Deep Deterministic Policy Gradient for Relay Selection and Power Allocation in Cooperative Communication Network

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Abstract—Cooperative communication is an effective approach to improve spectrum utilization. In this letter, we study the outage probability minimizing problem in a two-hop cooperative communication scenario, to improve the Quality-of-Service of the system through appropriate relay selection and power allocation. We propose a deep deterministic policy gradient based learning framework, which can find an optimal solution for the problem without any assumption or prior knowledge of channel state information. The proposed method can deal with continuous action space, which is more advanced than other existing reinforcement learning (RL) based approaches. Simulation results reveal that the proposed method outperforms traditional RL method, which can improve the communication success rate by about 5%.

Index Terms—cooperative communication, relay selection, power allocation, deep reinforcement learning

I. INTRODUCTION

In recent years, cooperative communication has been paid much attention, for it can help realizing resource collaboration between different nodes and obtaining diversified benefits in multi-user scenario [1], [2]. An outage occurs when the received signal-to-noise ratio (SNR) falls below a certain threshold [3], [4], and outage probability is usually used as a metric to measure the Quality-of-Service (QoS) of communication system. In order to minimize outage probability and improve QoS, it is intuitive to optimize relay selection and power allocation schemes. Traditional methods usually establish a probabilistic model based on the distribution assumption of channel uncertainty [5]–[7], and then propose their optimized relay scheme or power scheme. However, it is usually impractical to assume an exact channel state information (CSI) because of the inevitable noise. Therefore, these traditional methods can hardly be further applied to other situations.

There have been some studies to address the aforementioned issue with the help of reinforcement learning (RL), which is an emerging machine learning method good at solving complex optimization problems. RL methods use an agent, which can be taken as an intelligent robot, to interact with and learn from the communication environment, and thus do not need any prior knowledge or assumptions about the environment. Khan et al. [8] used SARSA-λ algorithm to make an adaptive power allocation. In [9] and [10], Q-learning algorithm was employed to help power control and relay selection, respectively. In [11] and [12], the authors developed the deep Q network (DQN) framework, which is the combination of RL and deep neural network (DNN), for relay-aided communication. However, none of these studies have successfully addressed power allocation problems with continuous action space. These methods have to set several optional power levels within the given power range for the agent to choose from, and thus the final scheme is usually not the optimal one.

Motivated by the aforementioned issues, in this letter, we propose a deep deterministic policy gradient (DDPG) based solution which realizes continuous action control [13]. The agent jointly optimizes its action policy for relay selection and power allocation, in order to minimize the outage probability in the two-hop relay network. In addition, we design an outage-based reward function for our DDPG learning framework, where the reward fed back from environment is only determined by a binary signal that represents success or failure of communication. The rest of this letter is organized as follows. Section II analyzes our system model and formulates the optimization problem. Section III describes our DDPG based solution for minimizing outage. Section IV presents the simulation results. Finally, Section V concludes this letter.

II. SYSTEM MODEL AND PROBLEM FORMULATION

As shown in Fig. 1, there is an $N_S$-antenna source $S$, an $N_D$-antenna destination $D$, and a group of single-antenna relays $R = \{R_1, R_2, \ldots, R_K\}$ in the two-hop wireless relay network. Suppose the source is far from the destination, and it does not have the direct link to destination. Therefore, the relay which uses amplify-and-forward (AF) protocol to processes the received signal, is needed to help communication.

We consider a half-duplex signaling mode because of equipment limitation, and only one relay is selected. Therefore, the communication from source $S$ to destination $D$ via the selected relay $R_k$ will take two time slots. In the first time
slot, the source broadcasts its signal, then relay and destination listen to this transmission. The received signal at $R_k$ can be written as

$$y_{sk}(t) = \sqrt{P_s} w^t_{sk} h_{sk}(t)x(t) + n_k(t),$$  \hspace{1cm} (1)$$

where $P_s \in [0, P_{\text{max}}]$ represents the transmission power at source, $x(t)$ represents data symbol at time $t$, $h_{sk}$ represents channel vector between source and relay $k$, where each element is a complex Gaussian random variables with zero mean and variance $\sigma^2_{sk}$, and $n_k$ is the complex Gaussian noise with variance $\sigma^2_n$ at relay. $w^t_{sk}$ is the normalized beamforming vector at source, which can be written as $w^t_{sk} = h_{sk} / \| h_{sk} \|$ according to principles of maximal ratio transmission.

In the second time slot, the selected relay amplifies and forwards the detected signal to destination. Then the received signal at the destination can be written as

$$y_{kd}(t) = \sqrt{P_r} h_{kd}(t) y_{sk}(t) + n_d(t),$$  \hspace{1cm} (2)$$

where $P_r \in [0, P_{\text{max}}]$ is the transmission power at relay, and similarly, $h_{sk}$ represents channel vector between relay and destination, $n_d \sim C(0, \sigma^2_n I_{N_d})$ is the complex Gaussian noise at destination. By employing maximal ratio combining methods, we multiply signal $y_{kd}$ by a beamforming vector $w^t_{kd} = h_{kd} / \| h_{kd} \|$ and have

$$x_{kd}(t) = \sqrt{P_s} P_r w^t_{kd} h_{kd}(t) w_{sk} h_{sk}(t) x(t) +$$

$$+ \sqrt{P_r} w^t_{kd} h_{kd}(t) \beta n_k(t) + w^t_{kd} n_d(t),$$  \hspace{1cm} (3)$$

where the amplification factor $\beta$ can be calculated by

$$\beta = \frac{1}{\sqrt{P_r \| h_{kd} \|^2 + \sigma^2_n}}.$$  \hspace{1cm} (4)$$

Similar to [11], [14], we have the following final end-to-end SNR after some manipulations.

$$\varphi_z = \frac{\varphi_{sk} \varphi_{kd}}{\varphi_{sk} + \varphi_{kd} + 1},$$  \hspace{1cm} (5)$$

where $\varphi_{sk} = P_s \| h_{sk} \|^2 / \sigma^2_n$ and $\varphi_{kd} = P_r \| h_{kd} \|^2 / \sigma^2_n$. Then we have the mutual information (MI) between the source and the destination.

$$I = \frac{1}{2} \log_2 (1 + \frac{\varphi_{sk} \varphi_{kd}}{\varphi_{sk} + \varphi_{kd} + 1}),$$  \hspace{1cm} (6)$$

We assume that the RL agent has access to all channel state information in the previous time slot, which can be denoted as $h(t) = \{ h_{sk}(t-1), h_{kd}(t-1) \}$. Then we define the following indicator function to represent the outage event.

$$f(t) \triangleq f(R_k(t), P_s(t), P_r(t); h(t)) \triangleq \mathbb{I}_{I<\lambda},$$  \hspace{1cm} (7)$$

where $\lambda > 0$ denotes the outage threshold.

Since the expectation of an indicator function can be used to calculate the probability of its original event, we formulate the optimization problem for minimizing outage probability as follows.

$$P_2 : \min_{R_k(t), P_s(t), P_r(t)} \frac{1}{T} \sum_{t=1}^T f(t)$$

s.t. $C_1 : R_k \in \{R_1, R_2, \ldots, R_K\}$,

$C_2 : P_s \in (0, P_{\text{max}})$,

$C_3 : P_s \in (0, P_{\text{max}})$,

$C_4 : P_s + P_r \in (0, P_{\text{max}})$,

III. DEEP DETERMINISTIC POLICY GRADIENT FOR RELAY SELECTION AND POWER ALLOCATION

In our proposed method, the RL agent estimates current channel state based on historical CSI, and accordingly selects relay and allocates transmission power. Afterwards, it receives a reward as feedback from the environment, which indicates whether the communication is successful. In this section, we model this process as a Markov decision process (MDP), and then propose a DDPG approach to solve the optimization problem proposed in (8).

A. Markov Decision Process and System Variables

An MDP consists of an environment $E$, a state space $S$, an action space $A$, and a reward space $S \times A \rightarrow R$. At each discrete time step $t$, the agent observes the current state $s_t \in S_t$, and selects an action $a_t \in A_t$ according to a policy $\pi : S_t \rightarrow P(A_t)$, which maps states to a probability distribution over actions. After executing action $a_t$, the agent receives a scalar reward $r_t \in R_t$ from the environment $E$ and observes the next state $s_{t+1}$ according to the transition probability $p(s_{t+1}|s_t, a_t)$. This process will continue until a terminal state is reached. According to cooperative communication environment, the system variables are defined as follows.

- **System State:** Full observation of the two-hop communication system consists of channel states between any two nodes in the previous time slot. Therefore, we consider historical channel state $h(t)$ as system state, which can be denoted as

$$S_t \triangleq \{ h_{sk}(t-1), h_{kd}(t-1) \}.$$  \hspace{1cm} (9)$$

- **System Action:** In each time slot, the agent needs to choose an optimal relay and make power allocation simultaneously. Therefore, our system action can be defined as

$$A_t \triangleq [a^{R}(t), a^{P}(t)],$$  \hspace{1cm} (10)$$

where $a^{R}(t) \in \{1, 2, \ldots, K\}$ and $a^{P}(t) \in (0, P_{\text{max}})$. Note that, the action for $P_r(t)$ is omitted, for it can be replace by the difference of $P_{\text{max}}$ and $P_r(t)$.

- **Reward Function:** Reward is given from the communication environment to evaluate the executed action. In
In this letter, we design an outage-based reward function. It only uses binary signals representing success or failure in communication, which can be denoted as $\mathcal{R} = \{0, 1\}$. According to (7), the reward received at time slot $t$ will be calculated by the following reward function.

$$r_t = 1 - f(\alpha^R(t), \alpha^P(t); h(t)). \tag{11}$$

The goal of the agent is to find the optimal policy to maximize the expected long-term discounted reward, which can be expressed as $J = \mathbb{E}[\sum_{t=0}^{T} \gamma^{t-i} r_i]$, where $T$ denotes total step, and $\gamma \in [0, 1]$ denotes the discount factor that trades off the importance of immediate and future rewards.

### B. DDPG Based Solution

To achieve the optimal action under different state, we can first define an action-value function as

$$Q^\pi(s_t, a_t; \theta) = \mathbb{E}_{a_{t+1} \sim \pi(s_{t+1}; \theta)}[J|s_t, a_t], \tag{12}$$

It describes the expected return after selecting action $a_t$ in state $s_t$ according to policy $\pi$, which is controlled by network parameter $\theta$. Then, the optimal action-value function is denoted as $Q^*(s_t, a_t; \theta) = \max_{\pi \in \Pi} Q^\pi(s_t, a_t; \theta)$, which obeys the following Bellman function.

$$Q^*(s, a; \theta) = \mathbb{E}_{s' \sim \mathcal{E}}[r + \gamma \max_{a'} Q^*(s', a'; \theta)], \tag{13}$$

where $s'$ and $a'$ are system state and optional action in the next time slot.

We choose to use deep neural network (DNN) to estimate each optional action and provide corresponding behavior policy, because DNN can make our agent have the ability of generalization, which means RL agent can still perform proper actions under system state that has never appeared before. Further, in order to deal with continuous action space, we propose a DDPG based learning framework for both discrete relay action and continuous power action control.

As shown in Fig. 2, the agent in the framework has two part, which are called actor and critic. RL agent employs two separate DNNs for their evaluate network, and each evaluate network has a copy of itself known as target network.

**Critic:** The critic is used to perform actions, and then estimate the action-value function by employing a DNN with parameter $\theta_Q$. It is worth noting that, a standard experience replay buffer $\mathcal{B}$ is adopted to store agent’s experience $e_t = \{s_t, a_t, r_t, s_{t+1}\}$ after each interaction. When training, we randomly sample a batch of experience from this buffer, and have the following loss function.

$$L(\theta_Q) = \mathbb{E}_{e_t \sim \mathcal{B}} [(y_t - Q(s_t, a_t; \theta_Q))^2], \tag{14}$$

with

$$y_t = r_t + \gamma \max_{a_{t+1}} Q(s_{t+1}, a_{t+1}; \theta_Q^{-}), \tag{15}$$

where $\theta_Q^{-}$ is a group of old parameters in the target network. In order to improve learning stability, they will be replaced following $\theta_Q^{-} \leftarrow \tau \theta_Q + (1 - \tau) \theta_Q$ with $\tau \ll 1$. Afterwards, parameters in evaluate network will be updated using RMSProp optimization method.

$$\theta_Q \leftarrow \theta_Q - \eta_Q \nabla_{\theta_Q} L(\theta_Q) \tag{16}$$

**Actor:** The actor is used to learn behavior policy and output actions for the critic. It maintains a parameterized actor function $\mu(s; \theta_\mu)$, which specifies the current policy by deterministically mapping states to a specific action. Following [15], we can derive the policy gradient of actor network.

$$\nabla_{\theta_\mu} J = \mathbb{E}_{s_t \sim \mathcal{S}} \left[ \nabla_{\theta_\mu} Q(s_t, \mu(s_t; \theta_\mu); \theta_Q) \right]$$

$$= \mathbb{E}_{s_t \sim \mathcal{S}} \left[ \nabla_{\theta_\mu} \mu(s_t; \theta_\mu) \nabla_{\theta_\mu} Q(s_t, \mu(s_t; \theta_Q))|_{a_t = \mu(s_t; \theta_\mu)} \right] \tag{17}$$

Then, similar to (16), we update its parameter $\theta_\mu$ as follows.

$$\theta_\mu \leftarrow \theta_\mu - \eta_\mu \nabla_{\theta_\mu} J \tag{18}$$
Pseudocode of our algorithm can be found in Algorithm 1.

**Algorithm 1** DDPG Based Discrete Relay Selection and Continuous Power Allocation

1. Initialize experience replay buffer $\mathcal{B}$.
2. Initialize evaluate network parameters $\theta_Q$ for critic and $\theta_\mu$ for actor.
3. Initialize target network with $\theta_Q^\tau = \theta_Q$ and $\theta_\mu^\tau = \theta_\mu$.
4. for episode $u = 1, 2, \ldots, u_{\text{max}}$ do
5. Initialize communication environment, get state $s_1$.
6. Initialize a random process $\Delta \mu$ as noise.
7. for time slot $t = 1, 2, \ldots, t_{\text{max}}$ do
8. Choose action $a_t = \mu(s_t; \theta_\mu) + \Delta \mu_t$ to determine the selected relay and power for transmission.
9. Execute action $a_t$, and observe reward $r_t$ and next state $s_{t+1}$.
10. Collect and save the tuple $(s_t, a_t, r_t, s_{t+1})$ in $\mathcal{B}$.
11. Sample a mini-batch of transitions $(s_j, a_j, r_j, s_{j+1})$ from $\mathcal{B}$.
12. Minimize the loss in (14), and update evaluate network of critic according to (16).
13. Calculate the sampled policy gradient in (17), and update evaluate network of actor according to (18).
14. Update parameters of corresponding target networks by $\theta_Q^\tau \leftarrow \tau \theta_Q + (1 - \tau)\theta_Q^\tau$ and $\theta_\mu^\tau \leftarrow \tau \theta_\mu + (1 - \tau)\theta_\mu^\tau$.
15. end for
16. end for

### IV. Evaluation

In this section, we first introduce the setup of simulation environment, and then carry out experiments to evaluate our proposed algorithms.

Similar to [11], the total maximum power $P_{\text{max}}$ for source and relay transmission is 4W. At destination node, the outage threshold is set as $\lambda = 1.0$. Learning rates for updating critic network and actor network are set as $\eta_Q = 0.005$ and $\eta_A = 0.001$, respectively. The size of experience replay buffer to store agent’s experiences is 10000, and mini-batch size which determines numbers of training cases is 128. In addition, parameter for soft update is set as $\tau = 0.001$. For comparison, the following baseline methods are employed.

**Random Selection**: When using random selection scheme, the agent randomly selects a relay to perform cooperative communication with random transmission power.

**DQN Based Approach**: The traditional DQN is another DRL framework, however, it can only solve problems with discrete action spaces. Therefore, when using this method, we divided the power into $L$ power levels for the agent to choose from, which can be denoted as $\frac{1}{L}P_{\text{max}}, \frac{2}{L}P_{\text{max}}, \ldots, P_{\text{max}}$.

As shown in Fig. 3, both DDPG method and DQN method can finally learn an action policy, while the performance of random selection is always very poor. The training time for these two learning methods to convergence is similar. The performance of DDPG method at the beginning is a little worse, because the continuous action space increases the learning difficulty. However, compared with DQN method where $L = 10$, DDPG method can achieve a better result with an improvement of about 5% in average success rate.

In addition, when the number of optional power levels increases from 10 to 100, the average success rate by using DQN does not improve as expected, but decreases by about 10%. It vividly shows that DQN method can not deal with high-dimensional or even continues action space, and too many optional actions will make DQN agent fail to learn the proper action policy, while our DDPG agent succeeds.

![Fig. 3: Average success rate with different methods.](image)

After training, we obtain the DDPG model and DQN model, and then test them in communication environment with different outage thresholds. The result is depicted in Fig. 4. our DDPG model (orange line) can still have better performance in other situations than DQN model with $L = 10$ (blue line). On the other hand, DQN model trained with a larger action space ($L = 100$, green line) performs badly. We can find the reason from Fig. 3, the fluctuation after convergence of DQN method with $L = 100$ is obviously larger than the others. It indicates that its action policy is not robust enough to deal with the current situation, let alone be further applied to other situations. From the above, our DDPG method can obtain a robust action poliks, which can effectively reduce outage probability and be applied to other situations.

![Fig. 4: Testing result under different outage thresholds.](image)
V. CONCLUSION AND FUTURE WORKS

In this letter, we propose a deep deterministic policy gradient method to dynamically select relay and allocate power in a two-hop cooperative relay network, in order to minimize outage probability under a total transmission power constraint. Unlike traditional studies, our method does not rely on any assumptions about channel distribution, and can deal with optimization variables which have continuous action space. Simulation results show that with our DDPG method, the average communication success rate can be increased by about 5% compared to existing RL method.

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