

Deep Reinforcement Learning Approach for EV Charger Control under Load Variation

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Abstract—In this paper, we propose an electric vehicle (EV) charger controller using a deep reinforcement learning algorithm to address load variations. The gain curve of the EV charger is derived to analyze its electrical characteristics. Subsequently, the deep deterministic policy gradient (DDPG) method is employed to optimize the control gains of PI controller. Simulation results demonstrate that the proposed method improves ripple reduction performance compared to a conventional PI controller under load resistance variations.

Index Terms—deep reinforcement learning, EV charger, adaptive PI controller, gain curve analysis

I. INTRODUCTION

The bi-directional power transfer capability of bi-directional power converters is attracting attention in energy storage systems, electric vehicles (EVs), and smart grid systems. Among bidirectional power converters, CLLC resonant converters have been used for their zero-voltage switching (ZVS) characteristics that reduce switch losses and wide output voltage range compared to conventional dual active bridge converters [2]–[5].

Proportional-integral-derivative (PID) controllers have been proposed to regulate the output voltage in EV chargers because of easy implementation and intuitive controller gain tuning guideline [7], [8]. However, it is not easy work to determine optimal PID controller gains because EV charger has nonlinearity depend on load resistance variation as well as other nonlinear characteristics even if it is important to choose and/or adaptive the control gains which covers whole operating frequency range. To remedy this problem, since variable model based optimization and robust controller have been proposed, these methods have disadvantages such as computational burden, parameter uncertainties, and so on [9]–[13]. Over the past few decades, deep reinforcement learning methodologies have been studied for other industrial application fields because it is possible to optimize the control performance regardless of an information of model parameters [14]–[17]. However, there is no study in the sense of the EV charger robust/optimal control against parameter variations.

In this paper, we propose an adaptive PI controller using deep reinforcement learning to select optimal controller gains

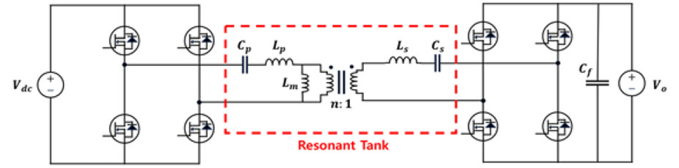


Fig. 1. DC-DC converter topology for EV charger

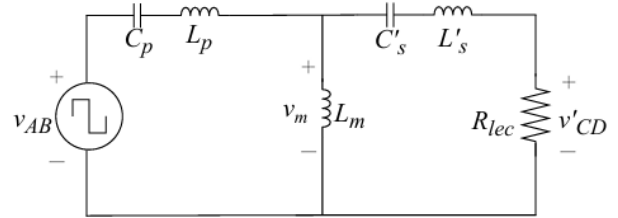


Fig. 2. Equivalent circuit model of the EV charger resonant tank

in EV charger. Firstly, mathematical model of EV charger is introduced to explain the effect on load resistance variation. Consequently, we provide gain curve analysis by showing 3-D gain curves between load resistance variation, voltage gains, and normalized frequency (switching frequency). Deep deterministic policy gradient (DDPG) algorithm is developed to adjust PI controller gain adaptation by define states and actions as deep reinforcement learning techniques. To show the effectiveness of the proposed adaptive PI controller, simulation results are shown by comparing classical PI controller under load resistance variation conditions.

II. MATHEMATICAL MODELING AND ANALYSIS FOR EV CHARGER

In this section, we introduce equivalent circuit model of the EV charger and also provide analysis of gain curve according to load resistance variation.

Fig. 1 shows DC-DC converter topology for EV charger. It has a symmetric structure of two sides and a symmetric resonant tank. The resonant tank consists of leakage inductances (L_s and L_p), resonant capacitors (C_s and C_p), magnetizing inductance L_m and high frequency transformer, providing

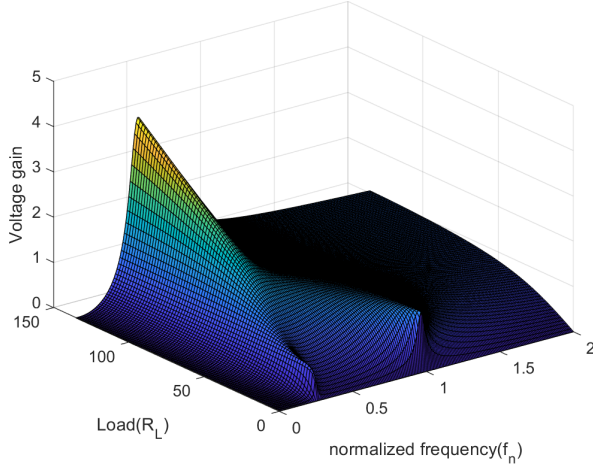


Fig. 3. 3-D gain curve according to load resistance and normalized frequency

galvanic isolation between primary side and secondary side. To obtain voltage gain from input voltage to output voltage, the equivalent circuit of EV charger can be described as shown in Fig. 2. The input voltage of the resonant tank, v_{AB} is square wave form, with its magnitude varying from $+V_{dc}$ to $-V_{dc}$. Using Fourier series and applying First Harmonic Approximation (FHA), the input voltage of the resonant tank can be described as follows:

$$v_{AB} = \frac{4V_{dc}}{\pi} \sin(2\pi f_s t) \quad (1)$$

where t and f_s are time and switching frequency, respectively. As the transformer has a turns ratio n , all parameters transformed from the secondary side to the primary side can be expressed as

$$L'_s = n^2 L_s, C'_s = \frac{1}{n^2} C_s, R_{lec} = n^2 \frac{8}{\pi^2} R_L \quad (2)$$

where R_L is load resistance of EV charger. let us define

$$Z_1 = sL_p + \frac{1}{sC_p}, Z_2 = \frac{1}{sC'_s}, Z_0 = \frac{sL_m(Z_2 + R_{lec})}{sL_m + Z_2 + R_{lec}} \quad (3)$$

In the equivalent circuit of the resonant tank, the output voltage can be derived as follows:

$$v'_{CD} = v_{AB} \frac{Z_o}{Z_o + Z_1} \frac{R_{lec}}{Z_2 + R_{lec}} \quad (4)$$

Therefore, the transfer function of voltage gain can be induced as follows:

$$H(s) = \frac{v'_{CD}}{v_{AB}} = \frac{Z_o R_{lec}}{(Z_1 + Z_o)(Z_2 + R_{lec})} \quad (5)$$

Substituting $j\omega_s$ for the 's' in (5), we can derive the following reformulated equation

$$|H(j\omega_s)| = \frac{1}{n\sqrt{F_A^2 + F_B^2}} \quad (6)$$

where

$$\begin{aligned} F_A &= \frac{1}{l} + 1 - \frac{1}{l\omega^2} \\ F_B &= \left(\frac{l'}{l} + 1 + \frac{1}{cl} + \frac{1}{c}\right) \frac{Q}{\omega} - \left(\frac{l'}{l} + 1 + l'\right) Q\omega - \frac{Q}{cl\omega^3} \\ l &= \frac{L_m}{L_p}, l' = \frac{L'_s}{L_p}, c = \frac{C'_s}{C_p}, \omega = \frac{\omega_s}{\omega_r} \\ \omega_r &= \frac{1}{\sqrt{L_p C_p}}, Q = \frac{\sqrt{L_p/C_p}}{R_{lec}} \end{aligned}$$

where $\omega_s = 2\pi f_s$, ω_r is the resonant frequency, Q is the quality factor.

Fig. 3 shows a 3-D gain curve according to the EV charger load resistance R_L and normalized frequency f_n which is the ratio of switching frequency and resonant frequency. The gain curve exhibits variations based on both the load resistance magnitude and switching frequency. So, it is important to adjust the frequency allows for achieving the desired gain. However, as shown in Fig. 3, the maximum value of the gain curve of EV charger varies depending on the change in the EV charger load resistance. In addition, the slope of the gain curve decreases rapidly according to load resistance variation. Therefore, fixed PI control gain is not suitable for output voltage regulation. It is highly required to adjust PI control gain

III. ADAPTIVE PI CONTROLLER USING REINFORCEMENT LEARNING

In this section, we review the DDPG algorithm and introduce DDPG-based adaptive PI controller.

A. DDPG algorithm

The DDPG agent is a reinforcement learning algorithm where the agent interacts with the environment. The agent receiving observations and rewards by sending actions to the environment. The agent interacts with the EV charger, where states s_t and action a_t are defined as follows respectively:

$$\begin{aligned} s_t &= (r(t), v_o(t), v_i(t), R_L(t)) \\ a_t &= \pi(S_i|\theta) \end{aligned} \quad (7)$$

The policy π is parameterized by a neural network θ and returns deterministic action based on the state. The state space consists of output voltage $v_o(t)$, input voltage $v_i(t)$, EV charger resistance $R_L(t)$, reference signal $r(t)$ of the EV charger. The action is the value passed from the agent to the environment, and in the DDPG agent, It returns the action value based on the state.

The structure of DDPG consists of an actor and a critic, where the actor returns the agent's action based on observations. The critic returns the expected long-term reward based on observations and actions. To enhance the stability of agent learning, it is trained through target actors and target critics with the same structure as the actor and critic. Mini-batches used in training utilize data samples stored in the DDPG

experience buffer. The loss function used to train the critic is defined as follows:

$$y_i = r_i + \gamma G^*(S_{i+1}, \pi^*(S_{i+1}|\phi^*)) \quad (8)$$

$$L = \frac{1}{2M} \sum_{i=1}^M (y_i - G(S_i, A_i|\phi))^2 \quad (9)$$

where y_i represents the sum of future rewards, r_i represents the reward, G^* and G are the outputs of the target critic's neural network and the critic's neural network, respectively. The target critic network is parameterized by ϕ^* , the critic network is also parameterized by ϕ . π^* represents the target actor which is parameterized θ^* . γ is the discount factor for rewards. The actor also updates its parameters using sampled data using the following policy gradient method:

$$\nabla_{\theta} J \approx \frac{1}{M} \sum_{i=1}^M \nabla_{\pi} G(S_i, A|\phi) \nabla_{\theta} \pi(S_i|\theta) \quad (10)$$

where $\nabla_{\pi} G$ represents the gradient of the critic's output with respect to actions, and $\nabla_{\theta} \pi$ denotes the gradient of actions with respect to actor parameters. Therefore, the actor undergoes neural network training over M samples using the product of these two types of gradients.

B. DDPG-based adaptive PI controller

The integral gain of the PI controller for controlling the voltage of the EV charger was obtained using the DDPG agent. The basic form of a PI controller is as follows:

$$K_p e(t) + K_i \int_0^t e(\tau) d\tau \quad (11)$$

$$e(t) = r(t) - v_o(t)$$

where K_p represents the proportional constant, K_i is the integral constant. Therefore, by dividing the integral component of the control input by the action value of the DDPG agent and the previously set integral constant component, we can obtain the following control input:

$$u(t) = K_p e(t) + (K_i + a_t) \int_0^t e(\tau) d\tau \quad (12)$$

where $u(t)$ represents the control input. Fig. 4 is a block diagram illustrating the generation process of the control input applied to EV charger.

IV. SIMULATION RESULTS

A. Simulation setup

To validate the proposed method, we utilized a EV charger and a DDPG agent within the MATLAB/Simulink environment. In (7), the input and output value of the EV charger are considered as observation values and passed to the DDPG agent. These observation values are returned as actions through the actor neural network, which adjusts the integral constant of the PI controller.

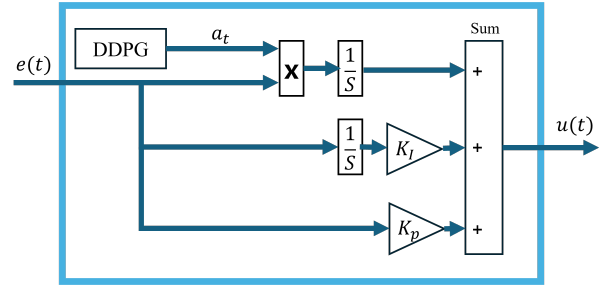


Fig. 4. Block diagram of PI controller with DDPG agent

B. Simulation results

To validate the performance of the proposed algorithm, we performed simulations for the following two cases:

Case 1) Classical PI controller;

Case 2) DDPG-based adaptive PI controller.

The load resistance variation for the two cases is shown in Fig. 5. The load resistance increases from 240 [Ω] to 80 [Ω] after 3 seconds. The input voltage is 400 [V] and the reference voltage is 250 [V]. Figs. 6 and 7 are the output voltage results of the EV charger for case 1 and case 2, respectively. It can be shown that the ripple of the output voltage in case 2 is reduced compared to case 1. Since the agent's action value changes according to the load resistance variation of the EV charger, the ripple reduction performance is improved compared to the classical PI controller.

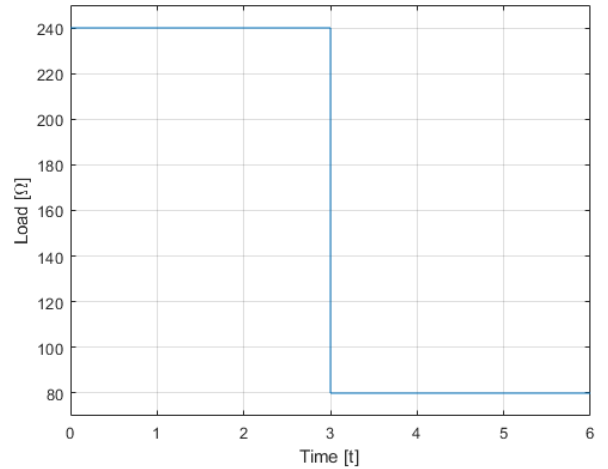


Fig. 5. Load resistance variation of the EV charger

V. CONCLUSIONS

In this paper, we proposed an adaptive PI controller using a DDPG agent for the EV charger with load resistance variation. The action of agent is varied according to the load resistance variation, and the action value is used to adjust the PI gain. The simulation is based on a scenario where the load resistance of the EV charger resistance changes. The results show that

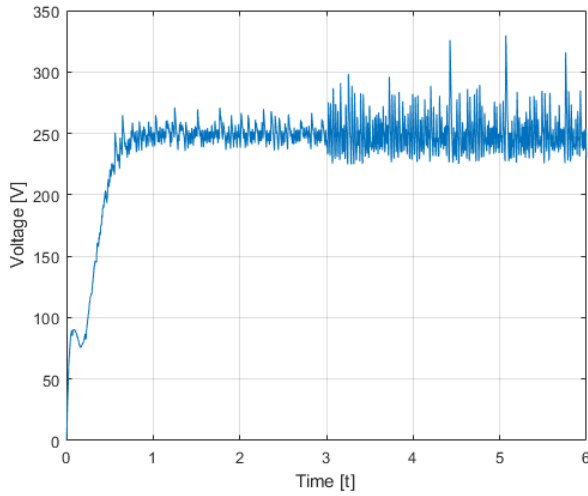


Fig. 6. Output voltage of classical PI controller

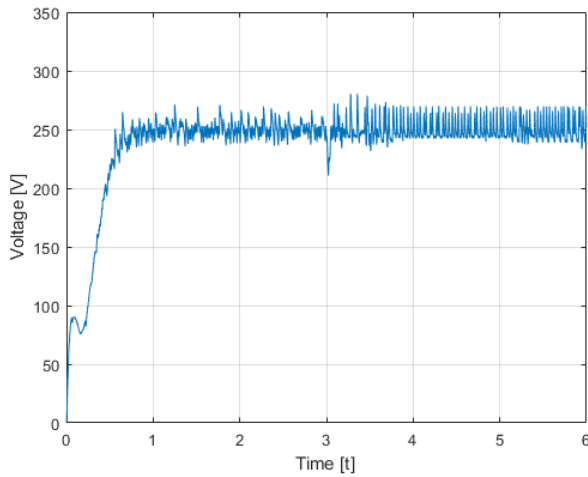


Fig. 7. Output voltage of proposed controller

the proposed method reduces the ripple of the output voltage compared to the classical PI controller.

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