Resource Allocation in Drone-Assisted Emergency Communication Systems

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Abstract

Due to low cost and high mobility, drones are considered important in emergency communications. In this thesis, we consider a unique drone assisted emergency communication system used in disaster scenarios, where the drone with limited power acts as a relay to improve the downlink sum rate through rational resource allocation. The wireless channel model between drones and ground users in emergency communications is different from conventional relay networks, while drones have their coverage area and data rate limits. Considering these specific characteristics, we formulate a joint power and subcarrier allocation problem to maximize data rate of users, which is limited by the transmit power budget per drone and the number of users on each subcarrier in emergency communications.

However, resource allocation in a unique drone assisted emergency communication system is a nondeterministic polynomial time (NP)-hard problem requiring brute force search, which has prohibitive computational complexity. Instead, efficient algorithms that provide a good trade-off between system performance and implementation practicality are needed.

The contributions of this thesis are proposing two different resource allocation schemes. Both schemes divide users into high-priority(HP) users and low-priority(LP) users and both guarantee minimum guaranteed rate for HP users.

The first scheme is an adaptive algorithm with low complexity. In this scheme, a suboptimal solution is proposed by dividing users into two priority groups: HP users (rescuers) and LP users (affected people). This procedure achieves quasi-linear complexity in terms of the number of users. Finally, the data of the brute force search method and this method were collected through simulation experiments. The data shows that the data rate of the proposed scheme was very close to the optimal data rate when there was a lack of resources.

The second scheme is an adaptive algorithm. In the proposed scheme, we formulate a joint power and subcarrier allocation problem to maximize data rate of users, which is limited by the transmit power budget per drone and the number of users on each subcarrier in emergency communications. Due to the intractability of the formulated problem, it is decomposed into two sub-problems: power allocation optimisation and subcarrier allocation optimization. Then a joint resource allocation algorithm is proposed. The simulation results show that the performance of the proposed method is close to that of the optimal solution but with much lower complexity.

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Acronyms

4G	fourth generation
5G	fifth generation
A2G	air-to-ground
AWGN	additive white Gaussian noise
BER	bit error rate
DF	decode-and-forward
FSO	Free Space Optics
HP	high priority
IoT	Internet of Things
LP	low priority
MMSE	minimum mean squared error
NOMA	non-orthogonal multiple access
NP	nondeterministic polynomial-time
OFDM	orthogonal frequency division multiplexing
OFDMA	orthogonal frequency division multiple access
QoS	quality of service
SNR	signal-to-noise ratio
UAV	Unmanned Aerial Vehicles

Notation

C	system capacity
$c_{k,n}$	indicator
D_k	the horizontal distance between user k and the drone on the terrestrial ground
d_k	the distance between user k and the drone
$\gamma_{k,n}$	SNR of user k on subcarrier n
H^2	the height of drone
$h_{k,n}$	the small scale fading of channel between user k and the drone on subcarrier n
I	number of iteration of subcarrier re-allocation
k	user k
K_h	number of HP users
K_l	number of LP users
$\mathcal{K}_h$	the sets of HP users
$\mathcal{K}_l$	the sets of LP users
L	Lagrange multiplier
λ	the path-loss exponent.
μ	water level
N	number of subcarriers in the system
N^*	all subcarriers that can be reassignable

P_{max}	transmit power constraint
$p_{min,k}$	the least transmit power of user k
$p_{k,n}$	the transmit power of user k on subcarrier n
$r_{k,n}$	is the achievable data rate on subcarrier n for user k
r_{th}	the required minimum data rate of HP user
Δr_{sys}	the sum data rate difference
$\sigma_{k,n}^2$	the AWGN power of user k on subcarrier n
Z	Lagrange dual function
$max\{\cdot\}$	maximal element
$\sum\{\cdot\}$	a sum of multiple terms

Chapter 1

Introduction

Contents

1.1 Motivation

Large-scale natural disasters cause massive and often unpredictable loss of lives and property. Various types of natural disasters have resulted in the loss of many lives, such as geophysical (earthquakes, tsunamis, volcanic eruptions, landslides and avalanches), hydrological such asflash floods, debris flows and floods, climatological (extreme temperatures, droughts and forest fires) and meteorological (tropical storms, hurricanes, sandstorms and heavy rains).

The number of deaths from natural disasters can vary greatly from year to year. In some years, there are very few fatalities from a large disaster event that may claims many lives. Looking at the average over the last ten years, approximately 60,000 people worldwide died each year from natural disasters. This is equivalent to 0.1% of global deaths[1]. In the visualizations shown here, we can see the annual fluctuations in the number and proportion of deaths from natural disasters over the past decades.

In many years, the number of deaths can be very low - often less than 10,000 and accounting for only 0.01% of total deaths. But we also see the devastating impact of shocking events: the famine and drought in Ethiopia in 1983-85, the Indian Ocean earthquake and tsunami in 2004, Cyclone Nargis that struck Myanmar in 2008, and the Port-au-Prince earthquake in Haiti in 2010, all of which pushed the number of deaths from disasters worldwide to over 200,000[3].

When disaster strikes, the survival rate is 90% within 24 hours, 50%-60% between 25 and 48 hours and 20%-30% between 49 and 72 hours. The most important thing is to save lives after a disaster. In this context, the first 72 hours after a disaster are the most critical time to find survivors [3][4]. This means that search and rescue operations (SAR) must be carried out quickly and efficiently.

With the increase in the number of natural disasters, material losses caused by such disasters have also increased in the order of 100%-150% between 1980 and 2015 [1]. Figure 1.1 shows that the total number of disasters increased by almost 100 percent between 1980 and 2010 in the world.

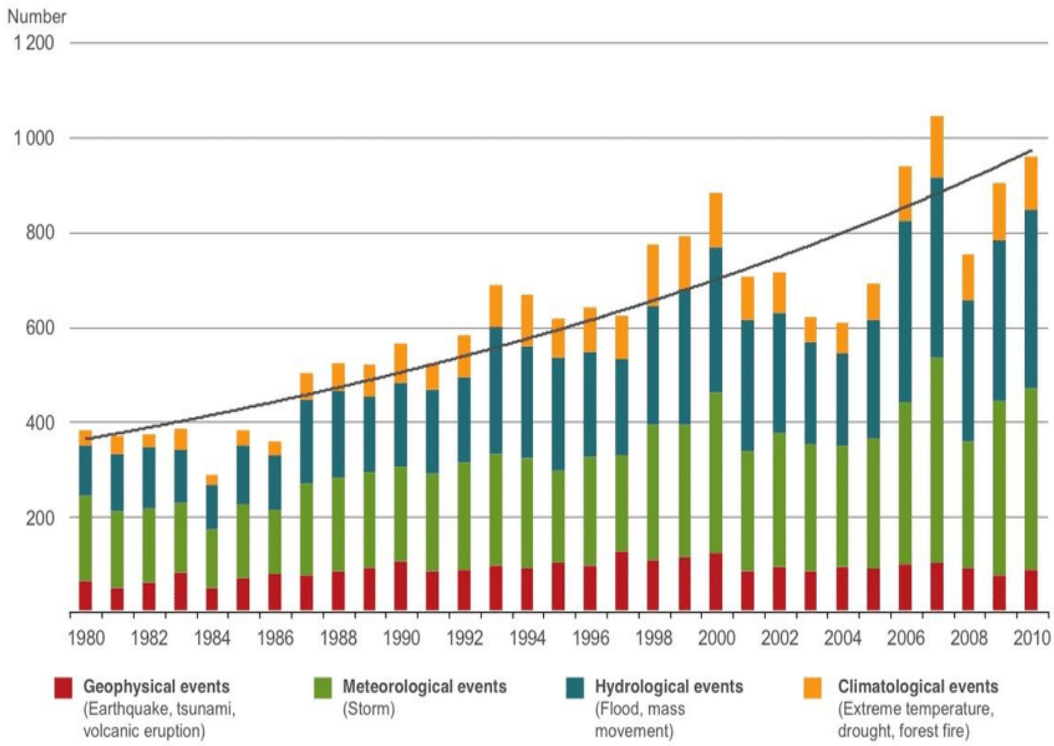


Figure 1.1: Number of natural catastrophes worldwide [2]

In the golden period of rescue, a good communication system is a great help for the search and rescue operations of the rescue team. However, natural disasters such as earthquakes and tsunamis often lead to a complete paralysis of the existing communication infrastructure, resulting in the loss of contact between rescue teams on the ground. When rescue teams lose contact with each other, their effectiveness drops drastically. To ensure communication between the search and rescue team and survivors so that they know in time in which areas survivors are waiting for rescue. Therefore, the quick deployment of an adaptable and efficient emergency communication network is essential. In emergency communications, it is also important to ensure the communication sustainability of rescue teams, so that the survivors can be rescued in time. In this regard, drones can be rapidly deployed to fulfill the vital needs of emergency communications [5]–[7].

In the nineteenth century, drones were originally developed for military tasks that were too ”tedious, dirty or dangerous” [3] for humans. In the twenty-first century, unmanned aerial vehicles or drone communications are new areas of research that can be used in both military and civilian applications. Drone communication maintains links between drones and a ground station at an appropriate data rate to amplify real-time transmissions. The infrastructure for drone communications must ensure high throughput, long range and enhanced coverage. Drones can be configured to provide cooperative services and extend the coverage network by acting as relays in traditional networks. The degree of mobility of a drone depends on the application and its flight configurations. The maneuverability of drones offers incipient opportunities for performance enhancement through dynamic adjustment of its states to best suit the communication environment.

Communication networks and strategies for cooperative drone swarms have received significant attention in recent years. Currently, the main emergency response mechanisms of Unmanned Aerial Vehicles (UAV) are classified as follows:

A. Aeronautical Remote Sensing Based on remote sensing technology, telemetry and remote control technology, wireless communication technology and differential GPS positioning technology, UAVs can realize automatic, intelligent and specialized acquisition and processing in real time, which meets the emergency decision-making requirements for mission command. Depending on the operating principle of the payloads, airborne remote sensors can be divided into those with visible light, tilt-photography, infrared, laser pan-tilt-zoom (PTZ), dual-light, lidar and miniature synthetic aperture radar [3].

B. Other Perceptive Sensors General purpose sensors, such as gas detection sensors, particulate matter concentration sensors, temperature and humidity detection sensors, are used to monitor the composition of gas pollutants, particulate matter concentration and other values of the airspace in emergency response scenarios. Meteorological payloads can be mounted to monitor wind speed, wind direction, temperature, humidity, precipitation and air pressure in emergency scenarios to meet the technical requirements for multi-dimensional information perception and application [8].

C. Supply Delivery The payload delivery thrower can help perform tasks such as supply delivery and rescue assistance. With the aiming function, it can accurately deliver supplies. In addition, by using the multi-time throwing function, the payload delivery thrower can deliver supplies separately within one flight, thereby further improving the rescue efficiency [8].

D. Emergency Rescue Support Payloads customized for on-site rescue needs and with equipment for communication relay, emergency lighting, drug spraying and other rescue support can be used to acquire on-site information and enable communication relay, night lighting and large-scale full-coverage spray in emergency response scenarios [5].

Due to advances in communication, embedded systems, sensor and energy storage technologies as well as carbon fiber-reinforced plastic materials, small scale UAVs became a feasible sensor platform. With a diameter below 1 m and less than 1 kg weight, those platforms are also known as Micro UAVs (MAV, MUAV). MUAVs can be equipped with a variety of sensors and steered to a region of interest for remote sensing without risking health and life of first responders in dangerous environments.

On the other hand, the mobility of drones enables the construction of highly efficient network topologies. Therefore, self-organisation capabilities such as node and relay placement, connectivity restoration, RF signal failure protection and compensation can be exploited to operate UAV teams in highly dynamic and complex environments [9].

For these reasons, drones play an important role in distributing critical information at the edge of the network and are also an aid in establishing long-term evolution networks in remote locations. In recent years, many researchers have focused on the various aspects of drone communication. In fact, drones are fast becoming the tool of choice for disaster relief around the world. Not only is drone technology more affordable and accessible than it used to be, it is often more effective in dealing with disasters than other methods currently in use.

1.2 Challenges

For the reasons mentioned in section 1.1, the use of unmanned aerial vehicles (drones) for various civil and military applications has experienced tremendous growth in recent years. Applications of drones include industrial inspection, remote sensing, precision agriculture, structural analysis, aerial photography and earth monitoring, to name a few [3], [4]. In addition, drones are expected to be an integral part of future wireless networks by expanding network coverage and data rate through the use of drones as mobile base stations. However, drones usually have limited computing and power resources due to their size and weight. Therefore, such systems should be equipped with highly efficient communication designs to meet these stringent requirements. To achieve this goal, it is necessary to address some further research challenges so that drones can be better applied to emergency communication networks.

In previous work, such as [10], the authors proposed a trajectory planning and resource allocation method for multiple drone cells based on hierarchical deep reinforcement learning to maximize the cumulative network throughput while ensuring fairness or satisfaction among users. fairness requirements of users. However, it does not take into account that in a post-disaster scenario, there are rescuers as well as normal users. In this scenario, the minimum guaranteed rate of the rescuers must be guaranteed. In practice, for example, the minimum guaranteed rate is needed for each rescuer. Therefore, in this thesis, users are divided into different priorities to deal with the different user groups in real scenarios.

Moreover, in [11], exploiting the Rician fading of the AG channel model, the problem is formulated as a joint optimization of power and subcarrier allocation to maximize the uplink throughput. At the same time, the thesis also satisfies the users' fairness requirements. However, the power and subcarriers that can be provided by UAVs in emergency communications affect the minimum guaranteed rate that drones can provide to emergency responders in emergency communications networks. Therefore, this thesis does not consider satisfying the minimum guaranteed rate of rescuers while ensuring fairness between users.

However, none of the above researches considered that in disaster scenarios it is necessary to guarantee the minimum guaranteed rate, e.g. the minimum guaranteed rate, for a specific group of users, i.e. rescuers. It would also be important to reveal how the communication performance of other non-rescuer users would be affected when the minimum guaranteed rate is provided to the rescuers. In summary, there is a need for novel resource allocation schemes in emergency communications that are capable of achieving near-optimal performance in a practical and simplified manner. In this thesis, a novel resource allocation scheme is presented that provides near-optimal performance considering various priority users.

Resource allocation in multicarrier systems requires joint optimization of subcarrier allocation and power allocation. However, many formulations of the resource allocation problem lead to a mixed-integer, non-deterministic NP-hard problem. Therefore, the optimal solution can only be found by exhaustive search, which is a combinatorial optimization problem. One approach to selecting the best set of users is brute force search, i.e. search over all possible combinations of users. Then select the one that provides the maximum data rate on each subcarrier. However, this causes prohibitive computational complexity. Therefore, it is necessary to investigate how to reduce the computational complexity of resource allocation in multicarrier systems, while achieving a performance close to optimal. To solve the high complexity problem, subcarrier allocation and power allocation are solved separately. This leads to a practical and efficient suboptimal solution. In summary, this thesis proposes a new resource allocation method that provides near-optimal performance with lower computational complexity.

1.3 Contributions

Despite the many possibilities that drones offer for emergency communications, much work is still needed to promote specific emergency scenarios. Other research programmes are mostly inadequate and focus mainly focus on two aspects. Firstly, the complexity of the system is too high, so that it cannot be realized in reality. Secondly, research into emergency communication systems does not take into account the differences between aid rescuers and disaster victims. Furthermore, it has not yet been proposed to improve the performance of emergency communication and reduce the complexity of implementation in specific scenarios.

The contributions presented in this thesis are two new resource allocation schemes. First, the subcarrier allocation algorithm is a very low-complexity subcarrier allocation and the algorithm achieves a user data rate close to the result of the brute force search algorithm under drone transmit power and subcarrier conditions. Second, a novel resource allocation scheme is presented that can achieve near-optimal performance with low computational complexity. These are summarized below.

1.3.1 Low-Complexity Subcarrier Allocation of Drone-Aided

In this work, an adaptive resource allocation algorithm is proposed. Besiding targeting to maximize the system data rate, a minimum data rate threshold for the rescuers in the system is introduced as a constraint to be satisfied by the resource allocation. Then, along with the consideration of limited transmit power of a drone, an optimization problem is formulated. Due to the non-convex property of the optimization problem, the brute force algorithm is a straightforward solution. However, its complexity is very high, which increases exponentially with the number of subcarriers in the system. Therefore, a sub-optimal solution is proposed in this chapter, by dividing the users in the system into two categories, high priority (rescuers) and low priority (normal) users. Then, subcarrier and power allocation are carried out for the high priority (HP) and low priority (LP) users, separately.

It has been shown that the complexity of the proposed scheme is much less than the optimal brute force solution. Simulation results demonstrated that the performance of the proposed resource allocation scheme is close to the optimal one when the total transmit power of a drone is not very high.

1.3.2 Resource Allocation in Drone-Aided Emergency Communications

So far, no research has been focused on disaster scenarios, which must guarantee the minimum guaranteed rate, e.g. the minimum guaranteed rate requirement of each rescuer. Meanwhile it is important to reveal how the rate performance of other non-rescuer users would be affected, when the minimum guaranteed rate is provided to the rescuers. Therefore, in this chapter, the users in the drone-assited OFDMA based emergency network include both HP users representing rescuers, and LP users representing non-rescuers. The drone-assisted resource allocation problem is then formulated with the objective of maximizing the system data rate while ensuring the minimum guaranteed rate for HP users with limited transmit power of the drone. Due to the non-convex property introduced by multiple priorities and integer constraints, the complexity of solving the formulated optimisation problem is extremely high. For example, the complexity of the optimal brute force search solution increases exponentially with the number of subcarriers and the number of users in the system.

Therefore, in this work, an adaptive and low complexity algorithm is proposed, which divides the resource allocation into two stages: subcarrier allocation and power allocation by dividing the user priorities. At the first step, with fixed power allocation, subcarrier allocation is carried out by guaranteeing the data rate constraints of HP users. Then, power allocation is performed by iteratively applying waterfilling algorithm for some individual HP users and globally among other users.

1.4 Structure of the Thesis

The rest of this thesis is organized as follows.

- Chapter 2 offers an overview of the basic principles of OFDMA technique and waterfilling algorithm.
- Chapter 3 presents research on resource allocation in drone-based emergency communication systems. An improved subcarrier allocation algorithm is developed that maintains the minimum guaranteed rate for HP users, and then optimization is used to try to maximize the total user data rate of drones with limited power.
- Chapter 4 proposes a low-complexity adaptive algorithm that divides resource allocation into two stages: Subcarrier allocation and power allocation considering user priorities. In the first stage, with fixed power allocation, subcarrier allocation is performed guaranteeing the data rate constraints of HP users. Then, power allocation is performed by iteratively applying the waterfilling algorithm for some individual HP users and globally for all other users. The simulation results have shown that the performance of the proposed method approaches the optimal solution with much lower complexity.
- Finally, in chapter 5, a summary of the work done in this thesis is given and

the main conclusions are highlighted. In addition, possible future research directions are discussed.

Chapter 2

Literature Review

Contents

The joint optimization of subcarrier assignment and power allocation in multicarrier systems normally leads to a mixed-integer problem, which was NP-hard [12] and it is, therefore, intractable. Hence, the optimal solution can only be found through brute force search method, which is a combinatorial optimization problem. One approach to select the best signal-to-noise ratio (SNR) user set on each subcarrier is to search over all possible combinations of users, then select the pair that optimizes a given system optimization parameter, such as the minimize the transmit power or maximize the system throughput. However, exhaustive search procedures require a computational complexity that is too large for implementation in practical systems. A more practical approach to solving the joint problem of user pairing and power allocation in multicarrier is to separate the problems of subcarrier allocation and power allocation, fix one of them and optimize the other [13]. This leads to suboptimal but practical and efficient solutions that provide a better trade-off between implementation complexity and system performance.

The main focus of this literature review is the study of existing works related to, first, resource allocation of drone in emergency communication networks, and second, the impact of other factors on drone.

2.1 Resource Allocation of Drone in Emergency Communication Networks

Existing researches have been carried out to investigate drone based orthogonal frequency division multiple access (OFDMA)[14][15] systems with the focus on improving the coverage area and system data rate for communication recovery from disasters [12][16]−[19]. In drone-based emergency communications using OFDMA [12], users on the ground are scattered over a large area, so a drone cannot cover the entire area. Due to the large distance between users, one channel is bad for one user but may be good for others. Therefore, there are a novel resource allocation scheme that considers the bit error rate (BER) requirements for different types of packets in a data stream and increases the spectral efficiency of wireless communication devices [11, 12]. Thus, the performance of drone-based emergency communications can be significantly improved by resource allocation. In [16], the relationship between drone's coverage and reliability of all communication links was analyzed in a disaster-resilient communication network. In [17], the drone is studied the optimal height for maximizing its effective coverage area. Considering high-mobility users, it is proposed a multi-drone cell trajectory planning and resource allocation scheme based on hierarchical deep reinforcement learning to maximize the accumulative network throughput while providing fairness among users or satisfying users' fairness requirement[18]. In [19], the number of users are maximized for downlink channel allocation in communication networks. In [20] authors propose a new balanced resource scheduling scheme with adaptive priority threshold to strike an excellent balance between quality of service (QoS) guarantee and system throughput for downlink transmission in OFDMA systems.

The authors in [21] focus on a cellular network where the drone is used as a relay by all users to improve their individual uplink rates. The problem of power allocation and scheduling in the uplink is studied, and optimal solutions for both AF and decode-and-forward (DF) protocols are derived to optimize the uplink sum rate. The authors in [22] study the problem of throughput maximization in mobile relaying systems using drones by optimizing the transmit power of the source/relay along with the trajectory of the drone considering practical mobility constraints. In [11], exploiting the Rician fading of the AG channel model, a joint subcarrier and power allocation algorithm is presented to solve the resource allocation problem of OFDMA uplinks in UAV-assisted emergency communications. The subcarriers can be allocated to the users according to the optimal solutions to maximize the uplink throughput.

Moreover, other related work focus on the relationship between throughput and drone positioning. For example, in [23], compared to the use of conventional terrestrial infrastructures, such as ground relays, aerial relay-assisted communications provides an effective way to extend the mm-wave transmission range, provide better signal quality and increase the data rate between two or more terrestrial nodes in the mm-wave bands. This is simply because placing UAVs at high altitude could effectively bypass the obstacles on the ground and they are more likely to have LoS links and thus better channel gain. Another work in the field of drone-based scenarios is [24], which studied the problem of maximizing end-to-end cooperative throughput for a network of UAV-enabled simultaneous wireless information and power transfer, in order to analyze drone position/height and throughput.

In [25], UAVs are assumed to be distributed in a 3D space below a certain altitude. The authors investigate spectrum sharing and analyze the success probability and total network throughput of a UAV-enabled network modeled by a 3D PPP. In [26], the authors proposed to optimize the trajectory of multiple UAVs. They formulated a mixed-integer non-convex optimization problem in which multi-user communication scheduling and association are jointly optimized with drone cell trajectory and power control to maximize the minimum downlink throughput for users on the ground. The work in [27] investigated the optimal deployment of UAVs and the association of UAV users for static ground users with the aim of meeting user requirements for data rate. In [28], take a UAV as a flying base station for serving ground users in order to achieving maximum throughput per user, by jointly optimizing the transmit power and the UAV path.

In [29], take a UAV as a flying base station for serving ground users in order to achieving maximum throughput per user, by jointly optimizing the transmit power and the UAV path. In [30], authors have focused on sum power minimization by optimal user allocation, power control, location planning, and computation capacity allocation. Their proposed bandwidth allocation strategy allocates available bandwidth to each user for data transmission. In [31] authors have proposed joint optimization of transmit power of UAV, location of UAV, and bandwidth allocation problem to maximize the rate of D2D pair for a downlink UAV aided communication system.

2.2 The Impact of Other Factors on Drone.

Systems based on the instantaneous position of the user assume that the locations of users on the ground are known. Based on such advance information, many drone deployment and association schemes have been investigated. For instance, from the point of view of reducing the power consumption of drones, the authors in [32] propose a mathematical solution to find the optimal position of a single drone to maximize its coverage area considering energy constraints.

Previous work assumed wireless links between a drone cell and a ground node, such as mmWave communications and Free Space Optics (FSO). However, instabilities in the air can degrade the communication quality of wireless links. The authors in [33] consider a set of drones with FSO transceivers, while an FSO backhaul is provided to each drone via FSO air-to-air links. The results show that higher backhaul data rates can be achieved compared to a terrestrial-only infrastructure solution.

In addition, other related work focus on the problem of drone positioning in mobile networks. For instance, because drone positioning has negatively affected network performance in terms of throughput, coverage, connectivity and revenue. In [33], the authors have presented a multi-tier drone cellular network that apprehends the terrestrial heterogeneous network. The authors attempt to find the best position of multiple drones analytically. The UAV-assisted wireless networks pose a particular design challenge due to the altitude dimension and the mobility of the aerial base stations. In particular, the 3D deployment of the UAVs is arguably the most influential design consideration as it directly affects the coverage, QoS and energy consumption of the network. Therefore, the authors in [34] attempt to find the optimal height of the drone for maximum coverage.

In addition, the work in [35] surveys network architectures for different scenarios, using DSCs for disaster management. In [36], the author proposed a framework for drone-assisted emergency communication networks with or without a terrestrial base station and also optimized the trajectory of the DSC in both scenarios.

In [37], an air-to-ground (A2G) pathloss model is developed for low altitude platforms including drone cells. A closed-form expression of the A2G pathloss model is proposed, in which the probabilities of both LoS and non-line-of-sight (NLoS) A2G connections are considered in different scenarios. The mathematical model was able to predict the optimal height of Low Altitude Platforms based on the statistical parameters of the underlying urban environment. In their extension work, the authors presented a model in [38] describing the path loss function associated with depression angle and the coverage area under the UAV based on extensive experimental measurements with vehicles and UAVs in suburban environments. The model indicates a trade-off in channel performance as the vertical angle between the drone cell and the BS increases. Using the Pathloss model in [37], some researchers focus on exploring the optimal drone-cell deployment that maximizes specific performance metrics.

In [39], a novel approach is proposed for deploying multiple mobile drones for energy-efficient uplink data collection from mobile ground-based Internet-of-Things (IoT) devices and placing drone cells to maximize information gain from ground-based IoT devices. The authors propose a holistic framework that deploys drone cells to assist 5G networks in high-traffic scenarios and develop a "first-selfish and second-share" approach for deploying drone cells [40]. The 3D placement problem is formulated in [41] for a single drone cell as a mixed-integer nonlinear programming (MINLP) problem and solve it using a bisection search algorithm. In [42], the use of multiple drone cells is further investigated and the minimum number of drone cells for a given coverage constraint by using the particle swarm optimisation (PSO) algorithm. An algorithm for optimal placement of drone cells that maximises the number of users served with minimum power consumptions was designed. In this way, the drone-cell deployment problem is decoupled in the vertical and horizontal dimensions and solved respectively.

In summary, current research in emergency communications system focuses mainly on the following three aspects.

1. Serving more users or maximizing cumulative network throughput by studying the location and trajectory of drones.

2. Proposing a new resource allocation scheme to allocate resources to users to maximize user throughput.

3. Power minimization is achieved through optimal user allocation, power control and computational capacity allocation.

The research direction of this paper is to maximize user data rate by proposing a new resource allocation scheme. The studies presented in the previous literature had two unavoidable shortcomings. First, although the performance of these research schemes is excellent, their complexity is very high, so their resource allocation schemes cannot achieve real-time resource allocation under emergency communication conditions. Second, these research programmes do not take into account the different resource allocation priorities resulting from different personnel in a disaster-affected environment.

Therefore, the improvements in this thesis are about the following three points.

1. Different categories of users will be prioritised to reflect the actual personnel and environment.

2. The proposed scheme will consider the situation of insufficient power and resources of drones.

3. To implement the scheme in the emergency communication environment, a low complexity scheme is proposed.

Chapter 3

Overview of Multiple Access Techniques and Power Allocation Algorithm for Drone

Contents

Due to their low cost, high mobility and flexibility, drones are expected to make an important contribution to mobile wireless communications as relays. They have evolved dramatically in cellular networks, mobile relaying systems and emergency communications where infrastructure has been damaged by natural disasters or, worse, is non-existent [3]. In drone-based emergency communications, using OFDMA, users on the ground are scattered over a large area, so a single drone cannot cover the entire area of interest. Due to the long distance between users, one channel may be bad for one user but good for others. Therefore, the performance of drone-based emergency communications can be greatly improved by allocating resources [16].

For power allocation, most previous work assumes equal sharing between subcarriers. For multiple-access channels, the information-theoretic foundations were laid by Cheng and Verdú [43], who studied the data rate ranges for multiple-access channels and found a generalisation of the waterfilling theorem for single users. In a waterfilling power spectrum, more power is allocated to better subcarriers with higher SNR so that the sum of data rates in all subchannels is maximised, where the data rate in each subchannel is related to the power allocation by Shannon's Gaussian data rate formula below [44]:

$$\gamma = Blog(1 + \frac{S}{N}) \tag{3.1}$$

where γ denotes channel data rate. S is represents the received signal power over the bandwidth B and N is the power of background noise.

However, since data rate is a logarithmic function of power, the data rate is usually insensitive to the exact power allocation unless the SNR is low. This motivates the search for simpler power allocation schemes that operate close to the optimum [5]. For this reason, system performance is expected to improve by applying the waterfilling principle for subcarrier and user power allocation. Below is a brief overview of Shannon's theorem, OFDMA and waterfilling technologies.

The rest of this chapter is structured as follows. The related Shannon's theorem is summarised in section2.1 and the basic principles of OFDMA are summarised in section 2.2. Section 2.3 presents the theoretical foundations of waterfilling with multicarrier systems.

3.1 Shannon's theorem

In information theory, Shannon's theorem states the maximum rate at which information can be transmitted over a communication channel with a given bandwidth in the presence of noise. It is an application of the noisy channel coding theorem to the archetypal case of a continuous-time analogue communication channel subject to Gaussian noise. The theorem establishes Shannon's channel capacity for such a communication link, a limit on the maximum amount of error-free information per unit time that can be transmitted with a given bandwidth in the presence of the noise interference, assuming that the signal power is limited and that the Gaussian white noise process is characterized by a known power or power spectral density [44].

The noise targeted by Shannon's theorem is Gaussian white noise, and Shannon's theorem must be modified for other noises [44]. The physical characteristics of the wireless channel are constantly changing, which is called a parametric variation channel. Fading phenomena are among the properties of wireless channels. For example, small-scale fading due to multipath effects and large-scale fading such as path loss due to range attenuation or shadow by obstacles. The size scale is divided by the wavelength. Large-scale fading protection includes pathloss and shadow.

In the next subsections, mainly small-scale fading and path loss are presented.

3.1.1 Basic Principles of Small-scale fading

Small-scale fading refers to the rapid changes of the amplitude and phase of a radio signal over a short period of time or a short distance. In small-scale fading, the instantaneous received signal power may vary as much as 30 to 40 dB when the receiver is moved by only a fraction of a wavelength. In a mobile-radio environment, each path has its own Doppler shift, time delay, and path attenuation, and multipath propagation results in a time-varying signal as the mobile moves position. Such a channel is linear, but time-varying [46].

Small-scale fading depends on the nature of the transmitted signal with respect to the characteristics of the channel. Depending on the relation between the signal parameters, such as the bandwidth and the symbol period, on the one hand, and the channel parameters, such as the coherence time, Doppler spread, coherence bandwidth and delay spread, on the other hand, different transmitted signals will experience different types of fading [44]. Delay spread leads to time dispersion and frequency-selective fading. Doppler spread leads to frequency dispersion and time-selective fading. Time dispersion and frequency dispersion are caused by independent propagation mechanisms.

Rayleigh fading

Rayleigh fading is also called Small-scale fading because when the number of versions of the transmitted signal which arrive at slightly different times is large, the envelope of the received signal is statistically described by a Rayleigh distribution if there is no line-of-sight component [45].

Rayleigh fading is a model that can be used to describe the form of fading that occurs in multipath propagation. In any terrestrial environment, a radio signal is transmitted from the transmitter to the receiver via a number of different paths [46]. The most obvious path is the direct path or line of sight. However, there are a great many objects in the vicinity of the direct path. These objects can serve to reflect, refract, etc. the signal. Therefore, there are many other paths by which the signal can reach the receiver.

When the signals reach the receiver, the total signal is a combination of all the signals that have reached the receiver through the multitude of different paths available. These signals are all added together, and the phase of the signal is important. Depending on how these signals add up, the strength of the signal varies. If they were all in phase, they would all add up. However, this is usually not the case, as some are in phase and some are out of phase, depending on the different path lengths, and therefore some will add to the total signal while others will subtract[45].

As the transmitter or receiver often moves, the path lengths may change and the signal level will vary accordingly. In addition, if any of the objects used to reflect or refract part of the signal move, this will also cause variations. This happens because some of the path lengths change and this in turn means that their relative phases change, resulting in a change in the sum of all the signals received.

The Rayleigh fading model can be used to analyze the propagation of radio signals on a statistical basis. It works best under conditions where there is no dominant signal, and in many cases mobile phones used in a dense urban environment fall into this category. Other examples where there is usually no dominant path include ionospheric propagation, where the signal reaches the receiver via a large number of individual paths. Propagation via tropospheric channels also exhibits the same patterns. Accordingly, The Rayleigh fading model is particularly useful in scenarios where the signal between the transmitter and receiver can be considered scattered.

3.1.2 Path loss

Radio signal path loss is a particularly important element in the design of a radio communication system or wireless system. The path loss of the radio signal determines many elements of the radio communication system, in particular the transmit power and the antennas, especially their gain, height and general location [44]. The radio path loss also affects other elements such as the required receiver sensitivity, the type of transmission and various other factors.

Therefore, it is necessary to understand the reasons for radio path loss and to be able to determine the amount of signal loss for a particular radio path.

Path loss is the power loss of a RF signal propagating through space. Path loss can be due to many effects, such as loss in free space, refraction, diffraction, reflection, coupling loss between aperture and medium, and absorption. Path loss is also affected by terrain contours, environment (urban or rural, vegetation and foliage), propagation medium (dry or moist air), the distance between the transmitter and the receiver, and antenna height and location [44].

Path loss usually include propagation losses caused by the natural expansion of the radio wave front in free space (which usually takes the form of an ever-increasing sphere), absorption loss (sometimes called penetration loss) when the signal passes through media that are not transparent to electromagnetic waves, diffraction loss when part of the radio wave front is obstructed by an opaque obstacle, and loss due to other phenomena.

The free-space path loss is the attenuation of radio energy between the feed points of transmitter and receiver, resulting from the combination of the receiving area of the receiver and the obstacle-free line-of-sight path through free space (usually air) [47]. the free- space loss is defined as the loss between two isotropic radiators in free space, expressed as a power ratio. It does not include power loss in the antennas themselves due to imperfections such as resistance. The free space loss increases with the square of the distance between transmitter and receiver, since radio waves propagate according to the inverse square law, and decreases with the square of the wavelength of the radio waves.

3.2 Basic Principles of OFDMA

The 4G wireless systems adopted OFDMA, in which a channel is divided into subcarriers by a mathematical function called the inverse fast Fourier transform. These subcarriers are divided into groups of subcarriers, each group being called a resource block. The grouping of subcarriers into groups of resource blocks is called subchannelisation. The spacing between subcarriers is orthogonal so that they do not interfere with each other, although there are no guard bands between them. This creates signal zeros in the adjacent subcarrier frequencies, preventing intercarrier interference and allowing multi-user detection with low complexity receivers.

OFDMA can be seen as an alternative to combining Orthogonal Frequency Division Multiplexing (OFDM) with Time-Division Multiple Access or Time-Domain Statistical Multiplexing. Low data rate users can transmit continuously with low transmit power. Constant delay and shorter delay can be achieved. OFDMA can also be described as a combination of frequency-domain and time-domain multiple access, where resources are partitioned in time-frequency space and slots are allocated along the OFDM symbol index as well as the OFDM subcarrier index.

In downlink OFDMA, the base station transmits data to a set of users whose channel conditions are time and frequency dependent. Due to the scarcity of spectrum and power resources, these must be allocated as effectively as possible at the transmitter to optimise a given system performance metric. To achieve a given goal, resource allocation in OFDMA systems involves three basic tasks: subcarrier allocation, bit allocation and power allocation[49]:

- Subcarrier allocation, which consists of allocating subcarriers to users in an efficient manner, depending on factors such as users' channel conditions.

- Bit allocation, which consists of varying the number of transmitted bits per symbol on each subcarrier according to the objective performance metric and the instantaneous subcarrier channel quality.

- Power allocation, which consists of effectively distributing the transmitted power among different subcarriers to maintain link quality and optimize the objective power function.

In [50], it was shown that in OFDMA systems with independent subchannels between users, the best performance was achieved when each subcarrier was allocated to the user with the best channel conditions on that subcarrier and the transmit power was allocated to the subcarriers according to the waterfilling principle [44].

3.3 Waterfilling

Waterfilling plays an important role in resource allocation. In any (general) waterfilling problem, powers are allocated to the resources of the transmitting user in order to maximize the transmitting user's data rate(or mutual information) while satisfying the constraint on the total power budget. The user's resources can be the subcarriers in OFDM or the normal frequency bands or the use of the same subcarriers in different time slots [51]. This means that the allocated power of the resource is inversely proportional to the noise level of the resource in the waterfilling problem to maximize data rate [52].

The solution to this class of problems can be viewed as "pouring a finite volume of water into a tank whose bottom has steps whose height is determined by the noise levels in each resource. The allocated power for the resource is the difference between the constant water level and the noise level of the resource." Just as water finds its level even when filled into part of a vessel with multiple openings, the amplification systems in repeaters or receivers of communication networks amplify each channel to the required power level as a consequence of Pascal's law, compensating for channel impairments. The Fig.3.1 is waterfilling illustration of optimal transmit power allocation.

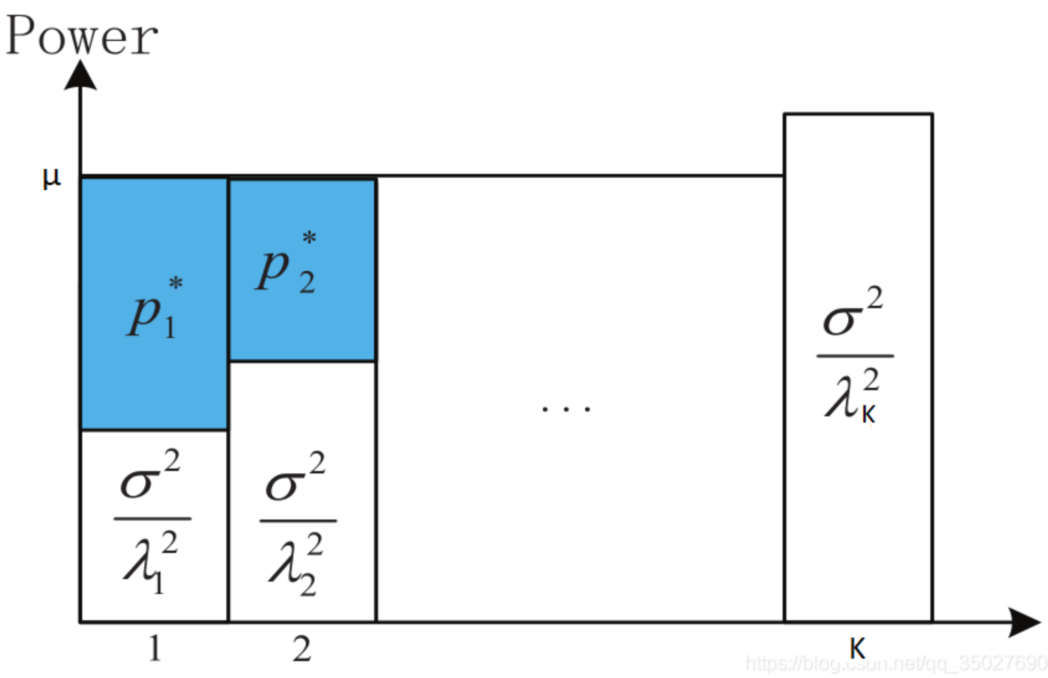


Figure 3.1: Waterfilling illustration of optimal transmit power allocation

Where μ is the water level. According to [51], we can state that the basic principle of the waterfilling algorithm is a convex function formed by the Lagrange multiplier method according to the Shannon formula and the restriction conditions. The classical result of waterfilling is the solution of the following constrained optimisation problem:

$$\max C = \sum_{k=1}^{K} \log_2 \left(1 + \frac{p_k}{\sigma^2}\lambda_k\right) \tag{3.2}$$

where number of users in the system is K and σ_k^2 is the AWGN variance at user k. The λ_k is channel gain at the user k. The optimization problem (3.1) belongs to the class of convex optimization problems in which the convex objective function must be minimized under a convex constraint. The above problem is a constraint problem that can be solved using the Lagrangian multiplier method. We define the Lagrange dual function Z:

$$Z(\lambda, p_n) = \sum_{n=1}^{N} \log_2 \left(1 + \frac{P_n}{\sigma^2}\lambda_n\right) + L\left(p_t - \sum_{n=1}^{N} p_n\right) \tag{3.3}$$

Taking the partial derivative of p_i. At the infimum, the partial derivative of the Lagrangian multiplier must be zero, and we obtain [51]:

$$\frac{\partial Z}{\partial p_t} = \frac{\frac{\lambda_n}{\sigma^2}}{1 + p_n\frac{\lambda_n}{\sigma^2}} \cdot \frac{1}{\ln 2} - L \tag{3.4}$$

Waterfilling power attempts to share the transmit power between the subcarriers and the user. Subcarriers with good SNR receive more power and subcarriers with poor CSI receive less power. The waterfilling power control policy can be formulated as follows [53 ,54]:

$$p_n = \mu - \frac{\sigma^2}{\lambda_n} \tag{3.5}$$

Since the constraints are that 1) the allocated power cannot be negative and 2) the sum of the power is equal to p, the problem is called waterfilling with a sum power constraint. The dashed horizontal line, which is the water level μ, must first be determined, and then the power allocated (water volume) above the step is solved.

Chapter 4

Low Complexity Resource Allocation in Drone-Assisted Systems

Contents

4.1 Introduction

4.1.1 Motivation

Due to the advantages that drone deployment is fast, adaptable and efficient, as presented in Section 1.1, drone-related content has been extensively researched in the past few years. Many of these works addressed research problems based on the perspective of the channel data rate and the system data rate, based on the Shannon formula [17, 18, 59]. In order for drones to fulfill the challenges of practical scenarios in emergency communication systems, it is necessary to address some further research challenges.

[8] proposed a 4G-based communication model to find the optimal height of the drone to be used, which is limited by the link reliability. In a catastrophic area where the drone cannot be directly deployed, a multi-hop D2D link can be established to relay signals to enlarge its coverage area [9]. Despite encouraging results, there are still many technical challenges, including interference management, power constraints, and coverage limitations. The authors in [11] proposed power allocation scheme under user interruption constraints in non-orthogonal multiple access (NOMA) systems. However, the previous work does not take into account that there are two different groups of people on the ground: Rescuers and disaster victims. Therefore, how to ensure the communication performance of on-site

rescuers/teams is very important in the emergency communication network.

Earlier work such as [12] also assumes different priority users. However, the application of this theoretical result might prove unrealistic in scenarios with a large number of users and subcarriers. This is because the complexity of the method is close to the brute force search algorithm. Therefore, given the power and coverage limitations of the drone, it is of paramount importance to understand how to reduce the complexity of the emergency communication network.

4.1.2 Contribution

In this chapter, an adaptive resource allocation algorithm is proposed. Besiding targeting to maximize the system data rate, a minimum data rate threshold for the rescuers in the system is introduced as a constraint to be satisfied by the resource allocation. Then, along with the consideration of the limited transmit power of a drone, an optimization problem is formulated. Due to the non-convex property of the optimization problem, the brute force algorithm is a straightforward solution. However, its complexity is very high, which increases exponentially with the number of subcarriers in the system. Thus, if the number of users and the number of subcarriers increase, the emergency communication network cannot obtain results through search. Like the brute force search algorithm, many other resource allocation methods cannot be implemented because of the high complexity.

Therefore, a sub-optimal solution is proposed in this chapter, this method focuses on reducing the complexity while satisfying the constraints. All users have been divided into two categories, HP users and LP users, in the system. Then, subcarrier and power allocation are carried out for the HP users and LP users, separately. It has been showing that the solution achieves quasi-linear complexity with respect to the number of users. Simulation results demonstrated that the performance of the proposed resource allocation scheme is close to the optimal one when the total transmit power of a drone is not very high. The rest of this chapter is organized as follows.

- Section 4.2 shows system model and the problem formulation.
- Section 4.3 presents the resource allocation problem formulation. Among them, the brute force search method is introduced in Section 4.31 and Sub-optimal resource allocation with low complexity is presented in Section 4.32
- Numerical results on the effect of transmitted power, coverage radius, number of users and number of subcarriers are provided in Section 4.4.
- Finally, Section 4.5 concludes the chapter

List of Related Publication

T. Chen, J. He, H. Zhu, L. Cai, P. Yue and J. Wang, ”Resource Allocation in Drone-Assisted Emergency Communication Systems,” IEEE INFOCOM 2020 - IEEE Conference on Computer Communications Workshops (INFOCOM WKSHPS), 2020, pp. 132-137, doi: 10.1109/INFOCOMWKSHPS50562.2020.9162742.

4.2 System Model

Consider a downlink drone-assisted OFDMA based emergency communication system with K users served by one drone, as shown in Fig. 4.1. All users are randomly distributed in the coverage area of the drone. The height and radius of the coverage area of the drone are denoted by H and r, respectively. It is assumed that there are K_h users in the rescue team, denoted as HP users, and K_l other users, denoted as LP users in an OFDMA based emergency communication system with $K_l + K_h = K$. The number of subcarriers in the system is N and each subcarrier is assigned to one user based on the instantaneous channel state information (CSI). Let us introduce a subcarrier assignment indicator $c_{k,n}$.

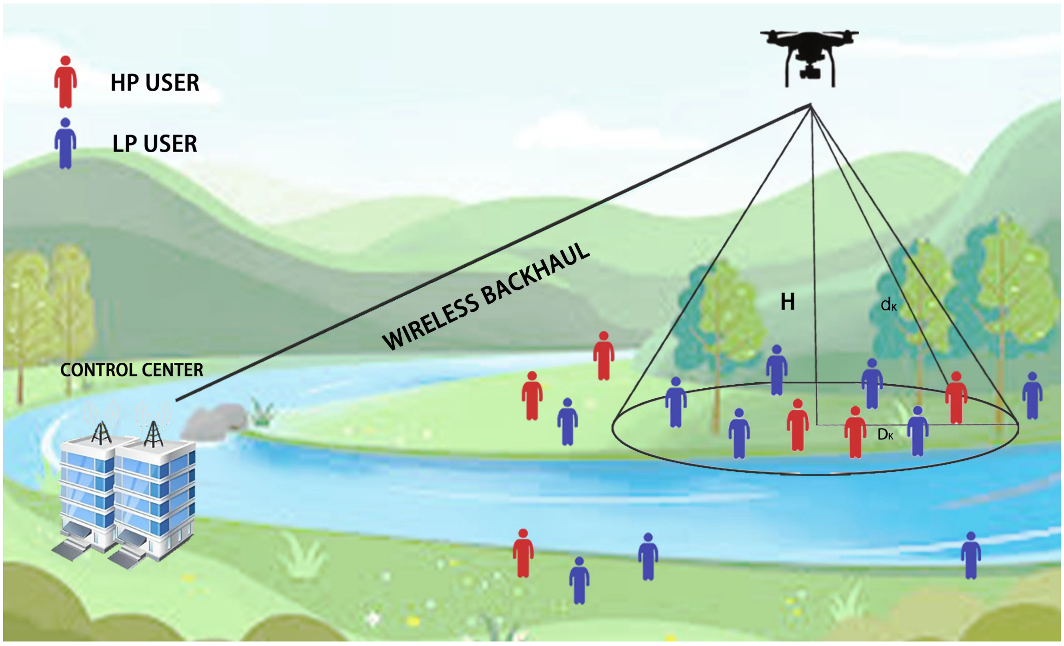


Figure 4.1: System model

If subcarrier n is allocated to user k, $c_{k,n} = 1$; otherwise, $c_{k,n} = 0$, where $k \in \mathcal{K} = \{1, \cdots, K\}$ and $n \in \mathcal{N} = \{1, \cdots, N\}$. The sets of HP users and LP users are denoted by $\mathcal{K}_h$ and $\mathcal{K}_l$, respectively. The small scale fading of channel between any user k and the drone on subcarrier n is denoted as $h_{k,n}$, which is assumed to be Rayleigh distributed and independent for all the users and subcarriers. With the assumption that additive white Gaussian noise (AWGN) is introduced at each user's receiver, the received SNR of user k on subcarrier n is given by

$$\gamma_{k,n} = \frac{c_{k,n} p_{k,n} h_{k,n}^2 d_k^{-\lambda}}{\sigma_{k,n}^2} \tag{4.1}$$

where $p_{k,n}$ denotes the transmit power on subcarrier n if it is allocated to user k. $\sigma_{k,n}^2$ is the AWGN power at user k on subcarrier n, which is assumed to be the same for all the users on all the subcarriers, i.e. $\sigma_{k,n}^2 = \sigma^2$, $\forall k$, $\forall n$. $d_k = \sqrt{H^2 + D_k^2}$ is the distance between user k and the drone. D_k represents the horizontal distance between user k and the projected point of the drone on the terrestrial ground. λ is the path-loss exponent.

Given the transmit power $p_{k,n}$ and the subcarrier allocation indicator $c_{k,n}$, the data rate of subcarrier n for user k is then given by

$$r_{k,n} = B \log_2 \left(1 + \frac{c_{k,n} p_{k,n} h_{k,n}^2 d_k^{-\lambda}}{\sigma^2} \right) \tag{4.2}$$

where B is bandwidth of subcarrier. Furthermore, the total achievable data rate is given by

$$r_{sys} = \sum_{k=1}^{K} \sum_{n=1}^{N} B \log_2 \left(1 + \frac{c_{k,n} p_{k,n} h_{k,n}^2 d_k^{-\lambda}}{\sigma^2} \right) \tag{4.3}$$

Consider that the total transmit power of the drone would be limited, which is denoted by p_{max}, Therefore, the following constraint will be set in the system:

$$p_{max} \geq \sum_{k=1}^{K} \sum_{n=1}^{N} c_{k,n} p_{k,n} \tag{4.4}$$

4.3 Resource Allocation Problem Formulation

This chapter aims to provide adaptive resource allocation to achieve the optimal data rate for the emergency communication provided by a drone to serve all K

users, while guaranteeing the data rate constraint of the K_h users in the rescue team. This problem could be formulated as the following optimization problem:

$$OP1: \max_{\{c_{k,n}, p_{k,n}\}} r_{sys} = \sum_{k=1}^{K}\sum_{n=1}^{N} \log_2\left(1 + \frac{c_{k,n}p_{k,n}h_{k,n}^2 d_k^{-\lambda}}{\sigma^2}\right) \tag{4.5}$$

$$s.t.\ c_{k,n} \in \{0,1\},\ \forall\ k \in \{1,...,K\}\ and\ \forall n \in \{1,...,N\} \tag{4.5a}$$

$$\sum_{k=1}^{K} c_{k,n} \leq 1,\ \forall n \in \{1,...,N\} \tag{4.5b}$$

$$p_{k,n} \geq 0,\ \forall\ k \in \{1,...,K\}\ and\ \forall n \in \{1,...,N\} \tag{4.5c}$$

$$\sum_{k=1}^{K}\sum_{n=1}^{N} c_{k,n}p_{k,n} \leq p_{max} \tag{4.5d}$$

$$r_{k_h} \geq r_{th},\ \forall\ k_h \in K_h \tag{4.5e}$$

The constraint (4.5b) guarantees that one subcarrier is only allocated to one user. (4.5d) indicates the transmit power constraint p_{max}. (4.5e) is used to ensure that the minimum data rate requirement of each HP user is satisfied, where r_{k_h} denotes the achievable data rate of HP user k_h and r_{th} is the required minimum data rate.

Due to the mixture of integer and continuous constraints, optimisation problem (4.5) is an NP-hard problem to solve [18]. It can be seen from (4.5) that in a multiuser OFDMA system, the resource allocation problem can be considered as a joint subcarrier and power allocation with an objective of maximizing data rate. A straight-forward solution is the brute force search algorithm, which is of high complexity.

4.3.1 Brute force search based resource allocation

In a multiuser OFDMA system, the joint resource allocation problem can be decoupled into subcarrier allocation and power allocation. Given subcarrier allocation, it is further proved in a multiuser OFDMA system that waterfilling algorithm can maximize data rate. Therefore, in the first step, we propose to allocate the power to each subcarrier equally. In the second step to allocate subcarriers, the brute force search carried out through all the possible subcarrier allocation combinations is a straightforward solution. Last step, the brute force search carried out through all the possible power level of subcarrier allocation combinations is a straightforward solution. Specifically, among all the subcarrrier allocation combinations that satisfy the constraints, the one achieving the highest data rate will be the optimal allocation result. The brute force method achieves the best result, its complexity increases exponentially with the number of users K number of power level L and the number of subcarriers N. Even if the brute force method achieves the best result, its complexity is K^N, which increases exponentially as the number of users and subcarriers increases. The complexity could be extremely high when the number of subcarriers is large. For example, there could be more than 1000 subcarriers in 5G wireless systems.

4.3.2 Sub-optimal resource allocation with low complexity

The target of the resource allocation in the emergency communication system is to maximize the total downlink data rate while ensuring data rate constraints for each HP user. In the downlink multiuser OFDMA system, for resource allocation without data rate constraints and user priorities, it has been proved that the maximum data rate can be achieved by allocating each subcarrier to the user with the best channel condition over the corresponding subchannel [12]-[15]. And then, the resource allocation could be divided into two steps, subcarrier allocation which allocates subcarriers to users first, and power allocation which then allocates power among all the subcarriers. In this chapter, the resource allocation is also divided into subcarrier allocation and power allocation for the priority based multiuser OFDMA system.

In order to guarantee the data rate constraints of the K_h HP users, the subcarrier and power allocation is first carried out for the HP users. Then, with the unallocated subcarriers and remaining power, subcarrier and power allocation are performed for the K_l LP users. Then, the optimization problem in (4.6) is divided into two optimization problems, described in (4.6) and (4.7).

Considering that after dividing the resource allocation to resource allocation for HP users and LP users, it is critical for the HP users to use minimum number of subcarriers to achieve their data rate constraints, so that LP users have maximum number of subcarrier (or bandwidth) to achieve high data rate. Define $N_h = \sum_{k_h \in K_h} \sum_{n=1}^{N} c_{k_h,n}$ as the number of subcarriers used by the HP users. Minimizing N_h means minimizing the total bandwidth allocated to the HP users. Then, the optimization problem formed in (4.6) is to maximize total achievable data rate for HP users, while minimizing the total bandwidth allocated. This target is equivalent to maximize the bandwidth efficiency of the system to serve the HP users, which is given by

$$OP2: \max_{\{c_{k_h,n}, p_{k_h,n}, N_h\}} \frac{1}{N_h} \sum_{k_h \in K_h} \sum_{n=1}^{N} \log_2 \left(1 + \frac{c_{k_h,n} p_{k_h,n} h_{k_h,n}^2 d_{k_h}^{-\lambda}}{\sigma^2}\right) \tag{4.6}$$

$$s.t.\ c_{k_h,n} \in \{0,1\}, \forall\ k_h \in K_h,\ \forall n \in \{1,...,N\} \tag{4.6a}$$

$$p_{k_h,n} \geq 0,\ \forall\ k_h \in K_h,\ \forall n \in \{1,...,N\} \tag{4.6b}$$

$$\sum_{k_h \in K_h} \sum_{n=1}^{N} c_{k_h,n} p_{k_h,n} \leq p_{max} \tag{4.6c}$$

$$r_{k_h} \geq r_{th},\ \forall\ k_h \in K_h \tag{4.6d}$$

After ensuring the minimum data rate constraint of each HP user is satisfied with highest energy efficiency being achieved, the optimization problem in (4.7) is formed to maximize the total achievable data rate of the K_l LP users over all the unallocated subcarriers with remaining power, which is given by

$$OP2: \max_{\{c_{k_l,n}, p_{k_l,n}\}} \sum_{k_l \in K_l} \sum_{n \in N/N_h} \log_2 \left(1 + \frac{c_{k_l,n} p_{k_l,n} h_{k_l,n}^2 d_{k_l}^{-\lambda}}{\sigma^2}\right) \tag{4.7}$$

$$s.t.\ c_{k_l,n} \in \{0,1\}, \forall\ k_l \in \{1,...,K_l\},\ \forall n \in \{1,...,N_l\} \tag{4.7a}$$

$$p_{k_l,n} \geq 0,\ \forall\ k_l \in K_l,\ \forall n \in \{1,...,N_l\} \tag{4.7b}$$

$$\sum_{k_l \in K_l} \sum_{n \in N/N_h} c_{k_l,n} p_{k_l,n} \leq p_{max} - p_h \tag{4.7c}$$

where N_h is the set of subcarriers allocated to the HP users. N/N_h is the set of unallocated subcarriers which will be allocated to the LP users. (4.7b) shows the power constraint of the resource allocation, after allocating subcarriers and power to the HP users, Based on the new optimization problem (4.6) and (4.7), the total achievable data rate is given by

$$\begin{aligned} r_{sys} = &\sum_{k_h \in K_h} \sum_{n \in N_h} \log_2 \left(1 + \frac{c_{k_h,n} p_{k_h,n} h_{k_h,n}^2 d_{k_h}^{-\lambda}}{\sigma^2} \right) \\ &+ \sum_{k_l \in K_l} \sum_{n \in N/N_h} \log_2 \left(1 + \frac{c_{k_l,n} p_{k_l,n} h_{k_l,n}^2 d_{k_l}^{-\lambda}}{\sigma^2} \right) \end{aligned} \tag{4.8}$$

Resource Allocation for the HP Users

As explained above, the resource allocation for the HP users is formed as an optimization problem in (4.6), which is neither a non-concave nor a non-convex problem, due to integer constraint $c_{k_l,n}$ and the integer characteristic of N_h. Therefore, a sub-optimal solution is proposed by introducing two steps: subcarrier allocation and power allocation.

1 Subcarrier Allocation:In a multiuser OFDMA system without data rate constraints, it has been proved that the maximum data rate can be achieved by allocating each subcarrier to the user with the best channel condition on the subcarrier. Then, given the subcarrier allocation result, it has been proved that waterfilling algorithm can achieve the maximum data rate in OFDMA systems [12]–[14]. It has also been shown in [12], [15], [17] and [22] that when the difference in channel condition is small over all the subcarriers, the performance of equal power allocation is almost the same as the performance of the waterfilling algorithm. Therefore, in the first step, equal power allocation is first assumed for all the subcarriers when allocating resources to the HP users. That is, the power allocated to each subcarrier is the same and fixed as p_{max}/N, for all the K_h users over the N subcarriers. Then, for the subcarrier allocation, each subcarrier is first allocated to the user with

the best channel condition on it. Then, for user k, among all the subcarriers allocated to it, assume all the subcarriers are ordered according to their channel condition. The best N_k subcarriers will be chosen as subcarriers allocated to user k, if the data rate constraint can be satisfied with equal power allocation over the N_k subcarrerier, but cannot be satisfied over the best N_k-1 subcarriers.

2 Power Allocation: After subcarrier allocation, for each user, e.g. user k, among the subcarriers allocated to it, waterfilling algorithm will be carried out under the power constraint of $N_k \times p_{max}/N$.

The resource allocation iterations for HP users procedure is described as Algorithm 1. The corresponding flowcharts for Algorithm 1 are represented in Fig.4.2.

Algorithm 1 Resource allocation iterations for HP users.

Input: $r_{th}, P_{max},;$

Initialization $p_{k,n} = \frac{P_{max}}{N}$

Output: $\{c_{k,n}\}_{k \in \mathcal{K}, \forall n \in \mathcal{N}}$

Find the assignable subcarrier set N^*

Find the set k_h^* of HP users with achieved rate smaller than r_{th}

Find the set subcarrier N_k that the data rate constraint can be satisfied with equal power allocation

$c_{k,n} = 0, k \in \mathcal{K}, \forall n \in \mathcal{N}$

for data rate of each user $r_k < r_{th}$ $\forall k \in k_h^*$ **do**

  for $n = 1$ to N^* **do**

    $\{k, n\} = arg \max_{k \in k_h^*} |h_{k,n}|^2 d_k^{-\lambda}$

    $c_{k,n} = 1$

    $N^* = N^* - n$

  end for

  Calculate data rate $r_k = \sum_{n=1}^{N} B \log_2 \left(1 + \frac{c_{k_h,n} p_{k_h,n} h_{k_h,n}^2 d_{k_h}^{-\lambda}}{\sigma^2}\right)$ $\forall k_h \in k_h^*$

end for

Calculate data rate r_k which waterfilling algorithm is carried out under the power constraint of $N_k P_{max}/N$.

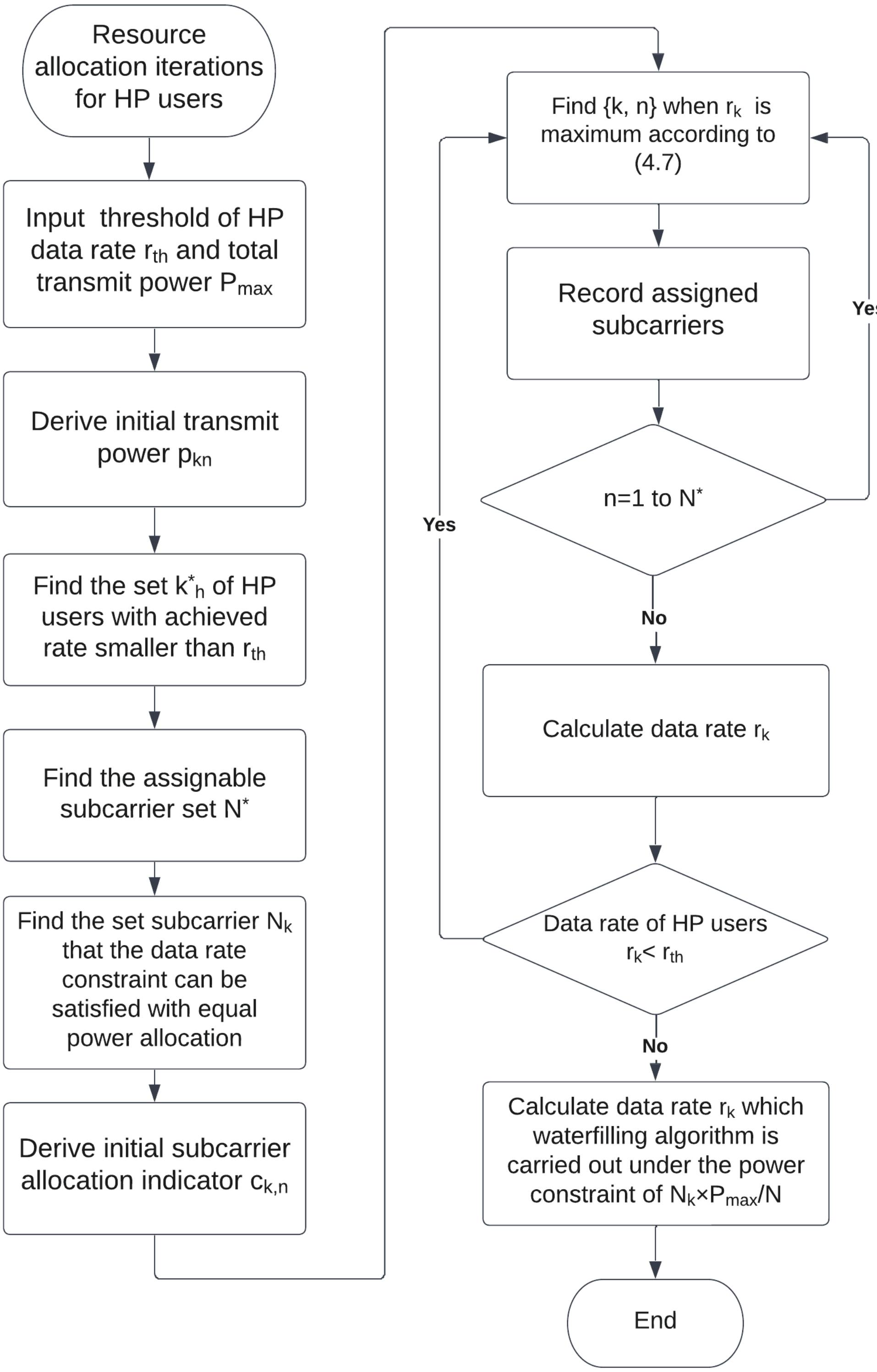


Figure 4.2: Resource allocation iterations for HP users flowcharts

Resource Allocation for the LP Users

After allocating resources to the HP users, over the unallocated subcarriers in the set of N/N_h, each subcarrier is allocated to the user with the best channel condition on the subcarrier. Then, the waterfilling algorithm is applied over all the subcarriers under the power constraint of $p_{max}-p_h$ to achieve the maximum data rate in OFDMA systems.

The resource allocation iterations for all users procedure is described as Algorithm 2. The corresponding flowcharts for Algorithm 2 are represented in Fig.4.3.

Complexity of the Proposed Resource Allocation Scheme

The complexity of the proposed resource allocation scheme mainly depends on the subcarrier allocation over N subcarriers and procedure of the waterfilling algorithm. Therefore, its complexity is $O(2N + Klog(N))$, which is much smaller than the complexity of the brute force search.

Algorithm 2 Resource allocation iterations for all users.

Input: $r_{th}, P_{max}, N_k, \{c_{k,n}\}_{k\in\mathcal{K},\forall n\in\mathcal{N}}$;

Initialization $p_{k,n} = \frac{P_{max}}{N}$

Output: $\{r_k\}_{k\in\mathcal{K}}$

Find the assignable subcarrier set N^* that contains the subcarriers not allocated to the HP users.

for $N^* \in N$ **do**

    for $n = 1$ to N^* **do**

        $\{k, n\} = arg\max_{k\in\mathcal{K}} |h_{k,n}|^2 d_k^{-\lambda}$

        $c_{k,n} = 1$

        $N^* = N^* - n$

    end for

    Calculate data rate $r_k = \sum_{n=1}^{N} B\log_2\left(1 + \frac{c_{k_h,n}p_{k_h,n}h_{k_h,n}^2 d_{k_h}^{-\lambda}}{\sigma^2}\right)\ \forall k\in\mathcal{K}$

end for

Calculate data rate r_k which waterfilling algorithm is carried out under the power constraint of $(N - N_k)P_{max}/N$.

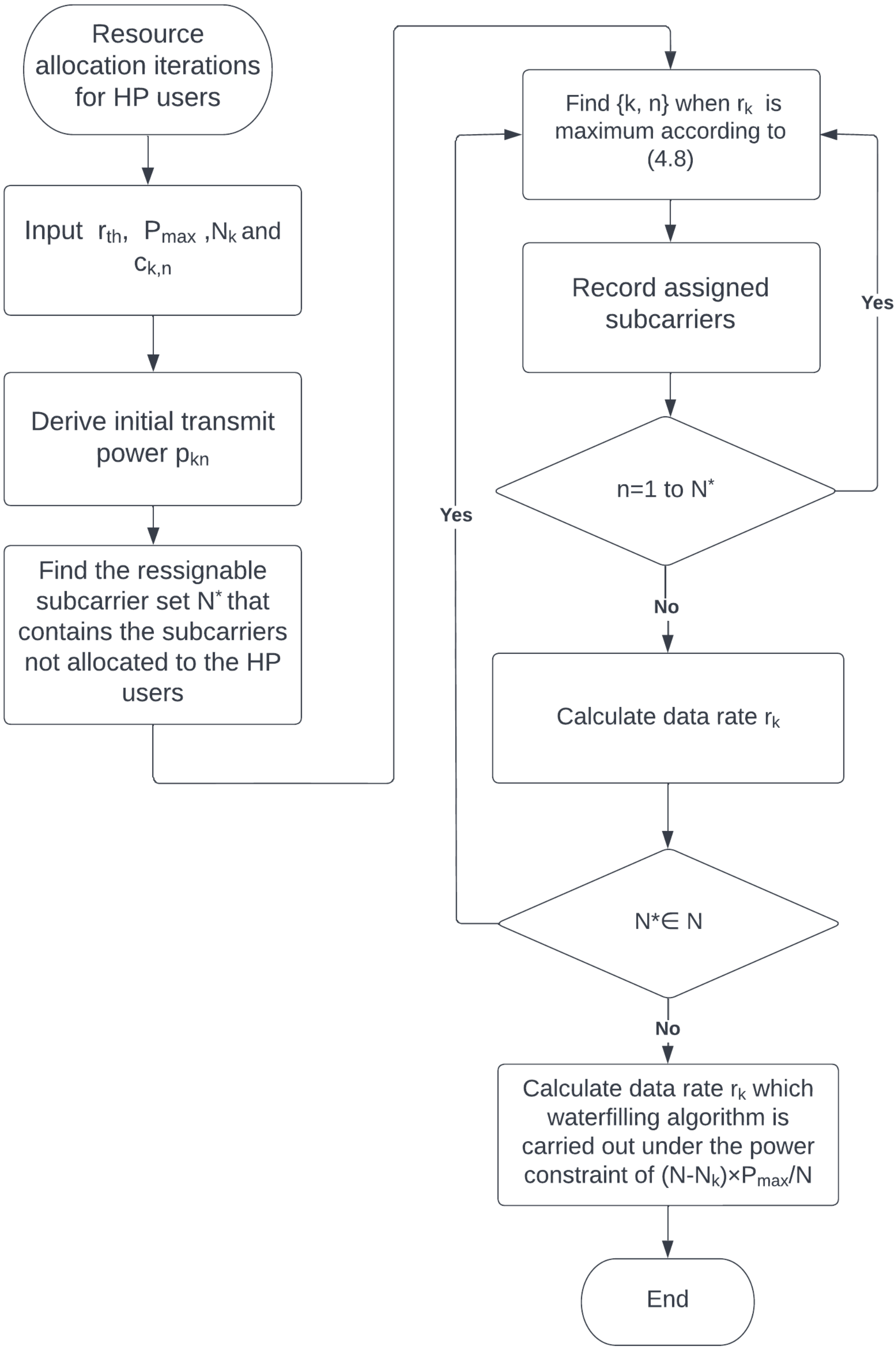


Figure 4.3: Resource allocation iterations for all users flowcharts

4.4 Simulation Results and Performance Analysis

In this section, we focus on evaluating the data rate achieved by the proposed resource allocation scheme in a drone aided emergency communication system. The drone is placed at a point with a height of 100 meters from the ground. Its serving radius covers from 500 to 1000 meters. In the system, the channel gain follows Rayleigh distribution. The path-loss exponent is set to 3. All users are randomly distributed in the drone service area. The simulations are done based on the parameters listed in TABLE 4.1.

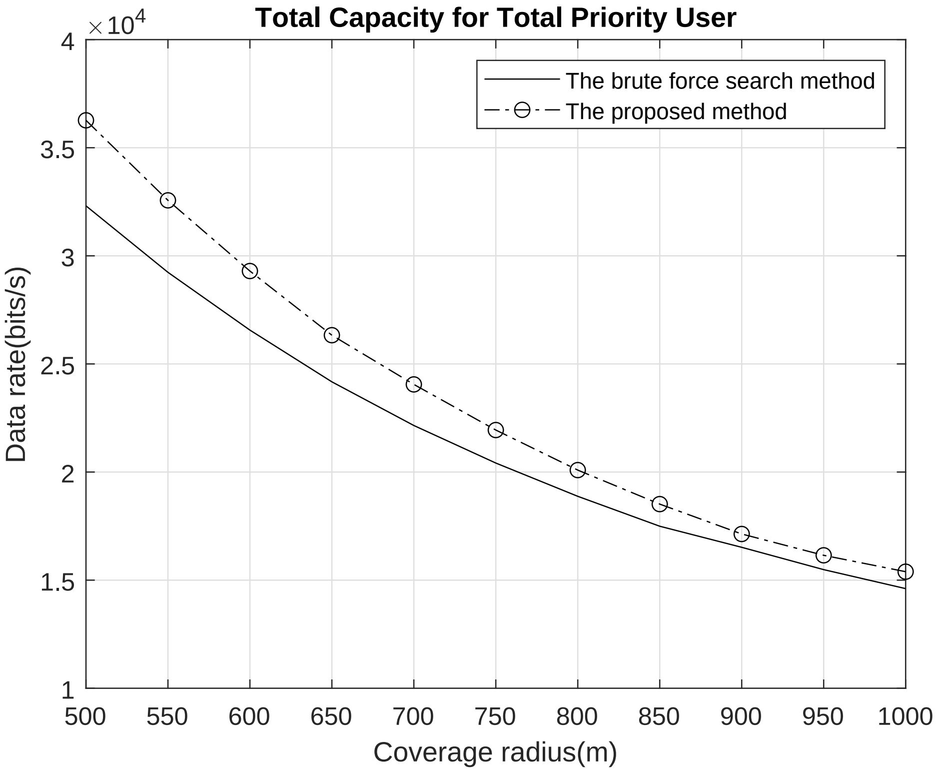
Parameter	Detail	Value
H	Height of Drone	100 m
B	Bandwidth	3 kHz per subcarrier
σ	The AWGN variance	1x10^{-10} Watt
r_th	Minimum data rate requirement of HP user	6k bit/s
N	Number of subcarriers	8
K_h	Number of HP users	2
K_l	Number of LP users	2
p_{max}	Total transmit power	0.08, 0.5 dBm
r	Radius of coverage area	500, 1000 m
	Number of simulations	10^4

Table 4.1: Simulation parameters

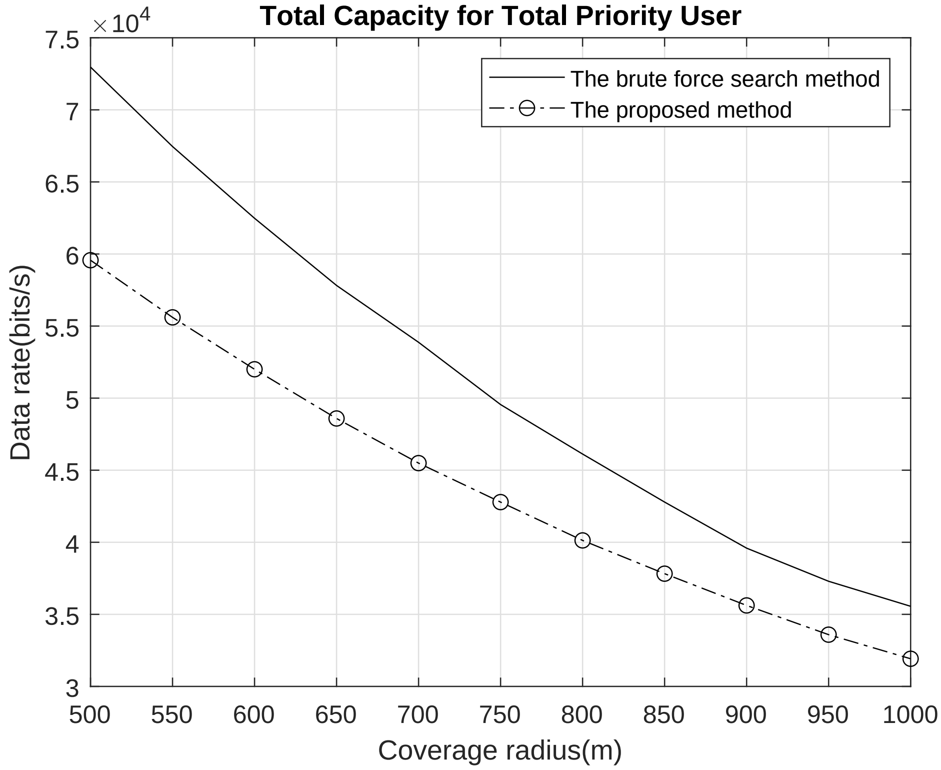
4.4.1 Impact of coverage radius of the drone on the data rate

Below, numerical results show the impact of varying the coverage radius of the drone on the data rate. Transmit power in Fig4.4(a) is $p_{max} = 0.08$ watt and transmit power in Fig4.4(b) is set to$p_{max} = 0.5$ watt.

Fig.4.4(a) and Fig.4.4(b) show the performance comparison between the proposed method and optimal brute force algorithm when the radius of the drone coverage area varies from 500 meters to 1000 meters.



(a) Total ransmit power is 0.08 watt



(b) Total transmit power is 0.5 watt

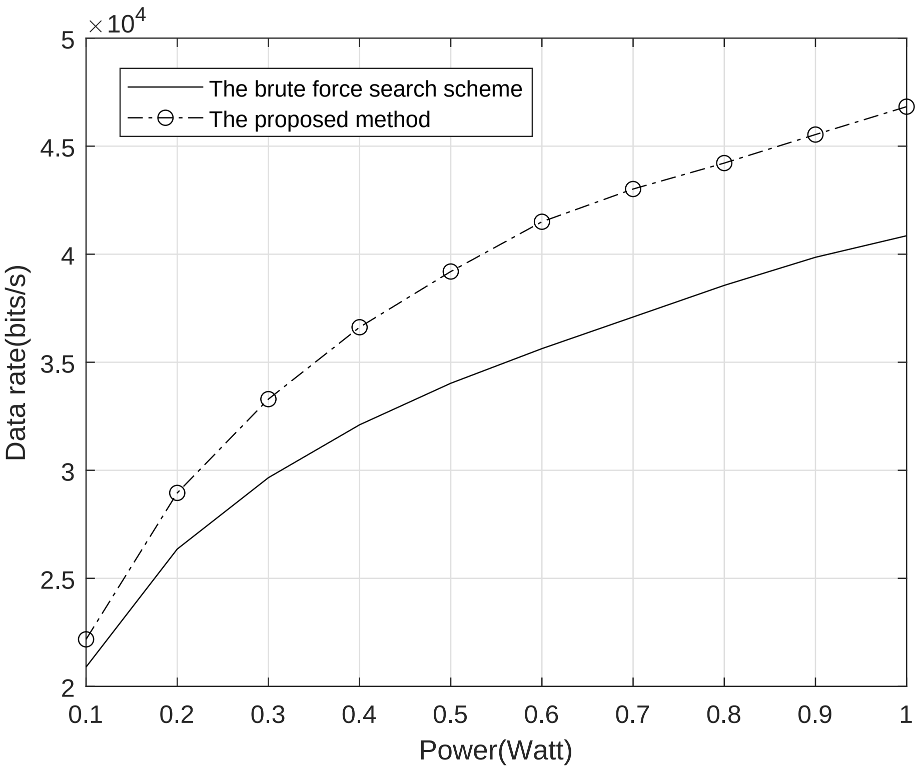
Figure 4.4: Total data rate vs. radius of the drone coverage

As the coverage radius of the drone increases, both graphs show a decrease in the user's data rate. The gap between the data rate of the proposed scheme and the brute force method decreases with increasing radius, which means the performance of the proposed scheme approaches the optimal performance. A comparison of Fig.4.4(a) and Fig.4.4(b) shows that the data rate gap of the proposed scheme does increase with the brute force search method when the power increases. But the increased power does not affect the tendency for the data rate to decrease as the radius increases. The main reason is explained as follows.

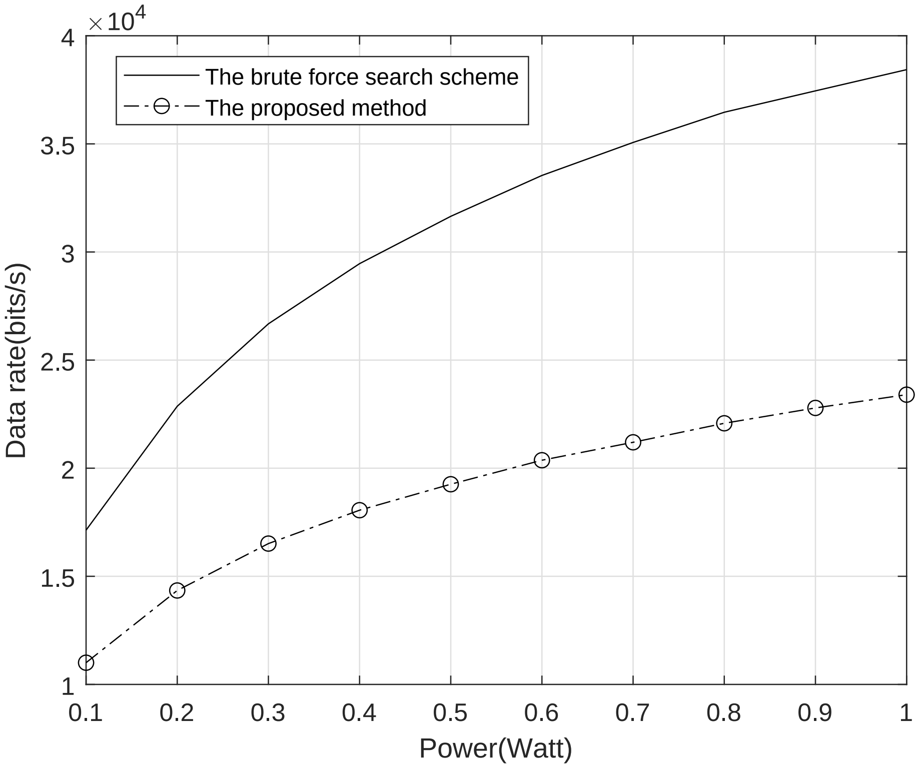
As the radius increases, the average SNR per user decreases. In order to satisfy the data rate constraint of the HP users, more subcarriers need to be allocated to the HP users. Then, the smaller the number of subcarriers allocated to the LP users, the smaller the performance gap between the two schemes. When the drone covers more than 1000 meters, the proposed method has almost the same performance as the best solution.

4.4.2 Impact of transmit power on the data rate

In this section, the data rate of users is studied in terms of the transmit power. Further, their effect on the overall system performance is studied. The coverage radius of the UAV in Fig.4.5 and Fig.4.6(a) is set to $r = 500$ meters, and the coverage radius of the UAV in Figure 4.6(b) is set to $r = 1000$ meters.



(a) HP Users



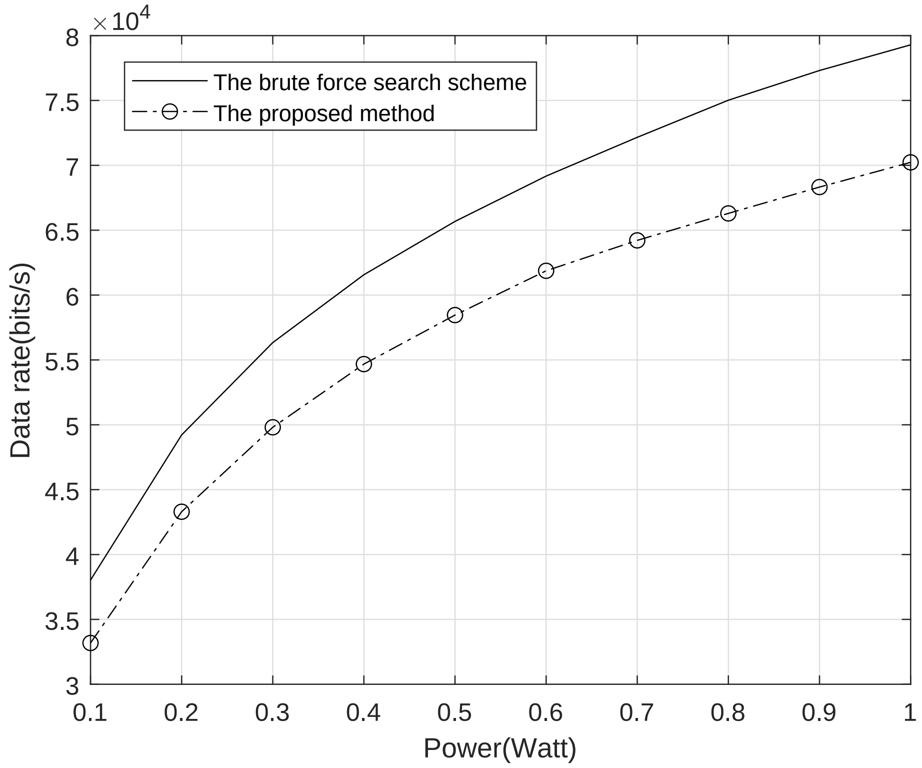
(b) LP Users

Figure 4.5: Total data rate vs. transmit power for HP users and LP users

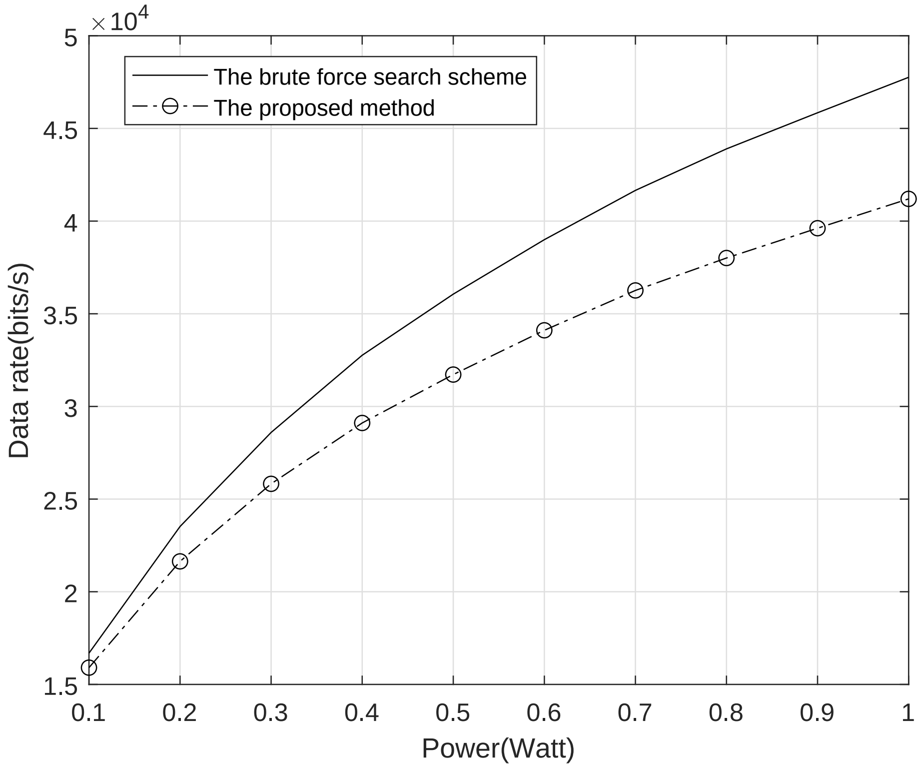
Fig.4.5(a) and Fig.4.5(b) show the relationship between the proposed method and the brute force search method for HP users and LP users. In Fig.4.5(a), the data rate of HP users in the proposed method is greater than that of the HP users in the brute force search method. When the transmit power provided by the drone increases, the rate of increase of the data rate of HP users in the proposed method is also greater than that of the HP in the brute force search method. In Fig.4.5(b), both the LP users data rate of the proposed method and the growth rate of the data rate are smaller than that of the LP users in the brute force search method.

A comparison of Fig.4.5(a) and Fig.4.5(b) shows that as the transmit power increases, the gap between the data rate of the HP users and the LP users of the proposed method increases. This means that the proposed method sacrifices the data rate of more LP users to preferentially meet the data rate requirements of HP users. And the more sufficient the transmit power, the greater the data rate loss for the LP users.

Fig.4.6(a) and Fig.4.6(b) show the relationship between the total data rate of all users and the transmit power when the coverage radius of the drone is 500 m and 1000 m respectively. As can be seen in both Fig.4.6(a) and Fig.4.6(b), the optimal solution for LP users has a larger rate of increase in the maximum rate at the beginning of the increase in transmit power than the proposed method. The increase in the percentage of HP users means that the proposed plan is larger.



(a) All users with coverage radius 500 m



(b) All users with coverage radius 1000 m

Figure 4.6: Total data rate vs. transmit power for all users

Overall, the total data rate of the proposed resource allocation scheme is close to that of the optimal solution when the transmit power is relatively low, e.g. less than 0.5 Watt. When the transmit power is high, e.g. greater than 0.5 Watt, the difference in performance increases.

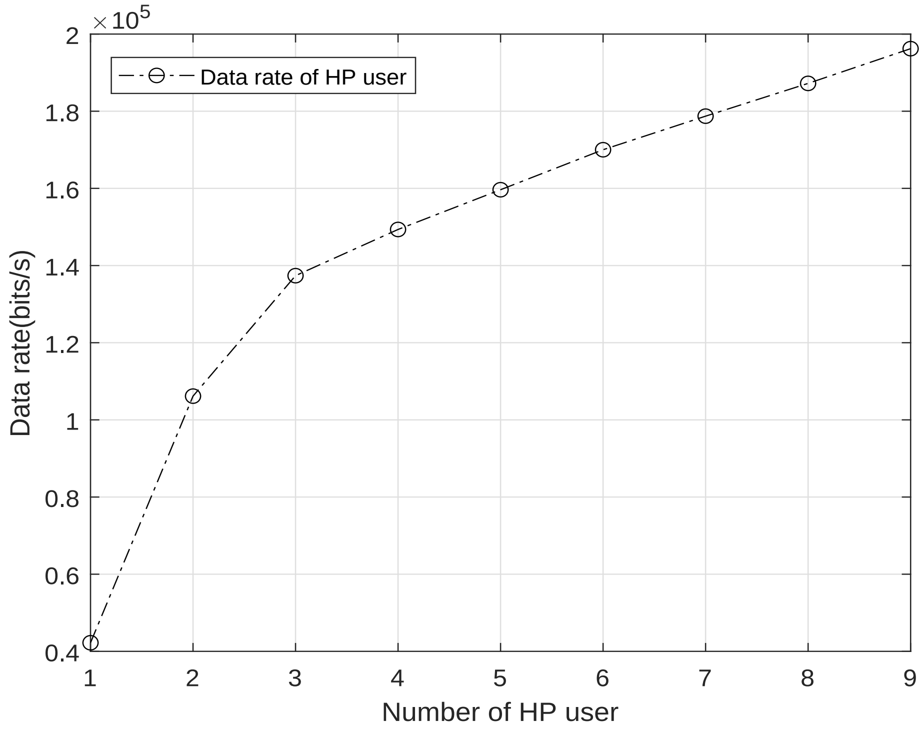
The reason is that, in the brute force search method, as long as the data rate constraint of the HP user can be satisfied, HP users may not need to be allocated to its best channels if there is LP users whose channel condition is much better. However, in the proposed scheme, in order to satisfy HP users data rate requirement, the data rate of LP user will be sacrificed by allocating some subcarriers to HP users which may not have the best channel condition on it or even has poor channel condition.

When the transmit power of each subcarrier is low, the sacrificed LP user data rate is lower to reach the minimum data rate of HP users, and when the transmit power of each subcarrier increases, the sacrificed LP user data rate also increases. Therefore, the difference in performance between the brute force search method and the proposed method becomes greater.

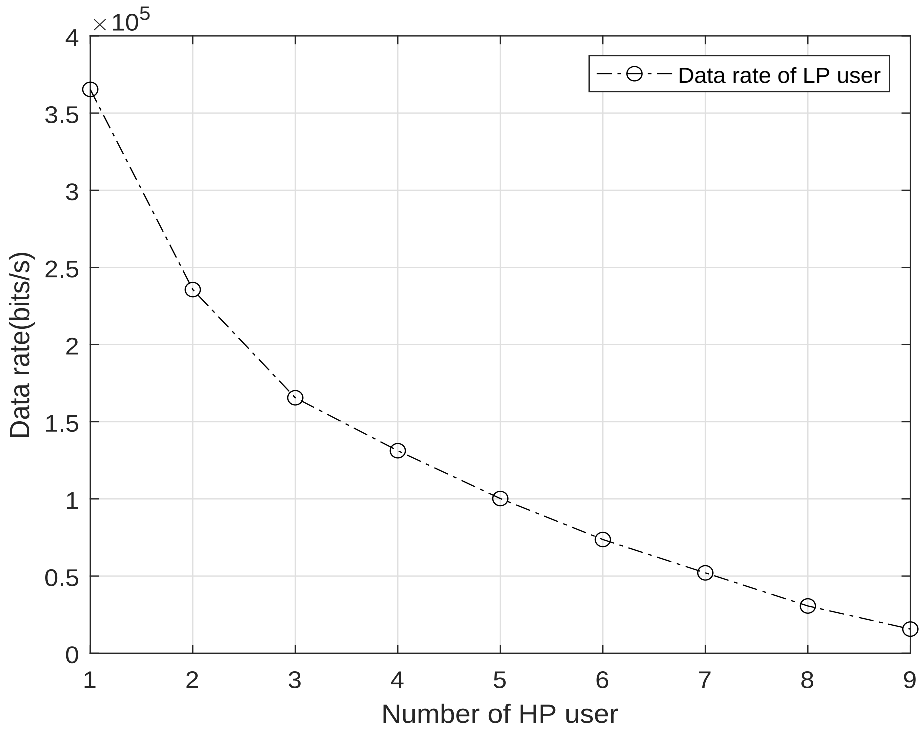
Comparing Figures Fig.4.5(a) and Fig.4.5(b) with Fig.4.6(a) and Fig.4.6(b), it is clear that when the transmit power of the drone is limited and a large area is covered, the average SNR of all users is relatively low, and the total user data rate obtained by the method proposed here is very close to the result of the brute force search method. This means that in case of emergency rescue, the coverage area of the drone can be maximized. This can greatly reduce the loss of user data rate when subcarriers are assigned, while ensuring the minimum data rate of disaster responders.

4.4.3 Impact of number of HP users on the data rate

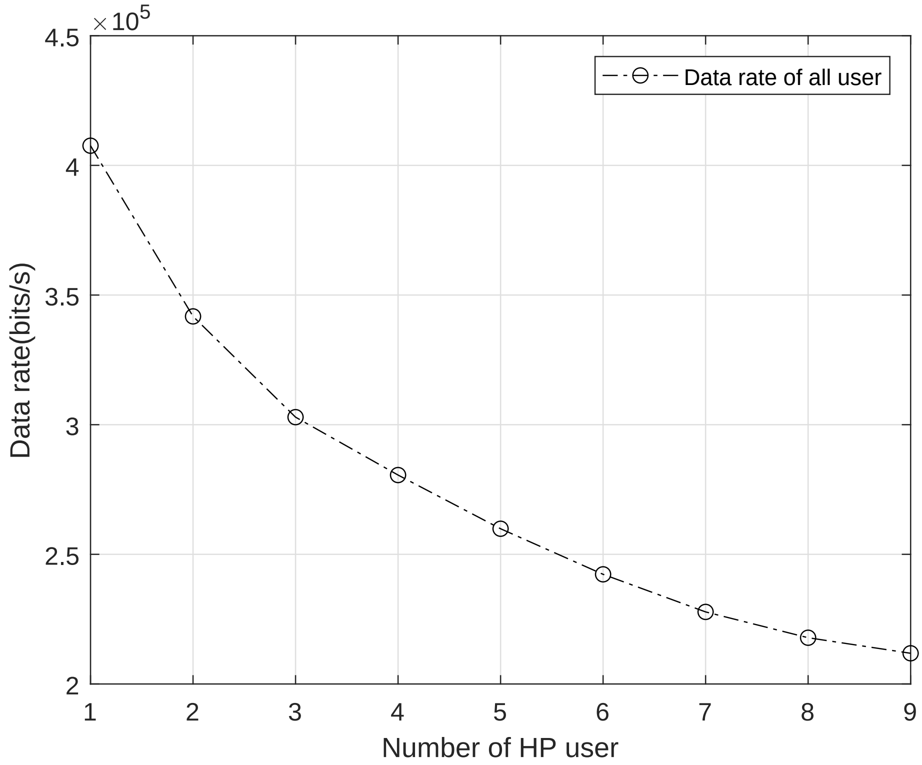
In this section, the performance of the emergency system is presented in terms of number of users variation and sum rate. In Fig.4.7, the total number of users is set to $K_h + K_l = 10$, with a minimum data rate for HP users of $r_{th} = 10$ kbit/s. The total transmit power is set to $p_t = 0.375$ watts and the number of subcarriers to $N = 30$. Since the complexity of the brute force search method is too high, all possible combinations in this section are too numerous and the optimal result cannot be searched. Therefore, only the simulation results of the proposed method are presented in this section.



(a) HP Users



(b) LP Users



(c) All Users

Figure 4.7: Total data rate of all users vs. number of HP users

Fig.4.7(a), Fig.4.7(b) and Fig.4.7(c) show the relationship between the user data rate and the number of HP users. As can be seen from Fig.4.7(c), the reduction in the total data rate decreases as the proportion of HP users increases. In Fig.4.7(a) and Fig.4.7(b), we can see that the data rate of HP increases as the number of HP users increases, and the data rate of LP decreases as the number of HP users increases. And at the beginning, the reduction of data rate is higher for LP users than for HP users. And from Fig.4.7(c), the decrease in data rate of LP with increasing number of HP users is reduced but always higher than the increase of HP users.

The reason for this is that when there are more HP users, more subcarriers have to be allocated to meet the minimum rate of all HP users. This also means that more and more subcarriers cannot be assigned to the users with the highest SNR. Therefore, the sacrificed data rate also increases with the number of HP users. The closer the proportion of HP users is to 100%, the lower the average SNR of the subcarriers assigned to HP users.

In summary, although the data rate of LP decreases significantly with the increase in users of HP, the actual average data rate of LP decreases from a maximum of $4 \cdot 10^4$ bits/s to $2.2 \cdot 10^4$ bits/s. Therefore, although the proposed method favours the minimum data rate requirement of HP users, it can still guarantee some of the data rate demand of LP users.

4.5 Conclusions

This chapter deals with resource allocation in emergency communication systems. Due to the complexity of the problem, it is divided into the subproblems of subcarrier allocation and power allocation. The two sub-problems are optimized respectively.

The algorithms in other literatures allocate resources equally to all users as they consider different users in an emergency environment. Compared to these literatures, the algorithm in this chapter prioritizes different types of users in an emergency environment. This also leads to the difference between the methods in this thesis and those in other publications that do not consider the fairness of all users.

Users are divided into HP users and LP users, and an algorithm for assigning seed carriers is proposed. For HP users, the minimum data rate is observed. For

LP users, sub-carriers are assigned based on the policy. The optimization objective is to maximize data rates for all users while ensuring minimum guaranteed rate for HP users.

In the subcarrier assignment problem, the complexity is greatly reduced as subcarriers are assigned preferentially to HP users. In this paper, a suboptimal subcarrier allocation method is proposed. The computational complexity of this method is linear with the number of users, while the computational complexity of the brute force search method is much higher.

In the power allocation problem, for each user, e.g. user k, on the subcarrier assigned to it, the water-filling algorithm is performed under the power constraint $N_k \cdot p_{max}/N$ with the objective of maximizing the data rate.

To verify the proposed method, we collected data on the force search method in UAV-assisted emergency communication and verified the proposed method through simulation experiments. The numerical simulation results show that the performance of this algorithm decreases when the power is reduced or the coverage area of the drone is increased, but the performance gap between this algorithm and the optimal algorithm becomes smaller when the power is reduced. This also means that the algorithm is efficient in resource utilization in the emergency communication environment when resources are scarce, and the performance of this algorithm is very close to the optimal algorithm.

Chapter 5

Scubcarrier Allocation and Power Allocation in Drone-Aided Emergency Communications

Contents

5.1 Introduction

5.1.1 Motivation

The first 72 hours after the disaster, also known as the Golden Rescue Period, are the most critical time to find survivors [4]. However, natural disasters such as earthquakes and tsunamis often lead to a complete paralysis of the existing communication infrastructure, which hinders the work of field staff. Therefore, deploying a fast, adaptable and efficient emergency communication network is essential [5]. The emergency communication network must also ensure the communication capability of search and rescue teams so that they know in time in which areas survivors are waiting for rescue. In addition, it should also ensure the ability of survivors to communicate with the outside world. To solve this problem, the drone can act as a flying BS and provide an emergency network in the disaster area [7]. For the above reasons, the drone as an emergency network technology has received much attention in recent years.

The key to improving emergency network of drone performance is resource allocation, which carries out the assignment of radio resources with the objective of optimizing a certain performance metric. Appropriate resource allocation comprises the joint optimization of subcarrier allocation and power allocation [11, 12], which quite often yields an intractable problem, for which finding the optimal solution requires of prohibitively complex algorithms such as brute force search and [58]. Therefore, in order to reduce the implementation cost of the drone-assited OFDMA-based emergency network, it is critical to investigate how to reduce the computational complexity of resource allocation, while achieving a performance close to optimal.

5.1.2 Contribution

In this chapter, several contributions are made in terms of resource allocation in the drone-assited OFDMA based emergency network. Due to the non-convex property introduced by users of multiple priorities and integer constraints, the complexity of solving the formulated optimization problem is extremely high.

Since the method in chapter 4 sacrifices the user's excessive data rate in order to reduce the complexity of the algorithm. Therefore, the focus of this chapter is to bring the data rate of the method as close as possible to that of the brute force search method and to reduce the complexity of the system to a realistically achievable level. Thus, this is divided into the sub-problems of subcarrier allocation, and power allocation. These two sub-problems are separately optimized.

First, for the subcarrier allocation problem, knowledge of Shannon's theorem and fading in emergency communication that maximize the achievable data rate in minimum data rate of HP user constrained scenarios is used to propose a suboptimal subcarrier allocation algorithm that has low complexity. This is achieved by implementing a comparison of the optimal data rate differences between different users. In contrast, the complexity of exhaustive search procedures is of the order of the squared number of users. Other suboptimal subcarrier allocation schemes in the literature [12] achieve much greater computational complexity than the algorithm presented in the thesis.

Second, the power allocation in an emergency communication system is solved by the waterfilling algorithm, with the objective of maximizing the HP user data rate. The waterfilling algorithm is applied to propose a novel power allocation algorithm for an emergency communication system with minimum HP user data rate constrained. Unlike existing works, different priorities of users are considered and power allocation is performed by iteratively applying the waterfilling algorithm for some individual HP users and globally for all other users.

Through numerical simulations, it is demonstrated that the performance of the proposed resource allocation scheme is close to the optimum and its complexity is less than that of other schemes such as [12] and the optimal brute force search method. The remaining of this chapter is organized as follows.

- Section 5.2 shows system model and the problem formulation.
- Section 5.3 presents the resource allocation problem formulation. Among them, the brute force search method is introduced in Section 5.31 and suboptimal resource allocation presented in Section 5.32.
- Numerical results on the effect of transmitted power, coverage radius, number of users and number of subcarriers are provided in Section 5.4.
- Finally, in section 5.5, a summary of the work done in this chapter is given and the main conclusions are highlighted.

List of Related Publication

T. Chen, J. Wang, H. Zhu, P. Yue, X. Yi, W. Cheng, H. Zhang, J. Wang, ”Resource Allocation in Emergency Communication system with different of user prioritys”, Submitting to Science China Information Sciences.

5.2 System Model

The system model in this chapter is the same as the system model in chapter 4, therefore the system model is not discussed in this chapter.

5.3 Resource Allocation Problem Formulation

The aim of this chapter is the same as in Chapter 4, aims to allocate resources to maximize the total system data rate for an emergency communications assisted by a drone, while guaranteeing the rate requirement of HP users in the rescue team. Therefore, the expression of this problem can directly refer to the optimization problem in Chapter 4

5.3.1 Brute force search based resource allocation

Chapter 5 is different from chapter 4, chapter 5 with brute force search, the procedure searches through all the possible subcarrier allocation combinations and power allocation combinations. Since the power in this paper is a continuous set of real values, deep reinforcement learning will be used to find the optimal power allocation method in order to discover the theoretical maximum of the data rate. The optimal joint subcarrier and power allocation result is then the combination of subcarrier allocation and power level allocation that achieves the highest data rate while satisfying the data rate constraint of HP users. However, its complexity is $O(K^N)$, which increases exponentially with the number of users K and the number of subcarriers N. The complexity could be extremely high when the number of subcarriers is large, e.g., fifth generation (5G) mobile systems has more than 512 subcarriers.

5.3.2 Sub-optimal resource allocation

In a downlink multiuser OFDM system, to maximize the system data rate without data rate constraints, the resource allocation can be decoupled into subcarrier allocation and power allocation[6][7] by firstly assigning each subcarrier to the user with the best instantaneous channel condition over the corresponding subcarrier, and then using waterfiling method for power allocation. For the optimisation problem in (5.6), in order to obtain the near-optimal system data rate and reduce the complexity at the same time, the resource allocation problem is also divided into two stages, subcarrier allocation and power allocation.

Stage 1 - Subcarrier Allocation

Subcarrier allocation will be an iterative process. Initially, following the case without data rate constraints, each subcarrier is assigned to the user with the best channel condition on it.

As the subcarrier allocation method mentioned above aims to maximize the data rate of the system, after the initial subcarrier allocation, the minimum data rate constraint may not be satisfied for all HP users. Therefore, the HP users whose data rate is smaller than the rate threshold in (5.5e) will be re-allocated with subcarriers from other users. In order to ensure that the rate loss is minimized, subcarrier re-allocation will be carried out subcarrier by subcarrier iteratively under equal power allocation. In the ith iteration of subcarrier re-allocation, once a subcarrier n is reallocated to user k, the sum data rate difference $\Delta r_{sys}(i)$ is determined by the data rate change on subcarrier n, $\Delta r_n(i)$, given by

$$\Delta r_{sys}(i) = \Delta r_n(i) = \Delta r_{k',n}(i) - \Delta r_{k,n}(i) \tag{5.1}$$

where k^* is the user allocated with subcarrier n before re-allocation. Here, a subcarrier is called a reassignable subcarrier if it belongs to an LP user or an HP user whose data rate is higher than the threshold. Among all the reassignable subcarriers, if the reallocation of a subcarrier belonging to an HP user makes the rate requirement of this user unsatisfied, this subcarrier will not be allowed for re-allocation. The iterative subcarrier re-allocation will be carried out until the data rate constraint is satisfied for all HP users. Assuming the number of iterations is I, the total reduction of system data rate is given by $\sum_{i=1}^{I} \Delta r_{sys}(i)$. It can be seen that in each iteration, if the subcarrier n^* satisfies

$$n^*(i) = arg \min_{n \in N^*(i)} \Delta r_n(i) \tag{5.2}$$

where N^* is all subcarriers that are reassignable. The reduction of the system data rate in (5.8) is minimized. Equivalently, under equal power allocation, the system data rate can be maximized, while the data rate constraint is satisfied for all HP users. In summary, the subcarrier allocation procedure for the subcarrier of the user n is described as Algorithm 3. The corresponding flowcharts for Algorithm 3 are represented in Fig.5.1.

Algorithm 3 Subcarrier allocation iterations.

Input: r_{th}, P_{max};

Initialization $p_{k,n} = \frac{P_{max}}{N}$

Output: $\{c_{k,n}\}_{k \in \mathcal{K}, \forall n \in \mathcal{N}}$

for $n = 1$ to N **do**

  $k = arg\max_{k \in \mathcal{K}} |h_{k,n}|^2 d_k^{-\lambda}$

  $c_{k,n} = 1$

  $c_{k,n} = 0, \in k^* \neq k$

end for

Calculate $r_k = \sum_{n=1}^{N} B \log_2 \left(1 + \frac{c_{k,n} p_{k,n} |h_{k,n}|^2 d_k^{-\lambda}}{\sigma^2}\right) \ \forall k \in \mathcal{K}_h$

Find the reassignable subcarrier set N^* that contains the subcarriers allocated to the LP users and the HP users with achievied rate higher than r_{th}

Find the set k_h^* of HP users with achieved rate smaller than r_{th}

while data rate of each user $r_k < r_{th} \ \forall k \in \mathcal{K}_h$ **do**

  for $n \in N^*$ **do**

    for $k_h \in k_h^*$ **do**

      Calculate the data rate change Δr_k according to (7)

    end for

  end for

  $\{k^*, n^*\} = arg\min_{n \in N^*, k \in \mathcal{K}_h} \Delta r_{k,n}$

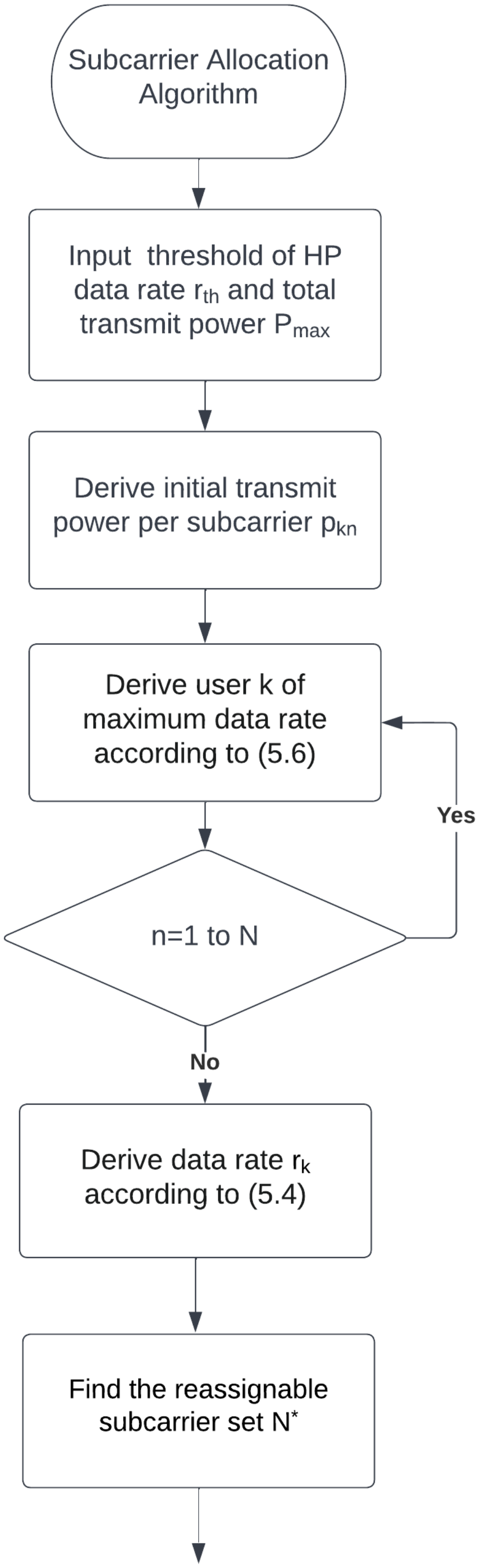
  if $r_k < r_{th}$ **then**

    $n^* = N^* - n^*, c_{k^*,n^*} = 1, c_{k',n^*} = 0, \forall k' \neq k^*$;

  end if

  Calculate $r_k = \sum_{n=1}^{N} B \log_2 \left(1 + \frac{c_{k,n} p_{k,n} |h_{k,n}|^2 d_k^{-\lambda}}{\sigma^2}\right) \ \forall k \in \mathcal{K}_h$

end while


Subcarrier Allocation Algorithm
Input threshold of HP data rate r_{th} and total transmit power P_{max}
Derive initial transmit power per subcarrier p_{kn}
Derive user k of maximum data rate according to (5.6)
Yes
n=1 to N
No
Derive data rate r_k according to (5.4)
Find the reassignable subcarrier set N^*

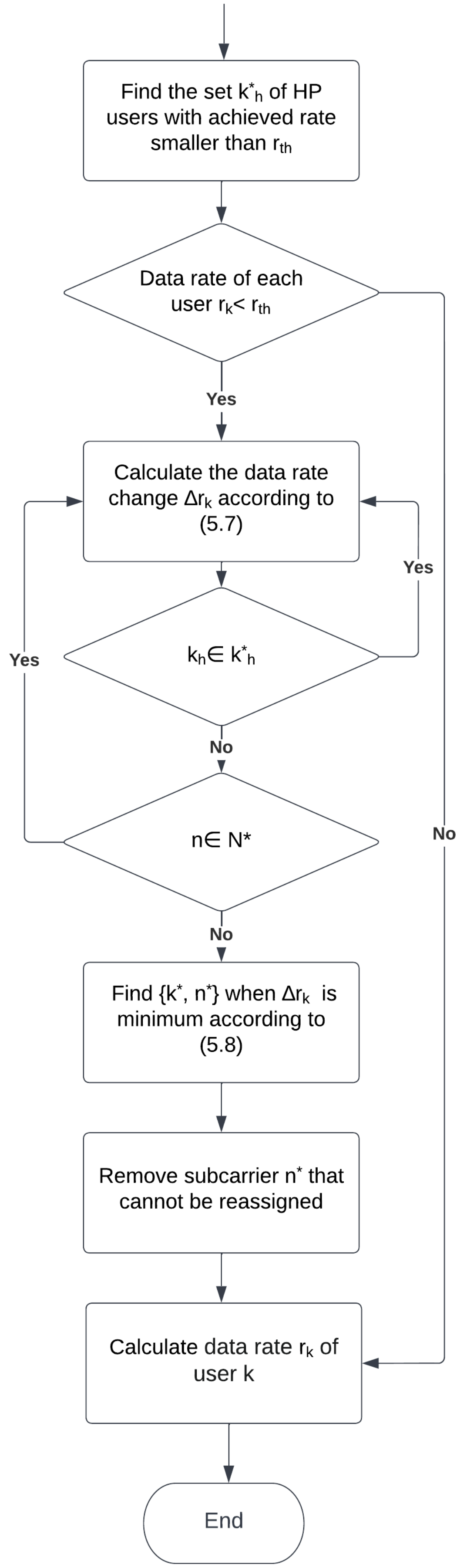


Figure 5.1: Subcarrier allocation iterations flowcharts

Stage 2 - Power Allocation

In a multiuser OFDMA system, waterfilling is the optimal power allocation algorithm to achieve the maximum data rate after allocating each subcarrier to the user with the best channel condition on it [16][17]. Therefore, in drone-assisted emergency communications, after subcarrier allocation, a modified waterfilling method is proposed to allocate the transmit power of the drone to the subcarriers. At first, all the subcarriers are put into the set of subcarriers for power allocation. Based on the subcarrier allocation result, under the total transmit power limit of the drone, P_{max}, waterfilling is applied to allocate power on each subcarrier. For an HP user k, if its minimum guaranteed rate constraint is not satisfied, by applying waterfilling method among the subcarriers allocated to this HP user k_h, a least transmit power allocated to HP user k, $p_{min,k}$, will be derived based on the minimum guaranteed rate constraint. Specifically, the transmit power required by HP user $k \in \mathcal{K}_h$, $p_{min,k}$, satisfies

$$\begin{cases} p_{k,n} = \mu_k - \frac{\sigma^2}{\left|h_{k,n}\right|^2 d_{k,n}^{-\lambda}} \\ \sum_{n=1}^{N} p_{k,n} = p_{min,k} \end{cases} \tag{5.3}$$

where μ_{k_h} is the water level of the HP user k_h. We then have

$$\mu_{k_h} = \frac{p_{min,k} + \sum_{k=1}^{K} \sum_{n=1}^{N} c_{k,n} \left|h_{k,n}\right|^2 d_{k,n}^{-\lambda}}{N} \tag{5.4}$$

$$p_{k,n} = \frac{p_{min,k} + \sum_{k=1}^{K} \sum_{n=1}^{N} c_{k,n} \left|h_{k,n}\right|^2 d_{k,n}^{-\lambda}}{N} - \frac{\sigma^2}{\left|h_{k,n}\right|^2 d_{k,n}^{-\lambda}} \tag{5.5}$$

As is shown in (5.6), given the data rate constraint r_{th}, the data rate $\sum_{n=1}^{N} r_{k,n}$ needs to be equal to r_{th}. p_{min,k_h} can be then obtained from (5.6) as

$$p_{min,k} = \sum_{n=1}^{N} \left(1 + \frac{c_{k,n} 2^{r_{th}}}{\frac{|h_{k,n}|^2 d_k^{-\lambda}}{\sigma^2}} \right) \tag{5.6}$$

When the received SNR is much greater than 1, it can be approximated as

$$p_{min,k} \approx \sum_{n=1}^{N} \left(\frac{c_{k,n} 2^{r_{th}}}{\frac{|h_{k,n}|^2 d_k^{-\lambda}}{\sigma^2}} \right) \tag{5.7}$$

Once the least transmit power $p_{min,k}$ is determined and allocated to the HP user k, the allocation algorithm removes the subcarriers allocated to user k from the set of subcarriers for power allocation and subtract its transmit power $p_{min,k}$ from the residual power. The next round of power allocation will be performed with the following three steps, until all the HP users' data rate constraint is satisfied: 1) applying waterfilling among the set of subcarriers for power allocation; and 2) based on (5.13), calculating the least transmit power for the HP user whose unsatisfied data rate is the highest among all unsatisfied HP users; 3) removing the subcarriers allocated to the HP user from the set of subcarriers for power allocation and subtracting its transmit power from total transmit power. In summary, the power allocation procedure for the subcarrier of the user k is described as Algorithm 4. The corresponding flowcharts for Algorithm 4 are represented in Fig.5.2.

Algorithm 4 Power allocation iterations.

Input: $r_{th}, P_{max}, r_k, \{c_{k,n}\}_{k\in\mathcal{K},\forall n\in\mathcal{N}}$;

Initialization $p_{k,n} = \frac{P_{max}}{N}$

Output: $\{r_k\}_{k\in\mathcal{K}}$

Calculate $\mu_k = \frac{p_{min,k}+\sum_{k=1}^{K}\sum_{n=1}^{N} c_{k,n}|h_{k,n}|^2 d_{k,n}^{-\lambda}}{N}$

Calculate $p_{k,n} = \mu_k - \frac{\sigma^2}{|h_{k,n}|^2 d_{k,n}^{-\lambda}}$

Calculate $r_k = \sum_{n=1}^{N} c_{k,n} r_{k,n}$ $\forall k \in \mathcal{K}_h$

while $r_k < r_{th}$ $\forall k \in \mathcal{K}_h$ **do**

  Find the set k_h^* of HP users with achieved rate smaller than r_{th}

  Calculate the least transmit power $p_{min,k_h^*} \approx \sum_{n=1}^{N} \left(\frac{c_{k,n} 2^{r_{th}}}{\frac{\left|h_{k,n}\right|^2 d_k^{-\lambda}}{\sigma^2}} \right)$

  Calculate $\mu_k = \frac{p_{min,k}+\sum_{k=1}^{K}\sum_{n=1}^{N} c_{k,n}|h_{k,n}|^2 d_{k,n}^{-\lambda}}{N}$

  Calculate $p_{k,n} = \mu_k - \frac{\sigma^2}{|h_{k,n}|^2 d_{k,n}^{-\lambda}}$

  $\mathcal{K}_h^* = \mathcal{K}_h^* - k_h^*$

  Calculate $r_k = \sum_{n=1}^{N} c_{k,n} r_{k,n}$ $\forall k \in \mathcal{K}_h$

end while

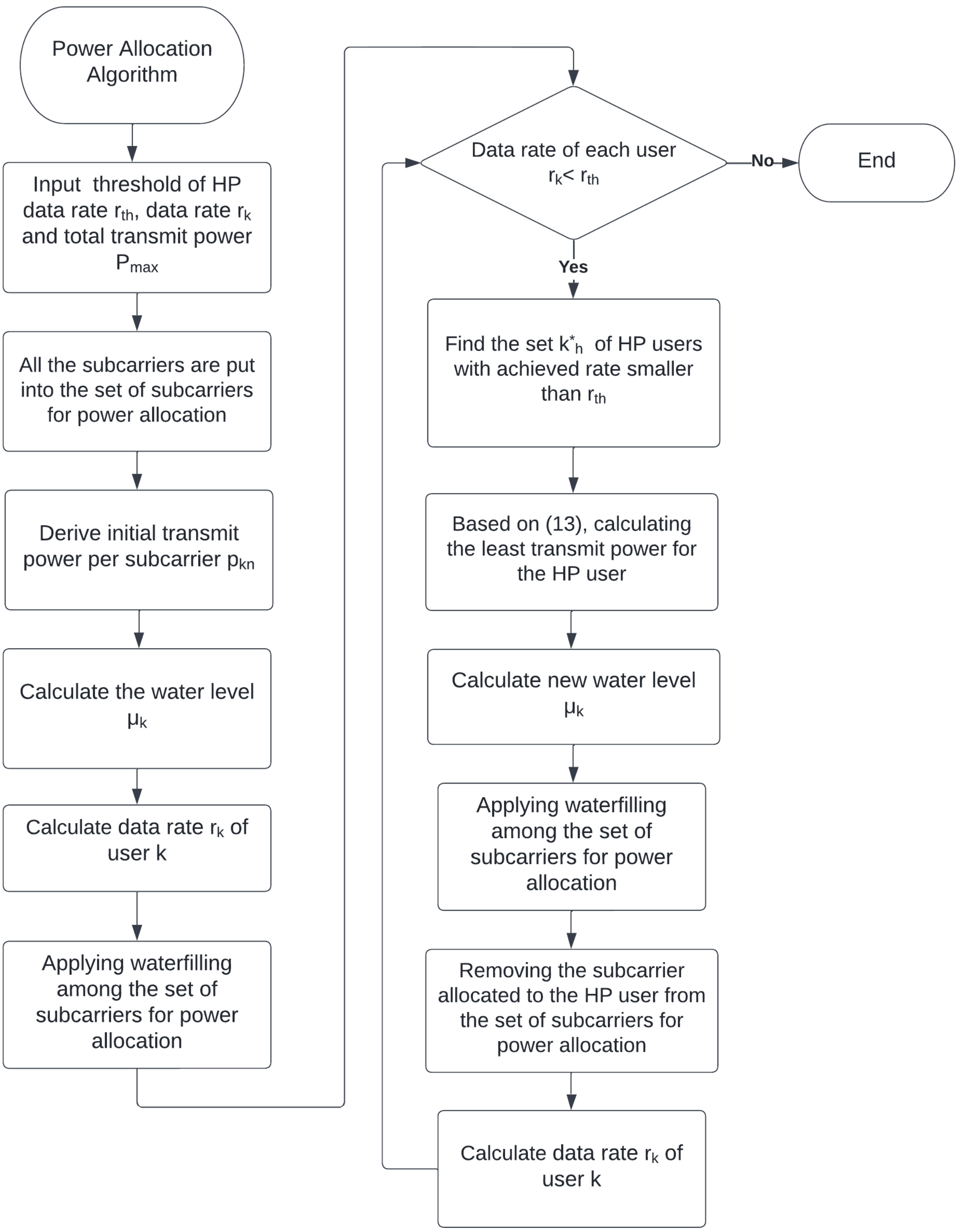


Figure 5.2: Power allocation iterations flowcharts

5.4 Simulation Result

In this section, the performance of the proposed resource allocation method is evaluated through simulations by comparing with the optimal brute force search and a benchmark algorithm [19]. In [19], the benchmark algorithm was proposed to handle the similar problem by assuming the modulation level (or transmit power per subcarrier) is the same for subcarriers within one chunk. In [19], to satisfy the data rate constraint for HP users, the first step is to assign each user a set of chunks over which users can transmit their data streams. After assigning chunks to users, the last two steps are performed individually for each user, which is the same as the method of chunk assignment and bit assignment for a data stream. The second step, block allocation, consists of assigning blocks to two queues, HQ queues and LQ queues, which correspond to HQ packets and LQ packets respectively. The final step, bit allocation, consists of assigning the corresponding bit (or modulation level) to each block combination assigned in the first step.

The simulated system model is formed by a single drone(BS) and a varying number of users. The simulations are done based on the parameters listed in TABLE 4.1. The normalized channel fading factor of all users on each subcarrier follows a Rayleigh distribution with mean square of one. The path-loss exponent is set to 3. The number of cycle simulation is 10^4 times, and the average of these 10^4 times is taken as the result.

In the simulations, users are uniformly distributed within the coverage of the drone. In order to show the impact of optimizing the power allocation, a method that only addresses subcarrier allocation by using step 1 in the proposed method will be adopted for performance comparison.

5.4.1 Impact of the transmitted power on the data rate

In this section, the performance of the emergency system is presented in terms of total transmit power variation and sum rate.

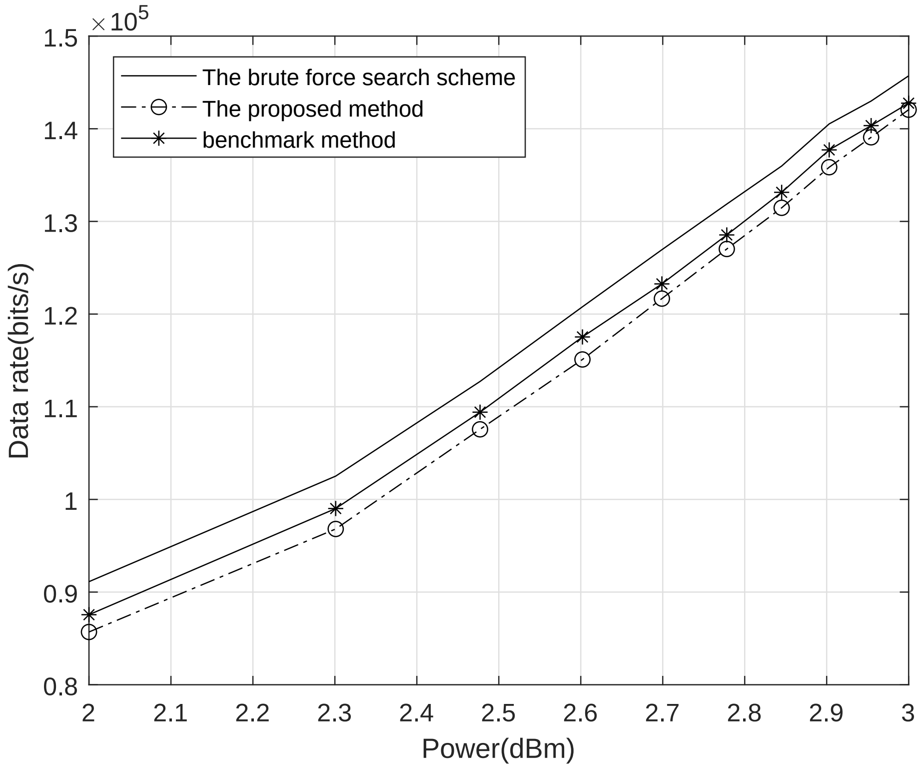


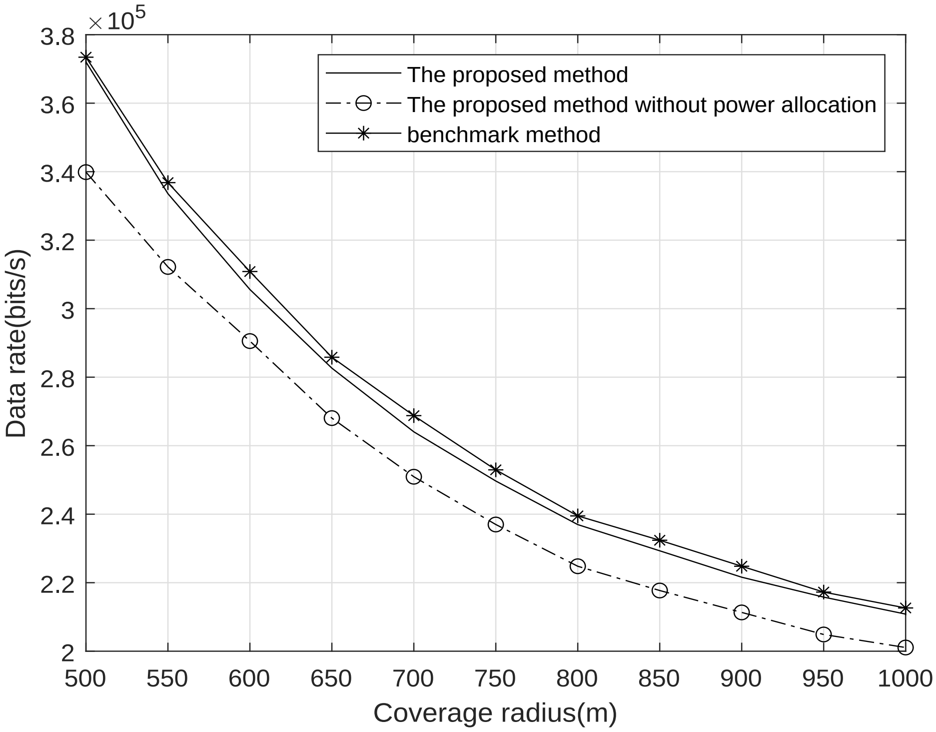
Figure 5.3: Data rate vs. total transmit power

Fig.5.3 presents the sum rate with the proposed scheme, the optimal brute force search, and the benchmark method. Due to the high complexity of the brute force search, 1 HP user, 1 LP user and 8 subcarriers are chosen in the scenario. The minimum data rate requirement of HP user r_{th} = 30 kbit/s. It can be seen from the figure that when the total power p_t increases, the data rate increases. Also, the data rate gap between the proposed method and the optimal solution decreases. The main reason is that in the brute force algorithm, as long as the data rate constraints can be satisfied, the HP user may not need to be allocated to its best channels if there is another user whose channel condition is much better.

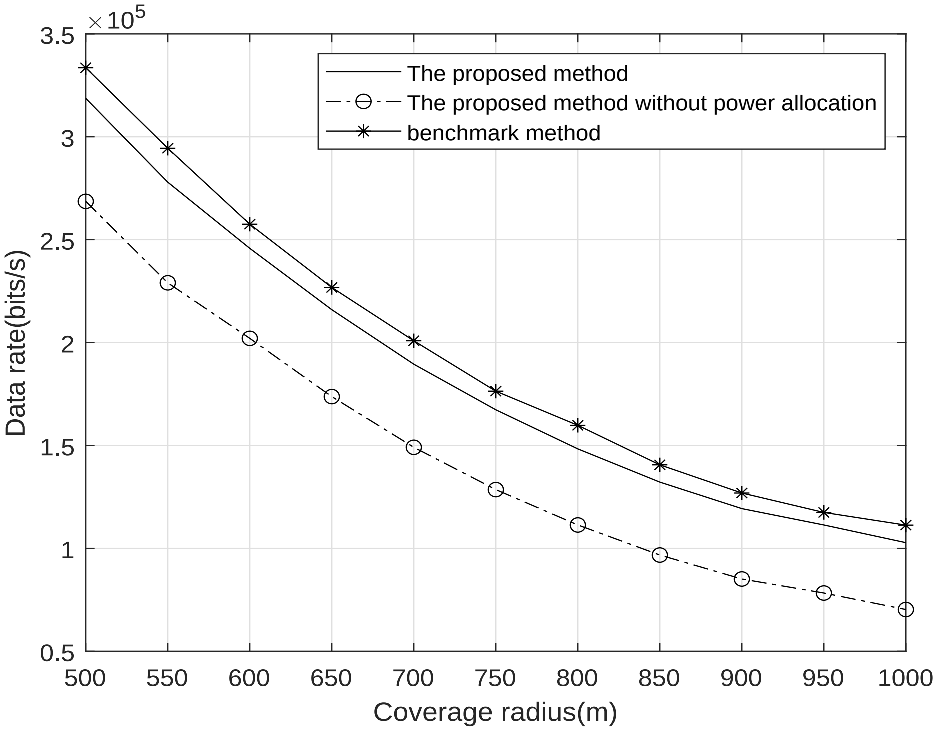
With the proposed scheme, when the power increases, the SNR per user increases, and the data rate increases. In order to satisfy the data rate constraint of the HP users, fewer subcarriers need to be allocated to the HP users. Therefore, more subcarriers are allocated to users with best SNR. When the average SNR is lower, in order to satisfy the HP user threshold, the method proposed in this chapter additionally allocates more subcarriers and power to them, while the allocation result obtained by the brute force search algorithm requires fewer additional subcarriers and less power. By increasing the transmit power, more and more subcarriers are allocated to the users with the best SNR with the proposed scheme. The data rate obtained by the proposed scheme is getting closer and closer to the optimal brute force search. Therefore the proposed method can actually make better use of subcarriers and power to approach the data rate of the optimal brute force search.

5.4.2 Impact of coverage radius of the drone on the data rate

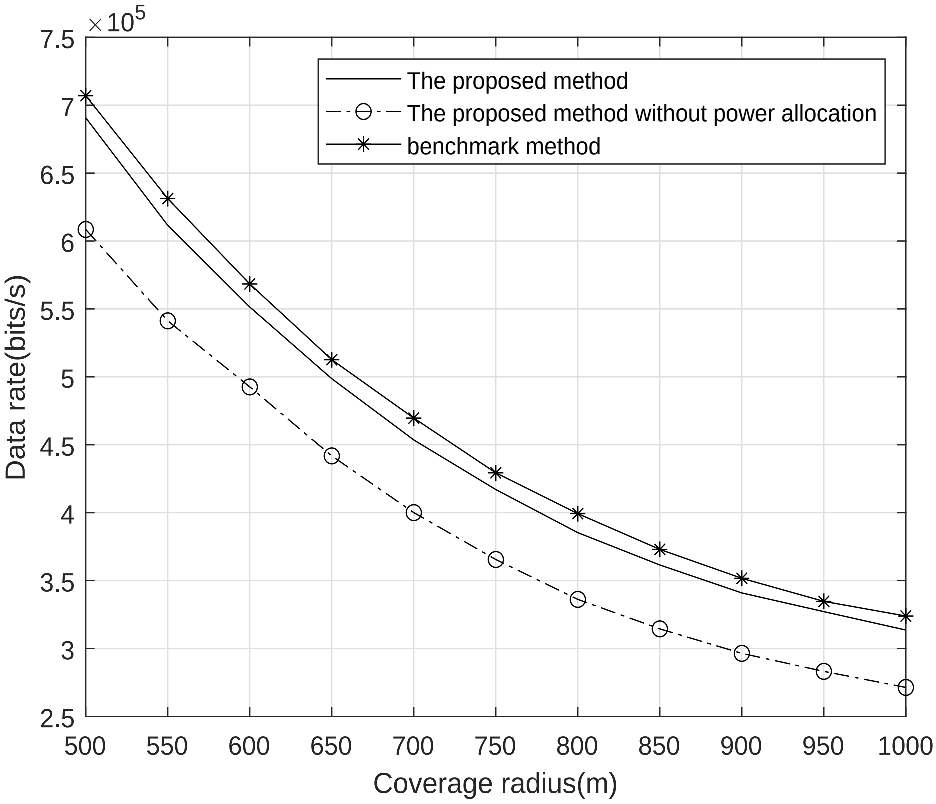
In this section, the performance of the emergency system is presented in terms of drone's coverage radius variation and sum rate. Due to the complexity of the brute force search method, the proposed method is mainly compared with the benchmark scheme.



(a) HP Users



(b) LP Users



(c) Total Users

Figure 5.4: Data rate vs. radius of the drone coverage

Fig.5.4(a) and Fig.5.4(b) show the relationship between the data rate and the drone coverage area for HP users and LP users respectively. In this figure, the number of HP users and LP users is $K_h = K_l = 2$, where the minimum data rate for HP users is $r_{th} = 6$ kbit/s. The total transmitted power is set to $p_t = 0.5$ watt and the number of subcarriers is set to $N = 64$. A comparison of Fig.5.4(a) and Fig.5.4(b) shows that in the proposed method without power allocation, the rate of HP users decreases by about 1.4×10^5 and the rate of LP users decreases by 2.1×10^5 as the radius increases. The reduction in data rate for HP users is much less than that for LP users. This means that more subcarriers are allocated to HP users to reach the minimum rate of the HP users in the subcarrier allocation. It can be seen from the figures that with sufficient power and subcarriers, subcarriers are indeed allocated with few reallocation steps. This means that real-time results can be achieved more quickly. When subcarriers and power are insufficient, the proposed scheme maximizes the data rate and also considers the overall balance of data rate of LP users as much as possible.

Fig.5.4(c) further presents the total data rate achieved with the proposed method with only equal power allocation, i.e. proposed method without power allocation, and the benchmark scheme when the radius of the drone coverage area varies from 500 meters to 1000 meters. It can be seen from Fig.5.4(c) that the performance of chunk-based resource allocation outperforms the subcarrier-based resource allocation when the number of subcarriers per chunk is properly chosen. But, the number of possible combinations in the benchmark method is $(2K)^N[Q_0^{(H)} + Q_0^{(L)}]/(2N')$, where N' is the number of subcarriers per chunk and the data per symbol for the kth user to transmit in an allocation period are $Q_0^{(H)}$ and $Q_0^{(L)}$ bits for the two types, respectively. The number of possible combinations in the proposed method is $(K_h - K'_h)^{(N-N'_h)}$, where K'_h is the HP user who has already fulfilled the data rate and N'_h is the subcarrier assigned to the HP user under the condition that the minimum guaranteed rate of the HP user is satisfied. In comparison, the complexity of the proposed method is much less than that of the benchmark method. This is because the rapid establishment of an adaptable and efficient emergency communication network is essential. The lower the complexity of the system, the more efficient the emergency communication network will be.

With the increase of the coverage radius, the total data rate and gap between the proposed method and the benchmark method decreases. The main reason for the increase in data rate is affected by the combined user subcarrier allocation and power allocation, but is not determined by the separate subcarrier allocation or power allocations.

5.4.3 Impact of number of users on the data rate

In this section, the performance of the emergency system is presented in terms of number of users variation and sum rate.

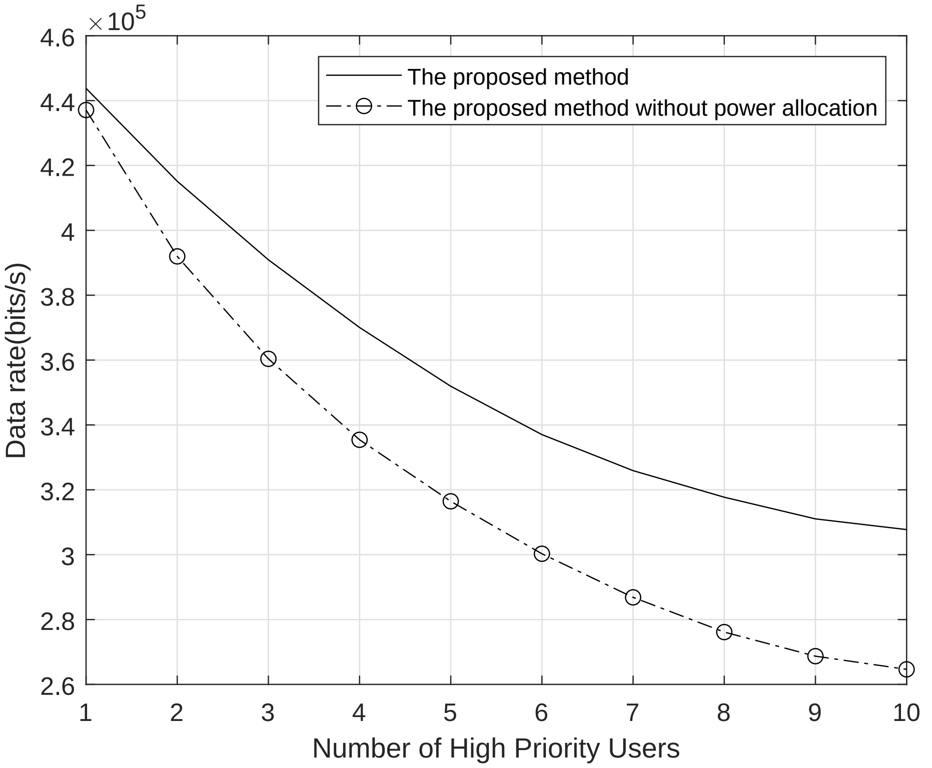
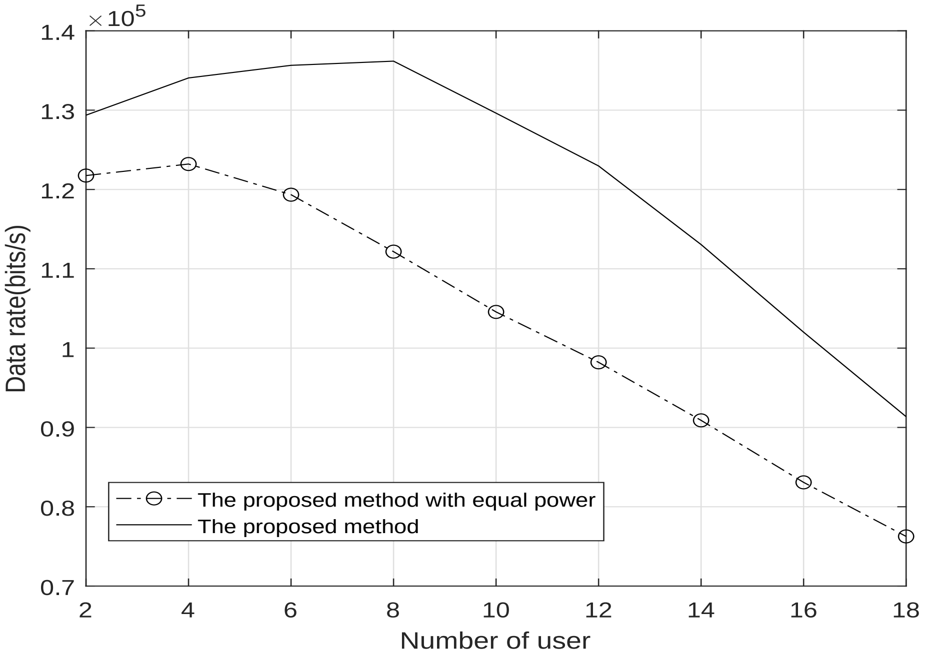


Figure 5.5: Total data rate of all users vs. number of HP users

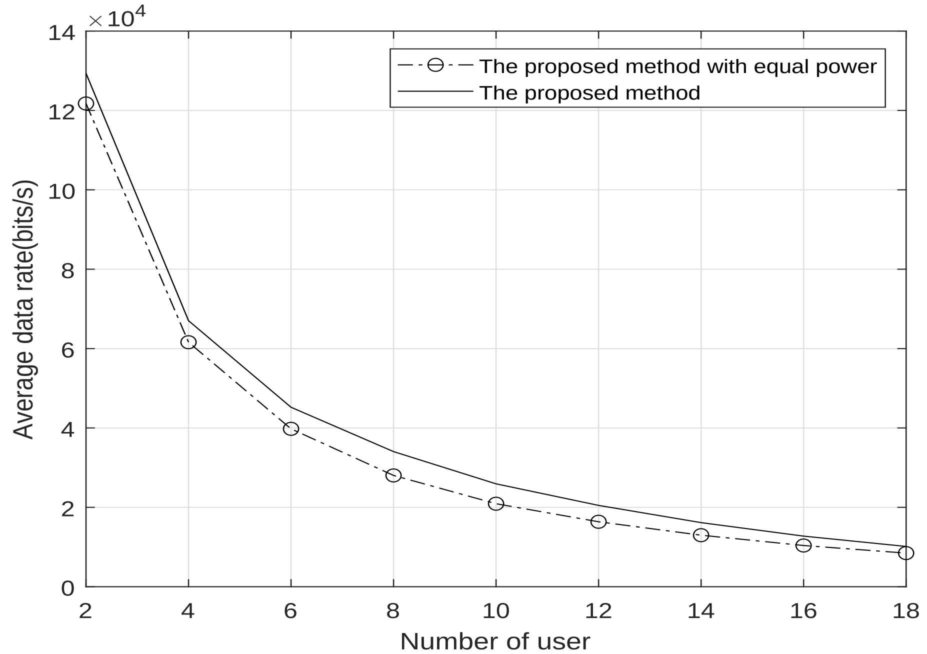
Fig.5.5 shows the data rate versus the number of HP users when the total number of users is constant. The total number of users is set to $K_h + K_l = 10$, where the minimum data rate for HP users is $r_{th} = 6$ kbit/s. The total transmitted power is set to $p_t = 0.375$ watt and the number of subcarriers is set to $N = 30$. It can be seen that when the number of subcarriers and the total number of users remain the same, the total data rate decreases when the proportion of HP users increases. Comparing the proposed method and the proposed method with equal power, the gap in total data rate increases. However, the decrease of the total data rate with the power allocation has slowed down. The reason for this result is that when HP users increase, in the subcarrier allocation stage, more subcarriers are allocated to suboptimal users to meet the minimum data rate of more HP users. This means that the average SNR of the subcarriers decreases, which increases the proportion of the increase in the power allocation of the waterfilling algorithm. This means that the average SNR of the subcarriers decreases and thus the share of the increased data rate due to the power allocation increases.

This is because as the proportion of HP users increases, the number of subcarriers allocated to users with the best SNR decreases. Therefore, the average SNR for each subcarrier decreases, which increases the performance gap between the two schemes. When the number of HP users increases, the method proposed in this chapter can effectively reduce the wastage of subcarriers and power, thereby increasing the overall data rate of users, as shown in the result in Fig.5.5.

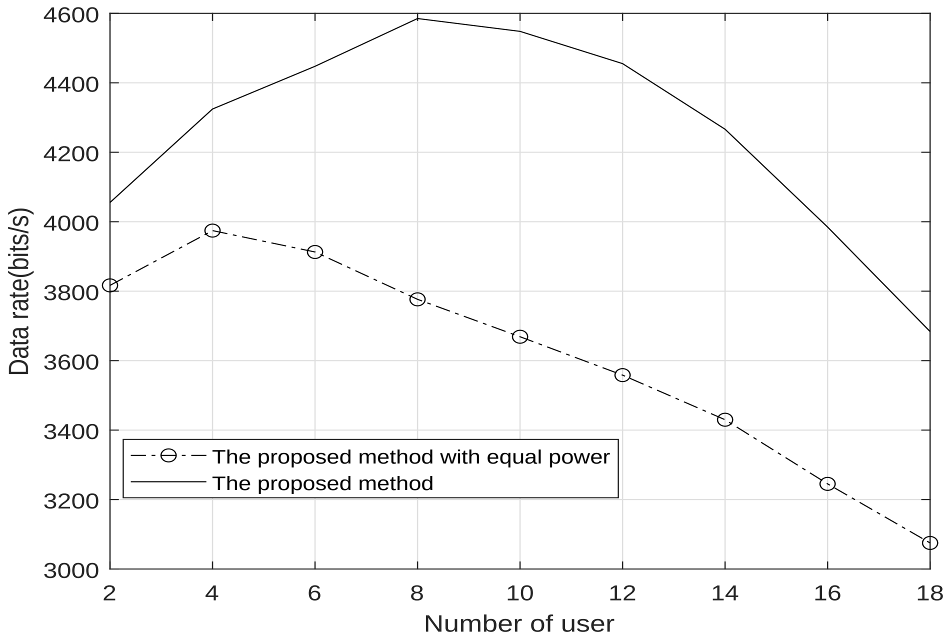
Fig.5.6(a) to Fig.5.8(a) show the relationship between the data rate and the number of users when the ratio of HP users to LP users is constant. Fig.5.6(b) to Fig.5.8(b) show the average data rate of users versus the number of users. The minimum data rate for HP users is $r_{th} = 6$ kbit/s The total transmitted power is set to $p_t = 0.5$ watt and the number of subcarriers is set to $N = 64$.



(a) Data rate of LP users



(b) Average data rate of LP users

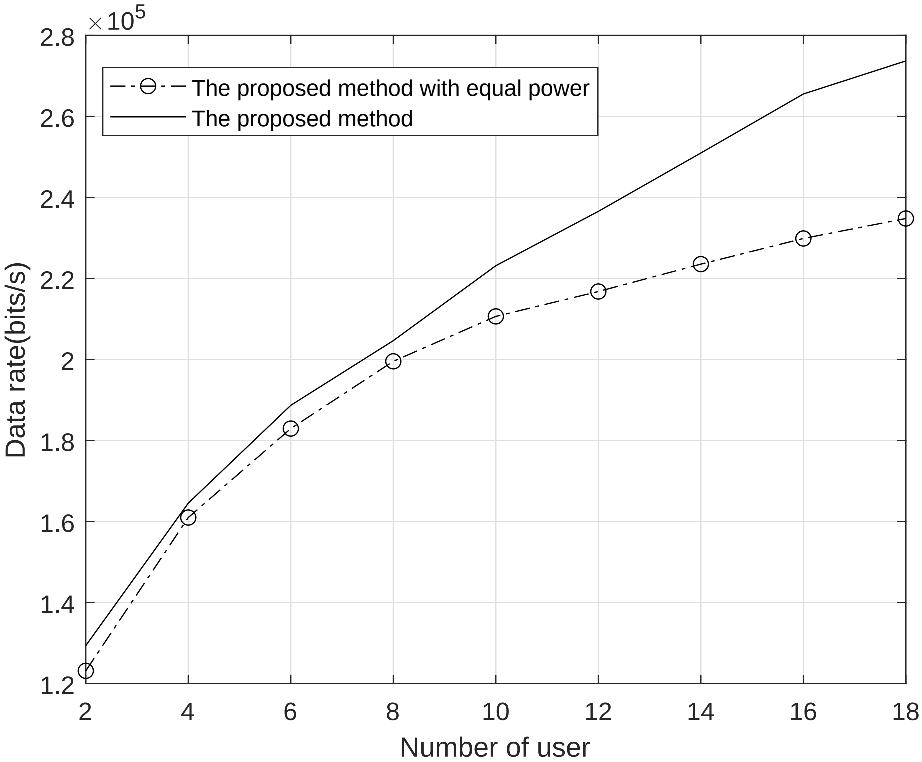


(c) Average subcarrier data rate of LP users

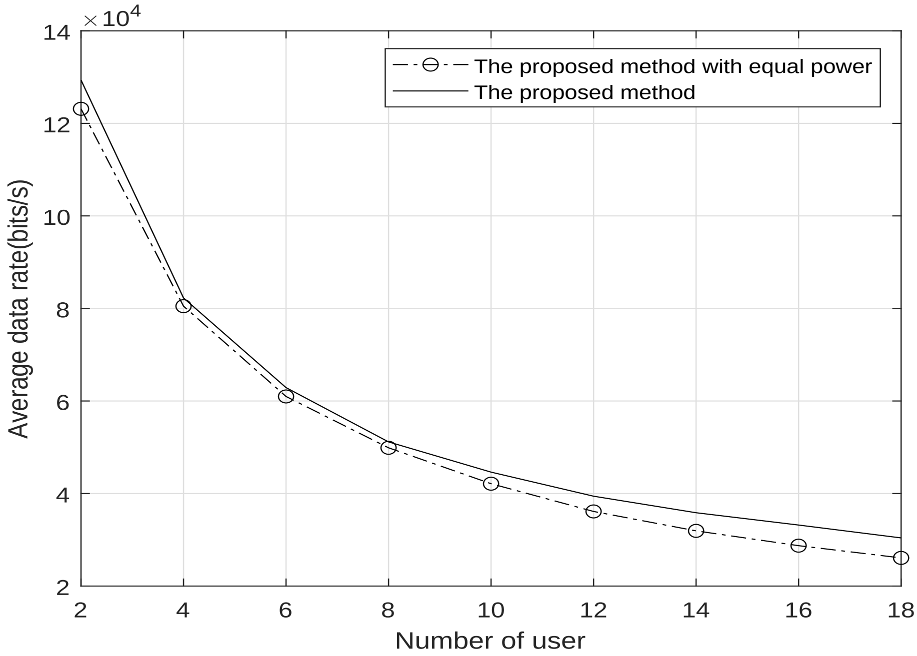
Figure 5.6: Data rate of LP users vs. number of users

Fig.5.6(a) shows the variation between the number of LP users and the data rate. Fig.5.6 (c) shows the variation between the number of users and the average subcarrier data rate belonging to LP users. The data rate of the proposed method with equal power reaches the maximum value when the number of users is equal to 4, and then the data rate and the average subcarrier data rate decrease when the number of users increases. The proposed method shows that when the total number of users is less than 8, the data rate increases as the number of users increases. When the number of users is equal to 8, the data rate of the proposed method reaches the maximum data rate and the gap between the data rate of the proposed method and the data rate of the proposed method with equal power also reaches the maximum value. After that, the data rate decreases as the number of users increases.

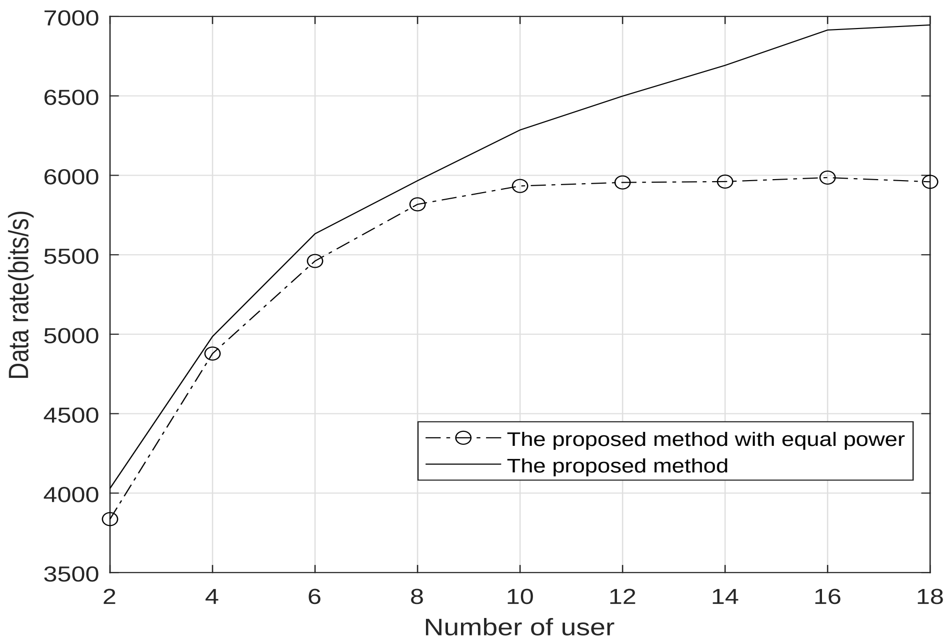
Fig.5.6(b) shows that the user data rate decreases as the number of users increases. When the number of users reaches 8, the gap between the data rate of the proposed method and that of the proposed method with equal power reaches the maximum value. When the number of users is greater than 8, the gap between the two decreases as the number of users increases.



(a) Data rate of HP users



(b) Average data rate of HP users



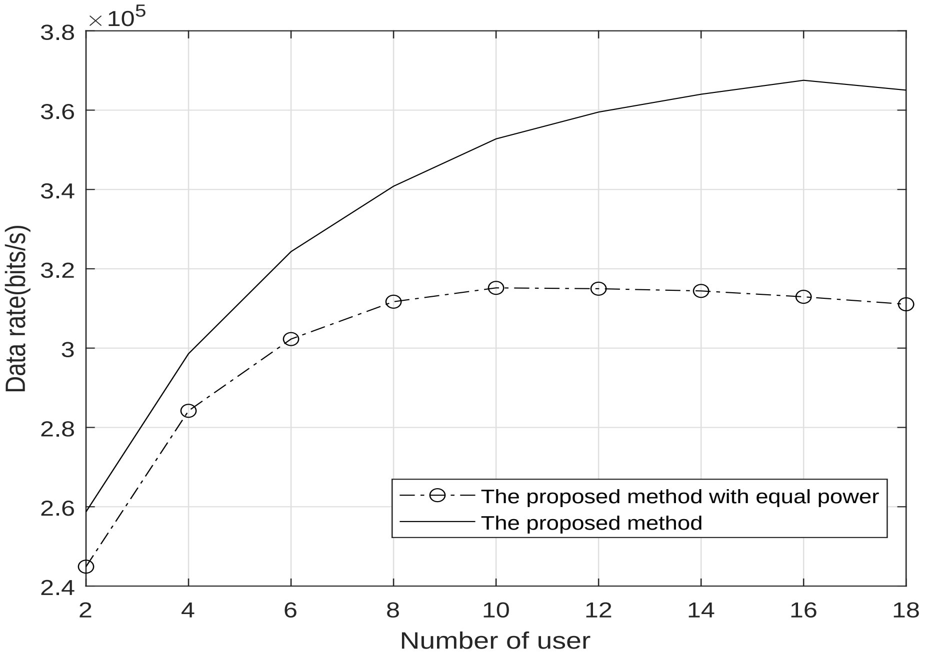
(c) Average subcarrier data rate of HP users

Figure 5.7: Data rate of HP users vs. number of users

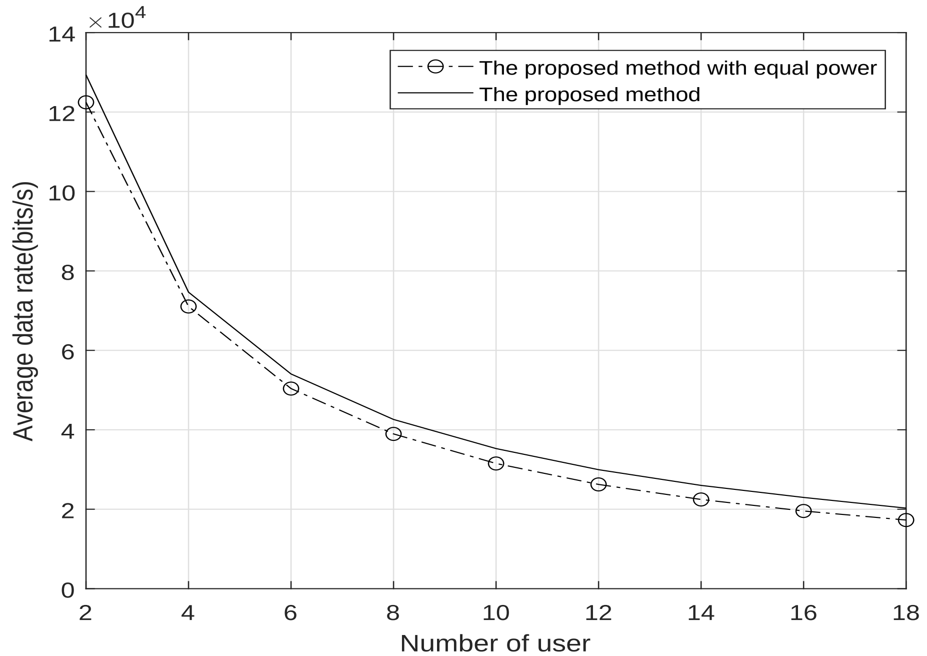
Fig.5.7(a) shows the change between the number of HP users and the data rate. Fig.5.7(c) shows the change between the number of users and the average subcarrier data rate of HP. When the total number of users increases, the total data rate and the average subcarrier data rate for HP users also increase, and the data rate increases as the power allocation increases. However, the magnitude of the increase decreases as the total number of users increases. The reason for this decrease is that as the number of HP users increases, more and more subcarriers are allocated to HP users with suboptimal SNR so that all HP users can meet the minimum rate requirement.

Fig.5.7(b) shows the change between the number of HP users and the average data rate. As the total number of users increases, the average data rate for HP users decreases and the trend is downward. The difference between the data rate of the proposed method and the proposed method with equal power is greater when the number of users is equal to two than when the number of users is between 4 and 8. The difference increases with the number of users when the number of users is greater than 8.

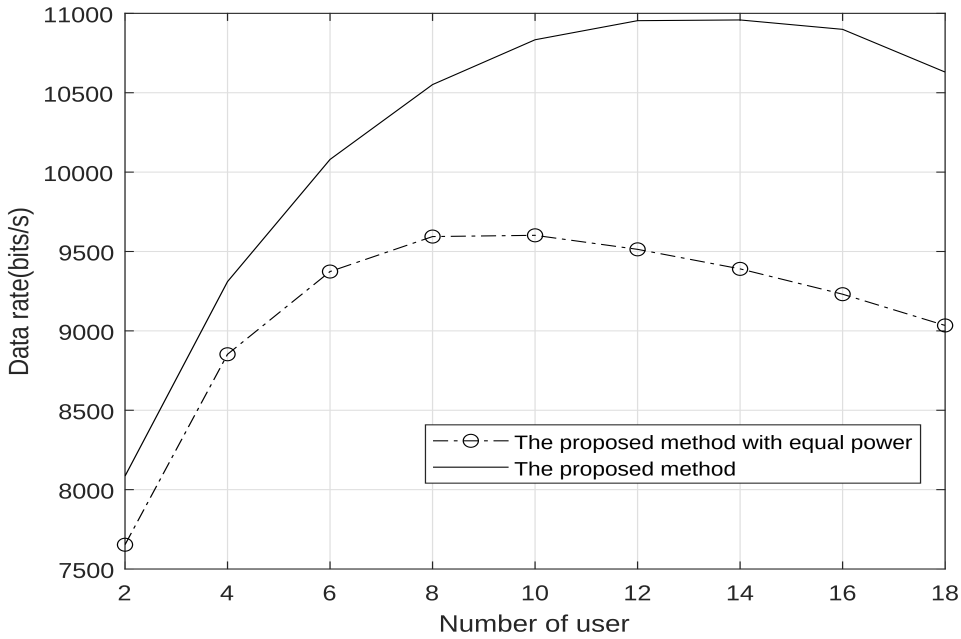
The relationship between the total data rate and the number of users can be seen in Fig.5.8(a). Fig. 5.8 (c) shows the variation between the number of users and the average subcarrier data rate for all users. The data rate of the proposed method increases with the number of users until the number of users reaches 16. The total data rate peaks when the number of users is 16.



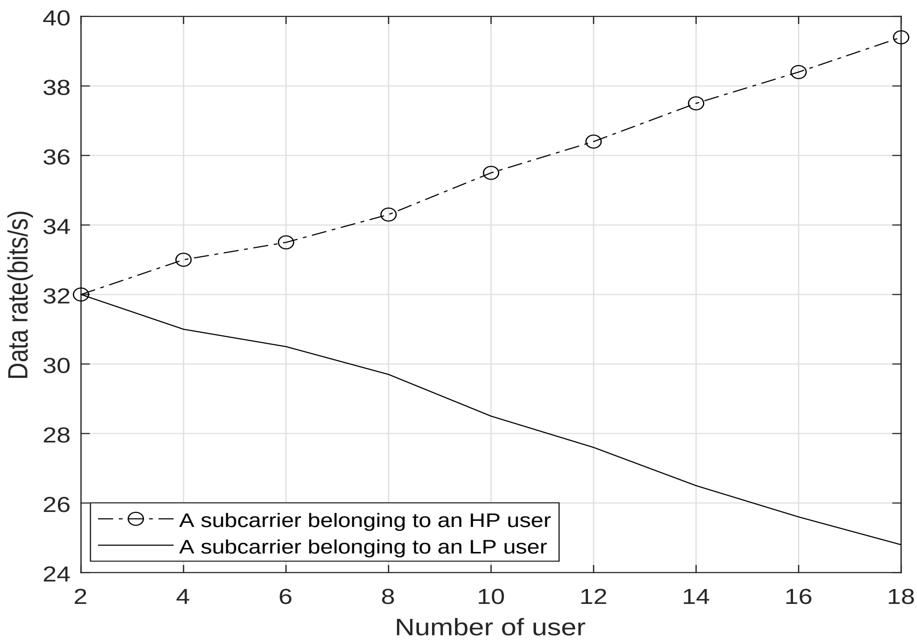
(a) Data rate of total users



(b) Average data rate of total users



(c) Average subcarrier data rate of total users



(d) Average data rate of total users

Figure 5.8: Data rate of total users vs. number of users

After that, the data rate decreases as the number of users increases. And the data rate of the proposed method with equal power continues to increase until the number of users reaches 10. When the number of users exceeds 10, the data rate of the proposed method with equal power decreases as the number of users increases, but the decrease is very small. This means that the power allocation method in the proposed method can effectively delay the drop in user data rate caused by too many users.

Fig.5.8(b) shows the change between the total number of users and the average data rate. As the total number of users increases, the average data rate of the total users decreases and the downward trend also decreases. It can be seen that the proposed method can effectively slow down the decrease in average data rate caused by the increase in the number of HP users.

Fig.5.8 (d) shows the variation between the number of users and the average number of subcarriers for different priority users. As the total number of users increases, the average number of subcarriers owned by users of HP increases steadily. The average number of subcarriers belonging to LP users steadily decreases. When the number of users is less than two, the number of subcarriers belonging to HP users is close to the number of subcarriers belonging to LP users.

From Fig. 5.6 to Fig. 5.8, it can be seen that if the number of users is very small, there are no other better users to assign subcarriers to, even if the SNR of a particular subcarrier for a particular user is relatively low. Thus, in Fig. 5.6(a) and (c), if the power and subcarriers are sufficient, as the number of users increases, the data rate of LP users also increases. However, as the number of users increases, the number of HP users also increases. Therefore, more and more subcarriers must be allocated to HP users so that all HP users have a data rate that is higher than the minimum required data rate. Fig. 5.7(b) also shows why the difference between the two values is greater for a number of 2 users than for a number of 2 to 8 users.

From this section, it can be seen that whether the number of users or the proportion of HP users to the total number of users increases, the proposed method can effectively reduce the loss of data rate while meeting the minimum data rate requirements of HP users. In summary, the more HP users, the greater the role the proposed method can play. This shows that the proposed algorithm is very suitable for the situation where the rescue team enters the disaster area and the rescue starts at the end of the disaster.

5.4.4 Impact of number of subcarriers on the data rate

In this section, presents the performance of the emergency system is presented in terms of variation in the number of subcarriers and the sum rate. For Fig.5.9 and Fig.5.10, the number of LP users is set to $K_l = 10$. The number of HP users is set to $K_h = 10$, where the minimum data rate for HP users is $r_{th} = 6$ kbit/s. The transmit power per subcarrier is set to $p_n = 0.0625$ watts. The abscissa representation of Fig.5.9 and Fig.5.10 is $log_2 * (N)$, where N is number of subcarriers.

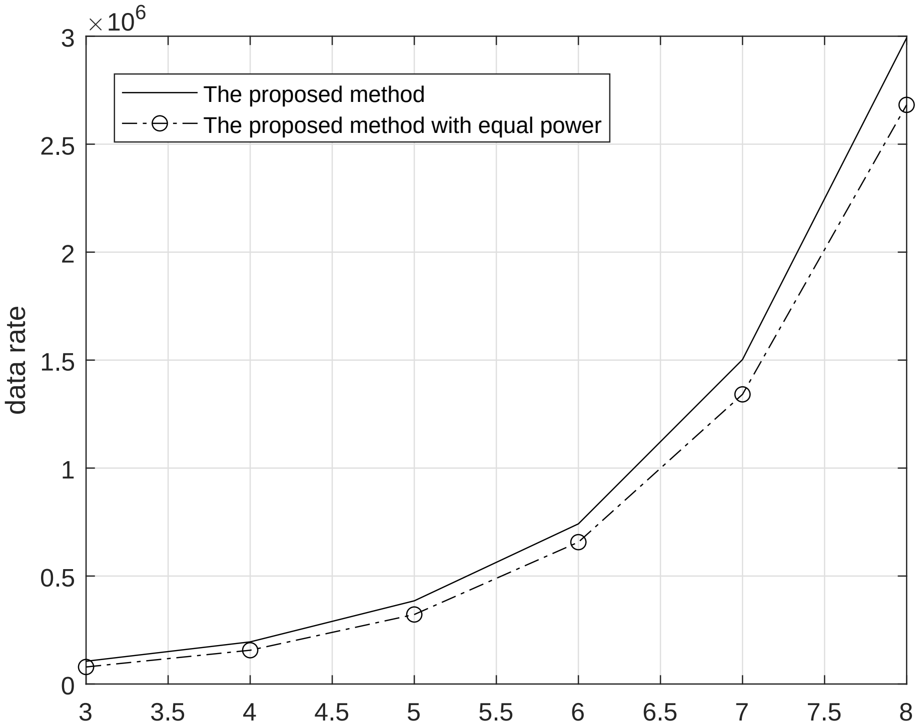


Figure 5.9: Data rate vs. number of subcarriers

It can be found from Fig.5.9 that when the number of users remains unchanged, as the sub-carriers increase, the total data rate increases. The gap between the data rate of the proposed method and the proposed method with equal power increases.

Fig.5.10 shows more intuitively that as the number of subcarriers increases, the data rate growth rate due to increased power allocation decreases.

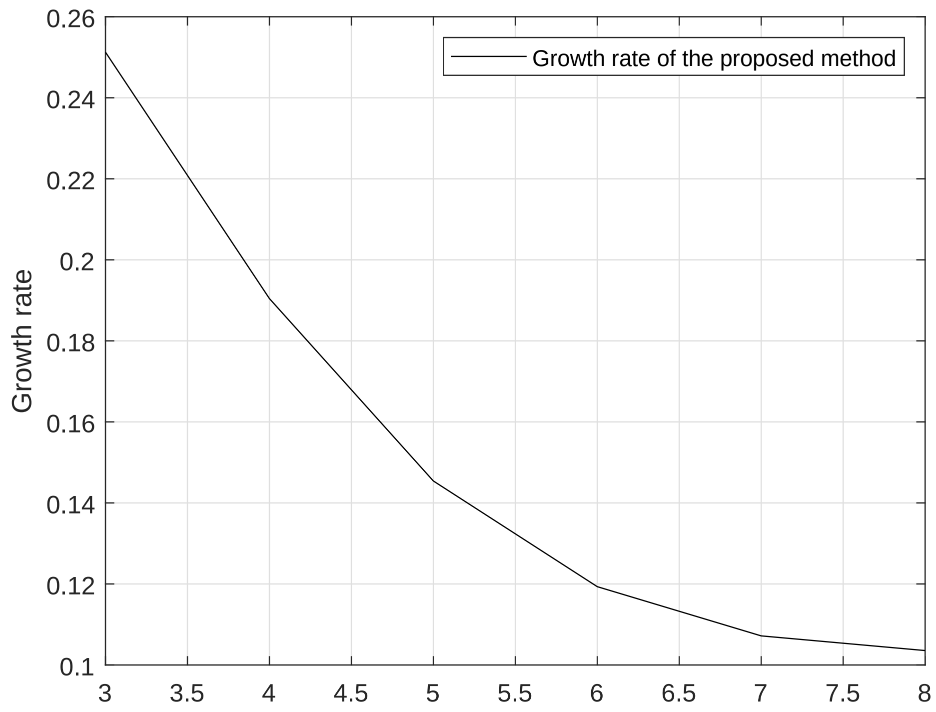


Figure 5.10: Growth rate vs. number of subcarriers

The data rate growth rate brought about by power allocation finally approaches ten percent.

Therefore, it can be seen from Fig.5.9 and Fig.5.10 that for a constant number of users and a constant ratio of HP users to LP users, as the average SNR of the subcarriers increases, the proportion of the user data rate increased by power allocation decreases.

In Fig.5.9 and Fig.5.10, the transmit power of each subcarrier remains unchanged. In contrast to Fig.5.9 and Fig.5.10, in Fig.5.11 to Fig.5.12 the total transmit power remains the same. The total transmit power is set to $p_t = 0.5$ watt. The rest of the factors remain unchanged.

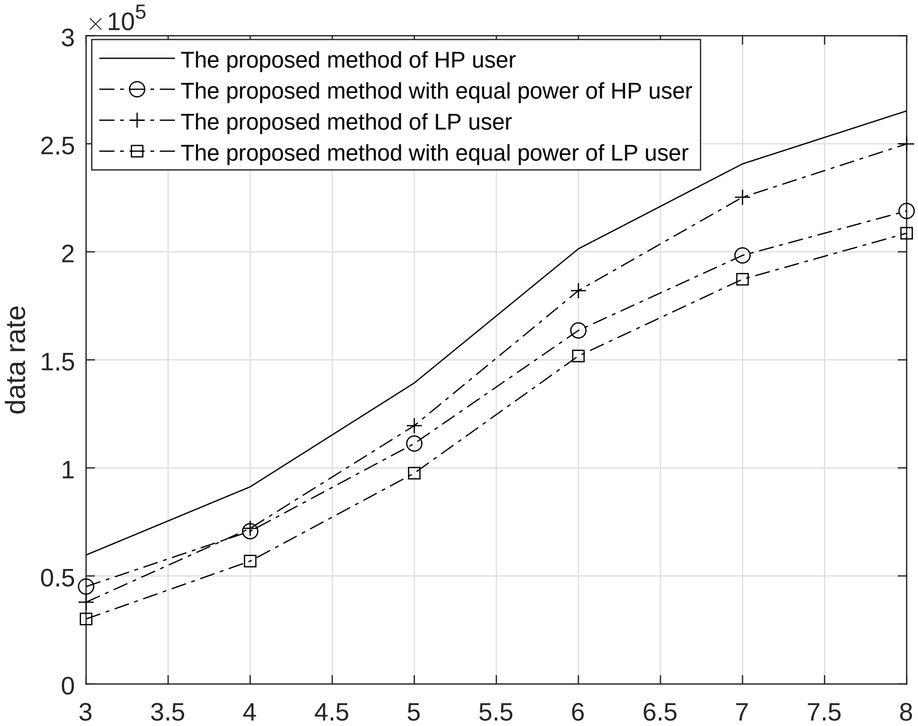


Figure 5.11: Data rate for HP users and LP users vs. number of subcarriers with constant power

Fig.5.11 shows the relationship between the data rate and the number of subcarriers for HP users and LP users. From this, it can be seen that the gap between the data rate of HP users and that LP users decreases as the number of subcarriers increases, regardless of the proposed scheme or the proposed scheme with equal power. The reason for this is as follows.

As the number of subcarriers increases, the average power allocated to the subcarriers decreases, but each HP user has more eligible subcarriers. This means that the proportion of additional subcarriers occupied by the minimum data rate requirements of HP users is also reduced. The gap between the data rates of HP users and LP users is thus reduced.

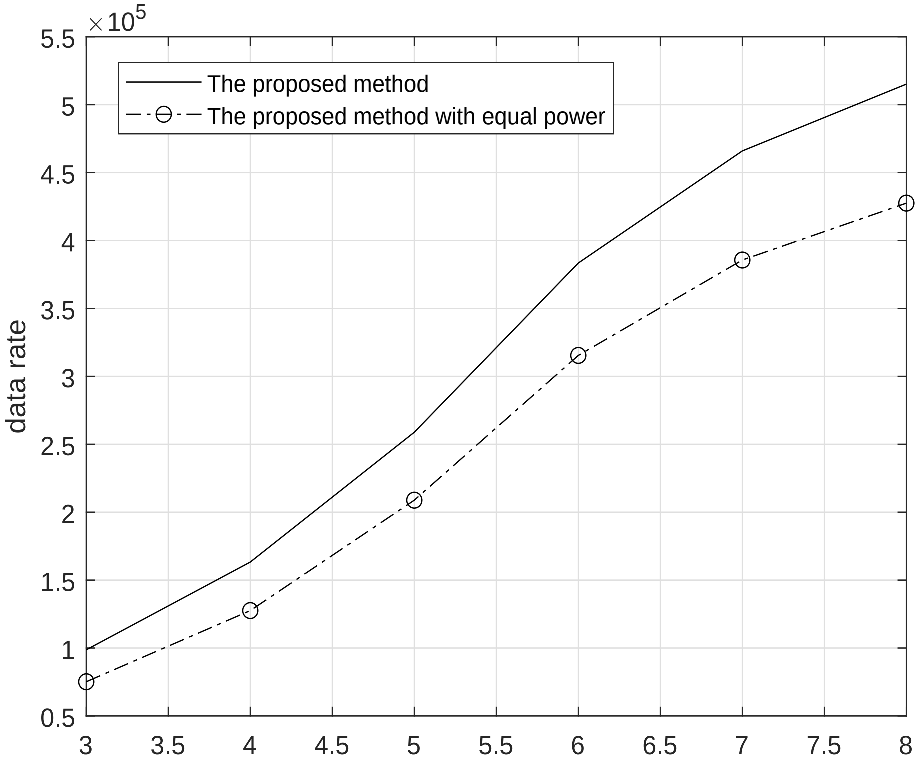


Figure 5.12: Data rate for all users vs. number of subcarriers with constant power

Fig.5.12 shows the relationship between the data rate and the number of subcarriers for all users.

Fig.5.12 shows that as the number of subcarriers increases, the gap between the user data rate of the proposed method and that of the proposed method with equal power increases. In contrast to Fig.5.9, with the increase in subcarriers, in Fig.5.12 the trend of increasing the user's data rate is much lower. The reasons for this are as follows.

Since the total transmit power is unchanged, as the subcarriers increase, the average power of each subcarrier decreases, which means that the average SNR of the subcarriers decreases. The reduction in the average SNR of the subcarriers allows the user data rate to increase more through power allocation. Thus, the gap between the two methods is increased.

As the total transmit power remains unchanged, the proportion of subcarriers allocated to the optimal user increases with the increase in subcarriers, which means that the data rate of the proposed method becomes closer and closer to the optimal solution. As a result, the upward trend in data rates has also slowed down.

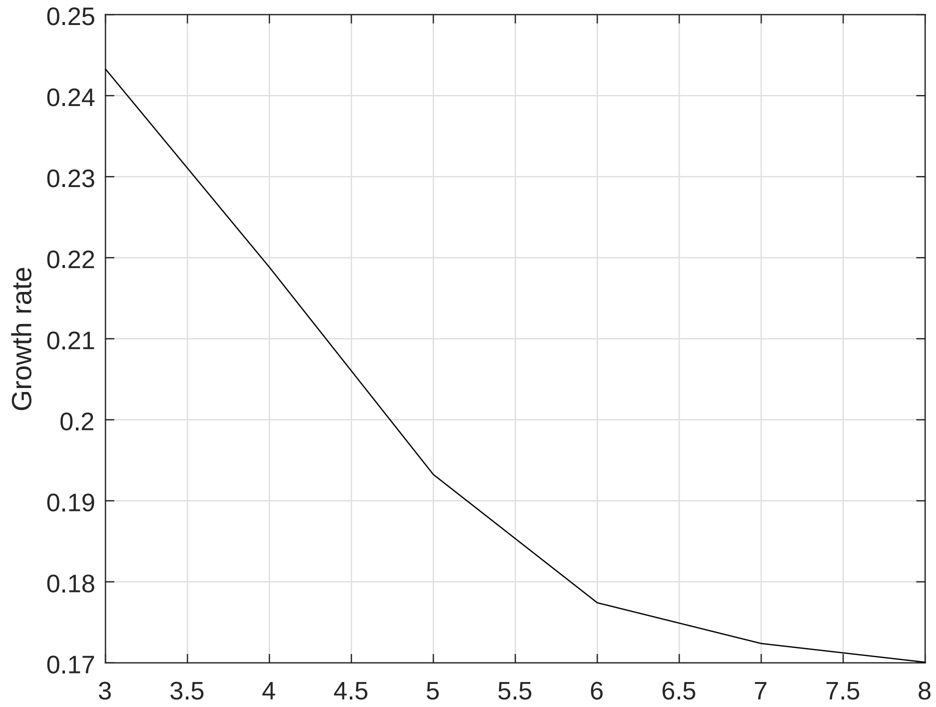


Figure 5.13: Growth rate vs. number of subcarriers with constant power

Fig.5.13 shows growth rates of data rates for the proposed method and the proposed method with equal power. This figure shows in a more intuitive way that the user data rate increases with the power allocation method. In Fig.5.13, the growth rate decreases as the number of subcarriers increases. In Fig.5.9, the lowest growth rate is closer to 10%. The lowest growth rate in this graph is 17%. Fig.5.13 shows a smaller decrease than Fig.5.9. This is because the average SNR of the subcarriers in Fig.5.13 also decreases, and the data rate increases more by power allocation.

5.5 Conclusions

To maximize the complexity of the algorithm proposed in Chapter 4, the performance difference between the algorithm and the brute force search method is somewhat large in the case of sufficient resources. Therefore, in Chapter 5, we propose a new algorithm to improve the shortcomings of the method in Chapter 4. Although the complexity of the algorithm in Chapter 5 is higher than that in Chapter 4, it is much lower than that of the reference method and methods in the literature. At the same time, Chapter 5 also takes into account user types in an emergency situation that do not appear in the rest of the literature.

In the subcarrier assignment problem, subcarriers are preferentially assigned to the best users of the channel, and then subcarriers are reassigned to the HP users who do not meet the rate by calculating the minimum rate differences, so that the complexity of the algorithm is greatly reduced. According to the above analysis, the computational complexity of this method is much lower than the brute force search method.

As for the power allocation, for each user, e.g. user k, on its assigned subcarrier, the water-filling algorithm is performed under the power constraint $N_k \cdot p_{max}/N$, and the power allocation is done by calculating the water level μ_{k_h} to achieve the maximum data rate.

In summary, compared to other schemes that cannot be realized due to high complexity, this chapter proposes an algorithm whose complexity maximizes the user's data rate within the range that can be realized in the emergency communication environment to maximize the use of communication resources.

Numerical simulation results show that the performance of the proposed method is close to that of the brute force cracking method regardless of the number of resources and users. When the number of users increases or the average user resource decreases, this method can effectively use the limited subcarriers and limited power to increase the total user data rate and bring the rate closer to the data rate of the brute force cracking method. Due to its low complexity, the algorithm can also be used in real-world applications.

Chapter 6

Conclusion and Future Research

Contents

6.1 Summary and Conclusions

With the application of flying BS drone technologies in emergency network systems, the drone can enable deploying a rapid, adaptable and efficient. Emergency network systems can ensure the communication capability of rescue teams and the ability of survivors to communicate with the outside world. In addition, the rescue teams can learn in good time in which areas survivors were waiting to be rescued through an emergency communication combination. However, some research challenges remain unresolved. For example, many previous works have investigated the joint optimization of subcarrier allocation and power allocation [11, 12]. The complexity of implementing this remains a major research challenge. Another major research challenge was to consider users with different priorities. Specifically, efficient resource allocation algorithms were needed that provide a good trade-off between system performance and implementation practicality.

The contributions in this thesis were proposed two different resource allocation schemes. Both schemes divide users into HP users and LP users and both guarantee minimum guaranteed rate for HP users.

The first scheme was an adaptive algorithm with low complexity. In this scheme, subcarriers were assigned to users according to the policy that they were first assigned to HP users. This procedure achieves quasi-linear complexity in terms of the number of users. Finally, the data of the brute force search method and this method were collected through simulation experiments. The data shows that the data rate of the proposed scheme was very close to the optimal data rate when there was a lack of resources.

The second scheme was an adaptive algorithm. In the proposed scheme, the two sub-problems of subcarrier allocation and power allocation were optimized separately. For the subcarrier allocation problem, a suboptimal low-complexity subcarrier allocation algorithm was proposed that uses Shannon's theorem and fading in emergency communication to maximize the achievable data rate with guaranteed minimum data rate for HP users in constrained scenarios. This was achieved by comparing the differences in optimal data rates between different users. For the power allocation problem, unlike in existing works, the different priorities of users were taken into account and power allocation was performed by iteratively applying a waterfilling algorithm to some individual HP users and globally to all other users. Numerical simulations prove that the performance of the proposed resource allocation scheme was close to the optimum and its complexity was much lower than that of the brute force search method.

6.2 Future Research Directions

Despite the many potential advantages that drones bring to emergency communications, such as rapid connectivity, flexibility and adaptability, etc., there are still many disadvantages, and some disadvantages cannot be overlooked, for example, the limited power of the drone. To make drones more suitable for use in future wireless networks, it is imperative to improve their efficiency and practicality in implementation. In terms of practicality, we need to think about the wireless communication environment of the wireless network. How to compensate for the imperfect channel state information caused by its rapid changes is an interesting research direction. As mentioned in this thesis, many systems cannot be applied in practise due to the complexity of implementation. Therefore, reducing complexity is also a research direction. Below are some interesting future research directions related to implementation complexity and the study of the effects of imperfect channel state information.

6.2.1 Implementation Complexity

Due to the low processing power of drones, complexity is an issue that needs to be considered. Another problem brought by the complexity of the multi-carrier drone assignment scheme is the huge resource consumption. Some future directions of study are proposed below to address these issues.

In order to maximize the data rate of transmission in the multi UAV OFDM system, a promising future direction of study is to apply the minimum mean squared error (MMSE) and evaluate the performance loss when the system optimization parameter update is delayed based on the channel correlation. A major source of MMSE complexity is the calculation of demodulation weights, which involves matrix inversion operations. In scenarios with high correlation between channel coefficients across adjacent symbols, the weight vector of the MMSE may not need to be calculated and updated for each modulation symbol, which drastically reduces the computational complexity. The computational complexity of the MMSE could also be reduced by applying chunk-based resource allocation [14,15] in multi-carrier systems. The key idea behind this solution is to transform the non-trivial allocation problem into an MMSE problem. In this way, the allocation problem can be solved by the alternating optimization method.

Since wireless communication environments can change rapidly and optimal resource allocation requires real-time computations, the application of machine learning techniques can achieve rapid adaptation of system parameters to the time-changing environments, thus significantly reducing the computational complexity of resource allocation. Therefore, a possible future direction of study is to apply machine learning techniques to develop low complexity resource allocation systems in multi-carrier systems. In addition, machine learning techniques can be used to adaptively calculate how often the parameters of the weight vector of the MMSE need to be updated according to the variability of the channel conditions in time, frequency and space.

6.2.2 Imperfect Channel State Information

If the channel state information is imperfect, it may lead to errors in subcarrier allocation and power allocation, thus affecting system performance. Therefore, understanding the channel state information of drones and users in real-world scenarios is critical to improving the performance of UAVs in emergency communication networks.

In this sense, an interesting research direction is to predict fading channels in wireless communication systems using machine learning. Then use different fading channels for different environments, such as the Rayleigh fading channel and the Rice fading channel. This could be applied to emergency communication systems with imperfect channel state information to develop techniques to improve system performance.

Another important line of research is the study of drones in more challenging channels of communication conditions, such as improving the realism of the environment by simulating the uncertain activities of the crowd. While the complexity of the environment increases, the performance of the drone can be improved by understanding the performance limits of the system in such scenarios.

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