UAV AS AUXILIARY BASE STATION USES DEEP LEARNING TO CONDUCT RESEARCH ON NETWORK RESOURCE ALLOCATION

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ABSTRACT

With the development of UAV technology, using UAV as a base station in the air can quickly restore vehicle communications after disasters. In order to reduce the delay and maximize the rational use of bandwidth and power, this paper applies TDMA technology to UAV communication network, and proposes a joint optimization allocation strategy of bandwidth and power. First of all, a deep learning network needs to be trained. The use of deep learning can improve the accuracy of prediction. The reward mechanism is set through the change of delay. The purpose of training is to enable the UAV to choose the optimal bandwidth allocation coefficient under the dynamic change of the environment. Then, a joint optimization strategy is proposed to set the SNR threshold to ensure the communication quality. The user's transmission rate is calculated according to the Shannon formula, Finally, the scheme with minimum delay is selected as the final bandwidth and power allocation value. In the simulation experiment, compared with the previous traditional algorithm, the network performance has been further improved in terms of reducing delay and energy consumption, and what needs to be improved may be the problem of computation.

KEYWORDS

UAV networking, wireless communication, resource allocation, power distribution， deep learning

1. INTRODUCTION

With the explosive growth of various network services in recent years, communication networks have become one of the most important infrastructures today, and people are increasingly relying on the various services provided by large-scale networks, which has also led to the booming development of the automotive industry. In the "Internet of Everything" information age, self-driving cars are envisioned as a promising technology to ensure road safety and traffic efficiency. The integration of autonomous vehicles has made the vehicle network system increasingly dependent on communication networks. However, in the face of natural disasters, the ground communication infrastructure will inevitably be damaged, it is difficult to maintain the original network requirements, and how to quickly restore vehicle communication after the disaster has become an urgent problem to be solved [1]. The development of drone technology has made it possible to solve this problem.

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UAVs have the characteristics of easy deployment, low cost and strong mobility, so that UAVs can adapt to various harsh and dangerous environments and assist in completing some tasks that are difficult to complete directly [2]. In recent years, UAV-assisted wireless communication has gradually become a hot spot for researchers. Using drones as air base stations to assist ground communication, then when ground communication falls into a certain period of loss during a disaster, it can quickly help ground users restore communication. How to let the drone quickly restore communication and ensure a certain communication quality is a problem that this article needs to solve.

In this paper, under the premise of considering limited power, we should reasonably allocate power resources to achieve rapid recovery of communication of self-driving cars after disasters. This paper proposes an algorithm, and the simulation results also show that this method can provide communication requirements for driverless cars when the ground base station is damaged and cannot provide services, or some (more than half) damage is difficult to maintain the current communication, so as to meet its safe and efficient driving.

2. SYSTEM MODEL

In view of the research points of this paper, we establish three models:system network model , system communication model and task calculation model, which are explained in the following three subsections.

2.1. System Network Model

Considering the scenario of the UAV as an auxiliary base station as shown in Figure 1 to restore post-disaster vehicle communication, under this system, there is a cellular cell, which is composed of ground base stations, from the perspective of existing technology, it can be considered as a 5G base station [3], and the collection of 5G base stations can be recorded as A={1,2,…,M}, M refers to the total number of 5G base stations. There is a swarm of drones, which on the one hand are the user equipment (UE) of the cellular cell, and on the other hand, they act as an air base station (ABS) to assist the ground base station to quickly and effectively restore the communication of vehicles after the disaster. The set of air base stations can be denoted as B={1,2,…,N},N is the total number of air base stations. There are vehicle users, they can accept services from 5G base stations and air base stations, and the vehicle user set is denoted as C={1,2,…,K},K represents the total number of vehicle users.

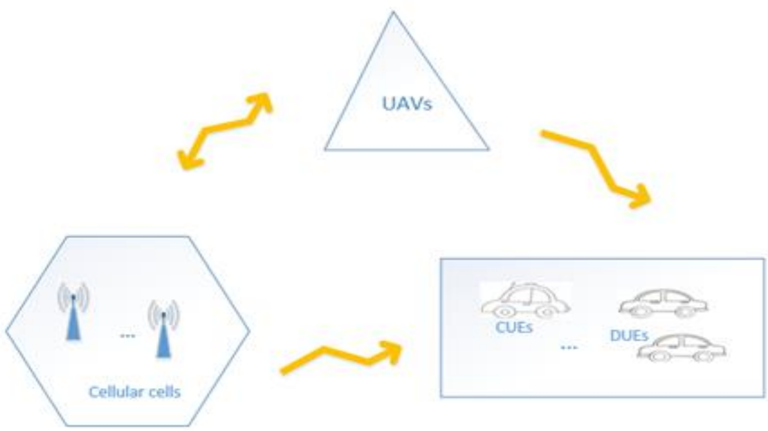

Figure 1. Model diagram of UAV as a base station auxiliary wireless vehicle communication network

2.2. System Communication Model

Combined with the actual situation, the possibility and frequency of natural disasters in mountainous areas are relatively high compared with plain areas, and it is more reasonable to set the post-disaster area in mountainous areas [4]. Considering the mountainous area with many trees and undulating mountains, the channel fading between the ground base station and the vehicle mainly considers the shadow fading [5], and the rest of the fading is regarded as an ideal situation and ignored, then the channel gain between the mth ground base station and the kth vehicle user can be written as h_m^k [6], h_m^k is given by

$$h_m^k=\beta_{m,k}d_{m,k} \quad (1)$$

$\beta_{m,k}$ means the shadow fading constant between the mth ground station and the kth vehicle user channel, and it obeys the lognormal distribution. $d_{m,k}$ means the distance between the mth ground base station and the kth vehicle user.

The UAV base station is at a high altitude, the wireless channel can be regarded as line-of-sight transmission, mainly considering the transmission loss, and the rest of the fading is regarded as an ideal situation negligible [7], then the channel gain between the nth UAV base station and the kth vehicle user can be recorded as h_n^k [8],$h_n^k$is given by

$$h_n^k=\mathrm{L}d_{n,k} \quad (2)$$

The meaning of L is the path loss

$$\mathrm{L} = 20\lg d_{n,k} + 20\lg f_c + 32.4 \quad (3)$$

the meaning of $d_{n,k}$ is the distance between the nth UAV base station and the kth vehicle user.
Then, if the kth vehicle user receives services from the 5G base station, the signal-to-noise ratio received by the kth vehicle user from the m-th 5G base station is recorded as $\eta_{m,k}$, $\eta_{m,k}$ is given by

$$\eta_{m,k}=\frac{h_m^k P_{t_m}}{\sigma^2+\sum_i^N h_n^k P_{t_n}+\sum_i^M I_{i,m} h_i^k P_{t_i}} \quad (4)$$

P_{t_m} means the transmit power of the m-5G base station, P_{t_n} means the transmit power of the nth air base station, $I_{i,m}$ is a sign factor, when i=m, $I_{i,m}$=0, otherwise $I_{i,m}$=1; if the kth vehicle user receives services from the air base station, the signal-to-noise ratio received by the kth vehicle user from the nth 5G base station is recorded as $\eta_{n,k}$, $\eta_{n,k}$is given by

$$\eta_{n,k}=\frac{h_n^k P_{t_n}}{\sigma^2+\sum_i^M h_i^k P_{t_i}+\sum_i^N I_{i,n} h_i^k P_{t_i}} \quad (5)$$

2.3. Task Calculation Model

The kth vehicle user, if it provides services for 5G base stations, the task processing time that occurs on it as t_1,$t_1$is given by

$$t_1=\frac{\sum N_{task}}{f_g} \quad (6)$$

the meaning of f_g is the computing processing power of the vehicle connected to the ground base station, and the meaning of N_{task} is the number of tasks that need to be processed, that is, the number of packets received; The propagation time is marked as$t_{m,k}$,$t_{m,k}$is given by

$$t_{m,k}=\frac{d_{m,k}}{R_{m,k}} \quad (7)$$

$R_{m,k}$ means the data transmission rate between the mth base station and the kth user; If the service is provided for the UAV base station, the task processing time that occurs on it as t_2,$t_2$is given by

$$t_2=\frac{\sum N_{task}}{f_a} \quad (8)$$

the meaning of f_a is the computing processing power of the vehicle connected to the air base station, and the propagation timeis marked as $t_{n,k}$,$t_{n,k}$is given by

$$t_{n,k}=\frac{d_{n,k}}{R_{n,k}} \quad (9)$$

$R_{n,k}$ means the data transmission rate between the nth base station and the kth user.

3. Problem Formulation

In order to be able to quickly restore vehicle communication after a disaster, it is necessary to minimize the delay time and ensure the communication quality, so the problem can be described in this study:

$$\min \textstyle\sum_K t \quad (10)$$

subject to:
C1:$\eta_{m,k} \geq \gamma$, $\eta_{n,k} \geq \gamma$
C2:$R_{m,k} < C_{max}$,$R_{n,k} < C_{max}$
C3:$\lambda B_m + (1-\lambda) B_n \leq B$
C4:$0 < P_{t_m} < P_{max}$，$0 < P_{t_n} < P_{max}$

C1 restricts the user from connecting to any base station, and its signal-to-noise ratio value cannot be lower than the threshold; C2 restricts the user, no matter what kind of base station the service is provided, the rate cannot exceed the maximum rate C_{max} theoretically (Shannon's theorem); C3 limits the overall bandwidth allocated to any user to exceed the maximum bandwidth range B; C4 restricts the user's receiving power to not exceed the maximum transmit power of the base station, assuming that the maximum transmit power of both base stations is the same, both are P_{max}.

3.1. Bandwidth Resource Allocation

First of all, let's simplify the problem, assuming that there are only two 5G base stations, one drone base station, and six driverless cars for resource allocation.

In the first case, two 5G base stations are damaged and cannot provide service for a short period of time, so the scene simplifies a drone to serve 6 driverless cars. The driverless car number is C_i,i={1,2,3,4,5,6}. Bandwidth allocation rules: (1) Priority allocation of bandwidth according to the principle of proximity, that is, when there is $d_{C_1} < d_{max}$，$d_{C_2} \geq d_{max}$, then the UAV will give priority to the C_1 to allocate bandwidth resources; (2) Priority allocation is made according to the length of waiting time, that is, when there is $t_{C_1} \geq t_{max}$, $t_{C_2} < t_{max}$, then the UAV gives priority to the C_1 to allocate bandwidth resources; (3) Bandwidth is prioritized according to the proportion of task volume, that is, when there is $N_{C_1} \geq N_{task}$, $N_{C_2} < N_{task}$, then the drone gives priority to the C_1 to allocate bandwidth resources.

In the second case, where one of the base stations is damaged, the scenario is simplified to a base station and a drone jointly serving 6 autonomous vehicles. The driverless car number is C_i,i=$\{1,2,3,4,5,6\}$. Bandwidth allocation principle: bandwidth allocation is prioritized according to whether there is a service, that is, when there is a C_1 that can be provided by the base station, C_2 cannot be provided by the base station, then the drone gives priority to the C_1 to allocate bandwidth resources; The principle of follow-up is the same as that of the first case .

Now think about the generalized scenario, that is, there are M base stations, N drones, K unmanned cars, and the scene algorithm selection is carried out according to the number of surviving base stations.

Since the decision made by the drone depends on the final state of each time slot and the feedback results, this process can be regarded as a Markov process, so the model framework is transformed into solving the Markov problem [9]. Among them, we treat each drone as an agent, the state set as the s_t, the action set as the a_t, and the reward function as the r_t. Now we explain these terms in detail as follows:

The state set s_t: s represents the user's transmission rate in each time slot, in this dynamic situation, the rate of each user is generally different, then the set specifically contains:

$$s_t=\{R_1^t, R_2^t, \dots, R_k^t\} \quad (11)$$

Action set a_t: In this framework, we need the drone as an agent for the allocation of bandwidth resources, so the parameters contained in the action set are the bandwidth parameters allocated to each user, which are expressed as:

$$a_t=\{B_1^t, B_2^t, \dots, B_k^t\} \quad (12)$$

Reward function r_t: In the research points of this paper, delay is the core issue of attention, so we take the feedback of delay as the composition of the reward function, which is specifically expressed as:

$$r_t=\sum_{i \in K} \mu t_{i,m}+\sum_{i \in K}(1-\mu) t_{i,n} \quad (13)$$

Loss function: DQN algorithm is a method of approximating the value function of the Q_learning through the neural network [10], the value function Q is not a specific value, but a set of vectors, the weight of the network in the neural network is , the value function is expressed as Q(s,a,θ), and finally the neural network converges is the value function [11]. Therefore, the core of the whole process becomes how to determine, so the core of the whole process becomes how to determine the θ to approximate the function, this paper uses gradient descent to minimize loss function to constantly debug network weights [12], so the core of the whole process becomes how to determineto approximate the function, the most classic practice is to use gradient descent to minimize loss function to continuously debug network weight, The Loss function is defined as:

$$\mathrm{L}(\theta)=\mathrm{E}\left[\delta(R+\gamma \max_{a_t' \in A} Q_t(s_t', a_t')-Q_t(s_t, a_t)\right]^2 (14)$$

To improve the accuracy of distribution, a DQN network needs to be trained.

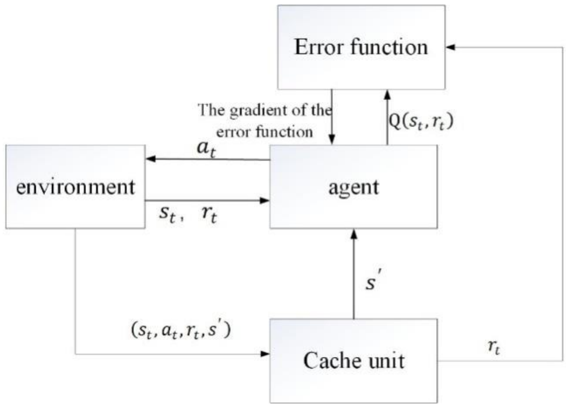

Figure 2. DQN training frame diagram

According to Bellman equation, we can get the equation to iteratively update the Q value, given by

$$Q_{t+1}(s_{t+1}, a_{t+1}) = Q_t(s_t, a_t) + \delta(R + \gamma \max_{a'_t \in A} Q_t(s'_t, a'_t) - Q_t(s_t, a_t) \quad (15)$$

Therefore, there is a summary of the bandwidth resource allocation algorithm and summarized as algorithm 1.

Algorithm 1 Deep Q-learning with Experience Replay

Initialize the network
Distribute bandwidth evenly and calculate latency
For episode=1, K do
  Randomly select users to access and initialize the storage unit data
  for t=1,T do
    The agent randomly selects an action
    $r_t = \sum_{i \in K} \mu t_{i,m} + \sum_{i \in K} (1 - \mu) t_{i,n}$
    Agent select an action from s_t
    $Q_{t+1}(s_{t+1}, a_{t+1}) \leftarrow Q_t(s_t, a_t) + \delta(R + \gamma \max_{a_t \in A} Q_t(s'_t, a'_t) - Q_t(s_t, a_t)$
    Store this data in the cache unit
  End for
End for

3.2. Power and Bandwidth Joint Allocation Policy

Considering the problem of energy consumption of UAVs as air base stations, so on the basis of algorithm 1, we integrate power control into it, and the specific algorithm is explained as follows: This study is aimed at users in the entire LAN, and we need to perceive the data of each user to ensure that each user can get a reasonable arrangement. Since we have been able to formulate the optimal bandwidth allocation for the random power allocation value in algorithm 1, we only need to filter out the conditions that meet the conditions in these reasonable power allocation values, that is, the signal-to-noise ratio is greater than the given threshold [13], and then return the conditions that meet the conditions to the cache unit, and determine the final preferred scheme through the comprehensive measurement formula.

Therefore, there are joint power and bandwidth allocation algorithm summarized as algorithm 2.

Algorithm 2 power and bandwidth allocation algorithms

Input: M, N, K, B, P_{max}, f_g, f_a, $d_{m,k}$
Output: Bandwidth weight factor, Power distribution weight factor
For n=1, N
    For t=1, T
        For m=1, M
            According to the principle of bandwidth priority allocarion, the bandwidth is allocated to vehicle users to obtain suers who are connected at t time
            The distribution of transmit power is selected based on the ε-gerrdy strategy
            If every SINR>γ
                Bandwidth allocation is based on the DQN network
                Calculate the total latency and store the current scenario
            Else end the current selection and return to the previous step
            In the temporary buffer, compare the delay size and select the best one
    End for
End for

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4. SIMULATION RESULTS

In order to prove the superiority of this scheme, we compare the algorithm with the bandwidth equalization algorithm [14] (algorithm 1) and power sharing algorithm [15] (algorithm 2), and obtain the simulation result figure as follows. It can be seen from Figure 3 that our proposed algorithm is superior to the two algorithms in terms of energy consumption, because the algorithm we propose dynamically allocates power according to real-time conditions, avoids high power output under low power consumption, reduces energy consumption to a certain extent, and improves power resource utilization. It can be seen from Figure 4 that the algorithm proposed by us is significantly better than the other two algorithms in reducing latency, because when we design the algorithm, we fully consider the problem of each user's delay, avoid the user's unreasonable queuing delay, reasonably arrange the priority order of users, and train the DQN algorithm model to improve the accuracy, which can solve the problem of UAV-assisted communication network to quickly restore communication in disaster areas to a certain extent.

The following table shows the values of some simulation parameters.

Table 1 values of some simulation parameters

Parameter name	Parameter value
Noise power spectral density σ^2	-114dBm
Shadow fading constant $\beta_{m,k}$	7.3
Total bandwidth B	20MHz
Maximum transmit power P_{max}	30dBm
Signal-to-noise ratio threshold γ	80dB
Initial learning rate	0.01
Cache unit	50000
UAV flight altitude	150m

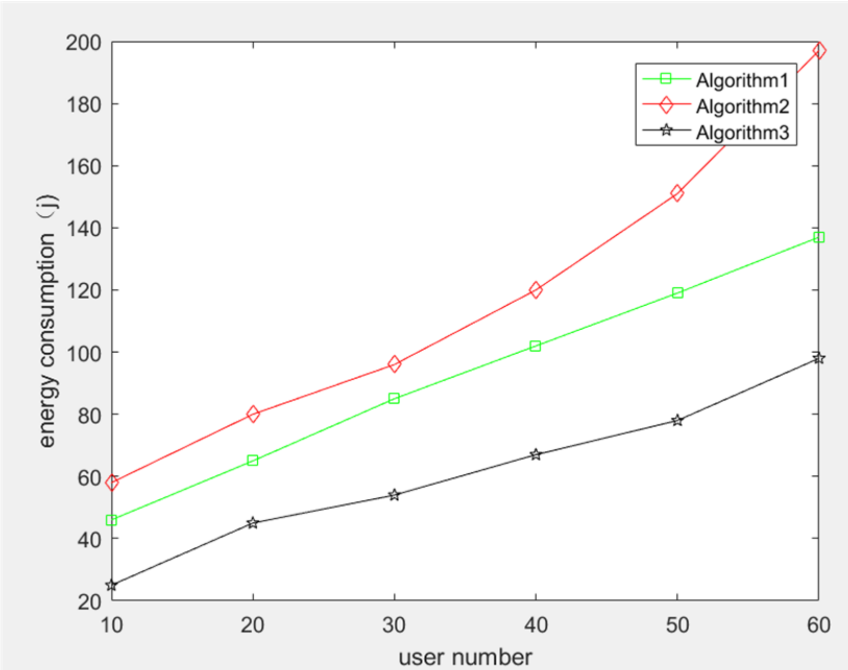

Figure 3. Energy consumption simulation comparison chart

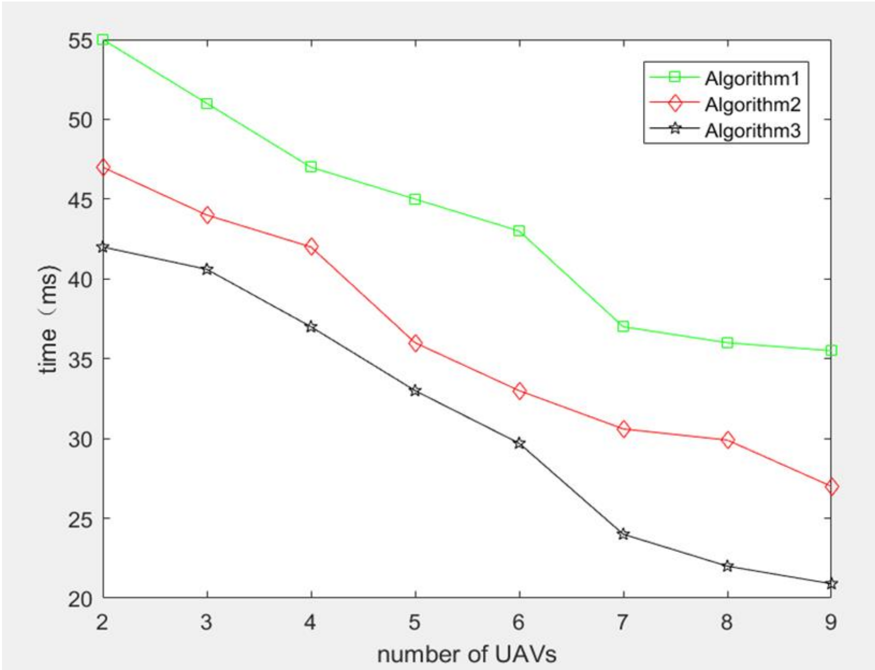

Figure 4. Latency simulation comparison chart

5. CONCLUSION

This paper delves into a resource allocation problem in UAV-assisted wireless communication networks to solve the delay problem. First, we divide resource allocation into two sub-problems: bandwidth resource allocation and power resource allocation. To solve the first problem, we train the DQN network to obtain a mature Markov decision model, and then in order to solve the second problem, we propose a joint optimization bandwidth power resource allocation algorithm, which organically combines the two by using Shannon's formula, and also ensures the communication quality by setting the signal-to-noise ratio threshold, and the simulation results also show that the scheme is superior to the traditional resource allocation algorithm in network performance.

In future work, we will also delve into DQN networks and consider the application of drone-assisted wireless communication networks to other scenarios, such as traffic congestion networks.

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