Distributed Imitation-Orientated Deep Reinforcement Learning Method for Optimal PEMFC Output Voltage Control

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In order to improve the stability of proton exchange membrane fuel cell (PEMFC) output voltage, a data-driven output voltage control strategy based on regulation of the duty cycle of the DC-DC converter is proposed in this paper. In detail, an imitation-oriented twin delay deep deterministic (IO-TD3) policy gradient algorithm which offers a more robust voltage control strategy is demonstrated. This proposed output voltage control method is a distributed deep reinforcement learning training framework, the design of which is guided by the pedagogic concept of imitation learning. The effectiveness of the proposed control strategy is experimentally demonstrated.

Keywords: distributed deep reinforcement learning, proton exchange membrane fuel cell, DC-DC converter, output voltage control, robustness

INTRODUCTION

The voltage of a proton exchange membrane fuel cell (PEMFC) is highly dependent on the temperature, pressure, humidity, and gas flow rate (Yang et al., 2018; Sun et al., 2019). In addition, the output voltage of PEMFC also fluctuates widely with varying load current (Yang et al., 2019a; Yang et al., 2021a). In order to improve the stability of the PEMFC output voltage, the PEMFC DC-DC converters should output a stable bus voltage in the event of fluctuating input voltage and output load so as to normalize the load (Yang et al., 2021b; Yang et al., 2021c).

There are a number of existing PEMFC output voltage control methods based on control of DC-DC converters, including the PID control algorithm (Swain and Jena, 2015), fractional order PID algorithm (Yang et al., 2019a; Yang et al., 2019b; Yang et al., 2020), sliding mode control algorithm (Bougrine et al., 2013; Jiao and Cui, 2013), model predictive control algorithm (Bemporad et al., 2002; Ferrari-Trecate et al., 2002), robust control method (Olalla et al., 2010), and optimal control algorithm (Jaen et al., 2006; Olalla et al., 2009; Montagner et al., 2011; Moreira et al., 2011) methods, and so on. Among them, the PID algorithms are traditional control algorithms whose advantages include simple structure and fast calculation speed. However, these are incompatible with non-linear PEMFC systems. The fractional order PID algorithm is an expanded algorithm based on the PID algorithm, which offers better robustness, but which cannot be adapted for non-linear PEMFC systems. Sliding mode control is an excellent candidate for variable structure systems such as DC-DC converters; however, it is not suitable for PEMFC systems in practice as it is affected by the “jitter” problem. The model prediction algorithm offers higher accuracy and strong robustness; however, the algorithm is heavily reliant on mathematical models, making the control results in reality very different from the theoretical ones. The goal of robust control is to establish feedback control laws...
accounting for system uncertainty in order to increase the robustness of closed-loop systems. However, the control performance of a controller employing robust control is compromised as it cannot operate at the optimal point.

Optimal control is one of the more advanced control algorithm designs. By exploiting the performance of a system as an objective function of time, state, error, and other combinations, optimal control selects an appropriate control law which enables the objective function to include extreme values in order to obtain the optimal performance of the system. As described by Jaen et al. (2006), the average model of the converter is linearised, and the optimal LQR is obtained by solving the algebraic Riccati equation using the pole configuration, frequency domain metric or integral metric as the optimisation objective function; however, this LQR is not robust enough to cope with large disturbances in the system.

Montagner et al. (2011) designed a discrete LQR and determined the existence of the Lyapunov function for the closed-loop system using the LMI method, thus ensuring the stability of the system. Olalla et al. (2009) organised the LQR optimisation problem in the form of an LMI, which was then solved using convex optimisation to obtain a robust linear quadratic regulator. In the study by Moreira et al. (2011), the application of a digital LQR with Kalman state observer for controlling a BUCK converter was tested in a series of simulations. However, the structure of the above optimal algorithm is complex and computationally intensive, leading to a reduction in its control real-time performance in practice (Li and Yu, 2021).

For these reasons, there remains the need for a simple structured model-free PEMFC optimal control algorithm for guiding DC-DC converters (Li et al., 2021).

The DDPG algorithm (Lillicrap et al., 2015) is a data-driven model-free optimal control algorithm, a kind of deep reinforcement learning, which is characterised by strong self-adaptive capability and decision-making ability, and which can arrive at decisions within a few milliseconds. It is used widely in power system control and robot coordination control, and for addressing UAV control problems (Zhang et al., 2016; Qi, 2018; Zhang et al., 2018; Zhang et al., 2019; Zhang and Yu, 2019; Zhang et al., 2020; Zhang et al., 2021; Zhang et al., 2021). However, the poor training efficiency of the DDPG algorithm explains the low robustness of controllers belonging to this class of algorithms, and their ineligibility for PEMFC systems.

In order to stabilise the output characteristics of the PEMFC and improve the stability of its output voltage, a data-driven output voltage control strategy for controlling the duty cycle of the DC-DC converter is proposed in this paper. To this end, an imitation-oriented twin delay deep deterministic policy gradient (IO-TD3) algorithm is proposed, the design of which reflects the idea of imitation learning. In this paper, we propose a distributed deep reinforcement learning training framework for improving the robustness of the PEMFC control policy. The effectiveness of the proposed control policy is experimentally demonstrated by comparing the proposed method with a number of existing algorithms.

This paper makes the following unique contributions to the research field:

1) A 75 kW ninth order output voltage PEMFC dynamic control model that takes into account the DC/DC converter is demonstrated.
2) A PEMFC output voltage control strategy based on an imitation-oriented twin delay deep deterministic policy gradient algorithm for the purpose of increasing robustness is proposed.

The remainder of this paper comprises the following sections: the PEMFC model is demonstrated in The PEMFC Model, and the proposed algorithm is described in Proposed Method; the experimental results are analysed and discussed in Experiment, and the findings in this paper are summarised in Conclusion.

THE PEMFC MODEL

PEMFC Modelling and Characterization

A PEMFC is a device that converts chemical energy directly into electrical energy by means of an electrochemical reaction, the individual output voltage of which can be expressed as follows:

\[ V_{\text{cell}} = E - \eta_{\text{act}} - \eta_{\text{ohm}} - \eta_{\text{con}} \]

For a fuel cell stack consisting of \( N \) single cells connected in series, the output voltage \( V \) can be expressed as follows:

\[ V = NV_{\text{cell}} \]

Theoretically, the electric potential of the PEMFC varies with temperature and pressure, as expressed in the following equation:

\[ E = 1.229 - 0.85 \times 10^{-3} (T - 298.15) + 4.3085 \times 10^{-5} T (\ln p_{H_2} + \ln p_{O_2}/2) \]

(3)

Thermodynamic Electric Potential

The thermodynamic electric potential of the single cell (i.e., the Nernst electric potential) can be obtained from the mechanism of the electrochemical reaction of the gas inside the PEMFC. This is represented by the following equation:

\[ E = \frac{\Delta G}{2F} + \frac{\Delta S}{2F} (T - T_{\text{ref}}) + \frac{RT}{2F} \left( \ln p_{H_2} + \frac{1}{2} \ln p_{O_2} \right) \]

(4)

Activation Overvoltage

The activation overvoltage of the PEMFC is expressed as follows:

\[ \eta_{\text{act}} = \xi_1 + \xi_2 T + \xi_3 T \ln c(O_2) + \xi_4 T \ln I \]

(5)

Whereby \( c(O_2) \) is the concentration of dissolved oxygen at the cathode catalyst interface, which can be expressed by Henry’s law as follows:

\[ c(O_2) = P_{O_2}/5.08 \times 10^6 \exp(-498/T) \]

(6)

Ohmic Voltage Drop

The ohmic overvoltage is represented by the following equation:
\[ \eta_{\text{ohm}} = IR_{\text{int}} = I(R_m + R_c) \]  

Empirically, the internal resistance of the PEMFC is expressed as follows:

\[ R_{\text{int}} = 0.01605 - 3.5 \times 10^{-3}T + 8 \times 10^{-5} \]  

\[ \eta_{\text{con}} = -\beta \ln(J/J_{\text{max}}) \]

**Dense Differential Polarization Overvoltage**

The differential overvoltage can be expressed as follows:

\[ V_d \]

**Dynamic and Capacitive Characteristics of the Double Layer Charge**

The dynamic characteristics of the double layer charge of the PEMFC are similar to those of the capacitor, and the equivalent circuit diagram is shown in Figure 1A:

- As detailed in the figure, the polarization voltage across \( R_d \) is \( V_d \) and the differential equation for the voltage change of a single cell is expressed as follows:

\[ \frac{dV_d}{dt} = \frac{1}{C} - \frac{V_d}{R_d C} \]

**PEMFC Stack Voltage**

The stack voltage is defined as the value of the voltage at the front end of the PEMFC as it passes through the DC/DC converter. It is assumed that hydrogen is supplied from a hydrogen tank, and is available in sufficient quantities at all times. The air, on the other hand, is controlled by a proportional valve, which allows the air to be controlled efficiently and in time to meet the PEMFC requirements.

\[ \frac{V_o}{8.314T} \times \frac{dP_{h2}}{dt} = m_{h2} - K(P_{h2} - P_{\text{atm}}) - \frac{0.5NI}{F} \]

**DC-DC Boost Converter Model**

The output voltage of the PEMFC is the tap voltage of the DC/DC converter. A boost converter is essentially a step-up power converter, i.e., the voltage is raised and then outputted. An DC/DC boost converter circuit is shown in Figure 1B:

Whereby the input and output voltage relationship are controlled output voltage by the switch duty cycle, as expressed in Equation:

\[ V_{\text{out}} = \left( \frac{1}{1 - u} \right) \times V_{\text{stack}} \]

The differential equation for \( V_{\text{out}} \) is as follows:

\[ \begin{cases} \frac{di_L}{dt} = \frac{1}{L} \cdot V_{\text{stack}} \\ \frac{dV_{\text{out}}}{dt} = \frac{1}{C} \cdot (-i_{\text{out}}) \end{cases} \]

**PROPOSED METHOD**

**Framework of Control Policy**

The control model includes a PEMFC stack, a DC/DC converter and its controller. The controller of the DC/DC converter is
equated to an intelligent agent which is trained to adapt to the non-linear characteristics of the PEMFC so as to improve the overall output voltage control performance. When applied online, the intelligent agent outputs the optimal duty cycle according to the state of the DC-DC converter and the state of the output voltage. The control interval of the agent is 0.01 s.

**Agent**

1) **Action space**

The action space is set to \( u/100 \), as follows:

\[
\begin{align*}
    a & = \left[\frac{u}{100}\right] \\
    0 & \leq u \leq u_{\text{max}}
\end{align*}
\]  

(14)

2) **State space**

The state space is expressed as follows:

\[
\left[ e \int_0^t edt \ U \right]
\]

(15)

3) **Reward function**

The reward function is expressed as follows:

\[
\begin{align*}
    r(t) & = -[\mu_i \dot{e}(t) + \mu_u(u(t-1)) + \beta] \\
    \alpha & = \begin{cases} 
        -0.3 & \dot{e}_i(t) > 0.09 \\
        0 & \dot{e}_i(t) \leq 0.09
    \end{cases}
\end{align*}
\]  

(16)

\[
\begin{align*}
    \alpha & = \begin{cases} 
        -0.3 & \dot{e}_i(t) > 0.09 \\
        0 & \dot{e}_i(t) \leq 0.09
    \end{cases}
\end{align*}
\]

(17)

**DDPG**

The Deterministic Policy Gradient (DDPG) policy determines an action via the policy function \( \mu(s) \), which is shown in the following equation:

\[
    a_i = \mu(s_i|\theta^P)
\]

(18)

This deep reinforcement learning algorithm uses a value network to fit the function \( Q(s) \) and the objective function \( J(\theta^P) \), the latter which is defined as follows:

\[
    J(\theta^P) = E_{\theta^P}[r_1 + yr_2 + y^2r_3 + \cdots]
\]

(19)

In this arrangement, the Q function can be expressed as the expected value of the reward for selecting an action under \( \mu(s) \).

In each step, a specific policy is randomly selected for the agent to be executed, and the best policy is selected by maximizing the fusion objective function. The different policy will be executed in different steps, so that an experience replay pool can be obtained for each agent. Finally, the gradient of the fusion objective function \( \nabla_\theta J \) is solved for the policy parameters of each agent, as expressed in the following equation:

\[
    \nabla_\theta J = \frac{1}{S} \sum_j \nabla_\theta \mu(\theta) \nabla_\theta Q^\pi \left( x', a', \cdots, a_{N} \right) |_{a_{N}=\mu(\theta)}
\]

(20)

Nevertheless, the DDPG algorithm suffers from low robustness. The main reasons for this are as follows:

1) The algorithm lacks effective bootstrapping techniques, and so it tends to fall into the local optimum solution, which undermines the robustness of the strategy.
2) Overestimation of the Q-value leads to overfitting of the algorithm’s policy, thus making it less robust.

**Framework for Offline Training of IO-TD3**

In order to address the low robustness of the DDPG algorithm, the IO-TD3 algorithm incorporates the following two innovations:

1) An imitation-oriented distributed training framework for deep reinforcement learning; and,
2) An Integrated anti-Q overestimation policy.

The large-scale deep reinforcement learning training framework for the IO-TD3 algorithm is illustrated.

The algorithm contains three roles, an explorer, an expert and a leader. A total of 36 parallel systems are included in the algorithm, each containing the same PEMFC system and different load disturbances, so as to enhance sample diversity.

**Explorer**

The Explorer contains only one actor network. The explorers in different parallel systems employ their own different exploration principles. The explorers described in this paper use the following exploration principles: greedy strategy, Gaussian noise, and OU noise.

The explorer in parallel system 1–6 uses an \( \epsilon \)-greedy strategy with the following actions:

\[
    d^j_\epsilon = \begin{cases} 
        \pi^j_\epsilon(s) & \text{With } \epsilon \text{ probability} \\
        a_{\text{rand}}^j & \text{With } 1 - \epsilon \text{ probability}
    \end{cases}
\]

(21)

The explorer in parallel system 7–12 uses an OU noise exploration strategy with the following actions:

\[
    d^j_{\text{OU}} = \pi^j_\epsilon(s) + N_{\text{OU}}^j
\]

(22)

The Gaussian noise exploration strategy used in parallel system 13–18 has the following actions:

\[
    a^m_{\text{Gaussian}} = \pi^m_\epsilon(s) + N_{\text{Gaussian}}^m
\]

(23)

**Expert**

On the basis of imitation learning, the proposed algorithm employs a large number of expert samples, which are used as learning samples, so that the algorithm can be effectively guided to learn correctly during the early stages of training. In this proposed method, the duty cycle of the DC/DC converter is controlled, whereby the parallel systems generate expert samples for the Leader (described below).
The expert itself uses a variety of controllers based on different principles, including PSO-PID and GA-PID algorithms. The objective function for parameter optimization is as follows:

\[ F(t) = \int_{0}^{\infty} t(e(t))^2 \, dt \]  

\[ y_t = r(s_t, a_t) + \gamma \min_{\pi \in \mathcal{A}} Q_{\theta}(s_{t+1}, \pi(s_{t+1})) + \epsilon \]  

\[ \epsilon \sim \text{clip}[N(0, \sigma), -c, c] \]  

**EXPERIMENT**

In order to verify the superior effectiveness of the proposed method, the IO-TD3 algorithm control strategy was tested against the following methods in case: Apex-MADDPG control algorithm (40), MATD3 control algorithm (41), MADDPG coordinated control algorithm (37), BP neural network control algorithm, RBF neural network control algorithm, PSO optimized PID control algorithm (PSO-PID), GA optimized PID control algorithm (GA-PID), PID control algorithm (PID), Fuzzy-FOPID control algorithm (Fuzzy-FOPID), and the PSO-optimized FOPID control algorithm (PSO-FOPID). The first six (including the IO-TD3 algorithm) are referred to as advanced algorithms, and the last five are conventional algorithms.

At 1 s, the load current magnitude appears as a load disturbance which begins at 72.6 A and rises to 250.0 A. The results are shown in Figure 2A-B.
2) Possible reasons for these promising patterns are as follows:

Firstly, other DRL algorithms tend to fall into local optima; they amount to sub-optimal control strategies as they are not effectively guided in pre-learning, resulting in large output voltage overshoot and output voltage fluctuations, which undermine PEMFC output performance.

The BP and RBF algorithms are too dependent on the trained samples, resulting in limited control performance. A neural network control algorithm which lacks self-exploration will have lower adaptive ability, leading to poorer control performance.

The PSO-PID and GA-PID algorithms within the conventional control algorithm group lack the adaptive capability for adjusting the PID parameters, and therefore struggle to adapt to the non-linearity of the PEMFC environment. The PSO-FOPID algorithm enables greater robustness in the environment, but is impaired by poor adaptive capability due to its fixed coefficients, which ultimately leads to severe output voltage overshoot and oscillation. The Fuzzy-FOPID algorithm, despite its better adaptive capability, is undermined by overly simple rules, resulting in poor control accuracy and therefore a large overshoot despite the fast response of the algorithm.

In summary, the IO-TD3 controller is a more suitable candidate for practical output voltage control systems, with its short response times, and good dynamic and static performance indicators.

CONCLUSION

In this paper, an imitation-oriented deep reinforcement learning output voltage control strategy for controlling the duty cycle of a DC-DC converter has been proposed. The proposed method is an imitation-oriented twin delay deep deterministic (IO-TD3) policy gradient algorithm, the design of which is structured on the concept of imitation learning. It embodies a distributed deep reinforcement learning training framework designed to improve the robustness of the control policy. The effectiveness of the proposed control policy has been experimentally demonstrated. The simulation results show that the IO-TD3 algorithm has superior control performance compared to other deep reinforcement learning algorithms (e.g., Ape-x-MADDPG, MATD3, MADDPG). Compared to other control algorithms (BP, RBF, PSO-PID, GA-PID, PID, Fuzzy-FOPID, PSO-FOPID), the IO-TD3 algorithm is more adaptable, and, in relation to the output voltage of the PEMFC, has better response speed and stability, and can more effectively track and control the output voltage in a timely and effective manner.

DATA AVAILABILITY STATEMENT

The original contributions presented in the study are included in the article/Supplementary Material, further inquiries can be directed to the corresponding author.

AUTHOR CONTRIBUTIONS

JL: conceptualization, methodology, software, data curation, writing-original draft preparation, visualization, investigation, software, validation. YL: Writing-Reviewing and editing. TY: Supervision.

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