Intelligent and Energy-efficient Distributed Resource Allocation for 5G Cloud Radio Access Networks

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***Abstract*—With the development of 5G, the distribution of base stations tends to be dense. Compared with the traditional network architecture, Cloud Radio Access Networks(C-RAN) architecture can satisfy the current requirements of high bandwidth, low latency and low energy consumption. Currently most energy-saving scheme for C-RAN is complex with time cost computing, which may not be suitable for large-scale region. For the problem of energy-efficient resource allocation for dense distribution of Remote Radio Heads(RRHs) in C-RAN, we use K-means clustering algorithm to simplify the network topology and reduce the complexity under a distributed manner. Aiming at the problem of network resource allocation in C-RAN, we use A3C algorithm to allocate network transmission power, and compare the total energy consumption, system energy efficiency and Signal to Interference plus Noise Ratio(SINR) value of terminal devices through simulation experiments. The experimental results show that in the same network environment, A3C algorithm has the highest energy efficiency, and can keep the SINR value of terminal devices in a reasonable range, which proves the effectiveness of A3C algorithm.**

***Index Terms*—5G Heterogeneous networks, C-RAN, K-means, A3C, Energy efficiency**

I. Introduction

With the rapid development and extensive commercial deployment of the 5th Generation Mobile Communication Technology(5G), we can use higher-speed and lower latency network services through 5G devices, which also leads to the further growth of mobile data traffic [1]. Access network is gradually becoming a bottleneck that seriously affects the system performance [2], so a new network framework is urgently needed [3].

Overall, the main challenges faced by operators are as follows: (1) High energy consumption due to the use of a large number of Base Stations(BSs) [4]. (2) Network operation and maintenance costs continue to increase. (3) Frequent migration of User Equipments(UEs) leads to low utilization efficiency of BSs [5].

In the face of the above challenges, advanced intelligent wireless network architecture will be adopted in the future to reduce network cost and meet the requirements of low latency and low power consumption [6]. Using C-RAN in 5G network will be the most favorable choice for mobile operators. C-RAN architecture not only reduces the operation and maintenance costs, but also provides advanced and energy-efficient transmission wireless communication system. However, it brings some technical challenges. In the C-RAN architecture, there are a large number of Building Base band Unites(BBUs) and RRHs. In order to ensure the efficient and stable operation of the system, the computing resources in BBU pool, the transmission power of RRHs and the connection relationship between RRHs and UEs should be controlled and distributed. How to efficiently and intelligently allocate resources for C-RAN is the problem this paper attempts to solve.

The research in this paper is based on C-RAN architecture. Firstly, we use K-means clustering algorithm to obtain the connection relationship between RRHs and UEs, and independently allocate network resources for each cluster of RRHs and UEs, so as to simplify the network topology and reduce the complexity and computation of the problem. Based on the connection relationship obtained by clustering algorithm, A3C algorithm is used to allocate network resources for each cluster. Finally, different reward functions and optimization algorithms are compared through simulation, and the advantages and disadvantages of different reward functions and optimization algorithms are analyzed and discussed to verify the effectiveness of the algorithm. The resource allocation mechanism proposed in this paper has better performance than Q-learning and DQN algorithms. It can make the system have higher energy efficiency on the premise of maintaining acceptable latency.

II. Related work

As a core technology of 5G, Ultra-Dense Network needs to apply clustering algorithm to simplify the network topology and reduce the complexity of the problem [7].

Several articles discuss the clustering algorithm in C-RAN. In [8], in order to reduce the interference and improve the utilization efficiency of network resources, a fast convergent KNN algorithm is designed. However, this study does not involve efficient allocation of network resources. In [9], this paper proposes a two step joint clustering and scheduling scheme for coordinated multipoint transmission in heterogeneous ultra dense networks, which considers the impact of load on the availability of network resources. Simulation results show that the scheme can effectively improve the average throughput of the system. In [10], in this study,

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a data driven resource management framework is proposed, which groups base stations into different clusters and identifies cluster centers. On this basis, the transmission power of the cluster center is reduced to reduce the interference to the adjacent base stations of the cluster. Compared with the above clustering algorithms, the K-means used in this paper has the advantages of simple calculation and efficient.

Meanwhile, articles that discuss the network resource allocation mechanism in C-RAN. In [11], this paper mainly considers the computing offload of IoT application in MIMO C-RAN. In this paper, a supervised deep learning algorithm is proposed to minimize the total transmit power of the Internet of Things while meeting the requirement of computing task latency. In [12], an integer linear programming with the objective of minimizing the total cost is proposed to optimize the function distribution of BBU pool and RRHs, and genetic algorithm is used to optimize the allocation of computing resources in C-RAN network. In [13], unsupervised feedforward neural network is applied to transmit power optimization of C-RAN system. Considering both uplink and downlink, the transmit power is optimized by using directly measurable channel gain without user location information. In [14], by using the dynamic remapping capability of C-RAN, the RRH is configured to the appropriate baseband cell sector in the time-varying service environment. At the same time, genetic algorithm and discrete particle swarm optimization are proposed to solve the network resource allocation problem. Simulation results show that the proposed algorithm can reduce the proportion of blocking users in the network. Obviously, the above algorithms are also very efficient in network resource allocation, but they do not take into account the complex network topology caused by the massive network devices in Ultra-Dense Network. On this basis, this paper uses clustering algorithm to reduce the complexity of network topology.

III. SYSTEM MODEL

In this section, we establish a mathematical model of network resources in C-RAN architecture. The network with $i = \{1, ..., N\}$ BBUs and $j = \{1, ..., M\}$ RRHs, each BBU can connect with several RRHs, which depends on the network traffic condition and the geographical position.

The BBU's power consumption consists of two parts: the static power consumption and the dynamic power consumption. The static power consumption is the power consumption of a BBU without any traffic load. The dynamic power consumption is the additional power consumption caused by baseband processing, cooling and etc. The power consumption rate of the i-th BBU is $P_i^{BBU}(t)$ at time t. The static power consumption and the dynamic power consumption are denoted as $P_i^S(t)$ and $P_i^D(t)$. $P_i^D(t)$ has linear relationship with traffic rate $r_i(t)$ on the i-th BBU, α_i is the coefficient. The power consumption rate of the i-th BBU $P_i^{BBU}(t)$ can be expressed as

$$P_i^D(t) = \alpha_i r_i(t) \tag{1}$$

$$P_i^{BBU}(t) = P_i^S(t) + P_i^D(t) \tag{2}$$

There are $k = \{1, ..., W\}$ UEs in this network, each UE can transfer data by connecting to a RRH. The SINR value of k-th UE which receives the j-th RRH is denoted as γ_{jk}. $s_{jk}(t)$ denotes the connection relationship between RRH j and UE k [15]. $s_{jk}(t) = 1$ denotes that the j-th RRH is connected with the k-th UE. Assuming that $p_{jk}(t)$ is the power of transmission allocated by the j-th RRH to the k-th UE. g_{jk} denotes the channel decay between j-th RRH and k-th UE. Additionally, σ is the Gaussian white noise in the environment. The expression of SINR value γ_k is

$$\gamma_{jk} = \frac{s_{jk}(t) p_{jk}(t) g_{jk}}{\sum_{i=1, i \neq j}^{M} s_{ik}(t) p_{ik}(t) g_{ik} + \sigma} \tag{3}$$

The power consumption rate of the j-th RRH is denoted as $P_j^{RRH}(t)$ [16]. The total energy consumption of the j-th RRH is EC_j^{RRH}.

$$P_j^{RRH}(t) = \sum_{k=1}^{W} s_{jk}(t) p_{jk}(t) \tag{4}$$

$$EC_j^{RRH} = \int_0^t P_j^{RRH}(t)\, dt \tag{5}$$

The total energy consumption of the i-th BBU is EC_j^{BBU}.

$$EC_i^{BBU} = \int_0^t P_i^{BBU}(t)\, dt \tag{6}$$

The total energy consumption can be expressed as:

$$EC_{total} = \sum_{i=1}^{N} EC_i^{BBU} + \sum_{j=1}^{M} EC_j^{RRH} \tag{7}$$

At time t, the k-th UE data transfer rate is denoted as $r_{jk}(t)$, and the j-th RRH required data rate is denoted as $r_j(t)$.

$$r_j(t) = \sum_{k=1}^{W} s_{jk}(t) r_{jk}(t) \tag{8}$$

$s_{ij}(t)$ denoted as the connectivity of the i-th BBU with the j-th RRH, the traffic load of i-th BBU $r_i(t)$ can be expressed as

$$r_i(t) = \sum_{j=1}^{M} s_{ij}(t) r_j(t) \tag{9}$$

The downlink channel capacity of the k-th UE is C_{jk}, which can be expressed as

$$C_{jk}(t) = \log_2(1 + \gamma_{jk}) \tag{10}$$

The transferring latency of k-th UE is denoted as $D_k(t)$, and $b_k(t)$ is the allocated bandwidth of k-th UE.

$$D_k(t) = r_{jk}(t) / b_k(t) \tag{11}$$

Our goal is to minimize energy consumption EC_{total}, meanwhile ensuring the coverage, signal strength, SINR value and transferring latency.

The constraints are:

$$\sum_{j=1}^{M} s_{jk}(t)p_{jk}(t)g_{jk}>\omega_{Min} \tag{12}$$

$$\gamma_{jk}>\phi_{Min} \tag{13}$$

$$P_i^{BBU}(t) \leq P_{Max}^{BBU} \tag{14}$$

$$P_j^{RRH}(t) \leq P_{Max}^{RRH} \tag{15}$$

$$T_{Max}(k)>D_k(t) \tag{16}$$

To be specific, constraint (12) indicates that the receiving power of UEs should meet the minimum constraint ω_{Min}, $\sum_{j=1}^{M} s_{jk}(t)p_{jk}(t)g_{jk}$ is the receiving power value. Constraint (13) indicates that the SINR value γ_{jk} should meet the minimum constraint ϕ_{Min}. Constraints (14-15) indicate that the power of BBUs and RRHs should be lower than the rated maximum power [17]. Constraint (16) indicates that the transferring latency $D_k(t)$ of k-th UE should be lower than the maximum transferring latency $T_{Max}(k)$, different types of services need to set different maximum transferring latency constraints which is adaptive to the UE ID k.

IV. DRL-BASED RESOURCE ALLOCATION MECHANISM

In this section, we proposed an DRL-Based resource allocation mechanism. This mechanism works in C-RAN architecture shown in Fig.1. In order to reduce the complexity of the problem and the amount of computation, we use K-means clustering algorithm to cluster UEs and allocate them to the nearest RRHs, and then use A3C algorithm to allocate the network resources in each cluster.

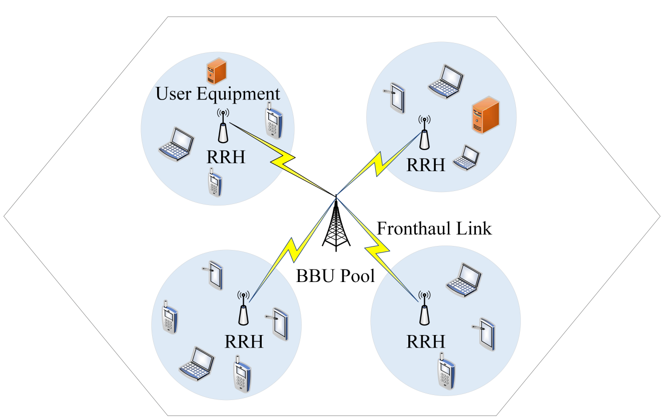

Fig. 1. The C-RAN architecture structure diagram.

K-means is an iterative clustering algorithm, which is the most commonly used clustering algorithm based on Euclidean distance. The algorithm considers that the closer the distance between two targets is, the greater the similarity is. Based on the result of this algorithm, UEs are assigned to the nearest adjacent RRHs. Then, the connection relationship between UEs and RRHs can be obtained. This step simplifies the network topology, reduces the complexity of the problem and the amount of computation required.

Next, A3C algorithm is used to allocate power and resources for each cluster. A3C is an actor-critic algorithm in reinforcement learning algorithms, which combines the advantages of value-based algorithms and policy-based algorithms. A3C algorithm not only can deal with discrete and continuous problems, but also can asynchronously update to improve learning efficiency. The algorithm flow chart is shown as Fig.2.

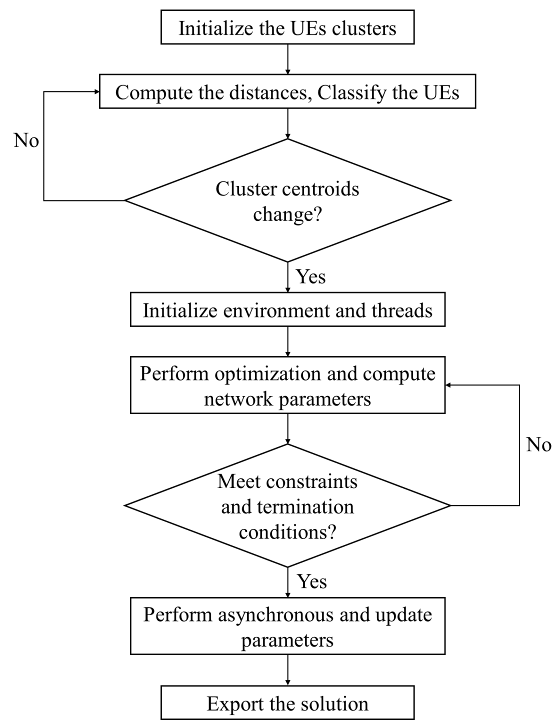

Fig. 2. The flow chart of the algorithm.

As shown in Fig.3, the A3C algorithm contains n worker threads. Each thread has the same network structure. These threads run independently and update the shared neural network model parameters without interference with each other. These threads regularly update their own neural network parameters to the public neural network to guide the environment interaction [18].

The agent manage to obtain the maximum reward according to the current environment, and chooses action based on it. The reward expectation can be expressed as:

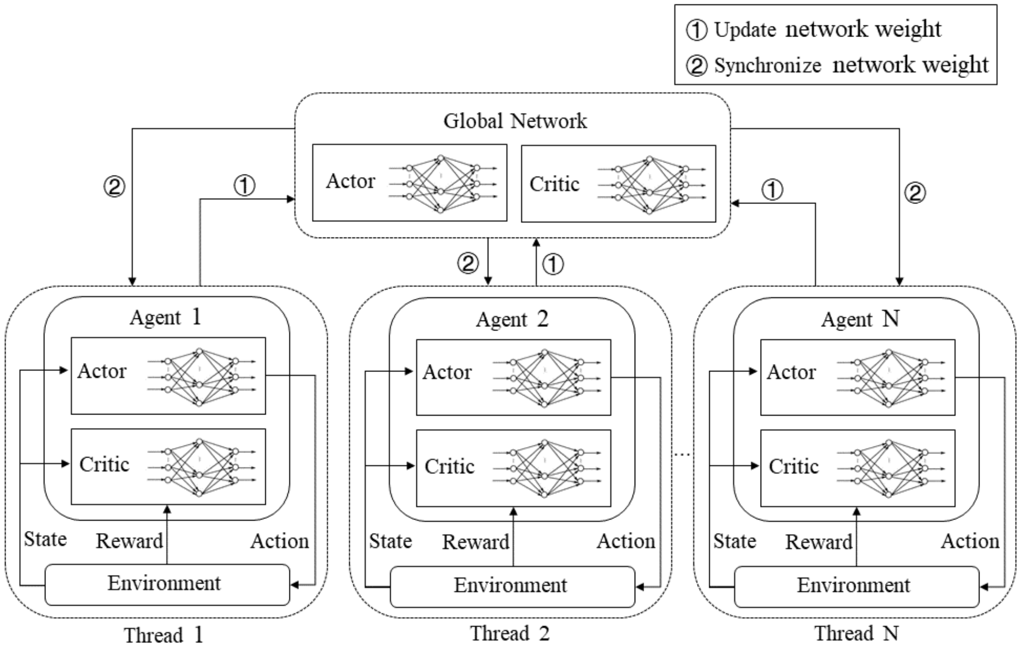

Fig. 3. Overall structure of A3C algorithm.

$$E_p[X] = \sum_i P_i X_i \tag{17}$$

Where X_i is each possible value of X and P_i is the probability of each corresponding X_i. The expectation of reward can be regarded as the weighted average of value X_i and weights P_i.

The value function $VF(s)$ is regarded as the expected reward. Specifically, the reward that can be obtained in the current state s is the sum of the next stats s' and the reward r during the state conversion. $\eta(s)$ denotes the probability of choosing action a in state s. $VF(s)$ can be expressed by the following equation:

$$VF(s) = E_{(\eta(s))}[r + \gamma VF(s')] \tag{18}$$

The action value function $QF(s,a)$ is the value function of A3C. $QF(s,a)$ is the value function corresponding to a single action:

$$QF(s,a) = r + \gamma VF(s') \tag{19}$$

The A3C algorithm defines the advantage function $AF(s,a)$, which can be used to evaluate the value of the current action relative to the average:

$$AF(s,a) = QF(s,a) - VF(s) \tag{20}$$

In each training epoch t, the network reports to the DRL agent the current status of all connections between BBUs and RRHs, RRHs and UEs. The status mainly includes the transmission power and SINR value. The DRL agent calculates the reward based on the value of the last action. Then, the agent makes an action decision according to the state s and the transmit power allocated from each BBU i to each RRH j and from each RRH j to each UE k and the SINR value of the UEs. The definitions of state space, action space and reward function of A3C are as follows:

State space: state space s mainly includes the connection relationship between BBUs, RRHs and UEs, the allocated transmission power and the SINR value of UEs.

Action space: action space a is defined as the allocation of transmission power and computing resources among BBUs, RRHs and UEs. The minimum particle size of power adjustment is 0.01W.

Reward: the reward represents the energy efficiency of the system and the performance of the mechanism. The greater the reward, the higher the energy efficiency. Here are three different reward functions considered:

(1)The first reward function $R1$ is defined as:

$$R1 = \frac{r_u}{EC_{total}} \tag{21}$$

where r_u is the total required data rate, and EC_{total} is the value of energy consumption after performing this action.

(2)The second reward function $R2$ is defined as:

$$R2 = \frac{r_u}{EC_{total} - q1E_{BBU-diff}} \tag{22}$$

Where $q1$ is the normalization coefficient of $E_{BBU-diff}$. $E_{BBU-diff}$ is the difference between the maximum energy available of BBUs and the power currently allocated by the BBUs:

$$E_{BBU-diff} = \int_{t=0}^{T} \sum_{i=1}^{N} (P_{Max}^{BBU} - P_i^{BBU}(t))\, dt \tag{23}$$

Here the P_{Max}^{BBU} is the maximum energy consumption of the i-th BBU, the $P_i^{BBU}(t)$ is the current power consumption of the i-th BBU. Sum the difference between the two values up, and integral it by time, the $E_{BBU-diff}$ will be obtained. By introducing the difference between the maximum energy available of BBUs and the power currently allocated by the BBUs, the power limit of BBUs can be guaranteed. When the power of BBUs decreases, the reward increases and the punishment decreases.

(3)The third reward function $R3$ is defined as:

$$R3 = \frac{r_u}{EC_{total} - q1 E_{BBU-diff} - q2 E_{RRH-diff}} \tag{24}$$

Where $q2$ is the normalization coefficient of $E_{RRH-diff}$. Here, $E_{RRH-diff}$ is the difference between the maximum power of RRHs and the current power consumption, which is given by the following equation:

$$E_{RRH-diff} = \int_{t=0}^{T} \sum_{j=1}^{M} (P_{Max}^{RRH} - P_j^{RRH}(t))\, dt \tag{25}$$

Where P_{Max}^{RRH} is the maximum transmitting power of the j-th RRH and $P_j^{RRH}(t)$ is the current power of the j-th RRH. Similar to the case of R2, the difference between the maximum power and the current power of RRH is also considered in R3. That is, the power limitation of the RRHs is also satisfied. When the power of RRH decreases, the reward increases and the punishment decreases.

V. Simulation Result and Discussions

In this section, we describe the parameters setting of simulations and the analysis and discussion of the results.

A. Parameter Settings

Next, we numerically evaluate the performance of the proposed AI-based resource allocation mechanism. We consider a network which includes 3 BBUs and 10 RRHs. That is, N=3, M=10 serving W=30 UEs. In this network, different types of UEs have different requirements for network resources, and the network resource requirements of the UEs change with time. The traffic data of each UE is randomly selected from an open source dataset, which logging the user activity within the TIM (Telecom Italia Mobile) cellular network for the city of Milan during the months of November and December 2013 [19]. And we set the pathloss between RRHs and BBUs at $148.1 + 29.3log_2(d)$. Other parameter settings can be found in TABLE I.

TABLE I
Simulation Parameters

Parameters [symbols]	Values [units]
Number of BBUs, N	3
Number of RRHs, M	10
Number of UEs, W	30
Noise power spectral density, σ	-174 dBm/Hz
Static energy consumption of BBU in active, $P_i^S(t)$	50 W
Static energy consumption of BBU in sleeping, $P_i^S(t)$	10 W
Dynamic energy consumption of BBU, $P_i^D(t)$	5-120 W
Energy consumption of RRH, $P_j^{RRH}(t)$	20-80 W
Data rate requirement of UE, $r_{jk}(t)$	2-10 Mbps
Minimum SINR of UE, ϕ_{Min}	-45 dBm
Maximum power consumption of BBU, P_{Max}^{BBU}	170 w
Maximum power consumption of RRH, P_{Max}^{RRH}	80 w
Maximum transferring latency, $T_{Max}(k)$	200 ms
Normalization coefficient of $E_{BBU-diff}$, $q1$	0.1
Normalization coefficient of $E_{RRH-diff}$, $q2$	0.3

B. Simulation of K-means Clustering Algorithm

The future network topology will become more and more complex. Therefore, it is necessary to cluster the whole dense network reasonably, simplify the network topology and reduce the computational complexity of resource allocation. In this paper, the UEs are clustered based on the distance, and then connecting to adjacent RRHs. Supposing in an area of 1000m×1000m×1200m, there are 30 UEs of various types distributed intensively and randomly. The distribution of UEs satisfies Poisson distribution. Based on K-means clustering algorithm, we obtains the clustering results of UEs, as shown in Fig.4, which is a possible UEs distribution in 3D space. It can be seen that all the UEs in the region is divided into three clusters, and there is enough isolation space between different clusters, which effectively avoids the interference between clusters.

C. Performance of Different Reward Functions Within A3C Algorithm

After connecting UEs with RRHs reasonably by using K-means clustering algorithm, A3C algorithm is used to control whether the BBUs sleep or not and the transmitting power of RRHs. The performance of A3C algorithm with different reward functions is analyzed by simulation. In DRL methods, the strategy is improved by numerical iteration to get the optimal value. At the same time, through policy iteration, the agent redefines the policy at each epoch step to obtain the optimal policy. It converges when the optimal policy and optimal value are found [20]. In this paper, if the compensation deviation is at least 10 steps in the range of (0,0.3), the method is considered to be convergent. Meanwhile, the exhaustive search method is used to obtain the global optimal value

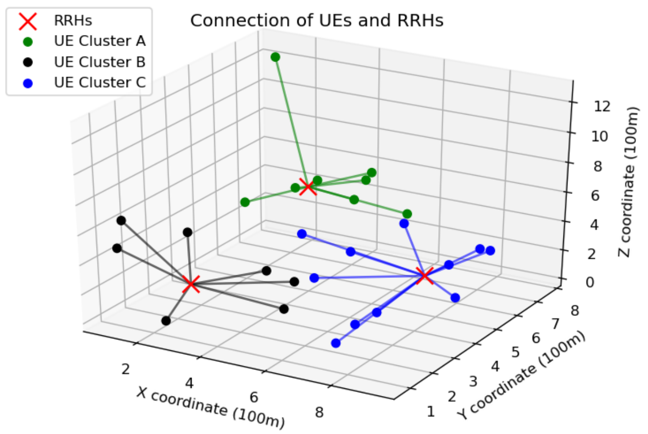

Fig. 4. Clustering result of UEs based on K-means algorithm.

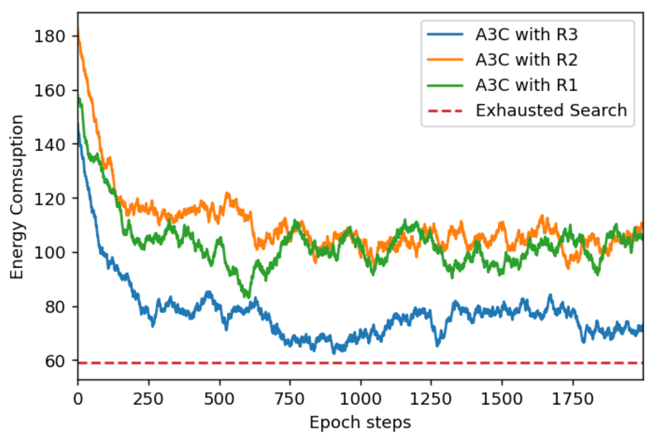

Fig. 5. Convergence analysis of A3C algorithm with different reward function.

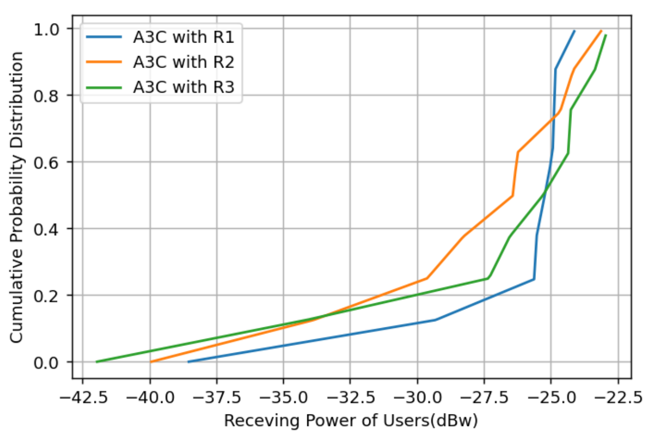

Fig. 6. The cumulative distribution of SINR of A3C algorithm with different reward function.

of energy efficiency as the benchmark. As shown in Fig.5, we can observe that A3C with R3 has the best performance, and the obtained scheme has the lowest energy consumption, while keeping the SINR value within a reasonable range. The performance of A3C with R1 is close to A3C with R2, but they are weaker than A3C with R3. Compared to A3C with R1 and A3C with R2, considering the power limitation of BBUs and RRHs, A3C with R3 has faster convergence speed and higher reward. The SINR values of the schemes based on the three reward functions meet the minimum threshold. The results are shown in Fig.6.

D. Performance of Different Resource Allocation Methods

In this part, A3C is compared with DQN and Q-learning respectively. Due to the superiority of R3 performance, it is used as a reward function. The result as shown in Fig.7 (a) and (b), compared to other two RL algorithm, A3C yielded higher rewards and lower energy consumption. The effectiveness of the A3C with R3 framework can be shown. The cumulative distribution of SINR of different algorithm with R3 as shown in Fig.8. Compared to the other two RL algorithm, A3C with R3 has the highest SINR value. The SINR value of the other two RL algorithm are very closing, but they are all lower than A3C with R3. Meanwhile, the SINR value of the three RL methods meet the constraints. Obviously, A3C algorithm achieves better performance than other algorithms, and the SINR value satisfies the constraints, which proves the effectiveness of our mechanism.

Among the three RL methods, A3C has the best performance, the highest reward, the highest energy efficiency. The main reason is that A3C method can learn stochastic policies by combining ”actor” and ”critic” as well as asynchronous workers. In addition to A3C, DQN performs best among the three RL methods, while Q-learning method performs poorly. Compared with Q-learning method, DQN method introduces experience replay and off-policy strategy to improve the performance.

VI. Conclusions and Future Work

The research goal of this paper is to optimize the energy efficiency and energy consumption of C-RAN heterogeneous network on the premise of ensuring network QoS and consuming less computing resources. K-means clustering algorithm is introduced to obtain the connection relationship between RRHs and UEs to simplify the network topology and problem size. On this basis, a DRL framework based on A3C algorithm is proposed to obtain the optimal solution. The algorithm solves each cluster to get the network resource allocation scheme. Through the analysis and discussion of the simulation results, the effectiveness of the framework is verified. Compared with other methods, the mechanism we proposed achieves better performance and meets the QoS requirements of different types of UEs.

In the future work, we need to consider a more complex scenario with more BBUs, RRHs and UEs as well as the mobility of UEs. Additionally, different clustering algorithms should be considered for further work. Different clustering algorithms have different advantages and disadvantages, suitable for different scenarios, we will discuss this kind of problems in the future work.

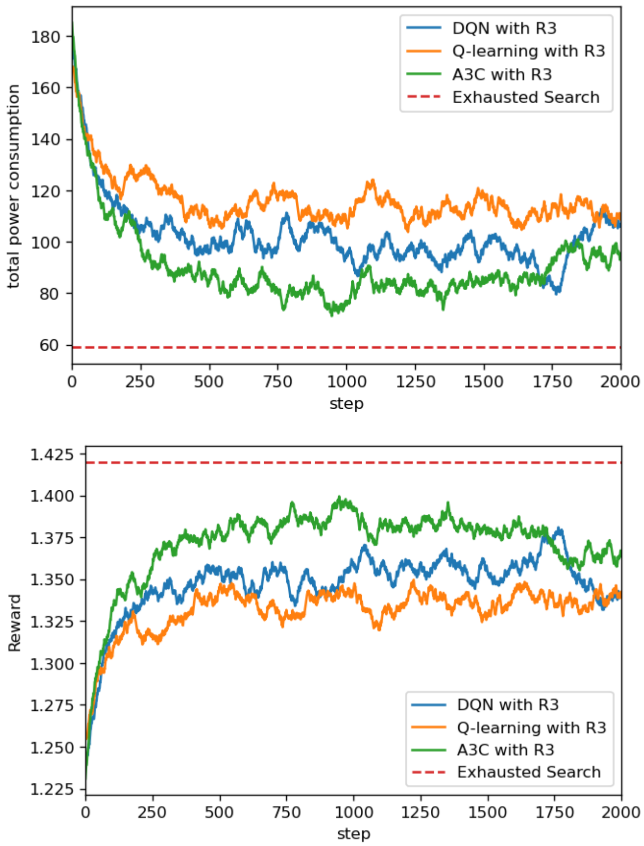

Fig. 7. Convergence analysis (a) Power consumption of different resource allocation method with R3, (b) Reward of different resource allocation method with R3.

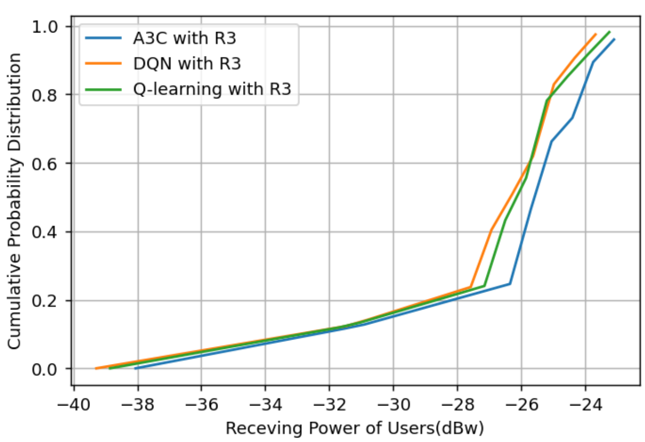

Fig. 8. The cumulative distribution of SINR of different algorithm with R3.

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