Deep Reinforcement Learning based Green Resource Allocation Mechanism in Edge Computing driven Power Internet of Things

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***Abstract*—Smart grid deploys a large number of smart terminals and sensing devices to form an edge network, as well as a virtual network of information space and the power Internet of Things. As a key component of 5G and future network, the latency of end-to-end and the traffic of backhaul link could be reduced by edge network. Nevertheless, the function of storage and computing are moved down to the edge nodes in mobile edge network which increases the complexity of resource management. So it is an important issue to find out a more effectively resources allocation mechanism as well as meeting the requirements of each user. Edge computing refers to the processing of large amounts of edge data in the edge space in the edge network, thereby reducing dependence on the data center, achieving limited self-governance of the edge network, and reducing off-line threats.Although Deep Reinforcement Learning (DRL) has been applied to many of the work related to edge networks, there lacks the applications for green resource allocation. A Deep Reinforcement Learning (DRL) based green resource allocation mechanism is proposed in this paper which aims at efficiently allocating the resources while satisfying the needs of mobile users. The value of energy efficiency can be obtained when the algorithm achieves convergence according to the simulation results. The efficiency of the DRL-based mechanism and its effectiveness in meeting user requirements and implementing green resource allocation are validated.**

Keywords—Deep Reinforcement Learning, Green Resource Allocation, Edge Computing, Power Internet of Things

I. Introduction

In recent years, power industrial control systems and the Internet of Things and other technologies are deeply integrated. Smart grid, especially the smart power distribution link, deploys a large number of smart terminals, perceptual devices and other forms the edge-aware network (hereinafter referred to as the edge network), forming the information space virtual network and physical space, physical network closely coupled collaborative interaction of the binary heterogeneous complex power Internet of Things. Through object perception or control and various wireless communication technologies, the edge network realizes information collection, power operation control and analysis decision support, as well as intelligent, interactive and informationtechnology of smart grid, which provides important application and functional support for intelligent power distribution.

The core idea of mobile edge network is to shift the functions of storage and computing down to the edge of the network (such as base stations, users, etc.). So that users can be provided with the required content or services from the nearer node, thereby reducing end-to-end delay and reducing backhaul link traffic [1].Energy-saving technology is an important technology in the next generation of mobile networks due to the consideration of ecological environment and economic cost[2-3]. Reinforcement Learning (RL) seeks the best strategy using agents' constant interaction with the environment. It is widely used to solve sequential decision problems in the natural and social sciences and engineering. Reinforcement learning consists of four basic elements: state, action, reward, and agency. The goal is to maximize long-term returns. How to link basic elements with optimization goals is very important [4-5].

In this paper, a DRL-based edge network green resource allocation framework is proposed. "green resource alloction" means that the goal of the paper is to minimize the energy consumption as the energy efficiency could be found. In the meanwhile, the needs of each user should be met and not exceeding the maximum power and bandwidth capacity of each base station. Our main contribution are summarized in the following:

- A DRL-based green resource allocation mechanism is proposed due to the limitation of resources in the mobile edge network.
- The state space, action space and the reward function are defined by the DRL agent with the purpose of statisfying the requirements of each user while

minimizing the energy efficiency. and the DNN approximate motion value function is applied (extracting information directly from the original state, avoiding manual features).

The article is organized as follows: In the section II, the related work is summarized. In section III, a system model is built that models goals and constraints to obtain the energy efficiency values of the edge network. Section IV proposes a framework for the allocation of green resources based on DRL. The simulation results in section V show the effectiveness of the algorithm. Finally, section VI summarizes this article.

II. Related Work

The problem of resource allocation in edge networks has been thoroughly studied. In the paper [1], a new joint task allocation and resource allocation method is proposed in the MEC architecture based on multi-user WiFi. The paper proposes a new strategy based on Q-Learning algorithm, named QL-Joint Task Assignment and Resource Allocation (QL-JTAR) to minimize the energy consumption on the mobile terminal side. However, the consumption of energy and energy efficiency are not taken into consideration in the paper where large loss of cost may be caused.

The paper [3] proposes an effective solution to solve the joint problem by decoupling bandwidth configuration and content source selection. In order to avoid frequent information exchange, the solution aims to solve the decoupling problem. However, this algorithm is less versatile and is not suitable for large-scale complex scenarios.

The paper [6] considers how to meet the ubiquitous user demand in the edge network and adapt to the explosive growth of mobile traffic, and proposes to use fog computing to solve. However, this algorithm brings high management and maintenance costs, and how to optimally place the Fog server is challenging because different user requires different locations.

The paper [7] is for the deterministic mission arrival scenario, that is, assuming that each mission will be completed after the completion of each mission. The analysis of the above papers is not applicable to the task flow scenario, that is, the data source continuously generates tasks, such as real-time computing, online games, virtual reality and other services. Different from the above papers, the paper [8] is aimed at the random task arrival model. They add tasks that have arrived but not yet performed to the task buffer queue and optimize their goals with long-term network performance.In the paper [9], in order to optimize the energy and delay consumption, a reinforcement learning based scheme was proposed to minimize the energy and delay consumption by jointly optimizing computational resources and network resource allocation.

The paper [10] proposes a positive Markov decision scheme by jointly controlling the local processor to calculate the frequency, modulation mode and data rate, which can minimize the delay and energy consumption. In the paper [11], considering the dynamic arrival and energy collection mechanism of the task, in order to minimize the delay and energy consumption, an online learning algorithm is proposed. Paper [12] considered energy harvesting and tasks with different priorities. In order to solve the problem of excessive time complexity of learning algorithms, a computational unloading scheme with low time complexity is proposed.

In this paper, DRL is applied to the edge network, taking into account the connection relationship between the base station and the user. The base station allocates power and bandwidth to the user, which makes the energy efficiency the lowest while satisfying the user's needs.

III. System Model

In this paper, we consider the scenario in a SDN- enabled heterogeneous network, in which contained a J $\coloneqq \{1, \dots, j, \dots \mathcal{J}\}$ as well as a core network N. The set of BSs I and the core network $\mathcal{N}$ are connected by wired backhaul links. The user's device j and the BS i are connected via wireless links. Fig. 1 shows the scenario.

Similar to [13], in the mentioned network, a set of flows F $\coloneqq \{1, \dots, \text{f}, \dots \text{F}\}$ are working on. m^f is the required size of packet, r^f is the required data rate of each flow and t_0 is the transmission time.

$$r^f = \frac{m^f}{t_0} \tag{1}$$

It is assumed that one flow is supported by one link, the data rate in flow f between the user j and the base station i is r_{ij}^f

The capacity of a wireless link depends on the ratio of the radio resources allocated by the network to the link. Therefore, by using Shannon boundaries, the spectral efficiency of a wireless link is defined as:

$$\Upsilon_{ij} = \log\left(1 + \frac{g_{ij} p_{ij}}{N_0 x_{ij} B_i}\right) \tag{2}$$

Where g_{ij} is the large-scale channel gain that includes pathloss and shadowing between the transmission node i (the source of the link l) and the receiving node j (the destination of the link l). p_{ij} is the transmission power of the wireless link. N_0 is the power spectrum density(PSD), B_i is the total available spectrum bandwidth of its source node. $x_{ij} \in [0,1]$ is the allocation ratio of its source node to the user.

The achievable data rate capacity of the wireless link is:

$$r_{ij} = x_{ij} B_i \Upsilon_{ij} \tag{3}$$

Assuming that a node $i \in I$ haa the caching function and stores S_n popular contents. In this proposed framework, total S content files are stored at the content server (cloud centers or the Internet source) and each content has the normalized size of 1. This assumption is feasible due to the content could be sliced into chunks meanwhile with the same length. As nodes only have limited storage capability in mobile networks, S_i is much smaller than the cloud center[14] ($S_i \leq S$,$\forall i \in I$).

Assuming that at the BS i the maximum scheduled CPU calculation frequency is C_i. To process the bit information, a c_i CPU cycle is required, which means that $c_i r^f$ (cycle/sec) is the minimum requirement to support the flow f from the BS i [2]. $s_{ij} \in \{0,1\}$ is used to express the relationship of connection between the user j and the base station i. $s_{ij} = 1$ representing that the user j is connected with the i base station. $s_{ij} = 0$

representing that the user j is not connected with the base station i [15-17].

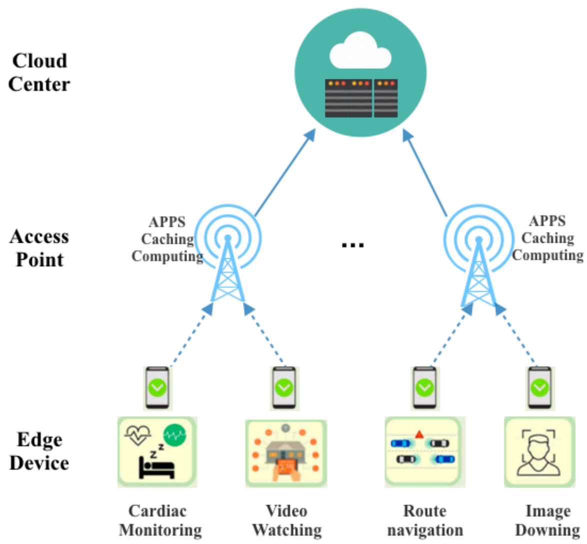

Fig. 1. BS Deployment

The energy consumed to support the $\mathcal{F}$ flow in the network includes two main parts, node operation energy and transmission energy. The node operating energy $E^C(s_{ij})$ shown below depends on fixed power consumption p_n^0 (eg, circuitry, control signals, content cache) and calculated power consumption p^C (watts/cycle)

$$E^C(s_{ij}) = t_0 \sum_{i \in I} (p_n^0 + \sum_{j \in J, f \in \mathcal{F}} s_{ij}\, c_i r^f p^C) \tag{4}$$

Where t_0 is the operation time. In addition, ignoring the energy used by the content server because our goal is to minimize the energy efficiency of the mentioned system.

The transmitting energy includes two parts which are the wireless transmitting energy and the backhaul transmitting energy. p_{ij} indicates the power allocated from the BS i to user j . $E^T(p_{ij}, s_{ij})$ is the wireless transmitting energy. The backhaul transmission power is expressed as P_w.

Among them, the wireless transmission energy is:

$$E^T(p_{ij}, s_{ij}) = \sum_{j \in J} \sum_{i \in I} t_0 p_{ij} s_{ij} \tag{5}$$

Where the backhaul transmission energy is:

$$E^B = t_0 P_w \sum_{f \in \mathcal{F}} r_{ij}^f \tag{6}$$

Therefore, the total energy consumption is:

$$\eta_{EE} = (E^C(s_{ij}) + E^T(s_{ij}, p_{ij}) + E^B) \tag{7}$$

Thus, the energy efficiency is:

$$E_b = \frac{\eta_{EE}}{\sum_{f \in \mathcal{F}} r^f} \tag{8}$$

The optimization problem is given by as follows:

$$min_{S,P} E_b \tag{9}$$

Subject to:

$$s_{ij} \in \{0,1\} \qquad \forall\, i \in I, j \in J \tag{10}$$

$$\sum_{i \in I} s_{ij} = 1 \qquad \forall j \in J \tag{11}$$

$$r_{ij}^f \le r_{ij}, \qquad \forall\, f \in \mathcal{F} \tag{12}$$

$$\sum_{j \in J} p_{ij} s_{ij} \le P_{max}, \forall i \in I \tag{13}$$

$$\sum_{j \in J} x_{ij} s_{ij} \le 1 \qquad \forall i \in I \tag{14}$$

$$\sum_{j \in J} p_{ij} g_{ij} \ge \omega \qquad \forall i \in I \tag{15}$$

$$SINR \ge \phi \qquad \forall i \in I, j \in J \tag{16}$$

In the constraint (10-11), $s_{ij} \in \{0,1\}$ is a binary decision variable which reflects the connection relationship of a certain user and a certain BS. At one time, each user could be served by only one BS. Constraint (12) reflects that the size of the flow carried by the wireless link cannot exceed its total achievable data rate capacity.The constraint (13-14) denotes that for each BS, the allocated transmitting power and bandwidth could not exceed its capability. The constraint (15-16) reflects the received power of user constraint and user's SINR constraint.

The above model comprehensively considers the computing and caching capabilities of edge network nodes, and seeks a green resource allocation framework with the goal of minimum energy efficiency. In the paper [1], Q-Learning is used to minimize the energy consumption value of the edge network, but the energy efficiency is not considered. Compared with Q learning, the speed of DRL training is faster, and more suitable for large action spaces cases. Compared to heuristic algorithms, DRL can avoid the situation of falling into local optimum and DRL can obtain global optimal solutions. So DRL is chosen to solve this optimization problem.

IV. DRL-BASED GREEN RESOURCE ALLOCATION FRAMEWORK

In this section, a DRL based green resource allocation framework in edge networks is proposed. The purpose of which is to minimize the energy efficiency of the considered model while satisfying the requirements of each mobile user and not exceeding capability of each base station. In order to reduce the state space size of the framework, under a certain connection relationship, the convex optimization method is firstly used to obtain the minimum wireless transmission energy, and then iterate with DQN. After that , the optimal connection and optimal power distribution value could be found on the basis of the convex optimization results, in order to calculate the optimal value of energy efficiency.

DRL consists of two parts: the agent and the external environment. The change of the external environment state is achieved by the agent taking different actions. Then the agent receives a reward from the external environment. Finding the optimal strategy to maximize the value of the reward is the purpose of the DRL.

The state space, action space and reward function of the proposed DRL-based framework are defined as follows:

- *State Space*: As can be seen from the definition above, 0 is used to indicate that a user is not served by a certain base station, and 1 means that the user is served by a certain base station. Assuming there are three base stations, so there are three types of connection relationships with the base station for any user: u_1=[1,0,0], u_2=[0,1,0], u_3=[0,0,1]. u_1 indicates that the user is served by the first base station, u_2 indicates that the user is served by the second base station, u_3 indicates that the user is served by the third base station. So our state space is a permutation of the three connection relationships for all users. To be specific, we assume that there are K users, so a certain relationship of connection between all the base stations and the users can be expressed as $\mathcal{M} = \{s_1, s_2, \dots, s_K\}$ where $s_1, s_2, \dots, s_K$ is one of a certain value of $\mathrm{u}_0, \mathrm{u}_1, \mathrm{u}_2$. So $S = \{\mathcal{M}_1, \mathcal{M}_2, \dots, \mathcal{M}_N\}$ can be indicated as the state space of the framework where $N = 3^K$ is the number of total connection relationship.
- *Action Space*: $A = \{1,2,\dots,N\}$ is defined as the action space. The DRL agent selects the next state by analyzing the minimum wireless transmission energy E^T in the current state obtained by the convex optimization method, that is, using the number in the action space A to indicate the position of the next state in the state space to obtain the next state.
- *Reward*: Reward is used to indicate compliance with the framework goal. The larger the reward, the more consistent with the optimization goal. In this framework, our goal is to minimize energy efficiency while satisfying constraints. So the lower the energy consumed, the greater the reward value. $E_{\max} - E$ is formulated as the instant reward. $E_{\max}$ denotes the maximum energy consumption which could be provided by the base stations and E represents the value of energy consumption after applying the action..

Deep Q-learning(DQN) perform the online dynamic control based on offline DNN. In the online learning process, at each time interval, the DRL agent uses the CNN to obtain the estimated Q value. And uses the ε greedy strategy to select the action, wherein the probability of ε is randomly selected, and with the probability of$(1 - \varepsilon)$ selects the action with the largest estimated Q value. After the action is selected, a certain connection relationship can be obtained, and the convex optimization method uses the connection relationship to calculate the minimum value of the wireless transmission energy described below:

$$E^T(p_{ij}, s_{ij}) = \sum_{j\in J}\sum_{i\in I} t_0 p_{ij} s_{ij} \tag{18}$$

Specifically, the determined connection relationship will be used as a known input to the convex optimization method. Based on this, the convex optimization method can find the optimal allocation power of each base station to each user according to the objective function and the constraint condition. That is, the minimum wireless transmission energy would be obtained under certain connection relationship. The total energy consumption is then calculated and the immediate reward r and the next state s' are observed in the interaction with the environment. The state transition (s, a, r, s') is stored in the memory memory, after which the DQN randomly extracts a portion of the data from the memory pool to iteratively estimate the parameters of the network. Algorithm 1 describes the green resource allocation framework based on DRL.

Algorithm 1 The DRL-based Framework

```
Initialize replay memory D to capacity N;
Initialize action-value function Q with random weights θ;
Initialize target action-value function Q̂ with weights θ⁻ = θ;
Repeat:
    Initialize sequence s_t and preprocessed sequence φ_1 = φ(s_1);
    With probability ε select a random action a_t;
    Otherwise a_t = argmax_a Q(s_t, a_t; θ), where Q(·) is estimated by the CNN.
    Observe the new state s_{t+1};
    Solving the convex optimization problem based on s_{t+1};
    Obtain the optimal value of power allocation between each BS and user;
    Calculate the minimize wireless transimission energy using optimal value;
    Obtain the total energy consumption
    Observe the reward r_t
    Store the state transition (s_t, a_t, r_t, s_{t+1}) into D;
    Randomly sample a minibatch of state transitions (s_t, a_t, r_t, s_{t+1})from D;
    Target y_t = r_t + γmax_a' Q(s_{t+1}, a'; θ⁻)
    Perform a gradient descent step Δθ = α[y_t − Q(s_t, a_t; θ)]∇Q(s_t, a_t; θ)
    Update network parameters θ = θ + Δθ;
    Every C steps reset Q̂ = Q;
Until finished().
```

V. Simulation Results

Three base stations and several users are included in the green resource allocation mechanism based on DRL of mobile edge network. The simulation of the paper is based on the single moment, which means the user mobilty is ignored. In this paper, four cases are selected: three users, four users, five users and six users respectively. Fig. 2 shows the comparison of rewards in four cases, Fig. 3 shows the comparison of energy efficiency in four cases. Fig. 4 shows the comparison of loss in four cases. The parameters of simulation are listed in Table I.

TABLE I. Simulation Parameters

Parameter	Value
Deployment	3 BSs
Max BS Power	3W
Path loss	103.8 + 20.9lg (d[km])

Noise PSD	-174dBm/Hz
Fixed power	4.8W
Computing power	10^{-9}watt/Hz
Backhaul power	0.2 watt/Mbps
Packet of flows	10M
Work load	750cycles/bit
Processing time	1s
Max bandwidth	20MHz
Bandwidth ratio	0.2
ϕ	-3dB

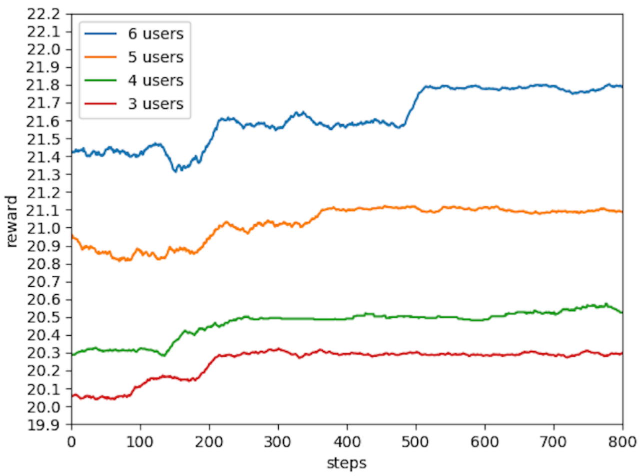

Fig. 2. Reward comparision of different users under the DRL mechanism.

The approximative value of steps and related results when DRL reaches convergence of four cases are described in table II.

As can be seen, the blue line represents the case of six users, the orange line represents the case of five users, the green line represents the case of four users, and the red line represents the case of three users. When the number of users increases, DRL requires more steps for convergence, which means the convergence speed would be slower. In addition, the value of energy efficiency also increases as the number of users increases.

Then, the cumulative probability distribution of user's receiving power and the SINR for these three different strategies are compared. The results could be found in Fig. 5and Fig. 6 respectively. The blue dotted line indicates the strategy of any two user clusters (UC), and the orange dotted line indicates the strategy of selecting the nearest distance (DA). The green dotted line indicates the strategy of adopting DRL. The DA indicates that the user selects the nearest base station to receive the service, and the DRL indicates the value of the DRL-based edge network green resource allocation framework mentioned in this paper when converging. The UC indicates that any two users are clustered and assigned to one of the base stations for service.

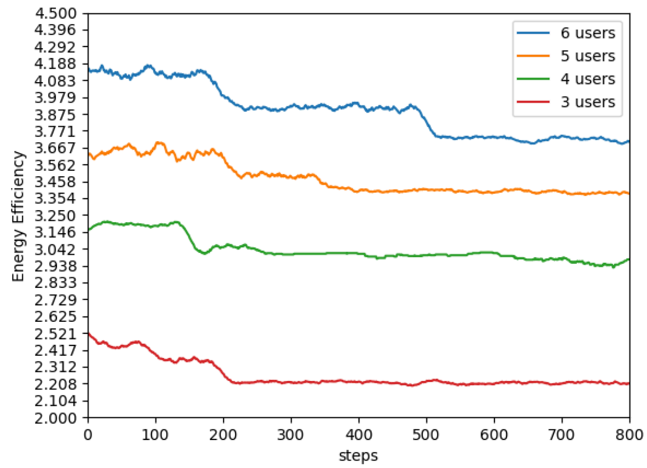

Fig. 3. Energy Efficiency comparision of different users under the DRL mechanism.

TABLE II. APPROXIMATE VALUES FOR CONVERGENCE

Users	Converge Step	Reward	Loss	Energy Efficiency
6 users	500	21.76	0.163	3.772
5 users	350	21.09	0.114	3.456
4 users	250	20.38	0.082	2.965
3 users	220	20.25	0.035	2.207

According to the cdf graph of the user's receiving power, the probability between -50dBm and -20dBm are compared, which shows that the value of DRL strategy is the largest, followed by the DA strategy, and finally the UC strategy. That is, the DRL strategy can relatively maximize the user's receiving power. In the cdf of SINR, the probability of SINR between 2dB and 4bB are compared, the result illustrates that the value of DRL strategy is the highest, followed by the strategy of DA, and finally the strategy of UC. That is, the DRL strategy can relatively minimize the value of the SINR. These proved that the DRL strategy performs best.

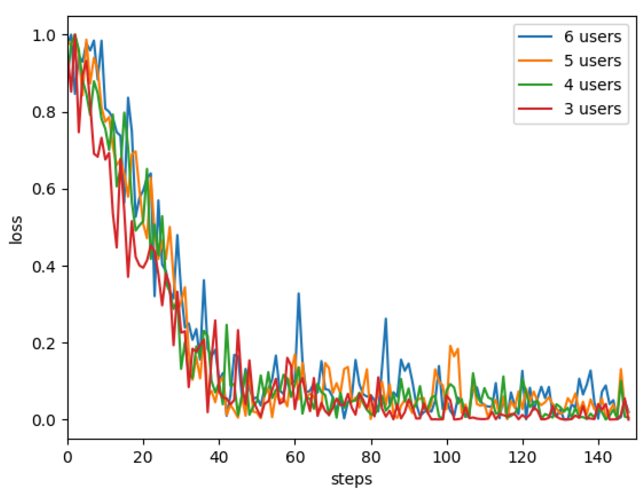

Fig. 4. Loss comparision of different users under the DRL mechanism

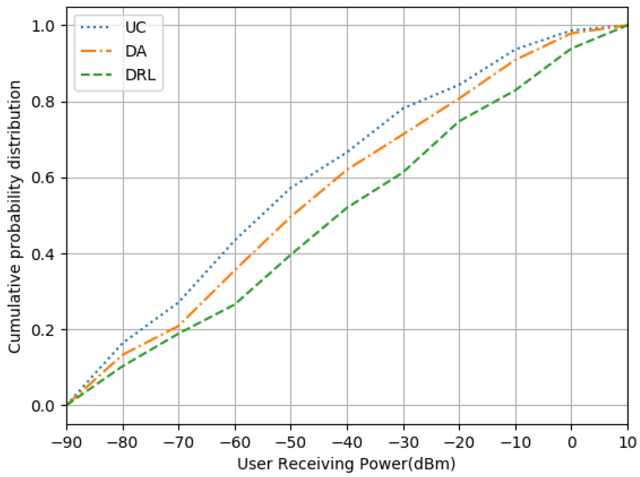

Fig. 5. Cumulative porbability distribution of user's receiving power for three strategies

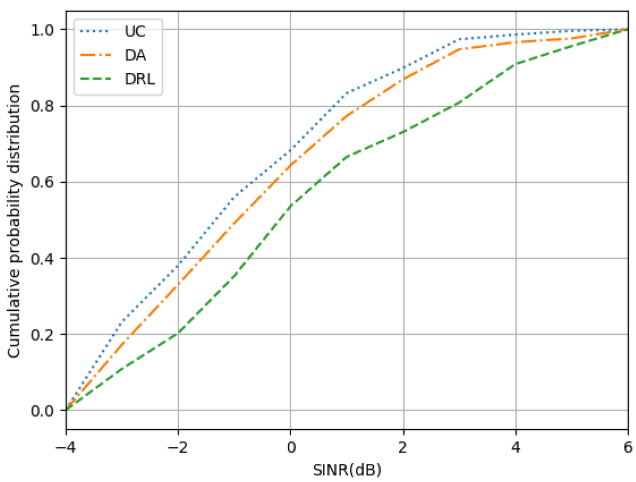

Fig. 6. Cumulative porbability distribution of SINR for three strategies

VI. Conclusion

In this paper, the proposed DRL-based framework solves the green resource allocation problem in mobile edge networks. To Minimize the energy efficiency as well as meet the needs of each user. A well-trained network achieves not only the aim of green energy-saving, but also solve the problem of resource allocation. The effectivess of the framework could be proved according to the results which compared with the other two strategies. Nevertheless, the simulation environment is kind of simple in this paper. In future work, more complex scenarios will be considered. And the proposed DRL-based green resource allocation algorithm would be compared with other algorithms and consider channel power allocation.

Acknowlegement

This work is supported by Science and Technology Project from of State Grid Corporation of China: "Key technology Research and Application for Ubiquitous Inter-networking Security for Power wireless private network services (No.5700-201918229A-0-0-00)

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