)	0.7123	DC voltage 3 (pu)	0.9635
Load 4 (pu)	0.8544	DC voltage 4 (pu)	0.9682	Load 4 (pu)	0.7928	DC voltage 4 (pu)	0.9534

Table 3. Droop coefficients and DC voltage reference values of DRL: Case 1- heavy load; Case 2- light load.

Action 1	Value	Action 1	Value	Action 2	Value	Action 2	Value
Droop coefficient 1	0.2501	Voltage reference 1	1.0285	Droop coefficient 1	0.4879	Voltage reference 1	1.0120
Droop coefficient 2	0.5012	Voltage reference 2	1.0035	Droop coefficient 2	0.5102	Voltage reference 2	1.0114
Droop coefficient 3	0.4988	Voltage reference 3	1.0030	Droop coefficient 3	0.4967	Voltage reference 3	1.0077
Droop coefficient 4	0.7997	Voltage reference 4	0.9081	Droop coefficient 4	0.5011	Voltage reference 4	0.9652

Table 4. Droop coefficients and DC Voltage reference values of traditional method: Case 1- heavy load; Case 2- light load.

Action 1	Value	Action 1	Value	Action 2	Value	Action 2	Value
Droop coefficient 1	0.5	Voltage reference 1	1.0645	Droop coefficient 1	0.5	Voltage reference 1	1.0106
Droop coefficient 2	0.5	Voltage reference 2	1.0040	Droop coefficient 2	0.5	Voltage reference 2	1.0115
Droop coefficient 3	0.5	Voltage reference 3	1.0031	Droop coefficient 3	0.5	Voltage reference 3	1.0180
Droop coefficient 4	0.5	Voltage reference 4	0.9307	Droop coefficient 4	0.5	Voltage reference 4	0.9959

**Fig. 4.** Simulation results of Conventional method in Case I: (a) AC frequency; (b) DC voltage.

In Fig. 4(a), four frequencies line decrease almost a same value. As a contrast, in Fig. 5(a), the frequency of AC grid 4 decreases most. It implies AC grid 4 provides the most of extra active power after the disturbance. Duo to a large droop coefficient (seen from Table 4), the DC voltage of converter 4 does not decrease out of permissible range (0.9 pu ~1.1 pu), which is shown in Fig. 5(b). By this way, the DRL method realizes distributing active powers according to their operation conditions. Thereby, DRL realizes improving the frequency support function.

In order to make the problem clearer, another case study is provided. Figs. 6 and 7 shows the simulation results. With the same disturbance as Case I, the frequencies and voltages in both figures have a similar trend. And they are all in permissible range (50 ± 0.2 Hz and 1 ± 0.1 pu). This implies that, in Case II, both two methods can help MTDC provide frequency support well. Case II is not used to demonstrate the DRL method is better in all conditions. It just helps make problem clearer.

From Table 2, it is easy to see that MTDC have a heavier transmission load in Case I than in Case II. This illustrate that, in light transmission load conditions, both method have a good performance in helping MTDC provide frequency support. Nevertheless, the DRL approach can still improve the frequency support function in heavy load operation conditions, where conventional method is failing in providing frequency support.

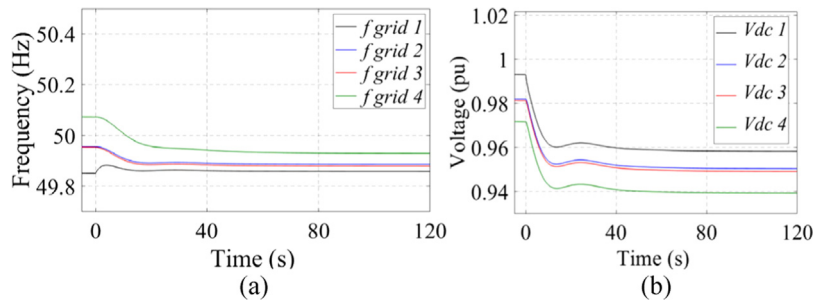


Fig. 5. Simulation results of DRL method in Case I: (a) AC frequency; (b) DC voltage.

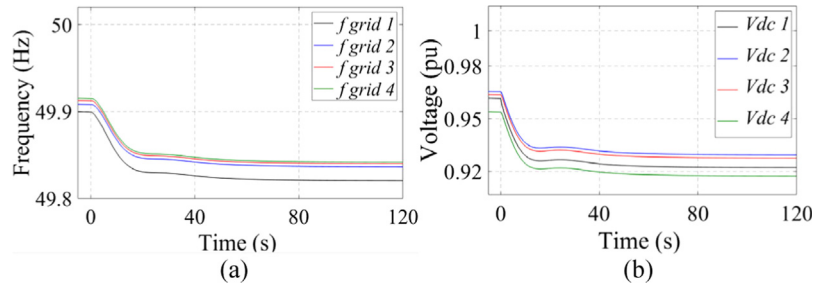


Fig. 6. Results of Conventional method in Case II: (a) AC frequency; (b) DC voltage.

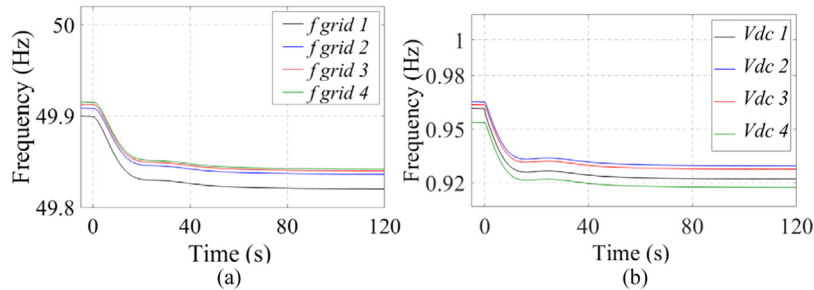


Fig. 7. DRL method results in Case II: (a) AC frequency; (b) DC voltage.

5. Conclusion

This paper adopts DRL method to train an agent for the self-tuning of the controller parameters for VSC, which improves the frequency support of hybrid AC/MTDC power system under different operation conditions. A time-domain simulation model of hybrid AC/MTDC power system is also built with MATLAB/Simulink for the purpose of demonstrating the proposed method. Two case studies illustrate that the proposed method has a similar performance with tradition method in the case of light transmission load, nevertheless, DRL method has batter performance in the case of heavy transmission load. It demonstrates that the proposed method can improve the frequency support of hybrid grids. Besides, the DRL-based agent is trained by numerous operation conditions, which makes it achieves a good adaptability to variety of conditions.

CRedit authorship contribution statement

Hao Wang: Investigation, Formal analysis, Validation, Writing - original draft. **Guozhou Zhang:** Data curation, Writing - review & editing. **Weihaio Hu:** Data curation, Writing - review & editing, Funding acquisition. **Di Cao:** Data curation, Writing - review & editing. **Jian Li:** Writing - review & editing. **Shuwen Xu:** Writing - review &

editing. **Dechao Xu:** Writing - review & editing, Funding acquisition. **Zhe Chen:** Conceptualization, Supervision, Writing - review & editing, Project administration, Funding acquisition.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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